An Experimental Evaluation of a Blockchain-based Peer-to-Peer Energy Trading Framework

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***Abstract*—Increasing penetration of Distributed Energy Resources (DERs) like solar PV, Battery Energy Storage Systems (BESS), electric vehicles and the digitization of power grids are turning consumers into prosumers. The excess energy generated by these prosumers can either be fed back into the grid or used for Peer-to-Peer (P2P) trading. P2P energy trading is a new paradigm that introduces flexibility among electricity users, where the energy from DERs is traded locally. This paper proposes an optimization model for P2P energy trading between prosumers and consumers such that the economic benefits of both groups are maximized by minimizing the total cost incurred in purchasing electricity. Further, it uses a blockchain-based platform for securing the transactions conducted during P2P energy trading. The proposed model's effectiveness is tested on a test rig developed at IIT Gandhinagar, which consists of two peers. One of the peers acts like a prosumer with solar PV generation and BESS, whereas the other peer is a consumer. Results reveal that the proposed model provides better economic benefits to the prosumers than the feed-in tariff model.**

***Index Terms*—Blockchain, linear programming, peer-to-peer (P2P) energy trading, smart contract**

I. Introduction

The proliferation of renewable energy resources into the electric grid is propelled by their environmental advantages and the financial incentives they provide to their owners. As the penetration of these DERs increases, owners will generate surplus energy, which will be fed back into the grid, and they will be paid at the prevailing Feed-in Tariff (FiT) rate for their energy injection. Prosumers have a vital role to play in deregulated energy markets. However, the energy obtained from renewable generation-based DERs is intermittent. A high degree of such DER penetration adversely affects the grid stability, which may lead to enforcing energy export limits on the prosumers. Further, the economic benefits of supplying surplus energy to the grid are insignificant. Due to the above reasons, the FiT scheme is losing its presence in the energy markets day by day [1].

Peer-to-Peer (P2P) energy trading emerges as an alternative to the current FiT scheme, where the prosumers trade the surplus energy with other prosumers or consumers without the influence of a central entity [2], [3]. Compared to the FiT scheme, P2P energy trading provides better economic benefits to both the consumer and the prosumer. Further, it empowers the consumers to choose the source of their energy consumption. Although the absence of a central entity reduces the trustworthiness of P2P energy trading, this limitation can be overcome using distributed ledger technology for securing transactions. Piclo, Vandebron, Peer Energy cloud, Brooklyn microgrid, and SonnenCommunity are some examples of P2P energy trading projects successfully running around the world [5].

The concept of P2P energy trading was first introduced in [4], [6]. A hierarchical system architecture for P2P energy trading is proposed in [7]. In this method, the peers involved in the trading can shift their role from prosumer to consumer and vice-versa. An optimization model for maximizing the economic benefits of P2P energy trading among different entities having solar PVs with and without energy storage is introduced in [8]. A two-stage control method for P2P energy trading in community networks is proposed in [9] to reduce the requirement for communication equipment. P2P energy trading between microgrids using a blockchain-based coalition algorithm is proposed in [1]. The algorithm converges faster and is better scalable than existing coalition algorithms. P2P energy trading using a game-theoretic model is proposed in [10]. In this work, the pricing competition between sellers and buyers is modelled as a Stackelberg game, whereas the pricing competition between sellers is modelled as a cooperative game. A P2P energy trading model is proposed in [11] to reduce prosumers' demand during the peak hours of the day using a cooperative Stackelberg game. Here, the central power system acts as the leader, and prosumers act as followers. The central power system determines the energy cost at peak periods, and the prosumers who curtail their demand during peak periods are given monetary incentives. A distributed day-ahead P2P trading method for multi-microgrids is proposed in [12] using game theory. A non-cooperative game model and the Stackelberg game model are constructed to analyze the relationship among sellers and between sellers and buyers of microgrid systems. The effect of adding network constraints in P2P energy trading through sensitivity analysis is studied in [1], [13]. The effectiveness of energy storage devices in P2P energy trading is investigated in [14] through Flexi market designs. A P2P energy trading model based on multi-bilateral trading and product differentiation is proposed in [15]. The main advantage of the proposed model is that it can be implemented without the requirement of a central agent using a distributed relaxed consensus innovation approach. The role of mediators or energy brokers in customer-to-customer energy trading in an event-driven market using reinforcement learning is explored in [16]. The model helps improve market efficiency and attain better local-level power balance while considering customers' behavioural characteristics. Further, blockchain technology is also used in this model to improve transaction security.

From the works mentioned above, it is clear that the different models of P2P energy trading have already been developed. However, experimental validation of the proposed algorithms has not been done in most of these works. Further, securing the transactions occurring during the trading using technologies like blockchain is implemented only in a few works. Considering these facts, this paper presents a blockchain-based model for P2P energy trading. In the proposed model, peers manage their electrical energy requirements among themselves such that the power sourced from the grid and the electricity bill are minimized. The proposed model is validated on the test bed, which has two peers, Peer A and Peer B. Among these peers, Peer A is a prosumer having solar PV and Battery Energy Storage Systems (BESS), whereas Peer B is purely a consumer. The proposed model helps achieve effective energy trading between these two peers, such that their economic benefits are improved compared to the FiT scheme. The novelty of the proposed model is as follows.

- Integration of energy meters at end-user nodes with the compact and portable device named Smart Agent to simplify installation and communication.
- Optimal scheduling of BESS using forecasting and optimization algorithm on the Smart Agent.
- Seamless interfacing of the proposed framework with a blockchain-based web application for the demonstration of P2P energy trading in a real-world environment.

The rest of the paper is organized as follows: Section II discusses the forecast and optimization framework for P2P energy trading and briefly introduces the test rig at IIT Gandhinagar. The blockchain-based web application developed for P2P energy trading is presented in section III. The results obtained from the experimental setup are detailed in Section IV. Finally, Section V concludes the paper.

II. System Description and Methodology

In order to test the performance of the proposed P2P trading framework, a demonstrative test rig is developed at IIT Gandhinagar. The prosumer in this test rig is treated as Peer A, which consists of a rooftop Solar PV system, BESS, and in-house loads. The consumer is named Peer B and is expected only to consume power. The loads are connected through the distribution boxes and metering infrastructure. A part of the test rig developed to showcase the proposed methodology's effectiveness is depicted in Fig. 1.

Both the peers are electrically connected through the grid. Peer A has a solar panel of 3 kW with a BESS of 7.5 kWh. The details of BESS installed at Peer A can be inferred from

Fig. 1. Demonstration test rig at IIT Gandhinagar

Table I. As Peer A has a BESS and a solar PV as DERs, it is considered a prosumer. On the other hand, Peer B has only electrical loads connected, and it derives the required power from these prosumers or the grid. Hence, it is considered a consumer. Apart from the electrical connection between these peers, there is also an information flow between them. This information is gathered using smart meters, which is subsequently transmitted into the Smart Agent database using Modbus RTU communication. The details of each peer are outlined in the following subsections.

A. Peer A

Peer A has a Solar PV and a BESS attached to it, as evident from Fig. 2. Solar PV generates energy during the day, which is used to fulfill residential energy requirements and charge the battery. The surplus energy, if present, will be used for P2P energy trading. The energy meters are installed at various locations within Peer A to measure residential consumption, solar PV generation, battery charging or discharging, and net power consumption. These meters continuously measure power and energy usage at 15-minute intervals, which are then stored in the historical table within the Smart Agent database of Peer A. The Smart Agent communicates with the meters

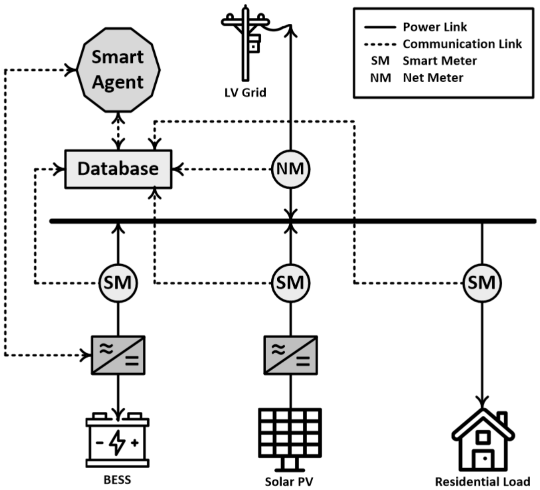

Fig. 2. Schematic diagram of Peer A

via serial communication using the Modbus RTU protocol, utilizing the RS485 communication standard.

B. Peer B

It is observed that, unlike Peer A, Peer B does not have any energy generation or storage device connected to it. Hence, this peer acts only as a consumer. A smart meter is connected at the point of common coupling to measure the load consumption of Peer B at 15-minute intervals. The measured value is fed into the historical table in the Smart Agent database. The data stored in the historical table is later used to forecast the load of Peer B.

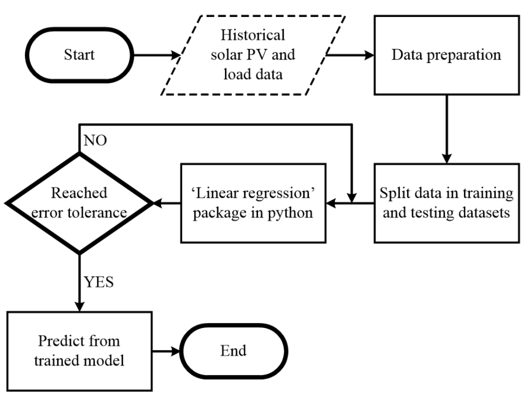

Fig. 3. Flowchart of the forecasting model

C. Forecast and optimization framework

As discussed earlier, peer A consists of the solar PV system, BESS, and in-house load. In order to make out an efficient day-ahead schedule, an accurate forecast is always required. A Linear Regression (LR) model-based machine learning algorithm is used in this work to forecast the solar PV generation and load demand. The LR-based model is chosen for solar and load forecasting due to its ability to handle linear relationships commonly found in solar PV generation and load demand patterns. Additionally, LR requires lesser computation resources, making it suitable for efficient day-ahead scheduling. Hence, it can be said that the considered model can work very well on small single-board computer used in the Smart Agent. The forecast is being done considering the 21 days of historical data on a 15-minute interval basis and fed to the algorithm as presented in Figure 3. LR tries to estimate the regression parameters based on the inputs from the training data set. A generalized equation of LR is as follows.

TABLE I
PEER A BESS PARAMETERS

BESS Parameters	Rating
Energy Capacity (E^b)	7.5 kWh
Initial SOE (SOE_0)	3.5 kWh
Maximum SOE (SOE_{max})	6.75 kWh
Minimum SOE (SOE_{min})	1.5 kWh
Minimum charging and discharging power ($P^{bc}_{min}, P^{bd}_{min}$)	0 kW
Maximum charging and discharging power ($P^{bc}_{max}, P^{bd}_{max}$)	3.3 kW
Charging and discharging efficiency (η^c, η^d)	97%

$$f_i = a + b_1 x_i^{(1)} + b_2 x_i^{(2)} + ... + b_n x_i^{(n)} \quad (1)$$

The LR model is trained using the Ordinary Least Square method, where f_i represents the predicted value of the i^{th} dependent variable. In this method, a is the coefficient determining the value of f when x is zero, while b_n determines the slope of the respective independent variable x^n.

The proposed objective function is minimized subject to the constraints (3) - (10) using linear programming in Python environment [18].

$$Cost = \sum_{t=1}^{T} (C_t^f P_t^g \Delta t), \quad \forall t \in \{1, 96\} \quad (2)$$

$$P_t^g + P_t^{PV} + P_t^{bd} = P_t^{bc} + P_t^l, \quad \forall t \in \{1, 96\} \quad (3)$$

$$SOE_t^b = SOE_{t-1}^b + [(P_t^{bc}\eta^{bc} - \frac{P_t^{bd}}{\eta^{bd}})\Delta t], \quad \forall t \in \{1, 96\} \quad (4)$$

$$SOE_T^b = SOE_0^b, \quad \forall t \in \{1, 96\} \quad (5)$$

$$P_t^{PV} + P_t^{bd} \le P_{max}^{Inv}, \quad \forall t \in \{1, 96\} \quad (6)$$

$$P_{min}^{bc} \le P_t^{bc} \le P_{max}^{bc}, \quad \forall t \in \{1, 96\} \quad (7)$$

$$P_{min}^{bd} \le P_t^{bd} \le P_{max}^{bd}, \quad \forall t \in \{1, 96\} \quad (8)$$

$$P_{min}^{g} \le P_t^{g} \le P_{max}^{g}, \quad \forall t \in \{1, 96\} \quad (9)$$

$$SOE_{min} \le SOE_t \le SOE_{max}, \quad \forall t \in \{1, 96\} \quad (10)$$

Equation (3) refers to the power balance equation. It states that the sum of grid power (P_t^g), solar PV power (P_t^{pv}), and battery discharge power (P_t^{bd}) will always be equal to the amount of load consumption (P_t^l) and battery charging power (P_t^{bc}). Here, t is the time slot of fifteen minutes. As the proposed P2P energy trading model works like a day-ahead market, this power balance equation requires the next day's solar power generation and load consumption. Although the solar PV generation and the load consumption will change continuously, a near-accurate estimate of these quantities can

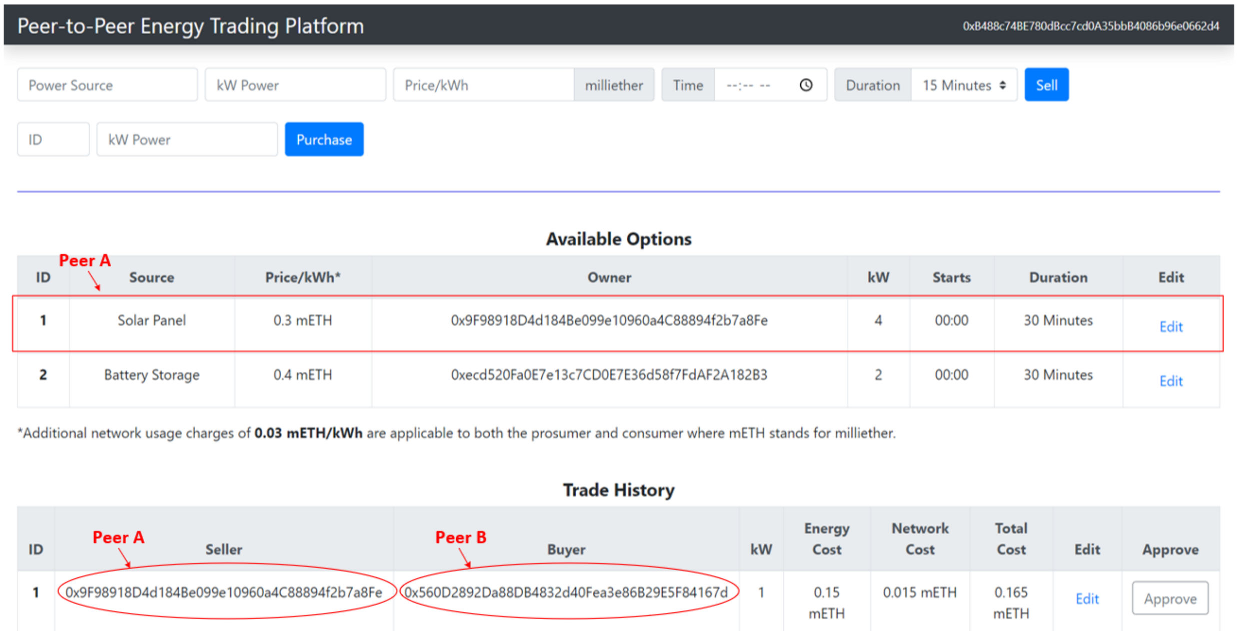

Fig. 4. Blockchain and smart contract-based web application for P2P trading

be forecasted using regression techniques. This model uses a linear regression method to forecast these values. The forecasted load consumption and solar PV generation values are stored in the Smart Agent database.

The State of Energy (SOE) of the battery is mathematically expressed in (4) and (5). The SOE of the battery at a particular instant is the sum of SOE at the last instant and the battery charging or discharging energy. This is mathematically represented in (4). The SOE of the battery will be the same at the starting and ending periods. This is mathematically expressed in (5). Equations (6) to (9) represent the limits of the grid power, battery charging and discharging power, and battery SOE.

III. Blockchain-based Web Application and P2P Energy Trading

In our previous work reported in [19], we have utilized blockchain technology within a smart contract-driven web application to enable secure and transparent P2P energy trading. The developed web platform is seamlessly integrated with the Smart Agent situated at the test rig in this work. Acting as a microcomputer, the Smart Agent gathers load and generation data from smart meters installed within the test rig environment. Subsequently, this data undergoes processing according to the proposed methodology, providing the optimal schedule for BESS to participate in P2P energy trading. The web application empowers users to place bids for purchasing or selling electricity. To gain access to the platform, each user must register an account and complete the necessary verification process by providing basic personal and energy asset details. Users are issued a digital wallet to conduct financial transactions upon successful registration. Fig. 4 depicts the blockchain and smart contract-driven web application, while

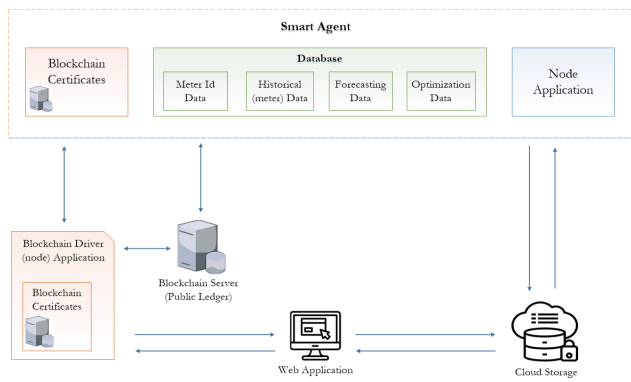

Fig. 5. Integration of the software and hardware layer

Fig. 5 showcases the coupling and information flow between the hardware and software.

The operating steps of the proposed P2P energy trading model are explained with the help of an example below. Let us consider a power trade between Peer A and Peer B. Both of these peers have created an account in the P2P energy trading web application where the information of the peers is stored. After forecasting the solar PV profile and load demand, the Smart Agent optimally schedules the BESS so that an efficient P2P schedule is made out.

1) Peer A creates a sell bid for the surplus power using the web application while mentioning the source, quantum, and time slot of the excess generation willing to sell as depicted in Fig. 4.
2) Consumers like Peer B who are looking to buy energy for this time period go through different sell bids and select the most appropriate one. As shown in the "Avail-

able Options" table of Fig. 4, the most economical bid is from Peer A. Hence, Peer A is selected to supply 1 kWh of energy to Peer B for the time period between slots 00:00 - 00:30.

3) The order is confirmed after Peer B makes the payment through the web application. The paid amount is stored in the account linked to the smart contract. It should be noted that the confirmed order can only be edited before the gate closure time, which is 1 hour before the actual trading time.
4) Power flow is triggered between the contracting parties as per the agreement. Meter readings at the beginning and end of the time slot are used to validate the trade, and if there are any deviations from the agreed quantity, then penalties are calculated accordingly.
5) The order is settled by transferring the amount received from Peer B in the smart contract account to Peer A's wallet, and the trade details are stored in the blockchain.

IV. Results

The performance of the proposed P2P trading model is validated on the test rig developed at IIT Gandhinagar. Peer A has a general lighting and HVAC system with a set of digital computers along with solar PV generation and BESS. The peer B consists of motor loads and lighting loads.

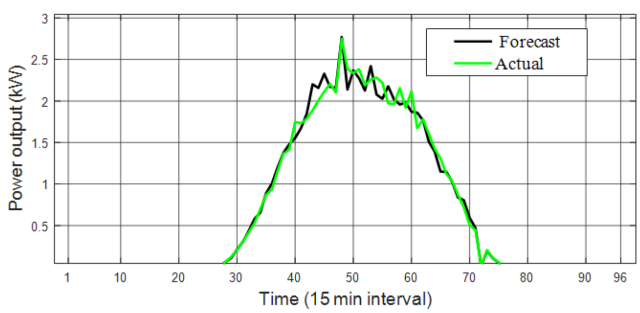

Fig. 6. Peer A solar PV profile

The actual and forecast values of solar PV output and load profile of Peer A on a particular day into consideration are

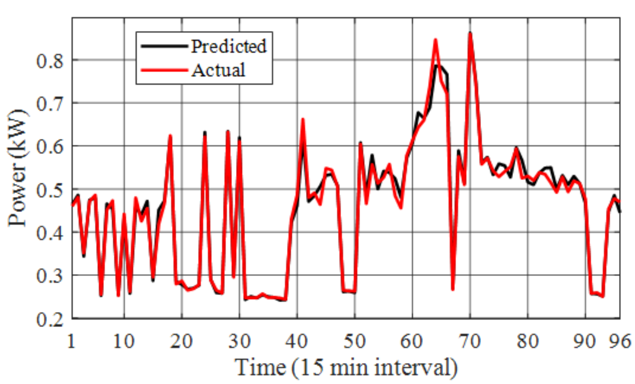

Fig. 7. Peer A load demand profile

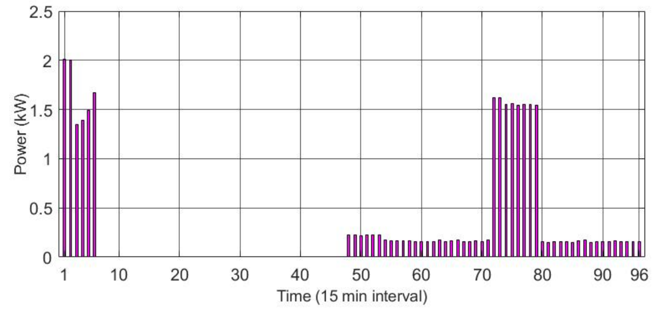

Fig. 8. Peer B load demand profile

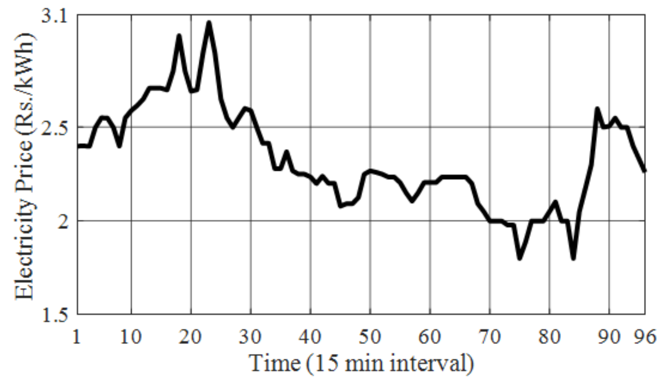

Fig. 9. Electricity price profile (from IEX)

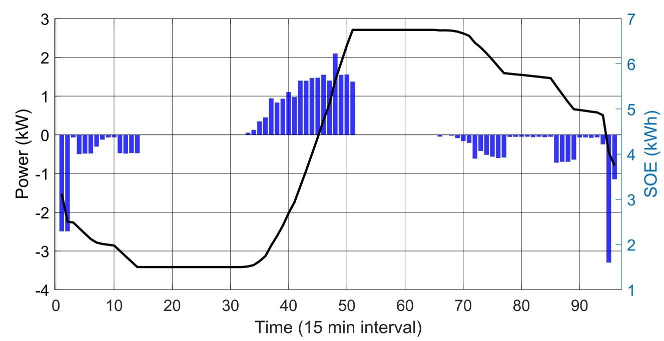

Fig. 10. Peer A BESS meter power profile

shown in Fig. 6 and 7. It can be observed that the actual and forecast values are not very distant, and hence, it can be said that the forecast model is accurate enough. Further, based on the forecast of solar PV and load in the PEER A, the battery schedule is obtained from the optimization algorithm considering the grid price signal from IEX presented in Fig. 9. The obtained BESS power schedule and the corresponding State of Charge of the battery are depicted in Fig. 10.

It is observed that at 00:00, BESS starts to discharge, and Peer B starts receiving the power. This is evident from the peer A BESS meter and net meter profiles, as shown in Fig. 10 and Fig. 11. The load profile of Peer B is displayed in Fig. 8. It is observed from the load profile of Peer B that there are

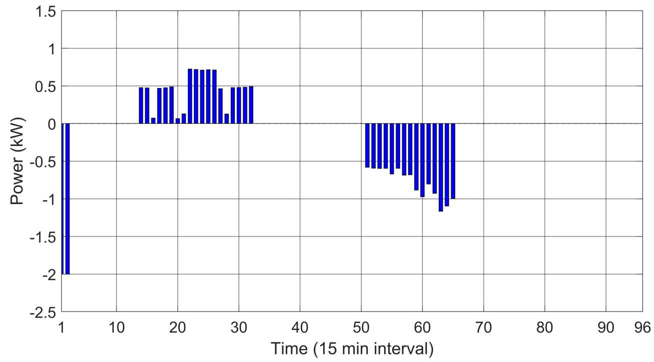

Fig. 11. Peer A net meter power profile

two peaks corresponding to the intervals 1^{st} to 7^{th} and 73^{rd} to 79^{th} respectively, due to the operation of compressor pump and the drainage pump connected to it. The load of Peer B for other intervals of the day is minimal. The first two peaks are fulfilled using the P2P energy trade, and the corresponding energy and financial transactions are stored on the blockchain. Hence, it can be concluded that the proposed model effectively trades the power between different peers while leveraging the benefits of blockchain technology.

V. Conclusion

A linear programming-based optimization model for P2P energy trading has been proposed in this paper. The proposed model uses a web-based user interface to simplify the energy trading process between peers. Further, it uses blockchain technology to secure the transactions associated with energy trading. The effectiveness of the proposed model has been validated using an experimental setup involving two peers at IIT Gandhinagar. It has been observed from these experiments that the proposed model can help effectively trade the energy between these peers without the help of a central entity. The proposed experimental setup can be scaled up to include more peers in future work.

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