Steady-state analysis of power distribution system with dynamic charging electric vehicles

Wang, Chuan

2020

Wang, C. (2020). Steady-state analysis of power distribution system with dynamic charging electric vehicles. Master's thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/140291>

<https://doi.org/10.32657/10356/140291>

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0).

Downloaded on 26 Apr 2023 19:59:07 SGT

Steady-state Analysis of Power Distribution System with Dynamic Charging Electric Vehicles

WANG CHUAN

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Master of Engineering

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

09-Jan-2020

.....

Date

WANG CHUAN

.....

WANG CHUAN

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

09-Jan-2020

.....

Date

.....

HUNG D. NGUYEN

Authorship Attribution Statement

This thesis contains the material from one paper accepted at a conference and one paper being reviewed in which I am listed as an author.

Chapter 2 is published as **Chuan Wang**, Hung D. Nguyen, “Steady-state voltage profile and long-term voltage stability of electrified road with wireless dynamic charging”, in Proceedings of the Tenth ACM International Conference on Future Energy Systems, ACM, 2019, pp. 165–169. DOI: 10.1145/3307772.3328294.

The contributions of the co-authors are as follows:

- Prof Nguyen provided the initial project direction and edited the manuscript draft.
- I prepared the manuscript drafts. The manuscript was revised and proofread by Prof Nguyen and me.
- I built up the model for the Wireless Dynamic Charging EV system with the help of Prof Nguyen.
- I carried out simulations and get the voltage profiles in MATLAB.
- Prof Nguyen and I proposed a new strategy to analyze the long-term voltage stability. I applied the method in simulations and obtained the nose curves.
- Prof Nguyen and I analyzed the simulation results.

Chapter 3 is part of Parikshit Pareek, **Chuan Wang**, and Hung D. Nguyen. “Non-parametric Probabilistic Load Flow using Gaussian Process Learning.” IEEE PESGM 2020 (Under Review) arXiv preprint arXiv:1911.03093 (2019).

The contributions of the co-authors are as follows:

- Prof Nguyen provided the initial project direction and edited the manuscript draft.

- Mr. Parikshit Pareek prepared the manuscript drafts. The manuscript was revised and proofread by Prof Nguyen and me.
- Mr. Parikshit Pareek, Prof Nguyen, and I co-designed the proposed method. Mr. Parikshit Pareek considered applying the GP-UCB method to get the probabilistic learning bound.
- Mr. Parikshit Pareek and I carried out simulations in the IEEE 30-bus and IEEE 118-bus systems. I conducted simulations in the IEEE 33-bus system for testing.
- Mr. Parikshit Pareek and I analyzed the simulation results and data.

09-Jan-2020

.....

Date

WANG CHUAN

.....

WANG CHUAN

Acknowledgements

First and foremost, I want to express my serious and sincere appreciation to my supervisor Professor Hung D. Nguyen for his patient and valuable guidance through my postgraduate career. Not only he has told me the appropriate way to do research, but also the correct attitude to be a researcher. He also serves as a good mentor in my life, teaching me to feel passion for life.

Secondly, I would like to sincerely thanks Mr. Parikshit Pareek and Mrs. Weng Yu, the Ph.D students under Professor Hung D. Nguyen. They gave me a lot of guidance in research and solve many problems for me. I could not finish this thesis without their help. I also appreciate Dr. Liu Yang who encourages me and supports me.

In addition, I would like to share my thanks to other students in the laboratory. We sat beside each other and overcome the challenges together. I was full of enthusiasm and did not feel lonely because of them. Besides, I would like to gratefully acknowledge Mrs. Chia-Nge Tak Heng and Ms. Lin Zhiren, technical staff at the Clean Energy Research Laboratory for all their support.

Lastly, I would like to thank all my friends and family members who have supported me in many ways during the course of my research work.

Besides, I want to share many thanks to my friends in a small group called "family". We fight together to win and they helped me upgrade my rank level in a game. When I was upset because of the problems in my research, they always bear the pain with me and encourage me a lot.

Contents

Statement of Originality	i
Supervisor Declaration Statement	ii
Authorship Attribution Statement	iii
Acknowledgements	v
Summary	ix
List of Figures	xi
List of Tables	xiii
Abbreviations	xiv
1 Introduction	1
1.1 Background and Motivation	1
1.2 Research Gap and Challenges	3
1.2.1 Steady-state Voltage Profile and Long-term Voltage Stability of Electrified Road with Wireless Dynamic Charging	3
1.2.2 Non-parametric Probabilistic Load Flow using Gaussian Pro- cess Learning	4
1.3 Major Contributions of the Thesis	5
1.3.1 Steady-state Voltage Profile and Long-term Voltage Stability of Electrified Road with Wireless Dynamic Charging	6
1.3.2 Non-parametric Probabilistic Load Flow using Gaussian Pro- cess Learning	7
1.4 Organization of the Thesis	8
2 Steady-state Voltage Profile and Long-term Voltage Stability with Wireless Dynamic Charging	9
2.1 Overview	9
2.2 Literature Review	11
2.2.1 Wireless Dynamic Charging	11
2.2.2 Electric Railway Power Supply Systems	12

2.2.3	New Power Flow Algorithms Relating to Electrified Tracks .	14
2.2.4	Regenerative Braking Energy and Topology of the Power Supply System	15
2.3	WDC EVs and Power Flow Study	17
2.3.1	Wireless Dynamic Charging System	17
2.3.2	Power Flow Study	19
2.4	Voltage Profile of WDC system	22
2.4.1	Parameter Values of Dynamic Charging EV System	22
2.4.2	Voltage Profile of One-way Road	23
2.4.2.1	WDC EVs System without Voltage Compensators and PVs	23
2.4.2.2	WDC EVs System with Voltage Compensators and PVs	25
2.4.3	Voltage Profile of Two-way Road	27
2.4.3.1	WDC EVs System without Voltage Compensators and PVs	27
2.4.3.2	WDC EVs System with Voltage Compensators and PVs	28
2.5	Long-Term Voltage Stability	29
2.5.1	CPF for a 2-bus System	29
2.5.2	Maximum Road Length with Fixed EV Fleet	31
2.5.3	Maximum Number of Vehicles on a Fixed Length Road	34
2.6	Conclusions	36
3	Non-parametric Probabilistic Load Flow using Gaussian Process Learning	38
3.1	Overview	38
3.2	Literature Review	40
3.2.1	Probabilistic Load Flow	40
3.2.2	Numerical Methods to Solve PLF Problems	41
3.2.3	Analytical Methods to Solve PLF Problems	43
3.2.4	Approximation Methods to Solve PLF Problems	44
3.3	Theory of GP Regression and GP-UCB Method	45
3.3.1	GP Regression	45
3.3.2	GP-UCB	47
3.4	Proposed Non-parametric Probabilistic Load Flow(NP-PLF) Method	47
3.4.1	Formulation of Uncertain Input	48
3.4.2	Main Methodology of NP-PLF Method	49
3.4.2.1	NP-PLF Learning	50
3.4.2.2	NP-PLF Testing	52
3.5	Simulation Results and Discussion	52
3.5.1	Uncertain Injection Variations	53
3.5.2	Uncertain EV Locations	59
3.6	Conclusions	62

4	Conclusions and Future Works	64
4.1	Conclusions	64
4.2	Future Works	65
	Appendix	67
	Author's Publications	69
	Bibliography	70

Summary

Increasing concerns about global carbon emission and the shortage of fossil fuels have shifted people's attention from traditional cars towards electric vehicles (EVs). For EVs, charging is of great importance and can be largely classified into wireless and plug-in types. Wireless dynamic charging technologies are gradually replacing the plug-in ones as they allow EVs being charged while they are in motion. In this way, those EVs become a new type of loads - the moving loads. They may change their locations constantly in the network. A large number of EVs charging to the grid creates a significant challenge to the stability and quality of the overall power system, like affecting the voltage control. To analyze the steady-state problem of dynamic charging, voltage profiles along the distribution system and probabilistic load flow problems should be both considered.

To study the effect of these moving loads on power distribution grids, this work first focuses on the steady-state analysis of electrified roads equipped with wireless dynamic charging. In particular, the voltage profile and the long-term voltage stability of the electrified roads are considered. We introduce a simple dynamic charging EV system and the power flow problem for the steady-state study. MATPOWER is used to construct the steady-state voltage profile. We analyze the problem for several different conditions including moving directions, power consumptions, charging efficiencies, photovoltaic panels integration, and reactive power compensation with capacitor banks. Unusual shapes of the voltage profile are observed such as the half-leaf veins for a one-way road and the harp-like shape for a two-way road. Voltage swings are also detected when the vehicles move in the two-way road configuration. Such new observations will contribute to the voltage regulation of

the distribution system. We also consider the long-term voltage stability of electrified roads where one can calculate the maximum length of a road for a fixed fleet of EVs and the maximum number of vehicles for a fixed road. A new method is introduced to use the continuation power flow (CPF) to find the critical length and number of allowed EVs. Varying segment sizes of the distribution system affect the results of both the maximum length of the road and the maximum number of vehicles. The voltage collapse phenomenon when the vehicles move beyond the maximum allowed length will also be analyzed.

In addition to the above deterministic analysis, we consider the probabilistic steady-state problem. In particular, we propose a non-parametric probabilistic load flow (NP-PLF) technique based on Gaussian Process (GP). The technique can provide “semi-explicit” power flow solutions by implementing a learning step and a testing step. The proposed NP-PLF leverages upon the GP upper confidence bound (GP-UCB) sampling algorithm. The salient features of this NP-PLF method are: i) applicable for power flow problem having power injection uncertainty with unknown class of distribution; ii) providing probabilistic learning bound (PLB) which controls the error and convergence; iii) capable of handling intermittent distributed generation as well as load uncertainties; and iv) applicable to both balanced and unbalanced power flow with different type and size of systems. The simulation results performed on the IEEE 33-bus, IEEE 30-bus, and IEEE 118-bus systems show that the proposed method is able to learn the state variable function in the input subspace using a small number of training samples. Further, the testing with different distributions indicates that more complete statistical information can be obtained for the probabilistic power flow problem.

List of Figures

2.1	General scheme of the traction power supply system simulation model using the Monte Carlo method [1]	16
2.2	Diagram of dynamic charging EV system[2]	17
2.3	The diagram of simplified dynamic charging EV system	19
2.4	Voltage profile of WDC EV system (one moving direction)	24
2.5	Voltage profile of WDC EV system considering more general settings (one moving direction)	25
2.6	Voltage profile of WDC EV system with voltage compensators and PVs (one moving direction)	26
2.7	Voltage profile of WDC EV system (two moving directions)	27
2.8	Voltage profile of WDC EV system with voltage compensators and PVs (two moving directions)	28
2.9	A two-bus system with one slack bus and one PQ bus [3]	29
2.10	Maximum road length of WDC EV system. The black arrow indicates increasing PV installation.	33
2.11	Voltage collapse phenomenon	34
2.12	Maximum number of vehicles of WDC system	35
3.1	$ V_{25} $ as a function of uncertain renewable power injection (P_{g4}) at bus 27 having uniform distribution between zero to 55 MW	54
3.2	$ V_{24} $ as a function of uncertain renewable power injection (P_{g5}) at bus 13 having uniform distribution between zero to 28 MW	55

3.3	$ V_{21} $ as a function of uncertain renewable power injection (P_{g3}) at bus 22 having uniform distribution between zero to 50 MW	56
3.4	Histogram for $ V_{25} $ with uncertain P_{g4} at bus 27 having normal distribution ($\mu = 28$ and $\sigma = 8$) using proposed NP-PLF and MCS method (50000 samples).	57
3.5	Histogram for $ V_{28} $ with uncertain P_{g4} at bus 27 having gamma distribution (shape parameter $a=8$ and scale parameter $b=3$) using proposed NP-PLF and MCS method (50000 samples).	57
3.6	$ V_j $ as a function uncertain P_{d30} in 30-Bus system	58
3.7	Bus voltage angle as a function uncertain power demand at bus 17 in 30-Bus system	59
3.8	$ V_{75} $ as a function of uncertain S_{d30} in 118-Bus system	60
3.9	$ V_5 $ as a function of uncertain P_{34} and EV location (between bus 3 and 4) in 33-Bus system	61
3.10	$ V_5 $ as a function of uncertain P_{34} and EV location (between bus 3 and 4) using proposed NP-PLF and MCS method (10000 samples) .	62
A	The diagram of the IEEE 30-bus system[4]	67
B	The diagram of the IEEE 33-bus system[5]	68
C	The diagram of the IEEE 118-bus system[6]	68

List of Tables

2.1	Parameter values of dynamic charging EV system	23
3.1	Results in NP-PLF Solution	53
3.2	Results Corresponding to NP-PLF Solution Shown in figure 3.6 . .	58
3.3	ξ_{max} , N and Computation Time Corresponding to NP-PLF Solution Shown in figure 3.7	59
3.4	Results in NP-PLF Solution with moving EV	60

Abbreviations

Electric Vehicle	EV
Monte Carlo Simulation	MCS
Gaussian Process	GP
Continuation Power Flow	CPF
Probabilistic Load Flow	PLF
Probability Density Function	PDF
Long-term Voltage Stability	LTVS
Wireless Dynamic Charging	WDC
Non-parametric Probabilistic Load Flow	NP-PLF
Probabilistic Learning Bound	PLB
Gaussian Process Upper-confidence Based	GP-UCB
Electric Multiple Units	EMUs
Online Electric Vehicles	OLEVs
Power Supply Capacity	PSC
Traction Power Supply Systems	TPSSs
Power Supply System	PSS
Port Algorithm	PA
High Frequency	HF
Alternating Current	AC
Direct Current	DC
Battery Management System	BMS
Photovoltaic	PV
Latin Hypercube Sampling	LHS

Latin Supercube Sampling	LSS
Multi-linear Gaussian Processe	MLGP
Gaussian Process Machine Learning	GPML
Reproducing Kernel Hilbert Space	RKHS
Newton-Rapson Load Flow	NRLF

Chapter 1

Introduction

In the first chapter, the research background, motivation and major contributions of this thesis are discussed.

1.1 Background and Motivation

Due to a large amount of carbon dioxide generated during the use of automobiles, exhaust emissions have caused serious environmental problems. Over the past few years, transportation equipment's demand for crude oil and its contribution to carbon dioxide emissions have increased significantly. In response to the environmental and energy issues brought about by the development of the automotive industry, countries around the world are actively taking measures to promote traditional automobiles. The development of new energy electric vehicles has become the international community consensus. New vehicles use new and unconventional vehicle fuel as the source of power. The fuel can be solar energy, fuel cells (fuels other than gasoline and diesel, such as natural gas), and other new energy storage (such as super-capacitors, flywheels).

At present, the new energy electric vehicles mainly promoted at home and abroad mainly include pure EVs, hybrid EVs, plug-in hybrid EVs, and fuel cell EVs.

Consumption of petroleum resources improves the efficiency of energy use. At the same time, it can also reduce the exhaust emissions caused by traditional cars to better achieve emission reduction targets in the transportation field. People also created a new wireless dynamic charging method to improve the charging efficiency of electric vehicles. This new technology can reduce the size of the battery inside the EVs.

However, the massive integration of electric vehicles will cause some problems. The variation of power generators and power loads may cause an unbalanced power flow and even voltage collapse in several nodes. Also, traditional methods like the combination of Monte Carlo Simulation and Newton-Raphson Method is used to solve deterministic power flow problems and get the nodal voltage along the electrified road. However, when it comes to the probabilistic power flow, those methods are time-consuming and inefficient.

In the vehicle-to-grid platform, the power consumption of EVs will affect the operation of the distribution system. Thus, it is necessary to regulate the voltage profile along the electrified road over time to be compliant with the voltage standards. Also, the power transfer along the distribution line is subject to physical and operational upper limits. Knowing the limitation of the maximum length and maximum number of EVs that the road can accommodate can help the distribution system to avoid voltage collapse and maintain the long-term voltage stability. As the voltage profile along the electrified road follows a trend when the EV is moving and the power consumption is changing, it is better to create a new probabilistic power flow method in place of the conventional MCS method. Under the premise of ensuring high accuracy of voltage results, a new non-parametric probabilistic load flow method based on GP regression can largely decrease the calculating time. This thesis focuses on the steady-state analysis of the power distribution system with dynamic charging electric vehicles.

1.2 Research Gap and Challenges

1.2.1 Steady-state Voltage Profile and Long-term Voltage Stability of Electrified Road with Wireless Dynamic Charging

Currently, the research trends focus on charging technologies mostly in the device level such as maintaining charging efficiency, regulating battery capacity, and improving economic benefits [7–9]. The effects of dynamic charging in the system level have not been studied extensively. Interestingly, a relevant research area, however, is railway electrification systems with a focus on electric locomotives. Most importantly, [10–15] carried out power flow analysis of electrified tracks, wherein several new power flow algorithms are introduced, based on which power supply capacity of traction power supply systems and voltage distribution in transmission systems can be analyzed. Another important research direction on trains, tramways, and buses is to apply regenerative braking energy and leverage the topology of the power supply system to enhance the system’s efficiency and economic operation [1, 16]. These works focus on energy consumption and control methods instead of the impact of moving vehicles on the voltage level and the stability of the distribution system.

However, when it comes to the dynamic charging system and electric vehicles, new challenges arise. The traditional charging system is a normal distribution system and electric vehicles consume power while they are in motion. This scenario is similar to the situation when loads are moving on a distribution system. As the state of system operation varies over time, different parameters of the distribution system will change, thus causing problems about system stability. Among the stability problem, new curves of voltage profiles and long-term voltage stability have caught our attention. However, two major challenges appear. As traditional power flow problems of a distribution system are based on fixed variable loads, things become difficult because of the moving positions of loads. Standard power

system package like MATPOWER, cannot handle moving constant-power buses, therefore, the structure of the charging system should be transferred into a novel one that is suitable for power flow calculations. Besides, continuation power flow (CPF) is used to analyze long-term voltage stability, but it assumes that the system network is fixed. Hence, new methods will be introduced to use CPF.

1.2.2 Non-parametric Probabilistic Load Flow using Gaussian Process Learning

At present, many previous works are interested in applying some new methods to solve probabilistic load flow problems [17–19]. However, those methods still have some drawbacks which need to be improved.

One of the most widely used numerical methods is Monte-Carlo simulation (MCS) which employs randomly generated variables to calculate the corresponding output by a large number of repetitive power flow calculations [20, 21]. Although MCS captures the non-linearity of power flow equations in totality, it needs a large number of iterations which will lead to a high computational cost and time. Further, many questions like how many points are sufficient and what can be the maximum error for any new point, cannot be answered using pure numerical approaches.

The other class, analytical methods in PLF, is mainly a statistical approach that aims to obtain the results of some special moments or the mean, variance, and PDFs for the state and output variables [22]. Among them, convolution techniques follow mathematical assumptions in order to simplify the power flow problem [23]. But these methods are not applicable to complex problems, such as AC power flow in unbalanced power distribution systems [24]. Further, for preserving power flow equations non-linearity, a set of deliberated operating conditions are used in point estimate methods [25]. However, their accuracy is low in estimating high order moments of probability distributions, especially for complex systems with many inputs [26]. The third analytical method is approximation expansions based on cumulants [27]. It is designed to obtain the cumulants of outputs from the cumulants

of inputs through a simple mathematical process. These analytical methods can indeed reduce the computational costs, however, they suffer main drawbacks like: 1) requirement of model simplifications and adjustment of parameters, essentially losing information of tails of PDFs, etc.; 2) need of linearizing power flow equations for a specific operating condition. With the high penetration of distributed energy resources, their accuracy will decline due to ignoring non-linearity [26]. Further, analytical methods are parametric in nature and work on a fixed, specific class of uncertainty distribution only. Essentially, the numerical methods capture non-linearity but are slow while analytical methods need approximations leading to lower accuracy.

1.3 Major Contributions of the Thesis

Chapter 2 and Chapter 3 present the two major contributions in this thesis. Chapter 2 mainly discusses the deterministic power flow problems in a simple distribution system. The voltage profile along the electrified road and the power-voltage node curve are only based on the changing location of EVs. In this way, the power injections are fixed as we considered. However, the power consumption of EVs will change while they are in motion, which makes the power inputs uncertain. The traditional method can only solve the power flow under such conditions through Monte Carlo Simulation which is time-consuming and not easy to implement. Therefore, we proposed a new effective method to do the steady-state analysis and obtain the voltage results in Chapter 3.

1.3.1 Steady-state Voltage Profile and Long-term Voltage Stability of Electrified Road with Wireless Dynamic Charging

While those aforementioned works also consider similar radial network configurations, no existing work studies the steady-state voltage profiles and the long-term voltage stability limits of electrified roads when vehicles are in motion. The traditional loads in power systems can vary the demands but resize at fixed locations in the network diagram. WDC vehicles, on the other hand, may consume the same amount of power, if they travel at a constant speed, but change the positions over time. The advent of these new moving loads may alter the distribution system operation and thus calls for new studies on this topic. This chapter, therefore, will construct a series of new patterns about the voltage profile along the electrified roads over time to study the voltage level change while the vehicles travel. This pattern can be used in voltage compensation design in order to maintain voltage levels across the network within a range specified by voltage regulation standards. Another important aspect of steady-state analysis considered in this work is the long-term voltage stability (LTVS) of the electrified road, which concerns the existence of a steady-state solution. While typical LTVS limits in power systems are regarded as the maximum loading level that the power line can support, the LTVS thresholds here can be quantified in terms of the maximum road length and the number of vehicles "safely" allowed to operate on the electrified roads equipped with WDC. We introduce a novel experimental setup below, relying on a widely-used power software package in the community, i.e., MATPOWER [28], to perform our analysis. To summarize, the objectives of the research were to:

- This part studies the effects of dynamic charging and moving loads at the system level in terms of voltage instead of charging technologies at the device level.
- Construct new patterns of the steady-state voltage profiles under various operating conditions.

- Introduce a new method to apply the continuation power flow to analyze long-term voltage stability (LTVS) of the electrified road.
- The new patterns of the steady-state along the distribution system considering the voltage and stability limits will raise new research in this field.

1.3.2 Non-parametric Probabilistic Load Flow using Gaussian Process Learning

While most existing methods are parametric as they require input uncertainty descriptions, this thesis, on the other hand, presents a non-parametric probabilistic load flow (NP-PLF) method using Gaussian process regression. The proposed method deals with two inherent difficulties faced in obtaining PLF solutions: i) the non-linearity of the power flow equation set, and ii) lack of statistical information about uncertainty and complexity in modeling PDFs. We develop probabilistic learning bound (PLB) using regret bounds of the so-called GP-UCB sampling algorithm. Here, the learning step of the proposed NP-PLF works without any PDF of input uncertainty and the testing step can obtain the state and output variables (e.g., nodal voltages) for any class and type of input uncertainty distribution. This two-step method makes the proposed approach semi-explicit in terms of the form of the power flow solution, while conventional numerical methods are implicit. The PLB provides control over the desired accuracy and confidence level of learning. The method can also serve as a multi-dimensional continuation power flow (CPF) to estimate the power-voltage curve with a given confidence level.

The main contributions of this part are as follows.

- A novel non-parametric probabilistic load flow (NP-PLF) method, which handles the uncertain power injections. The method is generic as it does not rely on the class of uncertainty distribution. It is fast and captures the non-linearity of power flow equations. The learning step provides a semi-explicit

form of power flow solutions, while the testing step can provide statistical information for the PLF solution.

- Development of probabilistic learning bound (PLB) for the power flow solution by GP learning and GP-UCB sampling. This PLB can serve as a convergence criterion for the algorithm used in the learning step.

1.4 Organization of the Thesis

The following parts of the thesis are organized as follows:

- Chapter 2 focuses on the effect of moving loads on the distribution system. Along the electrified roads equipped with wireless dynamic charging, the voltage profile and the long-term voltage stability of the electrified roads are considered. New strategies based on traditional power system packages are proposed to characterize the maximum length of a road and the maximum number of vehicles that the road can accommodate.
- Chapter 3 introduces a non-parametric probabilistic load flow (NP-PLF) technique based on the Gaussian Process (GP) learning. The technique can provide “semi-explicit” power flow solutions by implementing a learning step and testing step. Simulation results testing in the IEEE 30-bus, 33-bus and, 118-bus systems verify its efficiency and accuracy.
- Chapter 4 draws some conclusions for the thesis report and the future works are provided.

Chapter 2

Steady-state Voltage Profile and Long-term Voltage Stability with Wireless Dynamic Charging

2.1 Overview

The massive use of primary energy has promoted the rapid development of the global economy, but at the same time, it has also caused global warming, serious environmental pollution, and energy shortages. Besides, it has affected the sustainable development of the economy. In order to promote the development of the economy while protecting the environment, environmentally friendly products are receiving more attention. Among them, the automobile industry, which is mainly powered by oil, is constantly trying to utilize a more environmentally friendly source of power. Traditional vehicles are harmful to human beings and the environment because of harmful substances such as CO, HC, and NOX in the exhaust. In addition, the number of cars driving on the road is increasing. As a result, the environmental problems are even more serious.

Developing electric vehicles will be the best way to solve the above problems. The various methods of addressing the scarcity of fossil fuels and environmental issues are likely to involve the extensive use of electric vehicles. Using an electric vehicle will not only provide a cleaner and quieter environment but also significantly reduce operating costs compared to gas-powered vehicles. In addition, EVs have the advantage of integration flexibility to achieve better performance in the transportation sector. Energy generators such as fuel cells, solar panels, regenerative braking, and any other suitable generators can be integrated into the EV. These factors indicate that the technology and industrialization of electric vehicles are becoming the frontier of competition in the global automotive industry.

To solve the research challenges and achieve the objectives mentioned above, the methodology is as follows: We divide the whole electrified road into several segments with fictitious nodes so that the movement of EV loads can be modeled and traditional power packages become useful. We also transfer the normal power-voltage nose curve into the power-road length curve to get the long-term voltage stability analysis. The rest of the sections of this chapter are organized as follows:

- Section 2.2 describes the modeling of electric railway power supply systems and their improvement. A brief literature survey about researches on a related area like trains, tramways, and buses is presented.
- Section 2.3 introduces the dynamic charging EV system and the power flow problem for the steady-state study.
- Section 2.4 describes the steady-state voltage profile and analyzes it for several different conditions including moving directions, photovoltaic panels integration, and reactive power compensation with capacitor banks.
- Section 2.5 considers the long-term voltage stability of the distribution system where one can calculate either the maximum length of a road or the maximum number of vehicles that the road can accommodate.
- Section 2.6 draws some conclusions for this chapter.

2.2 Literature Review

In this section, the previous researches about the railway power supply system which is a related area comparing to dynamic charging EVs are discussed. To improve the operation of a locomotive system, previous studies have used new power flow algorithms, regenerative braking energy and novel topology of the system.

2.2.1 Wireless Dynamic Charging

EVs can be further classified as stationary and dynamic charging vehicles according to the charging method. The dynamic charging method allows charging in motions so it resolves problems of long charging time in the stationary counterpart. Among dynamic charging technologies, wireless dynamic charging (WDC) is emerging as it can charge vehicles on the move without connecting directly to power cables [29–31].

The wireless energy transmission can avoid the direct connection between the electrical equipment and the power grid. It also has the advantages of flexibility, safety, and reliability. Compared with the conventional wired transmission, the wireless energy transmission technology effectively overcomes the instability caused by the electrical contact and breaks certain limitations in the charging process of electrical equipment. Based on the above advantages, it has become an important supplementary method of the wired power supply mode and therefore has been valued by peers all over the world. Because of the unique characteristics of wireless charging technology compared with those of traditional charging, this technology will soon become the main way to charge the next generation of electric vehicles. Besides, wireless dynamic charging technologies are becoming a promising alternative solution to plug-in ones as they allow on-the-move charging for electric vehicles.

As for the feasibility of deploying WDC, we would like to refer to previous news below that a number of countries such as China and Sweden, have built electrified roads which can charge the batteries of cars and trucks driving on them. The

University of Auckland team is the earliest to research on wireless energy transmission technology and developed a two-way wireless charging system. The grid can charge the battery of the EV, and the battery can serve as an output source to transmit power to the primary side. It realizes a two-way wireless transmission that correspond to multiple receiving ends through one transmitting end. This method is to control the bidirectional energy transmission of multiple receiving ends by frequency jitter [32]. Sakamoto University of Tokyo's research on wireless charging of electric vehicles mainly proposes a maximum efficiency control method used on a secondary side. It used the equivalent impedance of the transmitting end to estimate the change of the coupling coefficient in real-time, using a feedforward controller to change the DC/DC converter's duty cycle for maximum efficiency control [33].

Oak Ridge National Laboratory has made in-depth research on the coupling mechanism in the WDC system of electric vehicles, including analyzing the transmission characteristics of different coupling coils and dielectric loss. In the system designed, the transmitting device is in the full bridge. The output of the inverter is connected in series with two primary windings and laid under the ground. The experimental results show that the positional shift between the electric vehicle and the transmitting device has a great influence on the efficiency of power transmission [8]. In August 2013, South Korea launched the first system in the world that can be charged during the driving of electric vehicles. The transmitting coils in the system are laid under the ground for 24 kilometers. The network is equipped with two "Online Electric Vehicles" (OLEVs) as the recipient of energy. Buses travel between the train station and the city [29].

2.2.2 Electric Railway Power Supply Systems

As the industry of wireless dynamic charging systems is still at an initial stage, the same problem about moving loads has raised in some relevant areas for trains, tramways, and trolleybuses. Those systems are so-called electrical railway power

supply systems. The electrified railway refers to a railway that uses electrical tractions. On electrified railways, railway electrification systems provide electricity for railway trains and trolley cars without the need for local fuel supplies. Power is commonly produced in enormous and generally proficient power plants, transmitted to the railroad system and dispersed to trains.

The electrified railway is one of the most important railway types in contemporary time. A large number of electrical equipment is provided along the way to provide continuous power for electric locomotives including EMUs (Electric Multiple Units) and non-EMUs. The electric locomotive does not have energy itself, and the required electrical energy is provided by the electric traction power supply system. A traction power supply system is mainly composed of two parts: traction substation and contact grid (or power supply rail) [34]. The substation is located near the railway. The contact grid and power rail are equipment that directly transmits electrical energy to electric locomotives. Electrified railways are originated from trams and they have been continuously extended to other types of railway systems after years of development and evolution.

With the fast improvement of rapid and heavy-haul railroads, the majority of railway lines have used huge electrical locomotives and EMUs. However, the required large power transmission has caused some problems with insufficient power supply capacity (PSC) of traction power supply systems (TPSSs) [34]. The requirement for enlarging the power supply capacity has proved that the disadvantages of normal systems of solving the high power problems while controlling the cost of the whole system as much reasonable as possible. In addition, nowadays, the innovation tendency from traditional electrical systems towards smart grids reminds human beings of evaluating carefully the appropriate directions. The technical problems of electric railway systems may depend on the historical and economical specialties of countries and regions [10]. Therefore, the better solutions for improving this new transportation system are required.

The usage of moving loads in electrical feeders has the same problems arising for

high speed or normal trains, tramways and trolleybuses. The electric vehicles area meets the same problems.

2.2.3 New Power Flow Algorithms Relating to Electrified Tracks

As trams, trains, and trolleybuses work the same way as electric vehicles in distribution systems, so many researchers focus on their operations and improvements. Interestingly, the similar research area is the electric railway power supply system focusing on moving electric locomotives. They conducted the power flow analysis on the electrified orbit and introduced several new power flow algorithms for better understanding the operation status of the network. On this basis, the power supply capacity (PSS) of the system and the nodal voltage along the road in the transmission system can be analyzed.

Ref [10] proposes a new power flow algorithm - port algorithm (PA). This method is able to calculate the power supply capacity of the system relying on Thévenin equivalent. Previous algorithms typically included two steps. The first step develops a node voltage or grid current equation based on the given input data. Then, the equation can be solved numerically. The PA method adds a step between two steps: transforming the fundamental nodal voltage equation to a port characteristic equation by using Thévenin Equivalent Method. In this way, it is only necessary to analyze the train nodes instead of all the nodes in the distribution system. Fewer parameters need to be considered compared to previous methods. The detailed process of PA is as follows: The new Thévenin equivalent network is used instead of the original feed portion to evaluate the relationship between the node voltage and the impedance matrix of the equivalent network. The starting value of trains' current vector is then set to solve the equation. Next, calculate the residual vector, the Jacobian matrix, and the correction equation. The calculation step is finished when the norm of ΔI is smaller comparing to the given reference. If not, subtracting ΔI from I and move to the next step. Also, if the iteration

times reaches the maximum allowed times N , the calculation fails. Or else, move to the previous step.

The Newton-Raphson method used in PA has quadratic convergence, which is more accurate than some previous fixed-point iterative methods. Therefore, the PA requires fewer iterations to reach the convergence criteria. On the other hand, this method can find multiple solutions in a shorter time. In the construction of the PV curve, various solutions were found under continuously varying power. The curve drawn by the PA is continuous around the power border, proving that PA does not experience numerical difficulties. Therefore, this new algorithm has been significantly simplified.

2.2.4 Regenerative Braking Energy and Topology of the Power Supply System

Another important research direction on trains, tramways, and buses is to apply regenerative braking energy and leverage the topology of the power supply system to enhance the system's efficiency and economic operation [1, 16].

An effective way to diminish energy consumption in the transportation system is by increasing the utilization of regenerative braking energy [1]. This research demonstrated the analysis of applying super-capacitors and changing the topology of the system for utilizing recovery energy. The methods are tested on the trolleybus network system in an urban city. The simulation results are also useful in other similar tram networks. Simulation models containing the repetition of the iteration loop structure and MCS are shown in Figure 2.1. The first step is to simulate the number of buses across the power supply sections with the help of the provided schedule lists and probability density function (PDF). The locations of trolley buses are calculated from the profile of velocity over time. After that, the procedure goes to the calculation of current consumption and PSS' parameters. Corrections of current flow on the buses are needed. They depend on the network voltage

FIGURE 2.1: General scheme of the traction power supply system simulation model using the Monte Carlo method [1]

and the limitations of the delayed current. New prediction of the power supply system parameters is taken considering the corrected current consumption. All those parameters are calculated repetitively by applying the nodal voltage analysis unless the calculation of voltages V in the final step reaches the convergence point.

Further analysis will only address the impact of the network in modern power supply systems on the economic efficiency and efficiency of energy transmission [16]. The network structure can be divided into three types: central power supply, unilateral distributed power supply, and bilaterally distributed power supply. The analysis demonstrated the significance of applying spatial structures of the overhead-line power supply system. This kind of system can reduce transmission losses and increase the effectiveness by using regenerative braking technologies.

It is better for those future new power systems to apply a bilateral decentralized overhead-line power supply system. This system has the lowest energy transmission loss and high energy recovery. However, it still has the following advantages: the substation structure is simpler; there is no related problem caused by maintaining the complex network; if the substation fails, the power supply system has greater flexibility and operability; the construction of the substation is unified which means

that the design and construction process is simpler; and it is easier to repair the substation.

2.3 WDC EVs and Power Flow Study

This section creates a simplified dynamic charging EV system that is suitable for the analysis of the steady-state condition. Besides, the power flow problem is solved for the steady-state study.

2.3.1 Wireless Dynamic Charging System

The basic structure of the proposed new charging distribution system can be seen in Figure 2.2. When the electric vehicles are passing by those power tracks, batteries inside of the EVs can absorb the power via the receiving resonator from the distribution system. In our framework, the WDC system is considered as a one-feeder

FIGURE 2.2: Diagram of dynamic charging EV system[2]

grid with the slack bus, or the reference bus, be the coupling point, PQ nodes are power tracks and the branch is the power cable line. The power generator is placed at the starting point of the electrified system, which could also be a coupling point connecting to the distribution line. The power cable is located under the electrified road connecting those power tracks, which are placed in sequence, to the power source. In practice, the wireless charging topology contains more devices between the vehicle side and the grid side.

In order to make sure that power can be transferred successfully from the transmission part to the receiving side, the main grid side needs to convert the AC current into high-frequency (HF) AC current through AC/DC converters and DC/AC converters. Many methods have been applied to increase the transmitting and charging efficiency of the whole system. For example, people use some compensation devices which can be combined in series or parallel and apply them in the transmitting sides and receiving sides. Then, those receiving resonators which are located below the EVs can convert the power to HF AC power again. Finally, the electricity is transformed into the stable DC form being stored in the on-board batteries. Besides, a system called the battery management system (BMS) is also included inside the vehicle. This system can deal with some safety issues and maintain the stable operation of the battery [35].

To make a simple analysis, we suppose that all electric vehicles are homogeneous, and they have the same speed which will not change. Besides, they are assumed to consume a fixed amount of active and reactive powers. In our work, we assume that vehicles have a very low level of battery and draw as much power as they can from the road. In the model of this thesis, power transferring loss between power tracks and batteries are ignored. Under this circumstance, EVs can be looked upon as moving loads shifting in a distribution network. The whole line is divided by a group of nodes uniformly. In summary, there are three types of buses:

1. A voltage source. Always assume on bus 1 as a reference bus.
2. PV buses. At the other generator buses.
3. PQ buses. At the load buses.

FIGURE 2.3: The diagram of simplified dynamic charging EV system

However, an EV should not be modeled as a conventional PQ node, which demands a specific level of power at a specific location because the EV moves during the study. Standard power system packages such as MATPOWER [28], unfortunately, do not handle these moving PQ buses. Instead, we propose to split the electrified road into equal-length segments marked with fictitious nodes such that, in each "snapshot" of power flow study at a time step, the fleet of vehicles arrives at a new set of fictitious nodes. Such a new set of fictitious nodes is then modeled as non-zero PQ buses. Except the reference bus, other nodes without EVs become intermediate buses that consume no power. As the EVs travel along the road, the set of PQ buses also changes. To study the evolution of the voltage profile along the road caused by on-the-move vehicles, we repetitively solve the power flow problem for such a series of time instants characterized by the set of PQ buses. Within this framework, the WDC system can be modeled, at one time-step, as a normal radial grid shown in Figure 2.3 and can be studied using standard power system analysis packages. For the steady-state analysis, we find the network voltage solution by solving the power flow equations that are presented in the next section.

2.3.2 Power Flow Study

Steady-state stability is characterized as, when there is a small disturbance in the power grid, the operating state can maintain its initial condition or it can reach a

new condition which is also stable near to the original one. The relating researches are always focusing on small and gradual changes in the system. In other words, the nodal voltages in the system should not have much large deviations compared with their nominal voltages. In this distribution system, the steady-state stability is also related to a limitation of the power transmitting. To be more concrete, the steady-state limit represents the appropriate locations of EVs so that the nodal voltage magnitude is in the safe region. The steady-state stability of wireless dynamic charging systems can be affected by various factors. In this study, we assume that the system is under normal operation and in steady state. We see the fancy voltage profile during the operation of charging. To get the voltage magnitudes and curves of nodes, we need to use power flow equations to solve the problem. These checks are usually done using power flow studies. In MATLAB, the power flow calculation uses the Newton-Raphson method. The basic steps of the Newton-Raphson method are as follows:

1. Build a nodal admittance matrix;
2. Give an original voltage value to each bus;
3. Change the nodal voltage in order to obtain the fixed vector of the modified equations;
4. Use the equations to obtain a Jacobian matrix;
5. Get the correction vector of the variable;
6. Try to obtain a new nodal voltage;
7. For a PV node, check whether the reactive power of the node is out of limits;
8. Check whether the convergence is converged. If not, using the new nodal voltage and starting the next iteration from step 3 for the initial value. Otherwise, just skip to step 9;
9. Obtain the distribution of branch power, reactive power of PV nodes and the input power of balance nodes from the power flow equations. Finally, we get the results.

First, we define the complex bus power [36]:

$$S_i \triangleq S_{Gi} - S_{Di} \quad (2.1)$$

S_i is what is left of generating amount S_{Gi} after stripping away the local load S_{Di} . Using conservation of complex power, we also have for the i th bus,

$$S_i = \sum_{k=1}^n S_{ik} \quad i = 1, 2, \dots, n \quad (2.2)$$

where we sum S_{ik} over all the transmission links connected to the i th bus. Bus current I_i can also be defined as:

$$I_i = I_{Gi} - I_{Di} = \sum_{k=1}^n I_{ik} \quad i = 1, 2, \dots, n \quad (2.3)$$

where I_i is the total current entering node i . The relationship between the injected node currents and the node voltages are shown as:

$$I_i = \sum_{k=1}^n Y_{ik} V_k \quad i = 1, 2, \dots, n \quad (2.4)$$

The i th bus power can be calculated as:

$$S_i = v_i \left(\sum_{k=1}^n Y_{ik} v_k \right)^* \quad i = 1, 2, \dots, n \quad (2.5)$$

(*) denotes the conjugate operator. The power flow equation can be derived from Kirchhoff's circuit laws and used to describe the steady state condition of a power system. For bus i , the equation is as follows:

$$P_i + jQ_i = \sum_{k=1}^n V_i V_k (\cos \theta_{ik} + j \sin \theta_{ik}) (G_{ik} - jB_{ik}) \quad (2.6)$$

where $Y_{ik} \triangleq G_{ik} + jB_{ik}$ represents the admittance of branch ik , $v_i \triangleq |V_i|e^{j\theta_i}$ is the nodal complex voltage at bus i , and $\theta_{ik} \triangleq \theta_i - \theta_k$ denotes the angle difference

between bus i and bus k [36]. Resolving (2.6) into real and imaginary part as

$$P_i = \sum_{k=1}^n |V_i||V_k|(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \quad (2.7)$$

$$Q_i = \sum_{k=1}^n |V_i||V_k|(G_{ik}\sin\theta_{jk} - B_{ik}\cos\theta_{ik}) \quad (2.8)$$

In this model, the active power and reactive power of each vehicle are constants, however, locations of vehicles have impacts on the power flow. Thus, for a fixed node i , P_i and Q_i depend on the location of moving vehicles, that is to say, P_i and Q_i are functions of time. Besides, G_{ik} and B_{ik} also change when vehicles are in motion. For the steady-state analysis, we solve the set of power flow equations (2.6) to find the nodal voltages for a given loading level P_i and Q_i , $i = 1, \dots, n$. We then construct the voltage profile along the road by recording the solution voltages at different node locations while the vehicles are passing by. In Section 2.5, we carry out further analysis of the long-term voltage stability of the charging system, which is the limits of the system ensuring the existence of an equilibrium [36].

2.4 Voltage Profile of WDC system

This section describes the steady-state voltage profile and analyzes it for several different conditions including moving directions, photovoltaic panels integration, and reactive power compensation with capacitor banks.

2.4.1 Parameter Values of Dynamic Charging EV System

The parameters of the WDC system are shown in Table 2.1. The parameters are as follows: active power per vehicle (P_{EV}): 30 kW; reactive power per vehicle (Q_{EV}): 15 kVar; resistance of cable line: $0.568\Omega/\text{km}$; reactance of cable line: $0.133\Omega/\text{km}$; on-board PV panel: 2 kW; on-board capacitor: 100 kVar; and fixed capacitor bank: 300 kVar. As no common standard of EVs or WDC exists, we rely on

TABLE 2.1: Parameter values of dynamic charging EV system

Parameter	Value
Active power per vehicle (P_{EV})	30 kW
Reactive power per vehicle (Q_{EV})	15 kVAr
Resistance of cable line	$0.568 \Omega/\text{km}$
Reactance of cable line	$0.133 \Omega/\text{km}$
On-board PV panel	0.5 kW
On-board capacitor	100 kVAr
Fixed capacitor bank	300 kVAr

several existing works in the literature that present the parameters of the used prototypes [37–39]. The power of PV panels and the capacitor bank value are chosen from [40, 41]. In Section 2.4, the length of the road and cable line are set to be 2 km. Ten fictitious nodes are evenly distributed throughout the road. The voltage profiles along this electrified road are presented in the following sections where we consider both one-way and two-way roads. Each moving direction has only one lane.

2.4.2 Voltage Profile of One-way Road

In this experiment, a fleet of two EVs moves from the slack bus to the end bus. At the first time step, the two EVs start from node 1 and 2.

2.4.2.1 WDC EVs System without Voltage Compensators and PVs

As shown in Figure 2.4, the voltage profiles, which collect the nodal voltages at the reference bus (node 1) to the end node (node 10), are constructed for nine different time instants, called time steps, from t_1 to t_9 . This set of voltage profiles resembles half-leaf veins. Each secondary vein is a voltage profile of a time step, while the main vein is the lower bound of all profiles which will be defined later in this section. The nodal voltage reaches its minimum value at time step t_9 when vehicles reach the farthest nodes from the reference bus.

FIGURE 2.4: Voltage profile of WDC EV system (one moving direction)

When the EV fleet moves towards the end of the road, the nodal voltage decreases monotonically as the “travel” impedance between the slack bus and the fleet’s position increases. The same is true for the voltage drop. We can draw a line implying the lower bound for the voltage profile and it demonstrates a monotonic decreasing trend. The lower bound of these voltage profiles can be characterized analytically as $V = V_1 - I_{max} Z$. This equation of the main vein shows the relationship between voltage and impedance. Here, V_1 is the constant voltage of the reference node, and I_{max} is the largest effective current that corresponds to the heaviest loading condition happening at the final time step as the vehicles approach the end node. Z is the effective “travel” impedance which scales linearly as the vehicles travel and thus it is proportional to the bus number in our experiment. The lower bound is plotted as the dashed red line or the main vein of the half-leaf veins in Figure 2.4. The monotonic voltage profiles and the main vein can help the system operators design voltage regulation and control, particularly, decide where and how much reactive power compensation is needed.

Although the deployed constant-power load model is simple, it is sufficient to capture the most fundamental pattern of the voltage profile along the electrified road when the vehicles move. This simple model, however, can be extended to more

FIGURE 2.5: Voltage profile of WDC EV system considering more general settings (one moving direction)

complicated settings with charging efficiency, weather's impact on the PV modules, variable power consumption, and variable speeds. For instance, we can model the effective power of a vehicle as $P = P_{EV} - \Delta P$ and $Q = Q_{EV} - \Delta Q$ where P_{EV} and Q_{EV} are the base power consumption. We introduce ΔP and ΔQ to represent the power variation, for example, due to non-unity charging efficiency and variable speeds. Figure 2.5 plots three representative voltage profiles with error bars which reflect that the power variation can vary randomly within 50% of the base power level. The error bars become wider if the variation range gets larger. Moreover, for a given variation range, one still can construct the bounds of voltages, by collating the corresponding extreme voltage values.

2.4.2.2 WDC EVs System with Voltage Compensators and PVs

In this experiment, PV panels or on-board capacitors are installed on each vehicle, whereas a fixed capacitor bank is set at bus 6 - the middle of the road. In Figure 2.6, we plot several voltage profiles to show the effect of added PVs and voltage compensators. The lowest voltage profile represents the case without PVs and voltage compensators, while the most effective compensation method is using a

FIGURE 2.6: Voltage profile of WDC EV system with voltage compensators and PVs (one moving direction)

fixed capacitor bank installed in the middle of the road. For capacitors, the reactive power of moving loads is compensated and the power factor is increased. On-board capacitors affect the voltage of the bus where vehicles move over it, but the fixed capacitor bank regulates voltage locally around bus 6. After adding on-board PV panels, the active power of moving loads is decreased. Above all, three voltage profiles can be regulated with the help of different compensators. More specific explanations of the impact are as follows: On-board capacitors and PV panels are installed on each electric vehicle and the fixed capacitor bank is set on bus 6. We have two equations $P = P_{EV} - \Delta P$ and $Q = Q_{EV} - \Delta Q$, where P and Q indicate the active power and reactive power which electric vehicles consume from the system. P_{EV} and Q_{EV} are the nominal active power and reactive power of each electric vehicle and they are constant. ΔP and ΔQ represent the power affected by adding compensators. ΔP and ΔQ are zero when no PV panels or voltage compensators are set. Thus, the power which EVs consume from the distribution system is equal to their nominal power. However, ΔP will increase with adding on-board PV panels and the installation of capacitors will increase ΔQ . Therefore, P and Q of each node will decrease which means that the moving loads consume less power on the bus.

2.4.3 Voltage Profile of Two-way Road

In this section, a two-vehicle fleet moves from the reference bus towards the end bus, while another fleet of two vehicles moves from the opposite direction. At the beginning time, each pair of vehicles is located at the first and the last two buses, respectively.

2.4.3.1 WDC EVs System without Voltage Compensators and PVs

Figure 2.7 illustrates the voltage profiles when two fleets of EVs move in two directions. Two interesting features of voltage profiles are observed in this case. First, the set of voltage profiles has a harp-like shape as all individual voltage profiles lie inside two boundaries corresponding to two special time steps. One time instant is when two fleets of vehicles are located at their beginning positions; the other time instant is when they meet near the middle of the road. However, if the number of vehicles in two fleets is different, the minimum value of voltage will appear when the fleet with more vehicles reaches the end bus corresponding to their moving direction. The second feature is the repetition of voltage profiles which

FIGURE 2.7: Voltage profile of WDC EV system (two moving directions)

creates voltage swings. As two fleets of vehicles meet and continue following their original directions, some voltage profiles are overlapped. This explains why some time instants such as t_1 and t_9 have the same voltage profile. In other words, some voltage profiles are repeated. The inserted figure shows the voltage fluctuation on bus 6. Other buses also exhibit voltage swings but with different magnitudes. These voltage swings may cause problems related to power quality, voltage regulation, and power transfer losses.

2.4.3.2 WDC EVs System with Voltage Compensators and PVs

Figure 2.8 shows the voltage profile when two fleets of vehicles meet and compare the differences between the original system and system with voltage compensators. The principle behind the curve in this figure is similar to the voltage profile which contains only one fleet of vehicles as shown in Figure 2.6. The lowest voltage profile represents the case without PV panels and voltage compensators, while the most effective compensation method is using on-board capacitor bank. On-board

FIGURE 2.8: Voltage profile of WDC EV system with voltage compensators and PVs (two moving directions)

capacitors affect the voltage of the bus where vehicles move over it, but the fixed capacitor bank regulates voltage locally around bus 6.

2.5 Long-Term Voltage Stability

In this section, the long-term voltage stability of the road is analyzed. One can calculate either the maximum length of a road or the maximum number of vehicles that the road can accommodate. In addition, we present a method to analyze the long-term voltage stability of the wireless dynamic charging EV system. Only one-way road is considered in this case, but one can also extend the results to the two-way road easily.

2.5.1 CPF for a 2-bus System

For the WDC system, there should be an inherent maximum bound of power that can be transmitted to the end of the line. A simplified two-bus circuit is shown in Figure 2.9 [42]. As V_1 constant, lowering the value of the load impedance is the only way to increase the power at the endpoint. However, this will also lead

FIGURE 2.9: A two-bus system with one slack bus and one PQ bus [3]

to increasing current and decreasing voltage of load bus V_2 , as well as larger line losses. At the above part of the normal P - V nose curve[42], the impact of the increase of current is larger than the decrease of V_2 , therefore the active power of load P increases. Up to a critical point, the trend reverses so that P cannot increase but reach its maximum value [3].

Continuation power flow method (CPF) has been used widely to quantify the maximum loadability corresponding to LTVS limits [43–45]. In CPF, one can increase the power injections gradually following a particular direction and then solve the resulting series of power flow problem for the voltage levels. By collating the power injections and voltage solutions, one can construct nose curves and determine the loadability limit at the tip of the nose curve [3]. However, the CPF assumes that the positions of the injections are fixed. The moving loads in the WDC problem, on the other hand, may maintain a fixed level of power consumption but change their locations during the experiment period. These moving loads, therefore, make CPF not directly applicable to an electrified road with WDC, except for a simple two-bus equivalent configuration. To show this, we consider a two-bus example with one slack and one PQ bus connecting through a line with the impedance of $R + jX$. The two nodal voltages are V_1 and V_2 . This configuration corresponds to the situation one vehicle travels on a one-way road. The consumption of the vehicle $P + jQ$ is fixed, but the distance it travels increases over time; and this can be captured by changing the line impedance duly.

Power flow equations for this toy example are as follows:

$$P = \frac{V_2}{X} V_1 \sin \psi + \frac{RQ}{X} \quad (2.9)$$

$$Q = \frac{V_2}{X} V_1 \cos \psi - \frac{V_2^2}{X} - \frac{RP}{X} \quad (2.10)$$

The angle ψ between $\mathbf{E}$ and $\mathbf{V}$ can be eliminated. After combining (2.9) and (2.10), we can get

$$(V_2)^4 + (2QX + 2PR - (V_1)^2) (V_2)^2 + (P^2 + Q^2)(X^2 + R^2) = 0. \quad (2.11)$$

If the power factor and X/R ratio are constant, rewrite (2.11) as

$$U^2 + (2PR(\tan \phi \tan \theta + 1) - (V_1)^2)U + (PR)^2(\sec \phi \sec \theta)^2 = 0 \quad (2.12)$$

where $\tan \phi = Q/P$, $\tan \theta = X/R$, and $U = (V_2)^2$. Let $1 + \tan \phi \tan \theta = A$, $1 + \tan^2 \phi = B$, $1 + \tan^2 \theta = C$, and the voltage at the load bus varies with respect to the active power P and resistance R as shown in (2.13)

$$V = \sqrt{\frac{E^2 - 2RPA}{2}} \pm \sqrt{\frac{(2RPA - E^2)^2}{4} - (PR)^2BC} \quad (2.13)$$

Apparently, R and P play the same role in (2.13) so that we can change the power injection P instead of the line resistance R in the CPF study. Unfortunately, this is not the case when we extend to more general network configurations. For the condition in this thesis, P is constant and R changes when vehicles move. Therefore, there must be a critical point for V_2 when resistance R reaches its maximum value. For a 2-bus system, we could calculate the critical point easily. However, the model of dynamic charging EV system contains more buses and several moving loads making things more complicated. Therefore, continuation power flow is needed to deal with this problem. For larger feeder networks representing WDC roads with more EVs, one needs to apply CPF differently, as will be presented in section 2.5.2.

2.5.2 Maximum Road Length with Fixed EV Fleet

When we analyze the steady-state voltage problem in a traditional distribution system, the locations of generators and all the loads are fixed. The only thing that gets changed is the power consumption of each load. However, in this case, the size and power consumption of the EV fleet are assumed to be fixed. What makes the power flow calculation difficult is the moving locations of loads. Therefore, the LTVS becomes the problem of finding the maximum length of the road that EVs

can safely travel. We need to make sure that the road can handle the most critical time instant, in particular, when vehicles reach the end of the road.

In a traditional distribution system as mentioned in section 5.1, people use the continuation power flow to obtain the voltage magnitude-power nose curve in order to find the maximum amount of power that can be transmitted by the system. This approach is known as the nose curve scenario in the typical long-term voltage stability study. A property is that for each power value there are two voltage solutions. But usually, the high-voltage/low-current solution is the normal working condition due to the lower transmission losses. The critical point at the end of the nose curve represents the maximum loadability. But in this study, the nose curve is no longer about the voltage and the power. Here we will construct voltage-road length curves. The maximum length of the road can be determined, for a fixed fleet of vehicles, by gradually increasing the length of the road until no voltage solution exists.

The detailed construction of such voltage-road length curves is as follows. In the beginning, we define the road length as 1 km, for instance, and use continuation power flow to construct the associated curve of voltage magnitude and active power—the normal PV curve. We can find voltage solutions corresponding to the loading condition when all vehicles arrive at the endpoint [43]. If the road length is less than the critical length, one can find two such voltage solutions, for example, the two red star-points in Figure 2.10. Then, we gradually increase the road length and collate all resulting voltage solutions to construct the voltage-road length curve. Continue this procedure until the tip C of the voltage-road length curve where the pair of voltage solutions merge. Any road with a longer length than the critical length at point C will result in no voltage equilibrium solutions when the fleet of vehicles reaches its endpoint. This situation is regarded as the voltage collapse.

Figure 2.10 depicts a number of voltage-road length curves from which the maximum road length can be determined. The blue line represents the base case without

FIGURE 2.10: Maximum road length of WDC EV system. The black arrow indicates increasing PV installation.

PV panels installed on the EVs. With more added PVs, the curves extend to the right that implies that the maximum length of the road can be larger. This effect makes sense from the steady-state study point of view. Another point to make is that the PV generation may vary depending on the weather conditions so that the maximum length can be different from the base case. This effect needs to be addressed properly in the network design and operation to ensure the safe operation of the road.

While most of the experimental results are intuitive, we discuss a non-intuitive result in this section. We consider a situation when the vehicles move beyond the maximum allowed length of the road then quickly “return back” within the safe length. Because the vehicle has returned to the safe length, one may expect the road is “safe”. However, Figure 2.11 shows an unexpected outcome: the voltage collapses and goes to zero. While the complete mechanism of this collapsing behavior is rather complicated [42], a simple explanation is that when the vehicles pass point C towards point B in the embedded figure in Figure 2.10, the solution follows the lower branch of the nose curve which contains the segment CB. Even the vehicles physically return to the safe length, the system voltage continues following the

FIGURE 2.11: Voltage collapse phenomenon

lower solution branch and does not return to point A. It finally goes to zero. This collapsing phenomenon develops in a short period from the time instant the vehicles arrive point C at $t_{critical}$ to $t_{collapse}$. The actual collapse event in practice has been also analyzed in [46].

2.5.3 Maximum Number of Vehicles on a Fixed Length Road

Except for considering the maximum length of the road that EVs can safely move, LTVS also becomes the problem of finding the maximum number of EVs that the road can accommodate. This setting considers a fixed-length road on which one needs to find the maximum number of EVs allowed to operate. From Figure 2.4, we observe that the heaviest loading condition is when vehicles approach the end of the road. We can use the same method for constructing the voltage-road length curves in the previous section to build the voltage-number of EVs counterparts, by gradually increasing the number of EVs operating on the road. One difference, in this case, is that the number of EVs is not continuous but has discrete values. Figure 2.12 shows that at most four EVs can be allowed to operate simultaneously on a 4-km road. Under this situation, the road was only designed for a certain

FIGURE 2.12: Maximum number of vehicles of WDC system

number of electric vehicles at the same time. Problems arose when it would not be possible to stop the flow of traffic without further effort if there are more electric vehicles that want to drive on it. To avoid that, we can just take a highway for example. First, we could calculate the maximum number of vehicles for a fixed road. It is easy to know how many vehicles enter the road from the entrance and how many vehicles leave the road from the exit. In this way, the real-time number of EVs on the road can be collected. If the real-time number is less than the maximum number, more vehicles can be allowed to enter. Otherwise, no more vehicles can enter unless several vehicles leave.

Varying segment sizes can change both the maximum length of the road and the maximum number of vehicles. In our experiments, we assume that all vehicle members in a fleet follow one another and that the gap between two consecutive members is equal to the segment size. If the segment size reduces, vehicle members run closer to each other and vice versa. Reducing the segment size will make the fleet closer to the road end at the final time step and thus burden the electrified road further. Therefore, with a smaller segment size, the maximum road length and the number of vehicles allowed to operate need to be reduced.

For the maximum road length, segment sizes do not affect the maximum road length when the fleet of vehicles has only one car because we choose the most critical time instant when vehicles reach the end of the road. In this way, only the length of the cable can affect the voltage. However, as more vehicles move on the road, the rest of the vehicles will be farther away from the end of the road if the segment size increases. Thus, the larger the segment size is, the longer the maximum road length is. For the maximum number of vehicles, the segment size also has an impact. As the number of cars increases, the vehicles behind are getting farther and farther from the end of the road. These distances will increase if the segment size increases, causing the estimated value of the maximum number of vehicles increases.

2.6 Conclusions

This study focuses on a new paradigm based on the moving electric vehicles on the wireless dynamic charging system. We present a EV charging system model with several moving loads that travel on a distribution system. Unlike traditional loads having variable power and fixed locations, the problem changes to solve power flow equations of loads with fixed locations. Among the problems that moving load may bring to the charging system, we study the effect of moving loads on the steady-state operation of a wireless dynamic charging system modeled as a one-feeder distribution gird.

In this study, new voltage profiles of various operating conditions with PV panels and voltage compensators are constructed. None of the previous literature has noticed the steady-state voltage profile along the electrified road over time. For each nodal voltage, there should be a criterion of limitation to keep the system stable and avoid the appearance of voltage collapse. This kind of curve is helpful to understand the higher boundary and lower boundary of the whole voltage profile. To compensate for the consumption of active power and reactive power from each

electric vehicles, on-board PV panels, on-board capacitors, and the fixed capacitor bank play a role in regulating the voltage distribution.

This study also presents a method to apply the continuation power flow for the long-term voltage stability of electrified roads to characterize the maximum length and maximum number of EVs that the road can accommodate. As the behavior of electric vehicles affects the process of transmitting power along the electrified road, there is a high probability that power cannot be transferred to the EVs when they travel too far away from the generator. From this study, we use CPF to get each group of two voltage solutions based on power flow calculation, and collate such parameters to obtain the voltage magnitude versus road length curve and the voltage magnitude versus number of EVs curve. The critical point which has only one voltage solution represents the safety boundary of the system. Besides, a phenomenon about voltage collapse when EVs exceed the length limitation is analyzed.

Chapter 3

Non-parametric Probabilistic Load Flow using Gaussian Process Learning

3.1 Overview

The power flow problem is fundamental but crucial to power system operation. The conventional power flow calculation uses the deterministic power flow models to obtain the determined operating status of the power system, including nodal voltage, branch power flow, and power loss, according to the given network structure, component parameters, nodal load requirements, and other operating conditions. These results of power flow calculations can provide a basis for quantitative analysis for judging the rationality, safety, and reliability of power system planning and operating methods. In addition, engineers can, therefore, improve the design of power systems based on relevant data.

Various deterministic power flow models are widely used to ensure the system's operational reliability and security. When using a set of known data in a deterministic manner, the system's state parameters can be fully obtained. However, there

are a lot of uncertain factors influencing the system. A large number of schemes need to be formed according to various possible changes if applying a deterministic power flow method. This whole procedure will take a lot of time. With the increasing integration of renewable sources, such as wind power and photovoltaic (PV) energy, the generation parts of electrical systems may face different scenarios [22]. On the other hand, there is also uncertainty in the load demand side, such as the impact of electric vehicles. Thus, new power flow algorithms considering uncertainties in the power system are needed.

To solve the research challenges and achieve the objectives mentioned above, the methodology is as follows: We first use GP regression to get the posterior distribution parameters $\mu(\mathbf{x})$ and $\sigma(\mathbf{x})$. Then, based on the GP-UCB regret bound, we can present the probabilistic learning bound (PLB) which helps us have the criteria to stop learning. In this way, the number of training points can be reduced and save the training time as well. Once the algorithm of the training part is done, we can obtain the results of outputs against any input PDF which is used as test points. The remaining sections of this chapter are organized as follows:

- Section 3.2 describes the probabilistic load flow problem and several main methods. A brief literature survey about researches on numerical methods, analytical methods, and approximation methods is presented.
- Section 3.3 introduces the theory of the Gaussian process regression and GP-UCB method.
- Section 3.4 describes the main idea of the proposed non-parametric PLF method. The whole process is divided into the learning stage and testing stage.
- Section 3.5 shows the simulation results on the IEEE 30-Bus, 33-Bus, and 118-Bus systems. The discussion of the results is also provided.
- Section 3.6 draws some conclusions for this chapter.

3.2 Literature Review

In this section, I mainly discuss the literature review containing the background of probabilistic load flow and three main types of previous PLF methods which had some improvements.

3.2.1 Probabilistic Load Flow

Typical power flow calculation equations are as follows:

$$\begin{cases} W = f(X, Y) \\ Z = g(X, Y) \end{cases} \quad (3.1)$$

In the equation above, W represents the system nodal power injection; X refers to the nodal voltage; Y is the parameter of the system network; and Z denotes the branch flow in the system. Probabilistic power flow is based on the above formula and also takes the probability characteristics of the input variables W and Y into consideration. In this way, the distribution of the system state variables X and Z is obtained. So that the system's operating conditions and probability characteristics are comprehensively given.

Probabilistic load flow (PLF) was first proposed in [47] considering the impact of the input variables with known uncertainty distribution characteristics. The PLF approach can provide the probability density functions (PDFs) of the output values like power flow and nodal voltages. The probabilistic power flow method considers the influence of various uncertain factors on the system power flow operation characteristics. This method regards uncertain factors such as nodal power and random faults as input random variables and obtains the nodal voltage based on its statistical characteristics of probability (e.g., digital characteristics such as expected value and standard deviation, probability distribution functions such as probability density function and statistical characteristics of uncertain output parameters such as branch flow and power loss).

Probabilistic power flow calculations can provide more comprehensive information for power system planning and operation, including the expected value, maximum value, minimum value, probability distribution of nodal voltages, branch power flows, the power outputs of generators and so on. The information serves as a reference for the reasonable determination of the power system planning design scheme and operation mode.

In previous literature, the traditional probabilistic load flow method has been improved through many kinds of technologies. Those methods and technologies can be classified into three types: numerical methods, analytical methods, and approximation methods [48].

3.2.2 Numerical Methods to Solve PLF Problems

MCS is an experimental method based on probability theory and mathematical statistics. This method transforms uncertain problems into a series of definite problems and has been widely used in the field of uncertain analysis. Its mathematical theory is based on the large numbers of simulations, that is, the frequency of occurrence of an event converges with the probability of the occurrence of this event with probability. The calculation steps of the method include: generating samples that satisfy the relevant conditions by the sample method according to the distribution characteristics of the input (like the edge distribution and correlation coefficient); substituting each group of input random variable samples into the power flow equations for calculation and obtaining multiple sets of calculated values of the output random variables; and using statistical methods to obtain their statistical characteristics of all calculated output random variables [49].

The main ways to improve the calculation accuracy include increasing the sampling scale and reducing the sampling standard deviation. In the case of a certain sampling standard deviation, a common measure to improve the accuracy of the calculation is to increase the sampling size of the input random variable. However, the

number of deterministic power flow calculations will be increased, thereby increasing the calculation time of the algorithm and reducing the calculation efficiency. In this way, although this method has the advantage of simple implementation and has high calculation accuracy when the sampling size is large enough, it takes a rather long time. Therefore, it is usually used as a benchmark for evaluating the accuracy of other probabilistic load flow algorithms [49]. Under certain calculation accuracy requirements, the key to improving the calculation efficiency is to reduce the number of deterministic power flow calculations, that is, to reduce the sampling scale. Generally, it can be achieved by reducing the sampling standard deviation.

The Latin Hypercube Sampling (LHS) can efficiently cover the entire distribution range of the input random variable and has the advantages of high sampling efficiency, good robustness, and simple implementation, and has been well applied in probabilistic power flow calculation [17, 50]. This work has two steps: sampling and permutation. The first step aims to produce typical sampling points to represent the distribution of all the input random variables. However, when the inputs are independent and have no close relationship between each point, then the second step becomes important. It focuses on decreasing the relationship between each variable of the whole input random variables. Therefore, it is able to make sure that the whole distribution of input variables can converge. Besides, it can also minimize the unacceptable relationships between samples of different input random variables. Latin Supercube Sampling (LSS) overcomes the drawback that Monte Carlo Simulation Method always needs large times of simulations [51]. This method has a special tool named digital nets. This tool has the advantage of reducing the sampling bias for the LSS method. In addition, LSS is able to alleviate the drawbacks of that tool when dealing with some high-dimensional questions. In this way, digital nets and LHS are working together to select sampling points for a large number of random variables. The correlation step helps achieve more accurate outputs. Therefore, the distribution of output variables is more accurately collected comparing with that of LHS.

3.2.3 Analytical Methods to Solve PLF Problems

The analytical methods comprise two representative methods: the convolution method and the cumulant method. These two methods utilize the known distribution characteristics of the input random variable and the linear statistical relationship between the output random variable and the input random variable.

The convolution method can process independent random variables with linear correlation, but it has a large amount of calculations. When the output variables are the linear function of the input variables and the input variables are independent of each other, it can be known from the convolution theory that the probability density function of the output random variable is the convolution of the probability density function of the input random variable. When the input random variable meets the linear correlation, the input can be expressed as a linear combination of a set of independent random variables through a conversion method, and then the statistical characteristics of the output random variable can be obtained by convolution calculations. When the number of input random variables is large, the traditional convolution method has the disadvantages of large calculation volume and slow calculation speed. For this reason, some previous researchers have introduced Laplace transform [18] and Fourier transform [52] into the probabilistic power flow calculation based on the convolution method, which improves the calculation speed of the algorithm but still has the disadvantage of low calculation efficiency.

Cumulant is a numerical characteristic of a random variable. When the output random variable and the input random variable satisfy a linear function relationship and the input random variables are independent of each other, the cumulant algebra is able to process the input random variables in place of the convolution calculation according to its additivity and homogeneity. Therefore, the calculation efficiency is improved. Its main calculation steps include: calculating the moments (a set of measures of the distribution characteristics of the variables) of each order according to the probability distribution function of the input random variable,

and then obtaining the cumulant of each order from the functional relationship; and calculating the power flow at the prediction point of the input variable. Then, obtaining the cumulant of each order of the output random variable from the linear relationship; Finally, calculating the probability distribution function by series expansion and other methods according to the cumulant of the output random variable. Based on the cumulant of each order of the output random variable, the probability distribution function of the output can be fitted through methods such as Gram-Charlier series expansion [27].

3.2.4 Approximation Methods to Solve PLF Problems

This technique approximates the distribution feature of the output variables according to the obtained probability characteristics of the input variables. The point estimation technology is one of the most major methods [25, 53]. It constructs the corresponding estimated points through the different stages of the input. After obtaining the estimated points of the inputs, the estimated points of the output can also be collected through the functional correlation between the output variables and the inputs. Thereby, the digital characteristics of the output random variables can be obtained by using statistical methods.

As for point estimation method, not only accurate nonlinear power flow equations are useful to calculate, but also knowing the order moments of the input random variables is enough for calculation. There are no strict requirements to know the probability distribution function of the input random variables. Only a few data information of input random variables is sufficient to be applied to situations where the probability distribution of the input variables is unknown. The amount of computation has a linear relationship with the number of input random variables. When the number of input random variables is small, the point estimation method has the advantages of fast calculation speed and high calculation efficiency. However, when the number of input random variables is large, the situation is the opposite. In addition, the accuracy of obtaining each order moment of the output

random variables will decrease if the order increases. Because of its advantages, such as high computational efficiency and low requirements on input data, the point estimation method is not only widely used in power system probabilistic power flow problems, but also plays an important role in other areas of uncertainty analysis.

Another commonly used method of the approximation method is the first-order second-moment method. Rather than using estimated points to approximate the input random variables, this method uses the first-order Taylor series to approximate the nonlinear system, so that the second-order of the output variables can be determined [19]. The models which are used in this method include linearized models, approximate second-order models, and complete second-order models. The first-order second-moment method can take into account the linear correlation between each variable of the whole input random variables and has a high calculation efficiency. Therefore, it has received a certain amount of attention in the field of probabilistic load flow. However, as this method can only obtain the first-order and the second-order of the output random variables, it is difficult to construct an intact probability distribution function and accurately describe the statistical characteristics when the output random variables do not follow a normal distribution.

3.3 Theory of GP Regression and GP-UCB Method

In this section, we introduce the GP regression and GP-UCB algorithm for sampling training points and for GP learning bounded by regret bounds.

3.3.1 GP Regression

The analogous extension of the multivariate Gaussian function and the distribution that interprets GP as a random function is intuitive and very effective as a non-parametric method, for modeling PDFs over functions [54]. In power systems, the

use of GP is limited to power and load forecasting applications. The GP method has been widely used in various forecasting problems, like wind power [55, 56], solar power [57], and electricity demand [58]. Other than these forecasting works, the idea of using GP to learn the dynamics and stability index behavior has been explored recently in [59, 60].

A general GP regression, with a training data set $\mathcal{D} = \{\mathbf{x}^{(i)}, \hat{y}(\mathbf{x}^{(i)})\}_{i=1}^N$ where $\hat{y}(\mathbf{x}^{(i)})$ is the measured function value for input $\mathbf{x}^{(i)} \in \mathbb{R}^n$ at the i -th step, is given as [54]:

$$\hat{y}(\mathbf{x}^{(i)}) = y(\mathbf{x}^{(i)}) + \varepsilon^{(i)}, \quad i = 1 \dots N. \quad (3.2)$$

In the probabilistic load flow problem, $\mathbf{x}$ can represent uncertain power injections such as those from intermittent renewable sources and the location of moving loads, and $\hat{y}(\mathbf{x})$ refers to the voltage numerical solution corresponding to a point of $\mathbf{x}$. In (3.2), $\varepsilon^{(i)}$ is independent distributed noise variable with zero-mean, and σ_n standard deviation normal distribution.

A sample set $\hat{y}_N = [\hat{y}(\mathbf{x}^{(1)}), \dots, \hat{y}(\mathbf{x}^{(N)})]^T$ at operating points $\mathcal{D}_N = \{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(N)}\}$ with Gaussian noise ε , and the analytic formula set can be obtained for posterior distribution corresponding to (3.2). The kernel functions $k(\mathbf{x}, \mathbf{x}')$ incorporate our comprehension of unknown function into GP. Following the extension of Bayesian rule [54], the analytic formula set for the posterior distribution of (3.3) will be

$$\mu_N(\mathbf{x}) = k_N(\mathbf{x})^T A^{-1} q_N \quad (3.3a)$$

$$k_N(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}, \mathbf{x}') - k_N(\mathbf{x})^T A^{-1} k_N(\mathbf{x}') \quad (3.3b)$$

$$\sigma_N^2(\mathbf{x}) = k_N(\mathbf{x}, \mathbf{x}) \quad (3.3c)$$

In the equations above, $k_N(\mathbf{x}) = [k(\mathbf{x}^{(1)}, \mathbf{x}), \dots, k(\mathbf{x}^{(N)}, \mathbf{x})]^T$ and $K_N = [k(\mathbf{x}, \mathbf{x}')]$. $A = K_N + \sigma_n^2 I$, $\mu_N(\mathbf{x})$ is the mean, $k_N(\mathbf{x}, \mathbf{x}')$ is the covariance, and the variance is given as $\sigma_N^2(\mathbf{x})$. The $\mathbf{x}$ and $\mathbf{x}'$ are two sample operating points from $\mathcal{D}_N$. In

this work, we use the squared exponential kernel function with zero mean and unit characteristic length.

3.3.2 GP-UCB

Sampling schemes contribute a lot in learning steps of the algorithm. This chapter relies on the GP-UCB method which was widely used in Bayesian optimization paradigm [61]. The target is to obtain the mean $\mu(\mathbf{x})$ for function $y(\mathbf{x})$ with least standard deviation $\sigma(\mathbf{x})$ and probability at least $1 - \delta$ with $\delta \in (0, 1)$. A joint function for multi-objective balance between exploration and exploitation is opted for obtaining next input point $\mathbf{x}^{(i)}$. With β_i taken independent of state vector and $\mathcal{S}$ being uncertain input subspace, the sampling strategy will be:

$$\mathbf{x}^{(i)} = \operatorname{argmax}_{\mathbf{x}^{(i)} \in \mathcal{S}} \left\{ \mu_i(\mathbf{x}) + \sqrt{\beta_{i+1}} \sigma_i(\mathbf{x}) \right\}. \quad (3.4)$$

Intuitively, (3.4) means that the sampled input point will be the one where weighted sum, $\mu_i(\mathbf{x}) + \beta_{i+1}^{1/2} \sigma_i(\mathbf{x})$, of mean and variance is maximum. For sequential optimization, $\sqrt{\beta_{i+1}} \sigma_i(\mathbf{x})$ aims at decreasing uncertainty, not just where maximum value might be. $\mu_i(\mathbf{x})$ aims to maximize the expected reward based on the posterior so far. Therefore, the combination strategy of two parameters works well to get the best function. Refer to [61] for more specific theories and details of this sampling strategy.

3.4 Proposed Non-parametric Probabilistic Load Flow(NP-PLF) Method

In this section, we present the proposed NP-PLF algorithm with the result of a probabilistic guarantee on bounds of power flow solution. Firstly, we introduce how we formulate the generic power flow and inverse power flow analogy for obtaining

an uncertain state vector corresponding to uncertain input. Secondly, we present the main results of the proposed NP-PLF method.

3.4.1 Formulation of Uncertain Input

Normally, the AC power flow equations are nonlinear in the nodal voltages, and can be expressed as:

$$\mathbf{x} = h(\mathbf{y}) \quad (3.5)$$

where the random input vector $\mathbf{y}$ represents active and reactive power injections at different buses. The state random vector including nodal voltage magnitude $\mathbf{V}$, angle θ , and other nodal parameters are expressed as $\mathbf{x}$. We assume that the power system for power flow studies operates normally without contingencies. The network structure is unchanged for conventional operation and the branch parameters change when considering moving electric vehicles. Further, the input can have some uncertain variables while some certain or non-random. Similarly, any subset of the output can be the uncertain output that we want to learn using GP regression.

Then, we want to learn one nodal voltage $V_i \in \mathbf{y}$ against variations with the input of power injections. In other words, we would like to learn the behavior of V_i in uncertain input subspace $\mathcal{S}$ of the power injections. In order to learn the voltage solution as a function of the random power injections, we need to learn the inverse power flow function $\mathbf{y} = h(\mathbf{x})$ from (3.5). This inverse function in the load flow context becomes

$$\mathbf{V} = f(\mathbf{S}) \quad (3.6)$$

where $f(\cdot) \equiv h^{-1}(\cdot)$.

Here, we assume that the Newton-Raphson Method we use in MATPOWER is able to converge when solving the power flow. In other words, the power flow of the power system network is solvable in the considered space of random power injections $\mathbf{S} \in \mathcal{S}$. In this way, the inverse power flow is well-defined. Once the voltage solution is known, other network quantities such as branch flows or power loss can be calculated in the same way.

We can say that the i -th nodal voltage magnitude is a function of random variable $\mathbf{x}$ representing the random power injections, inside an input subspace $\mathcal{S}$ as $V_i = f(\mathbf{x})$, $\mathbf{x} \in \mathcal{S}$. Because the power flow equation set $h(\cdot)$ are nonlinear, their inverse functions are not easy to characterize. Further, this inverse non-linearity is a major bottleneck in solving PLF using parametric methods. More importantly, any individual state variable will also get affected by the complete set of a nonlinear equation $f(\mathbf{x})$. Therefore, the uncertainty propagation requires various approximations and complex formulations [62, 63]. To deal with this, we present the main results on GP based NP-PLF below.

3.4.2 Main Methodology of NP-PLF Method

Following the analogy presented in (3.2), the Newton-Rapson Load Flow (NRLF) solution obtained for input sample $\mathbf{x}^{(i)}$ can be interpreted as $\hat{y}^{(i)}$ containing $f(\mathbf{x}^{(i)})$ with numerical computation noise as:

$$\hat{y}^{(i)} = f(\mathbf{x}^{(i)}) + \varepsilon. \quad (3.7)$$

Based on (3.7), using the GP learning (3.3), the posterior distribution parameters $\mu(\mathbf{x})$ and $\sigma(\mathbf{x})$ are obtained. Further, a straight forward method would be to keep obtaining more and more training samples $\hat{y}$ and keep updating the posterior distribution parameters. This approach has some major difficulties. This method does not provide any bound on the possible uncertainty of posterior distribution.

Using this method we have no criteria to stop learning and it will have the same issue as MCS with the question: *How many points are sufficient for learning?*

3.4.2.1 NP-PLF Learning

To overcome these difficulties, we present the probabilistic learning bound (PLB). The PLB defines a range within which the target state variable y will remain with the given probability. Now, based on GP-UCB regret bound [61], we present the PLB for any general random state variable $y = f(\mathbf{x})$ (e.g., $V_i = f(\mathbf{S})$ (3.6)) in the uncertain state subspace $\mathbf{x} \in \mathcal{S}$.

Theorem 3.4.1. For a given $\delta \in (0, 1)$, for any uncertain power system input vector $\mathbf{x}$, the inverse power flow solution function $f(\mathbf{x})$ will be bounded with probability $1 - \delta$ as

$$\mu_N(\mathbf{x}) - \xi_{max} \leq f(\mathbf{x}) \leq \mu_N(\mathbf{x}) + \xi_{max} \quad (3.8)$$

where $\xi_{max} = \max_{\mathbf{x} \in \mathcal{S}} \{ \sqrt{\beta_{N+1}} \sigma_N(\mathbf{x}) \}$ is PLB, and $\mathbf{x}$ lies in the uncertain state subspace $\mathcal{S}$.

Proof. The proof follows Theorem 6 in [61] and Theorem 1 in [59]. The result on regret bound, after N GP-UCB sampling points for training, provides the relation as [61]:

$$|f(\mathbf{x}) - \mu_N(\mathbf{x})| \leq \sqrt{\beta_{N+1}} \sigma_N(\mathbf{x}), \quad \forall \mathbf{x} \in \mathcal{S}. \quad (3.9)$$

Upon opening the modules, we obtain upper and lower bounds as a function of $\mathbf{x}$. Applying the maximum operator over the regret bound obtained after N sampling iterations of GP-UCB, $\xi = \sqrt{\beta_{N+1}} \sigma_N(\mathbf{x})$, we obtain the PLB in (3.8).

Theorem 3.4.1 provides a probabilistic guarantee for bounds of power flow solution. Further, the probabilistic learning bound ξ_{max} can serve as convergence criteria for

Algorithm 1 NP-PLF**Input:** $\mathcal{S}$, $\mathcal{X} \in \mathbb{R}^n$, δ , ξ_{max} , μ_o , σ_o , $k(\mathbf{x}, \mathbf{x}')$, $\mathbf{x}^{(1)}$, $\hat{y}(\mathbf{x}^{(1)})$ **Output:** $\mathbf{x}^{(i)}$, $\hat{y}(\mathbf{x}^{(i)})$, $\mu_i(\mathbf{x})$, $\sigma_i(\mathbf{x})$, β_{i+1} ; $i \in \{1, \dots, N\}$

```

while ( $\max_{\mathbf{x} \in \mathcal{S}} \{\sqrt{\beta_{i+1}} \sigma_i(\mathbf{x})\} \leq \xi_{max}$ ) do
  Select  $\mathbf{x}^{(i)} = \operatorname{argmax}_{\mathbf{x} \in \mathcal{S}} \mu_i(\mathbf{x}) + \sqrt{\beta_{i+1}} \sigma_i(\mathbf{x})$ 
  if  $\mathbf{x}^{(i)} \in \mathcal{X}$  then
    Select randomly  $\mathbf{x}^{(i)}$ 
  end if
  Sample  $\hat{y}(\mathbf{x}^{(i)}) = f(\mathbf{x}^{(i)}) + \varepsilon$  from (3.5) by NRLF
  Update  $\mu_i(\mathbf{x})$  and  $\sigma_i(\mathbf{x})$  from (3.3)
  Update  $\mathcal{X} = \mathcal{X} \cup \mathbf{x}^{(i)}$ 
  Update  $\beta_{i+1} = 2\|f\|_k^2 + 300\gamma_N \ln^3(i/\delta)$ 
  Update  $i = i + 1$ 
end while

```

the NP-PLF algorithm. The NP-PLF algorithm designed based on Theorem 3.4.1 is given as Algorithm 1. $\|f\|_k$ indicates the Reproducing Kernel Hilbert Space (RKHS) norm while γ_N is a constant [59]. The process of the learning step can be described in detail as follows: Firstly, we calculate the value of PLB from Theorem 3.4.1. Input an injection from the uncertain state subspace $\mathbf{x} \in \mathcal{S}$. This input becomes the first training sample. The judgment for continuing searching for new training points depends on the following criteria whether $\max_{\mathbf{x} \in \mathcal{S}} \{\sqrt{\beta_{i+1}} \sigma_i(\mathbf{x})\} \leq \xi_{max}$ or not. If not, we need to sample a new injection from (3.5). In this way, the number of training points increases. Then, update $\mu_i(\mathbf{x})$ and $\sigma_i(\mathbf{x})$ from (3.3) and also β_{i+1} . Criteria can be assessed again to check whether it is true or not. The above loop will stop until $\max_{\mathbf{x} \in \mathcal{S}} \{\sqrt{\beta_{i+1}} \sigma_i(\mathbf{x})\} \leq \xi_{max}$. Finally, sufficient training points are found.

Remark. The proposed NP-PLF does not require any specific PDF of input variable $\mathbf{x}$. However, it can be seen as working with *uniform probability distribution* where every value in the rectangular region, $\mathcal{S} = \{\mathbf{x} | \mathbf{x}^{min} \leq \mathbf{x} \leq \mathbf{x}^{max}\}$, has the same probability of occurrence.

3.4.2.2 NP-PLF Testing

In this step, once the Algorithm 1 converges, the state variable y can be obtained for distribution of test points using $\mathbf{x}'$ in (3.3). This means that for obtaining a probabilistic distribution of state variable against any input PDF, we use input PDF as test points over the output of the Algorithm 1, $\mu_N(\mathbf{x})$ and $\sigma_N(\mathbf{x})$. Further, from Theorem 3.4.1, the state of PDF will be bounded by error ξ_{max} with probability $1 - \delta$. Therefore, the testing step can be performed for any class of probability distribution. The process of the testing step can be described in detail as follows: Once we sample the sufficient training points, we can obtain the distribution of the outputs by using GP-regression on all the test points $\mathbf{x}'$ from (3.3). The value range of $\mathbf{x}'$ can be defined by the users.

Note that the CPF attempts to trace the $P - V$ curve by increasing the load, generally in one dimension [43]. The proposed method can learn the voltage variation curve in multiple dimensions as $\mathbf{x} \in \mathbb{R}^n$. Therefore, Algorithm 1 can also be interpreted as a GP based CPF method. Nevertheless, it still suffers from the same issue of Jacobian ill-conditioning near the critical point [64–67].

Another important point is that Algorithm 1 can work in parallel to learn many state variables simultaneously. For each state variable, this method will sample points to learn the particular y using GP-UCB (3.4) in parallel execution. Nevertheless, Multi-linear Gaussian Processes (MLGP) [68] can also be used to learn several variables simultaneously with Algorithm 1.

3.5 Simulation Results and Discussion

In this section, we will present the main results of nodal voltage magnitude under various power injections and changing locations of one bus. At first, we consider a situation when the renewable generator replaces the conventional generator in

the IEEE 30-bus system [69]. Later, the load uncertainties are considered in 30-bus and 118-bus systems [69] at different buses. As previous two test systems are normal transmission networks we use to verify the efficiency and accuracy of the proposed algorithm. Finally, we consider a standard distribution system - IEEE 33-bus system [69] to do the steady-state analysis of power distribution system with dynamic charging electric vehicles. In this system, we consider one electric vehicle moving along the branch. In other words, the inputs of the NP-PLF method include both the load uncertainties and the location uncertainties of an EV.

3.5.1 Uncertain Injection Variations

The biggest challenge in PLF involves the difficulty in modeling and obtaining the statistical distribution of random power generation variable, more so in case of solar power and vehicle-to-grid. Therefore, for the NP-PLF learning stage, we consider uniform distribution between zero to the maximum limit. However, other distributions can be considered in a similar way.

TABLE 3.1: Results in NP-PLF Solution

Uncertainty Renewable Generator	Variable	$\% \varepsilon_v$	N	Time (sec.)
P_{g_3} At bus 22	$ V_{21} $	0.0014	8	2.15
	$ V_{24} $	0.0001	7	1.39
P_{g_4} At bus 27	$ V_{25} $	0.0082	7	1.66
	$ V_{28} $	0.0055	8	1.88
P_{g_5} At bus 13	$ V_{15} $	0.0006	13	2.92
	$ V_{24} $	0.0049	7	1.89

In table 3.1, the number of training samples (N) required, to achieve $\xi_{max} \leq 1\%$ with probability ≥ 0.99 , is given with computation time. It is clear from table 3.1 that for various cases the proposed NP-PLF has been able to achieve the higher accuracy results with very less sampling points when compared to the MCS method. Because the MCS method needs to calculate all the points of the active power to get the final results. It is also obvious that under different situations, the number

of sampling points varies to achieve the error requirement. The computation time becomes longer and the average percentage relative error-index decreases if the number of training samples increases. The average percentage relative error-index $\% \varepsilon_v$, is defined as [24]:

$$\% \varepsilon_v = \frac{\sum_{k=1}^{N_s} \left| \frac{V_k^{MCS} - V_k^{GP}}{V_k^{MCS}} \right|}{N_s} \times 100 \quad (3.10)$$

Further, the following three figures show the voltage variation obtained as semi-explicit from learning algorithm 1 for one dimensional input subspace (active power of one generator). These curves also indicate that learning regret is higher at locations where training samples are not obtained. That is why the regret bound region is narrow when there is a training sample but becomes wider when there are no training samples. Thus, the regret bound region can further be decreased using more samples, especially with a higher value of the active power of the generator, P_{g4} . Most importantly, upon completion of the NP-PLF learning stage, the complete $P - V$ is obtained.

FIGURE 3.1: $|V_{25}|$ as a function of uncertain renewable power injection (P_{g4}) at bus 27 having uniform distribution between zero to 55 MW

FIGURE 3.2: $|V_{24}|$ as a function of uncertain renewable power injection (P_{g5}) at bus 13 having uniform distribution between zero to 28 MW

Figure 3.1 shows the magnitude of $|V_{25}|$ when the uncertain renewable power injection (P_{g4}) at bus 27 having uniform distribution between zero to 55 MW. Bus 25 is linked directly to bus 27 where generator 4 is located. The voltage profile indicates that with the increasing value of the active power of the generator, voltage magnitude will reach a peak value and then gradually decrease. The voltage deviation at bus 25 is small as it is lower than 0.1%.

Figure 3.2 shows the magnitude of $|V_{24}|$ when the uncertain renewable power injection (P_{g5}) at bus 13 having uniform distribution between zero to 28 MW. Figure 3.3 shows the magnitude of $|V_{21}|$ when the uncertain renewable power injection (P_{g3}) at bus 22 having uniform distribution between zero to 50 MW. The results show that the voltage magnitude will keep a trend of increasing or decreasing. As bus 24 is far away from bus 13 where generator 5 is located but bus 21 is close to bus 22 where generator 3 is located.

As mentioned before, the proposed NP-PLF method can work with any class of distribution through the testing phase. Figure 3.4 and figure 3.5 are obtained by varying the P_{g4} with normal and gamma distribution respectively. The comparison between histograms obtained using MCS and the proposed NP-PLF method

FIGURE 3.3: $|V_{21}|$ as a function of uncertain renewable power injection (P_{g3}) at bus 22 having uniform distribution between zero to 50 MW

validates that the proposed method can calculate any statistical features of PLF for any type of input distribution. Here, in figure 3.4, the distribution of the power injections follows a normal distribution and has 50000 samples. The distribution of the output $|V_{25}|$ is one-sided because $|V_{25}|_{max} = 99.02kV$ as indicated in figure 3.1. The maximum number of samples in P_{g4} is around the mean which leads to the voltage near maximum value. Thus in one-sided distribution, the maximum number of samples comes near $|V_{25}|_{max}$ making the shape in figure 3.4.

For indicating the effect of load variation, different nodal voltage magnitudes are expressed in semi-explicit form using the learning step and shown in figure 3.6. As indicated, $|V_{30}|$ gets affected the most with variations in load demand at bus 30 because bus 30 is the place where we change the load. $|V_{28}|$ and $|V_{26}|$ are nearly not affected by the load varies because they are located away from bus 30. In other words, the effect decreases largely while we move away. However, it is clear that the proposed method has been able to record the complete non-linearity of power flow equations and the effect on all nodal voltage magnitudes. Table 3.2 shows that the ξ_{max} values with N sampling points indicating on accuracy and speed of the proposed method when the function is the voltage magnitude.

FIGURE 3.4: Histogram for $|V_{25}|$ with uncertain P_{g_4} at bus 27 having normal distribution ($\mu = 28$ and $\sigma = 8$) using proposed NP-PLF and MCS method (50000 samples).

FIGURE 3.5: Histogram for $|V_{28}|$ with uncertain P_{g_4} at bus 27 having gamma distribution (shape parameter $a=8$ and scale parameter $b=3$) using proposed NP-PLF and MCS method (50000 samples).

Different nodal voltage angles are also expressed in semi-explicit form using the learning step and shown in figure 3.7. As shown in the figure above, even bus 17, bus 16, bus 10, and bus 9 have different network branches between bus 17, all the θ value in four buses get affected largely with variations in load demand at bus 17. In other words, the variation of power factor in one load demand will contribute to the change of voltage angle in all the buses of the system. Besides, it is obvious

that the proposed method has been able to record the effect on all nodal voltage angles. Table 3.3 shows that the ξ_{max} values with N sampling points indicating on accuracy and speed of the proposed method when the function is the voltage angle.

Other than the load demand or the power generated from the generator, the proposed method can learn any state variables in any $n - dimensional$ input subspace as well. Figure 3.8 shows $|V_{75}|$ variation in $2 - dimensional, P_{d75} - Q_{d75}$ space. It is important to understand that for this learning, MCS would require very large number of points while the proposed method has been able to do this with less points. Figure 3.8 is drawn with $\xi_{max} \leq 1\%$ and probability ≥ 0.99 .

FIGURE 3.6: $|V_j|$ as a function uncertain P_{d30} in 30-Bus system

TABLE 3.2: Results Corresponding to NP-PLF Solution Shown in figure 3.6

Variable	$\xi_{max}(kV)$	N	Time (sec.)
$ V_{30} $	0.0784	10	2.35
$ V_{29} $	0.0308	15	3.54
$ V_{28} $	0.0443	8	1.89
$ V_{26} $	0.0200	8	1.90

FIGURE 3.7: Bus voltage angle as a function uncertain power demand at bus 17 in 30-Bus system

TABLE 3.3: ξ_{max} , N and Computation Time Corresponding to NP-PLF Solution Shown in figure 3.7

Variable	$\xi_{max}(rad)$	N	Time (sec.)
θ_{17}	0.00036	5	≤ 1
θ_{16}	0.00095	5	≤ 1
θ_{10}	0.00027	5	1.91
θ_9	0.03017	9	2.18

3.5.2 Uncertain EV Locations

As the two previous test systems are power transmission systems, we change the system into a standard distribution system which is the IEEE 33-bus system [69] to do the steady-state analysis of power distribution system with dynamic charging electric vehicles. In this distribution system, we add a new thirty-fourth bus as the electric vehicle. As mentioned in Chapter 2, the integration of the EVs serves as moving loads in the distribution system. Not only the variable power consumption of electric vehicles contributes to the change of voltage along the road, but also the location of the new bus can affect the voltage profile. Therefore, we consider uniform distribution between zero to the maximum limit for the active power of

FIGURE 3.8: $|V_{75}|$ as a function of uncertain S_{d30} in 118-Bus system

the new bus. In the meantime, the location of the EV is also defined by a uniform distribution between zero to one on one branch. In table 3.4, we put one electric vehicle moving under three conditions. The average percentage relative error-index, number of training samples (N) required to achieve $\xi_{max} \leq 2\%$ with probability ≥ 0.99 , and computation time are given. Obviously, considering both the load variation and branch change takes the proposed method more time to learn. However, it is still more effective than the traditional MCS method under a quite low error.

For indicating the effect of load variation of the EV and its location uncertainties, the magnitudes of one nodal voltage are shown in figure 3.9. The three-dimensional

TABLE 3.4: Results in NP-PLF Solution with moving EV

Uncertainty Moving EV	Variable	$\% \varepsilon_v$	N	Time (sec.)
P_{34} Between bus 2 and 3	$ V_4 $	0.0030	13	2.79
	$ V_{13} $	0.0041	14	3.05
P_{34} Between bus 21 and 22	$ V_7 $	0.0038	16	2.98
	$ V_{17} $	0.0034	8	1.19
P_{34} Between bus 6 and 26	$ V_{18} $	0.0032	22	5.96
	$ V_2 $	0.0017	7	0.83

diagram is also shown in figure 3.10 using the proposed NP-PLF method and MCS method. As indicated, we just use one EV moving between bus 3 and bus 4 to test the proposed method for simplicity. The value of location represents the ratio of the distance between bus 3 and EV to the distance between bus 3 and bus 4. $|V_5|$ keeps constant no matter where the EV is when the power consumption of the EV is zero. However, the gradient of $|V_5|$ and the location of EV increases if the power consumption becomes larger. The reason is that more load demand will cause greater influence to the nodal voltage magnitude. In addition, from figure 3.10, the curve using the proposed NP-PLF method contains several learning points. However, the results of 10000 sampling points are nearly the same with the results using the MCS method.

Regarding time consumption, the GPML toolbox [70] with MATLAB 2018b running on a PC having Intel Xeon E5-1630v4 (3.70 GHz clock, 16.0 GB of RAM) is used for simulations. The time consumption increases with increment in the input subspace size. For larger problems, works on approximation methods (chapter 8 [54]), sparse GP [71] can be used for future works. Also, the proposed NP-PLF is divided into stages where the learning stage can be done offline. This improves

FIGURE 3.9: $|V_5|$ as a function of uncertain P_{34} and EV location (between bus 3 and 4) in 33-Bus system

FIGURE 3.10: $|V_5|$ as a function of uncertain P_{34} and EV location (between bus 3 and 4) using proposed NP-PLF and MCS method (10000 samples)

the overall computational performance. For NP-PLF, testing is very less time-consuming, and 50,000 points only take 0.073563 seconds to test in Figure 3.5. On the other hand, MCS needs 50,000 samples and takes 108.15 seconds.

3.6 Conclusions

In this chapter, a proposed non-parametric probabilistic load flow (NP-PLF) method is used to assess the nodal voltages for uncertain power injections and uncertain branch values. This technique has applied the theory of the Gaussian Process Regression and GP-UCB method. Firstly, we formulate the general power flow equations and the inverse equations to obtain uncertain state vectors according to random inputs. The method is effective to handle the non-linearity of power flow problems.

The main procedure is composed of two stages. In the learning step, the solution of the Newton-Raphson power flow can be interpreted through normal GP regression equations and be learned as a function of uncertain power injections. In addition, the "*semi-explicit*" form of the voltage solution has a probabilistic learning bound

which defines a region for the target variables. The regret bound regards the given probability and maximum error as the convergence criteria for the algorithm. As a result, the learning step is able to stop learning with fewer numbers of training points and keep the high accuracy of results as well. Then, once the learning step is completed, the proposed method can use the parameters from the kernel functions to test points in the testing step. As the proposed method has the ability to learn the statistical distribution of training points, it does not rely on any specific distribution of the uncertain power injections.

The proposed algorithm was simulated in the IEEE 30-bus, IEEE 118-bus, and IEEE 33-bus systems. The first two test systems are normal transmission system and the last one is a typical distribution system. The simulation results verify that the proposed NP-PLF algorithm can collect statistical data with the help of very few sampling points. It is able to handle the problems containing more than one input variable. Besides, the average percentage relative error-index is small enough to ignore and the calculating time is much less compared with the traditional Monte Carlo Simulation Method when considering sizeable samples.

Chapter 4

Conclusions and Future Works

This chapter concludes the significant contribution of the thesis and provides some possible future research directions.

4.1 Conclusions

This thesis focuses on the steady-state analysis of the distribution power system with wireless dynamic charging. The new kind of moving loads will introduce some problems to power system stability. Therefore, the voltage profile and long-term voltage stability play an important role in analyzing the steady-state stability. Also, the proposed algorithm to solve the new power flow problem is also discussed in the thesis. Some conclusions are presented below:

As most previous literature studied on charging technologies mostly at the device level, we introduce a new filed focusing on the system level of the wireless dynamic charging system. Besides, they created some new power flow algorithms, applied regenerative braking energy, and improved the topology of the power supply system in the railway electrification systems area. This thesis examines the voltage effect caused by dynamic charging EVs. We introduced a novel simplified WDC EV system which is suitable for the application of traditional power flow packages and

we constructed a series of new patterns about the steady-state voltage profile along the electrified roads over time. Various conditions including changing the number of EVs, various power consumption, adding voltage compensators, on-board PV panels, and capacitors. Furthermore, a new method is proposed to analyze the long-term voltage stability (LTVS) of the electrified road, which concerns the existence of a steady-state solution. Above all, the new patterns of the distribution system's steady-state equilibrium regarding both the voltage and stability limits call for new research in this new paradigm.

In order to solve the probabilistic load flow problems of the distribution system with wireless dynamic charging EVs, a novel non-parametric probabilistic load flow (NP-PLF) is presented to estimate the nodal voltages for uncertain power injections. The learning step applies the theory of GP regression to learn the solutions of Newton-Raphson power flow as a function of the inputs. It also utilizes the GP-UCB method to build a probabilistic learning bound which defines a region for the target variables. In this way, the number of training points can be reduced while keeping enough accuracy of the results. The testing step can learn the statistical distribution of training points and does not rely on a specific distribution of the inputs. The proposed algorithm was tested on the IEEE 30-bus, IEEE 33-bus, and IEEE 118-bus systems. The simulation results prove that the NP-PLF method is able to obtain statistical information using very few sampling points. Also, the relative error-index is sufficiently small, while the computational time consumption is less compared with that of the traditional MCS method.

4.2 Future Works

The future research directions for investigating the model of technique and the results presented in this thesis are described in the following paragraphs.

- Build a more realistic test system with more complicated settings to analyze the steady-state operation of the system

Because this thesis presents a simple model of the electrified road with one feeder to do the steady-state analysis, we plan to extend it to a more complicated distribution network with more detailed models in the future. We will add more EVs moving at the same time and have different moving directions on several branches. We need to use the proposed method to analyze whether the voltage solution of the steady-state operation exists under different conditions. Apart from changing the test system, the types of EVs will also be different. In future works, the fleet will contain different types of EVs. We will also consider the EV charging with the integration of PV generation sources and on-board capacitors.

- Analyze the small-signal stability of the electrified road with moving loads

In this work, we only consider the problems of the equilibrium steady-state voltage profile and the existence of the steady-state solution. But the results are based on the situation that the wireless dynamic charging system is under a stable environment without being affected by some contingencies or disturbances. In reality, the operation of the system cannot maintain such a stable level all the time. Thus, we need to improve the NP-PLF method to analyze the small-signal stability of the electrified road with moving loads. For example, we would consider a situation when the power consumption of one EV suddenly increases. The future work aims to find an algorithm to obtain the safety boundary of the dynamic stability of the system.

Appendix

FIGURE A: The diagram of the IEEE 30-bus system[4]

FIGURE B: The diagram of the IEEE 33-bus system[5]

FIGURE C: The diagram of the IEEE 118-bus system[6]

Author's Publications

Chuan Wang, Hung D. Nguyen, “Steady-state voltage profile and long-term voltage stability of electrified road with wireless dynamic charging”, in Proceedings of the Tenth ACM International Conference on Future Energy Systems, ACM, 2019, pp. 165–169.

Parikshit Pareek, **Chuan Wang**, and Hung D. Nguyen. ”Non-parametric Probabilistic Load Flow using Gaussian Process Learning.” IEEE PESGM 2020 (Under Review) arXiv preprint arXiv:1911.03093 (2019).

Bibliography

- [1] Štefan Hamacek, Mikołaj Bartłomiejczyk, Roman Hrbáč, Stanislav Mišák, and Vítězslav Stýskala. Energy recovery effectiveness in trolleybus transport. *Electric Power Systems Research*, 112:1–11, 2014.
- [2] Junwei Lu and Jahangir Hossain. *Vehicle-to-grid: Linking Electric Vehicles to the Smart Grid*, volume 79. IET, 2015.
- [3] S. Corsi and G. N. Taranto. Voltage instability - the different shapes of the “nose”. In *2007 iREP Symposium - Bulk Power System Dynamics and Control - VII. Revitalizing Operational Reliability*, pages 1–16, Aug 2007.
- [4] Bijay Baran Pal, Papun Biswas, and Anirban Mukhopadhyay. Ga based fgp approach for optimal reactive power dispatch. *Procedia Technology*, 10:464–473, 2013.
- [5] Seyed Abbas Taher and Seyed Ahmadreza Afsari. Optimal location and sizing of upqc in distribution networks using differential evolution algorithm. *Mathematical Problems in engineering*, 2012, 2012.
- [6] Pablo Fernández-Porras, Mathaios Panteli, and Jairo Quirós-Tortós. Intentional controlled islanding: when to island for power system blackout prevention. *IET Generation, Transmission & Distribution*, 12(14):3542–3549, 2018.
- [7] I. Hwang, Y. J. Jang, Y. D. Ko, and M. S. Lee. System optimization for dynamic wireless charging electric vehicles operating in a multiple-route environment. *IEEE Transactions on Intelligent Transportation Systems*, 19(6):1709–1726, June 2018.
- [8] J. M. Miller, P. T. Jones, J. Li, and O. C. Onar. Ornl experience and challenges facing dynamic wireless power charging of ev’s. *IEEE Circuits and Systems Magazine*, 15(2):40–53, Secondquarter 2015.

- [9] M. Yilmaz and P. T. Krein. Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles. *IEEE Transactions on Power Electronics*, 28(5):2151–2169, May 2013.
- [10] Junqi Zhang, Mingli Wu, and Qiujiang Liu. A novel power flow algorithm for traction power supply systems based on the thévenin equivalent. *Energies*, 11(1):126, 2018.
- [11] CJ Goodman and T Kulworawanichpong. Sequential linear power flow solution for ac electric railway power supply systems. *WIT Transactions on The Built Environment*, 61, 2002.
- [12] S. V. Raygani, A. Tahavorgar, S. S. Fazel, and B. Moaveni. Load flow analysis and future development study for an ac electric railway. *IET Electrical Systems in Transportation*, 2(3):139–147, Sep. 2012.
- [13] Wang Bin, Hu Haitao, Gao Shibin, and Han Xudong. Power flow calculation for traction networks under regenerative braking condition based on locomotive-traction network coupling. *Indonesian Journal of Electrical Engineering and Computer Science*, 11(2):848–854, 2013.
- [14] M Chymera, AC Renfrew, and M Barnes. Railway modelling for power quality analysis. *WIT Transactions on The Built Environment*, 88, 2006.
- [15] Thanatchai Kulworawanichpong. *Optimising AC electric railway power flows with power electronic control*. PhD thesis, University of Birmingham, 2004.
- [16] Mikołaj Bartłomiejczyk and Marcin Połom. The impact of the overhead line’s power supply system spatial differentiation on the energy consumption of trolleybus transport: planning and economic aspects. *Transport*, 32(1):1–12, 2017.
- [17] Han Yu, CY Chung, KP Wong, HW Lee, and JH Zhang. Probabilistic load flow evaluation with hybrid latin hypercube sampling and cholesky decomposition. *IEEE Transactions on Power Systems*, 24(2):661–667, 2009.
- [18] Meghdad Tourandaz Kenari, Mohammad Sadegh Sepasian, Mehrdad Setayesh Nazar, and Hossein Ali Mohammadpour. Combined cumulants and laplace transform method for probabilistic load flow analysis. *IET Generation, Transmission & Distribution*, 11(14):3548–3556, 2017.
- [19] Can Wan, Zhao Xu, Zhao Yang Dong, and Kit Po Wong. Probabilistic load flow computation using first-order second-moment method. In *2012 IEEE Power and Energy Society General Meeting*, pages 1–6. IEEE, 2012.

- [20] Zheng Zhang, Hung Dinh Nguyen, Konstantin Turitsyn, and Luca Daniel. Probabilistic power flow computation via low-rank and sparse tensor recovery. *arXiv preprint arXiv:1508.02489*, 2015.
- [21] Gonzalo Esteban Constante-Flores and Mahesh S Illindala. Data-driven probabilistic power flow analysis for a distribution system with renewable energy sources using monte carlo simulation. *IEEE Trans. on Industry Applications*, 55(1):174–181, 2018.
- [22] Armando Martins Leite da Silva and André Milhorce de Castro. Risk assessment in probabilistic load flow via monte carlo simulation and cross-entropy method. *IEEE Trans. on Power Systems*, 34(2):1193–1202, 2018.
- [23] ND Hatziargyriou, TS Karakatsanis, and M Papadopoulos. Probabilistic load flow in distribution systems containing dispersed wind power generation. *IEEE Trans. on Power Systems*, 8(1):159–165, 1993.
- [24] Hossein Nosratabadi, Mohammad Mohammadi, and Amin Kargarian. Non-parametric probabilistic unbalanced power flow with adaptive kernel density estimator. *IEEE Trans. on Smart Grid*, 10(3):3292–3300, 2018.
- [25] Juan M Morales and Juan Perez-Ruiz. Point estimate schemes to solve the probabilistic power flow. *IEEE Trans. on power systems*, 22(4):1594–1601, 2007.
- [26] Chengxi Liu, Kai Sun, Bin Wang, and Wenyun Ju. Probabilistic power flow analysis using multidimensional holomorphic embedding and generalized cumulants. *IEEE Trans. on Power Systems*, 33(6):7132–7142, 2018.
- [27] Pei Zhang and Stephen T Lee. Probabilistic load flow computation using the method of combined cumulants and gram-charlier expansion. *IEEE Trans. on power systems*, 19(1):676–682, 2004.
- [28] Ray Daniel Zimmerman, Carlos Edmundo Murillo-Sanchez, and Robert John Thomas. Matpower: Steady-state operations, planning, and analysis tools for power systems research and education. *IEEE Transactions on power systems*, 26(1):12–19, 2011.
- [29] S. Jeong, Y. J. Jang, and D. Kum. Economic analysis of the dynamic charging electric vehicle. *IEEE Transactions on Power Electronics*, 30(11):6368–6377, Nov 2015.

- [30] Lefteris Karagiannopoulos. Electrified roads: Swedish project could slash cost of electric vehicles, 2018. Online.
- [31] Daniel Boffey. World's first electrified road for charging vehicles opens in sweden, 2018. Online.
- [32] Hideki Ayano, Kouki Yamamoto, Noriaki Hino, and Ikuo Yamato. Highly efficient contactless electrical energy transmission system. In *IEEE 2002 28th Annual Conference of the Industrial Electronics Society. IECON 02*, volume 2, pages 1364–1369. IEEE, 2002.
- [33] H Fukuda, N Kobayashi, K Shizuno, S Yoshida, M Tanomura, and Y Hama. New concept of an electromagnetic usage for contactless communication and power transmission in the ocean. In *2013 IEEE International Underwater Technology Symposium (UT)*, pages 1–4. IEEE, 2013.
- [34] Daniel Serrano-Jiménez, Lars Abrahamsson, Sandra Castaño-Solís, and Javier Sanz-Feito. Electrical railway power supply systems: Current situation and future trends. *International Journal of Electrical Power & Energy Systems*, 92:181–192, 2017.
- [35] Chirag Panchal, Sascha Stegen, and Junwei Lu. Review of static and dynamic wireless electric vehicle charging system. *Engineering science and technology, an international journal*, 2018.
- [36] Arthur R. Bergen and Vijay. Vittal. *Power systems analysis /*. Pearson Education,, New Delhi, 2nd. edition, 2008.
- [37] I Karakitsios, E Karfopoulos, and N Hatziargyriou. Impact of dynamic and static fast inductive charging of electric vehicles on the distribution network. *Electric Power Systems Research*, 140:107–115, 2016.
- [38] J. G. Hayes, R. P. R. de Oliveira, S. Vaughan, and M. G. Egan. Simplified electric vehicle power train models and range estimation. In *2011 IEEE Vehicle Power and Propulsion Conference*, pages 1–5, Sep. 2011.
- [39] D Herron. Range confidence: Charge fast, drive far, with your electric car. *Kättesaadv: <https://greentransportation.info/ev-charging/range-confidence/chap8-tech/evdc-fast-charging-standards-chademo-ccs-sae-combo-tesla-supercharger-etc.html> (15.05. 18)*, 2017.
- [40] Jignesh Parmar. Defining size and location of capacitor in electrical system (1), 2016. Online.

- [41] the green age. How many solar panels can i fit on my roof?, 2014. Online.
- [42] Thierry Van Cutsem and Costas Vournas. *Voltage stability of electric power systems*. Springer Science & Business Media, 2007.
- [43] Venkataramana Ajjarapu and Colin Christy. The continuation power flow: a tool for steady state voltage stability analysis. *IEEE transactions on Power Systems*, 7(1):416–423, 1992.
- [44] H. D. Nguyen, K. Dvijotham, S. Yu, and K. Turitsyn. A framework for robust long-term voltage stability of distribution systems. *IEEE Transactions on Smart Grid*, pages 1–1, 2018.
- [45] Dhagash Mehta, Hung Dinh Nguyen, and Konstantin Turitsyn. Numerical polynomial homotopy continuation method to locate all the power flow solutions. *IET Generation, Transmission & Distribution*, 10(12):2972–2980, 2016.
- [46] CD Vournas, GA Manos, John Kabouris, and Thierry Van Cutsem. Analysis of a voltage instability incident in the greek power system. In *2000 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No. 00CH37077)*, volume 2, pages 1483–1488. IEEE, 2000.
- [47] Barbara Borkowska. Probabilistic load flow. *IEEE Trans. on Power Apparatus and Systems*, (3):752–759, 1974.
- [48] RN Allan, AM Leite Da Silva, and RC Burchett. Evaluation methods and accuracy in probabilistic load flow solutions. *IEEE Trans. on Power Apparatus and Systems*, (5):2539–2546, 1981.
- [49] Malvin H Kalos and Paula A Whitlock. *Monte carlo methods*. John Wiley & Sons, 2009.
- [50] Xiaoyuan Xu and Zheng Yan. Probabilistic load flow evaluation with hybrid latin hypercube sampling and multiple linear regression. In *2015 IEEE Power & Energy Society General Meeting*, pages 1–5. IEEE, 2015.
- [51] Mahdi Hajian, William D Rosehart, and Hamidreza Zareipour. Probabilistic power flow by monte carlo simulation with latin supercube sampling. *IEEE Transactions on Power Systems*, 28(2):1550–1559, 2012.
- [52] Daniel Villanueva, José Luis Pazos, and Andrés Feijoo. Probabilistic load flow including wind power generation. *IEEE Transactions on Power Systems*, 26(3):1659–1667, 2011.

- [53] Chun-Lien Su. Probabilistic load-flow computation using point estimate method. *IEEE Trans. on Power Systems*, 20(4):1843–1851, 2005.
- [54] Christopher KI Williams and Carl Edward Rasmussen. *Gaussian processes for machine learning*, volume 2. MIT press Cambridge, MA, 2006.
- [55] Duehee Lee and Ross Baldick. Short-term wind power ensemble prediction based on gaussian processes and neural networks. *IEEE Trans. on Smart Grid*, 5(1):501–510, 2013.
- [56] Juan Yan, Kang Li, Er-Wei Bai, Jing Deng, and Aoife M Foley. Hybrid probabilistic wind power forecasting using temporally local gaussian process. *IEEE Trans. on Sustainable Energy*, 7(1):87–95, 2015.
- [57] Hanmin Sheng, Jian Xiao, Yuhua Cheng, Qiang Ni, and Song Wang. Short-term solar power forecasting based on weighted gaussian process regression. *IEEE Trans. on Industrial Electronics*, 65(1):300–308, 2017.
- [58] Dennis W van der Meer, Mahmoud Shepero, Andreas Svensson, Joakim Widén, and Joakim Munkhammar. Probabilistic forecasting of electricity consumption, photovoltaic power generation and net demand of an individual building using gaussian processes. *Applied energy*, 213:195–207, 2018.
- [59] Chao Zhai and Hung D Nguyen. Region of attraction for power systems using gaussian process and converse lyapunov function–part i: Theoretical framework and off-line study. *arXiv preprint arXiv:1906.03590*, 2019.
- [60] Parikshit Pareek and Hung D Nguyen. Probabilistic robust small-signal stability framework using gaussian process learning. *arXiv preprint arXiv:1910.01588*, 2019.
- [61] Niranjan Srinivas, Andreas Krause, Sham M Kakade, and Matthias W Seeger. Information-theoretic regret bounds for gaussian process optimization in the bandit setting. *IEEE Trans. on Information Theory*, 58(5):3250–3265, 2012.
- [62] Miao Fan, Vijay Vittal, Gerald Thomas Heydt, and Raja Ayyanar. Probabilistic power flow studies for transmission systems with photovoltaic generation using cumulants. *IEEE Trans. on Power Systems*, 27(4):2251–2261, 2012.
- [63] Pouya Amid and Curran Crawford. A cumulant-tensor-based probabilistic load flow method. *IEEE Trans. on Power Systems*, 33(5):5648–5656, 2018.

- [64] Kenji Iba, Hiroshi Suzuki, Masanao Egawa, and Tsutomu Watanabe. Calculation of critical loading condition with nose curve using homotopy continuation method. *IEEE Trans. on Power Systems*, 6:584–593, 1991.
- [65] Tong Jiang, Kaiyao Wan, and Zhuocheng Feng. Boundary-derivative direct method for computing saddle node bifurcation points in voltage stability analysis. *International Journal of Electrical Power & Energy Systems*, 112:199–208, 2019.
- [66] Hung Nguyen Dinh, Minh Y Nguyen, and Yong Tae Yoon. A new approach for corrective and preventive control to unsolvable case in power networks having ders. *Journal of Electrical Engineering and Technology*, 8(3):411–420, 2013.
- [67] Franz-Erich Wolter and Benjamin Berger. Differential geometric foundations for power flow computations. *arXiv preprint arXiv:1903.11131*, 2019.
- [68] Rose Yu, Guangyu Li, and Yan Liu. Tensor regression meets gaussian processes. *arXiv preprint arXiv:1710.11345*, 2017.
- [69] Ray Daniel Zimmerman, Carlos Edmundo Murillo-Sánchez, and Robert John Thomas. Matpower: Steady-state operations, planning, and analysis tools for power systems research and education. *IEEE Trans. on power systems*, 26(1):12–19, 2010.
- [70] Carl Edward Rasmussen and Hannes Nickisch. Gaussian processes for machine learning (gpml) toolbox. *Journal of machine learning research*, 11(Nov):3011–3015, 2010.
- [71] Edward Snelson and Zoubin Ghahramani. Sparse gaussian processes using pseudo-inputs. In *Advances in neural information processing systems*, pages 1257–1264, 2006.