PROBABILISTIC OPTIMAL POWER DISPATCH CONSIDERING PRICE-BASED REAL-TIME DEMAND RESPONSE

Udoum Chhor

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การสั่งเดินเครื่องโรงไฟฟ้าที่เหมาะที่สุดแบบความน่าจะเป็นโดยคำนึงถึง
การตอบสนองด้านโหลด แบบอิงราคาตามเวลาจริง

นายอุดม โชร์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตมหาบัณฑิต

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มหาวิทยาลัยเทคโนโลยีสุรนารี

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PROBABILISTIC OPTIMAL POWER DISPATCH

CONSIDERING PRICE-BASED REAL-TIME

DEMAND RESPONSE

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

Thesis Examining Committee

____

(Assoc. Prof. Dr. Thanatchai Kulworawanichpong)

Chairperson

____

(Assoc. Prof. Dr. Keerati Chayakulkheeree)

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ในยุคของการพัฒนาทางเทคโนโลยี ระบบพลังงานมีบทบาทสำคัญอย่างยิ่งในการสร้างสมดุลระหว่างการผลิตและความต้องการพลังงานในอุตสาหกรรมอาคารพาณิชย์และที่อยู่อาศัย ซึ่งในขณะเดียวกันนี้โปรแกรมการตอบสนองทางด้านโหลด (Demand Response, DR) ได้เป็นเครื่องมือสำคัญของผู้บริหารจัดการระบบ (System Operator, SO) ในช่วงเวลาวิกฤตที่กำลังการผลิตไม่เพียงพอต่อความต้องการพลังไฟฟ้าหรือมีต้นทุนการผลิตที่สูงมาก ยิ่งไปกว่านั้นในปัจจุบันที่มีการผลิตไฟฟ้าจากพลังงานทดแทนขนาดเล็กในระบบจำหน่ายในสัดส่วนที่สูงยังสร้างความไม่แน่นอนในการพยากรณ์ความต้องการพลังไฟฟ้าซึ่งกระทบต่อการวางแผนการเดินเครื่องโรงไฟฟ้าในระบบไฟฟ้ากำลังเป็นอย่างมาก นอกจากนี้ DR ยังสามารถรักษาสมดุลระหว่างกำลังการผลิตและความต้องการพลังไฟฟ้าโดยไม่ต้องลงทุนในการเพิ่มกำลังการผลิต ดังนั้นในหลายงานวิจัยจึงได้มีการใช้เทคนิกการหาค่าเหมาะที่สุดในการหาคำตอบการเดินเครื่องโรงไฟฟ้าที่เหมาะสมที่สุดในระบบไฟฟ้าที่มี DR อย่างไรก็ตาม ในกาหาค่าที่เหมาะสมที่สุดที่เป็นเชิงเส้น วิธีโปรแกรมเชิงเส้น (Linear Programming, LP) ยังคงเป็นวิธีที่มีศักยภาพสูงในการหาต้นทุนต่ำสุดในการเดินเครื่องโรงไฟฟ้า

ในวิทยานิพนธ์นี้ การสั่งเดินเครื่องโรงไฟฟ้าที่เหมาะสมที่สุดแบบความน่าจะเป็น (probabilistic optimal power dispatch, POPD) โดยวิธี LP ได้เสนอสำหรับปัญหาการสั่งเดินเครื่องโรงไฟฟ้าในระบบไฟฟ้าที่มีการตอบสนองทางด้านโหลดแบบอิงราคาตามเวลาจริง (price-based real-time demand response, PRDR) โดยมีวัตถุประสงค์ในการหาค่าต่ำสุดในการเดินเครื่องโรงไฟฟ้าโดยคำนึงถึง PRDR ในแต่ละชั่วโมงของ 1 วัน ในการจัดการในรูปแบบของตลาดกลางซื้อขายไฟฟ้า ทั้งนี้ได้ใช้วิธีการทางความน่าจะเป็นในการพยากรณ์โหลดระยะสั้นที่คำนึงถึงความไม่แน่นอนของความต้องการพลังไฟฟ้าไว้ด้วย

ผลลัพธ์การจำลองได้แสดงให้เห็นอย่างชัดเจนว่าวิธีการที่นำเสนอสามารถใช้ในการหาคำตอบ POPD สำหรับค่ากำลังไฟฟ้าจริงของแต่ละโรงไฟฟ้าโดยคำนึงถึง PRDP โดยใช้ความน่าจะเป็นการกระจายทรังเคทแบบปกติ (probabilistic truncated normal distribution function, PTNF) ทั้งนี้ข้อดีของการใช้ PTNF คือความสามารถในการตัดคำตอบที่เป็นไปไม่ได้ออกจากการคำนวณ ซึ่งทำให้ผลลัพธ์มีระดับความแม่นยำที่สูงกว่าการใช้ฟังก์ชันการกระจายแบบปกติพื้นฐาน ผลการจำลองแสดงให้เห็นว่าวิธีการที่นำเสนอสามารถหาคำตอบต้นทุนการผลิตต่ำสุดของการสั่ง

เดินเครื่องโรงไฟฟ้าโดยคำนึงถึง PRDR และความไม่แน่นอนของโหลดได้อย่างมีประสิทธิภาพและประสิทธิผล

สาขาวิชา <u>วิศวกรรมไฟฟ้า</u> ลายมือชื่อนักศึกษา________________________

ปีการศึกษา 2561 ลายมือชื่ออาจารย์ที่ปรึกษา________________________

UDOUM CHHOR : PROBABILISTIC OPTIMAL POWER DISPATCH CONSIDERING PRICE-BASED REAL-TIME DEMAND RESPONSE. THESIS ADVISOR : ASSOC PROF. KEERATI CHAYAKULKHEEREE, Ph.D., 106 PP.

PROBABILISTIC OPTIMAL POWER DISPATCH/PROBABILITY DENSITY FUNCTION/LINEAR PROGRAMMING/DEMAND RESPONSE

In the era of technological development, power system plays a very important role to balance power supply and demand in industrial, commercial building, and residential area. For the meantime, a demand response (DR) program is a key element to serve the system operator (SO) in critical period in which the power generation is not sufficient to serve the demand or during high power generation cost period. Moreover, the present high penetration of small renewable energy generation at distribution system cause uncertainty in demand forecast and effect the operation planning in power system. In addition, DR is able to maintain the supply-demand balancing without extending the power supply due to investment cost. Therefore, many researches have been implemented various optimization technique to solve the optimal power dispatch with DR. However, in the linear optimization, linear programming (LP) is a potential optimization technique to handle the power dispatch known as cost minimization.

In this thesis, a probabilistic optimal power dispatch (POPD) using LP is proposed for solving the power generation dispatch with price-based real-time demand response (PRDR). The objective is to minimize the operating cost in considering PRDR of every single hour for one day, in the competitive electricity market. The expected

short-term load forecast is represented by a probabilistic distribution function in order to express the load uncertainty measures.

The simulation result has completely certified that the proposed method could handle the POPD solutions for real power dispatch considering PRDR by using probabilistic truncated normal distribution function (PTNF). The advantage of PTNF is its capability to eject the infeasible results during the computation. This would prime the results to the high degree of accuracy comparing to the normal sampling methods. The simulation results showed that the proposed method can efficiently and effectively minimize the total power generation cost while trading off the PRDR cost in the POPD problem with load uncertainty.

School of Electrical Engineering Student's Signature ____________

Academic Year 2018 Advisor's Signature ____________

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SYMBOLS AND ABBREVIATIONS

$\tilde{P}_{Di}$	=	Probabilistic Real Power Demand at Bus i
μ_D	=	Mean Value of Demand Data Profile
σ_D	=	Standard Deviation of the Demand Profile
AC	=	Alternating Current
ALSC	=	Available Load Supply Capability
BESS	=	Battery Energy-storage System
CL	=	Curtailable Load
CPP	=	Critical Peak Pricing
DB	=	Demand Bidding
DC	=	Direct Current
DemSi	=	Demand Response Simulator
DG	=	Distribution Generator
DisCo	=	Distribution Company
DLC	=	Direct Load Control
DR	=	Demand Response
DU	=	Distribution Utility
FFT	=	Fast Fourier Transforms
GA	=	Genetic Algorithm
IBP	=	Incentive-based Program
IEEE	=	Institute of Electrical and Electronics Engineers
ILP	=	Integer Linear Programming

SYMBOLS AND ABBREVIATIONS (Continued)

ILP	=	Integer Linear Programming
IRES	=	Integrated Renewable Energy System
ISO	=	Independent System Operator
JSQN	=	Johnson System and Sobol's Quasi-Random Numbers
LF	=	Load Flow
LHS	=	Latin Hypercube Sampling-based
LP	=	Linear Programming
LPOPD	=	Linear Programming Optimal Power Dispatch
MCP	=	Market Clearing Price
MCS	=	Monte Carlo Simulation
MO	=	Multi-objective
NRPF	=	Newton-Raphson Power Flow
OPD	=	Optimal Power Dispatch
OPF	=	Optimal Power Flow
PBP	=	Price-based Program
PDF	=	Probability Density Function
PE	=	Percentiles Estimation
PEM	=	Point Estimate Method
PLF	=	Probabilistic Load Flow
POPD	=	Probabilistic Optimal Power Dispatch
POPF	=	Probabilistic Optimal Power Flow
PRDR	=	Price-based Real-time Demand Response

SYMBOLS AND ABBREVIATIONS (Continued)

PSCAD	=	Power Systems Computer Aided Design
PTNF	=	Probabilistic Truncated Normal Distribution Function
PVDG	=	Photovoltaic Distributed Generation
RRC	=	Responsive Residential Consumer
RTP	=	Real-time Pricing
RV	=	Random Variable
SLP	=	Successive Linear Programming
SO	=	System Operator
SRS	=	Simple Random Sampling-based
TOU	=	Time-of-use

CHAPTER I

INTRODUCTION

1.1 General Introduction

An electric power system is a power grid that contains the electrical components installed to supply, transmission, and use of electric power. It is the grid that could be extended to other area ranged in the distance. Basically, the supply side is referred to the power generations, the transmission system is carried out the power from the generating centres to the load centres, and the distribution system is constructed to feed the power to nearby consumers. Figure 1.1 shows the simplified diagram of an alternating current (AC) electricity delivery from generation stations to consumers' service drop.

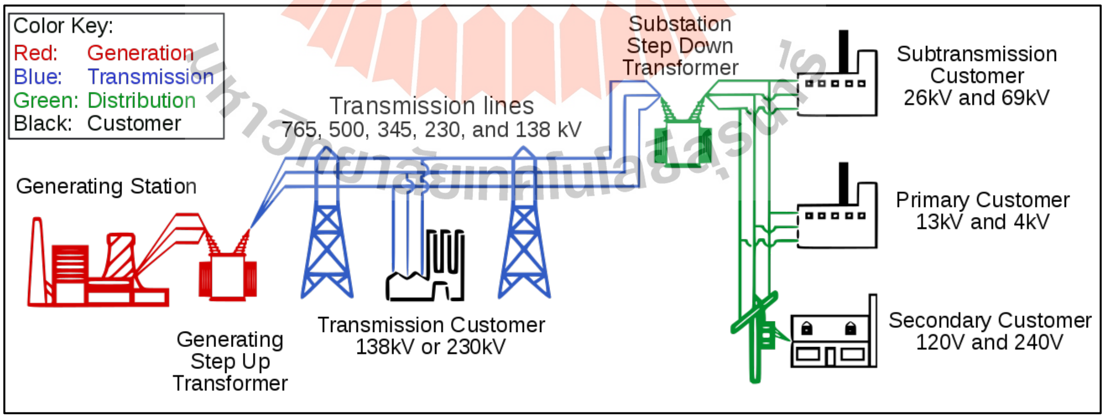

Figure 1.1 An Example of the Electric Power System.

In the power grid, the electric utilities need to be balanced the power generation and load considering economic operation with the grid reliability and quality of supply.

Therefore, optimal power flow (OPF) techniques for possible future power system operation are steadily proposed with various optimization techniques. Recently, the innovation of computer processor units has produced as a matter of engineering required to solve their problems as fast as possible in real time and online. Optimal power dispatch (OPD) has become one of the most extensive optimization tools adopted in the power system planning and electricity market. With the above issues, many researchers have endlessly studied optimization techniques to investigate the optimum operation of the power system. Many optimization algorithms have always been mentioned both artificial intelligence and conventional methods to obtain an OPD solution.

1.2 Problem Statement

At the present time, the supply-demand balancing issues are frequently occurred in the developing countries and some areas due to the growth of the business, industrial productivity, population, commercial, and residential requirements endlessly. System operator (SO) has an obligation to respond to this matter according to the customers' needs. Sometimes, the costly power generation has to operate indeed to meet the required demands, but it may have some complexities inside. In modern technological development, this kind of problem can be handled by a demand response (DR) program thorough notes of Section 2.5.2. The optimization technique is still a useful tool to figure out the expected optimal profits, while the nature of the linear programming (LP) can advance this kind of cost minimization problem very well, as many researchers ever developed up to now. Nevertheless, load variations are also the difficulties in this case study, however, it will be addressed by the powerful technique called Monte Carlo simulation, which can deal extensively with the uncertainties in the power system represented in Section 3.8.

Dealing with this problem, it has to be done immediately in the real-time process by SO and retailers relying on the customers' prerequisite, there is a proposed perspective in this research concept. The problem formulation is to model uncertainty loading variations using normal PDF and PTNF considering PRDR to balance between supply availability and demand side. Furthermore, linear programming optimal power dispatch (LPOPD) will provide the optimum solutions to SO by understanding the problems clearly gaging the known constraints.

1.3 Study Objective

The objective of the study is to minimize the total system investment cost in considering PRDR for every single hour for day-ahead in the distribution system. The developed framework aims to curtail the spiky demand in the distribution system. Apart from the settled procedures, the LPOPD is proposed for solving the power generation dispatch with PRDR. The Newton-Raphson power flow (NRPF) is used to obtain the losses and to test the feasibility of the dispatch solution. Therefore, the proposed method can efficiently and effectively illustrate the total power generation cost, while trading off the PRDR cost in the POPD problem with loading uncertainties. The aim of this work is to compensate for the power demand with the price-based power generation considering PRDR scheme, there are several expected benefits as,

i. Reducing the overall incremental production cost,

ii. Co-optimizing energy market and demand side,

iii. Promoting reasonable DR prices to clients by technological development,

iv. Forecasting elasticity of demand in hour-ahead or day-ahead, and

v. Hourly dispatch in a competitive market.

1.4 Scope and Limitation

In this work, LPOPD has implemented a plan in adapting the NRPF with the generators' operating costs for each generator in the system, which would be given by piecewise linear cost functions. The power generation dispatch and total diminished investment cost will be obtained from the computational procedure of LPOPD in Figure 3.4, while the forecasted load pattern hour-ahead or day-ahead with PRDR would be presented in the power grid participated in the objective function. The computational procedure of LPOPD will be tested with the initial system data of the modified IEEE 30-bus test system is shown in Figure 4.1 and the generators' operating costs for each generator as shown in Table 4.1 will be used in this procedure. After that, the LP has computed to co-optimize the total power generation and PRDR pattern in the projected time slot, and then the forecasted day-ahead load pattern will be considered of the case study. Moreover, the overall incremental production cost reduction and realistic DR prices will be claimed by DR participants.

1.5 Conception

Essentially, the LPOPD is proposed for solving the power generation dispatch in associated with PRDR. The proposed method neglects the overall investment cost in the case of power demand running on the peak period and co-optimize between power demand and available supply. The size of DR will be arranged in real-time depending on the proportion of actual peak load and forecasted load pattern hour-ahead or day-ahead. The simulation result has prosperously shown that the proposed method can handle the OPD solutions considering PRDR. Therefore, the proposed method can efficiently and effectively illustrate the total power generation cost, while trading off the PRDR cost in the OPF problem.

Figure 1.2 illustrates the characteristic of the DR concept in real-time in order to operate the system in participating with the curtailable aggregate load. The required contract between the SO and DR customers would settle in the appropriate conditions as well.

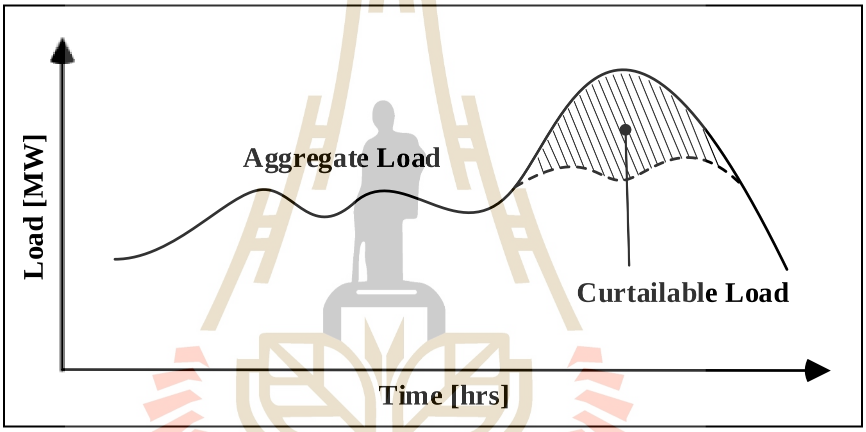

Figure 1.2 DR Concept in Real-Time.

1.6 Research Benefits

The proposed method accentuates the probabilistic inquiries in POPD solutions. The empirical rule will perform with important PTNF sampling method as a vital role in the computational procedure to avoid the infeasible load flow (LF) results during the computation. It uses to warrant the real-time simulation over the existing works is used the normal PDF to represent the uncertainty of variables in the system. The results will release preciously from simulation method with a fairly time frame.

1.7 Thesis Outline

Besides the introduction, this thesis is consisted of Chapter II introduces the model of uncertainties including DR schemes, expresses load modelling, probabilistic loading pattern, and sampling methods. Chapter III represents the problem formulation of the POPD using LP with DR programs, while the real power demand at load buses is represented by normal PDF with and without PTNF. Meanwhile, it explains the probabilistic technique and conditions for sampling the input variables to represent the real power demand and rules for Truncated normal PDF to state a specific range for the random variable to obtain better accuracy. Also, the proposed framework of Monte Carlo technique and performance of the simulation are denoted in this chapter. Chapter IV indicates the simulation results from the modified 30-bus test system. Moreover, it contains the parameter set and the required data. Lastly, Chapter V provides the conclusion.

1.8 Chapter Summary

This Chapter I presents the general introduction in power system problem on the distribution network considering DR strategy to capture the study objective in the electrical market. The problem statement is also provided in this section. Furthermore, the concept with limited scope is definitely provided to co-optimize between available supply and power demand. After that, it is implemented with the POPD computational procedure detailed in the methodology section to contend the benefits of this framework. Especially, the relevant study area of LPOPF and POPF with and without DR programs would provide in the literature review section.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

In an electrical grid, there are various techniques to be developed in power system optimization. This chapter provides a brief summary that many different proposed and practical system configurations are modified in order to understand how the optimization problems can be carried out with the OPF or to enhance the economic dispatch and methods of solution. In this case study, the economic dispatch considering PRDR is taken as a comprehensive analysis and discussion of the optimization problem.

Table 2.1 Summary Literature with its Term and Description

Proposed	Key Aspect	Description
Chauhan et al, 2017	ILP, DR strategy, IRES	Using ILP, a DR strategy based on energy consumption scheduling during summer and winter seasons obtained, then IRES sizes and system costs savings performed as well.
Babonneau et al, 2016	LP, DR, DG, flexible load, DER	LP introduced to model power distribution, market clearing processes for flexible load, and DERs could respond to marginal cost-based prices to provide DR, secondary reserves, and reactive power compensation.
Ongsakul et al, 2001	LP, MCP, hourly bus spot price	Optimal real power dispatched by LP and MCP is the equilibrium point of the aggregate supply and required demand.

Table 2.1 Summary Literature with its Term and Description (Continued)

Proposed	**Key Aspect**	**Description**
Viana et al, 2018	DR, PVDG, power utility planning	Integrated analysis the price-based DR by TOU and PVDG developed for power utility sustainable planning to reduce flexible energy bill of residential consumers.
Li et al, 2017	Economic dispatch, RTP, OPF	Economic dispatch for total system cost minimization in DC microgrid improved by RTP participation every single hour.
Shigenobu et al, 2016	RTP, OPF, electricity market	DisCo introduced RTP to electricity market whether high DGs penetration in distribution system initiating voltage deviation.
Moshari et al, 2016	DR, reliability assessment, smart grid	RTP and TOU applied to evaluate the short-term reliability of wind-integrated power systems.
Wang et al, 2011	Smart grid, DR pricing, energy management	Different proposed rates of pricing programs experienced effectually based on peak load reduction, bill bearings, and fulfilment of customers in a smart grid.
Ntakou et al, 2014	Price discovery, power marker, flexible load	Supply-demand balancing enabled to marginal cost in day-ahead market. Several scenarios made for the distribution market.
Faria et al, 2011	DR, competitive market, optimal RTP	Regarding efficiency level in competitive markers, retailer used DemSi to figure out consumer-based price elasticity approach supported by RTP.
Stoft, 2002	Power market, fundamental	Designing markets for electricity described the contents for power system economic.
Allan et al, 1981	PLF, MCS, FFT	Better accuracy and fast computation obtained a PLF using MCS compared numerical results of FFT and conventional method as uncertainty of random variation.

Table 2.1 Summary Literature with its Term and Description (Continued)

Proposed	Key Aspect	Description
Chayakulkheeree et al, 2013	POPF, MCS, PE,	POPF using percentiles algorithm determined magnificently for hour-ahead scheduling while system loading represented by Weibull PDF.
Zhang et al, 2013	Probabilistic evaluation, ALSC	Load uncertainty signified by LHS could overcome the SRS to achieve the ALSC problem by MCS in the distribution system.
Giraldo-Chavarriaga et al, 2014	POPF, PEM, MCS, PDF	POPF accounted for the uncertainty RVs made by PEM in different kinds of PDF.
Shargh et al, 2016	POPF, PEM, PDF,	PEM based Nataf transformation to solve POPF problem while uncertainty RVs of wind power and demand denoted by PDF.
Chayakulkheeree, 2015	PLF, MCS, PE, PDF	PVDG represented by Weibull PDF could greatly reduce the computational speed in PLF using PE.
Carpinelli et al, 2015	PLF, MCS, PDF, evaluation	Proposed technique gave the assessment of output RV using PDFs more accurate than classic MCS in PLF problem.
Villanueva et al, 2011	PLF, MCS, power plant, demand	Power plant and load generated by probabilistic values and performed by MCS to generate PDF of bus voltages and LF.
Matthiss et al, 2017	PLF, energy management, DG	Uncertainty variable forecasts made to appraise computational complexity and accuracy in energy management project between simulation and analytical methods.
Gu et al, 2016	Economic dispatch, MCS	Quasi-MCS based economic dispatch proposed to advance the conventional MCS.
Jorgensen et al, 1998	PLF, MCS, voltage quality	MCS applied to investigate the voltage quality and compared the cost of the grid if wind turbines installed.

Table 2.1 Summary Literature with its Term and Description (Continued)

Proposed	**Key Aspect**	**Description**
Zhang et al, 2016	PLF, MCS, JSQN	PLF based JSQN generator claimed better accuracy by MCS to study the uncertainties of wind power integration in the power network.
Burkardt, 2014	Normal PDF, randomness, PTNF	PTNF developed from normal PDF in order to eliminate the drawback and accumulate the probability density in a finite range.
Krenek et al, 2016	PTNF, convolution, application	Proposed PTNF convolution enhanced the accuracy and precision in real-world production processes.
Ni et al, 2016	PLF, PTNF, uncertainty quantification	Extended PTNF covered efficiently the truncated RVs in computation effort of grid planning and load management.
Mazzeo et al, 2018	PTNF, mixture, PDF, estimation	The validity of developed PTNF verified the wind speed estimation by various PDFs to greater accuracy.
Proposed method	POPD, MCS, LP, PRDR, PDF, PTNF	Operating cost minimization in considering PRDR of every single hour for one day, in the competitive electricity market.

2.2 Literature Overview

The linear programming is one of the most conventional methods which becomes a widely practical method in optimal power system operation. For example, a DR strategy based on energy consumption scheduling was modelled by integer linear programming (ILP) to prove the demand minimizing in peak period (Chauhan, A. and Saini R.P., 2017). The marker prices are exposed by LP proposed framework equivalent to the marginal cost for the utility (Babonneau, F., Caramanis, M., and Haurie, A., 2016). Similarly, it was used to minimalize the expensive fuel operating cost in extra high voltage (Tuaimah, F.M. and Meteb, M.F., 2014). Another proposed LP algorithm is to minimize the supply cost in power pool auction. In the power pool auction, the hourly bus spot price incorporating the marginal transmission loss and network quality of supply can be regulated (Ongsakul, W., Chirarattananon, S., and Chayakulkheeree, K., 2001; Wood, A.J., Wollenberg, B.F., and Sheblé, G.B., 2014). LP has the potential to capture optimal adaptive operating costs and provide the optimal dispatch module in both short and long terms optimization problems, such as numerous economic, social, military and real-time problems. In practice, the short-term load forecast for hour-ahead dispatch is usually uncertain in nature. Therefore, the probabilistic model representation for the system loading can be used to deal with uncertainty.

In trendy power grid, DR programs have been developed and studied in many researches in modern power systems. The purpose of developing DR models is to provide accurate dispatch balance and stability analysis of the future grid. DR is a specific program to motivate the end users' response to reduce or rearrange the electricity usage patterns during critical peak time. In developing an approach of the modern power grid, some models of DR have implemented to manage the higher prices during the peak demand in the system to avoid increasing power generation. Meanwhile, consumers have always billed their energy consumption through a tariff depending on the users' demands and had no any economic instructions or reports on how to plan to use or shift the consumption during peak periods. The aims of the evaluation methodology are to prove the peak demand and power consumption in economizing the total operating cost efficiency associated with DR program are extracted (Viana, M.S., Junior, G.M., and Udaeta, M.E.M., 2018). Real-time Pricing (RTP) is a well-known prospect of DR scheme proposed by the system operator (SO) (Li, C., Bosio, F.D., Chen, F., Chaudhary, S.K., Vasquez, J.C., and Guerrero, J.M., 2017; Shigenobu, R., Yona, A., and Senjyu, T., 2016). Aggregate consumers are encouraged to draw attention to reduce their demands accordingly to the required power balance in the system reliability. The DR programs in which price variations of energy over time produce changes at consumers' demand profile. It is necessary to improve the above problems to balance between supply and power demand side. To sum up, there are more details on DR programming and optimization algorithms (Vardakas, J.S., Zorba, N., and Verikoukis, C.V., 2015), practical indication and key-elements for global experience (Paterakis, N.G., Erdinç, O., and Catalão, J.P.S., 2017), demand-side elasticity and DR budding (Müller, T. and Möst, D, 2018), bearing investigation with its solution (Rahiman, F.A., Zeineldin, H.H., et al., 2014), and uncertainties in power systems (Moshari, A., Ebrahimi, A., and Fotuhi-Firuzabad, M., 2016).

In order to investigate the output target of the power system, there are three broadly used methods to solve the POPD problems such as analytical, approximation, and simulation methods. One of the most powerful techniques for POPD is Monte Carlo simulation (MCS) which is extensively used the method to deal with uncertainties in the power system; it is relied on repeated random sampling to get the numerical results and reliability analysis statistically. In the proposed framework, the normal probability density function (PDF) was transformed to be the Truncated normal PDF, and it was shown that small errors occurred in the computed expected values which could be compensated for by shifting the computed probability-density curve so that its expected value coincided with the value deduced from a conventional deterministic analysis. It was formerly used to examine how probabilistic load flow (PLF) can be evaluated and found out the greater accuracy throughout the computational optimum speed (Allan, R.N., Leite da Silva, A.M., and Burchett, R.C., 1981). Another point of view, MCS is used to perform the probabilistic short-term load forecast scheduling in a power system by assuming the PDF as the system loading, the total operating cost is effectually optimized (Chayakulkheeree, K., 2013). Furthermore, many similar researches have studied the effect of correlation of uncertain variables such as probabilistic appraisal of accessible load supply capability (Zhang, S., Cheng, H., Zhang, L., Bazargan, M., and Yao, L., 2013), POPF behavior and relationship of the wind power, load uncertainties and line parameters (Giraldo-Chavarriaga, J.S., Castrillón-Largo, J.A., and Granada-Echeverri, M., 2014; Shargh, S., Khorshid ghazani, B., Mohammadi-ivatloo, B., Seyedi, H., and Abapour, M., 2016), PLF for solar power using percentile estimation of Weibull PDF (Chayakulkheeree, K., 2015), probabilistic investigation when wind and photovoltaic generation connected to system (Carpinelli, G, Caramia, P., and Varilone, P., 2015) PLF based on correlated series of generation, loading, and wind farm (Villanueva, D., Feijóo, A., and Pazos, J.L., 2011), probabilistic comparison and evaluation with energy management application (Matthiss, B., Gaedke, P., Felder, M., and Binder, J., 2017), economic dispatch relied on Quasi-MCS is used to models the stochastic behaviors of wind speed and distributed loads (Gu, B.C., Chen, Z.M., Ji, T.Y., Zhang, L.L., Wu, Q.H., Li, M.S., and Huang, J.H., 2016), uncertainty of loads and wind speed is characterized by MCS to represent the total number of hours with overvoltage a year (Jorgensen, P., Christensen, J.S., and Tande, J.O., 1998), hybrid MCS is performed to evaluate PLF when a large-scale wind power integrated to power system (Zhang, L., Cheng, H., Zhang, S., Zeng, P., and Yao, L., 2016). All these probabilistic problems and some other relevance are modelled in different purposes to balance the system loading by adjusting the add-on power generation in the power system.

In this thesis, the linear programming optimal power dispatch (LPOPD) considering price-based real-time demand response (PRDR) is proposed to implement in the modified IEEE 30-bus test system. Based on the problem formulation, the piecewise linear cost function is used to represent the generator's operating cost. At the same time, the PRDRs participate in dispatching aggregator loads connected to the system. The purpose is to accomplish the supply-demand balancing without upward power supply. Many works were developed in the smart grid, distributed generation, and other energy sources to serve the growing demands. Those additional generations will add the extra production cost and many complexities along. The simulation output of LPOPD with and without PRDR are addressed and compared in the results.

2.3 Supply-Demand Balancing

One of the most compulsory difficulties in the electric power system is the number of losses along with the active power consumptions. There is a must between active power produced and active power consumed plus losses, in the case that more power is produced than consumed, the frequency will rise and vice versa. Even though, small divergence from the nominal frequency range can damage the synchronous machine and other appliances in the consumers' side. Maintaining the constant frequency is a common task for transmission system operators and many researchers are focusing on the power system optimization problem. In the European Union and some countries, this can be accomplished over a balancing market using ancillary services (Stoft, 2002).

2.4 Power Distribution

The power generation in every station can be produced in different potential depending on the desired voltage level, further relevant voltage levels are shown in Figure 1.1. The AC is regularly adopted in the long-distance generation and transmission, otherwise, the rectifiers will be used in order to invert from AC to direct current (DC) power supply respectively such as railway electrification system, industrial purposes etc. Anyway, both AC and DC with its advantages are practically modelled in different majorities and applications. From transmission to distribution, there must be power substation, which is a part of the electrical generation, transmission, and distribution network. Especially, each substation will regulate the voltage level according to the specific purposes and functions and then transmit the power to consumers nearby the area. There are several functions in the power substation as,

i. Enabling switches and circuit breakers to be connected or disconnected from the grid or distribution lines during the operation period,
ii. Transformers to be stepped up or down the voltage, and
iii. Busbars to be split the power distribution to customers in different directions.

The overhead distribution is mostly in a rural area, while urban area is mainly underground distribution or utility tunnel distribution sometimes. Distribution networks are divided into two types, radial or network. A radial system is arranged like a tree where each customer has one source of supply. A network system has multiple sources of supply operating in parallel. Spot networks are used for concentrated loads. Radial systems are commonly used in rural or suburban areas. Radial systems usually contain emergency connections where the system can be reconfigured in case of problems, such as a fault or planned maintenance. This can be completed by opening and closing switches to isolate a certain section from the grid. Long distance feeders will experience voltage drop or power factor distortion requiring capacitors or/and voltage regulators to be installed. Most of the world uses the 50 Hz rated at 220/230 V single-phase, or rated at 400V three-phase for residential and light industrial services. In this system, the primary distribution network supplies a few substations per area, and the 230V / 400V power from each substation is directly distributed to end users over a region of normally less than the 1km radius. Three live wires and the neutral are connected to the building for a three-phase service. Single-phase distribution, with one live wire and the neutral, is used domestically where total loads are light. In Europe, electricity is normally distributed for industry and domestic use by the three-phase, four wire system. This gives a phase-to-phase voltage of 400 volts wye service and a single-phase voltage of 230 volts between any one phase and neutral. In the UK a typical urban or suburban low-voltage substation would normally be rated between 150 kVA and 1 MVA and supply a whole neighbourhood of a few hundred houses. Transformers are typically sized on an average load of 1 to 2 kW per household, and the service fuses and cable are sized to allow anyone property to draw a peak load of perhaps ten times this. For industrial customers, three-phase 690/400 volt is also available or may be generated locally. Large industrial customers have their own transformer(s) with input from a high kV level.

2.5 Prevailing Economic Conditions using LPOPD and PRDR

Electric power system plan and operation are always involved with more than a few complex tasks. The long-term trend for electric supply, demand, and system costs are growing unreliable and unpredictable as of the objective of this study concept. The required power generation is fluctuating due to current energy deregulation lawmaking and also due to the expanding demands for energy in a global economy of rising fuel prices. The assortment of power generation energy efficiency resources is considered to meet the required customer demands each time period. The optimization methods play a very important role in the power grid despite the fact that the investment cost in these complexities is extremely costly to set up. Moreover, the LP is an important technique of operations research developed for optimum utilization of resources. It is used for selecting the best possible strategy from a number of alternatives, which can maximize the profit or minimize the cost of production. In this case, it is set up to minimize the cost of the overall incremental production, co-optimize the energy market including the demand response programming within hour-ahead or day-ahead.

2.5.1 Study Area of LPOPF

An integrated renewable energy system consists of micro hydropower, biogas, biomass, solar, wind and battery bank storage are considered in order to meet the electrical and cooling energy demands of the study area. Using ILP, a DR strategy based on energy consumption scheduling of appliances has been modelled in this reference. The Hybrid DC-AC coupled configuration of the integrated renewable energy system (IRES) is proposed for the study area as shown in Figure 2.1. It has been

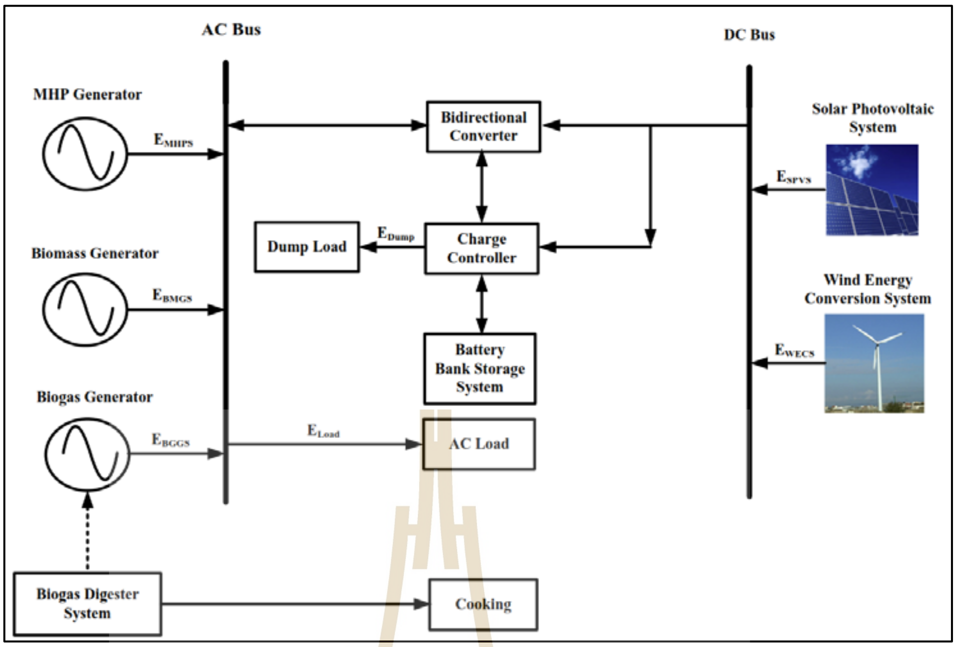

Figure 2.1 Proposed Configuration of IRES.

found that reduction of 1.82 kW and 23 kW in peak hourly energy consumption during summer and winter seasons respectively are obtained with DR strategy in comparison of the system without DR. Finally, size optimization of the proposed IRES without and with DR strategy has been performed using discrete harmony search algorithm. It has been observed that significant amount of savings in system sizes and costs are obtained with DR strategy compared to a system without DR (Chauhan, A. and Saini R.P., 2017).

The non-linear load flow distribution market clearing approach by Ntakou, E. and Caramanis, M. (2014) has been adapted to a computationally efficient linear programming approximation and has been extended to model flexible space conditioning loads and secondary reserves. It has been shown that a straightforward linearization with one or two iterations to improve on the linearization gap can provide

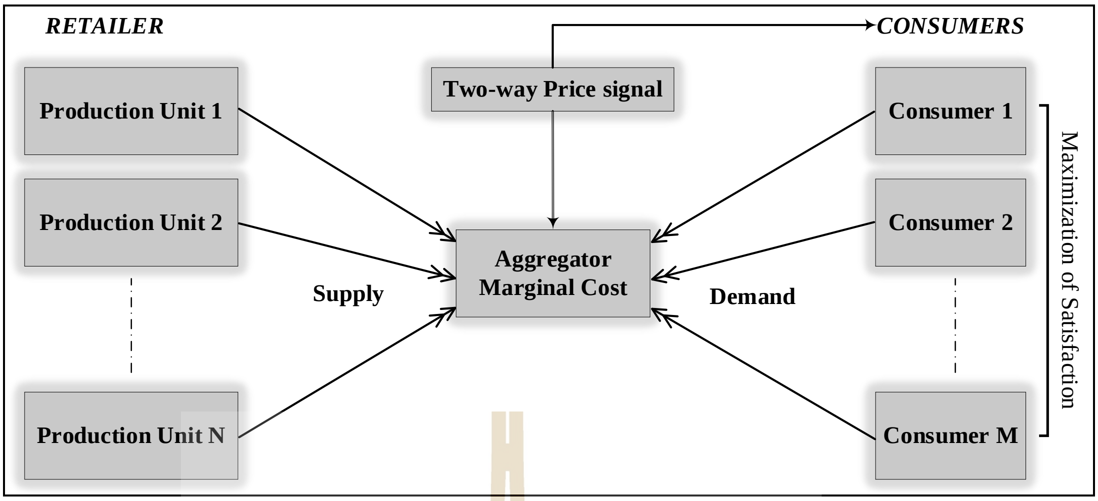

Figure 2.2 Illustration Information between Agents.

an accurate representation of market-based-marginal-cost-pricing incentives. Flexible loads and distributed energy resources can respond to marginal cost-based prices to provide demand response, secondary reserves, and reactive power compensation. In numerical illustrations of the model, it has been shown that these effects are non-negligible and one concluded that they should be considered in the regional integrated energy models that are currently developed in several countries (Babonneau, F., Caramanis, M., and Haurie, A., 2016). Figure 2.2 introduces the two-way communication between power retailers and customers that enables DR based on RTP defines a competitive framework involving the customers as agents having an influence on the price they are charged.

The LP algorithm is used for the first time on the Iraqi extra high voltage (400kV) grid for optimal power flow to minimize the active power generation cost. this reference has presented an LP-based. The problem constraints are the coupled linearized power flow equations and the system variable limits. A piecewise linear approximation of the objective function is built by adding iteratively a tangent cut in each iteration. It can be also noted that the results of the production cost are significantly decreased when using LP with the results derived in the case of NRPF. There is about 30.16% decrease in the production costs when using cheap fuel type, whereas there is about 28.2% decrease in production costs when using expensive fuel type as given by Tuaimah, F.M. and Meteb, M.F. (2014). The proposed method implementation is solved the optimal power by LP uses an iterative technique to obtain the optimal solution, it is called successive linear programming (SLP) method. There are several procedures of SLP as,

Step 1: Select the set of initial control variables,

Step 2: Solve the power flow problem to obtain a feasible solution that satisfies the power balance equality constraint,

Step 3: Linearize the objective function and inequality constraints around the power flow solution and formulate the LP problem. Then solve the LP problem and obtain the optimal incremental control variables ΔP_{Gi},

Step 4: Update the control variables $P_{Gi}^{k+1} = P_{Gi}^{k} + \Delta P_{Gi}$,

Step 5: Obtain the power flow solution with updated control variables, and

Step 6: Check the convergence. If ΔP_{Gi} in Step 4 is below the user-defined tolerance, the solution converges. Otherwise, go to Step 3.

The LP based optimal real power dispatching algorithm is successfully and effectively minimizing the supply cost in power pool auction. With the block bid protocol, the market clearing price is the equilibrium point of the aggregate supply curve and the required demand, in which the total generation satisfies the power balance, generator operating limits, and transmission line constraints. The hourly bus spot price including the marginal transmission loss and the network quality of supply is also determined (Ongsakul, W., Chirarattananon, S., and Chayakulkheeree, K., 2001). In this work, the market model used is Poolco and auction method is single sided (one buyer). The bid protocol is block bid protocol without considering elasticity on the demand side (non-demand bidding). The market allocation rule used is the uniform price rule in an hour-ahead market. In this model, the independent system operator (ISO) sorts the offered price in the ascending order to obtain the aggregate supply curve. The equilibrium point or the market clearing price (MCP) is the intersection of the aggregate supply curve and the required gross demand (total system load plus loss) as shown in Figure 2.3. Note the block bids are increasing staircase functions only.

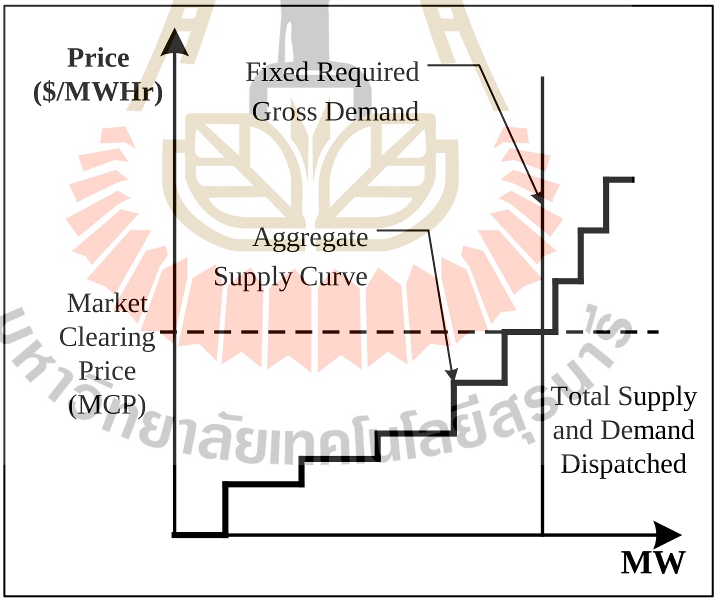

Figure 2.3 Uniform Price Rule Dispatch Model.

The thermal unit economic dispatch and methods of solution using the LP technique is used to carry out the power system optimization by Wood, A.J., Wollenberg, B.F., and Sheblé, G.B. (2014). There are N thermal-generating units connected to the system to serve the total demands with and without network transmission losses considered. The same procedure for other references is necessary to minimize the cost operating solution. The LP method using piecewise linear cost functions as shown in Figure 2.4 is discussed in this section with the lambda iteration method sometimes called binary search, dynamic programming, non-linear programming, and convex optimization. Therefore, the LP stands as one of the most powerful optimization technique ever developed.

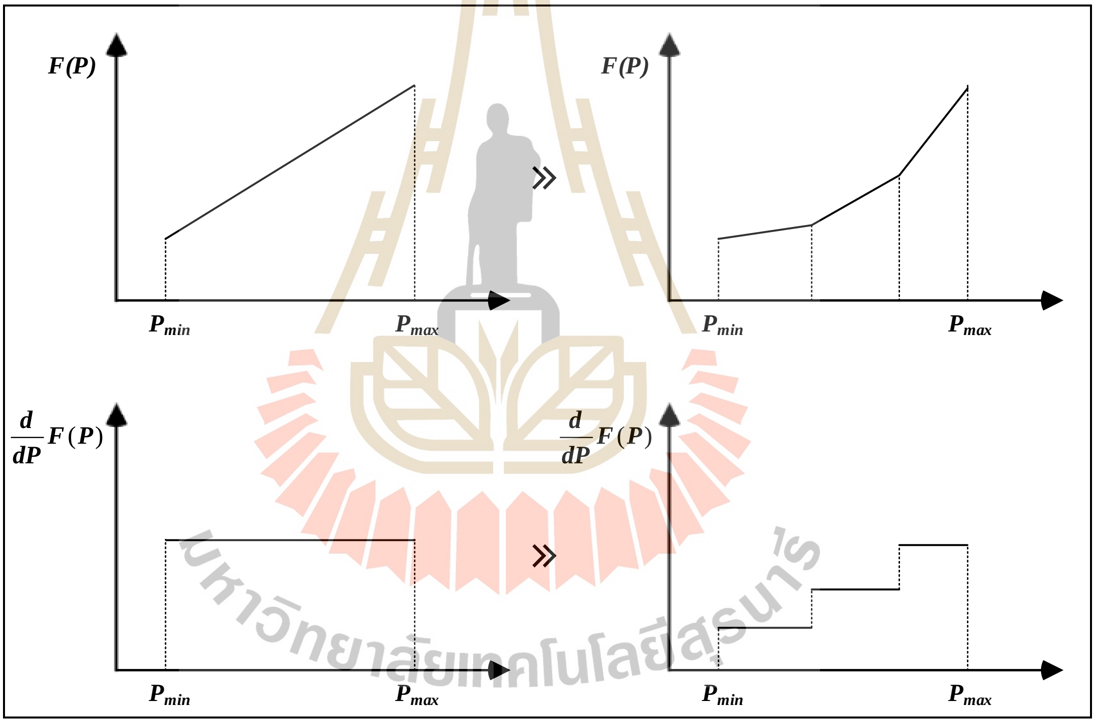

Figure 2.4 Piecewise Linear Cost Functions.

2.5.2 Study Area of DR

The untapped demand and energy in distribution systems with DR and photovoltaic distributed generation (PVDG) are resources for power utility planning, enabling deferring of network expansion investments and reduction in energy consumption from the substation. Reduction in technical losses contributes to the efficiency of the electrical system and energy conservation. Changes in regulation are needed to address the issue of responsibility of distribution utilities for the sale of energy to low-voltage retail captive consumers, such as in the current Brazilian system in the context of increasing PVDG penetration. The residential consumers can reduce the energy bill with DR, depending on their flexibility to change the consumption behaviour or through the implementation of PVDG. The adoption of a non-flat tariff as a consumer option, such as in the case of Brazilian white tariff (a survey performed by a distribution utility (DU) in Brazil is considered in the case study involving the optional time-of-use (TOU) tariff called white tariff), can make the simultaneous use of DR and PVDG not economically attractive for the consumer in comparison with PVDG only use, indicating a situation where a review of regulation can be assessed to stimulate DR. The method presented in this study enables an integrated analysis of DR and PVDG as resources for power utility planning, and is structured to make it feasible for adaptation to the analysis of other distributed energy resources or using different network models (Viana, M.S., Junior, G.M., and Udaeta, M.E.M., 2018). Practical PRDR, A flat tariff is considered for commercial and residential non-responsive consumers. For the responsive residential consumers (RRCs) defined two situations are considered on a weekday: the same flat tariff as that of non-responsive consumers for scenarios without DR and a TOU tariff for scenarios with DR. The TOU tariff price per kWh on weekend and on public holidays is the same as that in the off-peak hours. The following time classification is considered on a weekday:

- Peak hours: from 19:00 to 21:59,
- Intermediate hours: from 18:00 to 18:59, and

- Off-peak hours: from 0:00 to 17:59 and from 23:00 to 23:59.

In order to improve the system efficiency of a 380 VDC microgrid network as shown in Figure 2.5 while participating in DR, an optimal power flow problem is formulated. The cost function represents not only the operating cost within the microgrid incurred by the fuel and efficiency of the components and the power flows in the transmission line but also the DR requirements from the utility by considering RTP. The proposed algorithm is implemented by means of a heuristic method based on genetic algorithm (GA). A six-bus dc microgrid is tested to verify the proposed algorithm in a 24-hour span. The test results show that GA can find the optimal control

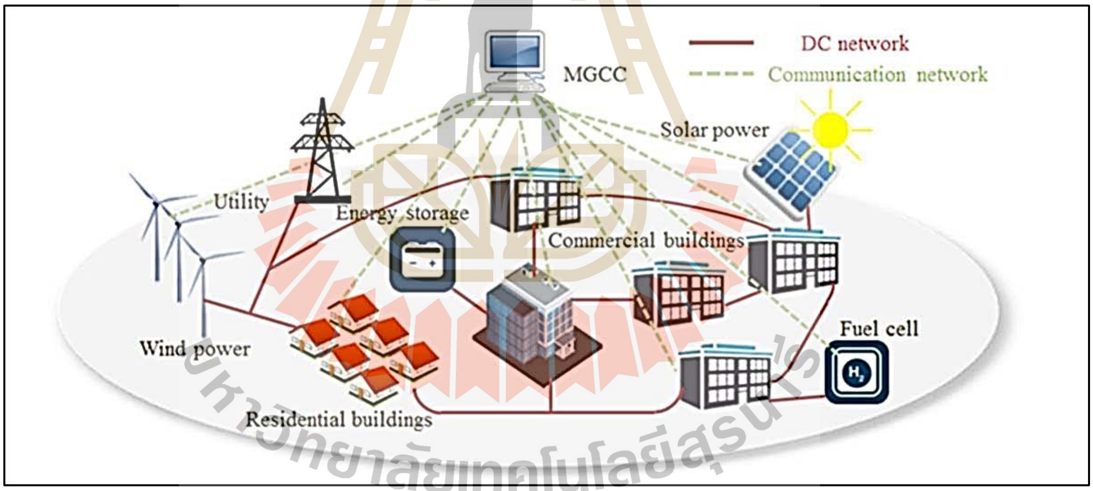

Figure 2.5 Schematic of DC-Microgrid Operating at 380 VDC (Li, C., Bosio, F.D., Chen, F., Chaudhary, S.K., Vasquez, J.C., and Guerrero, J.M., 2017).

parameters to optimally manage the dispatchable resources. Finally, the proposed algorithm successfully reduces the operating cost compared to the case study in which the system is managed without optimization (Li, C., Bosio, F.D., Chen, F., Chaudhary, S.K., Vasquez, J.C., and Guerrero, J.M., 2017).

A method for setting the electricity price for a distribution company (DisCo) considering the participation of customer in RTP is proposed by Shigenobu, R., Yona, A., and Senjyu, T. (2016), and reactive power incentive for to obey optimal scheduling cooperatively. From the simulation results, the consumer changed their load demand to the load that desirable at DisCo by RTP. By the RTP, which could achieve

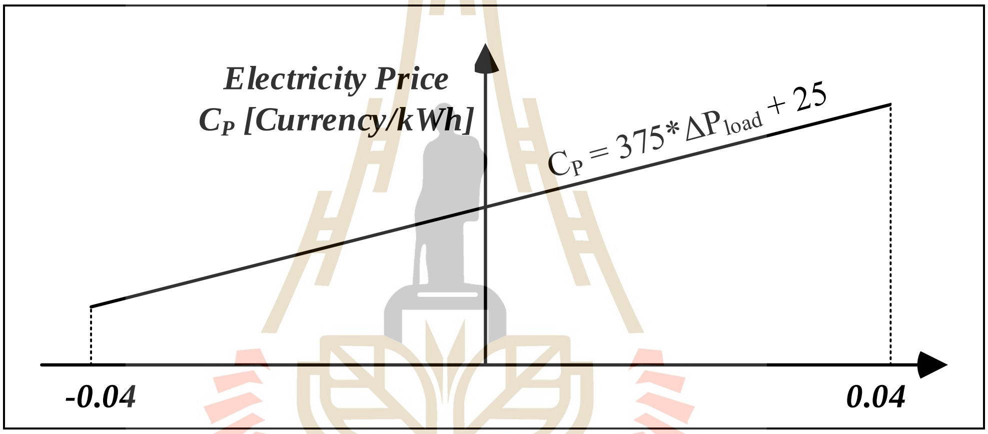

Figure 2.6 Typical day-ahead Electricity Price Setting Against ΔP_{load}

(Shigenobu, R., Yona, A., and Senjyu, T., 2016).

a reduction in the total cost of electricity price and could reduce the large battery energy-storage system (BESS). Reactive power incentive could reduce additional devices for high penetration distribution generators (DGs). It is confirmed that the proposed method can get the benefit for DisCo and customer each other. It is possible that they could take more profit that to use either method RTP of the reactive power system. This proposed method could promote the participation of customer in the electricity market. The electricity price C_P is first determined using the setting function shown in Figure 2.6 the day-ahead electricity price for ΔP_{load}. After that, consumers are notified about the electricity price C_P, which set to 25 [Currency/kWh] as a base price in this case, and the load demand shift is prompted by a cheap electricity price when the daytime reverse power flow occurs. It is confirmed that daytime electricity price C_P is cheaper than the base electricity price, and the nighttime price C_P is more expensive than the base price.

Moshari, A., Ebrahimi, A., and Fotuhi-Firuzabad, M., (2016) have studied the effects of DR programs on the short-term reliability of wind-integrated power systems. Here, a new modelling has been proposed for DR programs considering the uncertainties associated with these programs. In addition, a new reliability modelling has been developed for wind energy conversion systems to be applicable to the short-term reliability studies. We have also proposed an algorithm for short-term reliability evaluation of composite power systems, which includes the effect of different initial states of system components and the lead-time of DR and reserve resources. This work shows that issues like possible changes in components initial statuses and the lead-time of remedial resources may significantly affect the short-term reliability assessment of composite power systems. On the other hand, real-world uncertainties can seriously influence the reliability enhancement feature of DR programs. Therefore, incorporating these parameters in short-term assessments can significantly improve the effectiveness of DR resources planning. The results also reveal that DR programs improve the reliability level and the peak-load carrying capability of wind integrated power systems and can be a potential solution to eliminate the negative impacts of wind energy volatility.

Even though demand response is not a new concept, it can have much more relevant importance in the context of competitive electricity markets. In the scope of a competitive market, with technical and economic issues having to be equally considered, active demand players can bring the additionally required flexibility to attain the envisaged efficiency operation levels. This paper presented the most important demand response concepts and programs, as well as some relevant experiences in this field. Increasing interest in this area is leading to an increasing number of works. However, new approaches are required in order to take full advantage of demand response in the benefit of electricity market operation and electricity market players. This paper presented demand response simulator (DemSi), a demand response simulator that allows studying demand response actions and schemes, using a realistic network simulation based on power systems computer-aided design (PSCAD) software. DemSi allows simulating a variety of demand response methodologies and to optimally achieve a solution according to the available demand response opportunities. DemSi is used to support the case study presented in the paper. This case study is based on the retailer's perspective and includes a set of events with a load reduction level being envisaged for each one. The study considers both prices and loads reduction caps for each consumer. For each envisaged load reduction, the optimal demand response solution is determined using a non-linear programming approach. Results show that customer's demand depends on price elasticity of demand, and on the RTP tariff. The optimal solution also depends on the imposed price caps according to the concerned DR programs. The study includes simulations considering a normalized tariff for each consumer type and considering individual consumer tariffs. When comparing the results obtained imposing the use of a normalized tariff and those resulting from the consideration of individual consumer tariffs, it can be concluded that the retailer's benefits are almost the same. Considering normalized tariffs for each consumer type is a fairer strategy in comparison with applying different tariffs for consumers of the same type, being more prone to be well accepted by the consumers. This is an important conclusion to be taken into account when DR programs are designed (Faria, P. and Vale, Z., 2011).

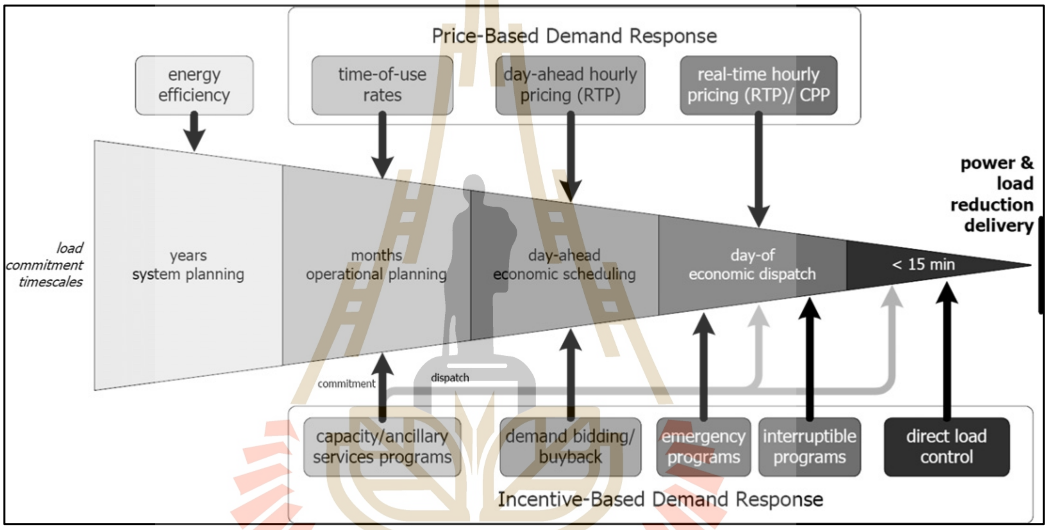

Figure 2.7 Demand Response Planning and Operations (US Department of Energy, 2010).

2.5.3 Study Area of POPF with and without DR

The basic PLF solution proposed by (Allan, R.N., Leite da Silva, A.M., and Burchett, R.C., 1981) was that proposed previously and is based on linearizing the LF functions around the expected value and using convolution to evaluate the relevant density functions of the output variables. This proposed work has extended these techniques by replacing conventional convolution with Fast Fourier Transforms (FFT). It has been shown that the FFT method is a very significant improvement in the conventional method and gives fast, very precise results. The problems associated with the central limit theorem to justify a normal distribution for the output densities have been discussed and clarified. The accuracy of the PLF solution has been tested using MCSs. This has shown that the performance of the linear model is very good within a certain range of uncertainty of random variation of the input data. It has also been shown that the convolution technique used in the PLF method to combine realistically an infinite range of solutions is a very powerful tool.

Chayakulkheeree, K. (2013) proposed POPF using parameter estimation by the percentile algorithm efficiently and effectively solves Weibull PDF parameters of the OPF variables. With the estimation of Weibull parameters from percentiles, the number of OPF runs can be substantially reduced in the proposed POPF process. The results show that the proposed POPF can successfully determine the PDF of OPF output variables, considering the Weibull PDF of system load. The proposed POPF is potentially applicable to the power system with probabilistic load due to good model representation, simple computation, and the minimum number of OPF sub-problem runs. Similarly, Chayakulkheeree, K. (2015) PLF using Weibull PDFs of photovoltaic power generation is investigated. The results show that the parameters estimation by percentile estimation is representative of the PLF variables. With the estimation of Weibull parameters from percentiles, the number of LF run, for preliminary probability study with a photovoltaic power plant in the distribution system can be substantially reduced.

In order to describe the impact of uncertainties, such as fluctuation of bus loads and intermittent behavior of renewable generations, on the available load supply capability (ALSC) of distribution system accurately and comprehensively, Zhang, S., Cheng, H., Zhang, L., Bazargan, M., and Yao, L. (2013) defines a series of meaningful indices for the probabilistic evaluation of ALSC. An efficient simulation method, Latin hypercube sampling-based Monte Carlo simulation (LHS-MCS), combined with step-varied repeated power flow method is proposed to compute the defined indices. Compared with simple random sampling-based Monte Carlo simulation (SRS-MCS), LHS-MCS is found to be more suitable for the probabilistic evaluation of ALSC. It can achieve more accurate and stable ALSC indices under relatively small sample sizes. The calculation speed of LHS-MCS is comparable with that of SRS-MCS under the same sample sizes, and the required CPU time of LHS-MCS is far less than SRS-MCS under the same calculation accuracy. Case studies carried out on the modified Baran & Wu 33-bus and the modified IEEE 123-bus distribution systems verify the feasibility of the defined indices and high performance of the proposed method.

Giraldo-Chavarriaga, J.S., Castrillón-Largo, J.A., and Granada-Echeverri, M. (2014), a validation of two proposed schemes of the point estimate method (PEM) is made, not only for normal distributions but also different kinds of PDF, such as Weibull and generalized extreme value and Shargh, S., Khorshid ghazani, B., Mohammadi-ivatloo, B., Seyedi, H., and Abapour, M. (2016) proposes a PEM based Nataf transformation to solve probabilistic multi-objective optimal power flow (MO-OPF) problem considering fuel cost and emission as objectives. Uncertainties in the wind power output and load demand are considered. The main contribution of the work reported here is to apply the Nataf transformation to the PEM in order to solve the probabilistic MO-OPF problem with correlated input random variables (RVs). This method only requires data for the marginal distribution function of each input RV and the correlation coefficients instead of their joint PDF. In this work, the effect of different correlation coefficients is observed on the control and output data of problem and on the accuracy of PEM. It is concluded that correlation among input RVs increases uncertainty in control and output data of MO-OPF problem which makes planning and forecast more complicated than before. The effectiveness of the method is demonstrated using a 30-bus test system. Results of the proposed method are compared to those of MCS which confirms high accuracy of the method.

2.6 Chapter Summary

This chapter II is provided with the introduction and overview of the electric power system that contains the electrical components installed to supply, transmission, and use of electric power. There are various research methodologies ever done by researchers as mentioned in the literature review Section 2.5. There are three main study areas presented in this section: study area of LPOPF proposed and experimented in similar objectives, study area of DR applied flexible strategies to server the power balance in electrical market, and study area of POPF with and without DR used different optimization techniques to advance the dispatch solutions and benefits for their studies. A similar standpoint is to serve the power demands with the optimum investment cost, while the known secure constraints in the distribution system are attached in the case study.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter represents the problem formulation of the POPD using LP with DR programs. It also contains the general mathematical formulation of the optimization formed into the LP optimization technique with the power balance and generator operating limit constraints. Moreover, the Monte Carlo technique is used to develop the proposed framework with sampling conditions. The normal distributed random variable is used to model the real power demand at the specific bus as load uncertainty during the simulations.

3.2 Problem Formulation and Methodology

Practically, optimization is an important tool in scientific solutions and in the analysis of physical systems. In order to make use of this tool, the *objective* has to be identified. The objective could be profit, time, potential energy, or any quantity or combination of quantities that can be represented by a single number. It can be depended on certain characteristics of the system, called *variables* or *unknown parameters*. The process of identifying objective, variables, and constraints for a given problem is known as *modelling*. Moreover, the variables are limited with some *constraints* to find values of the variables that optimize the objective. After the model has been expressed, an optimization algorithm will be used to find its solution assisted by a computer. It should be noted that the objective function in this work would be formulated and solved by the LP, which is expressed in Section 3.3.

3.3 General Mathematical Formulation of Optimization

Mathematically, the optimization is to minimize or maximize a function subject to constraints on its variables and use the following notation (Nocedal, J. and Wright, S.J., 2006),

i. x is the vector of *variables*, also called *unknowns* or *parameters*,

ii. f is the *objective function*, a (scalar) function of x that we want to maximize or minimize, and

iii. c_i are *constraint* functions, which are scalar functions of x that define certain equations and inequalities that the unknown vector x must satisfy.

From these three notations, the optimization problem can be formulated as,

$$\underset{x \in \mathbb{R}^n}{\text{Minimize}}\ f(x) \tag{3.1}$$

$$\text{Subject to} \quad \begin{cases} c_i(x) = 0, i \in \varepsilon \\ c_i(x) \geq 0, i \in \gamma \end{cases}$$

Here ε and γ are sets of indices for equality and inequality constraints, respectively.

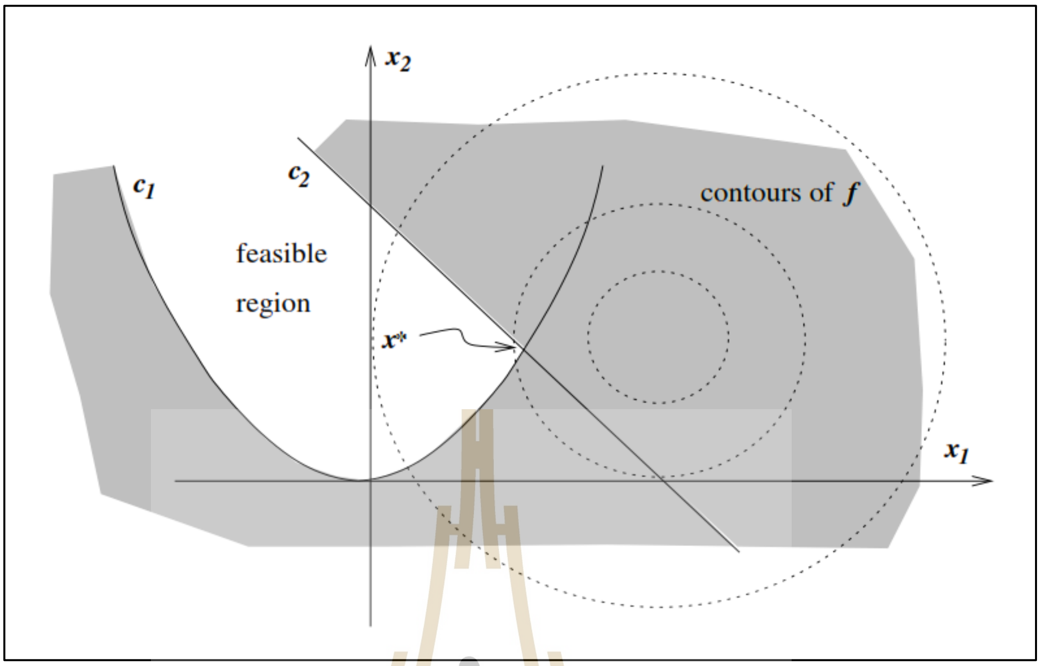

Figure 3.1 Geometrical Representation of the Problem.

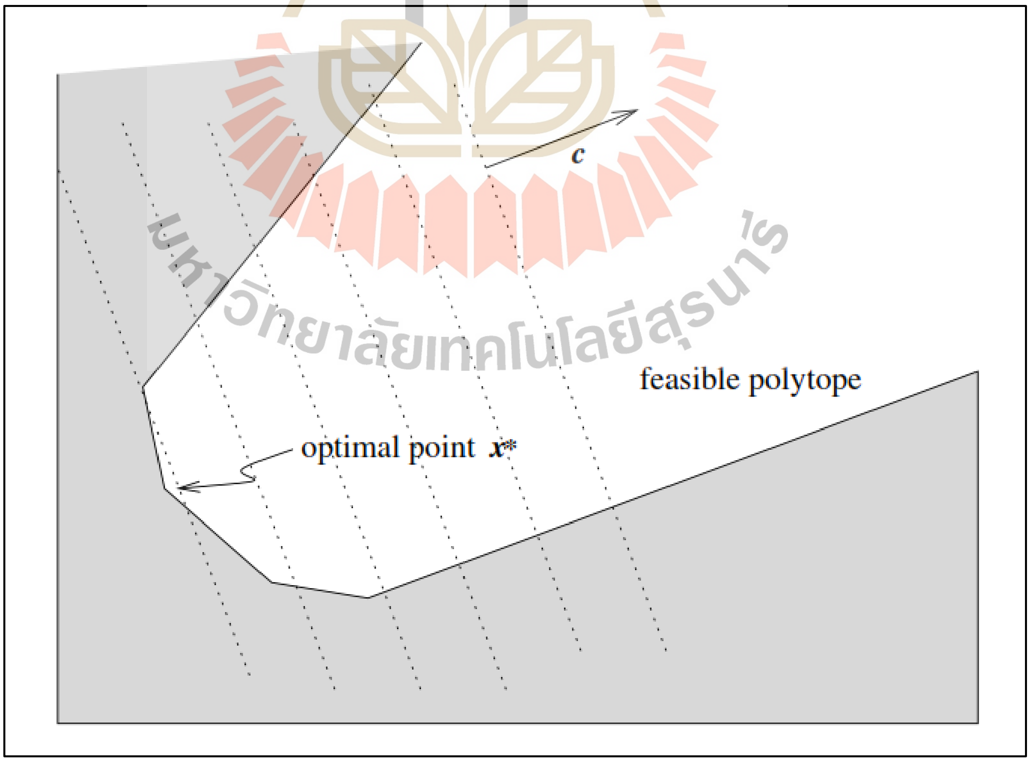

Figure 3.2 Linear Programming in 2-Dimension with Solution at x^*.

Formally, Linear programs have a linear objective function and linear constraints, which may include both equalities and inequalities. The feasible set is a polytope, a convex, connected set with flat, polygonal faces. The contours of the objective function are planar. Figure 3.2 depicts a linear program in two-dimensional space, in which the contours of the objective function are indicated by dotted lines. The solution, in this case, is unique—a single vertex. A simple reorientation of the polytope or the objective gradient c could, however, make the solution non-unique; the optimal value $c^T x$ could take on the same value over an entire edge. In higher dimensions, the set of optimal points can be a single vertex, an edge or face, or even the entire feasible set. The problem has no solution if the feasible set is empty (the infeasible case) or if the objective function is unbounded below on the feasible region (the unbounded case). Linear programs are usually stated and analyzed in the following standard form:

The LP can be summarized mathematically as cost minimization below,

$$\text{Minimize } c^T x \tag{3.2}$$

Subjected to the constraints,

$$Ax \le b \tag{3.3}$$

$$x \ge 0, \; x \in \mathbb{R}^n$$

Where,

x is an unknown $n \times 1$ vector

c is the $n \times 1$ vector of cost coefficients

A is the $m \times n$ matrix of constraint coefficients

b is the right-hand side $m \times 1$ vector

There are n variables in the x vectors represented the output, c^T represented the overall benefit to be optimized, and m constraint equations in the A matrix.

3.4 Problem Formulation

In this case study, the LPOPD adapted the NRPF with the operating cost for each generator which is given by piecewise linear cost functions, as shown in Figure 3.3. It can be used instead of the quadratic cost functions.

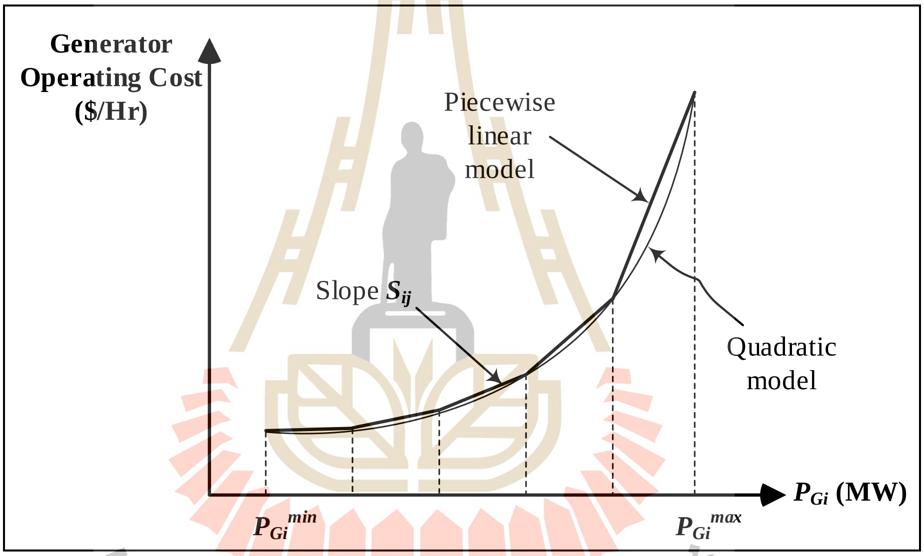

Figure 3.3 Piecewise Linear for Generator Cost Functions.

Hence, the objective function can be expressed by a piecewise linear optimization model (Ongsakul, W., Chirarattananon, S., and Chayakulkheeree, K., 2001; Wood, A.J., Wollenberg, B.F., and Sheblé, G.B., 2014). The objective function is to minimize the total power generating cost including cost of PRDR, and can be expressed as,

$$\text{Minimize } TC = \sum_{i=1}^{NG}\sum_{j=1}^{NSi} S_{ij} P_{G_{ij}} + \sum_{i=1}^{NB} D_i P_{DR_i} \ , \tag{3.4}$$

Subjected to the power balance constraint,

$$\sum_{i=1}^{NG} P_{G_i} + \sum_{i=1}^{NB} P_{DR_i} = \sum_{i=1}^{NB} \tilde{P}_{D_i}^{o} + P_{loss} \ , \tag{3.5}$$

In the cost formulation of the LPOPD, we have some variables to control this problem. The control variables could be the generator real power, generator voltage magnitude, and the transformer taps. The linearized incremental cost shown in Figure 3.3 is the most likely shape that may be occurred in the competitive generation environments.

Respecting to power balance, the constraint to consider in LPOPD are the constraints that represent the power balance between real and reactive power generated, and that consumed in the loads and losses. There are some constraints and limitation to minimize the objective function.

And the generator operating limit constraint,

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \ , \ i=1,2,\ldots,NG, \tag{3.6}$$

$$\sum_{i=1}^{NG} P_{G_i} = \sum_{i=1}^{NB} \tilde{P}_{D_i} + P_{loss} \ , \tag{3.7}$$

$$\tilde{P}_{D_i} = \tilde{P}_{D_i}^{o} - P_{DR_i} \ , \ i=1,2,\ldots,NB, \tag{3.8}$$

$$P_{G_i} = \sum_{j=1}^{NSi} P_{G_{ij}} + P_{G_i}^{\min}, \; i=1,2,\ldots,NG, \tag{3.9}$$

$$0 \le P_{G_{ij}} \le P_{G_{ij}}^{\max}, \; j=1,2,\ldots,NS_i, \tag{3.10}$$

$$|f_{lm}| \le |f_{lm}|^{\max}, \text{ and} \tag{3.11}$$

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max}, \; i=1,2,\ldots,NB. \tag{3.12}$$

For the NRPF technique, the bus power injections including active and reactive power for every bus can be reproduced in polar coordinates and expressed as,

$$P_{G_i} - \tilde{P}_{D_i} = \sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\cos(\theta_{ik} - \delta_{ik}), \; i=1,2,\ldots,NB, \tag{3.13}$$

$$Q_{G_i} - \tilde{Q}_{D_i} = -\sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\sin(\theta_{ik} - \delta_{ik}), \; i=1,2,\ldots,NB, \tag{3.14}$$

Where,

TC is the total system cost,

P_{G_i} is the real power generation at bus *i*,

S_{ij} is the linearized incremental cost curve for each segment of P_{G_i} at bus *i*,

D_i is the linearized incremental cost curve for each demand response at bus *i*,

NS_i is the number of segments of the linearized cost of the generator at bus *i*,

NG is the number of generators in the system,

NB is the number of buses in the system,

P_{DR_i} is the real power demand response at bus i,

$\tilde{P}_{D_i}$ is the probabilistic real power demand at bus i,

Q_{G_i} is the reactive power generation at bus i,

$\tilde{Q}_{D_i}$ is the probabilistic reactive power demand at bus i,

P_{loss} is the total transmission loss in the system,

$P_{G_i}^{\min}$ is the minimum real power generation at bus i,

$P_{G_i}^{\max}$ is the maximum real power generation at bus i,

$|f_{lm}|$ is the apparent power flow on the branch between bus l and m,

$|f_{lm}|^{\max}$ is the maximum limit at apparent power flow between bus l and m,

$|V_i|$ is the voltage magnitude at bus i,

$|V_i|^{\min}$ is the minimum voltage magnitude at bus i,

$|V_i|^{\max}$ is the maximum voltage magnitude at bus i,

$|y_{ik}|$ is the magnitude of the y_{ik} element of Y_{bus},

θ_{ik} is the angle of the y_{ik} element of Y_{bus}, and

δ_{ik} is the voltage angle between bus i and k.

3.5 DR Schemes

DR programs have essentially empowered because the evolution in the up-to-date technology required to tool them to regulate the target. An implication of DR is to consider the possibility of the power generation cost reduction, customers' electricity bill saving, and reliability of the power grid. PRDR is a program in which customers are paid for the load reduction in accordance with SO request. The PRDR price can be assigned by agreements for the real-time curtailable load. The demand of each load bus in the system has adjusted to maintain with the feasible power generation, principally, every customer would manage their power consumption to be a part of improving the efficiency and reliability of the system during peak periods. The system operator sometimes has to run costly power plant to adjust the total needs power generation to meet the peak demand while the promise pollution can be exceeded their authority, however, whether DR scheme has contributed to the system. Hence, there are persuasively two DR programs in vogue (Vardakas, J.S., Zorba, N., and Verikoukis, C.V., 2015; Paterakis, N.G., Erdinç, O., and Catalão, J.P.S., 2017) which are price-based programs (PBPs) and incentive-based programs (IBPs). PBPs are commonly cased study for researchers which provoke the consumers voluntarily provide load reductions by reacting to economic gestures. In spite of IBPs the customers have bided the payments in order to report an exact amount of load reduction over a specified time interval. Many economists are convinced that they are the most direct and efficient DR programs suitable for competitive electricity markets and should be the focus of policymakers.

3.5.1 Price-based Programs (PBPs)

All manner of PBPs, there are three subroutines of the PBPs were mentioned by the researcher. First is RTP, the pricing will be refreshed with a short time, as a rule, hourly or daily. During, RTP customers will be exactly reported to adapt their power usage patterns to SO in the case of the cost of the wholesale power generation market have to change accordingly. Second is TOU, basically, TOU pricing will be imitated the variations of the longer-term electricity supplying cost under average market conditions responding to the time within a day or a season, but it is not capturing the everyday instability of supply costs. Consumers are billed with flat prices are not alert to the varying cost of electricity. Flat rates represent average electricity supplying costs and may remain constant for years. Yet, its structure contains a peak rate, an off-peak rate, and possibly a shoulder-peak rate by the distinct time periods from the SO. Lastly, whereas RTP is a typical pricing scheme, Critical Peak Pricing (CPP) is applied tariff for the short-term electricity supply cost in the power system, which is the full-size RTP execution outstanding to the methodological limitation of DR. CPP tariff is a kind of the aggressive pricing scheme in combination of RTP and TOU enhancing also TOU rate and time-invariant rate in the critical peak prices dispatching in the computed CPP event. Moreover, CPP is relatively noticed for the limited number of hourly or/and daily a year, customarily, CPP customers will obtain a price discount in non-CPP periods. Nevertheless, CPP does not gain thriftily competent as RTP scheme, it is objectively able to condense the possible price hazard accompanying with RTP in reflecting critical period short-term cost. Whatever can help to inspire customers by decreasing the peak load of the electricity locating risk. Hence, CPP is more well-organized than TOU and CPP to reach better cooperation between TOU and RTP.

3.5.2 Incentive-based Programs (IBPs)

Latterly, IBPs have categorized into three subroutines. First is Direct Load Control (DLC), and the purpose is to participate a large number of the small kind of consumers, throughout the programs in which the SO in a related manner rounds a customer’s electrical utilization on a short-term to discourse system contingencies. DLC is principally granted to the residential and small commercial consumers’ loading participation. Participating customers will sometimes collect either incentive payments or rate discount depending on the customer certain duty round. Regularly, DLC is limited the number of times or hours for customer's usage to be turned off within year on year or seasonally. These programs will be achieved by the SO in resulting to the end-user is not alerted for an intermission. These events possibly will be trigged economic or reliability. Second is Curtailable Load (CL), are the programs directed to medium and large consumers. The selected participants will be gotten incentives to switch off the specific loads or to disconnect the power usage responding to calls emitted by the SO. Alike in DLC programs, the maximum number and interval of calls should be stated in the contracts. Presently, the SO has used these programs as effective tools to regulate the peak load. Lastly, Demand Bidding (DB) is earnestly mechanism to shift the power demand the consumption pattern overbidding, which is a part of electricity market competition and provide customers with the opportunity to triumph the economic rewards, at the same time, they may be required to submit the load reduction pattern by using the high-tech load management tools and strategies. These programs are mostly applied directly with small consumers and indirectly through third-party aggregators. Not only DB but also demand side may be associated with capacity and ancillary services to implement the load variations in the system within different time. And besides, DB can pointedly raise the elasticity of demand, discipline problem in the wholesale power market and price spikes. Consequently, the total needed power generation and CO_2 emission can be reduced with DR schemes. Another point of the profitable application of a DR scheme, the reduction of the total power generation can be obtained from this operation resulted in minimizing the loss of the system. Additionally, this objective has solved the overload operation in the distribution system in real-time problems to ensure the reliability of the system.

3.6 Customer Response

Practically, there are frequently three kinds of action from customers' response. The load will be lessened during critical peak load period, and then maintained the normal load pattern during off-peak time. This encouragement can serve a decrease in customers' side with relief as they are required to limit the electricity usage at a specific period but to condenses the overall consumption, consequently, reduced electricity bill even supplementary. One more action that could be engaged in order to answer high electricity prices or low availability is to equilibrium the electricity uses from peak to off-peak period. After that, this technique will maintain the load profile by both declining the peak load and filling up small consumption basins. Moreover, it does not only lower the regular amount of power demand used by the end-user but also it does increase the transmission and distribution efficiency and reliability as the system operates in a steadier state. After all, customers can use on-site generation to decrease consumption perceived by the SO. It will raise users' self-government, more reorganize generation and decrease the regular load on transmission and distribution networks. Then again, it will exploit system complication.

3.7 Optimization Technique

Dantzig's development of LP: the simplex method in the late 1940s marks the start of the modern era in optimization problem (Nocedal, J. and Wright, S.J., 2006). This method showed its possibilities for economists and researchers to formulate large models and analyze them in a methodical and efficient way. Dantzig's discovery matched with the advance of the first numerical optimization in the engineering field, and the simplex method became one of the most primitive important applications of this new and innovative technology (Luenberger, D.G.). Until now, computer implementations of the simplex method have been repeatedly improved and refined, the LP is without doubt one of the furthermost influential optimization techniques constantly developed (Bazaara, M.S., Jarvis, J.J., Sherali, H.D., 1990; Frederick, S.H., Lieberman, G.J., c1974). They have benefited principally from interactions with numerical analysis, a branch of mathematics that also came into its own with the appearance of computers in many research areas, and have now reached a high level of sophistication.

The LPOPD algorithm approach is based on an iterative computation between NRPF and LP. The computational procedure is shown in Figure 3.4. There are several procedures of LPOPD computational procedure as,

Step 1: Read the initial system data for the required variables and offered price of generators and PRDR,

Step 2: Determine the preliminary output data by NRPF technique,

Step 3: Determine the real power generations by LP optimization,

Step 4: Solve NRPF with the power generation outputs from ***Step 3***,

Step 5: Decide the LP outputs to match with NRPF outputs then go to ***Step 6***, or else, go to ***Step 3***, and

Step 6: Compute total power generation and DR costs.

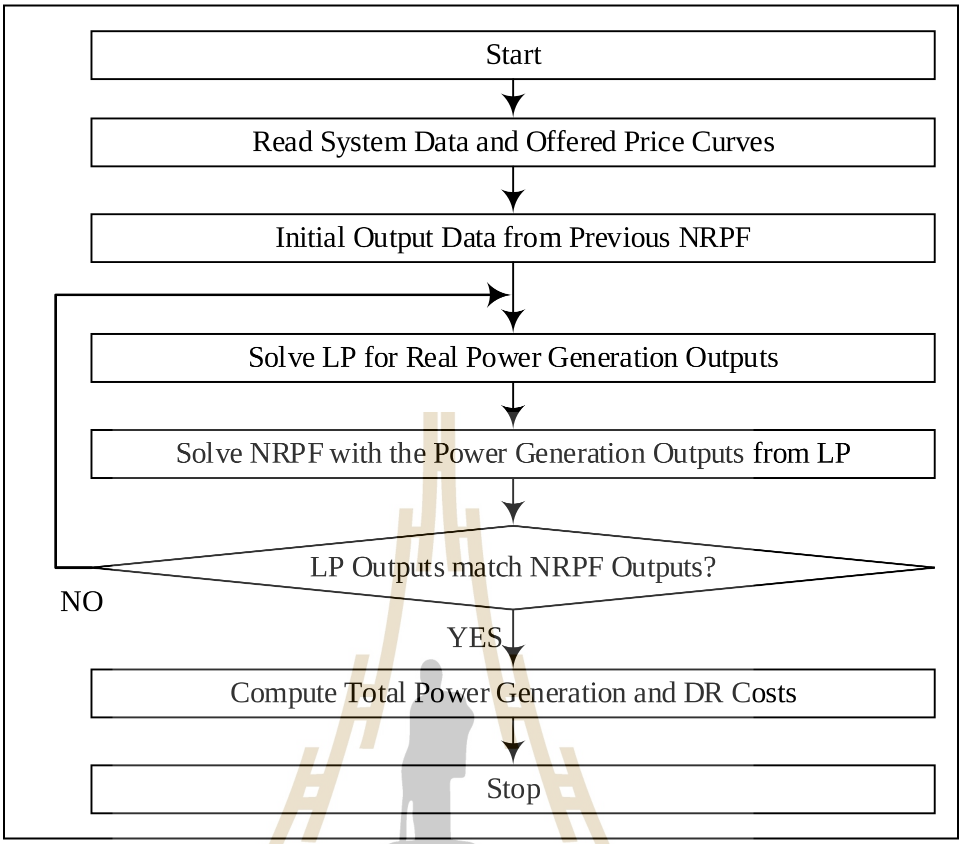

Figure 3.4 Computational Procedure of LPOPD.

3.8 Probabilistic Technique and Sampling Conditions

3.8.1 Monte Carlo Simulation

Essentially, the MCS framework is a combination of OPD computation, LP application in MATLAB toolbox, and file.m supplementary code for additional conditions as mentioned in this Section 3.8.3. In this thesis, the MCS is used for probabilistic power demand simulation and the OPD is run until the average total real power generation of the iteration $k+1$ (TPg_{avg}^{k+1}) is close to that of the iteration k (TPg_{avg}^{k}). More specifically, the MCS base OPD is run until $|TPg_{avg}^{k} - TPg_{avg}^{k+1}| < \varepsilon$, where ε is a very small real number. In this case study, the ε is set to 0.0001. There are several procedures of the proposed framework of MCS procedure as,

Step 1: Read the initial system data for the required variables and offered price of generators and PRDR,

Step 2: Create the PDF of power demand at every specified bus i in Table 4.2,

Step 3: Execute the iteration k = 1 where $TPg_{avg}^{k} = 0$,

Step 4: Determine the preliminary output data by NRPF technique,

Step 5: Determine the real power generations by LP optimization,

Step 6: Solve NRPF with the power generation outputs from ***Step 5***,

Step 7: Simulate the OPD problem with MCS,

Step 8: Decide the LP outputs to match with NRPF outputs then go to ***Step 9***, or else, go to ***Step 5***,

Step 9: Decide whether $|TPg_{avg}^{k} - TPg_{avg}^{k+1}| < \varepsilon$ at iteration k + 1 then go to ***Step 10***, or else, go to ***Step 7***, and

Step 10: Compute total power generation and DR costs.

MCS is widely used to investigate the power system operation and PDF to forecast the load and uncertainty variables in the system. However, to directly sampling the PDF can lead to infeasible solutions that need further variation process. Therefore, the PTNF could participate in this proposed framework to improve the technique over the existing POPD and lead to better precise results as addressed in Section 5. Without implementing PTNF in this study, the simulation will be included a number of infeasible LF solutions during the computational procedure. Therefore, it is noticeably shown that the proposed technique can handle the dispatch solutions considering PRDR effectively and accurately.

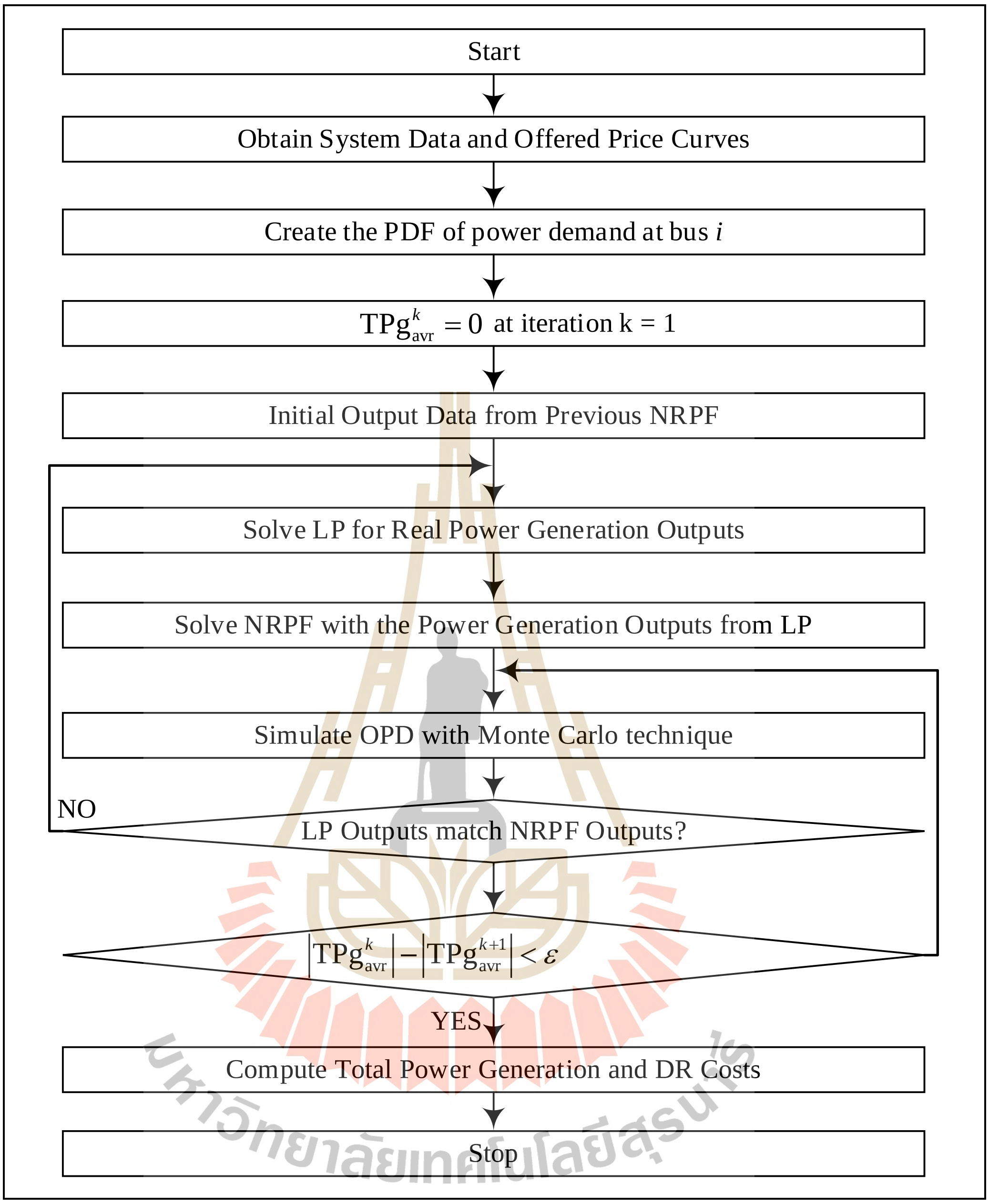

Figure 3.5 Framework of MCS Procedure.

3.8.2 Probabilistic Load Models

In probability and statistics manner, random variables or stochastic variables are variables whose represent possible numbers by using probability theory. Practically, the normal PDF is a common continuous probability distribution to produce real-valued random variables as load uncertainty. In this work, the normal distributed random variable is used to model the real power demand on the specific load bus.

For this purpose, the equivalent PDF can be formulated as,

$$f\left(\tilde{P}_{D_i} \mid \mu_D, \sigma_D^2\right) = \frac{1}{\sigma_D\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\tilde{P}_{D_i}-\mu_D}{\sigma_D}\right)^2} \tag{3.15}$$

Where,

$\tilde{P}_{D_i}$ is the probabilistic real power demand at bus *i*,

μ_D is the mean value, and

σ_D is the standard deviation of the demand profile.

3.8.3 Sampling Condition

Related to Section 3.8.2, the normal PDF is chosen to model the load uncertainty with the specified parameters μ_D and σ_D obtained from the practical data as shown in Section 4.1. One of the most important aspects of this simulation is to execute a specific range $x \in (a,b)$. Suppose that $x \sim \mathrm{N}(\mu_D, \sigma_D^2)$, $-\infty \le a < b \le \infty$. Then the normal distribution has become the Truncated normal PDF lying on the interval $a < x < b$. Formally, the Truncated normal PDF will be symbolized by $\Psi()$ (Burkardt, J., 2014). And it may be classified by the formula,

$$\Psi\left(\mu_D, \sigma_D, a, b; x\right) = \begin{cases} 0 & \text{if } x \le a \\ \Phi\left(\mu_D, \sigma_D^2, a, b; x\right) & \text{if } a < x < b \\ 1 & \text{if } b \le x \end{cases} \tag{3.16}$$

Where,

$$\Phi\left(\mu_D,\sigma_D^2,a,b;x\right)=\frac{\phi\left(\mu_D,\sigma_D^2;x\right)-\phi\left(\mu_D,\sigma_D^2;a\right)}{\phi\left(\mu_D,\sigma_D^2;b\right)-\phi\left(\mu_D,\sigma_D^2;a\right)} \tag{3.17}$$

From the above summary, it is clearly shown that $\Psi()$ is 0 at $x \leq a$ and 1 at $b \leq x$, and it is in-between the shifted version of the behavior of $\Phi()$ at $a < x < b$.

In statistics, there is a rule called the 68–95–99.7 rule to deal around the mean value in the normal distribution, sometimes known as the empirical rule, in order to get more accurately, 68.27%, 95.45% and 99.73% of the random variables within one standard deviation, two standard deviations, and three standard deviations of the mean, respectively.

To formulate the data in this study, the approximated normal PDF data set aimed at empirical data derivation. In this case, vector x generated randomly on a specific range as mentioned in Figure 3.6, represented by $x_{(a,b)}=[x_1,x_2,\ldots,x_{mcs}]$ which samples depending on how many times MCS will simulate in the 68–95–99.7 rule framework. The standard deviation σ_D of the power demand profile is a foremost part of modelling the significance of the random measurement error. When σ_D becomes wide-ranging, the measurement is moderately imprecise. As the result, a small value of σ_D will represent a minor error to prove a highly efficient output of random variation.

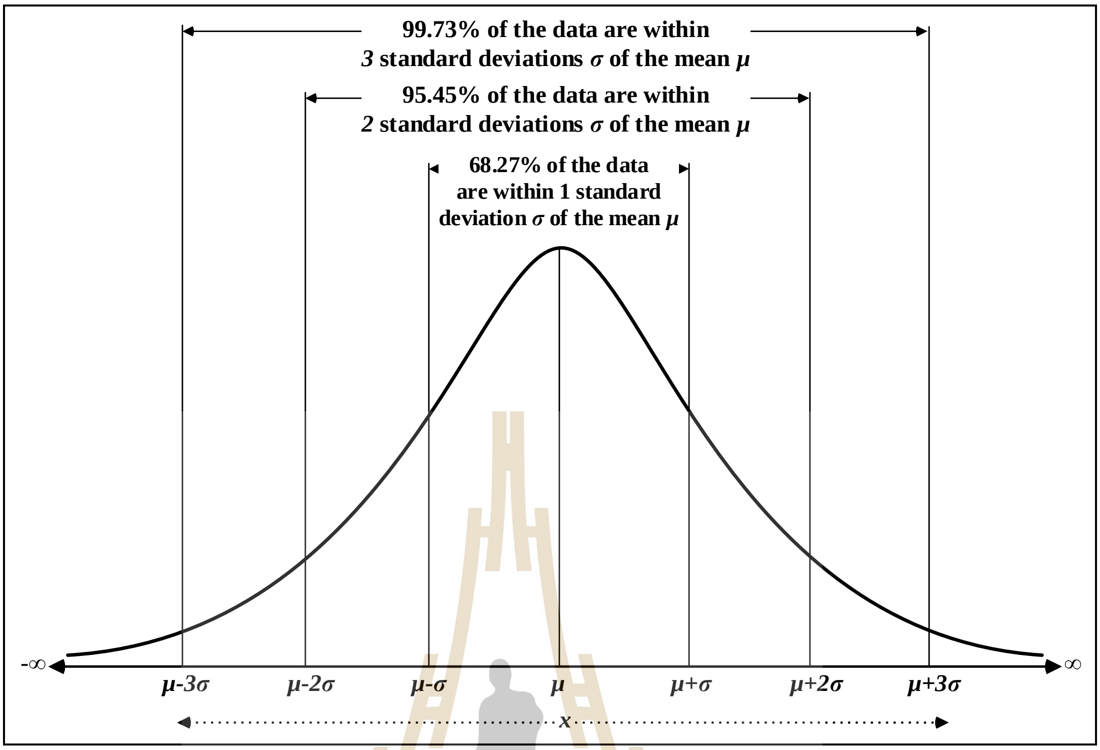

Figure 3.6 Graphical Illustration of the Empirical Rule.

3.9 Chapter Summary

This chapter III is represented the methods and applied optimization techniques to formulate the objective function. The general mathematical formulation of optimization is shown and linked with the linear programming to formulate the objective function as shown in Section 3.4 to state the feasible region of cost minimization. Also, the DR scheme participates in the cost function, and PRDR briefed in Section 3.5. To clarify the convergent solutions in the computational framework, a probabilistic technique called Monte Carlo simulation has implemented in procedure 2000 runs. The desired result will be palpably exposed in Chapter IV, and it is responded to the problem statement successfully.

CHAPTER IV

RESULT AND DISCUSSION

4.1 Introduction

This chapter represents the simulation results and discussion following the computational procedure. The proposed framework of MCS procedure in Figure 3.5 was implemented to prove the productivity and effectiveness in the power sector problem with day-ahead loading condition and the 24-hour loading pattern is shown in Section 4.2. The inclusive performance of the proposed framework was experienced with the modified IEEE 30-bus test system. The related results and discussion would offer as well in this section. Meanwhile, the accurate error will be slightly come along the provided output variables due to the nature of the simulation methods. The test system has nominated to program and simulated with MATLAB R2014a on the system window 10 Pro, Intel® Core ™ i7-4700MQ CPU @ 2.4GHz, RAM installed 16.00GB, 64-bit operating system. The simulation results from the POPD context are provided well investigation between the dispatch results of LPOPD with normal PDF and PTNF sampling methods. There are a few graphs and tables provided in order to express effectiveness and successful outputs from the proposed framework. As a result of the projected outcomes, the objective can be successfully determined and compared to other recently proposed methods as shown in the subsection.

4.2 Parameters and Required Data

The online diagram of the modified test system is shown in Figure 4.1, besides, bus data, branch data, generator data, generators' operating costs, and other related data for this system following the standard IEEE 30-bus test system.

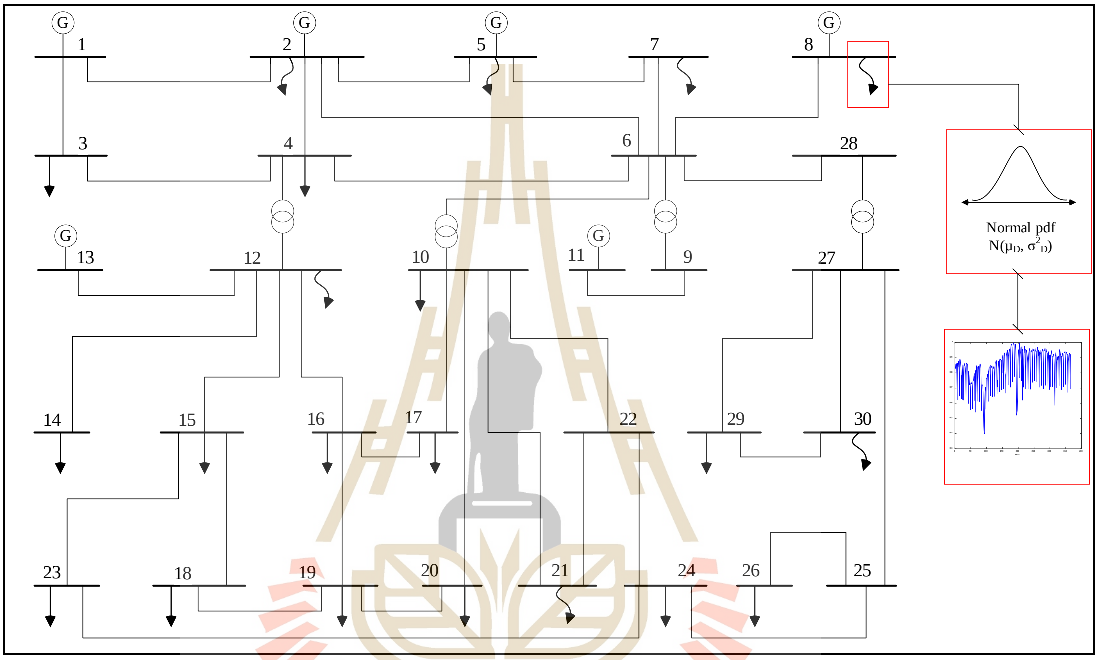

Figure 4.1 Diagram of the Modified IEEE 30-bus Test System.

4.2.1 Generators' Operating Costs using Piecewise Linear Cost Function

The piecewise linear cost function for every generator is provided in Table 4.1. The generators' operating costs for each generator are provided and linearized incremental cost curve for each segment of P_{Gi} as shown in Figure 3.3.

Some crucial data for the simulation is provided in Table 4.2 including P_{DRi} assuming the costs and quantities. With the piecewise linear staircase cost function, the real power generation of the individual segment is dispatched in merit order until reaching the P_{Gi}^{max} maximum real power generation.

Table 4.1 Generators' Operating Costs for Each Generator

Bus No.	Incremental From (MW)	Incremental To (MW)	Piecewise Linear Incremental Cost ($/MWHr)	P_G^{min} (MW)	P_G^{max} (MW)
1	50	71	4.540	50	200
	71	92	5.150		
	92	110	5.600		
	110	128	6.150		
	128	146	6.860		
	146	164	7.150		
	164	182	8.120		
	182	200	8.850		
2	20	40	5.050	20	180
	40	60	5.550		
	60	80	6.100		
	80	100	8.150		
	100	120	9.000		
	120	140	10.15		
	140	160	11.00		
	160	180	11.85		
5	15	31.9	4.050	15	150
	31.9	48.8	4.240		
	48.8	65.65	4.490		
	65.65	82.5	5.150		
	82.5	99.4	5.850		
	99.4	116.3	6.500		
	116.3	133.15	7.200		
	133.15	150	8.850		
8	10	25.6	4.750	10	135
	25.6	41.2	5.650		
	41.2	56.85	5.870		
	56.85	72.5	6.650		
	72.5	88.15	7.410		
	88.15	103.8	8.150		
	103.8	119.4	8.970		
	119.4	135	9.350		

Table 4.1 Generators' Operating Costs for Each Generator (Continued)

Bus No.	Incremental From (MW)	Incremental To (MW)	Piecewise Linear Incremental Cost ($/MWHr)	P_G^{min} (MW)	P_G^{max} (MW)
11	10	25	3.670	10	130
	25	40	4.350		
	40	55	5.670		
	55	70	6.050		
	70	85	6.670		
	85	100	7.170		
	100	115	7.970		
	115	130	8.950		
13	12	28	3.100	12	140
	28	44	5.350		
	44	60	5.450		
	60	76	6.000		
	76	92	7.600		
	92	108	8.150		
	108	124	9.200		
	124	140	10.50		

Table 4.2 Power Demand for the Modified 30-bus Test System

Bus No.	Power demand (MW)		Sizing of P_{DR}: P_{DR}^{min} (MW)	P_{DR}^{max} (MW)	($/MW)
2	$P_{D_2}^{*}$	$\tilde{P}_{D_2} - P_{DR_2}^{**}$	0	$\tilde{P}_{D_2} - P_{D_2}^{*}$	2.27
5	$P_{D_5}^{*}$	$\tilde{P}_{D_5} - P_{DR_5}^{**}$	0	$\tilde{P}_{D_5} - P_{D_5}^{*}$	3.22
7	$P_{D_7}^{*}$	$\tilde{P}_{D_7} - P_{DR_7}^{**}$	0	$\tilde{P}_{D_7} - P_{D_7}^{*}$	2.01
8	$P_{D_8}^{*}$	$\tilde{P}_{D_8} - P_{DR_8}^{**}$	0	$\tilde{P}_{D_8} - P_{D_8}^{*}$	2.51
12	$P_{D_{12}}^{*}$	$\tilde{P}_{D_{12}} - P_{DR12}^{**}$	0	$\tilde{P}_{D_{12}} - P_{D_{12}}^{*}$	2.12
21	$P_{D_{21}}^{*}$	$\tilde{P}_{D_{21}} - P_{DR21}^{**}$	0	$\tilde{P}_{D_{21}} - P_{D_{21}}^{*}$	1.78
30	$P_{D_{30}}^{*}$	$\tilde{P}_{D_{30}} - P_{DR30}^{**}$	0	$\tilde{P}_{D_{30}} - P_{D_{30}}^{*}$	2.15

**The power demand-based from the standard IEEE 30-bus test system.*

***The size of PRDR* $\boldsymbol{P_{DR}}$ *from LP optimization.*

Along with each generator data, the power demand data for the modified 30-bus test system are improved to adapt to the proposed framework. There are some required data to assume for the necessary parameters in order to simulate in this experimentation. The PRDRs are regulated on the load bus 2, 5, 7, 8, 12, 21, and 30 which ranged from 10.6 MW to 94.2 MW assuming to be the dispatchable aggregator loads. In comparing to the fixed price, consumers have participated in the PRDR program by decreasing their energy usage ranged by 11% to 21% in the whole year. Evidently, a reference (Wang, J., Biviji, M.A., and Wang, W.M., 2011) is represented by the average 12% of participants have saved their annual consumption pattern. In this work, the reactive power generating cost is not included in the result.

In the meantime, the 24-hour loading condition as shown in Figure 4.2 (Chayakulkheeree, K., 2015) is used to test the proposed algorithm and the annual data for every single hour are fitted into normal PDF to get the required data for sampling in the simulation as shown in Table 4.3. Based on the LP linear cost function, the limit constraint as mentioned in Equation (3.11) is applied to guarantee the well-balanced power generation equivalent to the power demand. Another thing to be taken into this approach is to assign the number of segments, which affects the dispatch solutions from LPOPD. As shown in Table 4.1, the generators' operating costs for each generator is provided with eight segments for each cost function to observe very close solutions to the target outputs in verifying with the lambda iteration method (Wood, A.J., Wollenberg, B.F., and Sheblé, G.B., 2014) and the Dommel-Tinney method (Alsac, O. and Stott, B., 1974).

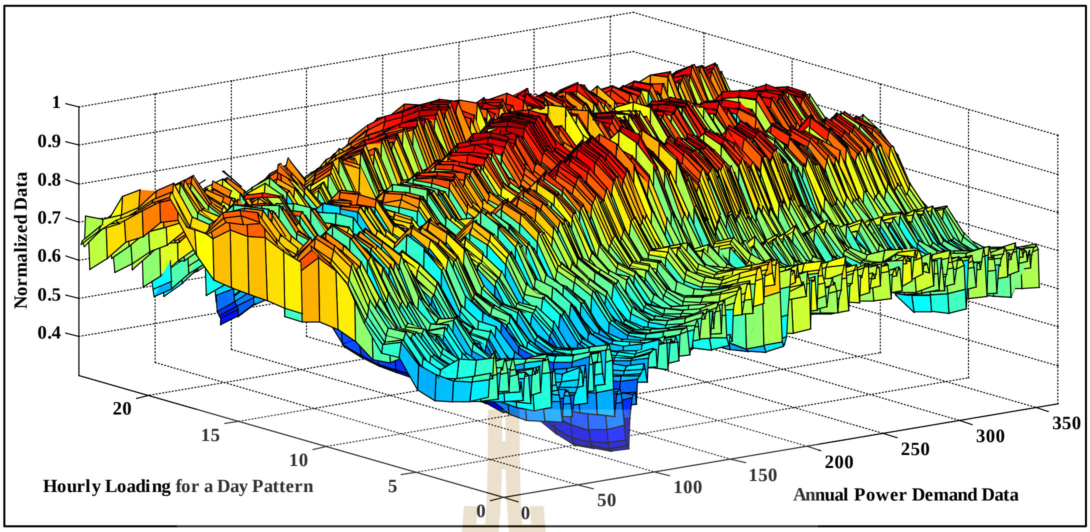

Figure 4.2 24-hour Loading Data from Annual Power Demand Record.

4.2.2 Probabilistic and Practical Loading Pattern

For this simulation, the practical loading patterns using parameters μ_D and σ_D are selected to use as power demand data patterns as shown in Figure 4.2 by transforming into the normal PDF and the PTNF.

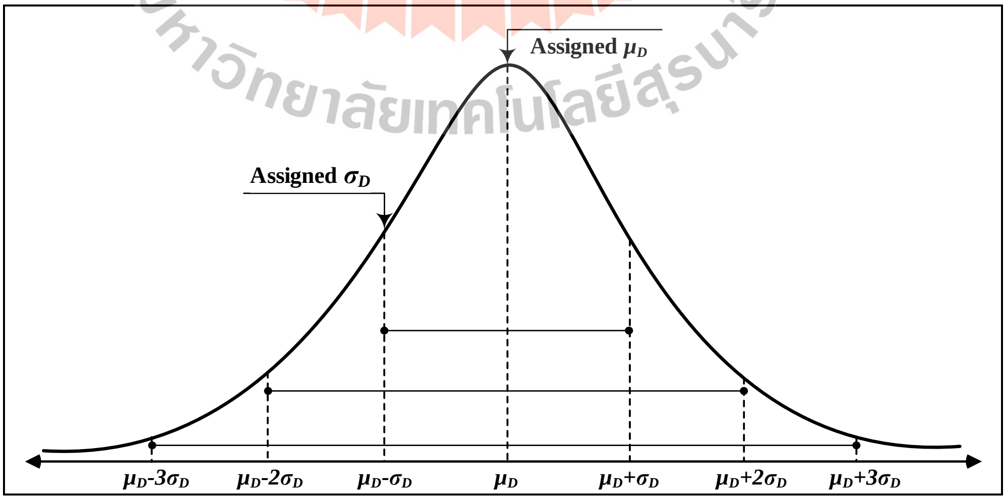

Figure 4.3 Parameters μ_D and σ_D for Power Demand Forecasting Pattern.

Consistently, the normalized annual data (Chayakulkheeree, K., 2013) has selected as a reference, while μ_D is taken from the peak loading day on 4th April 2010 and σ_D is assumed to be 5% of μ_D. After that, the parameters μ_D and σ_D will be obtained for use in the sampling conditions in Section 3.8.3 and exampled in Figure 4.3 and the required data are shown in Table 4.3.

Table 4.3 Parameters for Sampling Data

Hour	Parameters		Case 1: $\mu_D \pm \sigma_D$		Case 2: $\mu_D \pm 2\sigma_D$		Case 3: $\mu_D \pm 3\sigma_D$	
	μ_D	σ_D	*a*	*b*	*a*	*b*	*a*	*b*
1	0,7728	0,0386	0,7342	0,8114	0,6955	0,8501	0,6569	0,8887
2	0,7485	0,0374	0,7111	0,7859	0,6737	0,8234	0,6362	0,8608
3	0,731	0,0366	0,6945	0,7676	0,6579	0,8041	0,6214	0,8407
4	0,7064	0,0353	0,6711	0,7417	0,6358	0,7770	0,6004	0,8124
5	0,708	0,0354	0,6726	0,7434	0,6372	0,7788	0,6018	0,8142
6	0,7507	0,0375	0,7132	0,7882	0,6756	0,8258	0,6381	0,8633
7	0,7328	0,0366	0,6962	0,7694	0,6595	0,8061	0,6229	0,8427
8	0,7849	0,0392	0,7457	0,8241	0,7064	0,8634	0,6672	0,9026
9	0,9197	0,0460	0,8737	0,9657	0,8277	1,0117	0,7817	1,0577
10	0,9549	0,0477	0,9072	1,0026	0,8594	1,0504	0,8117	1,0981
11	0,9788	0,0489	0,9299	1,0277	0,8809	1,0767	0,8320	1,1256
12	0,9147	0,0457	0,8690	0,9604	0,8232	1,0062	0,7775	1,0519
13	0,9389	0,0469	0,8920	0,9858	0,8450	1,0328	0,7981	1,0797
14	1,0000	0,0500	0,9500	1,0500	0,9000	1,1000	0,8500	1,1500
15	0,9877	0,0494	0,9383	1,0371	0,8889	1,0865	0,8395	1,1359
16	0,9713	0,0486	0,9227	1,0199	0,8742	1,0684	0,8256	1,1170
17	0,898	0,0449	0,8531	0,9429	0,8082	0,9878	0,7633	1,0327

Table 4.3 Parameters for Sampling Data (Continued)

Hour	Parameters		Case 1: $\mu_D \pm \sigma_D$		Case 2: $\mu_D \pm 2\sigma_D$		Case 3: $\mu_D \pm 3\sigma_D$	
	μ_D	σ_D	*a*	*b*	*a*	*b*	*a*	*b*
18	0,8562	0,0428	0,8134	0,8990	0,7706	0,9418	0,7278	0,9846
19	0,9615	0,0481	0,9134	1,0096	0,8654	1,0577	0,8173	1,1057
20	0,9485	0,0474	0,9011	0,9959	0,8537	1,0434	0,8062	1,0908
21	0,9237	0,0462	0,8775	0,9699	0,8313	1,0161	0,7851	1,0623
22	0,8931	0,0447	0,8484	0,9378	0,8038	0,9824	0,7591	1,0271
23	0,8614	0,0431	0,8183	0,9045	0,7753	0,9475	0,7322	0,9906
24	0,8163	0,0408	0,7755	0,8571	0,7347	0,8979	0,6939	0,9387

4.3 Simulation Results

Regarding the results from Monte Carlo simulation with normal PDF and PTNF, the probabilistic investigation figures are intended that the output from the proposed method is demonstrated the convergence significantly. Even though, in the beginning, it seems a little bit worth divergence from the spot solution, it came out after some iterations. It is noticed that the yield is hereby indicated the active power demand, which is functioning to the total operating cost. On the one hand, PRDR will be instanced dependability in this study due to the contract in the DR program. In contrast, the reactive power generation and system losses are not considered in this framework. Still, it is certainly simplified the effectiveness of the proposed context. The dispatch results for day-ahead will be shown in Table 4.4 which will compare to some relevant methods respectively in Table 4.6.

4.3.1 Investigation Results of LPOPD with Normal PDF Sampling

The proposed framework was performed by POPD computational procedure with simulation 2000 runs. Figure 4.4 illustrates the MCS of the experimental studies, which represents the outputs of total operating cost from POPD simulation convergence with normal PDF. Besides, the simulation results were congregated in different trial point, in the same manner, there is the evidence to verify the simulations have converged magnificently with an hourly dispatch for day-ahead scheduling without applying PTNF.

As shown below figure, the outputs from POPD simulations using simple MCS computational framework are shown the good convergent solutions as well as many other references indicated in Section 2.5.3, the system loading was randomized by normal PDF to represent the uncertainties. In this case, the infeasible results are always getting along with the feasible results during the simulations due to the nature of normal PDF modelled in Section 2.8.2. This would cause a problem in the MCS simulations and lead to stop the program with divergent results. Anyway, it does not mean that this negative point will happen in every application, but it actually exists in the experimental process. In order to avoid the drawback in this thesis, the probabilistic technique and sampling conditions in Section 3.8 are implemented in the numerical computation.

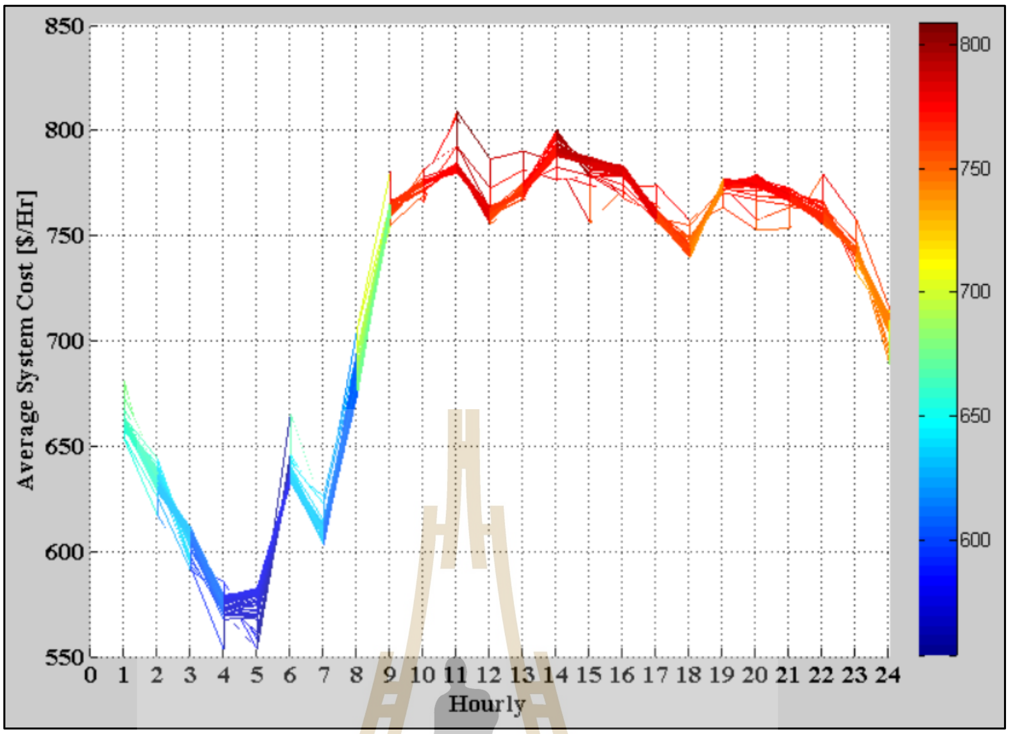

Figure 4.4 Convergence of MCS from Normal PDF for Day-ahead Loading.

The pattern of total system cost with and without DR program is shown in Figure 4.5 when the system loading represented by normal PDF sampling methods. Moreover, the proposed LPOPD framework is really dispatched with the probabilistic technique, the peak load point at 14:00 in Figure 4.5 is selected to inspect and evaluate with normal and PTNF sampling methods to check the simulation convergence. Anyways, the PTNF simulation results have provided in Section 4.3.2. It is simulated based on the modest MCS process and next section would indicate the better accuracy when PTNF is applied to the LPOPD procedure over this normal sampling method. The evidence for these entitlements is the convergent investigation from MCS simulation outputs in Figure 4.4 and Figure 4.6–4.8.

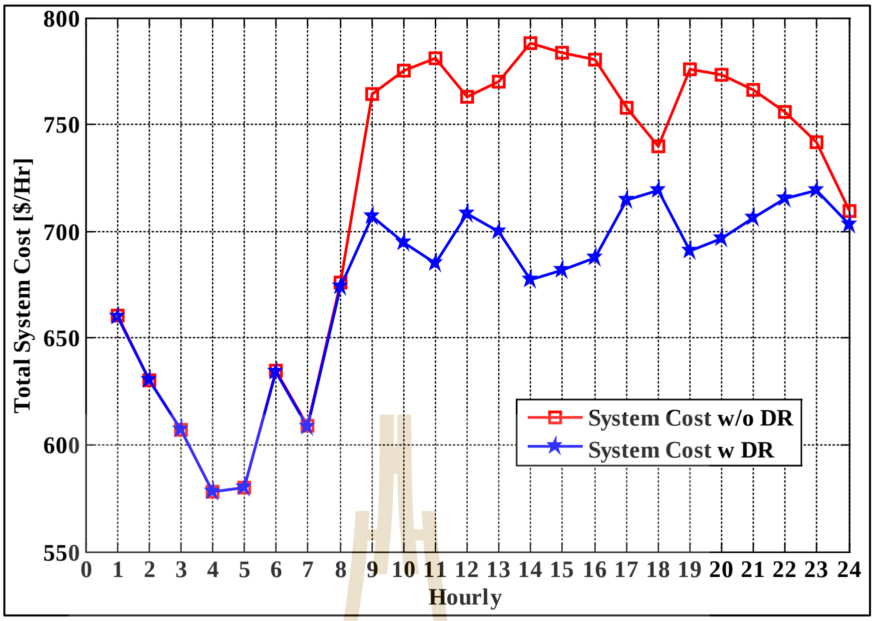

Figure 4.5 Total System Cost with and without DR when Load Uncertainties represented by Normal Sampling Methods.

4.3.2 Investigation Results of LPOPD with PTNF Sampling

Concerning the drawback of normal PDF sampling methods as mention in Section 4.3.1, the proposed framework in Figure 3.5 is developed with important PTNF sampling methods. It is used to ensure the convergent of MCS would come faster than simple MCS simulation and improve the precision of the computation when there is a kind of load uncertainties in the power system.

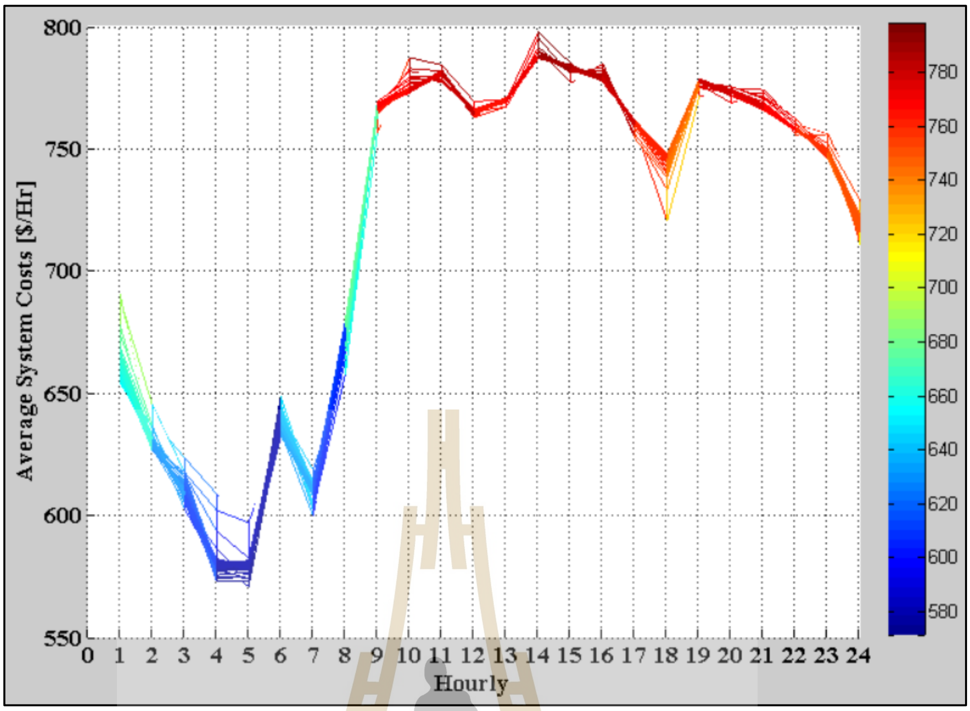

Figure 4.6 PTNF Output with Case 1 for Day-ahead Loading.

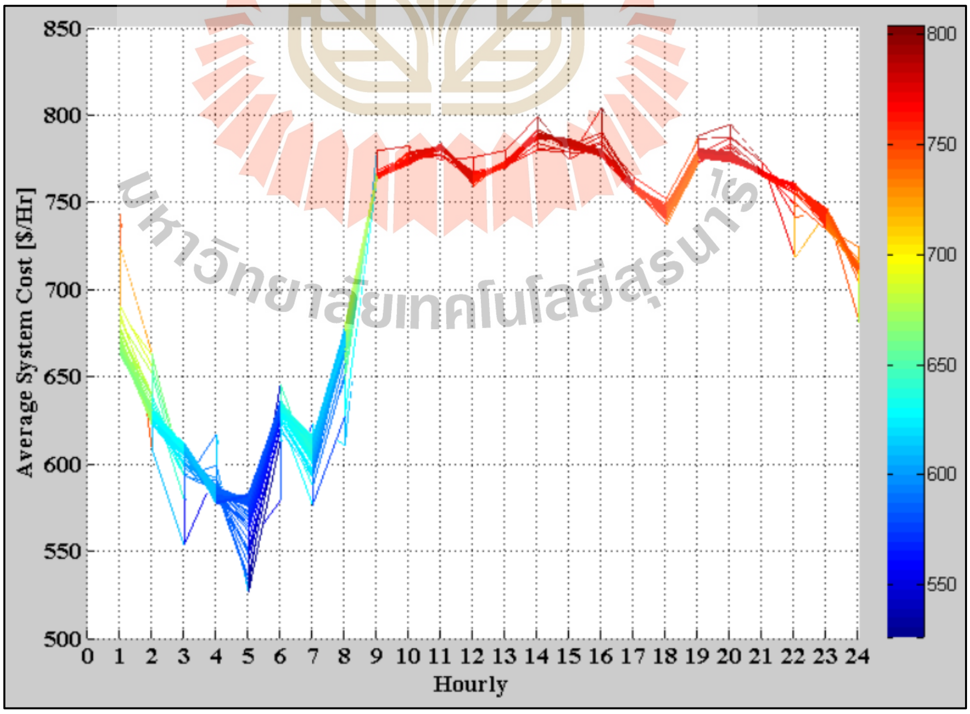

Figure 4.7 PTNF Output with Case 2 for Day-ahead Loading.

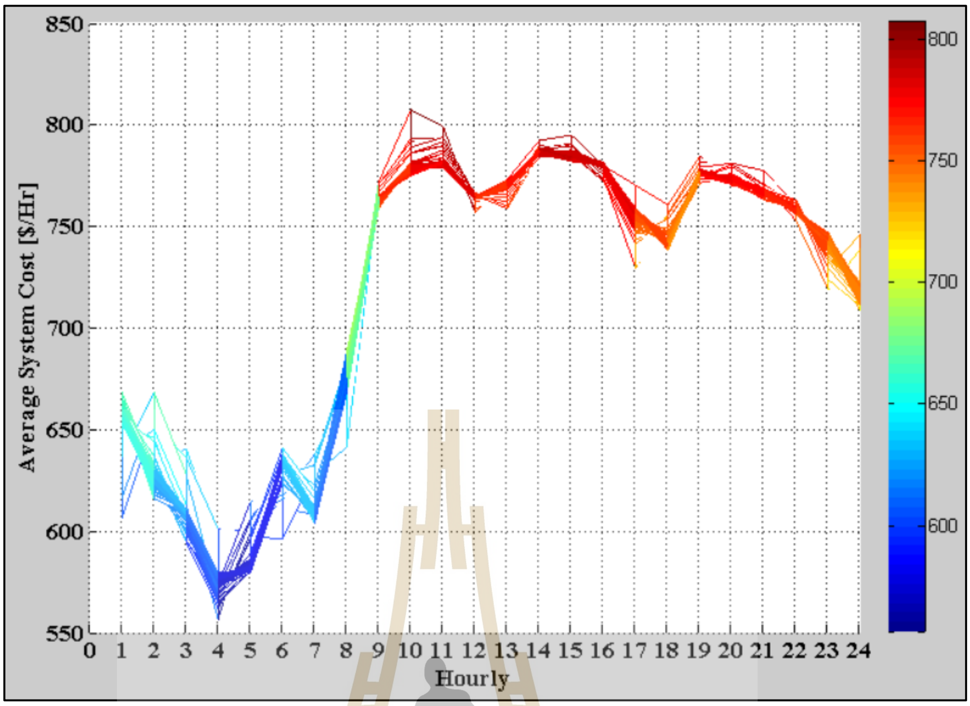

Figure 4.8 PTNF Output with Case 3 for Day-ahead Loading.

For the meantime, the proposed framework was still performed by POPD computational procedure with simulation 2000 runs. Figure 4.6–4.8 illustrate the MCS convergence of the experimental studies, which represents the outputs of the total operating cost from POPD simulation convergence with PTNF sampling methods. Moreover, the pattern of the total system cost with and without DR program is shown in Figure 4.9 when the system loading represented by PTNF sampling rules in order to confirm the practicality of the proposed setting. It is exposed that the proposed methods could offer the dispatch results as shown in Figure 4.5 and Figure 4.9 and it provided the neglected error less than one percent because of the output data were provided with an average value during the simulations. Furthermore, to explain that the proposed LPOPD framework is positively dispatched with the probabilistic technique and sampling conditions, the peak load point at 14:00 in Figure 4.10 is selected to inspect and evaluate with normal in Figure 4.5 and PTNF sampling methods to check the simulation convergence.

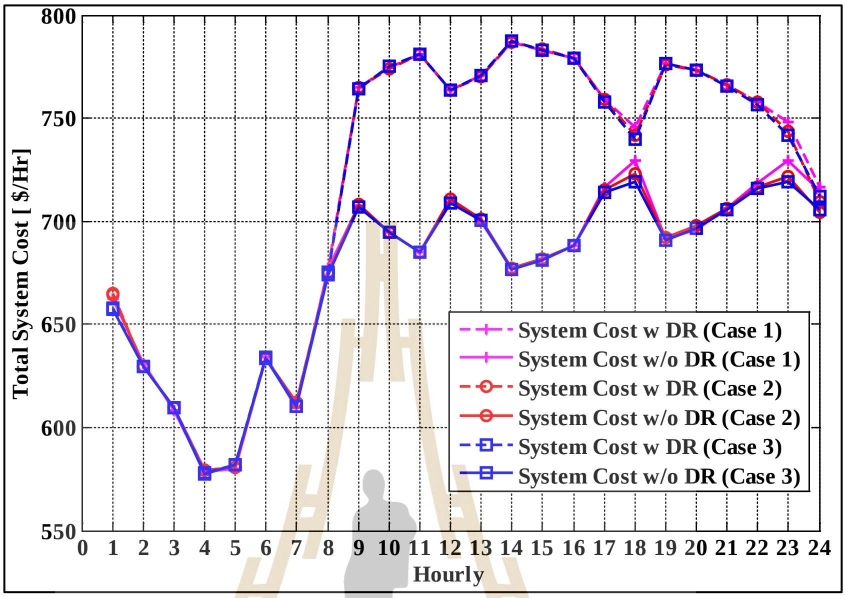

Figure 4.9 Total System Cost with and without DR when Load Uncertainties represented by PTNF Sampling Methods.

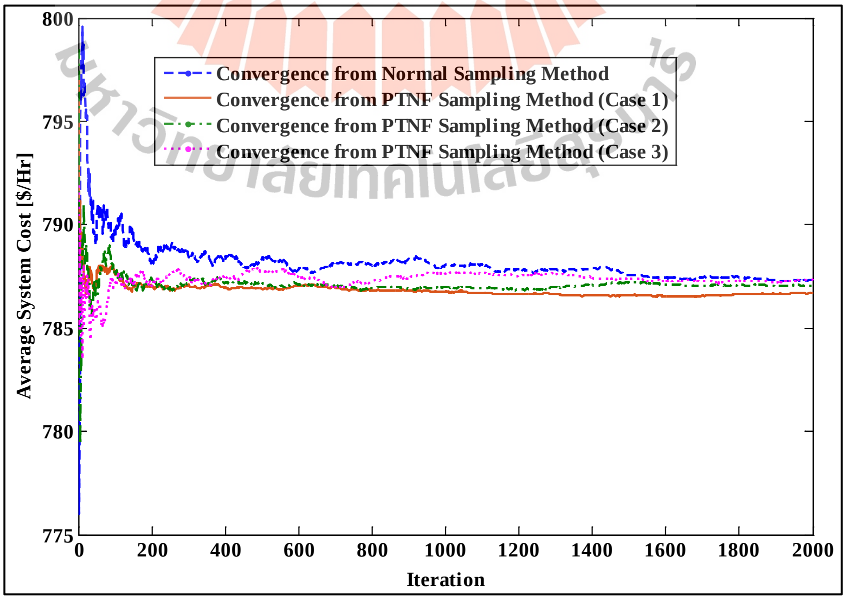

Figure 4.10 Convergence Investigation with and without PTNF Sampling Methods.

From the results represented in the above figure, normal PDF sampling variables with the computational framework processed at least 1540 trials to meet the convergent solution. Involvement in this study, it was enhanced after applying the empirical rule mentioned in Section 3.8.3. They are complicated in the computational procedure by refining to give the convergent solutions at least 411 trials within one standard deviation (Case 1) and at least 817 trials within two standard deviations (Case 2). Otherwise, within three standard deviations (Case 3), the convergence has met at least 1406 trials parallel to the case of normal PDF sampling methods. However, it was cleared that the standard deviation value σ_D became extensive then the measurement would be moderately inaccurate just like the theorist intended the idea (Wood, A.J., Wollenberg, B.F., and Sheblé, G.B., 2014; Burkardt, J., 2014; Mazzeo, D., Oliveti, G., and Labonia, E., 2018). It could be converged at least 1540 trials or more with the random numbers from the normal PDF random variables in the framework as shown in Figure 3.5 whereas it has the opportunity to get the faster convergent solutions at 411 trials. Meanwhile, the solutions were obtained with slightly errors of mean value between before and after applying the probabilistic model to the system simulation. It is because of the characteristics of simulation methods. In the same way, other developers (Krenek, R., Cha, J., and Cho, B.R., 2016) of the convolutions of PTNF random variables were successfully implemented with similar these sampling conditions in order to lead a better conceptualized with PTNF to represent the uncertainties in their framework and approximation production processes. Consistently, these important sampling methods were efficiently modelled based on simple MCS process (Ni, F., Nguyen, P.H., Cobben, J.F.G., and Tang, J., 2016). Anyway, this work was faced with several challenges and caused to an expensive computational effort.

Added advantages over these mentioned references, the proposed frameworks in this thesis lead the dispatch solutions for real power dispatch hour-ahead in participating by DR in the peak periods to keep power balancing in case of the power demand represented as load uncertainties. Especially, this work can provide competently time-consuming by numerical computation processes. Next subsection 4.3.3 provides accumulative dispatch results to confirm the above statements.

4.3.3 Dispatch Results

Apropos of results from MCS simulation with normal PDF and PTNF, the probabilistic investigation in Figure 4.4–4.10 are intended that the output from the proposed method is demonstrated the convergence significantly and handle the objectives very well. Even though it seems a little bit worth divergence from the spot solutions in the beginning, but it can be convergent after some iterations as mentioned detailed in Section 4.3.2. To be noticed that, the yield is hereby indicated the active power demand, which is functioning to the total operating cost. Another thing is PRDR sizing will be compensated depending on the proportion between the aggregated system loadings with forecasting demand-based. Table 4.4 indicates the simulation performance both normal sampling and important PTNF sampling methods for every single hour in a day-ahead competitive market and get a lump sum of 24-hour costs and quantities.

From the simulation results, it presented that the proposed method has fulfilled the objective function as mentioned in Section 1.3 to provide the dispatch solutions. To confirm the base case study of OPF, the computational procedure is successfully publicized in reference (Chhor, U., Leeton, U., and Chayakulkheeree, 2019). It has compatibly verified with reference (Alsac, O. and Stott, B., 1974) for OPF steady-state security solved by non-linear optimization and it is certainly made clear that the proposed LPOPD is successfully dispatched with a neglected slop error due to the nature of the piecewise linear optimization model. In Table 4.4, the POPD is run with normal PDF random variation input as loading uncertainties at the specified bus as shown in Table 4.2, which the size of P_{DR} was also enhanced from LP optimization to participate in the system and then it properly determined the total system operating cost dispatch 17,200 \$/day. After that, the PRDR is still directed on the system planning for aggregate loads.

Table 4.4 Dispatch Results for Day-ahead

Variable	Base Case	OPD w/o DR	POPD *N (μ, σ)*	POPD with PTNF *Case 1*	POPD with PTNF *Case 2*	POPD with PTNF *Case 3*
Total Generation [MWhr, MVARhr]	[7,885.6 ; 2002,7]	[7,885.2 ; 2,006.4]	[6,949 ; 1,980]	[6,950.8 ; 1,980.7]	[6,949.5 ; 1,980.9]	[6,949.3 ; 1,980.8]
Total P-Q Load [MWhr, MVARhr]	[7,806.2 ; 3,028.8]	[7,806 ; 3,028.8]	[6,876.5 ; 3,028.8]	[6,877.8 ; 3,028.8]	[6,876.2 ; 3,028.8]	[6,876 ; 3,028.8]
Total DR Size [MWhr]	–	–	[385.4]	[377.4]	[380.5]	[385]
Total Syst. Losses [MWhr, MVARhr]	[79.44 ; -412.32]	[78.96 ; -412.08]	[72.5 ; -438.77]	[73 ; -438.07]	[73.3 ; -437.81]	[73.3 ; -437.92]
Total Gen. Cost (\$/day)	18,996	17,739	16,178	16,228	16,206	16,181
Total DR Cost (\$/day)	–	–	1,022.6	1,001.6	1,009.7	1,022.6
Total Syst. Cost (\$/day)	18,996	17,739	17,200	17,229	17,216	17,204

Moreover, the rules of PTNF has applied to the LPOPD procedure then the total operating cost becomes much better. In probabilistic approach contained within sampling conditions, the total system operating cost is dispatched to 17,229 $/day when POPD with PTNF was applied to case 1 simulation. It continued to carry out the total dispatch operating cost at 17,216 $/day by case 2 simulation. Meanwhile, it is equally dispatched to 17,204 $/day by case 3 simulation. To be notified that there must be some clearance payments for PRDR customers as specified in Table 4.4 due to the PRDR contracts between customers and SO in this prospectus.

4.4 Discussion

According to Table 4.6 indicates the achievement of the proposed method comparing to other recently proposed methods. The probabilistic technique and sampling conditions in Section 3.8 play an imperative role in the computational process by producing only feasible solutions during the simulations and lead the results to the dispatch solutions as well as extra reliable and less time-consuming. The results are significantly achieved the good performance by applying PTNF in the computational framework. Without PTNF, the feasible load of PDF modelling cannot be established efficiently.

From an economic point of view, the total investment cost of the system for day-ahead, the proposed method is observably offered cheap system operating cost dispatch. It had total system cost of approximately 17,200 $/day less than the amount of 19,314 $/day by PEM (Shargh, S., Khorshid ghazani, B., Mohammadi-ivatloo, B., Seyedi, H., and Abapour, M., 2016). Regarding the proposed method, the approximate system cost in both normal PDF and PTNF sampling methods is satisfactory to confirm the effectiveness of the proposed framework. A set of evidence previously presented the convergence of the simulations in Section 4.3 and illustrated in Figure 4.4 and Figure 4.6–4.8.

Regarding the simulation method implemented in this work by MCS technique, the random number generator for power demand forecasting would be aimlessly due to a different sequence of numbers after each time and it produced different expected power demand. This led the convergence would come out with a different point. For the meantime, the investigation for 20-trial is made to ensure the certainty of convergent iteration at the peak load of the day at 14:00. Then these 20 data simulations of convergence are fitted with normal PDF in order to prompt the average number of convergent iterations as shown in Figure 4.11 and Table 4.5 indicated the number of iteration for convergence with standard deviation σ respectively. Furthermore, all figures for the convergence of each case study represented in Appendix I.

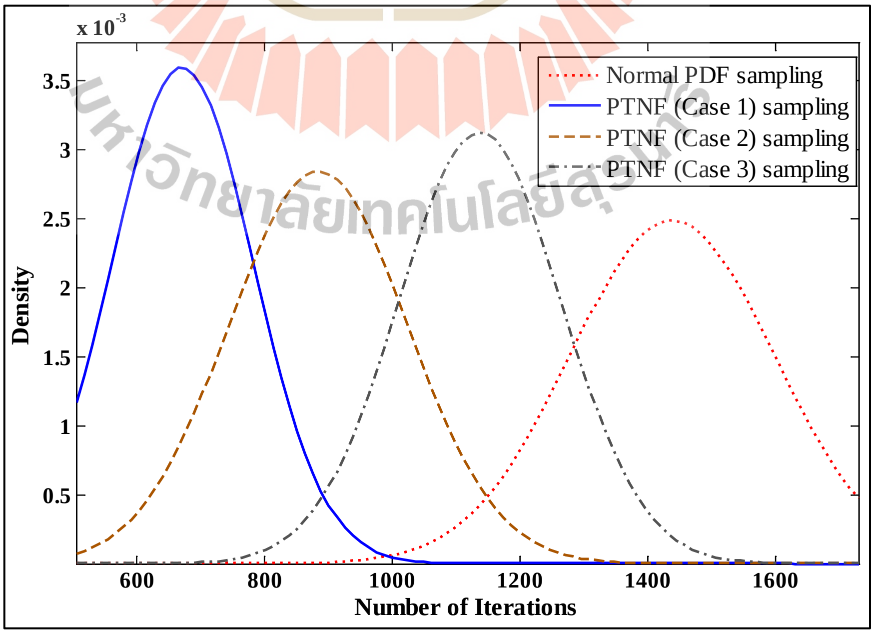

Figure 4.11 20-Data Simulation of Convergence are fitted with Normal Distribution.

Table 4.5 Number of Iteration for Convergence at 14:00 with 20 Trials

Sampling Variable	Number of Iteration			Standard Deviation (σ)
	Minimum	Average	Maximum	
Normal PDF	1229	1438.15	1718	160.36
PTNF (Case 1)	516	670.6	953	110.922
PTNF (Case 2)	668	883.6	1175	140.262
PTNF (Case 3)	942	1136.85	1387	127.679

Table 4.6 Data Comparison with Related Case Study

Sampling Variable	Average of Iteration	Total System Cost [$/day]
Normal PDF	1438	17,200
PTNF (Case 1)	671	17,229
PTNF (Case 2)	884	17,216
PTNF (Case 3)	1137	17,204

To conclude, the proposed PTNF framework could provide the results with high accurateness of convergence not only comparing to the normal PDF sampling methods but also it could improve the computation time and offer the better performance within the feasible solution region of the simulations. Furthermore, the conclusion and recommendation are provided in the next chapter.

4.5 Chapter Summary

Responding to Chapter I-III above, this chapter IV has applied the research methodology and problem formulation and lead to the prospective results. The necessary data such as generators' operating costs to participate in problem formulation is provided and probabilistic loading is also attached along in Section 4.2. As a result of simulations, the investigations with its statement have provided in Section 4.3 with normal PDF and PTNF sampling methods. Hence, the results are expressed to inspect the dispatch outcomes in Table 4.4 and relevant competitive methods in Table 4.6. The POPD computational procedure with simulation 2000 runs has illustrated the convergence as well since earlier iteration stated clearly in Section 4.3.1-4.3.2 on how PTNF sampling methods claimed its advantages over normal PDF and lead the results to the dispatch solutions as well as more reliable and cheap computational time. From Table 4.5 and Table 4.6, it is shown the average number of iterations: 1438 iterations from normal PDF simulation, 671 iterations from PTNF (Case 1) simulation, 884 iterations from PTNF (Case 2) simulation, and 1137 iterations from PTNF (Case 3) simulation. Accordingly, simulations could recommend that the results with high accuracy and exactness of convergence, it should advance considerably with these numbers of iterations as well. To end, this chapter is replied to the problem statement due to the objective function was intensely solved by the proposed framework.

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, the POPD based on LP is proposed to dispatch the power generations complemented by PRDR to minimize total operating cost. The objective function is to moderate the total system cost while compensating between the high peaking cost power generations and PRDR offered. In the same way, the predictable load uncertainties at the demand side are represented by the normal PDF with PTNF sampling methods as input variations in the framework of the MCS procedure. Therefore, the proposed method can effectively and efficiently curtail the total power generation cost, while the PRDR is a trade-off between the benefits of the SO and electricity users in the energy market. As a result, the proposed method enhances the benefits not only the SO but also the consumers, though they are able to claim their paybacks by participating in PRDR contracts. The only thing to do is to rearrange their consumptions during the peak periods or time-ahead from SO's request or contract and there are some possible solutions recommended in Section 5.2. As a final point, it is substantiated that the proposed method can potentially be used to deal with the future electricity supply market. It is definitely replied to the study objectives mentioned in Section 1.3,

i. Overall incremental production cost reduced by LPOPD participated by PRDR in peak periods for day-ahead,

ii. SO and demand side co-optimized and claimed individual benefits in the energy market,

iii. Rational DR prices promoted to clients by technological development,

iv. Elasticity of demand in hour-ahead and day-ahead forecasted and enhanced the advantages by important PTNF sampling methods, and

v. Hourly dispatch achieved in a competitive market.

5.2 Recommendation

Exploring the effectiveness of the proposed method basis, POPD simulation considering DR strategy has experimented with the curtailable aggregate loading pattern. Addition to this conception, the compulsory contract between the SO and PRDR customers would set up in the proper conditions as well. Furthermore, the emerging perception of MCS technique in Figure 3.5 shall be developed into a higher level of simulation approach and proposed an index to limit the number of trials in order to reduce very time-consuming. Another significant aspect of PRDR management, the load buses 2, 5, 7, 8, 12, 21, and 30 were presumed to be the aggregate loads with the proposed criteria. The next steps for electricity demand response (Eid, C., Koliou, E., Valles, M., Renese, J., and Hakvoort, R., 2016) is to engage additional roles for the grid and incorporate many customer technologies (The Future of Electricity, 2017) for bidirectional energy trading concept in order to enhance the system security (Shoreh, M.H., Siano, P., Shafie-khah, M., Loia, V., and Catalão, J.P.S., 2016) and participation of consumers.

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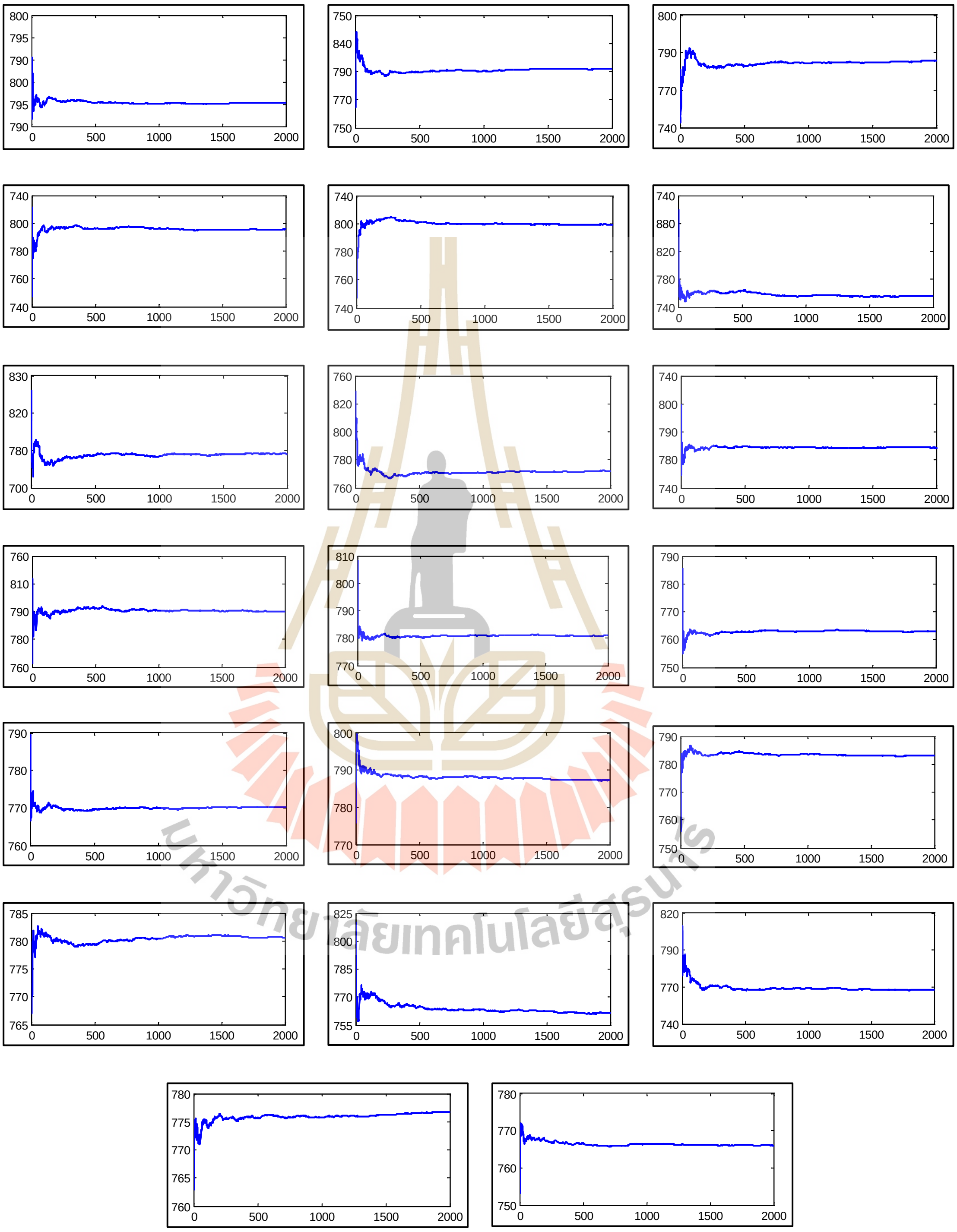
APPENDIX I

Data Convergence for Each Case Study

- Investigation for 20-trial convergence from normal PDF simulations,



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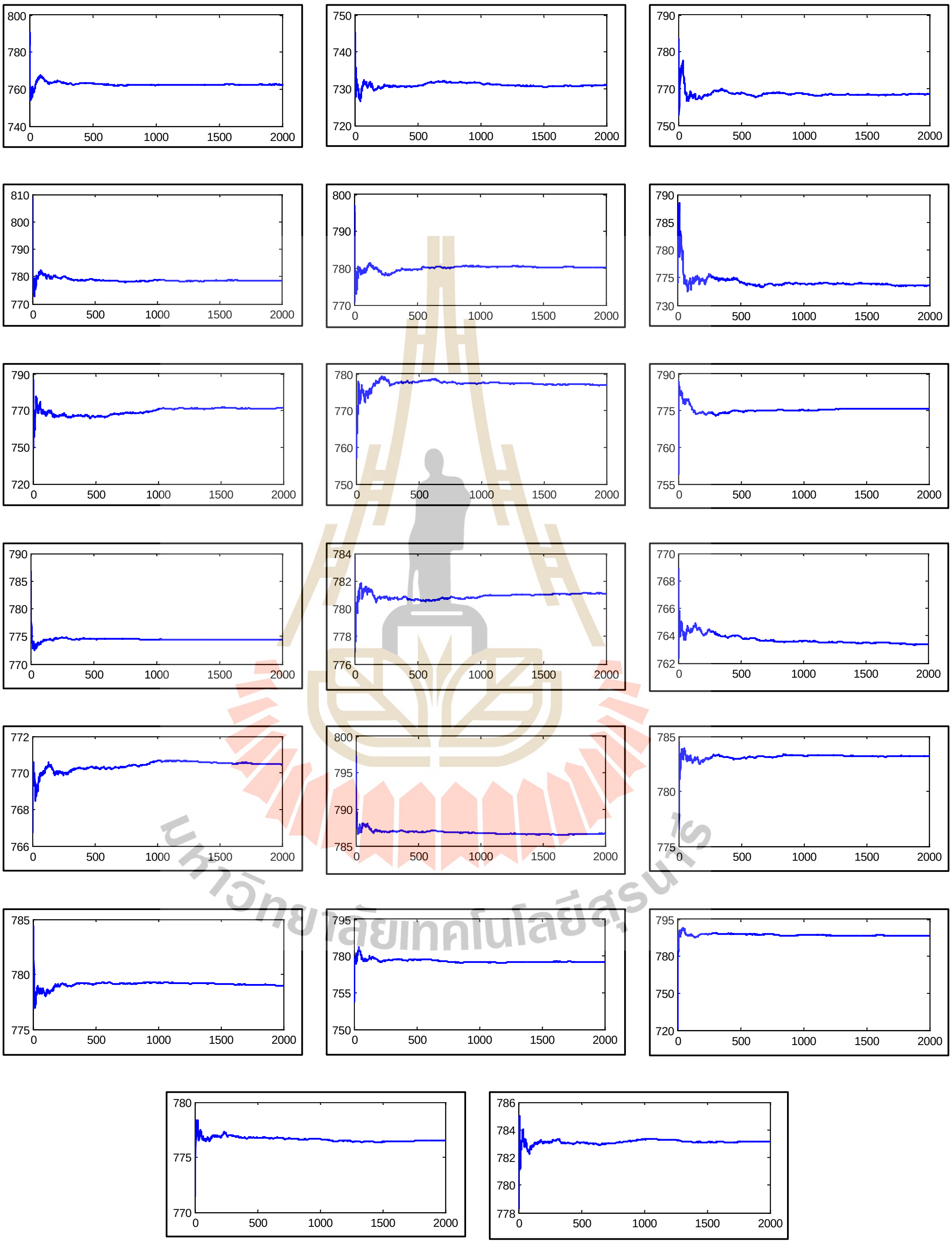

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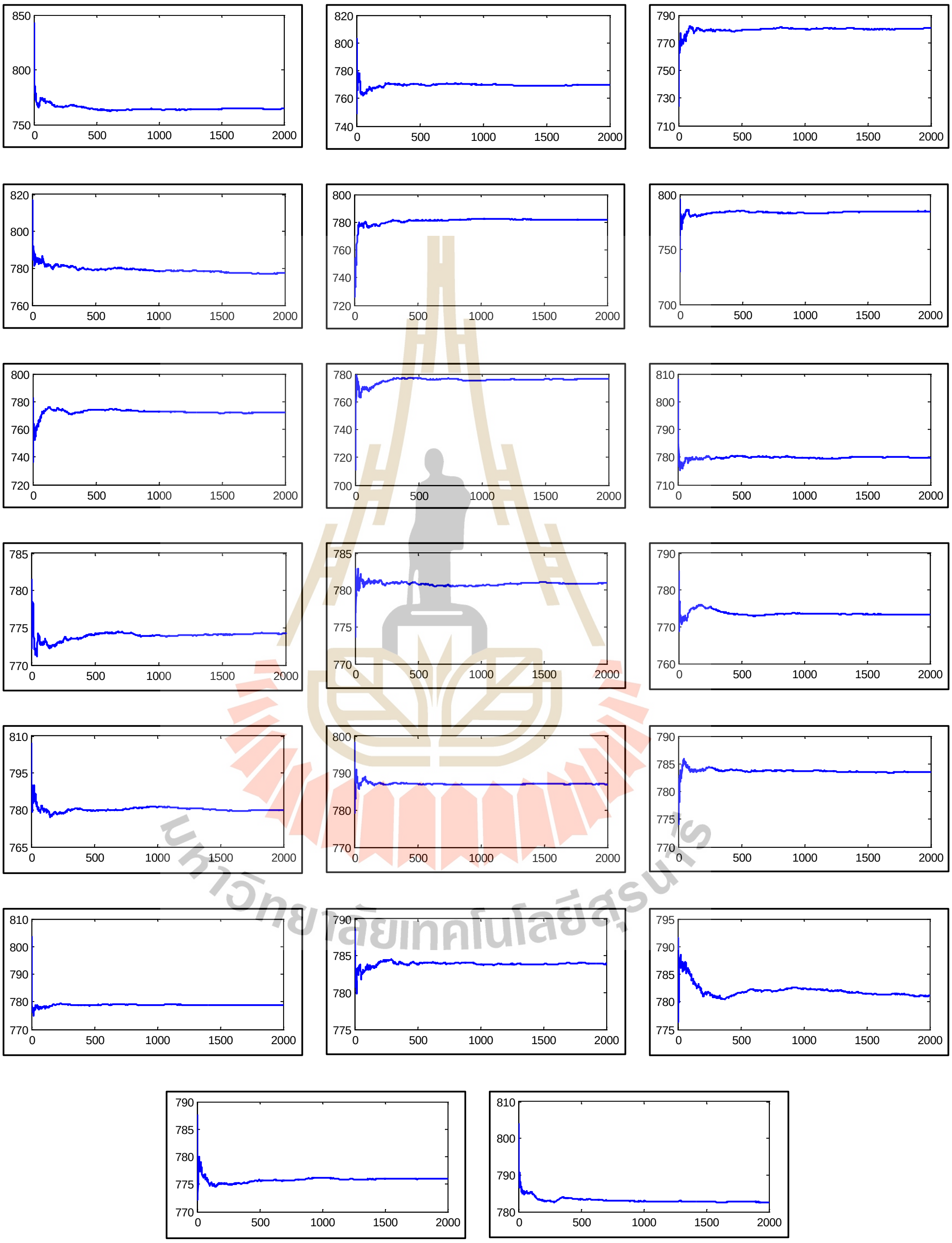
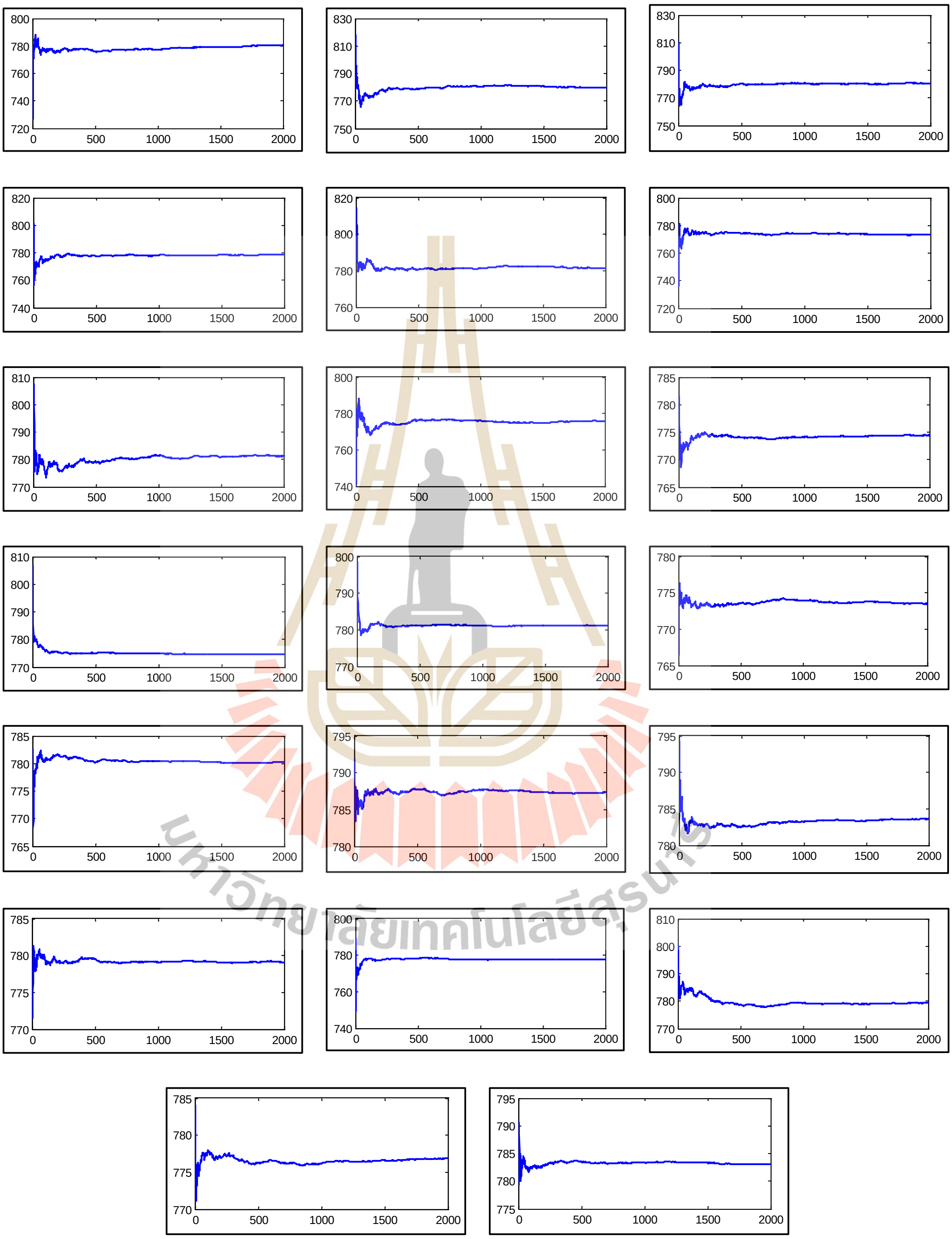


- Investigation for 20-trial convergence from case 3 simulations,



APPENDIX II

List of Publications

List of Publication

Chhor, U., Leeton, U., and Chayakulkheeree, K. (2019). Probabilistic Optimal Power Dispatch Considering Price-based Real-time Demand Response. **International Journal of Intelligent Engineering and Systems**, 12(1), 201-210.

Chhor, U. and Chayakulkheeree, K. (2018). Optimal Power Flow Considering Price-based Real-time Demand Response. **The 41st Electrical Engineering Conference (EECON-41)**, PW20, 89-92.

Chhor, U., Chayakulkheeree, K., Kulworawanichpong, T., and Leeton, U. (2018). A Probabilistic Load Flow Framework for Investigation of Traction Substation Load Impact to Distribution System. **International Conference on Transportation and Electric Railway, IEE Japan**, 18(18), 73-76.

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Probabilistic Optimal Power Dispatch Considering Price-Based Real-Time Demand Response

Udoum Chhor[1] **Uthen Leeton**[1] **Keerati Chayakulkheeree**[1]*

[1]*School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Thailand*
* Corresponding author's Email: keerati.ch@sut.ac.th

Abstract: In this paper, a probabilistic optimal power dispatch (POPD) using linear programming (LP) is proposed for solving the power generation dispatch with price-based real-time demand response (PRDR). The expected short-term load forecast is represented by a probabilistic distribution function. The simulation result has prosperously shown that the proposed method could handle the POPD solutions for real power dispatch considering PRDR by using probabilistic Truncated normal distribution function (PTNF). The PTNF is used in a vigorous part of the framework to eject the infeasible results during the computation. This would lead the results to the high degree of accuracy comparing to the normal sampling methods. The simulation results showed that the proposed method can efficiently and effectively minimize the total power generation cost while trading off the PRDR cost in the POPD problem with load uncertainty.

Keywords: Probabilistic optimal power dispatch, probability density function, linear programming, demand response.

1. Introduction

In the power grid, the electric utilities need to balance the power generation and load considering economic operation considering grid reliability and quality of supply. Therefore, optimal power dispatch (OPD) techniques for possible future power system operation are steadily proposed with various optimization techniques.

Recently, the innovation of computer processor units has produced as a matter of engineering required to solve their problems as fast as possible in real time and online. OPD has become one of the most extensive optimization tools adopted in the power system planning and electricity market. With the above issues, many researchers have endlessly studied optimization techniques to investigate an optimum operation of the power system. Many optimization algorithms have always been mentioned both artificial intelligence and conventional methods to obtain an OPD solution. The linear programming (LP) is one of the most conventional methods which becomes a widely practical method in optimal power system operation. For example, a demand response (DR) strategy based on energy consumption scheduling was modelled by LP to prove the demand minimizing in peak period in [1]. The marker prices are exposed by LP proposed framework equivalent to the marginal cost for the utility in [2]. Similarly, it was used to minimalize the expensive fuel operating cost in extra high voltage in [3]. Another LP proposed algorithm is to minimize the supply cost in power pool auction. In the power pool auction, the hourly bus spot price incorporating the marginal transmission loss and network quality of supply can be regulated [4-5]. LP has the potential to capture optimal adaptive operating costs and provide the optimal dispatch module in both short and long terms optimization problems, such as numerous economic, social, military and real-time problems. In practice, the short-term load forecast for hour-ahead dispatch is usually uncertain in nature. Therefore, the probabilistic model representation for the system loading can be used to deal with uncertainty.

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In trendy power grid, DR programs have been developed and studied in many researches in modern power systems. The purpose of developing DR models is to provide accurate dispatch balance and stability analysis of future grid. DR is a specific program to motivate the end users' response to reduce or rearrange the electricity usage patterns during critical peak time. In developing an approach of the modern power grid, some models of DR have implemented to manage the higher prices during the peak demand in the system to avoid increasing power generation. Meanwhile, consumers have always billed their energy consumption through a tariff depending on the users' demands and had no any economic instructions or reports on how to plan to use or shift the consumption during peak periods. The aims of the evaluation methodology are to prove the peak demand and power consumption in economizing the total operating cost efficiency associated with DR program are extracted in [6]. Real-time Pricing (RTP) is a well-known prospect of DR scheme proposed by the system operator (SO) [7–8]. Aggregated consumers are encouraged to draw attention to reduce their demands accordingly to the required power balance in the system reliability. The DR programs in which price variations of energy over time produce changes at consumers' demand profile. It is necessary to improve the above problems to balance between supply and power demand side. To sum up, there are more details on DR programming and optimization algorithms [9], practical indication and key-elements for global experience [10], demand-side elasticity and DR budding [11], bearing investigation with its solution [12], and uncertainties in power systems [13].

In order to investigate the output target of the power system, there are three broadly used methods to solve the POPD problems such as analytical, approximation, and simulation methods. One of the most powerful techniques for POPD is Monte Carlo simulation (MCS) which is extensively used method to deal with uncertainties in the power system; it is relied on repeated random sampling to get the numerical results and reliability analysis statistically. In the proposed framework, the normal probability density function (PDF) was transformed to be the Truncated normal PDF, and it was shown that small errors occurred in the computed expected values which could be compensated for by shifting the computed probability-density curve so that its expected value coincided with the value deduced from a conventional deterministic analysis. It was formerly used to examine how probabilistic load flow (PLF) can be evaluated and found out the greater accuracy throughout the computational optimum speed [14]. Another point of view, MCS is used to perform the probabilistic short-term load forecast scheduling in a power system by assuming the PDF as the system loading, the total operating cost is effectually optimized [15]. Furthermore, many similar researches have studied the effect of correlation of uncertain variables such as probabilistic appraisal of accessible load supply capability [16], POPF behavior and relationship of the wind power, load uncertainties and line parameters [17, 18], PLF for solar power using percentile estimation of Weibull PDF [19], probabilistic investigation when wind and photovoltaic generation connected to system [20] PLF based on correlated series of generation, loading, and wind farm [21], probabilistic comparison and evaluation with energy management application [22], economic dispatch relied on Quasi-MCS is used to models the stochastic behaviors of wind speed and distributed loads [23], uncertainty of loads and wind speed is characterized by MCS to represent the total number of hours with overvoltage a year [24], hybrid MCS is performed to evaluate PLF when a large-scale wind power integrated to power system [25]. All these probabilistic problems and some other relevance are modelled in different purposes to balance the system loading by adjusting the add-on power generation in the power system.

In this paper, the linear programming optimal power dispatch (LPOPD) considering price-based real-time demand response (PRDR) is implemented in the modified IEEE 30-bus test system. Based on the problem formulation, the piecewise linear cost function is used to represent the generator's operating cost. At the same time, the PRDRs participate in dispatching aggregator loads connected to the system. The purpose is to accomplish the supply-demand balancing without upward power supply. Many works were developed in the smart grid, distributed generation, and other energy sources to serve the growing demands. Those additional generations will add the extra production cost and many complexities along. The simulation output of LPOPD with and without PRDR are addressed and compared in the results.

The proposed method accentuates the probabilistic inquiries in POPD solutions. The empirical rule will perform as a vital role in the computational procedure to avoid the infeasible load flow (LF) results during the computation to warrant the real-time simulation over the existing works is used the normal PDF to represent the uncertainty of variables in the system. The results will release preciously from simulation method time frame.

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Besides the introduction, the paper is consisted of: Section 2 introduces the model of uncertainties including DR schemes, expresses load modelling and probabilistic loading pattern. Section 3 represents the problem formulation of the POPD using LP with DR programs, while the real power demand at load bus is represented by normal PDF. Section 4 explains the probabilistic technique and conditions for sampling the input variables to represent the real power demand and rules for Truncated normal PDF to state a specific range for the random variable to obtain a better accuracy. Also, the proposed framework of Monte Carlo technique and performance of the simulation are denoted in this section. Section 5 indicates the simulation results from the modified 30-bus test system. Lastly, Section 6 provides the conclusion.

2. DR schemes and probabilistic load models

2.1 DR schemes

DR programs have essentially empowered because the evolution in the up-to-date technology required to tool them to regulate the target. An implication of DR is to consider the possibility of the power generation cost reduction, customers' electricity bill saving, and reliability of the power grid. PRDR is a program in which customers are paid for the load reduction in accordance to SO request. The PRDR price can be assigned by agreements for the real-time curtailable load. The demand of each load bus in the system has adjusted to maintain with the feasible power generation, principally, every customer would manage their power consumption to be a part of improving the efficiency and reliability of the system during peak periods. The system operator sometimes has to run costly power plant to adjust the total needs power generation to meet the peak demand while the promise pollution can be exceeded their authority, however, whether DR scheme has contributed to the system. Hence, there are persuasively two DR programs in vogue [9, 10] which are price-based programs (PBPs) and incentive-based programs (IBPs). PBPs are commonly cased study for researchers which provoke the consumers voluntarily provide load reductions by reacting to economic gestures. In spite of IBPs the customers have bided the payments in order to report an exact amount of load reduction over a specified time interval. Many economists are convinced that they are the most direct and efficient DR programs suitable for competitive electricity markets and should be the focus of policymakers.

2.2 Load modelling

In probability and statistics manner, random variables or stochastic variables are variables which represent possible numbers by using probability theories. Practically, the normal PDF is a common continuous probability distribution to produce real-valued random variables as load uncertainty. In this paper, the normal distributed random variable is used to model the real power demand on every bus.

For this purpose, the equivalent PDF can be formulated as,

$$f\left(P_{D_i} \mid \mu_D, \sigma_D^2\right) = \frac{1}{\sigma_D \sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{P_{D_i}-\mu_D}{\sigma_D}\right)^2}, \tag{1}$$

Where,

P_{D_i} is the probabilistic real power demand at bus i,

μ_D is the mean value, and

σ_D is the standard deviation of the demand profile.

2.3 Probabilistic and practical loading pattern

For this simulation, a practical loading pattern of Thai power system [15] was selected to use as power demand data pattern by transforming into the normal PDF. The annual system loading at 14:00 was formed into normalized data and used in this paper.

Consistently, the normalized annual data has plotted a histogram of 365-day data while the normal PDF fit is explored in coordination with normal PDF curve as shown in Fig. 1. After that, the

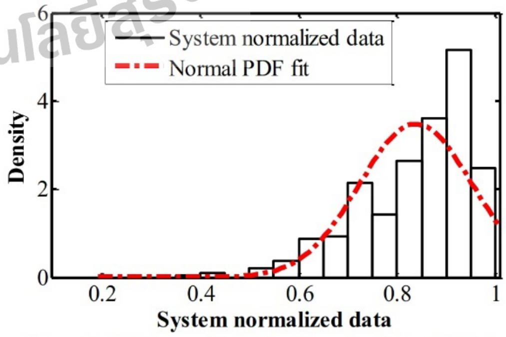

Figure. 1 PDF fitness for daily system loading at 14:00

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parameters μ_D and σ_D will be obtained for using in the sampling conditions in section 4.

3. Problem formulation

The objective of this paper is to minimize the total system investment cost in considering PRDR. The linear programming optimal power dispatch (LPOPD) is adapted to coordinate with Newton-Raphson power flow (NRPF). The power flow is used to obtain the losses and to test the feasibility of the dispatch solution.

3.1 OPD modelling

In this case study, the LPOPD adapted the NRPF with the operating cost for each generator which is given by piecewise linear cost functions. It can be used instead of the quadratic cost functions. Hence, the objective function can be expressed by a piecewise linear optimization model [4–5,15]. It is to minimize the total power generating cost including cost of PRDR, and can be expressed as,

$$\text{Minimize } TC = \sum_{i=1}^{NG}\sum_{j=1}^{NSi} S_{ij} P_{G_{ij}} + \sum_{i=1}^{NB} D_i P_{DR_i}, \tag{2}$$

subjected to the power balance constraint,

$$P_{G_i} - P_{D_i} = \sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\cos(\theta_{ik} - \delta_{ik}), i = 1,2,...,NB, \tag{3}$$

$$Q_{G_i} - Q_{D_i} = -\sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\sin(\theta_{ik} - \delta_{ik}), i = 1,2,...,NB, \tag{4}$$

$$\sum_{i=1}^{NG} P_{G_i} + \sum_{i=1}^{NB} P_{DR_i} = \sum_{i=1}^{NB} P^{o}_{D_i} + P_{loss}, \tag{5}$$

and the generator operating limit constraint,

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, i = 1, \ldots, NG, \tag{6}$$

$$\sum_{i=1}^{NG} P_{G_i} = \sum_{i=1}^{NB} P_{D_i} + P_{loss}, \tag{7}$$

$$P_{D_i} = P^{o}_{D_i} - P_{DR_i}, i = 1, \ldots, NB, \tag{8}$$

$$P_{G_i} = \sum_{j=1}^{NSi} P_{G_{ij}} + P_{G_i}^{\min}, i = 1, \ldots, NG, \tag{9}$$

$$0 \le P_{G_{ij}} \le P_{G_{ij}}^{\max}, j = 1, \ldots, NS_i, \tag{10}$$

$$|f_{lm}| \le |f_{lm}|^{\max}, \tag{11}$$

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max}, i = 1, \ldots, NB. \tag{12}$$

Where,

TC is the total system cost,
P_{G_i} is the real power generation at bus i,
S_{ij} is the linearized incremental cost curve for each segment of P_{Gi} at bus i,
D_i is the linearized incremental cost curve for each demand response at bus i,
NS_i is the number of segments of the linearized cost of the generator at bus i,
NG is the number of generators in the system,
NB is the number of buses in the system,
P_{DR_i} is the real power demand response at bus i,
P_{D_i} is the probabilistic real power demand at bus i,
Q_{G_i} is the reactive power generation at bus i,
Q_{D_i} is the reactive power demand at bus i,
P_{loss} is the total transmission loss in the system,
$P_{G_i}^{\min}$ is the minimum real power generation at bus i,
$P_{G_i}^{\max}$ is the maximum real power generation at bus i,
$|f_{lm}|$ is the apparent power flow on the branch between bus l and m,
$|f_{lm}|^{\max}$ is the maximum limit at apparent power flow on the branch between bus l and m,
$|V_i|$ is the voltage magnitude at bus i,
$|V_i|^{\max}$ is the maximum voltage magnitude at bus i,
$|V_i|^{\min}$ is the minimum voltage magnitude at bus i,
$|y_{ik}|$ is the magnitude of the y_{ik} element of Y_{bus},
θ_{ik} is the angle of the y_{ik} element of Y_{bus}, and
δ_{ik} is the voltage angle between bus i and k.

3.2 LPOPD algorithm

The algorithm approach is based on an iterative computation between Newton-Raphson power flow (NRPF) and LP. The computational procedure is shown in Fig. 2.

4. Probabilistic technique and sampling conditions

4.1 Conditional random variable

Regarding section 2, the normal PDF is chosen to model the load uncertainty with the specified parameters μ_D and σ_D obtained from the practical

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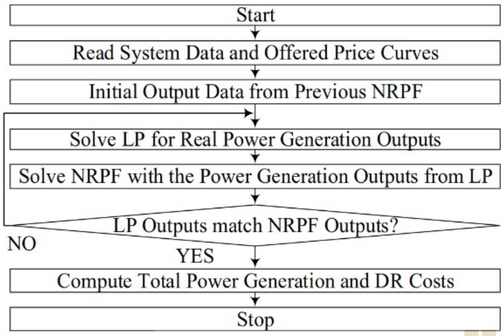

Figure. 2 Computational procedure of LPOPD

data as shown in Fig. 2. One of the most important aspects in this simulation is to execute a truncation range $x \in (a,b)$.

Suppose that $x \sim N(\mu_D,\sigma_D^2)$, $-\infty \leq a<b \leq \infty$. Then, the normal distribution has become the Truncated normal PDF lying on the interval $a<x<b$. In general, the Truncated normal PDF will be symbolized by $\Psi()$ [26]. And it is classified by the formula,

$$\Psi(\mu_D,\sigma_D,a,b;x)= \begin{cases} 0 & \text{if } x \leq a \\ \Phi(\mu_D,\sigma_D^2,a,b;x) & \text{if } a < x < b \\ 1 & \text{if } b \leq x \end{cases} \tag{13}$$

Where,

$$\Phi(\mu_D,\sigma_D^2,a,b;x)= \frac{\phi(\mu_D,\sigma_D^2;x) - \phi(\mu_D,\sigma_D^2;a)}{\phi(\mu_D,\sigma_D^2;b) - \phi(\mu_D,\sigma_D^2;a)} \tag{14}$$

From the above summary, it is clearly shown that $\Psi()$ is 0 at $x \leq a$, 1 at $b \leq x$, and it is in-between the shifted version of the behaviour of $\Phi()$ at $a < x < b$.

4.2 Rules for truncated normal PDF data

In statistics, there is a rule called the 68–95–99.7 rule to deal around the mean value in the normal distribution, sometimes known as the empirical rule [13, 27–29], in order to get more accurately, 68.27%, 95.45% and 99.73% of the random variables within one standard deviation, two standard deviations, and three standard deviations of the mean, respectively.

To formulate the data in this study, the approximated normal PDF data set aimed at empirical data derivation. In this case, vector x generated randomly on a specific range, represented by $x_{(a,b)}=[x_1,x_2,\ldots,x_{mcs}]$ which samples depending on how many times MCS will simulate in the 68–95–99.7 rule framework. The standard deviation σ_D of the power demand profile is a foremost part of modelling the significance of the random measurement error. When σ_D becomes wide-ranging, the measurement is moderately imprecise. As the result, a small value of σ_D will represent a minor error to prove a highly efficient output of random variation.

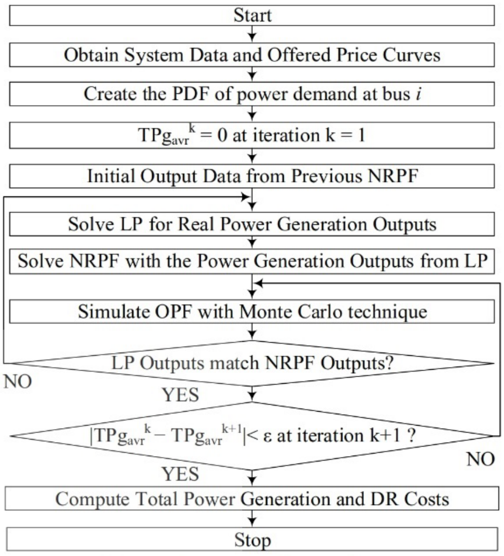

Figure. 3 Framework procedure

4.3 Monte Carlo simulation

In probabilistic concern, the MCS is commonly used to evaluate the computational model in order to randomize input variations and investigate probabilities outputs. And the framework is illustrated in Fig. 3.

In this paper, the MCS is used for probabilistic power demand simulation and the OPD is run until the average total real power generation of the iteration $k+1$ (TPg_{avg}^{k+1}) is close to that of the iteration k (TPg_{avg}^{k}). More specifically, the MCS base OPD is run until $|TPg_{avg}^{k} - TPg_{avg}^{k+1}| < \varepsilon$, where ε is a very small real number. In this paper, the ε is set to 0.0001.

MCS is widely used to investigate the power system operation and PDF to forecast the load and uncertainty variables in the system. However, to directly sampling the PDF can lead to infeasible solutions that need further variation process. Therefore, the PTNF could participate in this proposed framework to improve the technique over the existing POPD and lead to better precise results as addressed in Section 5. Without implementing

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PTNF in this study, the simulation will be included a number of infeasible LF solutions during the computational procedure. Therefore, it is noticeably shown that the proposed technique can handle the dispatch solutions considering PRDR effectively and accurately.

5. Simulation results

The proposed method is tested with the IEEE 30-bus system [30]. Moreover, the piecewise linear cost function for every generator is provided in Table 1. The generators' operating costs for each generator are provided to represent its linearized incremental cost curve for each segment of P_{Gi} as shown in Section 3.1. Some crucial data for the simulation is provided in Table 2 including P_{DRi} assuming the costs and quantities.

With the piecewise linear staircase cost function, the real power generation of individual segment is dispatched in merit order till reaching the P_{Gi}^{max} maximum real power generation.

Table 1. The generators' operating costs for each generator

Bus No.	Incremental From (MW)	Incremental To (MW)	Piecew. Linear Increm. Cost ($/MWHr)	P_G^{min} (MW)	P_G^{max} (MW)	Bus No.	Incremental From (MW)	Incremental To (MW)	Piecew. Linear Increm. Cost ($/MWHr)	P_G^{min} (MW)	P_G^{max} (MW)
1	50	71	4.540	50	200	8	10	25.6	4.750	10	135
	71	92	5.150				25.6	41.2	5.650		
	92	110	5.600				41.2	56.85	5.870		
	110	128	6.150				56.85	72.5	6.650		
	128	146	6.860				72.5	88.15	7.410		
	146	164	7.150				88.15	103.8	8.150		
	164	182	8.120				103.8	119.4	8.970		
	182	200	8.850				119.4	135	9.350		
2	20	40	5.050	20	180	11	10	25	3.670	10	130
	40	60	5.550				25	40	4.350		
	60	80	6.100				40	55	5.670		
	80	100	8.150				55	70	6.050		
	100	120	9.000				70	85	6.670		
	120	140	10.15				85	100	7.170		
	140	160	11.00				100	115	7.970		
	160	180	11.85				115	130	8.950		
5	15	31.9	4.050	15	150	13	12	28	3.100	12	140
	31.9	48.8	4.240				28	44	5.350		
	48.8	65.65	4.490				44	60	5.450		
	65.65	82.5	5.150				60	76	6.000		
	82.5	99.4	5.850				76	92	7.600		
	99.4	116.3	6.500				92	108	8.150		
	116.3	133.15	7.200				108	124	9.200		
	133.15	150	8.850				124	140	10.50		

Table 2. The power demand for the modified 30-bus test system

Bus No.	Power Demand (MW)	Power Demand (MVAR)	PRDR (MW)	PRDR ($/MW)
2	$\tilde{P}_{D_2} - P_{DR_2}$	12.70	2.604	1.422
5	$\tilde{P}_{D_5} - P_{DR_5}$	19.00	11.30	1.062
7	$\tilde{P}_{D_7} - P_{DR_7}$	10.90	2.736	1.062
8	$\tilde{P}_{D_8} - P_{DR_8}$	30.00	3.600	1.122
12	$\tilde{P}_{D_{12}} - P_{DR_{12}}$	7.500	1.344	1.260
21	$\tilde{P}_{D_{21}} - P_{DR_{21}}$	11.20	2.100	1.122
30	$\tilde{P}_{D_{30}} - P_{DR_{30}}$	1.900	1.272	1.122

In this research paper, the reactive power generating cost is not included in the result. In the meantime, the single loading condition is used to test the proposed algorithm.

Based on the LP linear cost function, the limit constraint as mentioned in Eq. (9) is applied to guarantee the well-balanced power generation equivalent to the power demand. Another thing to be taken into this approach is to assign the number of segments, which affects the dispatch solutions from LPOPD. As shown in Table 1, the generators' operating costs for each generator is provided with 8 segments for each cost function to observe very close solutions to the target outputs in verifying with

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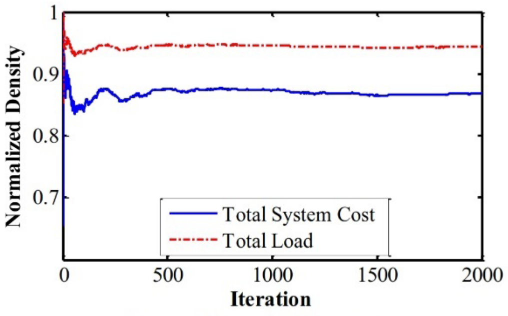

Figure. 4 Normal PDF output

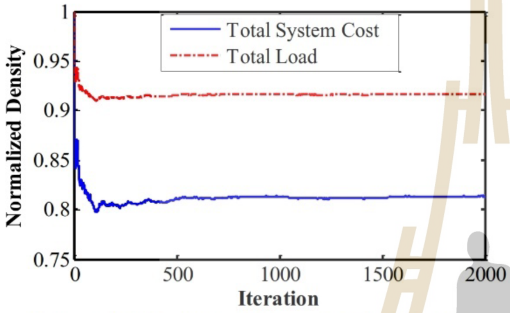

Figure. 5 PTNF output within one standard deviation

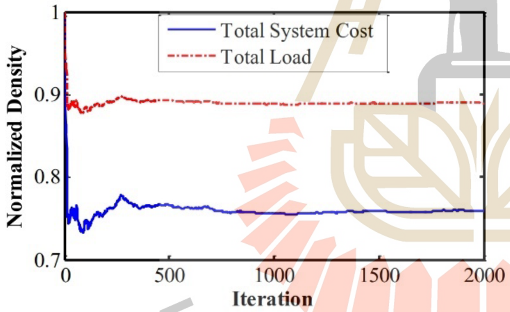

Figure. 6 PTNF output within two standard deviations

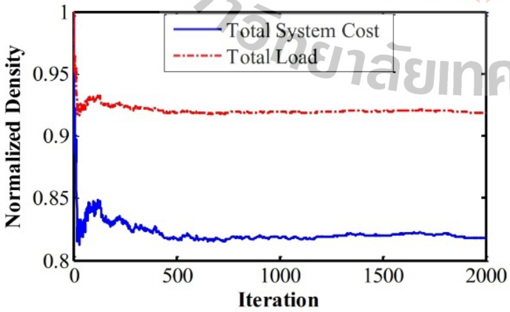

Figure. 7 PTNF output within three standard deviations

the lambda iteration method [21] and the Dommel-Tinney method [30].

Along with each generator data, the power demand data for the modified 30-bus test system are improved to adapt the proposed framework. The PRDRs are regulated on the load bus 2, 5, 7, 8, 12, 21, and 30 which ranged from 10.6 MW to 94.2 MW assuming to be the dispatchable aggregator loads. In comparing to the fixed price, consumers have participated in the PRDR program by decreasing their energy usage between 11% to 21% in the whole year. Evidently, reference [31] is represented by the average 12% of participants have saved their annual consumption pattern.

5.1 Investigation of the proposed framework

The output investigation by the proposed framework with the modified IEEE 30-bus test system as attached are demonstrated to certify the reliability of the results; the simulation 2000 runs were performed by POPD computational procedures as shown in Fig. 3. Figs. 4-7 represented the outputs of total operating cost and total power demand, which are obtained from POPD simulation with and without PTNF. From the simulation output, there is some evidence of how the results have converged.

From the results, normal PDF with the computational framework processed at least 1175 trials to give the convergent solution. Contribution to this study, it was improved after applying the empirical rule mentioned in Section 4. They are involved in the computational procedure by improving to give the convergent solutions at least 495 trials within one standard deviation and at least 713 trials within two standard deviations. In addition, within three standard deviations, the convergence has met at least 975 trials similar to the case of normal PDF. Nevertheless, it was cleared that the standard deviation value σ_D became widespread when the measurement is moderately inaccurate just like the theorist intended the idea [5, 26]. It could be converged at least 1175 trials or more with the random numbers from the normal PDF in the framework as shown in Fig. 3 whereas it has the opportunity to get the faster convergent solutions at 495 trials. Meanwhile, the solutions were obtained with slightly errors of mean value between before and after applying the probabilistic model to the system simulation. It is because of the characteristics of simulation methods.

5.2 Dispatch results

Concerning the results from Monte Carlo simulation with normal PDF and PTNF, the probabilistic investigation figures are intended that the output from the proposed method is

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demonstrated the convergence significantly. Even though, in the beginning, it seems a little bit worth divergence from the spot solution, it came out after some iterations. It is noticed that the yield is hereby indicated the active power demand, which is functioning to the total operating cost. On the one hand, PRDR will be instanced dependability in this study due to contract in the DR program. In contrast, the reactive power generation and the system losses are not considered in this framework. Still, it is certainly simplified the effectiveness of the proposed context. The dispatch results will be shown in Table 3 which will compare to some relevant methods respectively.

From the experiment results, it showed that the proposed method has satisfied the objective function to the dispatch solutions. To confirm the base case study of OPF, the computational procedure is shown in Fig. 2. It has verified with [30] and it is clarified that the proposed LPOPD is successfully dispatched with a neglected slop error 1.36% due to the nature of the piecewise linear optimization model. In Table 3, the POPD is run without PRDR and figured out the total system operating cost dispatch 739.13 \$/Hr. After that, the PRDR is conducted on the system, at the moment, the total system operating cost is dispatched to 601.51 \$/Hr. Although in probabilistic approach and sampling conditions. It continued to carry out the total dispatch operating cost at 445.57 \$/Hr by using normal PDF random variation input as loading uncertainties at the specified bus as shown in Table 2. Moreover, the rules for PTNF has applied to the LPOPD procedure then the total operating cost becomes much better at 440.45 \$/Hr, 441.24 \$/Hr, and 441.83 \$/Hr respectively to specific percentage range as mentioned in Section 4.2. To be notified that there must be some clearance payments for PRDR customers about 28.13 \$/MWHr due to the PRDR contracts between customers and SO in this prospectus.

In addition to Section 5.1, Table 4 indicates the accomplishment of the proposed method comparing to other recent proposed methods. The probabilistic technique and sampling conditions in Section 4 play an important role in the computational procedure by producing only feasible solutions during the simulation. The results are significantly achieved the good performance by applying PTNF in the computational framework. Without PTNF, the feasible load PDF modelling cannot be established efficiently.

Table 3. The dispatch results of the modified IEEE 30-bus test system

Variable		Base Case Load Flow	OPD without DR	OPD with DR	POPD	POPD with PTNF		
					$N(\mu, \sigma)$	$\mu \pm \sigma$	$\mu \pm 2\sigma$	$\mu \pm 3\sigma$
Power Generation (MW)	P_{G1}	55.5	79.97	71	70.19	73.64	69.74	69.34
	P_{G2}	46.5	40	48.57	24.47	20.31	23.99	24.44
	P_{G5}	48.3	72.88	65.65	64.55	63.46	64.79	64.68
	P_{G8}	55.7	25.6	25.6	18.54	19.05	18.63	18.5
	P_{G11}	35.2	40	40	39.48	39.98	39.24	39.42
	P_{G13}	45.7	28	28	28.01	28	28	28
Total Generation [MW, MVAR]		[286.71, 83.58]	[286.45, 83.6]	[278.82, 82.66]	[245.24, 80.5]	[244.44, 80.54]	[244.39, 80.38]	[244.38, 80.41]
Total P-Q Load [MW, MVAR]		[283.4, 126.2]	[283.16, 126.2]	[275.75, 126.2]	[242.63, 126.2]	[241.84, 126.2]	[241.8, 126.2]	[241.81, 126.2]
Total Syst. Losses [MW, MVAR]		[3.31, -17.18]	[3.29, -17.17]	[3.08, -18.11]	[2.6, -20.23]	[2.61, -20.19]	[2.58, -20.35]	[2.58, -20.32]
Total Gen. Cost (\$/Hr)		791.48	739.13	573.38	417.44	412.32	413.11	413.7
Total *DR* Cost (\$/MWHr)		–	–	28.13	28.13	28.13	28.13	28.13
Total Syst. Cost (\$/Hr)		791.48	739.13	601.51	445.57	440.45	441.24	441.83

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Table 4. Data comparison with relevant methods

Sampling Variables	Iter. [Trials]	CPU [s]	Tot. Syst. Cost [$/Hr]
Normal PDF	1175	33.9	445.57
PTNF ($\mu \pm \sigma$)	495	33.49	440.45
PTNF ($\mu \pm 2\sigma$)	713	33.56	441.24
PTNF ($\mu \pm 3\sigma$)	975	33.67	441.83
PE[15]	1504	–	–
JSQN[25]	–	48.39	–
PEM[18]	–	–	804.73

PE: Percentiles Estimation
PEM: Point Estimate Method
JSQN: Johnson system and Sobol's quasi-random numbers

6. Conclusion

In this paper, the LP based POPD is proposed for solving the power generation dispatch associated with PRDR to minimize total operating cost. The objective function is to diminish the total system cost while compensating between the high peaking cost power generation and PRDR offered. Moreover, the expected short-term load forecast is represented by the normal PDF with PTNF sampling technique. Hence, the proposed method can effectively and efficiently minimize the total power generation cost, while trading off the PRDR cost in the POPD problem with load uncertainty. Consequently, the proposed method enhances the benefits not only the SO but also the consumers, those are able to claim their paybacks by participating in PRDR contracts. The only thing to do is to rearrange the consumptions during the peak periods or time-ahead from SO's request or contract. It is substantiated that the proposed method can potentially be used to deal with the future electricity supply market.

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Optimal Power Flow Considering Price-Based Real-Time Demand Response

Udoum Chhor and Keerati Chayakulkheeree

School of Electrical Engineering, Institute of Engineering
Suranaree University of Technology, Thailand, keerati.ch@sut.ac.th

Abstract

In this paper, an optimal power flow (OPF) using linear programming (LP) has been used to solve the power generation dispatching with the price-based real-time demand response (PRDR). The simulation result has prosperously shown that the proposed method can handle the optimal solutions for real power dispatch considering PRDR. Therefore, the proposed method can efficiently and effectively minimize total power generation cost, while trading off the PRDR cost in the optimal power flow problem.

Keywords: Optimal power flow (OPF), linear programming (LP), demand response (DR).

1. Introduction

In the power grid, the electric utilities must balance the power generation and load all the time while maintaining the grid reliability and quality of supply. Most of these aspects, many researchers are endlessly working on an optimal power flow (OPF) for some possible future power system operation by using various optimization techniques.

In recent years, the innovation of computer processor units has produced as a matter of engineering required to solve their problems as fast as possible in real time and online program. OPF has become one of the most extensive optimization tools adopted in the power system planning and electricity market. In participating with the above issues, many researchers have studied continuously on optimization techniques to investigate an optimum operation of the power system approach shortly. There are many optimization algorithms have always been mentioned both artificial intelligence and conventional methods to obtain an OPF solution. The linear programming (LP) is one of the most competent conventional methods which becomes the most widely practical used method in optimal power system operation. LP has the potential to capture optimal adaptive operating costs and provide the optimal dispatch module in both short and long terms optimization problems [1 – 4], such as numerous economic, social, military and real-time problems.

In modern power grid, demand response (DR) programs have been developed and studied in many types of research in modern power systems [5 – 10]. The expected electricity price with and without DR is shown in Fig. 1, where P_{DR} and P_o are the total power generation with and without DR, respectively. Meanwhile, C_{DR} and C_o are the systems operating cost with and without DR respectively. In developing an approach of the modern power grid, some models of DR have implemented to manage the higher prices during the peak demand in the system to avoid increasing power generation. Meanwhile, consumers always billed their energy consumption through a tariff depending on the user demands and do not have any economic instructions or reports on how to plan to use or shift the consumption during peak periods. The system operator (SO) has to persuade and point out the consumers to reduce their demands accordingly to the required power balance in the system reliability. The DR programs in which price variations of energy over time produce changes at consumers' demand profile. It is necessary to improve the above problems to balance between supply and demand load.

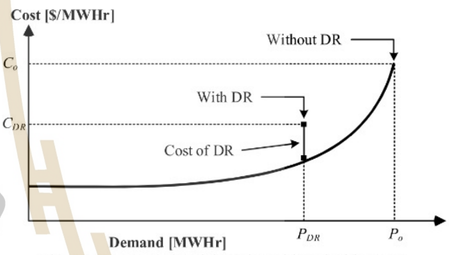

Fig. 1 Aggregated electricity price with and without DR

In this paper, the linear programming optimal power flow (LPOPF) considering PRDR is proposed and investigated with the 12-bus test system. In the problem formulation, the piecewise linear cost function is used to represent the generator's operating cost. Meanwhile, the PRDRs offered at different prices from the large dispatchable loads are connected to the system. The simulation results of LPOPF with and without PRDR are addressed and compared.

This paper was arranged into 5 sections as follow. Section 2 describes some brief classification of DR. Section 3 represents the problem formulation of the OPF using LP with DR programs. Section 4 indicates the results and discussion from the 12-bus test system. Finally, section 5 provides the conclusion.

2. DR Schemes

Overview of DR is taken into account for the power generation cost reduction, customer's electricity bill saving, and reliability of the power grid. The demand of each load bus in the system has adjusted to maintain with the feasible power generation, principally, every customer would be managed their power consumption to be a part of improving the efficiency and reliability of the system during peak periods. The system operator sometimes has to run costly power plant to adjust the total needed power generation to meet the peak demand while the promise pollution can be exceeded their authority, however, whether DR scheme has contributed to the system. There are two main different DR programs which are incentive-based programs (IBPs) and price-based programs (PBPs). PBPs are popularly cased study for researchers, many economists are convinced that they are the most direct and efficient DR programs suitable for competitive electricity markets and should be the focus of policymakers [7 – 8]. PRDR is a program in which customers are charged hourly fluctuating prices reflecting the real cost of electricity in the wholesale market. PRDR consumers are informed about the prices on a day-ahead or hour-ahead basis.

Accordingly, the total needed power generation and CO_2 emission can be reduced with DR schemes. Another point of the profitable application of a DR scheme, the reduction of the total power generation can be obtained from this operation resulted in minimizing the loss of the system. Additionally, this objective has solved the overload operation in the distribution system in real-time problems to ensure the reliability of the system.

3. Problem Formulation of OPF Considering PRDR

In this case study, the linear programming optimal power flow (LPOPF) is adapted to coordinate with Newton-Raphson power flow. The power flow is used to obtain the losses and to test the feasibility of the dispatch solution.

The operating cost for each generator is given by piecewise linear cost functions, as shown in Fig. 2, which can be used instead of the quadratic cost functions [4, 9].

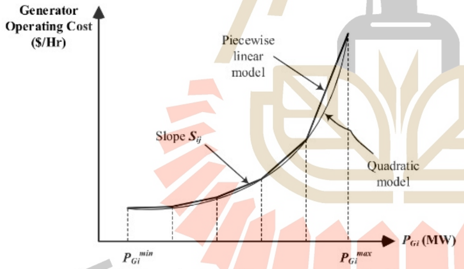

Fig. 2 A piecewise linear for generator cost functions

Therefore, the objective function can be expressed by a piecewise linear optimization model. The objective function is to minimize the total power generating cost including cost PRDR, and can be expressed as,

$$\text{Minimize } TC = \sum_{i=1}^{NG}\sum_{j=1}^{NSi} S_{ij} P_{G_{ij}} + \sum_{i=1}^{NB} D_i P_{DR_i} \,, \tag{1}$$

subjected to the power balance constraint,

$$P_{G_i} - P_{D_i} = \sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\cos(\theta_{ik} - \delta_{ik}), i = 1,2,\ldots,NB \,, \tag{2}$$

$$Q_{Gi} - Q_{Di} = -\sum_{i=1}^{NB} |V_i||V_k||y_{ik}|\sin(\theta_{ik} - \delta_{ik}), i = 1,2,\ldots,NB \,, \tag{3}$$

$$\sum_{i=1}^{NG} P_{G_i} + \sum_{i=1}^{NB} P_{DR_i} = \sum_{i=1}^{NB} P_{D_i}^{o} + P_{loss} \,, \tag{4}$$

and the generator operating limit constraint,

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \,, i = 1, \ldots, NG, \tag{5}$$

$$\sum_{i=1}^{NG} P_{G_i} = \sum_{i=1}^{NB} P_{D_i} + P_{loss} \,, \tag{6}$$

$$P_{D_i} = P_{D_i}^{o} - P_{DR_i} \,, i = 1, \ldots, NB, \tag{7}$$

$$P_{Gi} = \sum_{j=1}^{NSi} P_{G_{ij}} + P_{G_i}^{\min} \,, i = 1, \ldots, NG, \tag{8}$$

$$0 \le P_{G_{ij}} \le P_{G_{ij}}^{\max} \,, j = 1, \ldots, NS_i, \tag{9}$$

$$|f_{lm}| \le |f_{lm}|^{\max} \,, \tag{10}$$

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max} \,, i = 1, \ldots, NB. \tag{11}$$

Where,

TC is the total system cost,
P_{Gi} is the real power generation at bus i,
S_{ij} is the linearized incremental cost curve for each segment of P_{Gi} at bus i,
D_i is the linearized incremental cost curve for each demand response at bus i,
NS_i is the number of segments of the linearized cost of the generator at bus i,
NG is the number of generators in the system,
NB is the number of buses in the system,
P_{DR_i} is the real power demand response at bus i,
P_{D_i} is the real power demand at bus i,
Q_{Gi} is the reactive power generation at bus i,
Q_{D_i} is the reactive power demand at bus i,
P_{loss} is the total transmission loss in the system,
$P_{G_i}^{\min}$ is the minimum real power generation at bus i,
$P_{G_i}^{\max}$ is the maximum real power generation at bus i,
$|f_{lm}|$ is the apparent power flow on the branch between bus l and m,
$|f_{lm}|^{\max}$ is the maximum limit at apparent power flow on the branch between bus l and m,
$|V_i|$ is the voltage magnitude at bus i,
$|V_i|^{\max}$ is the maximum voltage magnitude at bus i,
$|V_i|^{\min}$ is the minimum voltage magnitude at bus i,
$|y_{ik}|$ is the magnitude of the y_{ik} element of Y_{bus},
θ_{ik} is the angle of the y_{ik} element of Y_{bus}, and
δ_{ik} is the voltage angle difference between bus i and bus k.

The algorithm approach is based on an iterative computation between Newton-Raphson power flow (NRPF) and LP. The computational procedure is shown in Fig. 3.

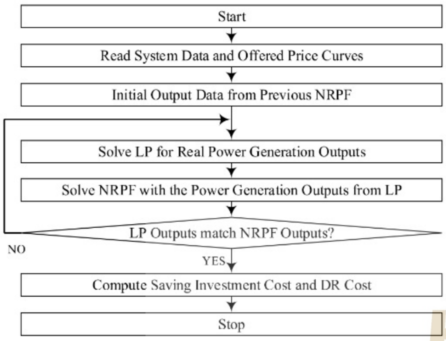

Fig. 3 Computational procedure

4. Results and Discussion

The test system used in this paper is the 12-bus system [9]. The single line diagram of the 12-bus system is shown in Fig. 4. The piecewise linear cost function for all generators are given in Table 1.

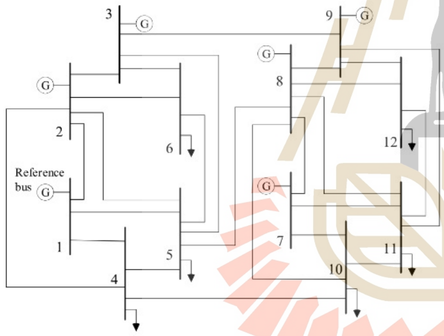

Fig. 4 The 12-bus test system

The generators' operating costs are represented in linear incremental cost form as illustrated in Fig. 2. The data for the 12-bus system is provided in Table 2 including P_{DRi} offered price and quantity. Whether each generator has found out the continuous piecewise linear staircase of its generation segment individually till reaching the P_{Gi}^{max} maximum real power generation, then the program will be considered to find the next power generation unit to fulfil the power demand required. In this paper, the reactive power generating cost is not included in the case study. Meanwhile, the single loading condition is used to test the proposed algorithm.

Table 1 The generators' operating costs

Bus	**Incremental** From (MW)	To (MW)	**Piecewise Linear Incremental Cost** ($/MWHr)	P_G^{min} (MW)	P_G^{max} (MW)
1	50	100	12.4685	50	200
	100	160	13.0548		
	160	200	13.5875		
2	37.5	70	11.2887	37.5	150
	70	130	12.1110		
	130	150	13.2042		
3	45	90	11.8333	45	180
	90	140	12.5373		
	140	180	13.2042		
7	50	100	12.4685	50	200
	100	160	13.0548		
	160	200	13.5875		
8	37.5	70	11.2887	37.5	150
	70	130	12.1110		
	130	150	13.2042		
9	45	90	11.8333	45	180
	90	140	12.5373		
	140	180	13.2042		

Table 2 The data for the 12-bus system

Bus	**Initial Power Gen.** (MW)	**Initial Volt. Magn.** (pu)	**Power Demand** (MW)	(MVAR)	**PRDR** (MW)	($/MW)
1	110	1.07	0	0	–	–
2	50	1.05	0	0	–	–
3	50	1.05	0	0	–	–
4	0	-	$110 - P_{DRi}$	15	15	11.5
5	0	-	$110 - P_{DRi}$	15	8	12.5
6	0	-	$110 - P_{DRi}$	15	20	11.85
7	110	1.07	0	0	–	–
8	50	1.05	0	0	–	–
9	50	1.05	0	0	–	–
10	0	-	$50 - P_{DRi}$	15	5	13.56
11	0	-	$50 - P_{DRi}$	15	10	11.716
12	0	-	$50 - P_{DRi}$	15	7	12.678

The simulation results have released as shown in Table 3. The dispatching results from LPOPF solutions with and without PRDR are solved and compared. The power generations, voltage magnitudes, losses, incremental cost, and DR cost of initial condition OPF with and without DR are shown in Table 3. The power generations based on operating limit constraint in Eq. (5) are acceptably dispatched through LPOPF with voltage magnitudes limit constraints of 0.95 p.u. $\leq |V_i| \leq$ 1.07 p.u. [9]. The total generation cost is reduced from 2952.46 $/MWHr (base case) to 2848.55 $/MWHr (OPF without DR) and 2243.12 $/MWHr (OPF with DR).

Table 3 The dispatching LPOPF results for each generator

Variable	At bus	Base Case	OPF without DR	OPF with DR
Power Generation (MW)	P_{G1}	188.80	50	50
	P_{G2}	50	96.7	70
	P_{G3}	50	90	90
	P_{G7}	110	50	50
	P_{G8}	50	130	94.3
	P_{G9}	50	90	90
Voltage Magnitude (V pu)	V_4	1.042	1.034	1.039
	V_5	1.048	1.041	1.044
	V_6	1.040	1.041	1.045
	V_{10}	1.057	1.051	1.054
	V_{11}	1.061	1.060	1.063
	V_{12}	1.055	1.056	1.058
Total Generation [MW, MVAR]	–	[498.79, -183.89]	[506.68, -175.33]	[444.34, -188.67]
Total Syst. Losses [MW, MVAR]	–	[18.80, -273.89]	[26.68, -265.33]	[21.34, -278.66]
Total Gen. Cost ($/MWHr)	–	2952.46	2848.55	2243.12
Total *DR* Cost ($/MWHr)	–	–	–	526.66
Total System Cost ($/MWHr)	–	2952.46	2848.55	2769.78

Furthermore, the SO has to clear some payments for their PRDR customers about 526.66 $/MWHr (by OPF with DR) due to PRDR contracts are included in this curriculum. However, the total operating cost, including power generation and DR costs, is shown to be the lowest. The proposed PRDR is explained in section 2, SO can change the prices of electricity aggressively from a day-ahead or hour-ahead scheduling [10].

5. Conclusion

In this paper, LPOPF considering PRDR is efficiently and effectively solved the optimal real power dispatch problem. The problem formulation provides a trade-off between dispatching the high-cost generator and DR offers. Moreover, the proposed method is not just for the SO profits, but also it is a good sign for PRDR consumers themselves to claim benefits from the SO, whether they can reschedule the controllable consumption during the peak periods or/and expensive tariff period. Finally, it is confirmed that the proposed method can challenge and encourage the consumers in the future electricity supply industry. The Algorithm can be extended for daily dispatching at the system.

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Biography

Udoum Chhor received his B. Eng. degree in electrical and electronic engineering (EEE) from Institute of Technology of Cambodia (ITC), Cambodia in 2015. He is currently a graduate student in power system program at Suranaree University of Technology (SUT). His current interests are in power system optimization and demand response.

Keerati Chayakulkheeree received his B. Eng in EE from KMITL in 1995, M. Eng. and D. Eng. degree in Electric Power System Management from AIT, in 1999 and 2004, respectively. He is currently an associate professor at School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Thailand.

A Probabilistic Load Flow Framework for Investigation of Traction Substation Load Impact to Distribution System

Udoum Chhor, Keerati Chayakulkheeree*, Thanatchai Kulworawanichpong, and Uthen Leeton

Graduate Student in Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000 THAILAND

*Corresponding author e-mail: keerati.ch@sut.ac.th

abstract

A random load of railway traction substation effect to the distribution system in both quality and reliability manners. Traction substation loads are highly fluctuation due to large moving loads on the catenary lines. The voltage unbalances and fluctuation, harmonic, and power factor problems are the issues required for detailed analyses. Meanwhile, the probabilistic load flow can be used to analyze those impacts to distribution system by transforming traction substation load to the probabilistic distribution function. This paper proposed the framework for the investigation of traction substation load impact to distribution system using probabilistic load flow. With the proposed framework, the load variation impact of traction substation to the distribution system can be investigated clearly with probability approach.

Keywords: Probabilistic Load Flow, Traction Substation, Railway Electrification

1. Introduction

Presently, the electrified railways are an important transportation system to provide the most efficient and economical power consumption for heavy traffic capacity. Meanwhile, traction power systems are corresponding to the moving load and corresponding time. Such inconstancy power demands can cause the current and voltage unbalances, voltage distortion, and harmonic disturbances in the distribution system. By the way, the probability of low voltage or overvoltage can be produced by this impactive presence.

To evaluate the effects of an electrified railway on the power system, both the managing strategies of the power utility and the operating schedule of the railway system should be considered. The main elements of such a consideration should include the means of supplying traction power, the characteristics of the traction motors and the scheduling of trains on the railway system. The first stage of any evaluation is to predict or simulate the daily load curves of traction substations along an electrical railway when trains are running. The related load distributions on each traction substation can be considered predictions or simulations. The unbalanced effects of single-phase traction loads on the power system can then be evaluated by using simplified or detailed circuit models in a three-phase power-flow program after such a simulation has been completed[1, 2].

A short while ago, some papers [1-18] have been published that have shown how the load flow problem can be modelled and solved probabilistically instead of deterministically. Some authors have produced an A.C. model using a linearization process and assuming a normal distribution for all the input nodal quantities, while others have produced a D.C. model that permits the nodal quantities to be specified by any reasonable and practical.

Probability density function (PDF), the latter model is more realistic from a system viewpoint, but only the angles and the active power flows can be computed. Moreover, some techniques were published that extended the previous D.C. model that allowed the angles, voltages, active power flows, reactive power flows and injected reactive powers to be computed using input nodal quantities that could still be specified by various practical distributions. It was shown that small errors occurred in the computed expected values which could be compensated for by shifting the computed probability-density curve so that its expected value coincided with the value deduced from a conventional deterministic analysis.

Accordingly, this paper presents the framework for the evaluation of the accuracy and convolution in the distribution system by investigation of traction substation load using probabilistic load flow (PLF). The selected traction substation loads would be analyzed by probability density function (PDF). After that, the impacts to distribution system could view with probability approach. Section 3 illustrates the framework procedure is Monte Carlo technique. The simulation results are provided in Section 4. Finally, the conclusion is given.

2. Electrified Railways and Load Characteristics

2.1 Electrified Railways

In this paper, an AC railways traction substation load behaviour is used for PLF investigation. The traction substation load is on the moving, its power demand and then the effects on the supply system depending on its operation and location. Hence the relationship between the power demand of an AC traction substation load and its movability is essential in case studies [1-2, 17-20].

In the AC railway systems, transformer substations are usually placed at secure positions on the feeding line with track sectioning points segregating feeding sections. The autotransformer (AT) feed system selected to study in many cases since the direct connection to the feed transformer secondary to the catenaries and rails is the most straightforward means of power feeding, booster transformer (BT) or AT placed within a feeding section have been widely adopted in AC railways to improve transmission efficiency and system regulation, reduce rail-to-earth voltage and earth current and suppress electromagnetic interference to the telecommunication circuits in close proximity. The feeding system thus consists of more parallel conductors and the distribution of current becomes more complicated.

Moreover, AT feeding would contribute better voltage regulation and confess longer distances between transformers and a piece to deduct the capital cost, which is wanted for service reliability in long-distance railways. Additionally, the AT feeding could afford to balance the voltage as well as the BT feeding could do on current balancing.

2.2 Load Characteristics The traction substation loads are usually changed dramatically with high fluctuation (2). Meanwhile, the traction substation load curve can be obtained by train simulations. Fig. 1 shows a typical daily load curve at traction substation from (2).

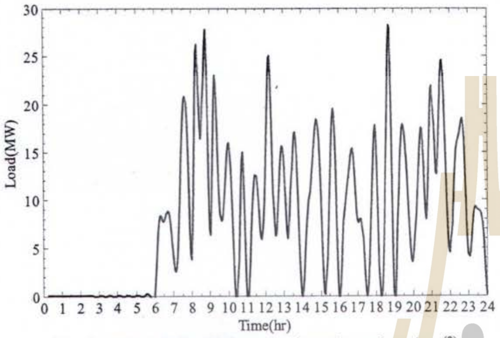

Fig. 1. typical daily load curve of traction substation (2).

3. Probabilistic Technique

Formerly, there are many authors (3-18) mentioned about the probabilistic model, names sometimes stochastic model. It was applied to accurate modelling of power networks, traction substation load, and possible efficiency.

3.1 Load Flow Model To conduct with a kind of load characteristic problem, the Newton-Raphson load flow equations with probabilistic traction substation power generations can be expressed as:

$$P_{Gi} - \tilde{P}_{Di} = \sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\cos(\theta_{ij} - \delta_{ij}), i = 1, 2, ..., NB \text{ ....(1)}$$

$$Q_{Gi} - Q_{Di} = -\sum_{j=1}^{NB} |V_i||V_j||y_{ij}|\sin(\theta_{ij} - \delta_{ij}), i = 1, 2, ..., NB \text{ ....(2)}$$

$$0 \le P_{Gi} \le P_{Gi}^{max}, \text{ for } i \in BG \text{ ....(3)}$$

Where,

$\tilde{P}_{Di}$: is the probabilistic traction substation real power demand at bus i (MW or p.u)
Q_{Di} : is the reactive power demand at bus i (Mvar or p.u)
P_{Gi} : is the real power generation at bus i (MW or p.u)
Q_{Gi} : is the reactive power generation at bus i (Mvar or p.u)
$|V_i|$: is the voltage magnitude of bus i (kV or p.u)
$|V_i^{max}|$: is the maximum voltage magnitude of bus i (kV or p.u)
$|V_i^{min}|$: is the minimum voltage magnitude of bus i (kV or p.u)
$|y_{ij}|$: is the magnitude of the y_{ij} element of Y_{bus} (ohm or p.u)
$|\theta_{ij}|$: is the angle of the y_{ij} element of Y_{bus} (radian)
$|\delta_{ij}|$: is the voltage angle difference between bus i and j (radian)
NB : is the total number of buses
BG : is the set of buses connected with generators

3.2 Monte Carlo Simulation One of the commonly used techniques for probabilistic load flow is Monte Carlo Technique. MCS is a technique that involves using random variations and probabilities to solve a probabilistic concern. It is a method for iteratively evaluating a deterministic model using sets of random variations as inputs. For a little while, we would use this technique to conduct with traction substation load impact to the distribution system.

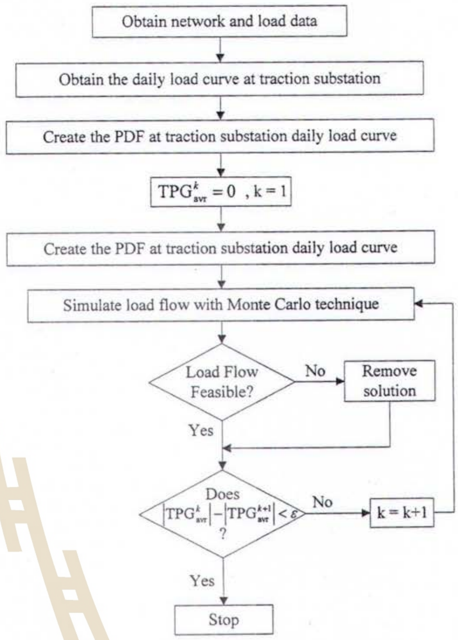

Fig. 2. framework procedure.

Since the random sample of the train position is the first selected and the corresponding train moving speed with varying time respectively. Then, to obtain the power demand of the train and transform into PDF as normal distribution in order to compute the load flow through Monte Carlo Simulation. So the typical daily load curve of traction substation in Fig. 2 would be used in this step.

For the statistical investigation, the MCS is illustrated by the computational procedure in Fig. 2. The average total power generation (TPG_{avr}^k) is computed by the equation (4) as shown below:

$$TPG_{avr}^k = \frac{\sum_{x=1}^{k} TPG^x}{k} \text{ ....(4)}$$

Where TPG^x is the total real power generation in iteration x. The step of iteration x would eliminate whether the small real value of ε is close to 0.0001(or 1e-4).

On the other hand, there is an important index to consider in order to verify which PDF is the most accuracy in the simulation or experiment. Based on the definition of an information criterion (AIC) index mentioned in (3, 21). The idea of AIC index is to indicate a goodness of probability model, the lower AIC shows a better representation of the fitting model and it can be defined by:

$$AIC = (-2)log(maximum\ likelihood) + 2n \text{ ....(5)}$$

Where n represents the number of independently adjusted parameters.

There are four PDFs have been selected for investigation, Fig.3 shows five curves fitted of traction substation load with different PDFs. After that the results followed the framework in Fig. 2 are shown in Section 4.

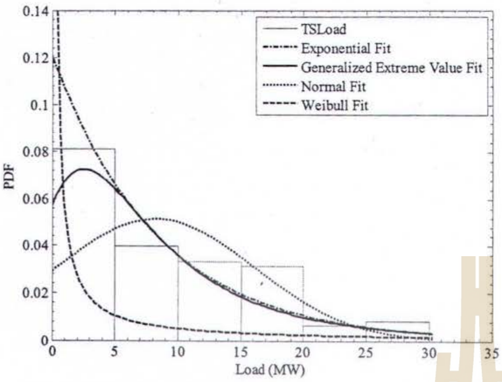

Fig. 3. PDFs of traction substation daily load curve in Fig. 1.

4. Result and Analysis

As mentioned in Section 3, the daily load of traction substation is selected from [2] as an example and shown in Fig. 1. It is used in the case study in this paper and considered by probabilistic technique. The traction substation load connected with a 6-bus of radial distribution test network as shown in Fig. 4. The network data is given in the Appendix.

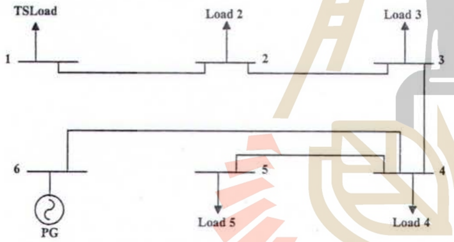

Fig. 4. 6-bus of radial distribution test network with traction substation load.

4.1 PDF Parameters and AIC of Traction Substation Load Behaviour

The result of transforming the traction substation load to investigate through the statistic toolbox as shown in Fig. 3. and some necessary parameters and data would be shown in Table 1.

Table 1. PDF parameters and data

PDF	Parameter		AIC	TPG_{avr}^k
Expo	μ	8.26	599.48	30.7191
GEV	k	0.28	657.57	49.0018
	μ	8.80		
	σ	5.26		
Norm	μ	8.26	668.92	24.9156
	σ	7.76		
Weibull	A	2.56	275.60	27.9174
	B	0.26		

4.2 Investigation on PLF with Traction Substation Load Behaviour

The computational procedures are studied with the PLF using MCS, as shown in Fig. 2, was tested with the 6-bus of radial distribution test network as shown in Fig. 4. To ensure the reliability of the simulation, the numbers of iteration were executed by 10000 times.

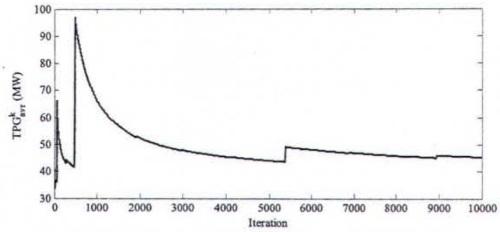

Fig. 5. application of MCS with normal distribution.

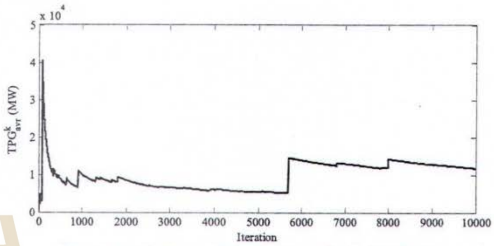

Fig. 6. application of MCS with weibull distribution.

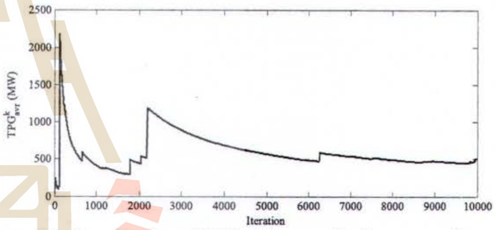

Fig. 7. application of MCS with generalized extreme value distribution.

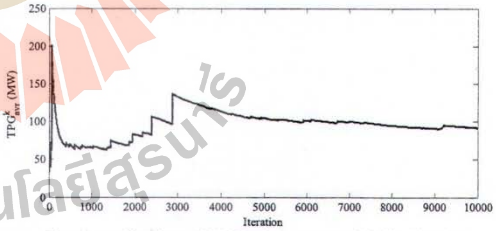

Fig. 8. application of MCS with exponential distribution.

Regarding the results from Monte Carlo simulation applied with four different PDF functions, we found that TPG_{avr}^k represented as the average power at generation bus supplied to five different kinds of loads, included traction substation load at bus 1. We found that some functions lead the Monte Carlo simulation results to divergent solutions as shown in Fig. 5, 6, 7, 8 above due to the nature of some PDF functions.

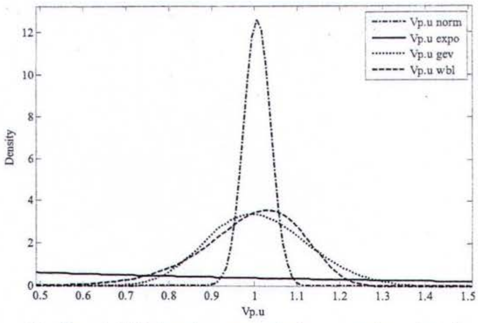

Fig. 9. probabilistic voltage magnitudes at traction substation with different PDFs.

The results are shown that the exponential PDF lead to the unrealistic PLF output. At the moment, the normal, generalized extreme value, and weibull PDFs resulted in the similar probabilistic voltage magnitudes with different standard deviations.

5. Conclusion

In this paper, the probabilistic load flow has been studied by the framework above to analyze the traction substation load impact to distribution system due to load variation has been investigated. The approach of MCS has been shown the probability clearly while the traction substation loads represented by using the random numbers of the probabilistic distribution functions. The results show that the PLF can be used for investigating the behaviour of traction substation load effect to the distribution system.

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Appendix

The 6-bus of radial distribution test network with traction substation load.

Table 2. 6-bus test data

Nº	mag_V	ang_V	P_gen	Q_gen	P_load	Q_load	Bus type
1	0.91	0	0	0	(TSL)	0	PQ
2	0.92	0	0	0	7	3	PQ
3	0.95	0	0	0	5	2	PQ
4	0.95	0	0	0	10	4	PQ
5	1.11	0	0	0	5	3	PQ
6	1.04	0	0	0	0	0	Slack

Table 3. line test data 6-bus

Line Nº	Bus Nº		Impedance (p.u)	
	From	To	R	X
1	1	2	0.032	0.151
2	2	3	0.101	0.550
3	3	4	0.075	0.237
4	4	5	0.115	0.579
5	4	6	0.063	0.355

BIOGRAPHY

Udoum Chhor was born in Kampong Cham province, Cambodia. He received his B. Eng. degree in electrical and electronic engineering (EEE) from Institute of Technology of Cambodia (ITC), Cambodia in 2015. After that, he pursued to Master degree of Electrical Engineering at Suranaree University of Technology (SUT), Thailand in 2017. His field of study interested in power system optimization and demand-side management.