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Research Paper

Community energy retail tariffs in Singapore: opportunities for peer-to-peer and time-of-use versus vertically integrated tariffs

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ABSTRACT

The deregulation of Singapore's retail electricity market in 2018 and the rapid adoption of solar rooftops have led to the emergence of a new type of energy transaction, wherein prosumers require flexible tariffs that reflect their willingness to respond to market price signals as well as new business models. The move toward community energy schemes, where prosumers can trade their surplus electricity locally, and the implications this has for tariff design motivates our study. We propose a portfolio of stylized retail tariffs for different market organizations. Among the proposed configurations are time-of-use (ToU), default vertical and peer-to-peer (P2P) tariffs, the last of which operates through a blockchain platform. In this study, each Singaporean district is balanced as a potential future microgrid. An iterative double-auction mechanism is designed to calculate a distributed P2P tariff, looking to maximize the benefit for stakeholders. This tariff is then cleared and compared with a bespoke retail ToU tariff as well as Singapore's monopolistic regulated vertical tariff.

Keywords: auctions; peer-to-peer (P2P); time-of-use (ToU); prosumers; retail; tariffs.

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1 INTRODUCTION

The progressive liberalization of the Singaporean electricity market, with its increase in contestable customers being allowed to choose their own electricity suppliers (Han 2014) and its government-orchestrated push toward adding solar panels to rooftops (Chang and Tay 2006), is leading to a more active profile of stakeholders emerging. Consumers can choose to become prosumers by producing and storing their own energy through a combination of solar panels and storage. Nowadays, the surplus of this domestic solar energy is injected back into the national grid, but prosumers might be willing to sell it to their neighbors through microgrids in the near future, leading to a decentralized peer-to-peer (P2P) configuration of market transactions. This new market structure – where prosumers generate their own electricity and share it with local consumers – will impact how energy flows and is billed (Zhang *et al* 2016).

This disruption of the traditional energy sector landscape requires an in-depth study of its impact on the whole system, including the technical field and consumer billing mechanisms. Particularly, prosumers will require flexible tariffs that reflect their willingness to respond to market price signals as well as new business models in order to move toward this new community energy scheme (Koirala *et al* 2016; Omnetric Group 2018).

Moreover, P2P trading and the way it would be implemented under the proposed system raises questions regarding security, trust and privacy. Indeed, this new configuration implies a decentralized electricity market scheme requiring transparent and secure market environments. A promising contender to tackle this problem is blockchain technology (Financial Conduct Authority 2017), due to its distributed ledger nature (Kang 2017).

Microgrids are being proposed as a system architecture to promote decentralized configurations in order to increase resilience, prevent energy losses, ease congestion at the national grid (El-hawary 2014), reduce grid costs for customers and, thus, incentivize people to turn to new community energy schemes. Moreover, decentralized, balanced microgrids would reduce message delivery delay, which is a significant issue for P2P energy trading (Lu *et al* 2013), and give more autonomy to the energy community to set their own consumption and performance goals.

It is interesting to combine auction approaches with this technology: in Section 1.3, we offer an example of this using the Kelly mechanism. Few studies reflect the current case in Singapore, which involves two categories of stakeholders, leading to a double auction; the Kelly mechanism solves for one-dimensional auctions (Srinivasan *et al* 2016). The liberalization of Singapore's energy market and the emergence of a new community energy scheme supported by combining microgrids and blockchain technologies motivate the evaluation of the P2P tariff in this study as an auction between consumers and prosumers.

1.1 The Singapore energy sector approach

Formerly vertically integrated (Chang 2004), ie, fully regulated by the government through the Public Utilities Board (PUB), Singapore's energy sector is now completing its move toward so-called full retail competition (FRC), which it began in 2018 (Chang 2007). The generation sector has been open to competition since 2001, while the retail sector has become progressively liberalized, with the threshold for market participation lowered by the Energy Market Authority (2017) from 8000 kWh in 2004 to 2000 kWh in 2015. Hence, contestable consumers, ie, businesses consuming more than 2 MWh, are now able to buy electricity directly from licensed retailers, paving the way for the remaining 1.3 million consumers to follow in their footsteps (Chang 2007). The goals of this deregulation are manifold. Allowing consumers to choose whether they purchase electricity from a licensed retailer, directly from the wholesale market or from the government-owned company Singapore Power Services (SP Services) addresses the question of consumer choice described by Foley *et al* (2010). Other expectations of the deregulation process include lower prices along with more efficient and reliable services. It is also hoped that it will encourage the rise of economically viable small-scale power generation (Wouters 2015).

Fully aware of microgrids' potential, Singapore has launched several research projects on smart grid operations. Since the Intelligent Energy Systems project was launched in 2009, several research-and-development platforms have been instigated, such as Singapore's Renewable Energy Integration Demonstrator (2014), which saw three microgrids built on Semakau Island (Yang *et al* 2014). Similarly, the Pulau Ubin Microgrid Test Bed, in operation since 2013, using thirty participants such as residential premises, small businesses and government agencies, has led to the current (as of writing) electricity price of S$0.80/kWh (Wouters 2015; Yang *et al* 2014). In 2016, a microgrid demonstration platform for exchanging renewable energy was launched using a decentralized digital currency, NRGcoin, based on blockchain technology, to execute transactions (Facchini 2017).

1.2 Blockchain technology

This type of technology first emerged from computer networks and cryptography to secure communications as a distributed ledger technology (PwC 2017) that could help to speed up P2P transactions (Morabito 2017). According to its very definition as a decentralized technology, blockchain has the capacity to change the traditional transaction consensus model. This transition to another energy landscape, a more decentralized system, will require new networking technology to support the increased flow of information within the energy system. In this respect, blockchain could become a future transversal technology that allows secured transactions between peers.

In a secured transaction environment that uses blockchain technology, each customer possesses one public decryption key that gives them access to the blockchain's transaction history, and one private encryption key that gives them access to a unique account from which the execution of transactions is possible (Munsing *et al* 2017). The transaction propositions are visible to every participant and are impossible to modify without the entire community noticing, which leads to a transparent and immutable process. Moreover, the private key leaves a unique signature, so when a bid or offer is executed the transaction source is detectable. Each transaction is temporarily stored in a block of transactions that is waiting to be validated by the other users. One block is acceptable if it has a valid hash value, which is obtained via a complicated computational problem that requires a significant amount of energy to solve. There are several consensus methods for validating blocks of transactions, which ensure both the security and the truthfulness of the trade (Zheng *et al* 2017).

1.3 Pricing decentralized auctions

Several pricing methods exist to incentivize customers to reduce their demand. The most natural way is to charge customers according to the real-time electricity price (RTP) (Borenstein 2002), a dynamic tariff that is directly dependent on wholesale market variations. As a result, the electricity cost will vary all day long and give consumers a true economic signal to favor an optimal socioeconomic use of electricity (Algarvio *et al* 2014). This tariff is more suited to large consumers, since they can afford to study the market to reduce their expenses. The digitalization and metering of the system will aid in applying this RTP tariff, allowing retailers to hedge themselves against uncertainty by buying electricity in the wholesale market under long-term contracts and selling it at spot prices to consumers. RTP tariff participants can be given a signal that indicates when electricity load reduction is particularly desirable; this is done by increasing the RTP using a value known as the reliability adder, which prevents excessively constraining market conditions from reaching smaller customers.

In electricity tariff design, employing a variable pricing method – such as the widely used time-of-use (ToU) pricing approach – is one possible way of providing customers with more accurate information about real electricity prices while keeping the tariff stable from month to month. A retail tariff is divided into different fixed prices: these are usually peak, shoulder and off-peak price. Each day is separated into time blocks, and the corresponding price is asked of the consumer when electricity is loaded within a particular time block. Similarly, weekends and holidays are considered to be off-peak periods: electricity used during this time is therefore charged at an off-peak price. Another option for achieving tariff accuracy and stability is by using a mixture of variable and dynamic tariffs. As an example, a customer baseline load (CBL) tariff would have its demand base charged at the ToU price, while the demand surplus of the customer is charged at the spot price (Triki and Violi 2007). To conclude, the main aim of demand-side prices is to lower demand at peak times in order to reduce both wholesale market prices and the risk of rolling blackouts (Samet 2016).

Reproducing auctions for electricity trading allows us to simulate a real energy market, with stakeholders interacting with each other as buyers or sellers, leading to the allocation of items such as goods or resources (Liang *et al* 2013). Different auction mechanisms exist. This study focuses on one unique divisible resource, electricity, which is going to be traded within the energy market. This type of homogeneous auction aims to efficiently allocate that resource – as well as the associated bidding price that results from the trade – through an optimization problem. The Vickrey–Clark–Groves (VCG) mechanism proposes a solution for the optimization problem via price anticipation (Triki and Violi 2007): the efficient allocation of the resource is done by considering the fact that users are adapting their bids according to its impact on trade. This is why the auction system must be party to others' bidding information (Koutsopoulos and Iosifidis 2010). However, for the purposes of our study, which involves a P2P configuration that is implemented by simulating a blockchain platform and constructed according to what has been said before, the blockchain technology involves privacy protection without reliance on a third party. Consequently, this mechanism is not suitable for the Singapore case study.

As for the Kelly mechanism, this solves the optimization problem via an optimal allocation of the resource through social optimization. It allows the problem to be solved in a decentralized manner (Kelly *et al* 1997). As a result, the auction involves a third party, the blockchain platform, as the auctioneer or broker; this iteratively computes the electricity allocation. Users then update their bidding price. These results converge until they reach the optimal solution of the social welfare optimization problem. The Kelly mechanism is an iterative one-dimensional auction whose algorithm runs in a distributed way, similar to the blockchain technology; therefore, designing a P2P tariff based on the Kelly mechanism for buyers' and sellers' interactions through the platform is a suitable proposal.

This paper is organized as follows. In Section 2, an overview of the techniques is presented. In Section 3, our trial objectives and challenges are further characterized. In Section 4, our conclusions, learnings, ideas for future work and recommendations are discussed.

2 TARIFF DESIGN CHARACTERIZATION: THE SINGAPORE PERSPECTIVE

2.1 Tariff design

Studies such as Huh and Seo (2016), Faqiry (2017), Iosifidis *et al* (2015), Yoon *et al* (2017) and Mihaylov *et al* (2016) were conducted on tariffs in deregulated environments, covering everything from load forecasting to tariff design. They also included comparisons between tariffs. Mills *et al* (2016) presented two general models that are commonly used in load profiling: the area and the category (groups of consumers) models. Load profiles can be extracted from data via statistical analysis or via a pattern recognition method using clustering algorithms. According to Mills *et al* (2016), the formulation of fixed or variable tariffs over time for tariff design is one of load profiling's main applications. Some dynamic pricing methods – such as a two-stage pricing scheme, determined through retailer revenue optimization (Borenstein 2002), or a usage-based dynamic RTP in a smart grid application (Triki and Violi 2007) – are also analyzed. The former study divides its price design into two stages, the first being a ToU tariff and the second being a dynamic tariff based on real-time extra demand. The latter defines a demand threshold to determine both peak and off-peak times.

An extensive literature exists for the auction approach, particularly in the fields of communication and networking: see, for example, the 1997 University of Cambridge study on rate control, which describes a basic network model and solves a utility optimization problem via a decomposition of the system (Kelly *et al* 1997). An iterative double-auction mechanism following the Kelly mechanism is designed to simulate interactions between mobile network operators and access points as well as to optimize mobile data traffic. A similar algorithm adapted to the energy field has been used in various papers for energy trading in microgrids (Panapakidis *et al* 2012; Samadi *et al* 2010; Sandholm 2002) or for P2P energy trading with electrical vehicles (Faqiry and Das 2016; Majumder *et al* 2014). Similarly, auctions following the VCG mechanism have been used in papers about microgrid energy trading simulations (Alvaro-Hermana *et al* 2016; Jargstorf *et al* 2015).

As for time-varying tariffs, the most popular type is the ToU tariff, which divides each day into pricing blocks. As an example, bilateral contracts between power producers and customers with three rate tariffs are studied via a maximization of power producers' profits to determine both prices and future customers to be targeted (Liang *et al* 2013). Other types of studies on tariff-related topics include comparisons of already-existing prices – such as in Russia, where retail prices and regulated prices were compared (Liu *et al* 2015) – or comparisons of tariff schemes through self-generation scenarios (regarding solar photovoltaics (PVs) and battery storage) (Kuleshov *et al* 2012).

As presented in Section 1, the deregulation of Singapore's energy market should lead not only to competition between electricity retailers but also to a rise in prosumers and their participation in the market. A special focus has been made on smart grids, which will allow prosumers market entry through a P2P energy configuration, supported by blockchain technology. As a result, three tariff options can be drawn from this changing landscape: a default tariff entirely regulated by the Singaporean government, a retail tariff with variable pricing depending on its use (ToU), and a P2P tariff that is traded in a blockchain environment.

2.2 Singapore's default tariff

It is assumed that after full deregulation, Singapore's government will implement a default tariff that is entirely regulated, as a backup or supplier-of-last-resort tariff on its customers. The upholding of a regulated tariff after full liberalization is currently still under debate, and its design varies from country to country (ITS Consultancy Services 2017). Therefore, the default tariff considered in this paper is set to equal the current regulated Singaporean electricity tariff, reviewed quarterly for energy cost and regulated by the Energy Market Authority (2017). This makes it easier to compare with other tariff options as the base tariff. According to SP Group, the current electricity tariff can be divided into four cost items, all of them in S$/kWh (Cheong 2000).

- Energy cost (14.58c/kWh): the cost of fuel, subject to market conditions, and the power generation cost, eg, manpower, maintenance and capital costs.

- Network cost (5.30c/kWh): the cost of transmitting and distributing electricity through the electricity network.

- Market support service (MSS) fee (0.37c/kWh): the customer service cost, eg, billing and metering costs.

- Market administration and power system operator (PSO) fee (0.05c/kWh): the cost of operating the power system and administrating the wholesale electricity market.

Prosumers who inject their solar-panel-produced electricity into the grid are paid based on the prevailing low-tension electricity tariff minus a grid charge. To compare this default tariff with the others, we will set its value at 0.203 S$/kWh: this is the value of the current regulated electricity tariff available from SP Group (Cheong 2000).

2.3 ToU retail tariff

Following a full deregulation of the market, consumers will potentially choose retailers without considering their level of electricity consumption. As described in Section 2.1, retail pricing can take different forms, from a fully fixed price to a dynamic price that varies over time. Knowing that only small consumers are considered in this case study, dynamic pricing cannot be used due to the risk of excessive instability (SP Group 2018). The widely adopted price scenario ToU pricing is thus chosen instead.

For simplicity, it is assumed that the retail tariffs used in this paper are only ToU prices in S$/kWh. According to SP Group, contestable consumers who have contracts with ToU pricing are charged off-peak prices from 23:00 until 07:00 and peak prices the rest of the time (Jaske 2002). As shown in Jaske (2002), the off-peak price is 60% of the peak price. Therefore, the retail tariff peak value used in this paper is the current regulated tariff of 0.203 S$/kWh, while the off-peak value is 60% of that, ie, 0.1218 S$/kWh.

2.4 P2P tariff

The P2P tariff option is for consumers who would like to sell (or buy) their electricity directly to (or from) their neighbors without interacting with a centralized entity or reducing the maximum possible use of the system. The approach chosen to calculate this tariff is an iterative double-auction method (Kelly *et al* 1997) adapted from the Kelly mechanism. Indeed, the interaction between consumers and prosumers for P2P trading can be modeled by a homogeneous auction that aims to optimally allocate resources and their associated bidding prices. As said in Section 2.1, the Kelly mechanism is the most well adapted for solving the optimization problem while maintaining users' privacy, which is one of the main reasons for using a blockchain platform.

2.4.1 Microgrid trading in a blockchain

Agreements are made online through a blockchain platform. This blockchain-technology-based website, operated as an intermediary, can provide consumers with both guaranteed privacy and cheaper transactions, while offering stakeholders access to vital information (Financial Conduct Authority 2017). A fixed-cost item is therefore assumed for platform operation and maintenance, which is determined through a P2P tariff calculation. A blockchain technology consensus depends on a network security protocol, which requires a certain amount of calculation time to find a hash matching some prerequisite requirements in order to validate modifications of information (Evangelopoulos *et al* 2016). This consensus-reaching protocol is costly in terms of energy, since the validation algorithm runs on electricity. As it stands, this amount of energy is included in one's electricity consumption profile, so there is no need to consider its cost in a P2P tariff; however, in future models, data center locations will need to be taken into consideration.

As aforementioned, a P2P configuration implies the use of local microgrids instead of the national grid, due to its very definition as a system of neighbor energy trading. Grid costs can be considered as users' contribution to losses, system load peaks and users' connection to the grid (Pop *et al* 2018). Knowing that a P2P electricity exchange between neighbors reduces transmission distance, due to the use of microgrids, as well as energy transmission losses (Evangelopoulos *et al* 2016), it can be assumed that the microgrid cost in each district is a portion of the grid cost, set at 70% of the national grid cost of 0.035 S$/kWh (Cheong 2000; Energy Market Authority 2017).

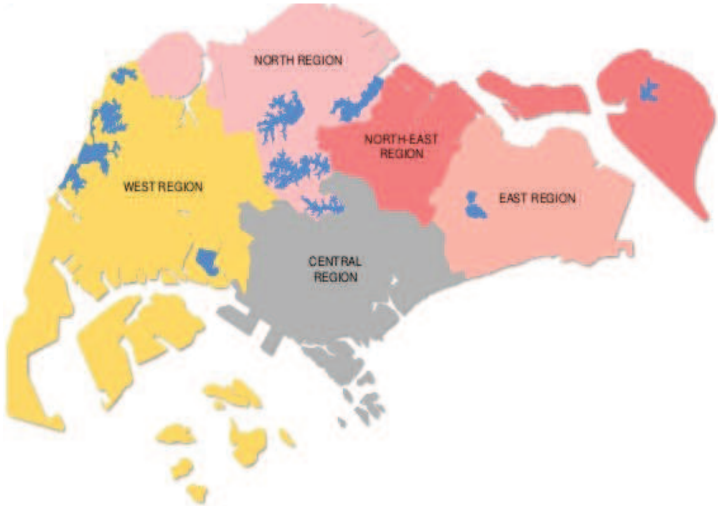
The cost of solar electricity generation is calculated using the levelized cost of electricity (LCOE) method, which is well established in energy finance and for policy (Chuan *et al* 2014). As a result, the solar panel electricity generation price is set depending on: the average capital cost of a basic solar panel composed of crystalline PV modules, the capital cost interest rate, the panel depreciation, and the operation and insurance costs. For the rest of our paper, this solar cost is set at 0.275 S$/kWh, calculated using the 2014 Singapore Solar Roadmap for a turnkey system price of 2500 S$/kWp and a cost capital of 8% (Chuan *et al* 2014).

3 DISTRIBUTED TARIFF MODELING

3.1 Singapore's context and tariff option assumptions

To model the liberalization of Singapore's electricity market, several assumptions will need to be made in this case study. These are as follows. Only small consumers, ie, residential consumers and small industrial or commercial consumers with low voltage (400/230 V), are considered. It is assumed that small consumers do not have the knowledge to buy electricity directly from the wholesale market. Every household can install a generation unit and share electricity. As noted previously, solar energy is one of the most viable renewable energy sources in Singapore, according to the Energy Market Authority (2017). Thus, prosumers' generation is only due to solar panel installation. Singapore has been divided into five areas by the Urban Redevelopment Authority (URA) in order to facilitate urban planning (Luther and Reindl 2014): the north block, the northeast block, the west block, the east block and the central block, as displayed in Figure 1. For P2P tariff simulation, only regions have been taken into consideration, since the data available from the Energy Market Authority is categorized by area. Therefore, this distribution will be referred to as a zone, district, region or area in the remainder of this study, without distinction, and each zone is considered to be a microgrid.

FIGURE 1 Map of Singapore area divisions by the URA.



Source: Energy Market Authority (2017).

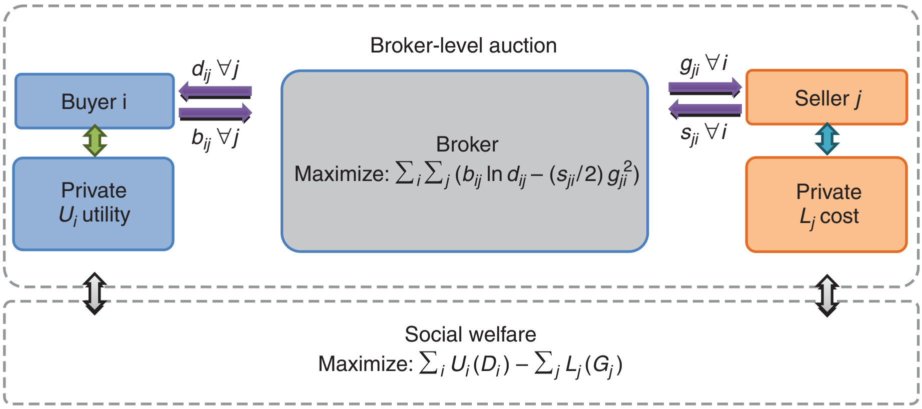
3.2 Iterative double auction for retail tariff design

The data pertaining to installed solar PV capacity per district and per consumer category (contestable and noncontestable consumers) in Singapore is provided by the Energy Market Authority (2017). Every hour, solar energy generation data per district is supplied by the National Renewable Energy Laboratory's (NREL's) PVWatts Calculator (Urban Redevelopment Authority 2016). This is calculated with the installed solar capacity for a 21% system loss. The data for solar energy generation is only available by district; this is then aggregated for fitting into the five district market participant areas of Figure 1.

The data covering monthly average electricity demand per household and the number of households per district is provided by the Energy Market Authority (2017). Thereafter, reduced to an hourly basis, the average electricity demand is multiplied by the number of households per district and then spread over one day.

The iterative double-auction mechanism based on the Kelly mechanism can simulate and provide solutions for an electricity trading system between a group of buyers and sellers, bidding through an energy broker, even if it only has partial information (see Figure 2). The broker, which takes the form of a blockchain platform in this paper, gradually optimizes the market equilibrium, ultimately reaching a social welfare efficient solution (Dobos 2013). The idea behind the social welfare optimization

FIGURE 2 Iterative double-auction processes flowchart.



problem is to maximize buyers' utilities (ie, the amount of electricity provided by sellers), while minimizing sellers' cost functions (ie, the cost of producing solar electricity and using the grid). This method was chosen because it incentivizes bidders to propose real values without any bias; this is because it is impossible for them to anticipate the impact of their bids on prices (Koutsopoulos and Iosifidis 2010). This reflects a realistic scenario, since small consumers are considered unlikely to spend time trading their electricity consumption in real time. To solve the social welfare optimization problem, the iterative double-auction mechanism resolves an optimization allocation subject to the same constraints, ie, sellers' and buyers' capacity constraints in this particular case. This is combined with pricing (for buyers) and reimbursement (for sellers) rules.

As a result, this process is a double auction wherein buyers and sellers interact by submitting their bidding price for each area (including themselves). Based on this, the broker calculates the amount of electricity received by the buyer and supplied by the seller, limited by each zone's maximum capacity, by solving the optimization problem. Bids are then adjusted at the following iteration, which leads to an adjustment of the traded electricity. The algorithm iterates until market equilibrium is reached.

Each of the studied areas in Singapore has an electricity demand value $D^{\max}$ and a solar electricity generation value $G^{\max}$, which are traded through a platform with each other to fix the exchange amount and the final price. $D^{\max}$ and $G^{\max}$ are the inputs of this auction system. Each area can trade with itself, since clusters of consumers and prosumers in the same area are considered. A blockchain platform is considered to act as a local energy broker that manages electricity trading between areas. To incentivize trading within the same area, a grid charge that is 30% less expensive than in other areas is considered.

3.3 Case study formulation

Consider a network with a set of areas that can both buy and sell electricity, since they all have a demand for energy and produce solar energy. To let them interact with each other, each area has two profiles, ie, a buying profile and a selling profile. Let buying electricity areas be denoted by i, $i = 1, \dots, N^{\max}$ (number of areas in Singapore), and selling electricity areas be denoted by j, $j = 1, \dots, N^{\max}$.

$D_i^{\max}$ is the total demand for electricity of area i, where D is the total electricity demand of Singapore traded in the auction and D_i is the electricity demand vector of area i, with d_{ij} the electricity demand of area i for discharging area j so that $D_i \triangleq \{d_{ij} \forall i \in N\}$ and $D \triangleq \{D_i \forall i \in N\}$ with $N = \{1, 2, \dots, N^{\max}\}$. Similarly, $G_j^{\max}$ is the total amount of solar electricity generated by area j, where G is the total electricity supply of Singapore traded in the auction and G_j is the electricity supply vector of area j, with g_{ji} the electricity supply of area j for charging area i, so that $G_j \triangleq \{g_{ji} \forall j \in N\}$ and $G \triangleq \{G_j \forall j \in N\}$ with $N = \{1, 2, \dots, N^{\max}\}$.

B_i is the buying price vector of area I so that $B_i \triangleq \{b_{ij} \forall i \in N\}$, and S_j is the selling price vector of area j so that $S_j \triangleq \{s_{ji} \forall j \in N\}$. Two functions – the utility (satisfaction) function for the buying profile and the cost function for the selling profile – are considered in (3.1) and (3.2):

$$U_i(D_i) = \sum_i \ln(d_{ij} + 1). \tag{3.1}$$

The satisfaction function corresponds to the level of satisfaction each buyer obtains as a function of its energy consumption. As users are interested in consuming as much electricity as possible before reaching their maximum capacity, the utility function is nondecreasing:

$$L_j(G_j) = \sum_i \frac{(\mathrm{SC} + \mathrm{GC}) g_{ji}^2}{2}, \tag{3.2}$$

where SC is the solar cost and GC is the grid charge. The cost function represents the cost of providing electricity to the sellers. As described above, the grid charge is cheaper when the transaction is within the same area, ie, when $i = j$.

3.3.1 Social welfare optimization problem

$$\mathrm{SW} = \max_{D,G} \biggl(\sum_i U_i(D_i) - \sum_j L_j(G_j) \biggr). \tag{3.3}$$

The objective of this problem is to maximize buyers' utilities, ie, the amount of energy they can buy, while minimizing sellers' electricity production and trading costs.

This maximization function is subject to three main constraints:

$$\sum_j d_{ij} \leqslant D_i^{\max}, \tag{3.4}$$

$$\rho g_{ji} = d_{ij}, \tag{3.5}$$

$$\sum_i g_{ji} \leqslant G_j^{\max}. \tag{3.6}$$

This objective function is strictly concave, continuous and differentiable through U_i, a natural logarithm function, and L_j, a quadratic function. Relaxation of the constraints leads to the following Lagrangian L1:

$$\begin{aligned} \text{L1:}\ \sum_i U_i(D_i) - \sum_j L_j(G_j) - \sum_i \alpha_i \Biggl(\sum_j d_{ij} - D_i^{\max}\Biggr) \\ - \sum_j \beta_i \Biggl(\sum_i g_{ji} - G_j^{\max}\Biggr) - \sum_i \sum_j, \end{aligned} \tag{3.7}$$

with $\alpha, \beta \geqslant 0$ the vectors of Lagrange multipliers corresponding to the constraints (3.4)–(3.6), and λ the matrix of Lagrange multipliers corresponding to the constraint (3.5). According to Kelly's study, λ can also be considered as a charge per energy unit. The social welfare function is strictly concave. Therefore, it possesses a unique optimal solution that can be described using the necessary Karush–Kuhn–Tucker (KKT) conditions. Hence, the optimal primal variables – D° and G° – and dual variables – α°, β° and λ° – are given as follows.

- Stationarity:

$$\frac{\partial U_i(D_i^\circ)}{\partial d_{ij}} = \alpha_i^\circ + \lambda_{ij}^\circ, \tag{3.8}$$

$$\frac{\partial L_j(G_j^\circ)}{\partial G_{ji}} = -\beta_j^\circ + \lambda_{ij}^\circ. \tag{3.9}$$

- Complementary slackness:

$$\alpha_i^\circ \Biggl(\sum_j d_{ij}^\circ - D_i^{\max}\Biggr) = 0, \tag{3.10}$$

$$\beta_j^\circ \Biggl(\sum_i g_{ji}^\circ - G_j^{\max}\Biggr) = 0. \tag{3.11}$$

3.3.2 Optimal allocation problem

$$\text{AL}: \max_{D,G}\left(\sum_i\sum_j\left(b_{ij}\ln d_{ij}-\frac{s_{ji}}{2}g_{ji}^2\right)\right). \tag{3.12}$$

This second optimization problem is subject to the same constraints as the social welfare one: (3.4)–(3.6).

As this new objective function is also strictly concave, continuous and derivable, it therefore admits a unique optimal solution. A relaxation of the constraints generates the following Lagrangian L2:

$$\begin{aligned}\text{L2}: \sum_i\sum_j\left(b_{ij}\ln d_{ij}-\frac{s_{ji}}{2}g_{ji}^2\right)-\sum_i\alpha_i\left(\sum_j d_{ij}-D_i^{\max}\right)&\\ -\sum_j\beta_i\left(\sum_i g_{ji}-G_j^{\max}\right)-\sum_i\sum_j\lambda_{ij}(d_{ij}-\rho g_{ji}).&\end{aligned} \tag{3.13}$$

The KKT conditions application yields the optimal variables α°, β°, λ°, D° and G°.

- Stationarity:

$$\frac{\partial b_{ij}\ln d_{ij}^\circ}{\partial d_{ij}}=\alpha_i^\circ+\lambda_{ij}^\circ=\frac{b_{ij}}{d_{ij}^\circ}, \tag{3.14}$$

$$\frac{\partial\frac{1}{2}s_{ji}g_{ji}^{\circ 2}}{\partial g_{ji}}=-\beta_j^\circ+\lambda_{ij}^\circ=s_{ji}g_{ji}^\circ, \tag{3.15}$$

$$\Rightarrow d_{ij}^\circ=\frac{b_{ij}}{\alpha_i^\circ+\lambda_{ij}^\circ}, \tag{3.16}$$

$$\Rightarrow g_{ji}^\circ=\frac{-\beta_j^\circ+\lambda_{ij}^\circ}{s_{ji}}. \tag{3.17}$$

- Complementary slackness:

$$\alpha_i^\circ\left(\sum_j d_{ij}^\circ-D_i^{\max}\right)=0, \tag{3.18}$$

$$\beta_j^\circ\left(\sum_i g_{ji}^\circ-G_j^{\max}\right)=0. \tag{3.19}$$

  It should be noted that (3.18) and (3.19) are similar to (3.10) and (3.11) since both objective functions are under similar constraints.

- Constraints similarity: the allocation problem yields a solution identical to the unique solution of the social welfare one, ie, $D^\circ \triangleq D^\circ$ and $G^\circ \triangleq G^\circ$.

Therefore, the following equations are deduced:

$$b_{ij} = \frac{\partial U_i(D_i^\circ)}{\partial d_{ij}} d_{ij}^\circ, \tag{3.20}$$

$$s_{ji} = \frac{(\partial L_j(G_j^\circ)/\partial G_{ji}) \cdot 1}{g_{ji}^\circ}. \tag{3.21}$$

The following optimal electricity buying and selling problems model bidders' behavior. Let $\mathrm{Pay}_i(B_i)$ be the payment function given to the buyer and let $\mathrm{Rew}_j(S_j)$ be the reward function given to the seller, both managed by the broker.

3.3.3 Optimal electricity buying problem

$$\mathrm{EB}(\text{electricity buying}) = \max_{B_i}(U_i D_i) - \mathrm{Pay}_i(B_i), \tag{3.22}$$

$$\mathrm{Pay}_i(B_i) = \sum_j b_{ij}. \tag{3.23}$$

PROOF According to (3.22),

$$\frac{\partial U_i(D_i)}{\partial d_{ij}} = \frac{\partial \mathrm{Pay}_i(B_i)}{\partial d_{ij}} = \frac{\partial \mathrm{Pay}_i(B_i)}{\partial b_{ij}} \frac{\partial b_{ij}}{\partial d_{ij}}.$$

According to (3.16),

$$\frac{\partial b_{ij}}{\partial d_{ij}} = \alpha_i + \lambda_{ij}.$$

So,

$$\frac{\partial \mathrm{Pay}_i(B_i)}{\partial d_{ij}} = 1.$$

□

3.3.4 Optimal electricity selling problem

$$\mathrm{ES}(\text{electricity selling}) = \max_{S_i}(\mathrm{Rew}_j(S_j) - L_j(G_j)), \tag{3.24}$$

$$\mathrm{Rew}_j(S_j) = \frac{(-\lambda_{ij} + \beta_j)^2}{S_{ji}}. \tag{3.25}$$

PROOF According to (3.24),

$$\frac{\partial L_j(G_j)}{\partial g_{ji}} = \frac{\partial \mathrm{Rew}_j(S_j)}{\partial g_{ji}} = \frac{\partial \mathrm{Rew}_j(S_j)}{\partial s_{ji}} \frac{\partial s_{ji}}{\partial g_{ji}}.$$

According to (3.17),

$$\frac{\partial s_{ji}}{\partial g_{ji}} = \frac{-S_{ji}^2}{\lambda_{ij} - \beta_j}.$$

According to (3.9),

$$\begin{aligned}\frac{\partial \mathrm{Rew}_j(S_j)}{\partial s_{ji}} &= \frac{((-\lambda_{ij} - \beta_j)/S_{ji}^2)\partial L_j(G_j)}{\partial g_{ji}} \\ &= \frac{-\lambda_{ij} - \beta_j}{S_{ji}^2}(-\beta_j + \lambda_{ij}) = \frac{-(-\lambda_{ij} + \beta_j)^2}{S_{ji}^2}.\end{aligned}$$

Buyers' and sellers' bids are determined by the users themselves. Since they know their own utility or cost functions, they can easily solve optimal electricity selling and buying problems with (3.20) and (3.21), leading to the following equations:

$$b_{ij} = \frac{d_{ij}^{\circ}}{d_{ij}^{\circ} + 1}, \tag{3.26}$$

$$s_{ji} = \mathrm{SC} + \mathrm{GC}. \tag{3.27}$$

Knowing (3.26) and (3.27), it should be mentioned that S_j represents the seller bidding price in S\$/kWh, while B_i is the buyer bidding price in S\$/kWh. Therefore, the latter requires further calculations to make it the same unit as the selling price. □

3.3.5 Dual variables calculation

After relaxing the optimization functions' constraints by forming the Lagrangians L1 and L2, the dual variables α, β and λ must be updated. As these constraints are convex and differentiable, the solution of their minimization is unique, so a gradient method can be used:

$$\alpha_i(t+1) = \left(\alpha_i(t) + s\left(\sum_j d_{ij} - D_i^{\max}\right)\right)^+, \tag{3.28}$$

$$\beta_j(t+1) = \left(\beta_j(t) + s\left(\sum_i g_{ij} - G_j^{\max}\right)\right)^+, \tag{3.29}$$

$$\lambda_{ij}(t+1) = \lambda_{ij}(t) + s(d_{ij}(t) - \rho d_{ji}(t)), \tag{3.30}$$

where s is a sufficiently small positive step size, t is the iteration index and $(\cdot)^+$ denotes the projection onto a nonnegative orthant.

3.3.6 Iterative double-auction algorithm

As the optimization problems above are solved using a dual decomposition method with a gradient approach for the updated dual variables, the algorithm we implement solves the problems over multiple iterations. For each iteration, the broker checks if the termination condition is satisfied, ie, whether the bid price satisfies the convergence criterion ε. The smaller this latter value, the more precise the bid price's difference between two iterations:

$$\text{Diff}\, B = \frac{b_{ij}^{k+1,t} - b_{ij}^{k,t}}{b_{ij}^{k+1,t}}, \qquad \text{Diff}\, S = \frac{s_{ji}^{k+1,t} - s_{ji}^{k,t}}{s_{ji}^{k+1,t}};$$

these are the bid prices tested at the end of each iteration.

The broker calculates the new amount of electricity that will potentially be exchanged as well as all the dual variables. This information is then transmitted to buyers and sellers and used to let them deduce their new bidding price. At the end of all the iterations for a time t, the reward and payment functions are determined. This iteration is reiterated for each period of time. The iterative double auction is described in detail in Algorithm 1. The initialization of primal (D, G) and dual (α, β, λ) variables is determined by the broker. α and β are chosen to satisfy the complementary slackness described in (3.18) and (3.19), while D and G must satisfy the constraint (3.5) for any value of λ. As an example, one can choose $\alpha = 0$, $\beta = 0$ and $\rho g_{ji} = d_{ij}$ for any λ.

4 RESULTS

The iterative double-auction algorithm has been implemented in Fortran for a convergence criterion $\varepsilon = 0.0001$ and with a gradient method step size of 0.05. The auction simulation takes into account five buyers and five sellers, which represent Singapore's aforementioned five districts. The auction is implemented each hour of a given day; here, we use a summer's day, August 15, 2015, as our reference day.

4.1 Convergence

4.1.1 Social welfare

The double-auction mechanism converges after fifty-five iterations for this convergence criterion. However, as shown in Figure 3, convergence can be considered compliant after nineteen iterations to achieve a more relaxed criterion.

Algorithm 1: Iterative double auction

Input : ε, s

Output: $D(k;t)$, $G(k;t)$, $B(k+1;t)$, $S(k+1;t)$, $\alpha(k+1,t)$, $\beta(k+1,t)$, $\lambda(k+1,t)$

Initialize $\alpha(k=0,t)$, $\beta(k=0,t)$, $\lambda(k=0;t)$, $D(k=0;t)$, $G(k=0;t)$, $k=0$

for $t = 0$ *to* T **do**

  Solve Problem EB (Input: $D(k;t), G(k;t)$; Output: $B(k+1;t)$) by (3.5)–(3.20)

  Solve Problem ES (Input: $D(k;t), G(k;t)$; Output: $S(k+1;t)$) by (3.5)–(3.21)

  Solve Problem Al (Input: $B(k;t), S(k;t), \alpha(k,t), \beta(k,t), \lambda(k,t)$; Output: $D(k;t), G(k;t)$) by (3.5)–(3.16) and (3.5)–(3.17)

  Update dual variables through the gradient method

  Calculate Diff B, Diff S

  $k = k + 1$

  repeat

    do these things

  until Diff $B < \varepsilon$ *and* Diff $S < \varepsilon$ $k = k - 1$;

end

Calculate reward price and payment price

4.1.2 Impact of λ

As presented in Section 3.3, λ is one of the dual variables (in S$/kWh) and is considered equivalent to the buyer's bidding price when the other dual variables α and β equal 0. Two simulations were run with two different values of λ. The first one employed λ equal to 0.25 and the other used λ equal to 0.6. The results do not change, but the second simulation converges after eighty-four iterations and the social welfare profile has different values for the earlier iterations, as displayed in Figure 4.

4.2 Blockchain platform fee

The final bidding prices between buyer 1 and other sellers are plotted in Figure 5 to highlight the difference between buyer and seller bidding prices. This means that the blockchain platform buys electricity from sellers at one price and sells it to buyers at a higher price, so the iterative double-auction mechanism is weakly budget balanced. This revenue can be considered as the maximum blockchain fee chargeable for using the platform. Thus, users wishing to be provided with electricity

FIGURE 3 Number of iterations' convergence for all areas and social welfare evolution.

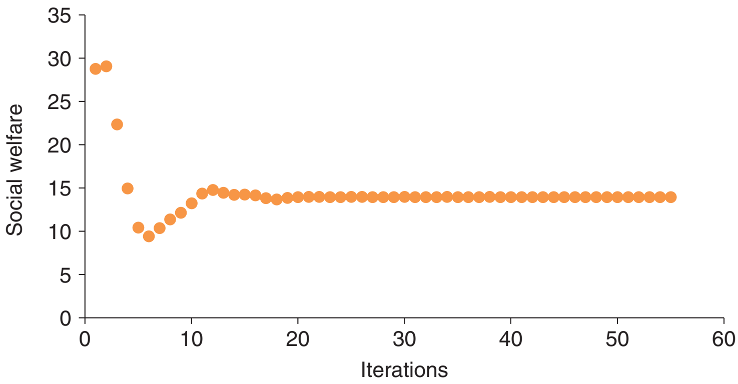
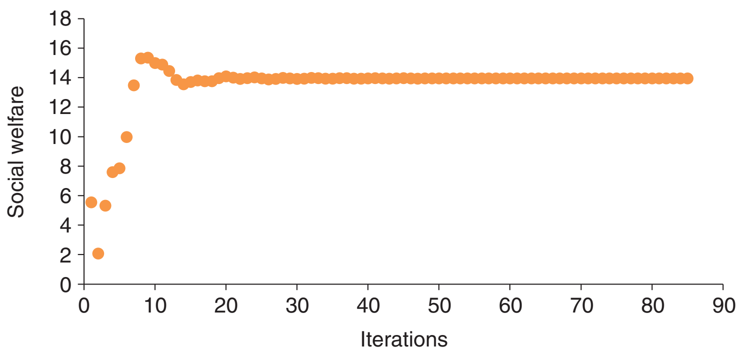


FIGURE 4 Social welfare profile and number of iterations with λ equal to 0.6.



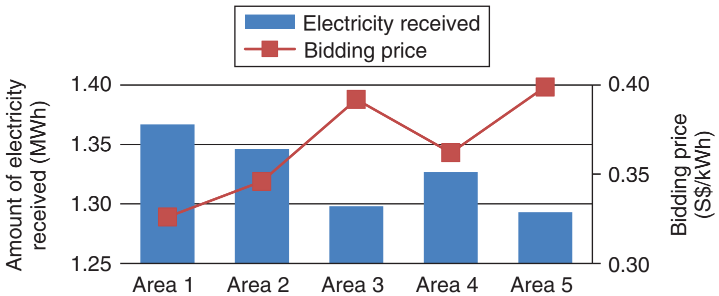
through a P2P configuration would have to pay a maximum blockchain platform fee of 0.10 S$/kWh, which represents 24% of their total selling price.

4.3 Microgrid incentive

According to Figure 6, electricity trading within the same area leads to a higher amount of electricity being exchanged at a lower price, since the buyer can receive 1.36 kWh at the tariff 0.424 S$/kWh instead of 1.316 kWh at 0.432 S$/kWh. As a result, users obtain a 2% discount for trading within the microgrid to which they are linked, which leads to 25 cents in savings per day while receiving an extra

FIGURE 5 Areas' bidding price comparison between sellers and buyers.

FIGURE 6 Impact of trading within the same area compared with auctioning in other areas.



1 kWh per day. Thus, users are incentivized to buy electricity from their own area through this discount on the grid charge, since using their area's microgrid instead of the national grid is less costly.

4.4 Location and seasonality in solar generation

According to the data provided by the Energy Market Authority and the NREL's PVWatts calculator, the amount of electricity generated by solar PVs varies greatly according to district (see Figure 7), since the solar PVs' installed capacity is heterogeneously spread over the city. It should also be highlighted that, according to Figure 8, there is only a slight difference between the amount of solar electricity produced in winter and in summer, that difference being 28.53 MW at the peak of each profile's day. Surprisingly, more electricity is generated on December 24 than on August 15. This might be due to Singapore's tropical rainforest weather, however,

FIGURE 7 Solar generation on August 15, 2016 for Singapore's districts.

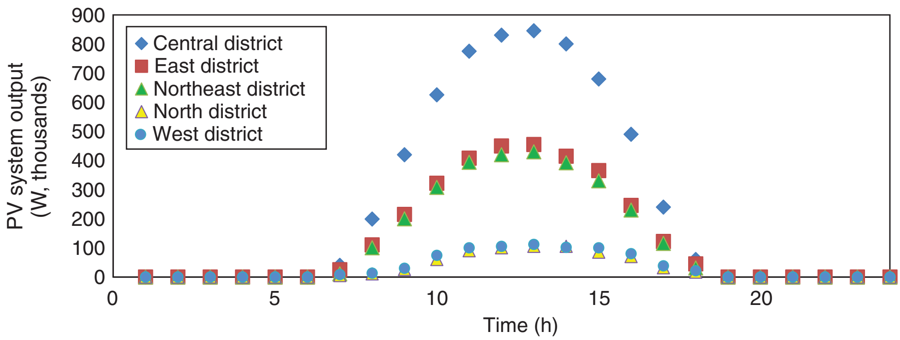
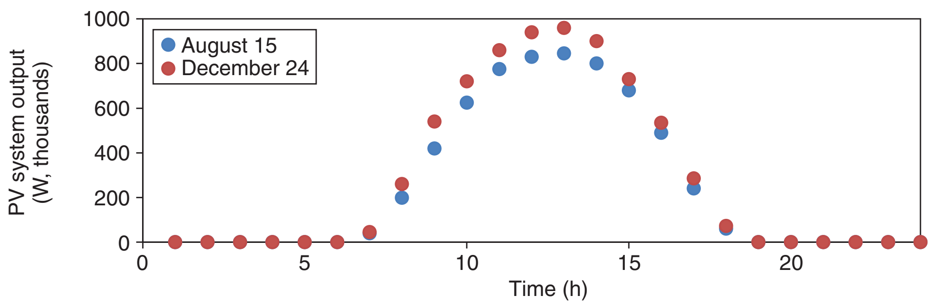


FIGURE 8 Singapore's central district solar generation for two representative days.



so the amount of electricity produced would depend more on the cloudiness of the day than on seasonality (Energy Market Authority 2017; Pop *et al* 2018).

4.4.1 Peers' contribution across the platform

The amount of electricity exchanged within one area varies slightly between the beginning and the end of the day. This can be explained by the amount of solar energy that is produced during a day. From 07:00 to 08:00, the energy generated is multiplied by twelve. Similarly, it is divided by five from 17:00 to 18:00. For the rest of the day, the electricity variation does not exceed 200%. A double auction was run using five areas selling and buying at 13:00 (August 15), when solar production is at its maximum. Table 1 displays the amount of electricity traded by each area at that time, both with each other and via self-production.

TABLE 1 Amount of electricity exchanged for five stakeholders.

	MWh	Area 1 (%)	Area 2 (%)	Area 3 (%)	Area 4 (%)	Area 5 (%)
Area 1	8.285	45	21	15	11	8
Area 2	7.238	32	44	17	4	3
Area 3	7.147	27	19	41	8	5
Area 4	3.216	21	6	13	39	21
Area 5	3.194	24	9	12	18	37

FIGURE 9 Buyer electricity demand for August 15, 2016.

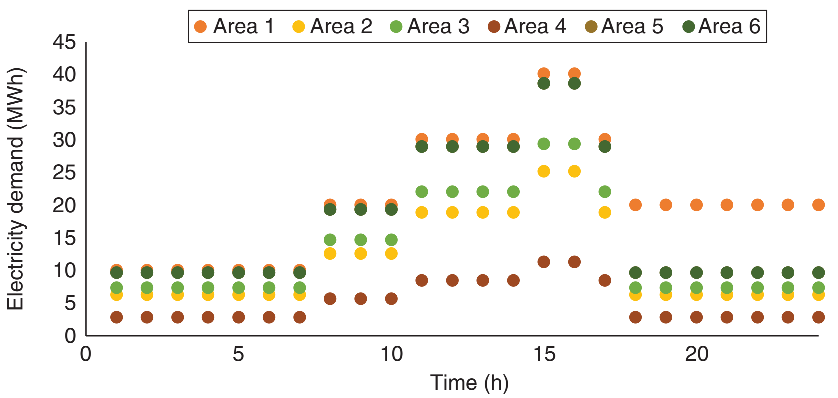
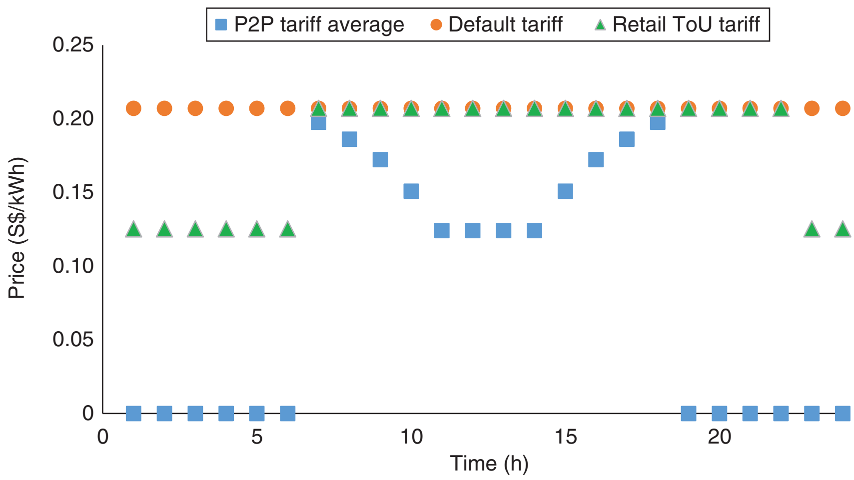


Figure 9 shows that stakeholders exhibit the same behavior. As highlighted before, more electricity is exchanged when a double auction takes place within the same area. It should be noted that the amount of electricity received by all areas depends on their solar generation and therefore the amount of flexible distributed generation allocated to the bidding pool.

4.5 Tariff comparison

First, it should be noted that the P2P tariff only applies to bids between 07:00 and 18:00 due to the settings of the case study and users' willingness to trade the produced solar power during this interval. To highlight this point, Figure 10 shows that P2P tariffs do vary throughout the day, following the profile of electricity exchanged during that day, with peak solar production hours being as low as 0.1242 S$/kWh. Therefore, the bidding price depends on the amount of electricity generated, the total demand and users' solar production.

FIGURE 10 6 × 6 users' configuration: comparison of tariffs on August 15.



Finally, because the P2P tariff is unavailable for the first and last hours of the day, the ToU tariff is the cheapest available tariff at these times. However, from 08:00 to 17:00 the P2P tariff becomes competitive as the amount of solar generation increases, being at central hours of the day 41% cheaper than the ToU or the default-regulated tariff.

4.6 Summary

This iterative double-auction algorithm has been implemented with bidders' privacy being ensured. As a result, buyers and sellers are the only ones who know their own utility or cost functions. Moreover, bids are supposed to be sent simultaneously to the broker in each iteration.

For both λ, the results are considered to be converging after around twenty-two iterations, which means this is a really fast process that requires almost instantaneous computational time. This finding aligns with results found in the literature regarding iterative double auctions, such as in Faqiry (2017), where convergence is achieved between seven and thirty-five iterations, depending on the step size chosen; and in Iosifidis *et al* (2015), where the algorithm converges after a maximum of 117 seconds and for less than fifty iterations, depending on the number of users involved in the energy trade. As a result, this algorithm converges to the optimal point of the social welfare problem, satisfying constraints (3.4)–(3.6) and consequently the complementary slackness conditions (3.10) and (3.11), as specified in Faqiry (2017).

Moreover, the high speed obtained and the few iterations needed to run the algorithm, as described in detail above, reveal the effectiveness and efficiency of this iterative double-auction algorithm.

It should be noted that, with the particular cost function set for sellers, their bidding price always corresponds to the real cost of producing energy plus the grid charge. This means that they are described as selfless through this function. The difference between these two prices varies between 0.06 and 0.11 S$/kWh, depending on whether the deal is within the same area, ie, made via a microgrid, or between two different areas. Being positive, this difference shows that the iterative double-auction mechanism is weakly budget balanced, as is supposed by various papers (see Iosifidis *et al* 2015; Srinivasan *et al* 2016). As a result, the presence of an average, positive price difference in this case study can also be found where the value equals S$0.35. This price represents the maximum amount that a broker will earn while operating the transaction. Therefore, the maximum blockchain platform considered would be 0.08 S$/kWh, which is the minimum difference between the bidding prices of the buyer and the seller.

According to Figure 10 and all of the data from the auction simulation, the bidding price is always lower when energy trading happens within the same area, ie, through self-supply. Moreover, the amount of energy exchanged within and between microgrids is higher than that for energy trading through the national grid. This assumption is due to the incentive introduced in the cost function, where the grid charge is 30% less expensive if electricity trading happens within the same region, ie, if energy trading is transmitted and distributed through a microgrid.

5 CONCLUSIONS

In this paper, an electricity market is simulated using an iterative double-auction algorithm that resolves a social welfare optimization problem based on the Kelly auction mechanism. It is adapted to the case of Singapore's district-to-district FRC, simulating the interaction between the country's five areas: these are considered to be prosumers who both generate solar energy and require a certain amount of electricity. Each region is considered to be a buyer as well as a seller, and they can provide services for themselves, as they may be considered microgrid balancing districts. The exchange of electricity with districts other than themselves is carried out via the traditional grid. A blockchain platform, which is used as the trading platform between users, plays the role of auctioneer (or broker) during the auction. This auction requires the presence of an auctioneer (the blockchain platform) and has to incentivize trading within the same area, which means that the electricity distribution goes through a microgrid instead of the traditional grid. The calculated P2P tariff is then compared with a regulated tariff, the default tariff and a retail tariff based on the ToU pricing design.

The algorithm converges after fewer than twenty iterations and maximizes the social welfare optimization problem to find a solution that satisfies all of the constraints. This is an effective approach since it does not require considerable calculation time. The auction satisfies the condition of privacy. On the one hand, the algorithm does not require full information on all users since each user bids a price according to the amount of electricity exchanged, calculated by the broker, and keeps for itself its utility and cost functions. On the other hand, privacy is also made possible by using a permissioned blockchain, where participants are licensed before joining.

A reasonable P2P tariff is proposed, which for hours where the production of solar energy is brought into the mix provides the lowest tariff available to prosumers. As this distributed business model is being discussed across the industry, we propose that the blockchain platform fee should be between 0.05 and 0.08 S$/kWh. Without having introduced incentives, the P2P value proposition offers a competitive rate during solar production hours compared with the default and retail ToU tariffs. It is assumed that introducing storage as a distributed resource could lower the current value proposition for this tariff by enabling it to become competitive during the remaining hours as well.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

REFERENCES

Algarvio, H., Lopes, F., Sousa, J. A., and Lagarto, J. (2014). Power producers trading electricity in both pool and forward markets. In *25th International Workshop on Database and Expert Systems Applications (DEXA), Munich, Germany*. IEEE (https://doi.org/10.1109/DEXA.2014.41).

Alvaro-Hermana, R., Fraile-Ardanuy, J., Zufiria, P. J., Knapen, L., and Janssens, D. (2016). Peer to peer energy trading with electric vehicles. *IEEE Intelligent Transportation Systems Magazine* **8**(3), 33–44 (https://doi.org/10.1109/MITS.2016.2573178).

Borenstein, S. (2002). The theory of demand-side price incentives. In *Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets*, Borenstein, S., Jaske, M., and Rosenfeld, A. (eds), pp. 5–31. Energy Foundation.

Chang, Y. (2004). Deregulation in the national electricity market of Singapore: competition and efficiency. In *IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies, Hong Kong, China*. IEEE (https://doi.org/10.1109/DRPT.2004.1338460).

Chang, Y. (2007). The new electricity market of Singapore: regulatory framework, market power and competition. *Energy Policy* **35**(1), 403–412 (https://doi.org/10.1016/j.enpol.2005.11.036).

Chang, Y., and Tay, T. H. (2006). Efficiency and deregulation of the electricity market in Singapore. *Energy Policy* **34**(16), 2498–2508 (https://doi.org/10.1016/j.enpol.2004.08.015).

Cheong, S. S. (2000). Deregulation of the power industry in Singapore. In *5th International Conference on Advances in Power System Control, Operation and Management, APSCOM-00, Hong Kong, China*. IET.

Chuan, L., Rao, D. M., Venkateswara, V., and Abhisek, U. (2014). Load profiling of Singapore buildings for peak shaving. In *Power and Energy Engineering Conference (APPEEC), 2014 IEEE PES Asia-Pacific*, pp. 1–6. IEEE (https://doi.org/10.1109/APPEEC.2014.7065998).

Dobos, A. P. (2013). PVWatts version 1 technical reference. Technical Report, NREL/TP-6A20-60272. National Renewable Energy Laboratory, Golden, CO (https://doi.org/10.2172/1096689).

El-hawary, M. E. (2014). The smart grid: state-of-the-art and future trends. *Electric Power Components and Systems* **42**(3–4), 239–250 (https://doi.org/10.1080/15325008.2013.868558).

Energy Market Authority (2017). Singapore energy statistics. Report. URL: https://bit.ly/2uKdvwt.

Evangelopoulos, V. A., Georgilakis, P. S., and Hatziargyriou, N. D. (2016). Optimal operation of smart distribution networks: a review of models, methods and future research. *Electric Power Systems Research* **140**, 95–106 (https://doi.org/10.1016/j.epsr.2016.06.035).

Facchini, A. (2017). Distributed energy resources: planning for the future. *Nature Energy* **2**(8), 17129 (https://doi.org/10.1038/nenergy.2017.129).

Faqiry, M. N. (2017). Efficient double auction mechanisms in the energy grid with connected and islanded microgrids. PhD Thesis, Kansas State University.

Faqiry, M. N., and Das, S. (2016). Double-sided energy auction in microgrid: equilibrium under price anticipation. *IEEE Access* **4**, 3794–3805 (https://doi.org/10.1109/ACCESS.2016.2591912).

Financial Conduct Authority (2017). Discussion paper on distributed ledger technology. Discussion Paper, April. URL: https://bit.ly/2oY6NMx.

Foley, A. M., Gallachoir, B., Hur, J., Baldick, R., and McKeogh, E. J. (2010). A strategic review of electricity systems models. *Energy* **35**(2), 4522–4530 (https://doi.org/10.1016/j.energy.2010.03.057).

Han, W. W. (2014). More businesses to benefit as electricity market further liberalised. *Today*, October 27.

Huh, J.-H., and Seo, K. (2016). *Futures/Option Electric Power Pricing in Smart Grid Using Game Theory and Hybrid AMI Based on Weather Clearness, Advanced Multimedia and Ubiquitous Engineering*. Lecture Notes in Electrical Engineering, Volume 393, pp. 477–483. Springer (https://doi.org/10.1007/978-981-10-1536-6_62).

Iosifidis, G., Gao, L., Huang, J., and Tassiulas, L. (2015). A double auction mechanism for mobile data offloading markets. *Transactions on Networking* **23**(5), 1634–1647 (https://doi.org/10.1109/TNET.2014.2345875).

ITS Consultancy Services (2017). Power share – battery storage leads the charge of the microgrid. Blog Post, ITS Consultancy. URL: https://bit.ly/2fXy9C4.

Jargstorf, J., Jonghe, C. D., and Belmans, R. (2015). Assessing the reflectivity of residential grid tariffs for a user reaction through photovoltaics and battery storage. *Sustainable Energy, Grids and Networks* **1**, 85–98 (https://doi.org/10.1016/j.segan.2015.01.003).

Jaske, M. (2002). Practical implications of dynamic pricing. In *Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets*. Energy Foundation.

Kang, J., Yu, R., Huang, X., Maharjan, S., Zhang, Y., and Hossain, E. (2017). Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains. *IEEE Transactions on Industrial Informatics* **13**(6), 3154–3164 (https://doi.org/10.1109/TII.2017.2709784).

Kelly, F., Maulloo, A., and Tan, D. (1997). Rate control for communication networks: shadow prices, proportional fairness and stability. Working Paper, University of Cambridge (https://doi.org/10.1038/sj.jors.2600523).

Koirala, B. P., Koliou, E., Friege, J., Hakvoort, R. A., and Herder, P. M. (2016). Energetic communities for community energy: a review of key issues and trends shaping integrated community energy systems. *Renewable and Sustainable Energy Reviews* **56**, 722–744 (https://doi.org/10.1016/j.rser.2015.11.080).

Koutsopoulos, I., and Iosifidis, G. (2010). Auction mechanisms for network resource allocation. In *8th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, Avignon, France*, pp. 554—563. IEEE.

Kuleshov, D., Viljainen, S., Annala, S., and Gore, O. (2012). Russian electricity sector reform: challenges to retail competition. *Utilities Policy* **23**, 40–49 (https://doi.org/10.1016/j.jup.2012.05.001).

Liang, X., Li, X., Lu, R., Lin, X., and Shen, X. (2013). UDP: usage-based dynamic pricing with privacy preservation for smart grid. *Transactions on Smart Grid* **4**(1), 141–150 (https://doi.org/10.1109/TSG.2012.2228240).

Liu, T., Tan, X., Sun, B., Wu, Y., Guan, X., and Tsang, D. H. K. (2015). Energy management of cooperative microgrids with P2P energy sharing in distribution networks. In *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm), Miami, FL*. IEEE (https://doi.org/10.1109/SmartGridComm.2015.7436335).

Lu, X., Wang, W., and Ma, J. (2013). An empirical study of communication infrastructure towards the smart grid: design, implementation and evaluation. *IEEE Transactions on Smart Grid* **4**(1), 170–183 (https://doi.org/10.1109/TSG.2012.2225453).

Luther, P. J., and Reindl, D. T. (2014). Solar photovoltaic (PV): roadmap for Singapore 2014. Report. URL: https://bit.ly/30qj7rE.

Majumder, B. P., Faqiry, M. N., Das, S., and Pahwa, A. (2014). An efficient iterative double auction for energy trading in microgrids. In *Symposium on Computational Intelligence Applications in Smart Grid (CIASG), Orlando, FL*. IEEE (https://doi.org/10.1109/CIASG.2014.7011556).

Mihaylov, M., Razo-Zapata, I., Radulescu, R., Jurado, S., Avellana, N., and Nowe, A. (2016). Smart grid demonstration platform for renewable energy exchange. In *Advances in Practical Applications of Scalable Multi-agent Systems*. PAAMS Collection/Lecture Notes in Computer Science, Volume 9662. Springer (https://doi.org/10.1007/978-3-319-39324-7_30).

Mills, D., Wang, K., Malone, B., Ravi, A., Marquardt, J., Chen, C., Badev, A., Brezinski, T., Fahy, L., Liao, K., Kargenian, V., Ellithorpe, M., Ng, W., and Baird, M. (2016). Distributed ledger technology in payments, clearing, and settlement. In *Finance and Economics Discussion Series 2016-095*. Board of Governors of the Federal Reserve System, Washington, DC (https://doi.org/10.17016/FEDS.2016.095).

Morabito, V. (2017). Blockchain technology and management. In *Business Innovation Through Blockchain: The B3 Perspective*, p. 10. Springer (https://doi.org/10.1007/978-3-319-48478-5_1).

Munsing, E., Mather, J., and Moura, S. (2017). Blockchains for decentralized optimization of energy resources in microgrid networks. In *2017 IEEE Conference on Control Technology and Applications (CCTA)*, pp. 2164–2171. IEEE (https://doi.org/10.1109/CCTA.2017.8062773).

Nelson, T., and Reid, C. (2014). Reconciling energy prices and social policy. *Electricity Journal* **27**(1), 104–114 (https://doi.org/10.1016/j.tej.2013.12.007).

Omnetric Group (2018). Power to the people: community energy as a major driver of change in the global energy ecosystem. Report, July. URL: https://bit.ly/2WaipiE.

Panapakidis, I. P., Alexiadis, M. C., and Papagiannis, G. K. (2012). Load profiling in the deregulated electricity markets: a review of the applications. In *9th International Conference on the European Energy Market (EEM), Florence, Italy*. IEEE (https://doi.org/10.1109/EEM.2012.6254762).

Pop, C., Cioara, T., Antal, M., Anghel, I., Salomie, I., and Bertoncini, M. (2018). Blockchain based decentralized management of demand response programs in smart energy grids. *Sensors* **18**(1), 162 (https://doi.org/10.3390/s18010162).

PwC (2017). Blockchain: an opportunity for energy producers and consumers? Report, PwC Global Power & Utilities.

Samadi, P., Mohsenian-Rad, A.-H., Schober, R., Wong, V. W., and Jatskevich, J. (2010). Optimal real-time pricing algorithm based on utility maximization for smart grid. In *IEEE International Conference on Smart Grid Communications (SmartGridComm), Gaithersburg, MD*. IEEE (https://doi.org/10.1109/SMARTGRID.2010.5622077).

Samet, H. (2016). Evaluation of digital metering methods used in protection and reactive power compensation of micro-grids. In *Renewable and Sustainable Energy Reviews* **62**, 260–279 (https://doi.org/10.1016/j.rser.2016.04.032).

Sandholm, T. (2002). Algorithm for optimal winner determination in combinatorial auctions. In *Artificial Intelligence* **135**, 1–54 (https://doi.org/10.1016/S0004-3702(01)00159-X).

SP Group (2018). Singapore billing structure. Report. URL: https://bit.ly/2nIv0sH.

Srinivasan, D., Rajgarhia, S., Radhakrishnan, B. M., Sharma, A., and Khincha, H. (2016). Game-theory based dynamic pricing strategies for demand side management in smart grids. *Energy* **126**, 132–143 (https://doi.org/10.1016/j.energy.2016.11.142).

Triki, C., and Violi, A. (2007). *Dynamic Pricing of Electricity in Retail Markets*. Springer (https://doi.org/10.1007/s10288-007-0056-2).

Urban Redevelopment Authority (2016). Master plan: introduction to master plan. Report. URL: https://bit.ly/1w3ezRQ.

Wouters, C. (2015). Towards a regulatory framework for microgrids: the Singapore experience (2015). *Sustainable Cities and Society* **15**, 22–32 (https://doi.org/10.1016/j.scs.2014.10.007).

Yang, W., Ho, T. C. T., Xiang, L., Chai, C. C., and Yu, R. (2014). An overview and evaluation on demand response program in Singapore electricity market. In *2014 IEEE Conference on Energy Conversion (CENCON)*, pp. 61–66. IEEE (https://doi.org/10.1109/CENCON.2014.6967477).

Yoon, Y., Chan, D., and Cameron, M. (2017). Key success factors for global application of micro energy grid model. *Sustainable Cities and Society* **28**, 209–224 (https://doi.org/10.1016/j.scs.2016.08.030).

Zhang, C., Cheng, J. W. M., Zhou, Y., and Long, C. (2016). A bidding system for peer-to-peer energy trading in a grid-connected microgrid. *Energy Procedia* **103**, 147–152 (https://doi.org/10.1016/j.egypro.2016.11.264).

Zheng, Z., Xie, S., Dai, H., Chen, X., and Wang, H. (2017). An overview of blockchain technology: architecture, consensus, and future trends. In *2017 IEEE International Congress on Big Data (BigData Congress)*, pp. 557–564. IEEE (https://doi.org/10.1109/BigDataCongress.2017.85).