PROBABILISTIC BI-LEVEL OPTIMIZATION ALGORITHM FOR TRADING QUANTITY AND SURPLUS MAXIMIZATION IN P2P ELECTRICITY MARKET

PAWIT SAKOLKIATKAJORN

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กระบวนการหาคำตอบที่เหมาะที่สุดเชิงความน่าจะเป็นแบบสองระดับ สำหรับการเพิ่มปริมาณการซื้อขายและการเพิ่มประสิทธิผลส่วนเกิน ในตลาดพลังงานไฟฟ้าแบบ P2P

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's degree

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ปวิธ สกลเกียรติขจร : กระบวนการหาคำตอบที่เหมาะที่สุดเชิงความน่าจะเป็นแบบสองระดับสำหรับการเพิ่มปริมาณการซื้อขายและการเพิ่มประสิทธิผลส่วนเกินในตลาดพลังงานไฟฟ้าแบบ P2P (PROBABILISTIC BI-LEVEL OPTIMIZATION ALGORITHM FOR TRADING QUANTITY AND SURPLUS MAXIMIZATION IN P2P ELECTRICITY MARKET) อาจารย์ที่ปรึกษา : รองศาสตราจารย์ ดร. กีรติ ชยะกุลคีรี, 140 หน้า

คำสำคัญ: การซื้อขายพลังงานแบบเพียร์ทูเพียร์, เส้นอุปสงค์และอุปทาน, การซื้อขายไฟฟ้า, ภาษีคาร์บอน, พลังงานหมุนเวียน, ปัจจัยการเลื่อน

ในยุคที่ตลาดพลังงานกำลังเปลี่ยนผ่านไปสู่ระบบแบบกระจายศูนย์และการบูรณาการพลังงานหมุนเวียน การซื้อขายพลังงานแบบเพียร์ทูเพียร์ได้กลายเป็นแนวทางที่มีศักยภาพสำหรับการแลกเปลี่ยนพลังงานไฟฟ้าอย่างมีประสิทธิภาพ อย่างไรก็ตามกรอบการซื้อขายพลังงานที่มีอยู่ยังคงเผชิญกับความท้าทายในการสร้างสมดุลระหว่างการเพิ่มปริมาณการซื้อขายสูงสุดกับการเพิ่มประสิทธิภาพส่วนเกินทางเศรษฐกิจและความยั่งยืนทางสิ่งแวดล้อม วิทยานิพนธ์ฉบับนี้นำเสนออัลกอริทึมการเพิ่มประสิทธิภาพเชิงสองระดับแบบความน่าจะเป็นสำหรับการเพิ่มปริมาณการซื้อขายและการเพิ่มประสิทธิผลส่วนเกินเพื่อเสริมสร้าง ประสิทธิภาพ ความเป็นธรรม และความยั่งยืน ของตลาดพลังงานแบบ P2P โดยอัลกอริทึมนี้ผสาน การเพิ่มประสิทธิภาพเชิงสองระดับเข้ากับการจำลองมอนติคาร์โลเพื่อคำนวณความไม่แน่นอนของราคาไฟฟ้าและพฤติกรรมอุปสงค์-อุปทาน ในกระบวนการเพิ่มประสิทธิภาพระดับบนมุ่งเน้นไปที่ การเพิ่มปริมาณการซื้อขายสูงสุด ขณะที่กระบวนการเพิ่มประสิทธิภาพระดับล่างเน้นที่ การกระจายส่วนเกินทางเศรษฐกิจ โดยนำผลกระทบจากผู้เข้าร่วมที่ไม่สามารถจับคู่ได้มาพิจารณา เพื่อให้ได้การประเมินประสิทธิภาพตลาดที่แม่นยำยิ่งขึ้น นอกจากนี้ งานวิจัยยังได้พัฒนา กลไกภาษีคาร์บอนแบบเก็บทั้งสองฝ่าย เพื่อให้ต้นทุนทางสิ่งแวดล้อมถูกรวมเข้าไปในกลไกการซื้อขายพลังงานและเพื่อกระตุ้นให้เกิดการใช้พลังงานหมุนเวียน ผลการจำลองด้วยกรณีศึกษา ตลาดพลังงาน P2P ที่มีผู้ซื้อ 50 ราย และผู้ขาย 50 ราย แสดงให้เห็นว่า PBLO-TQSM สามารถปรับปรุงประสิทธิภาพของตลาดและการกระจายทรัพยากรได้อย่างมีนัยสำคัญ โดยช่วยลดความไร้ประสิทธิภาพของตลาดลง 6.40% และเพิ่มส่วนเกินจากการซื้อขายขึ้น 13.24% เมื่อเทียบกับวิธีการแบบดั้งเดิม นอกจากนี้ DCTS ยังช่วยสร้างแรงจูงใจให้ตลาดพลังงานปรับตัวเข้าสู่แนวทางที่เป็นกลางทางคาร์บอน และสอดคล้องกับเป้าหมายความยั่งยืนระดับโลก

สาขาวิชาวิศวกรรมไฟฟ้า ลายมือชื่อนักศึกษา ....

ปีการศึกษา 2567 ลายมือชื่ออาจารย์ที่ปรึกษา ....

PAWIT SAKOLKIATKAJORN : PROBABILISTIC BI-LEVEL OPTIMIZATION ALGORITHM FOR TRADING QUANTITY AND SURPLUS MAXIMIZATION IN P2P ELECTRICITY MARKET

THESIS ADVISOR : ASSOC. PROF. DR. KEERATI CHAYAKULKHEEREE, D.ENG, 140 PP.

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

As energy markets transition toward decentralization and renewable integration, Peer-to-Peer (P2P) energy trading has emerged as a viable mechanism for efficient electricity exchange. However, existing trading frameworks face challenges in balancing trading quantity maximization, economic surplus optimization, and environmental sustainability. This thesis proposes a Probabilistic Bi-Level Optimization Algorithm for Trading Quantity and Surplus Maximization (PBLO-TQSM) to enhance market efficiency, fairness, and sustainability in P2P electricity markets. The algorithm integrates bi-level optimization with Monte Carlo Simulation (MCS) to model uncertainties in energy prices and supply-demand interactions. The upper-level optimization focuses on maximizing trading quantity, while the lower-level optimization refines surplus distribution by incorporating unmatched participant losses, ensuring a more accurate representation of market performance. The study further introduces a Double-Side Carbon Taxation Scheme (DCTS) to internalize environmental costs and incentivize renewable energy adoption. Extensive simulations with a case study of 50 buyers and 50 sellers demonstrate that PBLO-TQSM significantly improves resource matching efficiency and surplus distribution, reducing market inefficiencies by 6.40% and increasing trading surplus by 13.24% compared to conventional models. Additionally, DCTS effectively aligns market incentives with sustainability goals, promoting carbon neutrality within decentralized trading environments.

School of Electrical Engineering

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LIST OF ABBREVIATIONS

ADMM	=	Alternating direction method of multipliers
BLO-TQSM	=	Bi-level optimization algorithm for trading quantity and surplus maximization
BRP	=	Block rate price
CCTS	=	Consumer-side carbon taxation scheme
DCTS	=	Double-side Carbon Taxation Scheme
DERs	=	Distributed energy resources
MCP	=	Market clearing price
MCQ	=	Market clearing quantity
MCS	=	Monte carlo simulation
P2P MMM	=	Peer to Peer multi-stage matching mechanism
PBLO-TQSM	=	Probabilistic bi-level optimization algorithm for trading quantity and surplus maximization
PDF	=	Probability density function
PSO	=	Particle swarm optimization
STCS	=	Supplier-side carbon taxation scheme

LIST OF NOMENCLATURES

λ_{Di}	=	demand price of prosumer i.
$\tilde{\lambda}_{Di}$	=	PDF of demand price of prosumer i.
λ_{Si}	=	supply price of prosumer i.
$\tilde{\lambda}_{Si}$	=	PDF of supply price of prosumer i.
$\lambda_{Si,F}$	=	prices of fossil energy offered by sellers.
$\lambda_{Si,RE}$	=	prices of renewable energy offered by sellers.
$\lambda_{Si,F}^{B}$	=	seller's price at position i of fossil energy in buyer's perspective.
$\lambda_{Si,RE}^{B}$	=	seller's price at position i of renewable energy in buyer's perspective.
$\lambda_{Si,F}^{S}$	=	seller's price at position i of fossil energy in seller's perspective.
$\lambda_{Si,RE}^{S}$	=	seller's price at position i of renewable energy in seller's perspective.
α	=	shift factor.
c_1, c_2	=	the constant numbers.
D_{MWi}	=	demand quantity of prosumer i.
$gbest_i^t$	=	the best group position of particle i at iteration t.
n	=	step size.
N_d	=	population of demand.
N_s	=	population of supply.
ND	=	number of bid prices.
NP	=	number of populations.
NS	=	number of offer prices.
NSP_D	=	negative surplus of demand.

LIST OF NOMENCLATURES (Continued)

NSP_S	=	negative surplus of supply.
$pbest_i^t$	=	the best particle position of particle i at iteration t.
$P_{Di}^{\min}$	=	minimum power quantity of demand.
$P_{Di}^{\max}$	=	maximum power quantity of demand.
$P_{Si}^{\min}$	=	minimum power quantity of supply.
$P_{Si}^{\max}$	=	maximum power quantity of supply.
$\tilde{P}_{Di}^{\min}$	=	PDF of minimum power quantity of demand.
$\tilde{P}_{Di}^{\max}$	=	PDF of maximum power quantity of demand.
$\tilde{P}_{Si}^{\min}$	=	PDF of minimum power quantity of supply.
$\tilde{P}_{Si}^{\max}$	=	PDF of maximum power quantity of supply.
P_{unDi}	=	unmatched power of demand.
P_{unSi}	=	unmatched power of supply.
r_1, r_2	=	the random parameters.
S_{MWi}	=	supply quantity of prosumer i.
SP	=	surplus.
t	=	the number of iterations.
TQ	=	trading quantity.
v_i	=	the velocity for particle i.
w	=	the inertial weight.

CHAPTER I

INTRODUCTION

1.1 General Introduction

The global energy landscape is undergoing a significant transformation driven by the increased adoption of renewable energy sources, decentralization of power generation, and technological advancements. Traditional electricity markets, once dominated by centralized power pool systems, are increasingly being challenged by innovative trading mechanisms such as P2P energy trading. These changes reflect broader shifts towards sustainability, consumer empowerment, and enhanced energy efficiency, driven by advancements in blockchain, smart grids, and digital platforms that enable direct energy exchanges between prosumers (producers and consumers of energy).

Historically, the energy market evolved through three major phases. Initially, it was characterized by regulated monopolies where the government or a single company controlled the entire supply chain. The second phase saw the liberalization and deregulation of electricity markets, introducing competition and private sector involvement. The current phase is marked by the rise of decentralized energy resources, particularly renewable energy sources like solar and wind power, which have reshaped the energy market dynamics.

P2P energy trading represents a paradigm shift from the traditional power pool model, where energy is traded directly between consumers without the need for a central intermediary. This mechanism not only promotes localized energy exchanges but also reduces transmission losses, enhances grid resilience, and empowers consumers to play an active role in the energy market. However, while P2P trading fosters greater transaction volumes and encourages renewable energy adoption, it poses challenges in terms of market efficiency, social welfare, and the integration of environmental factors such as carbon emissions.

1.2 Problem Statement

Despite the significant advantages offered by P2P energy trading, several critical challenges remain unresolved. One of the issues is the inherent tradeoff between maximizing trading volumes and optimizing social welfare. Traditional power pool models, which operate under centralized control using optimization techniques like linear programming, have demonstrated the ability to achieve higher levels of social welfare by efficiently balancing supply and demand. These centralized systems ensure that resources are allocated optimally, maximizing economic benefits. However, in contrast, P2P models known for their decentralized and flexible nature facilitate a larger number of transactions by allowing direct energy exchanges between participants. While this increases market activity and promotes localized energy trading, it often comes at the expense of optimal social welfare. Due to the less structured and more fragmented nature of P2P trading mechanisms, these models frequently fall short in achieving the highest possible economic surplus, leaving gaps in market efficiency.

A further complication arises from the issue of unpaired participants, buyers unable to secure a purchase and sellers unable to complete a sale. This unpaired status represents a significant loss of opportunity in the market, as unused energy is wasted, and potential trades are left unfulfilled as shown in Figure 1.1. The failure to address this problem not only reduces market efficiency but also negatively impacts the overall benefits that could be derived from P2P energy trading. Current models often overlook this issue, resulting in market inefficiencies that undermine the potential of decentralized energy systems.

Additionally, with the growing global emphasis on sustainability and carbon reduction, many existing P2P trading models fail to incorporate environmental considerations, such as carbon emissions, into the trading process. As markets transition toward carbon neutrality and net-zero goals, it is essential to integrate environmental factors into energy pricing and trading mechanisms. The absence of these considerations can lead to missed opportunities for promoting renewable energy and mitigating the environmental impact of fossil fuel consumption.

The primary goal of this proposal is to develop and implement advanced energy trading mechanisms that address these critical challenges, particularly the loss of market opportunities and the tradeoff between social welfare and trading quantity. By incorporating the maximization of trading quantity alongside the maximization of social welfare after deducting loss of opportunity transaction, this research seeks to improve the efficiency, fairness, and overall social benefits of P2P energy markets. Moreover, by integrating environmental factors such as carbon costs, this proposal aims to align P2P trading systems with global sustainability goals. Through the introduction of innovative algorithms and trading frameworks, this study provides valuable insights for policymakers, market operators, and stakeholders in the energy sector, offering practical solutions for enhancing the future of decentralized energy trading.

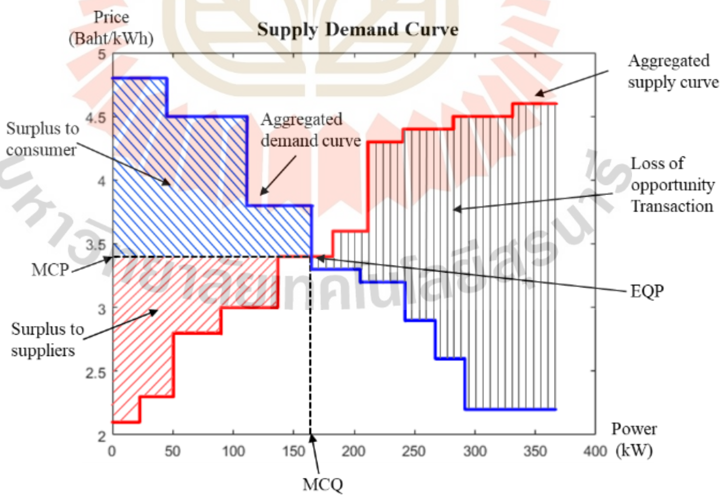


Figure 1.1 Aggregated supply and demand curves

1.3 Research Objectives

The primary objective of this research is to develop advanced mechanisms for P2P energy trading that effectively address both trading quantity and social welfare. Specifically, this study aims to:

1) Maximize the trading quantity in P2P energy markets while ensuring optimal matching between buyers and sellers.

2) Incorporate the maximization of social welfare after deducting loss of opportunity transaction into P2P trading.

3) Integrate environmental considerations, particularly carbon costs, into energy trading mechanisms through the use of Double-Side Carbon Taxation Scheme (DCTS).

1.4 Scope and limitations

1.4.1 Scope

This research focuses on the design, development, and implementation of energy trading mechanisms within P2P energy markets. The scope of the study four specific cases:

1) Price and quantity of participants in P2P energy market are obtained by Monte Carlo simulations (MSC) with a normal distribution.

2) The simulation model for P2P energy market includes 50 buyers and 50 sellers.

3) The P2P electricity trading market, clearing by multi-stage matching mechanism (P2P MMM), will be investigated.

4) The P2P electricity trading market, clearing by bi-level optimization algorithm for trading quantity and surplus maximization (BLO-TQSM), will be investigated.

5) The carbon taxing mechanism will be integrated into P2P electricity market by DCTS.

6) The sensitivity analysis of the price and quantity of the players is investigated.

1.4.2 Limitations

The participants' behavior including prices and quantities obtained by the MCS are based on specific assumptions, which may not fully reflect real-world complexities. The environmental impact in terms of carbon taxation is modeled using a fixed rate, and the study does not account for dynamic policy changes or fluctuating carbon prices over time.

1.5 Conception

The main contribution of this study is to evaluate both the trading quantity and social welfare while considering loss opportunity transaction under the P2P MMM and BLO-TQSM models. The simulations yield results using the Monte Carlo with normal distribution method for prices and quantities offers of 100 participants by MATLAB programming. The concept can be illustrated as Figure 1.2.

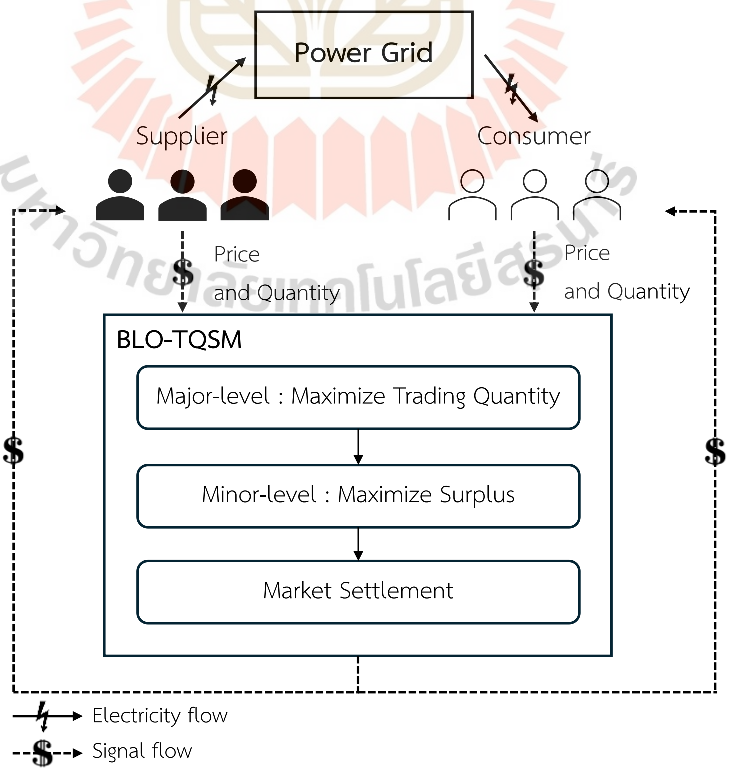


Figure 1.2 Conception of the study

1.6 Research Benefits

The proposed research offers significant benefits by advancing both the theoretical understanding and practical implementation of P2P energy trading systems. By introducing optimized mechanisms like the P2P MMM and BLO-TQSM, this study enhances trading quantity and social welfare in energy markets. The integration of DCTS promotes environmental sustainability by incentivizing the use of renewable energy and reducing the carbon footprint of energy transactions. Moreover, the P2P market participants' pricing behaviors can be treated in probabilistic manner by Monte Carlo Simulation.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

The emergence of P2P energy trading systems represents a significant shift in the structure of modern energy markets. Traditional energy markets, characterized by centralized control and linear optimization, are challenged by decentralized platforms where energy consumers and prosumers can directly engage in energy trading. Various market mechanisms, such as optimization-based, auction-based, and game-theory models, have been proposed to enhance the efficiency, social welfare, and environmental sustainability of these markets. Despite these advancements, a clear gap exists in the literature: most studies focus on optimizing either social welfare or trading quantity, rarely both. The need for a hybrid approach that balances both objectives has led to the development of innovative frameworks like the one proposed in this research.

2.2 Literature Overview

P2P energy trading allows prosumers to engage directly with other market participants, bypassing traditional intermediaries and leveraging digital platforms for energy exchange. A variety of mechanisms have been developed to facilitate this trading, each with its strengths and limitations. These mechanisms include optimization-based models, auction-based approaches, and game-theory applications, all aiming to improve market efficiency, maximize social welfare, and promote fairness. However, a significant research gap remains most existing models focus on optimizing either social welfare or trading volume, but not both simultaneously. Table 2.1 show these existing mechanisms, providing an overview of their objectives, including carbon taxation, and participants in case study.

Table 2.1 Summary of researchers related to optimal P2P market operation

Ref.	Objective		With carbon	Market mechanism	Model	Participants in case study
	Social welfare	Trading quantity				
Wang et al., 2014	✓	-	-	double auction	noncooperative game Nash equilibrium	11
Khorasany et al., 2017	✓	-	-	auction-based	Iterative algorithm	IEEE 13 node 5 buyers and 5 sellers participate
Zhang et al., 2018	✓	-	-	-	noncooperative game Nash equilibrium	10
Guerrero et al., 2018	✓	-	-	double auction	MILP	100
Khorasany et al., 2020	✓	-	-	auction-based	ADMM	27-bus case: A=5, case: B=26
Yang et al., 2022	✓	-	✓	double auction	-	13
Wirasanti & Yotha, 2022	-	✓	-	auction-based/game theory	double auction/NIRA	5
Mehdinejad et al., 2022	✓	-	-	optimization-based	FADMM	7

Table 2.1 Summary of researchers related to optimal P2P market operation (continued)

Ref.	Objective		With carbon	Market mechanism	Model	participants in case study
	Social welfare	Trading quantity				
Shuxin et al., 2023	-	✓	✓	optimization-based	multi-objective optimization	30-node 6-generator/participants
Wan et al., 2023	-	✓	✓	optimization-based	ADMM	IEEE 33-bus system 3 micro generators 3 BESSs 5 prosumers
Edussuriya et al., 2023	✓	-	✓	-	Stackelberg Game	6
Jamil et al., 2023	-	✓	-	auction-based	CDA	5
Li et al., 2022	✓	-	-	optimization-based	ADMM	69-node
Feng et al., 2022	✓	-	-	optimization-based	LR-DM and LMP	5
Yao et al., 2023	✓	-	✓	-	Stackelberg game	IEEE 33 bus
Hutty & Brown, 2024	✓	-	-	auction-based	CDA	25
Proposed method	✓	✓	✓	optimization-based	shift factor (BLO-TQSM)	100

2.3 P2P Market Mechanisms

P2P energy trading allows prosumers to directly engage in energy exchanges with consumers, bypassing traditional intermediaries. The mechanism design of these markets plays a crucial role in determining efficiency, fairness, and scalability. The following sections discuss various P2P market mechanisms and their respective strengths and limitations.

2.3.1 Optimization-Based

Optimization-based mechanisms are designed to maximize specific market outcomes usually social welfare or economic surplus through algorithms that ensure the most efficient allocation of resources. Khorasany et al. (2020) introduced an iterative algorithm designed to match participants in P2P energy trading by maximizing economic surplus. This algorithm incorporates greediness in the peer-matching process to ensure that each participant benefits from the trade. The study was conducted using a 27-bus system and showed significant improvements in economic surplus for participants. Similarly, Shuxin et al. (2023) focused on multi-objective optimization by minimizing both the cost of power generation and carbon emissions. This approach, tested on a 30-node system, demonstrated that incorporating environmental costs into optimization models can yield significant reductions in carbon emissions while maintaining economic efficiency. Wan et al. (2023) proposed a model for P2P energy and carbon emission trading, focusing on distributed energy resources (DERs). This study utilized an alternating direction method of multipliers (ADMM) to minimize trading costs and carbon emissions in a decentralized grid system.

However, while optimization-based models are effective at maximizing social welfare, they often prioritize economic surplus over trading volume. This creates a trade-off where fewer transactions are optimized for welfare, but many participants remain unpaired, resulting in lost trading opportunities. This limitation is a critical research gap that this study seeks to address.

2.3.2 Auction-Based

Auction-based mechanisms are widely used in P2P markets due to their ability to facilitate competitive and transparent pricing. Double auction systems, where buyers and sellers simultaneously submit bids and offers, are among the most popular methods used to match participants in P2P trading.

Yang et al. (2022) developed a blockchain-based double auction model for P2P energy trading that aimed to reduce the cost of energy transactions while improving social welfare. The system integrated carbon emission taxes calculated using a quadratic carbon emission function, allowing the model to account for environmental costs in the pricing mechanism. The results of the study, which was conducted in a 13-prosumer microgrid, showed that auction mechanisms could effectively balance economic outcomes with sustainability goals. Khorasany et al. (2017) studied an auction-based mechanism that considers both economic factors and the technical constraints of the power grid. The study emphasized the importance of maintaining grid stability while maximizing participant welfare. Using an IEEE 13-node system, the research demonstrated that auction-based mechanisms could increase transaction volumes significantly, but at the cost of lower social welfare optimization.

Guerrero et al. (2018) focused on network-constrained auctions, ensuring that trades did not violate low-voltage network constraints. By using a double auction model in a 100-participant system, the study highlighted the efficiency of auctions in managing decentralized energy transactions, although it pointed out that the system often struggled to achieve optimal welfare outcomes.

While auction-based systems are highly effective in increasing the number of transactions, they often do so at the expense of maximizing social welfare. This tradeoff between transaction volume and welfare maximization represents a key gap in existing literature.

2.3.3 Game-Theory

Game-theory models have been used to analyze strategic behavior in P2P energy markets, where participants act based on their own preferences and the decisions of others. These models offer insights into how participants can achieve equilibrium outcomes that balance individual and collective benefits.

Zhang et al. (2018) applied Nash equilibrium in a P2P microgrid to explore how non-cooperative games could optimize social welfare. In this model, participants made decentralized decisions, and the system achieved stable trading outcomes that optimized welfare without needing central coordination. The study, which involved 10 participants, demonstrated the potential of game theory to ensure fairness and stability in decentralized energy markets. Yao et al. (2023) employed a Stackelberg game model to balance carbon network fees and maximize demand response revenues. The study, conducted in an IEEE 33-bus system, focused on minimizing carbon-related charges while ensuring financial benefits for participants. The hierarchical structure of the Stackelberg game allowed the system to model real-world energy interactions where certain participants, like grid operators, have more power over pricing decisions than others.

Although game-theory models provide strategic insights into participant behavior and allow for decentralized decision making, they tend to focus on optimizing individual strategies rather than maximizing overall market welfare or transaction volumes. Additionally, the computational complexity of game theory models limits their scalability in larger markets.

The framework proposed in this study addresses the shortcomings of existing P2P market mechanisms by offering a hybrid approach that optimizes both social welfare and trading volume simultaneously. The Bi-level Optimization Algorithm for Trading Quantity and Surplus Maximization (BLO-TQSM) is designed to ensure that both the quantity of trades and the economic surplus are maximized, filling the research gap that existing models leave by focusing on one objective at the expense of the other. This framework integrates the pricing of energy with the internalization of carbon costs, ensuring that both economic and environmental objectives are balanced. By optimizing both social welfare and trading volume in P2P energy markets, this framework provides a comprehensive solution to the current trade-offs between maximizing transactions and ensuring market efficiency.

2.4 Carbon Taxation

As the global focus on sustainability intensifies, carbon taxation has become an essential tool for promoting the adoption of renewable energy while reducing the reliance on fossil fuels. In the context of P2P energy markets, carbon taxes serve to internalize the environmental costs associated with energy production, particularly from fossil fuels, by imposing financial penalties on carbon-intensive energy sources. However, existing carbon tax models often distribute the tax burden unevenly, applying it solely to one side of the transaction, such as the producer or consumer, rather than sharing the responsibility between both parties. This creates a partial incentive for transitioning to renewable energy but does not fully capitalize on the potential of carbon taxes to drive behavior change across all market participants.

Several studies have incorporated carbon taxes into P2P energy trading mechanisms, but most apply the tax exclusively to either the producer or the consumer of fossil-fuel-based energy. For instance, Shuxin et al. (2023) proposed a multi-objective optimization model that minimizes both carbon emissions and energy generation costs by applying a carbon tax to producers. This approach effectively reduces emissions but leaves the burden of taxation solely on the supply side, which may not be enough to encourage widespread shifts toward renewable energy consumption. Similarly, Yao et al. (2023) introduced a carbon network fee model within a Stackelberg game framework, focusing on reducing carbon-related charges for producers while maximizing demand response revenues. This model incentivizes producers to minimize carbon emissions, but the absence of a corresponding tax on consumers limits the overall impact on market behavior. Yang et al. (2022) incorporated carbon taxes into a blockchain-based double auction mechanism, where the tax was applied to the producer based on a quadratic carbon emission function. While this model accounts for emissions, it places the entire burden on energy producers, leaving consumers largely unaffected by the environmental costs of their energy consumption.

The primary limitation of these models is their one-sided approach to carbon taxation. By focusing the tax burden solely on producers, these frameworks do not fully incentivize consumers to make more sustainable energy choices. This incomplete internalization of environmental costs represents a significant research gap, as carbon taxation can be more effective when both producers and consumers are held accountable for their reliance on fossil fuels.

The carbon tax mechanism proposed in this study addresses the limitations of existing models by shifting the burden of taxation to both producers and consumers of fossil-fuel-based energy, while leaving consumers of renewable energy unaffected. This Double-Side Carbon Taxation Scheme (DCTS) imposes taxes on both buyers and sellers of fossil-generated electricity, ensuring that the full environmental costs of carbon emissions are internalized across all relevant transactions. By taxing both sides of the trade, the DCTS encourages both producers and consumers to transition to renewable energy sources, as renewable energy consumers are exempt from these additional costs.

This approach contrasts with previous models by ensuring that the shift to cleaner energy is driven by both market participants rather than placing the entire burden on producers. By including both parties in the taxation scheme, the proposed framework creates stronger incentives for behavior change, promoting renewable energy adoption more effectively. Consumers of renewable energy, who already contribute to sustainability goals, are not affected by these taxes, making the market more attractive for those seeking environmentally friendly energy options.

2.5 Thailand Situation

Thailand's energy sector is undergoing a significant transformation, driven by increasing electricity demand, sustainability goals, and advancements in decentralized energy trading. Historically, the country has relied heavily on natural gas, accounting for over 60% of total electricity production. However, concerns over energy security, carbon emissions, and renewable energy adoption have led to a shift toward a more diversified and sustainable power system. To address these challenges, Thailand introduced the Power Development Plan 2018–2037 (PDP2018), which serves as the country's primary energy policy framework. PDP2018 focuses on balancing energy security, economic efficiency, and environmental sustainability by promoting renewable energy integration, P2P energy trading, and carbon pricing mechanisms. One of its key targets is to increase the share of renewable energy to 30–35% of total installed capacity by 2037, encouraging the participation of small-scale prosumers in decentralized energy markets. The plan also supports P2P electricity trading, enabling direct transactions between consumers and prosumers through digital platforms and blockchain-based systems. This aligns with global trends in decentralized energy systems, improving market flexibility and reducing transmission losses. Additionally, PDP2018 advocates for carbon taxation policies to incentivize low-carbon energy generation, with frameworks such as DCTS being explored to fairly distribute carbon costs between energy buyers and sellers. While Thailand has initiated pilot projects, such as the Bangkok Smart Energy District, to test blockchain-based P2P trading, challenges remain, including regulatory barriers, infrastructure limitations, and the need for dynamic pricing mechanisms. Addressing these issues will require policy adjustments, smart grid investments, and financial incentives to ensure the success of decentralized energy trading and carbon taxation. With the right regulatory framework and technological advancements, Thailand is well-positioned to become a leader in sustainable, consumer-driven electricity markets, aligning with global energy transition goals.

CHAPTER III

POWER POOL VS P2P ENERGY TRADING MECHANISMS: A SOCIAL WELFARE PERSPECTIVE[1]

3.1 Introduction

The mechanisms for trading electrical energy have undergone significant evolution over the past several decades, reflecting broader changes in the electricity supply industry. This transformation can be categorized into three distinct phases:

1) Early Electricity Markets

The origins of electricity markets date back to the late 19th and early 20th centuries, coinciding with advancements in power generation technology. These early markets were typically localized and dominated by single entities controlling the entire supply chain, from generation to distribution. For much of the 20th century, the electricity supply industry operated as regulated monopolies, with vertically integrated utilities monopolizing the market (Green & Newbery, 1992).

2) Emergence of Wholesale Markets

The mid-20th century saw the formation of power pools, which allowed utilities to improve resource sharing and enhance reliability. This period marked the beginning of more organized energy markets, driven by growing regional grid connectivity. The latter part of the century witnessed a trend towards deregulation and market liberalization, introducing competition in electricity generation and retail sectors, and separating distribution, transmission, and generation functions (Joskow, 2008)

[1] Part of this chapter was presented at the "12th International Electrical Engineering Congress (iEECON2024)", Thailand, 2024.

3) Decentralization and the Rise of Renewable Energy

The early 21st century introduced significant changes to the electricity sector with the rapid expansion of renewable energy sources, particularly wind and solar power. This shift brought about new dynamics in the market, characterized by decentralized energy generation, such as rooftop solar panels. This development challenged traditional utility models and paved the way for innovative energy trading paradigms. Among these is P2P energy trading, which allows consumers to trade surplus energy directly with each other, enabled by advancements in blockchain and smart grid technologies (Tushar, Saha, Yuen, Smith, & Poor, 2020).

While P2P trading is still in its infancy, it represents a shift towards a consumer-centric, sustainable, and resilient energy system. However, the integration of P2P trading into existing systems presents challenges and opportunities for market efficiency and social welfare. Existing research has explored various models and mechanisms for energy trading, including double auction mechanisms, coalition game theory models, and systems that incorporate social and economic preferences (Huang, Nie, Lin, Wang, & Dong, 2020; Wu & Wu, 2020; Zhao, Luo, Yang, & Ranzi, 2022).

Several countries worldwide have started incorporating P2P technology in conjunction with conventional systems. For example, Azim, Tushar, and Saha (2020) suggests almost settled P2P energy trading in grid-connected networks without post-trade bus voltage protection. They tested the mechanism on an Australian low-voltage distribution network. Meanwhile, Yap, Tan, Ahmad, Wooi, and Wu (2020) proposes a motivational psychology paradigm for Malaysian P2P energy trading, focusing on residential prosumers, to increase user involvement. Heo and Jung (2020) introduces operator-driven block rate price (BRP) P2P energy trading in communities. A South Korean residential neighbourhood is used to validate the proposed technique. In addition, the emerging architecture of P2P energy trading and its various operating algorithms had been proposed by Shrestha et al. (2019) a case study of Nepal's energy system.

In Thailand, the rise of prosumers, who also produce energy has led to increased interest in P2P energy trading. This trading mechanism offers numerous benefits, such as reducing peak demand and improving system efficiency by allowing for the direct sale of excess electricity. However, there is a need for a comprehensive comparison between the traditional power pool market and the emerging P2P trading model, particularly in terms of social welfare maximization.

This chapter presents a comparative study of power pool markets and P2P energy trading mechanisms, utilizing linear programming and a proposed multi-stage matching mechanism (P2P MMM) to evaluate and contrast these models. The analysis aims to provide insights into the strengths and weaknesses of each trading mechanism, with a focus on volume and social welfare implications.

3.2 Electricity market models

In this section, Electricity market mechanisms, namely the power pool market and P2P energy trading mechanisms, are presented. These two models differ significantly in terms of structure, operation, and their impact on market efficiency and social welfare. The power pool market mechanism is solved by linear programing. Meanwhile, the P2P electricity market is settled by P2P MMM.

3.2.1 Power pool market

In the Power pool market, the objective function is maximizing the total social welfare by calculating the entire area under the supply and demand curves, which represents the collective benefit to both producers and consumers in the market considering constraints violation as.

Minimize $$B = \sum_{i=1}^{NS} (\lambda_{Si} \cdot S_{MWi}) - \sum_{i=1}^{ND} (\lambda_{Di} \cdot D_{MWi}) \tag{3.1}$$

Subject to: $$0 = \sum_{i=1}^{NS} S_{MWi} - \sum_{i=1}^{ND} D_{MWi} \tag{3.2}$$

In the above equations, B represents social welfare of supply and demand curves. Meanwhile, Equations 3.2 is the equality constraints of market balance equation. The chart of demand and supply are shown in Figures 3.1 and 3.2, respectively.

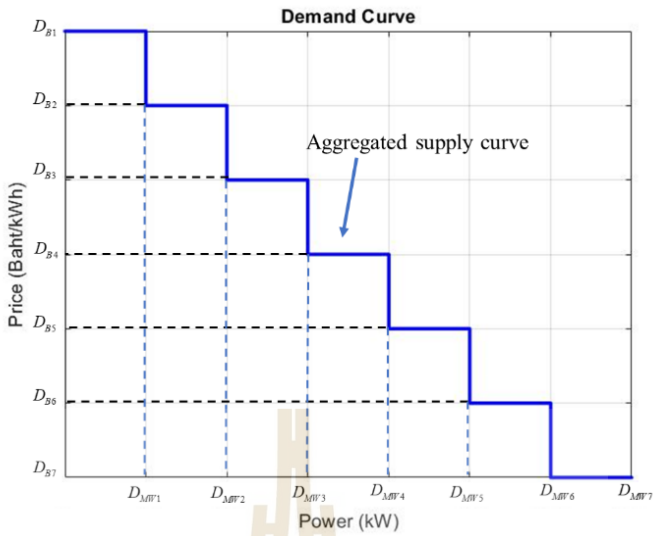


Figure 3.1 Demand curve

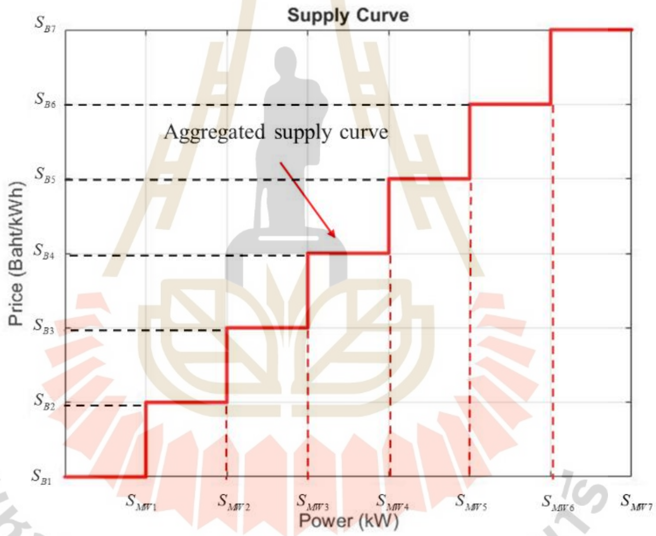


Figure 3.2 Supply curve

A demand curve is a fundamental economic graph that represents the relationship between the price of a good or service and the quantity that consumers are willing and able to purchase over a given period. The curve typically has a negative slope, indicating an inverse correlation between price and demand. This means that as the price of a product decreases, the quantity demanded by consumers increases, and vice versa. This relationship reflects basic consumer behavior, where individuals tend to buy more of a product when it becomes cheaper. In the context of electricity markets, Figure 3.1 demonstrates the aggregated demand curve at various price levels, capturing the collective behavior of all market participants buyers who are willing to purchase electricity at different price points.

On the other hand, the supply curve illustrates the direct relationship between the price of a product or service and the quantity that producers are willing and able to supply to the market. Unlike the demand curve, the supply curve has a positive slope, signifying that as the price rises, producers are more incentivized to supply a greater quantity. This reflects the basic economic principle that higher prices provide greater potential profit, motivating producers to increase production. Figure 3.2 shows the aggregated supply curve for electricity, where suppliers are represented by the players willing to sell electricity at various price levels.

The market clearing price (MCP) and the market clearing quantity (MCQ) are determined through linear programming, which identifies the intersection point of the supply and demand curves, as illustrated in Figure 3.3. Buyers whose bids exceed the MCP are entitled to purchase electricity at the MCP. The difference between the buyer's bid and the MCP is highlighted in the figure with a blue shading to represent this disparity visually. Conversely, sellers whose offers are below the MCP are allowed to sell electricity at the MCP. The difference between the seller's offer and the MCP is represented with red shading in Figure 3.3, showing the visual contrast between the offered price and the clearing price for sellers.

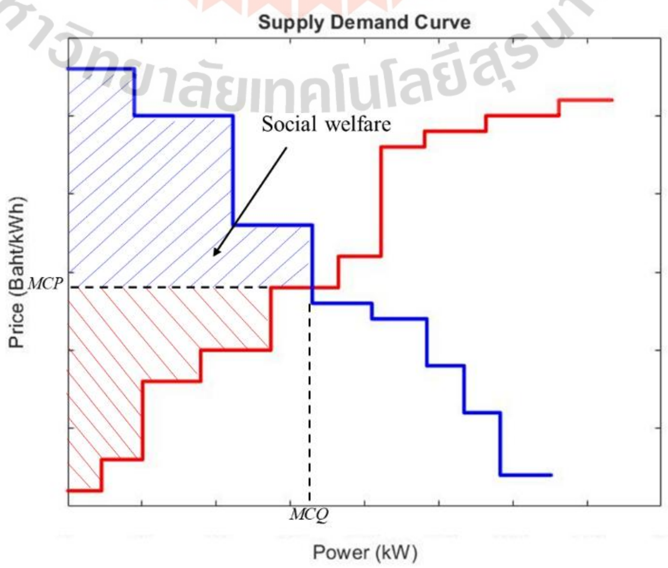


Figure 3.3 Supply Demand Curve

3.2.2 Peer to peer market

P2P MMM is an iterative algorithm that aims to align demand and supply. The algorithm's architecture differs from the power pool concept in that it mandates that members engage in the most feasible trading. P2P MMM imposes criteria that require the seller to be capable of selling at a price equal to or higher than the desired price. Meanwhile, the buyers obtain the electricity at a price equal to or lower than the desired price. Figure 3.4 illustrates the division of the algorithm into three sequential steps.

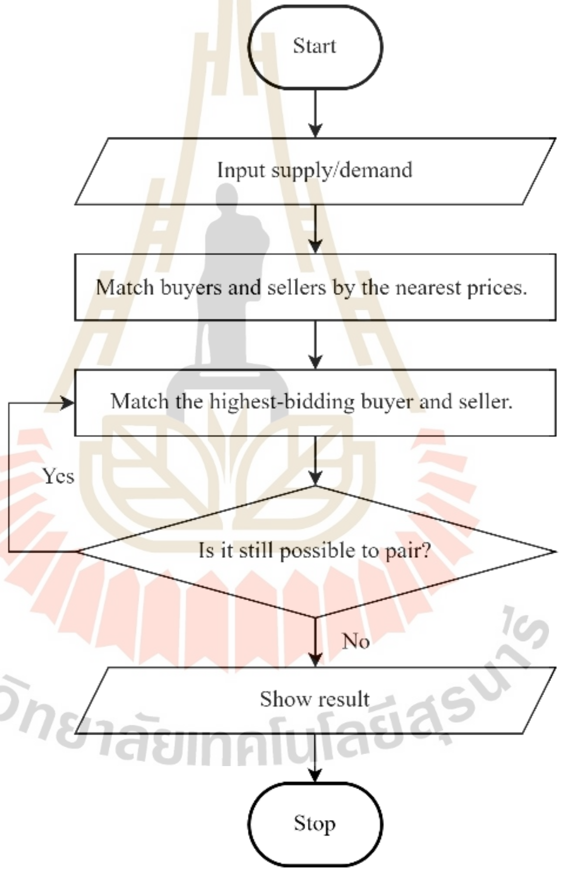


Figure 3.4 Flow chart showing the operation of P2P MMM

The proposed P2P MMM computational step can be illustrated as follows:

Step 1: From the perspective of the buyer, they are paired with the sellers who provide a price that is lower than but closest to the buyer’s price.

Step 2: There will now exist an unmatched quantity that cannot be equaled by anyone. The buyer who presents the most competitive buying price will prioritized and match with the seller who presents the highest selling price, but maintaining a price lower than that of the buyer.

Step 3: Proceed with Step 2 iteratively until there are no more buyers or sellers or until there is only a seller who offers a price higher than the buyer's price, which does not meet the specified conditions. The coupling will be deemed completely.

3.3 Simulation Result

Simulation is conducted to validate the proposed market mechanism. The programs are implemented in MATLAB and are executed on a computer with a window 11 operating system, a 2.3GHz Intel Core i5 processor and 16-GB memory.

3.3.1 Simulation Setup

The players in the established power pool energy trading market, which consist of 20 end consumers and prosumers, are simulated. 10 people take turns acting as energy buyers and sellers.

Table 3.1 The amounts and price of energy offered from buyers and sellers

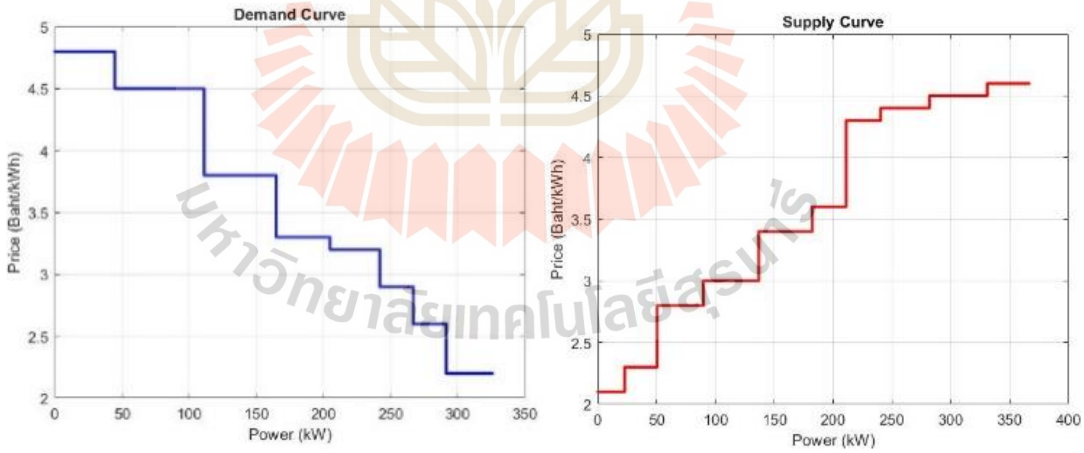
Supply		Demand	
THB	*kWh*	*kWh*	*THB*
4.6	35.7	44.8	4.8
4.5	49.2	40.3	4.5
4.4	41.3	26.2	4.5
4.3	29.4	29.5	3.8
3.6	28.7	24	3.8
3.4	45.5	40.1	3.3
3	47.3	37.1	3.2
2.8	39.2	25.1	2.9
2.3	27.7	24.4	2.6
2.1	22.7	34.3	2.2

The allowable energy selling price is randomly determined as a value in the range of [2 THB/kWh, 5 THB/kWh] for each seller, and the amount of available selling energy is created at random within the range of [20 kWh, 50 kWh]. The acceptable energy purchase price is randomly determined as a number in the range of [2 THB/kWh, 5 THB/kWh], and the energy demand for each buyer is produced randomly within the range of [20 kWh, 50 kWh].

In this demonstration, the amount and price of energy of buyers and sellers are shown in Table 3.1

3.3.2 The result of power pool market model

Figure 3.5 shows demand and supply derived from the data in Table 3.1. Red line and blue line represent supply and demand, respectively. Graphs can be identified at their points of intersection by applying the linear programming method to find the maximum area under the graph as shown in Figure 3.6. By running the objective functions and the constraints in Section 3.2, Participants who complete a trade are formed as shown in Table 3.2.



(a) (b)

Figure 3.5 (a): Demand curve and (b): Supply curve

Simulation from linear programming yields an equilibrium point of 3.4 THB. It can be seen that the sellers who are able to sell are those whose prices are lower than the equilibrium point. Meanwhile, the buyers who are able to buy are those whose prices are higher than the equilibrium point. In other words, it is the area to the left of the equilibrium point that is considered beneficial to the market. The area to the left of the equilibrium point is 259.69 THB, and the transaction is 164.8 kWh. Besides deriving these figures via linear programming, results can also be obtained from Table 3.2, where the trading volume represents the quantity sold by each side, and social welfare is calculated as the buyer's spending minus the seller's revenue. Conversely, the area to the right of the equilibrium point is considered unfavorable to the market.

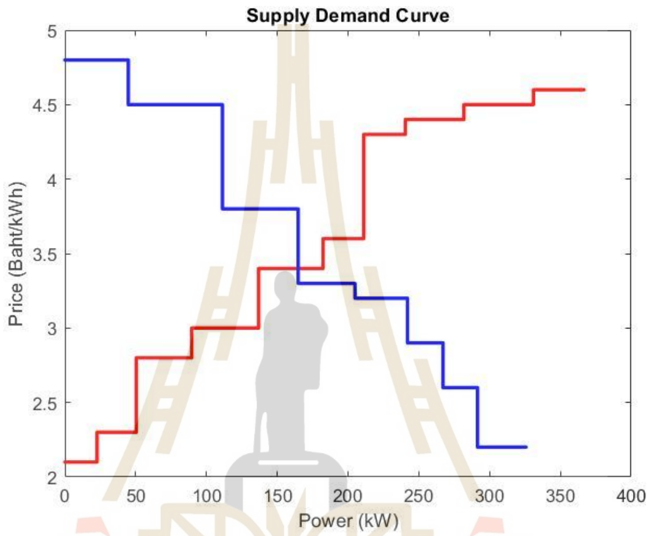


Figure 3.6 Demand supply curve

Table 3.2 Participants who complete a power pool trading

Supply		Demand	
THB	*kWh*	*kWh*	*THB*
4.6	35.7	0	4.8
4.5	49.2	0	4.5
4.4	41.3	0	4.5
4.3	29.4	0	3.8
3.6	28.7	0	3.8
3.4	17.6	40.1	3.3
3	0	37.1	3.2
2.8	0	25.1	2.9
2.3	0	24.4	2.6
2.1	0	34.3	2.2

The data shown in Table 3.2 shows that a supply of 4.6 THB cannot be sold for 35.7 kWh. Demand of 2.9 THB cannot be sold for 25.1 kWh. Conversely, the quantity of kilowatts supplied or demanded reaches zero at the given price. This implies that all of them can be sold or bought at that specific price.

3.3.3 The result of P2P MMM model

In P2P systems, a P2P MMM is a procedure for matching resources between peers in a decentralized network. P2P systems are specifically engineered to facilitate the direct sharing and distribution of resources among individual peers, eliminating the requirement for a central server. The utilization of a multi-stage matching mechanism can significantly improve the efficiency and effectiveness of the matching process between buyers and sellers in P2P networks.

In this simulation, the same data as the power pool simulation, as shown in Table 3.1, is used. Upon executing the 3-step procedure outlined in Section 3.2.2, participants who successfully carry out a trade are organized and presented in Table 3.3.

Table 3.3 Participants who complete P2P trading

Supply		Demand	
THB	*kWh*	*kWh*	*THB*
4.6	0	0	4.8
4.5	0	0	4.5
4.4	14.9	0	4.5
4.3	29.4	0	3.8
3.6	0	0	3.8
3.4	20.7	0	3.3
3	0	0	3.2
2.8	0	0	2.9
2.3	0	0	2.6
2.1	0	24.1	2.2

The data shown in Table 3.3 shows that a supply of 4.4 THB cannot be sold for 14.9 kWh. Demand of 2.2 THB cannot be bought for 24.1 kWh. Conversely, the quantity of kilowatts supplied or demanded reaches zero at the given price. This implies that all of them can be sold or bought at that specific price. The trading volume is derived from the absent volume on each side, totaling 301.7 kWh, while social welfare is calculated from the buyer's spending obtained by the seller's income, amounting to 74.85 THB.

The power pool model results indicate that the MCQ is 164.8 kWh. Meanwhile, MCP is 3.4 THB/kWh. This implies that buyers who bid above this price and sellers who bid below this price will take the market's social welfare. which the total social welfare of this market is 259.69 kWh. Regarding the P2P model, it was discovered that the amount of electricity traded was 301.7 kWh, and the corresponding social welfare value was 74.85 THB. Through the process of modeling the two models, it was determined that each model possesses distinct strengths and weaknesses. The P2P model of energy trading involves a higher volume of transactions compared to the power pool model. However, the power pool model results in a higher level of social welfare compared to P2P.

Table 3.4 Comparison of power pool and P2P markets outcomes.

	Transaction (kWh)	Social welfare (THB)
Power pool	164.8	259.69
P2P MMM	301.7	74.85

CHAPTER IV

BI-LEVEL OPTIMIZATION ALGORITHM FOR TRADING QUANTITY AND SURPLUS MAXIMIZATION IN P2P ELECTRICITY MARKET

4.1 Introduction

As energy markets continue to evolve in response to technological advancements and the increasing integration of renewable energy sources, P2P energy trading has emerged as a promising alternative to traditional, centralized energy distribution systems. The P2P model empowers individual consumers and prosumers those who generate surplus energy through renewable sources such as solar panels or wind turbines to directly trade electricity with other consumers. This decentralized approach enables localized energy transactions that can enhance grid resilience, reduce energy costs, and increase energy independence for communities. Moreover, P2P trading fosters a more flexible energy system that can better accommodate the variability of renewable energy sources, further supporting the global transition to a sustainable, low-carbon energy future.

However, the success of P2P energy markets hinges on the development of efficient mechanisms that can manage the complexities of matching supply with demand. Unlike centralized markets, where a single entity coordinates the balance of supply and demand, P2P energy trading involves multiple independent participants, each with their own energy generation and consumption needs. This requires advanced algorithms capable of not only maximizing the volume of trades but also optimizing the surplus for market participants. The efficient functioning of such markets is critical for ensuring that both buyers and sellers benefit from the transactions, creating a fair and profitable trading ecosystem. To address these challenges, this chapter introduces a bi-level optimization algorithm for trading quantity and surplus maximization

(BLO-TQSM) specifically designed for the P2P energy trading market. The BLO-TQSM algorithm operates on two levels: first, it maximizes the trading volume by finding the optimal match between buyers and sellers based on their bid and offer prices; second, it seeks to maximize the surplus, ensuring that the participants achieve the highest possible economic benefit from the trade. This dual optimization approach is crucial for improving the overall efficiency of the market, as it balances the competing objectives of maximizing trade volume and economic welfare.

In addition to the optimization of trading mechanics, this chapter also introduces a Double-Side Carbon Taxation Scheme (DCTS) into the BLO-TQSM algorithm. With growing global attention on environmental sustainability and the need to reduce carbon emissions, energy markets are increasingly being held accountable for their environmental impact. The DCTS mechanism directly addresses this by imposing a carbon tax on both buyers and sellers involved in the trade of electricity generated from fossil fuels. By integrating carbon tax considerations into the pricing structure, the DCTS incentivizes participants to prioritize renewable energy sources, such as solar and wind power, over carbon-intensive alternatives. This not only aligns the market with environmental goals but also ensures that participants are financially rewarded for making environmentally responsible choices.

The integration of the BLO-TQSM algorithm with the DCTS mechanism offers a comprehensive approach to modernizing P2P energy markets. It enhances market efficiency by optimizing trade volumes and surplus while also promoting the use of renewable energy, contributing to the broader global effort to achieve carbon neutrality.

4.2 Problem Formulation

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

4.2.1 BLO-TQSM algorithm

The BLO-TQSM is designed to address the challenges of P2P energy trading markets by optimizing both trading quantity and economic surplus simultaneously. Traditional market mechanisms often face a trade-off between maximizing the number of transactions and achieving optimal economic efficiency. BLO-TQSM introduces a bi-level, bi-objective optimization framework that resolves this trade-off, ensuring improved market efficiency, fairness, and sustainability.

In the bi-level structure of BLO-TQSM, the optimization problem is divided into two hierarchical levels: the major-level optimization, which prioritizes trading quantity maximization, and the minor-level optimization, which focuses on economic surplus maximization. The major-level optimization ensures that the highest possible volume of electricity is traded between participants, improving market liquidity and transaction fairness. Once the trading quantity is maximized, the minor-level optimization refines the surplus distribution by incorporating a shift factor, which aligns the supply and demand curves to maximize total market efficiency. This bi-level approach provides a structured solution to the inherent conflicts in decentralized energy trading, where individual profit-seeking behavior can lead to inefficiencies and unmatched participants.

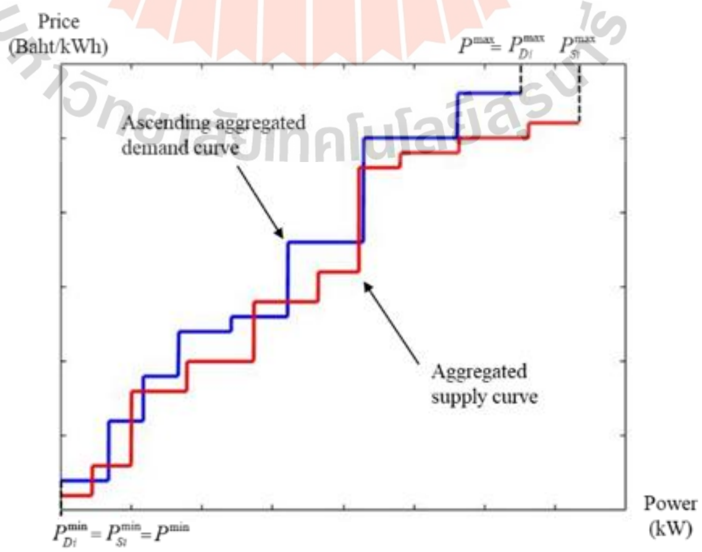


Figure 4.1 Typical aggregated supply and ascending aggregated demand curves

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 chapter. To maximize surplus of all participants, the proposed method ascending aggregated demand curve (blue line), as shown in Figure 4.1. 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; major-level objective, which is trading quantity maximization and minor-level objective, which is surplus maximization. The maximum transaction volume is calculated at the major-level and formulated as follows:

Maximize $$TQ = \sum_{i=1}^{N_{\max}} f_i(\lambda_i) \tag{4.1}$$

s.t. $$f(\lambda_i) = \begin{cases} \mathrm{n} & \text{for } \lambda_{Di} \geq \lambda_{Si} \\ 0 & \text{for } \lambda_{Di} < \lambda_{Si} \end{cases} \tag{4.2}$$

$$P^{\min} = \max\left\{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\right\} \tag{4.3}$$

$$P^{\max} = \min\left\{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\right\} \tag{4.4}$$

$$N_{\max} = \frac{P^{\max} - P^{\min}}{n} \tag{4.5}$$

$TQ_{\max}$ 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 in minor-level. The objective function of minor-level is shown in Equation 4.6. The objective function contains three terms, i.e., surplus of inverse demand curve, surplus of shifting supply curve and death penalty term (Yeniay, 2005).

Maximize $$SP = \int_{P^{\min}}^{P^{\max}} asc(\lambda_{Di} \cdot P_{Di})dP_{Di} - \int_{P^{\min}}^{P^{\max}} [(\lambda_{Si} \cdot P_{Si}) + \alpha]dP_{Si} - DPF \tag{4.6}$$

s.t. $$DPF = \begin{cases} +\infty, & \mathrm{TQ} \neq TQ_{\max} \\ 0, & \mathrm{TQ} = TQ_{\max} \end{cases} \tag{4.7}$$

$$P^{\min} = \max\left\{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\right\} \tag{4.8}$$

$$P^{\max} = \min\left\{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\right\} \tag{4.9}$$

Where, DPF is the death penalty function that ensure that TQ in minor-level optimization is equal to $TQ_{\max}$ in Eq. (4.1). " asc " denotes the ascending version of aggregated demand curve.

4.2.2 DCTS

This chapter proposes the DCTS mechanism for buyers who purchase electricity from fossil energy sources to 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 Figure 4.2. In order to facilitate comprehension, it can be divided into two perspectives and there are the following equations:

Buyer's perspective:

$$\lambda_{Si,F}^{B} = \lambda_{Si,F} + \frac{ct}{2} \tag{4.10}$$

$$\lambda_{Si,RE}^{B} = \lambda_{Si,RE} \tag{4.11}$$

Seller's perspective:

$$\lambda_{Si,F}^{S} = \lambda_{Si,F} - \frac{ct}{2} \tag{4.12}$$

$$\lambda_{Si,RE}^{S} = \lambda_{Si,RE} \tag{4.13}$$

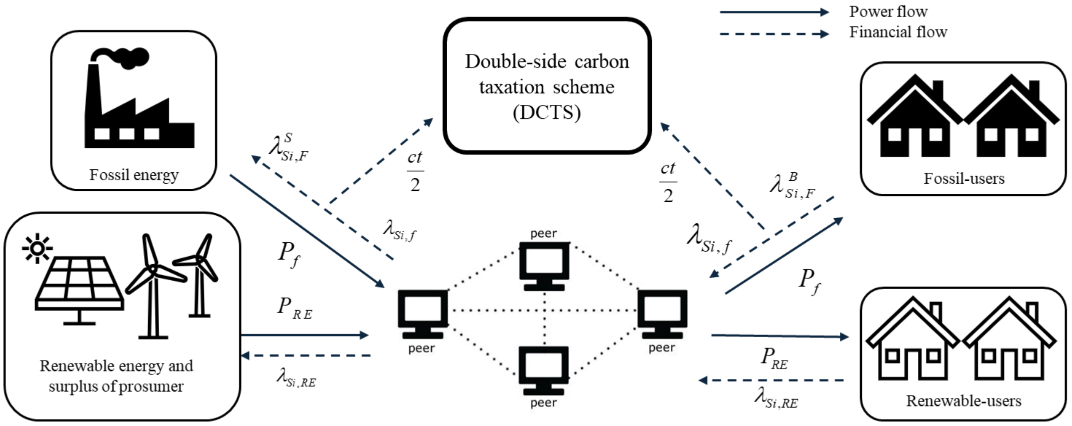


Figure 4.2 The proposed P2P market mechanism

From the buyer's perspective, the price of fossil energy will appear higher than normal due to the inclusion of the carbon tax. This tax represents an additional cost that the buyer is required to cover as part of the purchase. In the seller's perspective, carbon taxes are deducted before sellers of fossil energy receive payment, after the matching of P2P.

4.3 Computational procedure

The proposed method's computational procedure is illustrated in Figure 4.3. and Figure 4.4. The optimal values of the major-level and minor-level objectives were found using Particle Swarm Optimization (PSO). (Kennedy & Eberhart, 1995) provide a detailed explanation of the PSO mechanism. 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 chapter as follows:

$$\alpha = [\alpha_1, \alpha_2, ..., \alpha_{NP}] \tag{4.14}$$

$$\alpha_i = [\, P_{Di}^{\min} - P_{Si}^{\max} \;,\; P_{Di}^{\max} - P_{Si}^{\min} \,], \tag{4.15}$$

for $i = 1, 2, ..., NP$

The range of α_i is represented in Equation 4.15. The control of variables in Equation 4.14 are used for Equation 4.8 and Equation 4.9. Then, the new velocity of the particles is calculated by Equation 4.16, the new position of the particles is computed by Equation 4.17.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i^t - \alpha_i^t) + c_2 r_2 (gbest_i^t - \alpha_i^t) \tag{4.16}$$

$$\alpha_i^{t+1} = \alpha_i^t + v_i^{t+1}, \text{ for } i = 1, 2, ..., NP \tag{4.17}$$

PSO is used for both major-level and minor-level optimization. In the major-level optimization, the objective is computed by the TQ in Equation 4.1. 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 Equation 4.6.

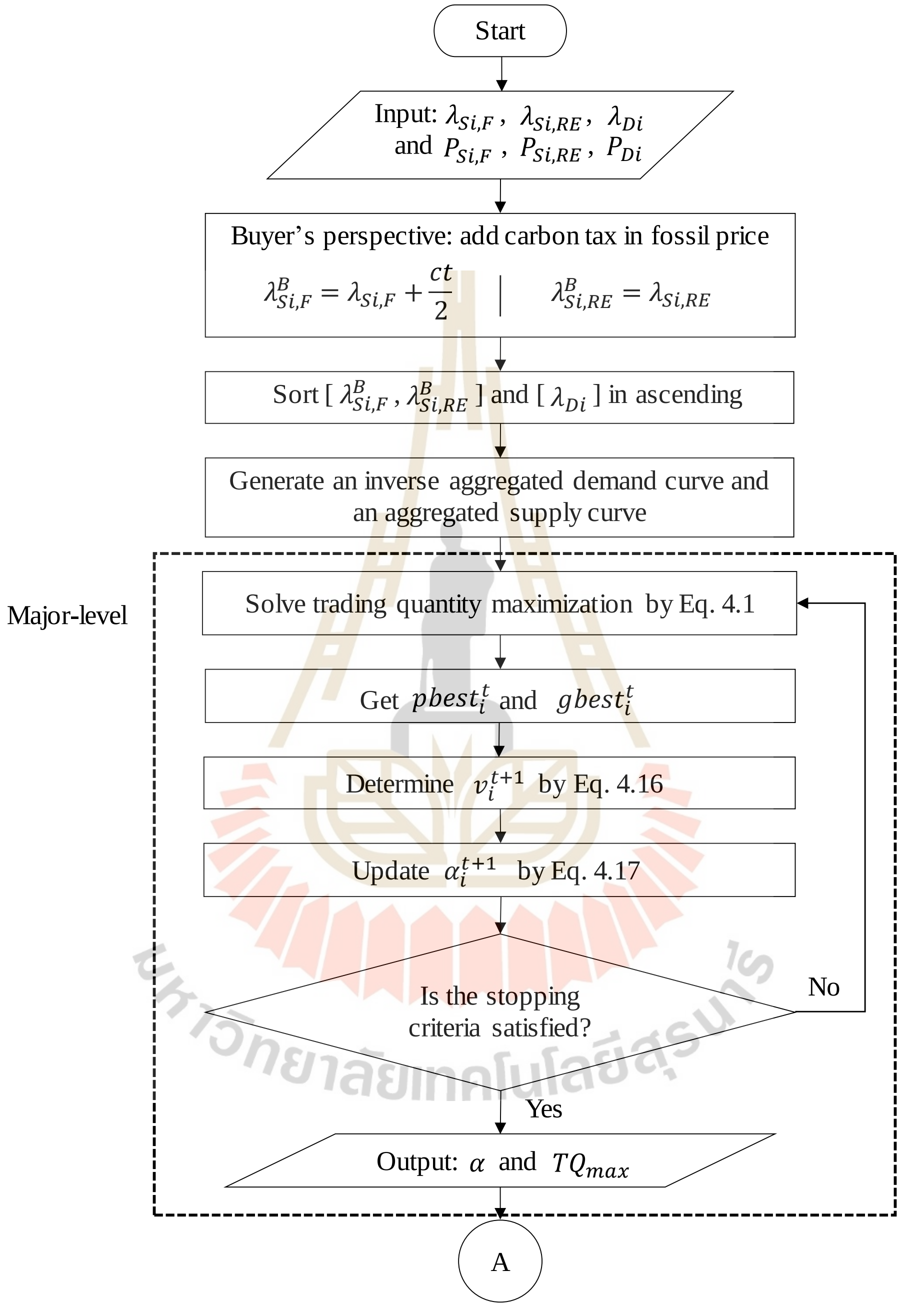


Figure 4.3 Major-level of BLO-TQSM algorithm computational procedure

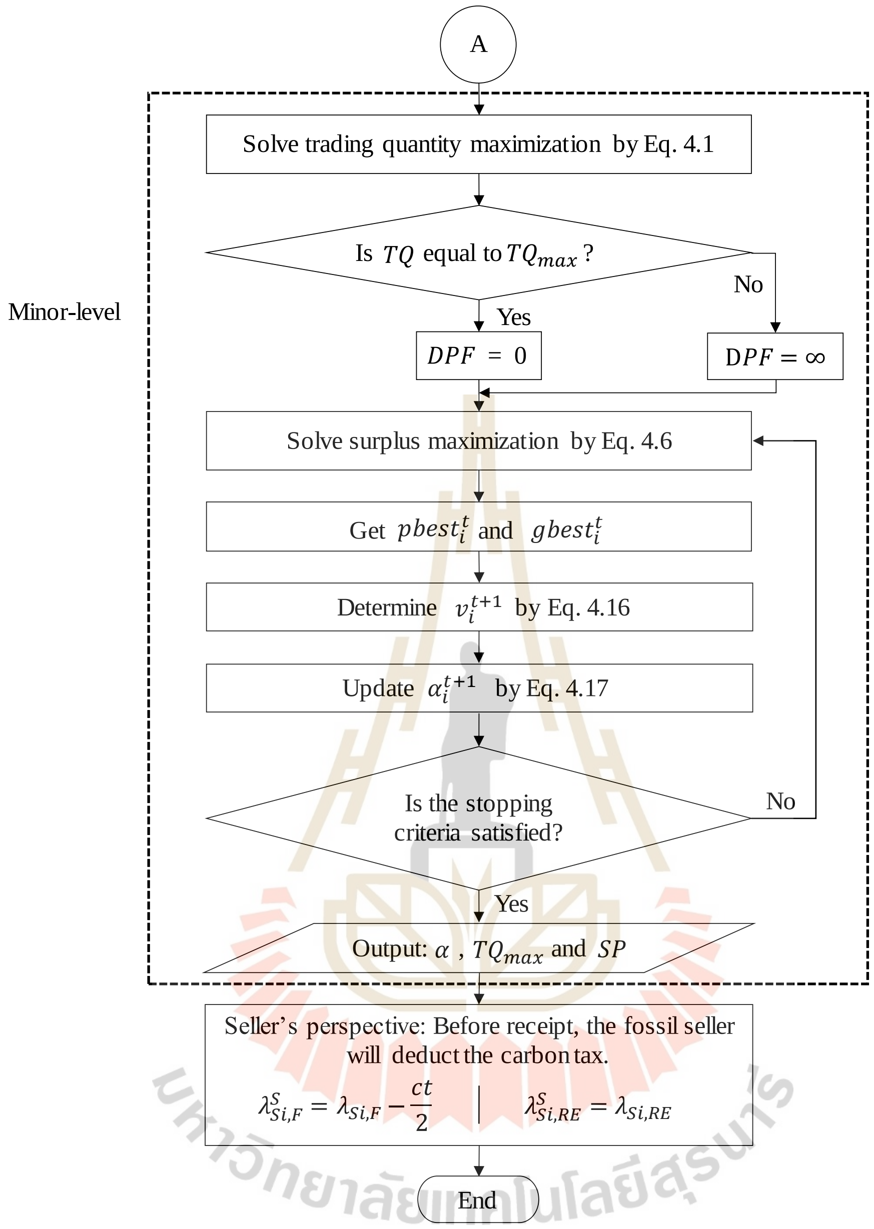


Figure 4.4 Minor-level of BLO-TQSM algorithm computational procedure

4.4 Simulation Setup

In this section, the trading quantity and surplus of the proposed P2P energy trading mechanism are simulated and analyzed for both the BLO-TQSM and DCTS algorithms. Furthermore, in order to enhance the comprehensiveness and clarity of this study, single-side carbon is contrasted with DCTS. Single-side carbon is further classified into two categories: Consumer side Carbon Taxation Scheme (CCTS) and

Supplier side Carbon Taxation Scheme (STCS). The case studies utilize data on participant numbers, electricity prices, and quantities from chapter 3, with prices ranging between [2 THB/kWh and 5 THB/kWh]. Fossil energy sellers and renewable energy sellers are represented by indices “0” and “1,” respectively, as shown in Table 4.1. Four cases were investigated and compared, as follows.

1) Case A: BLO-TQSM algorithm without DCTS algorithm to compare trading quantity and surplus with power pool model and P2P MMM from chapter 3.

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

3) Case C: The BLO-TQSM algorithm is used in conjunction with the CCTS algorithm to compare the financial data with case B.

4) Case D: The BLO-TQSM algorithm is used in conjunction with the SCTS algorithm to compare the financial data with case B.

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.

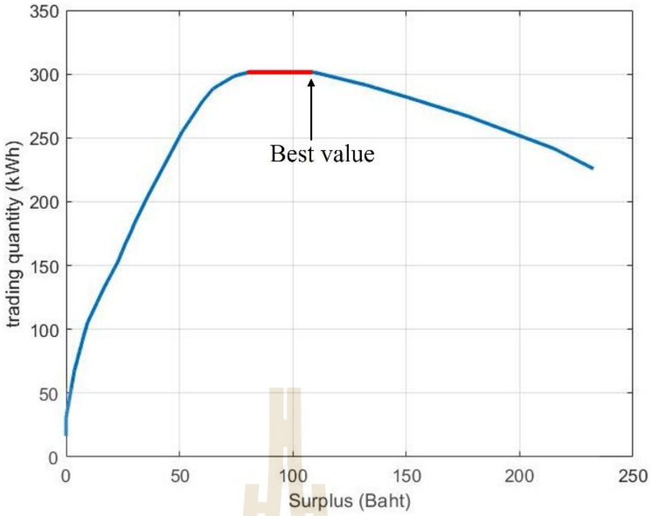
Table 4.1 The amount and price of energy offered from buyers and sellers

Supply				Demand		
Seller	*Index*	*THB /kWh*	*kWh*	*Buyer*	*THB /kWh*	*kWh*
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

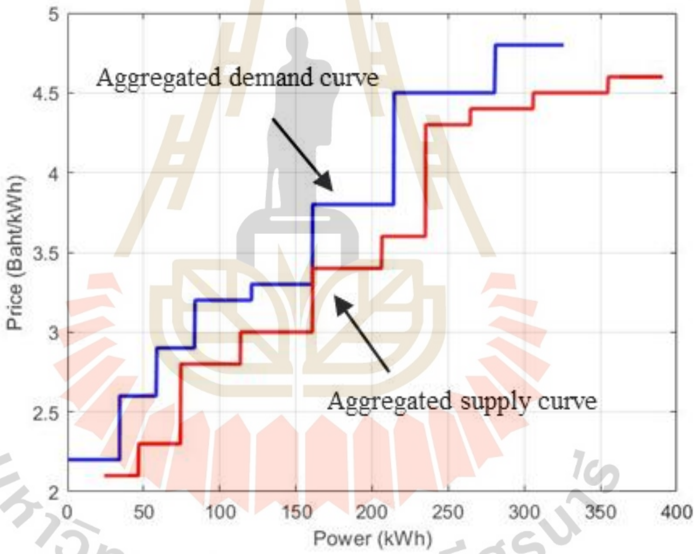
4.4.1 Case A: BLO-TQSM without DCTS

In the first case study, it is assumed that an immediate desire to purchase and sell is held by all participants. Table 4.1 lists the input value in algorithm. Result for energy trading in this case are represented in Figure 4.5 and Table 4.2 illustrates of shifting graph and matched participants. Figure 4.5(a) show correlation between surplus and trading quantity, while shift factor adjustments, that can be divided into three phases of volume; 1) Beginning phase, increased shift factor cause increased surplus and trading quantity; 2) Steady phase (red line), an increase in the shift factor leads to an increase in the surplus, while the trade quantity remains constant; 3) Regression phase, adding 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 THB and a maximum trading quantity of 301.7 kWh. Figure 4.5(b) shows the aggregated supply has shifted by 24.1 points and ascending aggregated demand curves. Table 4.2 shows the matching of seller and buyer for maximum surplus. 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 4.3 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 quantity. In 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 THB, which is higher than the surplus of P2P MMM, which is 74.85 THB. Figures 4.6 present convergence plots of surplus, along with 100 trials, showing the shift factor variations for Case A (without DCTS).



(a)

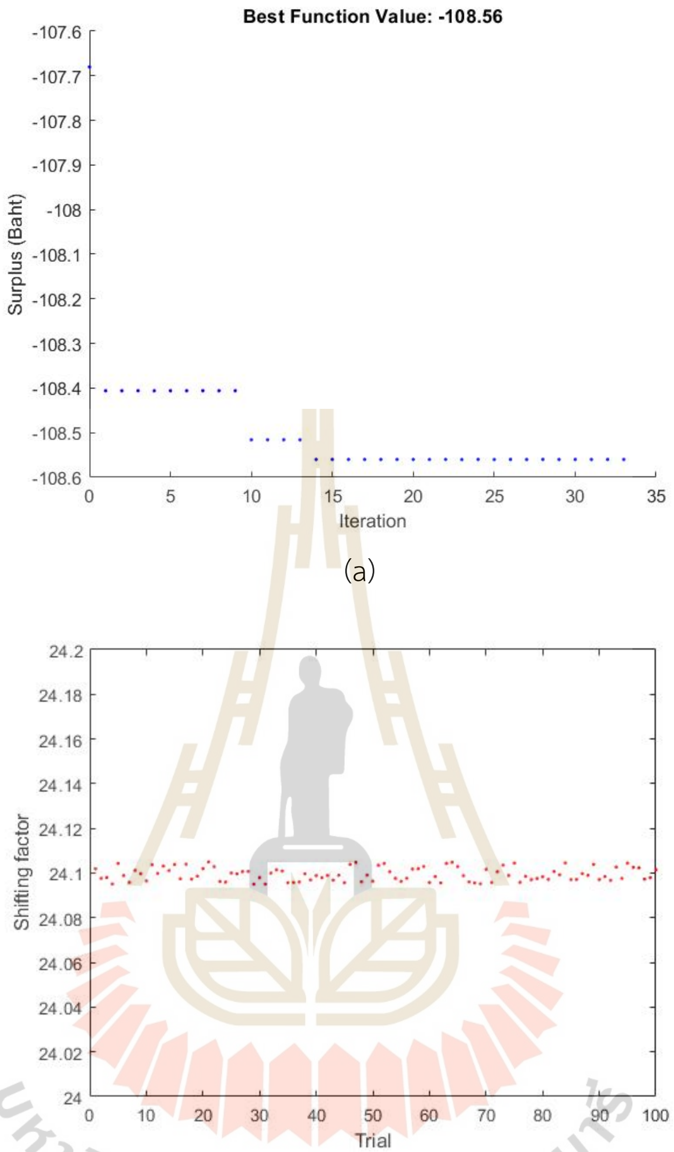


(b)

Figure 4.5 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

Table 4.2 Result of case A

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
S1	1	2.1	22.7	22.7	54.944	B1	2.2	34.3	10.19	22.418
S2	0	2.3	27.7	27.7	76.76	B2	2.6	24.4	24.41	63.466
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
		total		301.7	1127.314		*total*		301.7	1127.314



(a)

(b)

Figure 4.6 Result of case A: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots

Table 4.3 Comparison between power pool, P2P MMM and BLO-TQSM

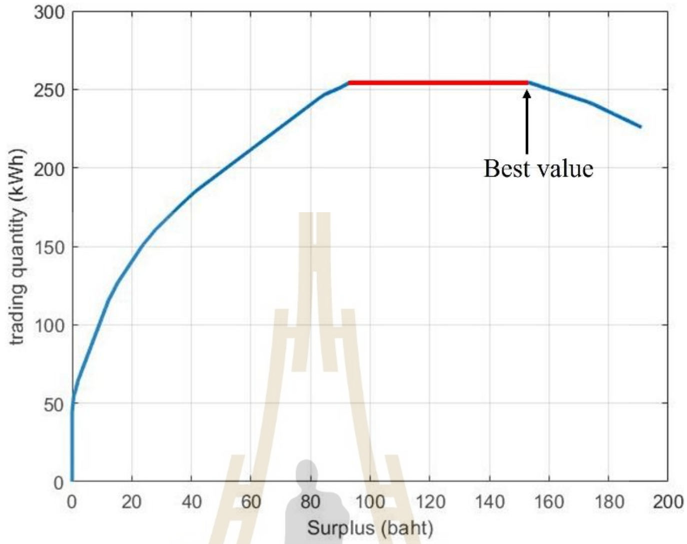
	Trading quantity (kWh)	Surplus (THB)
Power pool	164.8	259.69
P2P MMM	301.7	74.85
BLO-TQSM	301.7	108.56

4.4.2 Case B: BLO-TQSM with DCTS

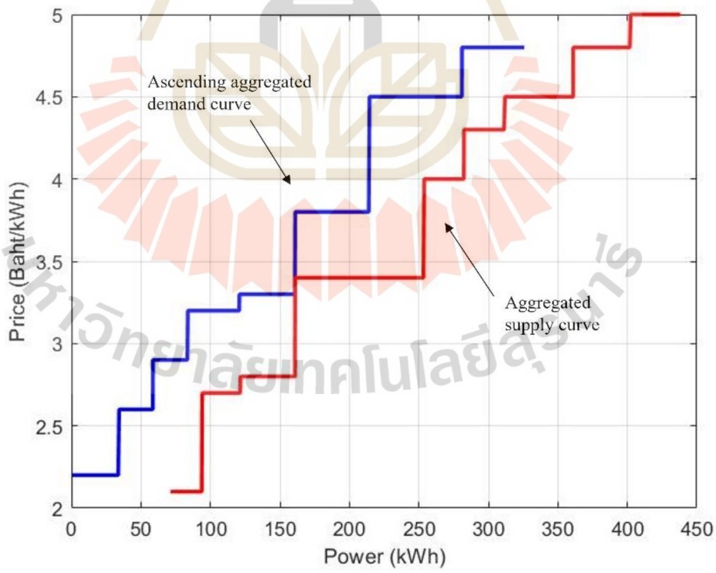
In this case study, the DCTS algorithm is integrated into the BLO-TQSM algorithm, utilizing the data provided in Table 4.1. The carbon tax rate is set at 0.8 THB/kWh, which reflects the additional cost of carbon emissions within the trading mechanism. The energy trading outcomes for this scenario are depicted in Table. 4.4, while Figure 4.7 provides a detailed illustration of the shifting supply and demand curves and the matching of participants.

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 Figure 4.7. For Case B, the optimal shift factor is identified as 71.4, resulting in a maximum achievable surplus of 153.09 THB and a trading quantity of 254.40 kWh, divided into purchases from fossil energy producers of 103.7 kWh and those from renewable energy producers of 150.7 kWh. The result in Table 4.4 indicates that the fossil energy producers are unable to sale 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 THB, while buyers made a total payment of 1004.6 THB. The resulting difference of 82.96 THB is due to the amount of fossil fuel energy sellers matched at 315.11 kWh, with the seller and buyer each paying 41.48 THB, which is allocated to offset carbon emissions, thereby contributing to achieving carbon neutrality within the market framework.

Figures 4.8 present convergence plots of surplus, along with 100 trials, showing the shift factor variations for 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.



(a)



(b)

Figure 4.7 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 4.4 Result of case B

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
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
total				254.4	921.64	*total*			254.4	1004.6

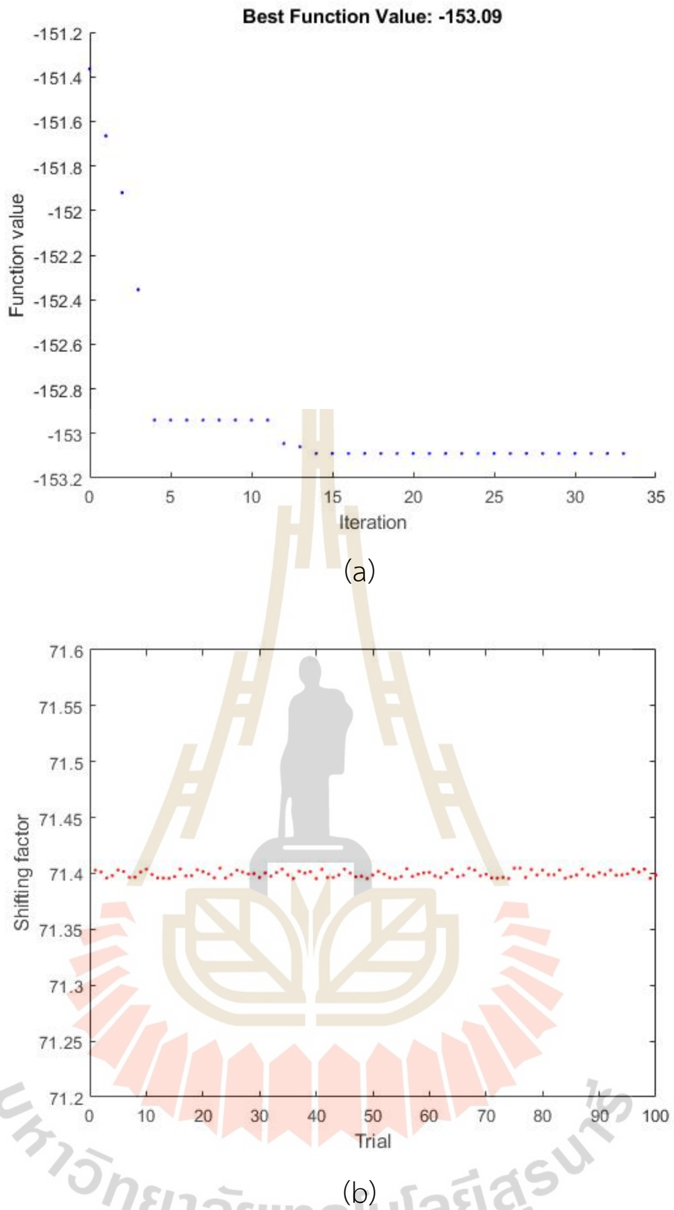


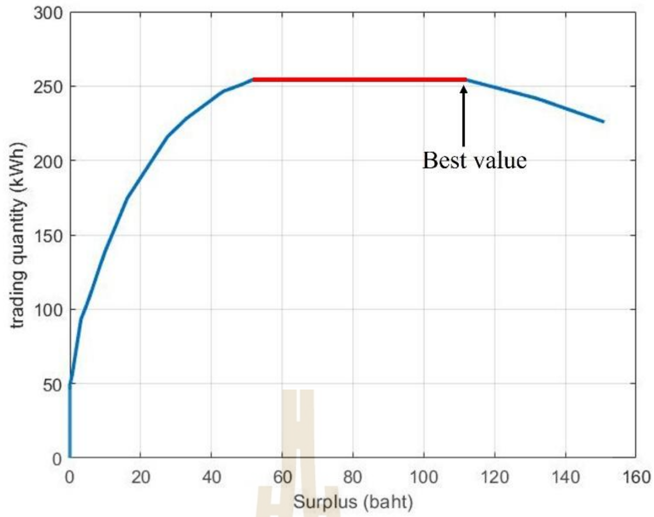
Figure 4.8 Result of case B: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots

4.4.3 Case C: BLO-TQSM with CCTS

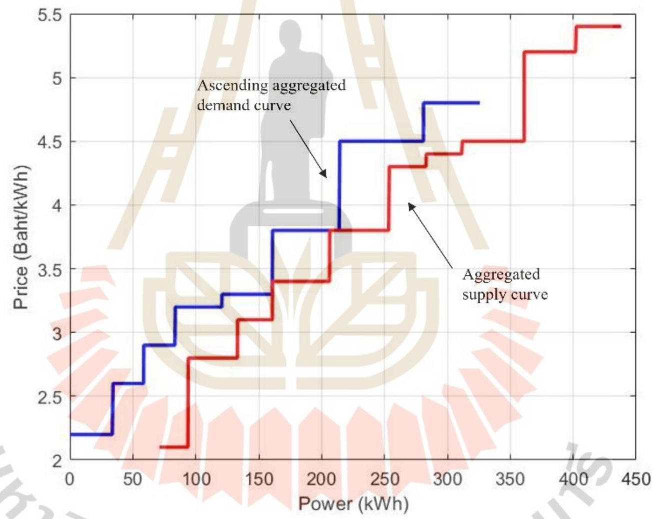
In this case study, the CCTS algorithm is integrated into the BLO-TQSM algorithm, utilizing the data provided in Table 4.1. The carbon tax rate is set at 0.8 THB/kWh, which reflects the additional cost of carbon emissions within the trading mechanism, which is passed on to consumers alone. The energy trading outcomes for this scenario are depicted in Table. 4.5, while Figure 4.9 provides a detailed illustration of the shifting supply and demand curves and the matching of participants.

In the CCTS algorithm, consumers fully absorb the carbon tax cost via increased prices from fossil energy producers. Figure 4.9 further demonstrates how 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. For Case C, the optimal shift factor is identified as 71.4, resulting in a maximum achievable surplus of 111.61 THB and a trading quantity of 254.4 kWh, divided into purchases from fossil energy producers of 103.7 kWh and those from renewable energy producers of 150.7 kWh. The result in Table 4.5 indicates that transferring the entire carbon tax burden to consumers by raising prices for fossil energy producers leads to higher prices for fossil energy producers in CCTS relative to DCTS, hence reducing market surplus. The study also sheds light on the financial ramifications for sellers, encompassing transaction revenue and payments related to buyers' energy usage. Collectively, sellers received a total revenue of 921.64 THB, while buyers made a total payment of 1004.6 THB. The resulting difference of 88.64 THB is allocated to offset carbon emissions, which consumers will unknowingly pay, thereby contributing to achieving carbon neutrality within the market framework. The differential utilized to offset the carbon price is equal to DCTS, as the quantity of electricity from fossil energy producers. remains equal.

Figures 4.10 present convergence plots of surplus, along with 100 trials, showing the shift factor variations for Case C (with CCTS), respectively.



(a)

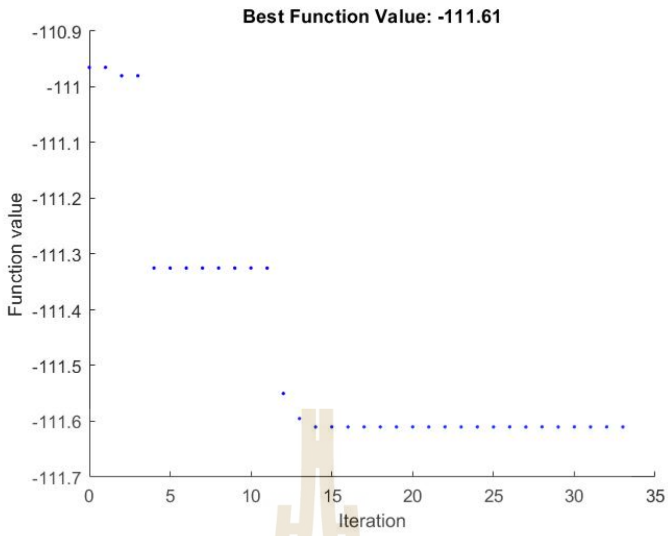


(b)

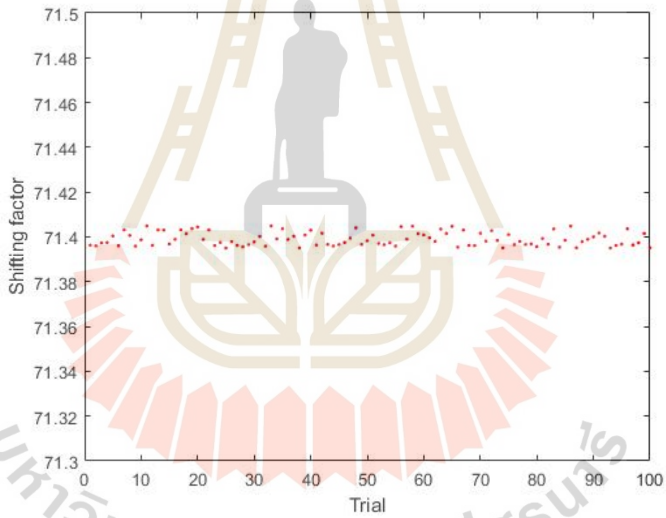
Figure 4.9 Result of case C: (a) the correlation between surplus and volume with shift factor adjustments and (b) aggregated supply and ascending aggregated demand curves after BLO-TQSM algorithm

Table 4.5 Result of case C

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
S1	1	2.1	22.7	22.7	68.92	B1	2.2	34.3	0	0
S3	1	2.8	39.2	39.2	126.68	B2	2.6	24.4	0	0
S2	0	3.1	27.7	27.7	69.25	B3	2.9	25.1	12.4	35.96
S5	1	3.4	45.5	45.5	172.9	B4	3.2	37.1	37.1	118.72
S4	0	3.8	47.3	47.3	169.41	B5	3.3	40.1	40.1	132.33
S7	1	4.3	29.4	29.4	132.96	B6	3.8	24	24	91.2
S6	0	4.4	28.7	28.7	114.8	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	5.2	41.3	0	0	B9	4.5	40.3	40.3	181.35
S10	0	5.4	35.7	0	0	B10	4.8	44.8	44.8	215.04
		total		254.4	921.64		***total***		254.4	1004.6



(a)



(b)

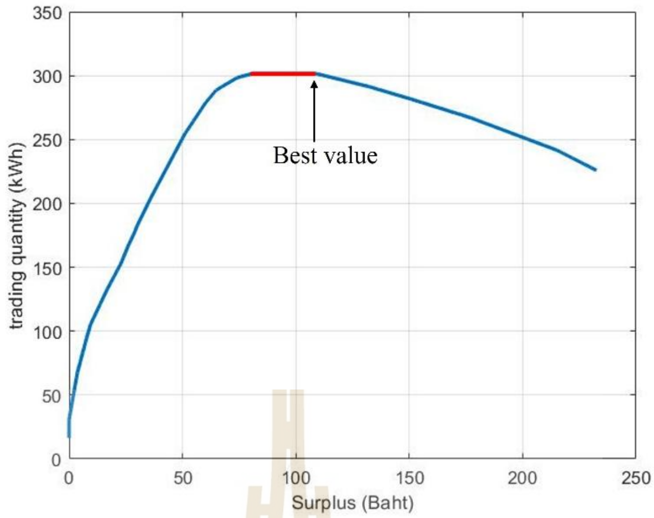
Figure 4.10 Result of case C: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots

4.4.4 Case D: BLO-TQSM with SCTS

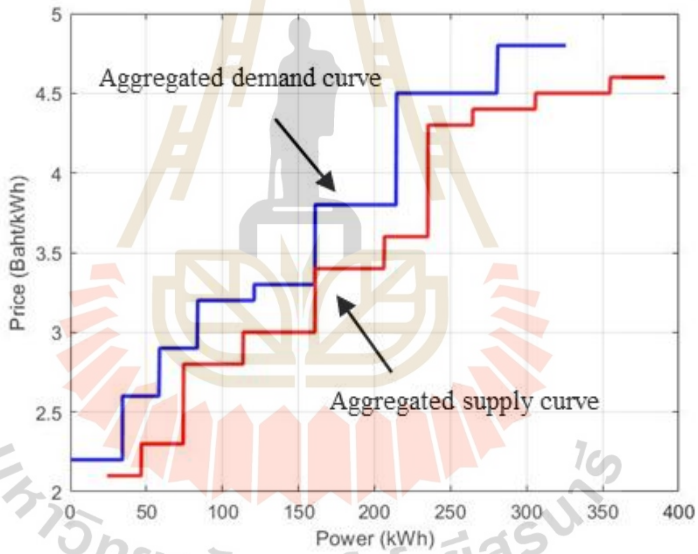
In this case study, the SCTS algorithm is integrated into the BLO-TQSM algorithm, utilizing the data provided in Table 4.1. The carbon tax rate is set at 0.8 THB/kWh, which reflects the additional cost of carbon emissions within the trading mechanism, which is passed on to suppliers alone. The energy trading outcomes for this scenario are depicted in Table. 4.6, while Figure 4.11 provides a detailed illustration of the shifting supply and demand curves and the matching of participants.

In the SCTS algorithm, the supplier pays a unilateral carbon tax. After the fossil energy producer is matched, the carbon tax is subtracted from the revenue prior to its return to the supplier. Figure 4.11 illustrates the impact of this price on the correlation between surplus and trading quantity, as well as the adjustments made to the shift factor and the aggregated supply and demand curves. In Case D, SCTS, being a deduction revenue after matching, does not increase the seller's price, resulting in a matching outcome that is identical to Case A. However, there will be differences once the revenue is recognized. The optimal shift factor is identified as 24.1, resulting in a maximum achievable surplus of 108.56 THB and a trading quantity of 301.7 kWh, divided into purchases from fossil energy producers of 145 kWh and those from renewable energy producers of 156.7 kWh. The outcome shown in Table 4.6 shows that when the carbon tax is taken out of the income of fossil energy producers and put on suppliers instead, the income of fossil energy producers in SCTS is lower than in Case A. The study also sheds light on the financial ramifications for sellers, encompassing transaction revenue and payments related to buyers' energy usage. Collectively, sellers received a total revenue of 1011.314 THB, while buyers made a total payment of 1127.314 THB. The resulting difference of 116 THB is allocated to offset carbon emissions, thereby contributing to achieving carbon neutrality within the market framework. In Case C, the difference used to offset carbon tax is greater than in Cases A and B due to the fact that the quantity of electricity from fossil fuel producers matched in Case C is greater than in Cases A and B.

Figures 4.12 present convergence plots of surplus, along with 100 trials, showing the shift factor variations for Case D (with SCTS), respectively. The results with 100 trials of the proposed BLO-TQSM is shown in Table 4.7.



(a)

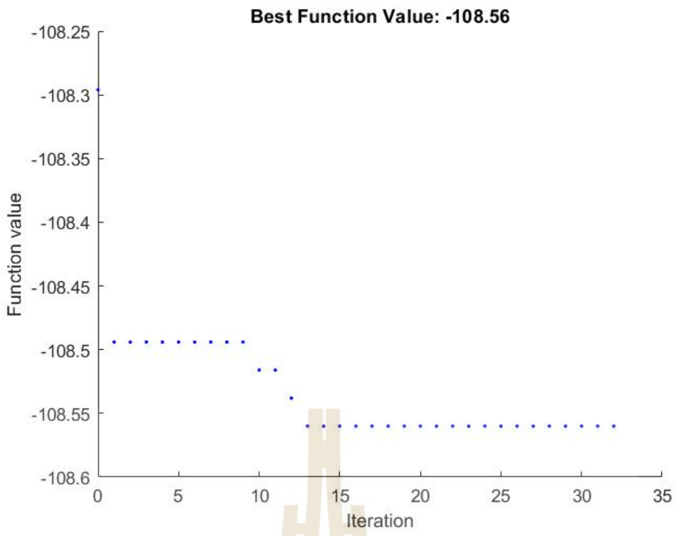


(b)

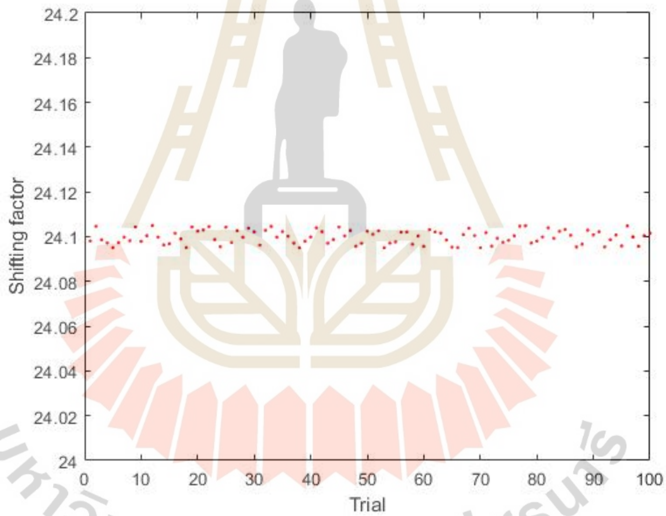
Figure 4.11 Result of case D: (a) the correlation between surplus and volume with shift factor adjustments and (b) aggregated supply and ascending aggregated demand curves after BLO-TQSM algorithm

Table 4.6 Result of case D

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
S1	1	2.1	22.7	22.7	54.944	B1	2.2	34.3	10.19	22.418
S2	0	2.3	27.7	27.7	54.6	B2	2.6	24.4	24.41	63.466
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	117.53	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	100.59	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	160.28	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
		total		301.7	1011.314		*total*		301.7	1127.314



(a)



(b)

Figure 4.12 Result of case D: (a) convergence plot of PSO and (b) shift factor obtained from 100 trial plots

Table 4.7 The result at 100 trials of the proposed

Shift factor	Case A	Case B	Case C	Case D
Max	24.105	71.4047	71.4047	24.1051
min	24.0951	71.3995	71.395	24.095
mean	24.1	71.4	71.4	24.1
SD	0.0028	0.0029	0.0027	0.0028

Table 4.8 shows the main differences between the four cases in terms of surplus, trading quantity, and shifting factors. This elucidates the impact of various carbon taxing schemes on the P2P energy market. In Case A, the BLO-TQSM algorithm achieves a trading quantity of 301.7 kWh, the highest among all cases, and a surplus of 108.56 THB with a shifting factor of 24.1. Although this case maximizes trading volume, it does not incorporate carbon tax and therefore lacks mechanisms to encourage renewable energy adoption or penalize fossil fuel usage, resulting in limited progress toward environmental sustainability. In contrast, Case B, which applies the DCTS, strikes a balance between economic and environmental objectives. This case achieves the highest surplus of 153.09 THB with a trading quantity of 254.4 kWh and a shifting factor of 71.4. By distributing carbon taxes equitably between buyers and sellers, DCTS incentivizes both parties to reduce reliance on fossil energy and adopt renewable sources. This balanced approach ensures that both economic efficiency and sustainability goals are met, making Case B the most favorable scenario in terms of promoting carbon neutrality while maintaining a competitive and fair market structure. Case C, employing CCTS, also achieves a trading quantity of 254.4 kWh but results in a lower surplus of 111.61 THB. In this scenario, the entire carbon tax burden is placed on consumers, leading to higher energy costs for buyers and reduced market efficiency. While CCTS addresses environmental concerns, its one-sided taxation disproportionately impacts consumers, creating an imbalance that undermines the market's overall fairness and inclusivity. On the other hand, Case D, which adopts the SCTS, results in the same trading quantity and surplus as Case A (301.7 kWh and 108.56 THB, respectively) with a shifting factor of 24.1. SCTS places the entire carbon tax burden on suppliers, but this fails to influence buyer behavior significantly, resulting in continued reliance on fossil energy and limited progress toward environmental goals. Figure 4.13 provides further insight into these dynamics, illustrating the distribution of power sold and financial outcomes across the four cases. In Cases A and D, fossil energy dominates due to the absence of mechanisms to internalize environmental costs. In contrast, Cases B and C demonstrate a more balanced mix of renewable and fossil energy, reflecting the impact of carbon taxation. Financially, Case B emerges as the most efficient mechanism, maximizing the income of renewable energy sellers and ensuring a fair distribution of financial benefits between buyers and sellers., indicating effective internalization of carbon costs. In Case C, buyer payments exceed those in Case B, underscoring the disproportionate burden on consumers. Meanwhile, the financial structure of Case D mirrors that of Case A, as the carbon tax borne solely by suppliers fails to influence overall market behavior; the results from Table 4.8 and Figure 4.13 clearly demonstrate that Case B with DCTS is the most effective mechanism for balancing economic and environmental objectives in the P2P energy market. DCTS achieves the highest surplus while maintaining a reasonable trading quantity, fostering a more equitable and sustainable energy trading environment. Compared to CCTS in Case C and SCTS in Case D, DCTS provides stronger incentives for renewable energy adoption and ensures a fairer distribution of carbon costs, making it the optimal solution for achieving carbon neutrality and promoting long-term market efficiency.

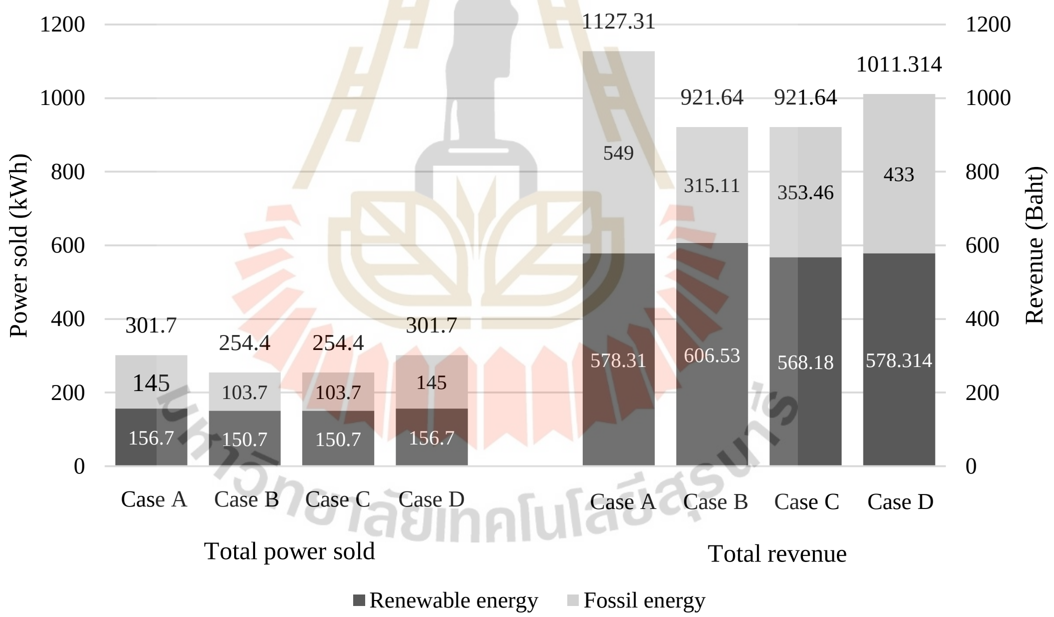


Figure 4.13 Power sold and financial comparison between case A, B, C and D

Table 4.8 Surplus, quantity trading and shifting factor comparison between cases A, B, C and D

	Case A	Case B	Case C	Case D
Surplus (THB)	108.56	153.09	111.61	108.56
Quantity trading (kWh)	301.7	254.4	254.4	301.7
Shifting factor	24.1	71.4	71.4	24.1

4.5 Renewable energy price sensitivity analysis

This section delves into the sensitivity analysis of renewable energy pricing by utilizing data from Case B in Table 4.4 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.

The sensitivity analysis of renewable energy pricing, as presented in Tables 4.9 and 4.10 and Figures 4.14 and 4.15, 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 THB to 880.88 THB. Payment for total energy buyers decreases from 1004.6 THB to 963.84 THB. 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 THB to 786.8 THB. Payment for total energy buyers decreases from 1004.6 THB to 869.76 THB. 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. 14. 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 THB 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. 15. 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.

Table 4.9 The result of increasing renewable energy prices by 10%

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
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*		240.5	963.84

Table 4.10 The result of increasing renewable energy prices by 20%

Supply						Demand				
Seller	*Index*	*THB/ kWh*	*offer (kWh)*	*power sell (kWh)*	*revenue (THB)*	*Buyer*	*THB/ kWh*	*bid (kWh)*	*power purchase (kWh)*	*payment (THB)*
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*		211.1	869.76

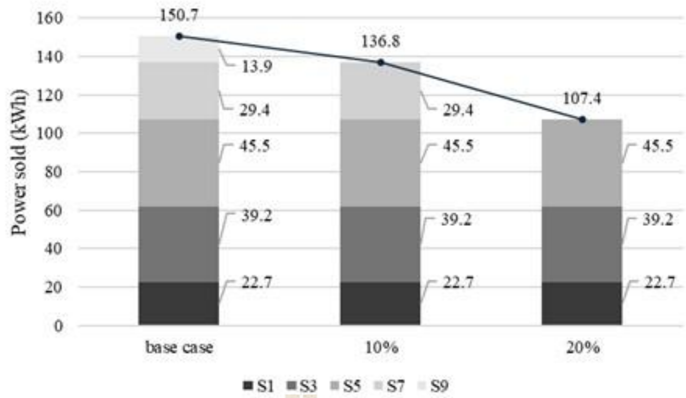


Figure 4.14 Comparative analysis of renewable energy sellers in each case

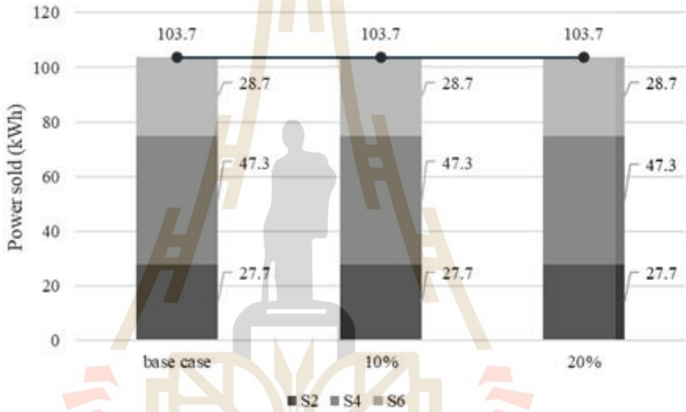


Figure 4.15 Comparative analysis of fossil energy sellers in each case

CHAPTER V

PROBABILITIC BI-LEVEL OPTIMIZATION ALGORITHM FOR TRADING QUANTITY AND SURPLUS MAXIMIZATION IN P2P ELECTRICITY MARKET

5.1 Introduction

The present study builds on earlier research to further develop efficient P2P energy trading mechanisms. It addresses key challenges in energy systems, particularly the need to balance trading quantity and economic surplus. As energy markets transition toward distributed, renewable-based systems, optimizing performance under variable market conditions remains essential. This research introduces a new algorithm called PBLO-TQSM for Trading Quantity and Surplus Maximization. It uses probabilistic methods to better reflect the uncertain nature of the real world.

The PBLO-TQSM framework incorporates Monte Carlo Simulation (MCS), a robust probabilistic method that accounts for uncertainties in pricing and trading quantities. By modeling the behaviors of buyers and sellers as probabilistic variables following a normal distribution, this study captures market variability and evaluates system performance under a range of realistic scenarios. The proposed algorithm operates across two levels: first, by maximizing trading quantity to facilitate efficient buyer-seller matching, and second, by optimizing economic surplus, thereby ensuring fairness and economic benefits for market participants. A critical challenge in P2P energy trading lies in addressing unmatched participants, i.e., buyers and sellers who fail to secure trades, resulting in negative surplus and market inefficiency. This study proposes a comprehensive solution by incorporating real surplus calculations, which deduct the loss of opportunity costs incurred by unmatched participants. Figure 5.1 illustrates how the proposed model more accurately assesses market performance, systematically accounting for all trade dynamics, including inefficiencies.

Through extensive simulations involving 50 buyers and 50 sellers, the PBLO-TQSM framework is benchmarked against existing mechanisms, including the Multi-Stage Matching Mechanism (P2P MMM). Results derived from MCS highlight the algorithm's superior ability to balance trading quantity, surplus optimization, and market efficiency, even under uncertain market conditions. By integrating environmental and economic considerations into energy trading mechanisms, the PBLO-TQSM framework offers a transformative approach for enhancing energy markets.

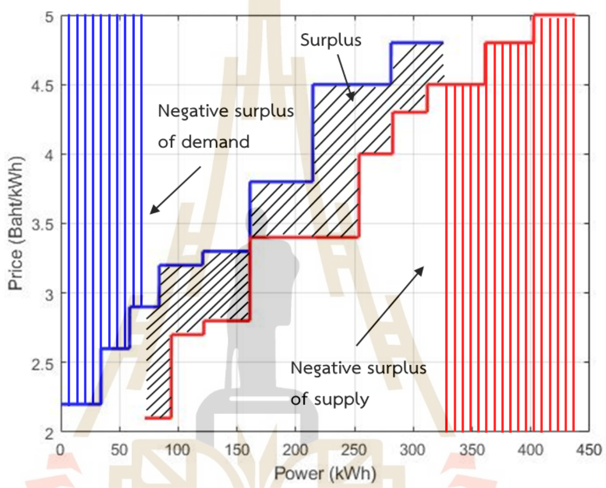


Figure 5.1 Surplus and negative surplus of the market

5.2 Problem Formulation

5.2.1 PBLO-Problem Formulation

The objective function of PBLO-TQSM can be split into bi-levels optimization; major-level objective and minor-level objective, which is similar to section 4.2.1. The maximum trading quantity is calculated at the major-level and formulated as follows:

Maximize $$TQ = \sum_{i=1}^{N_{\max}} f_i(\tilde{\lambda}_i) \tag{5.1}$$

s.t. $$f(\tilde{\lambda}_i) = \begin{cases} \text{n} & \text{for } \tilde{\lambda}_{Di} \geq \tilde{\lambda}_{Si} \\ 0 & \text{for } \tilde{\lambda}_{Di} < \tilde{\lambda}_{Si} \end{cases} \tag{5.2}$$

$$P^{\min} = \max\left\{\tilde{P}_{Di}^{\min}, \tilde{P}_{Si}^{\min} + \alpha\right\} \tag{5.3}$$

$$P^{\max} = \min\left\{\tilde{P}_{Di}^{\max}, \tilde{P}_{Si}^{\max} + \alpha\right\} \quad (5.4)$$

$$N_{\max} = \frac{P^{\max} - P^{\min}}{n} \quad (5.5)$$

Calculations at the major level will disclose several maximum values. To determine the shift factor that generates the best surplus while TQ reaches its maximum value, TQ must be established as a constraint at the minor level. The objective of minor-level is shown in Equation 5.6. The objective function contains three components: surplus of inverse demand curve, surplus of shifting supply curve and death penalty term (Yeniay, 2005).

Maximize $$SP = \int_{P^{\min}}^{P^{\max}} asc(\tilde{\lambda}_{Di} \cdot \tilde{P}_{Di})dP_{Di} - \int_{P^{\min}}^{P^{\max}} [(\tilde{\lambda}_{Si} \cdot \tilde{P}_{Si}) + \alpha]dP_{Si} - DPF \quad (5.6)$$

s.t. $$DPF = \begin{cases} +\infty, & \mathrm{TQ} \neq TQ_{\max} \\ 0, & \mathrm{TQ} = TQ_{\max} \end{cases} \quad (5.7)$$

$$P^{\min} = \max\left\{\tilde{P}_{Di}^{\min}, \tilde{P}_{Si}^{\min} + \alpha\right\} \quad (5.8)$$

$$P^{\max} = \min\left\{\tilde{P}_{Di}^{\max}, \tilde{P}_{Si}^{\max} + \alpha\right\} \quad (5.9)$$

5.2.2 Real Surplus Problem Formulation

The energy from participants that cannot be matched will be sold and bought with the grid at prices of G_S and G_B THB, respectively, resulting in a negative surplus of demand and negative surplus of supply as shown in Equations 5.10-5.11.

$$NSP_D = \sum_{i=1}^{N_d} (\lambda_{Di} - G_B)P_{unDi} \quad (5.10)$$

$$NSP_S = \sum_{i=1}^{N_s} (G_S - \lambda_{Si})P_{unSi} \quad (5.11)$$

In the calculations shown above, that will be subtracted from SP in order to calculate the real surplus as shown in Equation 5.12.

$$RSP = SP - NSP_D - NSP_S \quad (5.12)$$

5.3 Simulation Setup

5.3.1 Parameter of PSO

Selecting the right parameters for Particle Swarm Optimization (PSO) is crucial as it directly impacts the algorithm's efficiency, solution quality, and stability. Proper tuning ensures faster convergence to optimal or near-optimal solutions while avoiding premature convergence to suboptimal ones. It balances exploration (broad search) and exploitation (local refinement), adapting the algorithm to the problem's characteristics and preventing erratic behavior or excessive computational costs. For determining which of PSO's internal parameters are most suitable for the algorithm. The PBLO-TQSM simulation has been performed with 100 identical participants, each having different amounts of C_1, C_2, and W, setting C_1 and C_2 to 1, 1.49, and 2. Trials were conducted with four values of W: fixed values of 0.1, 0.6, and 1.1 in three cases, and an adaptive value within the range [0.1, 1.1] in one case, as seen in Figures 5.1-5.4, respectively. The result of the four-case comparison is shown in Table 5.1.

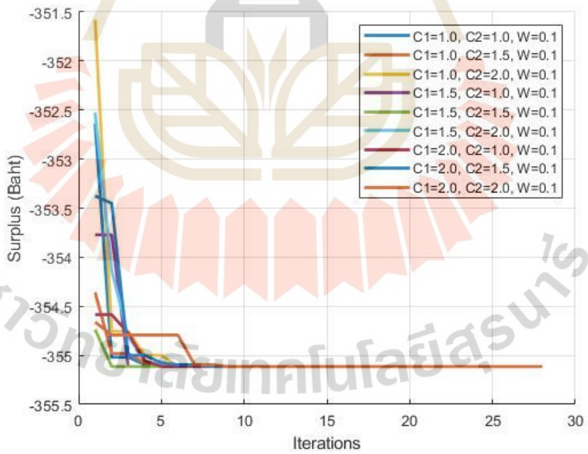


Figure 5.2 Comparison of PSO parameter values at W=0.1

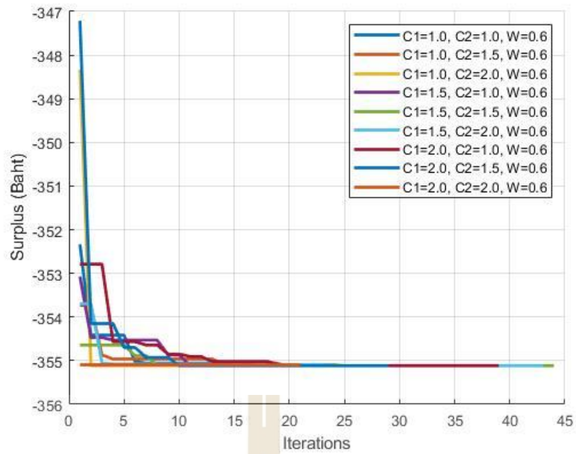


Figure 5.3 Comparison of PSO parameter values at W=0.6

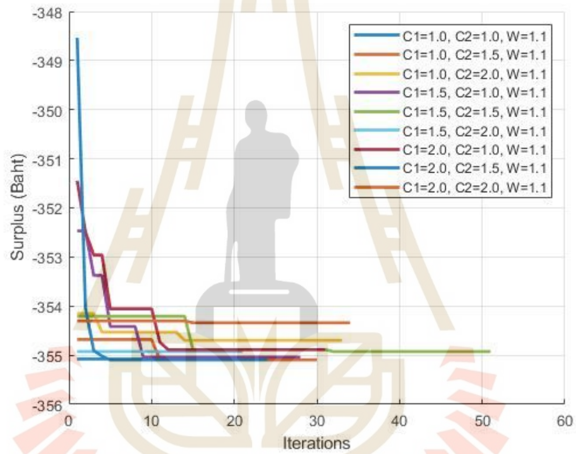


Figure 5.4 Comparison of PSO parameter values at W=1.1

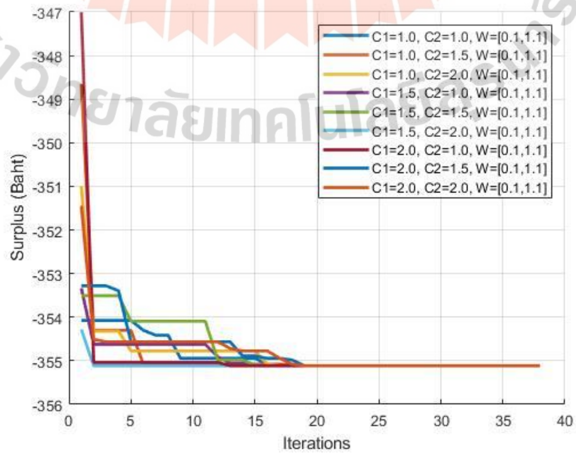


Figure 5.5 Comparison of PSO parameter values at W= [0.1,1.1]

Table 5.1 The result of the four-case comparison

Parameter			Shifting factor	Surplus	Quantity	Time
w	c_1	c_2				
0.1	1	1	79.92	355.11	1682.84	158.795
		1.49	79.92	355.11	1682.84	140.6645
		2	79.92	355.11	1682.84	149.7046
	1.49	1	79.92	355.11	1682.84	145.0467
		1.49	79.92	355.11	1682.84	161.6084
		2	79.92	355.11	1682.84	144.4245
	2	1	79.92	355.11	1682.84	179.7824
		1.49	79.92	355.11	1682.84	197.0689
		2	79.92	355.11	1682.84	227.1356
0.6	1	1	79.92	355.11	1682.84	264.1641
		1.49	79.92	355.11	1682.84	267.2793
		2	79.92	355.11	1682.84	193.9189
	1.49	1	79.92	355.11	1682.84	244.2568
		1.49	79.92	355.11	1682.84	289.0805
		2	79.92	355.11	1682.84	311.7267
	2	1	79.92	355.11	1682.84	253.3418
		1.49	79.92	355.11	1682.84	198.1556
		2	79.91	355.1	1682.84	162.1805
1.1	1	1	79.9	355.08	1682.84	178.1736
		1.49	79.91	355.1	1682.84	203.3715
		2	79.7	354.7	1682.84	223.5728
	1.49	1	79.88	355.04	1682.84	198.8304
		1.49	79.82	354.93	1682.84	246.6406
		2	79.82	354.93	1682.84	164.597
	2	1	79.8	354.89	1682.84	189.0123
		1.49	79.91	355.1	1682.84	157.7333
		2	79.51	354.34	1682.84	186.031

Table 5.1 The result of the four-case comparison (continued)

Parameter			Shifting factor	Surplus	Quantity	Time
W	C_1	C_2				
[0.1,11]	1	1	79.92	355.11	1682.84	155.5878
		1.49	79.92	355.11	1682.84	149.2487
		2	79.92	355.11	1682.84	151.5977
	1.49	1	79.92	355.11	1682.84	150.6145
		1.49	79.92	355.11	1682.84	147.6688
		2	79.92	355.11	1682.84	111.0742
	2	1	79.92	355.11	1682.84	140.1929
		1.49	79.92	355.11	1682.84	155.808
		2	79.92	355.11	1682.84	157.6065

The analysis of Table 5.1 reveals the impact of adjusting the PSO parameters on the simulation results for the PBLO-TQSM framework. The inertial weight (W), cognitive adjustment weight (C_1), and social adjustment weight (C_2) significantly influence computational performance, though they do not substantially affect the resulting surplus, trading quantity, or shifting factor. Fixed values of W, such as 0.1, 0.6, and 1.1, yield consistent surplus and trading quantity outcomes, but computational time increases with larger W values. This suggests that while smaller W values enable faster convergence, they may risk inadequate exploration, whereas larger W values favor exploration but increase computational costs. On the other hand, using an adaptive W ([0.1–1.1]) achieves a dynamic balance between exploration and exploitation, offering robust convergence behavior without sacrificing the accuracy of results. Adjustments to C_1 and C_2 have minimal effect on surplus, shifting factor, and trading quantity, which remain stable across parameter variations. However, higher values of C_1 and C_2 tend to increase computational time due to the extended search process required to refine solutions. This indicates that while larger cognitive and social weights enhance thoroughness in optimization, they come at the cost of increased computation time. Among all configurations, the combination of C_1 = 1.49 and C_2 = 2, along with W = [0.1–1.1], achieves a practical balance by taking the least computational time while maintaining consistent and robust results. To ensure that the selected parameters are stable in the simulation, 30 trials using W = [0.1–1.1], C_1 = 1.49, and C_2 = 2 were performed, as shown in Figure 5.6. These trials confirmed the stability and reliability of the chosen parameters, further validating their suitability for practical implementation. The PBLO-TQSM framework demonstrates robustness across different parameter settings, and the selected configuration is optimal for balancing computational efficiency, accuracy, and stability in large-scale simulations.

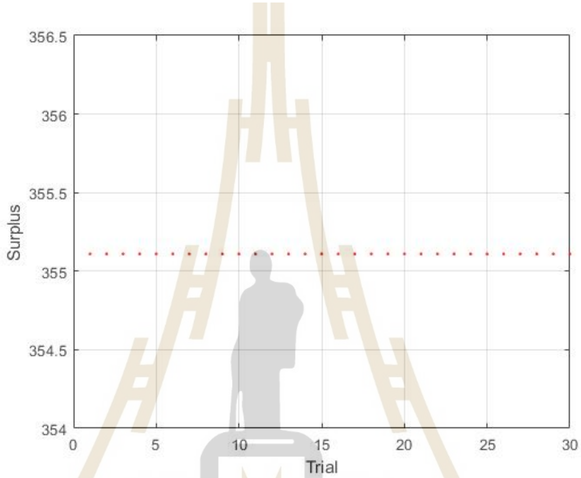


Figure 5.6 The 30 trial plots from C_1 = 1.49, C_2 = 2 and W = [0.1–1.1]

5.3.2 Monte Carlo Simulation

For probabilistic analysis, MCS is implemented using an iterative algorithm with deterministic P2P MMM and PBIO-TQSM. The set of iterative algorithms is carried out by price and quantity for each participant, which are obtained from PDF. The MCS continues until the average surplus is closed to those of the preceding iteration, ensuring consistency. MSC operation overview as shown in figure.5.7. The computational process is illustrated as follows, where ε is a small tolerance value, e.g., 0.01.

Step 1: Randomly price and quantity in accordance with a normal distribution.

Step 2: Set the average surplus, the average quantity trading and the average real surplus at $k = 0$ to zeros ($SP_{AV}^{0} = 0$, $TQ_{AV}^{0} = 0$ and $RSP_{AV}^{0} = 0$). Set iteration $k = 1$.

Step 3: Solved P2P MMM and PBIO-TQSM, at iteration k, with sampling price PDF and sampling quantity PDF.

Step 4: Record the solution of P2P MMM and PBIO-TQSM.

Step 5: Compute the average surplus, the average quantity trading and the average real surplus obtained from iterations 1 to k (SP_{AV}^{k}).

Step 6: Compare the average surplus and the average quantity trading obtained from iterations 1 to k (SP_{AV}^{k}) to the average surplus, the average quantity trading and the average real surplus obtained from iterations 1 to k-1 (SP_{AV}^{k-1})

1) If $\left|SP_{AV}^{k}-SP_{AV}^{k-1}\right|$ or $\left|TQ_{AV}^{k}-TQ_{AV}^{k-1}\right|>\varepsilon$, set $k=k+1$ and go to step 3,

2) If $\left|SP_{AV}^{k}-SP_{AV}^{k-1}\right|$ and $\left|TQ_{AV}^{k}-TQ_{AV}^{k-1}\right|\leq\varepsilon$, go to step 7.

Step 7: Compare the average surplus, the average quantity trading and the average real surplus of P2P MMM and the average surplus, the average quantity trading and the average real surplus of PBIO-TQSM.

Step 8: Stop.

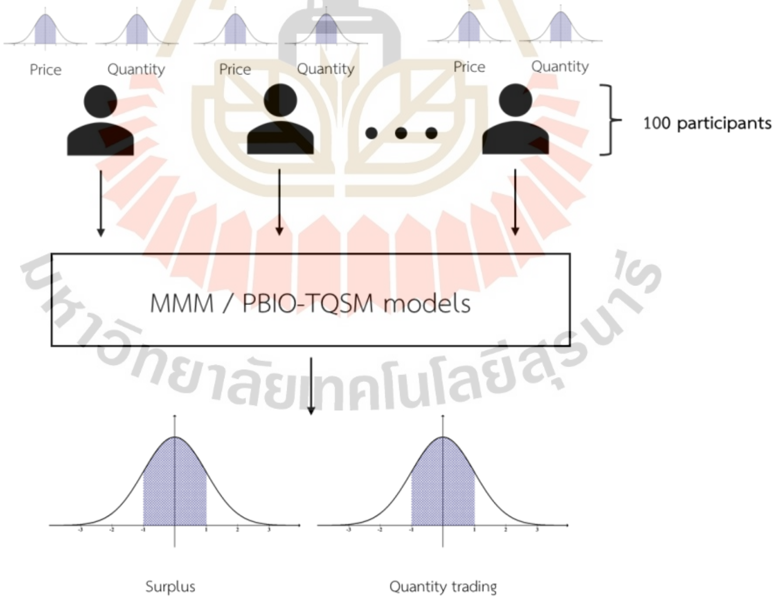


Figure 5.7 MCS operation overview

5.4 Simulation Result

This section simulates and analyzes the surplus, trading quantity, and real surplus of the proposed P2P energy trading mechanism, comparing the performance of the PBLO-TQSM and P2P MMM algorithms to evaluate their performance under various market conditions.

The simulation models a total of 100 participants as energy buyers and sellers. 50 participants act as sellers, and the other 50 act as buyers. Each seller's allowable energy selling price is randomly generated within the range of 2 THB/kWh to 5 THB/kWh, while the available energy for sale is distributed between 20 kWh and 50 kWh. Buyers' acceptable purchase price is also randomly determined within the same range, and their energy demand is similarly generated between 20 kWh and 50 kWh. The participants that cannot be matched will be sold and bought with the grid at prices of 2 and 5 THB, respectively. MCS is employed to simulate participant behavior and market conditions. All price and quantity values follow a normal distribution to reflect realistic market variability. The simulations are conducted in MATLAB and iterated until convergence is achieved. Two cases are considered and compared:

Case A: The BLO-TQSM algorithm is applied without the DCTS algorithm, and the results are compared with the P2P MMM algorithm under similar conditions, focusing on trading quantity, surplus, and real surplus.

Case B: The BLO-TQSM algorithm is combined with the DCTS algorithm, and its performance in terms of trading quantity, surplus, and real surplus is compared with the P2P MMM algorithm incorporating the DCTS algorithm.

5.4.1 Result of PBLO-TQSM and P2P MMM without DCTS

The result of PBLO-TQSM in case without DCTS is computed at 766 iterations to achieve a tolerance of less than 0.01 under the parameters that have been given, the raw results of which can be viewed in APPENDIX A. Figures 5.8 to 5.10 show the convergence of the MCS of PBLO-TQSM algorithm for average surplus, average quantity and average real surplus with a final average of 467.78 THB, 1534.6 kWh and –652.81 THB, respectively. Meanwhile, Figures 5.11 to 5.13 show the probability distribution function (PDF) of PBLO-TQSM for surplus, quantity and real surplus, respectively.

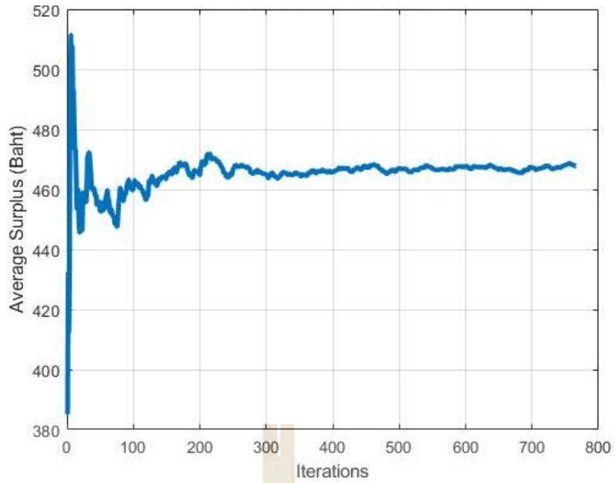


Figure 5.8 The convergence of MCS of PBLO-TQSM without DCTS for average surplus

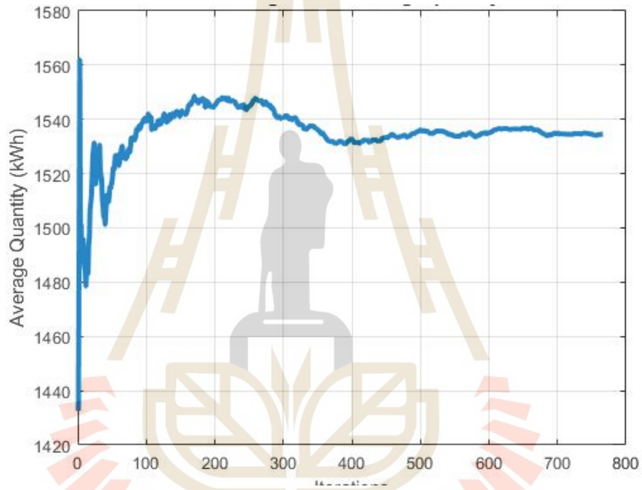


Figure 5.9 The convergence of MCS of PBLO-TQSM without DCTS for average quantity

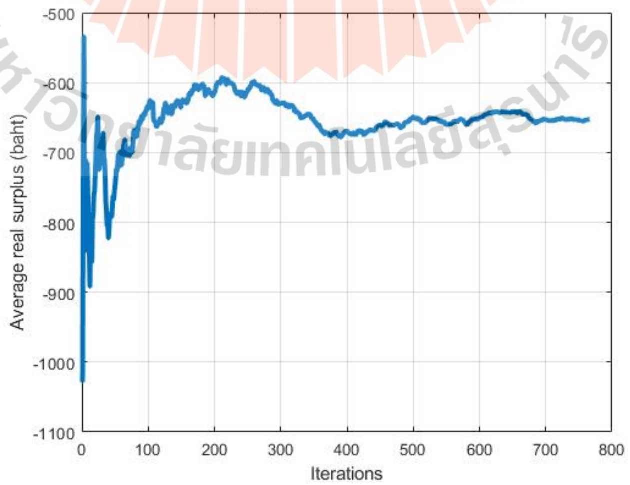


Figure 5.10 The convergence of MCS of PBLO-TQSM without DCTS for average real surplus

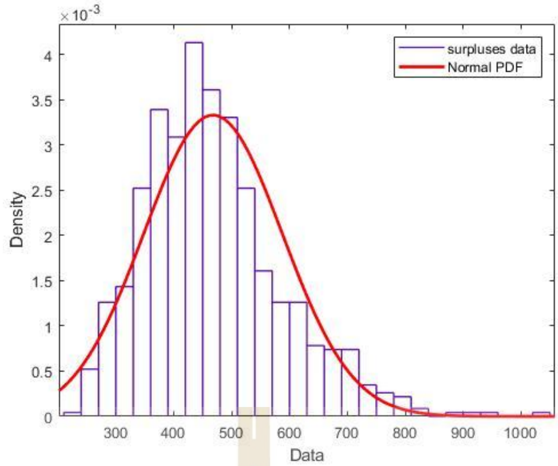


Figure 5.11 The PDF of PBLO-TQSM without DCTS for Surplus

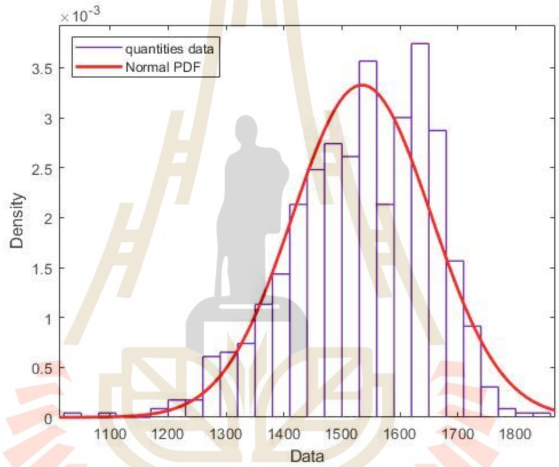


Figure 5.12 The PDF of PBLO-TQSM without DCTS for Quantity

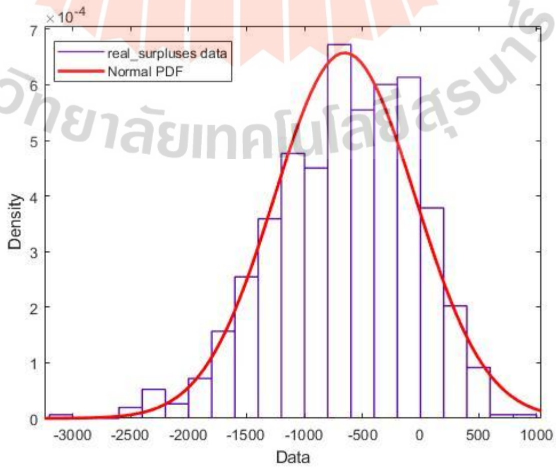


Figure 5.13 The PDF of PBLO-TQSM without DCTS for Real surplus

The result of P2P MMM in case without DCTS is computed at 1111 iterations to achieve a tolerance of less than 0.01 under the parameters that have been given, the raw results of which can be viewed in APPENDIX B. Figures 5.14 to 5.16 show the convergence of the MCS of P2P MMM algorithm for average surplus, average quantity and average real surplus with a final average of 413.08 THB, 1442.3 kWh and -909.54 THB, respectively. Meanwhile, Figures 5.17 to 5.19 show the PDF of P2P MMM for surplus, quantity and real surplus, respectively.

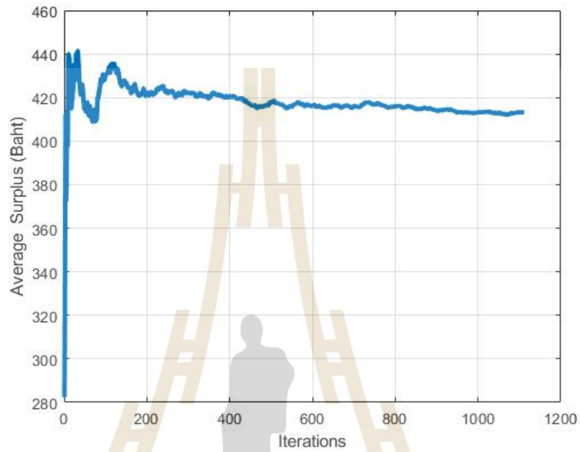


Figure 5.14 The convergence of MCS of P2P MMM without DCTS for average surplus

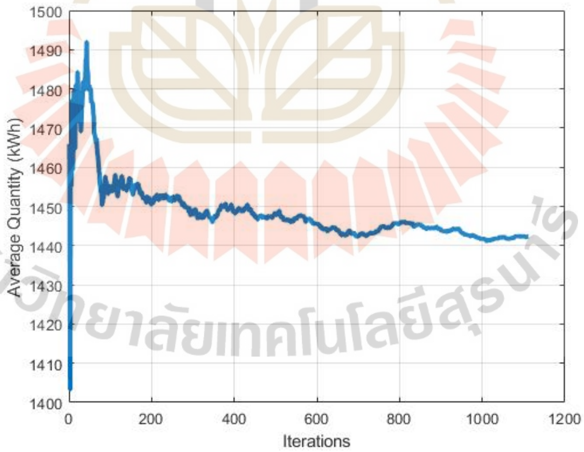


Figure 5.15 The convergence of MCS of P2P MMM without DCTS for average quantity

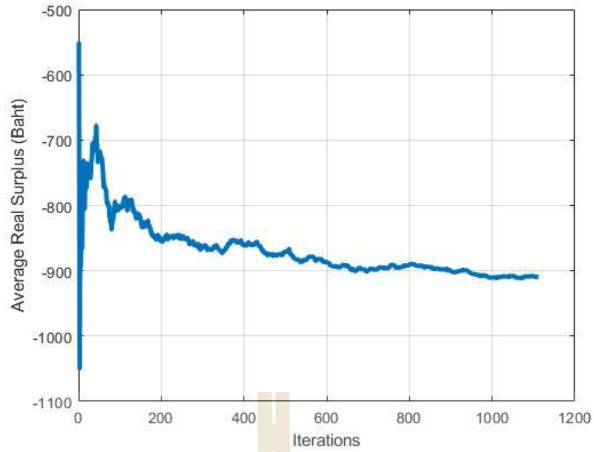


Figure 5.16 The convergence of MCS of P2P MMM without DCTS for average real surplus

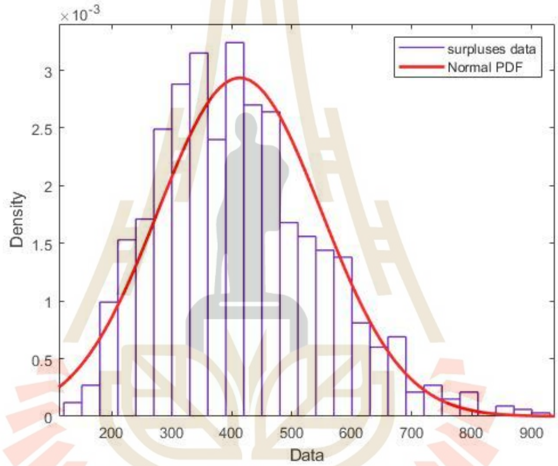


Figure 5.17 The PDF of P2P MMM without DCTS for Surplus

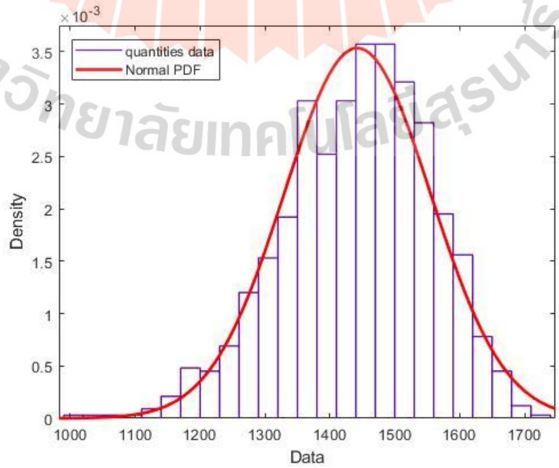


Figure 5.18 The PDF of P2P MMM without DCTS for Quantity

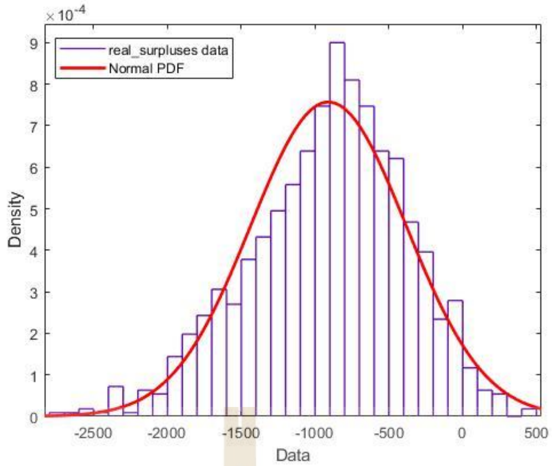


Figure 5.19 The PDF of P2P MMM without DCTS for Real Surplus

5.4.2 Result of PBLO-TQSM and P2P MMM with DCTS

The result of PBLO-TQSM in case with DCTS is computed at 690 iterations to achieve a tolerance of less than 0.01 under the parameters that have been given, the raw results of which can be viewed in APPENDIX C. Figures 5.20 to 5.22 show the convergence of the MCS of PBLO-TQSM algorithm for average surplus, average quantity and average real surplus with a final average of 393.09 THB, 1412.4kWh and –1386 THB, respectively. Meanwhile, Figures 5.23 to 5.25 show the PDF of PBLO-TQSM for surplus, quantity and real surplus, respectively.

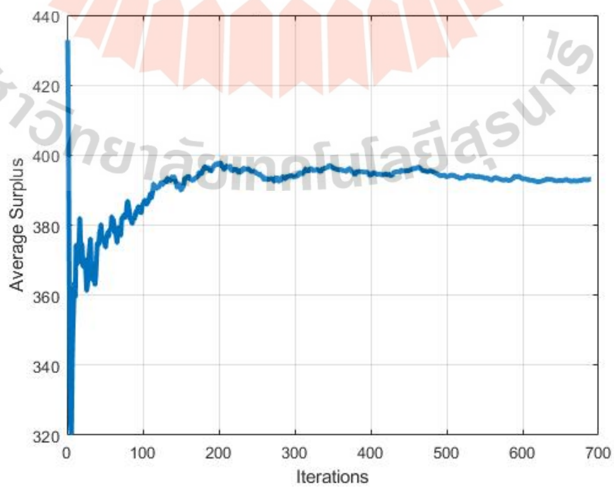


Figure 5.20 The convergence of MCS of PBLO-TQSM with DCTS for average surplus

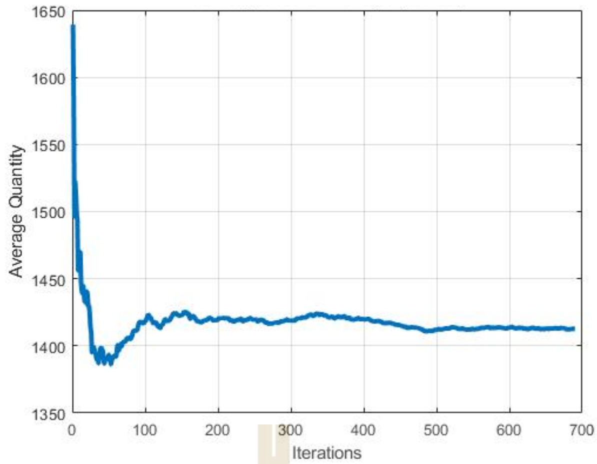


Figure 5.21 The convergence of MCS of PBLO-TQSM with DCTS for average quantity

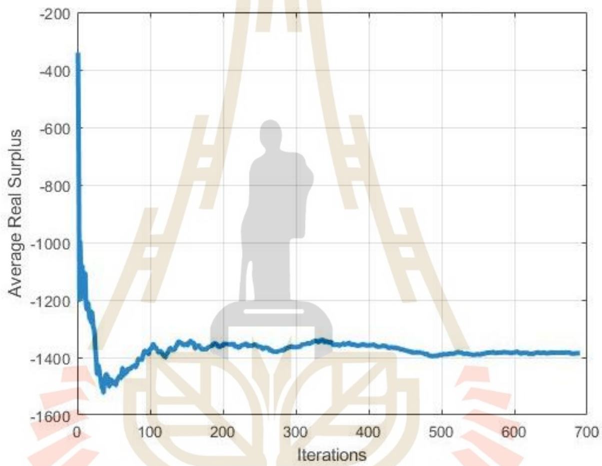


Figure 5.22 The convergence of MCS of PBLO-TQSM with DCTS for average real surplus

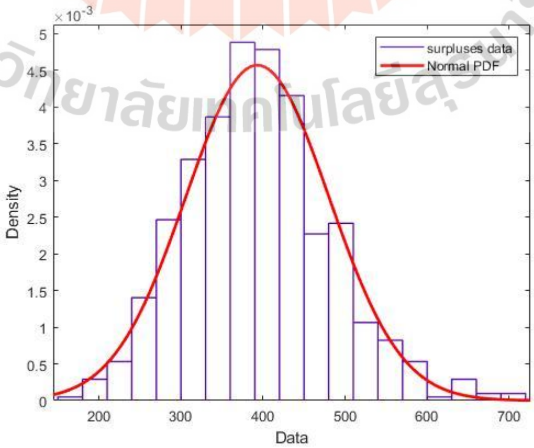


Figure 5.23 The PDF of PBLO-TQSM with DCTS for Real surplus

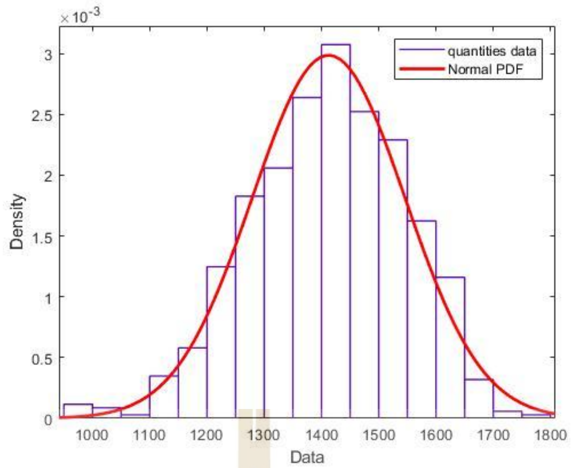


Figure 5.24 The PDF of PBLO-TQSM with DCTS for quantity

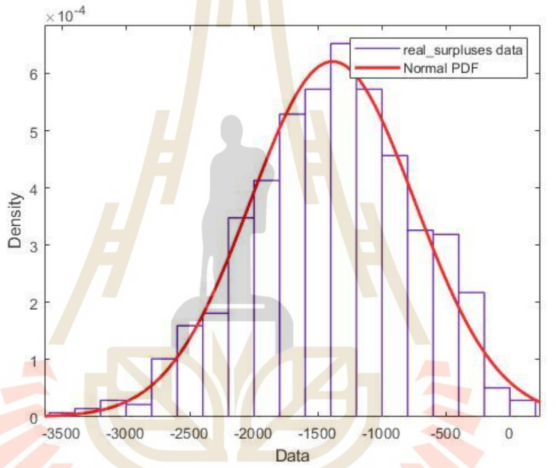


Figure 5.25 The PDF of PBLO-TQSM with DCTS for real surplus

The result of P2P MMM in case with DCTS is computed at 1127 iterations to achieve a tolerance of less than 0.01 under the parameters that have been given, the raw results of which can be viewed in APPENDIX D. Figures 5.26 to 5.28 show the convergence of the MCS of P2P MMM algorithm for average surplus, average quantity and average real surplus with a final average of 291.67 THB, 1382.9 kWh and -1448.1 THB, respectively. Meanwhile, Figures 5.29 to 5.31 show the PDF of P2P MMM for surplus, quantity and real surplus, respectively.

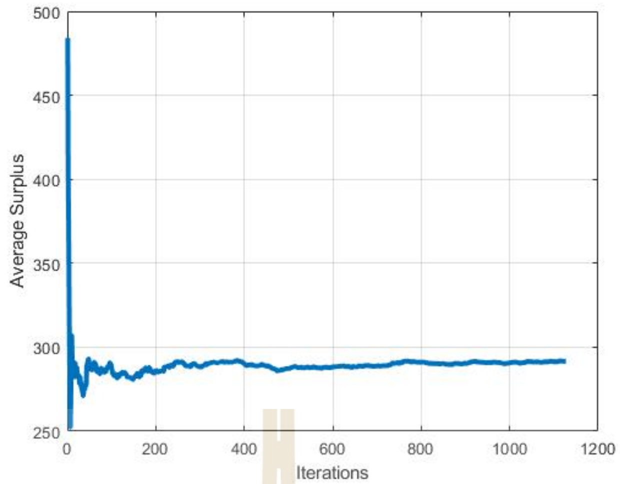


Figure 5.26 The convergence of MCS of P2P MMM with DCTS for average surplus

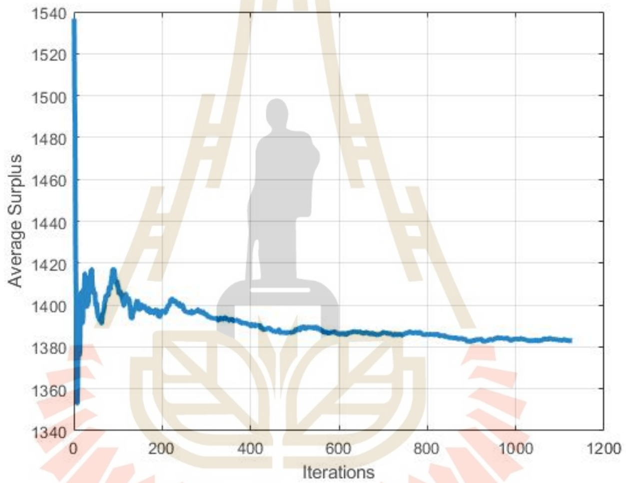


Figure 5.27 The convergence of MCS of P2P MMM with DCTS for average quantity

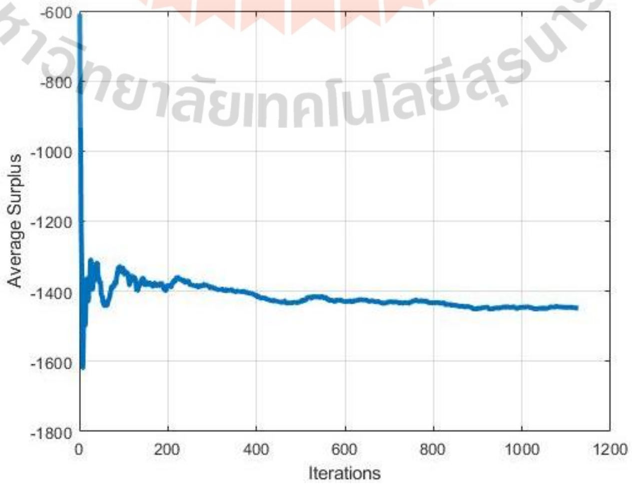


Figure 5.28 The convergence of MCS of P2P MMM with DCTS for average real surplus

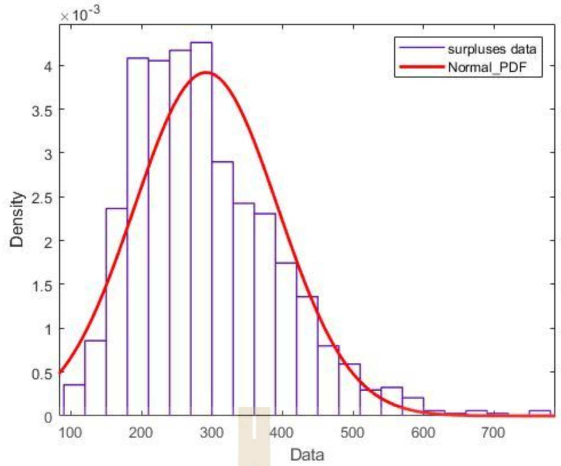


Figure 5.29 The PDF of P2P MMM with DCTS for surplus

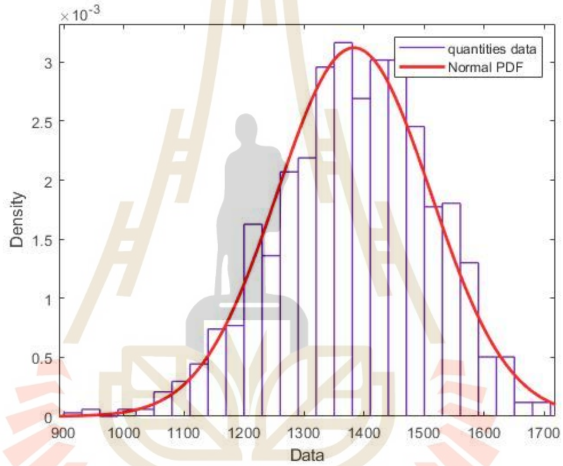


Figure 5.30 The PDF of P2P MMM with DCTS for quantity

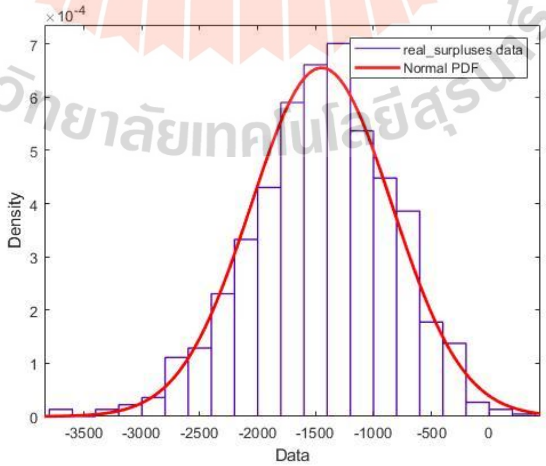


Figure 5.31 The PDF of P2P MMM with DCTS for real surplus

5.4.3 Discussion

A comparative analysis of the PBLO-TQSM and P2P MMM algorithms without DCTS and the PBLO-TQSM and P2P MMM algorithms with DCTS are summarized in Table 5.2 and Table 5.3, respectively.

Table 5.2 Comparative analysis of the PBLO-TQSM and P2P MMM algorithms without DCTS

Comparative analysis without DCTS	PBLO-TQSM		P2P MMM	
	Mean	SD	Mean	SD
Surplus (THB)	467.778	119.702	413.08	135.905
Quantity (kWh)	1534.56	119.856	1442.31	112.884
Real surplus (THB)	-652.806	606.651	-909.538	526.875

Table 5.3 Comparative analysis of the PBLO-TQSM and P2P MMM algorithms with DCTS

Comparative analysis with DCTS	PBLO-TQSM		P2P MMM	
	Mean	SD	Mean	SD
Surplus (THB)	393.087	87.301	291.67	101.79
Quantity (kWh)	1412.43	133.645	1382.94	127.76
Real surplus (THB)	-1385.96	642.451	-1448.09	608.615

Table 5.2 demonstrates that PBLO-TQSM outperforms P2P MMM across all key metrics, including surplus, trading quantity, and real surplus. Specifically, PBLO-TQSM achieves a higher average surplus (467.78 THB) than P2P MMM (413.08 THB) due to its two-level optimization method, which focuses on the overall market. When a graph shift occurs, it affects all market players equally. In contrast to the P2P MMM method, which prioritizes the highest bidder first, this approach results in inequity. Additionally, PBLO-TQSM generates a marginally greater trading quantity (1534.6 kWh versus 1442.3 kWh), ensuring more efficient energy matching and reducing unmet opportunities. A significant observation is the impact on real surplus, where P2P MMM incurs a larger negative real surplus (-909.54 THB) compared to PBLO-TQSM (-652.81 THB). This indicates that P2P MMM suffers from inefficiencies in pairing participants,

leading to higher unused market opportunities. By using a probabilistic framework and keeping the trading quantity and surplus in balance, PBLO-TQSM shows that it is strong and effective at fixing the problems that traditional matching mechanisms like P2P MMM have. The findings emphasize that PBLO-TQSM provides a more effective solution for enhancing economic and operational performance in decentralized P2P energy markets.

Table 5.3 examines the performance of the same algorithms when DCTS is incorporated. The inclusion of DCTS leads to reduced surpluses for both algorithms, with PBLO-TQSM achieving a mean surplus of 393.09 THB compared to 291.67 THB for P2P MMM. This decrease reflects the carbon taxation's impact on market dynamics, particularly the penalties imposed on fossil-based transactions. Interestingly, the trading quantities for both algorithms also decline, with PBLO-TQSM dropping to 1412.43 kWh and P2P MMM to 1382.94 kWh, showing the trade-off between environmental considerations and market efficiency. Real surplus figures reveal heightened losses, with PBLO-TQSM at -1385.96 THB and P2P MMM at -1448.09 THB, emphasizing the additional costs incurred due to carbon tax implementation. Despite these challenges, PBLO-TQSM continues to outperform P2P MMM, maintaining a better balance between economic and environmental objectives.

The comparison between Tables 5.2 and 5.3 reveals the profound impact of DCTS on market performance. The implementation of carbon taxation results in a reduction in both surplus and trading quantities for PBLO-TQSM and P2P MMM, highlighting the economic implications of integrating environmental costs into trading mechanisms. Despite these challenges, PBLO-TQSM consistently outperforms P2P MMM, achieving higher surpluses and trading quantities in both scenarios, demonstrating its robustness and adaptability to market changes. The increased negative real surplus with DCTS occurs because DCTS raises the prices of fossil electricity sellers. When these sellers cannot match with buyers due to their elevated prices, they are forced to sell their electricity to the grid at lower rates, creating a larger negative real surplus than without DCTS. PBLO-TQSM, however, showcases greater resilience, maintaining superior operational efficiency and equity compared to P2P

MMM under taxation. This comparison emphasizes the critical need for trading mechanisms that effectively balance economic performance with environmental sustainability in P2P energy markets.

5.5 Renewable energy penetration sensitivity analysis

In microgrids or villages, renewable energy sources such as solar are generally more abundant and accessible than fossil-based energy. As the global push for carbon neutrality accelerates, these decentralized systems are increasingly designed to prioritize renewable energy producers over fossil fuel counterparts. This section explores how renewable energy dominance impacts the performance of P2P electricity markets, with a focus on trading quantity and economic surplus.

In this study, the price and quantity for each player in the P2P energy market are designed to reflect realistic characteristics of both fossil and renewable energy producers. Fossil energy producers are assigned higher price ranges (3–5 THB/kWh, mean 4 THB/kWh) due to their operational costs, carbon taxation, and environmental externalities, while their supply quantities remain stable and consistent (30–50 kWh, mean 40 kWh). In contrast, renewable energy producers are modeled with lower price ranges (2–4 THB/kWh, mean 3 THB/kWh) to reflect their lower operational costs and environmental incentives. However, their supply quantities are more variable due to dependency on environmental factors, with ranges set between 20–40 kWh (mean 30 kWh). These values are generated using probabilistic distributions to incorporate natural fluctuations. Additionally, carbon taxation is applied to fossil producers, increasing their prices to account for environmental costs, while renewable producers are prioritized in the matching process to align with sustainability goals. This setup ensures a comprehensive analysis of the market under scenarios with varying proportions of renewable and fossil energy producers, reflecting real-world dynamics in small-scale power systems. To further evaluate the impact of renewable energy dominance on the P2P energy trading market, the PBLO-TQSM algorithm will be tested under DCTS in three case scenarios:

Case A: a balanced case with 50% renewable energy producers and 50% fossil energy producers.

Case B: a moderate renewable dominance case with 70% renewable energy producers and 30% fossil energy producers.

Case C: a strong renewable dominance case with 90% renewable energy producers and 10% fossil energy producers. These scenarios are designed to investigate how varying levels of renewable energy penetration affect market outcomes such as trading quantity, economic surplus, and environmental impact. By comparing the results across these cases.

5.5.1 Balanced case

The performance of the PBLO-TQSM algorithm with DCTS in the scenario involving 50% renewable energy producers and 50% fossil energy producers was analyzed. The algorithm achieved convergence after 1,034 iterations, satisfying a tolerance threshold of less than 0.01 under the predefined parameters. Figures 5.32 to 5.34 illustrate the convergence behavior of the MCS for the PBLO-TQSM algorithm, highlighting the trends in average surplus, average trading quantity, and average real surplus. The final computed averages for these metrics are 487.473 THB for surplus, 1,290.45 kWh for trading quantity, and –1,881.72 THB for real surplus, respectively. Furthermore, Figures 5.35 to 5.37 present the PDF of the PBLO-TQSM algorithm for surplus, trading quantity, and real surplus.

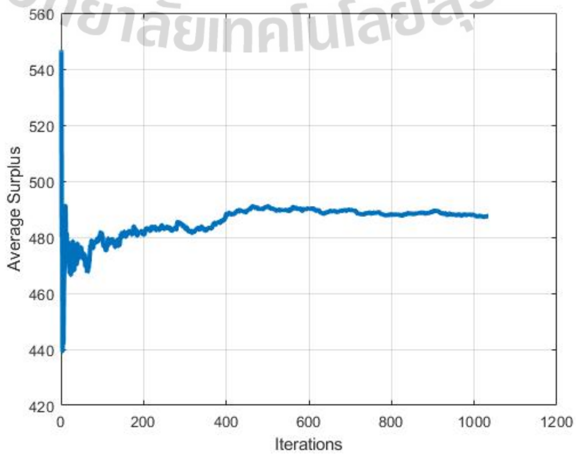


Figure 5.32 The convergence of MCS for average surplus in the 50% dominate

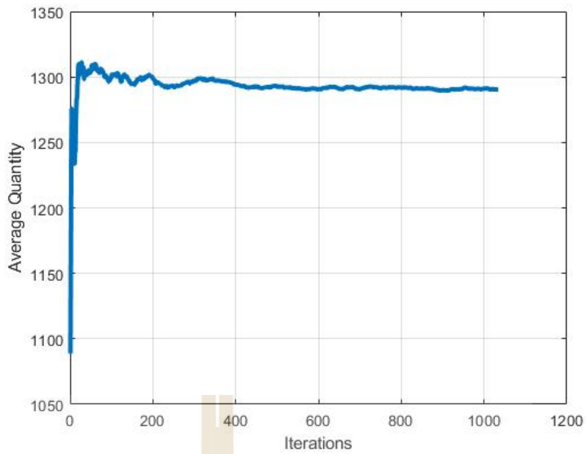


Figure 5.33 The convergence of MCS for average quantity in the 50% dominate

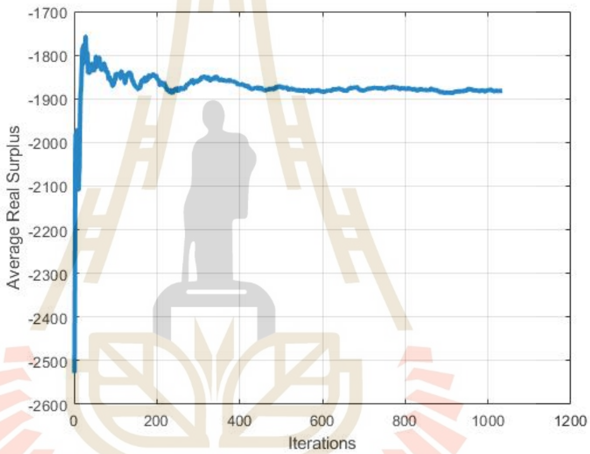


Figure 5.34 The convergence of MCS for average real surplus in the 50% dominate

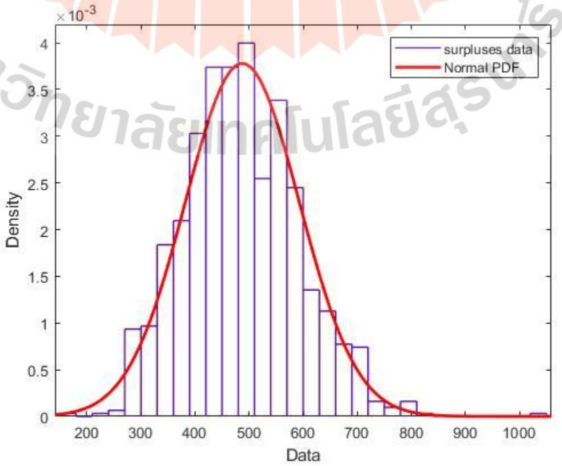


Figure 5.35 The PDF of surplus in the 50% dominate

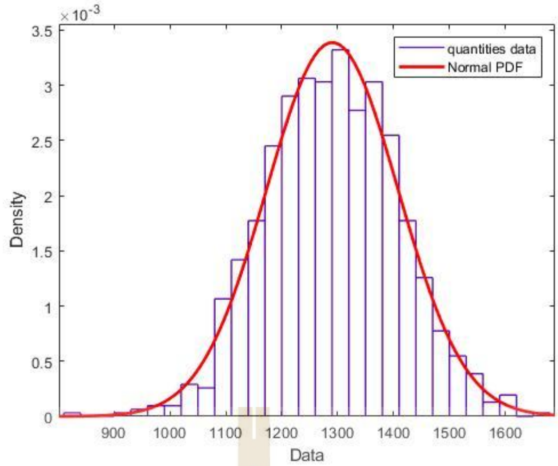


Figure 5.36 The PDF of quantity in the 50% dominate

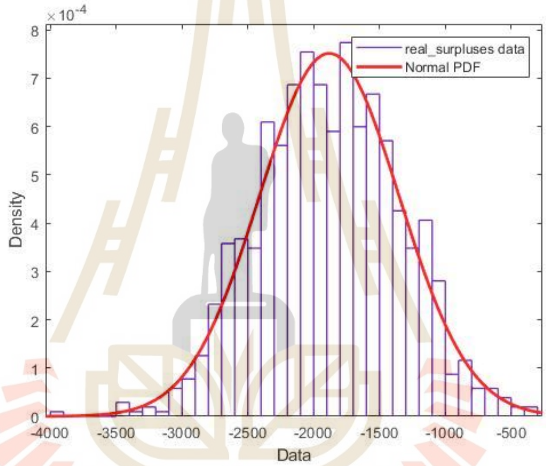


Figure 5.37 The PDF of real surplus in the 50% dominate

5.5.2 Moderate renewable dominance case

The performance of the PBLO-TQSM algorithm with DCTS in the scenario involving 70% renewable energy producers and 30% fossil energy producers was analyzed. The algorithm achieved convergence after 1,035 iterations, satisfying a tolerance threshold of less than 0.01 under the predefined parameters. Figures 5.38 to 5.40 illustrate the convergence behavior of the MCS for the PBLO-TQSM algorithm, highlighting the trends in average surplus, average trading quantity, and average real surplus. The final computed averages for these metrics are 586.534 THB for surplus, 1,452.52 kWh for trading quantity, and –745.636 THB for real surplus, respectively.

Furthermore, Figures 5.41 to 5.43 present the PDF of the PBLO-TQSM algorithm for surplus, trading quantity, and real surplus.

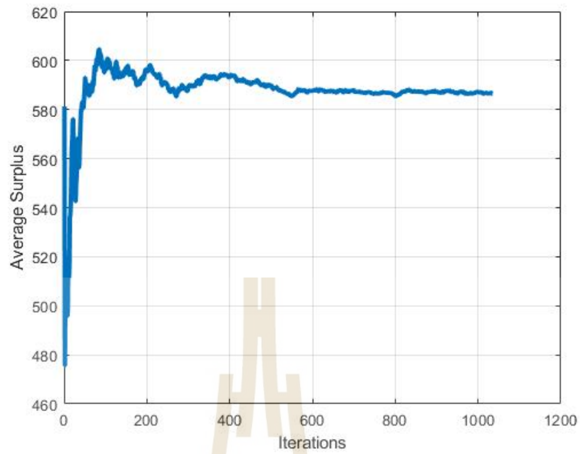


Figure 5.38 The convergence of MCS for average surplus in the 70% dominate

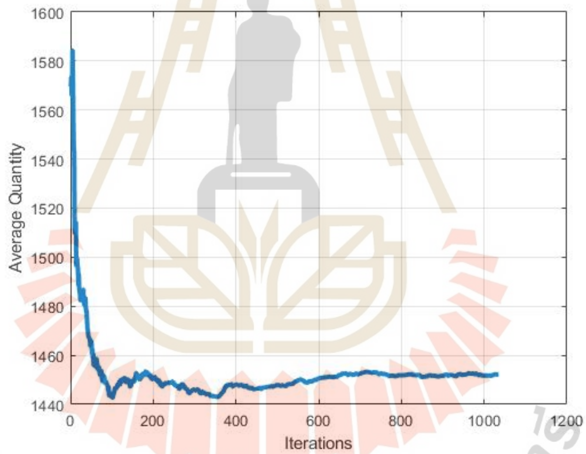


Figure 5.39 The convergence of MCS for average quantity in the 70% dominate

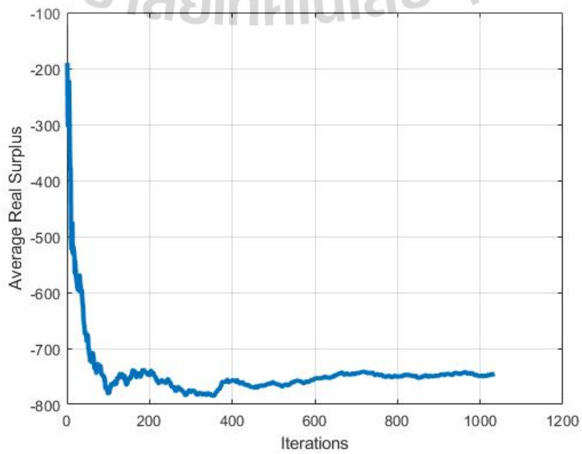


Figure 5.40 The convergence of MCS for average real surplus in the 70% dominate

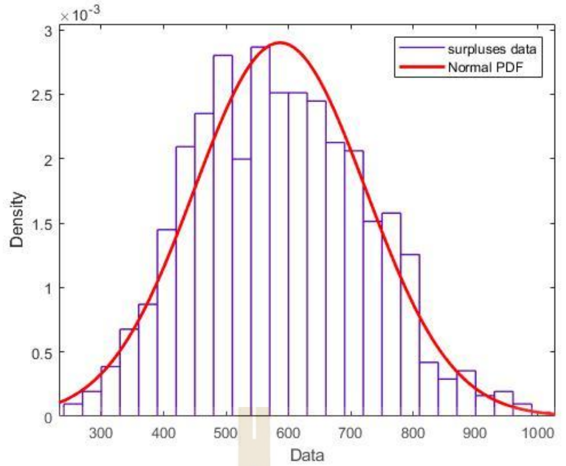


Figure 5.41 The PDF of surplus in the 70% dominate

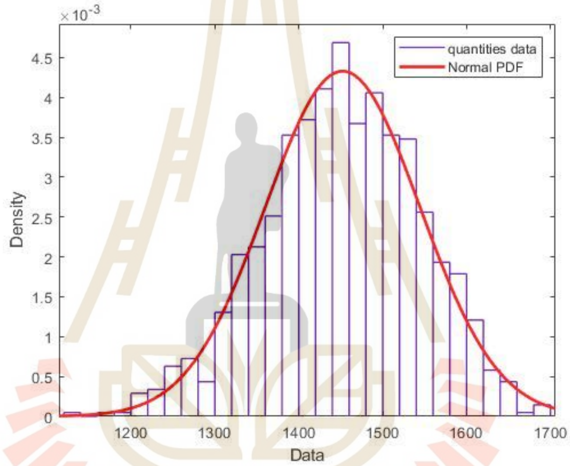


Figure 5.42 The PDF of quantity in the 70% dominate

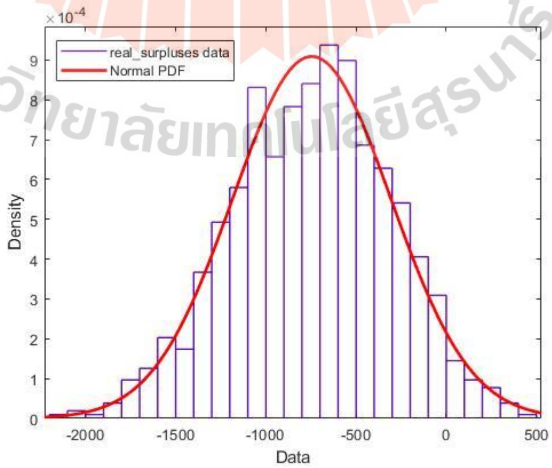


Figure 5.43 The PDF of real surplus in the 70% dominate

5.5.3 Strong renewable dominance case

The performance of the PBLO-TQSM algorithm with DCTS in the scenario involving 90% renewable energy producers and 10% fossil energy producers was analyzed. The algorithm achieved convergence after 912 iterations, satisfying a tolerance threshold of less than 0.01 under the predefined parameters. Figures 5.44 to 5.46 illustrate the convergence behavior of the MCS for the PBLO-TQSM algorithm, highlighting the trends in average surplus, average trading quantity, and average real surplus. The final computed averages for these metrics are 823.145 THB for surplus, 1,512.13 kWh for trading quantity, and 95.586 THB for real surplus, respectively. Furthermore, Figures 5.47 to 5.49 present the PDF of the PBLO-TQSM algorithm for surplus, trading quantity, and real surplus.

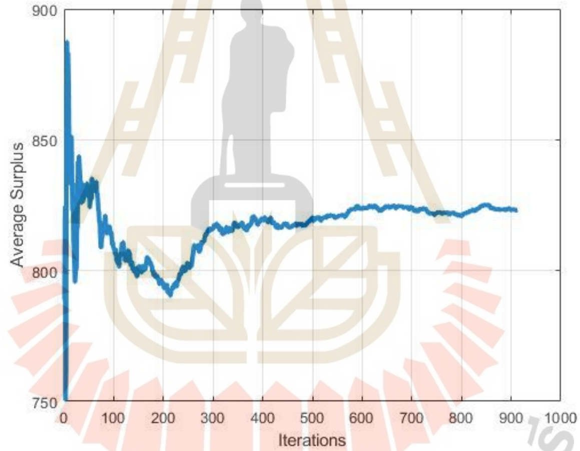


Figure 5.44 The convergence of MCS for average surplus in the 90% dominate

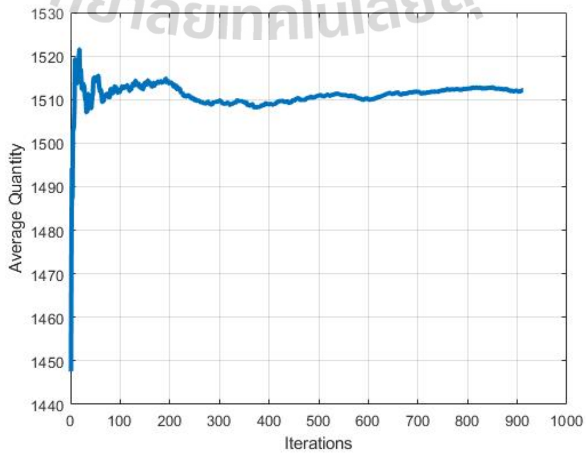


Figure 5.45 The convergence of MCS for average quantity in the 90% dominate

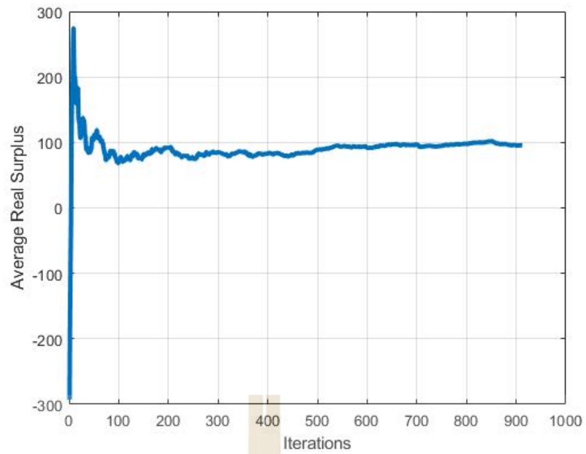


Figure 5.46 The convergence of MCS for average real surplus in the 90% dominate

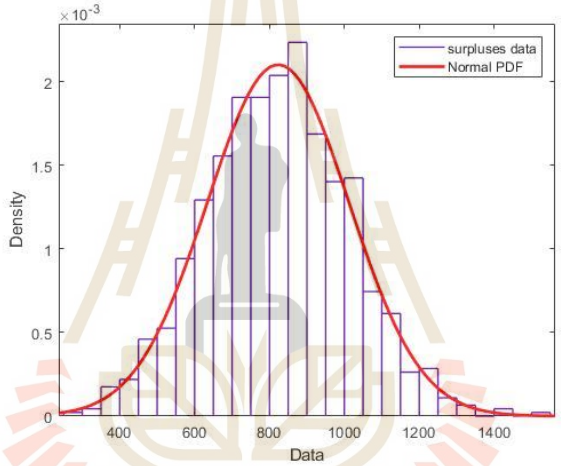


Figure 5.47 The PDF of surplus in the 90% dominate

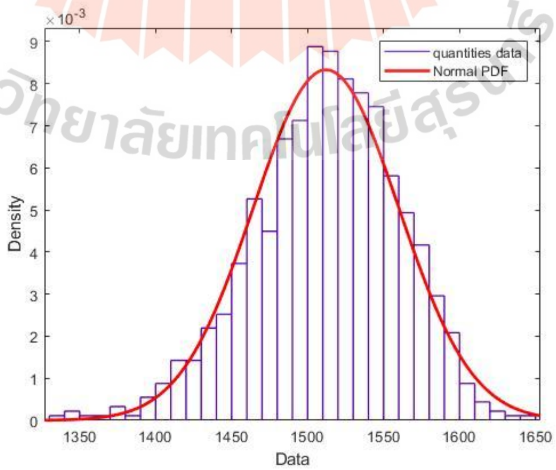


Figure 5.48 The PDF of quantity in the 90% dominate

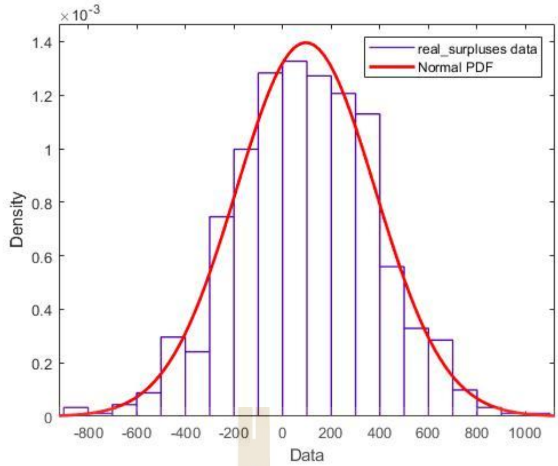


Figure 5.49 The PDF of real surplus in the 90% dominate

5.5.4 Discussion

A comparative analysis of the PBLO-TQSM algorithm with DCTS in different dominance cases is summarized in Table 5.4.

Table 5.4 Comparative analysis of the PBLO-TQSM algorithm with DCTS in different dominance cases

	Balanced case (50%)		Moderate renewable dominance case (70%)		Strong renewable dominance case (90%)	
	Mean	SD	Mean	SD	Mean	SD
Surplus (THB)	487.473	105.534	586.534	137.522	823.145	189.693
Quantity (kWh)	1290.45	117.768	1452.25	92.154	1512.13	47.878
Real surplus (THB)	-1881.72	530.68	-745.636	438.95	95.586	258.707

The study of the PBLO-TQSM algorithm with DCTS in various renewable energy situations shows that renewable energy is important for boosting market surplus, raising trading amounts, and increasing actual surplus. The results from Table 5.4 and sections 5.5.1 to 5.5.3 clearly show that as the share of renewable energy increases, the overall market performance improves. This is primarily because renewable energy, with an average price of 3 THB/kWh, is cheaper than fossil energy, which has an average price of 4 THB/kWh. Having more renewable energy in the system reduces trading costs, increases economic benefits, and enhances real profits, highlighting the financial advantages of using renewable energy in a peer-to-peer energy trading market. In the balanced case (50% renewable, 50% fossil), the trading quantity reached 1,290.45 kWh, with a surplus of 487.473 THB and a real surplus of -1,881.72 THB. The high carbon costs associated with fossil energy significantly impacted the market, resulting in negative real surplus values despite achieving a reasonable trading quantity. Computational convergence required 1,034 iterations, reflecting the complexities of balancing equal shares of renewable and fossil energy in a mixed-energy market. As the share of renewable energy increased to 70% in the moderate renewable dominance scenario, the system's performance improved considerably. The trading quantity increased to 1,452.52 kWh, and the surplus rose to 586.534 THB. Importantly, the real surplus improved significantly to -745.636 THB, showing that as more renewable energy entered the system, the economic burden caused by fossil energy taxation was reduced. This demonstrates that replacing fossil energy with renewable sources not only lowers trading costs but also reduces the financial losses imposed by carbon taxes. The number of convergence iterations remained stable at 1,035, indicating that the market was still efficiently clearing trade despite the shift toward a more renewable-dominant system. In the strong renewable dominance scenario (90% renewable, 10% fossil), the best market performance was observed. With a trading quantity of 1,512.13 kWh, a surplus of 823.145 THB, and a real surplus of 95.586 THB, the data confirms that as renewable energy becomes the primary energy source, market efficiency is maximized. The key driver behind this improvement is the lower price of renewable energy, which reduces the overall cost of trading while still allowing participants to maximize their economic benefits. The shift from a negative to a positive real surplus in this scenario confirms that a renewable-dominant market structure does not just minimize costs but also enhances profitability for market participants. Additionally, the number of convergence iterations decreased to 912, indicating that a system with more renewable energy results in faster market equilibrium due to the cost stability and predictability of renewable energy supply.

Table 5.4 and sections 5.5.1 to 5.5.3 show that as more renewable energy is used, market results improve. The presence of cheaper renewable energy reduces overall electricity costs, increases the trading quantity, and improves both surplus and real surplus values. This suggests that P2P energy trading markets should prioritize policies that incentivize renewable energy adoption to maximize economic benefits and ensure long-term financial sustainability. Governments and regulators should support renewable energy investments, introduce carbon tax benefits for renewable transactions, and develop smart grid solutions that facilitate higher renewable energy integration. By doing so, energy markets can transition toward a more cost-efficient, sustainable, and financially robust decentralized energy trading model, benefiting both consumers and suppliers.

CHAPTER VI
CONCLUSION AND FUTURE WORK

6.1 Conclusion

This study presents PBLO-TQSM in P2P electricity markets. As energy systems transition toward decentralized and renewable-based frameworks, this research addresses key challenges in maximizing trading efficiency, optimizing economic surplus, and incorporating environmental sustainability through carbon taxation mechanisms. The proposed algorithm integrates bi-level optimization with MCS to account for uncertainties in energy supply, demand, and pricing, offering a robust framework for modern energy trading systems. The PBLO-TQSM framework introduces an innovative approach that addresses significant gaps in existing P2P energy trading models: the major-level focuses on maximizing trading quantity to ensure effective resource matching between buyers and sellers, while the minor-level optimizes economic surplus, balancing fairness and market efficiency. By deducting opportunity losses from unmatched participants, the model provides a comprehensive assessment of market performance, accounting for inefficiencies in trading processes. Integrating DCTS that shares a carbon tax between buyers and sellers promotes renewable energy adoption, aligns market behavior with sustainability goals, and reduces the environmental impact of fossil fuel consumption. Using Monte Carlo Simulation, the model captures market variability and evaluates performance under realistic conditions, offering practical insights into dynamic energy markets. The PBLO-TQSM outperforms P2P MMM by achieving higher trading volumes and economic surplus, even under market uncertainty. The DCTS introduces significant shifts in trading patterns, with renewable energy sources becoming more competitive, effectively reducing fossil fuel transactions and supporting carbon neutrality. Sensitivity analysis showed the system's adaptability; while price increases led to a decline in trading quantity, the framework maintained balance between market efficiency and environmental goals. Simulations involving 50 buyers and 50 sellers demonstrated the framework's scalability and robustness, validating its applicability to real-world energy markets.

6.2 Future work

This research provides a foundational model for advancing P2P energy trading systems and suggests areas for future work, such as dynamic pricing models, integration of grid constraints and energy storage, pilot studies in real-world markets, and multi-objective optimization to balance economic, environmental, and social goals. By addressing trade-offs between trading quantity and social welfare, integrating carbon costs, and leveraging probabilistic methods, the PBLO-TQSM framework offers a robust solution for modern energy markets. It contributes valuable insights for policymakers, market operators, and stakeholders, paving the way for resilient and environmentally conscious energy systems.

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APPENDIX A

Example of raw result of PBLO-TQSM in case A (without DCTS)

Table A.1 Raw result of PBLO-TQSM in round 1

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2.28	42	42	2.06	35.29	0
2.37	22.89	22.89	2.4	24.7	0
2.49	30.06	30.06	2.52	36.07	0
2.59	20.67	20.67	2.54	28.85	0
2.65	40.83	40.83	2.68	33.13	0
2.71	26.4	26.4	2.72	27.67	0
2.76	41.17	41.17	2.77	30.37	12.34
2.79	28.07	28.07	2.85	20	20
2.8	36.13	36.13	2.9	41.85	41.85
2.82	23.9	23.9	2.92	21.27	21.27
2.82	44.97	44.97	2.98	27.25	27.25
2.95	28.69	28.69	2.98	34.95	34.95
2.98	39.88	39.88	2.98	37.87	37.87
3.01	41.93	41.93	3.01	20.29	20.29
3.13	40.1	40.1	3.12	34.63	34.63
3.15	41.39	41.39	3.14	29.31	29.31
3.26	31.26	31.26	3.15	31.96	31.96
3.35	35.46	35.46	3.2	38.49	38.49
3.38	30.04	30.04	3.33	42.4	42.4
3.42	28.56	28.56	3.37	48.92	48.92

Table A.1 Raw result of PBLO-TQSM in round 1 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
3.45	41.12	41.12	3.4	41.42	41.42
3.45	28.64	28.64	3.48	33.12	33.12
3.46	43.91	43.91	3.55	35.59	35.59
3.57	38.52	38.52	3.56	40.74	40.74
3.61	39.72	39.72	3.6	27.23	27.23
3.65	20	20	3.63	42.59	42.59
3.7	38.79	38.79	3.65	48.83	48.83
3.71	48.96	48.96	3.66	35.32	35.32
3.77	31.42	31.42	3.67	34.52	34.52
3.77	41.62	41.62	3.71	29.58	29.58
3.82	31.34	31.34	3.72	29.29	29.29
3.87	33.61	33.61	3.77	39.73	39.73
3.89	28.77	28.77	3.78	34	34
3.92	33.52	33.52	3.78	29.06	29.06
3.98	25.19	25.19	3.82	31.99	31.99
4.07	43.87	43.87	3.85	22.73	22.73
4.2	37.8	37.8	3.88	29.43	29.43
4.28	37.95	37.95	4.07	36.51	36.51
4.35	42.53	42.53	4.19	30.81	30.81
4.37	30.36	30.36	4.19	32.7	32.7
4.38	36.06	36.06	4.2	34.82	34.82
4.38	41.43	4.52	4.2	37.48	37.48
4.54	41.11	0	4.23	27.84	27.84
4.59	39.44	0	4.29	23.97	23.97
4.59	47.95	0	4.3	43.49	43.49
4.63	27.85	0	4.31	24.83	24.83

Table A.1 Raw result of PBLO-TQSM in round 1 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
4.7	36.79	0	4.49	33.68	33.68
4.73	37.15	0	4.5	28.15	28.15
4.77	39.38	0	4.86	25.51	25.51
5	34.6	0	4.89	26.13	26.13

Table A.2 Raw result of PBLO-TQSM in round 100

Supply			Demand		
THB/kWh	Offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2	32.86	32.86	2	36.35	0
2	33.19	33.19	2.09	32.05	0
2.23	41.52	41.52	2.49	26.78	0
2.33	30.07	30.07	2.63	31.29	0
2.35	33.98	33.98	2.65	35.39	0
2.41	41.33	41.33	2.71	43.4	0
2.43	35.49	35.49	2.72	46.12	12.04
2.53	27.11	27.11	2.75	40.01	40.01
2.66	43.37	43.37	2.76	47.16	47.16
2.8	39.6	39.6	2.88	42.71	42.71
2.9	42.2	42.2	2.92	29.97	29.97
2.91	28.14	28.14	3.02	42.73	42.73
2.92	33.4	33.4	3.04	34.42	34.42
3	26.18	26.18	3.06	37.28	37.28
3.03	43.29	43.29	3.08	30	30
3.03	32.6	32.6	3.14	40.9	40.9

Table A.2 Raw result of PBLO-TQSM in round 100 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
3.06	37.27	37.27	3.25	39.47	39.47
3.17	36.42	36.42	3.25	29.64	29.64
3.18	35.87	35.87	3.31	30.51	30.51
3.18	43.7	43.7	3.47	35.09	35.09
3.23	39.35	39.35	3.53	42	42
3.27	29.07	29.07	3.56	34.57	34.57
3.38	37.34	37.34	3.59	35.35	35.35
3.41	33.82	33.82	3.59	35.44	35.44
3.42	32.87	32.87	3.6	31.64	31.64
3.48	47.8	47.8	3.6	46.76	46.76
3.52	45.89	45.89	3.6	45.1	45.1
3.59	20.68	20.68	3.62	38.22	38.22
3.69	25.2	25.2	3.7	33.32	33.32
3.7	39.76	39.76	3.72	35.69	35.69
3.75	31.39	31.39	3.75	36.75	36.75
3.79	34.93	34.93	3.76	23.53	23.53
3.79	22.47	22.47	3.78	24.09	24.09
3.82	26.34	26.34	3.8	24.89	24.89
3.89	37.82	37.82	3.84	44.79	44.79
3.89	29.65	29.65	3.86	32.48	32.48
3.92	40.08	40.08	3.89	38.93	38.93
3.97	32.96	32.96	3.95	43.05	43.05
4	46.53	46.53	3.97	41.3	41.3
4.12	32.29	32.29	3.98	26.23	26.23
4.19	34.17	34.17	3.99	45.76	45.76
4.22	30.75	30.75	3.99	37.61	37.61

Table A.2 Raw result of PBLO-TQSM in round 100 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
4.26	25.92	25.92	4.03	46.29	46.29
4.28	40.19	34.55	4.05	35.82	35.82
4.29	37.97	0	4.33	23.23	23.23
4.36	34.94	0	4.41	30.69	30.69
4.4	31.14	0	4.58	38.59	38.59
4.67	35.19	0	4.85	23.82	23.82
4.74	43.15	0	5	20.91	20.91
5	20.31	0	5	20.44	20.44

Table A.3 Raw result of PBLO-TQSM in round 200

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2	22.37	22.37	2	38.63	0
2	23.45	23.45	2	30.43	0
2.51	41.36	41.36	2.25	38.14	0
2.53	50	50	2.4	45.38	0
2.6	36.63	36.63	2.64	38.31	12.49
2.69	38.59	38.59	2.72	28.87	28.87
2.76	26.96	26.96	2.81	35.84	35.84
2.76	29.43	29.43	2.83	44.39	44.39
2.79	35.13	35.13	2.86	25.03	25.03
2.88	31.32	31.32	2.89	37.16	37.16
2.89	37.83	37.83	2.93	29.75	29.75
2.89	44.06	44.06	2.98	33.36	33.36

Table A.3 Raw result of PBLO-TQSM in round 200 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2.95	23.9	23.9	3.01	30.4	30.4
3.1	26.36	26.36	3.03	32.84	32.84
3.15	37.48	37.48	3.04	32.74	32.74
3.17	47.88	47.88	3.13	44.18	44.18
3.18	44.07	44.07	3.15	38.54	38.54
3.18	39.93	39.93	3.2	40.86	40.86
3.23	36.14	36.14	3.32	26.23	26.23
3.33	25.77	25.77	3.38	37.6	37.6
3.38	38.59	38.59	3.38	34.28	34.28
3.39	29.09	29.09	3.57	32.79	32.79
3.41	34.48	34.48	3.58	32.85	32.85
3.41	33.48	33.48	3.62	32.54	32.54
3.45	31.59	31.59	3.65	35.11	35.11
3.52	43.8	43.8	3.65	28.12	28.12
3.55	34.19	34.19	3.69	31.99	31.99
3.64	23.03	23.03	3.69	36.38	36.38
3.72	20	20	3.72	35.24	35.24
3.78	37.48	37.48	3.76	39.2	39.2
3.82	39.17	39.17	3.77	26.52	26.52
3.93	41.22	41.22	3.82	36.81	36.81
4.12	33.02	33.02	3.91	35.7	35.7
4.12	27.6	27.6	3.92	44.57	44.57
4.25	39.07	39.07	4.13	42.96	42.96
4.25	31.27	31.27	4.15	39.39	39.39
4.28	30.12	30.12	4.24	36.53	36.53
4.3	40.29	40.29	4.24	34.14	34.14

Table A.3 Raw result of PBLO-TQSM in round 200 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
4.31	27.7	27.7	4.33	37.58	37.58
4.35	36.83	36.83	4.34	35.11	35.11
4.39	29.89	29.89	4.39	36.71	36.71
4.42	45.66	45.66	4.4	29.46	29.46
4.43	30.21	30.21	4.43	39.1	39.1
4.48	48.67	48.67	4.48	39.56	39.56
4.52	27.45	27.45	4.48	27.11	27.11
4.62	35.11	35.11	4.51	32.72	32.72
4.69	34.07	0.04	4.53	48.54	48.54
4.75	44.97	0	4.81	33.7	33.7
4.95	39.46	0	4.84	37.19	37.19
5	37.3	0	5	25.53	25.53

Table A.4 Variables considered during various rounds of PBLO-TQSM

Round	Shifting factor	Surplus	Real surplus	Quantity
1	203.74	385.08	-1029	1432.62
100	239.34	559.11	-574.96	1529.22
200	178.4	386.9	-547.6	1587.71
300	192.23	480.31	-800.27	1489.54
400	318.06	364.51	-1171.4	1423.79

APPENDIX B

Example of raw result of P2P MMM in case A (without DCTS)

Table B.1 Raw result of P2P MMM in round 1

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
5	46.31	46.31	5	49.14	49.14
5	28.33	0	5	32.42	32.42
4.76	41.19	41.19	4.91	34.73	34.73
4.53	43.95	43.95	4.64	32.06	32.06
4.47	34.75	34.75	4.57	26	26
4.36	27.81	27.81	4.56	25.07	25.07
4.35	39.12	29.81	4.36	24.4	24.4
4.3	20	0	4.28	50	50
4.23	35.7	35.7	4.27	29.02	29.02
4.09	31.3	31.3	4.14	34.02	34.02
4.04	31.81	31.81	4.1	31.31	31.31
4.04	32.6	0	4.08	35.57	35.57
3.97	48.01	48.01	4.02	29.7	29.7
3.9	23.2	23.2	3.96	25.81	25.81
3.88	39.93	39.93	3.91	23.86	23.86
3.86	32.22	32.22	3.84	27.4	27.4
3.81	36.36	36.36	3.84	43.94	43.94
3.81	28.27	0	3.8	32.54	32.54
3.7	27.87	27.87	3.71	50	50
3.62	22.88	22.88	3.7	28.11	28.11
3.61	24.39	24.39	3.66	39.24	39.24
3.6	32.66	32.66	3.64	31.13	31.13

Table B.1 Raw result of P2P MMM in round 1 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
3.58	33.34	33.34	3.63	38.03	38.03
3.56	39.38	39.38	3.61	43.35	43.35
3.56	20	0	3.57	33.25	33.25
3.5	26.78	26.78	3.55	30.54	30.54
3.44	32.21	32.21	3.55	34.65	34.65
3.35	40.09	40.09	3.54	26.86	26.86
3.29	40.06	40.06	3.53	37.55	37.55
3.29	37.46	0	3.51	30.69	30.69
3.24	30.99	30.99	3.51	20	20
3.22	44.01	44.01	3.5	33.21	33.21
3.21	33.28	33.28	3.42	20.73	20.73
3.13	36.96	36.96	3.32	20.6	20.6
3.12	36.97	36.97	3.29	28.55	28.55
3.1	35.14	35.14	3.23	27.78	27.78
3.06	33.46	33.46	2.93	37.7	37.7
3.05	26.24	26.24	2.93	31.37	31.37
3.04	27.67	27.67	2.92	31.51	31.51
3.03	38.92	34.53	2.9	38.57	38.57
3.02	43.79	0	2.83	34.85	34.85
2.9	25.04	25.04	2.8	29.44	29.44
2.87	30.04	30.04	2.79	50	50
2.86	20	20	2.45	32.74	32.74
2.84	37.84	37.84	2.36	30.47	18.53
2.81	33.04	33.04	2.27	31.67	0
2.8	40.08	40.08	2.2	26.11	0
2.54	38.31	38.31	2.04	23.1	0
2.44	42.15	42.15	2	32.7	0

Table B.1 Raw result of P2P MMM in round 1 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2.24	38.21	38.21	2	25.08	0

Table B.2 Raw result of P2P MMM in round 500

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
5	33.29	33.29	5	45.9	45.9
4.83	28.76	28.76	5	46.51	46.51
4.58	37.13	37.13	4.99	25.03	25.03
4.55	24.13	24.13	4.97	35.66	35.66
4.5	20	20	4.7	24.1	24.1
4.46	42.62	42.62	4.68	43.65	43.65
4.42	20.65	20.65	4.54	41.71	41.71
4.34	20	20	4.44	37.75	37.75
4.33	34.95	34.95	4.42	36	36
4.23	36.77	36.77	4.33	42.82	42.82
4.13	34.42	34.42	4.28	31.54	31.54
4.08	40.65	40.65	4.23	28.71	28.71
4.04	34.89	34.89	4.17	38.46	38.46
4.01	37.77	37.77	4.1	40.59	40.59
3.99	37.86	37.86	4.06	28.88	28.88
3.99	38.98	0	4.06	36.16	36.16
3.96	47.17	47.17	4.05	26.44	26.44
3.93	40.13	40.13	4.03	20	20
3.87	31.04	31.04	3.9	38.36	38.36
3.82	32.53	32.53	3.89	34.68	34.68

Table B.2 Raw result of P2P MMM in round 500 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
3.81	27.77	27.77	3.88	34.05	34.05
3.75	33.62	33.62	3.85	37.07	37.07
3.74	46.28	46.28	3.83	40.61	40.61
3.71	30.96	30.96	3.83	35	35
3.71	40.71	0	3.78	37.42	37.42
3.68	28.14	28.14	3.74	31.99	31.99
3.67	34.65	34.65	3.45	32.69	32.69
3.65	27.63	27.63	3.43	35.48	35.48
3.65	26.42	0	3.39	20.2	20.2
3.6	23.04	23.04	3.39	41.68	41.68
3.57	27.32	27.32	3.37	45.74	45.74
3.51	33.42	4.92	3.23	36.43	36.43
3.47	48.24	0	3.22	36.55	36.55
3.47	38.8	0	3.18	43.74	43.74
3.35	20.75	20.75	3.14	32.92	32.92
3.28	31.43	31.43	3.12	27.98	27.98
3.27	35.7	35.7	3.1	38.35	38.35
3.24	44.08	44.08	3.06	41.57	41.57
3.14	32.21	32.21	3.05	39.52	39.52
3.06	29.24	29.24	3.05	39.01	16.59
3.02	28.22	28.22	2.98	48.1	0
3.01	30.45	30.45	2.95	47.3	0
2.99	40.77	40.77	2.86	42.76	0
2.95	27	27	2.72	38.03	0
2.92	41.44	41.44	2.63	20.99	0
2.91	28.63	28.63	2.6	31.84	0
2.91	32.19	0	2.42	35.63	0

Table B.2 Raw result of P2P MMM in round 500 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2.79	27.98	27.98	2.27	22.44	0
2.65	37.93	37.93	2.26	22.63	0
2.38	33.61	33.61	2.15	29.65	0

Table B.3 Raw result of P2P MMM in round 1000

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
5	35.7	35.7	5	22.13	22.13
4.98	29.75	29.75	5	44.13	44.13
4.91	35.11	35.11	5	41.12	41.12
4.89	32.94	32.94	4.99	44.1	44.1
4.61	34.53	34.53	4.82	30.74	30.74
4.58	43.37	43.37	4.71	37.47	37.47
4.58	31.08	0	4.53	25.92	25.92
4.54	38.71	8.29	4.2	44.26	44.26
4.45	32.5	25.92	4.18	28.43	28.43
4.39	43.62	0	4.18	32.47	32.47
4.37	32.86	0	4.12	48.78	48.78
4.3	43.18	0	4.07	34.83	34.83
4.3	26.1	0	4.07	27.94	27.94
4.26	39.32	0	4.05	48.23	48.23
4.21	41.27	0	3.95	46.36	46.36
4.21	40.77	0	3.95	37.13	37.13
4.13	29.98	29.98	3.84	32.66	32.66
4.1	27.68	27.68	3.81	38.77	38.77
4.02	39.25	39.25	3.81	33.26	33.26

Table B.3 Raw result of P2P MMM in round 1000 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
4	44.68	44.68	3.78	28.02	28.02
3.99	30.33	30.33	3.78	48.53	48.53
3.9	50	50	3.7	33.73	33.73
3.85	36.13	36.13	3.66	30.93	30.93
3.85	38.69	0	3.62	32.1	32.1
3.79	20	20	3.55	30.66	30.66
3.74	36.16	36.16	3.54	34.99	34.99
3.73	22.93	22.93	3.51	28.99	28.99
3.66	50	50	3.43	41.99	41.99
3.59	38.57	38.57	3.39	26.54	26.54
3.59	22.16	0	3.35	41.4	41.4
3.49	36.87	36.87	3.34	22.67	22.67
3.49	39.83	0	3.32	32.89	32.89
3.48	24.79	24.79	3.26	28.99	28.99
3.47	36.13	36.13	3.24	34.05	34.05
3.39	37.63	37.63	3.23	27.78	27.78
3.36	38.97	38.97	3.19	32.66	32.66
3.35	22.27	22.27	3.16	32.3	25.74
3.29	37.63	37.63	3.15	25.11	0
3.28	24.21	24.21	3.12	27.9	0
3.17	38.84	38.84	3.01	25.58	0
3.08	43.64	43.64	2.85	20	0
3.06	30.75	30.75	2.84	28.65	0
3.04	27.78	27.78	2.83	34.63	0
3.04	35.92	0	2.69	43.9	0
3	48.51	48.51	2.59	35.34	0

Table B.3 Raw result of P2P MMM in round 1000 (continued)

Supply			Demand		
THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
2.9	36.72	36.72	2.57	32.38	0
2.89	21.73	21.73	2.47	33.34	0
2.84	21.01	21.01	2.47	34.25	0
2.66	32.59	32.59	2.42	27.99	0
2.57	50	50	2.27	32.03	0

Table B.4 Variables considered during various rounds of P2P MMM

Round	Surplus	Real surplus	Quantity
1	282.392	-549.66	1465.97
500	305.12	-927.85	1408.53
1000	316.33	-1610.2	1281.39

APPENDIX C

Example of raw result of PBLO-TQSM in case B (with DCTS)

Table C.1 Raw result of PBLO-TQSM in round 1

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	2	34.53	34.53	2	22.85	0
1	2.08	43.09	43.09	2	33.88	0
0	2.4	30.03	30.03	2.44	33.79	0
1	2.41	47.33	47.33	2.66	41.1	8.21
1	2.47	50	50	2.78	25.27	25.27
1	2.51	36.01	36.01	2.82	42.05	42.05
0	2.64	36.54	36.54	2.84	29.47	29.47
1	2.72	34.48	34.48	2.92	20	20
1	2.83	50	50	2.93	48.38	48.38
0	2.84	26.2	26.2	2.95	20	20
0	2.87	38.42	38.42	2.98	28.05	28.05
1	2.97	36.93	36.93	3	37.83	37.83
1	3.06	29.68	29.68	3.02	37.93	37.93
0	3.12	41.52	41.52	3.04	32.84	32.84
1	3.2	33.84	33.84	3.04	41.74	41.74
1	3.22	47.9	47.9	3.06	41.4	41.4
0	3.23	24.71	24.71	3.15	30.43	30.43
0	3.31	47.34	47.34	3.18	39.6	39.6
0	3.41	38.81	38.81	3.25	42.21	42.21
1	3.44	24.08	24.08	3.26	38.55	38.55
0	3.51	29.27	29.27	3.29	37.57	37.57
1	3.52	46.3	46.3	3.38	44.06	44.06

Table C.1 Raw result of PBLO-TQSM in round 1 (continued)

	Supply			Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	3.61	30.9	30.9	3.46	34.93	34.93
1	3.61	29.65	29.65	3.64	27.6	27.6
0	3.65	27.57	27.57	3.83	50	50
1	3.65	27.65	27.65	3.96	32.06	32.06
1	3.82	29.18	29.18	3.96	29.12	29.12
0	3.87	35.79	35.79	3.96	21.79	21.79
1	3.97	32.26	32.26	3.99	24.87	24.87
0	3.98	34.94	34.94	4.03	33.41	33.41
0	4.03	50	50	4.06	36.61	36.61
1	4.06	30.03	30.03	4.07	35.93	35.93
1	4.12	27.86	27.86	4.07	37.84	37.84
0	4.18	33.47	33.47	4.09	39.3	39.3
1	4.19	27.65	27.65	4.13	38.46	38.46
0	4.25	31.97	31.97	4.2	39.29	39.29
1	4.26	37.12	37.12	4.22	31.09	31.09
1	4.35	41.13	41.13	4.22	50	50
1	4.36	28.11	28.11	4.3	26.82	26.82
0	4.39	40.31	40.31	4.31	45.13	45.13
1	4.43	27.56	27.56	4.34	33.21	33.21
0	4.5	39.27	39.27	4.42	39.45	39.45
0	4.55	34.4	34.4	4.55	27.92	27.92
0	4.62	31.01	31.01	4.57	39.8	39.8
0	4.68	40.5	40.5	4.58	39.58	39.58
1	4.7	40.56	40.56	4.68	33.11	33.11
0	4.76	29.17	3.35	4.79	41.9	41.9

Table C.1 Raw result of PBLO-TQSM in round 1 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	4.82	38.96	0	4.83	37.61	37.61
0	4.92	36.82	0	4.99	30.22	30.22
0	5.23	46.69	0	5	36.61	36.61

Table C.2 Raw result of PBLO-TQSM in round 300

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	2	30.11	30.11	2	30.08	0
1	2.31	26.37	26.37	2	27.98	0
1	2.38	33.6	33.6	2	34.79	0
0	2.4	46.12	46.12	2.35	32.01	0
1	2.48	39.6	39.6	2.55	34.59	0
1	2.62	32.19	32.19	2.68	24.19	18.61
1	2.71	32.3	32.3	2.71	50	50
0	2.73	34.93	34.93	2.75	44.51	44.51
0	2.82	32.25	32.25	2.81	37.59	37.59
0	2.88	50	50	2.87	40.74	40.74
1	2.89	36.01	36.01	2.88	43.89	43.89
1	2.95	32.3	32.3	2.88	39.96	39.96
1	2.95	36.28	36.28	2.94	36.33	36.33
1	3.03	41.33	41.33	2.97	42.76	42.76
0	3.05	27.99	27.99	3.03	29.41	29.41
0	3.17	40.81	40.81	3.03	33.08	33.08
1	3.17	29.98	29.98	3.04	29.41	29.41

Table C.2 Raw result of PBLO-TQSM in round 300 (continued)

	Supply			Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	3.24	46.12	46.12	3.16	43.59	43.59
1	3.27	29.81	29.81	3.18	42.62	42.62
1	3.28	38.75	38.75	3.2	43.73	43.73
1	3.33	36.5	36.5	3.22	25.94	25.94
0	3.34	37.19	37.19	3.26	30.47	30.47
0	3.35	44.94	44.94	3.32	35.29	35.29
0	3.4	33.89	33.89	3.35	29.88	29.88
1	3.48	30.94	30.94	3.4	40.08	40.08
0	3.55	35.82	35.82	3.53	21.75	21.75
0	3.58	38.19	38.19	3.57	41.57	41.57
1	3.59	41.34	41.34	3.57	27.05	27.05
0	3.66	49.78	49.78	3.59	49.64	49.64
0	3.68	40.06	40.06	3.6	37.97	37.97
1	3.68	33.87	33.87	3.61	39.4	39.4
0	3.7	27.1	27.1	3.65	43.42	43.42
0	3.73	41.64	41.64	3.78	44.26	44.26
1	3.79	42.63	42.63	3.88	46.51	46.51
1	3.86	44.36	44.36	3.91	36.62	36.62
0	3.91	37.48	37.48	3.91	43.74	43.74
0	4.01	36.73	36.73	3.93	44.31	44.31
1	4.08	45.9	45.9	3.97	30.91	30.91
0	4.11	45.96	45.96	3.99	28.35	28.35
0	4.21	31.46	31.46	4	45.23	45.23
1	4.25	29.14	29.14	4.05	37.69	37.69
1	4.27	37.43	37.43	4.23	36.99	36.99

Table C.2 Raw result of PBLO-TQSM in round 300 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	4.39	38.25	38.25	4.27	28.79	28.79
0	4.49	28.61	28.61	4.46	24.04	24.04
1	4.57	27.01	27.01	4.48	37.38	37.38
0	4.67	26.76	7.05	4.53	50	50
1	4.83	38.6	0	4.87	23.14	23.14
0	4.97	20	0	5	33.04	33.04
0	5.03	24.39	0	5	34.86	34.86
0	5.33	35.49	0	5	35.57	35.57

Table C.3 Raw result of PBLO-TQSM in round 600

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	2.75	50	50	2.21	33.9	0
1	2.88	32.28	32.28	2.28	35.18	0
1	2.89	36.93	36.93	2.53	35.04	0
1	2.95	48.21	48.21	2.57	28.84	0
1	3.06	20	20	2.71	33.93	0
0	3.23	43.88	43.88	2.76	50	0
1	3.24	38.89	38.89	2.77	20	0
0	3.29	46.43	46.43	2.8	46.74	0
0	3.31	37.2	37.2	2.8	31.65	0
1	3.32	27.93	27.93	2.95	27.6	0
1	3.39	35.84	35.84	2.99	20	0
0	3.4	29.92	29.92	3.01	27.41	0
1	3.45	24.19	24.19	3.03	27.99	0

Table C.3 Raw result of PBLO-TQSM in round 600 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	3.48	41.53	41.53	3.03	26.51	20.55
1	3.51	29.48	29.48	3.05	29.14	29.14
0	3.6	37.36	37.36	3.05	39.7	39.7
1	3.6	29.46	29.46	3.07	23.21	23.21
1	3.62	21.23	21.23	3.2	33.65	33.65
0	3.69	30.19	30.19	3.21	41.17	41.17
0	3.74	32.31	32.31	3.28	30.58	30.58
1	3.76	25.26	25.26	3.34	27.77	27.77
0	3.84	40.3	40.3	3.37	50	50
0	3.85	42.41	42.41	3.4	38.6	38.6
0	3.88	37.97	37.97	3.54	27.11	27.11
1	3.89	31.93	31.93	3.68	23.66	23.66
1	3.92	38.63	38.63	3.7	43.32	43.32
0	3.93	29.96	29.96	3.71	40.87	40.87
1	4	36.15	36.15	3.73	34.77	34.77
0	4.02	47.48	47.48	3.82	41.59	41.59
1	4.06	37.84	37.84	3.86	38.54	38.54
0	4.1	44.58	44.58	3.89	41.52	41.52
0	4.16	31.4	31.4	3.89	32.31	32.31
1	4.17	24.63	24.63	3.92	39.4	39.4
1	4.24	38.06	38.06	3.97	46.04	46.04
1	4.26	44.52	44.52	4.1	25.7	25.7
0	4.31	44.27	44.27	4.1	41.76	41.76
1	4.39	33.83	5.96	4.11	29.36	29.36
0	4.39	31.24	0	4.15	24.62	24.62
1	4.43	33.8	0	4.21	27.63	27.63
0	4.44	29.45	0	4.24	39.19	39.19

Table C.3 Raw result of PBLO-TQSM in round 600 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	4.46	33.97	0	4.25	44.69	44.69
0	4.47	35.95	0	4.35	36.15	36.15
0	4.6	34.35	0	4.37	36.55	36.55
0	4.65	30.03	0	4.48	20	20
1	4.68	42.22	0	4.53	37.08	37.08
0	4.75	39.66	0	4.59	33.44	33.44
0	4.8	33.99	0	4.65	40.94	40.94
0	4.83	46.04	0	4.83	40.16	40.16
0	4.9	35.6	0	4.98	39.03	39.03
0	5.34	36.63	0	5	34.81	34.81

Table C.4 Variables considered during various rounds of PBLO-TQSM

Round	Shifting factor	Surplus	Real surplus	Quantity
1	123.41	432.88	-340.228	1639.25
300	165.03	346.91	-527.505	1660.12
600	424.24	377.26	-1904.39	1294.61

APPENDIX D

Example of raw result of P2P MMM in case B (with DCTS)

Table D.1 Raw result of P2P MMM in round 1

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	5.31	29.56	0	4.69	35.75	35.75
0	5.05	39.23	0	4.53	41.78	41.78
1	5	35.02	0	4.5	41.58	41.58
0	4.8	21.64	0	4.44	29.34	29.34
1	4.72	35.07	0	4.44	39.16	39.16
0	4.66	28.51	28.51	4.38	37.49	37.49
0	4.51	29.45	29.45	4.35	34.56	34.56
0	4.47	37.98	37.98	4.29	20.25	20.25
1	4.46	40.8	23.17	4.29	28.24	28.24
1	4.29	31.43	31.43	4.23	28.12	28.12
0	4.24	40.34	40.34	4.17	28.67	28.67
0	4.16	38.35	38.35	4.16	37.69	37.69
1	4.14	22.31	22.31	4.16	49.89	49.89
0	4.11	30.51	30.51	4.14	43.1	43.1
1	4.07	31.54	31.54	4.11	30.22	30.22
0	4.06	28.35	28.35	4.05	42.12	42.12
0	4.03	47.24	47.24	4.05	45.61	45.61
1	4	40.93	40.93	4.03	21.25	21.25
0	3.82	33.25	33.25	4.01	48.41	48.41
0	3.81	24.28	24.28	3.94	48.67	48.67
0	3.79	41.55	41.55	3.89	30.06	30.06
1	3.78	38.53	38.53	3.87	50	50

Table D.1 Raw result of P2P MMM in round 1 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	3.75	43.83	43.83	3.79	39.57	39.57
0	3.72	50	50	3.77	28.99	28.99
1	3.67	28.8	28.8	3.74	33.63	33.63
0	3.65	32.19	32.19	3.73	27.41	27.41
1	3.64	25.94	25.94	3.71	38.54	38.54
0	3.63	50	50	3.67	45.69	45.69
1	3.52	23.88	23.88	3.67	21.58	21.58
0	3.47	37.64	37.64	3.65	34.54	34.54
0	3.43	41.25	41.25	3.62	35.81	35.81
1	3.41	50	50	3.5	31.02	31.02
1	3.4	27.98	27.98	3.37	35.05	35.05
0	3.35	30.32	30.32	3.36	29.58	29.58
1	3.32	33.45	33.45	3.31	21.48	21.48
1	3.25	33.16	33.16	3.28	25.92	25.92
1	3.23	39.63	39.63	3.18	37	37
0	3.14	50	50	3.15	40.49	40.49
1	3.13	33.16	33.16	3.11	34.62	34.62
1	3.04	32.33	32.33	3.08	48.55	48.55
1	3.02	31.41	31.41	3.07	34.46	34.46
0	3	34.51	34.51	3.03	48.55	48.55
1	2.85	37.6	37.6	2.97	33.41	32.27
1	2.7	28.97	28.97	2.83	24.1	0
1	2.54	26.41	26.41	2.74	37.87	0
0	2.47	29.61	29.61	2.74	35.3	0
0	2.4	35.95	35.95	2.62	33.91	0
0	2.4	33.88	0	2.36	26.96	0
1	2.06	40.61	40.61	2.26	43.03	0

Table D.1 Raw result of P2P MMM in round 1 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	2	40.36	40.36	2	22.4	0

Table D.2 Raw result of P2P MMM in round 500

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	5.4	27.69	0	5	40.28	40.28
1	5	31.44	31.44	5	43.77	43.77
0	4.97	28.98	28.98	4.93	27.46	27.46
0	4.84	22.36	22.36	4.84	28.58	28.58
1	4.77	30.21	30.21	4.5	44.81	44.81
0	4.7	31.43	27.1	4.48	41.96	41.96
0	4.67	49.26	0	4.47	40.49	40.49
0	4.65	25.49	0	4.43	28.57	28.57
0	4.58	25.08	0	4.35	33.96	33.96
0	4.48	45.41	45.41	4.34	38.68	38.68
1	4.47	30.85	30.85	4.17	47.66	47.66
0	4.39	39.11	39.11	4.16	46.98	46.98
1	4.38	31.97	31.97	4.13	33.47	33.47
0	4.29	30.21	30.21	4.01	48.56	48.56
1	4.27	26.47	26.47	3.96	38.06	38.06
1	4.27	34.94	0	3.93	29.31	29.31
1	4.23	27.81	24.45	3.91	34.19	34.19
0	4.19	20	0	3.9	31.02	31.02
0	4.14	37.78	37.78	3.88	31.62	31.62
1	4.1	50	50	3.87	30.04	30.04

Table D.2 Raw result of P2P MMM in round 500 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	4.09	30.14	30.14	3.8	34.54	34.54
1	4.08	50	10.19	3.78	31.48	31.48
1	3.98	35.01	35.01	3.77	30.25	30.25
0	3.93	34.39	34.39	3.76	27.16	27.16
0	3.81	36.14	36.14	3.76	35.66	35.66
1	3.8	37.9	37.9	3.73	48.36	48.36
1	3.76	33.99	33.99	3.66	41.41	41.41
1	3.73	29.73	29.73	3.6	33.35	33.35
0	3.7	38.18	38.18	3.57	50	50
1	3.62	37.4	37.4	3.5	40.3	40.3
0	3.61	50	50	3.46	41.92	41.92
0	3.54	40.87	40.87	3.45	26.74	26.74
0	3.46	36.1	36.1	3.43	29.17	29.17
1	3.44	32.31	32.31	3.42	34.29	34.29
1	3.33	36.26	36.26	3.4	36.36	36.36
0	3.31	30.54	30.54	3.35	24.3	24.3
1	3.29	46.76	46.76	3.27	32.75	32.75
0	3.24	29.91	29.91	3.21	28.37	28.37
0	3.16	33.38	33.38	3.18	41.71	41.71
1	3.15	39.29	39.29	3.14	50	50
0	3.09	36.53	36.53	3.09	37.39	37.39
1	3.06	37.96	37.96	3.02	48.43	11.4
1	2.99	39.31	39.31	2.94	28.25	0
0	2.91	37.49	37.49	2.64	38	0
1	2.85	33.54	33.54	2.51	45.27	0
1	2.77	40.37	40.37	2.47	36.44	0
1	2.7	27.99	27.99	2.36	34.19	0

Table D.2 Raw result of P2P MMM in round 500 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	2.57	39.69	39.69	2.26	40.42	0
1	2.53	21.36	21.36	2.17	34.34	0
1	2.37	37.31	37.31	2	43	0

Table D.3 Raw result of P2P MMM in round 1000

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	5.36	22.06	0	5	47.82	47.82
0	5.01	39.14	0	4.75	42	42
1	5	38.35	38.35	4.72	46.96	46.96
0	4.72	34.63	34.63	4.66	41.97	41.97
1	4.66	30.78	30.78	4.57	41.1	41.1
0	4.64	27.88	27.88	4.5	37.45	37.45
1	4.56	27.48	27.48	4.46	26.5	26.5
0	4.39	47.05	47.05	4.3	34.15	34.15
0	4.33	36.24	36.24	4.24	45.81	45.81
1	4.29	44.05	44.05	4.24	38.33	38.33
0	4.2	34.62	34.62	4.24	23.37	23.37
1	4.16	37.87	37.87	4.23	42.84	42.84
0	4.15	40.59	40.59	4.17	35.83	35.83
1	3.99	50	50	4.16	35.79	35.79
0	3.99	28.14	28.14	4.13	40.21	40.21
0	3.95	27.96	27.96	4.06	36.05	36.05
1	3.89	50	50	4.06	48.57	48.57
0	3.85	44.88	44.88	3.96	48.37	48.37
0	3.84	36.39	36.39	3.95	23.52	23.52

Table D.3 Raw result of P2P MMM in round 1000 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
0	3.83	35.13	35.13	3.94	39.28	39.28
1	3.8	29.4	29.4	3.93	44.92	44.92
0	3.69	37.7	37.7	3.91	37.11	37.11
1	3.68	28.84	28.84	3.91	46.82	46.82
0	3.62	35.3	35.3	3.89	29.2	29.2
1	3.57	41.38	41.38	3.81	30.45	30.45
0	3.55	31.63	31.63	3.79	37.96	37.96
1	3.53	39.04	39.04	3.77	24.97	24.97
0	3.53	39.5	0	3.73	36.33	36.33
0	3.5	47.8	47.8	3.72	29	29
1	3.45	38.97	38.97	3.69	48.68	48.68
1	3.44	32.02	32.02	3.53	33.14	33.14
0	3.43	45.91	45.91	3.41	29.05	29.05
1	3.38	32.95	32.95	3.38	29.36	29.36
1	3.29	32.16	32.16	3.05	35.91	35.91
0	3.26	40.72	40.72	3.01	35.76	35.76
1	3.18	32.35	32.35	2.99	33.99	33.99
1	3.14	33.77	14.7	2.98	40.72	40.72
0	3.13	39.62	0	2.96	38.98	38.98
1	3.1	34.53	0	2.94	28.72	28.72
1	3.04	32.7	32.7	2.89	30.97	30.97
0	2.98	21.01	21.01	2.85	36.85	36.85
1	2.96	27.16	27.16	2.84	21.47	21.47
1	2.83	28	28	2.83	29.71	22.52
0	2.83	50	0	2.82	28.61	0
0	2.79	34.51	34.51	2.72	39.73	0
1	2.65	32.74	32.74	2.56	37.94	0

Table D.3 Raw result of P2P MMM in round 1000 (continued)

Supply				Demand		
Index	THB/kWh	offer (kWh)	Power sell (kWh)	THB/kWh	offer (kWh)	Power purchase (kWh)
1	2.48	33.79	33.79	2.55	36.78	0
0	2.4	31.73	31.73	2.4	36.52	0
1	2.39	34.58	34.58	2.29	36.36	0
1	2	49.67	49.67	2.2	32.55	0

Table D.4 Variables considered during various rounds of P2P MMM

Round	Surplus	Real surplus	Quantity
1	484.1239	-608.293	1536.71
500	338.8047	-1097.53	1506.38
1000	392.7395	-641.491	1558.8

APPENDIX E

LIST OF PUBLICATION

P. Sakolkiatkajorn and K. Chayakulkheeree (2024), Power Pool vs P2P Energy Trading Mechanisms: A Social Welfare Perspective, 2024 12th International Electrical Engineering Congress (iEECON), Pattaya, Thailand.

P. Sakolkiatkajorn and K. Chayakulkheeree (2024), Bi-level optimization algorithm for trading quantity and surplus maximization in P2P electricity market, ECTI transactions on electrical engineering, electronics, and communications.

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Power Pool vs P2P Energy Trading Mechanisms: A Social Welfare Perspective

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Abstract—This paper presents a comparative study of Power Pool and Peer-to-Peer (P2P) energy trading mechanisms from a social welfare perspective. Focusing on the evolving landscape of energy trading, particularly amidst the integration of renewable energy sources, this study utilizes linear programming and a multi-stage matching mechanism (MMM) to analyze and compare these two models. Our findings reveal that while the P2P model facilitates a greater volume of energy transactions, the Power Pool model achieves higher social welfare. This contrast highlights the distinct strengths and weaknesses of each market mechanism. The research underscores the importance of developing criteria for an efficient comparison between the two models and contemplates the inclusion of additional variables like carbon credits and the impact of geographical proximity on renewable energy trading. The study contributes to a deeper understanding of these trading mechanisms, providing insights crucial for shaping future energy markets.

Keywords—Power Pool Market, Peer-to-Peer Energy Trading, Social welfare, Linear Programming, Multi-stage Matching Mechanism (MMM).

I. Introduction

The exchange mechanisms of electrical energy has been significantly developed in the last several decades. The paradigm shift of the electricity supply industry can be divided into three phases. 1) Early electricity markets, the inception of electricity markets occurred during the late 19th and early 20th centuries, coinciding with the advent of power generation technology. These nascent markets were characterized by localized operations, often dominated by a single company that controlled the entire electricity supply chain, including generation, transmission, and distribution. The era of regulated monopolies ensued, with vertically integrated utilities monopolizing electricity provision for a substantial part of the 20th century [1]. 2) The emergence of wholesale markets, power pools were a result of utilities working together to improve resource sharing and reliability in the middle of the 20th century, and they laid the groundwork for more organized energy markets. Growing regional grid connectivity enhanced resource efficiency and paved the way for wholesale power trading. The latter half of the 20th century then saw a significant movement in many countries in the direction of deregulation and market liberalization. This change brought competition to the generation and retail sectors by disentangling the functions of distributions, transmissions, and generations [2]. 3) The Emergence of renewable energy and decentralization the electricity sector underwent a significant shift throughout the early 21st century, characterized by a notable expansion of renewable energy sources, including wind and solar power. The introduction of variable and decentralized resources of energy brought a new dynamic in electricity markets. The proliferation of rooftop solar panels exemplifies the expanding trend of distributed generation, resulting in a more decentralized energy framework that has posed challenges to the conventional utility model and facilitated the emergence of innovative energy trading paradigms. Significantly, the concept of peer-to-peer (P2P) energy trading has developed as an innovative phenomenon, facilitating the direct trade of surplus energy between customers who possess energy-generating capabilities, such as solar panels. The expansion of P2P trade has been significantly facilitated by technological advancements, specifically in blockchain and smart grid technologies. These advancements have played a crucial role in enabling secure, transparent, and efficient transactions between producers and consumers. Although P2P trading is still in its early phases, there is ongoing development of regulatory frameworks to support this innovative model. This indicates a transition towards an energy system that prioritizes consumers, sustainability, and resilience [3]. Power pool trading and P2P trading can be regarded as creative concepts that have experienced ongoing evolution. Extensive research and advancement have been conducted on these two trading mechanism. Reference [4] focuses on designing four type of double auction mechanisms, including the Walrasian equilibrium mechanism, the Vickrey-Clarke-Groves mechanism (VCG), the multi-unit double-auction mechanism (MUDA), and the MUDA-VCG mechanism, which are customized and evaluated based on real market data to identify their unique features and performances. In microgrids with distributed generation, including photovoltaic (PV) systems and battery energy storage systems (BESSs), [5] suggests a P2P energy trading model. Meanwhile, P2P electricity trading mechanism based on coalition game theory is incorporated into the model. Reference [6] introduces a novel P2P energy trading system that takes into account participants' multi-class energy trading preferences in addition to non-economic variables like social relationships and economic profit/cost considerations. A simulation is carried out using actual social media data to verify the efficacy of the suggested system. Reference [7] uses an ensemble learning algorithm for energy forecasting and power flow optimization for power scheduling, the paper proposes a decentralized electricity market framework to enable direct energy transactions

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between peers in the energy network. It also introduces a P2P energy transaction mechanism based on the discrete double auction model, which is compared through simulation tests with the conventional centralized market.

Several countries worldwide have started incorporating P2P technology in conjunction with conventional systems. For example, [8] suggests almost settled P2P energy trading in grid-connected networks without post-trade bus voltage protection. They tested the mechanism on an Australian low-voltage distribution network. Meanwhile, [9] proposes a motivational psychology paradigm for Malaysian P2P energy trading, focusing on residential prosumers, to increase user involvement. [10] introduces operator-driven block rate price (BRP) P2P energy trading in communities. A South Korean residential neighbourhood is used to validate the proposed technique. In addition, the emerging architecture of Peer-to-Peer (P2P) energy trading and its various operating algorithms had been proposed by [11] a case study of Nepal's energy system.

In Thailand, P2P energy trading is promoted in the public sector, as a result of constantly increasing in the number of prosumers. P2P trading provides options for using the excess electricity in many ways, such as selling excess electricity into the electricity system, selling electricity between each other, storing energy for use at nighttime, etc. The P2P mechanism will help reduce the peak and increase the efficiency of the system. While there is a lot of research in the field of developing power pool market and P2P energy trading mechanisms, a comparative study power pool market and P2P energy trading, in term of welfare maximization to the market, is an important issue.

Therefore, this paper presents the comparative study of the use of linear programming to determine the welfare of the power pool market comparing to the proposed multi-stage matching mechanism (MMM). The rest of this paper is organized as follows. Section II electricity market model used in this paper. Section III simulation result and discussion. Section IV conclusion and future work.

II. ELECTRICITY MARKET MODELS

This section presents the market models of power pool and P2P electricity markets. The power pool market mechanism is solved by linear programing. Meanwhile, the P2P electricity market is settled by MMM.

A. Power pool market

In power pool market, the objective function is maximizing the entire area under the supply and demand curve considering constraints violation as.

$$B=\sum_{i=1}^{NS}(S_{Bi}\cdot S_{MWi})-\sum_{i=1}^{ND}(D_{Bi}\cdot D_{MWi}) \tag{1}$$

Subject to the equality constraints of market balance equation as below.

$$0=\sum_{i=1}^{NS}S_{MWi}-\sum_{i=1}^{ND}D_{MWi} \tag{2}$$

Where S_{Bi} and D_{Bi} are the selling and purchasing price of electricity, respectively. ND and NS represent the number of bid and offer prices. S_{MWi} and D_{MWi} represents the amount of energy sold and purchased, respectively. The chart of demand and supply are shown in Figs 1 and 2, respectively.

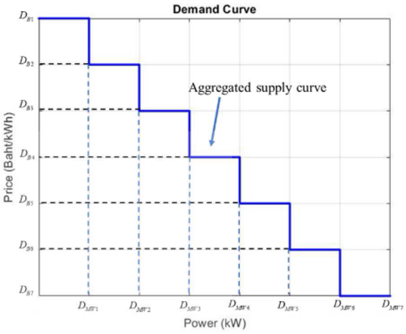


Fig. 1 Demand curve.

A demand curve is an economic graph that illustrates the negative correlation between the price of a product and the quantity of that thing that consumers are willing and able to buy. The graph generally has a negative slope, illustrating the inverse relationship between price and quantity demanded. Figure 1 depicts the aggregated demand curve at each price level, which results from players wanting to buy electricity at each price level.

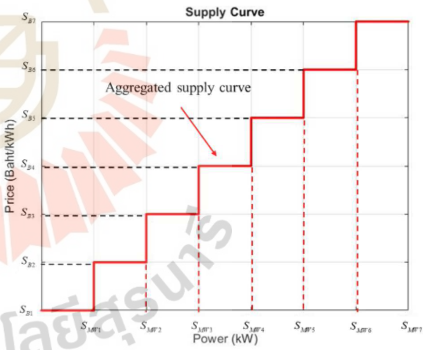


Fig. 2 Supply curve.

A supply curve is an economic graph that depicts the correlation between the price of a product or service and the amount that producers are willing and capable of providing to the market at various price levels, assuming all other conditions remain the same. The supply curve, in contrast to the demand curve, exhibits an upward slope from left to right, signifying that when the price of a product rises, the quantity supplied by producers also increases. In figure 2 shows the aggregated supply curve at each price level, which results from players wanting to sell electricity at each price level.

The market clearing price (MCP) and market clearing quantity (MCQ) are obtained by linear programing that corresponding to the intersection of supply and demand curves, as shown in Fig 3. Buyers who submit bids over the MCP threshold are eligible to purchase electricity at the MCP price. The disparity between the buyer's bid and the MCP price is visually shown by a blue shading. On the contrary, Sellers who submit offers under the MCP threshold are eligible to selling electricity at the MCP price. The disparity between the seller's offer and the MCP price is visually shown by a red shading in Fig 3, respectively.

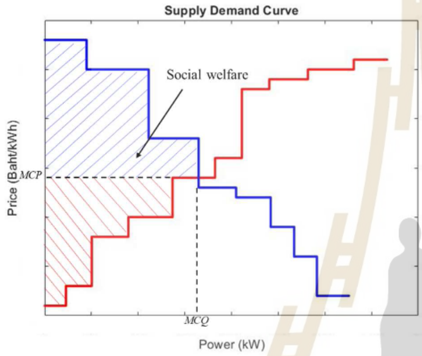


Fig 3 Supply Demand Curve

B. *P2P Multi-stage matching mechanism (MMM)*

MMM is an iterative algorithm that aims to align demand and supply. The algorithm's architecture diverges from the power pool concept by mandating members engage in maximum feasible trading. MMM imposes criteria requiring the seller to be capable of selling at a price equal to or higher than desired price. Meanwhile the buyers are obtained the electricity at the price equal to or lower than the desired price. The algorithm can be divided into three sequential steps as Fig 4. The proposed MMM computational step can be illustrated as follows.

Step 1: From the perspective of the buyer, they are paired with the sellers who provide a price that is lower than but closest to the buyer's price.

Step 2: There will now exist an unmatched quantity that cannot be equaled by anyone. The buyer who presents the most competitive buying price will prioritized and match with the seller who presents the highest selling price, but maintaining a price lower than that of the buyer.

Step 3: Proceed with Step 2 iteratively until there are no more buyers or sellers or until there is only a seller who offers a price higher than the buyer's price, which does not meet the specified conditions. The coupling will be deemed completely.

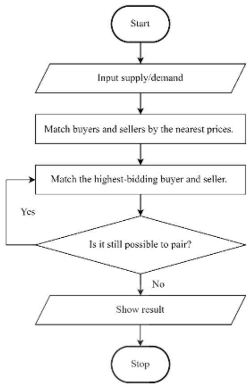


Fig 4 Flow chart showing the operation of MMM

III. SIMULATION RESULT AND DISCUSSION

Simulation is conducted to validate the proposed market mechanism. The programs are implemented in MATLAB and are executed on a computer with a window 11 operating system, a 2.3GHz Intel Core i5 processor and 16-GB memory.

A. *Simulation Setup*

The players in the established power pool energy trading market, which consist of 20 end consumers and prosumers, are simulated. 10 people take turns acting as energy buyers and sellers. The allowable energy selling price is randomly determined as a value in the range of [2 Baht/kW, 5 Baht/kW] for each seller, and the amount of available selling energy is created at random within the range of [20 kW, 50 kW]. The acceptable energy purchase price is randomly determined as a number in the range of [2 Baht/kW, 5 Baht/kW], and the energy demand for each buyer is produced randomly within the range of [20 kW, 50 kW].

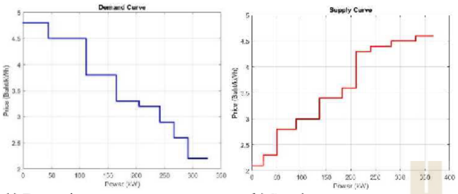
In this demonstration, the amount and price of energy of buyers and sellers are shown in Table I.

TABLE I THE AMOUNTS AND PRICES OF ENERGY OFFERED FROM BUYERS AND SELLERS

Supply		Demand	
Baht	*kW*	*kW*	*Baht*
4.6	35.7	44.8	4.8
4.5	49.2	40.3	4.5
4.4	41.3	26.2	4.5
4.3	29.4	29.5	3.8
3.6	28.7	24	3.8
3.4	45.5	40.1	3.3
3	47.3	37.1	3.2
2.8	39.2	25.1	2.9
2.3	27.7	24.4	2.6
2.1	22.7	34.3	2.2

B. *The result of power pool market model.*

Figure 5 shows demand and supply derived from the data in Table I. Red line and blue line represent supply and demand, respectively. Graphs can be identified at their points of intersection by applying the linear programming method to find the maximum area under the graph as shown in Figure 6. By running the objective functions and the constraints in Section II, Participants who complete a trade are formed as shown in Table II.



(a) Demand curve (b) Supply curve
Fig 5 Demand curve and supply curve.

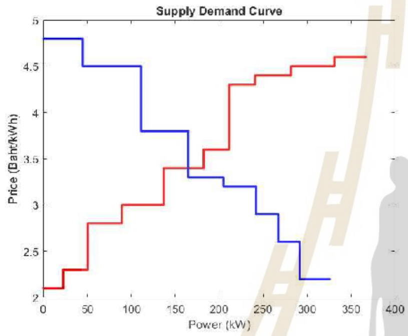


Fig 6 Demand supply curve.

Simulation from linear programming yields an equilibrium point of 3.4 Baht. It can be seen that the sellers who are able to sell are those whose prices are lower than the equilibrium point. Meanwhile, the buyers who are able to buy are those whose prices are higher than the equilibrium point. In other words, it is the area to the left of the equilibrium point that is considered beneficial to the market. The area to the left of the equilibrium point is 259.69 kW/h. Conversely, the area to the right of the equilibrium point is considered unfavorable to the market.

TABLE II. PARTICIPANTS WHO COMPLETE A POWER POOL TRADING.

Supply		Demand	
Baht	*kW*	*kW*	*Baht*
4.6	35.7	0	4.8
4.5	49.2	0	4.5
4.4	41.3	0	4.5
4.3	29.4	0	3.8
3.6	28.7	0	3.8
3.4	17.6	40.1	3.3
3	0	37.1	3.2
2.8	0	25.1	2.9
2.3	0	24.4	2.6
2.1	0	34.3	2.2

The data shown in Table II shows that a supply of 4.6 baht cannot be sold for 35.7 kW. Demand of 2.9 baht cannot be sold for 25.1 kW. Conversely, the quantity of kilowatts supplied or demanded reaches zero at the given price. This implies that all of them can be sold or bought at that specific price.

C. *The results of P2P MMM model.*

In P2P systems, a MMM is a procedure for matching resources between peers in a decentralized network. P2P systems are specifically engineered to facilitate the direct sharing and distribution of resources among individual peers, eliminating the requirement for a central server. The utilization of a multi-stage matching mechanism can significantly improve the efficiency and effectiveness of the matching process between buyers and sellers in P2P networks.

In this simulation, the same data as the power pool simulation, as shown in Table I, is used. Upon executing the 3-step procedure outlined in Section II, participants who successfully carry out a trade are organized and presented in Table III.

TABLE III. PARTICIPANTS WHO COMPLETE P2P TRADING.

Supply		Demand	
Baht	*kW*	*kW*	*Baht*
4.6	0	0	4.8
4.5	0	0	4.5
4.4	14.9	0	4.5
4.3	29.4	0	3.8
3.6	0	0	3.8
3.4	20.7	0	3.3
3	0	0	3.2
2.8	0	0	2.9
2.3	0	0	2.6
2.1	0	24.1	2.2

The data shown in Table III shows that a supply of 4.4 baht cannot be sold for 14.9 kW. Demand of 2.2 baht cannot be sold for 24.1 kW. Conversely, the quantity of kilowatts supplied or demanded reaches zero at the given price. This implies that all of them can be sold or bought at that specific price.

The power pool model results indicate that the MCQ is 164.8 kW. Meanwhile, MCP is 3.4 Bath/kWh. This implies that buyers who bid above this price and sellers who bid below this price will take the market's social welfare. which the total social welfare of this market is 259.69 kW/h. Regarding the P2P model, it was discovered that the amount of electricity traded was 301.7 kW, and the corresponding social welfare value was 74.85 kW/h. Through the process of modeling the two models, it was determined that each model possesses distinct strengths and weaknesses. The P2P model of energy trading involves a higher volume of transactions compared to the power pool model. However, the power pool model results in a higher level of social welfare compared to P2P.

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TABLE IV. COMPARISON OF POWER POOL AND P2P MARKETS OUTCOMES.

	Transaction(kW)	**Social welfare(Bath/h)**
Power pool	**164.8**	**259.69**
MMM P2P	**301.7**	**74.85**

IV. CONCLUSION AND FUTURE WORK

This study's comparative analysis of Power Pool P2P energy trading mechanisms highlights significant findings in the context of social welfare and the dynamics of energy markets. We observed that while the P2P model promotes a higher volume of energy transactions, the Power Pool model excels in maximizing social welfare. This delineation suggests that the choice of trading mechanism should be aligned with the specific objectives of the energy market, whether prioritizing transaction volume or social welfare maximization.

Furthermore, our analysis underlines the necessity of incorporating additional factors, such as carbon credits and geographical considerations, in future studies. These factors could play a crucial role in shaping more sustainable and efficient energy markets, especially as the world increasingly shifts towards renewable energy sources.

In conclusion, the findings of this study serve as a foundation for policymakers and stakeholders in the energy sector to make informed decisions about energy trading mechanisms. By understanding the strengths and limitations of Power Pool and P2P models, we can move towards an energy trading framework that not only supports robust transaction volumes but also enhances overall social welfare, thereby contributing to a more sustainable and equitable energy future.

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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, 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].

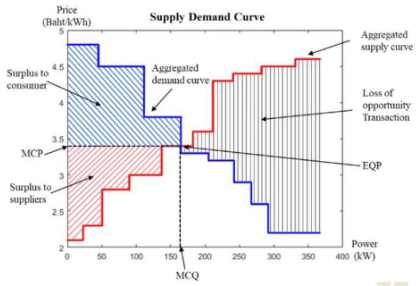


Fig. 1: *Aggregated supply and demand curves*

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

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

s.t.

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

$$P^{\min} = \max\left\{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\right\} \tag{3}$$

$$P^{\max} = \min\left\{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\right\} \tag{4}$$

$$N_{\max} = \frac{P^{\max} - P^{\min}}{n} \tag{5}$$

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

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

s.t.

$$DPF = \begin{cases} +\infty, & \text{TQ} \neq TQ_{\max} \\ 0, & \text{TQ} = TQ_{\max} \end{cases} \tag{7}$$

$$P^{\min} = \max\left\{P_{Di}^{\min}, P_{Si}^{\min} + \alpha\right\} \tag{8}$$

$$P^{\max} = \min\left\{P_{Di}^{\max}, P_{Si}^{\max} + \alpha\right\} \tag{9}$$

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.

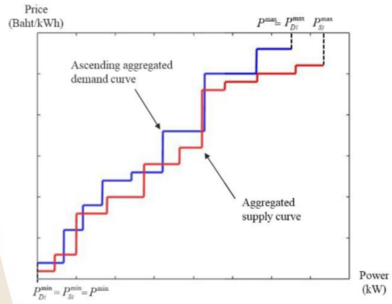


Fig. 2: *Typical aggregated supply and ascending aggregated demand curves*

2.2 DCTS

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

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

$$\lambda_{Si,RE}^{B} = \lambda_{Si,RE} \tag{11}$$

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;

$$\lambda^{S}_{Si,F} = \lambda_{Si,F} - \frac{ct}{2} \tag{12}$$

$$\lambda^{S}_{Si,RE} = \lambda_{Si,RE} \tag{13}$$

where, $\lambda^{S}_{Si,F}$ and $\lambda^{S}_{Si,RE}$ 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 $pbest^{t}_{i}$ and $gbest^{t}_{i}$. A formulation of the set of populations is presented in this paper as follows:

$$\boldsymbol{\alpha} = [\alpha_1, \alpha_2, ..., \alpha_{NP}] \tag{14}$$

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

The range of α_i 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.

$$v_i^{t+1} = wv_i^{t} + c_1 r_1 (pbest_i^{t} - \alpha_i^{t}) + c_2 r_2 (gbest_i^{t} - \alpha_i^{t}) \tag{16}$$

$$\alpha_i^{t+1} = \alpha_i^{t} + v_i^{t+1}, \quad \text{for } i = 1, 2, ..., NP \tag{17}$$

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.

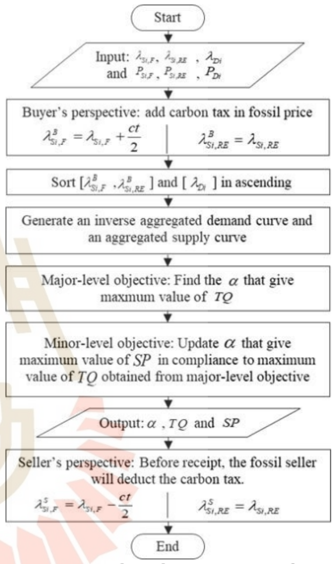


***Fig.3:** BLO-TQSM algorithm computational procedure*

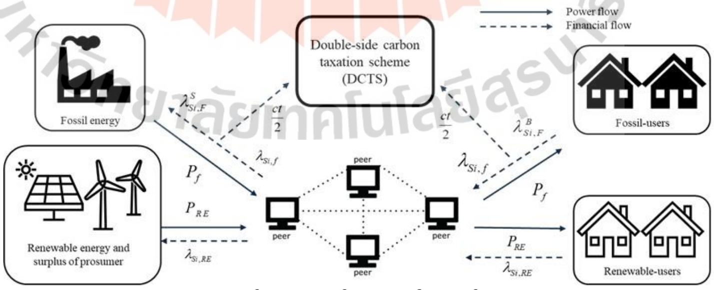


***Fig. 4:** The proposed P2P market mechanism*

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.

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

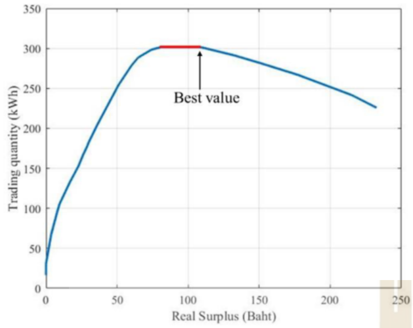
The computations for all case studies were conducted using MATLAB on a computer with a Windows 11 operating system, a 2.3 GHz Intel Core i5 processor, and 16 GB of memory.

4.1 Case A: BLO-TQSM without DCTS

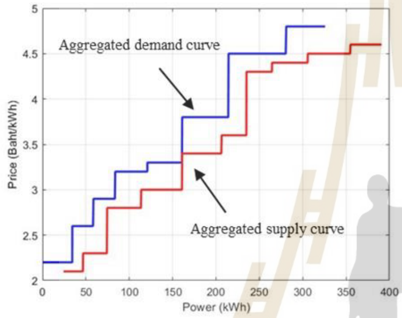
In the first case study, we assume that all participants have an immediate desire to purchase and sell. Table 1 lists the input value in the algorithm. The results for energy trading in this case are represented in Fig. 5, and Table 2 illustrates a shifting graph and matched participants that have average 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.

Table 2: *Result of case A*

Supply						Demand				
Seller	***Index***	***Baht/ kWh***	***offer (kWh)***	***power sell (kWh)***	***revenue (Baht)***	***Buyer***	***Baht/ kWh***	***bid (kWh)***	***power purchase (kWh)***	***payment (Baht)***
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
total				301.7	1127.31	***total***			301.7	1127.31



(a)



(b)

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*

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 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.

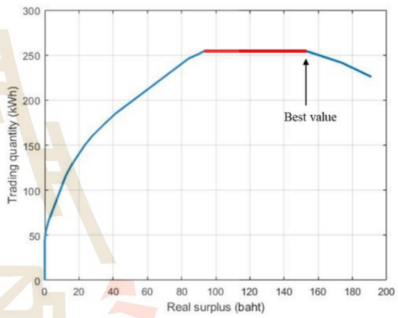
Table 3: *comparison between power pool, P2P MMM and BLO-TQSM*

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

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.



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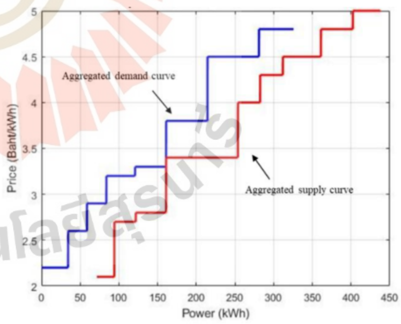
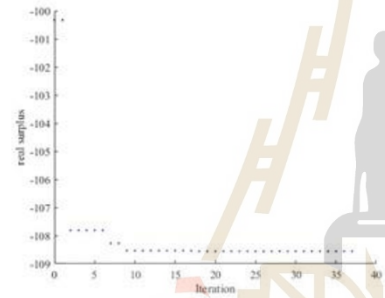


(b)

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				
Seller	***Index***	***Baht/ kWh***	***offer (kWh)***	***power sell (kWh)***	***revenue (Baht)***	***Buyer***	***Baht/ kWh***	***bid (kWh)***	***power purchase (kWh)***	***payment (Baht)***
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
total				254.4	921.64	***total***			254.4	1004.6



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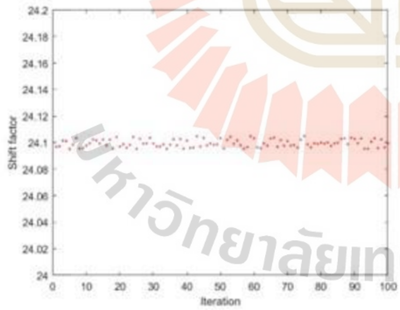
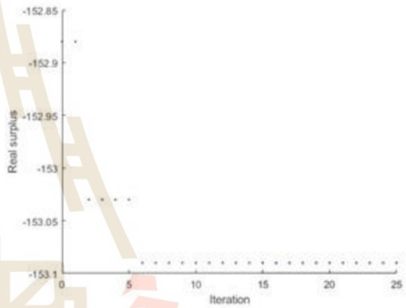
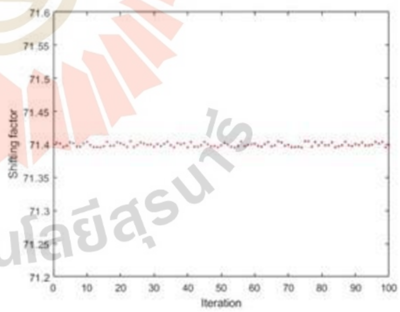


(b)

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



(a)



(b)

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

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.

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.

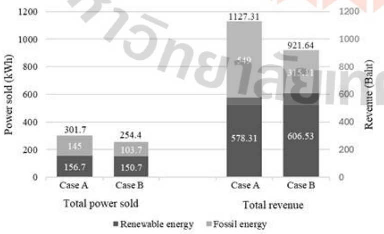


Fig. 9: *Power sold and financial comparison between case A and case B*

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

Table 5. The 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

4.3 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.

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.

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

Supply						Demand				
Seller	***Index***	***Baht/ kWh***	***offer (kWh)***	***power sell (kWh)***	***revenue (Baht)***	***Buyer***	***Baht/ kWh***	***bid (kWh)***	***power purchase (kWh)***	***payment (Baht)***
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***			240.5	963.84

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

Supply						Demand				
Seller	***Index***	***Baht/ kWh***	***offer (kWh)***	***power sell (kWh)***	***revenue (Baht)***	***Buyer***	***Baht/ kWh***	***bid (kWh)***	***power purchase (kWh)***	***payment (Baht)***
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***			211.1	869.76

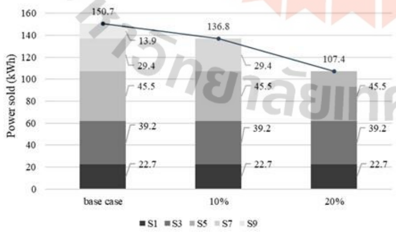


Fig. 10: *Comparative analysis of renewable energy sellers in each case*

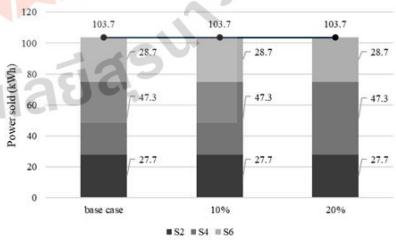


Fig. 11: *Comparative analysis of fossil energy sellers in each case*

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.

6. ACKNOWLEDGEMENT

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BIOGRAPHY

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