Model Predictive Optimization for Distribution Management in Smart Grids

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Abstract

There is a fatal problem in the traditional centralized power system. When some accidents occur in the power plants, a large number of users will be affected. Thus, the traditional centralized power system was replaced by the decentralized grid. However, the decentralized grid only focuses on the current electricity situation to process distribution. It not only wastes the remaining power generation but also keeps the electricity cost higher. To solve this cost saving problem, the Thesis proposed a Model Predictive Optimization (MPO) for distribution management system in smart grids. We can predict the future electricity situation by Autoregressive Integrated Moving Average (ARIMA) model and can determine the distribution attitude such as optimistic attitude and pessimistic attitude. Besides, according to the attitude, we use the Energy Storage System (ESS) effectively. After the prediction of bidding price and bidding capacity, we could find an optimal trading pairs through the Particle Swarm Optimization (PSO). For example, when the surplus electricity situation is predicted in the future and the future utility selling price is lower than the current price, we will discharge ESS to trade with other micro-grids to earn more cost. Conversely, while the power shortage is predicted in the future and the future utility buying price is higher than the current price, we can first buy more energy to charge the ESS to reduce the cost savings.

Therefore, our experimental results show that the error rate of prediction model is less than 10%. Besides, we can reduce the cost savings effectively in smart grids by our proposed MPO method. For one case, the proposed cost of our proposed method in one micro-grid is 177% of the traditional grid. Another case could show that the negative cost by our proposed method in another micro-grid is smaller than that by the traditional grid by 31.08%. For smart grids, our proposed MPO method totally saves the much more cost of 19.38% if four time slots is used for prediction. The overhead of prediction model and the optimization efficiency for our proposed MPO method are 5.65 seconds and 2.42 seconds.

Keywords: *Electricity Cost*, *Model Predictive Optimization (MPO)*, *Autoregressive Integrated Moving Average (ARIMA) model*, *Error Rate*, *Distribution Attitude*, *Energy Storage System (ESS)*, *Particle Swarm Optimization (PSO)*, *Distribution Management*

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Chapter 1

Introduction

In the past, the power line in the traditional grid is one-way from the power plants to the users such as residential areas, industrial areas, and business areas. This one-way power line is also known as the centralized power system, because the power suppliers are the small number of power plants. However, there is a fatal problem in the centralized power system. When some accidents occur in the power plants, a large number of users will be affected.

In the early years of the 20th century, with the development of renewable energy sources and the promotion of the green energy plants, smart grid design issues are being taken seriously around the world. Compared to the traditional grid as shown in Figure 1.1, the core architecture in the smart grid is largely distributed. Each zone can form a small-scale grid that includes multiple power generators (e.g., photovoltaic, wind turbines, fuel cells), energy storages, and power consumers (called loads), which constitute a *micro-grid*. In a network of micro-grids, there is a two-way transmission of electricity to reduce the risk of unexpected accidents in power plants.

When the evolution of the power control flow is from the centralized grid to the decentralized grid, the shortage of power capacity, power loss, and high-cost construction caused by long-distance transmission lines have been solved. However, new power distribution management issues are introduced in the framework design of smart grids.

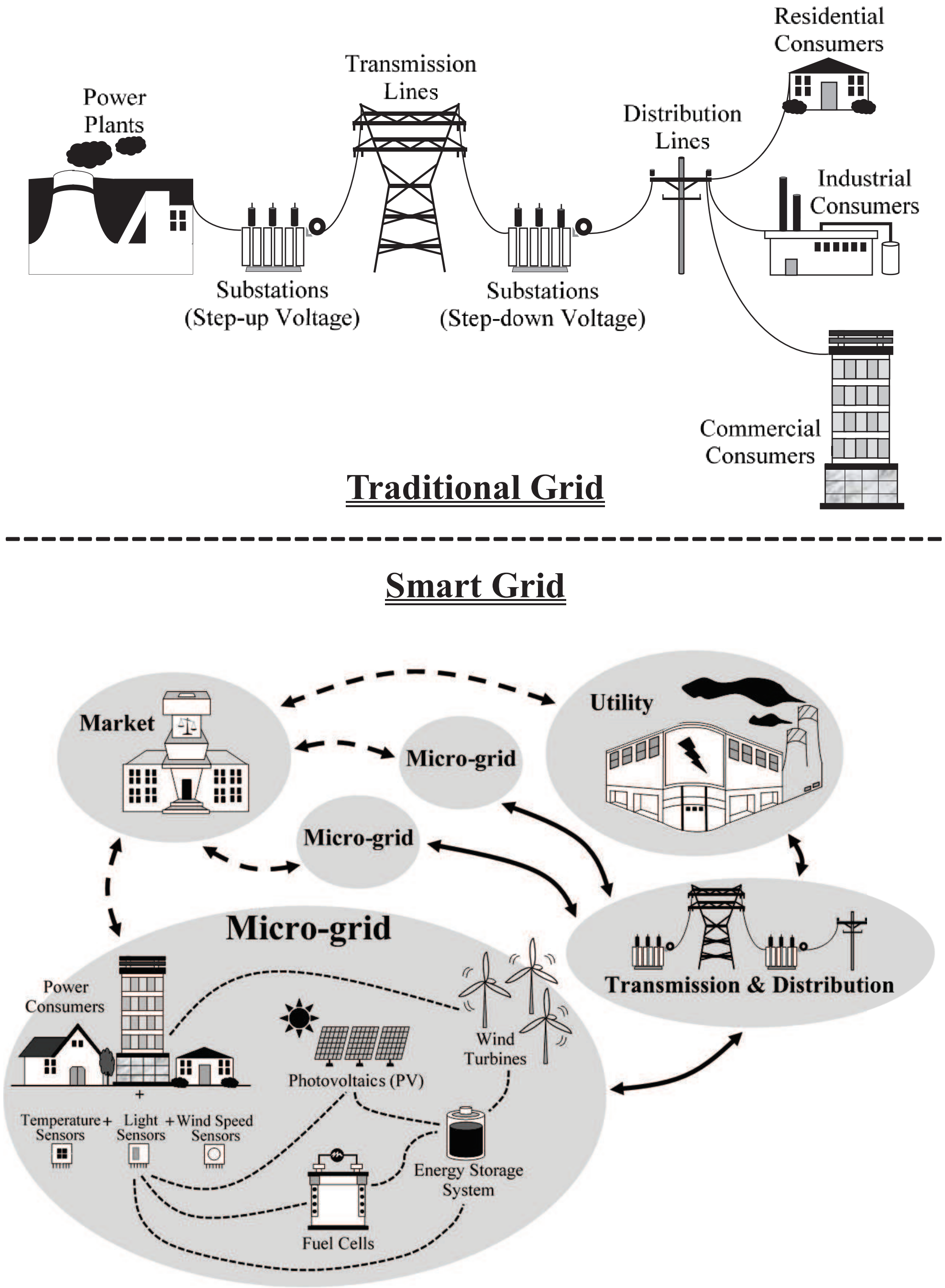


Figure 1.1: Comparison of Smart Grid with Traditional Grid

For example, based on the consideration that users expect to minimize electricity costs, users can choose the power resources and can exchange power with each other via bidding [2] in the smart grid. In this chapter, we will explain the distribution management problems that may be encountered while designing the smart grid model and will propose a solution to the problems.

Table 1.1: Electricity demand outlook by region (TWh) [1]

Continent	2012	2020	2025	2030	2035	2040	CAAGR 2012-40
OECD	9523	10393	10788	11136	11505	11922	0.8%
Americas	4645	5133	5335	5523	5722	5983	0.9%
Europe	3188	3406	3529	3635	3758	3881	0.7%
Asia Oceania	1690	1855	1925	1978	2026	2058	0.7%
Non-OECD	10039	13675	15973	18305	20645	22965	3.0%
E. Europe/Eurasia	1400	1554	1687	1820	1959	2086	1.4%
Asia	6317	9081	10733	12382	13982	15525	3.3%
Middle East	753	989	1142	1303	1442	1590	2.7%
Africa	620	852	1035	1258	1540	1868	4.0%
Latin America	948	1199	1376	1542	1722	1895	2.5%
World	19562	24068	26761	29442	32151	34887	2.1%

1.1 Background

According to the Energy Technology Perspectives 2014 [3] from the International Energy Agency (IEA), total energy demand for electricity has risen from 9% to over 17% since the 1970s. Simultaneously, the World Energy Outlook 2014 [1] from IEA indicates that the average annual growth rate of world electricity demand will be 2.1% from 2012 to 2040 as shown in Table 1.1.

With the rapid growth of electricity demand, there is an increasing electricity generation burden on the centralized power system. To address this issue, the architecture of *smart grids* [4] has been proposed. Through sensing and communication technology to combine the power generation, transmission, distribution, and consumption, the grid can automatically monitor the electricity network and analyze the information to optimize the energy utilization.

A smart grid is composed of a market, a utility, many micro-grids, transmission lines, and distribution lines as shown in Figure 1.1. The power and the bidding information can be exchanged in a smart grid. When there is a shortage of electricity in a micro-grid, this grid can buy electricity from the utility or from other micro-grids. On the contrary, when the electricity in a micro-grid is self-sufficient, this grid can sell the excess electricity to the utility or the other micro-grids.

For a detailed view of a micro-grid design, it comprises renewable resources, an energy storage system (ESS), and loads. Using renewable resources can help reduce the carbon pollution. But the generation capacity of renewable resources is affected by climate change and environmental changes, resulting in non-stability of power generation. Because of the intermittent renewable resources, it is difficult to maintain the power stability. The ESS plays an important role in satisfying requirements for electrical storage capacity, as well as, supply capacity. If the utility interrupts the power supply under abnormal conditions, the ESS can be an emergency power system. Then, the frequency and the times of load utilization determine the amount of electricity demands.

Moreover, many sensors such as temperature sensors, light sensors, and wind speed sensors are added into micro-grid model to predict the future generation and electricity demands. The prediction results help to adjust the distribution strategy. For example, when the prediction results indicate that there is an insufficiency of power supply in grid, the system will change power supply pattern from renewable resources to utility.

In summary, the advanced distribution management system (ADMS) [5] is what we should focus on. ADMS is the software platform that includes full suite of distribution management and optimization. There are many ADMS operation factors that include demand responses, distributed energy resources, electricity storages, customers interacting with the utility, micro-grids, etc. The ADMS will enhance the reliability, improve the energy efficiency, and achieve sustainability in smart grids.

1.2 Motivation

The three main problems addressed in this Thesis are how to accurately predict future electricity supply and demand, how to optimize power distribution, and how to have a reasonable fair bidding between micro-grids. In the prediction problem, when the error rates of electricity prediction are higher, it may cause the distribution system to make a mistake. If this happens in a commercial building or a factory, it will affect the economy and cause disaster. In the distribution problem, the distribution strategy that exhausts all renewable resources and all power in the ESS will lead to electricity shortage. On the contrary, the distribution strategy that retains all renewable resources and all power in the ESS will waste more renewable energy sources. In the bidding problem, if some micro-grids announce higher or lower bidding price continuously then power trading rights cannot be transferred to other micro-grids, it may cause a resource starvation.

To design an appropriate distribution management system to solve the three problems as mentioned previously, we will propose a *Model Predictive Control* (MPC) system [6] that includes prediction models such as time series analysis for the generators and loads in micro-grids and an optimization method such as *Particle Swarm Optimization* (PSO) [7]. Simultaneously, we observe the weather condition and use the optimistic attitude and pessimistic attitude to consider the distribution strategy as shown in Table 1.2. Optimistic attitude means that we can use energy in a more fervent manner, and pessimistic attitude means that we should save some energy against unexpected needs. We divide the two attitudes into multiple levels. The higher the level is, the more obvious the attitude is.

For example, when the estimated electricity generation in a grid is high and the estimated future weather condition is sunny, we will adopt a higher level of optimistic attitude for selling electricity. When the estimated electricity generation in the grid is low and the estimated future weather condition is rainy, we will adopt a lower level of pessimistic attitude for selling electricity. By this way, the distribution management system can be more flexible and reliable.

Let parts of electricity demands in the time periods that have high electricity price

Table 1.2: Example of the optimistic and pessimistic attitude for distribution strategy

<table>
<tr><th colspan="2">Future Period</th><th colspan="2" rowspan="2">Distribution Attitude</th></tr>
<tr><th>Electricity in Grid</th><th>Weather Condition</th></tr>
<tr><td rowspan="2">High</td><td>Sunny</td><td rowspan="2">Optimistic Level</td><td>4</td></tr>
<tr><td>Rainy</td><td>3</td></tr>
<tr><td rowspan="2">Low</td><td>Sunny</td><td rowspan="2">Pessimistic Level</td><td>2</td></tr>
<tr><td>Rainy</td><td>1</td></tr>
</table>

evenly distribute to the time periods that have low electricity price. This method achieves the goal of reducing the electricity cost. However, from the standpoint of users, we should not change the electrical behaviour arbitrarily. Although we can adjust the use time of non-critical demand load, adjustment in the total demand load is still not so much. Therefore, we select a cost reduction method that lets the use of renewable resources have highest priority. When a micro-grid needs power, renewable resources will be the first choice. If there is surplus power in a micro-grid, it can sell the power to other micro-grids to earn money and to reduce the electricity cost.

We propose a distribution management strategy in this Thesis and we will explain the framework in detail in the following chapters.

1.3 Thesis Organization

This Thesis is organized as follows. In Chapter 2, we introduce the related work on smart grid, MPC, prediction method, and PSO. The terminology used in our proposed model and problem definition are described in Chapter 3. Chapter 4 gives the overall framework and the details of proposed distribution management method. The experiments and test cases will be explained and compared in Chapter 5. In Chapter 6, we give the conclusions and future work for this Thesis.

Chapter 2

Related Work

In this chapter, we first review the different research work on power consumption, power generation, storage management, and distribution management. Then, we will introduce the related work on Model Predictive Control, prediction, and optimization in smart grids.

2.1 Smart Grid

The energy crisis and the global warming are the greatest threats to the survival of human race today. All countries begin to pay attention to the issues of sustainable development and the awareness of environment protection. The usage strategies of electricity and renewable energies have been proposed to achieve the objectives of energy saving and carbon reduction.

On the demand side, some researches indicate that shifting the non-urgent power demands from peak time to off-peak time will lower the total price of power consumption as shown in Figure 2.1. Koutsopoulos et al. [8] designed the optimal control policies for demand scheduling. Different consumer power requests include different power requirements, execution time, and execution deadlines. A new power request will be satisfied if the current power consumption is lower than the critical threshold of power

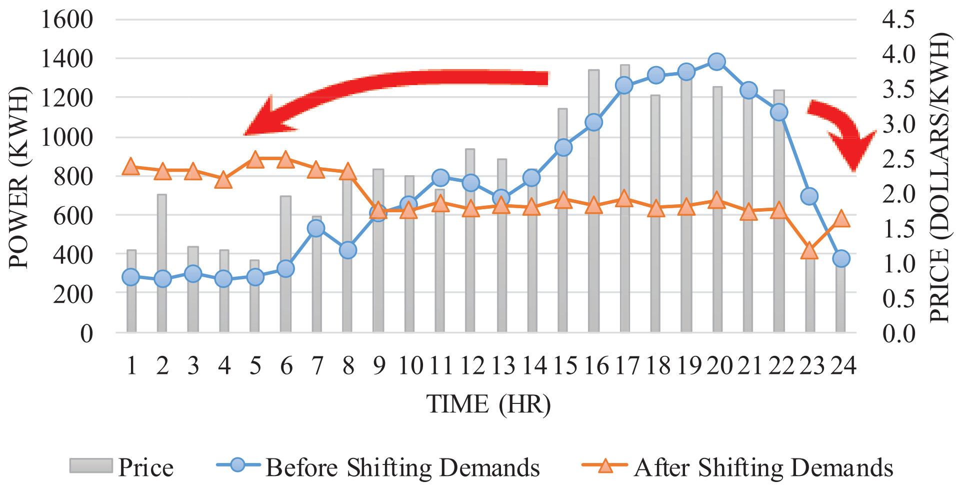
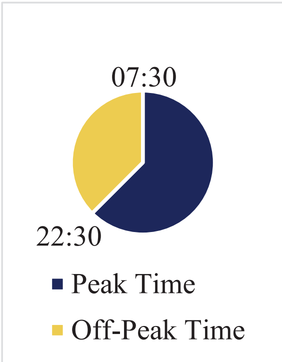


Figure 2.1: Shifting the non-urgent power demands from peak time to off-peak time

consumption, else the request will be queued. The queued requests are executed when the execution deadline expires or when the current consumption decreases below the critical threshold. Lee et al. [9] presented a power consumption scheduling by a *Genetic Algorithm* (GA) to reduce demands at peak time. At first, multiple schedules are generated. A schedule is constituted of different power consumption such as electric devices. For different power consumption at different time, the price of electricity will be different. Through the roulette wheel selection, the results show that the lower the total price of electricity is, the higher the selected probability is. After selecting two schedules, they are merged into one schedule via crossover and mutation. Then, the new schedule will replace the old schedule.

However, in the real situation, it is not appropriate for monitoring the electric devices and moving the power demands, this method not only infringes on the personal privacy but also affects the daily behaviour of users. Even if people can shift the power demands, the adjustment is not so much. It still has the limit to reduce the cost of electricity. For example, Taiwan Power Company [10] announces that the peak time is from 7:30 to 22:30, and the off-peak time is from 00:00 to 7:30 and from 22:30 to 24:00. The average peak demands for residential consumers are 52.58 kWh, and the price per demand is $3.98. The average off-peak demands are 31.55 kWh, and the price per demand



	Price ($/kWh)	Original Demands (kWh)	After Shifting Critical Demands (kWh)
Peak Time	3.98	52.58	47.32
Off-peak Time	2.06	31.55	36.81
Total Cost ($)		274.26	264.16

Figure 2.2: Cost comparison of original demands with shifted critical demands time

is $2.06. Thus, the total cost is $274.26. Furthermore, according to the statistics of Bureau of Energy, Ministry of Economic Affairs [11], the non-critical demands which can be shifted from peak time to off-peak time account for 10% of total demands. The total cost drops to $264.16. Consequently, it only saves 3.68% of the total cost after shifting critical demands as shown in Figure 2.2.

Therefore, many researchers begin to focus on the generation side, rather than only on the demand side. On the generation side, the renewable energy generation instead of the power from utility to supply loads during peak time can reduce environmental pollution and can lower electricity costs. Common renewable resources include solar, wind power, fuel cells, etc.

Solar power [12] is the conversion of sunlight into electricity. Different conversion efficiency will determine the output power of generation. A photovoltaic system is made up of many silicon solar cells with specific conversion efficiency. For example, the poly-silicon solar cell has a conversion efficiency of 20.4% [13]. Through the input of irradiance, the voltage and current are generated and are converted into electricity in the photovoltaic system. In addition, wind power [12] is the conversion of wind into electricity. The location of the wind turbines and the wind speed both affect the ability of power generation. Although the utilization of solar power and wind power can reduce the carbon pollution, their generation is heavily dependent on the weather conditions. Under unstable power generation, the stable renewable energy generation, such as fuel cells, will help to supply lack of power. A fuel cell [14] can convert chemical energy into electricity through a chemical reaction with oxygen and another oxidizing agent, but it needs more construction costs. If we use only renewable energy generation, it is insufficient to supply power to the grid due to the instability and higher cost of renewable energy generation.

To deal with the rapid growth of electricity demands and the limits of renewable energy generation, the power supply system around the world changes from the centralized system to distributed system [15]. Consumers can be classified into different kinds by their electrical behaviour, such as residential consumers, industrial consumers, and commercial consumers. For each instance of a particular kind of consumers, it could have small scale capacities of distributed renewable energy resources and energy storage systems, which constitute the power generation resources. Hence, a nearby generation can alleviate the issues of power loss and high-cost transmission from utility because of new power transmission from the nearby generation is at a shorter-distance. In addition, the construction cost of small scale distributed renewable energy generation is also becoming lower, year by year. Nevertheless, some renewable energies are still unstable generation resources, thus they have to be integrated with the traditional centralized generation system for stable power supply. At times of insufficient power from distributed renewable energy resources, power will be supplied by the centralized generation so as to maintain the balance between power supply and demand. This concept is the extension of the conventional grid into smart grids. If we can predict a future energy in balance situation accurately and accordingly adjust the distribution strategy beforehand, the current grid would be much more intelligent.

Therefore, in this Thesis, we will focus on how to apply model predictive control, prediction methods, and distribution methods with optimization to smart grids.

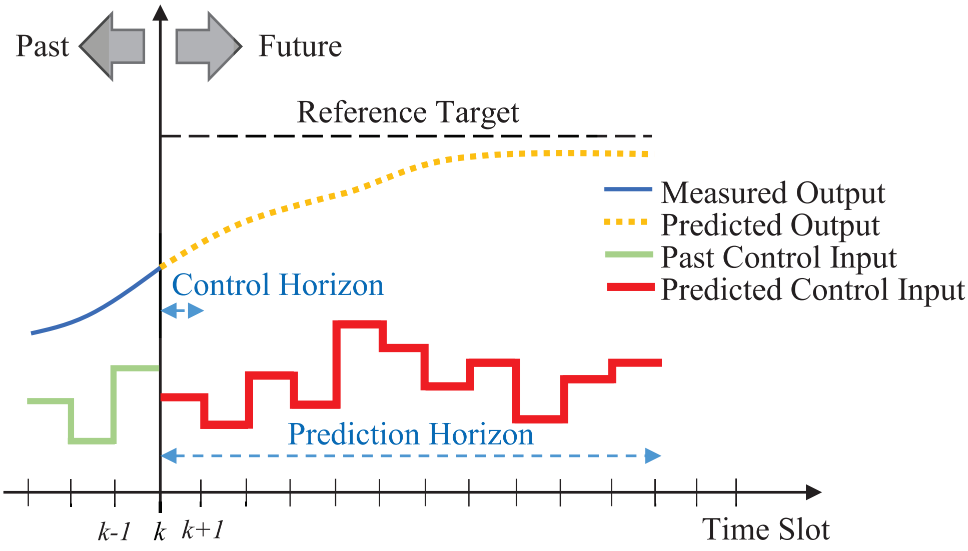


Figure 2.3: Basic concept for Model Predictive Control

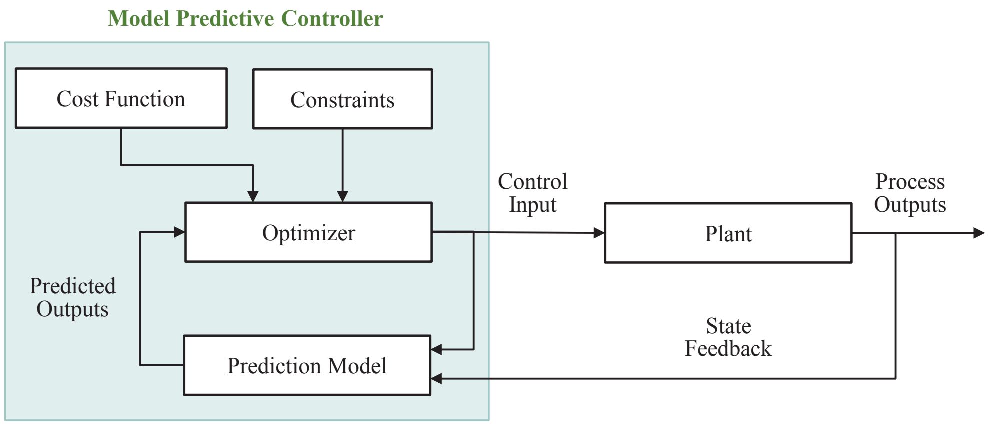


Figure 2.4: State feedback for Model Predictive Controller

2.2 Research On Model Predictive Control

The *Model Predictive Control* (MPC) method has been used in industrial process since the 20th century [16]. In recent years, it also has been used in digital control process and power system models. As shown in Figure 2.3, the core concept in MPC [17] is to consider the events in the future timeslots, and to implement control actions in the next timeslot only. As shown in Figure 2.4, MPC dynamically adjusts its prediction model based on the state feedback and can thus cope with dynamic changes in the plant process.

We will introduce the prediction methods and optimization methods in detail in

Section 2.3 and Section 2.4, respectively.

Yu et al. [18] presented a model predictive control system for controlling the turbofan engine starting. This application is a non-linear dynamic working procedure, so the authors used a prediction model based on *Neural Network* (NN) [19], which has ability to deal with non-linear systems. To get the best fuel supply rate, GA [20] was used to search for the global extreme value. Molina et al. [21] designed an MPC-based temperature regulation system in residential buildings. For prediction model, the *maximum-likelihood estimation* (MLE) method [22] was used to predict the parameters, including temperature and energy spent. For optimization, they used GA.

In addition, lots of energy applications leverage on application of MPC. Research work on renewable generation [23] and [24] are also based on MPC. The authors of [25] focus on electricity demand control. Furthermore, some literatures [26, 27] also apply MPC in smart grid designs.

Mayhorn et al. [28] proposed an optimal control of distributed energy resources using MPC. Their goal is to solve a multi-objective optimization problem, such as minimizing the costs of energy storages and maximizing the ability to balance real-time power supply and demand. In the MPC approach, they use the *Autoregressive Integrated Moving Average* (ARIMA) [29] and seasonal ARIMA models to predict the wind and load data accurately. When the wind generation is higher than a given threshold, the battery energy storage system will be charged. Conversely, the battery energy storage system will be discharged when the wind power generation is low. For power loads, the situation is reversed. When the energy demand is higher than a given threshold, the battery energy storage system will be discharged for providing power to loads. To maintain the balance among generations and loads, an optimizer uses a cost function that can maximize the generation penetration.

2.3 Research On Prediction

Prediction methods can be classified based on the stability or the instability, and the linearity or the non-linearity of experiment data. The linear prediction method is simple, but cannot deal with complicated data, such as estimating the wind speed for power generation. Such a prediction method can be applied only on linear data that exhibit periodicity. For example, Mathieu et al. [30] used a linear regression-based method to predict the demand response. The basic idea of linear regression is to find the unknown parameters a and b in Equation 2.1 and big historical data (x, y).

$$y = ax + b \tag{2.1}$$

For predicting the values of parameters y, new values of parameters x are applied in Equation 2.1.

As far as smart grids are concerned, especially renewable energy generation, there are both linear data, as well as, non-linear data. Thus, prediction methods for smart grid should be able to handle both linear as well as non-linear data. Box and Jenkins proposed an ARIMA model [31] for stationary time series. This method focuses on the analysis of history data, and checks the *Autocorrelation Function* (ACF) and *Partial Autocorrelation Function* (PACF) to build a stochastic prediction model. In the process of creating a prediction model, it can be divided into three parts included the *Autoregressive* (AR) model, derivation, and *Moving Average* (MA) model. The AR model is defined as follows:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{2.2}$$

This model observes the regression on variables X_{t-i} for p periods. The parameter φ_i is a weight, c is a constant, and ε_t is a white noise. The white noise is a random process characterized by zero mean or constant scale. The MA model is a shock-effect

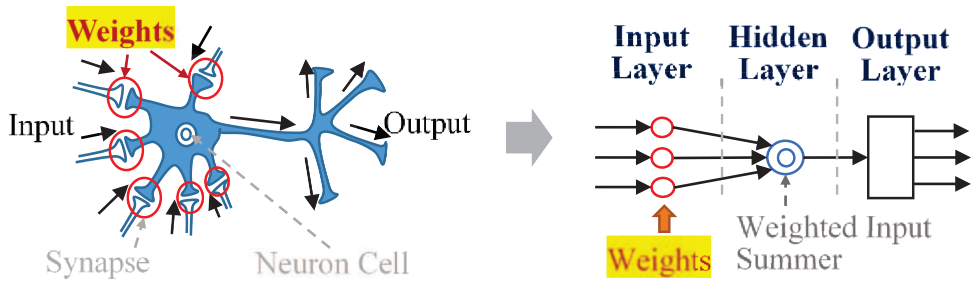


Figure 2.5: A model of an artificial neuron

of memory function with noise error terms or random shocks as follows:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2.3}$$

This model has a series of random errors ε_t for q periods. θ_i is a moving average parameter, and μ is a constant.

By combining the AR model and MA model, we can reduce the prediction error due to the precise noise model. Before the combination, we have to ensure the data set is a stationary time series. Through multi-order derivative, a non-stationary series can be transformed into a stationary one. As a result, the ARIMA model was introduced to predict linear data and non-linear data, simultaneously. Some approaches [32, 33] use the ARIMA model to analyze the applications of time series. This ARIMA model will be used in this Thesis.

The *Artificial Neural Network* (ANN) model can also be used to predict non-linear data. ANN has been used for predicting the electric load [34, 35] and the power generation by renewable resources [36, 37, 38]. As shown in Figure 2.5, ANN uses weighted information as derived from the nervous system. A nervous system can be divided into an input layer, a hidden layer, and an output layer. When the problem is more complex, a neural network with multiple hidden layers can be used for more accurate prediction.

2.4 Research On Optimization

Over the past few decades, a significant amount of research work focused on solving optimization problems. Among them, *Simulated Annealing* (SA) [39], *Tabu Search* (TS) [40], *Ant Colony Optimization* (ACO) [41], GA, and PSO are five representative algorithms. All of them try to avoid the local minima.

SA chooses one start step in the search space and calculates the probability to reach the next step from the current step. TS records the previous moving action to avoid circular repetition and uses the expectation rule to find the optimal solution. These two methods are not suitable for solving the large-scale problems because of the slow convergence and long execution time. To deal with this problem, increasing the number of search directions at each iteration during the convergence process is an appropriate method, such as ACO and GA. The ACO method determines the shortest path by the levels of pheromone. GA selects the parents for crossover and mutation, and then reserves the best next generation. To reach a more stable quality in finding the optimal solution, PSO is one method. In the process of PSO, each particle has the current position $X_i(t)$, the current speed $V_i(t)$, with records of the local best position X_{pbest} and the local best velocity V_{pbest} during past moves, and records of the global experience X_{gbest} and V_{gbest} of neighbours. Through self-adjustment and swarm learning ability, each particle goes to the next best position as shown in Figure 2.6.

Therefore, PSO is also appropriate in solving the distributed computing. In the distribution management in smart grids, this algorithm is considered to be the best choice [42, 43].

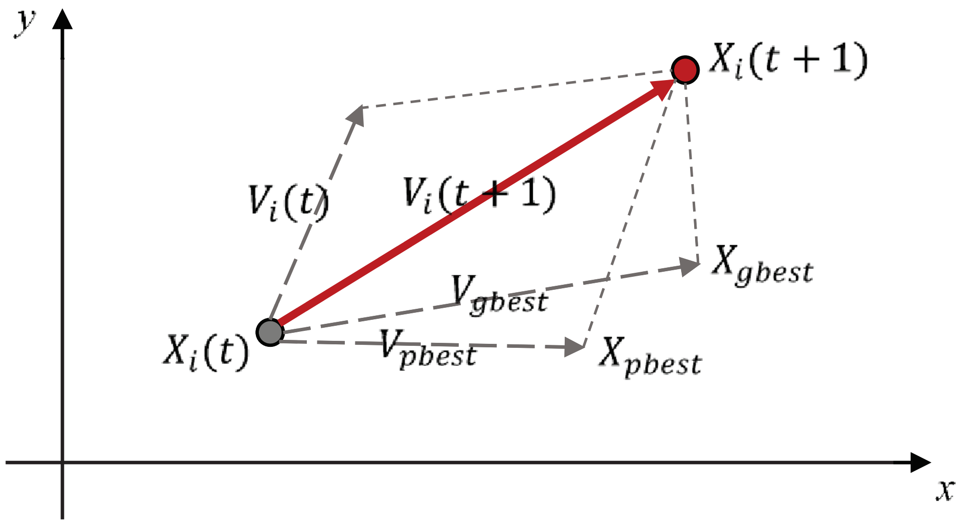


Figure 2.6: The basic concept of Particle Swarm Optimization

Chapter 3

Preliminaries

In this chapter, we first define our target problem. Then, we give the assumptions for our proposed method. After the assumptions, we describe the terminologies and parameter settings used in the proposed algorithms.

3.1 Problem Definition

For a stable and reliable smart grid, it must ensure that the power supply is sufficient for all micro-grids. Generally, power shortage is not allowed in smart grids, except in the case of power plant accidents. Therefore, our problem is defined as follows. On the condition of satisfying the given power demands, the goal is to reduce overall cost and to earn additional economic benefits. In other words, we should spend less money to satisfy all power demands and sell surplus power generation to compensate for the electricity expenses.

3.2 Assumptions

In this section, we will set the scope for the work, including the premise assumptions for the proposed methods which include architecture assumptions, electricity assumptions, and transaction assumptions. Architecture assumptions include device types and related restriction. Electricity assumptions include features of power supply and power usage. The operating conditions of the electricity market are given in the transaction assumptions.

3.2.1 Architecture Assumptions

- There are three types of renewable power generators including photovoltaic, wind turbines, and fuel cells.
- Lead-acid batteries are selected as ESS due to its stable operated voltage and large number of charge-discharge life cycles.
- The residential area, commercial area, and industrial area are three kinds of load demands.
- In the prediction, we need multiple sensing information. For example, the irradiance and wind speed are sensed from the irradiance sensors and the wind speed sensors, respectively. Weather conditions are collected from the bureau of meteorology.

3.2.2 Electricity Assumptions

- The amounts of power generated and the past energy demands are all recorded as history data.
- On a sunny day, the renewable energy generation is higher due to the high irradiance, high temperature, and high wind speed. By contrast, the renewable energy generation is lower on a rainy day because of the low irradiance, high humidity, and low wind speed.

- Apart from the power plant accidents, the power supply from the utility is so sufficient that all demands of micro-grids can be satisfied. The utility is a stable power supplier.

- The optimization decision is schedulable for electricity transaction. For example, the electricity voltage, distribution time, and distribution stability are feasible.

3.2.3 Transaction Assumptions

- In the electricity market, the system opens the electricity auction for buyers and sellers to exchange power with each other via bidding once per period of optimization time. We set this optimization time as 15 minutes.

- Each micro-grid plays the role of both a buyer and a seller at different times based on its demand or surplus of electricity. Its own trading price will be changed with time and environment.

- The utility plays not only the role of a buyer but also a seller. It has a fixed trading price list. At the peak time of power usage, the electricity price is high. However, the price is low at the off-peak time. Besides, based on the vested interests of traders, the setting of the selling price is higher than the buying price. As a result, the utility can earn more money.

- During each successful transaction, micro-grids can satisfy their own requests. For example, a buyer can buy all required electricity, without incoming power shortage. A seller can sell the surplus electricity to earn extra income.

3.3 Terminology

- Micro-Grid

  It is constituted of multiple power generators (e.g., photovoltaic, wind turbines, fuel cells), power loads, and energy storage systems (ESS). Two or more micro-grids can also form a global grid. They can exchange electricity with each other by distribution in a global grid.

- State-of-Charge (SoC)

  It is the equivalent of a fuel gauge for the ESS. It represents the current state of a battery in use. When the unit of SoC is 100%, it means that the ESS is fully charged. On the contrary, 0% of SoC means that the ESS is fully discharged.

- Buyer

  In smart grids, due to a large amount of power demands, the micro-grid that wants to buy electricity from other micro-grids and utility is called a buyer.

- Seller

  In smart grids, because of surplus renewable energy generation, the micro-grid that wants to sell the electricity to other micro-grids and utility is called a seller.

- Transaction Market

  In a transaction market, buyers and sellers announce their bidding price and bidding electricity capacity to compete with each other. The transaction market is also like a distribution manager. It will decide the trading combination of transaction agreement. Then, the electricity distribution works on the global grid.

- Trading

  It means that the process can achieve a profitable return in the transaction market.

- Bidding

  It is trading method, where sellers set a price for some goods (the amount the buyers are willing to pay for the goods) and buyers bid for the goods by making bids.

3.4 Parameter Settings

In this section, we describe the parameters used in our proposed method. The proposed method consists of two parts, including a prediction model and an optimizer.

3.4.1 Parameters for Prediction Model

- p: The order of the autoregressive parameters
- d: The order of the differencing for the stationary time series
- q: The order of the moving average parameters
- N: Number of sliding windows that per sliding window means one hour for prediction
- Irr_n: The irradiance (w/m^2) in the time period n
- $Speed_n$: The wind speed (m/s) in the time period n
- Num_{PV}: Number of photovoltaic generators
- Num_{WT}: Number of wind turbines
- Num_{FC}: Number of fuel cells
- $Gen_{PV,n}$: Generation (kWh) of photovoltaic generators in the time period n
- $Gen_{WT,n}$: Generation (kWh) of wind turbines at time in the time period n
- $Gen_{FC,n}$: Generation (kWh) of fuel cells at time in the time period n
- $Gen_{total,n}$: Total generation (kWh) in the time period n
- $Load_{Res,n}$: Demand loads (kWh) of residential area in the time period n
- $Load_{Com,n}$: Demand loads (kWh) of commercial area in the time period n

- $Load_{Ind,n}$: Demand loads (kWh) of industrial area in the time period n
- $Load_{total,n}$: Total Demand loads (kWh) in the time period n
- E_n: The surplus electricity or the demand requests (kWh) under the storage consideration in the time period n
- E_{gln}: Difference (kWh) between generation and load demands in the time period n
- Wei_n: Weights in [0, 1] of believing predicted values in the time period n
- SOC_n: State-of-charge in the time period n
- SOC_{max}: Maximum state-of-charge for an ESS
- SOC_{min}: Minimum state-of-charge for an ESS
- E_{ff}: The total electricity requests (kWh) in the future time periods apart from the next time period
- $Energy_n$: The state of energy requests that "1" means high energy requests, "0" means low energy requests in the time period n
- $Level_{total}$: Total number of attitude levels in future time periods
- $Level_f$: The future distribution attitude level
- $Attitude$: The proportion in [0, 1] of the distribution attitude
- Num_{Energy}: Number of $Energy_n$, such as two states include a high state and a low state
- $Num_{Weather}$: Number of weather conditions, such as sunny day and rainy day

- $Threshold_{Energy}$: The threshold for checking the state of energy requests. When the energy requests are higher than this threshold, its state of energy requests would be changed to "1". Conversely, when the energy requests are lower than this threshold, its state of energy requests would be changed to "0".
- UP_{sell}: The selling price of the utility
- UP_{buy}: The buying price of the utility
- $Price_{sell}$: The selling price of a micro-grid
- $Price_{buy}$: The buying price of a micro-grid
- Cap: The electricity bidding capacity (kWh)

3.4.2 Parameters for Optimizer

- Num_{MGs}: Number of micro-grids
- Num_{swarm}: Number of swarms
- $Num^{j}_{particle}$: Number of particles in swarm j
- T_{opt}: Optimization time
- T_{rest_opt}: The remaining time for optimization
- T_{trad}: Number of iterations in the PSO trading process
- $W_{i,j}$: The non-trading weight of particle i in swarm j
- $Role_{i,j}$: The role of particle i in swarm j, namely a buyer or a seller
- $X^{k}_{i,j}$: The position of particle i in swarm j on the time period k
- $P^{k}_{i,j}$: The local best position of particle i in swarm j on the time period k

- G_j^k: The global best position in swarm j on the time period k
- $V_{i,j}^k$: The velocity of particle i in swarm j on the time period k
- c_1: Acceleration constants of cognition part
- c_2: Acceleration constants of social part
- r_1, r_2: Random value in [0, 1]. The disturbance factor of c_1 and c_2

Chapter 4

Distribution Management System Design

In this chapter, the proposed design for distribution management system is described. We introduce the core techniques of MPC, the prediction model, and the optimization algorithm. Some examples are presented to explain the proposed algorithm.

4.1 Model Predictive Control

A MPC-based distribution management system is proposed in this work for smart grids. Figure 4.1 shows the system architecture. In addition to monitoring the power flows, each micro-grid is equipped with the capabilities of predicting power generation and load demands. Micro-grids exchange power via bidding. so as to save costs and earn additional economic benefits.

The distribution management system consists of two main parts, namely prediction models and an optimizer. Each micro-grid has its own prediction model. Through collecting history electricity data and sensor data, a micro-grid can forecast the electricity situation, that is whether it has surplus power or needs more power in the future. Then, the forecasted situation combined with the weather condition from the bureau of mete-

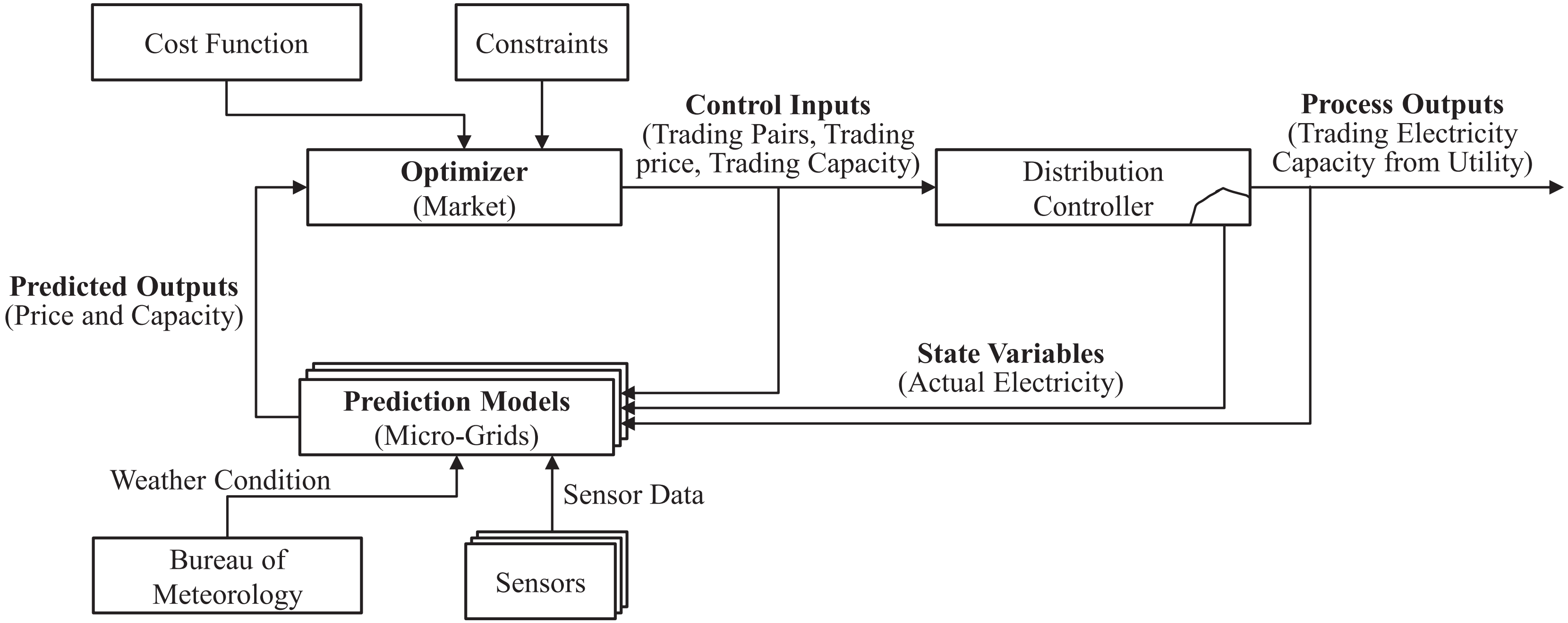


Figure 4.1: Architecture of Model Predictive Control based Distribution Management System

orology is used to predict the price and the electricity capacity. At the end of prediction, all micro-grids send the prediction information to the optimizer, which could be a transaction market.

When the optimizer receives the respective prices and capacities from all micro-grids, it will use an optimization algorithm to calculate future control inputs like trading pairs, trading price, and trading capacity. Based on the control inputs, the distribution controller performs the required exchange of electricity. Feedback on the actual trading of electricity with the utility is given to the prediction models. If there is a significant difference between the actual data and predicted data, then the prediction model is rectified (re-trained) based on the feedback.

4.2 Prediction with ARIMA model

The proposed prediction model is as shown in Figure 4.2. Its inputs consist of electricity data, sensor data, and weather condition. Electricity consists of the information from power loads, renewable energy resources, and an energy storage system. Sensor data consists of environment conditions collected via sensors such as temperature sensor, light sensor, and wind speed sensor. First, we use the ARIMA model proposed in the Box-Jenkins methodology [31] to forecast the power generation, power demands, and energy storages in the future as shown in Figure 4.3. The ARIMA (p, d, q) model is as defined in Equation 4.1.

$$x_t = \varphi_1 x_{t-1} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{4.1}$$

The forecasted data x_t is calculated by the autoregressive parameters from φ_1 to φ_p, the history series data from x_{t-1} to x_{t-p}, the moving average parameters from θ_1 to θ_q, and a series of random errors (or residuals) from ε_t to ε_{t-q}. Here, p is the order of the autoregressive parameters. The order of the moving average parameters is represented

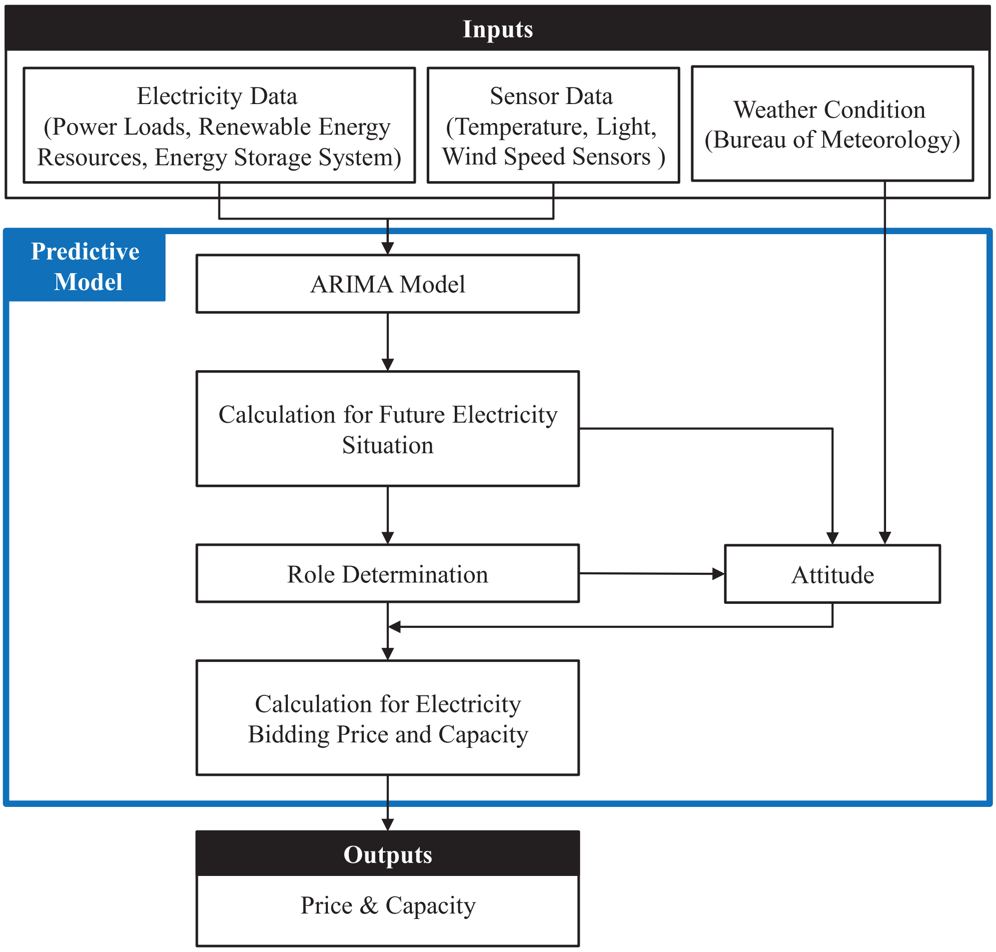


Figure 4.2: Prediction model

as q. The two values p and q are selected by observing the *autocorrelation function* (ACF) and *partial autocorrelation function* (PACF). The observing rules are as shown in Table 4.1. However, since the ARIMA model is only for stationary series, we have to make differencing of the non-stationary series. The order of differencing is d.

After the identification of ARIMA (p, d, q) model, we would use the *maximum-likelihood estimation* (MLE) to estimate the parameters of the model. We use the *Akaike Information Criterion* (AIC) [44] and the *Bayesian Information Criterion* (BIC) [45] to check for an adequate model. To get the best fitness of ARIMA model, we should find the minimum values of AIC and BIC as follows:

$$AIC = 2k + n \ln(RSS/n) \tag{4.2}$$

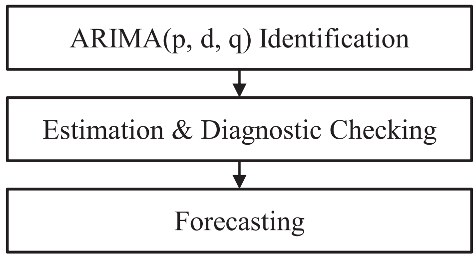


Figure 4.3: Flowchart of ARIMA model

Table 4.1: The identification rules of ARIMA (p, d, q) model

Model	**Autocorrelation Function**	**Partial Autocorrelation Function**
ARIMA (p, d, 0)	Infinite. Tails off.	Finite. Cuts off after p lags.
ARIMA (0, d, q)	Finite. Cuts off after q lags.	Infinite. Tails off.
ARIMA (p, d, q)	Infinite. Tails off.	Infinite. Tails off.

$$BIC = k\ln(n) + n\ln(RSS/n) \tag{4.3}$$

The sample size n, the number of estimated parameters k, and the residual sum of squares RSS from an estimated model are the factors for model selection. Finally, we can use the adequate ARIMA model to forecast the future electricity data.

When we have the forecasted electricity data such as generation and load demands, the future electricity situation, i.e., surplus or deficit in electricity can be estimated by Algorithm 1.

In Algorithm 1, a micro-grid not only forecasts the generation and load demands but considers the charge and discharge power of the ESS. If the amount of power generated is more than the total load demands, the ESS is charged with the maximum SoC, if enough. After charging ESS, if there is still excess power, then it is ready to be sold (steps 3 to 5 of Algorithm 1). On the contrary, the ESS is discharged for meeting load demands, if the amount of power generated is less than that required by load demands. The deficit power will be purchased (steps 6 to 8 of Algorithm 1).

After estimating the electricity situation for some future time periods, we can esti-

Algorithm 1: Estimating Future Electricity Situation

Input:
N: Number of sliding windows;
$Gen_{total,n}$: Total generation in the time period n;
$Load_{total,n}$: Total load demands in the time period n;
SOC_n: State of charge in the time period n;
SOC_{max}: Maximum SoC;
SOC_{min}: Minimum SoC;
Output:
E_n: Amount of surplus or deficit electricity in the time period n;
Variable:
E_{gln}: Difference between generation and load demands in the time period n;

for $n = 1$ *to* N **do**
    $E_{gln} = Gen_{total,n} - Load_{total,n}$;
    if $E_{gln} > 0$ **then**
        `// Surplus power is used to charge ESS, while the remaining is sold.`
        $E_n = E_{gln} - min(E_{gln}, SOC_{max} - SOC_{n-1})$;
        $SOC_n = SOC_{n-1} + min(E_{gln}, SOC_{max} - SOC_{n-1})$;
    else
        `// Discharge ESS for meeting load demands, while the remaining load demands are satisfied by purchasing electricity.`
        $E_n = E_{gln} + min(|E_{gln}|, SOC_{n-1} - SOC_{min})$;
        $SOC_n = SOC_{n-1} - min(|E_{gln}|, SOC_{n-1} - SOC_{min})$;
Return E_n;

mate the total electricity requests for the future time periods apart from the next time period by using Equation 4.4 and Equation 4.5. In Equation 4.4, the variable Wei_n is the weight of believing predicted values in the time period n. It is higher in the near time period in the future, because the predicted data is more accuracy in the near future.

$$Wei_n = \frac{N - n + 1}{1 + 2 + \cdots + N}, \sum_{n=1}^{N} Wei_n = 1 \tag{4.4}$$

$$E_{ff} = \sum_{n=2}^{N} (E_n \times Wei_n) \tag{4.5}$$

Algorithm 2: Role Determination of a Micro-Grid

Input:
E_1: Surplus or deficit electricity in the next time period;
E_{ff}: The future electricity requests apart from the next time period;
Output:
$Buyer$: The micro-grid that wants to buy power;
$Seller$: The micro-grid that wants to sell power;

if $E_1 > 0$ **then**
    `// Grid will have more power in the next time period.`
    Micro-grid is a $Seller$;
else if $E_1 = 0$ **then**
    if $E_{ff} \geq 0$ **then**
        `// Grid will have more power in the future, so it can sell some electricity from the storage.`
        Micro-grid is a $Seller$;
    else
        `// Grid will need power in the future.`
        Micro-grid is a $Buyer$;
else
    `// Grid will need power in the next time period.`
    Micro-grid is a $Buyer$;

Based on the information on future electricity requests, we can determine the role of a micro-grid. Algorithm 2 illustrates the role determination of micro-grids. Since the electricity situation in the next time period has a higher importance, we give higher priority to the power situation in the next time period. If a micro-grid will have surplus power in the next time period, it will be a seller (steps 1 to 2 of Algorithm 2). Conversely, the micro-grid will be a buyer when it will need power in the next time period (steps 8 to 9 of Algorithm 2). If the first two conditions are not satisfied, we consider the future electricity requests not included the next time period (steps 3 to 7 of Algorithm 2). The micro-grid will be a seller if it will have more power in the future. Otherwise, it will be a buyer.

Algorithm 3: Determination of an Energy State

Input:
N: Number of sliding windows;
E_n: Amount of surplus or deficit electricity in the time period n;
$Threshold_{Energy}$: The threshold for checking the state of energy requests;
Output:
$Energy_n$: The state of energy requests;

for $n = 1$ *to* N **do**
    if $|E_n| > Threshold_{Energy}$ **then**
        // High state
        $Energy_n = 1$;
    else
        // Low state
        $Energy_n = 0$;
Return $Energy_n$;

As a trader, the trading attitude of a micro-grid such as an optimistic attitude or a pessimistic attitude is determined by future electricity situations and weather conditions. Future electricity situations and weather conditions can be categorized into multiple states. In our proposed distribution management system, the electricity situation is divided into a high state ($Energy$ = "1") and a low state ($Energy$ = "0") as in Algorithm 3. The weather condition has two states including a sunny state (for a seller, $Weather$ = "1"; for a buyer, $Weather$ = "0") and a rainy state (for a seller, $Weather$ = "0"; for a buyer, $Weather$ = "1"). The weather state "1" implies the corresponding micro-grid desires to trade eagerly and has an optimistic (positive) attitude. Conversely, the weather state "0" implies the corresponding micro-grid is not very eager in trading and has a pessimistic (negative) attitude. Therefore, the distribution attitude level $Level_f$ can be calculated by using Equation 4.6 and Equation 4.7 as follows.

$$Level_{total} = (Num_{Energy} \times Num_{Weather})^N \tag{4.6}$$

$$\begin{aligned} Level_f = 1 + \sum_{n=1}^{N}(Energy_n \times \frac{Level_{total}}{(Num_{Energy})^n \times (Num_{Weather})^{n-1}} + \\ Weather_n \times \frac{Level_{total}}{(Num_{Energy})^n \times (Num_{Weather})^n}) \end{aligned} \tag{4.7}$$

The variables Num_{Energy} and $Num_{Weather}$ represent the number of energy states and the number of weather condition states, respectively. Hence, $Level_{total}$ is the total number of attitude levels in the future N time periods. The influence of the energy state and weather condition state in the near future time period is greater than that in the far future time period. To clearly explain Equation 4.7, we can give two examples as shown in Table 4.2 and Table 4.3. For a seller, when the energy state and the weather condition state in future time periods are respectively, high and sunny, the micro-grid will have a highly optimistic attitude for selling electricity. The reason is that there will be surplus power in the future. For a buyer, if the energy state and the weather condition state in future time periods are also high and sunny, the micro-grid will have a low optimistic attitude for buying electricity. The reason is that the buyers may have enough power and thus will not require much more electricity. Besides, the proportion of the distribution attitude $Attitude$ can also be represented as in Equation 4.8.

$$Attitude = \frac{Level_f}{Level_{total}} \tag{4.8}$$

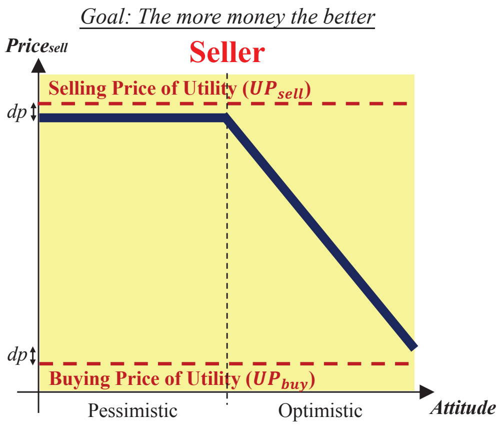
The attitude level and the proportion of attitude can be used to determine the bidding price and bidding capacity. First, the determination of the selling price and buying price

Table 4.2: The future level of seller attitude

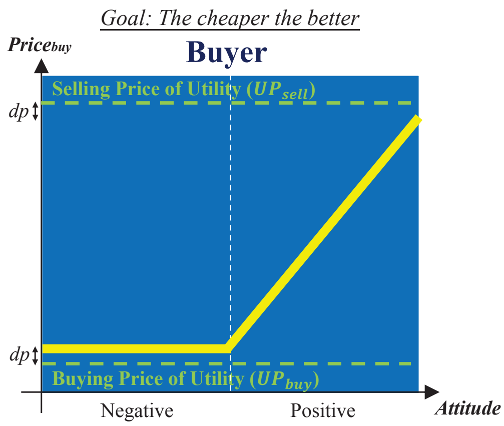
<table>
<tr><th colspan="2">Next Period</th><th colspan="2">After Next Period</th><th colspan="2" rowspan="2">Distribution Attitude for *Sellers*</th></tr>
<tr><th>Electricity in Grid</th><th>Weather Condition</th><th>Electricity in Grid</th><th>Weather Condition</th></tr>
<tr><td rowspan="8">High</td><td rowspan="4">Sunny</td><td rowspan="2">High</td><td>Sunny</td><td rowspan="8">Optimistic Level</td><td>16</td></tr>
<tr><td>Rainy</td><td>15</td></tr>
<tr><td rowspan="2">Low</td><td>Sunny</td><td>14</td></tr>
<tr><td>Rainy</td><td>13</td></tr>
<tr><td rowspan="4">Rainy</td><td rowspan="2">High</td><td>Sunny</td><td>12</td></tr>
<tr><td>Rainy</td><td>11</td></tr>
<tr><td rowspan="2">Low</td><td>Sunny</td><td>10</td></tr>
<tr><td>Rainy</td><td>9</td></tr>
<tr><td rowspan="8">Low</td><td rowspan="4">Sunny</td><td rowspan="2">High</td><td>Sunny</td><td rowspan="8">Pessimistic Level</td><td>8</td></tr>
<tr><td>Rainy</td><td>7</td></tr>
<tr><td rowspan="2">Low</td><td>Sunny</td><td>6</td></tr>
<tr><td>Rainy</td><td>5</td></tr>
<tr><td rowspan="4">Rainy</td><td rowspan="2">High</td><td>Sunny</td><td>4</td></tr>
<tr><td>Rainy</td><td>3</td></tr>
<tr><td rowspan="2">Low</td><td>Sunny</td><td>2</td></tr>
<tr><td>Rainy</td><td>1</td></tr>
</table>

Table 4.3: The future level of buyer attitude

<table>
<tr><th colspan="2">Next Period</th><th colspan="2">After Next Period</th><th colspan="2" rowspan="2">Distribution Attitude for Buyers</th></tr>
<tr><th>Electricity in Grid</th><th>Weather Condition</th><th>Electricity in Grid</th><th>Weather Condition</th></tr>
<tr><td rowspan="8">High</td><td rowspan="4">Rainy</td><td rowspan="2">High</td><td>Rainy</td><td rowspan="8">Positive Level</td><td>16</td></tr>
<tr><td>Sunny</td><td>15</td></tr>
<tr><td rowspan="2">Low</td><td>Rainy</td><td>14</td></tr>
<tr><td>Sunny</td><td>13</td></tr>
<tr><td rowspan="4">Sunny</td><td rowspan="2">High</td><td>Rainy</td><td>12</td></tr>
<tr><td>Sunny</td><td>11</td></tr>
<tr><td rowspan="2">Low</td><td>Rainy</td><td>10</td></tr>
<tr><td>Sunny</td><td>9</td></tr>
<tr><td rowspan="8">Low</td><td rowspan="4">Rainy</td><td rowspan="2">High</td><td>Rainy</td><td rowspan="8">Negative Level</td><td>8</td></tr>
<tr><td>Sunny</td><td>7</td></tr>
<tr><td rowspan="2">Low</td><td>Rainy</td><td>6</td></tr>
<tr><td>Sunny</td><td>5</td></tr>
<tr><td rowspan="4">Sunny</td><td rowspan="2">High</td><td>Rainy</td><td>4</td></tr>
<tr><td>Sunny</td><td>3</td></tr>
<tr><td rowspan="2">Low</td><td>Rainy</td><td>2</td></tr>
<tr><td>Sunny</td><td>1</td></tr>
</table>



(a) Selling price



(b) Buying price

Figure 4.4: Price determination

is as shown in Figure 4.4. The goals of the sellers and buyers are different. Sellers want to earn more money. However, buyers hope the buying price is low. Hence, when a seller is in a pessimistic attitude, the selling price is set to a fixed price, which is slightly lower than the selling price of utility. Note that when the ESS is charged to its fullest, i.e., SOC_{max}, any surplus electricity generation will be wasted. Thus, with an optimistic attitude, to sell a large amount of electricity, instead of wasting it, the selling price is decreased gradually. Conversely, when the ESS is discharged to its minimum, i.e., SOC_{min}, any amount of deficit electricity have to be purchased because the price is less than that from the utility. Thus, given a positive attitude of a buyer, it will be willing to pay more to satisfy its power demands. Based on the idea presented in Figure 4.4, we can use Equation 4.9 and Equation 4.10 to determine the selling price and the buying price, respectively.

$$Price_{sell} = \begin{cases} UP_{sell} - dp & \text{if } Attitude < 0.5 \\ \\ 2(UP_{buy} - UP_{sell} + 2dp) \times Attitude & \\ +2UP_{sell} - UP_{buy} - 3dp & \text{if } Attitude \geq 0.5 \end{cases} \tag{4.9}$$

$$Price_{buy} = \begin{cases} UP_{buy} + dp & \text{if } Attitude < 0.5 \\ \\ 2(UP_{sell} - UP_{buy} - 2dp) \times Attitude & \\ +2UP_{buy} - UP_{sell} + 3dp & \text{if } Attitude \geq 0.5 \end{cases} \quad (4.10)$$

In addition to the determination of bidding price, Algorithm 4 illustrates how electricity bidding capacity of a micro-grid is determined. The electricity bidding capacity contains the electricity requests on the next time period as well as the part of energy in the ESS. If the micro-grid will have surplus generation on the next time period and in the far future, the attitude is a factor that decides how much energy in the ESS the micro-grid should take to trade with other micro-grids (steps 3 to 4 and 9 to 10 of Algorithm 4). However, when the micro-grid will have power shortage on the next time period and in the far future, the micro-grid also buys the electricity to charge the ESS beforehand in the consideration of the attitude (steps 14 to 15 and 20 to 21 of Algorithm 4).

4.3 Particle Swarm Optimization

The market starts the trading processes after receiving the bidding prices and bidding capacities from all micro-grids. In the proposed optimizer, the optimization time is for several trading processes as shown in Figure 4.5. In each trading process, an instance of optimization is performed. For each micro-grid, saving energy costs and earning additional economic benefits are the goals. Hence, the price is the main consideration in the early periods of optimization. However, when the micro-grids are pressed for optimization time, they will hope to find a trading partner that can meet their electricity requests quickly. Thus, in the later periods of optimization, power capacity replaces

Algorithm 4: Determining Electricity Bidding Capacity of a Micro-Grid

Input:

E_1: Surplus or deficit electricity in the next time period;

E_{ff}: The future electricity requests apart from the next time period;

$Attitude$: Proportion of future distribution attitude;

SOC_n: State of charge in the time period n;

SOC_{max}: Maximum SoC;

SOC_{min}: Minimum SoC;

Output:

Cap: Electricity bidding capacity;

if $E_1 > 0$ **then**
    if $E_{ff} \geq 0$ **then**
        $Cap = |E_1| + min(SOC_1 - SOC_{min}, |E_{ff}| \times Attitude)$;
        $SOC_1 = SOC_1 - min(SOC_1 - SOC_{min}, |E_{ff}| \times Attitude)$;
    else
        $Cap = |E_1|$;
else if $E_1 = 0$ **then**
    if $E_{ff} \geq 0$ *and* $SOC_1 > SOC_{min}$ **then**
        $Cap = min(SOC_1 - SOC_{min}, |E_{ff}| \times Attitude)$;
        $SOC_1 = SOC_1 - min(SOC_1 - SOC_{min}, |E_{ff}| \times Attitude)$;
    else if $E_{ff} \geq 0$ *and* $SOC_1 \leq SOC_{min}$ **then**
        $Cap = 0$;
    else
        $Cap = min(SOC_{max} - SOC_1, |E_{ff}| \times Attitude)$;
        $SOC_1 = SOC_1 + min(SOC_{max} - SOC_1, |E_{ff}| \times Attitude)$;
else
    if $E_{ff} \geq 0$ **then**
        $Cap = |E_1|$;
    else
        $Cap = |E_1| + min(SOC_{max} - SOC_1, |E_{ff}| \times Attitude)$;
        $SOC_1 = SOC_1 + min(SOC_{max} - SOC_1, |E_{ff}| \times Attitude)$;

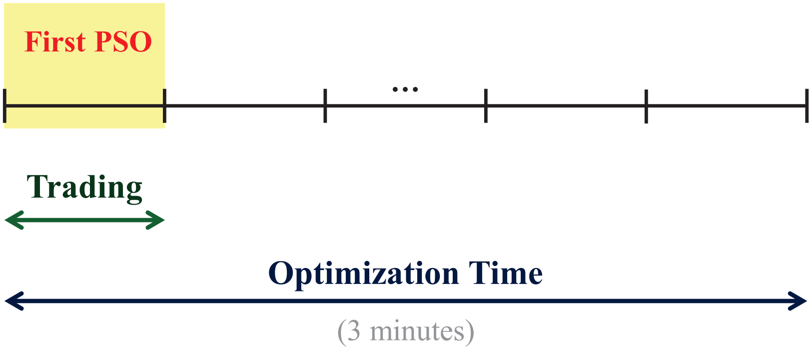


Figure 4.5: The relationship of optimization time and trading processes

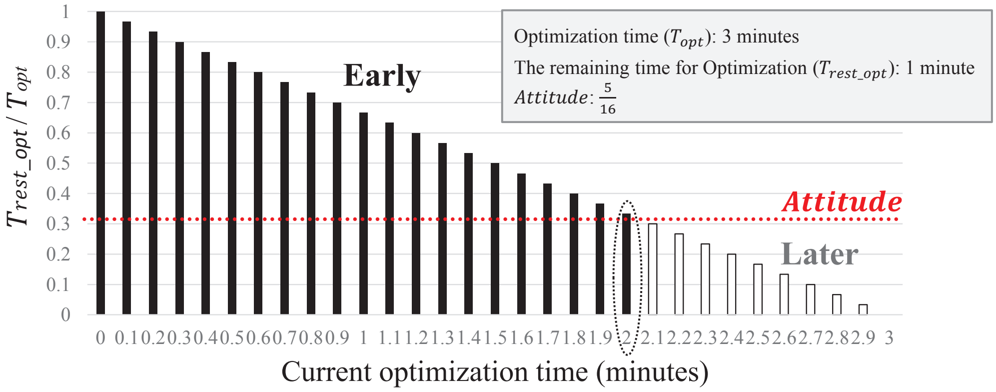


Figure 4.6: Example determination of the early or later period for the micro-grid

price as the main consideration. Thus, the attitude and the optimization time are used to determine the focus of traders, that is traders are classified into early and later.

$$\begin{cases} \text{The micro-grid is an } Early \text{ trader that focuses on price} & \text{if } Attitude < \frac{T_{rest\_opt}}{T_{opt}} \\ \text{The micro-grid is a } Later \text{ trader that focuses on capacity} & \text{if } Attitude \geq \frac{T_{rest\_opt}}{T_{opt}} \end{cases} \tag{4.11}$$

We use an example in Figure 4.6 to explain the determination of the early or later period for a micro-grid. It is assumed that each optimization time is 3 minutes long and the attitude of the micro-grid is determined as $5/16$. When the remaining time for optimization is 1 minute, the micro-grid is classified as an early trader and focuses on the price, instead of the capacity.

The classification of traders in PSO is introduced in Table 4.4. According to the

Table 4.4: The classification of traders in Particle Swarm Optimization

Particles	Objective
Early buyers	The seller with the lowest selling price
Later buyers	The seller with the largest selling electricity capacity
Early sellers	The buyer with the highest buying price
Later sellers	The buyer with the largest buying electricity capacity

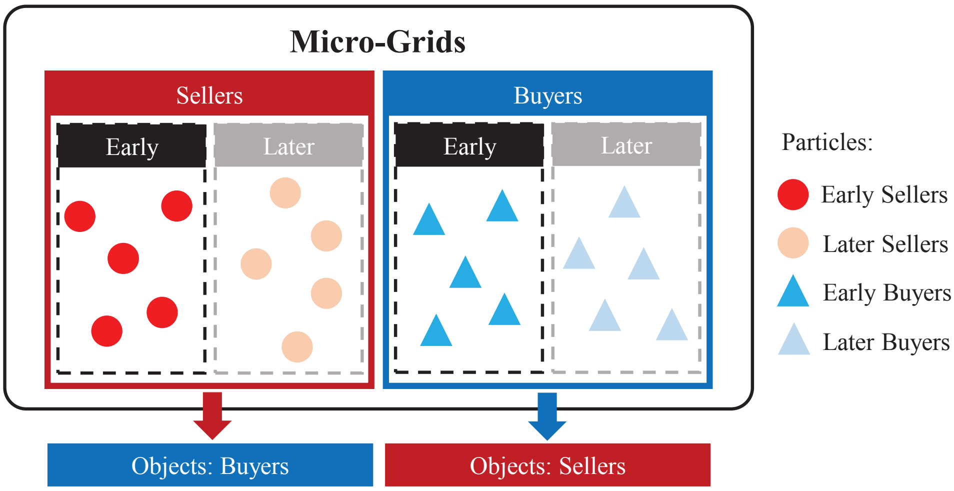


Figure 4.7: Multiple swarms in Particle Swarm Optimization

different objectives, there are different swarms in the market such as the early buyers, later buyers, early sellers, and later sellers. As shown in Figure 4.7, there are up to four swarms in our proposed PSO. If the buyers are particles, their objects would be sellers. Conversely, if the sellers are particles, their objects would be buyers. In Table 4.5, each particle (micro-grid) in the different swarms has some information. For example, the position, the personal best position, the global best position, the factors of moving velocity, time, and the attitude are included. Furthermore, every position has two pieces of information, including bidding price and bidding electricity capacity.

The adopted PSO method shows in Figure 4.8. At the beginning, we should initialize the parameters, the random positions X_i, and random velocities V_i for i is 1 to the number of particles. After initialization, we determine that the particles are in the early period or the later period. Accordingly, the cost functions for the different periods are

Table 4.5: The information of a particle

1. Position (X)
Bidding price
Bidding electricity capacity
2. Personal best position (P)
Personal best bidding price
Personal best bidding electricity capacity
3. Global best position (G)
Global best bidding price
Global best bidding electricity capacity
4. The factors of moving velocity
Velocity (V)
W (The weight without trading)
c_1, c_2 (Weighting factors)
r_1, r_2 (Random numbers between 0 and 1)
5. Time
Optimization time
The remaining time for optimization
Trading iterations
6. Attitude
$Attitude$

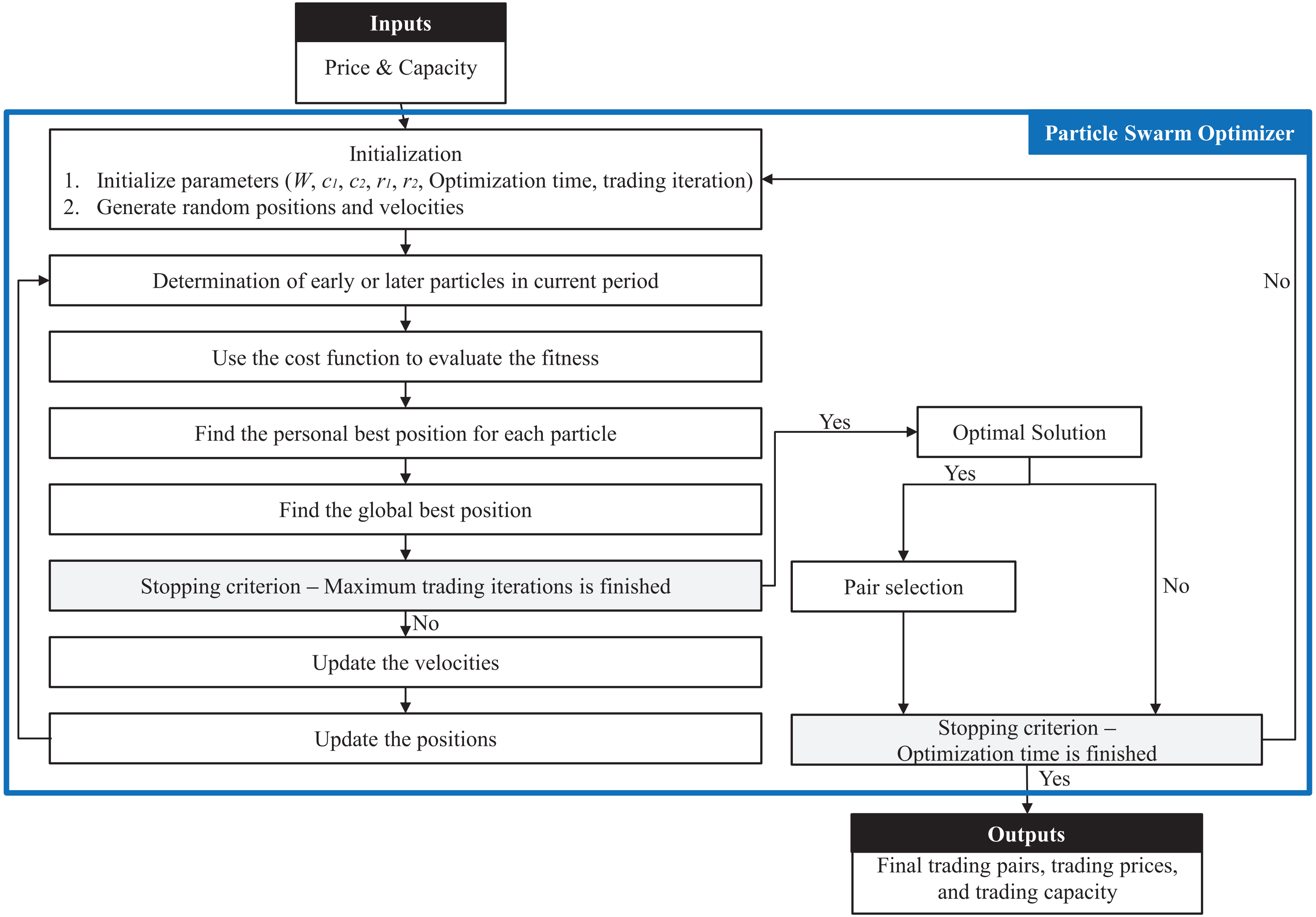


Figure 4.8: The Particle Swarm Optimizer

used to evaluate the fitness and to find the personal best position P_i and the global best position G on the k^{th} time period. The cost functions are as given in Equation 4.12 and Equation 4.13 for buyers and sellers, respectively.

$$F_{buy}(X) = \begin{cases} min(X_i^k \rightarrow findprice, P_i^k \rightarrow price) & \text{if the } i^{th} \text{ particle belongs to } Early \text{ buyers.} \\ max(X_i^k \rightarrow findcap, P_i^k \rightarrow cap) & \text{if the } i^{th} \text{ particle belongs to } Later \text{ buyers.} \end{cases} \tag{4.12}$$

$$F_{sell}(X) = \begin{cases} max(X_i^k \rightarrow findprice, P_i^k \rightarrow price) & \text{if the } i^{th} \text{ particle belongs to } Early \text{ sellers.} \\ max(X_i^k \rightarrow findcap, P_i^k \rightarrow cap) & \text{if the } i^{th} \text{ particle belongs to } Later \text{ sellers.} \end{cases} \tag{4.13}$$

If the iterations of a trading process has not ended, we update the velocities and positions as follows.

$$V_i^{(k+1)} = W_i \times V_i^{(k)} + c_1 r_1 (P_i^{(k)} - X_i^{(k)}) + c_2 r_2 (G^{(k)} - X_i^{(k)}) \tag{4.14}$$

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \tag{4.15}$$

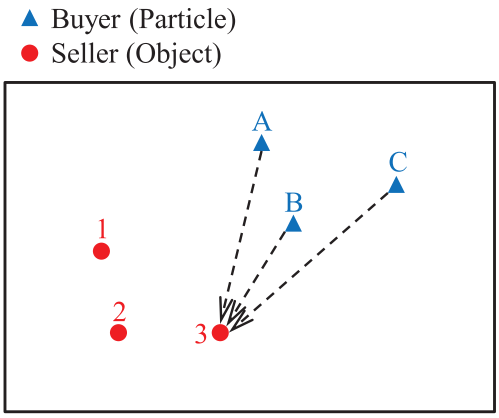


Figure 4.9: Internal conflict

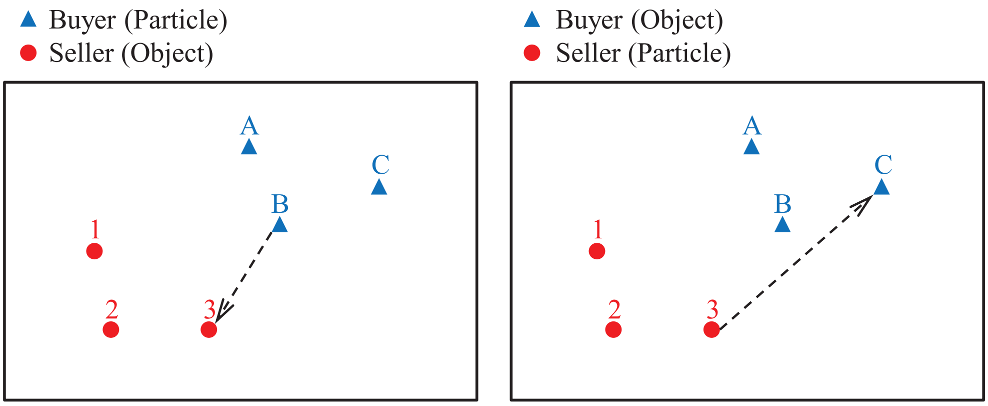


Figure 4.10: External conflict

When the maximum trading iterations are finished, the paired solutions could have conflicts, which are classified into two types. An internal conflict occurs if two more particles have targeted at the same optimal solution simultaneously as shown in Figure 4.9. An external conflict occurs if the same micro-grid when assuming two roles including both a particle and an object are paired with two different micro-grids as shown in Figure 4.10.

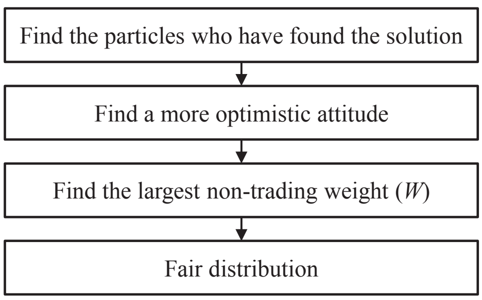


Figure 4.11: Pair selection

Table 4.6: Fair distribution in a swarm

Particle					Object			Trading	
No.	Price	Capacity	Attitude	*W*	No.	Price	Capacity	Price	Capacity
A (Buyer)	3.5	300	0.5	1	3 (Seller)	2.5	600	2.5	**240**
B (Buyer)	3.0	200	0.5	1				2.5	**160**
C (Buyer)	2.4	250	0.5	1				2.5	**200**

Table 4.7: Fair distribution between two different swarms

Particle					Object			Trading	
No.	Price	Capacity	Attitude	*W*	No.	Price	Capacity	Price	Capacity
B (Buyer)	3.0	200	0.5	1	3 (Seller)	2.5	600	2.5	**200**
3 (Seller)	2.5	600	0.5	1	C (Buyer)	2.4	250	2.4	**250**

Therefore, the pair selection is an important step and is introduced in Figure 4.11. First, we find the particles that have found the optimal solution. If there are several particles that have found the solution simultaneously, we choose the particle which has the largest weight to prevent starvation. Moreover, if the number of selected particles is more than two, we could find the particle which has a more optimistic attitude. Finally, if there are still two or more particles selected, a fair distribution strategy is employed to distribute the electricity capacities in proportion to the energy requests of selected particles. As shown in Table 4.6, take for an example, the seller (No. 3), which may trade with the buyers (No. A, No. B, and No. C) in a swarm. The trading capacity between the buyer (No. A) and the seller (No. 3) is $\frac{300}{300+200+250} \times min(300+200+250, 600)$. The trading capacity between the buyer (No. B) and the seller (No. 3) is $\frac{200}{300+200+250} \times min(300+200+250, 600)$. The trading capacity between the buyer (No. C) and the seller (No. 3) is $\frac{250}{300+200+250} \times min(300+200+250, 600)$. Besides, the trading price is dependent on the bidding price of the object such as the bidding price ($2.5) of the seller (No. 3). For another example, as shown in Table 4.7, the seller (No. 3) may trade with the buyers (No. B and No. C) between two different swarm. For the buyer (No. B) and the seller (No.3), their trading capacity is $\frac{200}{200+250} \times min(200+250, 600)$. The trading capacity between the buyer (No. C) and the seller (No. 3) is

$\frac{250}{200+250} \times min(200 + 250, 600)$. The non-trading weights of the final selected particles would be decreased because of their successful trading.

When the optimization time is not yet finished, we can re-do the optimization. If the optimization time is finished, we get the outputs that include the trading pairs, trading price, and trading capacity.

Chapter 5

Experiments

In this chapter, we present evaluations of the proposed MPO method for smart grids. We first introduce the experimental setup used for experiments. Then, we present the experimental results.

5.1 Experimental Setup

In this section, we describe the experimental environment and energy data used in our experiments.

5.1.1 Experimental Environment

As shown in Table 5.1, our method is implemented in the Python and Matlab programming language on a PC with Intel(R) Core(TM) quad-core 3.4 GHz CPU, 4 GB RAM running Windows 7 64-bit OS. The Python programming language is used for implementing the weather information parser. The Matlab programming language is used for realizing MPC distribution management.

Table 5.1: Experimental environment

CPU	Intel(R) Core(TM)2 Quad CPU Q8300 @ 3.40GHz
Memory	4GB RAM
Operating System	Windows 7 (64-bit)
Programming Language	Python and Matlab

5.1.2 Demand Load Data, Generation Data, ESS Specification, and Dynamic Utility Electricity Price

Three different types power of consumers including commercial consumers, industrial consumers, and residential consumers, were considered and their power load demands for one day are as shown in Figure 5.1. We refer the research [46] to simulate this three different types power of consumers. The consumption percentages of each type of power consumers are as shown in Figure 5.2. Industrial consumers account for 73% of the power usages. Commercial consumers account for 13%, and residential consumers account for 14%. By observing the consumption rates throughout a day, the power consumption behaviour can be classified into peak time and off-peak time as shown in Figure 5.3. For the commercial consumers, the peak time is from 8:00 to 16:00 during the open hours. For the industrial consumers, the peak time is from 7:00 to 22:00 due to the main day-shift working hours. Further, the peak time is from 7:00 to 9:00 and 15:00 to 22:00 for the residential consumers, because people are mostly at home during these time periods.

The dynamic utility electricity price for different time periods are as shown in Table 5.2. To reduce peak load demands, the utility sets the price higher at peak time than at off-peak time. Thus, the utility selling price per kWh is set to $4 at peak time and $3 at off-peak time. However, the utility buying price per kWh is set to $2 at peak time and $1 at off-peak time.

To balance the loads and generation, we use a penetration between loads and generation, as well as, between loads and ESS as shown in Table 5.3. Then, we parse the

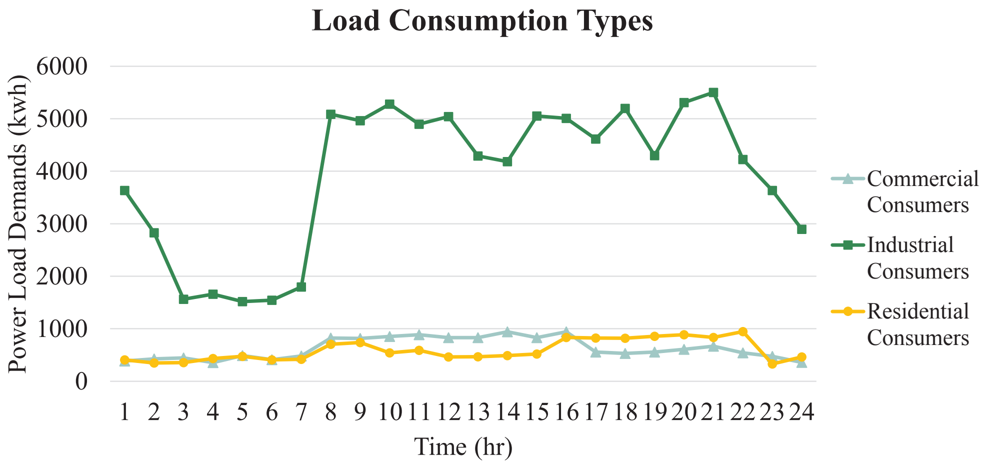


Figure 5.1: Type of power consumers in a smart grids

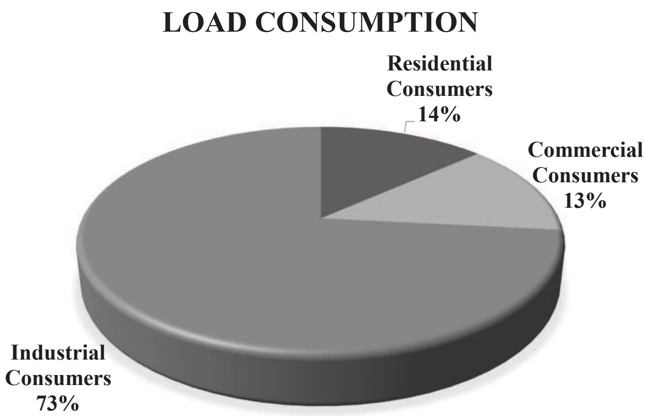


Figure 5.2: Load consumption

weather information such as wind speed and irradiance from the Central Weather Bureau to predict the generation power. The SoC range specification of ESS is from 20% to 80%.

5.2 Experimental Results

In this section, we first give an evaluation of the ARIMA model prediction. Second, we analyze the optimization efficiency. Finally, we describe the cost saving effect due to the proposed MPO methods for smart grids.

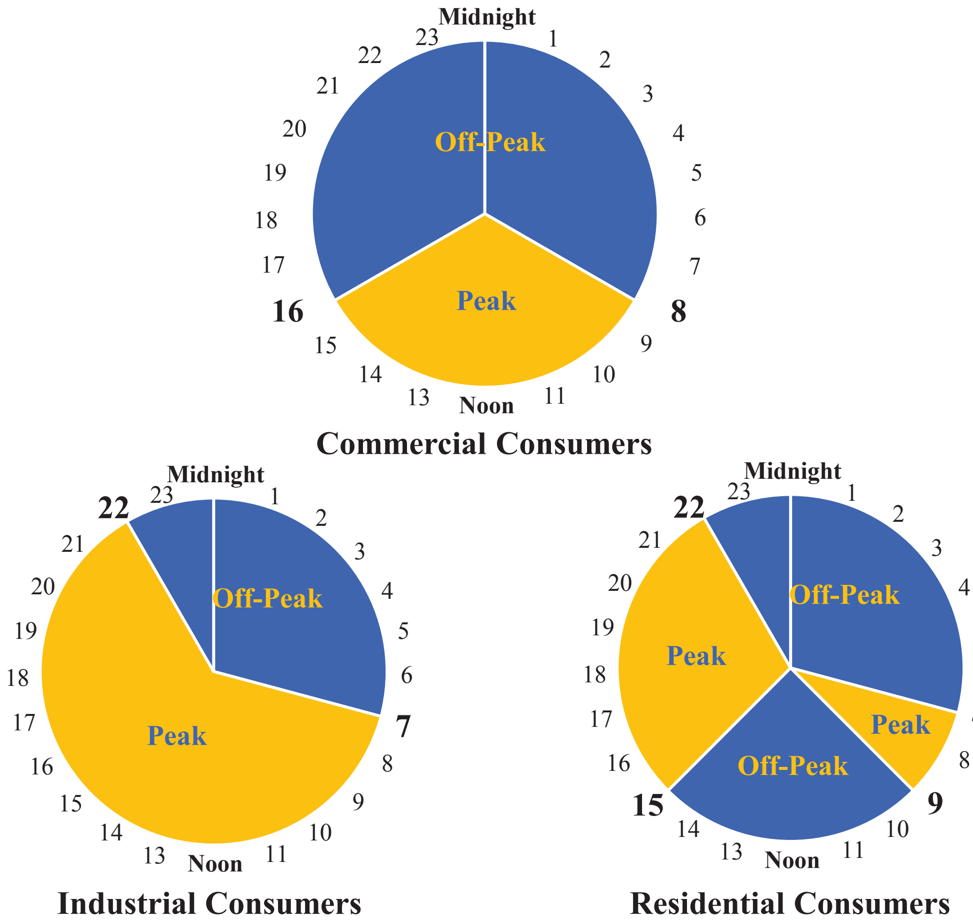


Figure 5.3: Time of use rates

Table 5.2: Utility price at peak time and off-peak time

	Selling Price (\$/kWh)	Buying Price (\$/kWh)
Peak Time	4	2
Off-peak Time	3	1

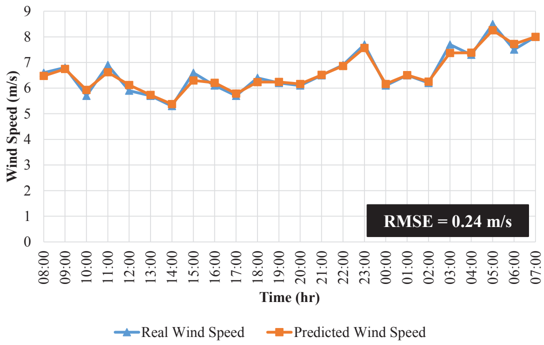
5.2.1 Evaluation of ARIMA Model Prediction

We use the ARIMA model to predict the power loads, wind speed, and irradiance. For predicting the values precisely, we use 200 historical data samples. We evaluate the prediction accuracy by the Root Mean Squared Error (RMSE) as shown in Equation 5.1. The use of RMSE makes an excellent general purpose error metric for a prediction method.

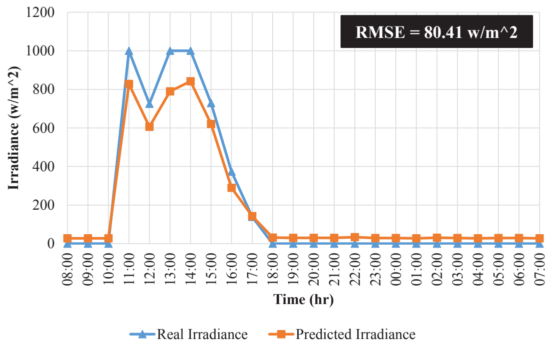
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \tag{5.1}$$

Table 5.3: Penetration among loads, generator modules, and ESS

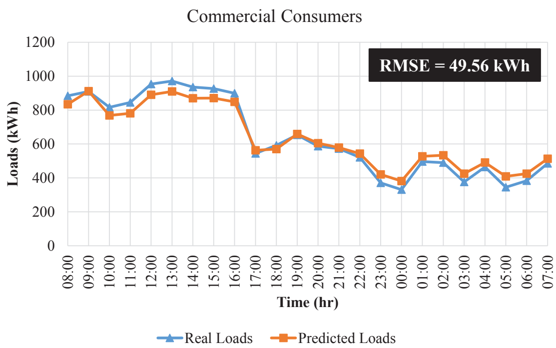
	Maximum Load Power	Maximum Generation Power			ESS
	Loads	Wind Turbine	Photovoltaic Generator	Fuel Cell	
Penetration	100%	250%	15%	20%	25%



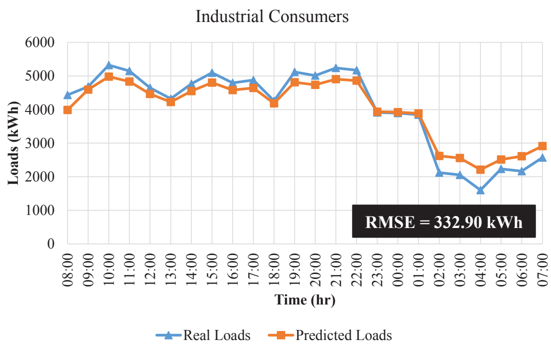
(a) Wind speed prediction



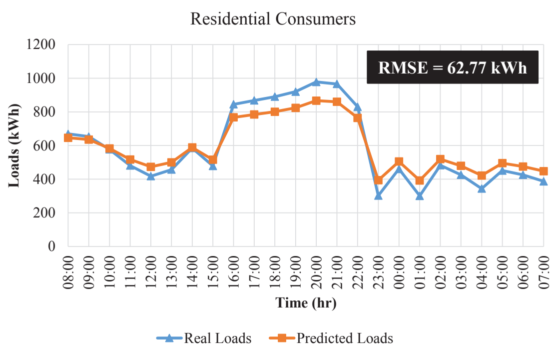
(b) Irradiance prediction



(c) Commercial consumption prediction



(d) Industrial consumption prediction



(e) Residential consumption prediction

Figure 5.4: Prediction results annotated with the respective RMSE value

Where n is the number of predicted data, y_i and $\widehat{y_i}$ are the real data and predicted data, respectively. When the data have the same units, the smaller the RMSE value is, the higher the prediction accuracy is. The prediction results for wind speed, irradiance, commercial consumption, industrial consumption, and residential consumption are as shown in Figure 5.4, where each prediction case is also annotated with the respective RMSE value. The RMSE of wind speed prediction is 0.24 m/s. The RMSE of irradiance is 80.41 w/m^2. The RMSE of commercial consumption, industrial consumption, and residential consumption are 49.56 kWh, 332.90 kWh, and 62.77 kWh. To evaluate the accuracy of the ARIMA model prediction precisely, we use the Equation 5.3 to explain the evaluation of error rate. The maximum error is the difference between the maximum and minimum value of data. Thus, the error rates of predicted data are illustrated as shown in Table 5.4. All error rates are smaller than 10%.

$$ErrorRate = (RMSE/MaximumError) \times 100\% \tag{5.2}$$

Table 5.4: Prediction error rate

	Wind Speed	Irradiance	Commercial Consumption	Industrial Consumption	Residential Consumption
Maximum Error	10 (m/s)	1000 (w/m^2)	1000 (kWh)	5500 (kWh)	1000 (kWh)
RMSE	0.24 (m/s)	80.41 (w/m^2)	49.56 (kWh)	332.90 (kWh)	62.77 (kWh)
Error Rate	**2.40%**	**8.04%**	**4.96%**	**6.05%**	**6.28%**

The prediction model is also used for predicting data for more than one future time slots, so that model-predictive optimization can be applied. However, we have to note that the average error rate grows with the number of look-ahead time slots.

$$\begin{aligned} AverageErrorRate = (&WindSpeedErrorRate + IrradianceErrorRate \\ &+ConsumptionErrorRate)/3 \end{aligned} \tag{5.3}$$

Table 5.5 and Table 5.6 illustrate the growing error rate for two different micro-grids. A consequence of the higher error rate is the lower confidence that can be associated to the results predicted for large number of time slots. Further, the attitudes, bidding prices, and bidding capacities, micro-grid will all depend the predicted loads, wind speed, and irradiance. As shown in Figure 5.5, the average prediction execution time is

5.65 seconds for a micro-grid.

Table 5.5: Prediction error rate for looking ahead future time slots in micro-grid 01

Error Rate	1 Time slot	2 Time slots	3 Time slots	4 Time slots	5 Time slots
Wind Speed Error Rate (%)	1.57	4.63	5.48	6.30	6.66
Irradiance Error Rate (%)	7.80	15.81	20.70	24.63	27.02
Consumption Error Rate (%)	4.38	8.59	11.64	13.74	15.28
Average Error Rate (%)	**4.58**	**9.67**	**12.61**	**14.89**	**16.32**

Table 5.6: Prediction error rate for looking ahead future time slots in micro-grid 27

Error Rate	1 Time slot	2 Time slots	3 Time slots	4 Time slots	5 Time slots
Wind Speed Error Rate (%)	0.52	2.31	2.70	3.05	3.34
Irradiance Error Rate (%)	3.75	13.96	18.84	21.87	24.89
Consumption Error Rate (%)	6.63	11.78	14.66	16.37	17.61
Average Error Rate (%)	**3.63**	**9.35**	**12.07**	**13.76**	**15.28**

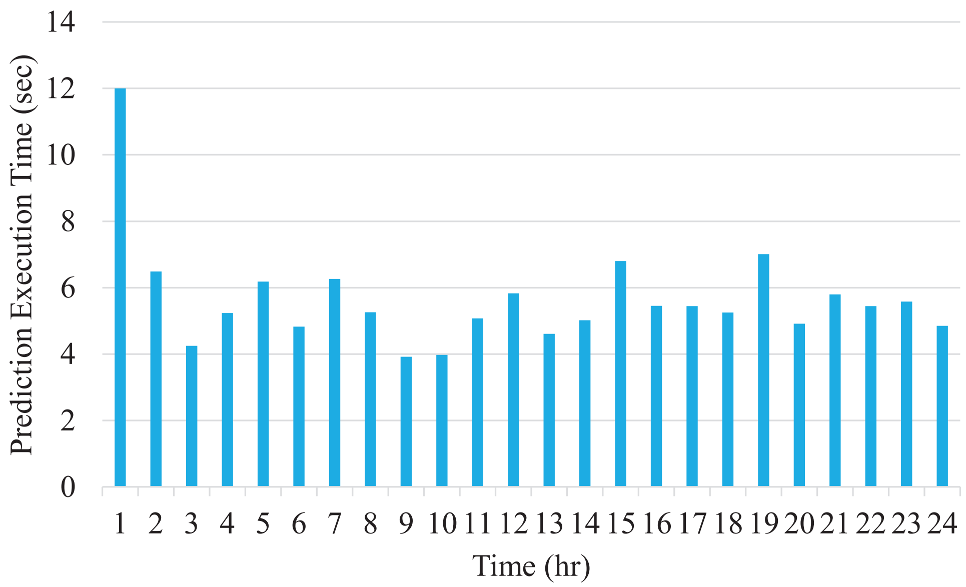


Figure 5.5: The overhead of prediction model

5.2.2 Optimization Efficiency

We use the PSO method to optimize the overall cost savings in smart grids. We assume 30 micro-grids engage in trading electricity. The 30 micro-grids are classified into four swarms including early sellers particles, later sellers particles, early buyers particles, and later buyers particles, respectively, according to their trading attitudes and the remaining optimization time. After the prediction once per hour, we set 3 minutes as the maximum optimization time to execute the optimizer. The maximum optimization time is divided into several trading process. In a trading process, 30 micro-grids execute the multiple swarms PSO to find their optimal trading pairs, trading prices, and trading capacities, simultaneously. A swarm means that it could execute one PSO. When all swarms finish their PSO processes, the number of PSO is increased by one, as well as, the PSO convergence iterations is also recorded. Then, they will re-execute the multiple swarms PSO method. Afterwards, if optimization time is equal to 3 minutes or all micro-grids complete pairing beforehand, the optimization will finish. We calculate the optimization execution time. The total convergence iterations is in Equation 5.4. As an efficiency results shown in Table 5.7, the average optimization execution time is 2.42 seconds, as well as, the longest optimization time is 4 seconds.

$$OptimizationConvergenceIterations = (NumberofPSO) \times (PSOExecutionIterations) \tag{5.4}$$

5.2.3 Cost Savings on the MPO Distribution Management

In our experiments, we assume 30 micro-grids engage in trading electricity based on the predicted bidding prices, bidding capacities, and attitudes for several look-ahead time slots including 1 time slot, 2 time slots, 3 time slots, 4 time slots, and 5 time slots. The transaction market (called optimizer) uses the PSO method to allow these 30 micro-grids to find the most appropriate electricity traders such that the overall cost is nearly optimal minimal. The resulting optimal trading control strategy will be used for distribution management in the following time period (hour here). The cost variations per hour for several different look-ahead time slots due to MPO are compared to that due to the traditional method and the open loop look ahead dispatch [28] as shown in Figure 5.6 and Figure 5.8. A positive cost (called net income) indicates profit and thus the larger the cost is, the better the earning is. Conversely, a negative cost indicates expense and thus the smaller the cost is, the better the paying is.

The differences among the traditional method, the open loop look ahead dispatch, and our proposed MPO method are as follows. In the traditional method, the ESS is used as a UPS, that is, for backup purposes, thus trading only addresses the electricity demand response issue for the current time slot. In the open loop look ahead dispatch, the ESS is also used as a UPS. The main difference with the traditional method is that trading addresses the electricity demand response issue for the predicted time slots once 24 hours. However, in MPO, we use the predicted future electricity demand response to determine the electricity amount that could be sold or bought. The ESS in our proposed MPO method does not play only a backup role, but also acts as an active electricity supplier. Although the total buying expenditure at 12:00 in Figure 5.6 is larger in MPO than in the traditional method and the open loop look ahead dispatch, the action of buying electricity beforehand (at 12:00) reduces the buying expenditure in the next time period (at 13:00).

As shown in Figure 5.7, the overall cost for micro-grid 1 is positive (profit earned) for MPO, traditional method, and open loop look ahead dispatch. Compared to the traditional method, the open loop look ahead dispatch method results in a profit decrease of 91%. However, MPO results in an increase of 177% profit if one time slot is used for prediction.

As shown in Figure 5.9, for micro-grid 27, the overall cost is negative (expenditure). The total budget for buying electricity required by open loop look ahead dispatch is larger than that by the traditional method by 35.48%. However, the total budget for buying electricity required by MPO is smaller than that by the traditional method by 31.08%.

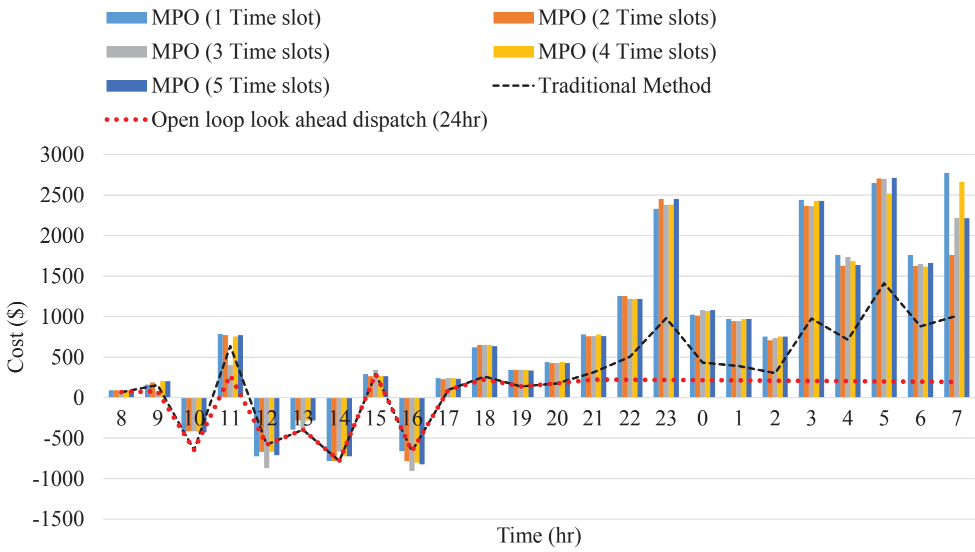


Figure 5.6: Cost variation in different look-ahead time slots, traditional method, and open loop look ahead dispatch per hour for micro-grid 1

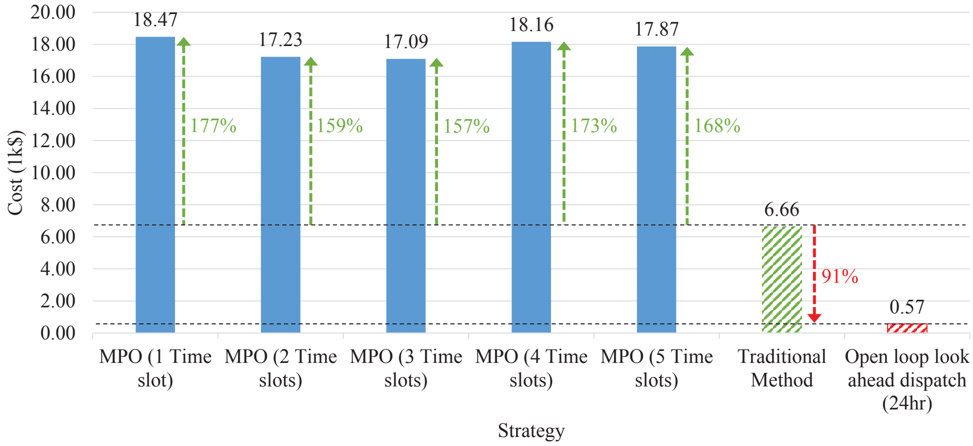


Figure 5.7: Comparison of total cost savings by our proposed MPO method with traditional method and open loop look ahead dispatch in one day for micro-grid 1

Further, as shown in Figure 5.10, for the smart grids including all 30 micro-grids, the overall cost is negative (expenditure). The total budget for buying electricity required by open loop look ahead dispatch is larger than that by the traditional method by 31.69%. However, The total budget for buying electricity required by MPO is smaller than that by the traditional method by 18.78%. Table 5.8 also summaries the results of total cost savings by our proposed MPO method with traditional method in one day for each micro-grid and all 30 micro-grids. We observe that the smart grids could save the much more cost of 19.38% if four time slots is used for prediction.

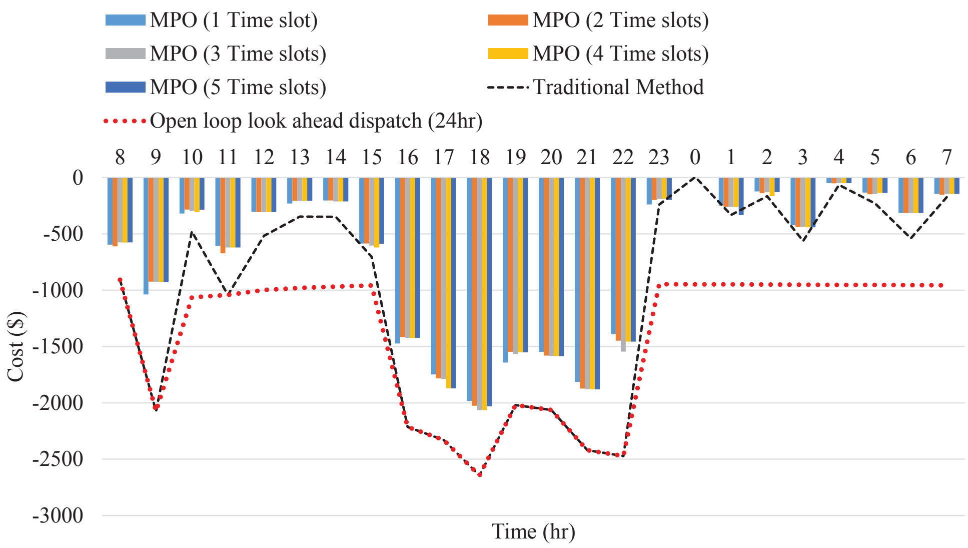


Figure 5.8: Cost variation in different look-ahead time slots, traditional method, and open loop look ahead dispatch per hour for micro-grid 27

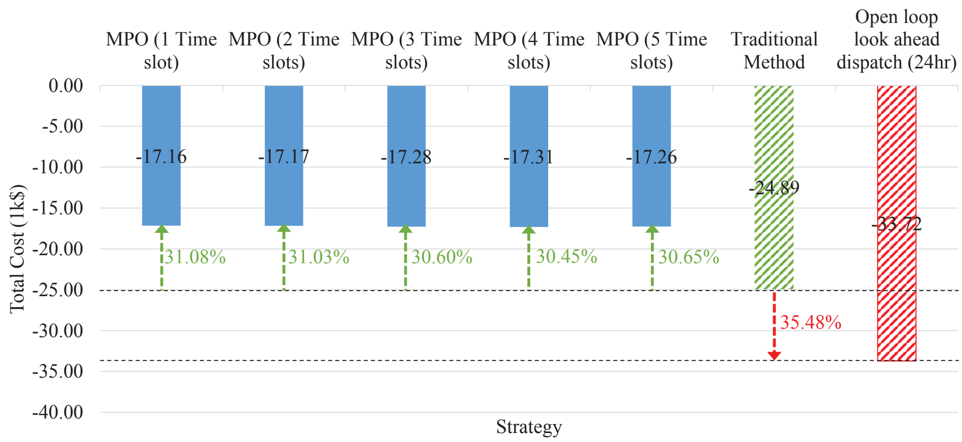


Figure 5.9: Comparison of total cost savings by our proposed MPO method with traditional method and open loop look ahead dispatch in one day for micro-grid 27

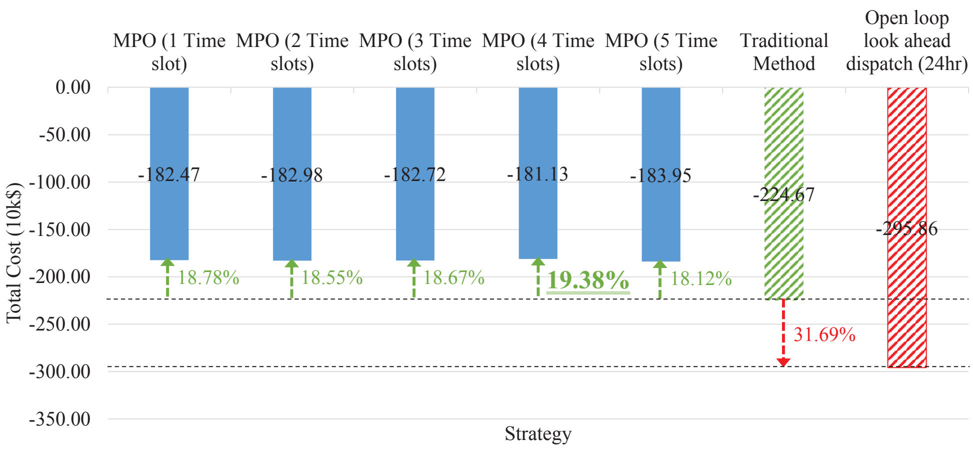


Figure 5.10: Comparison of total cost savings by our proposed MPO method with traditional method and open loop look ahead dispatch in one day for all 30 micro-grids

Table 5.7: Optimization efficiency for 30 micro-grids in one day

Hour	**Number of PSO**	**PSO Execution Iterations**	**Optimization Execution Time (sec)**
1	5	3	2.24
2	4	4	1.72
3	9	4	**4.00**
4	7	3	3.51
5	5	3	2.43
6	5	6	2.77
7	3	9	1.61
8	8	2	3.03
9	9	4	3.48
10	6	4	2.40
11	8	6	3.18
12	6	2	2.21
13	6	6	2.49
14	3	8	1.63
15	4	1	1.48
16	6	2	2.29
17	7	2	2.71
18	6	4	2.46
19	5	1	1.84
20	5	1	1.86
21	10	2	3.75
22	4	6	1.72
23	4	7	1.85
24	4	3	1.34
Average	**6**	**4**	**2.42**

Table 5.8: Total cost savings by our proposed MPO method with traditional method in one day for each micro-grid and all 30 micro-grids

Micro-Grid	1 Time slot	2 Time slots	3 Time slots	4 Time slots	5 Time slots
MG01	177%	159%	157%	173%	168%
MG02	23.29%	32.94%	29.02%	26.83%	24.52%
MG03	24.07%	26.99%	27.32%	28.92%	24.21%
MG04	28.75%	28.30%	31.94%	29.23%	29.73%
MG05	29.37%	21.89%	31.33%	30.76%	34.87%
MG06	28.65%	31.04%	30.14%	26.12%	25.75%
MG07	23.86%	23.08%	20.84%	25.51%	27.29%
MG08	48.11%	48.96%	48.79%	49.31%	48.58%
MG09	24.12%	23.05%	29.04%	23.90%	26.75%
MG10	26.62%	27.46%	16.26%	22.46%	22.42%
MG11	1006.69%	958.20%	962.56%	957.66%	931.06%
MG12	5.02%	4.54%	8.75%	2.31%	4.10%
MG13	1.02%	3.04%	6.80%	7.00%	8.61%
MG14	5.83%	7.58%	6.42%	5.57%	4.24%
MG15	12.33%	22.44%	9.66%	17.86%	5.54%
MG16	8.88%	1.73%	1.34%	10.36%	6.59%
MG17	5.18%	4.62%	5.55%	1.96%	5.04%
MG18	2.40%	7.04%	5.34%	8.69%	4.50%
MG19	7.70%	8.08%	7.20%	6.40%	3.87%
MG20	6.39%	1.93%	5.78%	7.56%	7.18%
MG21	24.90%	28.42%	29.90%	30.17%	29.35%
MG22	30.18%	28.64%	25.50%	27.45%	28.27%
MG23	31.79%	30.11%	33.02%	30.92%	31.32%
MG24	30.93%	30.00%	30.07%	29.77%	29.69%
MG25	29.68%	27.18%	28.60%	29.10%	27.23%
MG26	34.50%	21.43%	26.85%	32.42%	23.16%
MG27	31.08%	31.03%	30.60%	30.45%	30.65%
MG28	31.02%	28.37%	26.87%	26.02%	27.98%
MG29	46.56%	39.91%	23.96%	39.13%	38.38%
MG30	64.14%	66.84%	62.83%	65.80%	66.16%
Total	**18.78%**	**18.55%**	**18.67%**	**19.38%**	**18.12%**

Chapter 6

Conclusions and Future Work

In this Thesis, we proposed a model predictive optimization method for distribution management in smart grids. ARIMA model was used to predict the energy state, as well as, to set bidding prices and bidding capacities based on optimistic attitude and on pessimistic attitude. Through the RMSE error metric, we estimated the error rate of our prediction model to be smaller than 10%. Trading among micro-grids for electricity was performed through a novel multiple swarm PSO optimizer. The resulting electricity trading pairs, trading prices, and trading capacities were used as the input for a distribution controller. The distribution controller gives real energy feedback to the prediction model. In the closed loop feedback control system, our prediction model will be retrained once per hour. The total positive cost increased and the total negative cost was reduced due to the proposed MPO method. For one case, the proposed cost of our proposed method in one micro-grid was 177% of the traditional grid. Another case could show that the negative cost by our proposed method in another micro-grid was smaller than that by the traditional grid by 31.08%. For smart grids, our proposed MPO method totally saved the much more cost of 19.38% if four time slots was used for prediction. The overhead of prediction model and the optimization efficiency for our proposed MPO method are 5.65 seconds and 2.42 seconds.

For the future work, we will further explore more impacts of the ESS to our proposed method. We expect to dynamically adjust the threshold for checking the state of energy requests, i.e., $Threshold_{Energy}$, as shown in Algorithm 3 according to the storage capacity in use. When the storage capacity is less and less, buyers may desire to buy more electricity and sellers may reduce the desire of selling electricity. At this time, the threshold will decrease for buyers and will increase for sellers. Besides, we also plan to research the relationship between the number of look-ahead time slots and the amount of ESS. While the storage capacity is enough, the effect of multiple look-ahead time slots may be more significant. We hope that we can reduce more costs in smart grids in the future.

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