Blockchain-based Peer-to-Peer Energy Trading Method

Myles J. Thompson, Hongjian Sun, *Senior Member*, *IEEE*, and Jing Jiang, *Member*, *IEEE*

***Abstract*—For grid-connected neighbors within communities, blockchain-enabled peer-to-peer energy trading proves to be a coherent approach to trade energy from locally produced and distributed renewable energy resources. Effective matching among peers enables enhanced energy efficiency during energy transactions, thereby improving the power quality and preferentially increasing user welfare. The proposed algorithm builds upon work to develop a system of scoring an energy transaction. It employs a McAfee-priced double auction mechanism and assigns the scores based on the preference of factors like price, locality, and the type of energy generation, in addition to the quantity of energy being traded. These transactions are pre-evaluated by the said algorithm to determine the optimal transactional pathway. As a result, the transaction that is finally executed is the one holding the highest cumulative score. The proposed algorithm is simulated over a range of scenarios and tends to boost the user welfare percentile by an average of 75%. From an economic perspective, the algorithm may be implemented in small to large settlements while remaining stable. By reducing power loss, this energy trading algorithm empowers consumers to save around 25% on their energy costs and offers prosumers a 50% increase in revenue.**

***Index Terms*—Peer-to-peer energy trading, smart grid, blockchain, matching algorithm, renewable energy source.**

NOMENCLATURE

All the values are scalar unless stated otherwise.

a, b, c	Cost function parameters.
$\mathbb{B}$	Set of buyers.
B_k	kth buyer.
$C(\cdot)$	Cost function.
C_d	Distance charge.
$D_{B,k}, D_{S,k}$	Distance preference of kth buyer or seller.
$d_{i,j}$	Distance between ith and jth agents.
$E_{B,k}$, $E_{S,k}$	Energy to buy/sell of kth buyer/seller.
$E_{\mathbb{B}}$, $E_{\mathbb{S}}$	Total energy of set of agents.
$EP(\cdot)$	Energy function.
N	Degree of search for each level.
p	Clearing price.
P	Agent's price preference.
$\mathbb{S}$	Set of sellers.
S_k	kth seller.
$U(\cdot)$	Utility function.
$W_{B,k}$, $W_{S,k}$	Welfare of kth buyer or seller.
α, ω	Utility function parameters.
$\varepsilon_{B,k}$	kth buyer's energy generation preference.
$\varepsilon_{S,k}$	kth seller's energy generation type.
$\wedge$	Logical AND.

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I. INTRODUCTION

WITH the rise of decentralised energy production and households producing evermore renewable energy [1], the infrastructure throughout this paradigm is currently a key research area. It is thus essential for a trading mechanism to be developed which allows peers to trade energy. Peer-to-peer (P2P) energy trading allows neighbours within communities and within small groups of communities to share their renewable energy sources, combatting power quality issues, improving the welfare of the local community, and decreasing the demand for fossil fuel power. In the context of P2P, a peer refers to a user of the system, whether consuming, generating or prosuming (a concatenation of both).

A. Decentralisation of the Energy Utility: Blockchain

Blockchain-based P2P energy trading allows households to trade energy with their neighbours without a central utility company [2], [3], eliminating the vast levies placed by the utility companies, and promoting both localization of trading as well as localization of profits [4]. The benefits of decentralizing energy trading are not just limited to the localizing of systems. It grants households the choice of purchasing their electricity on the basis of personal preference, whether by generation type or quality. Decentralization also allows relative independence from the power grid: ensuring consistent power quality, and maintaining power supply even in the event of a major utility failure, e.g., due to extreme weather [5], [6].

The fundamental notion behind blockchain is the distributed ledger. The information on the transaction is not stored centrally, but distributed amongst all the users throughout the system [7]. A system of consensus is then used to determine the correct series of events. In combination with smart contracts, first formulated during the development of Ethereum in [8], blockchain is a model platform for deployment in local microgrids and increases resiliency through trust creation [9]. It is a decentralized system and functions in a trust-less or even negative-trust environment [10]. Unlike Bitcoin, Ethereum is not solely a platform, but its own Turing-complete coding environment [11]. This computational universality aids developers in building applications and running them successfully, directed at the automation of the energy trade. One example of blockchain-based P2P energy trading is the Brooklyn Microgrid [12], which exhibits desirable facets of the said trade, such as decreasing prices and power quality issues, and strengthening community spirit.

B. Current Trading Methods and Algorithms

The contemporary trading method adopts double auctions to facilitate the energy trade: the bid and ask prices are submitted to an auctioneer without being visible to the other participants. Subsequently, a clearing price is calculated as (most commonly) the median value. After that, all the bids below this price are eliminated, as are all the asks above this price. This can either materialize into a continuous auction, as is the case in [13] for example, or in most cases, a discrete one, as in [14], [15], and [16]. Discrete markets are typically known to be hour-ahead bids, implying that the bids are submitted based upon the predictive energy and generation data set obtained for the following hour, with the market open for a certain period (e.g., 15 mins), after which the auctioneer finalizes the biddings. This repeats hourly. The implementation of rapid trading algorithms facilitates the functioning of the market in an hour-ahead manner rather than day-ahead with more accurate predictions of energy consumption and generation. Thus, this pattern endows the users with better flexibility of choice and probably reduces the energy wasted owing to inaccurate predictions.

C. The Importance of Order Matching

Many authors have investigated both the structures of P2P energy trading systems and the various pricing strategies. However, the methods of trade matching have not been investigated sufficiently. To best explain the process of order matching, we have used the following example:

Consider the minimal example of two sellers, S_1 and S_2, who want to sell 50 kW·h and 100 kW·h, respectively. There are three buyers, B_1, B_2, B_3, and each wants to buy 50 kW·h of energy, they form a set $\mathbb{B}$. For now, the energy sold by the set of sellers, $\mathbb{S}$, is of consistent quality and type. Consider the following three potential scenarios that emerge for the above situation:

- **Scenario 1:** S_1 and S_2 have the same ask price, say £2/kW·h. This situation implies that the 150 kW·h of energy from $\mathbb{S}$ will be sold and distributed evenly amongst $\mathbb{B}$ and they will each be charged £300/$|\mathbb{B}|$.
- **Scenario 2:** S_1 and S_2 have different ask prices, say £2/kW·h and £3/kW·h respectively. It indicates that the same 150 kW·h of energy from $\mathbb{S}$ will be sold and distributed evenly amongst $\mathbb{B}$. However, the price paid by each would now be £400/$|\mathbb{B}|$, such that they receive £100 and £300.
- **Scenario 3:** The ask prices from scenario 2 are carried forward, however B_1 prefers the energy sold by S_1 because of geographical proximity. By selling all of the energy from S_1 to B_1, it ensures the satisfaction of B_1, but enforces a higher buying price for B_2 and B_3. On the other hand, the majority of B_1's energy can be purchased from S_1, leaving a small share of the lower price for B_2 and B_3—this increases the satisfaction of the other buyers at the expense of B_1.

By extending this example to multiple sellers with different prices, and likewise complex buyers' preferences, it can be established that achieving a match that is considered 'fair' by the majority is not easy. Potential simple solutions include a first-come first-serve method, or manual selection by each buyer [17]. If this scenario is applied to a commercial microgrid operation, every trade will be overlooked by the prosumers; however, the cumulative effect of the high bills will be such that it ultimately overthrows the objective of decentralization.

This paper proposes a system that reinforces decentralized P2P energy trading and its benefits. The main contributions of this paper are to:

- Propose a method of ranking potential renewable energy transactions dependant on their respective preferences.
- Devise an algorithm matching renewable energy sellers with the local buyers which is considered to be fair and as per the parties' preferences.
- Incentivize and stimulate the trading practice of renewable energy to multiply the value proposition of small-scale generation, thus boosting the energy efficacy of the associated industry.

The proposed system facilitates effective matching between buyers and sellers and appears to be conducive for consumers, prosumers, and communities.

II. Fundamentals and Relevant Work

Murkin [18] designed an algorithm in order to 'score' the hypothetical transaction between a buyer and a seller for every buyer and seller in that energy auction. Acquired from a traditional rank-order listing, it considers the price preference, energy type preference, and distance preference of both the buyer and the seller. The scoring was as undermentioned, and takes into account the price preference P, distance preference D, energy generation type ε, distance charge C_d, distance d between the two agents, and uses a function $EP(\cdot)$ to return the energy type preference from ε. The subscripts B and S represent the buyer and the seller, respectively. This can be used for any combination of ith buyer and jth seller, giving a value for their paring—the subscripts i and j have been omitted for ease of reading.

$$\text{score}(B,S) = (P_{\text{B}} - d \cdot C_d) \times \begin{cases} EP(\varepsilon_{\text{S}}), & \text{if } (d \leq D_B) \wedge (d \leq D_S) \\ \frac{1}{2}\left(\frac{D_S}{d} + EP(\varepsilon_{\text{S}})\right), & \text{if } (d \leq D_B) \wedge (d > D_S) \\ \frac{1}{2}\left(\frac{D_B}{d} + EP(\varepsilon_{\text{S}})\right), & \text{if } (d > D_B) \wedge (d \leq D_S) \\ \frac{1}{3}\left(\frac{D_B}{d} + \frac{D_S}{d} + EP(\varepsilon_{S,k})\right), & \text{if } (d > D_B) \wedge (d > D_S) \end{cases} \tag{1}$$

where D_{B} and D_{S} represent the distance preference of the buyer and the seller, respectively.

Murkin's algorithm then completes the sale for the highest scoring buyer and repeats yields minimal acknowledgment for sellers. The evaluation of this algorithm it until there are no more buyers or the satisfaction or welfare of the agents. Furthermore, Murkin's algorithm essentially appears to be greedy and only focuses on optimizing the score of a transaction, but not the interest of all the agents involved.

Consider the minimal example of a market with one seller, S_1, and eight buyers, $B_{1:8}$, arranged so that B_1 has the highest score and B_8 the lowest. S_1 has 100 kW·h of energy to sell. In total, the set of buyers, $\mathbb{B}$, wishes to buy 200 kW·h of energy. The distribution of energy values is as seen in Fig. 1, with the proportion of the order that would be filled represented by the filled circle.

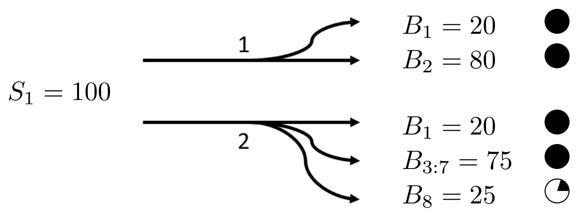


Fig. 1. Potential distribution paths.

In this scenario, one of the two paths can be taken; either way, 100 kW·h of energy will be sold, and the remainder will be purchased from the leading utility providers. Using a greedy algorithm, like Murkin's, which solely considers the score would take path 1 as B_2 has a higher score than B_3. Instinctively, however, rewarding the needs of most buyers using path 2 appears to be a better option.

Rahbari-Asr analogously evaluated this problem from an economics perspective in [19]. He expressed the welfare of both the buyer and the seller. The welfare of the kth buyer, $W_{B,k}$, is a function of the energy demand $E_{B,k}$ and the price p, with $U(\cdot)$ as the utility function:

$$W_{B,k} = U(E_{B,k}) - pE_{B,k} \tag{2}$$

which is also defined in [20]. It should be non-decreasing and saturate with higher power, while using selectable parameters ω and α.

$$U(E_{B,k}) = \begin{cases} \omega E_{B,k} - \alpha E_{B,k}^2 & E_{B,k} \leq \omega/2\alpha \\ \omega^2/4\alpha & E_{B,k} \geq \omega/2\alpha \end{cases} \tag{3}$$

For sellers, their welfare is the net profit for selling energy E_{S}:

$$W_{S,k} = pE_{S,k} - C(E_{S,k}) \tag{4}$$

where the cost function, $C(\cdot)$, is defined from [21] as:

$$C(E_{S,k}) = aE_{S,k}^2 + bE_{S,k} + c \tag{5}$$

where cost function parameters a, b, and c are determinable constants.

Rahbari-Asr optimized these functions, but he did not consider the same parameters as in Murkin's paper: energy type or distance. Furthermore, there is no executable form of the algorithm. Rahbari-Asr's optimization does, however, yield a Pareto optimal solution—a solution whereby no further change would produce a better result for any single individual [22]. These definitions of welfare for the buyers and the sellers establish a metric using which the proposed algorithm may be analyzed.

III. Algorithm Evolution

The algorithm proposed by Murkin matched transactions by selecting the highest scoring buyer for each seller, and repeating until there were no remaining possible transactions or no energy left to be transacted. The algorithm uses a basic median-clearing double auction. Matching is acheieved with a greedy algorithm: each buyer is looped through, transacting for its best seller, and proceeds further. To improve this, when compared using the metric of welfare from Section II, the pricing, scoring, and most saliently matching mechanisms were altered.

A. Pricing Improvements

The relevant research work by Babaioff [23] serves as a comparison of various pricing mechanisms for double auctions. There are three plausible implementations cases in energy trading: average pricing, identical to that used by Murkin; McAfee pricing; and trade reduction (TR) pricing. Even though other pricing mechanisms exist, they require the auctioneer to be in deficit. The definitions of these potential prices follow below, with the set of buyers, $\mathbb{B}$, and sellers, $\mathbb{S}$, in their natural ordering with counter k.

Average pricing:

$$p = (P_{B,k} + P_{S,k})/2 \tag{6}$$

McAfee pricing:

$$p = (P_{B,k+1} + P_{S,k+1})/2 \tag{7}$$

TR pricing:

$$p_{\mathbb{B}} = P_{S,k} \tag{8a}$$

$$p_{\mathbb{S}} = P_{B,k} \tag{8b}$$

All of these mechanisms are considered individually rational, truthful, and have a balanced budget (weakly in the case of TR) [23]. The performance of these three mechanisms was evaluated in the evolution process of the algorithm.

B. Scoring Improvements

The scoring metric used for the proposed system reflects that in [18]. This mechanism allows users to show preferences of price, locality, and energy type of their preferred supplier. An addition of scoring based upon the quantity of energy to be sold was added. This allows users who want to buy or sell more energy to be treated preferentially than those who bid for smaller quantities [24]. The score used in the proposed system thus takes the following form,

$$\mathrm{score}(B, S) = \min(E_{\mathrm{B}}, E_{\mathrm{S}}) + (P_{\mathrm{B}} - d \cdot C_d)\times$$

$$\begin{cases} EP(\varepsilon_{S,k}), & \text{if } (d \leq D_B) \wedge (d \leq D_S) \\ \frac{1}{2}(\frac{D_S}{d} + EP(\varepsilon_{S,k})), & \text{if } (d \leq D_B) \wedge (d > D_S) \\ \frac{1}{2}(\frac{D_B}{d} + EP(\varepsilon_{S,k})), & \text{if } (d > D_B) \wedge (d \leq D_S) \\ \frac{1}{3}(\frac{D_B}{d} + \frac{D_S}{d} + EP(\varepsilon_{\mathrm{S}})), & \text{if } (d > D_B) \wedge (d > D_S) \end{cases} \tag{9}$$

C. Matching Improvements

The matching algorithm was developed in two stages, firstly to eliminate bias towards any specific seller or buyer, and secondly to be ideally non-greedy and consider global optimization.

Murkin's algorithm has an inherent bias towards a certain buyer or seller during matching. Considering its matching method, the algorithm works sequentially through the sellers, only transacting the highest buyer for that seller each time, irrespective of the next highest score for that seller. The natural progression for this algorithm, thus, is to transact at the highest scoring sale globally, and update the scores for each iteration. This algorithm is represented in Algorithm 1. Although a clear improvement upon Murkin's, matching is still done in a greedy fashion: optimizing the score for each transaction, not globally.

Algorithm 1: Highest score

Data: Set of buyers, $\mathbb{B}$, with total energy $E_{\mathbb{B}}$; set of sellers, $\mathbb{S}$, with total energy $E_{\mathbb{S}}$; set of scoring parameters $\forall\ \mathbb{B} \wedge \mathbb{S}$
Result: Set of transactions
Initialisation:

```
foreach B ∧ S do
    Calculate the score from (9);
end
Matching loop:
while E_B > 0 ∧ E_S > 0 do
    Transact for the highest score;
    Recalculate scores from (9);
end
```

IV. Proposed Algorithm

The algorithm proposed in this paper seeks to tackle the greed of the matching algorithms discussed in Section III. The ideal algorithm would search through every possible sequence of transactions, comparing the cumulative scores, and executing the transaction path with the highest score. This would demand the utilization of computational resources and calculations that are far greater than what the devices are typically accustomed to conducting in a commercial setup. Although it would vary depending on the relative volume of energy being bought and sold, in an example of 10 buyers and 8 sellers, with equal energy deficit and excess respectively, there would be $\mathcal{O}(10 \times 8!)$ potential transaction paths. Implementing this situation to the commercially viable case of a medium-sized UK town with average number of UK renewable-generating households, would certainly lead to more than a googol potential transactional paths. Evidently, this is highly unfeasible.

The proposed solution is to pre-evaluate a limited number of these potential transactional paths. The terminology used subsequently refers to the concepts shown in Fig. 2. A level is used to describe the set of transactions available to a buyer accounting for any previous hypothetical transactions. The algorithm finds the top N level-1 transactions and evaluates the next best transaction in the hypothetical case of each level-1 transaction having taken place. We refer to this as a two-level transactional mapping. The resulting actual transaction is the level-1 sale associated with its highest cumulative score and highest potential scoring level-2 transaction. This algorithm is presented in Algorithm 2.

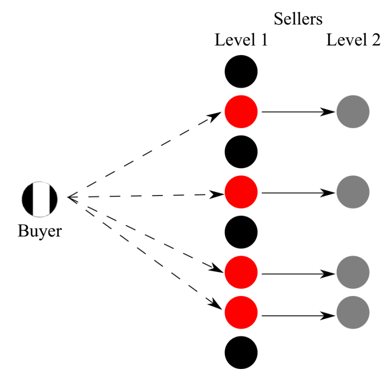


Fig. 2. Two-level transactional mapping where N is 4 and the number of sellers is 8. The red sellers are the top N level-1 sales. The level-2 transactions shown are the highest scoring transactions for each of the top N level-1 transactions. The algorithm selects the pathway with greatest combined level 1 and level 2 scores.

Algorithm 2: Proposed algorithm

Data: Set of buyers, $\mathbb{B}$, with total energy $E_{\mathbb{B}}$; set of sellers, $\mathbb{S}$, with total energy $E_{\mathbb{S}}$; set of scoring parameters $\forall\ \mathbb{B} \wedge \mathbb{S}$,
Result: Set of transactions

```
Initialisation: foreach B ∧ S do
    Calculate the score from (9);
end
Matching loop:
while E_B > 0 ∧ E_S > 0 do
    Find the top N potential transactions;
    i ← 1 ;
    while i ≤N do
        Recalculate scores given the ith level 1 transaction;
        Find the highest scoring potential transaction;
        i ← i + 1;
    end
    Transact for the path with the highest combined level-1
      and level-2 scores;
end
```

This algorithm is capable of adjusting the flow of transactions to accommodate for scenarios like that described in the example in Section II. The natural progression of this is to move a level deeper, forming a transactional mapping like the one shown in Fig. 3, where the ideal case would search through every level. Recalling the number of computations n, for $|\mathbb{B}|$ buyers and $|\mathbb{S}|$ sellers varies as,

$$n = \mathcal{O}(|\mathbb{B}| \cdot |\mathbb{S}|!) \tag{10}$$

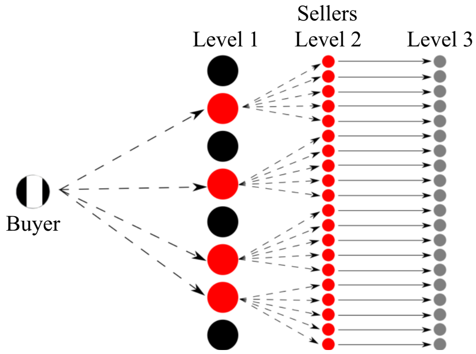


Fig. 3. Three-level transactional mapping. The red level-1 sellers are the top N sales. The red level-2 sales are the top potential sales given each red level-1 sales in turn (non-optimal level-2 sales are omitted for ease of reading). The algorithm selects the pathway with the greatest cumulative score from levels 1 to 3.

Here, it intensifies the algorithm, indicating that it must have a cut-off limit. This is most easily explored empirically through simulation results. A three-level transactional mapping, however, would take the form shown in Algorithm 3.

Algorithm 3: Proposed algorithm (3 levels)

```
Data: Set of buyers, 𝔹, with total energy E_𝔹; set of
      sellers, 𝕊, with total energy E_𝕊; set of scoring
      parameters ∀ 𝔹 ∧ 𝕊,
Result: Set of transactions
Initialisation:
foreach 𝔹 ∧ 𝕊 do
    Calculate the score from (9);
end
Matching loop:
while E_𝔹 > 0 ∧ E_𝕊 > 0 do
    Find the top N potential transactions;
    i ← 1 ;
    while i ≤N do
        Recalculate scores given the ith level 1
          transaction;
        Find the top N potential transactions;
        j ← 1;
        while j ≤N do
            Recalculate scores given the jth level 2
              transaction;
            Find the highest scoring potential
              transaction;
            j ← j + 1;
        end
        i ← i + 1;
    end
    Transact for the path with the highest combined
      levels 1–3 scores;
end
```

V. Results and Discussion

For the results to remain comparable, a simulation to test the proposed algorithm was set up in a similar fashion to that of Murkin. Accounts were assigned randomly by the 'mlfg6331_64' random number generator, with location, price and preferences listed in Table I. Cost and utility function parameters are also listed.

TABLE I
Simulation Parameters

Latitude		[50.95687 52.438562]	
Longitude		[-2.386779 0.292914]	
E_b	[1 6]	P_b	[0 16]
E_s	[5 10]	P_s	[4 6]
D	[5 10]	C_d	0.2
a	0.005	ω	14
b	6	α	0.07
c	1		

The energy function, $EP(\cdot)$, returns a value dependant on the energy type and preference inputted as follows,

$$EP(B_i, S_j) = (\varepsilon_{B,i} - \varepsilon_{S,j})^2 \tag{11}$$

This function is populated with values from $1-5$, for solar, micro CHP, wind, hydro, and anaerobic digestion, respectively. Distances are calculated 'as the crow flies', using the haversine formula.

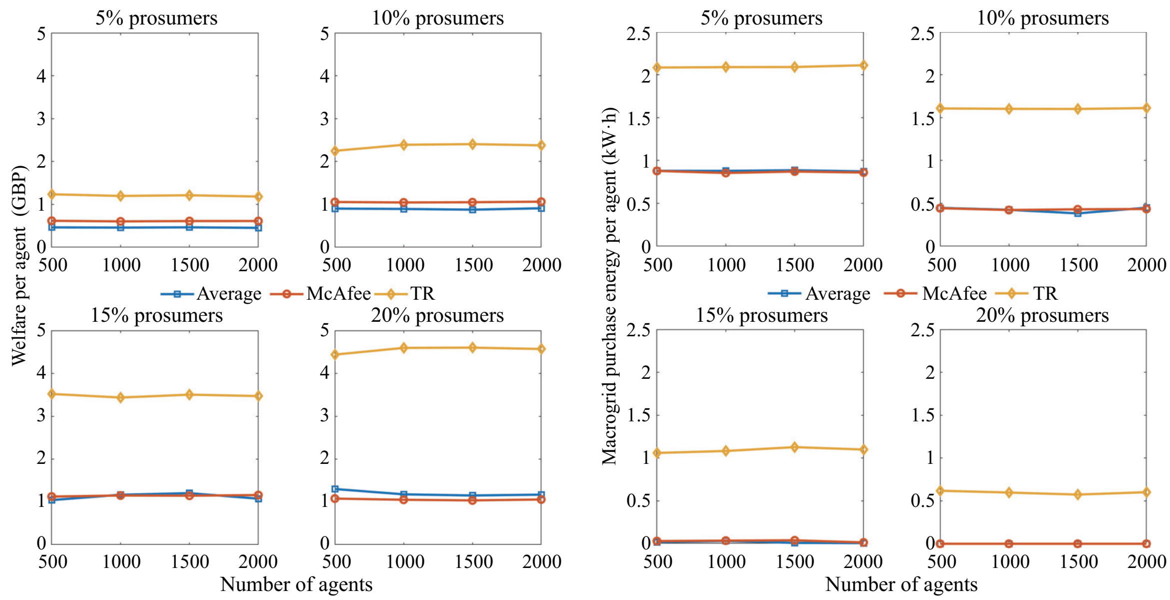
The simulation was run on Matlab for scenarios of 5%–20% sellers (stepping by 5%), with 500 to 2000 agents (stepping by 500). Each simulation was run 10 times, and the output was averaged, thus reducing the volatile nature of the random numbers and increasing the results' reliability. For all simulations, four primary data were extracted: the energy bought from the macrogrid, number of transactions, clearing price, and welfare as defined in (3) to (4). These serve to demonstrate the performance, stability, and 'fairness' of the algorithm. A well performing, stable and fair algorithm would have low macrogrid purchase, stable results independent of the number of agents, and high welfare.

A. Pricing Performance

To evaluate the performance of the three pricing strategies—average, McAfee, and TR—the welfare and macrogrid purchases were compared for each of them. These are plotted in Fig. 4 by running a range of agents and proportion of prosumers using Murkin's algorithm. It is clear that despite TR pricing yielding a higher welfare for each agent, this was detrimental to the macrogrid purchase. It was concluded that McAfee pricing offered a better balance between welfare and macrogrid purchase, and additionally stability. The proposed algorithm, thus allots prices according to the McAfee scheme. The standard deviation of the price, across all simulations, was approximately 0.1% of the mean value.

B. Relative Performance

The performance of the proposed algorithm demonstrates a significant improvement as compared to the more basic matching methods. Fig. 5 charts the averaged welfare and macrogrid purchase of each agent across a range of scenarios. These scenarios are driven by the quantities of agents and percentage of prosumers, as stated at the beginning of this section.



(a) Welfare per agent

(b) Macrogrid purchase energy per agent

Fig. 4. Comparison of three pricing regimes.

All the algorithms consistently match with all the marketable energy to buyers. This can be observed by the lack of variation of average macro-grid purchase across the range of algorithms. The random nature of the inputs causes slight fluctuation. Most prominently, Fig. 5 demonstrates the consistent increase in the welfare of each agent throughout the algorithm's evolution. The welfare of users using the proposed algorithm is, on average, more than 75% higher than those with Murkin's algorithm.

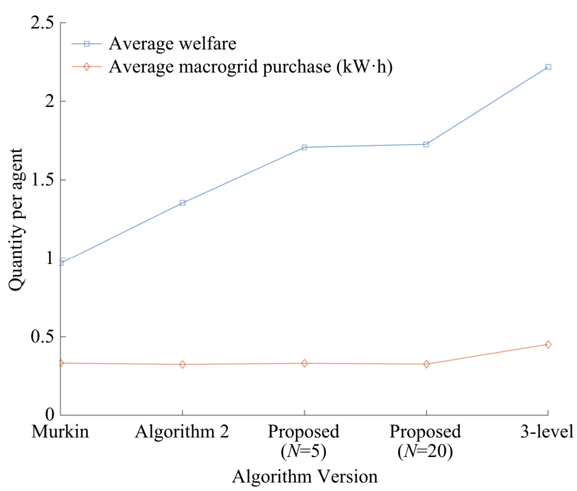


Fig. 5. Evolution of the matching algorithm.

The proposed algorithm was tested with varying N, the degree to which each level is searched. Across all data, little variation was shown increasing N from 5 to 20. This resulted, however, due to the detriment of computational time. An approximately $2.5\times$ increase in computational time was seen on average moving from $N = 5$ to $N = 20$. As the number of agents increases to the size of a large town with agents of the order of greater than 10^6, increasing the degree N would provide a greater benefit. Nonetheless, this steps out of the commercial context of this study.

Notably, the 3-level algorithm performs with an increase in welfare per agent. This is perhaps not surprising. The magnitude of the increase, however, is large. It is likely that the level 2 transactions evaluated by Algorithm 2 are, at least somewhat, the other top $N - 1$ transactions in level 1. By moving a level deeper, the algorithm considers transactions that would not make it to the top N level 1 transactions, thus it considers a more diverse range of transactional paths.

It is this reasoning that is also reflected in the stability of Algorithm 3. Fig. 6 shows some performance data for Algorithm 3. Noticeably, within each step of prosumers, the simulation outcome appears to be highly unstable; in particular, the data obtained suffered massive variations between identical simulations. The datapoints, although fluctuating, showed that Algorithm 3 did always at least match, if not outperform, Algorithm 2. This shows that, depending on the random agent profiles inputted, the level 3 transactions are often, but not always, distinct from the level 1 transactions. In total, however, the instability of Algorithm 3 is too great compared to its performance increase compared to Algorithm 2.

C. Scalability

The scalability of algorithms forms a vital aspect, especially within the context of blockchain. One of the key areas of research for blockchain currently is the scalability of the technology. With traditional blockchain technologies (including Ethereum), scaling its use to a commercial context can require extremely high computing power and thus, counterproductively, energy usage, and can lead to bottlenecking and system failure [25]. In order to confirm the scalability of the proposed algorithm, it was simulated in the context of a large and a small population. The smaller population ranged from

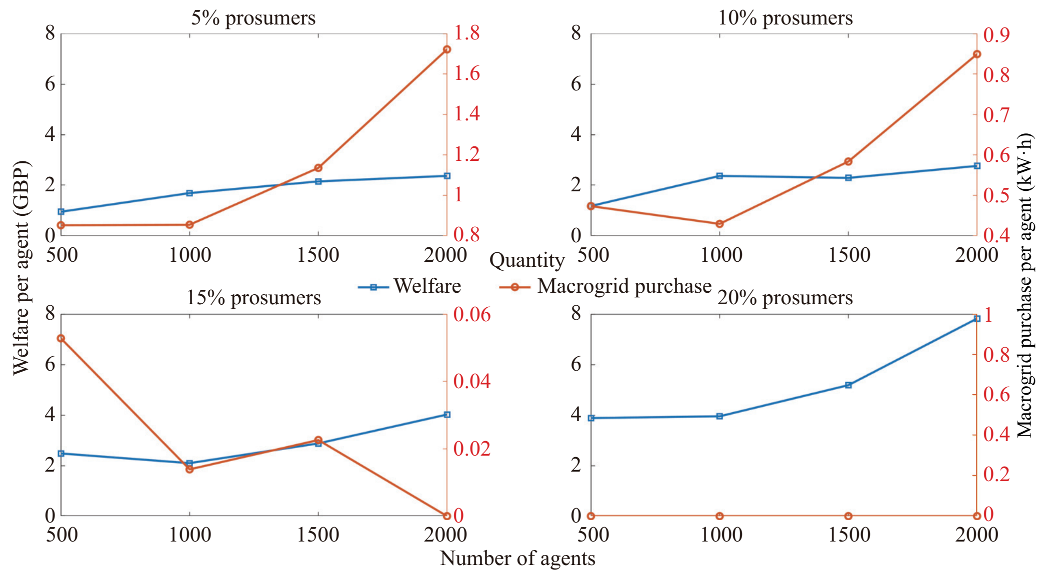


Fig. 6. Instability of 3-level algorithm.

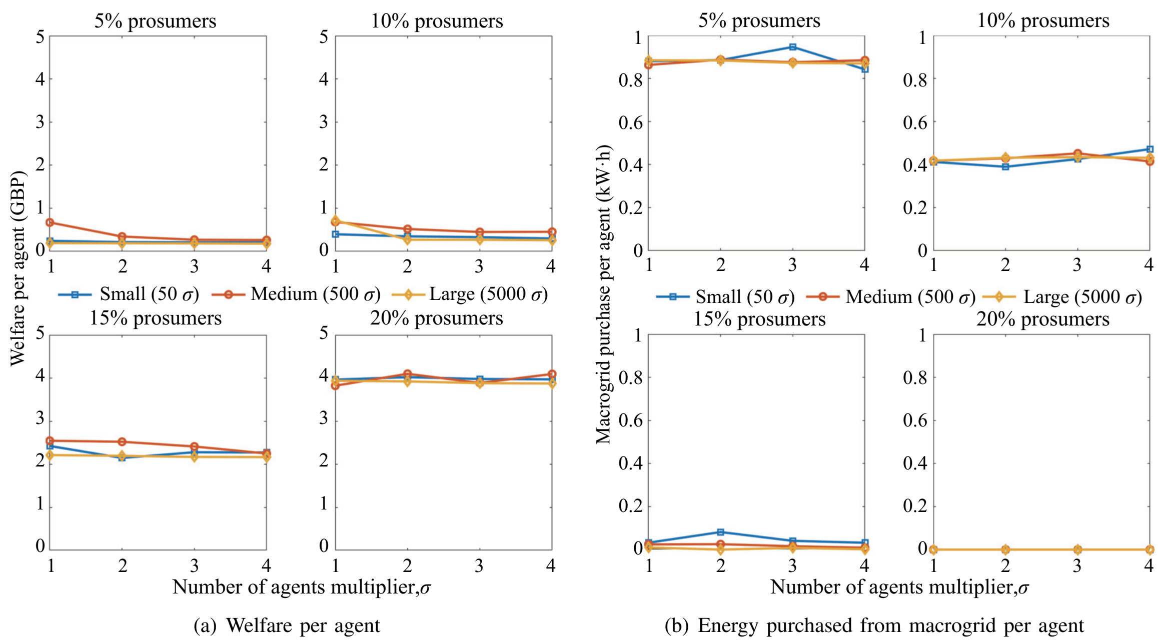


Fig. 7. Scalability of proposed algorithm for small, medium, and large scale use.

50 to 200 agents, and the large one ranged from 5000 to 20000 agents. These results can be seen in Fig. 7. Although the small population exhibits some slight instability, in the form of fluctuation within a proportion of prosumers, the percentage change is within an acceptable range. Noticeably, the algorithm remains stable on increasing the size to a large population, identical to that of a large UK town [26].

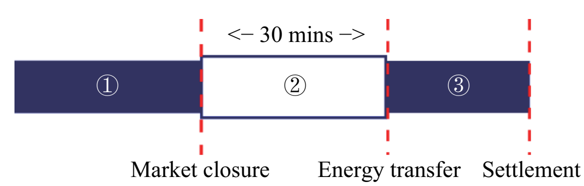


Fig. 8. Visualisation of market timings.

D. Commercial Context

The context in which this algorithm is applicable commercially is in the case of a blockchain-enabled P2P energy trading system. The market structure can be seen in Fig. 8. In phase one, prior to the market closure, half an hour before energy is to be transferred, bids are placed in the system. These would rely on both predictive energy usage data, and predictive generation and weather data. Half an hour before energy transfer, the market closes, and the system enters phase two. Within this phase the relevant data are gathered, the proposed algorithm is executed, and a list of trades to be executed is outputted. The energy is transferred after half an hour of the market period, and transactions are registered onto the blockchain. This is phase three, and it lasts up until the end of that billing period. Considering the number of transactions occurring in a day, bills should be issued monthly like a conventional energy system.

The half an hour market time, although conventional, is arbitrary. With improved weather prediction data and enhanced consumption and generation prediction, this market window may reduce further [27].

As a part of the scalability issue, a major weakness of blockchain is the rate of transactions. The transaction rate of Ethereum, for example, is approximately 10 transactions/s [28]. For a set of 2000 agents, where 20% are prosumers, the proposed algorithm returns almost 650 transactions. For larger sets, this number is likely to cause the blockchain's transaction rate to be the limiting factor of the market time. Platforms like Ethereum are developing techniques to overcome these throughput restrictions. Sharding is a proposed solution to this hurdle. Sharding divides the tasks of the blockchain across multiple chunks, processed by multiple nodes. This has the effect of partitioning the data and state of the network, creating multiple, smaller blockchains which can all communicate. This effectively reduces the amount of computation performed by a single node, thereby reducing time and increasing transaction rate. In the context of P2P energy trading, this could alternatively be realized by reducing the area across which the network runs, dividing towns into multiple smaller networks.

For users of the system, they would certainly experience some amount of change in the way they receive and pay for their energy. The proposed algorithm, on average, provides a two-thirds reduction in the amount of energy purchased from the macrogrid. This translates to approximately a 25% reduction in bills for consumers, and a 50% increase in payments to prosumers as compared to current UK Government FITs (feed-in tariffs) using the data in Table I and the mean clearing price from the algorithm tends to be approximately 10 p/kW·h [29]. By trading renewable energy for local usage, the major portion of the energy may be utilized efficiently instead of being lost in transmission. Furthermore, the moderated dependency of this technology on the macrogrid enables the incentive of various ecological benefits. If deployed alongside physical microgrids, this type of contemporary technology may also very well tackle the power quality issues and successfully reduce the reliance on large centralized points of generation.

VI. Conclusion

This paper has proposed an algorithm for use in P2P energy trading. It uses McAfee pricing for a double auction, whereby users are scored depending on their preferences of price, locality, and energy type and the quantity of energy they wish to trade. The algorithm matches buyers and sellers, in a non-greedy fashion, by pre-evaluating a limited number of transactions and proceeding with the transaction offering the highest score for the agents. It provides a greater than $1.75\times$ average increase in user welfare compared to similar greedy algorithms found in previous works. The proposed algorithm allows consumers to save 25% on their energy bills and helps prosumers obtain an additional 50% on the energy they sell. Commercial usage of this algorithm reduces the net carbon released by a state through more effective utilisation of individuals' generation capacity.

From a theoretical standpoint, this paper presents a complete system by which P2P energy trading can be executed. Some future research on this subject could focus on utilizing the proposed pricing, scoring, and matching mechanisms in a commercial setting. As discussed, the context of blockchain trading often deals with low-computational resources; thus, the exact implementation of the matching algorithm forms the key to its commercial success. Future research could also include a game-theoretical analysis of the matching algorithm. Using clearing prices and pricing preferences instead of hard boundaries, the nature of the algorithm could be exploited by the participant agents for financial advantage. During the commercial development, the algorithm could be altered to make it unsusceptible to cyber-attacks. Likewise, the security of the system is highly crucial, especially since large amounts of data are likely to be transmitted wirelessly and the trading information is entirely public.

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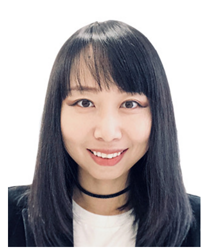

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