Designing a High Performance and High-Profit P2P Energy Trading System Using a Consortium Blockchain Network

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Abstract—**Renewable energy generating systems can be used to supply some or all of electricity needs, using technologies like solar, wind, or micro hydropower systems. Trading this kind of decentralized energy is essential to owners of these local systems. Regional p2p energy trading systems provide a solution for this issue. Due to expanding the concept of decentralization and blockchain-based trading models, some studies in recent years have proposed such models for local surplus energy trading. In this paper, we propose a distributed energy-trading framework based on a consortium blockchain for p2p energy trading energy of renewable energy systems. Our proposed model uses Jointgraph, a novel Byzantine fault-tolerance consensus algorithm, and a DAG-based consortium energy blockchain framework, which highly improves the performance of the trading model. Furthermore, we use Belief Distorted Nash Equilibrium (BDNE) for pricing strategy to increase the profitability of the system for both buyers and sellers. The implemented simulation confirms that the proposed framework outperforms similar p2p trading models in terms of both performance and profitability and can be used in real local energy trading systems.**

Keywords: Renewable energy system, Decentralized Energy Trading; Consortium Blockchain; Consensus algorithms; Pricing strategy; Belief Distorted Nash Equilibrium

I. INTRODUCTION

Along with many other businesses, decentralized solutions have received a lot of attention in energy management systems in recent years. They bring advantages such as privacy, transparency, security, lower costs, etc. in comparison with centralized solutions. In this paper, we proposed a novel energy trading system for surplus energy trading between renewable energy system owners as producer and their neighborhoods as consumers. We focus on the efficiency and profitability of the trading system.

Unlike traditional energy generation (by burning fossil fuels such as gas or coal), renewable energy is generated from natural sources that are continually replenished, such as sunlight, wind, or waves. When fossil fuels burn to meet the demands for energy, they emit carbon dioxide, the main greenhouse gas that is causing climate change. Local energy systems will play an important role in helping governments decrease their need for this energy and preventing climate change. Local energy systems are ones, which find ways to link the supply and demand of energy services within a local area. Consumers such as manufacturing industries, hospitals, buildings, large offices, and dry cleaners, who need a lot of energy during the day, can use these kind of systems to reduce their costs and contribute to the health of the earth. Another advantage of using renewable energy systems is that the local natural resources (solar, wind, etc.) can be used as primary energy in the system. These generated energies can be used locally and internally, but they can be transferred to power grids or individuals who need energy [1]. All of the benefits of the renewable energy systems lead to attracting people to this ecosystem.

Renewable energy systems may have an overabundance of energy sometimes. This extra energy of the system can be offered to others who need energy in the neighborhood, probably at lower prices (because of lower transfer costs and higher energy throughput). Such energy trading decreases the total cost of accessible energy and the operation cost of the renewable energy generation system [2].

In order to collect surplus energy for trading, buildings with renewable energy systems are equipped with an energy storage system (ESS). An equipped building in this context refers to a building that is equipped with a renewable energy system, ESSs, and smart meters connected to the distribution network. In this way, for selling surplus energy, the building must be operated in islanded mode. In this mode, the ESS is being charged with surplus power, especially during off-peak load intervals. Then this energy can be traded in the trading network [3]. Selling this extra energy through a reliable, accessible, and straightway trading network, especially to close and local customers, is profitable and economically attractive.

Few studies have focused on trading the energy produced by local renewable energy systems and making a profitable p2p network in this ecosystem. Most of these studies are based on blockchain and smart contracts. Some of them use public blockchains such as Bitcoin and Ethereum for trading [4]. Others propose using private or consortium blockchains [5]. Achieving acceptable performance in the order of thousands of transactions that enable the network to support many prosumers and a perfect pricing strategy, which increases profitability for both sellers and buyers of energy, are two substantial challenges unsolved by previous studies. Therefore, in this paper, we focus on these two challenges and propose a decentralized framework for energy trading in a local ecosystem. In fact, we propose an energy supply framework based on a decentralized energy exchange network built with a novel DAG-based consortium blockchain between owners of local renewable energy generator systems as producers and their local communities as customers. In addition, an optimal pricing model considering seller and buyer utilization among trading has been proposed, which uses Belief Distorted Nash Equilibrium (BDNE), a novel Nash equilibrium technique for distorted and non-cooperative game models.

II. Related Work

Today, distributed energy resources (DERs) and energy storage systems are becoming more and more popular. Accordingly, it is urgently requested to develop distributed system design and solutions for p2p energy trading. A p2p trading system is an integrated system that includes DERs and multiple electrical loads [6].

But, it is a fact that researches in this field are still at an early stage of development [11]. Most implementations are at the level of proof of concept. Public blockchain systems such as Bitcoin or Ethereum wallet services have emerged as an important factor in many areas. It allows automated transactions, and it is also likely to influence the energy sector [2]. Permissioned blockchain systems share the benefit that all players are known, which makes it possible to rely on less computationally complex consensus mechanisms—the protocol which ensures that all network participants have identical copies of the transaction log and agree on the state of the system [3]; this significantly increases the number of transactions the system can process and reduces the ecological footprint. However, the content of transactions remains visible to all network participants, complicating the implementation of privacy-preserving features [4], [5]. The scientific community calls for more research in this field and encourages investigating alternative blockchain frameworks. Hyperledger Fabric—originally contributed by IBM and Digital Asset and now hosted by the Linux Foundation—is one of the most mature permissioned blockchain frameworks [15]. Since its release in 2017, more and more projects rely on Hyperledger Fabric and leverage some of the framework's advantages: (1) its modularity, facilitating the integration with existing ICT infrastructure, for instance; (2) its good scalability, meaning it can process high levels of transactions in a short amount of time; and (3) its support for private transactions, making it possible to keep private data confidential between a subgroup of authorized parties. These advantages make Hyperledger Fabric a promising candidate for building a decentralized permissioned energy trading platform [7], [8].

In recent years, many solutions for local energy trading have been proposed, and appropriate designs are being discussed in scientific literature. The authors in [9] used the shared and internal energy trading approach to develop a P2P energy sharing model by applying the Stackelberg game approach and the Lyapunov optimization method. In [10], in order to optimize microgrid energy cost, a P2P energy dealing model for smart houses was introduced. The optimization factor was minimizing the cost of total energy. In another study based on P2P energy markets proposed in [11], the authors used bill sharing (BS) and mid-market rate (MMR) for residential customers. Prosumers contribute to trade energy in this approach. The mechanism to guarantee pricing stability is MMR. The researchers used the Feed-In-Tariff scheme to examine their study compared to other P2P energy trading solutions. Sharing energy storage ownership between multiple shared facility controllers (SFCs) is the basis of the proposed P2P trading mechanism introduced in [12]. In [13], a novel P2P energy trading mechanism was introduced that works in a cooperative market, analyzing optimality and fairness amongst prosumers. Enhanced control of landlords and automatic buying and selling in the P2P electricity market is the innovation of the study in [14]. The authors in [14] proposed a mechanism that automatically performs the purchase and sale of electricity with increased control to householders in the P2P electricity exchange network. In [15], researchers used Bayesian game theory to build a bidding strategy in p2p electricity trading that guarantees efficiency and fairness for each buyer. In [16], a p2p trading scheme is proposed with attention to the network constraints and the feasibility of p2p trading in a grid power network. A p2p energy exchange scheme focusing on residential prosumers is proposed in [17]. The authors investigate an optimal power flow problem using a multi-bilateral economic dispatch formulation as the objective function. Since price monitoring is a requirement for prosumers in the smart grid community, many researchers focused on this aspect of the trade. Demand Response (DR) is a parameter that is widely used in different researches. An incentive-based DR solution was proposed in [18]. The incentive in this solution is a fair amount of load change. A similar approach that does not use consumer behavior in the model is proposed in [19]. This model can predict house power consumption changes. Confidentiality of user information in the microgrid and maximizing the benefit to participants are the primary concerns addressed in [20]. Stackelberg competition is a model used in [21] to maximize the benefit of P2P energy trading. These are DR-based approaches in that consumers' behavior is modeled as an evolutionary game, and producers' behavior is modeled using the Stackelberg game. In [22], researchers introduced an algorithm to minimize the costs to all prosumers in the energy sharing market.

In [19] and [23], prosumers trade with others in the local network based on residential demand response schemes to balance supply and demand. In these studies, prosumers manage their energy usage and learn about other producers and consumers' production/consumption patterns. In [24], a marketplace for electricity was proposed using a blockchain-based shift load mechanism to represent a mixed complementarity problem. A producer in this model generates energy tokens based on load shifting, and consumers buy the tokens to pay their bills. The authors of [25] used a non-cooperative game-theoretic approach to propose a demand-side management system. In [11], a microgrid P2P electricity exchange model is introduced that uses blockchain as the transaction system. A blockchain-based Bidding System for Peer-to-Peer Energy Trading in a microgrid is proposed in [26]. It proposes a P2P energy trading system based on smart contract and a dynamic pricing approach on the Ethereum blockchain.

III. Proposed Method

In this section, our proposed approach for p2p energy trading has been discussed. First, we propose our decentralized system design. Then, Jointgraph as a consensus algorithm is presented. This algorithm causes efficiency improvement in the trading system. After that, our proposed pricing strategy, which is based on BDNE, is discussed. Using BDNE instead of NE increases the profitability of the system and causes to more people attract for joining to the system in the real world.

A. *Decentralized system design*

We propose a decentralized system consisting of prosumers (producers and consumers), smart elements, supervisor, energy storage systems (ESS), and a DAG-based blockchain, with a novel efficient consensus algorithm; Jointgraph. Fig. 1. illustrates a schematic view of the proposed system model. Each smart meter is connected to an ESS, and each prosumer has one ESS to transfer its receiving energy. Similar to [27], we assume that the smart element is a trusted, unbreakable device for measuring the amount of energy which users cannot manipulate. In addition, it is connected to the data network. The energy trading process is initiated by the prosumer who offers a price and amount of energy for buying or selling. Then the supervisor node collects all offers and runs a pricing algorithm based on BDNE. It calculates the fair price and announces it to all users. Then, each pair of seller/buyer users agree with each other, and a smart contract is signed and sent to the network for consensus, verification, and registration using Jointgraph.

We assume that EESs are connected to a transmission system mechanism. Thus, energy is transferred from the buyer ESS to the seller ESS after the agreement. In this paper, such as most similar studies, we do not deal with the details of power-transmission lines.

In our proposed framework, the supervisor is a mediator, and according to the seller-buyer matching information provided by the blockchain, it updates the seller and buyer information such as their credit scores, bills, etc. Users can anonymously negotiate with each other without revealing their identity to any third party. This functionality would be implemented in the trading mechanism by performing DAG-based decentralized systems. The strength of the designed system is using Jointgraph as a consensus method in blockchain, which leads to a high-performance consensus and makes the system usable for real-life and real-time transaction handling. On the other hand, the supervisor's energy price is determined by a non-cooperative game with a Nash equilibrium using BDNE, which causes mutual utilization for both buyers and sellers.

In the following, Jointgraph, BDNE, and the way we use them in the trading system have been discussed.

B. *Consortium blockchain based on Jointgraph*

As mentioned before, we use Jointgraph as a novel DAG-based blockchain and consensus algorithm for the first time in trading models. The main advantage of Jointgraph is its efficiency, which makes it perfect for real-life trading systems. Details of this algorithm and its usage in our proposed trading system will be presented below.

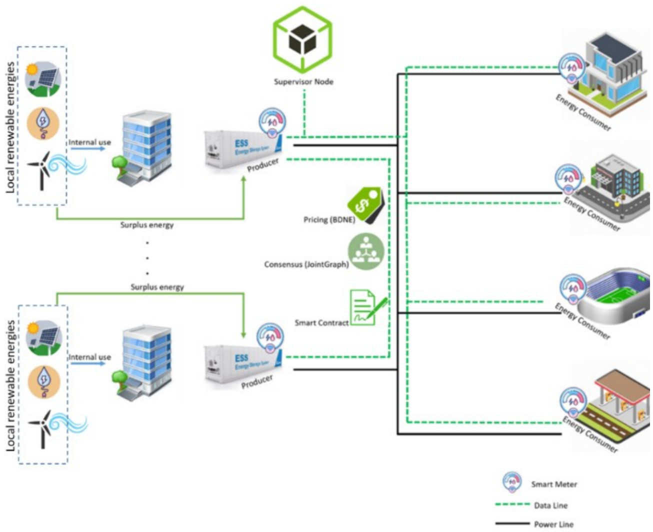

Fig. 1. A schematic view of the proposed system model

1) *What is Jointgraph*

Jointgraph is one of the newest and most efficient consortium blockchains. The consensus in Jointgraph is achieved using a Byzantine fault-tolerant algorithm. In this algorithm, each node reaches an agreement with another node on their transaction. The concept of the event is used in Jointgraph for a package of transactions. These packages transfer between nodes through a gossip protocol; it means any node can send events to any random node. Nodes in Jointgraph structure are categorized into two types: ordinary (user) nodes and supervisor node. Buyers and sellers in the trading application are user nodes that send transactions (events) when a trade has been done. Also, they are responsible for the validation of transactions of other users. If a user node can verify the transaction and add it to its own Jointgraph copy, he votes YES. The supervisory node has two responsibilities. The first one is the determination of pricing for energy based on the game model, which is explained in the following section. The second job is collecting votes in the consensus process and determination of the finality of events. This finality depends on the "YES" votes, and the minimum "YES" votes must be 2/3 of the total votes. Also, a supervisor node monitors the behavior of the user nodes and identifies malicious behavior [27].

2) *Consensus in Jointgraph*

The graph structure of the Jointgraph is dynamic and changeable during its lifetime. An edge from A to B means that event A has verified event B and event A in one of the children of B. User nodes validate the receiving events from each other. The validation means that transaction source and destination, transaction signature, and hashes of self-parent and other-parent are valid. The events that are invalid will be dropped by the receiver node. If an event is verified by more than 2/3 of all user nodes and the supervisory node, its finality will be confirmed. In the energy context, the events include energy trading transactions between a seller and a buyer. Along the lifetime of the trading system, the older events will be verified by the newcomers. Therefore, former event can participate in the consensus process. Fig. 2. shows the pseudocode of consensus algorithmthat is run by the user nodes and the supervisor node. The consensus process in Jointgraph is almost similar to this process in Hashgraph because of the use of gossip protocol [39]. However, using a supervisor node in Jointgraph, which does not exist in Hashgraph, makes a huge difference; Jointgraph only needs one round of voting, whereas Hashgraph needs no less than three rounds. In the worst case, a Jointgraph can go on without the supervisor node in the consensus process. In this unlikely case, the Jointgraph turns to a Hashgraph, and the system does not shut down.

C. *Pricing strategy*

In the proposed decentralized energy trading system, users do not have information about each other's demands and supplies. So, the information is not fully available, and the system has a non-cooperative game space. Therefore, we chose Belief distorted Nash equilibria (BDNE) theory to develop a profitable pricing strategy.

Joining the network and pricing process includes four steps:

1. Join & verification: for identification and verification to join the network, each prosumer (producer or consumer) of energy sends a request to the supervisor. If it is qualified to enter the market, the verified user's information is published to the network.

Algorithm 1 : Supervisor Node

Functions: Send, Receive, Find, Create Events. Monitor memory, Find malicious users in a life-time loop

```
While (system is running) Do in Parallel
    While (there is no any user) Do
        Send (one known event to one random user );
    End While
    While (Neighbor N send an event e) Then
        Receive(e);
        Create(New event);
        Set (other parent as last event from N);
        Find (new events that can reach to consensus);
    End While
    While ( )
        Monitor (system memory);
        Monitor (User's Behavior);
        If (memory usage > n% of memory size)
            Take_Snapshot( );
            Release_Memory( );
        End If
        If ( Node M is found Malicious or it is down for time t)
            Replace_Node(M);
        End If
    End While
End While
```

Algorithm 2 : User (Prosumer) Node

Functions: Send, Receive, Find, Create Events in a life-time loop

```
While (system is running) Do in Parallel
    While (there is no any user) Do
        Send (one known event to one random user );
    End While
    While (Neighbor N send an event e) Then
        Receive(e);
        Create(New event);
        Set (other parent as last event from N);
        If (Supervisor send a new event)
            Find (new events that can reach to consensus);
        End If
    End While
End While
```

Fig. 2. Pseudocode of consensus algorithm that is run by the user nodes and the supervisor node

2. Pricing step: each market entity announces its daily energy demand or supply and its offered price for buying or selling. Then according to the BDNE algorithm of dynamic games, the transaction price and transaction volume are determined by the supervisor.
3. Transaction execution step: each buyer chooses one or more sellers and makes a transaction contract with the seller(s). After that, users sign the smart contract according to price and transaction volume. Then, the transaction information is sent to the DAG-based blockchain network. If the consensus process verifies the transaction, recording it to the general ledger will complete the transaction.
4. Settlement step: after the transaction finalization, energy dispatching will complete by calling the dispatching system. Then, the supervisor reads the trusted smart meter's data to ensure the accuracy of the energy exchange.

Nash equilibrium is the most important concept in non-cooperative games. But, it is a complete solution when players have full information about the other users' data in the game, such as their payoff functions and strategies and the number of players. This information might be incomplete or even distorted in dynamic games, so as the proposed energy trading system. In these games, the Nash equilibrium (NE) algorithm cannot establish the desired mutual balance. Decentralized energy trading networks, like many real-life situations, have incomplete and ambiguous information. Thus NE must be extended to be applicable to such situations. Many studies have been done to extend the Nash equilibria concept to make it work in the case of incomplete information, including Bayesian equilibria [28], correlated equilibria [29], delta-rationalizability [30], self-confirming equilibria [31], and subjective equilibria [44]. BDNE is one of the most complete extensions of NE. It is proved that BDNE can be fully applied in dynamic games with incomplete information. This feature separates BDNE from any other related NE extensions. Also, it seems to be especially appropriate for games with many players [32]. Another advantage of BDNE is that it can scientifically model the problems of a particular structure, which is common in the socio-economic context[32]. These reasons make BDNE a practical algorithm for many real-life situations, like massive trading markets with high micro-transactions.

We assume that the pricing game is defined as

$$G = \{A_1, A_2, \dots, A_n, \theta_1, \theta_2, \dots, \theta_n, u_1, u_2, \dots, u_n\}$$

$$A_i(\theta_i), i = 1\ to\ n : \text{strategy space}$$

$$\theta_i, i = 1\ to\ n : \text{strategies}$$

$$u_i, i = 1\ to\ n : self - utility\ function \tag{1}$$

Each participant i relies on the strategy θ_i in the case of maximizing the self-utility function u_i.

So

$$a^* = \left(a_1^*(\theta_1), \dots, a_n^*(\theta_n)\right) \tag{2}$$

Is a belief distorted equilibrium, for any i, $a_i \in A_i(\theta_i)$.

According to the volume of each producer's surplus energy and the buyer's demand, the user load of each transaction can be found as

$$e_{L,i} = \left[e_{L,i}^1, e_{L,i}^2, \dots, e_{L,i}^d\right]$$

$$i = 1\ to\ n, d = 24h\ trading\ day \tag{3}$$

Where, n is the number of users in the market network. In our implemented simulation, one trading period is $24h$. In each trading period, the actors in the network play a game under the supervision of the supervisor node to reach an optimal price and the amount of energy trading. So, the sellers adjust their energy load $e_{L,i}$ to obtain more benefits.

The users of the proposed trading network are three types: sellers, buyers, and supervisors. N denotes the set of all users in the network, N_b represents the buyers' set, and N_s is the sellers' set. $e_{L,i}$ is positive ($e_{L,i} > 0$) for N_s, and negative ($e_{L,i} < 0$) for N_b.

The price of energy should satisfy the following conditions:

$$p_m < p^d < p_g \tag{4}$$

Where p_m is the price that renewable energy system owners (sellers) pay for power generation, p^d is the price of energy in a day, and p_g is the price of energy in the grid.

Sellers will adjust their surplus energy prices to obtain higher benefits in the competition of energy trading. The benefit function of sellers is:

$$u_i = \alpha_i\, ln(1 + e_{L,i}) + p(e_{L,i}) \tag{5}$$

Where u_i is the benefit factor of seller i in the period d, α_i is the adjustment coefficient of the seller's energy generation behavior, and p is the energy price.

Buyers need to pay lower purchase costs in comparison with buying energy from the power grid. The purchasing cost of the buyer is expressed as follows:

$$C_j = q_j p + e_{L,j} p_b \tag{6}$$

Where q_j is the amount of energy purchased during the lifetime of buyer j in the network, p is the total paid amount in this duration. $e_{L,j}$ is the current buyer need and p_b is the offered price for current need.

Finally, the buyer and the seller play a multi-participant dynamic game which is formulated as follows:

$$G = \{(N_b \cup N_s), \{E_i\}_{i \in N_s}, \{u_i\}_{i \in N}, P, C_T\} \tag{7}$$

Where the sellers in N_s offer the energy consumption plan (price and amount). E_i is the strategy set of energy consumption $e_{L,j}$ of buyer i. P points to the strategy set of energy prices in the network, C_T is the total cost of purchased energy by buyers.

Buyers want to pay the lowest cost for energy, and sellers wish to maximize their benefit from sales. So, the equilibrium of G as the game model is the optimal problem solution. The supervisor node finds the optimal price using BDNE, and the consumers adjust their consumption strategy based on the price.

The equilibrium (e^*, p^*) in period d of the game G is reached if and only if e and p satisfy the following conditions:

$$u_i(e^*, p^*) \geq u_i(e_i, e^*_{-1}, p^*) \quad \forall\, i \in N_s, \forall\, e_i \in E$$

$$C_t(e^*, p^*) \leq C_t(e^*, p) \quad \forall\, p \in P \tag{8}$$

Where

$$e^* = [e_{L,1}, e_{L,2}, \ldots, e_{L,N_s}]$$

$$e^*_{-1} = [e_{L,1}, e_{L,2}, \ldots, e_{L,i-1}, e_{L,i+1}, \ldots, e_{L,N_s}] \tag{9}$$

IV. Simulation of Proposed Framework

Through the deployment of the proposed chaincode, the network was implemented in Hyperledger fabric. Then, Hyperledger Caliper evaluated the performances of the trading model. Also, the utilization and trading benefits for both sellers and buyers were measured. Simulations are done on a VPS with four CPU cores and 16 GB of RAM, on which Ubuntu 18.04 x64 is installed. As mentioned before, the consensus mechanism used in these simulations is Jointgraph. Also, the pricing strategy is based on BDNE. Go language, as a compatible and well-known programming language for the Fabric environment, was used to code the deployed system.

In general, a sample of energy market trading scenarios between owners of renewable energy systems and local buyers was set up and simulated in a Fabric network environment. We considered daily trading periods. Finally, the simulation was performed for a two-week (14 days) duration of energy trading with daily transactions. The simulated trading network consists of five sellers, each with an ESS storage equipped with a trusted smart meter. There are ten buyers for energy with variable amounts of daily energy requirements. The ESS power of each seller in the network is shown in TABLE I. The initial (minimum) price of "surplus energy to the network" for local users has assumed 0.77 dollars (the minimum price that covers the store and buys surplus energy). This price is changed during trading based on the pricing strategy.

TABLE I. The ESS power of each seller in the simulated network in each day (Kw/h)

period	Seller 1	Seller 2	Seller 3	Seller 4	Seller 5
1	5.21	8.47	1.54	4.75	10.88
2	6.52	8.76	5.56	9.38	15.22
3	6.43	10.37	2.48	10.34	16.38
4	5.86	9.78	9.3	10.45	17.45
5	5.34	9.86	8.23	11.64	18.45
6	8.02	9.57	11.36	11.4	18.32
7	9.7	9.45	10.49	11.74	17.56
8	9.56	9.28	8.79	10.56	19.09
9	6.45	8.51	6.33	9.36	22.65
10	5.52	8.4	11.02	9.34	13.98
11	6.55	8.37	10.44	8.29	13.01
12	6.41	9.76	6.38	2.13	7.9
13	6.52	8.77	4.66	7.68	17.12
14	6.83	9.36	13.78	8.34	14.38

TABLE II. shows users' total power supply and needs. In period 7 and 8 the demand is less than surplus energy for sale. After selling energy to buyers by sellers, the surplus power remains for the next period of the market. In other periods, the power loads are less than the needs; therefore, after purchasing energy in the network, buyers have to buy their remaining needs from the power grid (with 0.77$).

TABLE II. The total power supply and demand of users in each day (Kw/h)

period	total energy for Sale	total energy need	total energy Sold based on NE	total energy Sold based on BDNE
1	30.85	-37.21	29.82	30.85
2	45.44	-48.57	43.27	45.44
3	46	-50.72	45.72	46
4	52.84	-53.02	51.93	52.84
5	53.52	-58.56	53.1	53.52
6	58.67	-61.51	58.67	58.67
7	58.94	-45.33	45.33	45.1
8	57.28	-36.12	36.12	36.12
9	53.3	-57.27	53.3	53.13
10	48.26	-49.84	47.63	48.26
11	46.66	-51.44	46.66	46.66
12	32.58	-44.65	27.15	30.24
13	44.75	-47.91	44.75	44.75
14	52.69	-58.7	48.14	50.29

V. Evaluation Results

The simulation results are discussed in two parts. The first one is the evaluation results of the pricing strategy of our trading model, and the performance test results of the transaction processing in the sample configuration are discussed in the second part.

A. Pricing Strategy Simulation Results

Fig. 3. shows the calculated optimal price for each period according to the sellers' offered price. As expected, the results show that the energy price is related to supply and demand. Remember that the initial cost of energy is 0.77 dollars.

Here we compare the purchase cost of our proposed trading model with the cost of purchasing energy using NE as a common pricing strategy. Also, the power sales benefit of the model and power sales benefit using NE are shown in **Error! Reference source not found.** The results of purchase costs and sale benefit show that our model has lower energy purchase costs than the model with NE. The energy sale benefit obtained from NE is significantly less than the benefit received by our BDNE-based proposed model. In general, the simulation results of the model show that using BDNE instead of NE in the decentralized trading model of the network preserves the profit, increases the seller's revenue, and reduces the buyer's energy purchase cost.

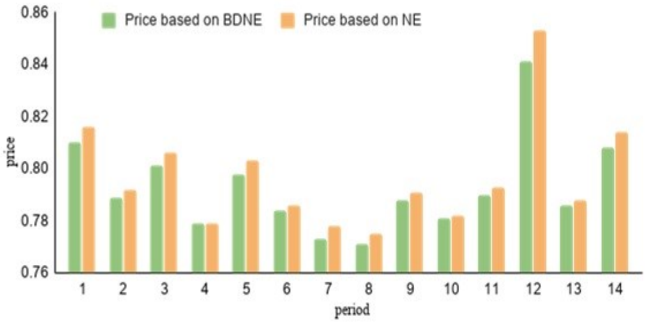

Fig. 3. The results of the optimal price which has been calculated for each period according to the offered price of energy by sellers

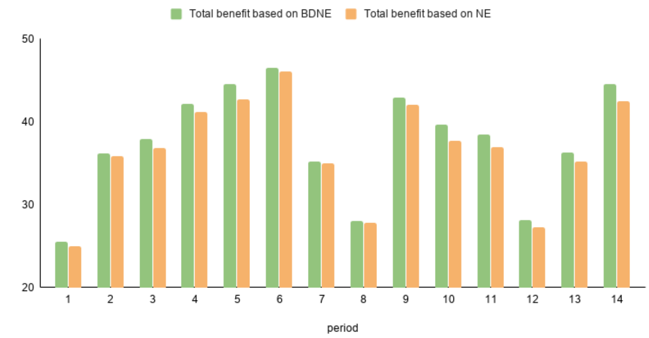

Fig. 4. The sales benefit of the proposed model (using BDNE) and sales benefit using NE . The vertical axis shows the total price of the benefit of sellers and buyers compared with buy or sale to the gird daily.

B. *Performance Evaluation*

The proposed trading model's performance was evaluated using Hyperledger Caliper, which is a performance benchmarking framework for blockchains developed by using Hyper Ledger Fabric [33].

The transaction processing capacity of a blockchain network can be reproduced by two metrics: throughput and latency. Throughput is an important reference metric to measure the performance of blockchain solutions, especially in real life. This index is presented as the number of network's handled transactions in a certain period. Tps (transactions per second) is used to determine the number of processed transactions per second. Latency is another important metric that shows the time a blockchain system needs to process a transaction. In performance evaluation, the latency of requests determines the amount of time a transaction needs to go from a client to the blockchain network. In general, ms (milliseconds) is used as the unit of this index. In the implemented evaluation bed, Caliper sends transaction requests to the blockchain network through a specific HTTP port. Then the trend of throughput and latency of the proposed model is measured. The results are shown in TABLE III.

To compare the performance of the proposed model with similar existing models, the data of throughput and latency for a model by Hashgraph consensus instead of Jointgraph, were extracted.

Throughput and latency were compared, respectively and shown in Fig. 5. And Fig. 6. It is apparent that in the whole period, for the proposed model, throughput is higher, and latency is less than in the other model.

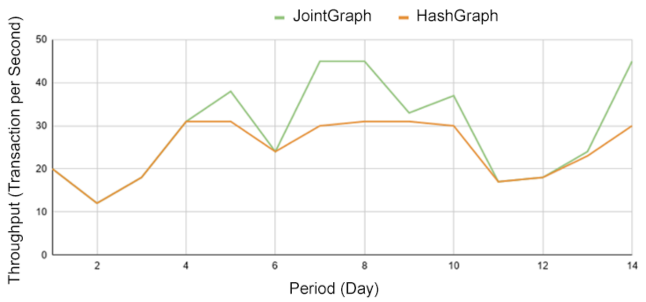

Fig. 5. The throughput of the system in each period using Jointgraph and Hashgraph as consensus method.

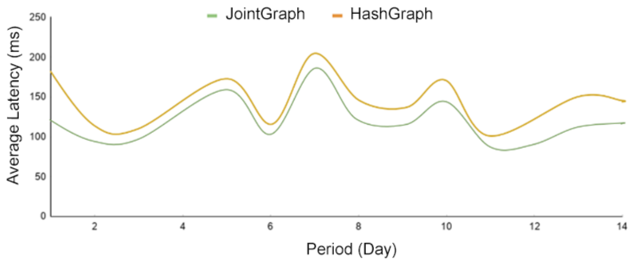

Fig. 6. The average latency of the system in each period using Jointgraph and Hashgraph as consensus methods.

TABLE III. THE RESULTS OF BENCHMARKING USING HYPERLEDGER CALIPER FOR THE PROPOSED BLOCKCHAIN NETWORK

Period	Success rate	Fail rate	Send Rate (Tps)	Max latency (ms)	Min latency (ms)	Avg. latency (ms)	Throughput (Tps)
1	100	0	20	160	40	120	20
2	100	0	12	115	33	94	12
3	100	0	18	127	35	98	18
4	100	0	31	187	58	132	31
5	100	0	40	201	66	160	38
6	100	0	24	132	32	101	24
7	100	0	64	219	43	187	45
8	100	0	53	184	50	120	45
9	100	0	33	175	53	115	33
10	100	0	37	181	46	143	37
11	100	0	17	117	38	89	17
12	100	0	18	120	29	92	18
13	100	0	24	166	58	111	24
14	100	0	54	182	42	118	45

VI. CONCLUSIONS

In this work, the Belief distorted Nash equilibrium theory has been combined with DAG-based consortium blockchain and Jointgraph consensus algorithm to develop an energy trading model for surplus energy trading in local ecosystems. The simulations and result evaluations show that the pricing strategy based on BDNE theory can reduce the cost of energy consumers by about 2%, and increase the benefits for both sellers and buyers by about 1.3% compared with the way of using NE, instead. In addition, the trading model based on DAG-based blockchain technology using Jointgraph as a consensus algorithm is better than a similar blockchain using a Hashgraph as consensus process in both metrics of Throughput and Latency. However, the implemented scenario in the simulation of the work is relatively simple, and the transaction rate is low in specific durations. So, the evaluation of the ability of the model in real-life application scenarios will be considered as future works.

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