OPTIMAL POWER FLOW IN DAY-AHEAD OPERATION CONSIDERING DEMAND ELASTICITY

PANSA KAIKRATHOK

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การหาคำตอบการไหลของกำลังไฟฟ้าที่เหมาะสมที่สุดสำหรับการบริหารจัดการล่วงหน้ารายวันโดยคำนึงถึงความยืดหยุ่นของความต้องการไฟฟ้า

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มหาวิทยาลัยเทคโนโลยีสุรนารี
ปีการศึกษา 2565

OPTIMAL POWER FLOW IN DAY-AHEAD OPERATION CONSIDERING DEMAND ELASTICITY

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

Thesis Examining Committee

....

(Asst. Prof. Dr. Supattana Nirukkanaporn)

Chairperson

....

(Assoc. Prof. Dr. Keerati Chayakulkheeree)

Member (Thesis Advisor)

....

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งานวิจัยนี้มีเป้าหมายที่จะนำเสนอการคำนวณการไหลของกำลังงานไฟฟ้าที่เหมาะสมที่สุด (Optimal Power Flow, OPF) โดยพิจารณาตอบสนองต่อความต้องการพลังงาน (Demand Response, DR) โดยทำการศึกษารูปแบบการตอบสนองต่อความต้องการพลังงานอยู่สองแบบ คือ การตอบสนองต่อความต้องการพลังงานแบบจูงใจ (Incentive base demand response, IDR) และการตอบสนองต่อความต้องการพลังงานแบบราคาไฟฟ้า (Price base demand response, PDR) สำหรับ OPF ที่พิจารณา IDR นั้น จะแก้ปัญหาการต่ำทุนของการผลิตทั้งหมด รวมถึงการปรับปรุงต้นทุน IDR โดยใช้เทคนิคการหาค่าเหมาะสมที่สุดแบบกลุ่มอนุภาค (Particle Swarm Optimization, PSO) ในขณะที่ OPF ที่พิจารณา PDR นั้น จะแก้ปัญหาการกระจายพลังงานจริงที่เหมาะสม โดยใช้เทคนิคการโปรแกรมควอดราติก (Quadratic Programming, QP) เพื่อหาส่วนประกอบของราคาสำหรับแต่ละโหนด spot price นอกจากนี้การควบคุมกำลังไฟฟ้ารีแอคทีฟที่เหมาะสมได้ถูกแก้ปัญหาโดย PSO เพื่อหาค่าแรงดันเครื่องกำเนิดและการปรับแทปหม้อแปลงที่เหมาะสม นอกจากนี้ความยืดหยุ่นของความต้องการไฟฟ้า (Demand Elasticity, DE) ถูกนำมาใช้ปรับความต้องการของระบบเพื่อให้การทำงานในวันถัดไปเป็นไปอย่างแม่นยำมากขึ้น ทั้งนี้วิธีการที่พัฒนาขึ้นถูกทดสอบด้วยระบบ IEEE 33-bus และ IEEE 30-bus โดยผลลัพธ์แสดงให้เห็นว่าสามารถรวมความยืดหยุ่นของราคาของอุปสงค์เข้ากับการจัดกำหนดการวันล่วงหน้าและลดต้นทุนการดำเนินงานทั้งหมดได้อย่างมีประสิทธิภาพ

สาขาวิชา วิศวกรรมไฟฟ้า
ปีการศึกษา 2565

ลายมือชื่อนักศึกษา พรรษา ไชกระโทก
ลายมือชื่ออาจารย์ที่ปรึกษา ....

PANSA KAIKRATHOK: OPTIMAL POWER FLOW IN DAY-AHEAD OPERATION CONSIDERING DEMAND ELASTICITY

ADVISOR: ASSOC. PROF. KEERATI CHAYAKULKHEEREE, D.ENG., 132 PP.

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This research proposes the optimal power flow (OPF) considering demand response. Two demand response (DR) models, which are Incentive base demand response (IDR) and price base demand response (PDR), had been investigated. For OPF considering IDR, the total generation cost including IDR cost minimization problem is solved by particle swarm optimization (PSO). Meanwhile, for OPF considering PDR, the optimal real power dispatch is solved by quadratic programming (QP) in order to obtain nodel spot price components and the optimal reactive power dispatch is solved by PSO for optimal generator voltage magnitude and transformer tap-changing. Consequently, the demand elasticity (DE) is applied to adjust the system demand for more accurate day-ahead operation. The proposed method was tested with the IEEE 33-bus system and the IEEE 30-bus system. The results showed that the proposed algorithm can incorporate price-elasticity of demand into day-ahead scheduling and effectively minimize total operating cost.

School of Electrical Engineering

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Student's Signature พรรษา ไกรกระโทก

Advisor's Signature ....

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LIST OF ABBREVIATIONS

DE	=	Demand elasticity
DR	=	Demand response
IDR	=	Incentive base demand response
NSP	=	Nodal spot price
OPD	=	Optimal power dispatch
OPF	=	Optimal power flow
OPRDR	=	Optimal price-based real-time demand response
PDR	=	Price base demand response
PRDR	=	Price-based real-time demand response
PSO	=	Particle swarm optimization
PSO-OPD	=	Particle swarm optimization based optimal power dispatch
QP	=	Quadratic programming

LIST OF NOMENCLATURES

a_i, b_i, c_i	=	generator cost coefficients
$a_{il,h}$	=	the line flow sensitivity factor at bus *i* at hour *h*
c_1, c_2	=	the acceleration constants
$D_i(P_{DRi})$	=	the cost function demand response
$EC_{i,h}$	=	electricity cost at bus *i* at hour *h*
$\lvert f_{lm} \rvert$	=	the MVA flow on the branch between bus *l* and *m*
$\lvert f_{lm,h} \rvert$	=	the MVA flow on the branch between bus *l* and *m* at hour *h*
$\lvert f_{lm} \rvert^{\max}$	=	the maximum MVA limit of the branch between bus *l* and *m*
$f_{l,h}$	=	the power flow at line *l* at hour *h*
$f_{l,h}^{0}$	=	the initial real power flow at line *l* at hour *h*
$\Delta f_{l,h}$	=	change in power flow at line *l* at hour *h*
$F_i(P_{Gi})$	=	the fuel cost of generator *i*
$FC_i\left(P_{Gi,h}\right)$	=	the fuel cost of the generator at bus *i* at hour *h*
$gbest_i^t$	=	the best group position of particle *i* at iteration *t*
$ITL_{i,h}$	=	the incremental transmission loss at bus *i* at hour *h*
NB	=	the total number of buses
NG	=	the total number of generators
NP	=	the total number of particles
$\mathbf{p_i}$	=	the position of particle *i*
$pbest_i^t$	=	the best particle position of particle *i* at iteration t
PNF	=	the penalty factor for constraints violations
P_{Di}	=	the real power demand at bus *i* with demand response
$P_{Di,h}$	=	the real power demand at bus i with demand response at hour *h*
P_{Di}^{0}	=	the real power demand at bus *i* without demand response
P_{DRi}	=	the real power demand response at bus *i*

LIST OF NOMENCLATURES (Continued)

P_{Gi}	=	the real power generation at bus *i*
$P_{Gi}^{\min}$	=	the minimum real power generation at bus *i*
$P_{Gi}^{\max}$	=	the maximum real power generation at bus *i*
$P_{Gi,h}$	=	the real power generation at bus *i* at hour *h*
$P_{Gi,h}^{\max}$	=	the maximum real power generation at bus *i*
$P_{Gi,h}^{\min}$	=	the minimum real power generation at bus *i*
$P_{i,h}$	=	the real injection power at bus *i* at hour *h*
$P_{Li,h}$	=	the power demand at bus *i* at hour *h*
$P_{Li,h}^{0}$	=	the initial power demands at hour *h*
$P_{Li,h}$	=	the power demand at bus *i* at hour *h*
P_{loss}	=	the total transmission loss in the system
$P_{loss,h}$	=	the power loss at bus *i* at hour *h*
$\Delta P_{i,h}$	=	change in real injection power at bus *i* at hour *h*
$\Delta P_{Li,h}$	=	change in power demand at bus *i* at hour *h*
Q_{Di}	=	the reactive power demand at bus *i*
$Q_{Di,h}$	=	the reactive power demand at bus *i* at hour *h*
Q_{Gi}	=	the reactive power generation at bus *i*
$Q_{Gi,h}$	=	the reactive power generation at bus *i* at hour *h*
$Q_{Gi}^{\max}$	=	the minimum reactive power of generator at bus *i*
$Q_{Gi,h}^{\max}$	=	the maximum reactive power demand at bus *i*
Q_{Gi}^{min}	=	the minimum reactive power of generator at bus *i*
$Q_{Gi,h}^{\min}$	=	the minimum reactive power demand at bus *i*
r_1, r_2	=	the random values within the range of [0,1]
S_{Gi}^{max}	=	the maximum apparent power of generator at bus *i*
t	=	the total number of iterations
TFC	=	the total system cost
v_i^t	=	the particle *i*'s velocity at iteration *t*
$\|V_i\|$	=	the voltage magnitude at bus *i*

LIST OF NOMENCLATURES (Continued)

$\lvert V_i \rvert^{\max}$	=	the maximum limit of voltage magnitude at bus *i*
$\lvert V_i \rvert^{\min}$	=	the minimum limit of voltage magnitude at bus *i*
$\lvert V_{i,h} \rvert$	=	the voltage magnitude at bus *i* at hour *h*
$\lvert V_{j,h} \rvert$	=	the voltage magnitude at bus *j* at hour *h*
w	=	the inertia weight factor
$\lvert y_{ij} \rvert$	=	the magnitude of the y_{ij} element of Y_{bus}
$\varepsilon_{i,h}$	=	the demand elasticity matrix at bus *i* at hour *h*
$\varepsilon_{i,j}$	=	position in the demand elasticity matrix representing self and cross demand elasticity
$\Delta\sigma_{i,h}$	=	change in spot price at bus *i* at hour *h*
$\sigma_{i,h}$	=	the spot price at bus *i* at hour *h*
$\eta_{L,ih}$	=	the marginal transmission loss component at hour *h*
$\eta_{QS,ih}$	=	the network quality of supply component at hour *h*
λ_h	=	the system marginal price at hour *h*
$\mu_{l,h}$	=	the constraint incremental relaxation price at line *l* at hour *h*
θ_{ij}	=	the angle of the y_{ij} element of Y_{bus}
δ_{ij}	=	the voltage angle between bus *i* and bus *j*
$\delta_{ij,h}$	=	the voltage angle between bus *i* and bus *j* at hour

CHAPTER I

INTRODUCTION

1.1 General Introduction

1.1.1 Definition of Demand Response

Demand response is a strategy used in the energy sector to manage and balance electricity supply and demand. It refers to the voluntary or involuntary reduction of electricity consumption by consumers in response to signals or incentives from grid operators or electricity providers. The goal of demand response is to adjust electricity usage during times of high demand or when the grid is stressed, thereby maintaining grid stability, avoiding blackouts, and optimizing the overall efficiency of the electricity system (Okur et al., 2021).

Demand response programs typically offer financial incentives, such as reduced electricity rates or payments, to consumers willing to reduce their electricity consumption during peak demand periods. These programs can be implemented through various mechanisms.

By engaging consumers in the demand response process, grid operators can better manage fluctuations in electricity supply and demand, optimize the utilization of existing infrastructure, and potentially reduce the need for additional power generation capacity. Demand response also promotes the integration of renewable energy sources by enabling the grid to accommodate intermittent generation, such as solar and wind power, more effectively.

Overall, demand response plays a crucial role in creating a more reliable, flexible, and sustainable electricity system by aligning consumer behavior with the grid's needs.

The study of DR is a crucial topic, and it is vital to identify the many DR schemes and real programs in order to determine their benefits and drawbacks. DR schemes have been proposed in various literature sources. DR systems can be precisely divided into two fundamental groups, as seen in Figure 1.1 According to the kind of control mechanism, DR systems are divided into two groups in the first category: Price base demand response (PDR). The second category: Incentive base demand response (IDR).

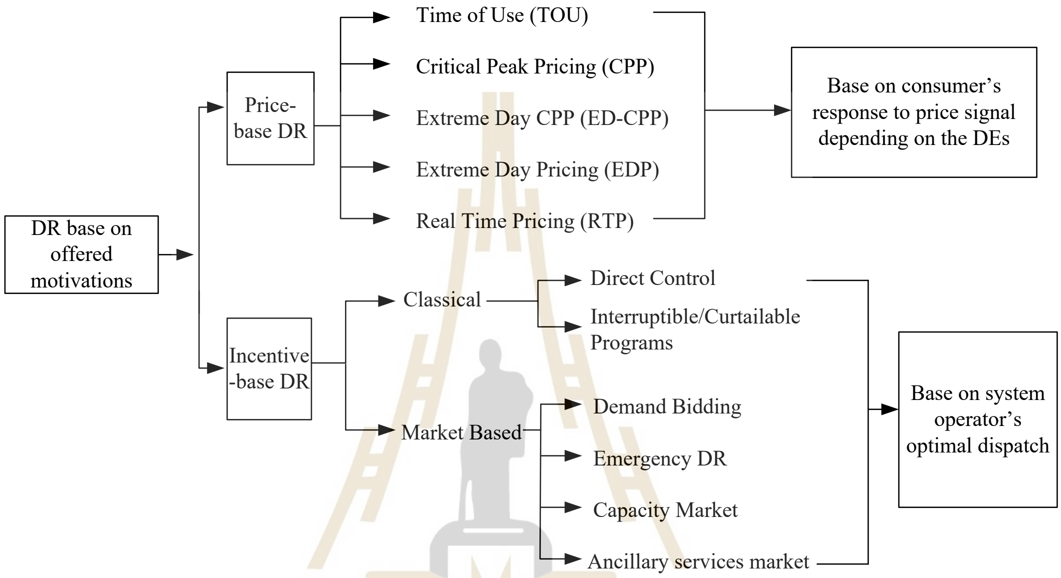

Figure 1.1 Classification of DR programs

1.1.2 Types of demand response programs

As was already said, DR has the potential to modify the pattern of electrical demand and provide a grid system with a different source of power to meet customers' increased electricity needs during periods of peak demand as opposed to peaking power plants. PDR or IDR programs can both be used for DR. The various DR programs and their function in the design and operation of electrical systems are depicted in Figure 1.1 (Stanelyte et al., 2022), and are further addressed in the following sections.

1.1.2.1 PDR programs

PDR program, electricity prices can vary based on the time of day, overall demand on the grid, or specific events such as peak demand periods. The prices are typically higher during periods of high demand or when the grid is stressed.

By providing consumers with real-time or advance notice of these price fluctuations, consumer make informed decisions about when to use electricity and adjust their consumption accordingly.

Consumers who participate in PDR programs can benefit from lower electricity rates during off-peak or low-demand periods. They may also have the opportunity to earn financial incentives, such as bill credits or payments, for reducing their electricity usage during peak demand periods when prices are higher. DR alternatives may be incorporated into system planning for various time frames utilizing one or both of the following (M. H. Albadi & E. El-Saadany, 2007):

1. Time of Use Tariff (TOU): The electricity tariff is calculated according to the period of use. By dividing the electricity bill according to different rates for each period of electricity use as on peak and off peak.
2. Critical Peak Pricing (CPP): Incentivizing power users to avoid using electricity during the expected peak times of the day by using a mechanism for electricity tariffs that is divided by period.
3. Extreme Day Critical Peak Pricing (ED-CPP): a specific type of pricing strategy used in demand response programs. It is designed to manage electricity demand during exceptionally high-demand periods or extreme weather conditions.
4. Extreme Day Pricing (EDP): EDP is comparable to CPP in that it charges a higher price for power, but it varies from CPP in that the price is in force for the whole 24 hours of the extreme day, which isn't known until the day in advance.
5. Real-time pricing (RTP): It is charged according to actual usage. It is a change in the price of electricity every specified period Typically hourly, which will be announced in advance to change the price. per minute or longer.

1.1.2.2 IDR program

IDR refers to a type of demand response program where consumers are offered financial incentives to reduce their electricity consumption during specific periods or in response to grid conditions. The program aims to motivate and reward consumers for adjusting their electricity usage to help balance supply and demand on the grid (M. H. Albadi & E. El-Saadany, 2007).

Classical programs and market-based programs are two further divisions of IDR. Classical IDR includes Direct Load Control and Interruptible/Curtailable. Market-based IBP includes Demand Bidding, Emergency DR, Capacity Market, and Ancillary services market as follow figure 1.1.

1.1.3 Thailand Load Response Program Experience

DR programs have been in use long before the advent of smart power systems. Thailand has implemented a total of 8 DR programs (NECTEC).

1.1.3.1 Interruptible Electricity Rate

The Interruptible Rate (IR) for electricity has been approved by the National Energy Policy Committee on December 3, (1995) and officially announced, starting from March 1, (1996) until the present. The Interruptible Rate is an alternative electricity rate for large-scale commercial electricity users with a power demand of 5,000 kilowatts and above. It allows for the interruption of electricity supply (Interruptible Demand) when requested by the electricity authority, provided that the requested interruptible demand is not less than 1,000 kilowatts.

The Interruptible Electricity Rate provides options regarding the number of interruptions and the duration of electricity suspensions (in hours per incident, number of incidents per day, month, or year). Electricity users who comply with the requested interruptions will benefit from a lower Interruptible Demand charge (in Baht per kilowatt per month) compared to the regular Time-of-Use (TOU) rate. Users who are able to adhere to the requested interruptions will receive the benefit of a lower electricity demand charge (in Baht per kilowatt per month) than the regular TOU rate. The notification for requesting electricity suspensions must be made in advance, not less than 1 hour, through means such as fax, telephone, or the internet. However, in practice, electricity authorities typically require notifications to be made at least 1 business day in advance.

Participants in the program can choose from three options, which are as follows:

Option 1: Electricity suspension for a maximum of 3 hours per incident, 2 incidents per day, 10 incidents per month, and 40 incidents per year.

Option 2: Electricity suspension for a maximum of 3 hours per incident, 1 incident per day, 10 incidents per month, and 20 incidents per year.

Option 3: Electricity suspension for a maximum of 6 hours per incident, 1 incident per day, 10 incidents per month, and 20 incidents per year.

Currently, there are only 4 electricity users enrolled in the Interruptible Electricity Rate program. These users consist of 1 user from the Metropolitan Electricity Authority and 3 users from the cement industry: Thai Asahi Factory, Siam City Cement Plant (2 locations), and TPi Cement Plant. Together, they have a total contracted electricity capacity of 56 megawatts. During the crisis caused by the suspension of maintenance on various natural gas sources in the past, these 4 users have been identified as important target groups for reducing electricity consumption during peak demand periods.

1.1.3.2 Peak Cut Program (2004 - 2005)

The Peak Cut Program is an initiative of the Electricity Generating Authority of Thailand (EGAT) aimed at supporting large-scale businesses and industries to utilize their own backup power generators during periods of high electricity demand instead of relying on EGAT's grid. The program encourages these entities to supply electricity to their own systems using their available backup generators, thereby reducing their reliance on electricity from EGAT's grid during peak demand times. The program sets a target to reduce electricity demand from the grid by 300 megawatts during peak demand periods.

On September 20, 2004, which marked the 120th anniversary of electricity usage in Thailand, a major operational exercise was conducted to test the reduction of electricity demand from the grid by 500 megawatts between March and

May, 2005. Subsequently, from 2006 onwards, the program was implemented with a target of reducing electricity demand by 500 megawatts in practice.

Business operators participating in the program will receive three types of compensation, including:

1. Installation and system upgrade expenses for installing meters and switching systems for electricity reception/production.
2. Availability Payment (AP) calculated based on the rate of reserve electricity demand, which is 66.45 baht per kilowatt-hour per month.
3. Energy Payment (EP) based on the actual electricity generation, calculated using the average diesel oil price of the respective month as announced by PTT Public Company Limited. For example, if the diesel oil price is 15 baht per liter and the electricity production is approximately 3 units per liter, the energy payment would be 5 baht per unit.

Business operators participating in the program must have backup electricity generators capable of substituting for their electricity demand from the main power grid, with a capacity of not less than 500 kilowatts. They are required to enter into an agreement with the Electricity Generating Authority of Thailand (EGAT). In cases where they are unable to fulfill the terms of the agreement, they will be subject to a penalty of twice the average AP cost per day of scheduled operation in that month. This penalty is calculated based on the difference between the reported production and the actual production during the operation.

The project achieved a certain level of success; however, it was temporarily suspended due to the high diesel oil prices during that period (in the year 2005).

1.1.3.3 Thai People's Unity Project to Combat the Electricity Crisis

The Ministry of Energy has launched a campaign to encourage cooperation from all sectors in reducing electricity consumption. Measures have been implemented to monitor and verify energy reduction in government agencies, serving as guidelines and examples for energy conservation among the general public. Furthermore, the Ministry of Energy has instructed the testing of alternative fuel sources for standby generators used in diesel-powered power plants. All power plants have been instructed to refrain from conducting maintenance during the natural gas supply interruption period. Additionally, collaboration with Small Power Producers (SPP) has been sought to increase electricity production capacity by an additional 110 megawatts. The Ministry has also coordinated with major energy producers in compliance with the Energy Conservation Promotion Act of 1992, focusing on emergency standby generator production. Cooperation has been established with 27 major license applicants, totaling 180 megawatts of power production capacity.

As a result of the Ministry of Energy's efforts in preparing for the natural gas supply interruption, the backup electricity production capacity has increased to 1,687 megawatts, ensuring that the power system meets the required standards.

1.1.3.4 Thailand Demand Response Pilot Project

The Energy Regulatory Commission (ERC), in collaboration with the Electricity Generating Authority of Thailand (EGAT), Metropolitan Electricity Authority (MEA), and Provincial Electricity Authority (PEA), has implemented the pilot project titled "Thailand Demand Response" from January 8th to 10th, 2014. This period coincided with the maintenance shutdown of the Yadana gas field, which affected the electricity production capacity from gas-powered plants.

The project involved the participation of 10 businesses, totaling 350 meters. During this pilot project, tests were conducted on load response mechanisms and the processing of data from Automated Meter Reading (AMR) systems. These tests served as a foundation for developing the role of Load Aggregators and the establishment of a Demand Bidding market for energy conservation in Thailand's future. The project yielded successful results, achieving a reduction of 70 megawatts in electricity consumption during peak periods, surpassing the initial target of 200 megawatts.

1.1.3.5 Collaborative Project to Reduce Electricity Usage during Natural Gas Supply Disruptions

The Energy Regulatory Commission (ERC) has assigned the Electricity Generating Authority of Thailand (EGAT) and Provincial Electricity Authority (PEA) to prepare a readiness plan for ensuring the stability of the electricity system in the southern region during natural gas supply disruptions. As part of the implementation, public announcements and requests for cooperation were made to all sectors through provincial governors, chambers of commerce, hotel associations, department stores, and various media outlets. Medium-sized and large-scale businesses that have installed meters capable of recording data every 15 minutes were invited to participate in the project. Compensation was provided to electricity consumers who could reduce their electricity consumption during peak periods, with a rate of 4 baht per kilowatt-hour saved.

The project successfully achieved a reduction of 48 megawatts in electricity consumption during peak periods, surpassing the initial target of 247 megawatts. Although the project did not achieve the intended electricity reduction target, the actual electricity demand during the peak periods was lower than projected, preventing power outages in the southern region during the specified period.

1.1.3.6 Collaborative Project to Reduce Electricity Usage, 1st Quarter of 2015

In April 2015, there was an anticipated disruption in the supply of natural gas from Yadana and Yetagun fields in Myanmar. To address this situation, the Energy Regulatory Commission (ERC) coordinated with the Electricity Generating Authority of Thailand (EGAT), Provincial Electricity Authority (PEA), and Metropolitan Electricity Authority (MEA) to organize the "Demand Response Project, 1st Quarter of 2015." This project was a continuation of the previous year's initiative. The goal of the project was to reduce electricity consumption during periods of high demand by 500 megawatts.

Medium-sized and large-scale businesses that were customers of EGAT, MEA, or PEA and had meters capable of recording energy consumption every 15 minutes for a minimum period of 31 days were eligible to participate. Participants were required to reduce their electricity consumption by at least 100 kilowatts per request during specific time periods. The project comprised four days: April 10, April 17-18, and April 20, 2015, with three time slots: (1) 10:00 am-12:00 pm (2 hours), (2) 2:00 pm-5:00 pm (3 hours), and (3) 7:00 pm-10:00 pm (3 hours). Compensation was provided at a rate of 3 baht per kilowatt-hour saved during the requested periods.

1.1.3.7 Load Response and Energy Management (2017-2021)

The Energy Management System (EMS), including Home Energy Management System (HEMS) for residential buildings, Building Energy Management System (BEMS) for commercial buildings, and Factory Energy Management System (FEMS) for industrial facilities, plays a crucial role in supporting effective and efficient Demand Response (DR) operations. Therefore, both topics have been combined under the first pillar of the driving plan, which aims to establish Load Aggregators for DR operations in Thailand. The plan also includes the purchase of reducible electricity capacity, known as Megawatts, amounting to 350 megawatts. This reduction in electricity consumption can replace the need for Peaking Plants, resulting in a reduction of 350 megawatts.

Furthermore, in the short term, the driving plan aims to enhance and modernize DR operations to ensure faster response times. Thailand has already implemented several DR initiatives in the past, such as the "Thai People Unite to Combat Electricity Crisis" project, the Thailand Demand Response pilot project, and the collaborative project to reduce electricity consumption during the suspension of natural gas supply from the JDA-18A field in the joint development area of Thailand and Malaysia. However, previous DR operations were manually controlled. In the short-term driving plan, the promotion of energy management systems will support DR operations, enabling them to transition towards semi-automated DR. By the year 2021, it is expected to further develop and advance towards fully automated DR in the medium and long term, following the master plan (EPPO, 2016).

1.1.3.8 Demand Response Pilot Project (2022-2023)

According to the Energy Policy and Planning Office (EPPO) and the three electricity authorities, a Demand Response Pilot Project was conducted during the years 2022-2023. The project aimed to test electricity demand reduction during system peak periods by implementing the Firm Commitment Capacity Demand Response Program. The program aimed to alleviate the burden on the electricity system, replace the need for new power plants, and reduce electricity production costs during system peak demand. The project's objective was to achieve a total reduction of 19.5 megawatts of electricity consumption between January and December 2023 during two time periods: 13:30-16:30 and 19:30-22:30. The project involved the Electricity Generating Authority of Thailand (EGAT) (S. Arunrangseewech and N. Chotiheerunyasakaya, 2022).

To be eligible to participate in the pilot project, electricity consumers had to fall into the categories of medium-sized businesses (Type 3), large businesses (Type 4), or specific businesses (Type 5) with the potential to reduce electricity consumption by at least 50 kilowatts per event. Selected participants in the pilot project received compensation in the form of an Availability Payment (AP) for their readiness to reduce electricity consumption and an Energy Payment (EP) for the actual amount of electricity reduced.

In recent years, there has been a sharp increase in the literature on optimal power flow (OPF) (Dommel, et al., 1968), with an emphasis on two areas: first, the approaches for finding solutions, and second, the contexts in which they might be used. A constant quest for better solutions to the OPF problem has been ongoing, made more so by OPF's natural allure and its potential for expansion into other application fields.

In this research, the real-time price-based demand response is proposed. The spot pricing is established utilizing the Optimal Power Flow (OPF) and demand-price elasticity, along with the price-based real-time demand response (PRDR). It is shown how to effectively reduce total operational costs by scheduling forcast days in advance. The topics of incentive-based DR and price-based DR are covered in Chapters 3 and 4, respectively.

1.2 Problem Statement

As mention above, DR programs are benefit to power system operation. However, different DR programs are implemented in variety form. In addition, optimal operation of power system can be improved when considering DR program into the problem formulation. Therefore, the development and study for incorporating DR to optimal power flow are the vital issues for modern power system's planning and operation.

1.3 Research Objectives

The objectives of this research are as follows,

1. To develop the optimal real power dispatch for market-based power system operation incorporating demand price elasticity for day-ahead operation.

2. To apply quadratic programming (QP) for optimal real power dispatch and nodal hourly spot price of power system.

3. To apply particle swarm optimization (PSO) for power system total loss minimization.

4. To investigate the effect of price elasticity to power system operation.

1.4 Scope of Research

The proposed scope of work is as follows,

1. Develop the optimal real power dispatch algorithm for market-based power system operation incorporating demand price elasticity for day-ahead operation using QP (for total cost minimization).

2. Develop the algorithm for the nodal real-time spot price of the power system using loss sensitivity and DC load flow method.

3. Develop the algorithm for real power loss minimization using PSO and coordinate to the optimal real power dispatch algorithm.

4. Test the proposed method with IEEE 33-bus system and IEEE 30-bus system.

5. Investigate the solution with different the elasticity coefficients.

1.5 Conception

The conception of the research can be shown in Figure 1.2. The primary optimal power dispatch provides the day-ahead hourly spot price and announced prior to the dispatch day. Then, it is estimating the consumer respond to the price-by-price elasticity and obtain the price-corrected load forecast. Finally, the price-corrected optimal power dispatch is obtained.

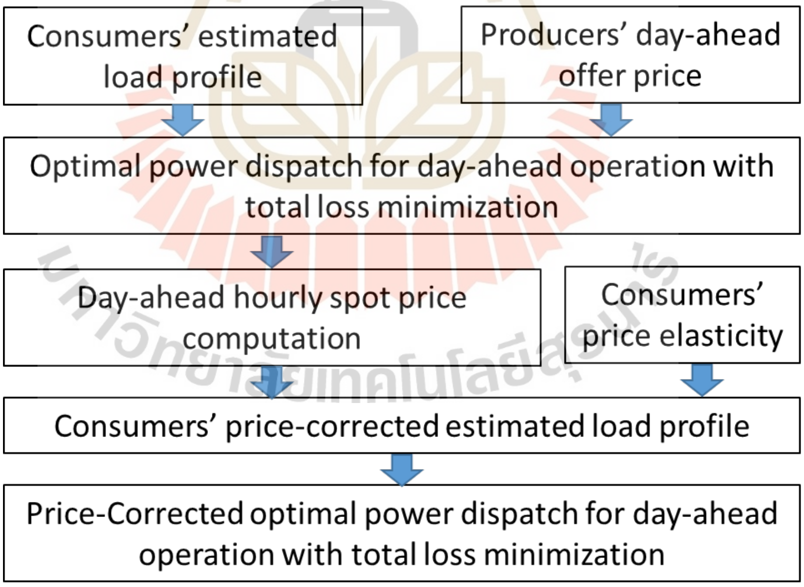

Figure 1.2 The concept of the proposed framework

1.6 Research Benefits

The expected benefits of research are as follows,

1. The improvement in optimal real power dispatch for market-based power system operation is archived.

2. The price-based demand response can be estimated using price elasticity.

3. Power system total loss can be reduced.

4. The effect of price elasticity to power system operation is obtained.

1.7 Structure of Research

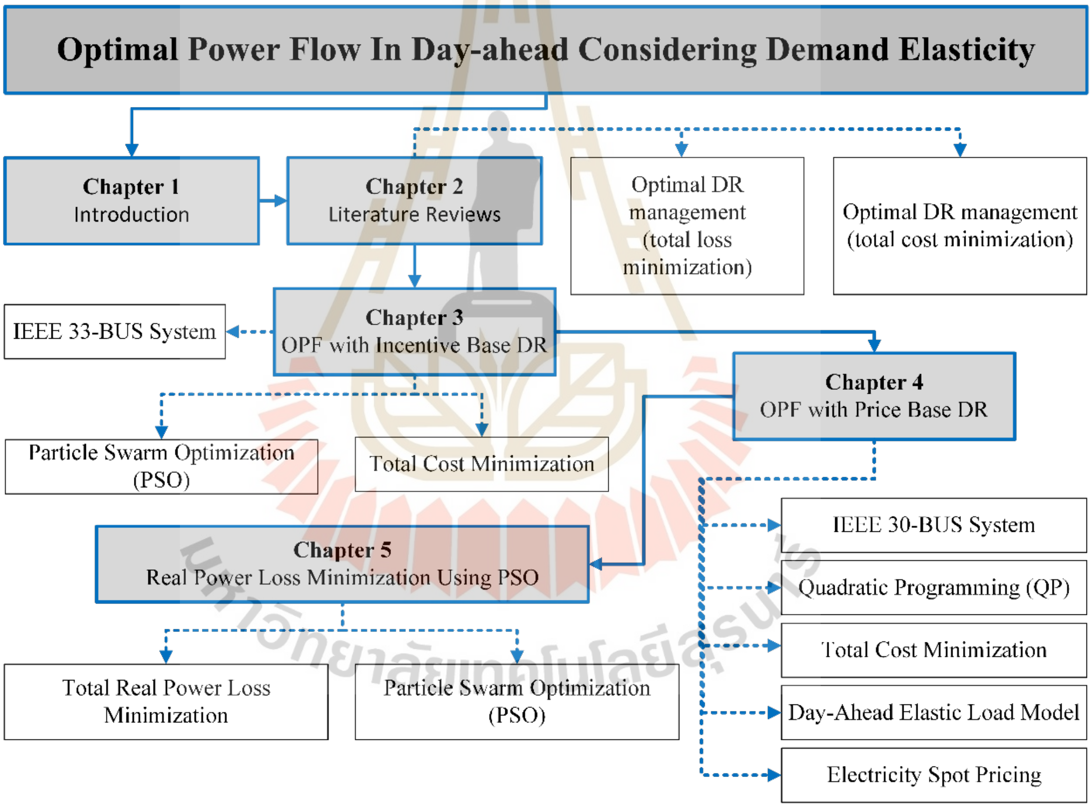

Figure 1.3 The structure of research

CHAPTER II
LITERATURE REVIEWS

2.1 Introduction

This literature review provides a comprehensive examination of the existing research on DR. By exploring theoretical frameworks, program designs, technological advancements, and impacts, it aims to contribute to the understanding of DR and offer insights for enhancing its effectiveness in achieving a more efficient, reliable, and sustainable energy system.

2.2 Literature Overview

Customers who participate in RTP programs pay hourly varying fees that represent the true cost of electricity on the wholesale market. RTP customers receive pricing notifications either a day or an hour in advance. Numerous economists believe that RTP programs are the most direct and effective DR programs appropriate for competitive power markets and that policymakers should concentrate on them (E. Bloustein, 2005).

The preliminary examination of home consumers' reactions to the CPP experiment in California, in which participants were sent high price signals 15 times annually by a local power distribution firm. We discover a load decrease that is statistically meaningful (K. Herter et al., 2007).

A. Yousefi et al (2008) proposes a risk-based approach for the provision of spinning reserve (SR) by means of an emergency demand response program. The program is implemented as a source of SR, which is essential to maintain system security in case of contingencies in the power system. The proposed method involves selecting certain numbers of demands according to a sensitivity analysis and simulating them as virtual generation units. The reserve market is cleared for SR allocation considering a probabilistic technique. The proposed method is evaluated through numerical studies based on the IEEE 57 bus test system. The results show that the proposed method is effective in terms of both economics and reliability.

HA. Aalami et al (2011) the implementation of two mandatory demand response programs, Interruptible/Curtailable service (I/C) and Capacity market programs (CAP), on the Iranian power system. The economic model of these programs is developed using the concept of Price Elasticity of Demand and Customer Benefit Function, and simulation studies are conducted to evaluate their performance. The study shows that these programs can reduce energy consumption and benefit customers, but their effectiveness depends on various factors such as the level of penalties and the load shape. The paper concludes that the implementation of these programs can be beneficial for the Iranian power system.

P. L. Joskow and C. D. Wolfram (2012) encourage the use of cost-based pricing strategies with variable price over time for deregulated utilities like electricity. Explain how the emergence of competitive wholesale markets, the emergence of less expensive two-way communications technologies, and the encouragement of the idea by the policy makers itself increased the possibilities for the adoption of dynamic pricing. Customers respond well to TOU (time of usage) and crucial peak pricing, according to the conclusions drawn from a number of dynamic pricing trials. According to the, the biggest barrier to the adoption of dynamic pricing strategies is the worry of significant displacement of spending. Prices for electricity might be fixed indefinitely or fluctuate over time. In contrast to dynamic pricing, which alter in response to shifting demand conditions, static prices remain constant throughout time.

Last, PTR scheme was introduced to assess its economic success. The PTR program is chosen as a notable illustration of a DR program that strongly depends on customer baseline load computation for its efficient implementation (S. Mohajeryami et al., 2016).

MT. Ahmed et al (2018) discusses the demand response possibilities of a residential electric water heater, the overall consumption profile, the temperature profile, and the financial benefit at the consumer level. The paper proposes and applies the direct load control demand response method yearly, considering real-time electricity pricing with incentive-based demand response to the direct load control with financial benefit to the consumers. The study includes the difference between normal consumption and consumption after using DLC, normal temperature profile, and temperature profiling after DLC. The results exhibit that there is a significant energy consumption reduction at the consumer level without causing any discomfort. The paper concludes that the participation of the EWH in the proposed DR is beneficial for both the aggregator and the consumer.

In recent years, they have contrasted TOU schemes and RTP. by doing the computation using QP. To examine the function of DR programs in the existing power grids, the system's operating costs are also looked at using the MATLAB MATPOWER package. The 14-bus IEEE test system is utilized for this purpose in order to appropriately build and replicate the suggested strategy (S. Nojavan et al., 2021).

Table 2.1 The several pricing policies

Author and publication year	Topic	type	Descript
E. Bloustein, 2005	Assessment of Customer Response to Real Time Pricing	RTP	- RTP represents the most direct and efficient demand response.
K. Herter et al., 2007	An exploratory analysis of California residential customer response to critical peak pricing of electricity	CPP	- The residential sector can provide substantial contributions to retail demand response. - for 15 months. - CPP in California.
A. Yousefi et al., 2008	A risk-based approach for provision of Spinning Reserve by means of Emergency Demand Response Program	Emergency DR	- Emergency demand response program as a source of spinning reserve, which is essential to maintain system security in case of contingencies in the power system. - The proposed method is evaluated through numerical studies based on the IEEE 57 bus test system.

Table 2.1 The several pricing policies (Continued)

Author and publication year	Topic	type	Descript
HA. Aalami et al., 2011	Economical and technical evaluation of implementation mandatory demand response programs on Iranian power system	Interruptible/ Curtailable service (I/C) and Capacity market programs (CAP)	- Implementation of two mandatory demand response programs, Interruptible/Curtailable service (I/C) and Capacity market programs (CAP), on the Iranian power system. - Using the concept of Price Elasticity of Demand and Customer Benefit Function.
P. L. Joskow and C. D. Wolfram, 2012	Dynamic pricing of electricity	TOU	- The use of cost-based pricing strategies with variable price over time for deregulated utilities.
S. Mohajeryami et al., 2016	The impact of customer baseline load (CBL) calculation methods on peak time rebate program offered to residential customers	PTR	- The impact of CBL's performance on PTR programs. - A case of 260 customers is investigated as a case study.

Table 2.1 The several pricing policies (Continued)

Author and publication year	Topic	type	Descript
MT. Ahmed et al., 2018	Financial Benefit Analysis of an Electric Water Heater with Direct Load Control in Demand Response	Direct control program	- Demand response possibilities of a residential electric water heater. - Applies the considering real-time electricity pricing with incentive-based demand response to the direct load control.
S. Nojavan et al., 2021	Optimal Power Flow Considering Time of Use and Real-Time Pricing Demand Response Programs	TOU and RTP	- Compare TOU schemes and RTP. - Using Quadratic Programming. - IEEE 14-bus system.

In addition, in power system optimal operation, the optimal power flow (OPF) is a critical analytical technique for electrical power and control (H. Dommel and W. Tinney, 1968). Many academics are working forever on OPF for some future power system operation utilizing various optimization strategies. There is a lot of researches being done with the goal of optimal management or real-time DR, such as using stochastic finite impulse response (FIR) models (G. Dorini et al., 2013), A genetic algorithm-based methodology (GA) (A. Alzahrani et al,2019), particle swarm optimization (Faria, Pedro et al.,2015), stochastic compromise programming (SCP) (H. Karimi and S. Jadid, 2020) fuzzy systems (T. Holtschneider and I. Erlich, 2012) have been used to determine the DR problem for the optimal working schedule. Each manner of working is unique, as is the efficacy of the outcomes. It is dependent on the approach selected.

The PSO approach put forth by (J. Kennedy and R. Eberhart, 1995) is an optimization technique based on the herd's foraging or moving habits. A flock of birds, in particular, has a particle for each bird in the flock. The PSO solution begins by randomly placing the particles to create a set (different placements of those particles are potential solutions). The best values are then changed, with each particle being adjusted by shifting its position in accordance with the best value, at each decision cycle, to provide the ideal values.

Alsac and B. Stott (1974) used quadratic programming for the objective function of minimization of generating costs and found that the inclusion of steady-state security constraints made the optimal load-flow calculation a more powerful and practical tool for system operation and design.

Table 2.2 Algorithms

Author and publication year	Topic	method	Descript
H. Dommel and W. Tinney, 1968	Optimal Power Flow Solutions	Newton Raphson	- Power flow solution by Newton's method. - Gradient adjustment algorithm for obtaining the minimum and penalty functions. - Automatic adjustment of control variables such as real and reactive power and transformer ratios to minimize costs or losses.
G. Dorini et al., 2013	Chance-Constrained Optimization of Demand Response to Price Signals	FIR	- The price-response is modeled using stochastic finite impulse response (FIR) models. - Based on a dataset composed by more than 500 households in Denmark.
Faria, Pedro et al.,2015	Demand Response Management in Power Systems Using a Particle Swarm Optimization Approach	PSO	- The developed to simulate the use of DR programs. DemSi uses Power Systems CAD.

Table 2.2 Algorithms (Continued)

Author and publication year	Topic	method	Descript
H. Karimi and S. Jadid, 2020	Optimal Energy Management for Multi-Microgrid Considering Demand Response Programs: A Stochastic Multi-Objective Framework	Stochastic compromise programming (SCP)	- A cooperative multi-objective optimization for the networked microgrids energy management.
A. Alzahrani, et al,2019	Minimization of Power Losses through Optimal Battery Placement in a Distributed Network with High Penetration of Photovoltaics	A genetic algorithm-based methodology (GA)	- The system losses and power quality issues associated with the high deployment of solar photovoltaics (PV) in a grid network can be feasibly solved with battery energy storage systems (BESS).
T. Holtschneider and I. Erlich, 2012	Modeling Demand Response of Consumers to Incentives using Fuzzy Systems	Fuzzy	- Introduces a completely new approach for a micro-economic model that estimates the price responsiveness of consumers to incentives in a rational decision-making model based on fuzzy technology.

Table 2.2 Algorithms (Continued)

Author and publication year	Topic	method	Descript
J. Kennedy and R. Eberhart, 1995	Particle Swarm Optimization	PSO	- The optimization of nonlinear functions using particle swarm methodology is introduced.
O. Alsac and B. Stott, 1974	Optimal load flow with steady-state security	Quadratic Programming	- Minimization of generating costs. - The optimal steady-state-secure system operating point.

L. Goel et al (2006) discusses the impact of demand-price elasticity on nodal spot price and reliability of deregulated power systems. The conventional electricity pricing system is being replaced by spot prices, which interact with loads through demand-price elasticity. The paper uses Optimal Power Flow (OPF) and reliability evaluation techniques to investigate the effects of demand-price elasticity on the system. The study shows that demand-price elasticity can reduce the volatility of nodal spot price while improving the system's reliability. The concepts are illustrated using a small but comprehensive reliability test system, RBTS. The paper also includes equations and a Lagrangian function to depict the concepts.

M.H. Albadi et al (2008) provides a summary of Demand Response (DR) in deregulated electricity markets. It defines DR and its classification, discusses potential benefits and associated cost components, highlights the most common indices used for DR measurement and evaluation, and presents some utilities' experiences with different demand response programs. The paper also presents a simulated case study to show the effect of demand response on electricity prices. The ultimate objective of DR programs is to reduce peak demand, and actual peak demand reduction is used as an indication of how successful a DR program is and to compare DR programs in similar situations.

H. Wu et al (2013) used a day-ahead scheduling model for power systems that considers hourly demand response and ramping costs of thermal generating units to reduce the system operation cost. The model formulates the scheduling problem as a mixed-integer quadratically constrained programming problem with quadratic energy balance constraint, ramping cost, and demand response constraints. A Lagrangian relaxation-based method is applied to solve the problem. Numerical tests are conducted on a 6-bus system and the modified IEEE 118-bus system to demonstrate the effectiveness of the proposed model. The results show that the proposed model can help power system operators to reduce the system operation cost by optimizing the power output trajectory of thermal generating units and incentivizing demand response.

Various techniques for enhancing the energy efficiency of electric infrastructure have been developed in the modern power supply business. Demand response (DR) is an effective method for adjusting for unanticipated changes in customer energy consumption in order to meet electricity price incentives. These incentives are used economically to lower peak electricity demand when the cost of producing is very high. This will enhance both the short- and long-term stability of electric power and help manage electrical energy emergencies. With the DR plan, the system's performance can be increased in a number of ways, including increased stability, increased mobility, increased stability, increased efficiency, and lower electricity costs. The DR provides a variety of project and roadmap options (J. S. Vardakas et al., 2015). New options for power distribution networks are now possible because to the DR technology's ongoing development.

In order to enable the price-elastic feature of demand in day-ahead power markets, Qinwei Duan (2016) offers a scheduling model that includes price-based demand bidding. The scheduling model's mathematical form is shown together with a visualization of the bidding process. It is demonstrated through simulations of the model on the IEEE 30-bus system that adding price-elastic demand bids to day-ahead scheduling can significantly lower the demand to average demand ratio. The suggested concept improves the social welfare of the electricity system while simultaneously providing surplus to the participating load serving entities (LSEs). The proposed model can offer a more adaptable and effective method of managing power systems, according to the paper's conclusion.

Power generation dispatching with price-base real-time demand response (PRDR) has been solved by C. Udoum et al. (2019) utilizing an optimal power flow (OPF) using linear programming (LP). The successful simulation result has demonstrated that the suggested method is capable of handling the ideal real power dispatch solution taking PRDR into account. As a result, the proposed approach effectively and efficiently reduces the total cost of power generation while balancing the PRDR cost in the optimal power flow problem.

S. Nojavan et al (2021) tested on an IEEE 14-bus system using the quadratic programming method in order to minimize the operation cost. using the MATPOWER toolbox in MATLAB. to compare real-time pricing (RTP) and time-of-use programs (TOU). The effect of time-based DR programs on the cost of 24-hour operation of a power system is presented. The effects of time of use and real-time pricing programs are different.

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Table 2.3 Optimal DR management (minimization total cost)

Author and publication year	Topic	Test system	method	Objective function	Descript
L. Goel et al.,2006	Reliability enhancement of deregulated power systems considering demand-price elasticity	6-bus system	- NEWTON-base OPF - Reliability evaluation techniques.	- Minimizes the cost of generating and transmitting electricity.	- The effects of demand-price elasticity on nodal spot price and reliability of deregulated power systems.

Table 2.3 Optimal DR management (minimization total cost) (Continued)

Author and publication year	Topic	Test system	method	Objective function	Descript
M.H. Albadi, et al., 2008	A summary of demand response in electricity markets	6-bus system	Quadratic Programming	- Minimize the total cost of generation for social welfare.	- The achieving a perfect balance between supply and demand in real-time for reliable operation of the electricity system. - The demand scheduling model for the day-ahead pricing discloses the anticipated prices for the following 24 hours. - Using demand price elasticity which represents the sensitivity of customer demand to the price of electricity.

Table 2.3 Optimal DR management (minimization total cost) (Continued)

Author and publication year	Topic	Test system	method	Objective function	Descript
H. Wu et al., 2013	Hourly Demand Response in Day-Ahead Scheduling Considering Generating Unit Ramping Cost	- 6-bus system - The modified IEEE 118-bus system.	Quadratic Programming	- Minimizing the overall cost of operation.	- Day-ahead scheduling model for power systems that considers hourly demand response and ramping costs of thermal generating units. - Optimize the generation dispatch and demand response to achieve a balance between supply and demand.
J. S. Vardakas et al., 2015	A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms	V2G systems and microgrids	-	- Reduction of the total power consumption.	- Present an analysis of various DR schemes and programs based on the incentives given to customers to join the program. - Demonstrate several optimization models and optimization algorithms.

Table 2.3 Optimal DR management (minimization total cost) (Continued)

Author and publication year	Topic	Test system	method	Objective function	Descript
Qinwei Duan, 2016	A Price-Based Demand Response Scheduling Model in Day-Ahead Electricity Market	IEEE 30-bus system	Quadratic Programming	- Minimize the total cost of generation.	- Programs from the major ISOs in the U.S. - The day-ahead price-based demand scheduling model is presented. - The bidding mechanism can enable the price-elastic feature of demand and provide a more flexible and efficient way of managing power systems.
C. Udoum et al., 2019	Optimal Power Flow Considering Price-Based Real-Time Demand Response	12-bus system	linear programming	- Minimize total power generator cost.	- The optimal power flow (OPF) has been used to solve the power generation dispatching with the price-based real-time demand response (PRDR).

Table 2.3 Optimal DR management (minimization total cost) (Continued)

Author and publication year	**Topic**	**Test system**	**method**	**Objective function**	**Descript**
S. Nojavan et al., 2021	Optimal Power Flow Considering Time of Use and Real-Time Pricing Demand Response Programs	14-bus system	Quadratic Programming	- Minimize the total cost of the power system operation.	- Providing a load modeling with the time-based DR program and 24-hour OPF problem formulation. - Used to elasticity price represents the mathematical model of the self-elasticity and cross-elasticity. - The MATPOWER toolbox in MATLAB. - Compare real-time pricing (RTP) and time of use programs (TOU).

R. Shigenobu et al (2016) proposes a method for demand response (DR) by a real-time pricing (RTP) in the electricity market to improve the problems caused by high distribution generator (DG) penetration in the distribution system. The proposed method provides reactive power incentives to cooperative customers to maintain distribution voltage within the proper range. The effectiveness of the RTP and reactive power incentive is shown through simulations for distribution company (DisCo) and customer profit. The paper also includes mathematical equations and constraints to support the proposed method.

To keep the voltage within the permitted range and improve the performance of the distribution network, C. Luo et al. (2017) propose a multi-stage robust optimum scheduling of active distribution. To fully capitalize on elastic load adjustment, the methodology incorporates the demand response method into the model. The three phases of the suggested method are completed. In the first phase, the uncertain parameters are identified, and an uncertain set is used to characterize the output uncertainty for renewable energy sources. By utilizing demand react theory and the elastic load, the load fluctuation is moderated in the second stage. The reactive output adjustment of distributed generation (DG) works in concert with the conventional voltage regulation approach in the third stage, which lowers the regulating times of switching device operations and system network loss. The PG&E 69-bus system is used to examine the created model's efficiency.

Table 2.4 Optimal DR management (minimization loss)

Author and publication year	Topic	Test system	method	Objective function	Descript
R. Shigenobu et al., 2016	Optimal Demand Response Considering the Optimal Power Flow in Electricity Market	Distribution system model include - Residential area - BESS - Office area	Setting the electricity price	- Minimize the distribution Losses	- Used to minimize the distribution losses in terms of the node voltages, the tap positions, and the reactive power output of the inverters interfaced with the PV. - Demand response (DR) by a RTP in electricity market and provide reactive power incentive to cooperative customer for maintain distribution voltage within the proper range.

Table 2.4 Optimal DR management (minimization loss) (Continued)

Author and publication year	Topic	Test system	method	Objective function	Descript
C. Luo et al, 2017	Optimal scheduling of active distribution network based on demand respond theory	The PG&E 69-bus system	- Using the extreme scenario method to cut down the field of sets. - Using elastic load.	- Reduce the power loss and voltage fluctuation in the distribution network.	- Proposing a multi-stage robust optimal scheduling method for active distribution systems that considers the uncertainty and variability of renewable energy sources.

D. S. Kirschen et al (2000) examines the impact of market structure on the elasticity of demand for electricity and proposes a method for modeling consumer behavior using a matrix of self- and cross-elasticities. The paper also demonstrates how these elasticities can be used to schedule generation and set electricity prices in a pool-based electricity market. The concepts are illustrated using a 26-generator system.

Demand response (DR) initiatives, which seek to lower energy costs, relieve transmission line congestion, improve security, and increase market liquidity, are the subject of H. A. Aalami et al.'s (2010) study. The research focuses on two incentive-based DR program types: capacity market programs (CAP) and interruptible/curtailable service (I/C). With the help of the customer benefit function and the idea of price elasticity of demand, the authors create an economic model for these programs. The suggested model aids the independent system operator (ISO) in locating and implementing pertinent DR programs that enhance the load curve's properties and are well-liked by customers. To assess the efficacy of the model, the authors run a simulation study utilizing the load curve from the Iranian power system grid's peak day in 2007. The study demonstrates how these programs affect load level and form, benefit customers, and cut down on energy use. In order to determine the priority of the scenarios, the outcomes of simulation studies for various situations are reviewed and looked into.

Using an econometric technique created by Deaton, M. de Fatima et al (2012) estimate the price and income elasticities of the demand for residential energy in Mozambique. Urban, rural, and northern Mozambican households are all taken into account when making the figures for all households at the national level. The factors impacting the home energy transition are also discussed in the article. The study found that low-grade sources such as firewood and charcoal are less elastic than candles, kerosene, and electricity. Income elasticities are highest for candles and kerosene and lowest for firewood and charcoal. The paper provides a detailed description of the econometric estimation method and the survey data used in the estimation.

A. Etxegarai et al (2018) introduces a methodology for time shifting of residential demand based on price-based Demand Response (DR) and applies it to a case study in an urban distribution network. The paper highlights the potential benefits of DR programs in modifying customers' demand patterns and improving the efficiency of electricity markets. The methodology can help in reducing peak demand, leading to a more stable and reliable electricity grid, and reducing electricity costs for customers while improving the utilization of existing infrastructure.

M. Song and M. Amelin (2018) proposes a short-term planning model for a price-maker retailer with flexible power demand to determine the bidding curves on a day-ahead market. The model takes into account risk factors such as conditional value-at-risk and volume deviation risk. The study investigates the influence of risk factors on the retailer's profit, risk levels, average spot price, and total consumption using data from the Nordic electricity market. The results show that the retailer can benefit from the flexibility in demand side in some cases, and the flexibility also leads to lower spot prices so that the customers in real-time price-based demand response can face a lower electricity price for per-unit power consumption.

R. Schumacher et al (2021) proposes a self-sustainable real-time pricing (RTP) tariff that can reduce demand peaks by using an economical approach, which presents advantages for both consumers and distribution power companies. The proposed tariff is revenue-neutral and protects both consumers and distribution power companies from being economically affected by varying price elasticity scenarios. The proposed dynamic tariff is compared with the Conventional Tariff and White Tariff, which are currently adopted by residential consumers in Brazil, through numerical simulations. The paper highlights the advantages of the proposed tariff and its potential to reduce operational costs, instability risks, and excessive use of fossil fuels in power systems under peak demand conditions.

Table 2.5 Elasticity Price

Author and publication year	Topic	Descript
D. S. Kirschen et al., 2000	Factoring the Elasticity of Demand in Electricity Prices	- Analyzes the effect that the market structure can have on the elasticity of the demand for electricity.
H. A. Aalami et al., 2010	Demand response modeling considering Interruptible/Curtailable loads and capacity market programs	-Demand response is Interruptible/Curtailable service (I/C) and capacity market programs (CAP) by aimed to electricity price reduction. - Using the load curve of the peak day of the Iranian power system grid in 2007.
M. de Fatima et al., 2012	Estimation of elasticities for domestic energy demand in Mozambique	- Calculates the price and the income elasticities of demand for domestic energy. - Using an econometric method developed by Deaton.

Table 2.5 Elasticity Price (Continued)

Author and publication year	Topic	Descript
A. Etxegarai et al.,2018	Impact of price-based demand response programs for residential customers	- impact of price-based demand response programs on residential customers. - It introduces a methodology for time shifting of residential demand based on price-based DR. - applies it to a case study in an urban distribution network. - in Spain.
M. Song and M. Amelin, 2018	Price-Maker Bidding in Day-Ahead Electricity Market for a Retailer with Flexible Demands	- Develops a short-term planning model for a price-maker retailer with flexible power demand to determine the bidding curves on a day-ahead market. - The study investigates the influence of risk factors on the retailer's profit, risk levels, average spot price, and total consumption. - Data from the Nordic electricity market.
R. Schumacher et al.,2021	Self-Sustainable Dynamic Tariff for Real Time Pricing-Based Demand Response A Brazilian Case Study	- Compared with the Conventional Tariff and White Tariff. - in Ipirange, Paraná, Brazil.

Schwepp et al (1987) the best electricity Spot pricing internalizes the costs and limitations of the power transportation network. By incorporating system security control issues into the model, we extend the spot pricing theory. A requirement for quickness and accuracy of response is imposed by the engineering and physics of system security control. We demonstrate the existence of socially optimal prices that internalize security control costs to decentralize security control. These prices can be established with appropriate information requirements by the market maker and are reliable.

Table 2.6 The selected literatures on the optimal spot pricing

Reference	**Formula**	**Main Price Components**	**Method**
Schwepp et al., 1987	$\rho_i = \lambda - \lambda(\frac{dP_{loss}}{dP_i}) - \sum_{i=1}^{NC} v_l(\frac{dP_l}{dP_i})$	- Marginal energy. - Marginal loss. - Congestion Relaxation.	DC load flow

CHAPTER III

OPTIMAL POWER FLOW WITH INCENTIVE BASE DEMAND RESPONSE

The optimal price-based real-time demand response (OPRDR) using particle swarm optimization (PSO) is proposed. In the proposed method, the price-based real-time demand response (PRDR) is integrated into optimal power flow (OPF) problem and solved simultaneously. The algorithm has been tested with the IEEE 33-bus system. The test results shown that the proposed algorithm can effectively minimize total operating cost by trading-off with PRDR cost in the optimal power dispatch.

3.1 Introduction

This chapter the OPF problem using PSO (Kennedy, J. et al.,1995), the method for integrating of OPRDR. The proposed problem formulation can be applied for both day-ahead and hour-ahead operation in electricity treading platform. The 33-bus distribution test system (Alzahrani et al., 2019) was used to test the proposed method. The recommended approach resulted in the lower cost of production. When include the PRDR management problem into the OPF.

3.2 Problem Formulation

The OPRDR model is used in this paper to solve the problem of determining the best control variables for minimizing total system operating expenses while adhering to numerous equality and inequality limit requirements. The following are the OPRDR problem formulations that have been proposed.

The objective function is to minimize total operating cost considering demand response as,

$$\text{Minimize} \quad TFC = \sum_{i=1}^{NG} F_{Gi}(P_{Gi}) + \sum_{i=1}^{NB} D_i(P_{DRi}) \tag{3.1}$$

subjected to the power balance constraint,

$$P_{Gi} - P_{Di} = \sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\cos(\theta_{ij} - \delta_{ij}), i = 1,...,NB \tag{3.2}$$

$$Q_{Gi} - Q_{Di} = -\sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\sin(\theta_{ij} - \delta_{ij}), i = 1,...,NB \tag{3.3}$$

and the generator operating limit constraint,

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1,...,NG \tag{3.4}$$

$$P_{Di} = P_{Di}^{0} - P_{DRi}, i = 1,...,NB \tag{3.5}$$

and line flow limit constraint,

$$|f_{lm}| \le |f_{lm}|^{\max} \tag{3.6}$$

and bus voltage limit constraint,

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max} \tag{3.7}$$

Note that the PNF is applied only when the result violates the constraints in Equation. (3.6)-(3.7).

3.3 PSO based integrated OPRDR and OPF

The PSO system proposed by (Kennedy, J. et al.,1995) is a method of optimization based on the traveling or foraging behavior of the herd. In particular, for a flock of birds, each bird in the flock is represented by a particle. The PSO solution starts by randomly locating the particles (which various positions of those particles are possible solutions) to produce a set. The optimal values are then determined by adjusting the values at each decision cycle. where each particle is adjusted by changing its position according to the best value.

PSO operation is an iterative computation process in which each cycle of operation the velocity of each particle is adjusted by $pbest^t_i$ and $gbest^t_i$. In this paper, the set of populations is formulated as,

$$\mathbf{p_i} = [p_i,..., p_{NP}] = [P_{G2},..., P_{NG}, |V_1|,...,|V_{NG}|, DR_1,..., DR_{NB}] \tag{3.8}$$

The control of variables in Equation (3.10) are used for Equations (3.1) - (3.7). Then, the new velocity of the particles is calculated by Equation (3.9), the new position of the particles is computed by Equation (3.10). Note that P_{Gi} or the real power generator at slack bus is not include in the optimization problem, and treated as dependent variable.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i^t - \mathbf{p}_i^t) + c_2 r_2 (gbest_i^t - \mathbf{p}_i^t) \tag{3.9}$$

$$\mathbf{p}_i^{t+1} = \mathbf{p}_i^t + v_i^{t+1} \tag{3.10}$$

The computational procedure of the proposed method is as follows,

Step 1: Obtain system data.

Step 2: k = 1.

Step 3: Initial PSO populations.

Step 4: Solve power flow solution in Equations. (3.2) - (3.3) of each population.

Step 5: Compute the objective function in Equation. (3.1). (If the solution violate constrains, PNF $=10^{12}$. If no constrain violation, PNF = 0.)

Step 6: Obtain $pbest^t_i$ and $gbest^t_i$ for each population.

Step 7: Compute v_i^{t+1} Equation. (3.9).

Step 8: Update $\mathbf{p}_i^{t+1}$ in Equation. (3.10).

Step 9: k = k+1.

Step10: If k > maximum iteration, go to Step 4. If k ≤ maximum iteration, go to Step 11.

Step11: Obtain output and stop.

3.4 Simulation Result

The proposed OPRDR based OPF was tested with modified IEEE 33-bus distribution test system (Alzahrani et al.,2019), as shown in Figure 2.

Six generators and DR are added in the distribution network, as shown in Figure 3.1 The generator are installed on buses 3, 8, 14, 25, 30, and 31. The DR are installed on buses 24 and 25, which are the buses connected to the large demands. Meanwhile, most at power is supplied from power grid at bus *i*.

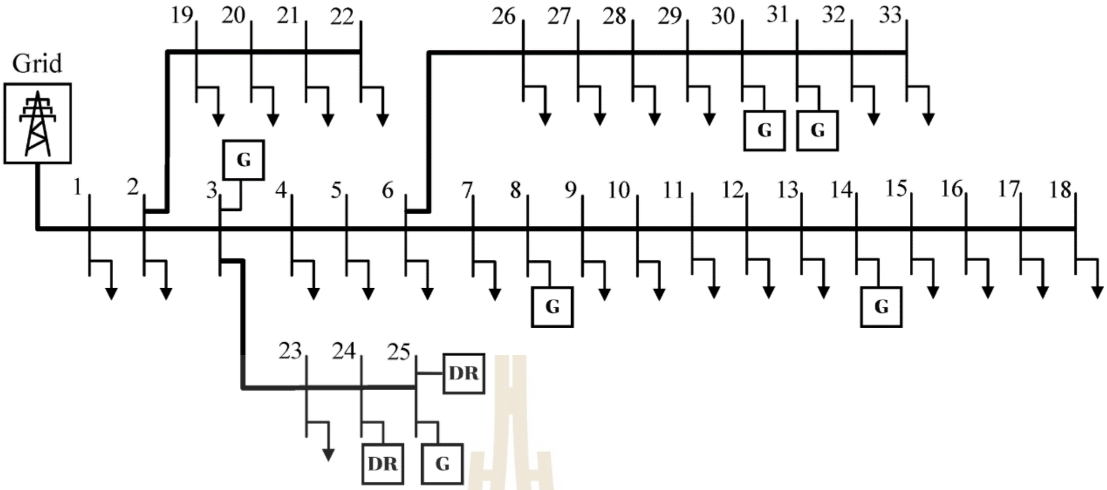


Figure 3.1 The modified IEEE 33-Bus system

The simulation study includes,

Case I : modified IEEE 33-bus distribution test system, OPF without DR, and

Case II: modified IEEE 33-bus distribution test system, OPF with DR.

In this chapter, the PSO parameters used are as follow, c_1 = 2, c_2 = 2, w_{min} = 0.9,w_{max} = 0.4, Population size =1000, and Maximum iteration = 50. Note that the simulation are performed under one hour basis.

TABLE 3.1 DR price for 1 hour of 33-bus system.

Bus	Power Demand		PRDR	
	(MW)	(MVar)	(MW)	($/MWhr)
24	420- P_{DRi}	200	100	20
25	420- P_{DRi}	200	100	10

In this chapter, the PRDR cost used are in constant price as shown in Table 3.1, where the prices of 20 and 10 ($/MWh) are fictitious to test this system.There are two PRDR, connected at buses 24 and 25, which are the buses with large load, for simulation. Meanwhile, the generator cost functions used are in quadratic form as shown in Table 3.2.

TABLE 3.2 Generator Data.

Bus	P_{min} (MW)	P_{max} (MW)	Q_{min} (MVar)	S_{max} (MVA)	Cost coefficients*		
					a_i	b_i	c_i
1	50	1000	-20	250	0	2.00	0.00375
3	50	500	-20	250	0	2.00	0.00375
8	50	500	-20	100	0	1.75	0.01750
14	50	500	-15	80	0	1.00	0.06250
25	50	500	-15	60	0	3.25	0.00834
30	50	500	-10	50	0	3.00	0.02500
31	50	500	-15	60	0	3.00	0.02500

*Generation cost $F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2$ \$/hr

Table 3.3 is a comparison of the modified IEEE 33-bus system for Case I and Case II. The proposed method PSO based integrated OPRDR and OPF. The optimal value of generator power output (P_{G2} - P_{G7}), generator voltage magnitudes ($|V_2|$-$|V_7|$), and purchasing DR at buses 24-25. The voltage based limit constraint used in this chapter is $0.95 \leq |V_i| \leq 1.05$ p.u..

In Case I, The generation cost is 29432.00 \$/hr, The losses total system is 0.0321 MW, and the total system cost is 29432.16 \$/hr. The convergence plot of Case I is shown in Figure. 3.2.

In Case II, The generation cost was reduced to 27940.00 \$/hr. The total system loss was reduced to 0.0325 MW. With the inclusion of DR cost, the total system cost 28940.12 \$/hr, lower than that of Case I even the total loss higler. Figure. 3.3 addresses the convergence plot of Case II.

The results of two cases shown that the total system generation cost can be reduced by PRDR mechanism. Meanwhile, the customers those who provide PRDR to the system gain the benefit from PRDR payment.

The solution shown that the system cost can be reduced when integrate the OPRDR with OPF problem. Moreover, DR reduces the need to invest in reserve capacity and utilization of the high fuel cost segment without wasting resources and is environmentally friendly. For PRDR, the consumer will receive a compensation rate or a discount on the electricity tariff.

TABLE 3.3 Comparison results of the IEEE 33-Bus system.

Variable	Case I	Case II
P_{G3}	500	500
P_{G8}	395.5768	381.8340
P_{G14}	120.0461	116.1286
P_{G25}	500	500
P_{G30}	251.9175	242.3788
P_{G31}	252.5813	243.0587
$\|V_3\|$	0.9951	0.9954
$\|V_8\|$	0.9797	0.9793
$\|V_{14}\|$	0.9673	0.9668
$\|V_{25}\|$	0.9925	0.9941
$\|V_{30}\|$	0.9796	0.9791
$\|V_{31}\|$	0.9785	0.9780
DR_{24}	-	0
DR_{25}	-	100
Total Gen. Cost ($/hr)	29432.00	27940.00
Total DR Cost ($/hr)	-	1000
Total system Losses (MW)	0.0321	0.0325
Total system Cost ($/hr)	29432.16	28940.12
Compulation time (sec)	710.55	1098.54

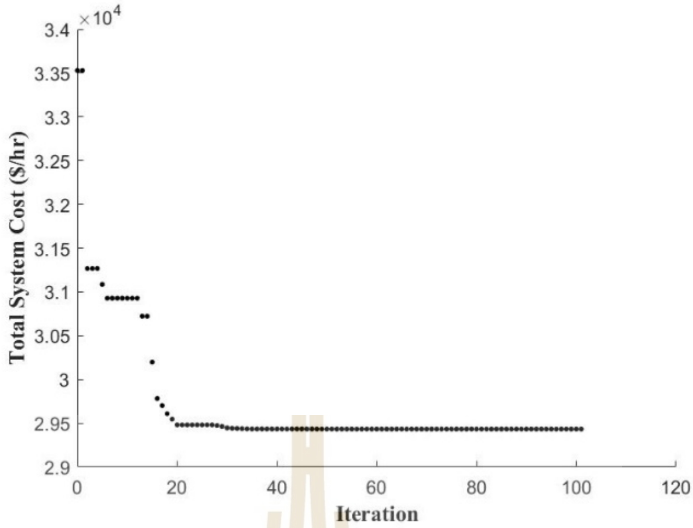


Figure 3.2 The convergence plot of Case I

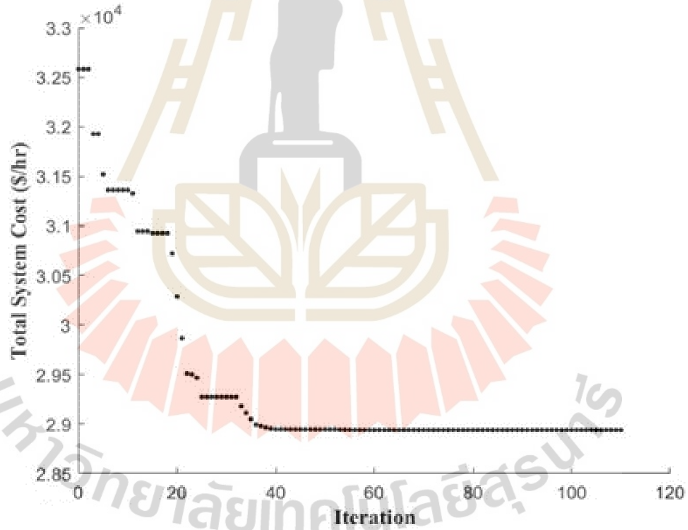


Figure 3.3 The convergence plot of Case II

The resulte with 20 trial of the proposed OPRDR is shown in Table 3.4 and Figure. 3.4.

TABLE 3.4 the result at 20 trials of the proposed OPRDR

Total system cost ($/hr)	Case I	Case II
Best	29432.1579124933	28940.1217262821
Mean	29432.1579126334	28940.1217266083
Worst	29432.1579139414	28940.1217275539

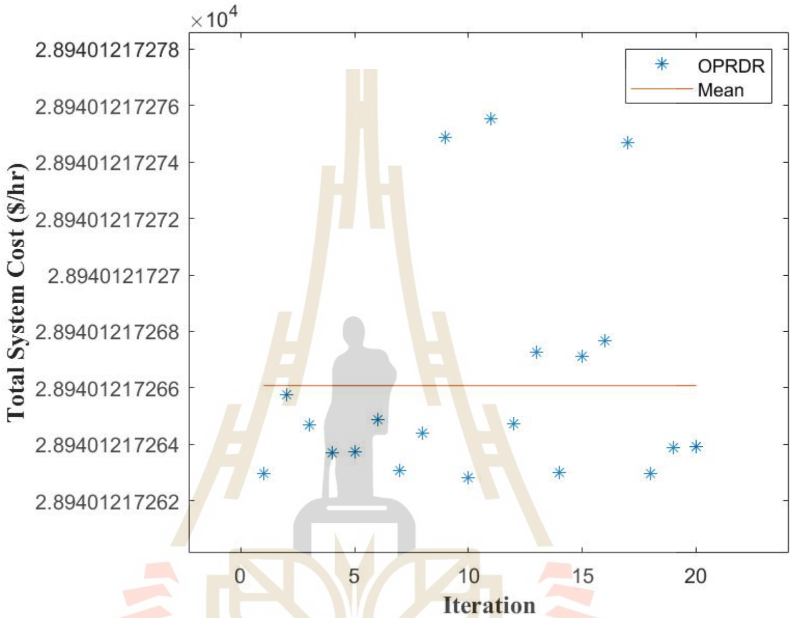


Figure 3.4 The solution with 20 trail of Case II

3.5 Conclusion

The OPRDR model is described. The effectiveness of the proposed methodology has been comparatively tested and validated on the modified IEEE 33-bus distribution test system. The results revealed that the proposed integrated OPRDR with OPF can reduce the overall system cost by taking into consideration generator management, voltage adjustment, and DR offers. In this chapter, we use the incentive base model, which takes into account the distribution system with electricity purchase contracts based on the electricity market. In the next chapter, we will use the price base model to determine the electricity cost from human behaviour, which will be considered in large systems.

CHAPTER IV
OPTIMAL POWER FLOW WITH PRICE BASE DEMAND RESPONSE

This chapter proposes the optimal power dispatch (OPD) considering price-based demand response (PDR). In the proposed framework, the nodal spot price (NSP) is use as a price signal to the consumers. In the proposed method, the optimal real power dispatch is solved by quadratic programming (QP) to minimize the total operating cost and obtain the NSP components. Consequently, demand elasticity (DE) is applied to estimate the system demand for more accurate day-ahead operations. In the DE matrix, the self-DEs represent the consumer consumption of hour h in response to the NSP of that hour. Meanwhile, the cross-DEs represent the response of consumer consumption of hour h to the NSP of other hours. The algorithm was tested with the IEEE 30-bus system with several cases of demand elasticity. The results show that the proposed algorithm can incorporate price elasticity of demand into day-ahead scheduling and effectively minimize total operating costs. The simulation study shown that, the operating cost can be reduced by 0.33-0.695% with self-DE of -0.1 ~ -0.2, by reducing the consumption respected to the NSP. Meanwhile, when applying cross-DE, the operating cost can be reduced by 0.015% under the same daily consumption with the consumer's load shifting respected to NSP.

4.1 Chapter Overview

This chapter proposes the optimal power dispatch (OPD) considering price-based demand response (PDR). Section 4.2 explain about day-ahead elastic load model. Section 4.3 describes the problem formulation. Section 4.4 explain the simulation result in the IEEE 30-bus system and obtains the optimal development of OPF for the OPRDR coordination scheme considering demand elasticity in the test system—section 4.5 conclusion.

4.2 Day-Ahead Elastic Load Model

An economic load model that depicts the shifts in customer demand in response to changes in demand prices is needed to define client engagement in DR schemes. DE is used to represent the demand response behaviors. The relative slope of the demand-price curve could be used to determine the demand-price elasticity as shown in Figure. 4.1 This elasticity coefficient significantly shows a change in a commodity's price would alter the relative level of demand for that commodity. It shall be assumed throughout this paper that all prices and quantities have been normalized about a certain equilibrium.

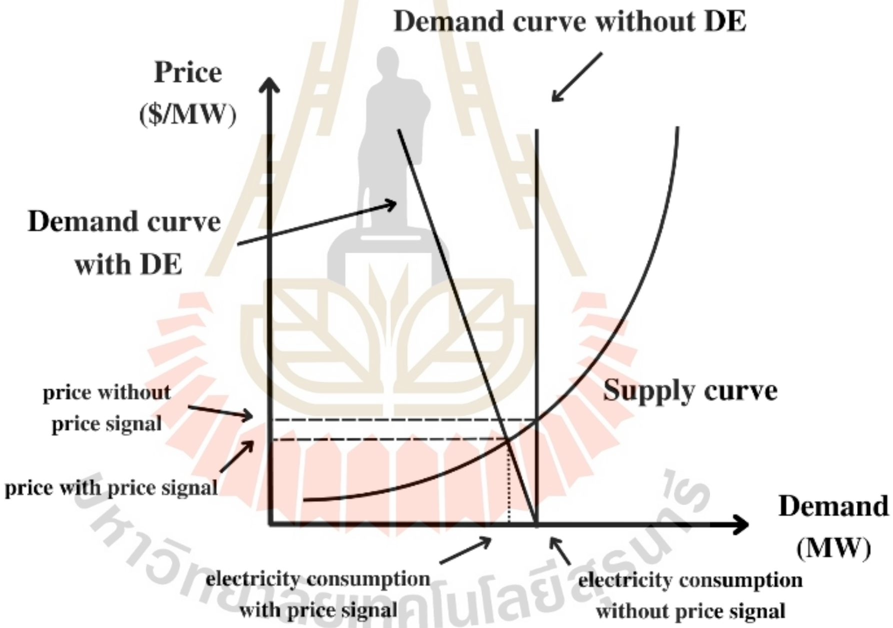


Figure 4.1 Bidding curve of demand

The fixed-demand bids are inelastic to the market price in terms of demand. To represent the consumer's behaviors, the DE can be formulated by the matrix consisted of "self-elasticity" and "cross-elasticity". The self-elasticity represents the DE of the demand corresponding to the price in the same hour. Therefore, if the higher price leads to the lower demand and the self-elasticity is then negative. On the other hand, the higher price in hour *i* (that reduce the consumption in hour *j*. Therefore, the cross-elasticity is then negative. An elasticity matrix can be followed as Equations (4.1) - (4.2),

$$\begin{bmatrix} \Delta P_{L1} \\ \Delta P_{L2} \\ \vdots \\ \Delta P_{L24} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,24} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \cdots & \varepsilon_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{24,1} & \varepsilon_{24,2} & \cdots & \varepsilon_{24,24} \end{bmatrix} \begin{bmatrix} \Delta \sigma_{1} \\ \Delta \sigma_{2} \\ \vdots \\ \Delta \sigma_{24} \end{bmatrix} \tag{4.1}$$

$$\varepsilon_{i,j} \leq 0, \text{ if } i = j, \text{ and } \varepsilon_{i,j} \geq 0, \text{ if } i \neq j \tag{4.2}$$

As was previously noted, the period under consideration affects how customers respond to changes in power prices. In this paper, we will focus on the response "short-term", which refers to the period between the price announcement for the subsequent 24-hour period and the actual demand periods. Therefore, hourly demand changes can be followed as Equations (4.3) - (4.4),

$$\Delta P_{Li,h} = \sum_{i=1}^{24} \varepsilon_{i,h} \Delta \sigma_{i,h}, \text{ and} \tag{4.3}$$

$$P_{Li,h} = P_{Li,h}^{0} + \Delta P_{Li,h}, i = 1,\ldots, NB, h = 1,\ldots,24. \tag{4.4}$$

The price of electricity each hour, taking into account the elasticity price can be followed as Equation (4.5),

$$EC_{i,h} = \sum_{i=1}^{NB} P_{Li,h} \cdot \sigma_{i,h}, i = 1,\ldots, NB, h = 1,\ldots,24. \tag{4.5}$$

4.2.1 Spot pricing of electricity

The spot price applied in this scheme including the system marginal price, marginal transmission loss, and network quality of supply (line congestion premium) (F. C. Schweppe et al., 1988) which can be calculated by,

$$\sigma_{i,h} = \lambda_h + \eta_{L,ih} + \eta_{QS,ih}, i = 1,...,NB, h = 1,...,24, \quad (4.6)$$

$$\eta_{L,ih} = \lambda_h \cdot (-ITL_{i,h}) = \lambda_h \cdot (\frac{dP_{loss,h}}{dP_{i,h}}), i = 1,...,NB, h = 1,...,24, \text{ and} \quad (4.7)$$

$$\eta_{QS,ih} = -\sum_{l=1}^{NB} \mu_{l,h}(a_{li,h}), i = 1,...,NB, h = 1,...,24. \quad (4.8)$$

The $ITL_{i,h}$ is the change in total system loss due to the change in real injection power at bus i. The constraint incremental relaxation price or $\mu_{l,h}$ is defined as the reduction in supply cost or increase can be followed as Equation. (4.9),

$$ITL_{i,h} = \frac{dP_{loss,h}}{dP_{i,h}}. \quad (4.9)$$

The line flow sensitivity factors ($a_{li,h}$) of line l to change in real injection power at bus i is followed as Equation. (4.10), then $\Delta f_{l,h}$ is the change in power flow on line l when $\Delta P_{i,h} \neq 0$ and $\Delta P_{i,h}$ is the change in real injection power at bus i at hour h as,

$$a_{il,h} = \frac{\Delta f_{l,h}}{\Delta P_{i,h}}. \quad (4.10)$$

The change of real power flow at line l will be $\Delta f_{l,h}$ and the power flow at line l will be expressed as follows Equation. (4.11),

$$f_{l,h} = f_{l,h}^0 + a_{li,h}\Delta P_{i,h}. \quad (4.11)$$

4.3 Problem Formulation

The conception of the paper can be shown in Figure. 1.3. The primary optimal power dispatch provides the day-ahead hourly spot price and is announced prior to the dispatch day (M. Song and M. Amelin, 2018), (L. Goel and Q. Wu, 2006).

The objective function is to minimize total operating cost considering demand response as,

$$\text{Minimize } TFC = \sum_{h=1}^{24}\sum_{i=1}^{NG} FC_i(P_{Gi,h}). \tag{4.12}$$

Where, the quadratic generator cost function has the following form,

$$FC_i(P_{Gi,h}) = a_i + b_i P_{Gi,h} + c_i P_{Gi,h}^2 \text{ (\$/hr)}, i = 1,\ldots,NB, h = 1,\ldots,24. \tag{4.13}$$

$$TCF = \frac{1}{2}\mathbf{P}_{\mathbf{Gi}}^{\mathbf{T}}\mathbf{H}\mathbf{P}_{\mathbf{Gi}} + \mathbf{f}^{\mathbf{T}}\mathbf{P}_{\mathbf{Gi}} \begin{cases} \mathbf{A}\cdot\mathbf{P}_{\mathbf{Gi}} \le \mathbf{b}, \\ \mathbf{A}_{\mathbf{eq}}\cdot\mathbf{P}_{\mathbf{Gi}} = \mathbf{b}_{\mathbf{eq}}, \\ \mathbf{lb} \le \mathbf{P}_{\mathbf{Gi}} \le \mathbf{ub} \end{cases} \tag{4.14}$$

$$\mathbf{H} = \begin{bmatrix} 2c_1 & 0 & \cdots & 0 \\ 0 & 2c_2 & \cdots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & 2c_{NG} \end{bmatrix} \tag{4.15}$$

$$\mathbf{f} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{NG} \end{bmatrix} \tag{4.16}$$

Subject to the power balance constraint,

$$P_{Gi,h} - P_{Di,h} = \sum_{j=1}^{NB} |V_{i,h}||V_{j,h}||y_{ij}|\cos(\theta_{ij} - \delta_{ij,h}), i = 1,\ldots,NB, h = 1,\ldots,24, \tag{4.17}$$

$$Q_{Gi,h} - Q_{Di,h} = -\sum_{j=1}^{NB} |V_{i,h}||V_{j,h}||y_{ij}|\sin(\theta_{ij} - \delta_{ij,h}), i = 1,\ldots,NB, h = 1,\ldots,24, \tag{4.18}$$

and the generator operating limit constraint,

$$P_{Gi,h}^{\min} \le P_{Gi,h} \le P_{Gi,h}^{\max}, i = 1,...,NG, h = 1,...,24, \tag{4.19}$$
$$Q_{Gi,h}^{\min} \le Q_{Gi,h} \le Q_{Gi,h}^{\max}, i = 1,...,NG, h = 1,...,24, \tag{4.20}$$

and line flow limit constraint,

$$| f_{lm,h} | \le | f_{lm,h} |^{\max}, h = 1,...,24. \tag{4.21}$$

The proposed method's computational process is as in Figure. 4.2

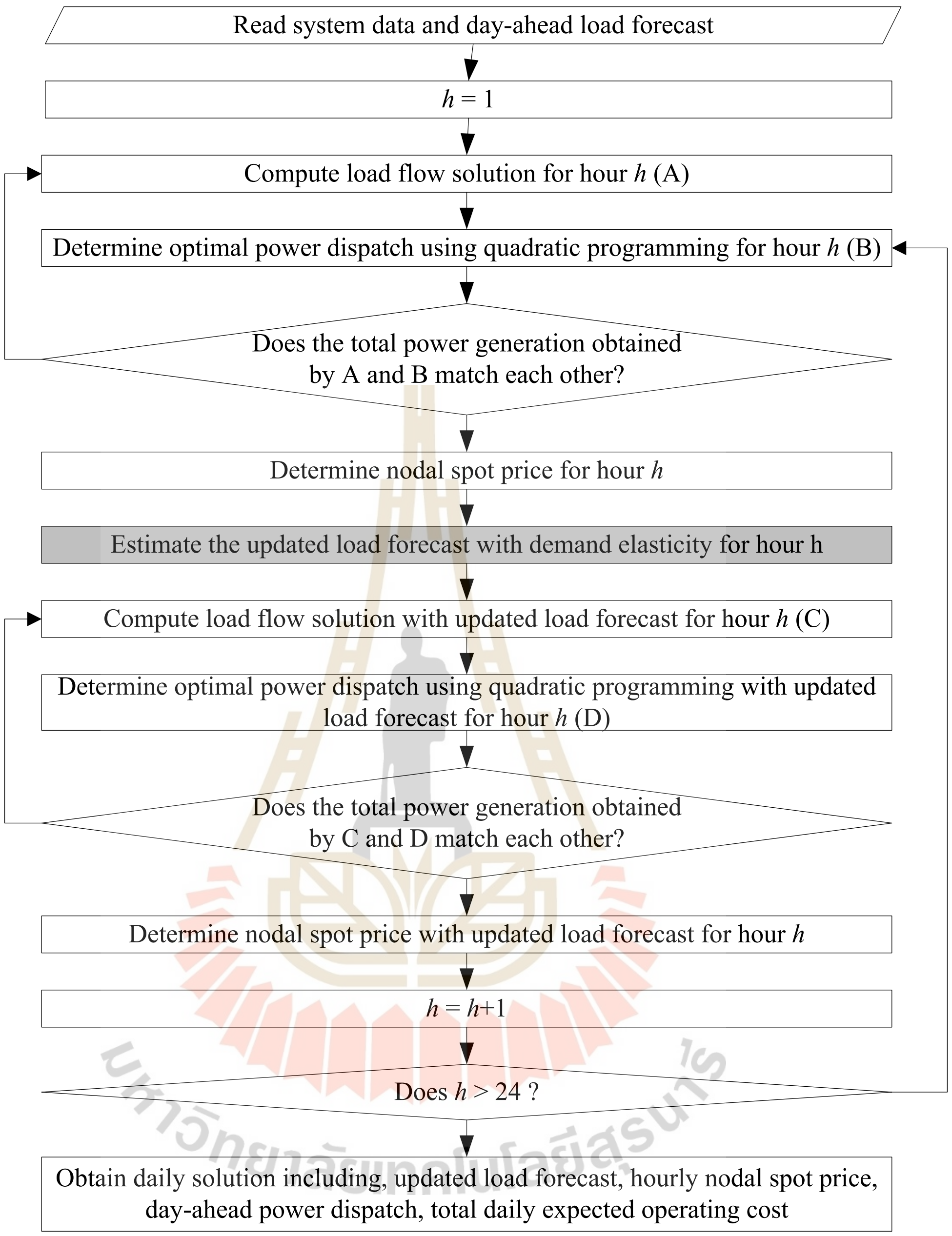


Figure. 4.2 Computational procedures

4.4 Simulation Result

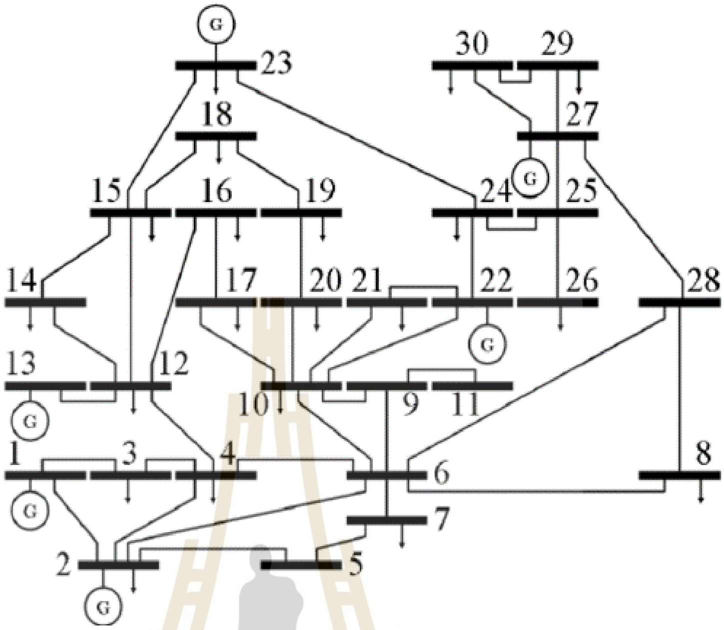


Figure 4.3 IEEE 30-bus system data

This section examines the proposed method by using the IEEE 30-bus test system. The IEEE 30-bus system used in this simulation.

Table 4.1 Generator data for the IEEE 30-bus system

BUS	P_{min} (MW)	P_{max} (MW)	Q_{min} (MVar)	Q_{max} (MVA)	Cost coefficient		
					a_i	b_i	c_i
1	50	200	-20	250	0	2.00	0.00375
2	20	80	-20	100	0	1.75	0.01750
5	15	50	-15	80	0	1.00	0.06250
8	10	35	-15	60	0	3.25	0.00834
11	10	30	-10	50	0	3.00	0.02500
13	12	40	-15	60	0	3.00	0.02500

*Generation cost $F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2$ \$/hr

Table 4.1 lists the quadratic cost functions for each generator in the IEEE 30-bus system according to [25]. To analyse the effects on different facets of the electricity system while incorporating price-elastic demand bids, the simulation for of 24 hours is used. The six generators are situated at buses 1, 2, 5, 8, 11, and 13 in the IEEE 30-bus system. Bus 1 has been designated as the slack bus.

The system's daily load profile in the summer peak day of Thailand 2018, which peaks of 20340.70 MW at hour 20 and light-load of 13681.76 MW at hour 8, as shown in Figure. 4.4 is used. The peak in demand occurs between 7:00 p.m. and 12:00 a.m., which is when there could be a significant need for power because of human activity.

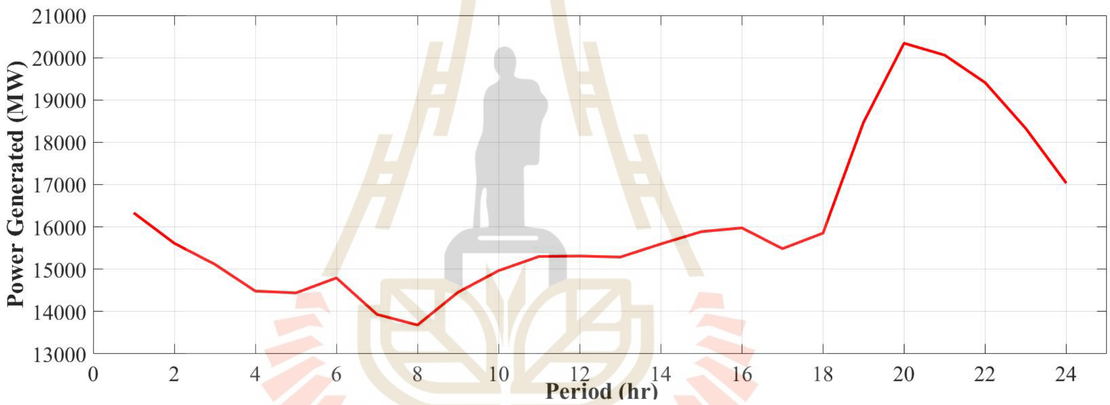


Figure. 4.4 System daily load curve

The simulation study includes,

Case I: Base case.

In this case, the price signal is not applied.

Case II: Self-elasticity -0.1 without cross-elasticity.

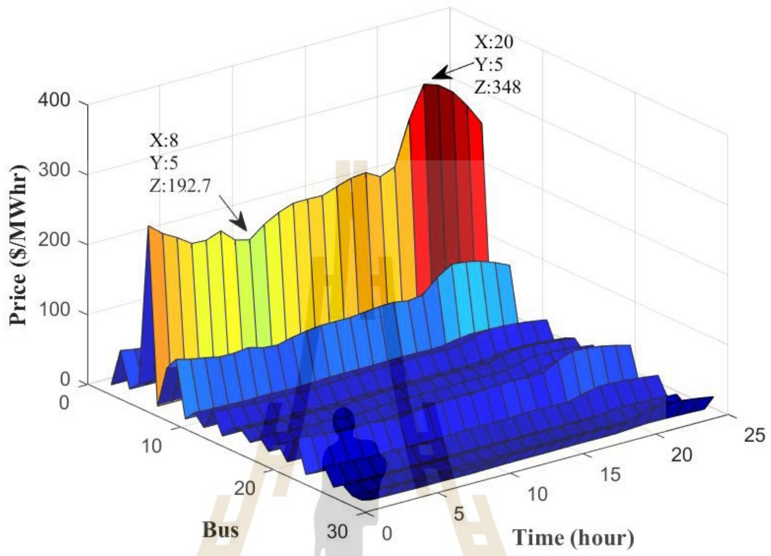
In this case, DE is considered for all buses in the system. The demand is changed after considering demand price-elasticity.

Case III: Self-elasticity -0.2 without cross-elasticity.

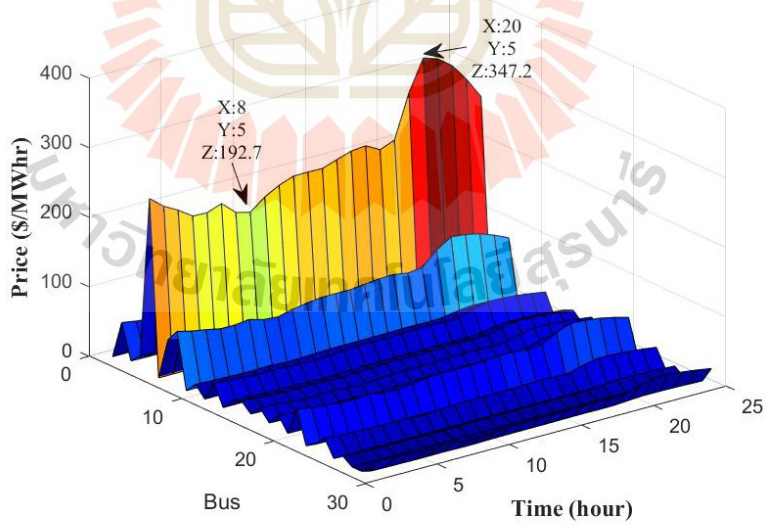
In this case, DE is considered for all buses in the system. The demand curve with DE is the same as in case II, but a price elasticity is set to -0.2.

Case IV: Self-elasticity -0.23 and cross-elasticity 0.01.

In this case, DE is considered for all buses in the system. The demand curve with DE has, a self-elasticity of -0.23 and a cross-elasticity of 0.01. We use this to represent the changes in the price of one hour affect the demand for another.

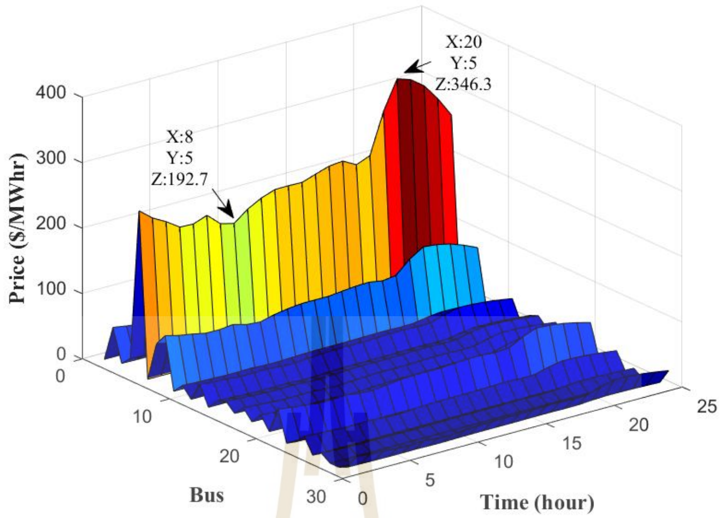


(a)

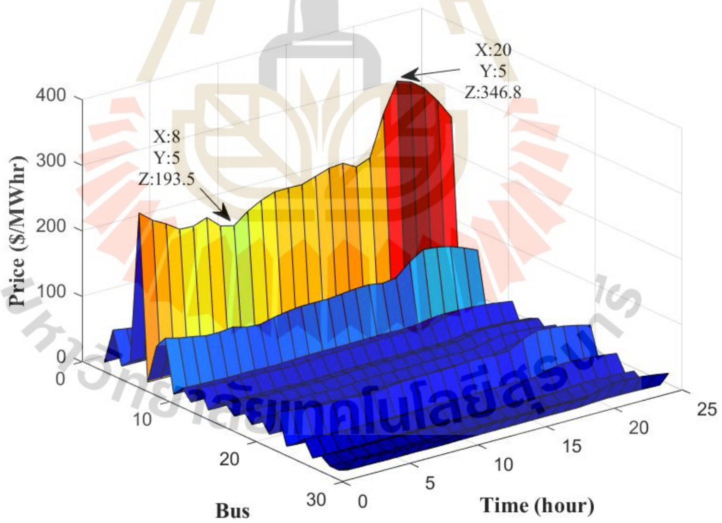


(b)

Figure. 4.5 Fuel cost (a) case I (b) case II (c) case III (d) case IV



(c)



(d)

Figure. 4.5 Fuel cost (a) case I (b) case II (c) case III (d) case IV (Continued)

The optimal total power generator for all cases is shown in Table 4.3, representing the effect of price elasticity on the system demand. Comparing the experimental results in each case, it can be seen that in Case III, the demand is 5503.423 MW per day, which is the least. Due to the cross-elasticity, the light-load demand, is higher, resulting in a better system load factor, as shown in Figure. 4.6

Table 4.2. Spot price at bus 5

	Hour	Price ($/MWh)	
Peak hour	20	Case I	3.6946
		Case II	3.6881
		Case III	3.6818
		Case IV	3.6853
Light-load hour	8	Case I	3.0417
		Case II	3.0417
		Case III	3.0417
		Case IV	3.0508

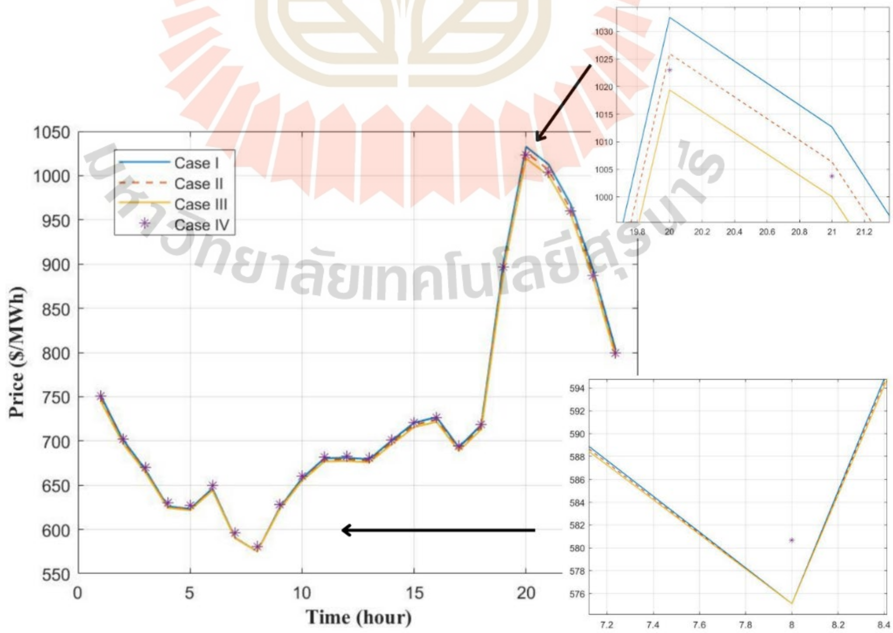


Figure. 4.6 Hourly fuel cost of IEEE 30-bus system

Table 4.2 shows the spot prices for the peak and light-load hours of bus 5. Bus 5 is the highest-demand bus. The hourly price of each bus in cases I-IV are shown in Figures 4.5(a)-(d), respectively. The results of the fuel cost comparison in Case I is served as a base case, with simulations indicating that the cost is higher in all scenarios as shown in Figure 4.5(a). In Figure 4.5(b), the result of Case II, self-elasticity is applied with a value of -0.1. It is observed that the cost has slightly decreased in comparison to the base case. Figure 4.5(c) shows the result of Case III, the self-elasticity is -0.2. Note that in this case, the total generation cost is the lowest. Finally, Figure 4.5(d) shows the result of Case IV, self-elasticity is -0.23 and cross-elasticity is also applied at 0.01.

Table 4.3. Comparison of the results of the generator in a 30-bus system

Hour	Case I (MW)	Case II (MW)	Case III (MW)	Case IV (MW)
1	234.0324	233.3893	232.7466	233.8191
2	223.3372	222.8731	222.4092	223.5481
3	215.9894	215.6468	215.3042	216.4881
4	206.6524	206.4622	206.2721	207.5125
5	205.9933	205.8138	205.6344	206.8787
6	211.2119	210.9475	210.6831	211.8960
7	198.5118	198.4531	198.3943	199.6833
8	194.8387	194.8387	194.8387	196.1496
9	206.2330	206.0496	205.8663	207.1092
10	213.7649	213.4587	213.1526	214.3500
11	218.7275	218.3397	217.9521	219.1192
12	218.8779	218.4877	218.0975	219.2638
13	218.4868	218.1030	217.7193	218.8880
14	223.0959	222.6359	222.1759	223.3163
15	227.4109	226.8790	226.3473	227.4610
16	228.7400	228.1852	227.6313	228.7368
17	221.4381	221.0056	220.5731	221.7237
18	226.8976	226.3743	225.8511	226.9680
19	265.7107	264.6265	263.5428	264.4245
20	293.2090	291.8292	290.4499	291.2146
21	289.0740	287.7390	286.4045	287.1861
22	279.4950	278.2635	277.0325	277.8532
23	263.6143	262.5552	261.4962	262.3873
24	244.4869	243.6671	242.8478	243.8539
All day	5529.830	5516.624	5503.423	5529.831

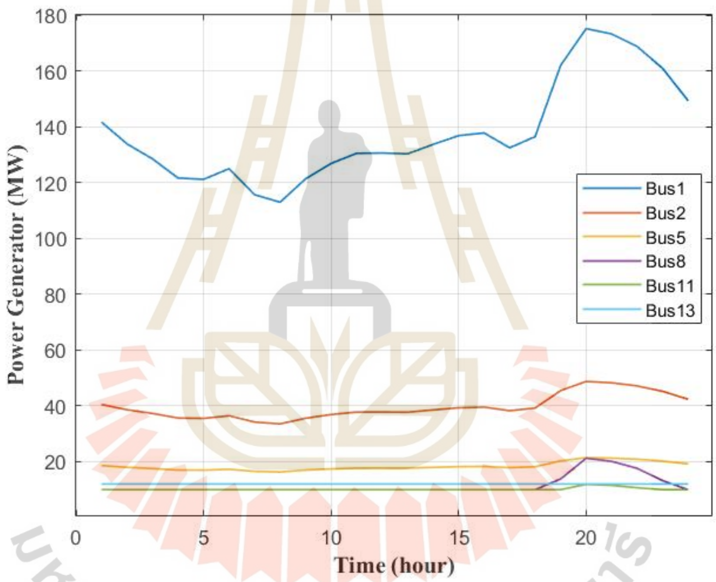
Table 4.4. Comparison of the results of the fuel cost the in the 30-bus system

Hour	Case I ($)	Case II ($)	Case III ($)	Case IV ($)
1	752.0372	748.9733	745.9161	751.0208
2	701.6643	699.5204	697.3800	702.6396
3	667.9710	666.4220	664.8750	670.2279
4	626.2246	625.3890	624.5540	630.0104
5	623.3228	622.5357	621.7492	627.2123
6	646.4610	645.2830	644.1061	649.5141
7	590.8004	590.5485	590.2967	595.8300
8	575.1123	575.1123	575.1123	580.6763
9	624.3773	623.5726	622.7684	628.2292
10	657.9165	656.5418	655.1686	660.5477
11	680.4396	678.6725	676.9078	682.2271
12	681.1278	679.3486	677.5718	682.8893
13	679.3396	677.5917	675.8463	681.1686
14	700.5464	698.4225	696.3021	701.5649
15	720.6651	718.1784	715.6963	720.8995
16	726.9135	724.3103	721.7148	726.8990
17	692.8850	690.8978	688.9135	694.1982
18	718.2583	715.8153	713.3767	718.5873
19	902.8454	897.8075	892.7829	896.8698
20	1032.560	1025.962	1019.385	1023.029
21	1012.679	1006.344	1000.028	1003.725
22	967.2195	961.4796	955.7555	959.5699
23	893.0503	888.1496	883.2608	887.3733
24	802.8380	798.8120	794.7972	799.7273
All day	17677.25	17615.69	17554.26	17674.63

In Case III, self-elasticity is utilized with a value of -0.2 resulting in the case with the lowest cost. Additionally, Case IV takes into account the impact of changes to one product on the cost of another product, as illustrated in Table 4.4.

Table 4.5 Cost rate per power generator ($/MWhr) for different price elasticity

Case	Case I	Case II	Case III	Case IV
Cost per power generator ($/MWhr)	3.1967	3.1932	3.1897	3.1962



(a)

Figure. 4.7 Hourly power generator for case III

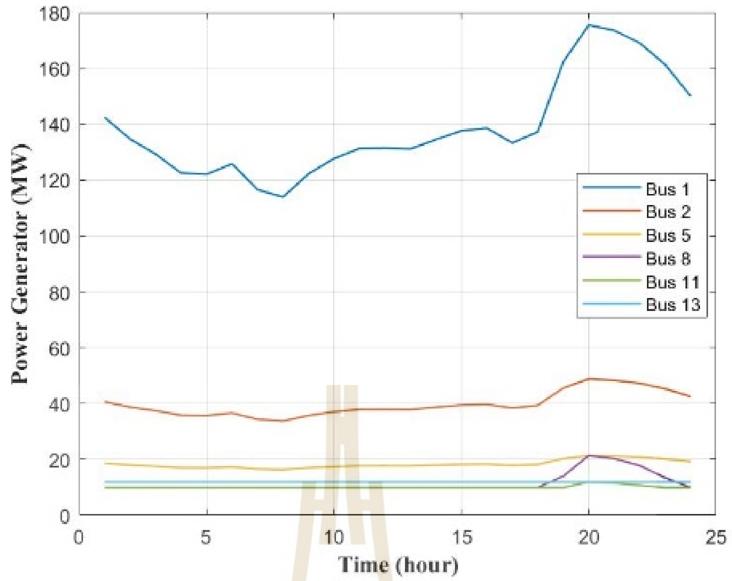


Figure. 4.8 Hourly power generator for case IV

As shown in Figure 4.7, the hourly price during peak hour of case III is the lowest due to only self-elasticity is applied. In case IV, the total power generation is the same as in Case I, but the demands in peak hours are lower as well as the demands in light-load hours are higher, leading to the lower total cost under the same total consumption as shown in Figure 4.8.

Table 4.6 Total cost for different price elasticity

Case	Case I	Case II	Case III	Case IV
Total daily operating cost ($)	17677.25	17615.69	17554.26	17674.63
Saving	-	0.35%	0.696%	0.015%

The power produced in each case shown in Table 4.3 has the same trend as the cost in Table 4.4, in which case III has the least power output. Figures 4.7 -4.8

address the hourly power generation of case III and IV, respectively. Meanwhile, Table 4.6 shows the comparison of cost rate per power generator ($/MWhr) for different price elasticity, table 4.6 shows the comparison of total cost for all cases. In case II, the total daily consumption was reduced from 5529.83 MW to 5516.624 MW, due to the consumer response to the NSP with self-DE, leading to the reduction in total daily operating cost from 17677.25$ to 17615.69$. Similarly, in Case III the total daily consumption and total daily operating cost were reduced to 5503.423 MW and 17554.26$, respectively, with the consideration of larger self-DE of -0.2. Meanwhile, with the balance seif- and cross- DEs, the total daily operating cost can be reduced to 17674.63 $ under the same total daily consumption of base case, due to the consumers' load shifting in response to the NSP. Accordingly, self-elasticity and cross-elasticity are both important measures of price elasticity in the electricity market. Self-elasticity measures the responsiveness of quantity demanded to changes in electricity use according to the NSP, while cross-elasticity measures the responsiveness of quantity demanded to changes in the price of other time intervals. Both measures provide different types of information about the responsiveness of demand to changes in NSP and are important in making informed decisions about power system operation and planning. More specifically, In the electricity market, self-elasticity is important for understanding how changes in the price of electricity affect the quantity demanded, while cross-elasticity is important for understanding how changes in the prices of related goods or services affect the demand for electricity.

4.5 Conclusion

An integrated OPD with DE model was proposed in this paper. The spot pricing concept has been successfully incorporated into the power system operation plan by using DE with self-elasticity and cross-elasticity. The effectiveness of the proposed methodology has been comparatively tested and validated on the IEEE 30-bus system. The results showed that the proposed method can lower the total system cost. In this chapter, the price base model is used to determine electricity costs from human behaviors, which will be considered in large systems. To increase the efficiency of the electrical system based on actual power loss with generator voltage magnitude limitations and transformer tab-changing, which will be considered in the next chapter.

CHAPTER V

REAL POWER LOSS MINIMIZATION USING PARTICLE SWARM

5.1 Introduction

Adjusting the generator's voltage magnitude and transformer tap-changing using Particle Swarm Optimization (PSO) and coordinating with the optimal power dispatch algorithm is a technique employed to optimize power system operation, minimize real power loss, and ensure system stability. Here's an introduction to how these control actions is integrated with PSO and coordinated with the optimal power dispatch algorithm:

Generator's Voltage Magnitude Adjustment. The voltage magnitude at generator buses plays a crucial role in power system operation and stability. By adjusting the voltage magnitude, the power system operator can influence power flow, reactive power exchange, and voltage profiles. Higher voltage magnitudes can enhance power transfer capability, while lower magnitudes can help reduce line losses.

In the context of PSO, the generator's voltage magnitudes can be considered as control variables or optimization parameters. The PSO algorithm seeks to find the optimal values for these variables that minimize real power loss while satisfying system constraints such as voltage limits and reactive power limits. The objective function in PSO incorporates the real power loss component, and constraints ensure that voltage magnitudes remain within acceptable limits.

Transformer tap-changing is the adjustment of tap positions on transformers to regulate voltage levels and control power flow. By modifying tap positions, the turns ratio of transformers can be altered, which impacts voltage magnitudes and power distribution in the system. To coordinate tap-changing with PSO and the optimal power dispatch algorithm, the tap positions are considered as additional control variables in the optimization process. The PSO algorithm explores the search space to find optimal tap positions that minimize real power loss, satisfy voltage constraints, and improve system performance.

In this chapter the development of real power loss minimization. By integrating particle swarm optimization (PSO) with the optimal power dispatch (OPD) algorithm, the coordination ensures that the generator voltage magnitudes and transformer tap positions are optimized simultaneously with the power generation allocation. This approach allows for comprehensive optimization of power system operation, considering real power loss, voltage constraints, and power flow, leading to improved system efficiency, reduced losses, and enhanced stability.

5.2 Problem Formulation

The PSO approach put out by (Kennedy, J. et al.,1995) is an optimization technique based on the herd's foraging or movement patterns. Each bird in a flock is specifically represented by a particle. The PSO solution begins by randomly placing the particles (with different placements of those particles being viable solutions) to create a set. The best values are then adjusted at each decision cycle, where each particle is altered by shifting its location in accordance with the best value.

For total real power loss minimization, the objective function is

$$\text{Minimize} \quad TL = \sum_{h=1}^{24} P_{loss,h}(|V_{i,h}|, T_{i-j,h}) \tag{5.1}$$

PSO operation is an iterative computing procedure in which *pbestt*$_i$ and *gbestt*$_i$ alter each particle's velocity during a cycle of operation. For each hour, the set of populations in this study is stated as follows

$$\rho_i = \left[|V_i|, |T_{i-j}| \right]^T \tag{5.2}$$

Where ρ_i is the position of particle *i*.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i^t - \mathbf{p_i^t}) + c_2 r_2 (gbest_i^t - \mathbf{p_i^t}) \tag{5.3}$$

$$\mathbf{p_i^{t+1}} = \mathbf{p_i^t} + v_i^{t+1} \tag{5.4}$$

The variables in Eq. (5.1) are controlled. After that, Eq. (5.2), which determines the particles' new location and velocity, is applied to the data (5.3).

5.2.1 System operating limit constraints

The generator constraints are the limit on generators' voltage magnitude, as formulated in Equations (5.5). Equations (5.6) present transformer tap-changing limits.

$$|V_i|^{min} \leq |V_i| \leq |V_i|^{max}, i = 1, ..., NB. \tag{5.5}$$

$$|T_{i-j}|^{min} \leq |T_{i-ji}| \leq |T_{i-j}|^{max}, i = 1, ..., NT. \tag{5.6}$$

The proposed method's computational process is as in Figure 5.1

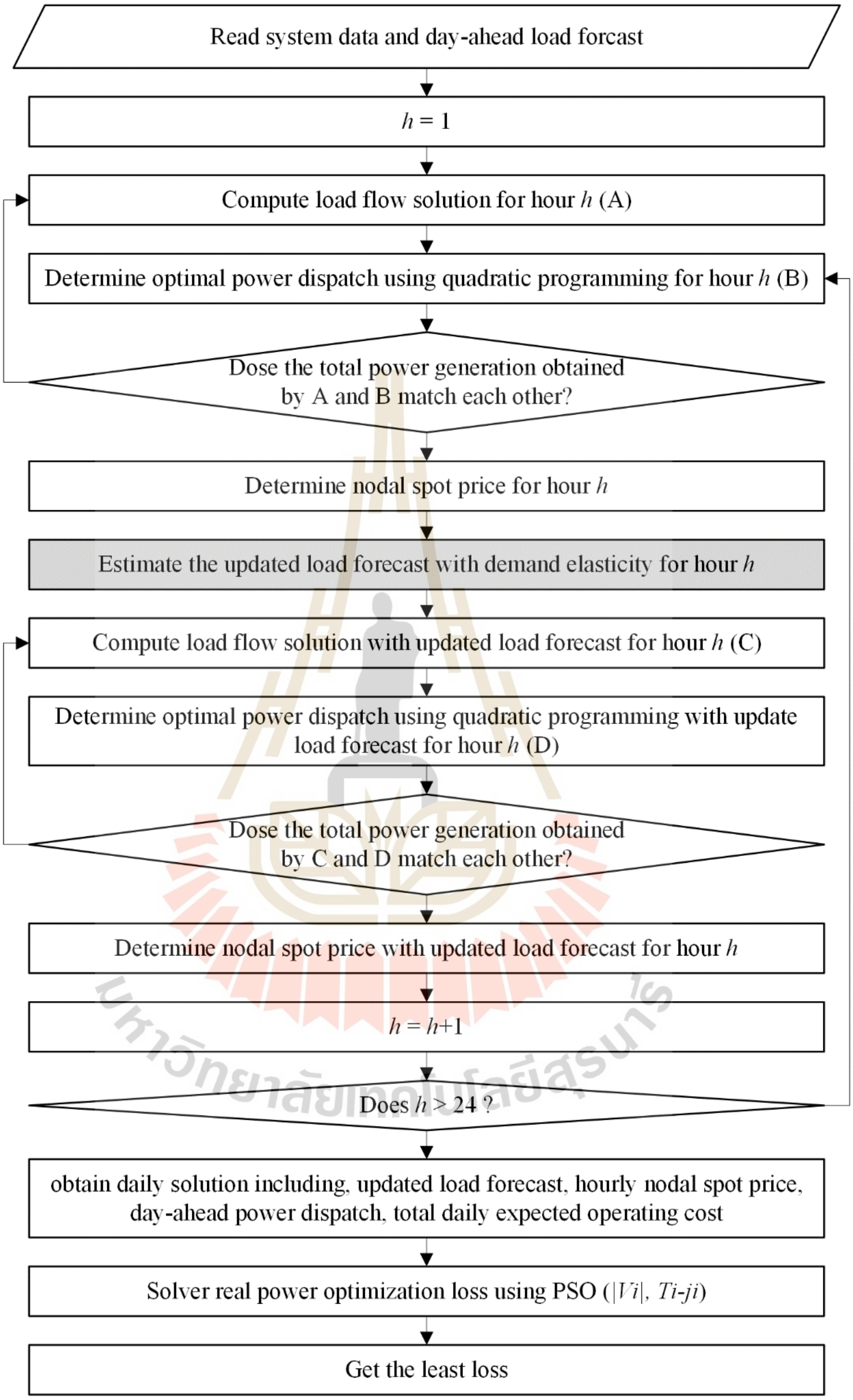


Figure 5.1 Computational procedures

5.3 Simulation Result

In this section, we provide a comprehensive analysis of the simulation results obtained from adjusting the generator voltage magnitude and transformer tap positions in the power system. The results are presented in Tables 5.1 to 5.8, corresponding to the Base Case, Case II, Case III, and Case IV, respectively. These tables offer valuable insights into the performance improvements achieved through the optimization process.

Table 5.1 and Table 5.2 represents the simulation results for the Base Case, which serves as a benchmark for comparison. It provides a baseline measurement of the power system's real power loss, voltage profiles, and overall system stability before any adjustments were made.

Table 5.1 The generator voltage magnitudes in Base Case

Hour	V_1	V_2	V_5	V_8	V_{11}	V_{13}
1	1.1	1.0988752	1.0856804	1.0859471	1.1	1.1
2	1.1	1.0891114	1.0675611	1.0723898	1.1	1.1
3	1.1	1.0888242	1.0671326	1.0721594	1.1	1.1
4	1.1	1.0886236	1.0668588	1.0720037	1.1	1.1
5	1.1	1.0883593	1.0664783	1.0717955	1.1	1.1
6	1.1	1.0883598	1.0664788	1.0717955	1.1	1.1
7	1.1	1.0884916	1.0666675	1.0719004	1.1	1.1
8	1.1	1.0881582	1.0662023	1.0716392	1.1	1.1
9	1.1	1.0880654	1.0660479	1.0715636	1.1	1.1
10	1.1	1.0883593	1.0664785	1.0717958	1.1	1.1
11	1.1	1.0885680	1.0667847	1.0719624	1.1	1.1
12	1.1	1.0886994	1.0669748	1.0720646	1.1	1.1
13	1.1	1.0887120	1.0669863	1.0720738	1.1	1.1
14	1.1	1.0886937	1.0669466	1.0720580	1.1	1.1
15	1.1	1.0888134	1.0671254	1.0721532	1.1	1.1
16	1.1	1.0889336	1.0673047	1.0722500	1.1	1.1
17	1.1	1.0889779	1.0673690	1.0722840	1.1	1.1
18	1.1	1.0887691	1.0670615	1.0721179	1.1	1.1
19	1.1	1.0889198	1.0672903	1.0722376	1.1	1.1
20	1.1	1.0901344	1.0690893	1.0742816	1.1	1.1
21	1.1	1.0912599	1.0708567	1.0773420	1.1	1.1
22	1.1	1.0910815	1.0705728	1.0768665	1.1	1.1
23	1.1	1.0906645	1.0699222	1.0757495	1.1	1.1
24	1.1	1.0900535	1.0689656	1.0740724	1.1	1.1

Table 5.2 The transformer tap positions in Base Case

Hour	TR_1	TR_2	TR_3	TR_4
1	0.9814717	1.0941055	0.9000000	0.9725986
2	0.9847974	1.0850382	0.9045817	0.9677456
3	0.9848754	1.0849062	0.9046667	0.9676588
4	0.9849397	1.0849625	0.9045886	0.9675977
5	0.9850269	1.0849440	0.9045830	0.9675227
6	0.9850294	1.0849067	0.9046198	0.9675229
7	0.9849893	1.0849158	0.9046278	0.9675624
8	0.9850841	1.0849090	0.9045866	0.9674627
9	0.9851335	1.0849435	0.9045726	0.9674422
10	0.9850269	1.0849381	0.9045883	0.9675230
11	0.9849441	1.0850888	0.9044848	0.9675911
12	0.9849123	1.0849680	0.9045884	0.9676195
13	0.9849149	1.0849761	0.9045880	0.9676250
14	0.9849292	1.0849904	0.9045863	0.9676229
15	0.9848883	1.0850022	0.9045820	0.9676571
16	0.9848469	1.0850353	0.9045661	0.9676921
17	0.9848349	1.0850140	0.9045852	0.9677047
18	0.9849015	1.0849993	0.9045791	0.9676436
19	0.9848432	1.0851026	0.9044899	0.9676775
20	0.9839827	1.0848101	0.9045215	0.9681413
21	0.9827146	1.0864209	0.9026028	0.9686935
22	0.9828820	1.0861522	0.9028862	0.9685965
23	0.9830546	1.0832919	0.9061301	0.9685319
24	0.9840697	1.0848399	0.9045300	0.9681025

Table 5.3 The generator voltage magnitudes in Case II

Hour	V_1	V_2	V_5	V_8	V_{11}	V_{13}
1	1.1	1.0952621	1.0772640	1.0840340	1.1	1.1
2	1.1	1.0891115	1.0675613	1.0723897	1.1	1.1
3	1.1	1.0888267	1.0671367	1.0721626	1.1	1.1
4	1.1	1.0886237	1.0668591	1.0720038	1.1	1.1
5	1.1	1.0883593	1.0664783	1.0717956	1.1	1.1
6	1.1	1.0883593	1.0664783	1.0717956	1.1	1.1
7	1.1	1.0884902	1.0666668	1.0718970	1.1	1.1
8	1.1	1.0881581	1.0662023	1.0716391	1.1	1.1
9	1.1	1.0880652	1.0660478	1.0715637	1.1	1.1
10	1.1	1.0883601	1.0664789	1.0717977	1.1	1.1
11	1.1	1.0885664	1.0667834	1.0719600	1.1	1.1
12	1.1	1.0886994	1.0669745	1.0720640	1.1	1.1
13	1.1	1.0887115	1.0669858	1.0720732	1.1	1.1
14	1.1	1.0886935	1.0669461	1.0720575	1.1	1.1
15	1.1	1.0888134	1.0671254	1.0721531	1.1	1.1
16	1.1	1.0889337	1.0673042	1.0722484	1.1	1.1
17	1.1	1.0889775	1.0673685	1.0722838	1.1	1.1
18	1.1	1.0887691	1.0670624	1.0721180	1.1	1.1
19	1.1	1.0889203	1.0672925	1.0722387	1.1	1.1
20	1.1	1.0901350	1.0690894	1.0742818	1.1	1.1
21	1.1	1.0912600	1.0708565	1.0773418	1.1	1.1
22	1.1	1.0910814	1.0705729	1.0768666	1.1	1.1
23	1.1	1.0906685	1.0699341	1.0757621	1.1	1.1
24	1.1	1.0900036	1.0689027	1.0739379	1.1	1.1

Table 5.4 The transformer tap positions in Case II

Hour	TR_1	TR_2	TR_3	TR_4
1	0.9823427	1.0855173	0.9053544	0.9711336
2	0.9847948	1.0850443	0.9045734	0.9677440
3	0.9848896	1.0850266	0.9045683	0.9676632
4	0.9849412	1.0849654	0.9045886	0.9675968
5	0.9850268	1.0849412	0.9045865	0.9675231
6	0.9850270	1.0849474	0.9045802	0.9675228
7	0.9848769	1.0898645	0.9000000	0.9675130
8	0.9850871	1.0848954	0.9046025	0.9674626
9	0.9851331	1.0849316	0.9045837	0.9674418
10	0.9850225	1.0849875	0.9045441	0.9675283
11	0.9849575	1.0849416	0.9046003	0.9675820
12	0.9849175	1.0849660	0.9045965	0.9676241
13	0.9849096	1.0849376	0.9046188	0.9676230
14	0.9849299	1.0849889	0.9045872	0.9676232
15	0.9848883	1.0850028	0.9045807	0.9676571
16	0.9848500	1.0850095	0.9045851	0.9676891
17	0.9848322	1.0850077	0.9045895	0.9677066
18	0.9849015	1.0850238	0.9045594	0.9676447
19	0.9848450	1.0850043	0.9045790	0.9676857
20	0.9839852	1.0848512	0.9044911	0.9681427
21	0.9827113	1.0864353	0.9025876	0.9686919
22	0.9828826	1.0861533	0.9028852	0.9685966
23	0.9829769	1.0850045	0.9045412	0.9685281
24	0.9841155	1.0848833	0.9044999	0.9680730

Table 5.5 The generator voltage magnitudes in Case III

Hour	V_1	V_2	V_5	V_8	V_{11}	V_{13}
1	1.1	1.0988752	1.0856805	1.0859471	1.1	1.1
2	1.1	1.0891113	1.0675609	1.0723891	1.1	1.1
3	1.1	1.0888262	1.0671368	1.0721624	1.1	1.1
4	1.1	1.0886238	1.0668592	1.0720041	1.1	1.1
5	1.1	1.0883592	1.0664782	1.0717956	1.1	1.1
6	1.1	1.0883593	1.0664783	1.0717957	1.1	1.1
7	1.1	1.0884912	1.0666683	1.0718995	1.1	1.1
8	1.1	1.0881542	1.0661953	1.0716322	1.1	1.1
9	1.1	1.0880651	1.0660477	1.0715638	1.1	1.1
10	1.1	1.0883549	1.0664770	1.0717899	1.1	1.1
11	1.1	1.0885670	1.0667847	1.0719604	1.1	1.1
12	1.1	1.0886991	1.0669743	1.0720643	1.1	1.1
13	1.1	1.0887119	1.0669857	1.0720739	1.1	1.1
14	1.1	1.0886935	1.0669461	1.0720577	1.1	1.1
15	1.1	1.0888133	1.0671252	1.0721530	1.1	1.1
16	1.1	1.0889333	1.0673051	1.0722494	1.1	1.1
17	1.1	1.0889779	1.0673687	1.0722840	1.1	1.1
18	1.1	1.0887692	1.0670619	1.0721182	1.1	1.1
19	1.1	1.0889206	1.0672934	1.0722394	1.1	1.1
20	1.1	1.0901344	1.0690894	1.0742816	1.1	1.1
21	1.1	1.0912605	1.0708560	1.0773426	1.1	1.1
22	1.1	1.0910815	1.0705727	1.0768668	1.1	1.1
23	1.1	1.0906694	1.0699195	1.0757631	1.1	1.1
24	1.1	1.0899671	1.0688326	1.0738350	1.1	1.1

Table 5.6 The transformer tap positions in Case III

Hour	TR_1	TR_2	TR_3	TR_4
1	0.9814715	1.0941059	0.9000000	0.9725988
2	0.9847954	1.0850240	0.9045960	0.9677459
3	0.9848894	1.0850113	0.9045823	0.9676625
4	0.9849426	1.0849862	0.9045676	0.9675979
5	0.9850270	1.0849397	0.9045861	0.9675225
6	0.9850272	1.0849397	0.9045876	0.9675231
7	0.9849846	1.0849394	0.9045988	0.9675609
8	0.9851276	1.0845650	0.9048920	0.9674522
9	0.9851337	1.0849200	0.9045927	0.9674424
10	0.9850734	1.0849543	0.9045990	0.9675243
11	0.9849554	1.0849666	0.9045758	0.9675810
12	0.9849138	1.0849746	0.9045813	0.9676210
13	0.9849150	1.0849911	0.9045723	0.9676261
14	0.9849315	1.0849991	0.9045793	0.9676249
15	0.9848875	1.0850012	0.9045822	0.9676564
16	0.9848429	1.0849992	0.9045894	0.9676888
17	0.9848359	1.0850071	0.9045931	0.9677055
18	0.9849015	1.0849988	0.9045810	0.9676441
19	0.9848471	1.0850010	0.9045835	0.9676858
20	0.9839828	1.0848197	0.9045127	0.9681411
21	0.9827081	1.0865065	0.9025193	0.9686941
22	0.9828815	1.0861590	0.9028781	0.9685959
23	0.9829353	1.0846997	0.9047287	0.9685340
24	0.9841716	1.0848609	0.9045560	0.9680644

Table 5.7 The generator voltage magnitudes in Case IV

Hour	V_1	V_2	V_5	V_8	V_{11}	V_{13}
1	1.1	1.0988752	1.0856804	1.0859471	1.1	1.1
2	1.1	1.0891114	1.0675611	1.0723898	1.1	1.1
3	1.1	1.0888242	1.0671326	1.0721594	1.1	1.1
4	1.1	1.0886236	1.0668588	1.0720037	1.1	1.1
5	1.1	1.0883593	1.0664783	1.0717955	1.1	1.1
6	1.1	1.0883598	1.0664788	1.0717955	1.1	1.1
7	1.1	1.0884916	1.0666675	1.0719004	1.1	1.1
8	1.1	1.0881582	1.0662023	1.0716392	1.1	1.1
9	1.1	1.0880654	1.0660479	1.0715636	1.1	1.1
10	1.1	1.0883593	1.0664785	1.0717958	1.1	1.1
11	1.1	1.0885680	1.0667847	1.0719624	1.1	1.1
12	1.1	1.0886994	1.0669748	1.0720646	1.1	1.1
13	1.1	1.0887120	1.0669863	1.0720738	1.1	1.1
14	1.1	1.0886937	1.0669466	1.0720580	1.1	1.1
15	1.1	1.0888134	1.0671254	1.0721532	1.1	1.1
16	1.1	1.0889336	1.0673047	1.0722500	1.1	1.1
17	1.1	1.0889779	1.0673690	1.0722840	1.1	1.1
18	1.1	1.0887691	1.0670615	1.0721179	1.1	1.1
19	1.1	1.0889198	1.0672903	1.0722376	1.1	1.1
20	1.1	1.0901344	1.0690893	1.0742816	1.1	1.1
21	1.1	1.0912599	1.0708567	1.0773420	1.1	1.1
22	1.1	1.0910815	1.0705728	1.0768665	1.1	1.1
23	1.1	1.0906645	1.0699222	1.0757495	1.1	1.1
24	1.1	1.0899974	1.0688730	1.0739310	1.1	1.1

Table 5.8 The transformer tap positions in Case IV

Hour	TR_1	TR_2	TR_3	TR_4
1	0.9814717	1.0941055	0.9000000	0.9725986
2	0.9847974	1.0850382	0.9045817	0.9677456
3	0.9848754	1.0849062	0.9046667	0.9676588
4	0.9849397	1.0849625	0.9045886	0.9675977
5	0.9850269	1.0849440	0.9045830	0.9675227
6	0.9850294	1.0849067	0.9046198	0.9675229
7	0.9849893	1.0849158	0.9046278	0.9675624
8	0.9850841	1.0849090	0.9045866	0.9674627
9	0.9851335	1.0849435	0.9045726	0.9674422
10	0.9850269	1.0849381	0.9045883	0.9675230
11	0.9849441	1.0850888	0.9044848	0.9675911
12	0.9849123	1.0849680	0.9045884	0.9676195
13	0.9849149	1.0849761	0.9045880	0.9676250
14	0.9849292	1.0849904	0.9045863	0.9676229
15	0.9848883	1.0850022	0.9045820	0.9676571
16	0.9848469	1.0850353	0.9045661	0.9676921
17	0.9848349	1.0850140	0.9045852	0.9677047
18	0.9849015	1.0849993	0.9045791	0.9676436
19	0.9848432	1.0851026	0.9044899	0.9676775
20	0.9839827	1.0848101	0.9045215	0.9681413
21	0.9827146	1.0864209	0.9026028	0.9686935
22	0.9828820	1.0861522	0.9028862	0.9685965
23	0.9830546	1.0832919	0.9061301	0.9685319
24	0.9841338	1.0848536	0.9045490	0.9680795

Table 5.9 Comparison of the results of the power loss

Hour	Base Case (MW)	Case II (MW)	Case III (MW)	Case IV (MW)
1	2.0132616131	2.9434153313	2.0132616131	2.0132616131
2	5.6601887438	5.6601887440	5.6601887440	5.6601887438
3	5.7731838743	5.7731838662	5.7731838658	5.7731838743
4	5.8485288491	5.8485288493	5.8485288494	5.8485288491
5	5.9538781054	5.9538781054	5.9538781054	5.9538781054
6	5.9538781062	5.9538781054	5.9538781054	5.9538781062
7	5.9009720660	5.9009761634	5.9009720644	5.9009720660
8	6.0316073789	6.0316073790	6.0316074556	6.0316073789
9	6.0758649879	6.0758649876	6.0758649874	6.0758649879
10	5.9538781054	5.9538781084	5.9538781558	5.9538781054
11	5.8690890116	5.8690889942	5.8690889943	5.8690890116
12	5.8169202388	5.8169202395	5.8169202388	5.8169202388
13	5.8138235847	5.8138235862	5.8138235849	5.8138235847
14	5.8249431835	5.8249431832	5.8249431834	5.8249431835
15	5.7762523461	5.7762523461	5.7762523461	5.7762523461
16	5.7279584269	5.7279584271	5.7279584268	5.7279584269
17	5.7109391902	5.7109391907	5.7109391903	5.7109391902
18	5.7934653968	5.7934653973	5.7934653968	5.7934653968
19	5.7309988073	5.7309988019	5.7309988016	5.7309988073
20	5.0935968601	5.0935968610	5.0935968601	5.0935968601
21	4.3629431720	4.3629431719	4.3629431738	4.3629431720
22	4.4705839101	4.4705839101	4.4705839102	4.4705839101
23	4.7264077135	4.7264075611	4.7264077460	4.7264077135
24	5.1466493895	5.1772982156	5.2064915070	5.1847550004
All day	131.0298	131.9906	131.0897	131.0679

The power loss analysis presented in Table 5.9 demonstrates the effectiveness of the optimization process in minimizing power loss in the IEEE 30-bus system. The notably low power loss of 131.0298 MW in the Base Case, but compare Case II, Case III, and Case IV while using elasticity price, which shows that Case IV has the lowest power loss of 131.0679 MW by highlighting the success of the applied adjustments to the generator voltage magnitude and transformer tap positions. These findings underscore the value of optimization techniques in enhancing power system efficiency and reducing energy waste.

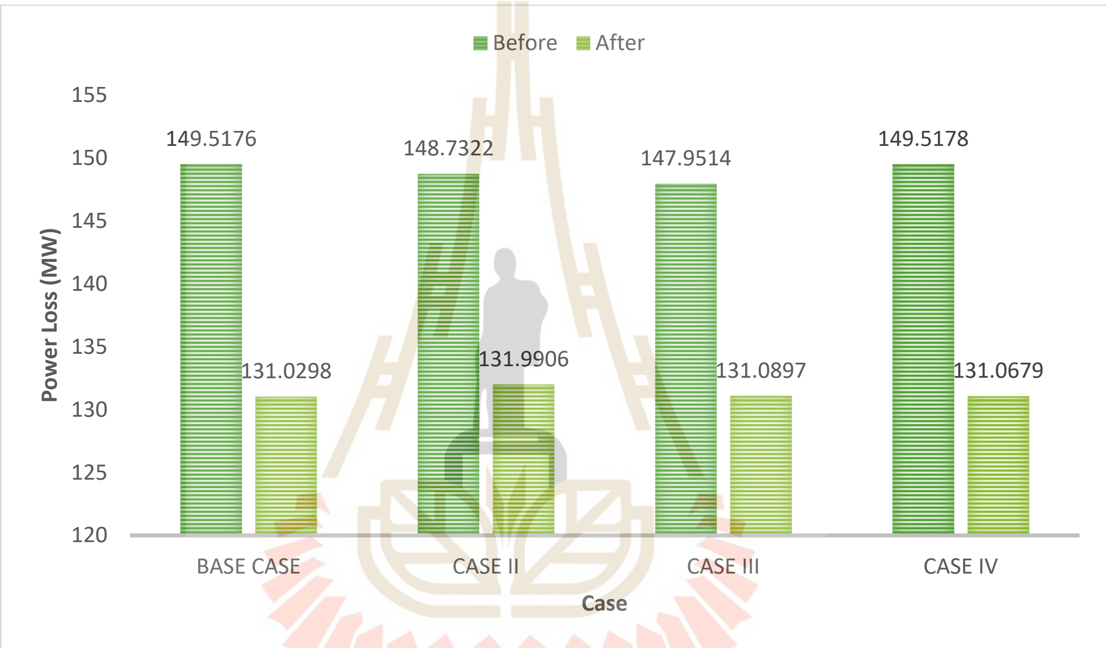


Figure. 5.2 Comparison of results

Table 5.10 The result of 30 trials of the proposed PSO-OPD in Case IV

Total System Cost ($)	Case IV
Best	14704.977
Mean	14704.97757
Worst	14704.98583

The results presented in Tables 5.10 provide a comprehensive analysis of the economic performance of the proposed PSO-OPD approach in Case IV. The 30 trials offer a range of total system costs, reflecting the influence of different control variable combinations. The best value of 14704.977 $ demonstrates the algorithm's ability to identify highly cost-efficient solutions, while the mean value and worst value provide additional insights into the economic variability and potential challenges in power system operation. These findings underline the effectiveness of the PSO-OPD algorithm in optimizing the total system cost and supporting economically viable power system operations.

5.4 Conclusion

To improve power efficiency, minimize power loss and improve power stability, Particle Swarm Optimization (PSO) is used in cooperation with Optimal Power Dispatch (OPD) to achieve Generator voltage amplitude and transformer tap-changing. The PSO finds the optimal value for these variables, taking into account the constraints. It is seen from the experiment that the power loss of the system decreases. When comparing power loss in Chapter 4, which doesn't have variable adjustment.

CHAPTER VI
CONCLUSION

This thesis focuses on the integration of OPF with DR in the context of two DR models: IDR and PDR. The objective is to optimize power system operation by considering the cost minimization problem associated with IDR and PDR and incorporating DE for accurate day-ahead scheduling. For the OPF considering IDR, the research utilizes PSO to solve the minimization problem of total generation cost, which includes the IDR cost. This approach allows for the optimization of the system considering both the traditional generation cost and the incentives provided to consumers for demand response participation. On the other hand, for the OPF considering PDR, the research employs QP to determine the optimal real power dispatch. This dispatch calculation provides NSP components that reflect the price elasticity of demand. Additionally, the optimal reactive power dispatch is solved using PSO to optimize generator voltage magnitude and transformer tap-changing.

The research incorporates DE to adjust the system demand accurately. This consideration allows for a more precise day-ahead operation, taking into account the responsiveness of consumers to price signals and incentive mechanisms. To validate the proposed algorithm, it will be tested using the IEEE 33-bus system and the IEEE 30-bus system. By conducting these tests, the research aims to demonstrate the effectiveness of the proposed algorithm in incorporating price elasticity of demand and minimizing the total operating cost in day-ahead scheduling.

In conclusion, the research presents a novel approach to OPF with the integration of IDR and PDR. By utilizing PSO and QP algorithms, the proposed method considers the cost minimization problem associated with PDR, determines nodal spot prices, and optimizes generator voltage magnitude and transformer tap-changing. The inclusion of demand elasticity enhances the accuracy of day-ahead scheduling. The algorithm's performance will be evaluated using benchmark power system models to showcase its effectiveness in minimizing total operating costs.

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APPENDIX

APPENDIX A

IEEE 33-bus system test data

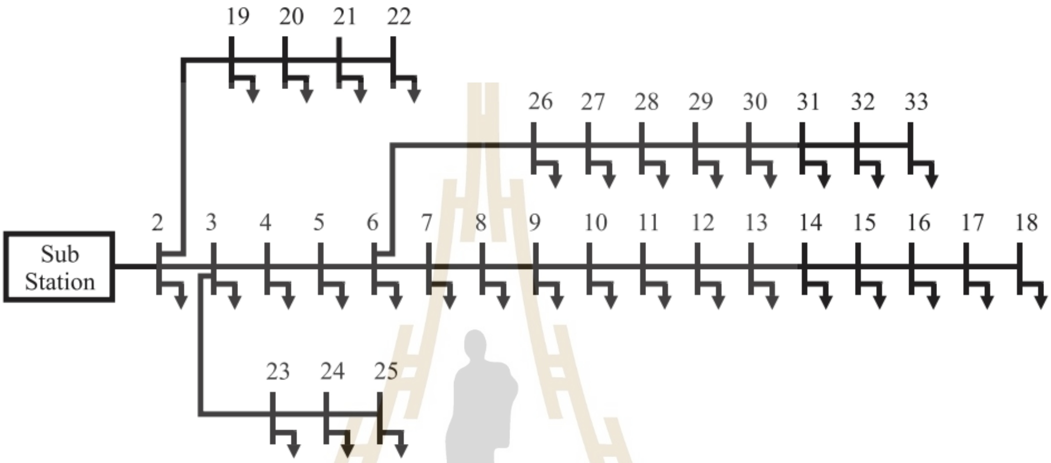

Figure A.1 The IEEE 33 bus system network diagram.

Table A.1 Line parameter of IEEE 33-bus test system

Line	From (Bus)	To (Bus)	R (p.u.)	X (p.u)	Real Load Power (kw)	Reactive Load Power (kvar)
1	1	2	0.0922	0.0477	100	60
2	2	3	0.4930	0.2511	90	40
3	3	4	0.3660	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.8190	0.7070	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	1.7114	1.2351	200	100
8	8	9	1.0300	0.7400	60	20
9	9	10	1.0400	0.7400	60	20
10	10	11	0.1966	0.0650	45	30
11	11	12	0.3744	0.1238	60	35
12	12	13	1.4680	0.1550	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.5910	0.5260	60	10
15	15	16	0.7463	0.5450	60	20
16	16	17	1.2890	1.7210	60	20
17	17	18	0.7320	0.5740	90	40
18	2	19	0.1640	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	50
23	23	24	0.8980	0.7091	420	200
24	24	25	0.8960	0.7011	420	200
25	6	26	0.2030	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.0590	0.9337	60	20
28	28	29	0.8042	0.7006	120	70

Table A.1 Line parameter of IEEE 33-bus test system (Continued)

Line	From (Bus)	To (Bus)	R (p.u.)	X (p.u)	Real Load Power (kw)	Reactive Load Power (kvar)
29	29	30	0.5075	0.2585	200	600
30	30	31	0.9744	0.9630	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.3410	0.5302	60	40

APPENDIX B

IEEE 30-bus system test data

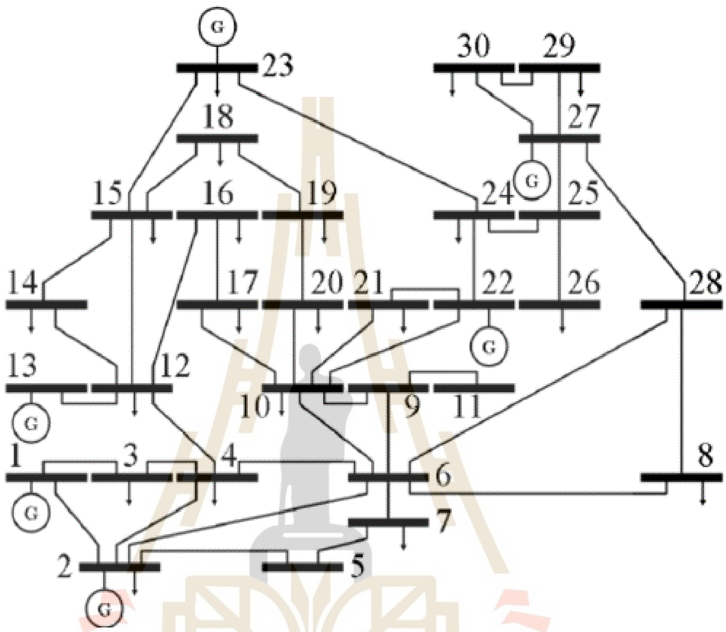

Figure B.1 IEEE 30-bus system data

Table B.1 Line parameter of IEEE 30-bus test system

Line	From (Bus)	To (Bus)	R (p.u.)	X (p.u.)	Tap Ratio	Rating (p.u.)
1	1	2	0.0192	0.0575		0.3000
2	1	3	0.0452	0.1852	0.9610	0.3000
3	2	4	0.0570	0.1737	0.9560	0.3000
4	3	4	0.0132	0.0379		0.3000
5	2	5	0.0472	0.1983		0.3000
6	2	6	0.0581	0.1763		0.3000
7	4	6	0.0119	0.0414		0.3000
8	5	7	0.0460	0.1160		0.3000
9	6	7	0.0267	0.0820		0.3000
10	6	8	0.0120	0.0420		0.3000
11	6	9	0.0000	0.2080		0.3000
12	6	10	0.0000	0.5560		0.3000
13	6	11	0.0000	0.2080		0.3000
14	9	10	0.0000	0.1100	0.9700	0.3000
15	4	12	0.0000	0.2560	0.9650	0.6500
16	12	13	0.0000	0.1400	0.9635	0.6500
17	12	14	0.1231	0.2559		0.3200
18	12	15	0.0662	0.1304		0.3200
19	12	16	0.0945	0.1987		0.3200
20	14	15	0.2210	0.1997		0.1600
21	16	17	0.0824	0.1932		0.1600
22	15	18	0.1070	0.2185		0.1600
23	18	19	0.0639	0.1292	0.9590	0.1600
24	19	20	0.0340	0.0680		0.3200
25	10	20	0.0936	0.2090		0.3200
26	10	17	0.0324	0.0845	0.9850	0.3200
27	10	21	0.0348	0.0749		0.3000

Table B.1 Line parameter of IEEE 30-bus test system (Continued)

Line	From (Bus)	To (Bus)	R (p.u.)	X (p.u.)	Tap Ratio	Rating (p.u.)
28	10	22	0.0727	0.1499		0.3000
29	21	22	0.1160	0.0236		0.3000
30	15	23	0.1000	0.2020		0.1600
31	22	24	0.1150	0.1790		0.3000
32	23	24	0.1320	0.2700	0.9655	0.1600
33	24	25	0.1885	0.3292		0.3000
34	25	26	0.2544	0.3800		0.3000
35	25	27	0.1093	0.2087		0.3000
36	28	27	0.0000	0.3960		0.3000
37	27	29	0.2198	0.4153	0.9810	0.3000
38	27	30	0.3202	0.6027		0.3000
39	29	30	0.2399	0.4533		0.3000
40	8	28	0.0636	0.2000	0.9530	0.3000
41	6	28	0.0169	0.0599		0.3000
33	24	25	0.1885	0.3292		0.3000

Table B.2 Reactive power limit data of IEEE 30-bus test system

Bus	Q_{min} (p.u.)	Q_{max} (p.u.)	Bus	Q_{min} (p.u.)	Q_{max} (p.u.)
1	-0.2000	0.0000	16		
2	-0.2000	0.2000	17	-0.0500	0.0500
3			18	0.0000	0.0550
4			19		
5	-0.1500	0.1500	20		
6			21		
7			22		
8	-0.1500	0.1500	23	-0.0500	0.0550
9			24		
10			25		
11	-0.1000	0.1000	26		
12			27	-0.0055	0.0550
13	-0.1500	0.1500	28		
14			29		
15			30		

Table B.3 Bus load and injection data of IEEE 30-bus test system

Bus	Load (MW)	Bus	Load (MW)
1	0.00	16	3.50
2	21.70	17	9.00
3	2.40	18	3.20
4	67.60	19	9.50
5	34.20	20	2.20
6	0.00	21	17.50
7	22.80	22	0.00
8	30.00	23	3.20
9	0.00	24	8.70
10	5.80	25	0.00
11	0.00	26	3.50
12	11.20	27	0.00
13	0.00	28	0.00
14	6.20	29	2.40
15	8.20	30	10.60

APPENDIX C

Thailand daily load profile

(Between 7:00 p.m. and 12:00 a.m. on 14 April 2018)

Table C.1 Thailand dairy load profile

Hour	Load (MW)	Hour	Load (MW)
1	16332.61	13	15286.36
2	15613.91	14	15596.55
3	15116.66	15	15888.20
4	14483.81	16	15976.69
5	14440.41	17	15485.55
6	14794.30	18	15852.90
7	13932.05	19	18472.05
8	13681.76	20	20340.70
9	14456.66	21	20059.30
10	14966.06	22	19409.56
11	15301.96	23	18328.10
12	15312.25	24	17034.40

APPENDIX D

The result of 30 trials for the total system cost

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV

Iteration /Hour	1	2	3	4	5
1	751.6298157	751.6311352	751.6283946	751.6283946	751.6283946
2	605.2994414	605.2984615	605.2983188	605.2983188	605.2983188
3	605.3641376	605.3638079	605.3638013	605.3638012	605.3638012
4	605.5543729	605.5539704	605.5537966	605.5537963	605.5537963
5	605.970501	605.9711301	605.9704577	605.9704574	605.9704574
6	605.9923129	605.9925109	605.9922601	605.9922611	605.9922606
7	605.7466802	605.7466702	605.7466246	605.7466246	605.7466246
8	606.4587682	606.4586677	606.4581353	606.4581353	606.4581353
9	606.7393493	606.7395831	606.7391882	606.7391881	606.7391881
10	605.9924776	605.9926342	605.9922601	605.9922601	605.9922601
11	605.6275038	605.6274528	605.6274065	605.6274063	605.6274063
12	605.4656643	605.4655739	605.4655517	605.4655516	605.4655516
13	605.455247	605.4548008	605.4545742	605.4545743	605.4545743
14	605.4778108	605.4779803	605.4777981	605.4777981	605.4777984
15	605.3711337	605.3711237	605.371087	605.371087	605.371087
16	605.3093051	605.3092026	605.3091431	605.3091431	605.3091436
17	605.2982554	605.297717	605.2976453	605.2976452	605.2976452
18	605.4055795	605.4049536	605.4046291	605.4046291	605.4046291
19	605.3137247	605.3134153	605.3130845	605.3130845	605.3130845
20	607.5144232	607.5143564	607.514345	607.514345	607.514345
21	614.0206356	614.020314	614.0202993	614.0203205	614.0203324

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV (Continued)

22	612.7705854	612.77102	612.77045	612.7704457	612.7704422
23	610.2166526	610.21691	610.216318	610.2163184	610.2163339
24	606.9914511	606.9915355	606.9914421	606.9914417	606.991442
Iteration /Hour	**6**	**7**	**8**	**9**	**10**
1	751.6283946	751.6283947	751.6283946	751.6283946	751.6283946
2	605.2983188	605.2983188	605.2983188	605.2983188	605.2983188
3	605.3638013	605.3638012	605.3638013	605.3638012	605.3638012
4	605.5537965	605.5538015	605.5537966	605.5537963	605.5537963
5	605.9704574	605.9704574	605.9704577	605.9704574	605.9704574
6	605.9922602	605.9922601	605.9922601	605.9922611	605.9922601
7	605.7466248	605.7466246	605.7466246	605.7466246	605.7466246
8	606.4581353	606.4581353	606.4581353	606.4581353	606.4581353
9	606.7391881	606.7391881	606.7391882	606.7391881	606.7391883
10	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
11	605.6274063	605.6274063	605.6274065	605.6274063	605.6274064
12	605.4655517	605.4655516	605.4655517	605.4655516	605.4655516
13	605.4545743	605.4545742	605.4545742	605.4545743	605.4545742
14	605.4777981	605.4777981	605.4777981	605.4777981	605.4777984
15	605.371087	605.3710871	605.371087	605.371087	605.3710871
16	605.3091432	605.3091431	605.3091431	605.3091431	605.3091432
17	605.297658	605.2976453	605.2976453	605.2976452	605.2976453
18	605.4046291	605.4046291	605.4046291	605.4046291	605.4046291
19	605.3130845	605.3130845	605.3130845	605.3130845	605.3130845
20	607.514345	607.514345	607.514345	607.514345	607.514345
21	614.0202968	614.0202918	614.0202993	614.0203205	614.0202949
22	612.7704445	612.7704628	612.77045	612.7704457	612.7704433
23	610.2163189	610.2163261	610.216318	610.2163184	610.2163191

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV (Continued)

24	606.9914416	606.9914416	606.9914421	606.9914417	606.9914418
Iteration /Hour	**11**	**12**	**13**	**14**	**15**
1	751.6283946	751.6283946	751.6283946	751.6283946	751.6283946
2	605.2983188	605.2983188	605.2983188	605.2983315	605.2983188
3	605.3638012	605.3638012	605.3638012	605.3638012	605.3638012
4	605.5537963	605.5537963	605.5537963	605.5537968	605.5537964
5	605.9704574	605.9704574	605.9704574	605.9704574	605.9704574
6	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
7	605.7466246	605.7466246	605.7466246	605.7466246	605.7466246
8	606.4581353	606.4581353	606.4581353	606.4581353	606.4581355
9	606.7391881	606.7391881	606.7391881	606.7391881	606.7391881
10	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
11	605.6274063	605.6274063	605.6274063	605.6274063	605.6274068
12	605.4655516	605.4655517	605.4655516	605.4655516	605.4655516
13	605.4545743	605.4545742	605.4545743	605.4545742	605.4545742
14	605.4777982	605.4777981	605.4777982	605.4777984	605.4777981
15	605.371087	605.371087	605.371087	605.371087	605.371087
16	605.3091432	605.3091431	605.3091431	605.3091431	605.3091431
17	605.2976453	605.2976452	605.2976453	605.2976453	605.2976453
18	605.4046291	605.4046291	605.4046291	605.4046299	605.4046291
19	605.3130846	605.3130845	605.3130845	605.3130845	605.3130846
20	607.5143452	607.514345	607.514345	607.514345	607.514345
21	614.0202987	614.0203159	614.0202912	614.0203012	614.0202958
22	612.7704542	612.7704435	612.7704508	612.7704708	612.7704421
23	610.2163198	610.2163343	610.2163194	610.21632	610.2163179
24	606.9914417	606.9914417	606.9914416	606.9914416	606.9914416

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV (Continued)

Iteration /Hour	16	17	18	19	20
1	751.6283946	751.6283946	751.6283946	751.6283946	751.6283946
2	605.2983188	605.2983189	605.2983188	605.2983188	605.2983188
3	605.3638012	605.3638012	605.3638012	605.3638012	605.3638012
4	605.5537963	605.5537963	605.5537963	605.5537963	605.5537963
5	605.9704574	605.9704574	605.9704574	605.9704577	605.9704574
6	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
7	605.7466246	605.7466246	605.7466246	605.7466246	605.7466246
8	606.4581353	606.4581353	606.4581355	606.4581353	606.4581358
9	606.7391881	606.7391881	606.7391881	606.7391881	606.7391884
10	605.9922601	605.9922601	605.9922601	605.9922601	605.9922602
11	605.6274064	605.6274063	605.6274063	605.6274066	605.6274063
12	605.4655516	605.4655516	605.4655522	605.4655517	605.4655516
13	605.4545742	605.4545742	605.4545742	605.4545743	605.454587
14	605.4777981	605.4777982	605.4777981	605.4777982	605.4777981
15	605.371087	605.371087	605.371087	605.371087	605.371087
16	605.3091431	605.3091431	605.3091431	605.3091431	605.3091431
17	605.2976453	605.2976453	605.2976452	605.2976453	605.2976452
18	605.4046291	605.4046291	605.4046291	605.4046291	605.4046296
19	605.3130846	605.3130845	605.3130845	605.3130845	605.3130845
20	607.514345	607.514345	607.5143451	607.5143453	607.5143456
21	614.0202961	614.0202952	614.0202962	614.0202966	614.020299
22	612.7704485	612.7704534	612.7704499	612.7704453	612.7704439
23	610.2163184	610.2163243	610.2163182	610.2163218	610.216318
24	606.9914416	606.9914416	606.9914417	606.9914416	606.9914416

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV (Continued)

Iteration /Hour	21	22	23	24	25
1	751.6283946	751.6283947	751.6283946	751.6283946	751.6283946
2	605.2983188	605.2983188	605.2983193	605.2983188	605.2983188
3	605.3638012	605.3638012	605.3638012	605.3638012	605.3638013
4	605.5537963	605.5537963	605.5537963	605.5537968	605.5537963
5	605.9704576	605.9704574	605.9704574	605.9704574	605.9704574
6	605.9922603	605.9922601	605.9922601	605.9922601	605.9922601
7	605.7466246	605.7466248	605.7466246	605.7466246	605.7466246
8	606.4581353	606.4581353	606.4581353	606.4581353	606.4581353
9	606.7391881	606.7391881	606.7391881	606.7391881	606.7391881
10	605.9922601	605.9922601	605.9922601	605.9922601	605.9922602
11	605.6274063	605.6274063	605.6274063	605.6274063	605.6274063
12	605.4655516	605.4655522	605.4655527	605.4655516	605.4655517
13	605.4545743	605.4545742	605.4545742	605.4545742	605.4545743
14	605.4777983	605.4777981	605.4777981	605.4777982	605.4777984
15	605.371087	605.3710875	605.3710998	605.371087	605.371087
16	605.3091431	605.3091432	605.3091433	605.309144	605.3091431
17	605.2976452	605.2976453	605.2976452	605.2976452	605.2976453
18	605.4046291	605.4046291	605.4046291	605.4046291	605.4046293
19	605.3130845	605.3130845	605.3130845	605.3130845	605.3130845
20	607.514345	607.514345	607.514345	607.5143457	607.514345
21	614.0202937	614.020296	614.0202974	614.0203277	614.0202968
22	612.770445	612.770446	612.7704549	612.7704462	612.7704441
23	610.2163192	610.2163179	610.2163215	610.2163186	610.2163201
24	606.9914416	606.9914417	606.9914417	606.9914418	606.9914416

Table D.1 The result of 30 trials for the total system cost ($) of the proposed PSO-OPD in Case IV (Continued)

Iteration /Hour	26	27	28	29	30
1	751.6283947	751.6283946	751.6283946	751.6283946	751.6283946
2	605.2983188	605.2983188	605.2983188	605.2983188	605.2983199
3	605.3638012	605.3638013	605.3638012	605.3638012	605.3638012
4	605.5537963	605.5537963	605.5537963	605.5537963	605.5537963
5	605.9704574	605.9704575	605.9704574	605.9704574	605.9704575
6	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
7	605.7466246	605.7466246	605.7466246	605.7466246	605.7466246
8	606.4581353	606.4581353	606.4581353	606.4581353	606.4581353
9	606.7391881	606.7391881	606.7391883	606.7391881	606.7391881
10	605.9922601	605.9922601	605.9922601	605.9922601	605.9922601
11	605.6274063	605.6274063	605.6274063	605.6274065	605.6274063
12	605.4655516	605.4655516	605.4655518	605.4655516	605.4655517
13	605.4545742	605.4545742	605.4545742	605.4545742	605.4545742
14	605.4777981	605.4777981	605.4777982	605.4777981	605.4777983
15	605.3710873	605.371087	605.371087	605.371087	605.371087
16	605.3091431	605.3091432	605.3091431	605.3091431	605.3091431
17	605.2976453	605.2976452	605.2976453	605.2976452	605.2976452
18	605.4046291	605.4046291	605.4046291	605.4046297	605.4046291
19	605.3130845	605.3130847	605.3130846	605.3130846	605.3130845
20	607.5143452	607.5143453	607.514345	607.5143507	607.514345
21	614.0202937	614.020291	614.0202916	614.0203213	614.0203017
22	612.7704434	612.7704444	612.7704428	612.7704438	612.7704636
23	610.2163183	610.2163176	610.2163193	610.2163196	610.2163208
24	606.9914416	606.9914416	606.9914416	606.9914416	606.9914417

APPENDIX E

The convergence plots for each hour in iteration 1

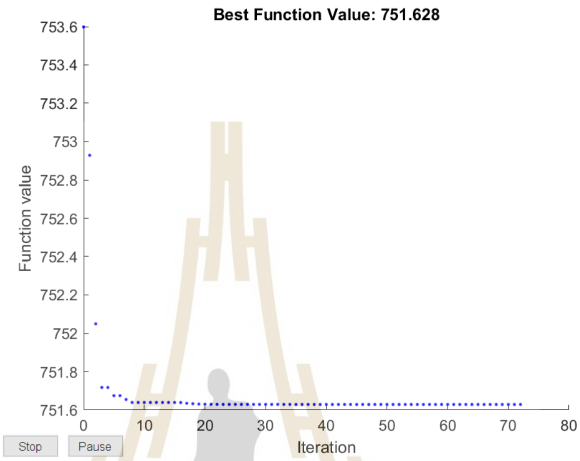

Figure E.1 The convergence plot of hour 1

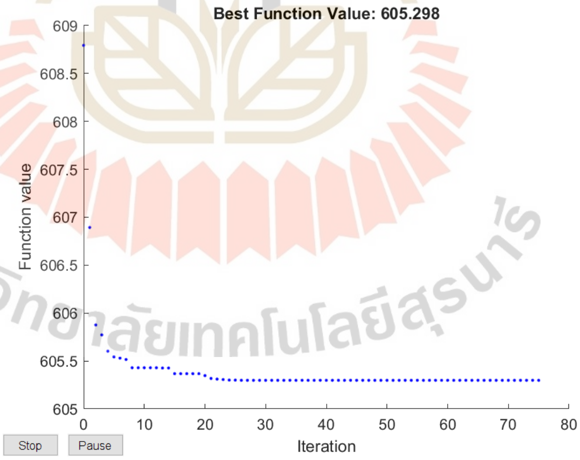

Figure E.2 The convergence plot of hour 2

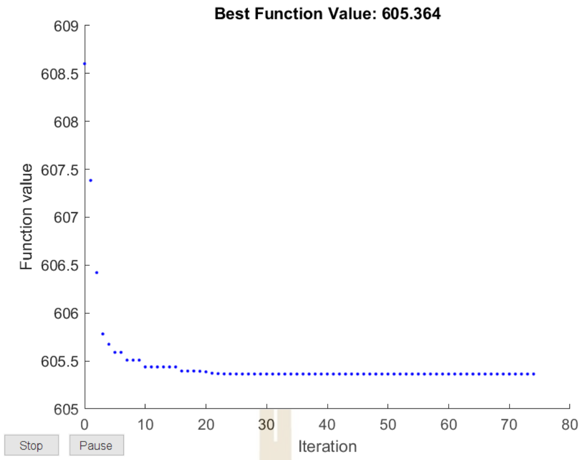

Figure E.3 The convergence plot of hour 3

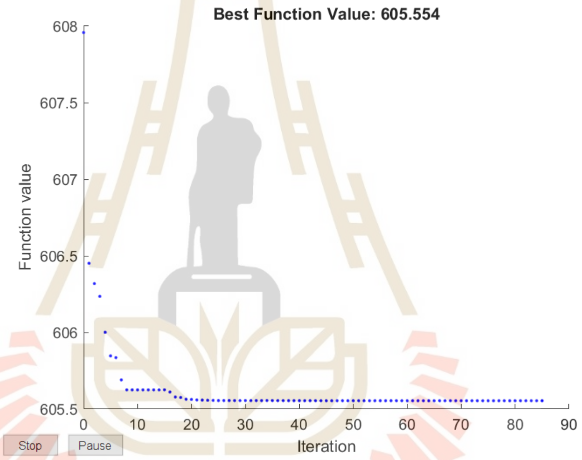

Figure E.4 The convergence plot of hour 4

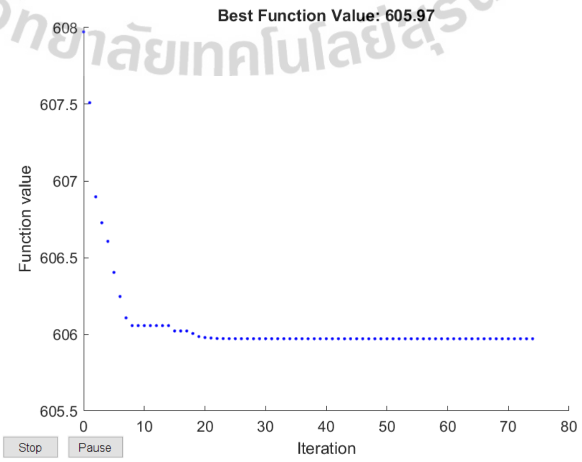

Figure E.5 The convergence plot of hour 5

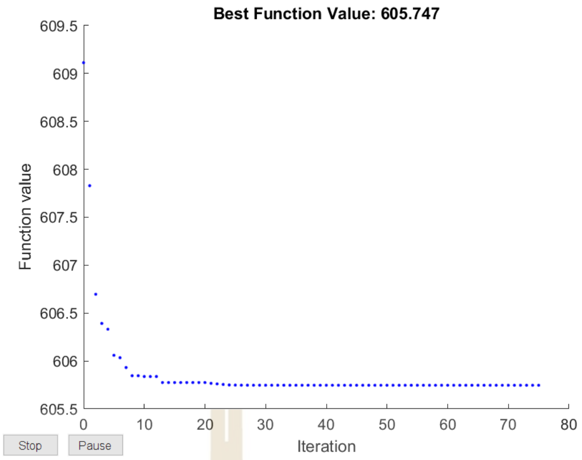

Figure E.6 The convergence plot of hour 6

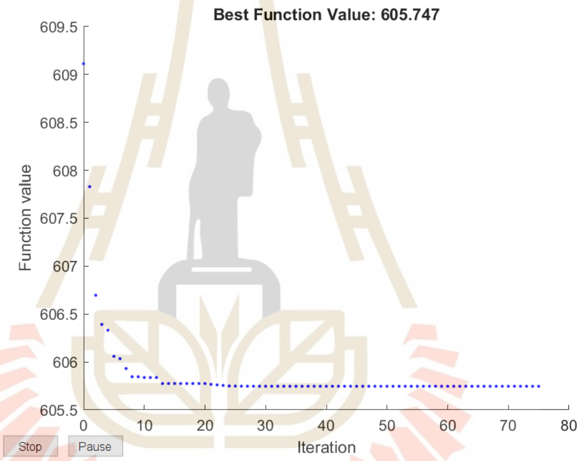

Figure E.7 The convergence plot of hour 7

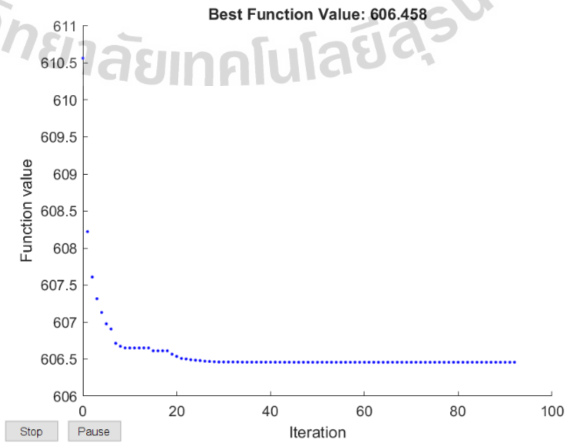

Figure E.8 The convergence plot of hour 8

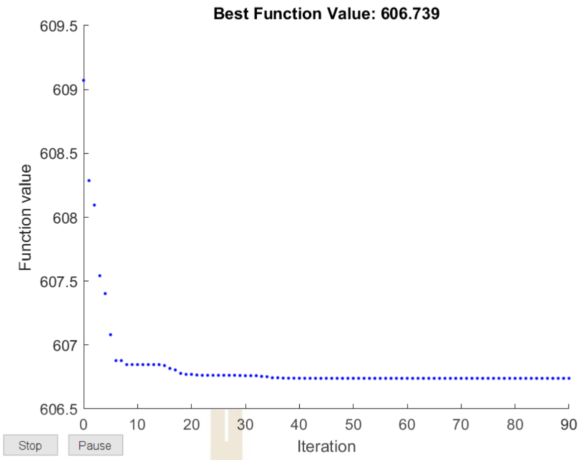

Figure E.9 The convergence plot of hour 9

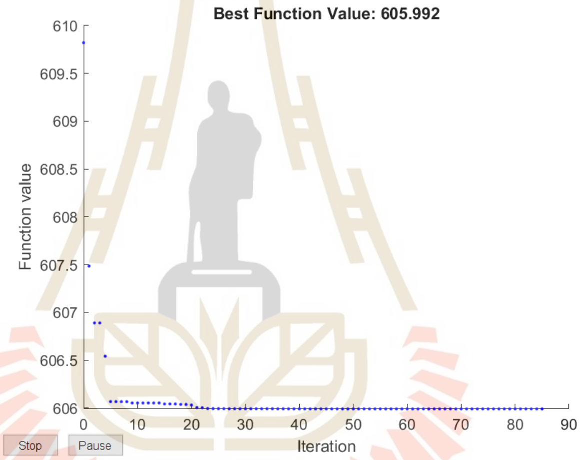

Figure E.10 The convergence plot of hour 10

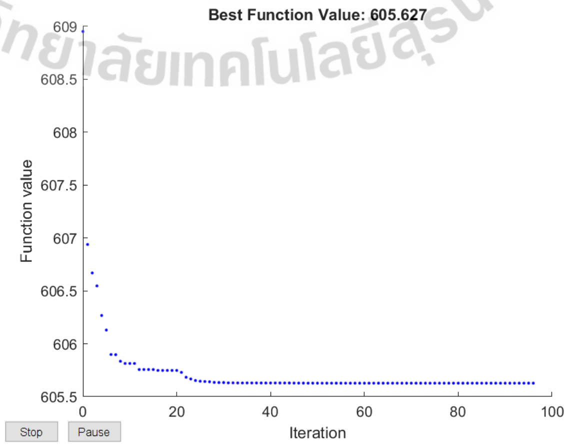

Figure E.11 The convergence plot of hour 11

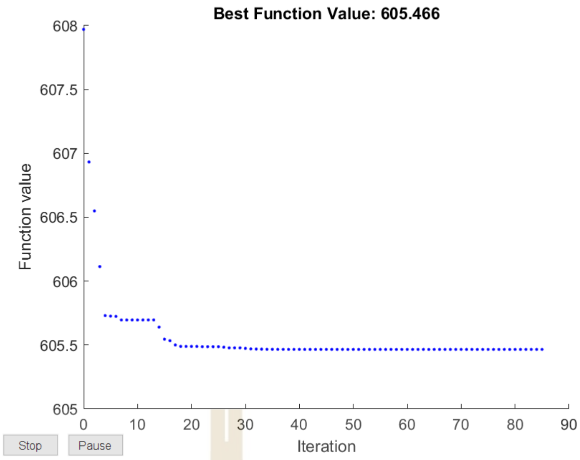

Figure E.12 The convergence plot of hour 12

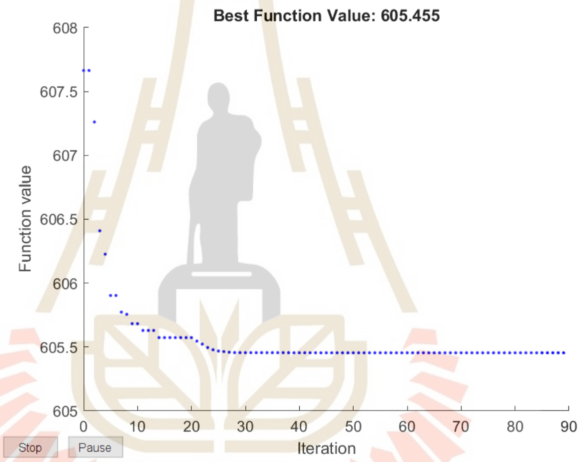

Figure E.13 The convergence plot of hour 13

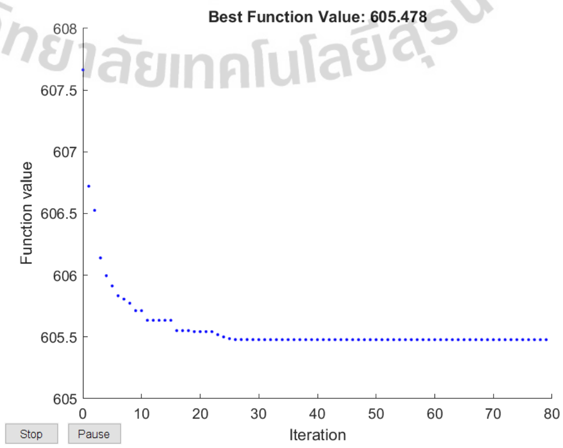

Figure E.14 The convergence plot of hour 14

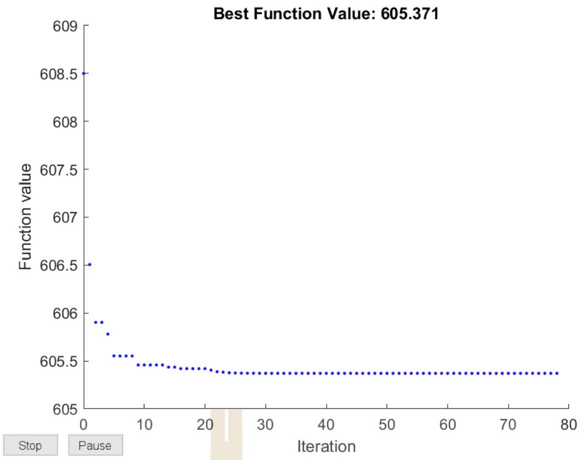

Figure E.15 The convergence plot of hour 15

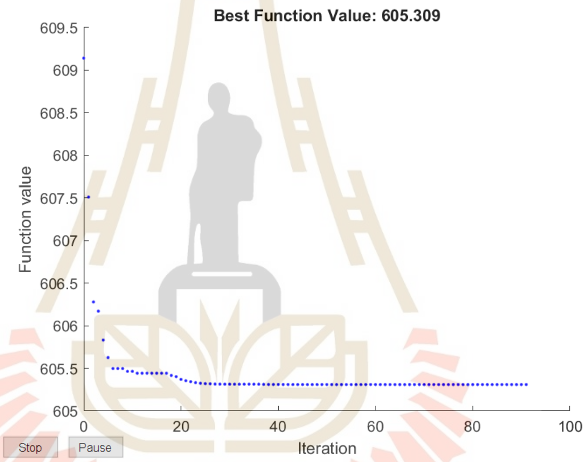

Figure E.16 The convergence plot of hour 16

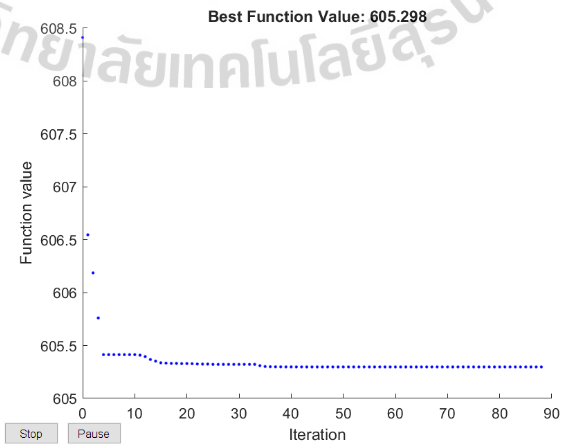

Figure E.17 The convergence plot of hour 17

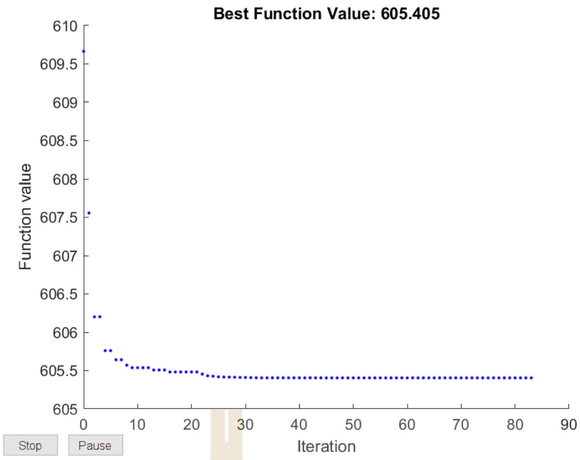

Figure E.18 The convergence plot of hour 18

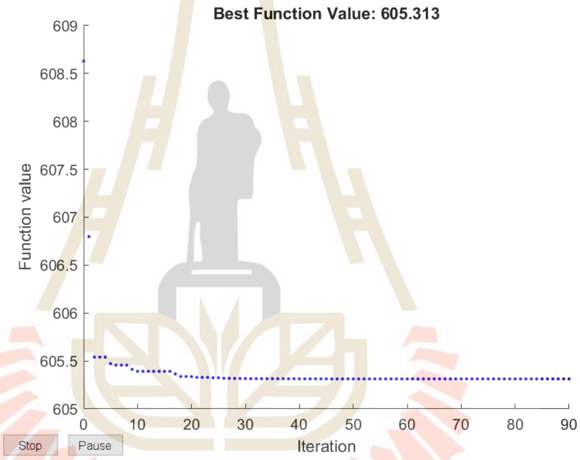

Figure E.19 The convergence plot of hour 19

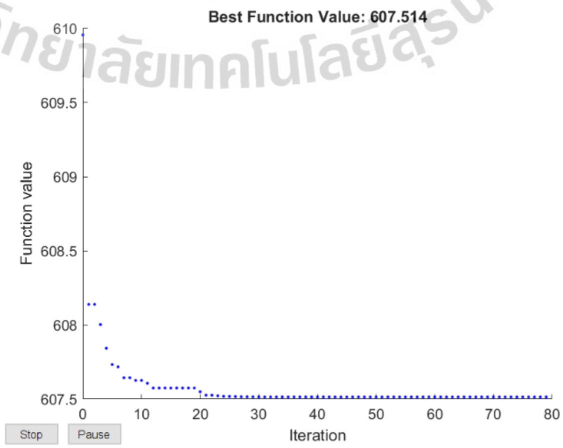

Figure E.20 The convergence plot of hour 20

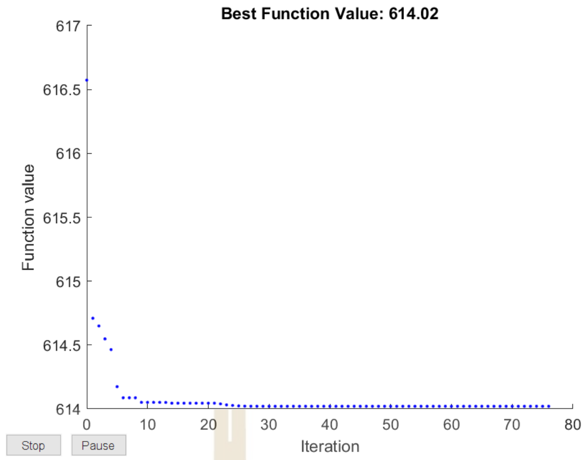

Figure E.21 The convergence plot of hour 21

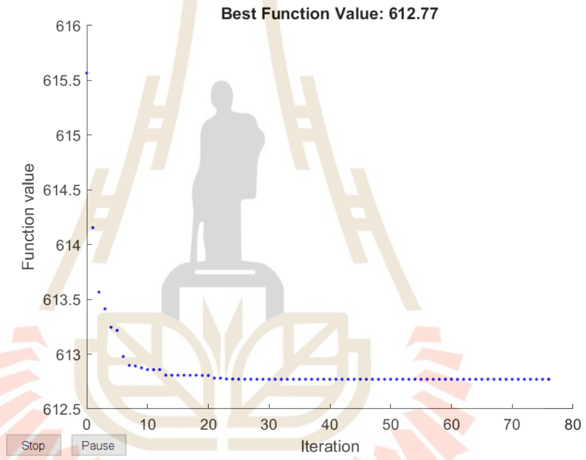

Figure E.22 The convergence plot of hour 22

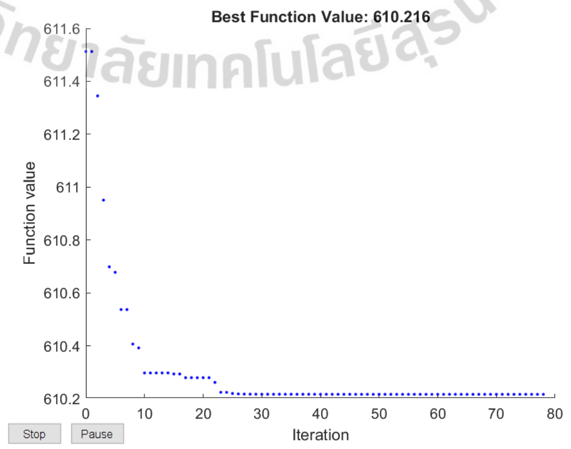

Figure E.23 The convergence plot of hour 23

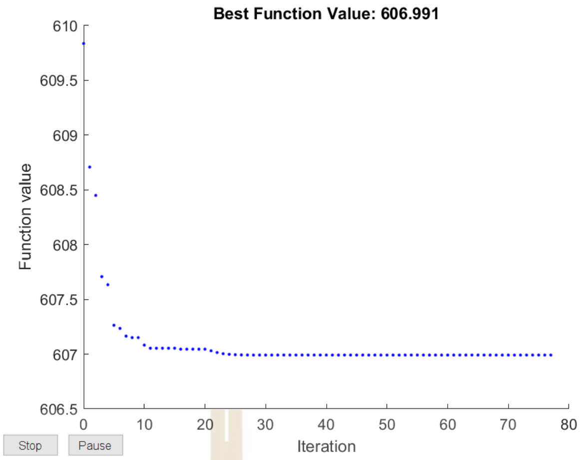

Figure E.24 The convergence plot of hour 24

APPENDIX F

LIST OF PUBLICATIONS

P. Kaikrathok and K. Chayakulkheeree (2022), Optimal Price-Based Real-Time Demand Response in Distribution System with Distributed Generators Using Particle Swarm Optimization, 2022 International Electrical Engineering Congress (iEECON2022), Khon Kaen, THAILAND.

P. Kaikrathok and K. Chayakulkheeree (2023), Optimal Power Dispatch for Day-Ahead Power System Operation Considering Demand Elasticity, International Journal of Applied Power Engineering (IJAPE).

Optimal Price-Based Real-Time Demand Response in Distribution System with Distributed Generators Using Particle Swarm Optimization

Pansa Kaikrathok **Keerati Chayakulkheeree**

School of Electrical Engineering
Institute of Engineering, Suranaree University of Technology
Nakhonrachasima, Thailand
E-mail: pansakhaikrathok@gmail.com , keerati.ch@sut.ac.th

***Abstract*— In this paper, the optimal price-based real-time demand response (OPRDR) using particle swarm optimization (PSO) is proposed. In the proposed method, the price-based real-time demand response (PRDR) is integrated into optimal power flow (OPF) problem and solved simultaneously. The algorithm has been tested with the IEEE 33-bus system. The test results shown that the proposed algorithm can effectively minimize total operating cost by trading-off with PRDR cost in the optimal power dispatch.**

Keywords—optimal power flow, particle swarm optimization, demand response

Nomenclature

c_1, c_2 : the acceleration constants
$D_i(P_{DRi})$: the cost function demand response
$|f_{lm}|$: the MVA flow on the branch between bus l and m
$|f_{lm}|^{\max}$: the maximum MVA limit the branch between bus l and m
$F_i(P_{Gi})$: the fuel cost of generator i
$gbest_i^t$: the best group position of particle i at iteration t
NB : the total number of buses
NG : the total number of generators
NP : the total number of particles
$\mathbf{p}_i$: the position of particle i
$pbest_i^t$: the best particle position of particle i at iteration t
PNF : the penalty factor for constraints violations
P_{Di} : the real power demand at bus i with demand response
P_{Di}^0 : the real power demand at bus i without demand response
P_{DRi} : the real power demand response at bus i
P_{Gi} : the real power generation at bus i
$P_{Gi}^{\min}$: the minimum real power generation at bus i
$P_{Gi}^{\max}$: the maximum real power generation at bus i
P_{loss} : the total transmission loss in the system
Q_{Di} : the reactive power demand at bus i
Q_{Gi} : the reactive power generation at bus i
r_1, r_2 : the random values within the range of [0,1]
t : the total number of iterations
TC : the total system cost
v_i^t : the particle i 's velocity at iteration t
$|V_i|$: the voltage magnitude at bus i
$|V_j|$: the voltage magnitude at bus j
$|V_i|^{\max}$: the maximum limit of voltage magnitude at bus i
$|V_i|^{\min}$: the minimum limit of voltage magnitude at bus i
w : the inertia weight factor
$|y_{ij}|$: the magnitude of the y_{ij}
θ_{ij} : the angle of the y_{ij} element of Y_{bus}
δ_{ij} : the voltage angle between bus i and bus j

I. Introduction

In the modern electricity supply industry, various methods for improving the energy efficiency of electric infrastructure have been developed. Demand response (DR) is an efficient technique for balancing off unexpected increases or decreases in customer energy usage in order to fulfill electricity pricing incentives, economic which are used to reduce peak demand for electricity when the production costs are very high. This will aid in the management of electrical energy emergencies and improve the short-term and long-term stability of electric power. With DR scheme, the performance of system can be improved, for examples, enhancing power system reliability, improving power system efficiency, increasing stability, improving power system mobility, and reducing the cost of electricity. The DR offers a wide range of roadmaps and projects [1]. The ongoing development of DR technology has opened up new possibilities for electricity distribution networks.

In addition, in power system optimal operation, the optimal power flow (OPF) is a critical analytical technique for electrical power and control [2]. Many academics are working forever on OPF for some future power system operation utilizing various optimization strategies. There is a lot of researches being done with the goal of optimal management for real-time DR, such as using linear programming (LP) [3], stochastic finite impulse response (FIR) models [4], particle swarm optimization [5], stochastic compromise programming (SCP) [6], setting the electricity price method [7], fuzzy systems [8] have been used to determine the DR problem for the optimal working schedule. Each manner of working is

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unique, as is the efficacy of the outcomes. It is dependent on the approach selected.

This paper presents the OPF problem using PSO [9], the method for integrating of optimal price-based real-time demand response (OPRDR). The proposed problem formulation can be applied for both day-ahead and hour-ahead operation in electricity treading platform. The 33-bus distribution test system [10] was used to test the proposed method. The recommended approach resulted in the lower cost of production. When include the PRDR management problem into the OPF.

This paper is arranged as follows. The proposed method's problem formulation was addressed in Section II. The PSO approach for tackling the integrated OPRDR and OPF problem is then introduced in section III. Section IV addresses and discusses the findings of the planned OPRDR with IEEE 33-bus system. Finally, in Section V, there is a conclusion.

II. PROBLEM FORMULATION

The OPRDR model is used in this paper to solve the problem of determining the best control variables for minimizing total system operating expenses while adhering to numerous equality and inequality limit requirements. The following are the OPRDR problem formulations that have been proposed:

The objective function is to minimize total operating cost considering demand response as,

$$TC = \sum_{i=1}^{NG} F_{Gi}(P_{Gi}) + \sum_{i=1}^{NB} D_i(P_{DRi}) + PNF, \quad (1)$$

subjected to the power balance constraint,

$$P_{Gi} - P_{Di} = \sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\cos(\theta_{ij} - \delta_{ij}), i = 1, \ldots, NB, \quad (2)$$

$$Q_{Gi} - Q_{Di} = -\sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\sin(\theta_{ij} - \delta_{ij}), i = 1, \ldots, NB, \quad (3)$$

$$\sum_{i=1}^{NG} P_{Gi} + \sum_{i=1}^{NB} P_{DRi} = \sum_{i=1}^{NB} P_{Di}^{0} + P_{loss}, \quad (4)$$

and the generator operating limit constraint,

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}, i = 1, \ldots, NG, \quad (5)$$

$$\sum_{i=1}^{NG} P_{Gi} = \sum_{i=1}^{NB} P_{Di} + P_{loss}, \quad (6)$$

$$P_{Di} = P_{Di}^{0} - P_{DRi}, i = 1, \ldots, NB, \quad (7)$$

and line flow limit constraint,

$$|f_{lm}| \le |f_{lm}|^{max}, \quad (8)$$

and bus voltage limit constraint,

$$|V_i|^{min} \le |V_i| \le |V_i|^{max}, i = 1, \ldots, NB. \quad (9)$$

Note that the PNF is applied only when the result violate the constraints in Eqs. (8)-(9).

III. PSO BASED INTEGRATED OPRDR AND OPF

The PSO system proposed by [9] is a method of optimization based on the traveling or foraging behavior of the herd. In particular, for a flock of birds, each bird in the flock is represented by a particle. The PSO solution starts by randomly locating the particles (which various positions of those particles are possible solutions) to produce a set. The optimal values are then determined by adjusting the values at each decision cycle. where each particle is adjusted by changing its position according to the best value.

PSO operation is an iterative computation process in which each cycle of operation the velocity of each particle is adjusted by $pbest^t_i$ and $gbest^t_i$. In this paper, the set of populations is formulated as,

$$\mathbf{p}_i = [p_1, \ldots, p_{NP}] = [P_{G1}, \ldots, P_{NG}, |V_1|, \ldots, |V_{NG}|, DR_1, \ldots, DR_{NB}]. \quad (10)$$

The control of variables in Eq. (10) are used for Eqs. (1-9). Then, the new velocity of the particles are calculated by Eq. (11), the new position of the particles are computed by Eq. (12). Note that P_{Gi} or the real power generator at slack bus is not include in the optimization problem, and treated as depedent variable.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i^t - \mathbf{p}_i^t) + c_2 r_2 (gbest_i^t - \mathbf{p}_i^t), \quad (11)$$

$$\mathbf{p}_i^{t+1} = \mathbf{p}_i^t + v_i^{t+1}. \quad (12)$$

The computational procedure of the proposed method is as follows,

Step 1: Obtain system data.
Step 2: k = 1.
Step 3: Initial PSO populations.
Step 4: Solve power flow solution in Eqs. (2)-(3) of each population.
Step 5: Compute the objective function in Eq. (1). (If the solution violate constrains, $PNF = 10^{12}$. If no constrain violation, $PNF = 0$.)
Step 6: Obtain $pbest^t_i$ and $gbest^t_i$ for each population.
Step 7: Compute v_i^{t+1} in Eq. (11).
Step 8: Update $\mathbf{p}_i^{t+1}$ in Eq. (12).
Step 9: k = k+1.
Step 10: If k > maximum iteration, go to Step 4. If k ≤ maximum iteration, go to Step 11.
Step 11: Obtain output and stop.

IV. TEST RESULTS

The proposed OPRDR based OPF was tested with modified IEEE 33-bus distribution test system[10], as shown in Fig.1.

Six generators and DR are added in the distribution network, as shown in Fig. 1. The generator are installed on buses 3, 8, 14, 25, 30, and 31. The DR are installed on buses 24 and 25, which are the buses connected to the large demands. Meanwhile, most at power is supplied from power grid at bus *i*.

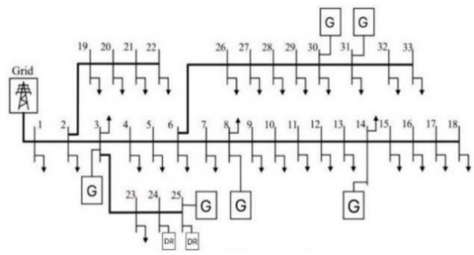

Fig. 1. The modified IEEE 33-Bus system

The simulation study includes,

Case I : modified IEEE 33-bus distribution test system, OPF without DR, and

Case II: modified IEEE 33-bus distribution test system, OPF with DR.

In this paper, the PSO parameters used are as follow, $c_1 = 2$, $c_2 = 2$, $w_{min} = 0.9$, $w_{max} = 0.4$, Population size =1000, and Maximum iteration = 50. Note that the simulation are performed under one hour basis.

TABLE I. DR PRICE FOR 1 HOUR OF 33-BUS SYSTEM

Bus	Power Demand		PRDR	
	(MW)	(MVar)	(MW)	(\$/MWhr.)
24	420- P_{DRi}	200	100	20
25	420- P_{DRi}	200	100	10

In this paper, the PRDR cost used are in constant price as shown in Table I. There are two PRDR, connected at buses 24 and 25, which are the buses with large load, for simulation. Meanwhile, the generator cost functions used are in quadratic form as shown in Table II.

TABLE II. GENERATOR DATA

Bus	P_{min}	P_{max}	Q_{min}	S_{max}	Cost coefficients*		
	(MW)	(MW)	(MVar)	(MVA)	a_i	b_i	c_i
1	50	1000	-20	250	0	2.00	0.00375
3	50	500	-20	250	0	2.00	0.00375
8	50	500	-20	100	0	1.75	0.01750
14	50	500	-15	80	0	1.00	0.06250
25	50	500	-15	60	0	3.25	0.00834
30	50	500	-10	50	0	3.00	0.02500
31	50	500	-15	60	0	3.00	0.02500

*Generation cost $F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2$ \$/hr

Table III is a comparison of the modified IEEE 33-bus system for Case I and Case II. The proposed method PSO based integrated OPRDR and OPF. The optimal value of generator power output (P_{G2}-P_{G7}), generator voltage magnitudes ($|V_2|$-$|V_7|$), and purchasing DR at buses 24-25. The voltage based limit constraint used in this paper is $0.95 \leq |V_i| \leq 1.05$ p.u.

TABLE III. COMPARISON RESULTS OF THE IEEE 33-BUS SYSTEM

Variable	Case I	Case II
P_{G3}	500	500
P_{G8}	395.5768	381.8340
P_{G14}	120.0461	116.1286
P_{G25}	500	500
P_{G30}	251.9175	242.3788
P_{G31}	252.5813	243.0587
$\lvert V_3 \rvert$	0.9951	0.9954
$\lvert V_8 \rvert$	0.9797	0.9793
$\lvert V_{14} \rvert$	0.9673	0.9668
$\lvert V_{25} \rvert$	0.9925	0.9941
$\lvert V_{30} \rvert$	0.9796	0.9791
$\lvert V_{31} \rvert$	0.9785	0.9780
DR_{24}	-	0
DR_{25}	-	100
Total Gen. Cost (\$/hr)	29432.00	27940.00
Total DR Cost (\$/hr)	-	1000
Total system Losses (MW)	0.0321	0.0325
Total system Cost (\$/hr)	29432.16	28940.12
Compulation time (sec)	710.55	1098.54

In Case I, The generation cost is 29432.00 \$/hr, The losses total system is 0.0321 MW, and the total system cost is 29432.16 \$/hr. The convergence plot of Case I is shown in Fig.2.

In Case II, The generation cost was reduced to 27940.00 \$/hr. The total system loss was reduced to 0.0325 MW. With the inclusion of DR cost, the total system cost 28940.12 \$/hr, lower than that of Case I even the total loss higler. Fig.3 addresses the convergence plot of Case II.

The results of two cases shown that the total system generation cost can be reduced by PRDR mechanism. Meanwhile, the customers those who provide PRDR to the system gain the benefit from PRDR payment.

The solution shown that the system cost can be reduced when integrate the OPRDR with OPF problem. Moreover, DR reduces the need to invest in reserve capacity and utilization of the high fuel cost segment without wasting resources and is environmentally friendly. For PRDR, the consumer will receive a compensation rate or a discount on the electricity tariff.

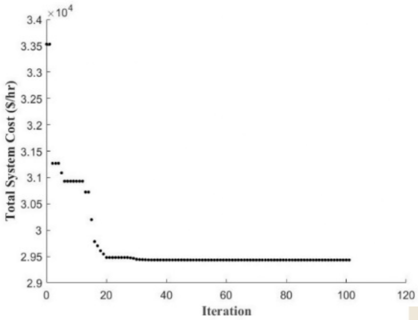

Fig. 2. The convergence plot of Case I

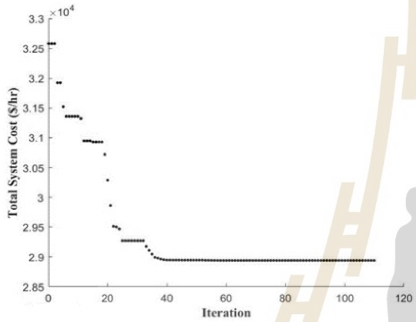

Fig. 3. The convergence plot of Case II

The resulte with 20 trial of the proposed OPRDR is shown in Table IV and Fig.4.

TABLE IV. THE RESULT AT 20 TRIAL OF THE PROPOSED OPRDR

Total system cost ($/hr)	Case I	Case II
Best	29432.1579124933	28940.1217262821
Mean	29432.1579126334	28940.1217266083
Worst	29432.1579139414	28940.1217275539

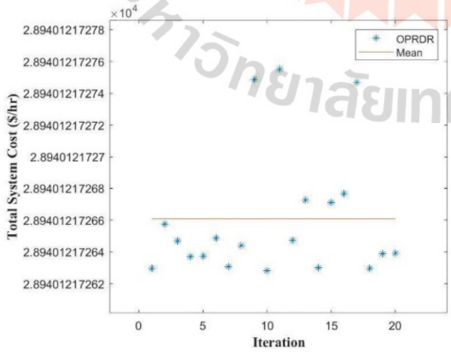

Fig. 4. The solution with 20 trail of Case II

V. CONCLUSION

In this paper, the OPRDR model is described. The effectiveness of the proposed methodology has been comparatively tested and validated on the modified IEEE 33-bus distribution test system. The results revealed that the proposed integrated OPRDR with OPF can reduce the overall system cost by taking into consideration generator management, voltage adjustment, and DR offers.

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BIOGRAPHY

Ms. Pansa Kaikrathok received B.Eng in EE (Second Class Honors) from SUT, Thailand in 2021. She is now a master student at School of Electrical Engineering, Institute of Engineering, SUT. Her current research interests include distribution system analysis and microgrid system optimization.

Associate Professor Dr. Keerati Chayakulkheeree received B.Eng. in EE from KMITL, Thailand, in 1995, M.Eng. and D.Eng. in EPSM from AIT in 1999 and 2004, respectively. He is currently an Associate Professor at School of Electrical Engineering, Institute of Engineering, SUT. His research interests are in power system optimization and AI application to power system.

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Optimal Power Dispatch for Day-Ahead Power System Operation Considering Demand Elasticity

Pansa Kaikrathok[1], Keerati Chayakulkheeree[1]
[1]School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhonratchasima, Thailand

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ABSTRACT

This paper proposes the optimal power dispatch (OPD) considering price-based demand response (PDR). In the proposed framwork, the nodal spot price (NSP) is use as a price signal to the consumers. In the proposed method, the optimal real power dispatch is solved by quadratic programming (QP) to minimize the total operating cost and obtain the NSP components. Consequently, demand elasticity (DE) is applied to estimate the system demand for more accurate day-ahead operations. In the DE matrix, the self-DEs represent the consumer consumption of hour *h* in response to the NSP of that hour. Meanwhile, the cross-DEs represent the response of consumer consumption of hour *h* to the NSP of other hours. The algorithm was tested with the IEEE 30-bus system with several cases of demand elasticity. The results show that the proposed algorithm can incorporate price elasticity of demand into day-ahead scheduling and effectively minimize total operating costs. The simulation study shown that, the operating cost can be reduced by 0.33-0.695% with self-DE of -0.1~ -0.2, by reducing the consumption respected to the NSP. Meanwhile, when applying cross-DE, the operating cost can be reduced by 0.015% under the same daily consumption with the consumer's load shifting respected to NSP.

Corresponding Author:

Keerati Chayakulkheeree
111, Suranaree University of Technology
Maha Witthayalai Road, Mueang Nakhon Ratchasima District, Nakhon Ratchasima, Thailand
Email: keerati.ch@sut.ac.th

Nomenclature

a_i, b_i, c_i : generator cost coefficients

$a_{il,h}$: the line flow sensitivity factor at bus *i* at hour *h*

EC^h : electricity cost at hour *h*

$|f_{lm,h}|$: the MVA flow on the branch between bus *l* and *m* at hour *h*

$|f_{lm}|^{max}$: the maximum MVA limit of the branch between bus *l* and *m*

$f^0_{l,h}$: the initial real power flow at line *l* at hour *h*

$\Delta f_{l,h}$: change in power flow on line *l*

$FC_i(P_{Gi,h})$: the fuel cost of the generator at bus *i* at hour *h*
NB : the total number of buses
NG : the total number of generators
$P_{Di,h}$: the real power demand at bus i with demand response at hour *h*
$P_{Gi,h}$: the real power generation at bus *i* at hour *h*
$P_{Gi,h}^{\max}$: the maximum real power generation at bus *i*
$P_{Gi,h}^{\min}$: the minimum real power generation at bus *i*
$P_{i,h}$: the real injection power at bus *i* at hour *h*
$P_{Li,h}$: the power demand at bus *i* at hour *h*
$P_{Li,h}^{0}$: the initial power demands at hour *h*
$P_{Li,h}$: the power demand at bus *i* at hour *h*
$P_{loss,h}$: the power loss at bus *i* at hour *h*
$\Delta P_{i,h}$: change in real injection power at bus *i* at hour *h*
$\Delta P_{Li,h}$: change in power demand at bus *i* at hour *h*
$Q_{Di,h}$: the reactive power demand at bus *i* at hour *h*
$Q_{Gi,h}$: the reactive power generation at bus *i* at hour *h*
$Q_{Gi,h}^{\max}$: the maximum reactive power demand at bus *i*
$Q_{Gi,h}^{\min}$: the minimum reactive power demand at bus *i*
TFC : the total system cost
$|V_{i,h}|$: the voltage magnitude at bus *i* at hour *h*
$|V_{j,h}|$: the voltage magnitude at bus *j* at hour *h*
$|y_{ij}|$: the magnitude of the y_{ij} element of Y_{bus}
$\varepsilon_{i,h}$: the demand elasticity matrix at bus *i* at hour *h*
$\varepsilon_{i,j}$: position in the demand elasticity matrix representing self and cross demand elasticity
$\Delta\sigma_{i,h}$: change in spot price at bus *i* at hour *h*
$\sigma_{i,h}$: the spot price at bus *i* at hour *h*
$\eta_{L,ih}$: the marginal transmission loss component at hour *h*
$\eta_{QS,ih}$: the network quality of supply component at hour *h*
λ_h : the system marginal price at hour *h*
θ_{ij} : the angle of the y_{ij} element of Y_{bus}
$\delta_{ij,h}$: the voltage angle between bus *i* and bus *j* at hour *h*

1. INTRODUCTION

Nowadays, the power system operation has created several techniques for increasing the market-based energy efficiency of electric infrastructure. Demand response (DR) is one of the effective tools for balancing unexpected electricity price spikes and decreases in customer energy use to satisfy electricity price incentives. These price signals lower peak power demand when the cost of production is very high. This process also increases the reliability of electricity both in the short and long term. Therefore, the system's performance can be enhanced with the DR plan, for instance, boosting power system dependability, efficiency, stability, and mobility, as well as cutting down on electricity costs. As a result, a variety of roadmaps and initiatives are available for the DR scheme. New options for power system operation are now possible because of the DR technology's continual development.

Many DR's have planned the introduction of contemporary power supply responses to industrial needs. DR schemes have been proposed in various sources of literature [1]. DR systems can be specifically divided into three basic groups [2]. According to the kind of control mechanism, offered motivation, decision variable are provided to customers to lower their energy use. In general, programs can be categorized by their mechanism as shown in Figure 1 Economically, DR can be classified into incentive base DR (IDR) [3], [4] and price-based DR (PDR) [5], [6]. In this article, we will focus on PDR.

PDR is a strategy used by energy providers to manage electricity demand during peak periods. The idea is to incentivize customers to reduce their energy consumption during times of high demand by offering them lower prices for their electricity usage [7]. Energy providers will offer different pricing tiers based on the time of day and the overall demand for electricity. During peak periods when electricity demand is highest, prices will be higher, while during off-peak periods, prices will be lower. This encourages customers to reduce their energy consumption during peak periods and shift their usage to off-peak periods.

PDR scheduling has lately been studied in [8]-[11]. In [8] and [9], the operational challenge takes into account demand shifting and peak shaving. In [10], the day-ahead unit commitment model treats curtailable and changing requests separately. Best practices for scheduling the hourly demand response taking renewable energy uncertainties into account in the day-ahead market [11].

The PDR consists of a time of use (TOU) program [12], [13], critical peak pricing (CPP) [14], [15], extreme day CPP (ED-CPP), extreme day pricing (EDP) [16] and real-time pricing (RTP) [17]-[19]. In [20] overview of two types of demand response, namely price-based and incentive-based, and gives examples of price-based responses. by focusing on the role of electricity companies in influencing consumer behavior to reduce the stress on the electricity grid. The mechanism behind these programs is electricity prices that change over time.

The fluctuation in the price of electricity reflects the cost of electricity production in each period. The main aim of the program is to make the power consumption curve smoothest by charging high prices during peak times and lower prices during off-peak periods. RTP programs, in the opinion of many economists, are the most direct and effective DR programs appropriate for competitive electricity markets and need to be the main focus of policymakers [19].

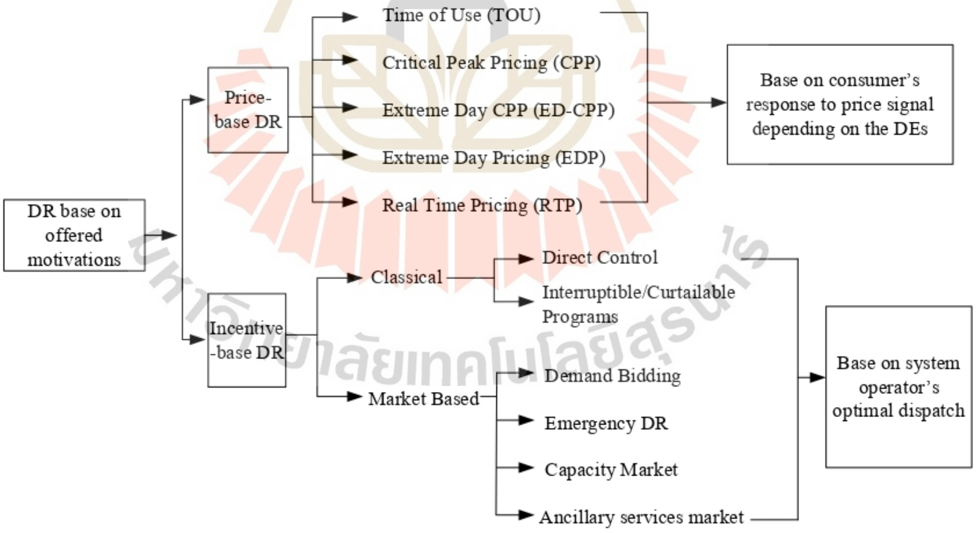

Figure 1. DR program

In this paper, demand elasticity (DE) is used to analyze the optimal power dispatch (OPD) for the PDR program using RTP. In the proposed RTP-PDR program the electricity users are informed of the day-ahead RTP prior to the dispatch day. Therefore, the electricity load forecast is adjusted according to the DE. Then, the system operator re-dispatch with the smoother load profile, leading to a lower electricity price.

As shown in Figure 2, In the fixed price strategy or without price signal to consumers, the demand curve is the vertical line. In other words, the buyers are willing to pay whatever price to meet the demand. But with price signals to the consumer, the customers' electricity usage habits will vary depending on the price at the time in according to DE. If the price is high, the demand will be less. If the price is low, the demand will be high. Then, it is estimating the consumer response to the price by elasticity price [21] and obtaining the price-corrected load forecast. Finally, the price-corrected optimal power dispatch is obtained. Accordingly, in this paper, the optimal real power dispatch algorithm for market-based power system operation incorporating demand price elasticity for day-ahead operation using quadratic programming (QP) is proposed. The nodal real-time spot price algorithm for a power system with loss sensitivity and the DC line flow method is determined. The proposed method was tested by using the IEEE 30-bus system and investigate the solution with different elasticity coefficients.

The contributions in this paper are summarized as follows:

- The optimal real power dispatch algorithm for market-based power system operation incorporating demand price elasticity for day-ahead operation using QP (for total cost minimization) is developed.
- The algorithm for the nodal real-time spot price of power system using loss sensitivity and DC line flow method is incorporated into the proposed optimal real power dispatch.
- Several different elasticity coefficients had been investigated and discussed.

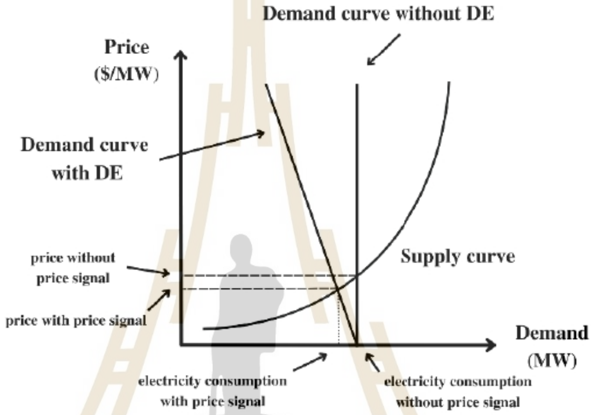

Figure 2. Bidding curve of demand

The remainder of the paper is structured as follows. Section 2 focuses on the dynamic load economic model. The formulation of the proposed mathematical problem is described in Section 3. Simulation results are in Section 4. Section 5 serves as the paper's conclusion.

2. DAY-AHEAD ELASTIC LOAD MODEL

An economic load model that depicts the shifts in customer demand in response to changes in demand prices is needed to define client engagement in DR schemes. DE is used to represent the demand response behaviour. The relative slope of the demand-price curve could be used to determine the demand-price elasticity as shown in Figure 2 This elasticity coefficient shows significantly a change in a commodity's price would alter the relative level of demand for that commodity. It shall be assumed throughout this paper that all prices and quantities have been normalized about a certain equilibrium.

The fixed-demand bids are inelastic to the market price in terms of demand. To represent the consumer's behaviors, the DE can be formulated by the matrix consisted of “self-elasticity” and “cross-elasticity”. The self-elasticity represents the DE of the demand corresponding to the price in the same hour. Therefore, if the higher price leads to the lower demand and the self-elasticity is then negative. On the other hand, the higher price in hour *i* (that reduce the consumption in hour *j*. Therefore, the cross-elasticity is then negative. An elasticity matrix can be followed as (1)-(2),

$$\begin{bmatrix} \Delta P_{L1} \\ \Delta P_{L2} \\ \vdots \\ \Delta P_{L24} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,24} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \cdots & \varepsilon_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{24,1} & \varepsilon_{24,2} & \cdots & \varepsilon_{24,24} \end{bmatrix} \begin{bmatrix} \Delta\sigma_1 \\ \Delta\sigma_2 \\ \vdots \\ \Delta\sigma_{24} \end{bmatrix}. \tag{1}$$

$$\varepsilon_{i,j} \le 0, \text{ if } i = j, \text{ and } \varepsilon_{i,j} \ge 0, \text{ if } i \ne j. \tag{2}$$

As was previously noted, the period under consideration affects how customers respond to changes in power prices. In this paper, we will focus on the response "short-term", which refers to the period between the price announcement for the subsequent 24-hour period and the actual demand periods. Therefore, hourly demand changes can be followed as (3)-(4),

$$\Delta P_{Li,h} = \sum_{i=1}^{24} \varepsilon_{i,h} \Delta\sigma_{i,h}, \text{ and} \tag{3}$$

$$P_{Li,h} = P_{Li,h}^{0} + \Delta P_{Li,h}, i = 1,\ldots, NB, h = 1,\ldots,24. \tag{4}$$

The price of electricity each hour, taking into account the elasticity price can be followed as (5),

$$EC_{i,h} = \sum_{i=1}^{NB} P_{Li,h} \cdot \sigma_{i,h}, i = 1,\ldots, NB, h = 1,\ldots,24. \tag{5}$$

2.1. Spot pricing of electricity

The spot price applied in this scheme including the system marginal price, marginal transmission loss, and network quality of supply (line congestion premium) [22] which can be calculated by (6)-(8),

$$\sigma_{i,h} = \lambda_h + \eta_{L,ih} + \eta_{QS,ih}, i = 1,\ldots, NB, h = 1,\ldots,24, \tag{6}$$

$$\eta_{L,ih} = \lambda_h \cdot (-ITL_{i,h}) = \lambda_h \cdot (\frac{dP_{loss,h}}{dP_{i,h}}), i = 1,\ldots, NB, h = 1,\ldots,24, \text{ and} \tag{7}$$

$$\eta_{QS,ih} = -\sum_{l=1}^{NB} \mu_{l,h}(a_{li,h}), i = 1,\ldots, NB, h = 1,\ldots,24. \tag{8}$$

The $ITL_{i,h}$ is the change in total system loss due to the change in real injection power at bus i. The constraint incremental relaxation price or $\mu_{l,h}$ is defined as the reduction in supply cost or increase can be followed as (9),

$$ITL_{i,h} = \frac{dP_{loss,h}}{dP_{i,h}}. \tag{9}$$

The line flow sensitivity factors ($a_{li,h}$) of line l to change in real injection power at bus i is followed as (10), then $\Delta f_{l,h}$ is the change in power flow on line l when $\Delta P_{i,h} \neq 0$ and $\Delta P_{i,h}$ is the change in real injection power at bus i at hour h as,

$$a_{il,h} = \frac{\Delta f_{l,h}}{\Delta P_{i,h}}. \tag{10}$$

The change of real power flow at line l will be $\Delta f_{l,h}$ and the power flow at line l will be expressed as follows (11),

$$f_{l,h} = f_{l,h}^{0} + a_{li,h} \Delta P_{i,h}. \tag{11}$$

3. Problem formulation

The conception of the paper can be shown in Figure 3. The primary optimal power dispatch provides the day-ahead hourly spot price and is announced prior to the dispatch day [23],[24].

The objective function is to minimize total operating cost considering demand response as (12),

$$\text{Minimize } TFC = \sum_{h=1}^{24} \sum_{i=1}^{NG} FC_i(P_{Gi,h}). \tag{12}$$

Where, the quadratic generator cost function has the following form (13),

$$FC_i(P_{Gi,h}) = a_i + b_i P_{Gi,h} + c_i P_{Gi,h}^2 \text{ (\$/hr)}, i = 1,\ldots, NB, h = 1,\ldots,24. \tag{13}$$

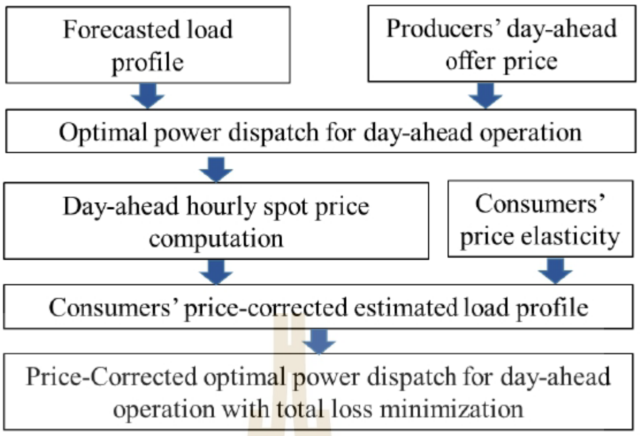

Figure. 3 The conception of the proposed framework

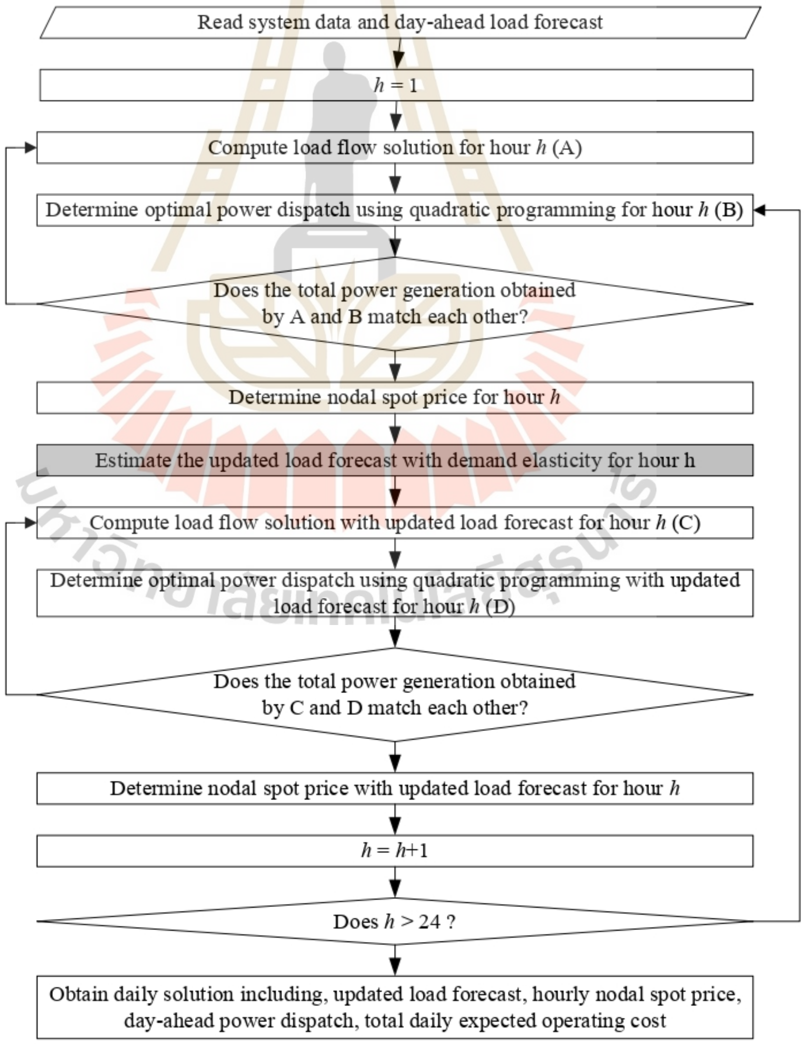

Figure. 4 Computational procedures

Subjected to the power balance constraints in (14)-(15),

$$P_{Gi,h} - P_{Di,h} = \sum_{j=1}^{NB} |V_{i,h}||V_{j,h}||y_{ij}|\cos(\theta_{ij} - \delta_{ij,h}), i = 1,...,NB, h = 1,...,24, \quad (14)$$

$$Q_{Gi,h} - Q_{Di,h} = -\sum_{j=1}^{NB} |V_{i,h}||V_{j,h}||y_{ij}|\sin(\theta_{ij} - \delta_{ij,h}), i = 1,...,NB, h = 1,...,24, \quad (15)$$

and the generator operating limit constraints in (16)-(17),

$$P_{Gi,h}^{\min} \le P_{Gi,h} \le P_{Gi,h}^{\max}, i = 1,...,NG, h = 1,...,24, \quad (16)$$

$$Q_{Gi,h}^{\min} \le Q_{Gi,h} \le Q_{Gi,h}^{\max}, i = 1,...,NG, h = 1,...,24, \quad (17)$$

and line flow limit constraint in (18),

$$|f_{lm,h}| \le |f_{lm,h}|^{\max}, h = 1,...,24. \quad (18)$$

The proposed method's computational process is as in Figure 4.

4. SIMULATIONS RESULT AND DISCUSSION

This section examines the proposed method by using the IEEE 30-bus test system. The IEEE 30-bus system used in this simulation. Table 1 lists the quadratic cost functions for each generator in the IEEE 30-bus system according to [25].

To analyze the effects on different facets of the electricity system while incorporating price-elastic demand bids, the simulation for of 24 hours is used. The six generators are situated at buses 1, 2, 5, 8, 11, and 13 in the IEEE 30-bus system. Bus 1 has been designated as the slack bus.

Table 1. Generator data for the IEEE 30-bus system [25]

BUS	P_{min} (MW)	P_{max} (MW)	Q_{min} (MVar)	Q_{max} (MVA)	Cost coefficient a_i	b_i	c_i
1	50	200	-20	250	0	2.00	0.00375
2	20	80	-20	100	0	1.75	0.01750
5	15	50	-15	80	0	1.00	0.06250
8	10	35	-15	60	0	3.25	0.00834
11	10	30	-10	50	0	3.00	0.02500
13	12	40	-15	60	0	3.00	0.02500

The system's daily load profile in the summer peak day of Thailand 2018, which peaks of 20340.70 MW at hour 20 and light-load of 13681.76 MW at hour 8, as shown in Figure 5 is used. The peak in demand occurs between 7:00 p.m. and 12:00 a.m., which is when there could be a significant need for power because of human activity.

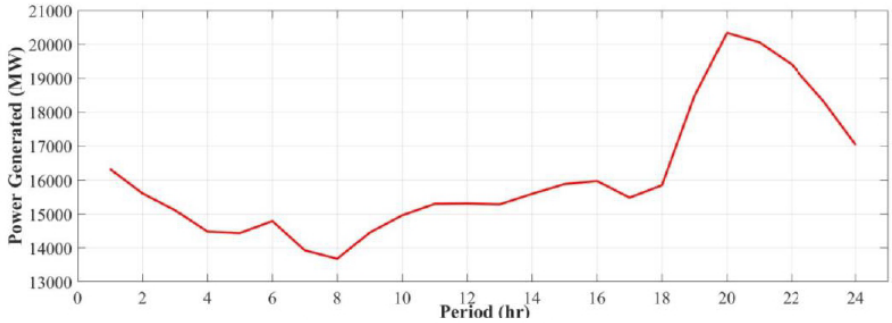

Figure. 5 System daily load curve

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The simulation study includes,
- **Case I: Base case.** In this case, the price signal is not applied.
- **Case II: Self-elasticity -0.1 without cross-elasticity.** In this case, DE is considered for all buses in the system. The demand is changed after considering demand price-elasticity.
- **Case III: Self-elasticity -0.2 without cross-elasticity.** In this case, DE is considered for all buses in the system. The demand curve with DE is the same as in case II, but a price elasticity is set to -0.2.
- **Case IV: Self-elasticity -0.23 and cross-elasticity 0.01.** In this case, DE is considered for all buses in the system. The demand curve with DE has, a self-elasticity of -0.23 and a cross-elasticity of 0.01. We use this to represent the changes in the price of one hour affect the demand for another.

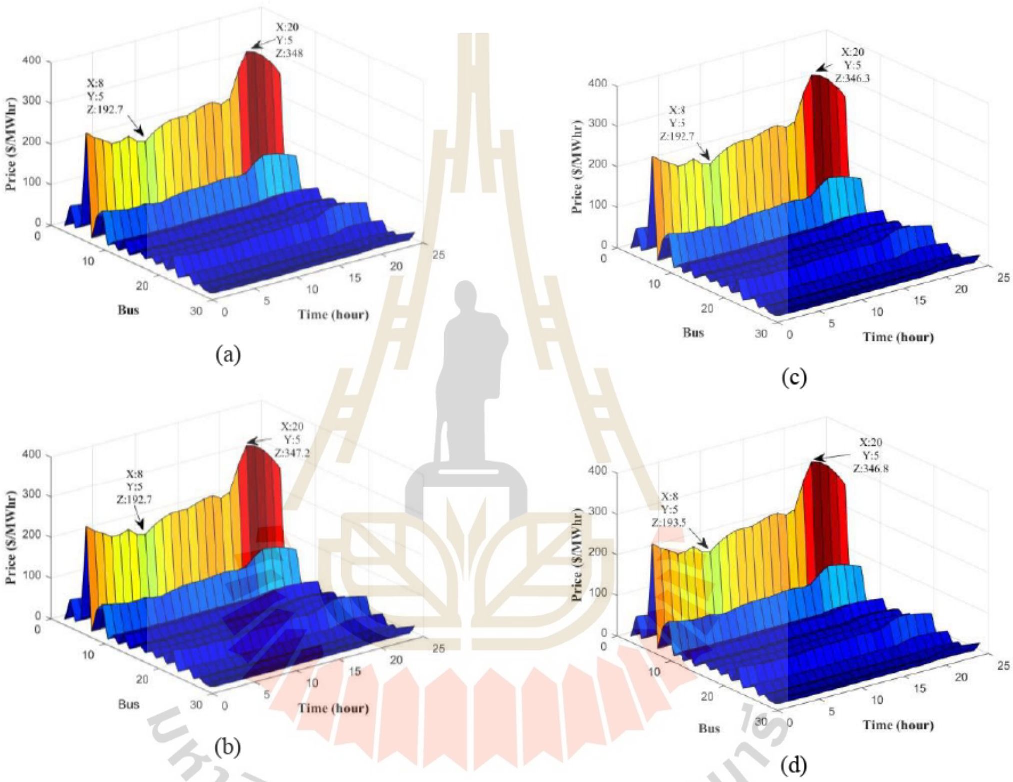


Figure. 6 Fuel cost (a) case I (b) case II (c) case III (d) case IV

Table 2. Spot price at bus 5

	Hour	Price ($/MWh)	
Peak hour	20	Case I	3.6946
		Case II	3.6881
		Case III	3.6818
		Case IV	3.6853
Light-load hour	8	Case I	3.0417
		Case II	3.0417
		Case III	3.0417
		Case IV	3.0508

Table 2 shows the spot prices for the peak and light-load hours of bus 5. Bus 5 is the highest-demand bus. The hourly price of each bus in cases I-IV are shown in Figures 6(a)-(d), respectively. The results of the fuel cost comparison in Case I is served as a base case, with simulations indicating that the cost is higher in all scenarios as shown in Figure 6(a). In Figure 6(b), the result of Case II, self-elasticity is applied with a value of -0.1. It is observed that the cost has slightly decreased in comparison to the base case. Figure 6(c) shows the result of Case III, the self-elasticity is -0.2. Note that in this case, the total generation cost is the lowest. Finally, Figure 6(d) shows the result of Case IV, self-elasticity is -0.23 and cross-elasticity is also applied at 0.01.

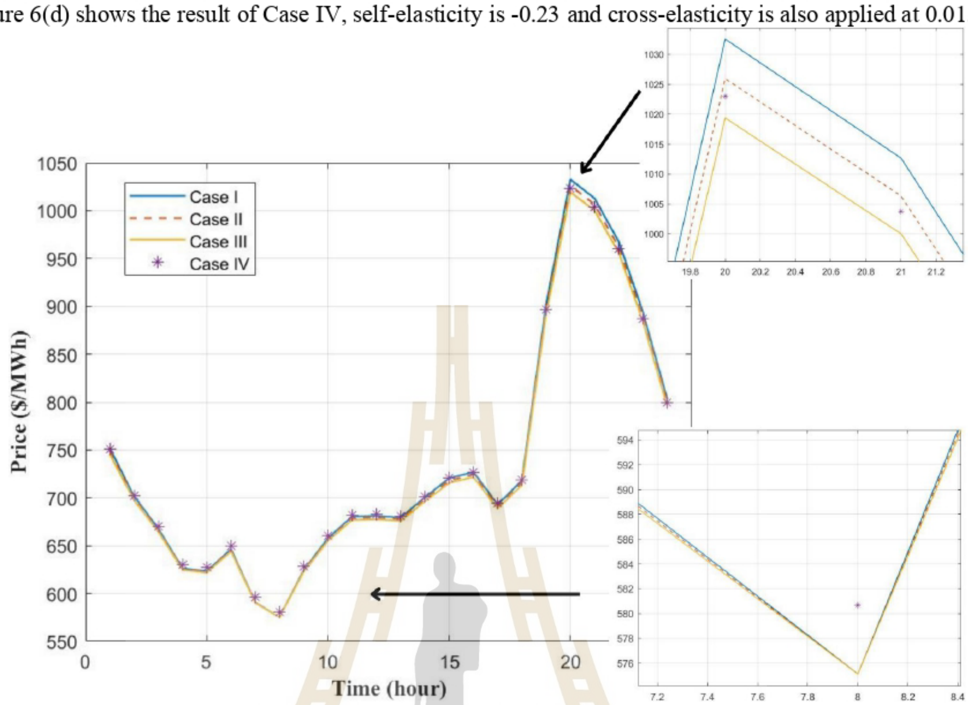


Figure. 7 Hourly fuel cost of IEEE 30-bus system

Table 3. Comparison of the results of the generator in a 30-bus system

Hour	Case I (MW)	Case II (MW)	Case III (MW)	Case IV (MW)
1	234.0324	233.3893	232.7466	233.8191
2	223.3372	222.8731	222.4092	223.5481
3	215.9894	215.6468	215.3042	216.4881
4	206.6524	206.4622	206.2721	207.5125
5	205.9933	205.8138	205.6344	206.8787
6	211.2119	210.9475	210.6831	211.8960
7	198.5118	198.4531	198.3943	199.6833
8	194.8387	194.8387	194.8387	196.1496
9	206.2330	206.0496	205.8663	207.1092
10	213.7649	213.4587	213.1526	214.3500
11	218.7275	218.3397	217.9521	219.1192
12	218.8779	218.4877	218.0975	219.2638
13	218.4868	218.1030	217.7193	218.8880
14	223.0959	222.6359	222.1759	223.3163
15	227.4109	226.8790	226.3473	227.4610
16	228.7400	228.1852	227.6313	228.7368
17	221.4381	221.0056	220.5731	221.7237
18	226.8976	226.3743	225.8511	226.9680
19	265.7107	264.6265	263.5428	264.4245
20	293.2090	291.8292	290.4499	291.2146
21	289.0740	287.7390	286.4045	287.1861
22	279.4950	278.2635	277.0325	277.8532
23	263.6143	262.5552	261.4962	262.3873
24	244.4869	243.6671	242.8478	243.8539
All day	5529.830	5516.624	5503.423	5529.831

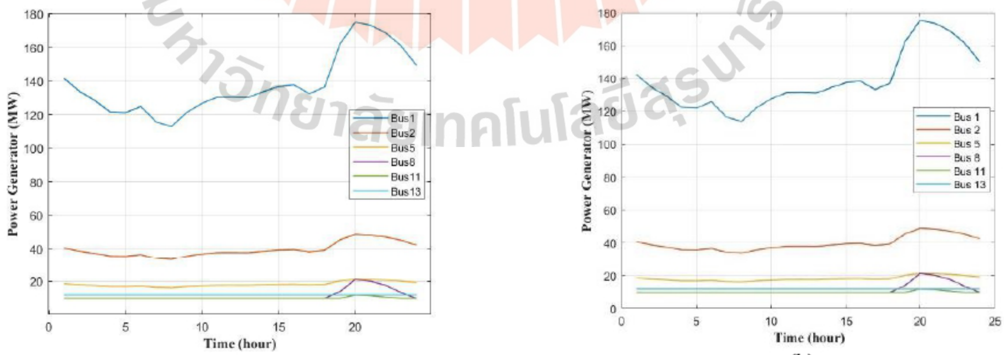
The optimal total power generator for all cases is shown in Table 3, representing the effect of price elasticity on the system demand. Comparing the experimental results in each case, it can be seen that in Case

III, the demand is 5503.423 MW per day, which is the least. Moreover, due to the cross-elasticity, the light-load demand, is higher, resulting in a better system load factor, as shown in Figure 7.

Table 4. Comparison of the results of the fuel cost the in the 30-bus system

Hour	Case I ($)	Case II ($)	Case III ($)	Case IV ($)
1	752.0372	748.9733	745.9161	751.0208
2	701.6643	699.5204	697.3800	702.6396
3	667.9710	666.4220	664.8750	670.2279
4	626.2246	625.3890	624.5540	630.0104
5	623.3228	622.5357	621.7492	627.2123
6	646.4610	645.2830	644.1061	649.5141
7	590.8004	590.5485	590.2967	595.8300
8	575.1123	575.1123	575.1123	580.6763
9	624.3773	623.5726	622.7684	628.2292
10	657.9165	656.5418	655.1686	660.5477
11	680.4396	678.6725	676.9078	682.2271
12	681.1278	679.3486	677.5718	682.8893
13	679.3396	677.5917	675.8463	681.1686
14	700.5464	698.4225	696.3021	701.5649
15	720.6651	718.1784	715.6963	720.8995
16	726.9135	724.3103	721.7148	726.8990
17	692.8850	690.8978	688.9135	694.1982
18	718.2583	715.8153	713.3767	718.5873
19	902.8454	897.8075	892.7829	896.8698
20	1032.560	1025.962	1019.385	1023.029
21	1012.679	1006.344	1000.028	1003.725
22	967.2195	961.4796	955.7555	959.5699
23	893.0503	888.1496	883.2608	887.3733
24	802.8380	798.8120	794.7972	799.7273
All day	17677.25	17615.69	17554.26	17674.63

In Case III, self-elasticity is utilized with a value of -0.2 resulting in the case with the lowest cost. Additionally, Case IV takes into account the impact of changes to one product on the cost of another product, as illustrated in Table 4.



(a) (b)

Figure. 8 Hourly power generator (a) case III (b) case IV

As shown in Figure 8(a), the hourly price during peak hour of case III is the lowest due to only self-elasticity is applied. In case IV, the total power generation is the same as in Case I, but the demands in peak hours are lower as well as the demands in light-load hours are higher, leading to the lower total cost under the same total consumption as shown in Figure 8(b).

Table 5. Total cost for different price elasticity

Case	Case I	Case II	Case III	Case IV
Total daily operating cost ($)	17677.25	17615.69	17554.26	17674.63
Saving	-	0.35%	0.696%	0.015%

The power produced in each case shown in Table 3 has the same trend as the cost in Table 4, in which case III has the least power output. Figure 8 address the hourly power generation of case III and IV, respectively. Meanwhile, Table 5 shows the comparison of total cost for all cases. In case II, the total daily consumption was reduced from 5529.83 MW to 5516.624 MW, due to the consumer response to the NSP with self-DE, leading to the reduction in total daily operating cost from 17677.25 $ to 17615.69 $. Similarly, in Case III the total daily consumption and total daily operating cost were reduced to 5503.423 MW and 17554.26 $, respectively, with the consideration of larger self-DE of -0.2. Meanwhile, with the balance seif- and cross-DEs, the total daily operating cost can be reduced to 17674.63 $ under the same total daily consumption of base case, due to the consumers' load shifting in response to the NSP. Accordingly, self-elasticity and cross-elasticity are both important measures of price elasticity in the electricity market. Self-elasticity measures the responsiveness of quantity demanded to changes in electricity use according to the NSP, while cross-elasticity measures the responsiveness of quantity demanded to changes in the price of other time intervals. Both measures provide different types of information about the responsiveness of demand to changes in NSP and are important in making informed decisions about power system operation and planning. More specifically, In the electricity market, self-elasticity is important for understanding how changes in the price of electricity affect the quantity demanded, while cross-elasticity is important for understanding how changes in the prices of related goods or services affect the demand for electricity.

5. Conclusion

An integrated OPD with DE model was proposed in this paper. The spot pricing concept has been successfully incorporated into the power system operation plan by using DE with self-elasticity and cross-elasticity. The effectiveness of the proposed methodology has been comparatively tested and validated on the IEEE 30-bus system. The results showed that the proposed method can lower the total system cost.

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BIOGRAPHIES OF AUTHORS

Miss. Pansa Kaikrathok received B.Eng in EE (Second Class Honors) from SUT, Thailand in 2021. She is now a master student at School of Electrical Engineering, Institute of Engineering, SUT. Her current research interests include distribution system analysis and microgrid system optimization. She can be contacted at email: pansakhaikrathok@gmail.com.

Associate Professor Dr. Keerati Chayakulkheeree received B.Eng. in EE from KMITL, Thailand, in 1995, M.Eng. and D.Eng. in EPSM from AIT in 1999 and 2004, respectively. He is currently an Associate Professor at School of Electrical Engineering, Institute of Engineering, SUT. His research interests are in power system optimization and AI application to power system. He can be contacted at email: keerati.ch@sut.ac.th.

BIOGRAPHY

Ms. Pansa Kaikrathok received B.Eng in EE (Second Class Honors) from SUT, Thailand in 2021. She is now a master student at School of Electrical Engineering, Institute of Engineering, SUT. Her current research interests include distribution system analysis and microgrid system optimization.