

Bi-Level Optimization Algorithm for Trading Quantity and Surplus Maximization in P2P Electricity Market

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ABSTRACT

The increasing adoption of renewable energy and the evolution of energy markets have led to the need for innovative trading mechanisms, particularly in peer-to-peer (P2P) energy markets. This paper proposes a bi-level optimization algorithm for trading quantity and surplus maximization (BLO-TQSM) in P2P energy trading, incorporating a double-side carbon taxation scheme (DCTS). The BLO-TQSM algorithm is designed to optimize both the trading quantity and surplus by finding the best matching of participants in the market, while the DCTS mechanism integrates carbon tax considerations into the pricing of fossil and renewable energy sources. The shift factor, obtained by particle swarm optimization (PSO), is introduced to find the proposed bi-level maximization algorithm. The proposed method was tested in two scenarios: one without DCTS and one with DCTS. The results show that the algorithm significantly improves trading quantity and surplus in the P2P market compared to traditional power pool models. Moreover, the inclusion of DCTS further enhances the market's environmental sustainability by promoting the use of renewable energy and moving toward a carbon-neutral market.

Keywords: Peer-to-peer, Supply demand curves, Electricity trading, Carbon tax, Renewable energy, Shift factor

1. INTRODUCTION

Throughout the past period, the characteristics of energy customers have seen several changes. Due to technological advancements, consumer behavior, and greenhouse gas (GHG) regulations such as the Kyoto Protocol in 1995, along with other significant international conferences focused on global energy policy and combating global warming. The characteristics of energy customers can be categorized into three eras [1-3]: 1)

Early electricity markets, an era of regulated monopolies: Only the government can sell electricity; 2) The emergence of wholesale markets: The electricity market was liberalized; the private sector can compete, and in this era, the power pool model has been used; 3) The emergence of renewable energy and decentralization, an era characterized by the expansion of renewable energy sources, such as wind energy and solar energy. In addition, consumers become prosumers. So P2P markets play an important role in this era. It is evident that this shift represents a switch from utilizing conventional energy to renewable energy. This type of transformation will be observed in numerous countries. Such as, the percentage of renewable energy in France's primary energy mix has increased significantly. The percentage increased from 6.6% to 10.7% between 2007 and 2017. The percentage of fossil energy dropped from about 95% to 50% between 1960 and 2015 [4]. The share of renewable energy in the U.S. electricity generation mix was projected to increase from 10% in 2010 to 16% by 2035 [5]. It is obvious that renewable energy, such as solar energy and wind energy, has become increasingly prevalent in recent years. Currently, solar energy production and usage in homes are widely available. However, sales of generated energy are rare worldwide. There have been numerous studies conducted on the mechanism that enables buyers and sellers to engage in direct buying and selling, or the P2P mechanism.

The trading mechanism for electrical energy has undergone a gradual evolution in the past. Initially, power pools developed, which were composed of numerous generators that combined electricity production under the control of a regulator responsible for pricing. Until the start of research into the application of the P2P trading mechanism in the electrical system. P2P trading mechanisms have many advantages, such as reducing energy costs and balancing local load generation and demand [3]. Moreover, numerous countries have conducted research and experiments on P2P systems in microgrids. For example, [6] suggests that P2P energy trading in grid-connected networks without post-trade bus voltage protection is nearly established. The mechanism was evaluated on a low-voltage distribution network in Australia. Meanwhile, [7] proposes a motivated psychology paradigm for Malaysian P2P energy trading, with a specific focus on residential users.

P2P energy trading was categorized into three different mechanisms: game theory-based, auction-based,

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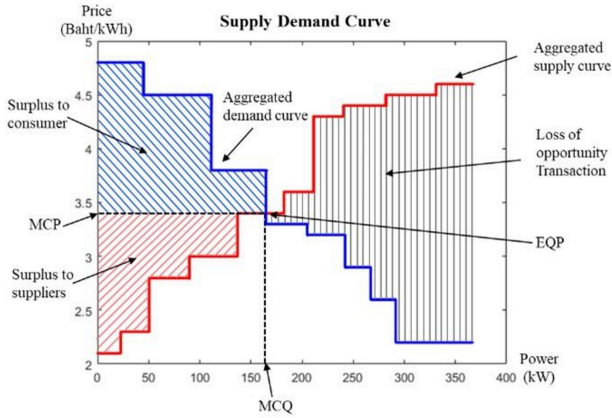


Fig. 1: Aggregated supply and demand curves.

and optimization-based in [3]. Game theory can be employed to simulate the conduct and choices of individuals in the market, both in cooperative and non-cooperative scenarios [8-10]. In auction-based markets, the mechanism can be divided into three models: 1) A single-side auction, which is a unidirectional auction in which bidding takes place on either the supply side or the demand side only [11]; 2) A double auction is a bidirectional auction where both supply and demand are concurrently auctioned [12, 13]; and 3) Continuous double auction (CDA). It is a double auction that is continuous over several consecutive periods [14, 15].

Optimization-based models can be solved using various optimization techniques, such as LP, MILP, NLP, ADMM, etc [16-18]. However, the different mechanisms discussed above are mostly optimization problems. Even game theory problems involve the use of optimization, which mostly has an objective function of minimizing cost and maximizing economic surplus. Furthermore, an auction-based mechanism will provide an equilibrium point (EQP), which makes an equilibrium point that maximizes the economic surplus in the market as shown in Fig. 1. Market clearing price (MCP) is the price applied for all market participants at the market clearing quantity (MCQ). This method of thinking just analyzes EQP's left side, regardless of the right side of EQP. This means that participants on the EQP's right side will not trade in this market. Power sellers on the right side of EQP will not sell, and that energy will be wasted. Power buyers on the right side of EQP will not buy and will be compelled to buy on the grid. In these 2 cases, it will cause a negative surplus in the market. The surplus in the market decreased.

Besides the energy trading environment, carbon neutrality and net zero emissions have been widely discussed in the past decade due to the rapid increase in global temperature. Hence, the Paris Agreement was established in 2015 with the aim of enabling member nations to enhance their capacity to address the challenges posed by climate change, and there is even more pushing at the United Nations Climate Change Conference 2021 (COP

26) [19]. Global warming, or rising global temperatures, is caused by humans producing more GHG resulting in numerous consequences, such as the elevation of water levels, leading to recurrent inundation in certain regions. Crop yields are being impacted by droughts [20]. Carbon dioxide (CO₂) is the most important greenhouse gas because of its naturally high concentration in the atmosphere and its ability to trap heat [21]. In addition, the energy industry is the primary emitter of GHG emissions [22]. Therefore, reducing CO₂ from the energy sector will significantly reduce the problem of global warming.

Carbon footprint (CFP) is a measure of the amount of greenhouse gases [23]. A carbon credit is a general term that refers to a tradable certificate or license that represents the right to emit one ton of carbon dioxide or the mass of another greenhouse gas equivalent to one ton of carbon dioxide [24]. A carbon tax is an additional fee that is calculated according to the quantity of CFP emissions produced by a fuel, product, or service. This tax can be offset off with carbon credits [25]. Hence, a carbon trading market has been established to enable producers of CFP to buy carbon credits to offset their emissions. Nowadays, the government and numerous corporations have a requirement to decrease carbon emissions to mitigate the greenhouse effect. Individuals are increasingly opting to utilize renewable energy sources for electricity consumption while implementing measures to discourage the use of electricity generated from fossil fuels.

Several recent research studies have focused on integrating the carbon trading market into P2P energy trading that can be divided into two groups: 1) Power pricing includes carbon, [26-28] suggests integrating carbon emissions into the objective function to simplify the mechanism. 2) Multi-objective optimization is a methodology used to address problems that involve many variables, such as Many-Objective Marine Predators Algorithm [29], including electricity and carbon emissions [17, 30-32]. This method possesses an intricate mechanism and requires a substantial time to generate outcomes. However, most of the previous studies will be discussed with a focus on minimizing the cost of the system without considering the finances of participants. Sellers of fossil fuels will be penalized for their carbon emissions, and buyers of fossil fuels will also be penalized. This process is namely double-taxation mechanisms [18].

The current shift toward renewable energy and decentralized energy markets has presented intricate issues in energy trading. P2P energy marketplaces have arisen as a mechanism to facilitate decentralized energy transactions, empowering customers to act as prosumers who create, use, and sell energy independently. However, conventional P2P processes face limitations in simultaneously enhancing trading quantity while optimizing social welfare and accounting for environmental factors like carbon emissions.

This paper presents a novel approach to these challenges by introducing a bi-level optimization algorithm for trading quantity and surplus maximization (BLO-TQSM), integrated with a double-sided carbon taxation scheme (DCTS) designed specifically for P2P energy markets. This proposed BLO-TQSM algorithm aims to maximize trading quantity and optimal surplus. The DCTS, an innovative component of this model, introduces a dual-sided carbon tax applied to fossil-based energy transactions, incentivizing the use of renewables and supporting carbon neutrality.

The rest of this paper is organized as follows: Section 2, address the problem formulation; Section 3, computational procedure for BLO-TQSM and DCTS; Section 4, provides the case studies and discusses the results. Finally, conclusions are summarized in section 5.

2. PROBLEM FORMULATION

This paper presents two main mechanisms: 1) BLO-TQSM algorithm is used to find the best matching of participants that maximizes the value of surplus; 2) DCTS, this mechanism will mitigate consumption and production of fossil energy in demand and supply sides. In addition, carbon tax in the form of a carbon double-taxation will transform this market into a carbon neutrality market.

2.1 BLO-TQSM algorithm

In the P2P electricity market, the participants submit their own preferred prices and quantities into the P2P energy trading mechanism. The pay-as-bid settlement is used in this paper. To maximize surplus of all participants, the proposed method in an ascending aggregated demand curve (blue line), as shown in Fig. 2. After that, the aggregated supply curve (red line) is shifted by the shift factor (α) to maximize the trading quantity and find the best value of surplus.

The objective function of BLO-TQSM can be split into bi-levels optimization: the major-level objective, which is trading quantity maximization, and the minor-level objective, which is surplus maximization. The maximum transaction volume is calculated at the major-level and formulated as follows:

Maximize

$$TQ = \sum_{i=1}^{N_{\max}} f_i(\lambda_i) \quad (1)$$

s.t.

$$f(\lambda_i) = \begin{cases} n & \text{for } \lambda_{Di} \geq \lambda_{Si} \\ 0 & \text{for } \lambda_{Di} < \lambda_{Si} \end{cases} \quad (2)$$

$$P^{\min} = \max \{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\} \quad (3)$$

$$P^{\max} = \min \{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\} \quad (4)$$

$$N_{\max} = \frac{P^{\max} - P^{\min}}{n} \quad (5)$$

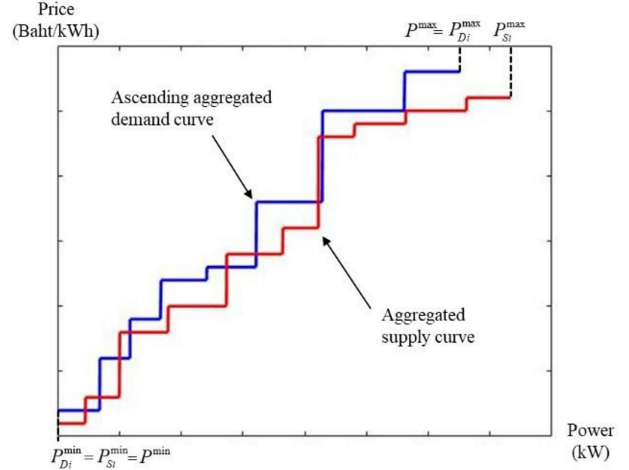


Fig. 2: Typical aggregated supply and ascending aggregated demand curves.

where, TQ is trading quantity; λ_{Di} and λ_{Si} are price of demand and supply position i in the graph, respectively; P_{Di} and P_{Si} are power quantity of demand and supply position i in the graph, respectively; n is step size; α is shift factor and $P^{\min}, P^{\max}, P_{Di}^{\min}, P_{Si}^{\min}, P_{Di}^{\max}, P_{Si}^{\max}$ can be explained in Fig. 2.

Major-level calculations will reveal many identical maximum values. To find the shift factor that generates the best surplus while TQ has a maximum value, TQ must be imposed as a constraint at the minor-level. The objective function of minor-level is shown in Eq. (6). The objective function contains three terms, i.e., surplus of inverse demand curve, surplus of shifting supply curve, and death penalty term [33].

Maximize

$$SP = \int_{P^{\min}}^{P^{\max}} asc(\lambda_{Di} \cdot P_{Di}) dP_{Di} - \int_{P^{\min}}^{P^{\max}} [(\lambda_{Si} \cdot P_{Si}) + \alpha] dP_{Si} - DPF \quad (6)$$

s.t.

$$DPF = \begin{cases} +\infty, & TQ \neq TQ_{\max} \\ 0, & TQ = TQ_{\max} \end{cases} \quad (7)$$

$$P^{\min} = \max \{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\} \quad (8)$$

$$P^{\max} = \min \{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\} \quad (9)$$

where, SP is surplus; DPF is the death penalty function that ensure that TQ in minor-level optimization is equal to TQ_{\max} in Eq. (1). "asc" denotes the ascending version of aggregated demand curve.

2.2 DCTS

This paper proposes the DCTS mechanism for buyers who purchase electricity from fossil energy sources to

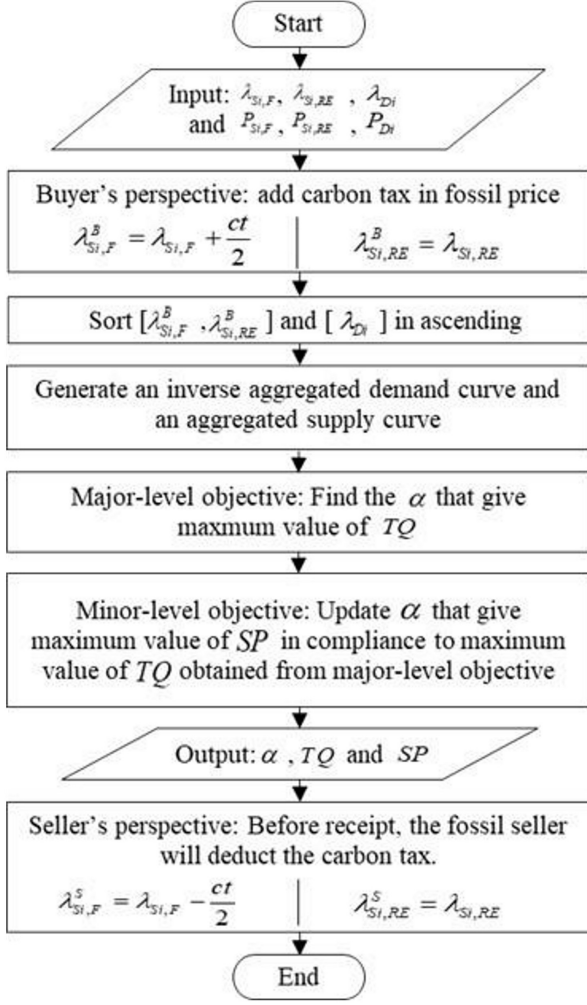


Fig. 3: BLO-TQSM algorithm computational procedure.

be charged half the amount of carbon tax by both the buyer and seller. This mechanism forces consumers that consume electricity from fossil energy sources to pay a higher price, while fossil energy source sellers receive lower prices than before. This mechanism can be explained as shown in Fig.4. In order to facilitate comprehension, it can be divided into two perspectives, and there are the following equations:

Buyer's perspective;

$$\lambda_{Si,F}^B = \lambda_{Si,F} + \frac{ct}{2} \quad (10)$$

$$\lambda_{Si,RE}^B = \lambda_{Si,RE} \quad (11)$$

where, $\lambda_{Si,F}^B$ and $\lambda_{Si,RE}^B$ are seller's price at position i of fossil energy and renewable energy in buyer's perspective, respectively; $\lambda_{Si,F}$ and $\lambda_{Si,RE}$ are prices of fossil energy and renewable energy offered by sellers, respectively; ct is carbon tax.

From the buyer's point of view, the price of fossil energy will be perceived as elevated above the usual level.

The carbon tax is the additional cost that the purchaser is responsible for paying.

Seller's perspective;

$$\lambda_{Si,F}^S = \lambda_{Si,F} - \frac{ct}{2} \quad (12)$$

$$\lambda_{Si,RE}^S = \lambda_{Si,RE} \quad (13)$$

where, $\lambda_{Si,F}^S$ and $\lambda_{Si,RE}^S$ are seller's price at position i of fossil energy and renewable energy in seller's perspective. Carbon taxes are deducted before sellers of fossil energy receive payment, after the matching of P2P.

3. COMPUTATIONAL PROCEDURE

The proposed method's computational procedure is illustrated in Fig. 3. The optimal value of major-level objective and minor-level objective was found by particle swarm optimization (PSO).

The PSO operation is an iterative computational process in which, during each cycle, the velocity of each particle is modified based on $pbest_i^t$ and $gbest_i^t$. A formulation of the set of populations is presented in this paper as follows:

$$\alpha = [\alpha_1, \alpha_2, \dots, \alpha_{NP}] \quad (14)$$

$$\alpha_i = [P_{Di}^{\min} - P_{Si}^{\max}, P_{Di}^{\max} - P_{Si}^{\min}], \quad \text{for } i = 1, 2, \dots, NP \quad (15)$$

The range of α_1 is represented in Eq. (15). The control of variables in Eq. (14) are used for Eq. (8-9). Then, the new velocity of the particles is calculated by Eq. (16), the new position of the particles is computed by Eq. (17). NP is the number of populations.

$$v_i^{t+1} = wv_i^t + c_1r_1(pbest_i^t - \alpha_i^t) + c_2r_2(gbest_i^t - \alpha_i^t) \quad (16)$$

$$\alpha_i^{t+1} = \alpha_i^t + v_i^{t+1}, \text{ for } i = 1, 2, \dots, NP \quad (17)$$

where, $pbest$ is the best shift factor of each particle; $gbest$ is the best shift factor of all particles; t and $t + 1$ are the iteration; v_i is the velocity for particle i ; c_1 and c_2 are a constant numbers; r_1 and r_2 are a random parameters; w is inertial weight. PSO is used for both major-level and minor-level optimization. In the major-level optimization, the objective is computed by the TQ in Eq. (1). Meanwhile, in the minor-level optimization, the objective function is computed by the SP with penalty function to keep maximum TQ from the major-level optimization TQ_{\max} in Eq. (6).

The decision to employ the classical PSO algorithm was made after careful consideration of several factors, including simplicity of PSO algorithm that make it easier to validate and analyze the results, particularly in the context of our bi-level optimization for P2P energy trading. PSO also offer improvements in convergence speed or solution quality. However, we acknowledge the potential benefits of newer algorithms and plan to explore their application in future research to further enhance the robustness and efficiency of our proposed methodology.

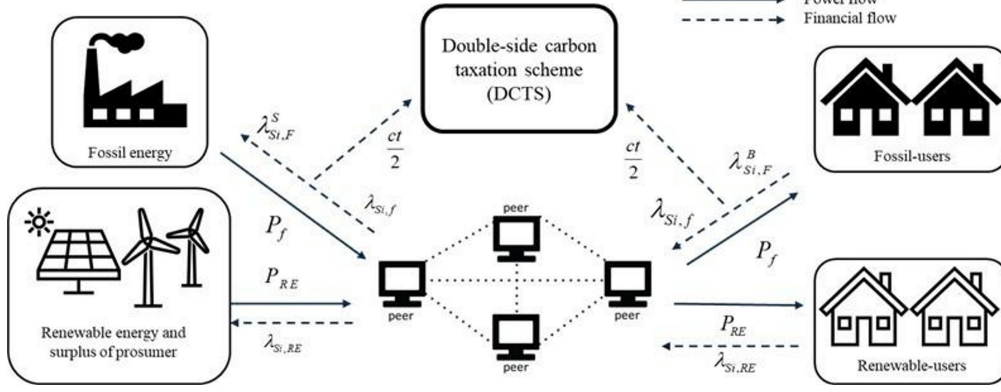


Fig. 4: The proposed P2P market mechanism.

Table 1: The amount and price of energy offered from buyers and sellers.

Supply				Demand		
Seller	Index	Baht /kWh	kW	Buyer	Baht /kWh	kW
S1	1	2.1	22.7	B1	2.2	34.3
S2	0	2.3	27.7	B2	2.6	24.4
S3	1	2.8	39.2	B3	2.9	25.1
S4	0	3	47.3	B4	3.2	37.1
S5	1	3.4	45.5	B5	3.3	40.1
S6	0	3.6	28.7	B6	3.8	24
S7	1	4.3	29.4	B7	3.8	29.5
S8	0	4.4	41.3	B8	4.5	26.2
S9	1	4.5	49.2	B9	4.5	40.3
S10	0	4.6	35.7	B10	4.8	44.8

4. RESULT AND DISCUSSION

In this section, the trading quantity and surplus of the proposed mechanism for P2P energy trading are simulated and numerically analyzed for the BLO-TQSM and DCTS algorithms. The case studies are carried out using the variables of participant number, price, and quantity of electrical energy from [34], with a price range of [2 Baht/kWh, 5 Baht/kWh]. The index for fossil energy sellers and renewable energy is “0” and “1”, respectively, as shown in Table 1. Two cases were investigated and compared, as follows.

- Case A: The BLO-TQSM algorithm without the DCTS algorithm to compare trading quantity and surplus with the power pool model after deducting the loss of opportunity transaction and P2P multi-stage matching mechanism (MMM) form [34].

- Case B: The BLO-TQSM algorithm is used in conjunction with the DCTS algorithm to compare the financial data with case A.

The computations for all case studies were conducted using MATLAB on a computer with a Windows 11 operating system, a 2.3 GHz Intel Core i5 processor, and 16 GB of memory.

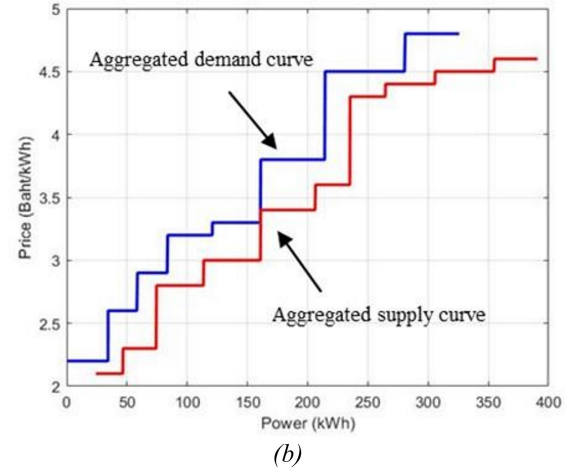
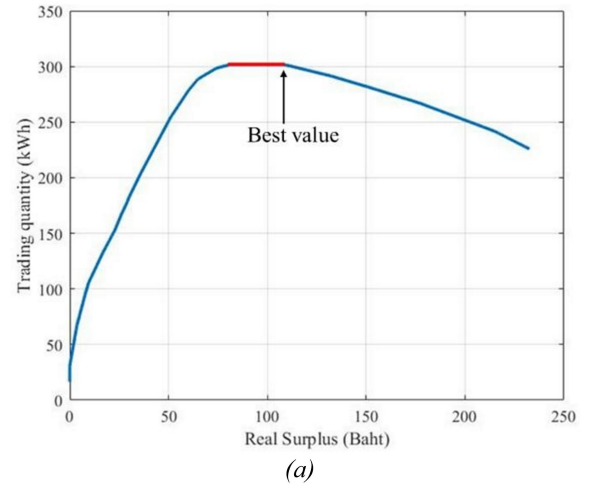


Fig. 5: Result of case A: (a) the correlation between surplus and volume with shift factor adjustments and (b) aggregated supply and ascending aggregated demand curves after BLO-TQSM algorithm.

4.1 Case A: BLO-TQSM without DCTS

In the first case study, we assume that all participants have an immediate desire to purchase and sell. Table 1 lists the input value in the algorithm. The results for energy trading in this case are represented in Fig.

Table 2: Result of case A.

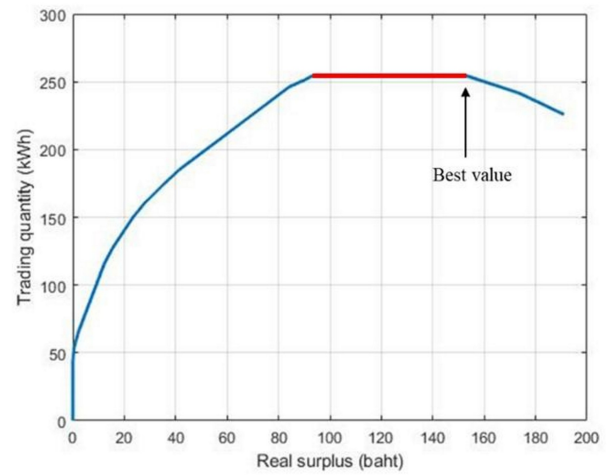
Supply						Demand				
<i>Seller</i>	<i>Index</i>	<i>Baht/ kWh</i>	<i>offer (kWh)</i>	<i>power sell (kWh)</i>	<i>revenue (Baht)</i>	<i>Buyer</i>	<i>Baht/ kWh</i>	<i>bid (kWh)</i>	<i>power purchase (kWh)</i>	<i>payment (Baht)</i>
S1	1	2.1	22.7	22.7	54.94	B1	2.2	34.3	10.2	22.44
S2	0	2.3	27.7	27.7	76.76	B2	2.6	24.4	24.4	63.44
S3	1	2.8	39.2	39.2	122.65	B3	2.9	25.1	25.1	72.79
S4	0	3	47.3	47.3	155.37	B4	3.2	37.1	37.1	118.72
S5	1	3.4	45.5	45.5	172.9	B5	3.3	40.1	40.1	132.33
S6	0	3.6	28.7	28.7	123.55	B6	3.8	24	24	91.2
S7	1	4.3	29.4	29.4	132.3	B7	3.8	29.5	29.5	112.1
S8	0	4.4	41.3	41.3	193.32	B8	4.5	26.2	26.2	117.9
S9	1	4.5	49.2	19.9	95.52	B9	4.5	40.3	40.3	181.35
S10	0	4.6	35.7	0	0	B10	4.8	44.8	44.8	215.04
<i>total</i>				301.7	1127.31	<i>total</i>			301.7	1127.31

Table 3: Comparison between power pool, P2P MMM and BLO-TQSM.

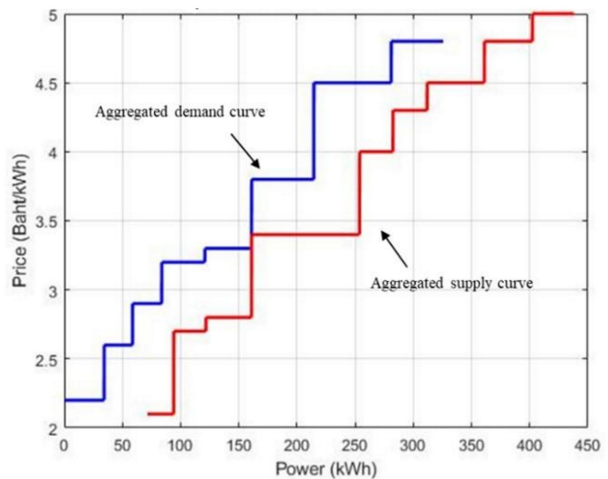
	Trading quantity (kWh)	Surplus (Baht)
Power pool	164.8	259.69
P2P MMM	301.7	74.85
BLO-TQSM	301.7	108.56

5, and Table 2 illustrates a shifting graph and matched participants that have average computational times equal to 4.36 seconds. Fig. 5(a) show the correlation between surplus and trading quantity, while shift factor adjustments can be divided into three phases of volume: 1) The beginning phase, where an increased shift factor causes increased surplus and trading quantity; 2) The steady phase (red line), where an increase in the shift factor leads to an increase in the surplus, while the trade quantity remains constant; 3) The regression phase, where adding a shift factor at this phase no longer results in an increase in quantity. Despite the continuing increase in surplus, the quantity trading declined. Therefore, the shift factor, equal to 24.1, represents the last value in the steady phase before the regression phase. It results in a maximum surplus of 108.56 Baht, a maximum trading quantity of 301.7 kWh. Fig. 5(b) shows the aggregated supply has shifted by 24.1 points and ascending aggregated demand curves. Table 2 shows the matching of seller and buyer for maximum surplus; sellers received a total revenue, and buyers made a total payment of 1127.31 Baht. It is clear that sellers who set their prices high will not find buyers who are willing to pay that amount. Conversely, buyers who pay a low price will also not find a match.

Result in Table 3 is a comparison of the two systems: 1) the Power pool market mechanism and 2) the P2P market mechanism (P2P-MMM, BLO-TQSM). The power pool market mechanism has notable benefits in terms of surplus, but it has disadvantages in terms of trading



(a)

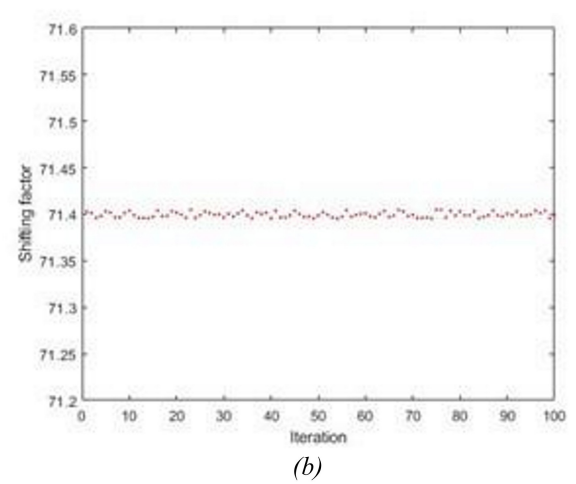
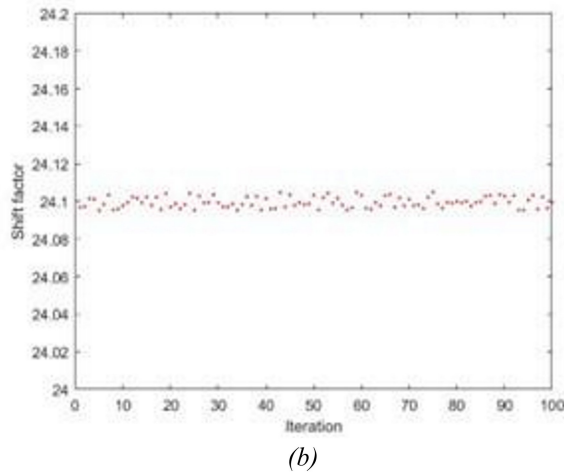
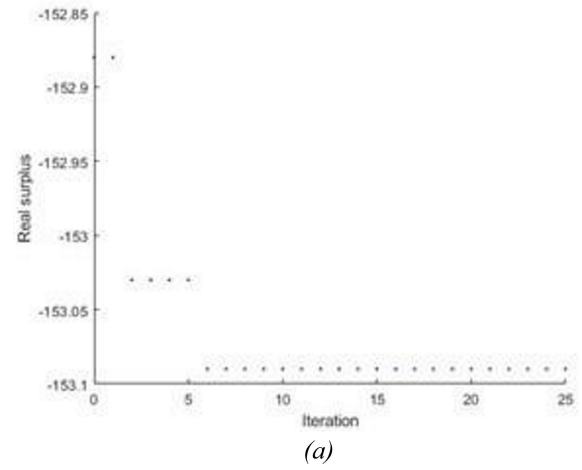
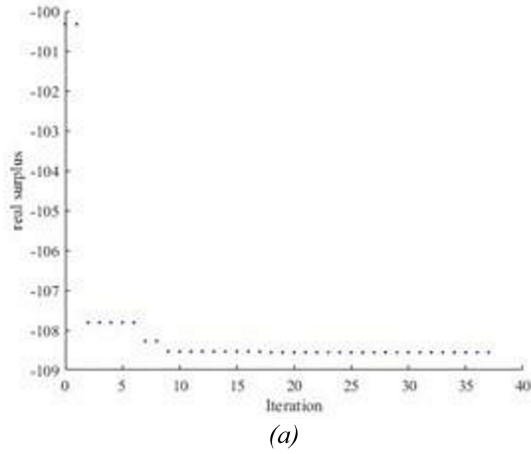


(b)

Fig. 6: Result of case B: (a) the correlation between surplus and volume with shift factor adjustments and (b) aggregated supply and ascending aggregated demand curves after BLO-TQSM algorithm.

Table 4: Result of case B.

Supply						Demand				
<i>Seller</i>	<i>Index</i>	<i>Baht/ kWh</i>	<i>offer (kWh)</i>	<i>power sell (kWh)</i>	<i>revenue (Baht)</i>	<i>Buyer</i>	<i>Baht/ kWh</i>	<i>bid (kWh)</i>	<i>power purchase (kWh)</i>	<i>payment (Baht)</i>
S1	1	2.1	22.7	22.7	68.92	B1	2.2	34.3	0	0
S2	0	2.7	27.7	27.7	66.57	B2	2.6	24.4	0	0
S3	1	2.8	39.2	39.2	129.36	B3	2.9	25.1	12.4	35.96
S4	0	3.4	47.3	47.3	141.9	B4	3.2	37.1	37.1	118.72
S5	1	3.4	45.5	45.5	200.41	B5	3.3	40.1	40.1	132.33
S6	0	4	28.7	28.7	106.64	B6	3.8	24	24	91.2
S7	1	4.3	29.4	29.4	141.12	B7	3.8	29.5	29.5	112.1
S9	1	4.5	49.2	13.9	66.72	B8	4.5	26.2	26.2	117.9
S8	0	4.8	41.3	0	0	B9	4.5	40.3	40.3	181.35
S10	0	5	35.7	0	0	B10	4.8	44.8	44.8	215.04
<i>total</i>				254.4	921.64	<i>total</i>			254.4	1004.6

**Fig. 7:** Result of case A: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots.**Fig. 8:** Result of case B: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots.

quantity. On the other hand, the P2P market mechanism has significant advantages in terms of the trading quantity. Both P2P-MMM and BLO-TQSM have a trading

quantity of 307.1 kWh. However, the surplus of BLO-TQSM is 108.56 Baht, which is higher than the surplus of P2P-MMM, which is 74.85 Baht.

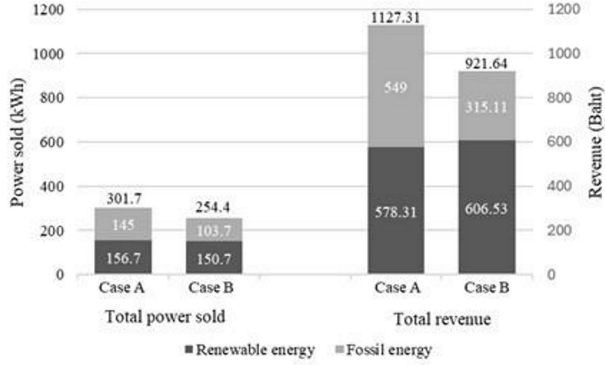


Fig. 9: Power sold and financial comparison between case A and case B.

Table 5: he result at 100 trials of the proposed.

Shift factor	case: A	case: B
Max	24.1050	71.4047
min	24.0951	71.3995
mean	24.1000	71.4000
SD	0.0028	0.0029

4.2 Case B: BLO-TQSM with DCTS

In this case study, the DCTS algorithm is integrated into the BLO-TQSM algorithm, utilizing the data provided in Table 1. The carbon tax rate is set at 0.8 Baht/kWh, which reflects the additional cost of carbon emissions within the trading mechanism. Table 4 depicts the energy trading outcomes for this scenario. Fig. 6 provides a detailed illustration of the shifting supply and demand curves and the matching of participants that have average computational times equal to 3.96 seconds.

The inclusion of the carbon tax affects the pricing dynamics of sellers, especially those relying on fossil fuels. This rearrangement of prices influences the correlation between surplus and trading quantity, as well as the adjustments of the shift factor and the aggregated supply and demand curves, which are further demonstrated in Fig. 6. For Case B, the optimal shift factor is identified as 71.4, resulting in a maximum achievable surplus of 153.09 Baht and a trading quantity of 254.40 kWh.

The result in Table 4 indicates that the fossil energy producers are unable to sell the electricity, highlighting the impact of the carbon taxation mechanism. The study also provides insights into the financial implications for sellers, including the revenue generated from transactions and the payments made concerning the buyers' energy consumption. Collectively, sellers received a total revenue of 921.64 Baht, while buyers made a total payment of 1004.6 Baht. The resulting difference of 82.96 Baht is allocated to offset carbon emissions, thereby contributing to achieving carbon neutrality within the market framework.

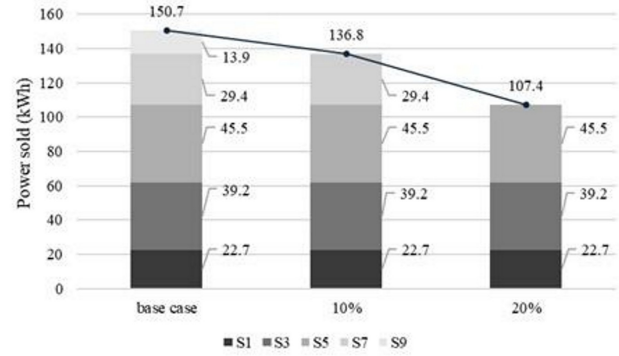


Fig. 10: Comparative analysis of renewable energy sellers in each case.

Figures 7 and 8 present convergence plots of surplus, along with 100 trials, showing the shift factor variations for both Case A (without DCTS) and Case B (with DCTS), respectively. These visualizations demonstrate how the integration of DCTS influences the optimization process and leads to better alignment of trading quantities and market surplus, fostering a more sustainable P2P energy trading environment.

Figure 9 illustrates the total power sold and a financial comparison between case A and case B. In case A, the renewable energy seller and fossil fuel seller sold 156.7 kWh and 145 kWh and received revenue of 578.31 Baht and 549 Baht, respectively. In case B, the renewable energy seller and fossil fuel seller sold 103.7 kWh and 150.7 kWh and received revenue of 606.53 Baht and 315.11 Baht, respectively. It can be observed that when including the DCTS algorithm, total power sold of fossil energy and renewable energy is reduced by 28.48% and 3.83%, respectively. The total revenue of fossil energy is reduced by 42.60%. Conversely, the total revenue of renewable energy is increase by 4.88%. Renewable energy sellers will experience slight changes as fossil sellers' prices change, resulting in different matching. Fossil energy sellers are adversely affected by the DCTS method, which enables purchasers to see elevated pricing, thus hindering certain sellers from transacting and forcing them to remit half of their taxes prior to receiving revenue. This mechanism indirectly supports carbon neutrality.

The results with 100 trials of the proposed BLO-TQSM is shown in Table 5.

4.3 Sensitivity analysis

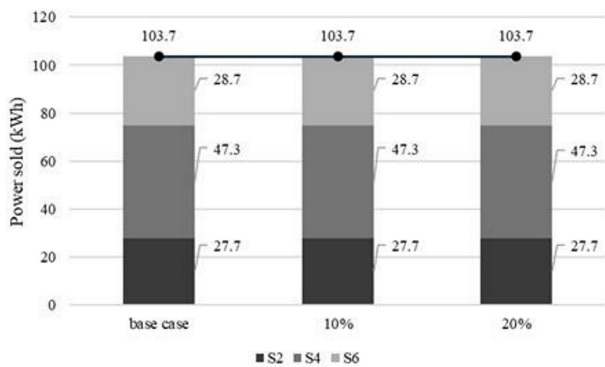
This section delves into the sensitivity analysis of renewable energy pricing by utilizing data from Case B in Table 4 as the base case. The analysis investigates the impact of increasing renewable energy prices by 10% and 20% on key performance metrics, such as trading quantity and surplus. These increments aim to provide insights into the market's response to changes in renewable energy pricing, highlighting the implications for sellers within the P2P energy trading framework.

Table 6: The result of increasing renewable energy prices by 10%.

Supply						Demand				
<i>Seller</i>	<i>Index</i>	<i>Baht/ kWh</i>	<i>offer (kWh)</i>	<i>power sell (kWh)</i>	<i>revenue (Baht)</i>	<i>Buyer</i>	<i>Baht/ kWh</i>	<i>bid (kWh)</i>	<i>power purchase (kWh)</i>	<i>payment (Baht)</i>
S1	1	2.3	22.7	22.7	72.64	B1	2.2	34.3	0	0
S2	0	2.7	27.7	27.7	67.96	B2	2.6	24.4	0	0
S3	1	3	39.2	39.2	136.31	B3	2.9	25.1	0	0
S4	0	3.4	47.3	47.3	147.29	B4	3.2	37.1	35.6	113.92
S5	1	3.7	45.5	45.5	204.75	B5	3.3	40.1	40.1	132.33
S6	0	4	28.7	28.7	110.81	B6	3.8	24	24	91.2
S7	1	4.7	29.4	29.4	141.12	B7	3.8	29.5	29.5	112.1
S8	0	4.8	41.3	0	0	B8	4.5	26.2	26.2	117.9
S9	1	4.9	49.2	0	0	B9	4.5	40.3	40.3	181.35
S10	0	5	35.7	0	0	B10	4.8	44.8	44.8	215.04
total				240.5	880.88	total				963.84

Table 7: The result of increasing renewable energy prices by 20%.

Supply						Demand				
<i>Seller</i>	<i>Index</i>	<i>Baht/ kWh</i>	<i>offer (kWh)</i>	<i>power sell (kWh)</i>	<i>revenue (Baht)</i>	<i>Buyer</i>	<i>Baht/ kWh</i>	<i>bid (kWh)</i>	<i>power purchase (kWh)</i>	<i>payment (Baht)</i>
S1	1	2.5	22.7	22.7	74.29	B1	2.2	34.3	0	0
S2	0	2.7	27.7	27.7	71.3	B2	2.6	24.4	0	0
S3	1	3.4	39.2	39.2	148.96	B3	2.9	25.1	0	0
S4	0	3.4	47.3	47.3	167.87	B4	3.2	37.1	6.2	19.84
S6	0	4	28.7	28.7	106.19	B5	3.3	40.1	40.1	132.33
S5	1	4.1	45.5	45.5	218.19	B6	3.8	24	24	91.2
S8	0	4.8	41.3	0	0	B7	3.8	29.5	29.5	112.1
S10	0	5	35.7	0	0	B8	4.5	26.2	26.2	117.9
S7	1	5.1	29.4	0	0	B9	4.5	40.3	40.3	181.35
S9	1	5.4	49.2	0	0	B10	4.8	44.8	44.8	215.04
total				211.1	786.8	total				869.76

**Fig. 11:** Comparative analysis of fossil energy sellers in each case.

The sensitivity analysis of renewable energy pricing, as presented in Tables 6 and 7 and Figures 10 and 11, demonstrates the impact of price increases on trading

quantities within the P2P energy market. When renewable energy prices are increased by 10%, the trading quantity decreases slightly from 254.4 kWh in the Case B baseline to 240.5 kWh, representing a modest 5.5% reduction. Revenue for total energy sellers decreases from 921.64 Baht to 880.88 Baht. Payment for total energy buyers decreases from 1004.6 Baht to 963.84 Baht. The decrease in trading quantity led to a decrease in revenue and payment. However, with a 20% increase in renewable energy prices, the trading quantity declines more significantly to 211.1 kWh, a reduction of 17% from the baseline. Revenue for total energy sellers decreases from 921.64 Baht to 786.8 Baht. Payment for total energy buyers decreases from 1004.6 Baht to 869.76 Baht. The rise in renewable energy prices has led to a decline in trading quantity, which is attributable to a decrease in renewable energy sales as shown in Fig. 10. The difference in payment and revenue between the base case and the case where the renewable energy price increases

by 10% and 20% is equal to 82.96 Baht in all cases. This is because an increase in renewable energy prices does not affect the trading quantity of fossil energy sellers, which was 103.7 kWh, as shown in Fig. 11. In this study illuminates that two fossil energy sellers, S8 and S10, cannot be aligned with purchasers. Due to the DCTS algorithm, their prices exceeded the purchasers' bid prices and hence were not matched.

5. CONCLUSION

The proposed BLO-TQSM integrated with DCTS offers a comprehensive and innovative approach to enhancing P2P energy trading in microgrids. By optimizing trading quantity and surplus while integrating environmental considerations through carbon taxation, the mechanism addresses both economic and ecological goals. Case A, which applies BLO-TQSM without DCTS, demonstrated significant advancements in trading efficiency, achieving a higher trading quantity and surplus compared to traditional P2P-MMM and power pool mechanisms. On the other hand, Case B, which incorporates the DCTS, revealed the potential of this dual-taxation approach to discourage fossil energy reliance while promoting renewable energy adoption. The mechanism not only improved market dynamics by reallocating costs to reflect environmental impacts but also contributed to a carbon-neutral energy trading framework. The research highlights the versatility and effectiveness of combining economic incentives with carbon taxation in P2P markets, illustrating a path toward sustainable energy solutions. The DCTS effectively shifted the economic advantage toward renewable energy sellers, reduced the overall trading of fossil-based energy, and reallocated carbon tax revenues to offset emissions. These findings reinforce the potential for energy markets to balance financial objectives with ecological imperatives.

Future work will expand upon this framework by incorporating a comparative analysis between the MMM and BLO-TQSM algorithms using Monte Carlo simulations (MCS) with a normal distribution to model diverse market scenarios. This extension will account for variability in participant behavior, energy prices, and quantities, providing a more realistic simulation of decentralized energy markets. Additionally, the development of a probabilistic bi-level optimization algorithm (PBLO-TQSM) will enable the robust evaluation of trading performance under uncertain and dynamic conditions. This next step will ensure the algorithm's adaptability and scalability in optimizing trading volume, surplus, and environmental outcomes across varying market environments, further advancing the transition to sustainable energy systems.

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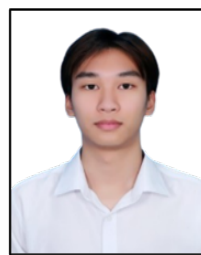
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REFERENCES

- [1] R. J. Green and D. M. Newbery, "Competition in the British electricity spot market," *Journal of political economy*, vol. 100, no. 5, pp. 929-953, 1992.
- [2] P. L. Joskow, "Lessons learned from electricity market liberalization," *The Energy Journal*, vol. 29, no. 2_suppl, pp. 9-42, 2008.
- [3] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, "Peer-to-peer trading in electricity networks: An overview," *IEEE transactions on smart grid*, vol. 11, no. 4, pp. 3185-3200, 2020.
- [4] F. Belaïd, "Understanding the spectrum of domestic energy consumption: Empirical evidence from France," *Energy Policy*, vol. 92, pp. 220-233, 2016.
- [5] W. Su, "The role of customers in the us electricity market: Past, present and future," *The Electricity Journal*, vol. 27, no. 7, pp. 112-125, 2014.
- [6] M. I. Azim, W. Tushar, and T. K. Saha, "Regulated P2P energy trading: A typical Australian distribution network case study," in *2020 IEEE Power & Energy Society General Meeting (PESGM)*, 2020: IEEE, pp. 1-5.
- [7] Y. H. Yap, W.-S. Tan, N. A. Ahmad, C.-L. Wooi, and Y.-K. Wu, "Motivational game-theory P2P energy trading: A case study in Malaysia," in *2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES)*, 2020: IEEE, pp. 480-485.
- [8] J. Dixon, T. Morstyn, L. Han, and M. McCulloch, "Flexible cooperative game theory tool for peer-to-peer energy trading analysis," in *2018 IEEE Power & Energy Society General Meeting (PESGM)*, 2018: IEEE, pp. 1-5.
- [9] R. R. Trivedi, C. P. Barala, P. Mathuria, R. Bhakar, and S. Sharma, "Peer-to-Peer Energy Trading: Energy Pricing Using Game Theory Models," in *2023 IEEE IAS Global Conference on Renewable Energy and Hydrogen Technologies (GlobConHT)*, 2023: IEEE, pp. 1-6.
- [10] P. Wirasanti and P. Yotha, "Comparative Clearing Approaches in the Local Energy Market Based on the Prosumer Case Study," *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 20, no. 1, pp. 96-104, 2022.
- [11] H. M. Manjunatha, G. K. Purushothama, Y. Nanjappa, and R. Deshpande, "Auction-Based Single-Sided Bidding Electricity Market: An Alternative to the Bilateral Contractual Energy Trading Model in a Grid-Tied Microgrid," *IEEE Access*, 2024.
- [12] J. Guerrero, A. C. Chapman, and G. Verbič, "Decentralized P2P energy trading under network constraints in a low-voltage network," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5163-5173, 2018.
- [13] J. Yang, H. Huang, Y. Zhang, J. Dai, and H. B. Gooi, "Tron Blockchain Based Pricing Scheme for Energy Trading Considering Carbon Emissions

- Taxes,” in *2022 IEEE PES Innovative Smart Grid Technologies-Asia (ISGT Asia)*, 2022: IEEE, pp. 335-339.
- [14] T. D. Hutty and S. Brown, ”P2P trading of heat and power via a continuous double auction,” *Applied Energy*, vol. 369, p. 123556, 2024.
- [15] E. Jamil, J. Cuenca, and B. Hayes, ”Assessment of a Network-Constrained P2P Energy Trading Scheme through Auction Mechanism,” in *2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, 2023: IEEE, pp. 1-5.
- [16] M. Khorasany, A. Paudel, R. Razzaghi, and P. Siano, ”A new method for peer matching and negotiation of prosumers in peer-to-peer energy markets,” *IEEE Transactions on Smart Grid*, vol. 12, no. 3, pp. 2472-2483, 2020.
- [17] L. Shuxin, L. Zhihao, and L. Zhuoying, ”Carbon tax utility analysis based on multi-objective optimization and market equilibrium in power system,” in *2023 IEEE International Conference on Energy Technologies for Future Grids (ETFG)*, 2023: IEEE, pp. 1-6.
- [18] T. Wan, Y. Tao, J. Qiu, and S. Lai, ”Distributed energy and carbon emission right trading in local energy systems considering the emission obligation on demand side,” *IEEE Systems Journal*, 2023.
- [19] I. Wahyuni, R. F. Harris, and E. Sujatmoko, ”The Road to Net-Zero Emission in Indonesia: Legal Loopholes in National Carbon Tax Scheme,” *Media Iuris*, vol. 6, no. 3, 2023.
- [20] A. Hartley and A. Tandon, ”The impacts of climate change,” *Frontiersin.org*, vol. 716479, p. 10, 2022.
- [21] H. Mohajan, ”Greenhouse gas emissions increase global warming,” 2011.
- [22] W. F. Lamb et al., ”A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018,” *Environmental research letters*, vol. 16, no. 7, p. 073005, 2021.
- [23] A. C. S. W. M. E. Ar. Namita Singh, ”Strategies for Reducing Carbon Footprints: A Cross-Sectional Study of Experts’ Opinion,” *European Economic Letters (EEL)*, vol. 13, no. 1, pp. 297-303, 03/09 2023, doi: 10.52783/eel.v13i1.171.
- [24] S. Ingole, A. Nagpurkar, and A. Kakde, ”Research Paper Environment Carbon Credits-A Solution to Global Warming,” *Environment*, vol. 2, no. 5, 2013.
- [25] A. Baranzini and S. Weber, Carbon taxes. Edward Elgar Publishing Limited, 2023.
- [26] W. Hua and H. Sun, ”A blockchain-based peer-to-peer trading scheme coupling energy and carbon markets,” in *2019 international conference on smart energy systems and technologies (SEST)*, 2019: IEEE, pp. 1-6.
- [27] J. Li et al., ”An electricity and carbon trading mechanism integrated with TSO-DSO-prosumer coordination,” *Applied Energy*, vol. 356, p. 122328, 2024.
- [28] F. Song, K. Liu, L. Wang, S. Zhao, Q. Lv, and L. Wang, ”Distributed Optimization Operation of Multimicrogrid with Electricity-Carbon Trading,” in *2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)*, 2023: IEEE, pp. 1973-1978.
- [29] S. Khunkitti, A. Siritaratiwat, and S. Premrudeepreechacharn, ”A Many-Objective Marine Predators Algorithm for Solving Many-Objective Optimal Power Flow Problem,” *Applied Sciences*, vol. 12, no. 22, p. 11829, 2022. [Online]. Available: <https://www.mdpi.com/2076-3417/12/22/11829>.
- [30] H. T. Doan, H. Nam, and D. Kim, ”Optimal peer-to-peer energy trading under load uncertainty incorporating carbon emission and transaction cost for grid-connected prosumers,” *IEEE Access*, vol. 10, pp. 106202-106216, 2022.
- [31] J. Xu, Y. Yang, W. Pei, H. Li, H. Wang, and C. Liu, ”A P2P Electricity Carbon Joint Trading Strategy for Multiple Virtual Power Plants Based on ADMM,” in *2024 IEEE 7th International Electrical and Energy Conference (CIEEC)*, 2024: IEEE, pp. 3663-3668.
- [32] Z. Lu, L. Bai, J. Wang, J. Wei, Y. Xiao, and Y. Chen, ”Peer-to-peer joint electricity and carbon trading based on carbon-aware distribution locational marginal pricing,” *IEEE transactions on power systems*, vol. 38, no. 1, pp. 835-852, 2022.
- [33] O. Yeniay, ”Penalty function methods for constrained optimization with genetic algorithms,” *Mathematical and computational Applications*, vol. 10, no. 1, pp. 45-56, 2005.
- [34] P. Sakolkiatkajorn and K. Chayakulkheeree, ”Power Pool vs P2P Energy Trading Mechanisms: A Social Welfare Perspective,” in *2024 12th International Electrical Engineering Congress (iEECON)*, 2024: IEEE, pp. 1-5.



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