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Optimizing Renewable Energy Integration for Sustainable Cryptocurrency Mining

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The increasing energy demands and environmental impacts of cryptocurrency mining have intensified the need for sustainable solutions. This study develops a deterministic optimization model to integrate solar energy into mining systems, aiming to maximize profitability while enhancing renewable energy utilization. Unlike prior studies that focused only on isolated energy flows or fixed operational setups, the proposed model systematically manages energy allocations, mining operations, and investment planning across a 12-month seasonal horizon. Results demonstrate the system's ability to achieve 95.88 % renewable energy utilization and maintain profitability within practical investment limits, with an ROI of 71.59 %. Scenario analysis highlights the capital thresholds required for breakeven performance and identifies the onset of diminishing returns. These findings validate the potential for cost-effective, sustainable cryptocurrency mining through strategic renewable energy integration, establishing a foundation for future enhancements involving operational flexibility and uncertainty modelling.

1. Introduction

Cryptocurrency mining, fundamental to blockchain networks, requires significant computational power and electricity. Bitcoin mining consumed approximately 173.42 TWh between 2020 and 2021, surpassing many countries' energy usage (Li et al., 2018). This high consumption exacerbates environmental degradation and operational costs, posing sustainability challenges. Traditional mining operations rely largely on non-renewable energy, significantly contributing to carbon emissions and straining power grids (Chamanara and Madani, 2023). Renewable energy integration, particularly solar power, has emerged globally as a promising solution. Such integration aligns with Sustainable Development Goal 7, improving sustainability and lowering operational costs (Gundaboina et al., 2022). Studies on operational optimization have explored hybrid renewable systems to improve sustainability outcomes (Esteso et al., 2023), while others have applied multi-objective frameworks to balance environmental and economic goals in energy planning (San Juan et al., 2018). However, many models still emphasize cost minimization or geographic site selection, overlooking the time-dependent operational demands of cryptocurrency mining and the variability of renewable energy supply. Renewable-powered mining systems have been proposed (Bhatt et al., 2024), and microgrid-based solutions explored (Lotfi et al., 2023), yet both lack attention to machine-level planning and energy flow decisions over time. Efforts to enhance system-level flexibility in electricity markets (Augustin et al., 2016) and studies framing mining as virtual energy storage (Hajiaghapour-Moghimi et al., 2024) similarly overlook seasonal dynamics and long-term energy allocation.

This study addresses these gaps with a deterministic optimization model that manages energy allocation among mining, battery storage, and grid interactions over a 12-month planning horizon. Unlike existing single-flow or static models, the proposed framework integrates multi-period decisions on mining machine procurement and operations, considering seasonal solar variations. A deterministic approach was adopted to simplify the model structure and focus on core investment and energy allocation strategies under seasonal conditions. This serves as a foundational step before incorporating uncertainty in future work. However, the model does not account for real-world variability in solar generation, electricity prices, or equipment degradation, which may affect its accuracy in practice.

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2. System Definition

The system under study is a solar-powered cryptocurrency mining operation focused on optimized energy management and profitability. It comprises solar panels generating electricity, battery storage units, mining machines, and interactions with the electrical grid.

Solar-generated energy can power mining directly, stored in batteries, or be sold to the grid. When solar output is insufficient, grid electricity supplements mining activities. Multiple mining machine types with distinct startup costs, hash rates, and energy efficiencies are considered, with all machines purchased initially for simplified planning.

The optimization model identifies the optimal count of solar panels, initial mining machine procurement, and the monthly allocation of energy across mining, storage, and grid interactions. Seasonal solar variability and profitability objectives guide these decisions, while capital constraints ensure realistic financial planning.

3. Model Formulation

3.1 Assumptions

The model assumes that all mining machines are purchased at the start of the 12-month planning horizon, with no additional purchases allowed thereafter. Cryptocurrency price, mining difficulty, and electricity prices are considered constant over the entire period, with the fixed-price assumption recognized as a limitation given the volatility of cryptocurrency markets and its potential to increase or decrease profitability depending on market direction. Solar energy can be directly used for mining operations, stored in batteries for future use, or sold to the grid, while electricity from the grid supplements mining needs when necessary. The cost structure accounts only for initial system investments, grid electricity purchases, and mining pool fees, with other operational expenses such as cooling energy use and maintenance costs excluded to maintain model clarity and emphasize core energy allocation and investment strategies. These exclusions are acknowledged as limitations. A capital constraint limits the total initial investment in solar panels, battery storage, and mining machines.

3.2 Objective Function

The objective of the model is to maximize total profit, defined as total revenues minus total costs over the 12-month planning horizon, as shown in Eq(1).

$$\text{Max Profit} = \text{Revenue} - \text{Cost} \tag{1}$$

Revenue consists of two components: the earnings from selling surplus solar energy to the grid and the revenues generated from cryptocurrency mining operations, expressed in Eq(2). The mining revenue per machine per h is calculated in Eq(3) based on the machine's hash rate, the network difficulty, the block reward, and the cryptocurrency price (Hajiaghapour-Moghimi et al., 2021).

$$\text{Revenue} = \left(\sum_t GR_t\, E_{grid,t} + \sum_j \sum_t \left(CMBR_{jt} \cdot 720\, \frac{h}{month} \right) \right) \tag{2}$$

$$CMBR_{jt} = \left(\frac{3600 \cdot H_j \cdot BR}{2^{32} \cdot DF} \right) \cdot CP \cdot CM_{jt} \quad \forall jt \tag{3}$$

Total cost, detailed in Eq(4), accounts for the initial investment in the renewable energy system and mining machines, along with the monthly cost of purchasing electricity from the grid. The breakdown of the initial system investment (SPI) is given in Eq(5), covering the costs of solar panels, inverters, and batteries. The mining machine-related costs (CMM) are captured in Eq(6), reflecting the initial machine purchase costs and the mining pool fees, which are computed as a percentage of mining revenues as indicated in Eq(7).

$$\text{Cost} = SPI + \sum_t GC_t\, GP_t + CMM \tag{4}$$

$$SPI = (PC \cdot SN) + IC + BC \tag{5}$$

$$CMM = \sum_j CMIC_j\, CMP_j + \sum_j \sum_t M_{jt} \tag{6}$$

$$M_{jt} = CMR_{jt} MP \quad \forall jt \tag{7}$$

3.3 Constraints

The capital constraint in Eq(8) ensures that the total initial investment, including the renewable energy system and mining machines, does not exceed the available capital budget.

$$SPI + \sum_{j} CMIC_j \, CMP_j \leq CAP \tag{8}$$

Eq(9) calculates total monthly solar energy production by multiplying the number of active panels with their rated capacity, efficiency, and the average number of daily peak sunlight h, scaled over a month. This formulation captures how energy generation varies with system size and seasonal solar conditions. Eq(10) ensures that active panel count each month does not exceed the total installed, allowing the model to adjust usage depending on capital allocation. Once monthly production is determined, Eq(11) governs its allocation across three uses, mining operations, battery storage, and grid sales. Energy not used immediately for mining or sold to the grid is directed to battery storage, ensuring that all generated energy is accounted for within the system.

$$EP_t = 30 \cdot SE \cdot SC \cdot SD_t \quad \forall t \tag{9}$$

$$SP_t \leq SN \quad \forall t \tag{10}$$

$$SP_t EP_t = \sum_{i} E_{it} \quad \forall t \tag{11}$$

Eq(12) tracks battery storage by accounting for discharge and remaining energy each month. Eq(13) ensures stored energy does not exceed battery capacity.

$$E_{storage,t-1} = EBU_t + E_{storage,t} \quad \forall t \tag{12}$$

$$E_{storage,t} \leq B \quad \forall t \tag{13}$$

Eq(14) sets a monthly upper limit on the amount of electricity that can be sold to the grid. Eq(15) defines the maximum electricity that can be purchased from the grid within the same period.

$$E_{grid,t} \leq GS \quad \forall t \tag{14}$$

$$GP_t \leq GB \quad \forall t \tag{15}$$

Mining machine operation limits are set in Eq(16), where the number of active mining machines cannot exceed the initial number purchased at setup.

$$CM_{jt} \leq CMP_j \quad \forall jt \tag{16}$$

Eq(17) ensures that the total energy supplied by solar, battery, and grid sources is sufficient to meet the mining demand. Eq(18) calculates monthly energy usage by multiplying the number of active machines per type with their rated power draw and full-time runtime. This energy requirement is not fixed but depends on how many machines the model chooses to operate in each period, based on energy availability and profitability. Eq(19) connects this energy consumption to mining capacity by linking machine hash rates with energy efficiency, allowing the model to estimate potential revenue from each configuration.

$$E_{mining,t} + EBU_t + GP_t = \sum_{j} CME_{jt} \quad \forall jt \tag{17}$$

$$\frac{CMEI_j}{1000} \cdot 720 \, \frac{h}{month} \cdot CM_{jt} = CME_{jt} \quad \forall jt \tag{18}$$

$$H_j = \frac{CMEI_j}{EE_j} \quad \forall j \tag{19}$$

Eq(20) enforces non-negativity for all energy-related variables. Eq(21) ensures panel and machine quantities are whole numbers.

$$E_{it}, EBU_t, GP_t, CME_{jt} \geq 0, \quad \forall ijt \tag{20}$$

$$SN, SP_t, CM_{jt}, CMP_j \in \text{integer}, \quad \forall jt \tag{21}$$

4. Illustrative Case Study

The case study models a solar-powered cryptocurrency mining operation over a 12-month planning horizon. Solar energy production parameters, including average daily peak sunlight h, were based on climatological data for Manila, Philippines (Manila Climate: Weather by Month, Temperature, Rain – Climates to Travel, 2020). Solar panel efficiency was set to 40.00 %, with rated capacity reflecting commercial photovoltaic system specifications, and this efficiency value was applied directly in the solar energy generation equations. Cryptocurrency parameters, such as Bitcoin network difficulty, block reward, and market price, were fixed at observed November 2024 values to stabilize revenue projections.

Table 1: Cryptocurrency Mining Machines Specifications

Machines	CMP1	CMP2	CMP3
Hash Rate (TH/s)	1,786.67	1,157.33	528.00
EE (J/TH)	3	3	3
Power (W)	5,360	3,472	1,584
CMIC (USD)	4,200	3,100	2,000
CMF (%)	10.00	10.00	10.00
MP (%)	2.00	2.00	2.00
UL (Months)	24	24	24

Three cryptocurrency mining machine types were considered, summarized in Table 1 as CMP1, CMP2, and CMP3, corresponding respectively to Bitmain Antminer S21 Hyd, MicroBT WhatsMiner M30S++, and Antminer T17+. These specifications represent idealized but plausible performance metrics to highlight system behavior, recognizing that they may not reflect the latest operational industry standards. A capital constraint of 100,000 USD was set to simulate financial planning conditions in renewable energy deployment, aligned with observed capital ranges in similar mining case studies (McDonald et al., 2022). More comprehensive data for the illustrative case study can be provided upon request.

Table 2. Optimal Solution

ROI (%)	Profit (USD)	BTC	SN	Mean Utilization	CMP1	CMP2	CMP3	Mean GP (kWh)
71.59	71,088.46	2.02	363	99.82 %	3	1	1	518.03

The optimal configuration determined by the model is summarized in Table 2. A return on investment (ROI) of 71.59 % and total profit of 71,088.46 USD were achieved. A total of 363 solar panels were installed, along with CMP1, CMP2, and CMP3 mining machine types. The mean solar panel utilization rate was 99.82 %, reflecting effective alignment between generation and demand. Monthly solar energy use averaged 12,045.67 kWh, with only 518.03 kWh purchased from the grid, demonstrating significant reliance on renewable sources. Model accuracy was verified by comparing the calculated bitcoin output of 2.02 BTC with the CryptoCompare Bitcoin Mining Calculator, confirming consistency in the energy-to-revenue computation.

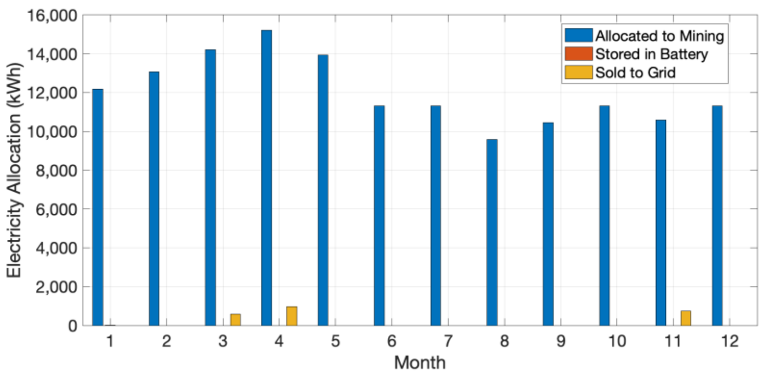

Figure 1: Monthly Allocation of Solar Energy to Mining, Storage, and Grid Sales

Figure 1 indicates that most solar energy directly powered mining operations. Battery storage and grid sales were minimal, as the model prioritized immediate solar use for profitability.

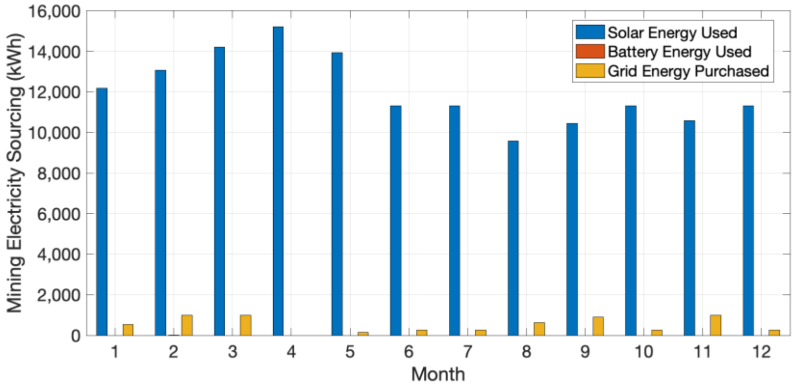

Figure 2: Monthly Sourcing of Mining Electricity from Solar, Battery Storage, and Grid Purchases

Figure 2 shows that solar energy supplied 95.88 % of mining electricity, with grid purchases making up 4.12 %. Battery discharge supported mining during peak solar periods, and grid purchases addressed shortfalls during periods of low solar availability.

5. Scenario Analysis

To better understand the relationship between capital size and profitability, scenario analysis was conducted by evaluating ROI at different investment levels. As shown in Figure 3, ROI follows a logarithmic trend, increasing rapidly at first and then slowing as capital investment grows. The minimum profitable capital was identified at around 12,000 USD, where ROI first turns positive at 16.43 %. Beyond this point, returns continue to improve until leveling off at approximately 52.37 % near the 40,198.58 USD mark.

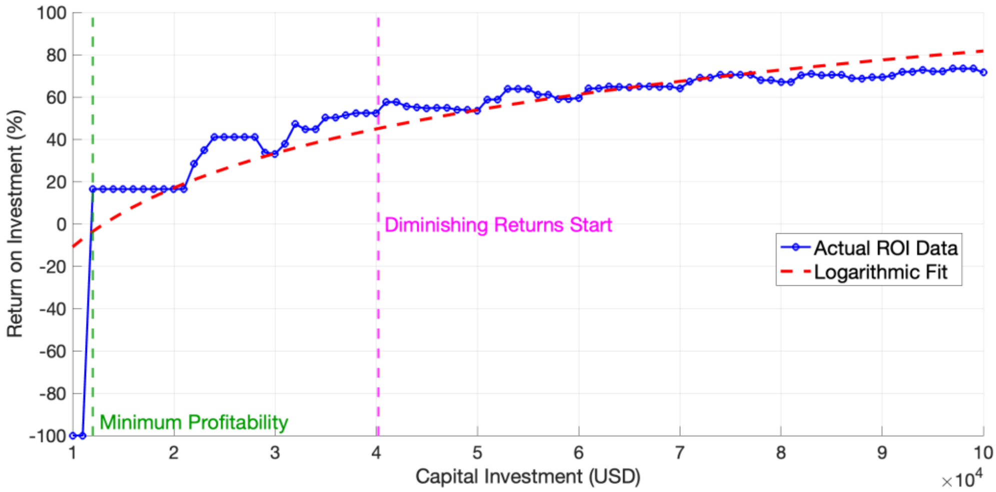

Figure 3: ROI vs Capital Investment (Logarithmic Fit)

This plateau reflects a natural economic saturation point, where further capital can still improve absolute profit but yields smaller ROI gains. While additional machines could theoretically absorb more solar energy, the fixed machine types, their upfront costs, and the limited 12-month horizon mean that each added unit contributes less value relative to its investment. As a result, the model gradually shifts from allocating capital to new machines or panels toward holding uninvested capital or accepting marginal returns. These results suggest an optimal capital range for system deployment, where profit can be maximized without overspending. The ROI curve also provides a practical reference for capital planning, helping investors decide when further expansion yields minimal returns. Future improvements could explore machine flexibility, variable electricity pricing, or additional operational levers that may shift the plateau higher or delay its onset.

6. Conclusion

This study formulated a deterministic optimization model for solar-powered cryptocurrency mining, demonstrating that substantial profitability and high renewable energy utilization can be achieved within realistic capital constraints. The model enabled over 95 % reliance on solar energy while minimizing grid dependency, achieving meaningful financial performance without requiring excessive investment. Scenario analysis identified a breakeven capital threshold near 12,000 USD, with diminishing returns observed beyond 40,000 USD, illustrating the typical saturation behavior seen in renewable energy systems. These findings validate the technical and economic feasibility of integrating renewables into energy-intensive operations and offer a practical framework for optimizing investment strategies in emerging energy markets. Building on this foundation, future work can incorporate operational cost considerations such as cooling and maintenance expenses, and flexible machine purchasing decisions across time. Uncertainty in solar production, electricity market conditions, and cryptocurrency price should also be examined. Exploring alternative optimization methodologies can further enhance system robustness and better capture the dynamic nature of high-demand energy environments.

Nomenclature

i – index for energy allocation
j – index for mining machine type
t – index for time period
SN – number of solar panels installed in system
SP_t – number of solar panel operational at period t
SE – solar system efficiency, -
SD_t – average peak sunlight h per day at period t, h/day
SC – capacity rating of a single solar panel, W
MP – mining pool fee, -
H_j – hash rate of mining machine type j, TH/s
GR_t – grid electricity selling price at period t, USD/kWh
GP_t – grid electricity purchased at period t, kWh
GC_t – grid electricity purchase price at period t, USD/kWh
EP_t – solar energy produced at period t, kWh
E_{it} – energy for allocation i at period t, kWh
EBU_t – battery energy discharged at period t, kWh
CMP_j – number of mining machines of type j purchased at initial setup
CM_{jt} – number of operational mining machines of type j at period t
CMR_{jt} – monthly mining revenue generated by machine type j at period t, USD
$CMIC_j$ – purchase cost of mining machine type j, USD
$CMEI_j$ – rated power consumption of mining machine type j, W
B – battery storage capacity, kWh
CAP – capital investment limit, USD

References

Augustin S., Smejkal T., Heussen K., 2016, Optimization of local microgrid operation in day-ahead electricity markets. Electric Power Systems Research, 141, 301–310.

Bhatt A., Bouri E., Das M., 2024, Renewable energy in cryptocurrency mining: Opportunities and challenges. Energy Reports, 10, 234–245.

Chamanara J., Madani K., 2023, Environmental externalities of cryptocurrency mining: A systematic review of Bitcoin's energy and carbon footprint. Renewable and Sustainable Energy Reviews, 176, 113184.

Esteso A., Alemany M.M.E., Ortells J., 2023, Sustainable management of hybrid renewable energy systems: An operational optimization approach. Renewable Energy, 208, 1513–1527.

Gundaboina R., Maddala V.R., Chamola V., Hassija V., 2022, Blockchain-based solutions for energy trading and sustainability: Challenges, solutions, and opportunities. Sustainable Energy Technologies and Assessments, 51, 101926.

Hajiaghapour-Moghimi S., Abbaspour A., Kargar S., 2024, Optimal scheduling of cryptocurrency mining as virtual energy storage for smart grid flexibility. Energy Reports, 10, 1234–1245.

Li Y., Andoni M., Robu V., Flynn D., 2018, Optimal design of low-carbon electricity markets: Blockchain and distributed energy resources integration. Applied Energy, 232, 663–678.

Lotfi M., Ameli M.T., Fotuhi-Firuzabad M., 2023, Renewable-powered microgrids for sustainable Bitcoin mining: A site-robust optimization approach. Electric Power Systems Research, 210, 108088.

McDonald M.T., Hayibo K.S., Hafting F., Pearce J., 2023, Economics of open-source solar photovoltaic powered cryptocurrency mining. Ledger, 8, 1-26.

Manila Climate: Weather by Month, Temperature, Rain – Climates to Travel, 2020, <climatestotravel.com/climate/philippines/manila>, accessed 09.12.2024.

San Juan J.L.G., Sy C.L., Tan R.R., 2018, A Multi-Objective Optimization Model for the Design of a Biomass Co-Firing Supply Network. Chemical Engineering Transactions, 70, 223–228.