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Energy Blockchain for Demand Response and Distributed Energy Resource Management

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***Abstract*—The high impact of demand reduction on the energy grid management and the importance of reducing loss of distributed energy resources (DERs), in addition to the necessity of a secure distributed data storing system motivate us to propose an energy blockchain solution. This paper presents a demand response (DR) solution utilizing energy blockchain to reduce demand, save the extra DERs, and efficiently incorporate customers block mining ability. In this work, a real dataset of customer demand profiles and PV generation in the Ottawa region is used to deploy a DR Stackelberg game between a control agent (CA) and local customers to negotiate demand reduction by integrating the block mining method as DERs saving. This article presents a novel and well-suited consensus algorithm, Proof of Energy Saving (PoES), that is used to incentivize the customers to reduce their demand, discharge their electric vehicle (EV) and maximize their chance for block mining to earn monetary rewards and DER savings. This results in lower peak demand, customer bill reduction, and transforms energy savings into monetary resources. Furthermore, the results show that our proposed consensus algorithm is robust and secure against malicious actions of users.**

I. Introduction

Demand response (DR) is an important application in smart grid that controls the demand and supply, and eliminates the surplus need for energy import, and prevents peak time slots [1]. To encourage the customers to contribute to a demand reduction program, an incentive-based DR control model is presented in this article that is integrated with an energy blockchain to provide a secure, distributed architecture.Due to the complexity of the energy trading market management on surplus distributed energy resources (DERs), some demand response studies [2, 3] have used the surplus energy to run blockchain for network supervision and mine cryptocurrencies that work similar to energy storage systems. The main idea of having an energy blockchain is to employ the customer's potentials (surplus energy and hardware equipment) in organizing a data storage system without waste of resources. In other words, this is a profitable model for both customers and the control agent (CA), where the storage system design and maintenance cost for the CA decreases, and customers can invest their surplus energy in blockchain architecture and receive rewards. In another perspective, the energy blockchain could perform as an electricity storage system in DR programs while the extra resources are consumed for block generation and rewards are allocated in return. Furthermore, this is a distributed ledger architecture that could be used for agreement on demand management between the CA and customers [4].

Authors in [5] have discussed the side effects of negative electricity pricing in markets due to the surplus generation, and for solving this issue, they have elaborated cryptocurrency mining as a DR mechanism. Cryptocurrency mining could be used for energy storage when the demand for the distribution network is less than the generation. Therefore, surplus energy could be used for block mining and contribute to the cryptocurrency economy. During the high demand and low generation, the agent can buy electricity from other sources and pay the bill with cryptocurrencies. In the same way, authors in [6] have introduced the idea of storing wind farm surplus generation as cryptocurrency (Bitcoin). A cryptocurrency storage system has been implemented in California to reduce the waste of renewable energies [7]. Moreover, to eliminate the high cost of battery installation and its maintenance expenses, blockchain mining can enhance the value of surplus energy by acting as an implicit storage medium for household customers.

Authors in [3] have used the blockchain for an automated energy trading model where all the entities collaborate without the supervision of the distribution system operator (DSO). A pricing-based Stackelberg game [8, 9] model has been presented in [10] that provides an energy trading market between the prosumers to find the market price using an energy blockchain peer-to-peer platform. Gallo *et.al.* [11] have described a DR mechanism that uses blockchain and smart contract to develop a decentralized peer-to-peer communication network between the system operator and customers. To bring agents to an agreement on selecting the next block miner node(s), consensus algorithms are required [12]. Apart from common consensus algorithms, such as proof of work (PoW) [13] and proof of stake (PoS) [14], there are some specific consensus algorithms that are designed for systems with distinct functionalities. For instance, Asheralieva *et al.* [15] presented a consensus mechanism that uses voting, and only the high reputation agents are eligible to vote and are selected as miners. Moreover, an energy trading model has been implemented between the virtual power plants (VPPs) and DERs, where the block mining protocol, proof of energy market (PoEM), selects the VPP with the highest traded energy as a block miner [16]. In another work, a novel peer-to-peer energy trading consensus algorithm, proof of energy (PoE), has been presented to elect an individual prosumer as a block miner where its generation is almost equal to the consumption,[17]. Different than prior work, authors in [18] have presented an energy market mechanism to balance the demand and response utilizing two consensus algorithms, proof of energy generation (PoEG) and proof of energy consumption (PoEC), to select the miners based on either generation or consumption. Furthermore, proof of benefit (PoB) consensus algorithm has been illustrated in [19] where an electric vehicle (EV) with the maximum influence on the grid performance (within its charging and discharging) was selected as a miner. Data privacy has to be incorporated in the consensus algorithm [20] to protect users against malicious actors; this has been considered in our proposed model. Thus, in our research a demand reduction model is associated with the block mining consensus algorithm to incentivize customers to participate more in demand reduction and increase their chance of being selected as a block miner.

Our Contributions: A demand response (DR) Stackelberg game is developed between the control agent (CA) and customers to design a novel DR solution integrated with energy blockchain. Our model incentivizes customers to maximize their demand reduction profit value, charge and discharge EV efficiently, and maximize their chance to gain rewards through block mining. We design an energy blockchain to store the energy transaction data securely and use the surplus household DERs for block mining to reduce the waste of energy (unlike the traditional PoW Bitcoin platform). The customers (miners) not only receive block mining monetary rewards but also maximize the profit of demand reduction and EVs state of charge using DERs.

The remainder of this paper is organized into three sections. Section II defines our proposed architecture, consensus algorithm, and utility functions, strategies, and constraints for CA and customers. In section III, the simulation results are presented, and finally, section IV concludes the paper with a summary of our findings.

II. System Model

In our model, the DSO intends to offer an incentive-based demand reduction to decrease the demand of customers at peak to minimize the energy import. To implement this idea, a DR Stackelberg game is designed between the control agent (CA) and customers to reduce demand using household photovoltaic (PV) generation, electric vehicle (EV) capacity. Based on Fig.1, the DSO sends a DR request to the customers through the CA during peak time slots. The CA is an intelligent agent interacting with customers and reduces the work load of DSO. To provide a trustful and distributed data storage system, the grid transactions (such as game negotiations and DR control signals) are stored on the blockchain where customers, CAs, and DSO are the nodes of the energy blockchain. There are private blockchains (PB) in the network where customers are the nodes that can distribute the transactions and blocks through wireless communication. Every PB requires a block miner to generate a block of transactions and attaches it to the chain. To pick a miner between the agents, we present proof of energy saving (PoES) consensus algorithm that works similar to the proof of stake (PoS). The node with the highest consensus ratio (energy saving) at a mining event is selected as the miner and validates the transactions. Our consensus algorithm considers the reputation of the node, demand reduction (that is calculated by the Stackelberg game), and available energy for block mining.

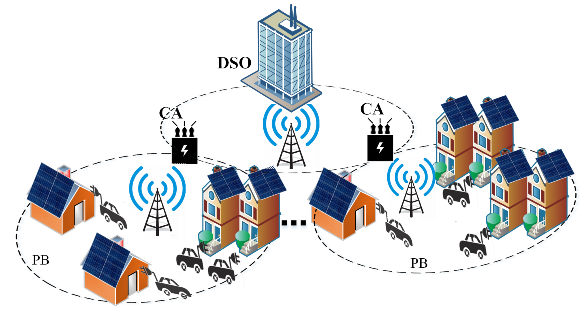

Fig. 1: Illustration of our DR Architecture and the smart grid.

A. Proof of Energy Saving Consensus Algorithm

A miner is a node from the network that is selected through the consensus algorithm. In this work, a consensus mechanism is proposed to use the surplus DERs of customers for the block mining operation, which is similar to a storage system that saves energy into monetary resources. In our consensus mechanism, each node has a consensus value that is measured with availability, reputation, and compliance ratio factors. Therefore, the consensus value for customer i, where $i \in \mathcal{N}_c = \{1, 2, \dots, N_c\}$, is calculated with the average of three factors (A_i, R_i, ρ_i). 1) **Availability** $(A_i \in [0, 1])$; for mining, a node spends mining energy equal to χ and can supply the energy by PV generation (x_{i1}^{PV}), demand (x_{i1}^{demand}) (that is a part of customer desired consumption) and discharging its EV capacity (x_{i1}^{EV}). The availability is calculated as below.

$$A_i = \frac{(x_{i1}^{PV} + x_{i1}^{demand} + x_{i1}^{EV})}{\chi} \tag{1}$$

2) **Reputation** $(R_i \in [0, 1])$; nodes can rank their experience of interacting with other nodes as trusted, untrusted or uncertain according to [15]. Smart contract is an execution code that runs by all the nodes in the blockchain network to check the transaction validation before being added to the block. Therefore, the smart contract can validate a transaction and detect a node with malicious action. In our model, customers with malicious actions lose their reputation value due to the untrusted votes other customers submit. 3) **Compliance Ratio** $(\rho_i \in [0, 1])$; this is the ratio of a customer's total electricity reduction to its total requested reduction. The set e is the index of a DR event

and E is the number of events happened in a window of one week, where $e \in \mathcal{E} = \{1, \ldots, E\}$. The value c_i^e is customer i's demand reduction at event e and r_i^e is the amount of demand reduction the CA asks the customer i at event e where we have $\mathbf{c}_i = (c_i^1, c_i^2, \ldots, c_i^E)$, $\mathbf{r}_i = (r_i^1, r_i^2, \ldots, r_i^E)$. The compliance ratio of a customer is defined as follows;

$$\rho_i = \frac{\sum_{e=1}^{E-1} c_i^e + (x_{i2}^{PV} + x_{i2}^{demand} + x_{i2}^{EV})}{\sum_{e=1}^{E} r_i^e}, \tag{2}$$

where $\sum_{e=1}^{E-1} c_i^e$ represents the summation of demand reduction until event $(E-1)$ and $\sum_{e=1}^{E} r_i^e$ is the summation of demand request within a week. In other words, the c_i^e for the recent DR event (E) is equal to $c_i^e = x_{i2}^{PV} + x_{i2}^{demand} + x_{i2}^{EV}$. Customer can reduce its demand using PV generation (x_{i2}^{PV}), actual demand reduction (x_{i2}^{demand}) (by shaving or shifting the demand), and discharging EV capacity (x_{i2}^{EV}) to handle the request. Hence, a customer with a considerable history of demand reduction has more chance to be selected as a block miner. By averaging these three factors, the consensus value of customer i would be $ARC_i \in [0, 1]$, and the customer with the maximum ARC value is selected as the block miner in each mining event. This means that miners with high availability, high reputation and high compliance factors will be favoured. Proof of energy savings (PoES) consumes less energy for block mining in comparison with PoW and PoS, while only one node is responsible for the mining process. Moreover, it is a well-suited consensus algorithm for incentive-based DR architectures that consider the combination of reputation and energy contribution to select a miner.

B. Utility Functions

Distribution system operator (DSO) predicts the total demand using the support vector regression (SVR) [21] prediction engine and recognizes the peak time slots and high-demand situations a day-ahead. Therefore, it sends DR requests (demand reduction signal) to maximize the contribution of customers and minimize the monetary reward paid for compensation according to (3). After the DSO initiates the Stackelberg game, the control agent (CA) starts interacting with customers and allocates different DR requests $r_i^e, \forall i \in \mathcal{N}_c$, based on the compliance ratio of customers ρ_i for the recent DR event (e). The strategy vector of the CA at the recent event e is $r^e = (r_1^e, r_2^e, \ldots, r_{N_c}^e)$. Thus, the utility function of the CA is defined as

$$U_d = \ln(A + \alpha \sum_{i=1}^{N} c_i^e) - \frac{\beta \sum_{i=1}^{N_c} (\rho_i r_i^e)}{A}, \tag{3}$$

subject to;

$$\sum_{i=1}^{N_c} r_i^e \geq G$$

$$r_i^e \geq l_i, \forall i \in \mathcal{N}_c.$$

The value α is the associated DR profit price for the DSO, G is the desired minimum energy reduction of the DSO, l_i is the minimum available DR reduction for customer i, β is the allocated reward value for the customer reduction, c_i^e is the customer i's electricity reduction for the recent event (e), A is the scaling parameter, and ρ_i is customer i compliance ratio which helps the CA to allocate demand reduction accordingly. In (3), the first constraint is used to keep the total DR request more than the minimum reduction threshold, and the second constraint keeps the DR request more than the minimum availability of the customer.

Before the game starts, the customers submit the reputation values and rate each other, but the availability and compliance ratio are calculated during the Stackelberg game due to their dependence on the demand reduction. In this game, customers are the followers, and their goal is to find the best strategy (c_i^e), that maximizes their probability for block mining (ARC_i), and maximizes the profit of EV charging and demand reduction reward at the recent DR event (e). The customers can use their PV generation, demand, and EV capacity for both block mining and demand reduction. Moreover, the PV generation is first consumed for mining, then demand, and the surplus is used to charge the EV. The customer's utility function is presented as

$$U_c = \gamma(ARC_i) + \theta x_{i3}^{EV} + \beta c_i^e, \tag{4}$$

subject to;

$$x_{i2}^{PV} + x_{i2}^{demand} + \sigma_i x_{i2}^{EV} \leq r_i^e$$

$$x_{i1}^{PV} + x_{i1}^{demand} + \sigma_i x_{i1}^{EV} = \chi$$

$$x_{i1}^{PV} + x_{i2}^{PV} + \sigma_i x_{i3}^{EV} \leq P_i$$

$$B_i^{min} \leq B_i^{current} + \sigma_i(x_{i3}^{EV} - x_{i1}^{EV} - x_{i2}^{EV}) \leq B_i^{max}$$

$$x_{i1}^{demand} + x_{i2}^{demand} \leq p_i - d_i.$$

The ARC_i was represented in the previous section, and γ is the allocated reward for block mining. According to (4), the second term maximizes the EV charging profit, and the third term maximizes the reward of demand reduction. The values θ and β are the profit rate of charging EV through PV and the reward value of demand reduction, respectively. In addition, x_{i3}^{EV} represents the extra PV energy used for EV charging. The value P_i is the total PV generation of customer i at the recent DR event, x_{i1}^{PV}, x_{i1}^{demand} and x_{i1}^{EV} are the unknown variables used to find the optimized value of PV, demand, and discharged EV energy allocation for block mining respectively. Moreover, x_{i2}^{PV}, x_{i2}^{demand} and x_{i2}^{EV} are the unknown variables use to show the amount of PV, demand, and discharged EV energy usage for demand reduction, respectively. Note that $c_i^e = x_{i2}^{PV} + x_{i2}^{demand} + x_{i2}^{EV}$ is the reduction strategy of the customer i in the game, and all the x's are the unknown variables.

Based on (4), the first constraint keeps the demand reduction less than CA's DR request (r_i^e), the second provides the required mining energy, the third constraint controls the PV generation (P_i), the fourth monitors the EV charging and discharging and keeps the current capacity $B_i^{current}$ between the minimum B_i^{min} and maximum B_i^{max} battery capacity, and the final constraint keeps the demand reduction $(x_1^{demand} + x_2^{demand})$ always less than the predicted consumption (p_i) minus the essential household demand (d_i) of customer i. The binary value σ_i represents the state of EV, $\sigma_i = 1$ means EV is parked at home and the customer can discharge/charge it, otherwise, $\sigma_i = 0$. Then, after the game is converged, the consensus value of each customer is calculated (according to above subsection), and the one with the maximum ARC value is selected as block miner.

The aforementioned scheme mainly focuses on the block mining process at DR events, but from the network supervision perspective, the DSO requires real-time demand information of customers to monitor the distribution network. Then, customers will send their demand profile to the CA regularly for monitoring purposes, and a block mining process is also required to store the supervision data on the blockchain. Therefore, for the sake of storing supervision data on the blockchain, customers need to maximize their utility function (4) to find the values of $x_{i1}^{PV}, x_{i1}^{demand}, x_{i1}^{EV}$ and x_{i3}^{EV} and exclude other variables and their corresponding constraints. Then, the consensus values are calculated to find the block miner for the supervision case.

C. Stackelberg Game

The equilibrium strategy for the follower(s) in a Stackelberg game is any strategy that establishes an optimal response to the one adopted by the leader(s) [22]. This model is a forward leader-follower game among the controlling agent (CA) ($\mathcal{N}_d = 1$), as a leader, and customers ($\mathcal{N}_c = N_c$) as followers with the total $\mathcal{N} = \mathcal{N}_d \cup \mathcal{N}_c$ number of players. Therefore, a unique equilibrium point exists in our Stackelberg game $\Gamma = (\mathcal{N}, \{S_n\}_{n\in\mathcal{N}}, \{U_n\}_{n\in\mathcal{N}})$, where the set of strategy for player n (S_n) is non-empty, convex/concave and compact in Euclidean space. Moreover, according to (3) and (4) both utility functions (U_d and U_c) are continuous and differentiable on their set of strategies, and (3) is concave which guarantees the game has a maximum and unique strategy. The game initiates by announcing a set of strategy from CA (r^e) to the customers, and then, the customers will choose their best response strategy as follows;

$$c_i^{e*} = \underset{C}{\operatorname{argmax}}\, U_c(r_i^e), \forall i \in \mathcal{N}_c \tag{5}$$

Let c_i^{e*} be the best response strategy of customer i and $c^{e*} = (c_1^{e*}, c_2^{e*}, \ldots, c_{N_c}^{e}{}^*)$ be the follower's best strategy profile and C represents the constraints in (4). The leader will accordingly calculate its best strategy r^{e*} by;

$$r^{e*} = \underset{D}{\operatorname{argmax}}\, U_d(c^{e*}, \beta), \tag{6}$$

where D represents the constraints in (3). These steps repeat till a feasible set of strategies is obtained. Therefore, (c^{e*}, r^{e*}) would be a Stackelberg Equilibrium (SE) set for the game at event e.

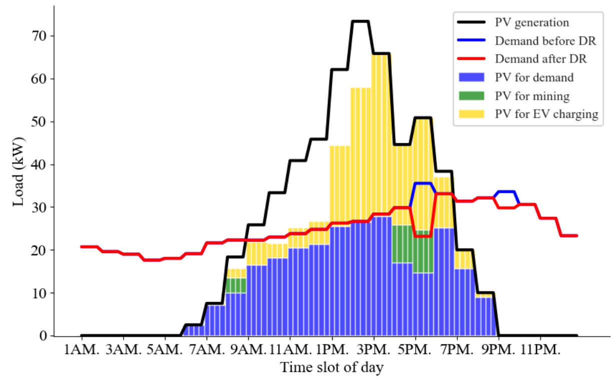

Fig. 2: Total demand profile and allocated energies of customers in a day in July

III. Simulation Results

A critical concern in the block mining process is to estimate the required energy for block generation. The energy usage mainly depends on the number of transactions, the difficulty level of the hash function, and the energy consumption of miner [23, 24]. In a recent work [25], the authors have found that in a small private blockchain network, a miner with a 2 core CPU and 8 GB RAM processing system requires 1 Watt to process one transaction. Consequently, in our proposed distribution network, the miner (customer) with the same hardware features requires almost $\chi = 3.2$ kW (the mempool size is 3200 transactions) electricity to generate a block. Since we have $N_c = 100$ customers, the CA initiates DR requests by sending 100 individual transactions, and then we run the Stackelberg game for 15 iterations (30 bidirectional transactions) to settle the results. From the network supervision perspective, customers send their demand profiles to the CA every 15 minutes, then they transmit almost 400 monitoring signals (transactions) in one hour, and every eight hours the block mining process runs to store the data on the blockchain (due to the size of the mempool). Thus, three block minings are required to store 24-hours monitoring data on blockchain that occur at 8 am, 4 pm, and 12 am every day.

For the simulation part, a real dataset of customers consumption profiles over a year is used that was collected by Hydro Ottawa Limited, in Ottawa, Ontario. We focus on the customer usage profile in July because the photovoltaic (PV) panels have the maximum energy generation in the Ottawa region, and we employ a dataset of PV electricity generation collected by the University of Ottawa SUNLAB during that period [26]. A support vector regression (SVR) model is applied to predict the demand profile of customers a day ahead. To simulate the proposed architecture, Python and MATLAB are used, and assumed that each customer has a PV system (with maximum 4kW capacity), Electric Vehicle (EV) (with a total capacity of 40kW), and a Home Energy Management System (HEMS) with 2 cores CPU and 8 GB RAM

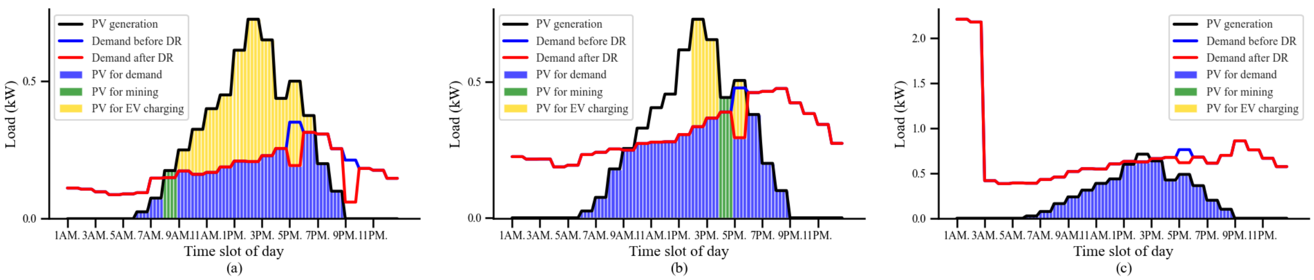

Fig. 3: Consumption profile of three customers in a day in July that keep EV at home (a) 100% (b) 50% and (c) 0% of working hours

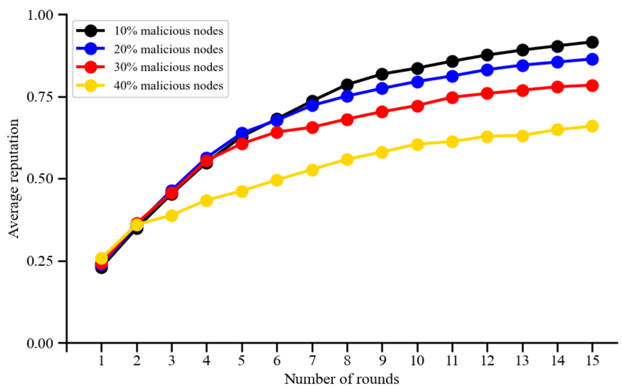

Fig. 4: Average reputation value during 15 block mining events for different percentage of customers with malicious action

for mining and monitoring purpose. To implement a realistic EV pattern of usage, we applied the probability distribution of EV usage taken from [27]. Based on this article, EVs are usually parked at home from 11 pm to 7 am the next day, and only 63% of EVs are parked at home during working hours. For the simulation part, the initial reputation is considered as $R_i = 0.1$, $\forall i \in \mathcal{N}_c$ and the rest of values are $\alpha = 0.2\$/kWh$ (based on dispatching price), $\beta = 0.13\$/kWh$ and $\theta = 0.082\$/kWh$ (based on time of use (ToU) pricing in Ontario), and $\gamma = 5\$$ is the block mining reward.

A. *Impact of EV Usage Pattern*

Figure 2 denotes the network demand profile before and after DR during a day in July with two DR events at 5 pm and 9 pm. The figure also shows PV generation (dark solid line) and the amount of PV used for demand (blue bars), allocated block mining energy by customers (green bars), and EV charging (yellow bars). Hence, there are total five mining processes (3 for monitoring and 2 for DR events) during a day that only three of them (at 8 am, 4 pm, and 5 pm) use the PV generation for the mining process, and the reset (9 pm and 12 am) use EV capacity and demand. Moreover, the peak is reduced almost 35%. To show more details on customers profiles, we select three different customers to keep an EV at home 1) 100% 3.(a), 2) 50% 3.(b) and 3) zero percent 3.(c) of working hours (from 8 am to 8pm) slots. They have nearly the same PV generation but have different demand profiles. In Fig. 3.(c), the customer charges its EV during the mid-night (1 am-2 am), and the car is out during the mining events that reduce the chance of the customer to win the block mining. According to Fig.3.(a) and (b), customers win the mining at 8 am and 4 pm respectively and charge their EV with PV generation as well. To present more details, Table I illustrates the output results and profits of five types of customers (keep EV at home for 100%, 70%, 50%, 30%, and 0% of working hours). We found that the customer with 70% of EV at home did not win the block mining because of the inappropriate time slots of keeping EV at home and less demand reduction. But, it charges its EV more than others and increases its charging profit. Then, the customer with 0% EV at home only receives the profit of demand reduction. Customers with 100% and 50% EV receive the reward of mining, EV charging, and demand reduction. Consequently, the customer who keeps EV at home exactly at mining hours (similar to the customer with 50% EV) and reduces demand equal to the DR request can achieve significant profits (calculated by 4) and provides EV usage satisfaction during the daytime. Therefore, by keeping EV at home during mining events, customer can increase the chance to win the block mining and charge EV to enhance the profit values.

B. *Impact of Malicious Customers*

To present our system security and robustness against the users with malicious actions, Fig. 4. represents the network average reputation value that is reducing while the number of users with malicious actions increase. The reputation value is formulated based on article [15] where the blockchain security is guaranteed if the number of malicious nodes doesn't exceed half of the nodes. The reputation algorithm increases the reputation of users when they truthfully submit transactions and successfully mine the block, and it decreases when they send fraudulent information (users can detect the fraudulent transaction using a smart contract). Furthermore, according to our proposed consensus algorithm, the consensus value of customers with malicious action will drop as their reputation values decreased, and their chance to be selected as a block miner will tend to zero. Thus, blockchain privacy and security are guaranteed. Then to clarify how consensus value

TABLE I: Average profit value for different EVs usage pattern.

Working hours EV parked at home (%)	Before DR		After DR		EV charged with PV (kW)	Block mining event	Total profit ($)
	Total demand (kW)	Total cost ($)	Total Demand (kW)	Total cost ($)			
100	17.69	0.68	16.45	0.55	10.26	Event 1	3.96
70	11.25	0.41	10.95	0.38	13.22	-	1.15
50	30.14	1.57	29.41	1.49	3.82	Event 2	3.35
30	16.14	0.58	15.41	0.51	8.05	-	0.68
0	69.22	4.45	68.63	4.39	0	-	0.07

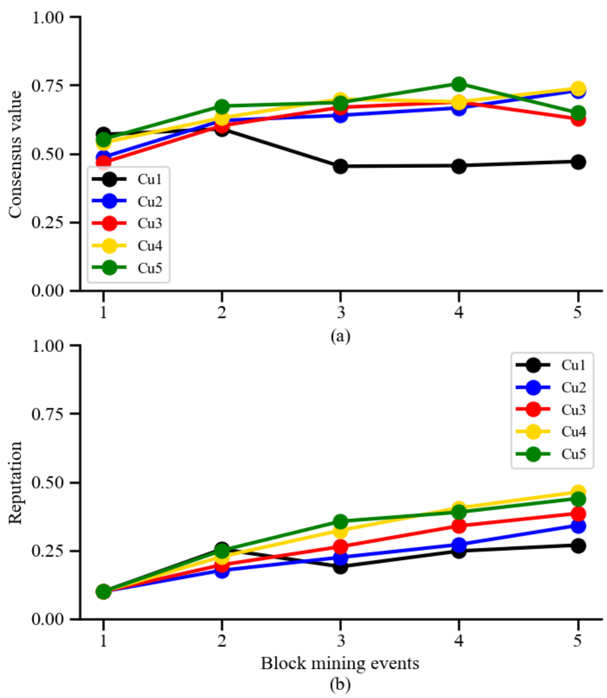

Fig. 5: (a) Consensus value and (b) reputation values of 5 customers during five events (8 am, 4pm, 5pm, 9pm and 12 am) while customer 1 maliciously acts in event three.

and reputation of customers change, we apply k-means clustering on 100 customer demand profiles and categorize them into five groups. Fig. 5. shows 5 customers (from different clusters) in five block mining events (defined before). At the beginning, customers have the same reputation value (0.1), and customer 1 was selected as a miner due to its higher demand reduction, and no malicious action was detected among users. In the next block mining event, customer 5 was selected as a block miner and successfully increased its reputation. But at event three, customers detected a fraudulent transaction submission by customer 1, which reduces its reputation and accordingly decreased its consensus value. Then, customers 4, 5, and 4 were selected as block miners for events three, four, and five respectively. After customer 1 was detected with malicious action, it did not select as a miner in reset of mining events due to its least reputation. But it still has chances to increase its reputation by acting truthfully and building its history for future events.

IV. Conclusion

In this paper, a novel demand response Stackelberg game model is presented that includes a new DER saving mechanism using energy blockchain to develop a collaborative distributed storage system and interactive demand reduction in a residential area. Our main goal was to engage customers to reduce their demand at peak time slots, compete on block mining to win and receive rewards, transform their surplus DERs into monetary resources, and incentivize them to discharge and charge their EVs. In other words, this mining strategy works like a storing mechanism for the DER system that is less expensive and more efficient than installing a battery inside a house. Our results show that the proposed scheme can truly manage the DER resources by efficiently allocating PV resources, demand, and EV to the block mining process, and incentivizing customers to discharge EV and reduce their consumption 35% during the peaks. Furthermore, we demonstrated that our proposed consensus algorithm is robust and secure against users with malicious actions. Certainly, this work maximizes the chance of block mining for customers and allocate rewards in addition to maximize the profit of the DSO by reducing the total demand.

Acknowledgment

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