Leveraging Bitcoin Mining Machines in Demand-Response Mechanisms to Mitigate Ramping-Induced Transients

Elinor Ginzburg-Ganz, Ittay Eyal, Dmitry Baimel, Leena Santosh, Juri Belikov, Yoash Levron

Abstract—**Several previous works examine the use of cryptographic mining machines, for instance Bitcoin mining machines, in demand-response mechanisms, as part of the portfolio of assets managed by the grid operator. This paper extends this formulation by addressing the effects of fast ramping transients, which may often occur in power grids rich with renewable energy sources. The resulting optimization problem is solved based on Pontryagin's minimum principle. The solution is used to examine the profitability and usage of these machines in a real-world settings, based on data from the California ISO and the "Noga" grid operator. A sensitivity analysis is conducted, considering the effects of several key parameters, such as the electricity price, and the machines' price, hashrate and monetary revenue. These are examined for several different machine types that are available in the market today. The main conclusion is that the profitability of the discussed mechanism is highly influenced by the cost of the mining machines, and the percentage of renewable sources within the energy mix, where some scenarios are more profitable then others.**

Keywords—**Bitcoin, Demand response, Energy storage, Power demand, Power system transients, Renewable energy sources**

I. Introduction

RAMPING, or the ability of power systems to rapidly adjust generation output to match sudden fluctuations in electricity demand or supply, presents a significant challenge in modern power systems, particularly with the increasing integration of renewable energy sources. In addition to traditional demand-response strategies, utilizing massive power consumers like Bitcoin mining machines presents a novel approach for balancing the grid demand. These machines are significant power consumers, and may be operated when there is a need to increase power usage during periods of low energy consumption, to abstain from powering off generators and reducing ramping costs, or when there is an abundance of renewable energy generation, to avoid energy curtailment. By doing so, they help substantially reduce ramping costs and absorb excess energy that might otherwise be wasted, providing a flexible demand source that can be dialed up or down based on grid conditions very quickly. Moreover, the revenue from mining is another incentive to use these machine in for enhancing grid stability, instead of other proposed solution such as storage or curtailment. The profits from these machines might cover their operational costs, thus resulting in an economically feasible solution for power plant operators. This not only maximizes the utilization of renewable energy but also helps maintain grid stability by smoothing out fluctuations in demand and supply, making the overall power system more resilient and efficient.

In the recent literature, many researchers study this problem from different perspectives. One approach is demand response based control for ramping mitigation (DR-RM), which uses Bitcoin mining machines (BMMs) as flexible loads that adjust their power consumption dynamically in response to grid conditions [1], [2]. For instance, [3] focuses on smart grid systems necessitating secure demand response management schemes for real-time decision-making, to increase the effectiveness, stability and security of smart grid systems. The authors propose a secure DRM scheme for home energy management that is based on a Q-learning algorithm and an Ethereum blockchain protocol to make optimal decisions regarding price. From a different outlook, curtailment absorption using flexible mining loads (CA-DR) is yet another methodology for transient mitigation using BMMs. With this approach, the main objective is to absorb excess renewable energy that would otherwise be curtailed, preventing waste and ensuring grid stability [4], [5]. For instance, work [6] addresses the problem of peak shaving. In this article, the authors design and implement a blockchain-based prosumer incentivization system, in which the smart contract logic is based on an in-depth analysis of the "Ausgrid" dataset. Another example is the extensive review paper [7]. Here, the authors examine the potential of combining blockchain technology and machine learning techniques for the development of smart grids. The different approaches and some of their main properties are summarized in Table I.

Contribution: As shown in the literature review above, recent works have already proposed strong methods for operating mining machines (for Bitcoins, or other cryptocurrencies) for regulating the load and enhancing the grid stability. These methods typically follow the usual patterns of demand-response mechanisms, where generally the lower the total load, the more power is supplied to mining machines, and vice-versa [6], [8]. Previous works have

The work of J. Belikov was partly supported by the Estonian Research Council grant PRG1463.

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Paper submitted to the International Conference on Power Systems Transients (IPST2025) in Guadalajara, Mexico, June 8-12, 2025.

TABLE I

COMPARISON OF DIFFERENT APPROACHES TO BALANCE TRANSIENTS IN POWER SYSTEMS USING BITCOIN MINING MACHINES

Approach	Response Time	Implementation Complexity	Grid Benefit	Economic Feasibility
DR-RM	Seconds to minutes	Medium	Reduces ramping transients	Profitable if electricity price is low
CA-DR	Seconds	Low to Medium	Prevents renewable curtailment	Viable in high-renewable grids
A-DR	Seconds	High	Supports grid balancing & reserves	Revenue-generating but requires regulatory adaptation

investigated many aspects of this problem, and examined for instance the profitability of these machines in the context of demand-response, and the use of smart contracts when renewable energy sources are included in the generation mix.

The objective of this paper is to extend these previous works by including the aspect of ramping constraints, which is crucial in power systems with high penetration levels of renewable energy sources, as demonstrated by the famous "duck curve". In comparison to previous works, it is assume that machine owners are compensated not only for the generated power and lowering the power peak, but also for mitigating fast ramps, which are challenging for the system operator. Thus, this study explores an optimization problem that takes into account the electricity costs for the grid operator, the ramping costs (which assign a cost to the power derivative), and the revenue from the machines. We show that this problem can be efficiently solved based on Pontryagin's minimum principle, and thoroughly explore the profitability of the machines in this scenario. The simulations are based primarily on data taken from the "Noga" grid operator, which is examined under changing ratios of energy production from renewable sources. A sensitivity analysis is conducted, considering the effects of several key parameters, such as the electricity price, and the machines' price, hashrate and monetary revenue. These are examined for several different machine types that are available in the market today. The main conclusion is that the profitability of the discussed mechanism is highly influenced by the cost of the mining machines, and the percentage of renewable sources within the energy mix, where some scenarios are more profitable then others.

The proposed approach may be useful to both system operators and policymakers. From the perspective of system operators, the proposed approach may serve as an assisting tool for planning the cost efficiency of using Bitcoin mining machines for reducing ramping costs and mitigating the associated transient effects. For example, in the considered case study, real data from "Noga" grid operator is examined, and a scheduling mechanism is proposed. Alternatively, for policymakers, this paper aims to present the potential benefit of this demand-response mechanism, and motivates an open discussion to explore new tariff structures or incentive programs to encourage Bitcoin miners to act as flexible loads. As will be presented in the paper, there are grid operators that may benefit from this mechanism, such as ERCOT's large flexible load programs in Texas.

II. TECHNICAL BACKGROUND

Pontryagin's Minimum Principle is a method for finding an optimal control policy for a dynamic system, stating that the optimal control minimizes a certain Hamiltonian function. Consider the dynamic system $\frac{dx}{dt} = f(x,u)$, with the initial condition $x(0) = x_0, \quad u(t) \in \Omega$, and the cost function $J(u) = \int_0^{t_1} L(x,t,u)dt$, where t_1 is fixed and known. The objective is to find a control law u^* that minimizes the overall cost. Several additional assumptions are considered:

- The functions $f(x,u)$ and $L(x,u)$ are continuously differentiable with respect to x and u.
- The optimal control $u^*(t)$ is piecewise continuous in t.
- The set Ω is closed, or includes the entire space of $u(\cdot)$.

Necessary conditions for an optimal solution are related to the Hamiltonian $H(x,u,\lambda) = L(x,u) + \lambda^T f(x,u)$, and may be stated as follows:

1) $\frac{dx^*}{dt} = f(x^*,u^*)$, with the initial condition $x(0) = x_0$.
2) $\frac{d\lambda^*}{dt} = -\nabla_x H(x^*,u^*,\lambda^*)$, with the terminal condition $\lambda^*(t_1) = 0$.
3) $H(x^*,u^*,\lambda^*) \leq H(x^*,u,\lambda^*), \forall u \in \Omega$. This also leads to the condition that if u is unbounded and $\nabla_u H(x^*,u^*,\lambda^*)$ exists, then $\nabla_u H(x^*,u^*,\lambda^*) = 0$.
4) The Hamiltonian is constant over time $H(x^*,u^*,\lambda^*) = \text{constant}, \forall t \in [0,t_1]$.

III. MAIN RESULT

Consider a power system operator that attempts to balance its load demand using cryptocurrency mining machines (for instance, Bitcoin mining machines), which will be referred to as "miners". The simplified model consists of a grid-connected mining machine and an aggregated load. The load is described by its active power demand, which is represented by the function $p_L(t) : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ over a finite time interval $[0,T]$ for some given and known time T. The power supplied by the generator is denoted by $p_g(t) : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ and is associated with a cost function of the fuel consumption $c_g(t)$. More generally, this cost function may represent a general cost function with various objectives, such as carbon emission influenced by power generation. The miner is characterized by its power demand $0 \leq p_m(t) \leq \bar{P}$, and the profit obtained by its operation is $c_m(t)$. It is assumed that the miner's power consumption is much smaller than the total system's mining power (all Bitcoin miners), thus, it is justified to use a cost function $c_m(t)$ which is linear in the miner's power consumption. The instantaneous cost of electricity is

$$F(t) = c_g(t)p_g(t) + c_d(t)\left(\frac{\mathrm{d}p_g}{\mathrm{d}t}\right) - c_m(t)p_m(t). \quad (1)$$

This cost reflects (a) the fuel cost associated with the generated power, (b) the cost associated with rapid changes in generated power, which is represented by the term $c_d(t)\frac{\mathrm{d}p_g}{\mathrm{d}t}$, and (c) the revenue of the grid operator from using the mining machines. The objective of the grid operator is to minimize the total cost $\int_0^T F(t)\mathrm{d}t$ by choosing the optimal function $p_m(t)$, where the time horizon T is known. This leads to the following optimization problem:

$$\begin{aligned} \min_{\{p_m(\cdot)\}} \quad & \int_0^T \left(c_g(p_g(t)) + c_d\left(\frac{\mathrm{d}p_g}{\mathrm{d}t}\right) - c_m(t)p_m(t) \right) \mathrm{d}t, \\ \text{s.t.} \quad & p_g(t) = p_L(t) + p_m(t), \\ & 0 \leq p_m(t) \leq \bar{P}, \end{aligned} \tag{2}$$

where all the functions and constants are known and given, and the decision variable is the function $p_m(\cdot)$. It is assumed that $c_g(\cdot), c_d(\cdot) \in \mathcal{C}^2$ are strictly convex functions, and that the derivatives of c_g, c_d, denoted as c_g', c_d', define a mapping from $\mathbb{R}$ to $\mathbb{R}$. In addition, $p_L(t), c_m(t)$ are smooth periodical functions with a period T. The function ξ is used to eliminate the inequality constraint,

$$\xi(p_m) = \begin{cases} 0, \text{ for } 0 \leq p_m \leq \bar{P} \\ \alpha p_m^2, \text{ for } p_m < 0 \\ \alpha(p_m - \bar{P})^2, \text{ for } p_m > \bar{P} \end{cases} \tag{3}$$

where α is a constant.

The new formulation that arises is

$$\begin{aligned} \min_{\{p_m(\cdot)\}} & \int_0^T c_g(p_g(t)) + c_d\left(\frac{\mathrm{d}p_g}{\mathrm{d}t}\right) - c_m(t)p_m(t) + \xi(p_m)\mathrm{d}t, \\ \text{s.t. } & p_g(t) = p_L(t) + p_m(t), \\ & \xi(p_m) = \begin{cases} 0, \text{ for } 0 \leq p_m \leq \bar{P} \\ \alpha p_m^2, \text{ for } p_m < 0 \\ \alpha(p_m - \bar{P})^2, \text{ for } p_m > \bar{P} \end{cases} \end{aligned} \tag{4}$$

Note that when α approaches infinity, this last formulation is equivalent to (2).

one approach for solving this problem is Pontryagin's Minimum Principle [9]. To apply this principle, the following definitions are used:

$$\begin{aligned} x(t) &= p_g(t), \\ u(t) &= \frac{\mathrm{d}}{\mathrm{d}t}p_g(t), \\ \Omega &= [-\infty, \infty], \\ t_1 &= T, \\ f(x,u) &= u, \\ L(x,u,t) &= c_g(x) + c_d(u) - c_m(t)(x - p_L(t)) \\ &\quad + \xi(x - p_L(t)). \end{aligned} \tag{5}$$

Now, let us define the Hamiltonian

$$H(x, \lambda, u, t) = L(x, u, t) + \lambda f(x, u).$$

Using Pontryagin's minimum principle, the necessary conditions for an optimal solution $x^*(t), u^*(t), \lambda^*(t)$ to exist are the following ones:

1) $\frac{\mathrm{d}}{\mathrm{d}t}x^*(t) = u^*(t)$,
2) $\frac{\mathrm{d}}{\mathrm{d}t}\lambda^* = -c_g'(x^*) + c_m(t) - \xi'(x^* - p_L(t))$,
3) $H(x^*, \lambda^*, u^*, t) \leq H(x^*, \lambda^*, u, t)$ for all u.
4) $x^*(0) = x^*(T)$, and $\lambda^*(0) = \lambda^*(T)$. This is because $p_L(t), c_m(t)$ are periodical, and so the optimal solution must be periodical as well.

Here $c_g'(\cdot)$ is the derivative of $c_g(\cdot)$, and $\xi'(\cdot)$ is the derivative of $\xi(\cdot)$. The third condition is

$$c_d(u^*) + \lambda^* u^* \leq c_d(u) + \lambda^* u \quad \text{for all } u. \tag{6}$$

Since both sides of the equation are convex, the optimal u^* can be found by zeroing the derivative:

$$c_d'(u^*) + \lambda^* = 0. \tag{7}$$

According to the assumptions above, $c_d'(\cdot)$ is strictly monotonically increasing, and defines a mapping from $\mathbb{R}$ to $\mathbb{R}$, so one can write

$$u^* = (c_d')^{-1}(-\lambda^*). \tag{8}$$

This leads to the following explicit conditions for an optimal solution:

1) $\frac{\mathrm{d}}{\mathrm{d}t}x^*(t) = u^*(t)$,
2) $\frac{\mathrm{d}}{\mathrm{d}t}\lambda^* = -c_g'(x^*) + c_m(t) - \xi'(x^* - p_L(t))$,
3) $u^* = (c_d')^{-1}(-\lambda^*)$,
4) $x^*(0) = x^*(T)$, and $\lambda^*(0) = \lambda^*(T)$.

An equivalent feedback loop reflecting these conditions is presented in Fig. 1.

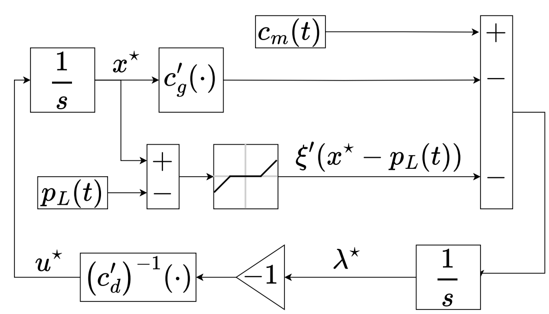


Fig. 1. A control loop that implements the optimal scheduling of the miner, as derived from Pontryagin's Minimum Principle.

IV. Case Studies and Numerical Results

In this section the profitability and characteristics of Bitcoin mining machines, as part of the portfolio of the "Noga" grid operator, are examined. Specifically, the objective is to reduce ramping charges, and to investigate how the profitability of the machines is affected by renewable energy penetration to the market. The files relevant for the analysis may be viewed in [10]. Further, realistic properties of these machines are explored, in terms of machine price, their power consumption, and hashrate, to ensure maximal revenue for the operator. It is assumed that the machine price directly affects the initial investment and payback period, while power consumption influences the ongoing operational costs, especially in energy-intensive mining processes. Hashrate, a measure of computational power, determines the machine's efficiency in solving cryptographic puzzles, and earning monetary rewards. Together, these factors are essential for evaluating the assumed profitability of mining operations in relation to other resources.

An evaluation is conducted, examining how the following factors influence the profitability of using these machines: (1) The influence of the ratio of renewable energy production out of the total production on electricity costs and thus on the profits gained from mining machines. (2) The influence of the ratio of renewable energy production out of the total production on ramping costs and thus on the profits gained from mining machines. Next, an investigation is performed, to quantify the potential profitability of using BMMs by the power company "Noga" for mitigating ramping effects and consuming excess power that is generated in the Israeli grid.

As the next step, an examination of several machine parameters is presented, focusing on machine prices, power consumption, and machine hash rate, upon which routing the excess energy during off-peak hours to the Bitcoin mining machines, will not only reduce ramping costs, and help sustain the longevity of infrastructure, but also produce profit to the machine operators. For each parameter set the optimal operation scheduling is presented. In each scenario, different types of loads and ratio of renewable energy production is examined, while trying to find the optimal parameter set, which will produce maximal revenue for the system operator over a time horizon of few years. The analysiz takes into account the growing percentage of renewable energy production, changing electricity costs, and profit decay of the machines.

An initial analysis is conducted to determine the effect of renewable energy production, specifically from solar sources, on the electricity prices. This data is not available for this grid operator, but it is available for the state of California, which has similar sun irradiation conditions. Hence, to perform this evaluation, historical data from the state of California is used. The dataset includes information about renewable and primary production, in addition to electricity prices, between the years 1970-2022, and may be accessed through [11]. In Fig. 2, one can easily observe that as more and more renewable energy sources penetrate into the market, and their share in the overall production increases, then electricity prices rise. This happens partially due to grid defection [12], and also to account for the inertia and reactive power correction that must be supplied by power plant operators, to keep the stability of the grid [13].

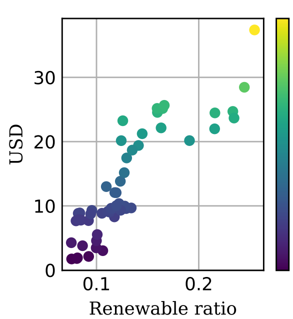


Fig. 2. Renewable energy production in % out of overall production effect on electricity prices in the state of California between the years 1970-2022.

The profitability of Bitcoin mining machines is very sensitive to changes in electricity prices. Following this analysis, an estimation may be calculated, regarding how the increasing percentage of renewable energy penetration, such as the trend observed in California and Israel, affects the mining machines' profitability. For the simulation, several popular BMMs were used. The BMMs parameters are displayed in Table II, and they are based on data acquired from [14].

TABLE II
BITCOIN MINING MACHINES PARAMETER SETS TAKEN FROM BITCOIN MINING COMPANIES

Machine	**Demand** [W]	**Hashrate** [Th/s]	**Income** [$/day]	**Electricity costs** [$/day]
Antminer S21	5360	335	15	0.1
Whatsminer M63	7283	334	14.49	0.1
Antminer S19	3250	110	5.05	0.06

The dependency of Bitcoin mining machines profit upon the electricity costs is quite complex, and is extensively discussed in [15]. However, in literature it is common to rely on a simplified model in which the monetary revenue of the Bitcoin mining machine is linear in the electricity price, for example, as seen in [16]. In work [16] the authors analyze a complex revenue model, accounting for marginal factors such as network hash rate, machine hash rate, and the time to mine a block, alongside with other factors including transaction fees and block reward, their hashing power and the probability of successfully mining a block. They show that the most influential factor on the profitability of a machine is the electricity prices, hence, giving the incentive to use a linear model for the relation between machine income and the electricity costs. Thus, the following relation describes the dynamics:

$$\text{Profit} = a - b \cdot \text{Electricity-Price}. \tag{9}$$

The parameter a describes the maximal daily monetary profit that can be achieved, meaning, the daily monetary revenue from the Bitcoin mining machine when the electricity price is zero, and b is a linear coefficient that represents how profit changes with electricity price. For the simulation realistic parameters are used, based on the following work [16] and standard machine properties acquired online from sites providing updated information on Bitcoin mining, such as [17]. The values are $a = 14$, and $b = 0.1$. From Fig. 3, it may be seen that there is a steep incline in the plot profile, meaning that the effect of renewable sources penetration is considerable when looking at mining machines' profits.

Following, a trend describing the ramping costs as the percentage of renewable energy sources grows is presented. The duck curve is a well-known problem that visually displays the escalation in ramping costs, as may be viewed in [18].

Figure 4 displays the ramping costs, assuming a quadratic relation between the transient profile calculated in units of MW/h and the monetary value (based on [19]), as a function of renewable energy production in percentage, out of overall production, is presented for the state of California. It is clear that there is a substantial escalation in ramping costs, as more

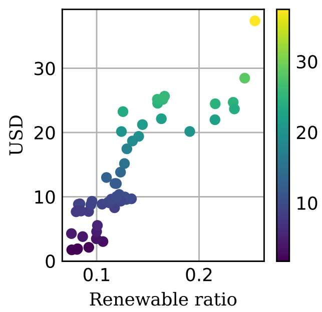


Fig. 3. Bitcoin mining machines profitability in [$], as a function of ratio of solar energy sources production.

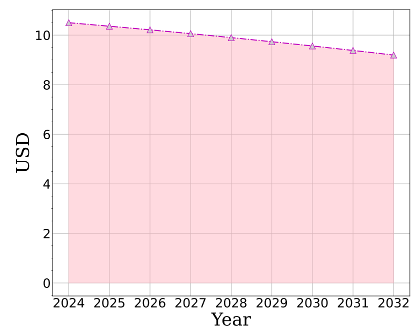


Fig. 5. The operator's revenue from Bitcoin mining machines over time, due to renewable energy sources integration and plummeting electricity prices.

renewable energy sources take a bigger chunk of the overall energy supply.

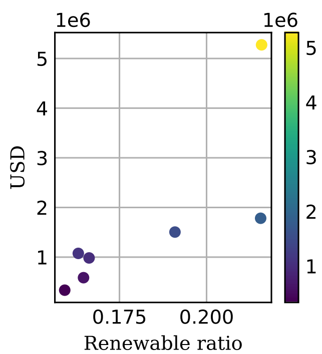


Fig. 4. Renewable energy penetration effect on daily ramping costs in USD per Watt in California, based on historical data.

Consequently, based on Figs. 3 and 4 it may be inferred that there is tension between rising electricity prices, which reduce the profitability of Bitcoin mining machines, and the increasing ramping costs, which incentivize the utilization of flexible and quick to respond consumers like Bitcoin mining machines. The idea is shown in Fig. 5, which presents power plant operators revenue from mining, which takes into account a prediction of electricity prices and ramping costs based on historical data. It may be observed that when excluding machine prices, even for a modest revenue of 14 USD it is profitable to utilize these mining machines in the next years, as the share of renewable sources increases.

Building on the aforementioned results, there is a need to determine the optimal machine parameters that companies in Israel, managing power production, could use in their plants to mitigate ramping costs, and use profits from these Bitcoin mining machines to sustain their operation. The simulation uses load and generation data acquired by "Noga" which are available to the public [20], normalized to represent a single power plant production. Realistic Bitcoin mining machine parameters are used. These are based on three families of Bitcoin mining machines: "Antminert-S19", "Antminert-S21 Pro", and "Whatsminerm63". Since the parameters may change slightly between providers, estimated prices are used, and labeled the Bitcoin mining machines tested by the labels: "1"-"3". The parameters of the tested Bitcoin mining machines are presented in Table III.

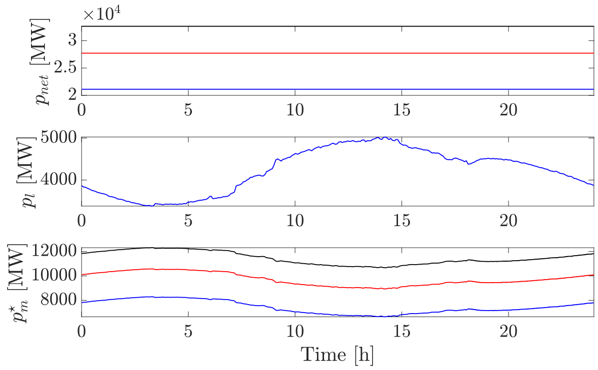
TABLE III
BITCOIN MINING MACHINES PARAMETER SETS

Type	**Demand** [W]	**Hashrate** [Th/s]	**Income** [$/day]	**Electricity costs** [$/W]
1	5360	335	15	0.1
2	7283	334	14.49	0.1
3	3250	110	5.05	0.06

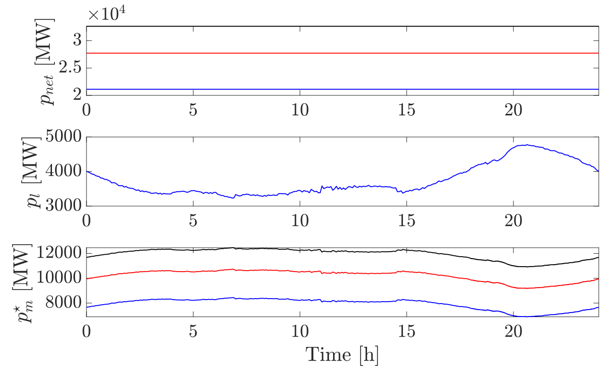
In the analysis, quadratic cost functions are considered. This assumption is well-known in literature [19]. The cost function considered for power generation is given by $c_g(x) = gx^2$, where $g = k \cdot (\text{Electricity cost}/\text{Power consumption}^2)$ and k is a constant, which has the value of $k = 0.0014$ for machines number "1" and "3", and $k = 0.0012$ for machine number "2". The cost of ramping is $c_d(x) = x^2$. The revenue per kWh is given by $c_m = \text{income}/\text{consumption}$, where the income, calculated in USD/day is based on average profits declared by miners and presented in sources such as [17]. The consumption is defined by the machine power consumption over 24-hour time horizon: consumption $=$ machine power consumption $\cdot$ 24. The parameter of the function ξ used for eliminating inequality constraints is $\alpha = 1$. The initial conditions are $x_0 = c_m/2g$ and $\lambda_0 = 0$.

The results are shown in Fig. 6. In the graphs, there are four sampled days representing a typical load behavior over the year. For each figure, the top subplot exhibits the energy generation for that day; the second subplot presents the consumption for that day, and the last subplot presents the operational scheduling of the mining machines. As seen from the results, the generation profiles are constant, clearly leading to an optimal reduction in ramping costs.

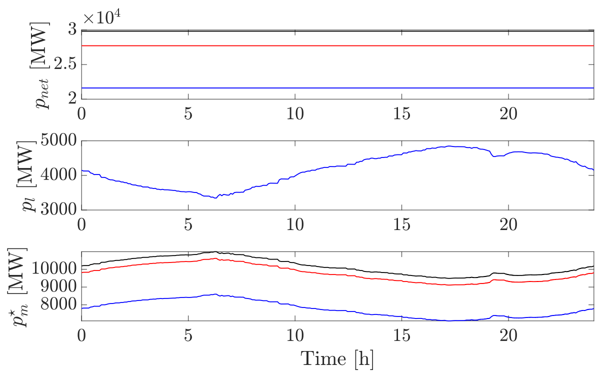
In Table IV, the generation costs, and revenue from the machine are presented, calculated for 4 months: April, July, and October of 2023, and January of 2024, that represent diverse renewable energy production profiles, and various consumer behaviors patterns during the year. It is clear from the generation patterns that the ramping costs are eliminated if a perfect knowledge of the load profile exists. In the analysis, the number of machines from each type, that are used to stabilize the solutions are: 2853 machines of type "1", 2175



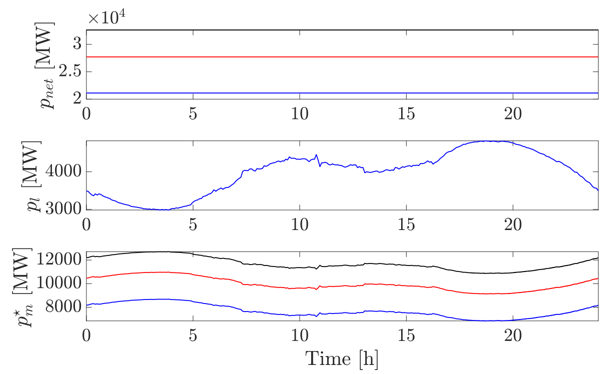
(a) October



(b) April



(c) July



(d) January

Fig. 6. The top subplot of each figure exhibits the total consumption prediction $p_{\text{net}} = p_m^* + p_L$; the second subplot presents the consumption for that day after the subtraction of the PV production according to different months in a year: (a) October; (b) April; (c) July; (d) January, and the last subplot presents the operational scheduling of the mining machines. The black line represents machine number "1" machine, the blue line shows results for "2" machine and the red line represents the "3" machine.

machines from type "2", and 2924 machines from type "3". Thus, taking into account the machine price of 7400 for machine of type "1", 5200 for machine of type "2", and 6500 for machine of type "3" (considering machine lifespan of 2 years), the annual revenue from the machines, and the ramping costs reduction is significant. Nonetheless, although this idea might sound attractive, there is a sting in its tail.

TABLE IV
NET PROFIT FROM MINING CONSIDERING MACHINE COSTS AND ELECTRICITY COSTS FOR SINGLE MACHINE OVER ONE DAY PER [KW]

Month	**Machine**	**MSRP** [$/day]	**Operating costs** [$/day]	**Net profit** [$/day]
April	1	10.14	23.77	1.48
	2	7.12	31.18	3.76
	3	8.90	23.19	2.7
July	1	10.14	22.22	1.64
	2	7.12	29.14	3.97
	3	8.90	21.68	2.92
January	1	10.14	22.91	1.57
	2	7.12	30.05	3.88
	3	8.90	22.35	2.86
October	1	10.14	22.06	1.65
	2	7.12	28.93	3.98
	3	8.90	21.52	2.95

Looking at the revenues expected over a time horizon of 6 years, it is clear that for machine prices close to machine of type "1", the revenue does not account for the purchasing costs and the company will incur financial losses. Figure 7 presents this idea. Consequently, until Israel reaches 40% of renewable energy production, it seems to be beneficial for power plant operators to utilize mining machines for ramping cost reduction, as long as the daily profit from mining are greater than 5$ and the mining machine price does not exceed 6947$. As the daily monetary profit from mining, represented by V, increases, it allows the system operator to invest more money in the mining machine's purchase, as long as the price of the machine, denoted by C, submits to the following:

$$\frac{C}{2 \cdot 365} - 8.9 \leq V - 5. \tag{10}$$

V. Comparative Analysis of Demand-Response Mechanisms

The recent literature explores various demand-response mechanisms. Among these, "Incentive-Based Demand Response" offers financial incentives for voluntary load reduction, and "Automated Demand Response" (Auto-DR) employs automation for rapid load adjustments. This paper focuses on "Bitcoin Mining-Based Demand Response", which utilizes the flexible and scalable nature of Bitcoin mining to

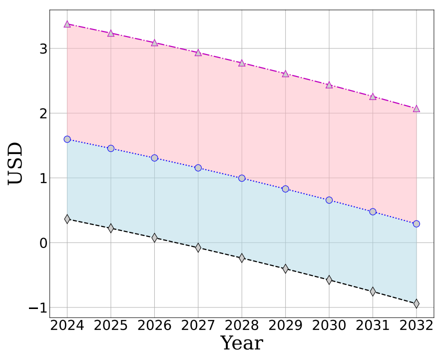


Fig. 7. The operator's net profit from Bitcoin mining machines, based on average parameters, over a time horizon of 6 years.

stabilize the grid. This section will qualitatively evaluate the cost-benefit trade-offs and real-world adoption trends of these approaches.

Table V presents a qualitative comparison of these three key demand-response (DR) mechanisms: Incentive-Based DR, Auto-DR, and Bitcoin Mining-Based DR. This comparison focuses on critical aspects, including initial investment, operational costs, response time, net revenue potential, and scalability, providing a broad understanding of each approach's strengths and weaknesses. Incentive-Based DR typically involves moderate investment and operational costs, yielding moderate revenue through direct payments. Auto-DR, utilizing IoT and automation, requiring significant upfront investment, which is compensated by low operational costs, rapid response times, and high scalability. Bitcoin Mining-Based DR, while demanding high investment and operational expenditures due to mining equipment and electricity, provides instant response, substantial revenue from mining and DR participation, and high scalability. To underscore the practical relevance of these approaches beyond theoretical constructs, the table includes examples of real-world programs, showcasing their global deployment. This table facilitates an elementary yet informative comparison of these DR strategies, highlighting the critical considerations for their implementation in modern power systems.

VI. Sensitivity Analysis of Bitcoin Mining Machine Characteristics

To further analyze the impact of external factors on the optimal scheduling of BMMs as a demand-response tool, a sensitivity analysis is performed, considering Bitcoin price, network hash rate growth, electricity tariffs, and government regulations. These factors influence the profitability of BMMs and, consequently, the optimal control policy u^* derived from Pontryagin's minimum principle. As was discussed in Section III, the optimal control policy u^* is given by $u^* = (c_d')^{-1}(-\lambda^*)$, where λ^* follows the adjoint equation $d\lambda^*/dt = -c_g'(x^*) + c_m(t) - \xi'(x^* - p_L(t))$. This analysis explores how the optimal control, u^*, is influenced by changes in several key parameters. The analysis is based on work [16], that presents the expected value for the miners' profits, taking into account the operational costs, revenue potential, and orphaning risk $\langle\Pi\rangle = (H/H_{net})(M + R) \cdot \exp(-\tau/T) - \eta H_{net}T$, where H is the miners hashing rate, H_{net} is the network's hashing rate, M are the transaction fees, R represents the block rewards, τ is the block propagation delay, T is the time to mine a block, and η is the costs of the hash value. For simplicity, small transaction fees are assumed, meaning M is negligible, thus $M + R \approx R$, which is proportional to the Bitcoin prices, meaning that $R \propto P_B$, where P_B is the Bitcoin price. Bitcoin mining profitability declines as the total network hash rate increases due to the difficulty adjustment mechanism. Thus, this study relies on the assumption that the mining revenue per unit power consumption is given by $c_m(t) = k_B P_B H(t)/H_{net}(t)$, where k_B is a proportionality constant. Since $c_m(t)$ appears directly in the adjoint equation, an increase in P_B increases $c_m(t)$, resulting in more mining activity. In contrast, if $H_{net}(t)$ grows faster than $H(t)$, then $c_m(t)$ declines, decreasing mining operation. Moreover, examining the objective function, it is evident that higher electricity prices make Bitcoin mining less profitable, and tends to reduce mining activity. Finally, regulatory constraints on mining (e.g., power caps, taxation), in scenarios where they are relevant, introduce an additional penalty function $R_g(p_m)$ into the cost function. If $R_g(p_m)$ increases due to stricter regulations, it discourages mining activity. In this paper it is assumed that there are no regulatory restrictions, meaning that $R_g(p_m) = 0$, and as done in [16], the Bitcoin mining profits are assumed to be proportional to the electricity prices.

VII. Conclusion

Previous works have shown how cryptographic mining machines, for instance Bitcoin mining machines, may be used in demand-response mechanisms, as part of the portfolio of assets managed by the grid operator. In this paper this formulation is extended by addressing the effects of fast ramping transients, which may often occur in power grids rich with renewable energy sources. The resulting optimization problem is solved based on Pontryagin's minimum principle, and the solution is utilized for examining the profitability and usage of these machines in a real-world settings, based on data from the California ISO and the "Noga" grid operator. Based on these datasets, a trend of increasing electricity prices and ramping costs is analyzed. This trend results from the increasing penetration of renewable energy sources. Following, a sensitivity analysis is conducted, considering the effects of changing electricity prices, machine prices, hashrate, and monetary revenue of the machines. Based on this sensitivity analysis, a comparative study is conducted, using the aggregated data to further emphasize the effect of the different properties of these machines, and comparing different machine types available in the market. From the results in Table IV and Fig. 6, it may be suggested that for today's typical data and prices, it is more profitable for a grid operator to utilize low-cost machines with lower hashrate. The analysis also shows that various trends may be observed, depending on the electricity price, and the price and hashrate of the machines. For instance, one non-intuitive trend that may be observed (For example in Fig. 2 and

TABLE V
COMPARING THE KEY CHARACTERISTICS OF DEMAND-RESPONSE MECHANISMS

DR Mechanism	Response Time	Revenue Potential*	Scalability	Real-world program
Incentive-Based DR	Minutes to Hours	Moderate	Medium	EnerNOC's DR project [21]
Auto-DR	Seconds to Minutes	Moderate	High	Google's AI-Optimized Data Center Cooling [22]
Bitcoin Mining-Based DR	Instant	High	High	ERCOT Texas [23]

Fig. 4) is that as the ratio of production from renewable sources increases, the cost of electricity rises, which eventually results in increased operational prices of the machines, but also in elevated ramping costs. This conclusion however may change drastically, depending on the data and cost of operating renewable and conventional sources, and on the machines' parameters. In addition, the economic analysis focuses on direct mining revenues, overlooking financial mechanisms like carbon credits that could affect feasibility. Moreover, transient stability under extreme conditions remains unaddressed, and future work may investigate robust control strategies for resilience. Nevertheless, in many scenarios the machines may play a supportive role which may help reduce the ramping effects caused by renewable sources.

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