Blockchain-Based Peer-to-Peer Energy Trading Method

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***Abstract*—Blockchain-enabled peer-to-peer energy trading provides a method for neighbours and communities to trade energy generated from local and distributed renewable energy sources. Effective matching can facilitate greater energy efficiency during transmission, increases user welfare through preference and improves power quality. The proposed algorithm builds upon work to develop a system of scoring an energy transaction. It uses a McAfee-priced double auction, and scores based upon preference of price, locality, and energy generation type, alongside the quantity of energy being traded. The algorithm pre-evaluates transactions to determine the optimal transactional pathway. The transaction carried out is that leading to the greatest cumulative score. Simulated over a range of scenarios, the proposed algorithm provides an average increase in user welfare of 75%. Commercially, the algorithm may be deployed in small to large settlements whilst remaining stable. By reducing power loss, the algorithm allows consumers to save 25% on their cost of energy, whilst providing a 50% increase in the revenue earned by prosumers.**

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

NOMENCLATURE

All values are scalar unless otherwise stated.

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. A peer, in the context of P2P, is 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]. This eliminates the vast levies placed by the utility companies, and encourages both locality of trading but also locality of profits [4]. The benefits of decentralising energy trading are not limited to locality, however. It allows households the choice of purchasing their electricity on the basis of personal preference, whether that is generation type or quality. Decentralisation also allows relative independence from the power grid: ensuring consistent power quality, and maintaining supply in the event of a major utility failure, e.g., due to extreme weather [5] [6].

The fundamental notion underlying blockchain is the distributed ledger. The information on the transaction taking place is not stored centrally, but distributed amongst all users throughout the system [7]. A system of consensus is then used to agree upon the correct series of events. In combination with smart contracts, first realised in 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 decentralised and works 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 allows developers to build applications and run them ideal for automating the trading of energy. One example of blockchain-based P2P energy trading is in the Brooklyn Microgrid [12], where decreasing prices and power quality issues, and increasing community spirit are demonstrated.

B. Current trading methods and algorithms

The state of the art is to use double auctions to facilitate the trade of energy: bid and ask prices are submitted to an auctioneer without being visible to others and a clearing price is calculated as (most commonly) the median value. From this, all bids below this price are eliminated, as are all asks above this price. This can take form as either a continuous auction, as is the case in [13] for example, but most commonly discrete, as in [14], [15] and [16]. Discrete markets are commonly hour-ahead, meaning that bids are submitted based upon predictive energy and generation data for the following hour, with the market open for a period (e.g. 15 mins), after which the auctioneer finalises. This repeats hourly. The use of rapid trading algorithms facilitates the market to operate hour-ahead over day-ahead with more accurate predictions of energy usage and generation. This allows users greater flexibility of choice, but furthermore likely reduces energy wasted through 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. The methods by which trades are matched, however, have not been sufficiently investigated. To best explain the process of order matching, an example will follow.

Consider the minimal example of two sellers, S_1 and S_2, who wish to sell 50 kWh and 100 kWh, respectively. There are three buyers, B_1, B_2, B_3, who each wish to buy 50 kWh 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 which emerge:

- **Scenario 1:** S_1 and S_2 have the same ask price, say 2 £/kWh. This situation implies that the 150 kWh 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£/kWh and 3£/kWh respectively. It means the same 150 kWh of energy from $\mathbb{S}$ will be sold and distributed evenly amongst $\mathbb{B}$. The price paid by each, however, must now be £400/$|\mathbb{B}|$ such that S_1 receives £100, and S_2 £300.
- **Scenario 3:** The ask prices from scenario 2 carry 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 that ensures the satisfaction of B_1, but enforces a higher buying price for B_2 and B_3. Alternatively, 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, that achieving a matching that is considered 'fair' by the majority is not trivial. Potential trivial solutions include a first-come first-serve method, or manual selection by each buyer [17]. Transferring this scenario to a commercial microgrid operation, each single trade will go unnoticed by the prosumers; the cumulative effect, however, of increased bills will be, and ultimately defeats the objective of decentralisation.

This paper proposes a system underpinning the decentralised 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.
- Propose an algorithm matching renewable energy sellers to local buyers which is considered to be fair and is based upon the preference of both parties.
- Incentivise the trading of renewable energy to increase the value proposition of small-scale generation and to increase the energy efficiency of the energy industry.

The proposed system enables effective matching between buyers and sellers, and is demonstrated to have benefits 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. Based upon a traditional rank-order listing, it considers the price preference, energy type preference, and distance preference of both the buyer and seller. The scoring was as follows, 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 buyer and 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.

$$\text{score}(B,S) = (P_B - d\cdot C_d)\times$$
$$\begin{cases} EP(\varepsilon_S), & \text{if } (d \le D_B) \wedge (d \le D_S) \\ {}^1\!/_2({}^{D_S}\!/_d + EP(\varepsilon_S)), & \text{if } (d \le D_B) \wedge (d > D_S) \\ {}^1\!/_2({}^{D_B}\!/_d + EP(\varepsilon_S)), & \text{if } (d > D_B) \wedge (d \le D_S) \\ {}^1\!/_3({}^{D_B}\!/_d + {}^{D_S}\!/_d + EP(\varepsilon_{S,k})), & \text{if } (d > D_B) \wedge (d > D_S) \end{cases} \tag{1}$$

where D_B and D_S represent the distance preference of buyer and seller, respectively.

Murkin's algorithm then completes the sale for the highest scoring buyer and repeats until there are either no more buyers, or no more sellers. The evaluation of this algorithm gave little acknowledgement to the satisfaction or welfare of the agents. Furthermore, Murkin's algorithm may be described as fundamentally greedy and looks to maximise the score of a transaction, not the welfare of all the agents.

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

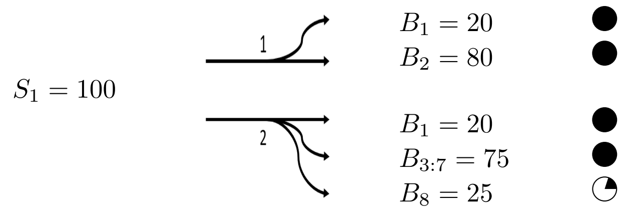


Fig. 1: Potential distribution paths

In this scenario, one of the two paths can be taken; either way, 100kWh of energy will be sold, and the remainder bought from the main utility providers. Using a greedy algorithm, like Murkin's, which solely appraises the score would take path 1 as B_2 has a higher score than B_3. Instinctively however, satisfying the needs of the majority of buyers using path 2 appears to be better.

Rahbari-Asr similarly analyses the problem from an economics standpoint in [19]. He defines the welfare of both the buyer and 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, and uses 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 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 performs an optimisation of these functions, however does not take into account the same parameters as in Murkin's paper: energy type or distance. Furthermore, there is no implementable form of algorithm. Rahbari-Asr's optimisation does, however, yield a Pareto optimal solution- a solution whereby no further change would yield a better result for any one individual [22]. These definitions of welfare for buyers and sellers provide a metric by which the proposed algorithm may be evaluated.

III. Algorithm Evolution

The algorithm proposed by Murkin matched transactions by selecting the highest scoring buyer for each seller, and repeating until either there are no remaining possible transactions, or there is 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 moving on. 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 work of Babaioff, [23], serves as a comparison of various pricing mechanisms for double auctions. There are three plausible cases for use in energy trading: average pricing, like that used by Murkin; McAfee pricing; or trade reduction (TR) pricing. Other pricing mechanisms exist, however require that the auctioneer is in deficit. The definitions of these potential prices follow, 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 for users wishing to either buy or sell more energy to be treated preferentially to those only bidding for small quantities [24]. The score used in the proposed system thus takes the following form,

$$\text{score}(B,S) = \min(E_B, E_S) + (P_B - d \cdot C_d)\times$$
$$\begin{cases} EP(\varepsilon_{S,k}), & \text{if } (d \leq D_B) \wedge (d \leq D_S) \\ {}^1\!/_2({}^{D_S}\!/_d + EP(\varepsilon_{S,k})), & \text{if } (d \leq D_B) \wedge (d > D_S) \\ {}^1\!/_2({}^{D_B}\!/_d + EP(\varepsilon_{S,k})), & \text{if } (d > D_B) \wedge (d \leq D_S) \\ {}^1\!/_3({}^{D_B}\!/_d + {}^{D_S}\!/_d + EP(\varepsilon_S)), & \text{if } (d > D_B) \wedge (d > D_S). \end{cases} \tag{9}$$

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 optimisation.

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,

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 $\mathbb{B} \wedge \mathbb{S}$ **do**
  Calculate the score from (9);
end
Matching loop:
while $E_{\mathbb{B}} > 0 \wedge E_{\mathbb{S}} > 0$ **do**
  Transact for the highest score;
  Recalculate scores from (9);
end

irrespective of the next highest score for that seller. The natural progression for this algorithm, thus, is to transact for the highest scoring sale globally, and update the scores for each iteration. This algorithm is represented in Alg. 1. Although a clear improvement upon Murkin's, matching is still done in a greedy fashion: optimising the score for each transaction, not globally.

IV. Proposed Algorithm

The algorithm which this paper proposes seeks to combat the greediness 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 greatest score. This would require computational resources of magnitude far greater than the devices which would be carrying out these calculations 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. Scaling this to the commercially viable case of a medium-sized UK town with the UK average number of renewable-generating households, this would result in more than a googol potential transactional paths. Evidently this is unfeasible.

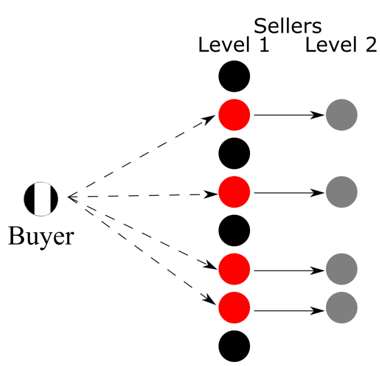


Fig. 2: Two-level transactional mapping where N is 4 and the number of sellers is 8. The red sellers are the top N level-1 sales. The level-2 transactions shown are the highest scoring transactions had each of the top N level-1 transactions. The algorithm selects the pathway with greatest combined level 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 $\mathbb{B} \wedge \mathbb{S}$ **do**
  Calculate the score from (9);
end
Matching loop:
while $E_{\mathbb{B}} > 0 \wedge E_{\mathbb{S}} > 0$ **do**
  Find the top N potential transactions;
  $i \leftarrow 1$;
  while $i \leq N$ **do**
    Recalculate scores given the ith level 1 transaction;
    Find the highest scoring potential transaction;
    $i \leftarrow i + 1$;
  end
  Transact for the path with the highest combined level-1 and level-2 scores;
end

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 the highest cumulative score of it and its highest potential scoring level-2 transaction. This algorithm is presented in Alg. 2.

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 that 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,

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

deepening the algorithm, 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 Alg. 3.

V. Results and Discussion

In order for 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.

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

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

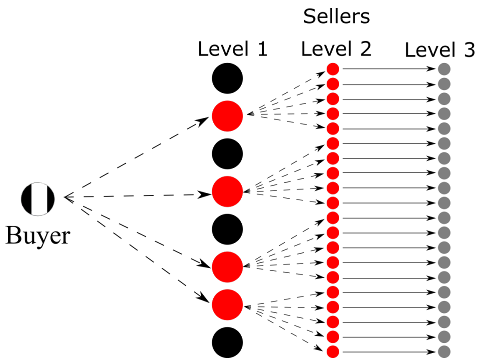


Fig. 3: Three-level transactional mapping. The red level-1 sellers are the top N sales. The red level-2 sales are the top potential sales given each red level-1 sales in turn (non-optimal level-2 sales are omitted for ease of reading). The algorithm selects the pathway with the greatest cumulative score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

Algorithm 3: Proposed algorithm (3 levels)

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 $\mathbb{B} \wedge \mathbb{S}$ **do**
  Calculate the score from (9);
end
Matching loop:
while $E_{\mathbb{B}} > 0 \wedge E_{\mathbb{S}} > 0$ **do**
  Find the top N potential transactions;
  $i \leftarrow 1$;
  while $i \leq N$ **do**
    Recalculate scores given the ith level 1 transaction;
    Find the top N potential transactions;
    $j \leftarrow 1$;
    while $j \leq N$ **do**
      Recalculate scores given the jth level 2 transaction;
      Find the highest scoring potential transaction;
      $j \leftarrow j + 1$;
    end
    $i \leftarrow i + 1$;
  end
  Transact for the path with the highest combined levels 1-3 scores;
end

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.

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 simulation was run within MATLAB for scenarios of 5%-20% sellers (stepping by 5%), with 500 to 2 000 agents (stepping by 500). Each was run 10 times, and the output averaged- this reduced the erratic nature of the random numbers, 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 (2) to (5). 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 respectively.

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. These are plotted in Fig. 4 with a range of number of agents and proportion of prosumers running 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, prices using the McAfee regime. The standard deviation of the price, across all simulations, was approximately 0.1% of the mean value.

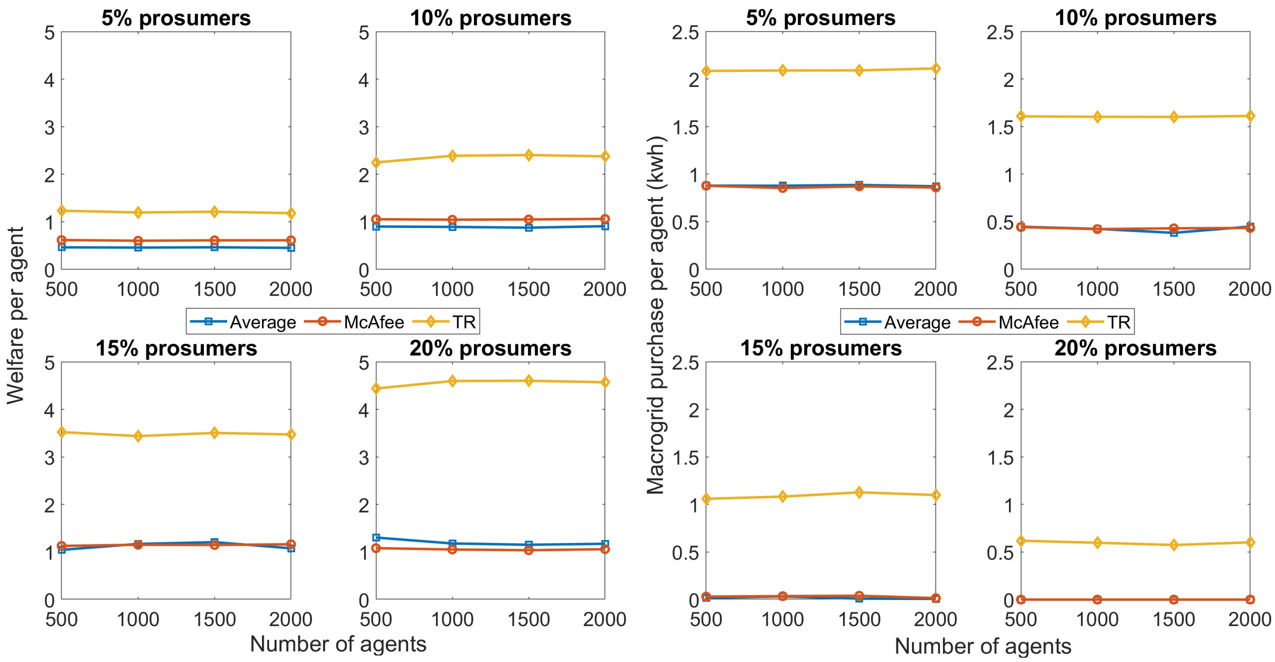
B. Relative performance

The performance of the proposed algorithm has been shown to be a great improvement upon more basic matching methods. Fig. 5 charts the averaged welfare and macrogrid purchase of each agent across a range of scenarios. These scenarios are stepped quantities of agents and percentage prosumers as stated at the beginning of this section.

All algorithms consistently match all saleable energy to buyers. This can be seen by the lack of variation of average macrogrid purchase across the range of algorithms. The little fluctuation is from the random nature of the inputs. Most saliently, Fig. 5 shows 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.

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 came, however, at 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. This does, however, move out of the commercial context of this report.

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 Alg. 2 are, at least somewhat, the other top $N-1$ transactions in level 1. By moving a level deeper, the algorithm considers transactions which wouldn't



(a) Welfare per agent (b) Macrogrid purchase per agent

Fig. 4: Comparison of three pricing regimes

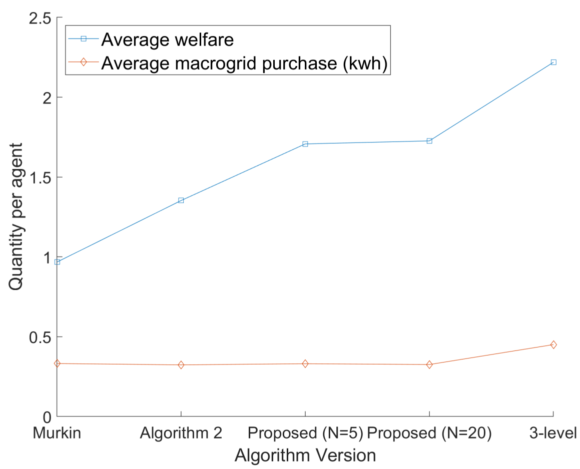


Fig. 5: Evolution of the matching algorithm

appear in 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 Alg. 3. Fig. 6 shows some performance data for Alg. 3. Notably, within each step of prosumers the simulation outcome is highly unstable, most saliently the data shown varied greatly between identical simulations. The datapoints, although fluctuating, showed that Alg. 3 did always at least match, if not outperform, Alg. 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 Alg. 3 is too great compared to its performance increase compared to Alg. 2.

C. Scalability

Scalability of algorithms is important, 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, counter-productively, 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 small population. The smaller population ranging in size from 50 to 200 agents, and the large, from 5 000 to 20 000 agents. These results can be seen in Fig. 7. Although the small population showed some slight instability, in the form of fluctuation within a proportion of prosumers, the percentage change is within an acceptable range. Saliently, when increasing the population to the size of a large population, similar to that of large UK town [26], the algorithm remains stable.

D. Commercial Context

The context in which this algorithm would sit commercially is that 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 to 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 phase two is entered. Within this phase the relevant data are gathered, the proposed algorithm is executed, and a list of trades to be executed is outputted. After the half hour market period, the energy is transferred, and transactions logged on the blockchain. This is phase three, and this lasts

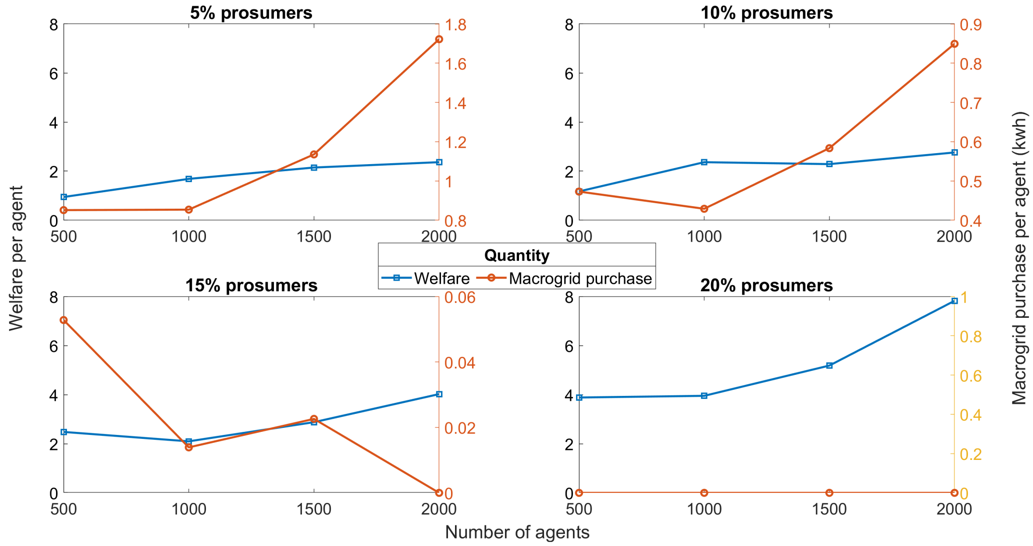
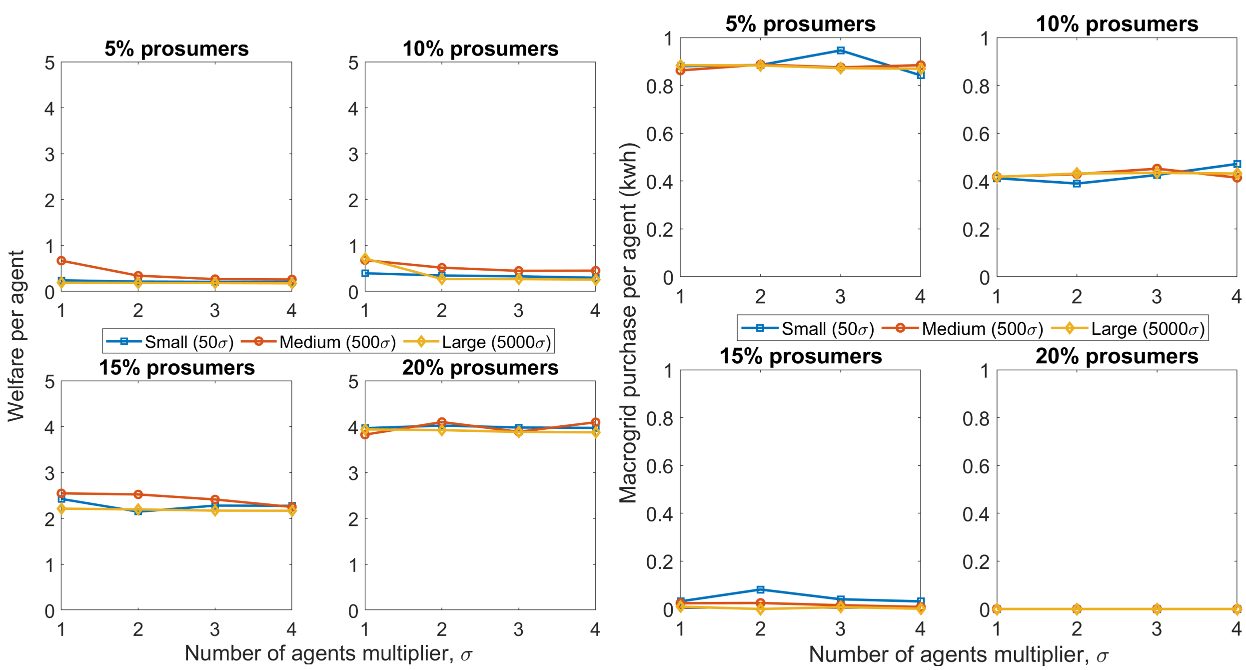


Fig. 6: Instability of 3-level algorithm



(a) Welfare per agent

(b) Energy purchased from macrogrid per agent

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

up until the end of that billing period. Considering the number of transactions occurring a day, bills should be issued monthly like a conventional energy system.

The half-hour market time, although conventional, is arbitrary. As weather prediction data is improving, and additionally consumption and generation prediction, this market window can reduce [27].

As part of the scalability issue, a major weakness of blockchain is the rate of transactions. The transaction rate of Ethereum, for example, is approximately 10transactions/s [28]. For a set of 2 000 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. 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 that any one node has to do, reducing time and increasing transaction rate. In the context of P2P energy trading, this could alternatively be realised as reducing the area over which the network is run-dividing towns into multiple, smaller networks.

For users of the system, little would obviously change in the

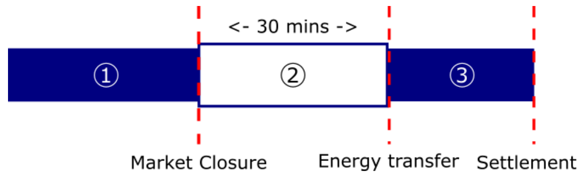


Fig. 8: Visualisation of market timings

way they receive and pay for their energy. The proposed algorithm, does, on average, provide 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 approximately 10 p/kWh [29]. By trading renewable energy for local usage, the majority may actually be used, instead of being lost in transmission. Furthermore, this technology's reduced dependency on the macrogrid allows for ecological benefits. If deployed alongside physical microgrids, this type of technology can also more effectively combat power quality issues and reliance on large centralised points of generation.

VI. Conclusions

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 has been shown to provide a greater than $1.75\times$ average increase in user welfare compared to similar greedy algorithms found in literature. The proposed algorithm allows consumers to save 25% on energy bills, and prosumers make a further 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.

This paper presents a complete system by which P2P energy trading can be carried out from a theoretical standpoint. Future work could focus on using the proposed pricing, scoring, and matching mechanisms in a commercial setting. As discussed, the context of blockchain trading is often with low-computational resources, thus the exact implementation of the matching algorithm in particular is key to its commercial success. Future research work could include a game theoretic evaluation of the matching algorithm. Using clearing prices and pricing preferences instead of hard boundaries, it is possible that the nature of the algorithm could be exploited by agents for financial advantage. During commercial development, the algorithm could be adjusted such that it is not vulnerable to cyber attacks. Likewise, security of the system is important, especially considering large amounts of data will likely be transmitted wirelessly.

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