IMPACT OF PLUG-IN HYBRID ELECTRIC VEHICLES CHARGING ON DISTRIBUTION NETWORKS

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IMPACT OF
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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and, any editorial work, paid or unpaid, carried out by a third party is acknowledged.

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AEMO	Australia Energy Market Operator
APLR	Additional Power Loss Ratio
EA	Evolutionary Algorithm
EV	Electric Vehicle
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
KCL	Kirchhoff’s Current Law
KVL	Kirchhoff’s Voltage Law
MOPSO	Multi-Objective Particle Swarm Optimization
PHEV	Plug-In Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
RTP	Real Time Pricing
DSL	Dynamic Simulation Language

ABSTRACT

This thesis is dedicated to study how the charging behaviours of plug-in hybrid vehicles affect the local distribution network. This study focuses on two issues: the power loss and charging cost optimization. The multi-objective particle swarm optimization technique is applied to achieve the optimal charging schedule, resulting in acceptable additional power loss ratio and charging cost.

The power loss on electric lines is correlated to the load demand. However, due to the complexity of the distribution network including the transformers and unbalances of loads, it is necessary to understand the power loss-load demand model. The loss-load modelling is based on the distribution network structure and power flow analysis. The two classic distribution networks (IEEE 13-Node and IEEE 34-Node) are employed for power flow analysis. As the consequence of power flow analysis, a new power loss-load demand model is presented. In this thesis, the additional power loss ratio (APLR) is analysed to present the plug-in hybrid electric vehicle (PHEV) impact of power losses on distribution network.

To study the charging cost impacts of PHEV, the least square error method is employed to curve fit the data of Australia electricity market and the electricity price-load and further charging cost-load equations are derived.

Particle swarm optimization method is used in the optimization and Multi-Objective optimization is conducted to achieve the optimal charging schedule for PHEV to cause less APLR at acceptable charging costs.

All the methodologies and algorithms are verified by simulations. The power losses and charging cost impacts and optimizations are simulated by DigSilent Power Factory and MATLAB.

Chapter 1

INTRODUCTION

1.1 Prologue

A plug-in hybrid electric vehicle (PHEV), is a hybrid vehicle which utilizes rechargeable batteries, or another energy storage device, that can be restored to full charge by connecting a plug to an external electric power source (usually a normal electric wall socket). A PHEV shares the characteristics of both a conventional and electric vehicle, having an electric motor and an internal combustion engine (ICE), having a plug to connect to the electrical grid.

Recently, the research of PHEVs has gained momentum due to their benefits to the environment. Key aspects studied include PHEV driving patterns, energy efficiency, and charging characteristics. However, the potential impacts of PHEV charging on distribution grid networks have been less attended, which is considered to be critical for the future to address the climate change.

According to the few researches on PHEV charging impacts [Venayamoorth et al, 2009; Anderson et al, 2010; Axsen & Kurani, 2010; Clement-Nyns et al, 2010; Farmer et al, 2010; Bashash et al, 2011; Deilami et al, 2011; Qian et al, 2011; Shiau et al, 2011; Wang, 2011], the system power losses and charging costs reduction are attracting attention. These researches have applied the popular optimization techniques such as Particle Swarm Optimization (PSO) to minimize power losses or charging costs. However, the algorithms for power losses and charging costs employed are lack of the accurate modelling of distribution networks and proper understanding of electricity pricing systems. These disadvantages are consequently influencing the solution effectiveness.

This thesis is devoted to study the residential distribution system power losses caused by PHEV charging and the charging costs problems. An optimal charging schedule is calculated for minimizing distribution grid power losses at an acceptable charging cost simultaneously.

The rest of this chapter is organized as follows. Section 1.2 introduces the PHEV and battery concepts. Section 1.3 describes the residential distribution grids. Section 1.4 outlines the electricity pricing theories. Section 1.5 elaborates the research motivation and scope. Section 1.6 justifies the goals and contributions of this thesis. The following chapters will be previewed in section 1.7.

1.2 Plug-In Hybrid Electric Vehicle and Charging

1.2.1 EVs, HEVs and PHEVs

Electric Vehicles (EVs) first attracted attention of public since they have almost zero pollution. However, the relative short operation range per battery charge and low energy density barred the deployment of EVs.

Hybrid Electric Vehicles (HEVs), which apply two power sources and contain the advantages of both internal combustion engine (ICE) (an engine in which the fuel and an oxidizer combust in a combustion chamber that is an integral part of the working fluid flow circuit) vehicles and EVs and overcome the advantages. PHEVs make the charging of HEVs at home possible [Fig.1.1].

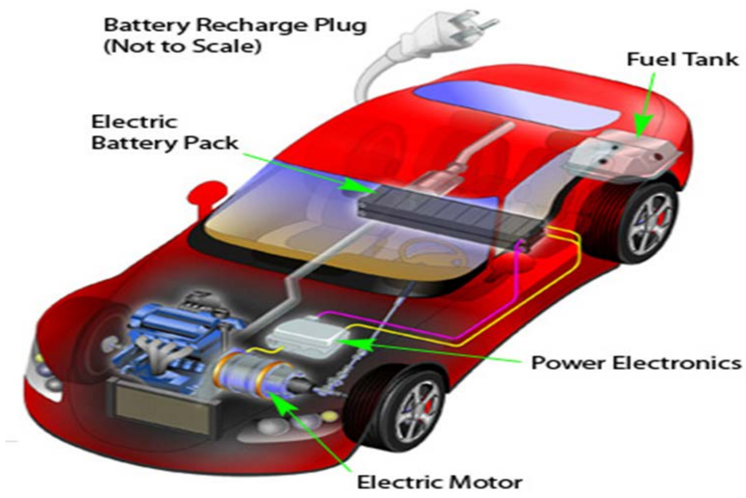


Fig 1.1 Diagram of the Plug-In Hybrid Electric Vehicle

HEV/PHEV Drive Train Architectures can be classified into four types shown as Fig.1.2 [Ehsani et al, 2010]: series (electrically coupling); parallel (mechanical coupling); series-parallel (mechanical and electrical coupling); complex (more complicated mechanical and electrical coupling).

The series hybrid drive train is shown in Fig. 1.2 (a). The feature of this type is that the vehicle is propelled only by electric motor. Both fuel and battery are electric energy sources for this type of vehicle. The battery provides electric power to the vehicle. The fuel provides dynamic energy through IC engine and converted to electric power through the generator. Both of the energies are converted to electric motor by the same power converter.

The dynamic energy generated by IC engine can also be transferred to electric energy to charge battery.

The main disadvantages of this architecture are

1. The dynamic energy of IC engine must be converted to electric energy which will cause more power loss.

2. Once the sole electric motor propel system is damaged or stops working by some accident, it will fail the whole vehicle to propel.

Fig 1.2 (b) represents the parallel hybrid drive train. The main feature of this type is that the vehicle can be propelled in parallel by both dynamic energy and electric energy. The fuel provides dynamic energy through IC engine as conventional petrol driven vehicles. The battery also contributes with electric energy through power converter and electric motor.

Fig 1.2 (c) represents the series-parallel hybrid drive train. Compared to the parallel hybrid drive train, the distinguishing feature is the dynamic energy can be transferred to electric energy to drive the car even if the ICE stops working by accidents. The battery also can be charged by ICE. For the above advantages, this architecture is most widely used in PHEV industry.

Fig 1.2 (d) shows the complex series-parallel hybrid architecture. The distinguishing feature is that the battery can not only propel the car through electric motor, its energy can also be transferred to dynamic energy to propel the car. The complex architecture requires extra power converter and motor compared to series-parallel type and more energy conversions. Currently, this type of structure is not widely used.

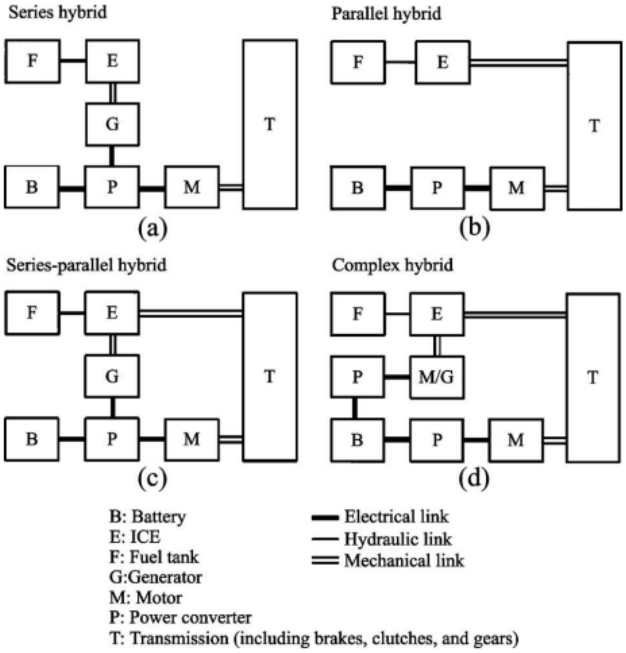


Fig 1.2 Common HEV/PHEV Architectures

1.2.2 PHEV Battery

Currently, the most popular batteries in the market for the PHEV include sealed lead-acid (SLA), nickel-cadmium (NiCd), and NiMH and Li-ion types [Ehsani et al, 2010]. The battery pack capacities of PHEV are in the range of 5-25 kWh [Table 1.1].

Table 1.1 EVs, HEVs and PHEVs Battery Parameters

Powertrain	Battery pack capacity (kWh)	Example
HEVs	1 – 2	Toyota Prius: 1.3 kWh
PHEVs	5 – 25	Prius conversion: 9.0 kWh
		GM Chevy Volt: 16 kWh
EVs	> 25	Tesla Roadster: 56 kWh

1.2.3 Battery Charging

One way to apply the charging method is the Constant Current Charging (Fig 1.3). According to the Australian Standard AS/NZS 3112 [Wikipedia, “AS/NZS_3112”], the most possible charging powers are

- 1.2kW(240 VAC, 5A)
- 2.4kW(240 VAC, 10A)

Taking GM Chevy Volt as an example (16kWh battery capacity), the battery charge will need at least 6-7 hours. The large charging power for such a long time causes concerns from electrical professionals about distribution network burdens.

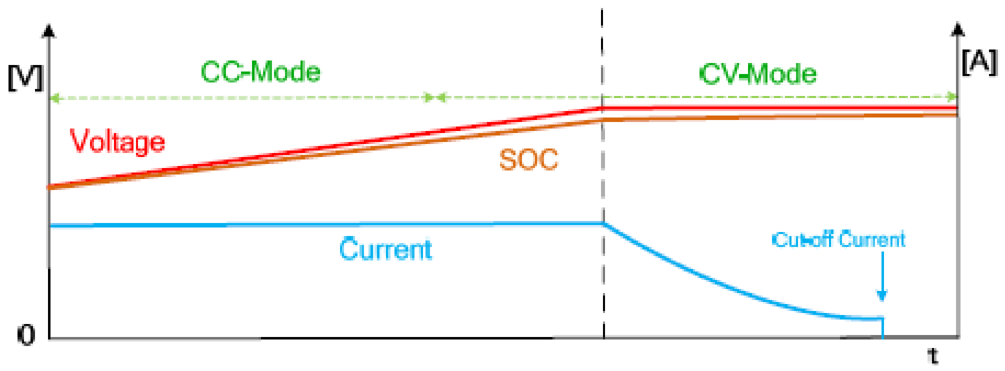


Fig 1.3 Battery Charging Curves

Fig 1.3 describes the whole battery charging process [Lee et al, 2011]. The battery starts charging with constant currents (CC) while battery voltage and state of charge (SOC) (the usable energy scaled to energy capacity) increase linearly. Once the state of charge reaches 90%, the battery will be charged at a constant voltage (CV) while charging current dramatically reduce to approximately one-third.

In this research, we assume that the PHEV charged at constant current and ignore the constant voltage charging step.

1.3 Electric Power System

An electric power system is defined as a network of electrical components that can supply, transmit and use electric power. It is usually combined with generation system, transmission and distribution system as Fig 1.4[Kersting, 2007].

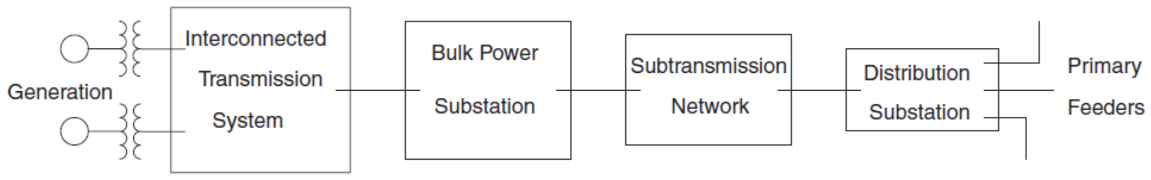


Fig 1.4 Electricity Power System Structure

The first part is the generation system where electricity is generated at around 3kV voltage. The generated electricity runs through step up transformers which will raise the voltage to transmission level. Bulk Power Substations consist of circuit breakers, cables, transformers and switchers. They are responsible for transmission safety, reliability and efficiency. The electric voltage is further raised to bulk voltage level that is effectively reducing transmission losses. For the economic issue, sub-transmission networks are applied to step down voltage to distribution system level instead of connecting the distribution substation to transmission system directly with larger and more expensive equipment. The Distribution substation will further step down voltage level to utility level. The electricity consumers connect electric devices to primary feeders.

In this thesis, we study the distribution system that includes the distribution substations and primary feeders.

1.3.1 Distribution System

The brief structure of distribution system can be shown in Fig 1.5. The distribution system typically starts with the distribution substation including substation transformers. The electricity travels along distribution lines with sub-connection nodes. To avoid huge voltage drops caused by large load demands, voltage regulators (usually the shunt capacitors, step voltage transformers and the line drop compensators) are applied. In some area, if the distribution line is long, the in-line transformers are essential. To avoid the overload problems, the circuit protection devices such as fuses, circuit breakers will be applied on the feeders. The customers are connected to these utility feeders with the sub-distribution system through distribution transformers which transfer voltage down from distribution voltage (4.8kV) to low voltage (240V)

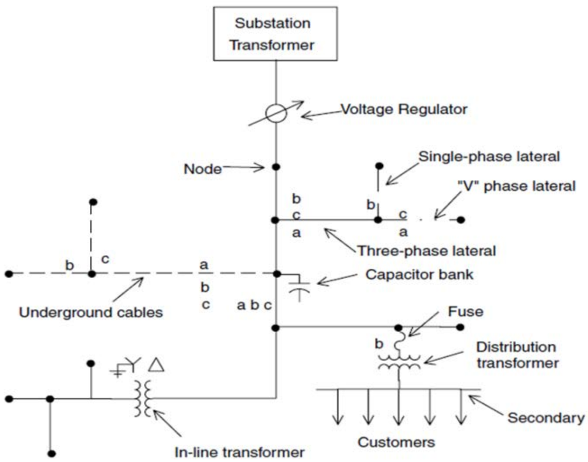


Fig 1.5 Distribution System Structure

1.3.2 Test Distribution System

As the complexity of real world distribution systems increases, it is difficult and unnecessary to model the real world distribution systems for analysis because

- Practical power system data are confidentially controlled by power companies or local governments.
- Both static and dynamic data are not documented.
- It is hard to calculate scenarios with large number of data set.

As the result, the test distribution systems are usually applied for the purpose of simulation and analysis.

These distribution systems are combined with load models, overhead lines, underground lines, conductors, shunt capacitors and voltage regulators. A sample 31-bus distribution system with utilities connected on is shown as Fig 1.6 [Deilami et al, 2011].

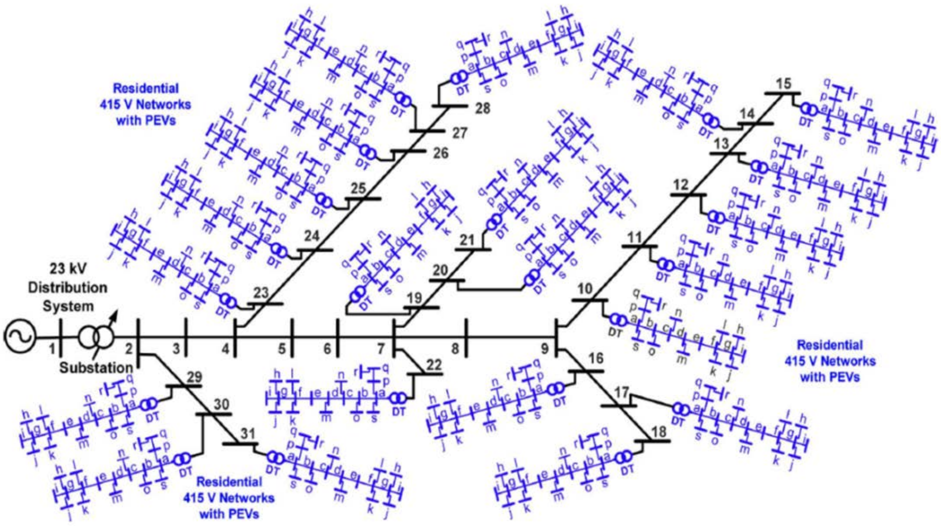


Fig 1.6 31-Node Test Feeder Distribution System

This system consists of 1 primary feeder, 29 sub-branches, 1 tie switcher, spot loads and balanced loads. Except for the primary feeder (feeder No.1) that works at 23kV voltage, the system is working at 11kV voltage.

Each sub-branch is connected with 19 residential consumers who work at 415V line to line voltage.

1.3.3 Power Loss

Power loss analysis is always an issue for electrical professionals. Large distribution power losses lower the system efficiency, increase heats and consequent accident possibility, and increase the total costs of the whole system operation.

From the analysis of test systems and simulation results, it can be concluded that

1. The power loss-load demand relationship is complicated
2. A huge load demand disturbance caused by large-scale PHEV charging leads to dramatic power losses that cannot be neglected

It is essential to study the power losses quantitatively on distribution system with large-scale PHEV charging. To achieve that, the simulation model requires a mathematical model.

1.4 PHEV Charging Cost

As the other barrier of PHEV deployment, PHEV charging cost is supposed to be optimized. To achieve this goal, how the electricity consumptions are priced must be studied.

1.4.1 Electricity Real Time Pricing

Since the 1990s', with the privatisation of energy markets in USA, Europe, UK, Australia and New Zealand, real time pricing (RTP) systems have been widely applied.

RTP is based on the fact that the marginal cost of electricity production changes dramatically according to the time. To reflect this real time variation, the costs of electricity consumption are supposed to vary hour by hour.

RTP systems differ from country to country according to the power systems and market structures and features. There are four main RTP systems in application now: The USA ISO-

New England system; UK Power Pool system (Run by National Grid); Scandinavian Nord Pool system; Australia Energy Market Operator (AEMO) system.

1.4.2 Price-Load Relationship

According to the load demand data, the system load demands are varying with time. Some researches indicated one important feature of the RTP system study: Electricity Real Time Prices are highly correlated to Electricity Load Demand [Vucetic et al, 2001].

The immediate question will be: How are the electricity prices and load demands correlated?

The questions will be answered in Chapter 4.

1.5 Motivation and Objectives

1.5.1 Motivation

Currently, the climate change and relevant environment protection are hot issues. One of the critical problems is how to reduce emissions.

According to the latest developments in batteries (such as higher power density and capacity) and power management efficiency, the deployment of environmentally friendly vehicles such as EVs, HEVs and PHEVs is considered as essential to reduce emissions dramatically.

To make this evolution acceptable, the following cutting edge problems must be studied in details and solved

1. The additional power loss on residential distribution grid minimization by PHEV charging
2. Costs reduction caused by PHEV charging

The potential huge load demands on distribution systems by large-scale PHEV battery charging could bring threats to the distribution system efficiency and safety with dramatic power losses. Additionally, the substantial additional power loss ratio by PHEV charging is a huge disturbance to the existing distribution system.

PHEV large-scale charging also leads to huge electricity costs. The effects are more severe during peak hours. This thesis will put forward an optimal charging schedule for PHEVs aiming at reducing the power loss levels on residential distribution network and charging costs.

1.5.2 Objectives

This thesis analyses the power losses and charging costs impacts caused by PHEVs charging on distribution networks. Optimization method is applied to achieve the optimal charging schedule.

The objectives of this thesis include

- The power distribution networks are mathematically modelled and the power loss-load demand equations are quantified, which are fundamental objective functions for optimization.
- The correlation between the real time electricity price and load demand is mathematically modelled for AEMO data. The electricity price-load demand and charging cost-load demand equations are obtained, which are essential objective functions for optimization.
- MOPSO method is applied to achieve the optimal charging schedule that considers APLR and charging costs optimization simultaneously.

1.6 Contributions

In summary, the contributions of this thesis are

- **The relationship between power loss, additional power loss ratio and load demand in test distribution system is analysed.** It is essential to mathematically model power losses caused by PHEV charging on distribution networks. They are considered to be correlated to load demands.
- **A high correlation between real time electricity price and load demand is detected in AEMO system.** The correlation coefficient calculation with AEMO data shows the high correlation between electricity price and load demand in Australian electricity market.
- **Electricity price-load demand equations are put forward to study Australia electricity pricing market.** Mathematical methods such as least squares error and curve fit make it possible to work out the price-load relationship with price-load equation.
- **Applied multi-objective optimization method to achieve the equilibrium charging.** The charging cost and additional power loss optimization results show that these two optimizations are conflicting targets. Consequently, multi-objective optimization is necessary for developing the charging schedule, which provides low additional power loss ratio with acceptable charging cost simultaneously.

1.7 Thesis Structure

The thesis consists of 6 chapters.

Chapter 1 introduces the concepts of PHEV charging, distribution network power loss and electricity real time pricing system. It also presents the goals and contributions of this thesis.

Chapter 2 presents a literature review of the current optimal PHEV charging research, and analyses the main advantages and disadvantages of these researches. This chapter also discusses the critical problems that have not been solved or less touched. The concepts and case studies of classical stochastic optimization methods are described. In addition, the main advantages and disadvantages of recent population based heuristic optimization technologies are discussed.

Chapter 3 investigates the charging circuits and charging patterns of PHEVs. Based on this investigation, the level of power loss impacts on residential distribution networks while charging is qualitatively analysed. A distribution network test model will be applied for simulation. The distribution network is mathematically modelled with the power loss quantitatively calculated.

Chapter 4 addresses the electricity real time pricing systems of main electricity markets especially the AEMO system. The correlation level between electricity price and load demand is analysed. The high correlation coefficients indicate that the electricity prices are highly determined by real time load demands. Electricity price-load demand equations are investigated for time segments.

Chapter 5 analyses the dynamic features of PHEV charging and optimization methods choice. PSO is considered to be the most suitable optimization technique. The optimal charging schedule is worked out to reduce APLR and charging costs simultaneously.

Chapter 6 concludes the thesis by reviewing the contributions. Suggestions for future research in this field are stated as well.

Chapter 2

LITERATURE REVIEW

2.1 Overview

This chapter aims to give a literature review which will introduce the research background and developments of PHEV relevant researches and the topics and methodologies of these researches.

This chapter is organised as follows. Section 2.2 briefly introduces the current research and developments and methodologies of researches in PHEV fields. Section 2.3 discusses the current methodologies and analyses their advantages and disadvantages. Section 2.4 introduces the methodologies of this research. As the chosen optimization method, section 2.5 briefly introduces the meta-heuristic optimization and discusses the main advantages of this optimization technique.

2.2 Introduction

PHEVs have been gaining momentum recently with the advantages of low emissions and less petrol consumption. The most popular research approaches of PHEV are now focused on following fields

- Environmental impacts such as emissions reduction
- Performance of PHEVs including car efficiencies and drive cycle characteristics
- Costs associated with battery and charging
- Impact on load demands such as extra currents on distribution power grid

Substantial researches have been done to study PHEV performances including driving power management, driving cycle characteristics and efficiencies. A power-electronic based energy storage and management system for PHEV was applied in [Amjadi & Williamson, 2010] to improve battery life and enhance temperature adaptability and simplify the overall energy management strategy. Various methodologies were discussed in [Gao & Ehsani, 2010] on battery and power capacity design, all electric range (AER) and charge depletion range (CDR) control strategies, a constrained engine on and off control strategy for charge-sustained operation. An energy model was developed in [Mapelli et al, 2010] to analyze and optimize the power flux between the different parts. A detailed analysis was performed to improve the driving range. A direct self-control strategy was presented to reduce the inverter losses. A real time energy management controller with a PSO algorithm was designed in [Banvait et al, 2009] to increase the fuel economy. The controller also contributed to better vehicle performance. An optimal model integrating vehicle physics simulation, battery degradation data and US driving data was developed in [Shiau et al, 2011], which minimized the life cycle cost, petroleum consumption and greenhouse gas emissions. A methodology was described in [Shahidinejad et al, 2010] for statistical analysis of the fleet data.

Environmental impacts for example Carbon Dioxide emission levels of PHEV have also been investigated. A marginal electricity mix platform was applied in [McCarthy & Yang, 2010] to investigate the greenhouse gas emission levels in California, USA. The emissions of PHEVs were reduced compared to conventional gasoline vehicles through improved vehicle efficiency. The effects of a PHEV fleet in Ohio State, USA were analyzed in [Sioshansi et al, 2010]. The analysis concluded that there were 70% reductions in gasoline consumption for each vehicle and up to 24% reduction in Carbon Dioxide emissions compared to conventional vehicles. The emissions impacts on the US western grid were investigated in [Jansen et al, 2010]. The results indicated that emissions can be reduced depend on the PHEV fleet charge scenario. The effect of relative vehicle cost and all-electric range on the timing of PHEV market entry were investigated in [Karplus et al, 2010]. It was suggested that PHEVs have potentiality to reduce Carbon Dioxide emissions and petrol demand.

PHEV cost has also been discussed which is believed to be one of the main barriers for PHEV deployment. The costs and macro-economic impacts of advanced vehicles include PHEVs were investigated in [Wang, 2011]. Results indicated negatively that the great costs of advanced vehicles would offset the petroleum costs saved from conventional vehicles. A case study was done in Sweden and Germany in 2008 in [Anderson et al, 2010] investigating the profits of PHEVs working as a power regulator through V2G network. The results showed that the Swedish power regulating markets did not provide any profits for PHEV. It is suggested in [Shiau et al, 2011] that Li-ion battery pack costs must fall $590/kWh at a 5% discount for PHEV to be competitive. An optimization methodology was applied to minimize both cost of fuel and electricity in [Bashash et al, 2011]. In 2009, a real-time model was implemented in [Venayamoorthy et al, 2009] to optimize PHEV charging costs through V2G network. Charging cost was minimized through optimized charging schedule and charging rates.

Another challenge for PHEV deployment is the impact on distribution grids and the consequent energy management. An EV Project titled “Electric Vehicle Charging Infrastructure Summary Report” done by the U.S. Department of Energy during April through June 2011 showed that in a small region like CA Metropolitan Area, Los Angeles, a 22.84MWh load demands on distribution grid could be created by 3365 EV charging events. Besides that report, a few other researchers have paid attention on the distribution grid impacts. It was suggested to defer all recharging to off-peak hours to eliminate all additions to daytime electricity demand from PHEVs in [Axsen & Kurani, 2010]. A PHEV distribution circuit model (PDCIM) was introduced in [Farmer et al, 2010] to estimate the impacts of an increasing number of PHEVs on transformers and underground cables. The simulation results indicated that the deployment of PHEVs in a distribution circuit would have diverse effects on the distribution infrastructure. The voltage deviation and power loss impacts on Belgium distribution grids caused by PHEV charging were investigated in [Clement-Nyns et al, 2010] and [Qian et al, 2011]. Dynamic optimized charging on V2G network [Clement-Nyns et al, 2010; Qian et al, 2011] were applied to minimize the voltage deviation and power loss levels.

As introduced above, it can be concluded that PHEV costs, especially battery charging costs together with the extra load demands and subsequent voltage deviation and power loss impacts on distribution are not enough and deeply studied which are critically concerned by PHEV consumers.

2.3 Disadvantages of Current Methods

The current solutions to minimize charging costs [Bashash et al, 2011; Venayagamoorthy et al, 2009] are to optimize charge schedules. The common disadvantage of these methodologies is that they isolate the electricity real-time price from electricity load demand. From the AEMO study, electricity real time prices are highly correlated to real-time load demands. As a consequence, the dynamic change of load demands on distribution grid will lead to change of real time price. This change will cause the objective function change and optimum solution change.

The power loss investigations [Clement-Nyns et al, 2010, 2011; Qian et al, 2011; Deilami et al, 2011] are based on either simulation results or simple models instead of theoretical analysis on the test distribution model. According to the power loss studies of IEEE 13-Node Test Feeder and 34-Node Test Feeder Models in this thesis, power loss is not only dependent on the selected nodes line current and impedance, but also on the distribution network’s structure and other electricity equipment such as transformers.

There is currently a lack of the study on power loss and electricity price internal relationships. According to [Yang et al, 2011], power loss-load demand and electricity-load demand equations are two conflicting objectives.

In addition, the current research is only interested in the total power losses instead of the additional power losses caused by PHEV charging which indicates the disturbance of PHEV charging to electricity distribution grids' efficiencies. In this thesis, APLR is studied and optimized.

2.4 Methodology of This Research

This thesis studies appropriate power loss models and electricity pricing models. The power loss and charging costs internal relationship is also studied.

More practical power loss models on test distribution networks and the mathematical relationship of total load demand-total power loss are investigated. Based on the equation, a PHEV optimal charging schedule with minimized APLR is evaluated.

The electricity price-load demand relationship and further PHEV charging cost-load demand relationship are also investigated. Based on these equations, a PHEV optimal charging schedule with minimized charging costs is evaluated. The dynamic change of APLR and consequent real time electricity prices are also considered.

Due to the conflicts between power loss-load demand and PHEV charging costs-load demand equations, the multi-objective optimization technique is applied to evaluate the optimal charging schedule for PHEV to APLR and charging costs simultaneously.

2.5 Meta-heuristic Optimizations

Optimization methods are essential to control the power losses and charging costs for PHEVs. As a class of approximate optimization techniques, meta-heuristics are increasingly popular recently for the capability to solve industrial and science problems effectively [Lee et al, 2008]. The main advantage of meta-heuristics is the less time consuming feature and consequently well accepted to solve specific engineering optimization problems which are concerned with the time rather than accuracy such as decision making problems. In this research, we apply a population-based meta-heuristic optimization technique.

Compared to deterministic algorithm optimization, meta-heuristic optimization solves the problems, where

1) The convergence is dependent on initial conditions.
2) The problem of sticking to suboptimal solutions.

The main reason that meta-heuristic optimization technology is chosen instead of the traditional deterministic optimization methods is based on the fact of this research that both the charging cost and power loss optimizations require huge amounts of real time recorded data, which is very time consuming.

Meta-modelling is an important step to reduce objective function’s complexity by approximating the objective function and replacing the original function. In some cases, it is difficult to find an analytic objective function. Using the approximated objective function generated by physical experiments or simulations is an acceptable solution. In this thesis, two meta-models are introduced: electricity price-load demand and power loss-load demand equations.

Meta-heuristic optimization is a process of replacing the initialized population of solutions with a new population of solutions. The mostly utilized optimization methods are evolution algorithms and swarm intelligences.

Meta-heuristic optimization is widely applied recently to solve engineering optimization problems including optimal power flows problems [Guo et al, 2008; HomChaudhuri et al, 2012; Leeton et al, 2010; Mohamed et al, 2010] optimal pricing problems [Venayagamoorthy et al, 2009] and optimal routing problems [Bell et al, 2004; Gianni, 2004].

2.5.1 Evolutionary Algorithms

Evolutionary algorithms (EAs) have been successfully applied to solve many real-world and complex problems. EAs are based on competitions and can be described as Fig 2.1.

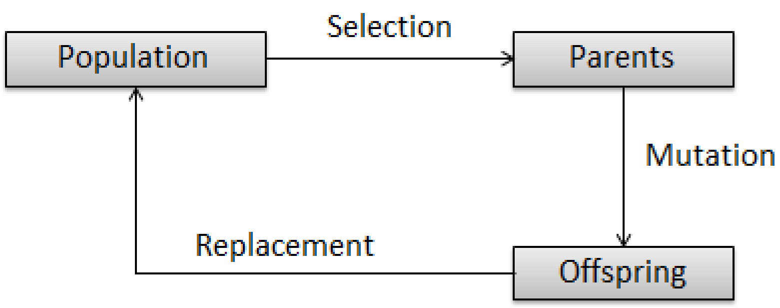


Fig 2.1 Flow Chart of EvolutionaryAlgorithms

The best known evolutionary algorithm is the genetic algorithm which was developed by J. Holland in the 1970s to understand natural systems' adaptive processes. Since 1980, it has been applied to optimization and machine learning problems [Goldberg, 1989].

The common concepts of EAs can be concluded as

1) Representation
2) Population Initialization
3) Objective Function
4) Selection Strategy
5) Reproduction Strategy: Designing the suitable mutation and crossover operation to produce new generation
6) Replacement Strategy: New offspring competition and replace the old relegated individuals
7) Stopping Criteria: The condition for the evolution to stop and put out optimal solution

2.5.2 Swarm Intelligence

Swarm intelligences are quickly drawing attention as a collection of nature-inspired algorithms and applied to many optimization problems in a variety of fields (optimal scheduling, economy, and optimal routes). As population based algorithms, they mimic the species behaviours (ant colony, birds foraging and fish schooling) with that individual swarm stochastically improves its behaviour and finally converge to the optimal solution. Ant colony and PSO are the most studied and applied methods.

Since introduced by M. Dorigo in 1992, Ant Colony Optimization (ACO) has become popular in solving the route optimization problems [Dorigo, 2005, 2006; Pei et al, 2012]. These problems usually consist of nodes and arcs such as power system optimization [Guo et al, 2008], travelling salesman problems [Li et al, 2008], vehicle optimal routing [Bell et al, 2004] and telecommunication routing problems [Gianni, 2004].

ACO mimics the foraging behaviours of ants. Population-based ants show high intelligence to optimize their route for food hunting. A group of ants will randomly choose all possible routes to find food with pheromone left. However the fact of pheromone evaporation will decrease the attractions of pheromone. The shortest route will cost less time for ants to travel and consequently remain more pheromone and attracting more fellows. Finally, all of the ants will be attracted to the optimal route.

PSO was invented in [Kennedy & Eberhart, 1995]. It is a stochastic optimization method which mimics the behaviour of bird foraging. Unlike the ACO which guides the fellows to optimal route with pheromones, PSO individuals are comparing their behaviours with neighbours to decide the local optimal ones and the global optimal one. This process is called fitness process. After the fitness step, each individual will travel at revised velocity which follows the local optimal and global optimal particles. During the whole search duration, every particle is moving at an updated velocity.

To solve the problem of less satisfactory searching ability of the original PSO, PSO neighbourhood operators are modified in [Suganthan, 1999].

Adaptive PSO was introduced in [Hu & Eberhart, 2002] to meet requirements of dynamic systems. The adaptive PSO monitors the change of global best behaves by re-evaluating fitness. As the response, it will re-randomize a number of particles and reset other particles once a change is detected.

Recently, PSO is widely used to solve power system optimization problems [Valle et al, 2008] including power generation loading [Li et al, 2008], units placing optimization [EI-Zonkoly, 2011] and reactive power control [Vlachogiannis & Lee, 2005].

Chapter 3

PHEV CHARGING POWER LOSS ANALYSIS

3.1 Overview

This chapter analyses the power losses on distribution networks. It introduces the PHEV battery charging, analyses the distribution network power flow and power loss analysis on test feeders. Finally, based on the power loss analysis, the APLR equation is concluded.

This chapter is organised as follows. Section 3.2 introduces the PHEV charging basics including the battery capacities and charging rates. Section 3.3 gives the distribution network analysis including the line impedances calculation, power flow calculation and power loss calculation on test feeders. Based on the results of Section 3.3, the power loss – load demand and APLR – load demand equations are concluded in Section 3.4. Section 3.5 presents simulation results with DigSilent Power Factory on a classic distribution network (13-node, 34-node test feeder) Section 3.6 summarises this chapter.

3.2 PHEVs

3.2.1 PHEV/EV Brands and Battery Parameters

The manufacture of PHEV/EVs is well advanced. The mainstream market is shown in Table 3.1.

Table 3.1 Mainstream PHEV/EVs

Brand	Range	Battery Type	Battery Energy
Chrysler TEVan	80km	Nickel-cadmium	32.4kWh
Chevrolet Volt	56km	Li-ion	16.5kWh
Fisker Karma (PHEV)	51km	Li-ion	20kWh
Toyota Prius (PHEV)	23-26km	Li-ion	4.4kWh
Tesla Model S	260-426km	Li-ion	40-85kWh
Ford Focus Electric	122km	Li-ion	23kWh
BMW ActiveE	125km	Li-ion	32kWh

Obviously, Li-ion battery is the most popular with relative high energy density for PHEV/EVs. Most battery energies are within the range of 16-32kWh. Table 3.1 also shows that the Tesla Model S EV contains the maximum travel range and battery energy which indicates the peak that PHEV/EVs can achieve.

3.2.2 PHEV Charging Levels

According to [Morrow et al, 2008], PHEV charging can be sorted into three types as shown in Table 3.2.

Level 1: Slow charge

Level 1 charge allows 1.8kW charging rate which is defined as slow charge. They are typically suitable for household charge. The disadvantage of this method is obvious that it is too slow. For a 20kWh battery, it takes more than 10 hours to finish the charge process.

Level 2: Moderate charge

This charge allows 9.6kW charging rate which takes approximate 2 hours for a 20kWh battery to complete the charge. This charge provides an acceptable charging time. However the charge power requires special equipment such as the public charger shown in Fig.3.1.

Level 3: Fast charge

Level 3 charge is usually called fast charge and applicable to commercial and public. For 60kW charge power, the commercial charge stations similar to petroleum stations are necessary.

Table 3.2 PHEV Charge Levels

Charge Level	Voltage	Current
1	120VAC	15Amp
2	240VAC	40Amp
3	480VAC	125Amp

Fig 3.1 Level 2 “Conductive”-type electric vehicle service equipment

3.2.3 PHEV Charge in Australia

Recently, there is a Victorian Electric Vehicle Trial organised mainly by CSIRO, RACV and AGL. According to the Australia Standard (AS) [Wikipedia, “AS/NZS_3112”], the PHEVs are recommended to charge at the rate of 240V, 15A/ 3.6kW.

3.3 Distribution Networks

As complicate and unbalance networks, the extra power flows caused by PHEV charging on modern distribution networks deserves to be studied. The common problem of current researches [Farmer et al, 2010; Clement-Nyns et al, 2010, 2011; Deilami et al, 2011; Venayagamoorthy et al, 2009] is these results (voltage deviation and power losses) are based on the blur garbage in and garbage out measurements by commercial simulation programs like MATLAB/ Simulink and Siemens PSS/E. The potentially incorrect parameters are highly possible to bring wrong results and conclusions without full understanding of the distribution network.

To properly analyse modern distribution networks, the following components must be included

- The detailed structure and components
- The data of each component such as transformers (High & Low side voltages, capacity in KVA, impedances), distribution lines (impedances units in Ω/Km, length and phasing type) and spot load data (balance/unbalance)
- Voltage levels of buses

This thesis conducts a full feeder analysis of the classical distribution network with PHEV plug in. The analysis is based on the distribution network modelling theory [Kersting, 2007]. Relatively accurate power loss-load demand equations are calculated with test distribution networks [IEEE Distribution Networks] for the optimization purpose.

3.3.1 Lines and Line Impedances

Before the distribution feeder analysis, it is critical to determine the series impedances of both overhead and undergrounded lines. The lines of distribution network can usually be divided into transposed and un-transposed three phase lines.

Transposed three-phase lines are widely used for high-voltage lines which are balanced (equal loads and same physical positions).

Un-transposed lines are used for distribution networks to serve the unbalanced loads. Both self and mutual impedances are required to be identified. The ground return path for unbalanced currents also needs to be considered.

The primitive impedance matrix is the key to identify line impedances

$$[\widehat{Z_{primitive}}] = \begin{bmatrix} [\widehat{z_{ij}}] & [\widehat{z_{in}}] \\ [\widehat{z_{nj}}] & [\widehat{z_{nn}}] \end{bmatrix} \tag{3.1}$$

where $\widehat{Z_{primitive}}$ represents the primitive impedances and $\widehat{z_{ij}}\ldots\widehat{z_{nn}}$ are the line impedances.

Using the Kron reduction technique, the equation can be simplified to

$$[z_{abc}] = \begin{bmatrix} z_{aa} & z_{ab} & z_{ac} \\ z_{ba} & z_{bb} & z_{bc} \\ z_{ca} & z_{cb} & z_{cc} \end{bmatrix} \Omega/\text{km} = [\widehat{z_{ij}}] - [\widehat{z_{in}}][\widehat{z_{nn}}]^{-1}[\widehat{z_{nj}}] \tag{3.2}$$

The voltage equations in matrix form for the line segment are

$$\begin{bmatrix} V_{ag} \\ V_{bg} \\ V_{cg} \end{bmatrix}_n = \begin{bmatrix} V_{ag} \\ V_{bg} \\ V_{cg} \end{bmatrix}_m + \begin{bmatrix} Z_{aa} & Z_{ab} & Z_{ac} \\ Z_{ba} & Z_{bb} & Z_{bc} \\ Z_{ca} & Z_{cb} & Z_{cc} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{3.3}$$

$$Z_{ij} = z_{ij} * length$$

In most cases, the analysis of a feeder will use only the positive and zero sequence impedances for the line segments

$$[Z_{012}] = [A_s]^{-1}[Z_{abc}][A_s] = \begin{bmatrix} Z_{00} & Z_{01} & Z_{02} \\ Z_{10} & Z_{11} & Z_{12} \\ Z_{20} & Z_{21} & Z_{22} \end{bmatrix} \tag{3.4}$$

$$A_s = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a_s^2 & a_s \\ 1 & a_s & a_s^2 \end{bmatrix},\ [A_s]^{-1} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a_s & a_s^2 \\ 1 & a_s^2 & a_s \end{bmatrix},\ \ a_s = 1\measuredangle 120 \tag{3.5}$$

where Z_{00} is the zero sequence impedance, Z_{11} is the positive sequence impedance and Z_{22} is the negative sequence impedance.

If the line is transposed, the impedance matrix can be modified as

$$[z_{abc}] = \begin{bmatrix} z_s & z_m & z_m \\ z_m & z_s & z_m \\ z_m & z_m & z_s \end{bmatrix} \tag{3.6}$$

The self and mutual impedances are defined as

$$z_s = \frac{1}{3}(z_{aa} + z_{bb} + z_{cc}) \tag{3.7}$$

$$z_m = \frac{1}{3}(z_{ab} + z_{bc} + z_{ca}) \tag{3.8}$$

$$Z_{00} = Z_s + 2Z_m \tag{3.9}$$

$$Z_{11} = Z_{22} = Z_s - Z_m \tag{3.10}$$

3.3.2 Line Power Flows

Once line impedances are determined, the next critical step is to calculate line power flows. The line segment flows are following the Kirchhoff's Current Law (KCL) and Kirchhoff's Voltage Law (KVL).

The voltage status can be stated as follow

$$[VLG_{abc}]_n = [a][VLG_{abc}]_m + [b][I_{abc}]_m \tag{3.11}$$

where

$$[a] = [U] + \frac{1}{2}[Z_{abc}][Y_{abc}]$$

$$[b] = [Z_{abc}]$$

Current status can be represented as the following equation

$$[I_{abc}]_n = [c][VLG_{abc}]_m + [d][I_{abc}]_m \tag{3.12}$$

where

$$[c] = [Y_{abc}] + \frac{1}{4}[Y_{abc}][Z_{abc}][Y_{abc}]$$

$$[d] = [U] + \frac{1}{2}[Z_{abc}][Y_{abc}]$$

Meanwhile, the voltage at *m* node can be described as

$$[VLG_{abc}]_m = [A][VLG_{abc}]_n - [B][I_{abc}]_m \tag{3.13}$$

where

$$[A] = [a]^{-1}$$

$$[B] = [a]^{-1}[b]$$

3.3.3 Transformer

The complex of distribution network requires a variety of voltage levels to serve industry, commercial and residential applications. In Australia, the industrial voltage standard is 22kV line-line, 11kV line-line and 6.6kV line-line. The commercial and residential voltage standard is 415V line-line and 240V line-ground respectively. To meet these requirements, the impacts of transformer cannot be ignored.

The relationship between the primary and secondary voltage can be explained as follows

$$[VLN_{ABC}] = [a_t][V_{tabc}] \tag{3.14}$$

where

$$[a_t] = \frac{-n_t}{3}\begin{bmatrix} 0 & 2 & 1 \\ 1 & 0 & 2 \\ 2 & 1 & 0 \end{bmatrix}$$

$$[Vt_{abc}] = [A_t][VLN_{ABC}] \tag{3.15}$$

where

$$[A_t] = \frac{1}{n_t}\begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 0 \\ -1 & 0 & 1 \end{bmatrix}$$

The primary voltage and current can also be calculated by

$$[VLN_{ABC}] = [a_t][VLG_{abc}] + [b_t][I_{abc}] \tag{3.16}$$

where

$$[b_t] = [a_t][Zt_{abc}] = \frac{n_t}{3}\begin{bmatrix} 0 & 2Zt_b & Zt_c \\ Zt_a & 0 & 2Zt_c \\ 2Zt_a & Zt_b & 0 \end{bmatrix}$$

$$[I_{ABC}] = [c_t][VLG_{abc}] + [d_t][I_{abc}] \tag{3.17}$$

where

$$[d_t] = \frac{1}{n_t}\begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$[c_t] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

n_t: voltage transform ratio

3.3.4 Distribution Feeder Analysis

A power flow analysis is essential to determine the total distribution feeder power losses. The keys to measure power loss are the voltage and current status of the feeder studied.

Due to the radial structure and phase unbalances on loads, voltages and currents, iterative techniques are usually applied to analyse the distribution feeder status.

In addition, the complex power loads result in the distribution network of nonlinear nature.

As a result, the power flows in distribution network will experience the forward and backward processes. This process is called the ladder iteration.

Ladder iteration application:

Assume there is an unbalance 3-phase lateral as indicated in Fig3.2.

The phase impedance matrices for the two line segments are:

$$[Z_{line1}] = \begin{bmatrix} 0.1414 + j0.5335 & 0.0361 + j0.3225 & 0.0361 + j0.2752 \\ 0.0361 + j0.3225 & 0.1414 + j0.5335 & 0.0361 + j0.2955 \\ 0.0361 + j0.2752 & 0.0361 + 0.2955 & 0.1414 + j0.5335 \end{bmatrix}$$

$$[Z_{line2}] = \begin{bmatrix} 0.1907 + j0.5035 & 0.0607 + j0.2302 & 0.0598 + j0.1751 \\ 0.0607 + j0.2302 & 0.1939 + j0.4885 & 0.0614 + j0.1931 \\ 0.0598 + j0.1751 & 0.0614 + j0.1931 & 0.1921 + j0.4970 \end{bmatrix}$$

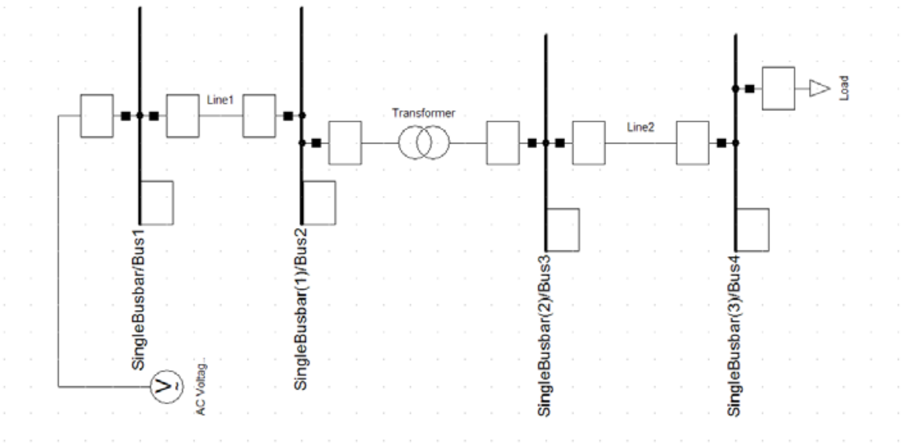


Fig 3.2 Unbalanced Three- Phase Lateral

Assume the feeder serves an unbalanced three phase wye connected constant PQ (P is active power and Q is reactive power) load of

$$S_a = 400kVA\measuredangle 14$$

$$S_b = 600kVA\measuredangle 18.4$$

$$S_c = 1000kVA\measuredangle 16.7$$

The transformer bank is shown in Table 3.3

Table 3.3 Delta-wye Step-Down Transformer

Connection	kVA	kVLL-high	kVLL-low	R - %	X - %
Step-Down	6,000	12.47	4.16	1.0	6.0

Generalized matrices are

Source line segment (Line1):

$$[a_1] = [d_1] = [U] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$[b_1] = [Z_{line1}]$$

$$= \begin{bmatrix} 0.1414 + j0.5335 & 0.0361 + j0.3225 & 0.0361 + j0.2752 \\ 0.0361 + j0.3225 & 0.1414 + j0.5335 & 0.0361 + j0.2955 \\ 0.0361 + j0.2752 & 0.0361 + 0.2955 & 0.1414 + j0.5335 \end{bmatrix}$$

$$[c_1] = [0]$$

$$[A_1] = [a_1]^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$[B_1] = [a_1]^{-1}.[b_1]$$

$$= \begin{bmatrix} 0.1414 + j0.5335 & 0.0361 + j0.3225 & 0.0361 + j0.2752 \\ 0.0361 + j0.3225 & 0.1414 + j0.5335 & 0.0361 + j0.2955 \\ 0.0361 + j0.2752 & 0.0361 + 0.2955 & 0.1414 + j0.5335 \end{bmatrix}$$

Load line segment (Line 2)

$$[a_2] = [d_2] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$[b_2] = \begin{bmatrix} 0.1907 + j0.5035 & 0.0607 + j0.2302 & 0.0598 + j0.1751 \\ 0.0607 + j0.2302 & 0.1939 + j0.4885 & 0.0614 + j0.1931 \\ 0.0598 + j0.1751 & 0.0614 + j0.1931 & 0.1921 + j0.4970 \end{bmatrix}$$

$$[c_2] = [0]$$

$$[A_2] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$[B_2] = \begin{bmatrix} 0.1907 + j0.5035 & 0.0607 + j0.2302 & 0.0598 + j0.1751 \\ 0.0607 + j0.2302 & 0.1939 + j0.4885 & 0.0614 + j0.1931 \\ 0.0598 + j0.1751 & 0.0614 + j0.1931 & 0.1921 + j0.4970 \end{bmatrix}$$

Transformer:

The transformer impedance is

$$Z_{base} = \frac{4160^2}{6000} = 2.88 \ \ \Omega$$

Zt_{low} =(0.01+j0.06).2.88=0.0288+j0.1728 Ω

The transformer phase impedance matrix is

$$[Zt_{abc}] = \begin{bmatrix} 0.0288 + j0.1728 & 0 & 0 \\ 0 & 0.0288 + j0.1728 & 0 \\ 0 & 0 & 0.0288 + j0.1728 \end{bmatrix}$$

The turn ratio is

$$n_t = \frac{12.47}{4.16/\sqrt{3}} = 5.192$$

The transformer ratio

$$a_x = \frac{12.47}{4.16} = 2.9976$$

The generalized matrices are

$$[a_t] = \frac{-n_t}{3}\begin{bmatrix} 0 & 2 & 1 \\ 1 & 0 & 2 \\ 2 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & -3.4614 & -1.7307 \\ -1.7307 & 0 & -3.4614 \\ -3.4614 & -1.7307 & 0 \end{bmatrix}$$

$$[b_t] = \frac{-n_t}{3}\begin{bmatrix} 0 & 2Z_t & Z_t \\ Z_t & 0 & 2Z_t \\ 2Z_t & Z_t & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & -0.0996 - j0.5982 & -0.0498 - j0.2991 \\ -0.0498 - j0.2991 & 0 & -0.0996 - j0.5982 \\ -0.0996 - j0.5982 & -0.0498 - j0.2991 & 0 \end{bmatrix}$$

$$[c_t] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$[d_t] = \frac{1}{n_t}\begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0.1926 & -0.1926 & 0 \\ 0 & 0.1926 & -0.1926 \\ -0.1926 & 0 & 0.1926 \end{bmatrix}$$

$$[A_t] = \frac{1}{n_t}\begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} = \begin{bmatrix} 0.1926 & 0 & -0.1926 \\ -0.1926 & 0.1926 & 0 \\ 0 & -0.1926 & 0.1926 \end{bmatrix}$$

$$[B_t] = [Zt_{abc}]$$

$$= \begin{bmatrix} 0.0288 + j0.1728 & 0 & 0 \\ 0 & 0.0288 + j0.1728 & 0 \\ 0 & 0 & 0.0288 + j0.1728 \end{bmatrix}$$

The bus 4 loads are

$$[S_4] = \begin{bmatrix} 400kVA\angle 14 \\ 600kVA\angle 18.4 \\ 1000kVA\angle 16.7 \end{bmatrix} kVA$$

Define the bus1 line-to-line and line-to-neutral voltages

$$[ELL_s] = \begin{bmatrix} 12{,}470\angle 30 \\ 12{,}470\angle -90 \\ 12{,}470\angle 150 \end{bmatrix} V$$

$$[ELN_s] = \begin{bmatrix} 7200\angle 0 \\ 7200\angle -120 \\ 7200\angle 120 \end{bmatrix}$$

Iteration 1:

Set the line currents to zero and perform the forward sweep

$$[V2] = [A_1][ELN_s] = \begin{bmatrix} 7200\angle 0 \\ 7200\angle -120 \\ 7200\angle 120 \end{bmatrix} V$$

$$[V3] = [A_t][V2] = \begin{bmatrix} 2400\angle -30 \\ 2400\angle -150 \\ 2400\angle 90 \end{bmatrix}$$

$$[V4] = [A_2][V3] = \begin{bmatrix} 2400\angle -30 \\ 2400\angle -150 \\ 2400\angle 90 \end{bmatrix}$$

Now start the backward sweep

$$Iabc_i = \left(\frac{S_i}{V4_i}\right) = \begin{bmatrix} 166.67\angle 1.01 \\ 250\angle 73.12 \\ 416.67\angle -24.3 \end{bmatrix} A$$

The voltage and current and at node 3

$$[V3] = [a_2][V4] + [b_2][Iabc] = \begin{bmatrix} 2481.2\angle 82.7 \\ 2384.2\angle 45.5 \\ 2601.7\angle -63.3 \end{bmatrix} V$$

$$[V2] = [a_t][V3] + [b_t][Iabc] = \begin{bmatrix} 6116.4\angle 69.1 \\ 7547.5\angle -73.6 \\ 7005.2\angle 71 \end{bmatrix} V$$

$$[I_{ABC}] = [c_t][V3] + [d_t][I_{abc}] = \begin{bmatrix} 80.04\angle 52.8 \\ 128.4\angle 48.4 \\ 48.98\angle 41.1 \end{bmatrix} A$$

$$[V1] = [a_1][V2] + [b_1][I_{ABC}] = \begin{bmatrix} 6109.6\angle 63.1 \\ 7565.7\angle -78.3 \\ 6999.5\angle 67.7 \end{bmatrix} V$$

$$V_{error} = \begin{bmatrix} 0.151 \\ 0.0508 \\ 0.0278 \end{bmatrix} per\ unit$$

The voltage errors are obviously greater than tolerance; the forward sweep begins again with the voltage in tolerance.

3.3.5 Simulation Results

Because of the unbalance and complexity of modern distribution network, there is no possibility to measure power flows node by node. A number of computer based soft-wares have been applied to simulate and analyse power systems such as MATLAB Simulink [MATLAB Simulink Software] and PSS/E [Siemens PSS/E Software]. In this thesis, simulations are based on DigSilent Power Factory Version 14.0 [DigSilent Power Factory Software].

Fig 3.3 shows the voltage levels on bus4 and power losses on feeder line

All calcula Time	Bus4 u1/p.u.	Bus4 U1/kV	Line1 u1:bus1/p.u	Line1 u1:bus2/p.u	Line1 I1:bus1/kA	Line1 I1:bus2/kA	Line1 Psum:bus1/M	Line1 Psum:bus2/M	Line1 Qsum:bus1/M	Line1 Qsum:bus2/M	Line1 Losses/kW
-0.1000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7047	-0.6973	3.5734
DIgSI/pcl - (t=000:000 ms) Control Switch Event 'Switch Event' not possible. No valid switch found.											
0.0000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.1000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.2000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.3000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.4000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
DIgSI/pcl - (t=500:000 ms) Control Switch Event 'Switch Event(1)' not possible. No valid switch found.											
0.5000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.6000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.7000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.8000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734
0.9000	0.9679	2.3248	1.0000	0.9975	0.1001	0.1001	2.0437	-2.0401	0.7045	-0.6972	3.5734

Fig 3.3 DigSilent Power Factory Simulation

Line impedance of line1 is

$$[Z_{line1}] = \begin{bmatrix} 0.4576 + j1.078 & 0.1559 + j0.5017 & 0.1535 + j0.3849 \\ 0.1559 + j0.5017 & 0.4666 + j1.0482 & 0.158 + j0.4236 \\ 0.1535 + j0.3849 & 0.158 + j0.4236 & 0.4615 + j1.0651 \end{bmatrix} \Omega/\text{mile}$$

3.4 Power Loss - Load Demand Equations

From the above power flow analysis and calculations, the power loss-load demand relationship can be described as below

$$P_{loss} = L^2 * (\frac{R}{V^2\ a_t{}^{2n}}) \tag{3.18}$$

where L is distribution load demand, R is line impedance, V is feeder voltage, a_t is transformer ratio and n is transformer number.

According to the power loss – load demand equation, the power loss impacts caused by charging PHEV can be presented as

$$\varDelta P_{loss} = (L_{PHEV}{}^2 + 2L_{PHEV}L_{Background})(\frac{R}{V^2\ a_t{}^{2n}}) \tag{3.19}$$

where L_{PHEV} is PHEV load demand and $L_{Background}$ is background real time load demand

APLR:

$$\%\varDelta P_{loss} = [\frac{L_{PHEV}{}^2}{(L_{Background}+L_{PHEV})^2} + 2\frac{L_{PHEV}L_{Background}}{(L_{Background}+L_{PHEV})^2}](\frac{R}{V^2\ a_t{}^{2n}}) \tag{3.20}$$

The equations above indicate that if the PHEV is charged at peak hours, both total power losses and the loss increase by PHEV are larger. However, the APLR by PHEV is lower which leads to fewer disturbances on distribution network.

3.5 Classical Test Distribution Networks Simulation

3.5.1 13-Node Network with PHEV Plug-In

The 13-node network is a common test distribution network applied by researchers for simulation purposes as shown in Fig 3.4.

In this thesis, this network is simulated with PHEVs plug-in at low-end nodes with background loads. According to [Victorian Electric Vehicle Trial], the PHEV charging can cause 30% extra loads at peak hours in Victoria State. The Victorian electricity consumption rate is between 4000-8000MW, average at 6000MW.

To simulate the Victoria distribution network, 2.4 MW PHEV loads are connected to the network with 6MW background loads.

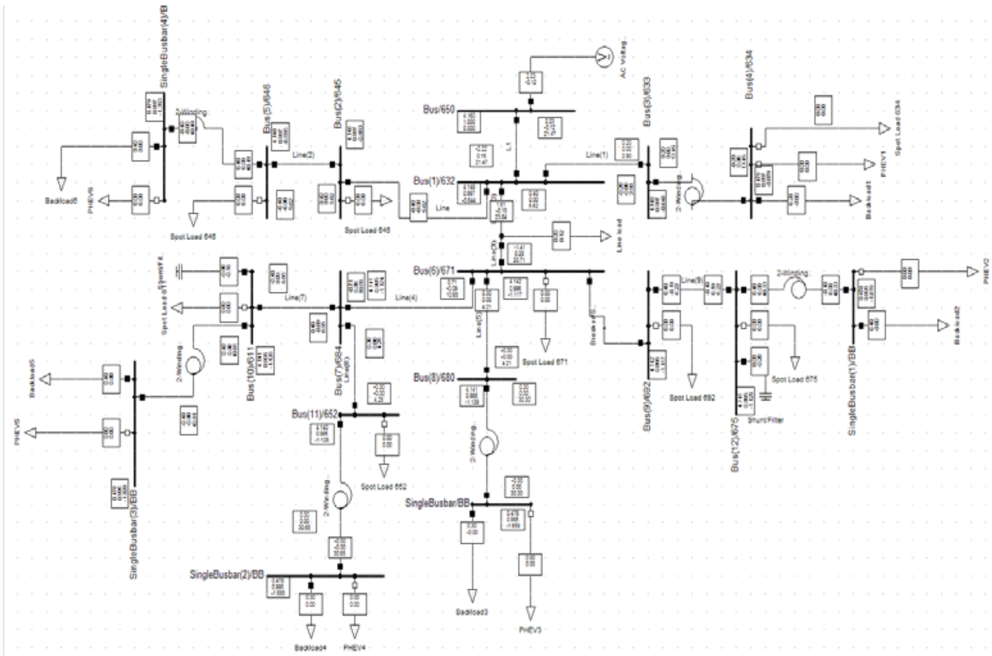


Fig 3.4 13 Nodes Test Feeder With PHEV Plug-In

The dynamic simulation results considering daily real time electricity consumption profile in AEMO data are shown as Fig 3.5.

```
    0.1000     1.2226     1.6058     1.9762     1.6069     1.9767     1.9576     0.9844     1.2220     -8.6644    119.6849
    0.2000     1.2226     1.6058     1.9762     1.6069     1.9767     1.9576     0.9844     1.2220     -8.6644    119.6849
DIgSI/pcl  - (t=300:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=300:000 ms) 'Simple Distribution Grid\SingleBusbar(3)\CB3.ElmCoup':
DIgSI/pcl  - (t=300:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
DIgSI/pcl  - (t=300:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=300:000 ms) 'Simple Distribution Grid\SingleBusbar(4)\CB3.ElmCoup':
DIgSI/pcl  - (t=300:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
    0.3000     1.2226     1.6058     1.9762     1.6069     1.9767     1.9576     0.9844     1.2220     -8.6644    119.6849
DIgSI/info - (t=300:000 ms) Element 'AC Voltage Source' is local reference in separated area of '2'
DIgSI/wrng - (t=300:000 ms)   10 area(s) are unsupplied.
DIgSI/info - (t=300:000 ms) Grid split into 12 isolated areas
DIgSI/info - (t=300:000 ms) Element 'AC Voltage Source' is reference in 50.0 Hz-system
    0.4000     1.2197     1.5985     1.9660     1.6113     1.4870     1.4714     0.9861     1.1077     -7.8694     98.3541
DIgSI/pcl  - (t=500:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=500:000 ms) 'Simple Distribution Grid\Bus(4)\CB4.ElmCoup':
DIgSI/pcl  - (t=500:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
DIgSI/pcl  - (t=500:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=500:000 ms) 'Simple Distribution Grid\SingleBusbar\CB3.ElmCoup':
DIgSI/pcl  - (t=500:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
    0.5000     1.2228     1.6055     1.9755     1.6112     1.4869     1.4713     0.9861     1.1100     -7.8848     98.7475
DIgSI/info - (t=500:000 ms) Element 'AC Voltage Source' is local reference in separated area of '2'
DIgSI/wrng - (t=500:000 ms)   12 area(s) are unsupplied.
DIgSI/info - (t=500:000 ms) Grid split into 14 isolated areas
DIgSI/info - (t=500:000 ms) Element 'AC Voltage Source' is reference in 50.0 Hz-system
    0.6000     0.7228     1.0929     1.9630     1.6155     1.4908     1.4740     0.9878     0.9931     -7.0677     79.0528
DIgSI/pcl  - (t=700:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=700:000 ms) 'Simple Distribution Grid\SingleBusbar(1)\CB3.ElmCoup':
DIgSI/pcl  - (t=700:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
    0.7000     0.7328     1.1088     1.9731     1.6152     1.4906     1.4738     0.9878     0.9971     -7.0959     79.7017
DIgSI/info - (t=700:000 ms) Element 'AC Voltage Source' is local reference in separated area of '2'
DIgSI/wrng - (t=700:000 ms)   13 area(s) are unsupplied.
DIgSI/info - (t=700:000 ms) Grid split into 15 isolated areas
DIgSI/info - (t=700:000 ms) Element 'AC Voltage Source' is reference in 50.0 Hz-system
DIgSI/pcl  - (t=800:000 ms) -------------------------------------------------------------
DIgSI/pcl  - (t=800:000 ms) 'Simple Distribution Grid\SingleBusbar(2)\CB3.ElmCoup':
DIgSI/pcl  - (t=800:000 ms) Circuit-Breaker Action: 'Open' - 'All Phases'.
    0.8000     0.7284     1.0991     1.4577     1.6182     1.4933     1.4753     0.9887     0.9370     -6.6752     70.3867
DIgSI/info - (t=800:000 ms) Element 'AC Voltage Source' is local reference in separated area of '2'
DIgSI/wrng - (t=800:000 ms)   14 area(s) are unsupplied.
DIgSI/info - (t=800:000 ms) Grid split into 16 isolated areas
DIgSI/info - (t=800:000 ms) Element 'AC Voltage Source' is reference in 50.0 Hz-system
    0.9000     0.7286     1.0990     1.4672     1.1226     1.4958     1.4765     0.9896     0.8815     -6.2850     62.2942
    1.0000     0.7297     1.1026     1.4697     1.1226     1.4958     1.4765     0.9896     0.8823     -6.2908     62.4113
```

Fig 3.5 DigSilent Power Factory DSL Results

The results show that the power loss-load demand equation is appropriate to present the power loss and load demand relationship.

3.6 Summary and Discussion

Although the above analysis has described power loss and load demand relationship, it is still an approximate evaluation. There are some issues that must be discussed here

1. The voltage level at the far end V4 will drop. To fix this voltage deviation, voltage regulators are usually applied and implement currents on lines. In other words, in modern distribution networks, the voltage deviations do not exist while power losses caused by huge consumptions exist.

2. The power loss on transformer exists. The real-world distribution network design such as Melbourne CBD distribution network that consists of 4498 transformers [Citipower & Powercor Network Information], cannot ignore the transformer power losses.

This chapter mathematically modelled the distribution networks and obtained the power loss-load demand equations which are essential objective functions for optimization in Chapter 5.

Chapter 4

ELECTRICITY PRICING AND PHEV CHARGING COST ANALYSIS

4.1 Overview

The other issue concerned by PHEV customers is the PHEV charging cost. To calculate PHEV charging cost, it is essential to study electricity pricing rules. Since 1990s, there has been a privatization trend for electricity industry in most developed countries to encourage competitions and obtain higher efficiencies. These deregulated electricity markets require more accurate market oriented electricity pricing systems. One of the widely applied systems is the real time pricing system.

This chapter investigates the real time pricing features of Australia electricity market. The whole chapter is divided into 4 sections. Section 4.1 briefly introduces the real time pricing systems. Section 4.2 tests the correlation of real time electricity price and load demand and proves that they are highly correlated. In addition, Section 4.2 studies the electricity pricing concepts and discusses the possible price-load function. Based on the analysis in Section 4.2, Section 4.3 applies a mathematical method to fit the exact price-load and cost-load functions. Section 4.4 summarises this chapter.

4.2 Real Time Pricing

With the trend of deregulation and privatization, real time pricing systems are introduced in the electricity market. Unlike flat price market or time of use market (on/off peak prices), real time pricing charges electricity costs dynamically.

Compared to conventional charging methods, RTP is more accurate in charging customers with less waste and price spikes which increase social benefits.

The best known RTP systems include

- The USA ISO-New England system
- UK Power Pool system (Run by National Grid)
- Scandinavian Nord Pool System
- Australia Energy Market Operator (AEMO) system

This thesis analyses price-load relationship in AEMO system. A sample weekly real time load demand-electricity price graph can be shown in Fig 4.1.

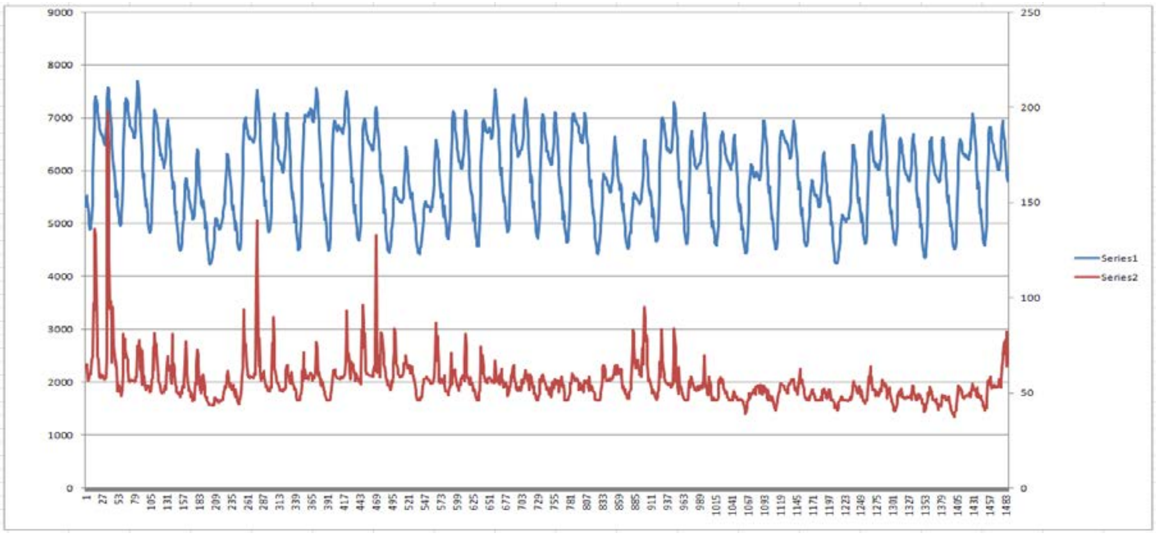


Fig 4.1 Real Time Weekly Load Demand and Electricity Price Profiles (1/8/2012-7/8/2012)

4.2.1 Australia Energy Market Operator

As the national energy market operator and planner, AEMO plays an important role in supporting the industry to deliver a more integrated, secure, and cost effective national energy supply.

AEMO provides real time electricity data graph of load demands and trading prices.

The sample daily data below tell some features

1. Numerically, electricity real time prices are highly correlated to the load demand
2. The electricity price tariff over time is not the same as load demand tariff. This feature indicates the distinction of AEMO pricing system

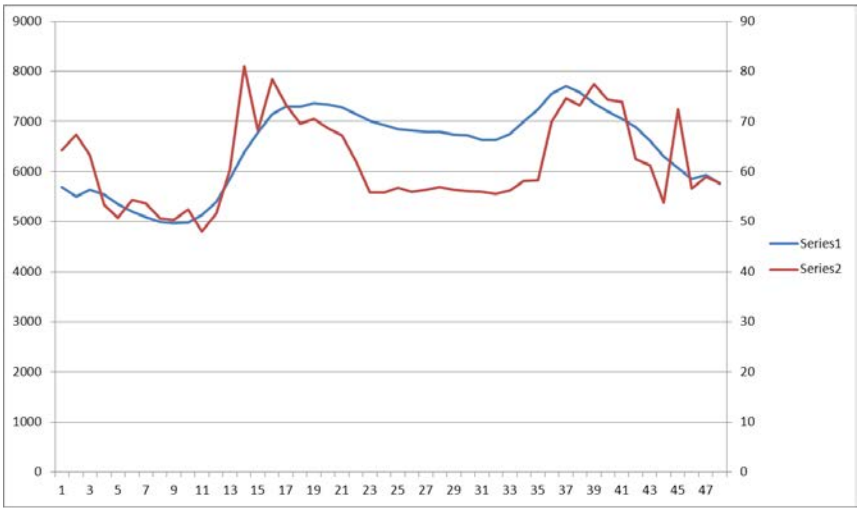


Fig 4.2 Real Time Daily Electricity Price and Load Demand Graph (1st July, 2012)

4.3 Electricity Pricing Versus Load Demand

The electricity pricing mathematical modelling usually takes the following issues into account

- Load Demands
- Transmission and generation losses
- Bidding strategy
- System Congestion
- Market rules

Most of these factors are unreleased or unpredictable except for load demands. Load demands play a key role to decide periodic electricity prices. Evidences indicate that electricity real time price is highly correlated to real time load [Lo et al, 2004; Vucetic et al, 2001]. On the other hand, load shifting responding to electricity price can dramatically reduce energy costs [Albadi et al, 2007, 2008; Kirschen et al, 2000; Farahani et al, 2011; Aalami et al, 2008; Mohsenian-Rad & Leon-Garcia, 2010].

4.3.1 Electricity Price-Load Demand Correlation Test

Before studying the electricity price-load demand equations, it is essential to test the correlation level. Correlation coefficients (CC) are usually applied to indicate the dependences of two components. It is a quantity that gives the quality of a least squares fitting to the original data. If CC is equal to or larger than 0.8, the two components are regarded as highly dependent. If CC is equal to or larger than 0.5, the two components are regarded as dependent.

In this thesis, daily electricity price-load demand profiles are used to measure price-load correlations by Pearson product-moment correlation coefficient equation:

$$r = \frac{\sum_{i=1}^{n}(X_i-\overline{X})(Y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}} \tag{4.1}$$

Six random daily records are employed and the MATLAB simulation results are as Table 4.1

Table 4.1 Price-Load Correlation Coefficients

Date	Price-Load Correlation
1st of July, 2012	CC = 0.84
2nd of July, 2012	CC = 0.65
7th of July, 2012	CC = 0.91
8th of July, 2012	CC = 0.91
22nd of August, 2012	CC = 0.55
23rd of August, 2012	CC = 0.81

It can be seen that, all of the correlation coefficients are large than 0.5 which indicates that the real time electricity prices are highly correlated to electricity load demands in Victoria.

4.3.2 Electricity Price Elasticity

Elasticity represents the sensitivity of one variable to another. It is often used to measure the percentage change occurred in one variable responding to one per cent change in another variable.

To represent the price-load mathematical model, the first important subject to be studied is the electricity price elasticity. According to [Albadi et al, 2007, 2008; Kirschen et al, 2000; Farahani et al, 2011; Aalami et al, 2008; Mohsenian-Rad & Leon-Garcia, 2010], the electricity price has elasticity relationship against load demands as Eq.4.2 and Fig 4.3.

$$E_p = \frac{p_0}{q_0}\frac{\Delta \mathrm{q}}{\Delta \mathrm{p}} \tag{4.2}$$

$p_0: Equilibrium\ Price$

$q_0: Equilibrium\ Load\ Demand$

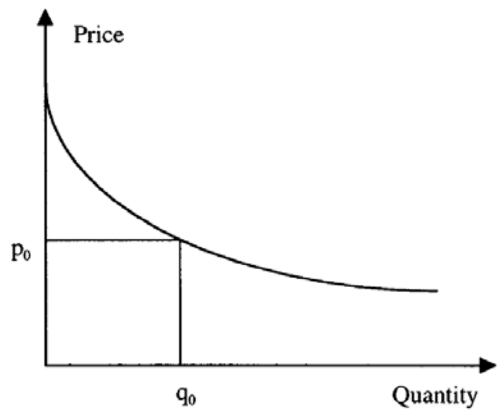


Fig 4.3 Electricity Price Elasticity

4.3.3 Electricity Pricing (Marginal Price)

The electricity production is the same as other products where its purchasing price obeys the marginal pricing rule. As Fig 4.4 shows, the electricity purchasing price is the equilibrium point of price-generation and price-load elasticity curves.

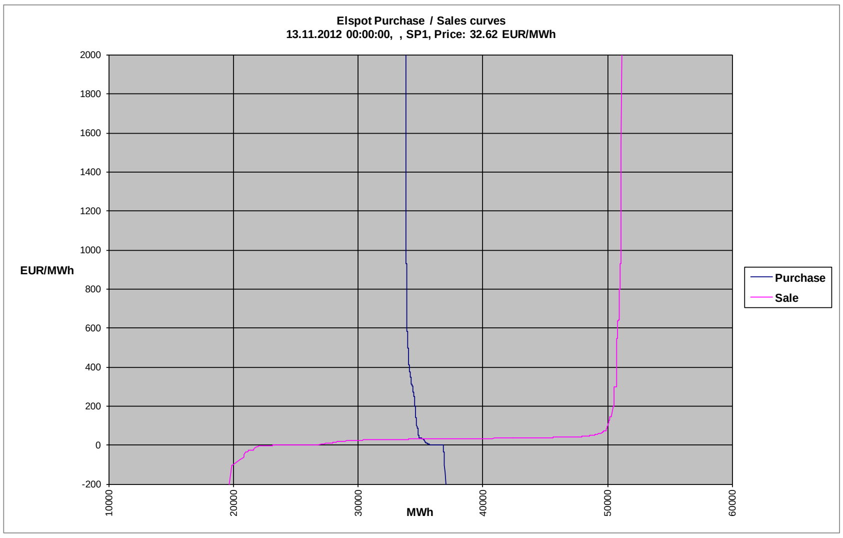


Fig 4.4 Purchase/Sales price curves (Nord Pool, Scandinavia)

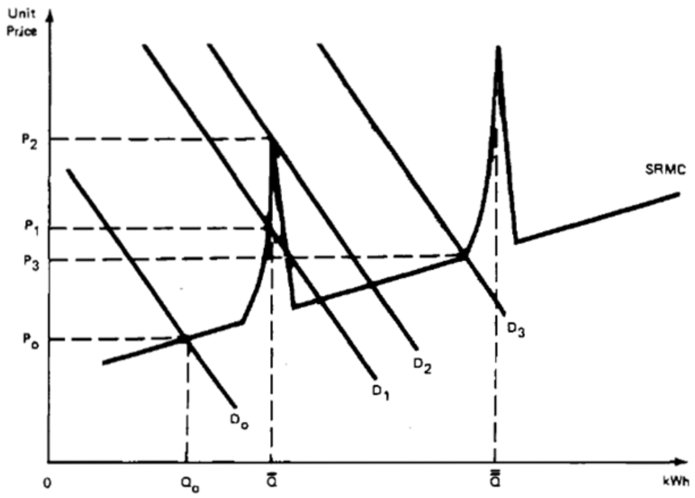


Fig 4.5 Real Time Electricity Price-Load Demand Graph

(SRMC: Short-Run Marginal Costs)

The key issue needs to be mentioned is that the average load demand level is the base of price-load equation. According to AGL Energy [AGL Electricity Price Information], the daily load demand can be divided into 4 levels (valley, shoulder, peak, off-peak), which are based on 4 periods (0am-7am, 7am-2pm, 2pm-9pm, 9pm-12am).

4.4 Electricity Price-Load Demand Equations

In this thesis, a sample daily real time electricity price – load demand graph (1st July, 2012) is studied to discover the real time price-load equations during 4 periods.

Before presenting the electricity price –load demand relationships, it is necessary to analyse the AEMO.

AEMO provide the real time data of electricity price and load demands. This data are regarded as the important source to investigate electricity price and load demand relationship.

As discussed previously, it is proven that electricity prices are highly dependent on load demand level. The daily load demand profile can be divided into four levels (valley, shoulder, peak and off-peak). As a consequence, there are four electricity price-load equations in four periods.

4.4.1 Data Modelling

To determine the relationships of two series of data, data modelling is important. The data modelling and analysis can be divided into linear and nonlinear approaches.

According to the above analysis, it can be assumed that the electricity prices and load demands following the relationship as

$$P = \alpha L^n + \beta L^{n-1} \ldots + \gamma L + b \tag{4.3}$$

where P is electricity price, L is load demand, α, β, γ and constant b are coefficients.

The next step is to ascertain the coefficientsα, β, γ and constant b. Curve fitting is one of the mostly used data modelling methods to find the curve that best fitting the price-load data.

In this research, the least squares method is used which minimizes the square of the error between the original data and the values predicted by the equation. This method is simple and well understood. The least squares fits consist of: linear, polynomial, exponential, logarithmic and power [Curve Fitting Tutorial]. In this research, the polynomial is employed to fit the electricity prices and load demands data.

Polynomial fits the data with a curve function of:

$$y = f(x) = P_1 x^n + P_2 x^{n-1} \ldots\ldots P_{n-1} x + P_n \tag{4.4}$$

where $P_1 \ldots\ldots P_n$ are coefficients and n represents the fit order. The higher the order, the higher accuracy of the curve fits. However, the high order increases the complications of the function and not necessary in most engineering problems. In this research, the fit order is set to 3.

Take the 0am-7am data on 1st of July 2012 as an example, the MATLAB codes are as follows

```
pops1=(y1(1:14)-mean(y1(1:14)))./std(y1(1:14)); % Pre-process of data

[P1,S1]= polyfit(pops1,v1(1:14),3)

pop1=polyval(P1,pops1);

figure; plot(pops1,v1(1:14),'bo',pops1,pop1,'r-');
```

There are two issues that must be mentioned

1) The data is supposed to be pre-processed before curve fitting
2) The data is recorded every 30 minutes, hence there are 14 numbers being recorded

The results are as follows

P1 =-1.973032661548887   6.785783950417247   6.795252686287477 45.741479790303828

S1 = R: [4x4 double]

df: 10

normr: 13.118443974495005

This gives the fitting function as below

$$y = f(x) = P_1x^3 + P_2x^2 + P_3x + P_n \tag{4.5}$$

$P_1 = -1.97$

$P_2 = 6.79$

$P_3 = 6.8$

$P_n = 45.74$

The price-load equations of this day are represented by Table 4.2.

Table 4.2 Price-Load Equations

Time Periods	Price-Load Equations
0am-7am	$P = -1.97L^3 + 6.79L^2 + 6.8L + 45.74$
7am-2pm	$P = -3.26L^3 - 8.38L^2 + 2.92L + 63.36$
2pm-9pm	$P = 3.34L^3 - 2.57L^2 + 1.76L + 68.24$
9pm-12pm	$P = 1.02L^3 - 3.52L^2 - 0.09L + 70.51$

According to Chapter 3, PHEV batteries hold 16-32 kWh capacities. To charge at 4kW power will take 4-8 hours to fully charge the vehicles. In this thesis, it assumes the battery has a capacity of 20 kWh. The charging is 5 hours.

Applying the price-load equations, the PHEV charging cost equations are as Table 4.3.

Table 4.3 PHEV Charging Cost-Load Equations

Time Periods	PHEV Charging Cost-Load Equations
0am-7am	$\int_{t=t_1}^{t=t_2} P(L)\,dt = \int_{t=t_1}^{t=t_2} (-1.97L^3 + 6.79L^2 + 6.8L + 45.74)dt$
7am-2pm	$\int_{t=t_1}^{t=t_2} P(L)\,dt = \int_{t=t_1}^{t=t_2} (-3.26L^3 - 8.38L^2 + 2.92L + 63.36)dt$
2pm-9pm	$\int_{t=t_1}^{t=t_2} P(L)\,dt = \int_{t=t_1}^{t=t_2} (3.34L^3 - 2.57L^2 + 1.76L + 68.24)dt$
9pm-12pm	$\int_{t=t_1}^{t=t_2} P(L)\,dt = \int_{t=t_1}^{t=t_2} (1.02L^3 - 3.52L^2 - 0.09L + 70.51)dt$

t_1: Charging start time

$t_2 = t_1 + 5h$: Charging end time

The next step is to study the load-time relationship. Curve fitting the load demand data with time, the fit function can be calculated as

$$Load = (-0.0001448t^5 + 0.02019t^4 - 1.187t^3 + 33.15t^2 - 334.3t + 5577)Mwh \tag{4.6}$$

4.5 Summary and Discussion

This chapter has analysed the electricity pricing concepts and shown that electricity prices are highly correlated to load demands on distribution networks. As a consequence, the daily price-load equations have been worked out taking the price elasticity into account.

According to the electricity price-load demand relationship, the electricity profiles are divided into four periods. As a result, four price-load equations have been measured by curve fitting. Considering the PHEV charging, the charging costs-load equations have been presented.

There is one issue worth mentioning. The charging costs-load equations are based on daily electricity profiles. The coefficients vary day to day.

To minimise the charging costs considering the complexity of costs-time equations, it is essential to apply a less time consuming optimization technique to calculate the optimal charging schedule.

Chapter 5

OPTIMAL PHEV CHARGING SCHEDULE

5.1 Overview

This chapter discusses the methodologies to solve the two problems demonstrated in Chapters 3 and 4: additional power loss ratios and charging costs optimizations. According to the problem features, PSO is considered to be the appropriate method to achieve optimal charging schedules. Multi-Objective PSO (MOPSO) is applied to achieve the equilibrium charging schedule due to the conflicting features of the two issues: APLR minimization and charging costs minimization.

This chapter is organised as follows. Section 5.2 states the background to solve the two main problems and analyses the APLR and charging costs minimization problems. Section 5.3 introduces the common optimization methodology. According to the complexity, difficulty to diverge and time consuming at the problem, Section 5.4 discusses the way to choose a suitable optimization technique and MOPSO is introduced in section 5.5. Section 5.6 states the simulation results and demonstrates that MOPSO is efficient to achieve the optimum PHEV charging schedule.

5.2 Introduction to PHEV Charing Scheduling

In Chapters 3 and 4, the real time power losses and costs of PHEV charging have been analysed. The loss-load and cost-load equations mathematically described the internal relationships of three items: power losses, charging costs and load demands. The real time load demands are dependent on time.

For the sake of electricity suppliers, APLR is a main issue to be considered to minimize. In addition, taking customers' interests into account, charging cost is the main issue for them to minimize.

To solve these problems, optimization is immediately considered to be applied to optimally schedule the PHEV charging. The optimization usually follows the process as below

1. Introduction and representation of the problems to be solved
2. The objective functions representing the problems investigated
3. Analysis of the problems and apply the most appropriate optimization control technology

The previous chapters have done Tasks 1 and 2. This chapter analyses the power loss and charging cost equations and applies the appropriate optimization method.

In this research, two problems are to be solved: APLR on distribution grid caused by PHEV charging and minimization charging costs.

The two problems are both highly related to load demand levels which is dynamic. Optimal scheduling is thus considered to be an appropriate solution to minimize both APLR and charging costs which are conflicting with each other.

The objective functions (loss-load equation and charging cost-load equations) and optimization problems follow the rules as

- The objective functions are highly correlated to load demands.
- The objective functions are complex and difficult to diverge.
- The optimization process is time-consuming for the huge number of data.

Based on these features, the following sections introduce the main solution process including

1. The optimization method selection.

2. Multi-objective optimization.

5.3 Optimization Methodology

Optimization methods are widely applied recently to solve practical engineering problems including production planning, transportation scheduling and optimal routing to maximize profits or minimize costs.

There are a variety of optimization methodologies [Deb, 2001] and can be grouped into two types: deterministic and heuristic optimizations.

5.3.1 Deterministic Optimization

The deterministic optimization is a classic method that consists of direct and gradient-based methods [Li, 2009].

The direct methods converge to the optimum directly based on the transition rule.

Gradient-based methods calculate the minimum or maximum by differentiating the objective function and setting the equation to zero.

$$\frac{\partial f(x)}{\partial x} = 0$$

The gradient-based methods require clear objective equations to be continuous and differentiable.

5.3.2 Meta-heuristic Optimization

Unlike the deterministic methods, meta-heuristic optimizations do not require the continuity, differentiability of the objective function. This advantage allows them to solve complex real-world engineering problems which usually contain discrete, nonlinear and non-differentiable models.

The meta-heuristic optimizations are stochastic methods which search the space intelligently. Usually they mimic the natural behaviours of insects. In this research, one of the meta-heuristic methods is considered to be an appropriate optimization technique for the advantages of

- Flexibility: Algorithms do not need to follow strict rules (continuous, differentiable)
- High performance: Meta-heuristic methods find optimums for complicated problems with less time consumed

5.4 The Optimization Method Selection

To be a suitable optimization method, the selected method must be appropriate to the problem nature and the objective function shouldn't be too complicated.

PSO is population-based and achieves the solution with stochastic searching and cooperation instead of mutation and elimination. Compared to the other mainstream evolutionary computation paradigms, the genetic algorithms (GAs) which are prone to converge to local optimum and time consuming and the population selected are concentrated to the ones near to the best individual.

In this research, the daily electricity load demand is a dynamic function of time. Consequently, the optimal solution varies between the constraints. The elimination of the individuals who are potential optimal solutions have tendency to converge to local optimization.

Besides the swarm diversity, PSO is easier to implement and needs less parameters need setting.

5.5 MOPSO

The PSO algorithm is expressed as follow

$$v_{id}(t+1) = v_{id}(t) + c_1 * r_{1id}(t)\big(pBest_{id}(t) - x_{id}(t)\big) + c_2 * r_{2id}(t)(lBest_{id}(t) - x_{id}(t)) \quad (5.1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (5.2)$$

$x_{id} = (x_{i1}, x_{i2}, \ldots x_{iD})$ represents *i-th* particle in a D-dimensional search space; $pBest_{id}(t)$ denotes the best position of the particle's previous flight; *lBest* represents the local best position of the neighbourhood; $v_{id} = (v_{i1}, v_{i2}, \ldots v_{iD})$ denotes the velocity of particle i; c_1 and c_2 are the cognitive and social constants respectively; r_{1id} and r_{2id} are random numbers distributed in range of [0,1]; t is the iteration number.

The PSO algorithm has been developed with several variants [Li, 2007] as Eqs 5.3 and 5.4.

$$v_{id}(t+1) = \chi[wv_{id}(t) + c_1 * r_{1id}(t)\big(pBest_{id}(t) - x_{id}(t)\big) + c_2 * r_{2id}(t)(lBest_{id}(t) - x_{id}(t))] \quad (5.3)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (5.4)$$

where w is the inertia weight which is critical for the convergence of PSO; χ is called the constriction coefficient. It is believed valuable to properly set the c_1 and c_2 for quicker convergence and local minima alleviation [Parsopoulos, 2002]. Any c_1 and c_2 restricted in the range of $c_1 + c_2 = 4$ are acceptable according to [Carlisle & Dozier, 2001] and set of $c_1 = c_2 = 2$ was further suggested in [Kennedy, 2002].

The MOPSO has been investigated by several researchers.

A dynamic neighbourhood strategy was introduced in [Hu & Eberhart, 2002] to select the global best. The personal best is determined by the Pareto-dominance concept.

A grid method was presented in [Coello & Lechuga, 2002] in which the objective space is divided into small hyper cubes. A fitness value is assigned to each hypercube depending on the number of elite particles that lie in it. The personal best is updated by the Pareto-dominance concept.

The weighted aggregation technique was introduced in [Parsopoulos & Vrahatis, 2002]. According to this strategy, all objectives are summed to a weighted combination. By this way a multi-objective problem can be simply converted into a single objective problem.

In this research, the MOPSO with weighted aggregation technique is applied for the simplicity of this method. The problems concerned in this research are the APLR and the PHEV charging costs.

These two problems can be represented by the following objective functions

$$f_1(t) = (P_{loss\ total} - P_{loss\ initial})/P_{loss\ total} \tag{5.5}$$

$$f_2(t) = \sum_{t=t_1}^{t=t_2} Price \tag{5.6}$$

where t_1 is the charging commence time and t_2 is the charging end time

According to the weighted aggregation technique, Eqs 5.5 and 5.6 can be combined into Eqs 5.7 and 5.8.

$$F(t) = \alpha f_1(t) + \beta f_2(t) \tag{5.7}$$

$$\alpha + \beta = 1 \tag{5.8}$$

5.6 Addition Power Loss Ratio and Charging Costs Optimization

5.6.1 Additional Power Loss Ratio Simulation

In this study, DigSilent Power Factory is applied to investigate the power losses of power distribution network caused by PHEV charging. Two classic distribution networks are employed: IEEE 13-Node distribution network and IEEE 34-Node distribution network. The networks are as in Fig 5.1 and Fig 5.2.

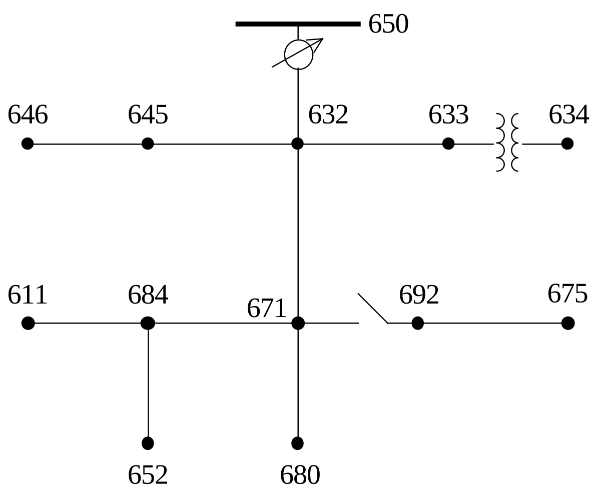


Fig 5.1 IEEE 13-Node Network

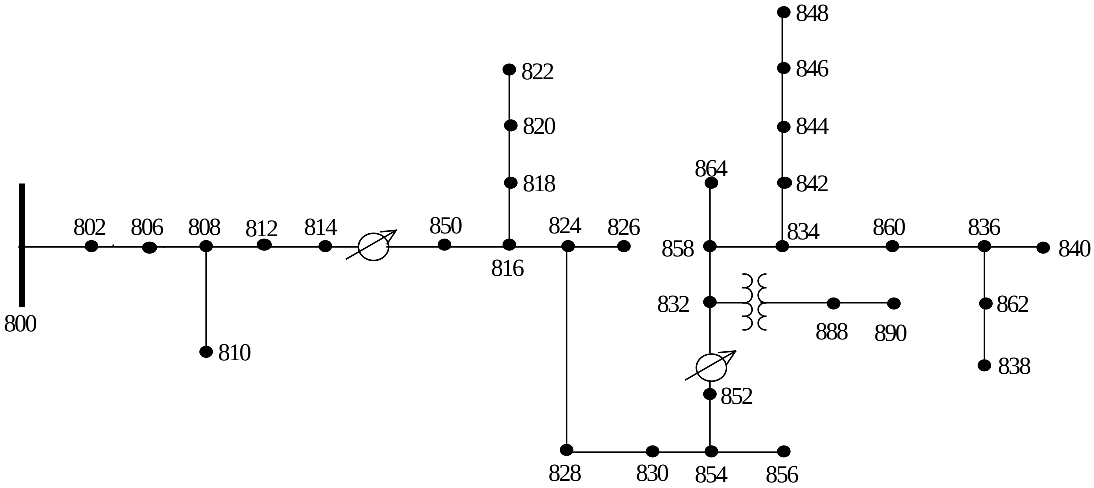
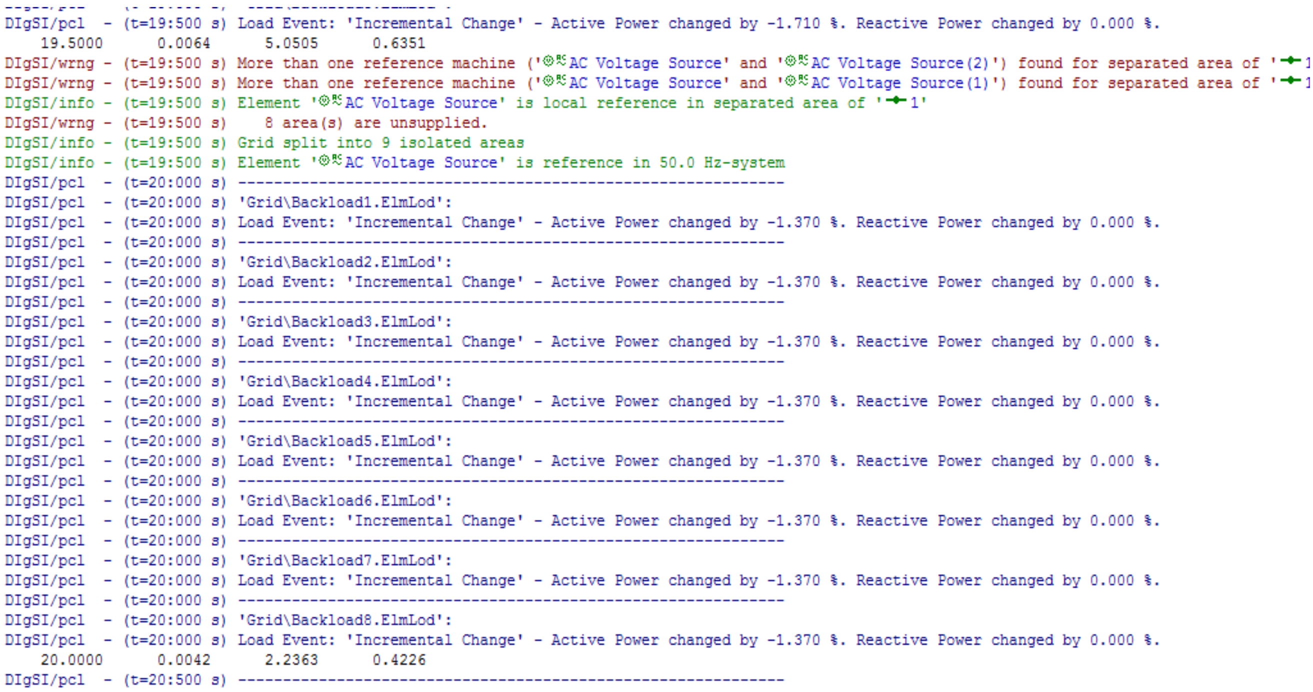


Fig 5.2 IEEE 34-Node Network

The Dynamic Simulation Language is run by DigSilent Power Factory to real time monitor the distribution network and calculates power losses on test feeders with PHEV plug-in or off. Fig 5.3 represents the sample DSL progress.



```
DIgSI/pcl  - (t=19:500 s) Load Event: 'Incremental Change' - Active Power changed by -1.710 %. Reactive Power changed by 0.000 %.
    19.5000      0.0064      5.0505      0.6351
DIgSI/wrng - (t=19:500 s) More than one reference machine ('AC Voltage Source' and 'AC Voltage Source(2)') found for separated area of '1
DIgSI/wrng - (t=19:500 s) More than one reference machine ('AC Voltage Source' and 'AC Voltage Source(1)') found for separated area of '1
DIgSI/info - (t=19:500 s) Element 'AC Voltage Source' is local reference in separated area of '1'
DIgSI/wrng - (t=19:500 s)    8 area(s) are unsupplied.
DIgSI/info - (t=19:500 s) Grid split into 9 isolated areas
DIgSI/info - (t=19:500 s) Element 'AC Voltage Source' is reference in 50.0 Hz-system
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload1.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload2.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload3.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload4.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload5.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload6.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload7.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
DIgSI/pcl  - (t=20:000 s) -------------------------------------------------------------
DIgSI/pcl  - (t=20:000 s) 'Grid\Backload8.ElmLod':
DIgSI/pcl  - (t=20:000 s) Load Event: 'Incremental Change' - Active Power changed by -1.370 %. Reactive Power changed by 0.000 %.
    20.0000      0.0042      2.2363      0.4226
DIgSI/pcl  - (t=20:500 s) -------------------------------------------------------------
```

Fig 5.3 DigSilent Power Factory DSL Progress

In this study, the APLR caused by PHEV charging is employed to indicate the power loss levels. The ratio can be mathematically described by Eq.5.5.

The simulation results are represented by Tables 5.1 - 5.4.

Table 5.1 Additional Power Loss Ratio (13-Node Network)

Duration\PHEV Penetration	20%	40%	60%	80%	100%
0 – 5am	22.3%	38.7%	50.2%	58.8%	65.3%
5am – 10am	23.7%	39.5%	51.6%	60.1%	66.5%
10am – 3pm	20.2%	34.9%	46.3%	54.9%	61.5%
3pm – 8pm	19.4%	33.9%	44.8%	53.2%	59.8%
7pm – 12am	19.6%	34.6%	45.7%	54.3%	60.9%

Table 5.2 Additional Power Loss Ratio (34-Node Network)

Duration\PHEV Penetration	20%	40%	60%	80%	100%
0 – 5am	29.6%	48.3%	60.7%	69.1%	75%
5am – 10am	33.9%	52.3%	63.4%	71.5%	77%
10am – 3pm	25.9%	44.1%	56.1%	64.4%	71%
3pm – 8pm	26.7%	44.2%	55.7%	63.8%	70.1%
7pm – 12am	25.7%	43.2%	55.5%	64.1%	70.5%

Applying single-objective PSO, the optimums are as Tables 5.3 and 5.4.

Table 5.3 Optimal Additional Power Loss Ratio (13-Node Network)

Duration\PHEV Penetration	20%	40%	60%	80%	100%
3pm – 8pm	19.4%	33.9%	44.8%	53.2%	59.8%

Table 5.4 Optimal Additional Power Loss Ratio (34-Node Network)

Duration\PHEV Penetration	20%	40%	60%	80%	100%
3pm – 8pm	26.7%	44.2%	55.7%	63.8%	70.1%

5.6.2 Charging Costs Simulation

The PHEV charging costs can be mathematically described by Eq. 5.6. The simulation results are represented by Tables 5.5 and 5.6.

Table 5.5 Random Charging Costs

Duration	Charging Cost
0 – 5am	$1.04
5am – 10am	$1.09
10am – 3pm	$1.2
3pm – 8pm	$1.4
7pm – 12am	$1.36

Table 5.6 Optimal Charging Cost

Duration	Charging Cost
1:30am – 6:30am	$0.95

5.6.3 Optimal Charging Schedule

Through the comparison of Tables 5.3, 5.4 and 5.6, it is obvious that the APLR optimum is conflicting with the charging cost optimum. While the APLR reaches its minimization with PHEVs charging from 3pm to 8pm, the minimal charging cost occurs at 1:30am to 6:30am schedule. For this reason, an optimal charging schedule is needed to balance both interests. The optimal charging schedule is reached after MOPSO is applied and presented in Table 5.7.

Table 5.7 Optimal Charging Schedule (13-Node Network)

Duration\PHEV Penetration	20%	40%	60%	80%	100%
0 – 5am	22.3%	38.7%	50.2%	58.8%	65.3%
Cost	$1.04				

5.7 Summary

This chapter has introduced the optimization method, MOPSO to derive an optimal charging schedule for PHEVs to reduce both APLR and charging costs simultaneously.

This chapter has proven that the mathematical models of APLR and charging costs quantified in Chapters 3 and 4 are appropriate by simulation results.

PSO has been proven to be efficient find to optimize APLR and charging costs. Simulation results show that APLR and charing costs optimizations are conflicting targets. MOPSO has been proven to be appropriate tool to solve the conflicting targets and achieved the optimal charging schedule finally.

Chapter 6

CONCLUSIONS AND FUTURE RESEARCH

6.1 Overview

This chapter summaries the whole work of this thesis and highlights the research results achieved. Section 6.2 outlines the results of this thesis and its main contributions. Section 6.3 discusses the recommendations for future research.

6.2 Results and Main Contributions

This thesis has investigated the two mainly concerned impacts of PHEVs charging on distribution networks: APLR and charging cost. It has demonstrated that the power loss – load demand equations and charging costs- load demand equations and load demand – time equations are correlated. The optimal charging schedule is finally achieved to reduce power loss ratio and charging costs simultaneously by applying MOPSO.

The power flow analysis on the classic distribution networks (13-Node, 34-Node) demonstrates that the total power losses and APLR are functions of the real time load demands. In addition, the additional power losses decrease with the load demands increase (minimal APLR at peak load hours). Single-objective particle swarm optimization effectively finds the optimal charging schedule with lowest APLR.

The electricity pricing analysis has demonstrated that the electricity prices are highly correlated to load demands. The least square curve fitting gives the electricity price – load demand and further charging costs – load demand equations. Single-objective particle swarm optimization finds the optimal charging schedule with minimal costs.

This thesis has also used MOPSO to find the otpimal charging schedule.

The major results and contributions of this thesis can be summarized as

- The distribution network is mathematically modelled and loss-load equation on selected test feeder is calculated, which is the fundament for precise power loss impact analysis with large-scale PHEV charging
- High correlation between the real time electricity price and load demand is detected for AEMO data
- The electricity price-load demand and charging costs-load demand equations are obtained
- The minimization of APLR and charging costs minimization is done by MOPSO to achieve an optimal charging schedule considering the APLR and charging costs optimization simultaneously

6.3 Future Research

Based on the results of this research, there are a few suggestions to the future research in this field

- In the analysis of power losses, only the IEEE standard classic distribution networks (13-Node and 34-Node) are employed. Due to the simplicity of these networks, the power losses on transformers are ignored in this research. It would be more useful to conduct power flow and power loss analysis by considering the transformer impacts in real-world distribution networks
- For simplicity, this research assumes all PHEVs charging at same schedule. To consider more complex and asynchronous charging schedules in the real world will

be very interesting. The optimal charging schedule of individual will be dependent on other consumers' status

- The price-load model derived in this thesis is not able to represent the price-load relationship in extreme or unusual cases such as the windy and extremely hot days. It will be interesting to modify the price-load model considering other components such as temperature
- To simplify the problems in this research, the charging rate is assumed constant and the charging time is continuous. It will be interesting to consider that charging rates are variable and the charging time are flexible for optimization purposes

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