Distribution Network Design for Distributed Renewable Energy Sources

by

Ben Zhang
B.Eng., Beijing University of Posts and Telecommunications, 2011

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ABSTRACT

Future electrical power networks should support the integration of distributed renewable energy sources, which may be contributed by individual customers instead of utility companies. Such a demand poses new challenges to power distribution network design, since the energy generation, energy consumption, and power flows all become highly dynamic. An inappropriate network design may not only waste much energy in power distribution but also incur high cost in network construction. In this thesis, we study the optimal network design problem under a dynamic current injection model. We investigate different optimization methods to obtain the optimal network structure that can better adapt to dynamic energy generation/consumption requirements and is more efficient than traditional tree-structured power distribution networks. By predicting users' potential load in the network, network design with our method results in significant energy saving.

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Chapter 1

Introduction

1.1 Motivation

Harvesting green energy such as wind and solar power is of great importance in sustainable development in virtually every country. Building large-scale wind or solar power plants, however, is a non-trivial task that requires a large amount of investment. Recent years have seen an increasing number of small-scale renewable energy sources generated by small companies or even homes to meet their own needs. In most cases, these small energy sources may have a surplus, but the surplus is usually wasted because the owners cannot afford expensive energy storage devices and the existing power distribution system does not support bi-directional energy trade. If the future power distribution system can accommodate these small-scale renewable energy sources and support the free trading of small-scale renewable energy, energy consumers will have a high incentive to harvest renewable energy resources and contribute the surplus energy to other consumers. To this end, distributed energy sources may become the major driving force for the development and deployment of green energy technology. In fact, many countries have initiated such effort via government subsided programs such as the Feed-In Tariff (FIT) program [62][39][6].

Despite clear demand technical challenges pose a great hurdle to the integration of distributed renewable energy sources into the existing power grid because the current power distribution system was originally designed for the one-way model, i.e., utility companies generate and distribute energy to end consumers. Accepting current injection from end users will generate a quite dynamic network with fully distributed, time-varying energy sources and energy sinks (consumers). It requires the power distribution network to be robust to voltage variations, stable to state transition, and able to support bi-directional power flows [26]. A new design of power distribution network is required.

The planning of a new power distribution network and retrofitting existing power distribution networks have been active research fields in recent decades [57], driven by the increasing demand. For instance, in quickly developing countries like China, many power distribution networks need to be redesigned or expand every several years to meet the energy need in emerging residential or industrial zones. Designing a power distribution network involves a large set of optimization problems [57], many of which are NP-hard. These problems include optimal transformer allocation, substation planning, optimal conductor selection, load forecast, reliability, and so on.

Due to the complexity in power distribution network design, more often than not people adopt simplified abstract models to quickly obtain a design schema. In the simplified models, some physical details of electric power, such as voltage scaling and Volt/Var control [10], are ignored or approximated. The main advantage of adopting a simplified model is to make the problem computationally tractable. The design schema from a simplified model could be used as the basic blueprint, based on which further refined details could be added to meet various design constraints.

Current work on the development of new power distribution networks to support distributed renewable energy sources mostly focuses on network reliability and network protection. In this paper, we address the problem from another angle by investigating the network topological structure, which can better adapt to dynamic changing loads of energy. In particular, we assume that the network nodes may both generate and consume energy at different times. We also consider the energy loss during distribution and the cost of weighted building cost, where weights are introduced to capture the practical constraints (e.g., geographical conditions) in the network construction. Following existing practice, we use a simplified model, which will be illustrated in Chapter 3. Our objective is to design a power distribution network that minimizes the energy loss under given constraints on network construction cost and satisfies the dynamic power distribution needs.

Direct current grid (DC-Grid) has been of increasing importance in current power networking design [5]. Most renewable energy and energy storage devices provide electricity in the form of direct current (DC). Using DC-Grid avoids the expense in voltage conversion equipment as well as energy loss in voltage conversion. Moreover, since most of the distributed renewable energy resources are not stable, the power quality of renewables depends on environmental conditions, and under this circumstance DC-Grid is more adaptable for distributed energy resources [34] [42]. Currently, a lot of development and research efforts have been devoted to DC-Grid [25][27]. In addition, it has been claimed that network design problems in DC-Grid could be considered as a good approximation of the same problems in AC-grid [33]. Based on the above considerations, the network design problems in this thesis are based on DC-Grid.

1.2 Contributions

The contributions of this thesis are the following:

1. We consider the users' energy profile, in particular their statistical time varying amount of surplus energy, to capture the dynamics in future distribution power networks, where distributed renewable energy sources become the norm.

2. Different from existing work on network design, we model the network as a geometric graph to explicitly consider the geometric constraint in the optimal network design, which plays an important role in network planning for the current network structure design as well as in the design for future potential customers.

3. We solve the network optimization problem constructed in this work with different methods, including the Steepest-Descent Method, the Newton Method and the Quasi-Newton Method. We demonstrate that the Quasi-Newton Method is superior in optimizing the distribution network with dynamic changing loads of energy. The network structures that we get from the optimization are more flexible than tree-based network structures.

4. Based on the method presented in this work, we propose a network design method that takes the prediction of potential customers into consideration when constructing the network. From the experimental results, we demonstrate that network design with the prediction of potential customers leads to more energy saving. If the energy consumption prediction is reliable, our method leads to the minimum energy loss in energy transmission, and the network approaches optimal network structure design.

1.3 Work Arrangement

The rest of this thesis is organized as follows:

- In Chapter 2, we introduce the background of this work. This chapter includes the development of renewable energy, characteristics of renewable energy, problems and strategies for renewable energy development, network structure design for power network, and network design for distributed renewable energy networks.

- In Chapter 3, we formally formulate the power network, build a mathematical model from the practical scenario, and formulate the optimal design problem for future power distribution networks.

- In Chapter 4, we first combine the constraint with the objective function to translate the constrained optimization problem to an unconstrained optimization problem. To make sure that the unconstrained objective function can also satisfy the constraint conditions, we introduce the *Bisection* method. We present the pseudo codes for solving the optimization problem and the pseudo code for the Bisection method.

- In Chapter 5, we present one case study to demonstrate the effectiveness of our model and evaluate the performance of different algorithms. We first demonstrate three scenarios, and then we construct the networks according to these scenarios with the method introduced in this thesis. Second, we evaluate each scenario with different algorithms and compare the efficiency of the algorithms. Third, for each scenario, we compare the network design based on dynamic energy changes and the network design based on maximum requirement. Finally, we extend the work and demonstrate the benefit of (partial) pre-construction of the future network. Based on the prediction of the future energy profile, we may invest accordingly to over-engineer the current network construction. This can benefit not only the current electricity transmission, but also the future construction when the prediction becomes true.

- In Chapter 6, we pose an additional constraint to the previous problem to limit the number of connections on network to make the network construction easier in reality. We first apply the optimization method introduced in the previous chapter to optimize a network with 25 nodes and demonstrate the optimized network structure. We then add an additional constraint on the previous problem to limit the total number of connections in the network. In this way, we can "clean" the network to have fewer connecting lines. Finally, we present an algorithm to solve this problem and show the structure of the cleaned network.

- In Chapter 7, we conclude the thesis and present the future research.

Chapter 2

Background and Related Work

2.1 Benefits of Renewable Energy

With the fast development of modern industry, energy crises have become a critical issue all around the world. The increasing global population and its high dependence on traditional forms of energy like fossil fuels have created serious threats to the natural environment, causing world-wide problems such as global warming, air pollution, and acid precipitation. For the sustainable development of human society, the development of renewable energy is of substantial importance [16].

As existing legacy energy systems mainly rely on fossil fuel, the development of renewable energy technologies will be a slow, painful and highly uncertain process [31]. Nevertheless, over the last several decades, we have seen some well-established renewable energy sources being integrated into existing power systems, including for example hydro power and geothermal power.

Among the continuing efforts to develop renewable energy, many countries in recent years [7] [28] [52] [12] have started to explore green energy such as wind and solar energy. In particular, many European countries have invested heavily in renewable energy [48] [50] [54] and have started to benefit from such investments. Renewable sources such as wind and solar energy currently constitute a very small share (less than 15%) of the total energy supply. However, the environmental problems caused by traditional fossil fuel will sooner or later reach the limit and,as a consequence, the cost of traditional energy will become prohibitive. For this reason some European countries, such as Denmark, have realized the great potential of renewable energy and have increased the share of renewable energy substantially during the last decade[44].

The advantages of using renewable energy can be summarized as follows [61]:

- Renewable energy is more environmentally friendly. Even though renewable energy might also cause some environmental problems such as the pollution involved in manufacturing solar cells, renewable energy is generally much cleaner than traditional fossil fuel.
- Renewable energy, like wind energy and solar energy, can provide nearly infinite energy if used properly. This is quite different from the traditional energy resources such as fossil fuels. Non-renewable energy resources normally require a long time to generate. Once the non-renewable energy is used up, its regeneration is impossible in the near future.
- Renewable energy resources are usually decentralized, and as such the use of renewable energy is more flexible. Instead of depending on national network management, renewable energy can work in small scale and becomes self-supportive in the local community. For instance, people can harvest solar energy over the rooftop as a supplement energy source. If the power network provides a way to integrate such distributed energy sources, people can trade extra energy over the network. Such flexibility will fundamentally change the energy market in that end customers can be both energy consumers and energy contributors.

2.2 Challenges in Renewable Energy Development and Management

Typically, three major technological changes are involved in the development of renewable energy [44]: energy saving on the demand side [8], efficiency of renewable energy production [40] [41], and replacement of fossil fuels by various sources of renewable energy [1] [2]. To some degree, these technologies are the necessary components for success in developing renewable energy.

Although renewable energy brings many benefits, the available amount of renewable energy depends on the local environmental conditions and thus is uncertain. The environmental conditions of a certain area can be stable over a long period of time, but in a short period they may vary quickly. In this case, the supply from renewable energy resources may not satisfy users' requirements all the time. In other words, although the expected amount of renewable energy generated in one area, such as solar energy, may be stable over a long period of time, the amount of energy generated in short periods may have a large variance.

The uncertainty regarding the available amount of renewable energy, together with the distributed energy generation, leads to non-trivial challenges in the management of renewable energy resources. For instance, the uncertain available energy amount in the future requires new technologies such as large energy storage devices to smoothen the gap between energy demand and energy supply. In addition, since the energy sources are geographically distributed, the construction of a power distribution network is more difficult. As we will disclose in this thesis, the traditional tree-structure network may no longer be optimal.

It is also challenging to integrate a high share of intermittent resources into the energy system, especially the electricity supply [18]. Recently, good progress has been made to address this problem. For instance, the possible solution of large-scale integration of wind power into the Danish system has been well studied [4] [47] [45] [46]. In addition, a number of studies on the integration of wind energy and solar energy have been carried out, and new technologies such as fuel cells and hydrogen have been applied in distributed energy generation [3] [56] [51] [30]. These studies demonstrate the possibility of successfully integrating intermittent resources into the energy system, and also show that the ability to integrate renewable energy is determined by the flexibility of the rest of the supply system [43]. The development of new distribution power networks has become one critical issue.

2.3 Network Design for Renewable Energy

A well designed network should have the following features. First, it should be conductive to the easy identification of problems occurring in the network. Second, it should be efficient and cost-effective for energy distribution. Third, it should be flexible enough for ease integration of distribution of energy sources. In many cases, the network structure also reflects the current and future development of a certain area, and in this sense good network design may need to consider future demand and network expansion.

In relation to the flexibility of renewable energy, Kalogirou and Soteris [35] introduce the technology of artificial intelligence in designing a network for renewable energy. Their method enables the renewable energy resources in the network to cooperate with each other [19]. The system parameters, used to design the network are obtained from the learning process of history data. However, since different resources' history data can be large and various, it is not easy to select proper sample data and set learning accuracy to start the learning process.

Cormio et al. [14] present a regional energy planning method, which considers renewable energy sources and environmental constraints. The method is based on the energy flow optimization model (EFOM) [20] aiming to reduce environmental impact and to save cost. The optimization process provides feasible generation settlements. They also introduce two models: the Brookhaven energy system optimization model (BESOM), which attaches all costs to energy flows and minimizes their sum over a one-year period and the time-stepped energy system optimization model (TESOM), which makes consecutive BESOM-type optimizations for single years [59]. In addition, they study the problem in the context of the energy market and propose a market allocation model (MARKAL). These methods take the industry environmental impacts and policy applications into consideration when constructing the model.

Methods for designing network structure can vary considerably. Hines et al. [24] propose a minimum-distance graph method, which produces networks with properties approximately matching those of known power grids. The electrical structure for the power grids is a weighted graph. Kershenbaum et al. propose a topological optimization method for a mesh network [38]. The matrices of this method specify the cost of links between all pairs of nodes and the internodes, and the objective function of the method is to obtain a topology with the minimum total cost. Bohn and Magnasco [9] construct an optimization function to minimize the dissipation rate of an electrical network. The optimization results demonstrate that the optimizations lead either to tree topology or to no structure at all. Although a radial tree structure is cheap and simple, it may not be flexible in practice, since a tree structure may have security and reliability issues [49].

The conventional methods for constructing power distribution network structures are based on the assumption that there exists a centralized power station and power is delivered from the power station to end users. This assumption does not hold anymore when we try to integrate distributed energy sources into the power system. Over existing power distribution networks, power fluctuations caused by the intermittency of renewable energy sources may bring adverse impacts on power quality of the main grid. The interconnection to the existing network may not provide utilities and distributed energy resources owners with the support and benefits promised [17].

Microgrids [36] have been introduced to the use of distributed energy resources. Microgrids can couple multiple distributed energy resources, energy storage systems, and loads, within the same framework. Based on Microgrids, recent work [13] [32] uses Agent-Based methods [23] [29] [58] to design and manage the network.

Ochoa and Harrison use a multi-period AC Optimal Power Flow to determine the optimal accommodation of renewable energy to minimize the system energy losses. They also consider the characteristics of Smart Grid, and their control schemes are expected to be part of the future Smart Grid [53]. Timbus et al. employ standardized communications and modern information technologies, such as communication standards IEC 61400-25 and IEC 61850, for the integration of renewable energies and the deployment of active distribution management [60]. Rau and Wan present a method to optimally locate the distributed resources in a network to minimize losses, line loadings, and reactive power requirements [55]. Papers [37] [15] [22] propose methods of optimizing the scale and resources of the energy in network with the consideration of distributed energy resources. Since the energy requirements are determined by customers and the availability of distributed energy sources is uncertain, these methods may need further improvement to easily adapt to changing requirements.

Chapter 3

Problem Formulation

In this chapter, we formulate the design problem of electric power distribution networks.

- We present a geometric graph. We define parameters and show the structure of the geometric graph. We also consider the geographical conditions in the geometric graph when constructing the model.
- We abstract a mathematical model from the geometric model. Our object is to minimize the total energy loss in the distribution network.
  - We formulate the total energy loss during the network transmission as our objective function.
  - We take the characteristics of renewable energy into consideration. We present a dynamic load profile and construct an energy loss function based on the dynamic changes in energy consumption/demand.
  - Furthermore, we consider investment as a constraint in the network construction. We combine the expense of wire connection and geographical condition and take this as the construction cost which should fall within the given budget.
  - At the end of this chapter, we formulate the network optimization problem with constraints for both the case with the consideration of dynamic

energy scenario and the case without the consideration of dynamic energy scenario.

3.1 Network Model and Assumptions

We model the power distribution network as a geometric graph $G =< V, E, L, K >$ on a two-dimensional plane, where

- $V = \{1, 2, \ldots, n\}$ denotes the set of n nodes on a 2-D plane. Each node represents the basic nodal unit in consideration in the power distribution network, which could be a customer, a power station, or even a small community. We use point and node interchangeably in the rest of the paper.

- E is the $n \times n$ adjacent matrix of the graph $[e_{ij}]_{n\times n}$, where $e_{ij} = 1$ if there is a power line between node i and node j, otherwise $e_{ij} = 0$.

- Associated with each node i is a load value l_i, representing the current injection or current draw at that node. In our work, we use a positive value to represent current injection (i.e., energy contribution) from the node and a negative value to represent current draw (i.e., energy consumption) at the node. A load value of 0 means the node is a relay node. Note that the load value at a node may change over time but it is fixed at a given time instance. We use an n dimensional column vector $l = [l_1, l_2, \ldots, l_n]^T$ to denote the load profile at a given time instance. For the network to be stable, we require $\sum_{i=1}^{n} l_i = 0$. We use L to denote the set of load profiles.

- Each line is assigned a value k_{ij}, representing the conductance (inverse resistance) value of the line connecting node i and node j. We define the *conductance matrix* of the network by

$$K = \sum_{(i,j)} k_{ij}(e_i - e_j)(e_i - e_j)^T$$

  where $e_{ij} = 1$ and e_i is an n dimensional standard basis vector whose i-th element is 1.

In one area, we have n nodes, for $i = 1, 2, ..., n$, $j = 1, 2, ..., n$, K can be expressed as the following matrix,

$$K = \begin{pmatrix} 2*(k_{12}+k_{13}+...+k_{1n}) & -2*k_{12} & ... & -2*k_{1n} \\ -2*k_{12} & 2*(k_{12}+k_{23}+...+k_{2n}) & ... & -2*k_{2n} \\ ... & ... & ... & ... \\ -2*k_{1n} & -2*k_{2n} & ... & 2*(k_{1n}+k_{2n}+...+k_{n-1,n}) \end{pmatrix}$$

In addition, we assume the availability of energy profile in the power distribution network. We define the energy profile of the power distribution network as a set of load vectors $L = \{l^1, l^2, \ldots, l^m\}$, where each load vector in the set denotes a possible load scenario in the network. We assume the probability that load vector l^i occurs, denoted by P_i, is known and $\sum_{i=1}^{m} P_i = 1$. This assumption is reasonable because network planning cannot be performed without knowing the requirement (i.e., the energy profile). The energy profile can be built with statistical analysis and prediction with historical data.

We remark that different from existing work [11] [33], we model the network as a geometric graph and explicitly consider the geographical condition constraints in the model. Since the geographical conditions between pairs of nodes are different, the construction costs between pairs of nodes are different. We set weights to the connections of pairs of nodes according to the condition and costs, do optimization to achieve best use of the definite amount of investment, and design a network of which energy loss is minimized. This geometric constraint, as we will see later in Section 5.2, plays an important role in network design when we have the freedom to select the position of relay nodes, do prediction, or add a new node to the current network.

For ease of reference, we list the main notations used in this work in Table 3.1. Some intermediate notations are omitted.

3.2 The Optimal Network Design Problem

In this part, we focus on the problem of designing a power distribution network that minimizes energy loss within a given total cost budget. First, we formulate

Table 3.1: Table of Notation

symbol	meaning
k_{ij}	the conductance of the link between nodes i and j
K	the conductance matrix of a power network
l_{ij}	current on the line from node i to node j
l_i	the load value at node i
l	a load vector ($\in R^n$) presenting a possible load scenario (load vectors are indexed as $l^h, h = 1, \ldots, m$)
P_i	the probability that a load vector l^i occurs
d_{ij}	the distance between nodes i and j
D	the distance matrix $[d_{ij}]_{n\times n}$
e_i	unit n dimensional vector whose i-th element is 1

the energy loss function as objective function. Second, we consider the dynamic energy changing characters and formulate an energy loss function, which adapts to the dynamic energy changing situation. Third, we construct constraints which combine unit connection cost and the distance of connections. At the end of this part, we present the objective functions with constraints for the case that considers dynamic energy changing character and the case without dynamic energy changing.

3.2.1 Objective Function

We first need to formally describe the objective function: energy loss during transmission. We assume that conductance value $k_{ij} = k_{ji}$. Denote the potential of node i as u_i and denote the potentials of all nodes as a row vector u. Following Ohm's Law, the current flow from node i to node j is $l_{ij} = k_{ij}(u_i - u_j)$. Since $k_{ij} = k_{ji}$, it holds that $l_{ij} = -l_{ji}$, and it is easy to verify that for each node i, the sum of injected current and the current on the branches equals to zero, $l_i + \sum_{k\neq i} l_{ki} = 0$. The total power loss on the due to resistive heating of the line is given by:

$$\mathcal{L}(k_{ij}) = \sum_{e_{ij}=1} k_{ij}(u_i - u_j)^2 = u^T K u. \tag{3.1}$$

We use $\mathcal{L}(k_{ij})$ to emphasize that the power loss is a function of conductance. It is not easy to use Equation (3.1) in practice because we normally know the injected currents (load). To make it practical, we need to solve the following equation in order to replace u with l.

$$Ku = l. \tag{3.2}$$

Equation (3.2) has the following properties:

1. K has a single zero eigenvalue associated with the "ones" eigenvector, i.e., $K\mathbf{1} = \mathbf{0}$. The practical meaning is that for load $l = \mathbf{0}$, we must have uniform electric potentials.

2. For any eigenvector $Ku = \lambda u$ other than the "ones" eigenvector, it holds that $\mathbf{1}^T u = 0$ and $\lambda > 0$.

Equation (3.2) has a one-dimensional space of solution of the form $\{u' + c\mathbf{1} | c \in R\}$ for any u' solving $Ku' = l$, that is, the solution is "uniquely" determined if we consider the same two solutions differ with an overall additive shift of the electrical potentials. We can "regularize" the problem of computing u such that the solution becomes truly unique. To this end, we define $K' \equiv K + \mathbf{1}\mathbf{1}^T$. Since K' is a symmetric matrix, it is easy to see that K' is invertible. Then the regularized solution to Equation (3.2) is given by

$$u' = K'^{-1} l. \tag{3.3}$$

It is worth mentioning that using the regularized solution to Equation (3.2) does not have any impact on $argmin\mathcal{L}(k_{ij})$, because an overall additive shift of the regularized solution multiplies $\mathcal{L}(k_{ij})$ by a constant factor.

Applying (3.3) into (3.1), we have

$$\mathcal{L}(k_{ij}) = l^T K'^{-1} K K'^{-1} l = l^T K'^{-1} l. \tag{3.4}$$

3.2.2 Modeling Dynamic Load Profiles

One key feature in a network with distributed energy sources is the dynamic power load. Following the assumption in Section 3.1, possible energy load on the network and probability of the occurrence of these scenarios can be obtained.

A designed network should satisfy the maximum load requirement. Moreover, an optimized design network should best use the network connection. That is to say, we want to have fewer redundant connections and make full use of all the connections.

Even if energy load requirements are less than the maximum load on the network, instead of becoming a redundant connection, the network construction can still benefit the current requirements.

Based on the above facts, we combine different scenarios with different probability, and the long-term expected energy loss over the power network can be calculated as:

$$\bar{\mathcal{L}}(k_{ij}) = \sum_{i=1}^{m} P_i (l^i)^T K'^{-1} l^i. \tag{3.5}$$

The above objective function describes the average energy loss over different scenarios. Since our model has considered the maximum load situation for each scenario, the maximum load situation can be satisfied. There is no safety issue on this constructed model. We want to do optimization to the above function to get the minimum energy loss.

3.2.3 Modeling Constraints

The construction cost of line between nodes i and j depends on its conductance and the geographical conditions. Following the same model in [33], the cost of a line (i, j) can be calculated as $\alpha_{ij} k_{ij}$, where α_{ij} is the cost coefficient. In our work, we take geographical conditions as one of the factors which affect the value of α. It could be calculated as $\alpha_{ij} = \rho d_{ij}^2 \theta$, where ρ is a constant depending on the price of copper (per unit volume), and θ is a coefficient which is determined by geographical conditions, if the geographical condition, for example, the distance between two nodes is long, θ could be large, otherwise it could be small.

Therefore, the total construction cost of the whole network is:

$$\mathcal{C} = \frac{1}{2} \mathbf{1}^T (K \cdot D \cdot D) \mathbf{1}, \tag{3.6}$$

where $\cdot$ is the Hadamard product (i.e., point-wise product) of two matrices. For the nodes whose geometrical addresses are definite, the distance between the nodes is a constant. Suppose the expected investment for constructing the network is S.

$$C(k_{ij}) \leq S,$$

that is

$$\Sigma_{i=1,j=1}^{i=n,j=n}\alpha_{ij}k_{ij} \leq S$$

3.2.4 The Network Optimization Problem

We next solve the following two optimal network design problems.

Problem 1.

$$\begin{aligned} \min_{k_{ij}} \quad & \mathcal{L}(k_{ij}) \\ s.t. \quad & \\ & \mathcal{C}(k_{ij}) \leq S \end{aligned}$$

Problem 2.

$$\begin{aligned} \min_{k_{ij}} \quad & \bar{\mathcal{L}}(k_{ij}) \\ s.t. \quad & \\ & \mathcal{C}(k_{ij}) \leq S \end{aligned}$$

Chapter 4

Problem Solving

In this chapter, we first transfer the objective optimization problem with constraints in 3.2.4 into the objective optimization problem without constraints. Then, to make sure that the non-constraint objective function can also satisfy the constraint condition, we introduce the Bisection method. We presented the pseudo codes for solving the optimization problem and the pseudo code for the Bisection method. The additional methods used inside the optimization process are Steepest-Descent Method, Newton Method, and Quasi-Newton Method.

4.1 Objective Function Formulation

As presented in paper [21], function $\mathcal{L}(k_{ij})$ and $\bar{\mathcal{L}}$ in Problem 1 and Problem 2 are both convex functions, and the local minimal values for these functions are the global minimal values. The constraints in both Problem 1 and Problem 2 are linear constraints. When combining linear constraints and convex function, the minimal value of convex functions is not changed. Based on this fact, the above problems can be replaced equally by:

Problem 3.

$$\min_{k_{ij}} \quad \mathcal{L}(k_{ij}) + \lambda \mathcal{C}(k_{ij})$$

Problem 4.

$$\min_{k_{ij}} \quad \bar{\mathcal{L}}(k_{ij}) + \lambda \mathcal{C}(k_{ij})$$

$\lambda > 0$ is a Lagrange multiplier. Originally, we set $\lambda = 1$. We need to calculate a proper λ value to make sure that it can satisfy the linear constraint. In the next part of this section, we will introduce the method we use to calculate λ in optimizing the above objective function. It is worth mentioning that the initial value of λ does not affect the final optimization result. The objective function is a convex function. Different initial λ values only affect the number of iteration to search a λ which can satisfy the original linear constraint.

Problem 3 can be treated as a specific case of Problem 4. Problem 3 is the case that $P_1 = 1, P_2 = P_3 = ... = P_n = 0$ in Problem 4. To make the case general, our optimization and case study are all based on Problem 4.

4.2 Optimizing Objective Function

In this section, we focus on calculating weight of λ in the objective function. From the objective function in Problem 4, the weight of λ directly relates to the linear constraint. An accurate weight for λ represents the accuracy of cost function adapting to linear constraints.

In this work, we used Steepest-Descent Method, Newton Method, and Quasi-Newton Method to do further optimization to minimize the objective function. We further compared the time efficiency of the three methods in optimizing the objective function. We present the experiments' results in Chapter 5.

We start by setting $\lambda = 1$. Then we use one of the optimization methods to do optimization to the current objective function. From this round of optimization, we can get a group of conductance weights which minimize the current objective function ($\lambda = 1$). We take the group of conductance weights back into linear constraint to check if the linear constraints can satisfy the expected investment. If the linear constraint is satisfied, then we output the optimized value; otherwise, we use bisection algorithm to change the value of λ and do optimization again. We do not stop doing this round of optimization until the linear constraint is satisfied.

The pseudo code for searching the value of λ is in Algorithm 1. The pseudo code of the bisection method, which is used to update the value of λ, is in Algorithm 2.

Algorithm 1 Minimizing Objective Function

Require: Initial value for conductance $\mathcal{X}_I$

$\lambda \leftarrow 1$

$xs \leftarrow OptimizationMethod(ObjectiveFunction(X_0, \lambda))$

for $\mid LinearConstraint(xs) - S \mid > tolerance$ **do**

  $\lambda \leftarrow BisectionMethod(\lambda)$

  $xs \leftarrow OptimizationMethod(ObjectiveFunction(xs, \lambda))$

end for

if $\mid LinearConstraint(xs) - S \mid < tolerance$ **then**

  $Outputoptimizedvalue$

end if

Algorithm 2 Bisection Method

Require: Input optimal value xs

$set1 \leftarrow 0;$
$set2 \leftarrow 0;$
$maxm \leftarrow 2 * \lambda;$
$mini \leftarrow 0;$
if $LinearConstraint(xs) > S$ **then**
  $mini \leftarrow \lambda;$
  if $set2 == 1$ **then**
    $\lambda \leftarrow 0.5 * (maxm - mini) + mini;$
    $set1 \leftarrow 1;$
  end if
  if $set2 == 0$ **then**
    $\lambda \leftarrow 2 * \lambda$
    $set1 \leftarrow 1$
  end if
end if
if $LinearConstraint(xs) < S$ **then**
  $maxm \leftarrow \lambda$
  if $set1 == 1$ **then**
    $\lambda \leftarrow 0.5 * (maxm - mini) + mini$
    $set2 \leftarrow 1$
  end if
  if $set1 == 0$ **then**
    $\lambda \leftarrow 0.5 * \lambda$
    $set2 \leftarrow 1$
  end if
end if

Chapter 5

Case Study 1

In this chapter, we demonstrate the effectiveness of constructing the network based on optimization methods introduced in this work.

First, we present three basic network construction scenarios. For every scenario, we compared the energy loss in transmission of the network constructed based on maximum load on branches with the network constructed based on the optimization method introduced in this work. We also compared the efficiency of three convex optimization methods, Steepest-Descent Method, Newton Method, and Quasi-Newton Method, in solving the optimization problem. From the efficiency comparison, we came to the conclusion that the Quasi-Newton Method is more efficient than the other two methods.

Based on the method introduced above, we did an energy loss prediction for future potential users before constructing the network. For the same amount of investment in network construction, we compared energy loss in the network without prediction and energy loss in the network with prediction of the future customer. Experimental results demonstrate that network construction with prediction of the future potential user is more efficient.

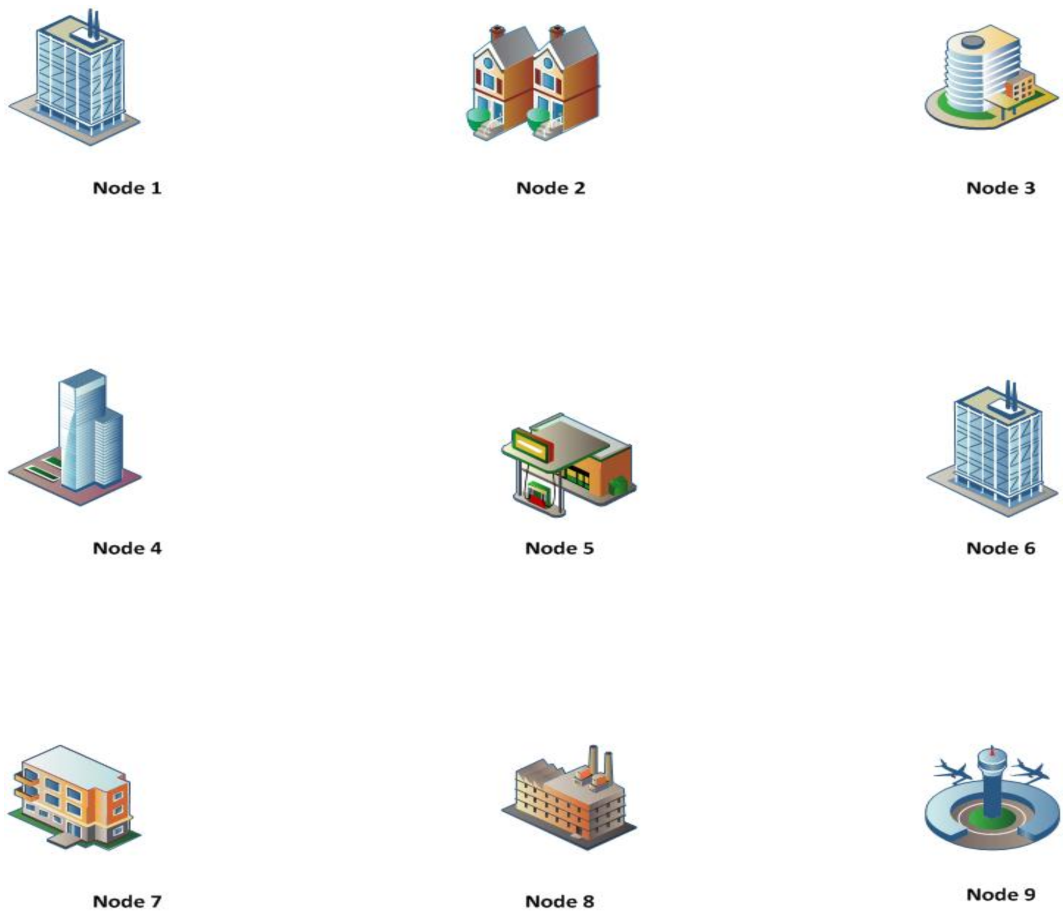

Figure 5.1: Nodes in the Network

5.1 Scenario Demonstration

As previous stated, we consider our network to be an energy dynamic changing network: energy in the network can be renewable energy, quality of energy depends on environmental condition, and energy consumption in the network is also changing in different periods of time. In the long term, the amount of energy changing can be ascertained by statistical collecting. In our case study in this work, we consider that we have four groups of possible energy consumption for each scenario. We construct the network in one area with 9 nodes as shown in Figure 5.1.

The three scenarios we present are:

- One node in the network works as generator, the rest are consumers or relay nodes.

- Two nodes in the network work as generators, the rest are consumers or relay nodes.

- Nodes in the network can be both generators and consumers.

For every scenario,

1. We construct the dynamic energy changing network scenario numerically.
2. We do optimization for two situations in three optimization methods (Steepest-Descent Method, Newton Method, and Quasi-Newton Method): we do optimization to the dynamic energy changing situation and the network constructed based on maximum load situation.
3. Finally, we compare the expected energy loss of these two situations.

For every scenario, we also calculate the elapsed time of the three methods in optimizing the objective function and we compare the efficiency of these three methods in optimizing the objective function.

We draw figures for the optimization results for every scenario. The thickness of the connection in the figures represents the conductance value of that connection.

We make the assumption that the construction weight is 1 for node i to connect the nodes whose geographical positions are upper, lower, left, or right. For example, $Node$ 2 is on the left geographical position of $Node$ 1, and the construction weight between $Node$ 1 and $Node$ 2 is 1. The construction weight between the nodes on the diagonal line is 2, for example, $Node$ 5 is on a diagonal line of $Node$ 1, and the construction weight between $Node$ 5 and $Node$ 1 is 2. In this case, the linear construction cost constraint is set.

5.1.1 Scenario 1

Network Based on Dynamic Energy Changing

The network has 9 nodes as shown in Figure 5.1. For this first scenario, we take $Node$ 5 as a generator and the rest of the nodes as consumers. Although the loads of energy on the network change dynamically, the long-term expected energy loss with different expectations over the power network can be obtained. Energy load on these nodes has four groups of expectation values with related probabilities as demonstrated below. $L = \{l^1, l^2, l^3, l^4\}$

$$l^1 = \begin{pmatrix} -1 \\ -1 \\ -1 \\ -1 \\ 8 \\ -1 \\ -1 \\ -1 \\ -1 \end{pmatrix} \quad l^2 = \begin{pmatrix} -8 \\ -1 \\ -2 \\ -1 \\ 26 \\ -10 \\ -1 \\ -1 \\ -2 \end{pmatrix} \quad l^3 = \begin{pmatrix} -9 \\ -7 \\ -1 \\ -6 \\ 29 \\ -1 \\ -1 \\ -3 \\ -1 \end{pmatrix} \quad l^4 = \begin{pmatrix} -1 \\ -9 \\ -1 \\ -1 \\ 32 \\ -1 \\ -7 \\ -1 \\ -11 \end{pmatrix}$$

$P_1 = 0.25, P_2 = 0.3, P_3 = 0.1, P_4 = 0.35$, and $P_1 + P_2 + P_3 + P_4 = 1$.

We take the statistics and the related probabilities into the objective function and apply the optimization process introduced in Chapter 4. We do optimization in Steepest-Descent Method, Newton Method, and Quasi-Newton Method separately. Figure 5.2 presents the network construction with the consideration of the expectation of energy generation and consumption.

Network Based on Maximum Load

Traditionally, to make sure that the network can satisfy all users' requirements, the network is constructed based on maximum load. Among the four groups of load, the maximum load on the network is the situation $l = l^4$. We take $l = l^4$ as the maximum load of the network. Fig. 5.3 is the network built based on the maximum load.

From the above optimization results, it can be seen that Figure 5.3 is still a tree structure network, while Figure 5.2 is no longer a tree structure network. Non-tree based structure is more practical and stable than tree-based structure [49]. The optimized mesh connection in the network leads it to a better adaptation to the energy change situation. When unexpected extra energy load occurs, it is more likely be distributed to the whole network; it isn't likely to become a threat to certain branches of the connection or defeat the current network. Besides that, when a certain connection on the network goes down, the related node and the whole network may

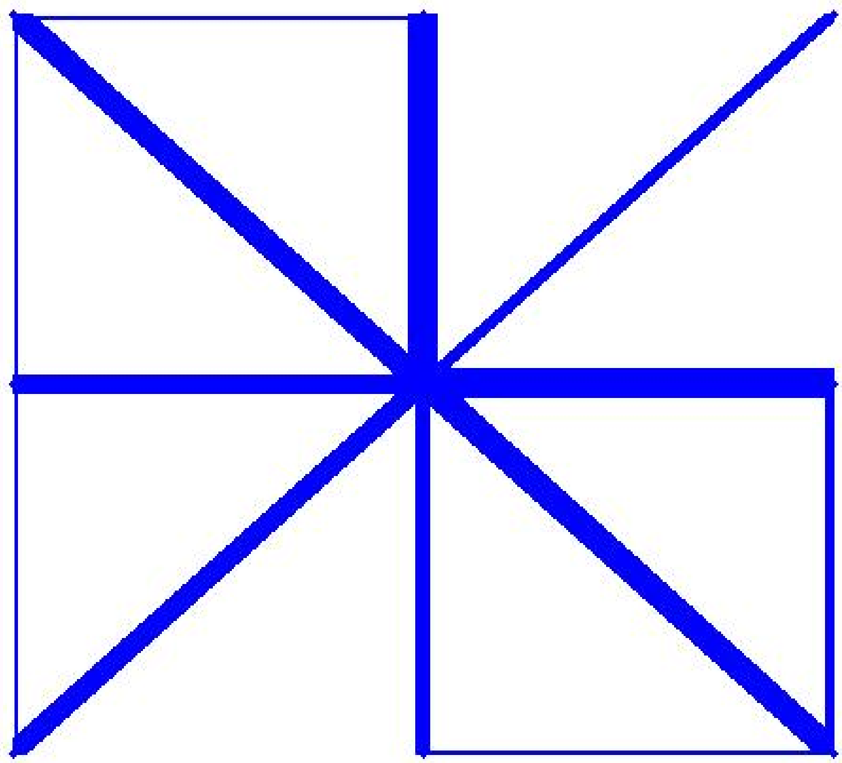

Figure 5.2: Optimized Network with One Generator

still be able to work. Even though the energy management scenario may be not at optimum, it provides time for people to fix the broken connection.

Figure 5.4 presents a comparison of expected energy loss in Figure 5.2 and Figure 5.3 with the same amount of investment for these two situations. Expected energy loss in the network constructed with consideration of the energy dynamic changing is 8.37% less than the expected energy loss in the network based on maximum load design. This benefit of energy saving by network design based on dynamic energy changing character increases with the increasing of energy load on the network.

We apply Steepest-Descent Method, Newton Method, and Quasi-Newton Method separately in optimization. We calculate the efficiency of these three methods and demonstrate the efficiency of the optimization methods for the one generator scenario in Table 5.1.

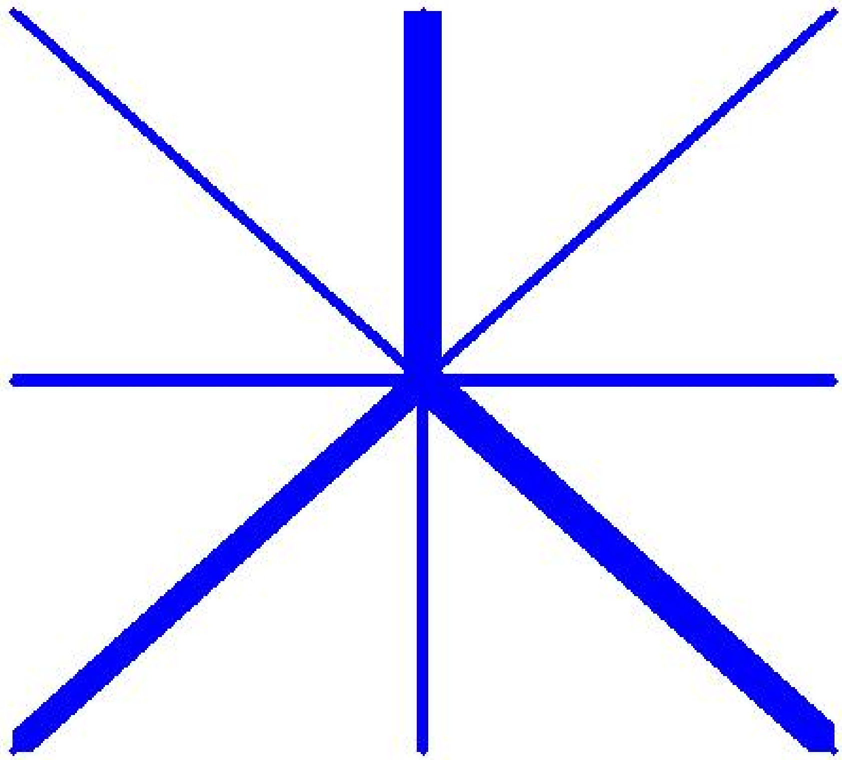

Figure 5.3: Network with One Generator Based on Max Load

5.1.2 Scenario 2

Network Based on Dynamic Energy Changing In this scenario, we make the assumption that $Node$ 1 and $Node$ 9 are both generators for this whole area and the other nodes are consumption nodes. Similar to the previous scenario, suppose after a sufficienty long period of time in statistics collection, the expectation of loads can be treated as four groups. They are l^1 with the probability of P_1, l^2 with the probability

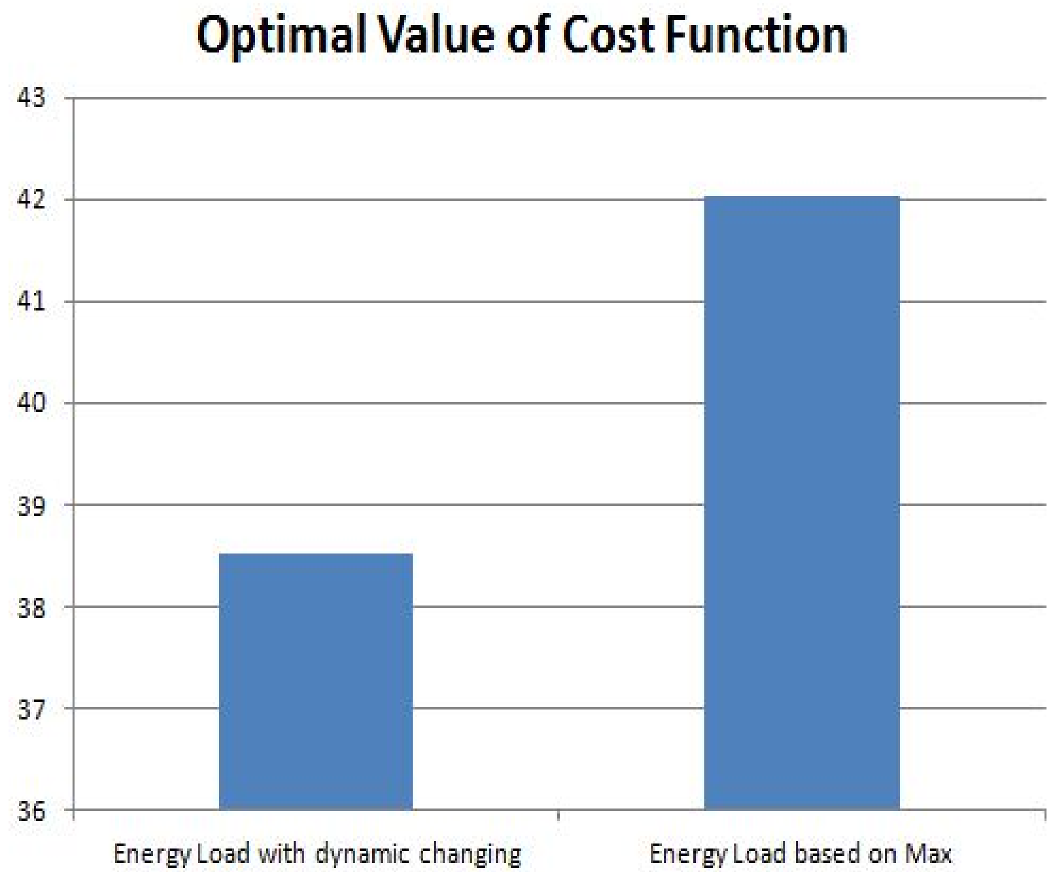

Figure 5.4: One Generator Network Consumption Comparison

of P_2, l^3 with the probability of P_3, and l^4 with the probability of P_4,

$$l^1 = \begin{pmatrix} 1 \\ -1 \\ -1 \\ -1 \\ -4 \\ -2 \\ -1 \\ -1 \\ 10 \end{pmatrix} \; l^2 = \begin{pmatrix} 8 \\ -3 \\ -2 \\ -1 \\ -6 \\ -1 \\ -1 \\ -7 \\ 13 \end{pmatrix} \; l^3 = \begin{pmatrix} 15 \\ -7 \\ -1 \\ -6 \\ -2 \\ -4 \\ -1 \\ -3 \\ 9 \end{pmatrix} \; l^4 = \begin{pmatrix} 20 \\ -9 \\ -7 \\ -3 \\ -2 \\ -11 \\ -7 \\ -1 \\ 20 \end{pmatrix}$$

$P_1 = 0.15, P_2 = 0.4, P_3 = 0.1$, and $P_4 = 0.35$.

Table 5.1: Efficiency of the Optimization Methods for One Generator Case

Methods	Elapsed time(s)	Number of Iterations
Steepest-Descent Method	23.583902	999
Newton Method	4.419429	14
Quasi-Newton Method (BFGS)	3.633526	62

We take these statistics and the expectations into the objective function and apply the optimization process with the three optimization methods. Figure 5.5 presents the network with consideration of the expectation of energy generation and consumption.

Network Based on Maximum Load

Among the four groups of currency, the maximum load on the network is the situation $l = l^4$. We take $l = l^4$ as the maximum load of the network. Figure 5.6 is the network built based on the maximum load.

Comparing Figure 5.5 and Figure 5.6, we get similar conclusions as in the previous scenario. The energy transmission in Figure 5.5 is well distributed on the whole network. This optimized mesh connection leads it to a better adaptation to the energy change situation. The network is relatively stable. However, from Figure 5.6 it can be seen that only the consumption nodes and generator nodes are connected. Once the connection breaks down, the consumption node will stop working.

Figure 5.7 presents the comparison of energy loss in Figure 5.5 and Figure 5.6. Expected energy loss in network design, which considers the dynamic changing property is 27.38% less than the expected energy loss in the network constructed based on maximum energy.

In Table 5.2, we present the efficiency of Steepest-Descent Method, Newton Method and Quasi-Newton Method in optimizing this two-generator scenario. It can be seen that even though Quasi-Newton Method takes more number of iterations than Newton Method, the elapsed time is shorter than Newton Method. Elapsed time of Quasi-Newton Method is also shorter than the elapsed time of Steepest-Descent Method.

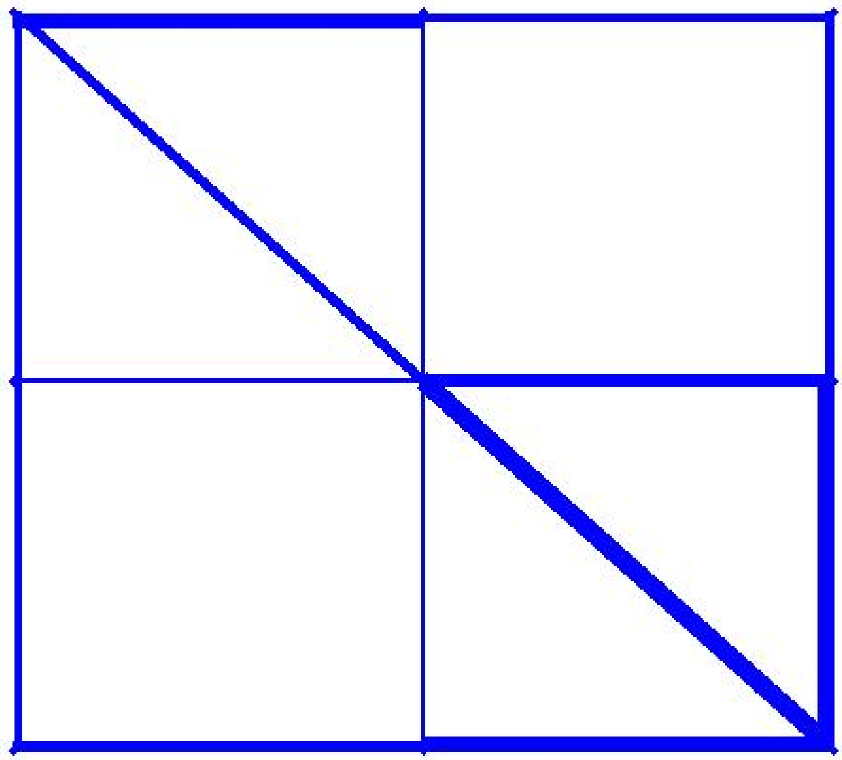

Figure 5.5: Optimized Network with Two Generators

5.1.3 Scenario 3

Network Based on Dynamic Energy Changing

For the third scenario, we consider the situation that $Node$ 1, $Node$ 2, $Node$ 5, $Node$ 6 and $Node$ 9 can be both generators and consumers. After a sufficient period of statistics collection, as in previous scenarios, the expectations of energy load and probabilities are demonstrated into four groups:

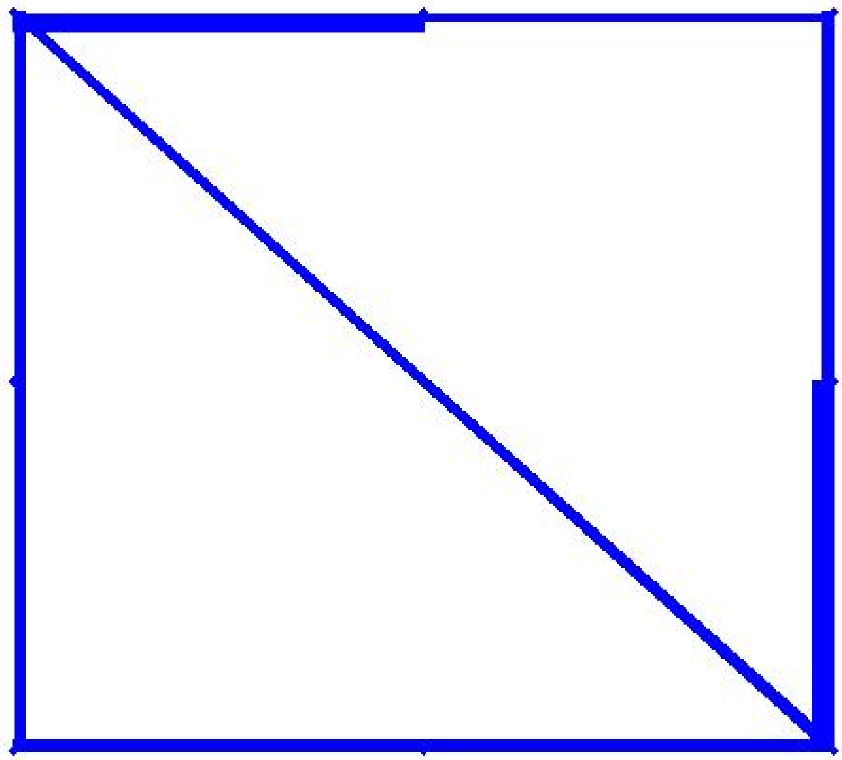

Figure 5.6: Network with Two Generators Based on Max Load

$$l^1 = \begin{pmatrix} -1 \\ -1 \\ -1 \\ -1 \\ 8 \\ -1 \\ -1 \\ -1 \\ -1 \end{pmatrix} \quad l^2 = \begin{pmatrix} 3 \\ -1 \\ -2 \\ -1 \\ -5 \\ 10 \\ -1 \\ -1 \\ -2 \end{pmatrix} \quad l^3 = \begin{pmatrix} -9 \\ -7 \\ -1 \\ -6 \\ 29 \\ -1 \\ -1 \\ -3 \\ -1 \end{pmatrix} \quad l^4 = \begin{pmatrix} -1 \\ 6 \\ -1 \\ -1 \\ 2 \\ -1 \\ -7 \\ -1 \\ 4 \end{pmatrix}$$

$P_1 = 0.15, P_2 = 0.4, P_3 = 0.1$, and $P_4 = 0.35$.

This time, we take these statistics with expectations into the objective function. Figure 5.8 presents the network with consideration of the expectation of energy gen-

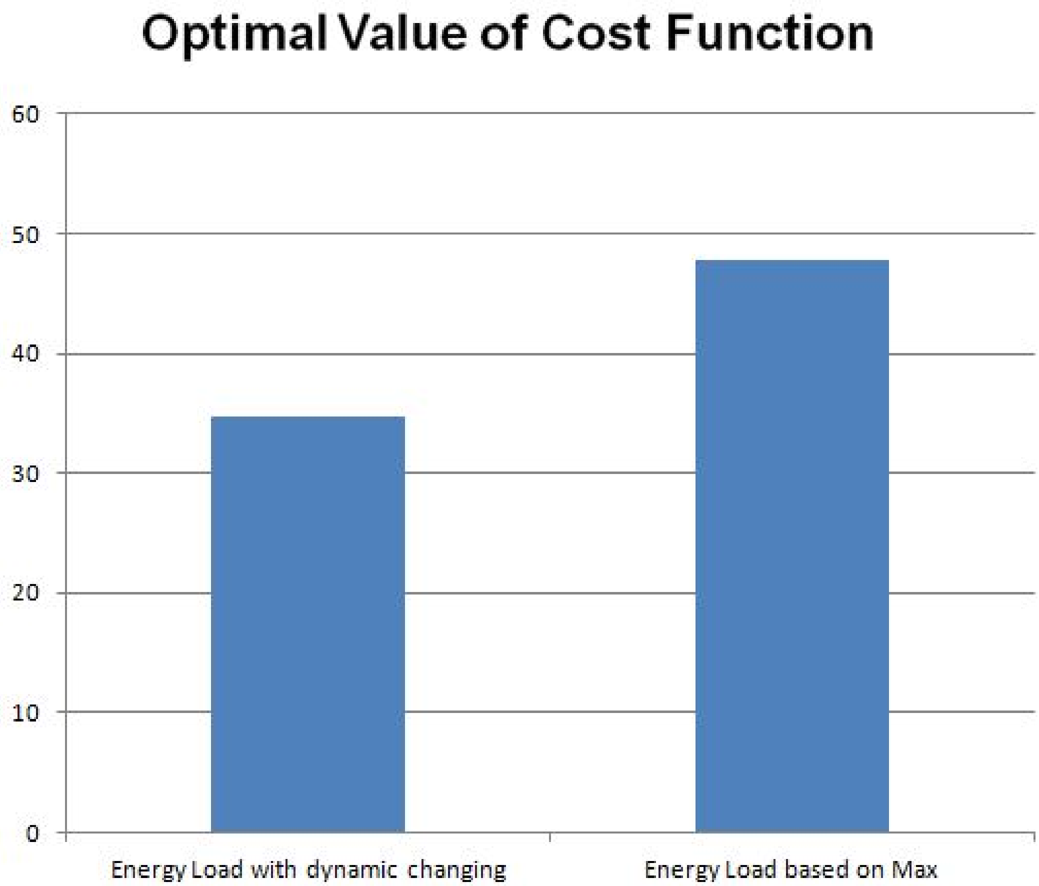

Figure 5.7: Two Generators Network Consumption Comparison

eration and consumption.

Network Based on Maximum Load

Among the four groups of currency, we choose the group with maximum current load on the nodes as the currents required by the network. Figure 5.9 is the network built based on the maximum load $l = group$ 3.

Comparing Figure 5.8 and Figure 5.9, energy transmission in Figure 5.8 is well distributed on the whole network. Network construction in Figure 5.9 is tree structure based. The network work design based on the dynamic energy change scenario is relatively more stable. Moreover, even though the network constructed in Figure 5.9 is based on maximum energy load on the network, it is not able to adapt to dynamic changing situation. That is to say, if consumer nodes become generators or some

Table 5.2: Efficiency of the Optimization Methods for Two Generators Case

Methods	Elapsed time (s)	Number of Iterations
Steepest-Descent Method	4.156938	161
Newton Method	4.355576	14
Quasi-Newton Method (BFGS)	1.272268	49

generators fail to generate energy, the network may not be able to work well. To make this kind of network work well, additional connections and expense are needed.

Figure 5.10 presents the comparison of energy loss in Figure 5.8 and Figure 5.9. The expected energy loss in the optimized network costs 53.97% less than the expected energy loss in the network based on maximum load design.

Table 5.3 presents the effectiveness of Steepest-Descent Method, Newton Method, and Quasi-Newton Method in optimizing the objective function in this scenario.

Table 5.3: Efficiency of the Optimization Methods for Two Generators Case

Methods	Elapsed time (s)	Number of Iterations
Steepest-Descent Method	5.825941	252
Newton Method	5.352468	17
Quasi-Newton Method (BFGS)	0.989629	40

5.1.4 Summary for Scenarios Presentation

From the above three scenarios, network structure designed with consideration of energy dynamic changing can better adapt to dynamic energy changing situations and the network structure is more stable compared to the network structure designed based on maximum energy load. With the same amount of investment for construction expense, taking the dynamic changing situation into consideration results in more expected energy saving.

Tables 5.1, 5.2 and 5.3 demonstrate that Quasi-Newton Method is superior in elapsed time compared to the other two methods. Even though Newton Method requires fewer iterations than Quasi-Newton Method, the elapsed time required by Newton Method is longer. Besides, when executing Newton Method, it is necessary to calculate the Hession matrix of the objective function. Calculating Hession is expensive and the calculation may even become impossible with the increasing number of nodes on the network. In summary, Quasi-Newton Method is a more effective

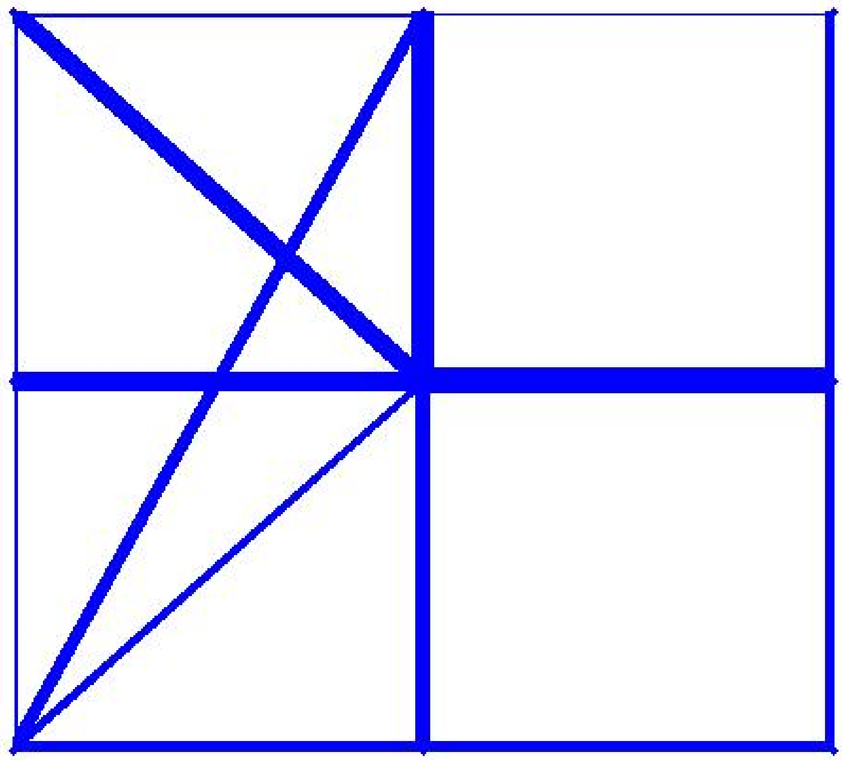

Figure 5.8: Optimized Network for Dynamic Nodes

method in optimizing the distribution network with dynamic changing loads of energy.

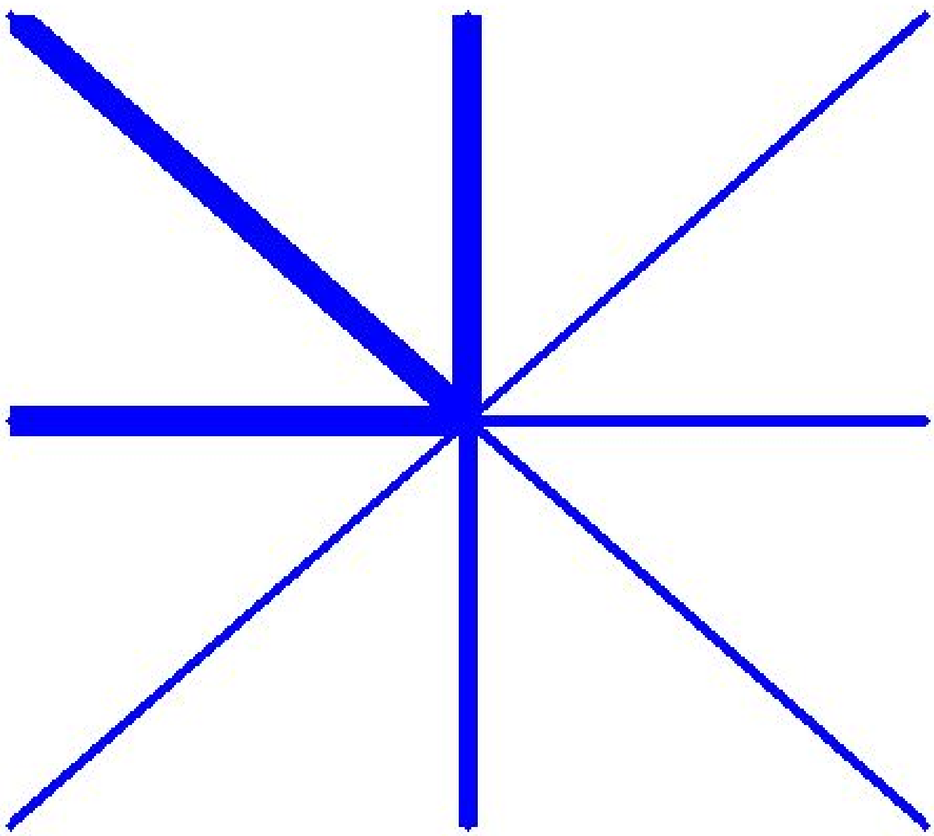

Figure 5.9: Network Based on Max Load

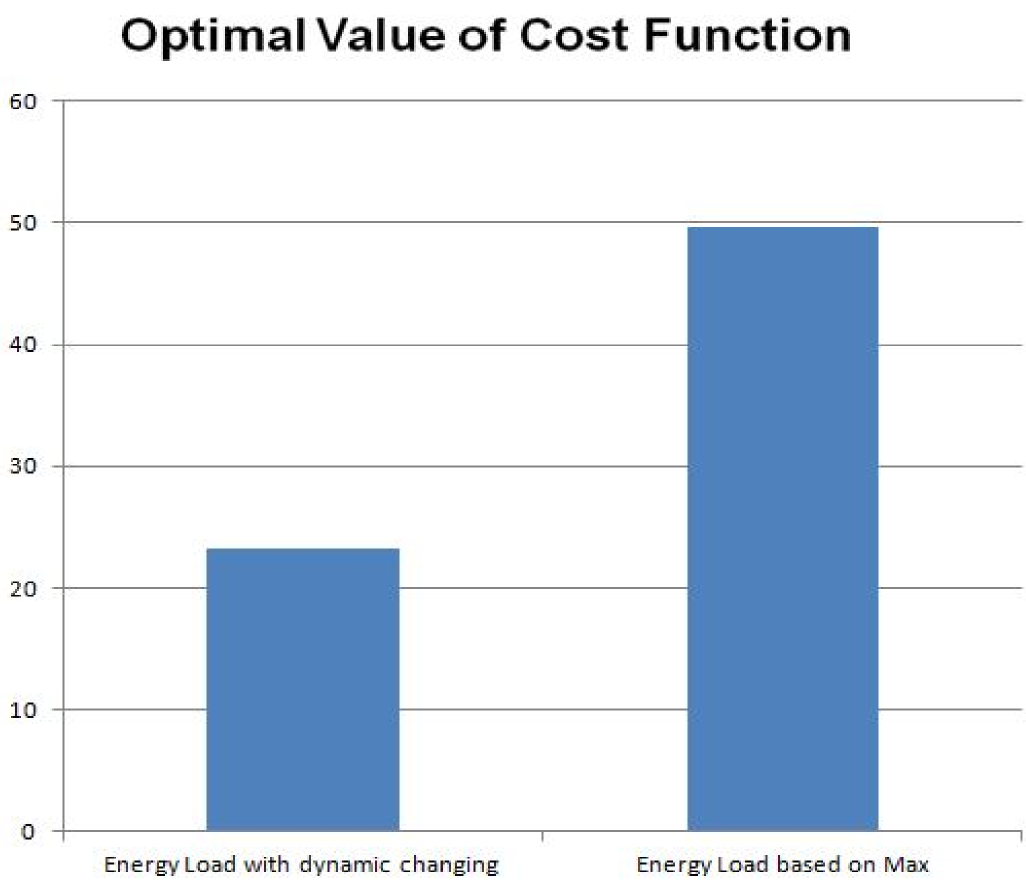

Figure 5.10: Network Consumption Comparison

5.2 Network Design with Prediction of Future Energy Consumption

In this section, we take the prediction of future energy consumption into consideration when constructing the network. We use the network design method introduced in this thesis to design a network which can not only satisfy current customers' requirements, but also can benefit future construction when potential customers become real customers.

- We first describe the construction scenario we are going to work with.
- Second, we introduce the optimization method process for designing the network.
- Third, we do experiments to demonstrate the benefit of predicting future energy consumption in network design.

We come to the conclusion that with the same amount of total investment, constructing a network with the prediction of future energy consumption can reduce current energy loss in transmission as well as reduce energy loss when potential customers become real customers in the future. The amount of investment on the network construction depends in the precision of prediction.

5.2.1 Scenario Description

Development of industry in one area may lead to energy requirements changing. People may be able to predict the future energy requirements based on the environmental conditions and the industrial development of the area at that time. For example, city A is a developing industrial city. A large group of customers may join in area B of city A in a few years with probability p_{join}.

Traditionally, people construct the network based on current requirements. That is to say, links between generators and customers are constructed based on the requirements at that time. Even though the prediction of future energy requirements may be obtainable, people cannot construct the network based on prediction since the physical customers do not exist. This may result in extra expense when the potential customers become real customers in the future, because the network will have to be re-constructed. This is expensive.

Using the technique introduced in previous sections, we want to design a network which can not only satisfy the current energy requirements of the customers but also be reused in the future when potential customers become real customers. In this case, we take the predicted future energy consumption into consideration when constructing the current network. Based on current requirements, we first do optimization to get a group of conductance weights that can satisfy the current requirements; second, based on the accuracy of prediction, we do optimization again with investment according to prediction; third, we combine the previous two steps and take the combined value as the optimal construction value. The detailed development process is introduced in the next section.

5.2.2 Network Design with Predicted Future Energy Consumption

The process of designing a network with the predicted future energy consumption is summarized in Figure 5.12 and the network designing process without predicted future energy consumption in summarized in Figure 5.11.

In the design process introduced below, we make the assumption that the network needs future extension. The total expected budget is T. The budget for network extension is $S_2 = T - S_1$.

Network Design Without Predicting Energy Consumption

1. We start the optimization based on the requirements of current customers. Suppose the investment for constructing the network in this step is S_1. We take

$$\mathcal{C}(k_{ij}) \leq S_1$$

as linear constraint.

From this round of optimization, we can get a group of optimized conductance $Value$ 1. For the network constructed without prediction, this would be the current optimal conductance value.

2. When network extension is needed, budget is S_2. We get the updated customers' requirements as well as customers' information, which includes energy load and construction cost determined by geographical conditions. We update these values in the objective function.

3. We set a new group of variables to represent the connections between these pairs of nodes.

4. We take $Value$ 1 and the new group of conductance variables back into objective function.

   We take S_2 as the investment for constructing the connection of predicted customers. This works as linear constraints for this round of optimization.

$$\mathcal{C}(k_{ij}) \leq S_2$$

5. After these steps, we apply optimization methods. From this optimization process, we would get a new group of conductance values $Value$ 2. In this case, $Value$ 2 is a group of value that can be treated as the modification of $Value$ 1. When coming to construct the network, for the existing connection in the network, we extend the existing connection according to the values in $Value$ 2; for the connection between new customers and existed customers, the connection is constructed directly from $Value$ 2.

   The value of objective function is the minimized energy loss.

Network Design with Prediction of Energy Consumption

1. Similar to the first step in network design without predicted energy consumption above, we start the optimization based on the requirements of current customers. Suppose the investment for constructing the network in this step is S_1. We take

$$\mathcal{C}(k_{ij}) \leq S_1$$

as linear constraint.

From this round of optimization, we can get a group of optimized conductance $Value$ 1. This can satisfy the current customer requirements.

2. For the network designed with predicted future energy consumption, after we get optimized values which can satisfy the current requirements from step 1, we get the predicted customers' information, which includes predicted energy load and construction cost determined by geographical conditions.

3. We do similar optimization as introduced in the case of constructing network without prediction detailed above. The differences resulting from the above process are that:

   (a) the updated customer information is based on prediction;

   (b) the new group of variables we set in this process is to represent the connections between predicted nodes and existed nodes; and

   (c) the investment S_e in this process is also different from the above process S_2.

   The amount of this investment S_e would increase with the reliability of prediction for the future energy consumption. If the probability of potential customers becoming real customers is high, people may safely invest the expense for predicted network construction. This can save current energy costing. Moreover, when potential customers become real customers, modification of the network based on this network is more likely to achieve optimal design. We demonstrate the importance of doing investment later in section 5.2.3.

We take S_e as the investment for constructing the connection of predicted customers. This works as linear constraints for this round of optimization.

$$\mathcal{C}(k_{ij}) \leq S_e$$

4. From this optimization process, we would get a new group of conductance values $Value\ e$. Since this process of optimization is based on current requirements as well as predicted requirements, if the prediction is precise the future construction value would be the combination of $Value\ 1$ and $Value\ e$. When constructing the current network, we can delete the conductance values relating to predicted nodes and use the rest of the conductance values in $Value\ e$ combined with $Value\ 1$, $(Value\ e + Value\ 1)$ as the conductance weights for current network construction. In this case, $Value\ e$ is a group of value that can be treated as the modification of $Value\ 1$.

5. When the potential customers become real customers, we re-use the existing connection $(Value\ 1 + Value\ e)$ and do optimization again as in the process of optimization without predicted energy consumption. The extension investment is $S_2' = T - S_1 - S_e$. We get the customers' updated requirements and update these values in objective function. The values of variables are the new connections that need to be added. The minimal value of the objective function is the minimized total energy loss.

5.2.3 Evaluation Results

In this section, we compare the energy loss in the network constructed with future energy loss prediction and the energy loss in the network constructed without doing prediction.

As introduced in 5.2.2, we make the assumption that the investment that can satisfy the current customers energy requirements is S_1. We also make the assumption that the total expected investment for the network construction is T. In this case, the expected investment on network re-construction

$$S_r = T - S_1.$$

We assume that $S_r = 60\ Investment\ Unit$.

For the case of constructing the network without energy loss prediction, $S_2 = S_r$, $S_2 = 60\ Investment\ Unit$, $S_e = 0$ we apply the optimization without predicted energy consumption process introduced in 5.2.2.

For the case of network construction with energy consumption prediction, as we have introduced in 5.2.2, the value of S_e is determined by the reliability of prediction. From our further optimization, we can see when the prediction is reliable, the more investment in S_e, the more energy is saved. In the experiment presented here, the total investment is defined as T, the range of S_e is changing from 0 to 60 $Investment$ $Unit$, and, according to this, the value of S_2' is changing from 60 $Investment\ Unit$ to 0.

Energy loss in network design without prediction and in network design with future energy requirements is presented in Figure 5.13. The horizontal axis represents S_e. It can be seen that the energy loss decreases with the increase of investment in prediction construction. For network construction without prediction, the energy loss is a constant since both S_1 and S_2 are constant.

Generally, energy loss in the network designed with prediction is less than energy loss in the network without prediction. If the prediction is reliable more would be invested in expected construction S_e, which can satisfy current customers' requirements and contribute to the improvement of current conductance, and energy loss is reduced in current transmission. When the potential customers become real customers, the network connections can be reused, network reconstruction is easy, energy loss is approaching minimal, and the network design is approaching optimal network design.

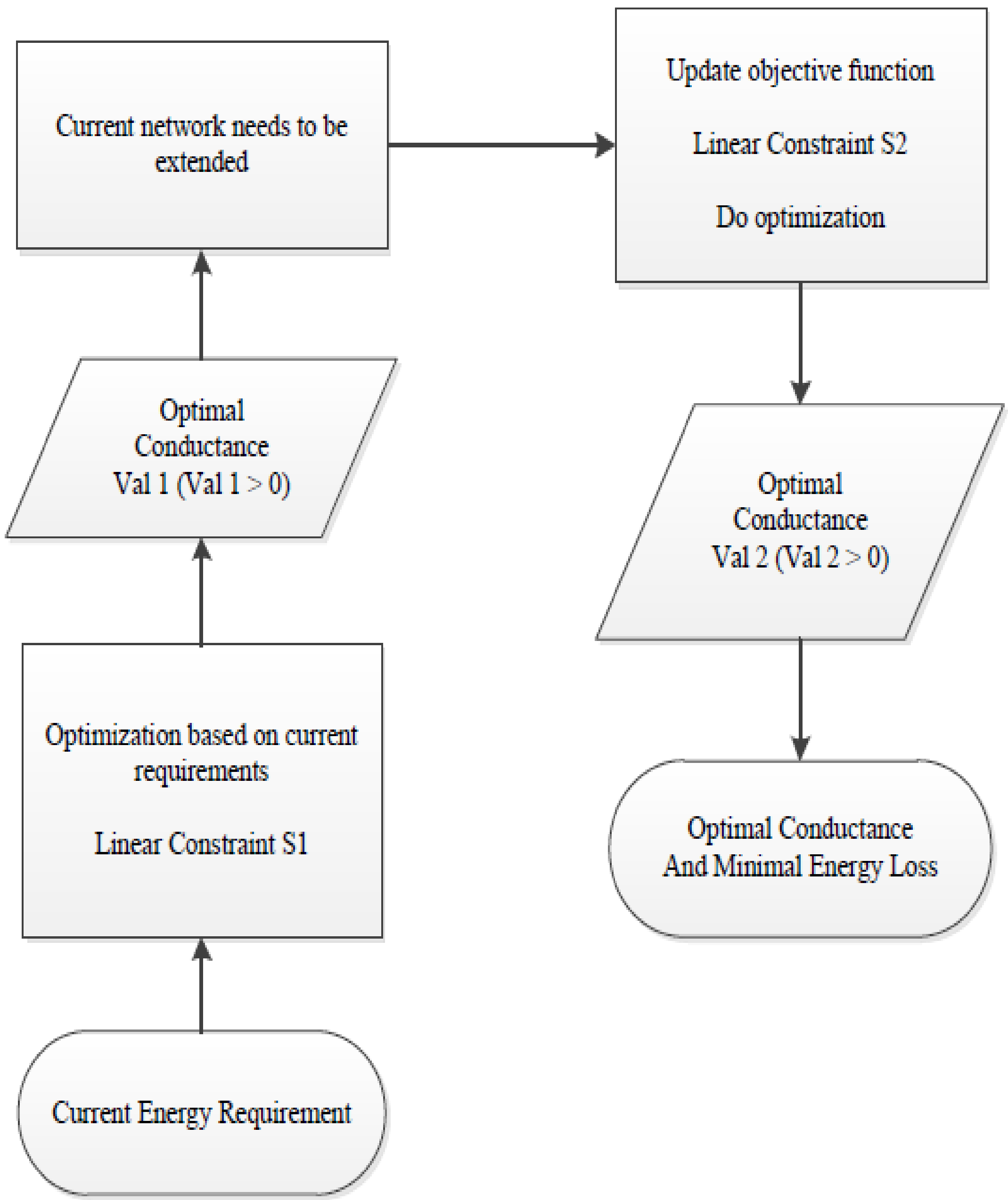

Figure 5.11: Network Design Process without Prediction

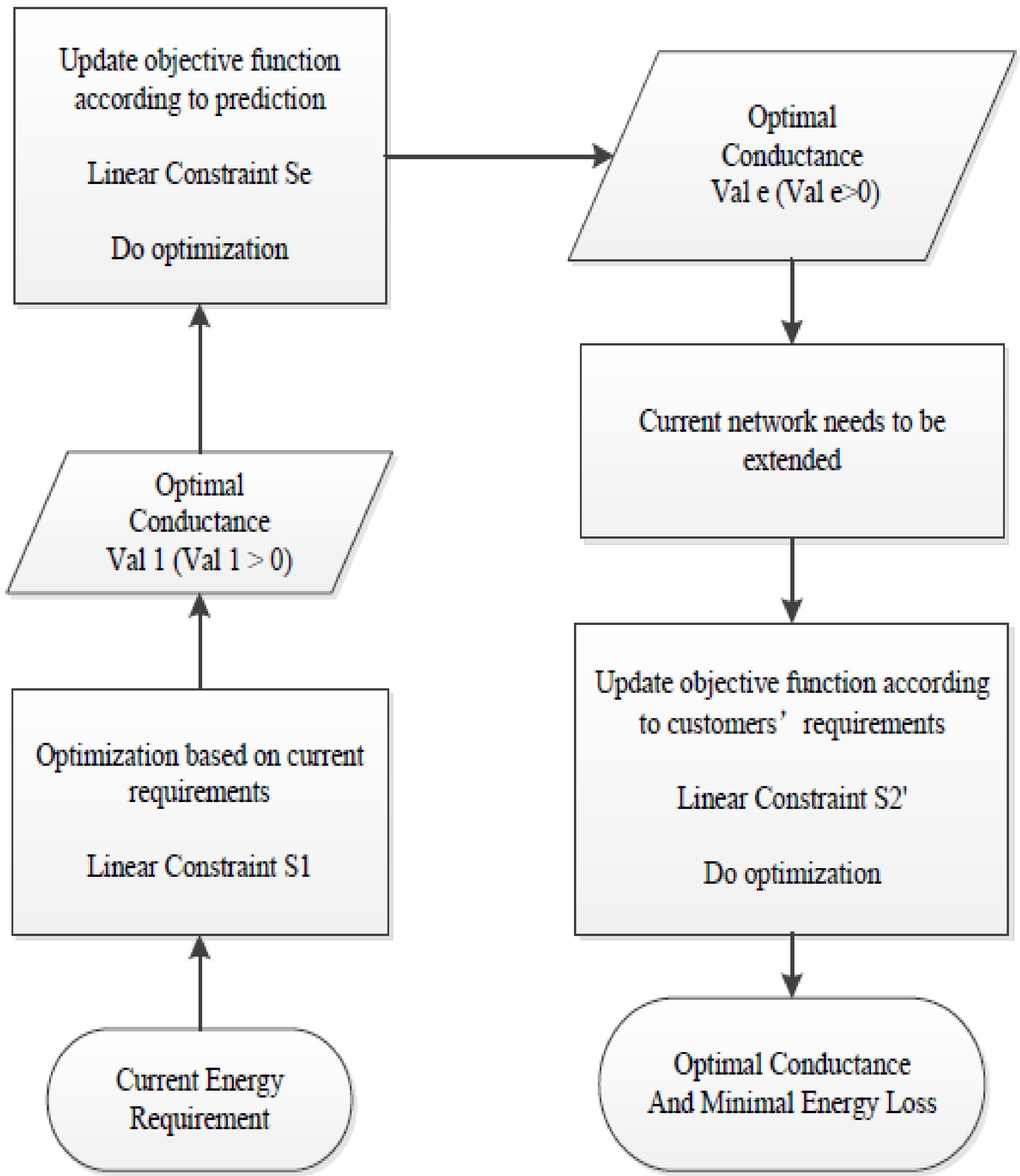

Figure 5.12: Network Design Process with Prediction

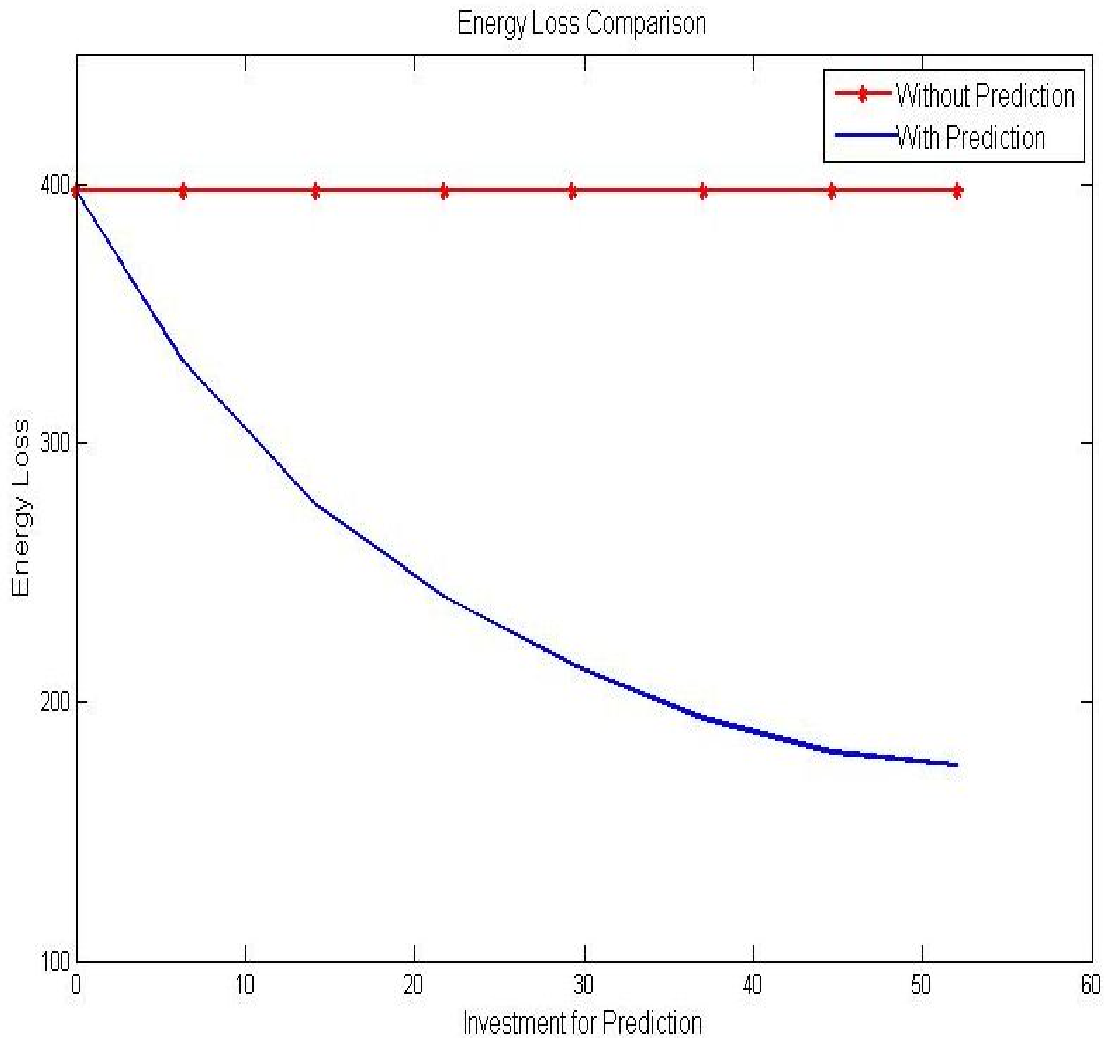

Figure 5.13: Energy Loss Comparison

Chapter 6

Case Study 2

In the previous chapter, we presented the simulation for a network with 9 nodes. In practice, the number of nodes in one area may be large. The number of connections increases quickly with the increase of number of nodes in the network. In this case, the network structure tends to include too many links. It will be hard when people try to implement the structure in practice. It is necessary to simplify the network after we obtain an optimal network design, i.e., approximating the optimal network design with a smaller number of links.

In this chapter, we apply the technology introduced in this thesis to obtain the optimal structure for a network with 25 nodes. First, we present the simulation result; second, we formulate a connection cleanup problem by adding additional constraints; and third, we solve this problem and present a cleaner network structure.

6.1 Optimized Network Structure

We apply the method introduced in Chapter 4 to do simulation for the network with 25 nodes. We assume that the network contains 3 energy generation nodes and 22 energy consumption nodes. The energy loads on the nodes are diverse. We also assume that the energy load on the network can be summarized into four groups of possibilities. We set specific weights for the pairs of nodes in the network. The weights are determined by the geographical conditions and the construction costs between each pair of nodes. The optimization result is demonstrated in Figure 6.1.

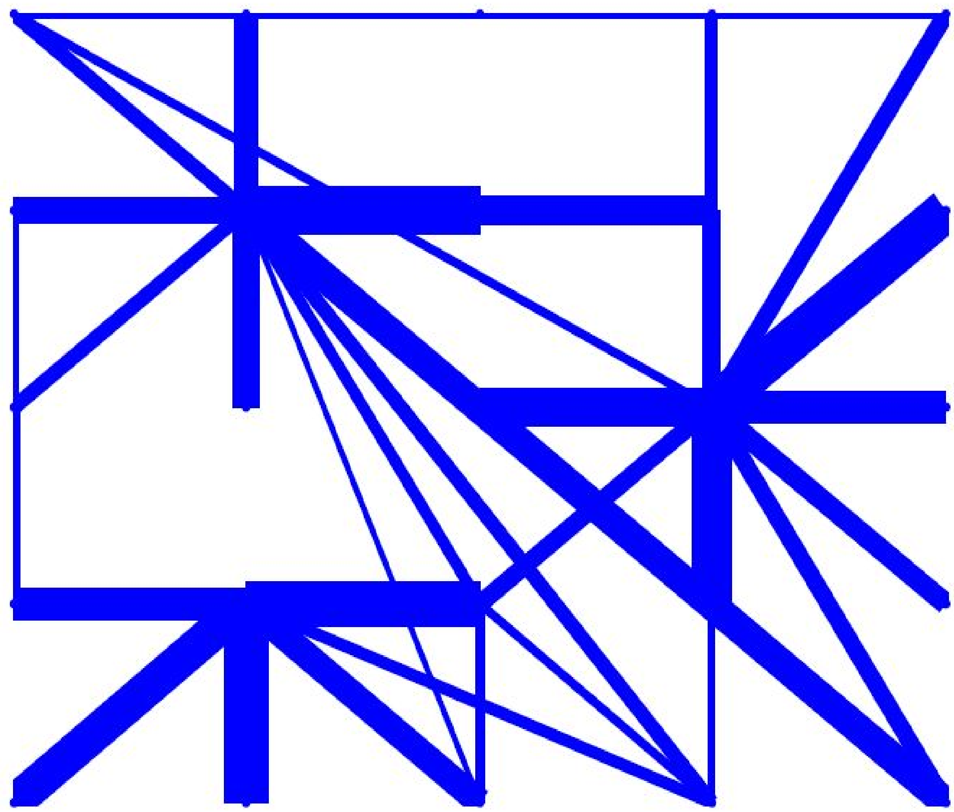

Figure 6.1: Network Design With 25 Nodes

6.2 The Connection Cleanup Problem

Figure 6.1 presents that there are large differences between the strength/conductance of the connections in the network; the value is big for some connections but small for others. Moreover, the number of connections is large, which makes it challenging to build the network in practice. To overcome this problem, we need to simplify the network design by using a smaller number of connections. This is achieved by adding a constraint to limit the total number of connections in the network. The optimization problem is formulated as follows:

Problem 5.

$$\min_{k_{ij}} \quad \mathcal{L}(k_{ij}) + \lambda \mathcal{C}(k_{ij})$$
$$\mathcal{N}(k_{ij}) \le \delta$$

Problem 6.

$$\min_{k_{ij}} \quad \bar{\mathcal{L}}(k_{ij}) + \lambda \mathcal{C}(k_{ij})$$
$$\mathcal{N}(k_{ij}) \le \delta$$

$\mathcal{N}$ is the number of connections on the network. δ is the threshold value of number of connections on the network.

6.3 Evaluation Results

6.3.1 Problem Solution

The problem presented in 6.2 is hard to solve directly because it is difficult to estimate the number of necessary connections from the existing conditions. Improper estimation of the number of connections may lead to infinite loops. Moreover, this process is not helpful in improving the original network structure to get a simpler structure.

We solve the problem from a different angle. Figure 6.1 presents the nodes that have more than one connection that are "thin" compared to the other connections. From the assumption we have made in Chapter 3, the strength of the connection represents the importance of that connection. At this point, we want to combine the thin connections to reduce the total number of connections.

After doing optimization to the 25 nodes network, we get the weights (conductance values) of connections for all the pairs of nodes. We then begin to run the following connection cleanup process:

- Set the threshold value for the weights read from previous optimization results:
  - For the weights which are smaller than the threshold, check to see if each node on the connection has more than one connection. If the node has more than one connection, then the cost constraint value of that connection is set to be extremely large, which means the connection for that pair of nodes is deleted. If the node only has one connection, whose weight is smaller than the threshold value, the original cost constraint value is kept;
  - For the weights which are bigger or equal to the threshold, the original cost constraint value is kept;
- Apply the optimization process with the new set of cost;
- Improve the threshold value and do the above process again to simplify the network connection.

The pseudo code for the above steps is present in Algorithm 3:

Algorithm 3 Cleaning Connections on Optimized Network

Require: Original optimized conductance value $\mathcal{X}$
  $ThresholdVaule \leftarrow ThresholdValue + ThVa_0$
  $\eta \leftarrow ThresholdValue$
  for $i = 1; i \leq n(n-1)/2;\ i++$ **do**
    if $x_i \leq \eta$ **then**
      if $CheckUniq(x_i) == TRUE$ **then**
        $OriginalCostConstraint \leftarrow OriginalCostConstraintValue$
      end if
      if $CheckUniq(x_i) == FALSE$ **then**
        $OriginalCostConstraintValue \leftarrow ExtrLargeVal$
      end if
    end if
    $OriginalCostConstraint \leftarrow OriginalCostConstraintValue$
  end for
  $OptimizationMethod(ObjectiveFunction(X_0, \lambda))$
  $ThVa_0 \leftarrow ThVa_0 + \theta$

6.3.2 Evaluation

Figures 6.2 and Figure 6.7 show the results from the cleanup process. As shown from Figure 6.2 to Figure 6.4, the number of connections in the network decreases with the increase of threshold value. With the further increase of threshold, new branches are needed to satisfy the load requirements of the network, as shown from Figure 6.5 to Figure 6.7, where the total number of connections increases. We thus conclude that Figure 6.4 presents the best network design that balances the simplicity (i.e., small number of network links) and optimality (i.e., small energy loss).

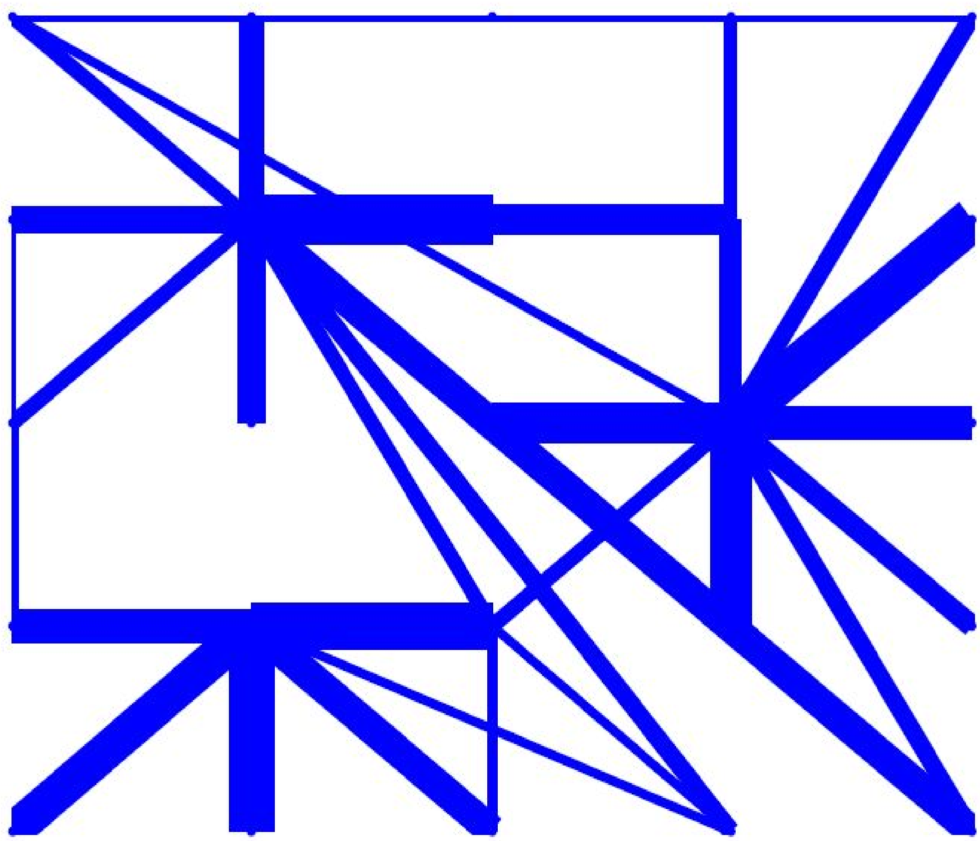

Figure 6.2: First Round of Cleanup

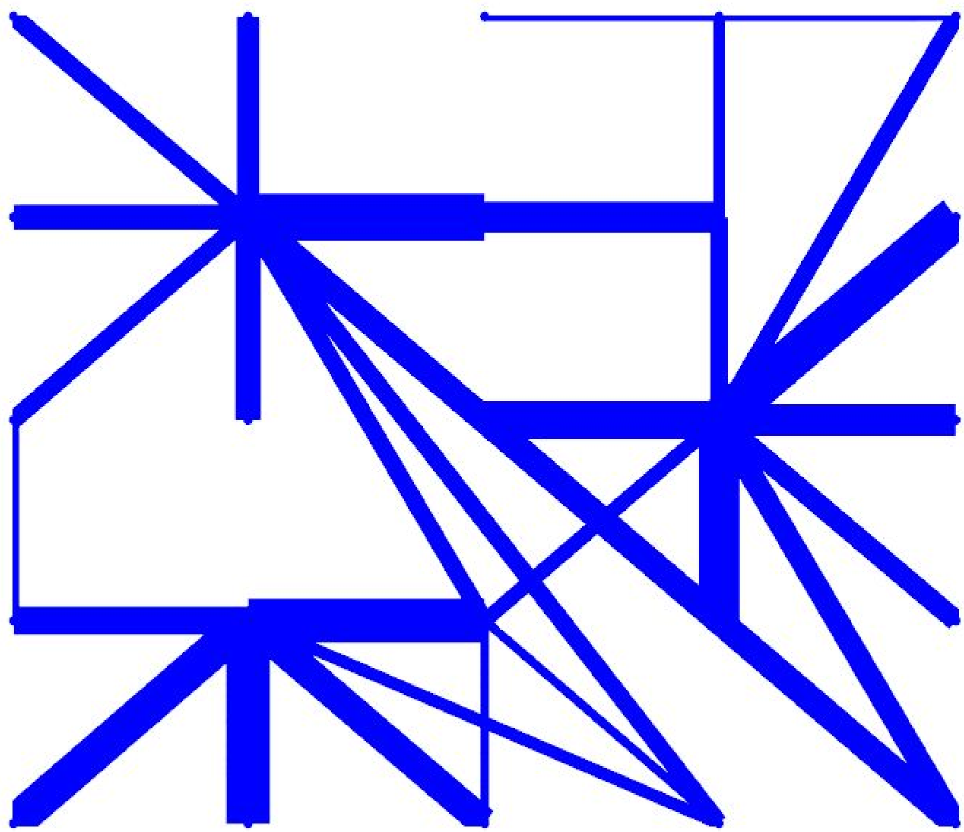

Figure 6.3: Second Round of Cleanup

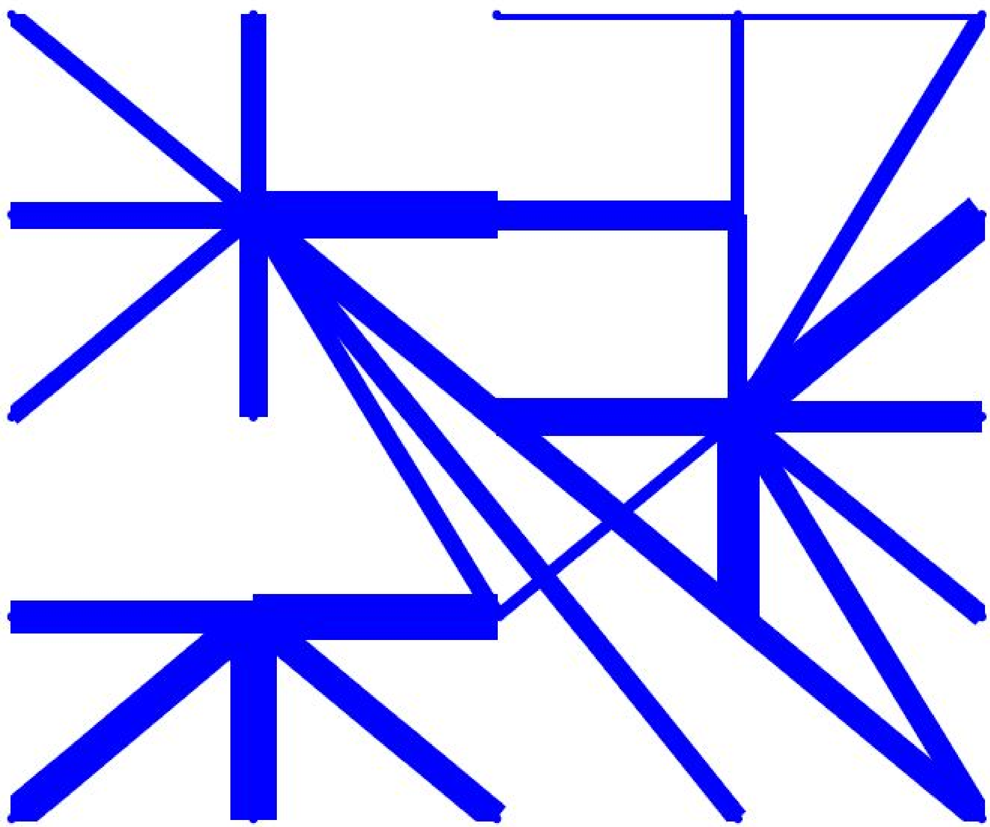

Figure 6.4: Third Round of Cleanup

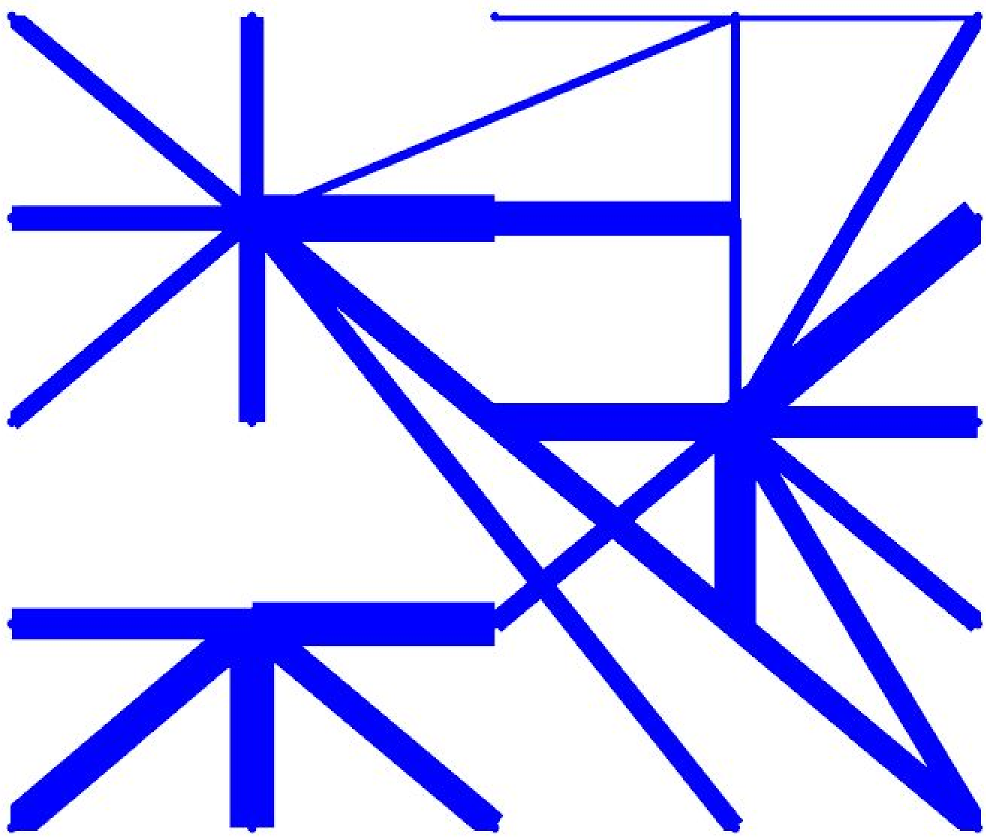

Figure 6.5: Fourth Round of Cleanup

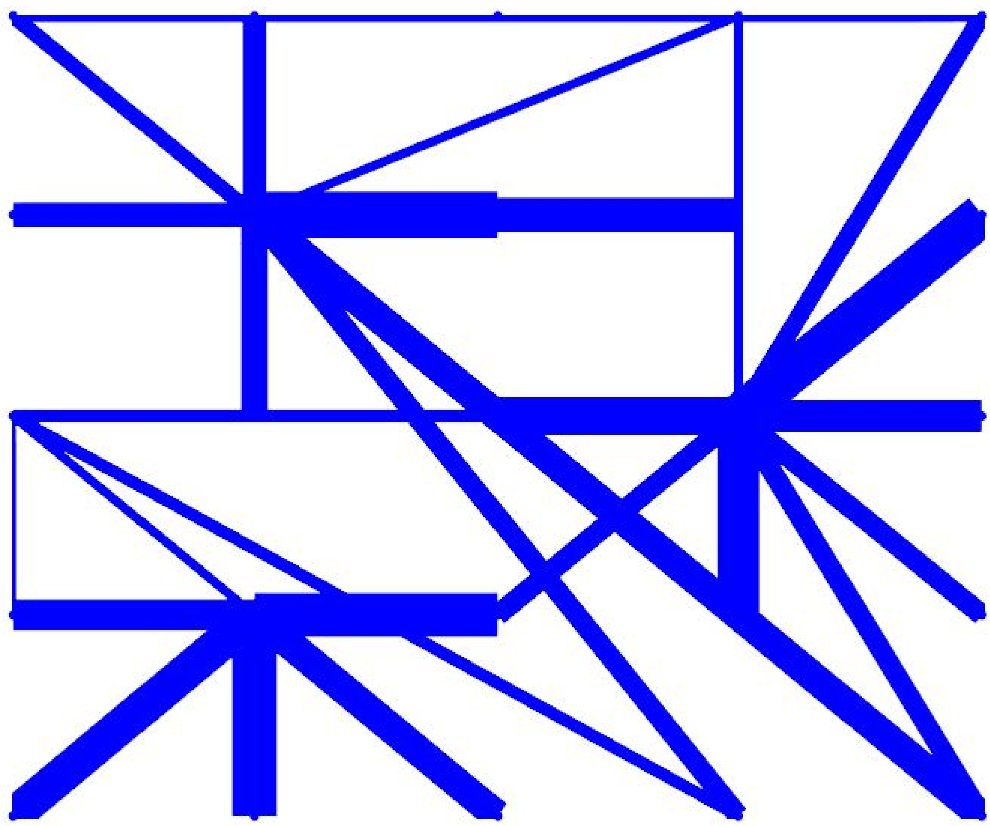

Figure 6.6: Fifth Round of Cleanup

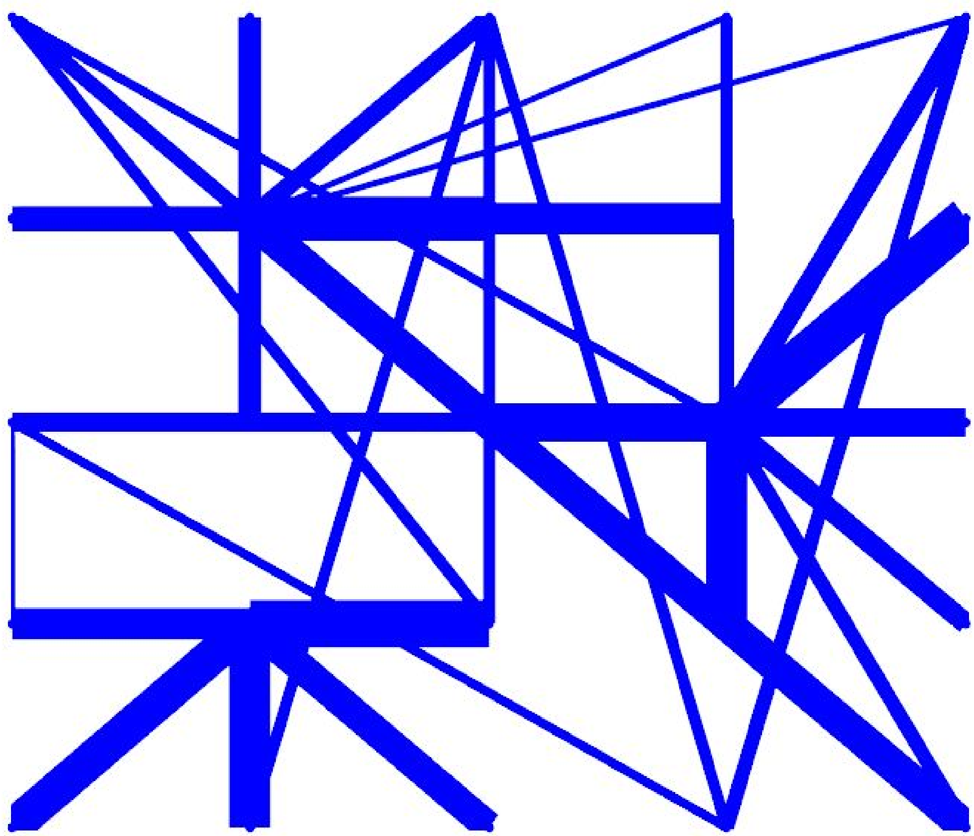

Figure 6.7: Sixth Round of Cleanup

Chapter 7

Conclusions and Future Work

7.1 Work Summary

In this thesis, we first introduce the background information, including the characteristics of renewable energy, problems and strategies for renewable energy development, network structures design for power network, and network design with distributed renewable energy networks.

Based on the background introduction, we present a network model better adapted to the characteristics of distributed renewable energy resources.

- We consider the users' energy profile, in particular their varying amounts of surplus energy, to capture the dynamics in future distribution power networks, where distributed renewable energy sources become the norm.

- The model we built is on a two-dimensional plane, where the nodes in the network can represent both energy generator and energy consumer.

- We define the total energy loss on the network transmission as the objective function. Our optimization problem is to minimize the energy loss function.

- We take geometric conditions and the network construction cost as the constraints. In practice, the geometric conditions and connection cost can be determined with users' input, which depends on the cost estimation of building a connection in practice.

- We convert the optimization problem with constraints to an optimization problem without constraints. We perform optimization to minimize the objective function. By comparing the efficiency of three different optimization methods, we conclude that Quasi-Newton method is more efficient in optimizing the distributed energy generation and consumption network.

- We test the optimization algorithm on three network scenarios. For each scenario, we present the optimal network construction based on the case of dynamic energy change and the optimal network construction based on maximum energy load. From the test results, we conclude that constructing a distributed energy network based on the characteristic of distributed energy can improve the efficiency of energy transmission.

- We propose an approximate method to obtain simpler, more practical network design, by applying a cleanup method to limit the number of connections on the network.

Experimental results demonstrate that the methods we present in this thesis bring the following benefits:

- The network can better adapt to dynamic changes in energy generation/consumption, compared to traditional network design.

- The structure of the network is well distributed in the whole area. This type of structure is different from the traditional tree-based structure and is more stable.

- With the same amount of investment, network design based on the characteristic of distributed energy results in more energy saving.

- Energy loss in a network built with the prediction of potential users is smaller than that built without the prediction. Network with the prediction can better serve the requirements of current customers and better adapt to future changes in the network. If the prediction of the future power requirement is reliable, the network is more likely to approach the optimal design for energy saving.

7.2 Future Work

As future work, we plan to test other optimization methods to optimize the objective function more efficiently. Further, to make our design method broadly applicable, we will design other scenarios and pose various practical constraints for the network structure. We also plan to test the network design method with real-world data in a distribution network, including energy generation and consumption, the geographical conditions, the construction cost, etc. It would be interesting to demonstrate the energy saving with our method in real-world distribution networks.

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