Multilevel Optimization for Resilient Planning and Operations of Interdependent Infrastructures

by

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DEDICATION

To my youth

Table of Contents

List of Figures **8**

List of Tables **9**

Abstract **10**

Chapter 1. Introduction **13**
- 1.1. Background and Motivation 13
- 1.2. Overview of Interdependent Infrastructures 17
- 1.3. Overview of Multilevel Optimization 21
- 1.4. Contributions 26
  - 1.4.1. Energy and water systems 26
  - 1.4.2. Optimal power flow with renewable energy integration 27
  - 1.4.3. Power grid and communication network 27

Chapter 2. Coordinated Long-Term Planning for Interdependent Energy and Water Systems **29**
- 2.1. Introduction 30
- 2.2. Optimization Model for Interdependent Energy and Water Systems . 36
  - 2.2.1. Long-term planning 37
  - 2.2.2. Operations of water system $W = (N, A)$ 39
  - 2.2.3. Operations of energy system $P = (B, E, G)$ 41
  - 2.2.4. Operations for interdependency between two systems 43
  - 2.2.5. Coordinated planning and operations 45
- 2.3. Solution Approach 46
- 2.4. Numerical Experiments 49
  - 2.4.1. Test for IEEE 6-bus power system and 1-tank-1-pump water system 50
  - 2.4.2. Test for IEEE RTS-96 power system and 3-tank-2-pump water system 55
  - 2.4.3. Running time 62
- 2.5. Conclusions 63

Chapter 3. Optimization of power system operations with renewable energy integration and water limitations **64**
- 3.1. Introduction 65
- 3.2. Robust Optimization for Power System Operations with Renewable Energy Integration 67

Table of Contents—*Continued*

3.2.1. Unit commitment 69
3.2.2. Optimal power flow model 70
3.2.3. Water limitations 71
3.2.4. Objective function without uncertainty renewable energy . . . 72
3.2.5. Renewable energy uncertainty 73
3.3. Solution Approach and Numerical Experiments 74
3.4. Conclusions 83

Chapter 4. Vulnerability analysis for power grid and its control communication network **85**
4.1. Introduction 86
4.2. Cascading Failure Process and Steady State 88
4.2.1. Cascading failure 88
4.2.2. Steady state and assumptions 91
4.3. Integer Programming Formulations for Vulnerability Analysis 91
4.3.1. Parameters and decision variables 92
4.3.2. Cascading failure process 93
4.3.3. Integer programming model for vulnerable node identification 102
4.3.4. Integer programming model for vulnerable edge identification . 105
4.4. Numerical Experiments 106
4.4.1. Identification of vulnerable nodes 107
4.4.2. Identification of vulnerable edges 110
4.5. Conclusions 112

Chapter 5. Conclusions and Future Work **114**

References **116**

List of Figures

Figure 1.1. Interdependent networks systems 19

Figure 2.1. IEEE 6-bus power system and 1-tank-1-pump water system . . 50
Figure 2.2. 3-year planning results 53
Figure 2.3. 10-year planning results 54

Figure 3.1. Water usage analysis in IEEE 6-bus system 80
Figure 3.2. Sensitivity analysis of water coefficients in IEEE 6-bus system . 82
Figure 3.3. Water usage analysis in IEEE 30-bus system 82
Figure 3.4. Sensitivity analysis of water coefficients in IEEE 30-bus system 83

Figure 4.1. Interdependent network with bidirectional interdependency links and cascading failures 89
Figure 4.2. Interdependent network with directional interdependency links and cascading failures 90
Figure 4.3. Vulnerable nodes in interdependent networks 107
Figure 4.4. Vulnerable nodes in interdependent network based on IEEE 14-bus system 108
Figure 4.5. Vulnerable nodes in interdependent network based on IEEE 30-bus system 109
Figure 4.6. Vulnerable nodes in interdependent network based on IEEE 30-bus system and communication network with different densities 110
Figure 4.7. Vulnerable nodes in interdependent networks 111
Figure 4.8. Vulnerable edges in interdependent networks 113

List of Tables

Table 2.1. Energy network generator data — IEEE 6-bus power system . . 51
Table 2.2. Energy network transmission data — IEEE 6-bus power system . 51
Table 2.3. Water network node data — 1-tank-1-pump water system 52
Table 2.4. Water network pipeline data — 1-tank-1-pump water system . . 52
Table 2.5. Interlinks data 53
Table 2.6. Energy network generator data — IEEE RTS-96 power system . 56
Table 2.7. Energy network transmission data — IEEE RTS-96 power system 57
Table 2.8. Water network node data — 3-tank-2-pump water system 58
Table 2.9. Water network pipeline data — 3-tank-2-pump water system . . 59
Table 2.10. (Cont'd)Water network pipeline data — 3-tank-2-pump water system 60
Table 2.11. Interlinks data 61
Table 2.12. 3-year planning results 61
Table 2.13. 10-year planning results 62
Table 2.14. Run time for different solution approaches to the examples . . . 63

Abstract

In general, infrastructure is defined as "the physical components of interrelated systems providing commodities and services essential to enable, sustain, or enhance societal living conditions" (Fulmer, 2009). With the development of scientific technology and social economy, many infrastructures become highly interconnected and interdependent. The interdependence is the mutual reliance between two or more groups. To satisfy future human needs for a better quality of life and sustainable society development, the planning and operations or management of infrastructures should not only meet the resilience standards, but also consider the complexity factors such as interdependencies among infrastructures to achieve societal and economic goals. Interdependencies are significant at specific of hazard intensities and tend to quickly propagate the effects. An event in one system will lead vulnerabilities of the other systems, which means the failure of partial elements in one system may trigger failures of dependent elements in other systems, and this may happen recursively as cascading failures. Vulnerability analysis is helpful to detect the critical parts of infrastructures which should be protected, especially under potential cascading failures.

In this study, we apply multilevel optimization approaches to model the interdependent infrastructure planning and operations or management. Multilevel optimization focuses on the hierarchy structure, in which the decisions are taken in different levels. The constraint domain associated with a multilevel optimization problem is implicitly determined by a series of optimization problems which must be solved in predetermined sequences. Generally, multilevel optimization is suitable for the problems in which each decision maker just controls part of decision variables, and there is a hierarchy of all decision makers.

First, we study interdependent energy and water networks. Energy network pro-

vides power for water extraction, collection, pumping operation and water or wastewater treatment. Water network supplies water to energy generation, cooling system and equipment cleaning. These two networks comprise an interdependent network, and rely on each other. The nexus between energy and water has emerged as a significant issue concerning the economics, reliability, and resilience of both systems. Most of current approaches deal with the planning and operations or management of an isolated network as an integration, but few research on system expansion has considered the interdependence between energy and water systems, resulting in plans that might have poor performance due to water or energy availability in the future. It is the time to consider water and energy as interdependent network to make multilevel decisions in the planning and operations or management periods. We propose a long-term energy and water system expansion planning framework that not only models the operations of both systems but also captures the interdependence between the operations of energy and water systems. This is a coordinated and unified intelligent system-wide optimization approach to incorporate intra- and inter-infrastructure decisions.

Second, we propose a mixed integer programming model to study the operations of power grid with renewable energy integration and water limitations. The development of the renewable energy helps decrease the energy resources shortage pressure and greenhouse gas emissions. However, the intermittency issues of renewable energy put a burden for integration. We propose the robust optimization modeling approach to deal with the uncertainty issue of the renewable energy. Considering the electricity generation, water is the most important resource. It is necessary for thermal power plants, hydropower plants, and also the renewable energy power plants. The amount of water used in the cooling system is large. But the water supply amount may be strictly limited in some areas due to the different water availability. The electricity power generation could be affected by the total water supply amount in the system.

On the other hand, the water usage to generate per unit of electricity power in different types of energy sources could be changed in the future as technology develops. These are two aspects we need to consider about the water sensitivity analysis.

Last, we choose the power grid and its control communication network as a case to analyze the vulnerability of interdependent infrastructures. The power grid provides power for the communication network's operation, and the communication network controls the power grid's performance. Due to the complex connections between them, the vulnerability of each network increases dramatically. The removal of critical nodes or edges in power grid will not only affect the nodes and edges in this network, but also influence the nodes and edges in the communication network. The presence of interdependencies could dramatically augment the vulnerability of infrastructures through cascading failures. The failures may initially happen in the power grid, then go through into the communication network, and go back to the power grid, repeating this process till the final steady state. This cascading failure could trigger the most severe loss in the interdependent networks. We propose integer programming models to identify the most vulnerable network elements (nodes and edges) whose removal will result in minimal survivable mutually connected components after the cascading failure process. Taking some measurements to protect the most vulnerable elements could help redesign and rebuild the networks more resilient.

Chapter 1
Introduction

This chapter introduces the background, motivations and contributions of the dissertation. In Chapter 1.1, the motivation of the proposed research is explained after introducing the background and needs of the research. In Chapters 1.2 and 1.3, the overviews of both interdependent infrastructures (especially the focused ones in this research) and corresponding methodology multilevel optimization are reviewed, respectively. Chapter 1.4 states the contributions and organization of this dissertation.

1.1 Background and Motivation

Infrastructure is defined as "the physical components of interrelated systems providing commodities and services essential to enable, sustain, or enhance societal living conditions" (Fulmer, 2009). It is composed of public improvements such as water supply system, electrical grids, telecommunication networks, supply chain, and transportation networks. In engineering, the infrastructure refers to the network aspects of most of the structures, and to accumulated value of investments in the networks as assets. As the population grows, climate changes, individual and institutional perception vary, technology advances, and urban America expands, the demands, both quality and quantity, of these commodities and services are increasing and becoming more and more uncertain. Besides these long-term disruption factors, short-term events, sometimes have more severe consequences for infrastructures to be functional, such as transmission line failures in power grids, extreme energy and water demands, energy, fuel and water supply interruptions. To this end, according to the National

Infrastructure Advisory Council (NIAC), the Infrastructure Resilience is the ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event (NIAC, 2009).

In order to ensure the infrastructure resilience, the decisions for planning and operations or management should meet certain standards. The planning deals with the systematic expansion or investment for one or more years into the future, such as locating the new generation and transmission facilities in power grids, new storage and treatment facilities in water networks, new logistics facilities for food supply, new streets, highways, bike lanes and public transport lines, and new substation and connections in communication network design. The operations or management direct the commodities or services among infrastructures to meet demands of human beings or others, in relative short periods, monthly, daily, hourly or even seconds. In addition to the definition of infrastructure resilience, four properties are explicitly defined by NIAC (2010): (i) robustness - the ability to absorb shocks and keep operating; (ii) resourcefulness - the ability to skillfully manage a crisis as it unfolds; (iii) rapid recovery - the ability to get services back as quickly as possible; and (iv) adaptability - the ability to incorporate lessons learned from past events to improve resilience. For different infrastructures, there may or may not exist standards for long-term and short-term decisions. For example, the electrical energy system is a critical infrastructure and needs to meet reliability standards, developed and defined by North American Electric Reliability Corporation (NERC, 2013) to ensure power systems reliability in North America, under various contingency conditions. However, there are no general standards for other infrastructure systems. Therefore, systematic and comprehensive analysis should be performed to evaluate the influences or consequences of disruptive events following the four properties, and clear standards for infrastructure resilience should be provided for policy makers.

One of the most challenging issues in decision-making is the uncertainties in infrastructures. The uncertainties can be classified into three categories: (i) demand uncertainty. Because of the population growth and migration, individual and institution perception changes, and society development, the demand on commodities and service such as water, energy, food, transportation, communications will increase. (ii) supply uncertainty. As the climate changes and technological advances, the water scarcity is becoming a critical issue in many areas, and other commodities and services are becoming more uncertain. For example, the intermittent renewable energy integration into the power system brings planning and operational issues; Shared transport and electric vehicles provide wide choices for transport and in the meanwhile bring other issues. (iii) infrastructure component failures. These short-term disruptive events can be further categorized into two cases: failures because of internal factors, and failures caused by external factors or influenced by another system.

The three types of uncertainties can be classified as long-term uncertainties (e.g., the demand and supply uncertainties), short-term disruptions (e.g., component failures) and short-term variations (e.g., variations on the changes of supply and demand, such as solar energy generation in one day). As an example for the latter case, more and more prominent affections from water scarcity, variability and uncertainty are potentially leading to vulnerabilities of energy system. Also, the old (more than 50 years old of US power grid) and complex (larger portion of intermittent renewable and distributed resources) electrical energy system is unreliable to failures due to natural causes and intelligent adversaries, and has negative effects on water system. Additionally, it is targeted that 80 of total US electricity demand in 2050 will be provided by renewable generation (Mai et al., 2012), and the uncertainty introduced by renewable energy will cause a lot of issues not just the energy infrastructure but also all related infrastructures. Some stochastic or robust optimization approaches have proposed for dealing with these uncertainties. However, it still lacks of systematical and intelligent approaches to deal with them. Additionally, because of huge number of possible future supply and demand scenarios and component losses, making resilient decisions based on the available information still requires adaptive solutions.

In summary, long-term uncertainties and short-terms disruptions of infrastructure systems together encourage actions that are not necessarily optimal and can conflict with each other in achieving societal and economic goals. The existing quantitative tools to support decision-making for planning and management are inadequate. Considering the broader impacts, to society and the US economy, of infrastructure resilience in the planning and operations or management, there is a great opportunity for the managers to perform research through optimization and data analytic approaches for decision-making to meet resilience standards.

For policy makers, system planners and managers, the planning and operations or management of these infrastructures is becoming a challenging and complex issue. The challenges include not only considering these long-term and short-term disruptive events, but also being cognizant of the impacts, pressures, and opportunities of the shared systems. That is, these infrastructure systems are highly interconnected and interdependent. For example, the Water-Energy Nexus (2014), Water-Energy-Food Nexus (Platform, 2016), water, energy, land use, transportation and socioeconomic nexus (Minne et al., 2011), are critically important in the US. Therefore, to satisfy future human needs for a better quality of life and sustainable society development, the planning and operations or management of infrastructures should not only meet the resilience standards, but also consider the complexity factors such as interdependencies among infrastructures to achieve societal and economic goals.

The current state-of-the-art approach typically treats planning and operations or management problems in a separate way for each single system, making decisions independent of each other. This usually results conflicting decisions between different systems, and the costs to correct are usually huge. Additionally, even inside one system, the planning and operations have mutual and sometimes conflicting impacts in their decision-making. For example, the lack of consideration of future failures or renewable integration in power grid will make the operations be unreliable for supplying adequate electricity to customers. In practice, for example, energy and water services are provided and controlled by different utility agents. Hence the stand-along approach often fails to find a set of consistent optimal solutions and sometimes even results in decisions that damage the overall resilience requirements. Therefore, a coordinated and unified intelligent system-wide optimization approach that incorporates intra- and inter-infrastructure decisions is necessary for upgrading current infrastructure systems to smarter ones and fully achieving their potentials.

1.2 Overview of Interdependent Infrastructures

With the development of scientific technology and social economy, infrastructure systems in reality become highly interconnected and interdependent. The interdependence is the mutual reliance between two or more systems, that is, two infrastructures are interdependent if both infrastructures require each other's services (RIPS, 2014). For example, the electrical power system depends on the delivery of fuels to power generating stations through transportation services, the production of those fuels depends in turn on the use of electrical power, and those fuels are needed by the transportation services. The levels of interdependence in organizational structure could be divided into pooled interdependence, sequential interdependence, reciprocal interdependence, and comprehensive interdependence. The power grid and its supportive infrastructures, as a typical example representing the interdependent infrastructures, are shown in Fig. 1.1. The core ideas of this study are making optimal planning and operations or management decisions and doing the vulnerability analysis for the interdependent networks. We focus on energy network, with full consideration of its corresponding interdependent infrastructures, such as energy and water networks system, power grid and its control communication network system.

Interdependencies are significant at specific ranges of hazard intensities and tend to quickly propagate main effects. For the interdependent infrastructures, the function of one infrastructure affects the function of the other infrastructures. The interdependency between two infrastructures not only influences future planning but also the short-term disruptive events, i.e., an event in one system will lead vulnerabilities of the other system. For example, weather and environment factors (e.g., severe droughts, hurricanes, climate change, population growth) and technology advances (e.g., integration of renewable energy into energy systems, desalination waters, advances in cooling systems) intensively affect the relationships between water and energy systems. The year 2014 is the third year of Californias worst drought in the past century, and water shortages and restrictions not only influence the residents regular use, but also badly affect Californias energy, economy and emissions goals (Rice, 2014; CA-EC, 2015). The 2012 hurricane Sandy made damages totaling $65 billion around 24 states and cut many electric generation stations and transmission lines, and vital water infrastructures lost power (ArcGIS, 2015). The interconnectedness of the infrastructure systems also makes them vulnerable to disruptions. Once interdependent infrastructures are disturbed by external or internal perturbations, system failures are not isolated events and they can spread rapidly to other correlative infrastructures and sometimes even back to the originated infrastructure making the infrastructure systems more fragile to various kinds of disturbances. This may cause the whole system lose its function and collapse (Wang et al., 2011). Here, the external factors include natural disasters, terrorism, and malicious behavior of humans, while the internal factors may include technical failures of components, systemic failures, and human errors.

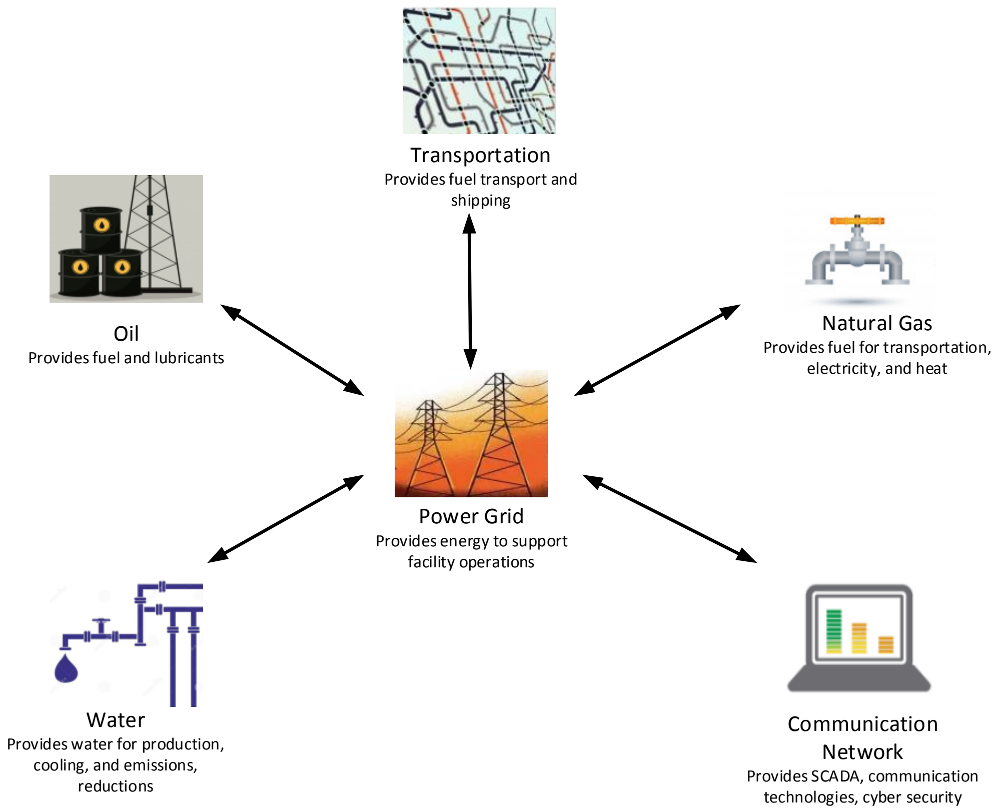


Figure 1.1: Interdependent networks systems

As mentioned above, the infrastructures are interdependent. The complex mesh of interdependencies mutually benefits and more importantly limits planning and operational effectiveness of critical infrastructures. The presence of interdependencies can dramatically augment the vulnerability of infrastructures through cascading failures. It is defined as one part of failure in one network will trigger the most severe successive failures in the whole system. For example, the power grid and communication infrastructures are interdependent. The power grid depends on the communication network for control, and the communication network relies on the power grid for electricity supply. Because of interdependency, a dramatic real-world example of cascading failures is the electrical blackout that affected much of Italy on September 28, 2003. The shutdown of power stations directly led to the failure of nodes in the internet communication network, which in turn caused further breakdown of power stations (Buldyrev et al., 2010). Therefore, network theories and computational analysis are necessary and critical for understanding and decision-making across complex interdependent infrastructures, from mutual supply-demand benefits to vulnerability analysis of cascading failures. The current research on interdependent infrastructure systems consist of inoperability input-output Leontief methods, agent-based modeling, data-based methods, network and complexity-theory approaches, and simulation-based network modeling approach. There exist some developed interdependent infrastructure examples such as power grid and transportation network, power grid and oil network, power grid and natural gas network, power grid and communication network. For these interdependent infrastructures, different models and approaches are applied to simulate the network and solve them.

In power grid and transportation network, a single integrated mathematical framework (Gil et al., 2003), a long-term investment planning co-optimization model (Krishnan et al., 2013), and city intelligent energy and transportation network (Wang, Wang, and Tian, 2014) are ever been applied to represent the interdependence relation between the them. In power grid and oil network industries, a field trail of data communication approach (Castor et al., 2016) is selected to connect the interdependent network. In power grid and natural gas network, the researchers refer to the topics about resilience analysis of electricity generation and natural gas systems (Judson, 2013), marketed-based architectural frameworks for gas-electric coordination (Zlotnik, 2017), a robust day-ahead scheduling model for the optimal coordinated operations (He et al., 2017), and a coordinated optimization model between the two networks (He et al., 2017). In power grid and communication network, they consider a two phase control policy to mitigate the cascade of failures (Parandehgheibi, Modiano, and Hay, 2014), interdependency matrices among the two networks (Rueda and Calle, 2017), unintentional random failures and malicious targeted attacks between interdependent network (Chai et al., 2016), and a resilient communication network to control the power grid (Martins, 2017). But there is few research related to the interdependent energy and water systems.

1.3 Overview of Multilevel Optimization

The planning and operations of power grid consist of long-term planning, such as expansion or strategic investment planning, operational planning, such as maintain scheduling, real-time normal-state operations, such as economic dispatch, and post-contingency state operations, such as flow dispatch to meet reliability criteria. In power grid, the long-term planning decisions affect the operational planning decisions, and the operational planning decisions affect the decisions in operations periods, containing the normal-state and the post-contingency state. In another direction, the decisions made in operations periods provide feedbacks to the decisions in planning periods. For water network, the planning and management are corresponding to water facilities planning, such as building storage and treatment facilities, operations in normal-state for water distributions, such as pump and water flow operations, and water operations under failures, such as unsatisfied demands. The decisions from facilities planning periods will influence the following decisions in operations or management periods. And in addition, the decisions obtained from the operations supply some feedbacks to the decisions in planning periods. The planning and operations or management of these infrastructures should be multilevel decisions, moreover, each decision affects the others. Thus, the multilevel optimization could be applied as an useful approach to model the planning and operations of the infrastructures and to present the connections among different level decisions.

In mathematics, computer science and operations research, mathematical optimization is the selection of a best element with regard to some criterion from available alternatives. Optimization is also known as mathematical programming, the collection of mathematical principles and methods used for solving quantitative problems in many disciplines. The optimization problem is the problem of finding the best solution from all feasible solutions. Mathematical programming includes the study of the mathematical structure of optimization problems, the invention of methods for solving these problems, the study of the mathematical properties of these methods, and the implementation of these methods on computers. Optimization problems typically have three fundamental elements, objective function which is to be maximized or minimized, a collection of variables whose values could be manipulated in order to optimize the objective, and a set of constraints which are restrictions on the variable values. Optimization problems are ubiquitous in science, engineering, and even daily life.

In an optimization problem, if there is an hierarchy of decision-makers in many decision processes, it is called the multilevel optimization problem. Multilevel programming focuses on the whole hierarchy structure, in which the decisions are taken in different levels. In terms of modeling, the constraint domain associated with a multilevel optimization problem is implicitly determined by a series of optimization problems which must be solved in a predetermined sequence (Migdalas, Pardalos, and Värbrand, 1998). The multilevel optimization method, as a powerful tool to dramatically out-perform traditional optimization methods, is designed to solve the problems efficiently by taking explicit advantages of the hierarchy of models. The hierarchical structures can be found in scientific disciplines such as environment, ecology, biology, chemical engineering, mechanics, classification theory, databases, network design, transportation, game theory and economics. Generally whenever there is a hierarchy of decision maker in such a way that each decision maker controls part of the decision variable, multilevel optimization problem model is the one suitable for the situation (Rao, 2009). The multilevel optimization is applied in agricultural economics (Candler, Fortuny-Amat, and McCarl, 1981), engineering design (Barthelemy and Riley, 1988), and transport network (Marcotte, 1984).

Due to its many applications, multilevel programming, in particular bilevel programming, has evolved significantly (Faisca et al., 2007; Pistikopoulos, Georgiads, and Dua, 2007). The general multilevel optimization problem can be formulated as follows (Migdalas, Pardalos, and Värbrand, 1998):

$$\begin{aligned} \min_{x_1,\cdots,x_k} \; & f_1(x_1, x_2, \cdots, x_k) \\ s.t. \; & g_1(x_1, x_2, \cdots, x_k) \leq 0 \end{aligned}$$

where x_2 solves

$$\begin{aligned} \min_{x_2,\cdots,x_k} \; & f_2(x_1, x_2, \cdots, x_k) \\ s.t. \; & g_2(x_1, x_2, \cdots, x_k) \leq 0 \\ & \cdots \end{aligned}$$

where x_k solves

$$\begin{aligned} \min_{x_k} \; & f_k(x_1, x_2, \cdots, x_k) \\ s.t. \; & g_k(x_1, x_2, \cdots, x_k) \leq 0 \end{aligned}$$

The problem corresponding to x_1 is called the first level problem and related to the highest level in the hierarchy. The first level decides the variables x_1 and minimizes the function f_1. And similarly, the problem corresponding to x_k is the k^{th} level problem and related to the lowest level in the hierarchy.

In the 1990s, approaches with periodic property (Bahatia and Biegler, 1999) and stochastic programming method (Acevedo and Pistikopoulos, 1998) are proposed for the multilevel optimization problems. Some new algorithms based on parametric programming theory (Dua and Pistikopoulos, 2000; Dua, Bozinis, and Pistikopoulos, 2002; Pistikopoulos, Dua, and Ryu, 2003; Li and Lerapetritou, 2007) are developed in the next decade. The multilevel techniques are ever used for the exact resolution of the trust-region subproblem in the nonlinear optimization problems (Mendonça, 2009). This method could guarantee the convergence of the trust-region algorithm to a second-order critical point. The applicability of an hierarchical optimization algorithm has been discussed through practical examples in production control problems (Filip et al., 1985). In engineering design problems, some techniques are described whereby a particular multilevel method can assess the properties of the optimization problem, with the goal of automatically determining whether the optimization problem is well suited for the multilevel algorithm (Nash, 2009). The optimization-based multilevel methods generalize model-management approaches for solving engineering design problems. The combination of different models or levels of representations can lead to an objective function surface characterized by multiple values at a single point. The sequential multilevel optimization, gradually mixed multilevel optimization, and totally mixed multilevel optimization are presented and compared as different strategies of multilevel optimization with genetic algorithm (El-Beltagy and Keane, 1998). The solution of the equality-constrained optimization problems is presented by a multilevel optimization approach to accelerate the progress of the optimization on the finest level (Nash, 2011). In resource allocation or planning problems, a novel algorithm inspired by natural adaptation is introduced to obtain the solutions according to the objective function in each level going through all the levels down (Tilahun, Kassa, and Ong, 2012).

If only two levels are considered, the two decision makers are referred to as the leader and follower, respectively. Bilevel Optimization is defined as a mathematical program, where an optimization problem contains another optimization problem as a constraint. For any given upper level decision vector, there is a corresponding lower level optimization problem to be solved, which provides the optimal response of the follower for the leader's decision (Sinha, Malo, and Deb, 2018). The mathematical formulation is shown as follows (Migdalas, Pardalos, and Värbrand, 1998):

$$\begin{aligned}&\min_{x,y}\ c_1^T x + d_1^T y\\&s.t.\ A_1 x + B_1 y \leq b_1\end{aligned}$$

where y solves

$$\begin{aligned}&\min_{y}\ c_2^T x + d_2^T y\\&s.t.\ A_2 x + B_2 y \leq b_2\end{aligned}$$

Most of the solution methods proposed are mainly for bilevel optimization problems with linear or convex property. The classical approaches for bilevel optimization includes extreme-point approach, complementary pivoting method (Colson, Marcotte, and Savard, 2007), single-level reduction, descent methods, penalty function methods, and trust-region methods. The evolutionary approaches for bilevel optimization consist of nested methods, single-level reduction, and metamodeling-based methods. Among the metaheuristic algorithms, which are not affected by behavior of the objective functions, evolutionary algorithm (Wang, Jiao, and Li, 2005; Deb and Sinha, 2009; Sinha, 2011) and particle swarm optimization (Kuo and Huang, 2009; Gao et al., 2011; Zhang et al., 2012) are used in many applications. The evolutionary approaches offer a significant scope for solving discrete bilevel optimization problems, as they are potent for handling difficulties such as discreteness and non-differentiabilities (Sinha, Malo, and Deb, 2017). The production-distribution planning problems always refer to multiobjective bilevel optimization, which involve several objectives simultaneously for decision makers at two different levels. In these problems, the lower level problem is usually transformed into an equivalent single-objective programming problem by a weighted aggregation method (Jia, Wang, and Fan, 2014).

1.4 Contributions

This study focuses on the resilient planning and operations of interdependent infrastructures, which consist of energy and other networks. We apply the multilevel optimization approach to deal with the decisions for the interdependent infrastructures' planning and operations or management. The analysis through this mathematical method provides a framework for the policy makers, system planners, and managers to avoid some conflicts among the decisions in different levels. The framework is grounded in advanced optimization approaches and modern data analytics, and will properly address the intra- and inter-infrastructure issues. Besides the multilevel optimal decisions, we also propose integer programming to model the cascading failure process in the interdependent infrastructures. The vulnerability analysis through the optimization programming helps us find the critical nodes and edges, whose removal trigger the most severe cascading failure. The identification of the most vulnerable nodes and edges could provide some measurements to better protect the infrastructure, and better resign the future network.

1.4.1 Energy and water systems

The nexus between energy and water has emerged as a significant issue concerning the economics, reliability, and resilience of both systems. However, few research on system expansion has considered the interdependence between energy and water systems, resulting in plans that might have poor performance due to water/energy availability in the future. In Chapter 2, we propose a long-term energy-water system expansion planning framework that not only models the operations of both systems but also captures the interdependence between the operations of energy and water systems. To reduce the computational complexity of the coupled system operations, we propose a decomposition algorithm. We demonstrate the effectiveness of the proposed model and algorithm on some test cases constructed by combining IEEE standard power systems and water systems from EPANet .

1.4.2 Optimal power flow with renewable energy integration

The problem of optimal power flow has been marked as one of the most operational needs. There are several approaches have been developed to solve the optimal power flow model. In Chapter 3, we propose a mixed integer programming model to connect the unit commitment with the optimal power flow model. The percentage of intermittent renewable energy in all kinds of energy sources is increasing, which will bring the uncertainty issues to the system. We could apply a robust optimization model to deal with this problem. In the process of the electricity power generation, water is needed in several phases. It is necessary to consider the effects of the water supply limitations in the generation and operation system. In the numerical experiments, we apply the column-and-constraint generation (C&CG) method to solve the optimization model.

1.4.3 Power grid and communication network

The interdependent network can be applied to model two or more infrastructure systems with mutual reliance. The failure of elements in one system may lead to failure of dependent elements in other systems, and this may happen recursively leading to a cascade of failures. In Chapter 4, integer programming models are proposed to identify the most vulnerable network elements (nodes and edges) whose removal can result in minimal survivable mutually connected components after the cascading failure process. Numerical experiments are performed on several interdependent networks consisting of power grid and control communication network, to validate the proposed models and to identify the vulnerable network elements.

The dissertation is organized as the follows. In Chapter 1, we introduce the research background, major concepts and methodologies applied in the dissertation, also the contributions. In Chapter 2, we focus on the topic about coordinated long-term planning for interdependent energy and water systems. In Chapter 3, we work for the optimization of power system operations with renewable energy integration and water limitations. Next, vulnerability analysis for power grid and its control communication network is stated in Chapter 4. In Chapter 5, we provide the conclusions and some future research directions.

Chapter 2
Coordinated Long-Term Planning for Interdependent Energy and Water Systems

In this chapter, we consider the coordinated planning for both power and water systems, co-optimizing the long-term investments. The operations of both systems will be modeled and the interdependency between the two systems will be captured. Specifically, we consider the investment decision such as construction of power generators and transmission lines, and construction of water storage and treatment utilities. The long-term benefits of these investments will be evaluated by operational costs at typical seasons. We model the interdependency between the two systems as demand and supply balance constraints. This chapter presents a mixed integer programming (MIP) model for long-term coordinated planning of two systems considering budget limitations, and future operations of two systems with demand requirements of each other in different time periods. For planning, we provide decisions for several years or decades in future, and we consider the operations of water system monthly and energy operations daily. The whole MIP model is large scale, with both physical constraints for both water and energy operations to check the feasibility of planning decisions. To solve it, we apply Benders decomposition approach, and also perform some numerical experiments based on modified systems made of IEEE power system testing cases and water system testing cases from EPANet. Through the decomposition, the variables are divided into two subsets, one for master problem and the other for subproblem. Then add possible feasibility cuts into the master problem and resolve. These are actually new added constraints applying in this algorithm.

The remainder of this chapter is organized as follows. Chapter 2.1 introduces background and motivation of this research. Chapter 2.2 introduces the long-term planning constraints for both systems, operations of water system and also operations of energy system. It also includes the interdependency of two systems. In Chapter 2.3, the Benders decomposition algorithm is applied for this problem. The results of numerical experiments are shown in Chapter 2.4, while the last Chapter 2.5 concludes the chapter with some potential future research directions.

2.1 Introduction

Nowadays, energy and water systems are becoming more interconnected and interdependent than ever (Water-Energy Nexus, 2014). This interdependence is often referred to as the water-energy nexus: water is used to energy production, and energy is used to water pump, transport, and treatment (Dziedzic and Karney, 2015). On one hand, meeting energy needs requires water, often in large quantities, for mining, fuel production, hydropower, and power plant cooling for thermal power stations, and hydraulic fracturing for oil and gas production, etc. (Torcellini, Long, and Judkoff, 2003). Around 65 percent of US electricity comes from power generators that require water cooling and electric power generation is responsible for almost 40% of freshwater withdrawals in US. It expected that the withdrawals will increase by about 20% between 2010 and 2035 (WEO, 2012). On the other hand, energy is needed for pumping, treatment, and distribution of water for household and industrial use. In US at least 521 million MWh energy are used on water-related operations each year, counting to 13% of total electricity consumption (River Network, 2014). In US, the predominant use of electricity is for water pumping in the conveyance and distribution system — this represents about 80% to 85% of the total electricity consumption for surface water. For many municipal governments, drinking water and wastewater plants typically are the largest energy consumers, often accounting for 30 to 40 percent of total energy consumed (Energy Efficiency, 2017). Global values from The United Nations World Water Development Report 2014 show that energy costs currently represent on average 30 - 40% of the operational costs of the water services (Mamade et al., 2017). Due to the population growth, deteriorating water scarcity, and tightening drinking water regulations, energy usages for water systems can also reach as high as 40% and is expected to increase 20% in next 15 years (EPA, 2013).

The interdependency between water and energy, although known for many decades, has not received enough attention until recent events under extreme weather conditions (especially droughts). The 2001 water crisis caused by a severe drought in the Northwest significantly reduced hydroelectric power production, leading to the loss of thousands of jobs in the energy-intensive aluminum industry (Washington Plan, 2004). On one hand, water and several types of energy supplies have become increasingly scarce; the demand on water and energy continues to grow. Besides, the climate change has become more and more disruptive (i.e., intensity and frequency of extreme events), causing severe challenges to both systems simultaneously. Even Illinois, a traditionally water-rich state, suffered severe droughts in 2012, resulting shutdowns of some power plants. Power plants in the East generally withdrew more water for each unit of electricity produced than plants in the West, because most have not been fitted with recirculating, dry cooling, or hybrid cooling technologies. Freshwater withdrawal intensity was 41 to 55 times greater in Virginia, North Carolina, Michigan, and Missouri than in Utah, Nevada, and California. In 2008, power plants withdrew 84percent of their cooling water from rivers and lakes. However, in some regions, notably the arid Southwest, cooling water came from a broader array of sources, including groundwater and wastewater. In the Southwest, power plants withdrew an average of 125 million to 190 million gallons of groundwater daily. The Palo Verde nuclear power station's average electric power production is about 3.3 gigawatts (GW). The data from Averyt et al. (2011) shows around 20 billion gallons (60,000 acrefeet) water used at Palo Verde evaporates each year. In 2008, Massachusetts Department of Environmental Protection collected the total energy intensity of public water supply and corresponding distribution is 1,500 kWh/MG. In 2006, Southern and Northern California Energy Commission separately collected the data to show the the total energy intensity of public water supply and corresponding distribution are 3,500 kWh/MG and 11,110 kWh/MG. The plant which consists of a sequencing batch reactor (SBR) and UV disinfection with an average daily flow of 6 MGD uses electricity about 13,513 kWh/day; this translates into an overall energy intensity of 2,250 kWh/MG. The facility treats an average of 20 MGD using a trickling filter, including primary and secondary clarifiers uses 30,458 kWh electricity per day which equates to an overall energy intensity of 1,520 kWh/MG. The electricity use for an advanced wastewater treatment plant providing biological nutrient removal (BNR) and treating an average flow of 85 MGD is 173,040 kWh/day, which translates into 2,040 kWh/MG before energy recovery (Water Research, 2013). Secondly, because of these interdependencies between energy and water systems, weather and environment factors (e.g, severe droughts, hurricanes, climate change, population growth) and advances of technologies (e.g., integration of renewable energy into power systems, desalination waters, advances in cooling systems) intensively affect the relationships between these two systems and infrastructures. For example, the year 2014 is the third year of California's worst drought in the past century, and water shortages and restrictions not only influence the residents' regular use, but also badly affects California's energy, economy and emissions goals (Rice, 2014; CA-EC, 2015). The 2012 hurricane Sandy made damages around $65 billion around 24 states and cut many electric generation stations and transmission lines, and vital water infrastructures lost power (ArcGIS, 2015).

Lessons learned from the incidents above suggest the importance of coordinated planning of energy and water systems. To the best of our knowledge, the expansion planing for either energy systems or water systems has not considered the interdependency on the other systems. We summarize the typical planning approaches in energy systems and water systems as follows. Based on the knowledge of water-energy nexus, we put forward the concept of coordinated planning for both systems. Long-term planning and real-time operations need to be optimized for power grid to most efficiently meet electricity demands of customers (including water system). The efforts of electrical energy system, or now to be upgraded to smart grid, aim at a diverse set of goals including facilitating greater competition between providers, encouraging greater use of renewable energy, implementing automation and monitoring capabilities needed for bulk transmission, and enabling the use of market forces to drive energy conservation. To achieve above goals, optimization over both long-term planning and real-time operations are necessary. The long-term planning of power grid deals with systematic expansion or investment of transmission elements and generators for one or more years. To achieve a reliable operation of the power grid, the planning should consider future real-time operations to avoid conflicting impacts. In the realistic grid, long-term planning and real-time operations have mutual and sometimes conflicting impacts in their decision making. Hence the stand-along approach often fails to find a set of consistent optimal solutions and sometimes even results in decisions that damages the overall reliability of the grid. Therefore, an "intelligent system-wide optimization" (Werbos, 2011) approach that incorporates all the planning and operations into one integrated model is necessary for upgrading current power system to a smarter grid and fully achieving its potential. In the last few years, research in the area of synthesis transmission planing models interact with the planner in order to provide one or more quasioptimal transmission plans, but usually is limited to settings adjustments while the model is running. Latorre et al. (2003) updated a review which is presented of the most relevant publications concerning transmission planning considering the solution method. Based on the approximation of the expected-cost-to-go functions of stochastic dynamic programming by piecewise linear functions, Pereira and Pinto (1991) present a methodology for the solution of multistage stochastic optimization problems in energy planning. An optimal expansion planning model for an energy hub with multiple energy systems is presented in Zhang et al. (2015). The multiple energy system planning problem would optimally determine appropriate investment candidates for generating units and transmission lines. A novel offline restoration planning tool for harnessing wind energy to enhance grid resilience is presented in Golshani et al. (2017). It discusses a stochastic mixed-integer linear programming problem with different generated energy scenarios. Taking into account both transmission and generation expansion, the authors in Chen et al. (2014) put forward a mixed-integer programming formulation of designing an electric power system at minimum cost. An open-source Matlab-based power system simulation package shown in Zimmerman, Murillo-Sanchez, and Thomas (2010) provides steady-state operations, planning and analysis tools for power systems. This chapter presents the details of network planning and operation modeling and problem formulations used by this tool. Energy planning problems are complex problems with multiple decision makers and multiple criteria. The term multiple criteria decision analysis in Løken (2007) describes various methods developed for aiding decision makers in reaching better decisions. The authors in Beccali, Cellura, and Mistretta (2003) show an application of the multiple criteria decision-making methodology used to assess an action plan for the diffusion of renewable energy technologies at regional scale. This methodological tool gives the decision-maker considerable help in the selection of the most suitable innovative technologies in the energy sector, according to preliminary fixed objectives. In Cormio et al. (2003), a bottom-up energy system optimisation model is proposed in order to support planning policies for promoting the use of renewable energy sources. A linear programming optimisation methodology based on the energy flow optimisation model is adopted. The optimisation process, aiming to provides feasible generation settlements that take into account the installation of combined cycle power plants, wind power, solid-waste and biomass exploitation together with industrial combined heat and power systems.

Similarly, a water supply system is a large and intricate network system of water or wastewater treatment and storage facilities, pumping stations and water transport structures (e.g., pipes, canals), that collect, treat, store, and distribute water from water sources to consumers (including energy system). The source water needs to be treated at a water treatment plant before being conveyed to satisfy potable and non-potable user demands with certain quality standards. The wastewater after potable consumption is collected and treated at a wastewater treatment plant. The reclaimed (treated) water can be directly supplied for non-potable purposes, or recharged into the recharge facility (e.g., the groundwater aquifers) before being pumped for potable uses. The water system planning includes the allowable construction for different types of facilities and restrictions on potential facility locations, for a planning period. Its management or operations is to decide the water flows among transport structures to meet water demands with certain quality standards. Loucks and Beek (2017) provide guidelines for initiating and carrying out water resource system planning and management projects, and also introduce alternative optimization, simulation, and statistical methods useful for project identification, design, siting, operation and evaluation and for studying post-planning issues. The approaches that have been used in the optimization of water management include linear programming, mixed integer and quadratic programming, differential dynamic programming, nonlinear programming, and simulation (Yeh, 1992) or Fuzzy methods (Bender and Simonovic, 2000) for planning under uncertainty. In Kang and Lansey (2014), novel scenario-based planning and optimization approaches are studied for the optimal design of regional-scale water supply infrastructure in a multi-period planning framework under different water demands.

Current state-of-the-art approach typically treats above planning and operations/ management in a separate way, either for a single energy or water system, making decisions independent of each other. The research for studying the interdependencies between these two systems is limited. In practice, these planning and operations have mutual impacts, and sometimes, conflict decisions are made within a single system or between two systems. Planning for energy supply traditionally gave scant consideration to water supply issues, and planning for water supply often neglects to fully consider associated energy requirements. Therefore, models and analysis are necessary and important for understanding and decision-making across complex coupled energy and water systems for resilience and reliable operations for both systems. As pointed in Holden et al. (2013), infrastructures are becoming increasingly interconnected and it is essential to develop models that account for interdependencies between infrastructure systems at different scales.

2.2 Optimization Model for Interdependent Energy and Water Systems

In this chapter, we consider the planning and operations of a coupled interdependent system consisting of an electric energy system and a water supply system. First we list the index sets and indices for planning and operations periods, and system components. Here we consider planning periods consisting of several years, monthly operations of water system and daily operations of energy system.

- $\mathcal{T}$: time period set for long-term planning, e.g., years;
- τ: time period index (yearly for planning) and also set of indices t for operations of water system, $\tau \in \mathcal{T}$;
- t: time period index (monthly for operations of water system) and also set of indices t' for operations of energy system, $t \in \tau$;

- t': time period index (daily for operations of energy system), $t' \in t$;

- $W = (N, A)$: water supply network;
- N: set of nodes/junctions in water supply network (indexed by $u \in N$);
  - N_S: set of storage nodes;
  - N_{NS}: set of non-storage nodes;
  - N_T: set of water or wastewater treatment plants;
- A: set of arcs/pipelines in water supply network (indexed by $(u, v) \in A$);
  - A_P: set of arcs with water pumps;

- $P = (B, E, G)$: power grid for electric energy system;
- B: set of buses in power grid (indexed by $i \in B$);
- E: set of transmission elements in power grid (indexed by $(i, j) \in E$);
- G: set of generating units in power grid (indexed by $g \in G$);
  - G_i: set of generating units at bus i in power grid.

2.2.1 Long-term planning

In the long-term planning period τ, water system contains building water or wastewater treatment facilities, and water storage facilities. Energy system consists of adding transmission elements and generation units. In the following, we first list parameters, decision variables and constraints relevant to the planning.

Parameters for planning:

- $c^T_{u\tau}$: capital cost for building water treatment or wastewater treatment facility in node u in period τ;
- $c^S_{u\tau}$: capital cost for building storage source in node u in period τ;
- B^W_τ: planning budget for water system in period τ;
- $c^E_{ij,\tau}$: investment cost of transmission element (i,j) in period τ;
- $c^G_{g\tau}$: investment cost of generation unit g in period τ;
- B^P_τ: planning budget for energy system in period τ.

Decision variables for planning:

- $x^T_{u\tau} \in \{0,1\}$: water or wastewater treatment facility in node u is built in period τ if $x^T_{u\tau} = 1$, and otherwise $x^T_{u\tau} = 0$;
- $x^S_{u\tau}$: water storage facility in node u is built in period τ if $x^S_{u\tau} = 1$, and otherwise $x^S_{u\tau} = 0$;
- $x^E_{ij,\tau}$: power transmission element (i,j) is added in period τ if $x^E_{ij,\tau} = 1$, and otherwise $x^E_{ij,\tau} = 0$;
- $x^G_{g\tau}$: power generation unit g is added in period τ if $x^G_{g\tau} = 1$, and otherwise $x^G_{g\tau} = 0$.

To simplify the formulations in the following, for existing facilities, we set their corresponding planning decision variables as 1, and corresponding budgets are adjusted to reflect this. The related constraints include the budget for building water or wastewater treatment and storage facilities in water supply network in period τ,

$$\sum_{u \in N_S} c^S_{u\tau} x^S_{u\tau} + \sum_{u \in N_T} c^T_{u\tau} x^T_{u\tau} \le B^W_\tau, \quad \forall \tau \in \mathcal{T}; \tag{2.1}$$

the budget for adding transmission elements and generation units in power grid in time period τ,

$$\sum_{(i,j) \in E} c^E_{ij,\tau} x^E_{ij,\tau} + \sum_{g \in G} c^G_{g\tau} x^G_{g\tau} \le B^P_\tau, \quad \forall \tau \in \mathcal{T}; \tag{2.2}$$

and binary decision requirements,

$$x^S_{u\tau}, x^T_{u\tau}, x^E_{ij,\tau}, x^G_{g\tau} \in \{0, 1\}. \tag{2.3}$$

2.2.2 Operations of water system $W = (N, A)$

Water system is the infrastructure for the collection, transmission, treatment, storage and distribution of water for homes, commercial establishments, industry and irrigation. It must meet both quality and quantity requirements for public, commercial and industrial activities. The planning of water system considered in this chapter mainly consists of building new storage and treatment facilities to meet rapid growth on the demand of water. Additionally, to ensure the reliable planning of water system and also check the feasible management, the operations under planning periods τ will be considered monthly for each period $t \in \tau$. In the following, the constraints and limitations related to operations of water system are presented.

Parameters related to operations of water system include:

- c_{uvt}: operational cost for carrying unit water flow through arc (u, v) in water network in period t;

- η_{uv}: leakage multiplier for water flowing through arc (u, v);
- b_{ut}: net water supply/demand in water supply network associated with node u in period t;
- d^e_{utg}: demand of water in node u from power grid generator g in period t;
- P_{ut}: supply capacity of source node u in period t;
- R_{ut}: water recharge capacity of node u in period t;
- WT_{ut}: water or wastewater treatment capacity of node u in period t;
- Q_{uvt}: pipeline capacity of arc (u, v) in period t

The decision variables for operations of water system include:

- q_{uvt}: water flow on arc (u, v) in period t;
- W_{ut}: storage level of node $u \in N_s$ at the end of period t

For each storage node $u \in N_s$ in water supply network in period $t \in \tau$, the inflow and storage level $W_{u,t-1}$ in previous time period $t-1$ is equal to outflow and storage level W_{ut} in current time period t:

$$\begin{aligned} &\sum_{\{v:(v,u)\in A\}} \eta_{vu} q_{vu,t-1} + W_{u,t-1} x^S_{u,t-1} \\ =&\sum_{\{v:(u,v)\in A\}} q_{uvt} + W_{ut} x^S_{ut}, \quad \forall u \in N_S, t \in \tau. \end{aligned} \tag{2.4}$$

For each non-storage node in water supply network, the generalized flow constraints define mass balance of flow in period $t \in \tau$. As the net water supply/demand associated with node u in period $t \in \tau$, b_{ut} is equal to the negative of the demand for user nodes. Except the general demand in water system, the water demand at this node u from power grid is presented as $\sum_{g\in G^u} d^e_{utg}$, where G^u is the set of generators rely on the water supply from node u in water system. If the decision made in planning period builds storage facilities in non-storage nodes, then there should consider the storage level for new facilities in the balancing equation:

$$\begin{aligned} &\sum_{\{v:(u,v)\in A\}} q_{uvt} - \sum_{\{v:(v,u)\in A\}} \eta_{vu} q_{vut} + W_{ut} x^S_{ut} = b_{ut} - \\ &\sum_{g\in G^u} d^e_{utg} + W_{u,t-1} x^S_{u,t-1}, \quad \forall u \in N_{NS}, t \in \tau. \end{aligned} \tag{2.5}$$

Constraint (2.6) bounds the total flow out of a node by the pumping capacity P_{ut} from the source node u.

$$\sum_{\{v:(u,v)\in A\}} q_{uvt} \le P_{ut}, \quad \forall u \in N, t \in \tau. \tag{2.6}$$

Constraint (2.7) bounds the total flow into a node by its recharge or treatment capacity R_{ut}, depending on the type of the node. $WT_{ut}x^T_{ut}$ denotes the added capacity to node u due to the construction of treatment facilities in period $t \in \tau$.

$$\begin{aligned} \sum_{\{v:(v,u)\in A\}} \eta_{vu} q_{vut} \le R_{ut} + WT_{ut} x^T_{ut}, \\ \forall u \in N, t \in \tau. \end{aligned} \tag{2.7}$$

The bounding restrictions on the operational variables are listed as:

$$\begin{aligned} 0 \le q_{uvt} \le Q_{uvt}, W_{ut} \ge 0, \quad \forall (u,v) \in A, \\ \forall u \in N_S, t \in \tau. \end{aligned} \tag{2.8}$$

2.2.3 Operations of energy system $P = (B, E, G)$

To ensure the reliable planning of energy systems, the operations of energy system under the planning periods are considered. In energy system operations, the flow balances in generators and transmission elements need to be considered. This optimal power flow problem is modeled in period $t' \in t$. The period $t \in \tau$ occurs in water supply network, and it usually presents one month. In power grid, the operational period t' usually presents one day. The same period t as monthly should be applied for both as coupling networks.

Parameters for operations of energy system includes:

- $c_{gt'}$: operational cost for generating unit power flow in generator g in period t';
- $D_{it'}$: general energy demand in bus i in period t';
- $D^w_{it'u}$: energy demand in bus i from water or waterwater treatment in node u in period t';
- $D^w_{it'uv}$: energy demand from in bus i from water pumping in arc (u, v) in period t';
- B_{ij}: electrical susceptance of transmission element (i, j);
- F_{ij}: flow capacity of transmission element (i, j);
- $P_{gt'}$: generating capacity of generator g in period t'

The decision variables for operations of energy system includes:

- $p_{gt'}$: power flow generated by generator g in period t';
- $f_{ijt'}$: transmission flow through element (i, j) in period t';
- $\theta_{it'}$: phase angle of bus i in period t'

The total inflow and generation in period $t' \in t$ satisfy the balance of demands and total outflow. The demands include the general demand in power grid $D_{it'}$ and the demands from treating water or wastewater $\sum_{u \in N_T^i} D^w_{it'u}$ and pumping water $\sum_{(u,v) \in A_P^i} D^w_{it'uv}$. N_T^i is the set of nodes in water supply system connected with bus i in power grid, and A_P^i is the set of arcs with pumps in water supply system corresponding to bus i in power grid.

$$\begin{aligned}&\sum_{j:(j,i)\in E} f_{jit'} + \sum_{g \in G_i} p_{gt'} x^G_{gt'} = D_{it'} + \sum_{u \in N_T^i} D^w_{it'u} + \\ &\sum_{(u,v) \in A_P^i} D^w_{it'uv} + \sum_{j:(i,j)\in E} f_{ijt'}, \quad \forall i \in B, t' \in t.\end{aligned} \tag{2.9}$$

The flow in transmission elements in period $t' \in t$ is the product of susceptance and phase angle difference.

$$B_{ij}(\theta_{it'} - \theta_{jt'}) x^E_{ij,t'} = f_{ijt'}, \quad \forall (i,j) \in E, t' \in t. \tag{2.10}$$

The flow limitations in all edges and generators in period $t' \in t$ are presented as follows:

$$\begin{aligned}&- F_{ij} x^E_{ij,t'} \le f_{ijt'} \le F_{ij} x^E_{ij,t'},\ 0 \le p_{gt'} \le P_{gt'} x^G_{gt'}, \\ &\forall (i,j) \in E, \forall g \in G, t' \in t.\end{aligned} \tag{2.11}$$

2.2.4 Operations for interdependency between two systems

As introduced above, water is used in many phases of energy production and energy is used for operations of water system. In the following, we assume that each generator $g \in G$ is requiring water to support its generation, and the required amount is depending on the type of generator (e.g., solar, wind, nuclear, hydro, biomass, coal and natural gas). For energy usage in water system, we mainly consider two types of consumptions, the water or wastewater treatments and water pumps. There are some related factors to influence the required energy amount for treatment facilities and water pumps. These factors are explained in the following parameters:

- α_g: water usage supplied by water system to generate one unit power in energy system (gal/MWh). For example, solar, wind, nuclear, hydro, biomass, coal and natural gas have different coefficient α_g because of their different generation types (Cormio et al., 2003).

- β_u: energy usage supplied by energy system to treat one unit water or wastewater in water system (MWh/gal). The related factors to influence β_u contain user opinions and satisfaction, community management, level of service, financial status, material and equipment, personnel, and work order control (Omran, 2011).

- γ_{uv}: energy usage supplied by energy system to pump one unit water in water system (MWh/gal). The related factors to influence γ_{uv} consist of the horsepower imparted to the water by the pump, the efficiency of the pumping plant (the pump, power unit and right angle drive) (Irrigation Management, 2018).

The exact values of these parameters will be discussed in Chapter 2.4. During the monthly operation period t of water supply network, the generator g connected to water node u has demand d^e_{utg} for water is used over all operation periods $t' \in t$ of power grid. Thus, we have the following water demand constraint for power generation:

$$d^e_{utg} = \alpha_g \sum_{t' \in t} p_{gt'}, \quad \forall g \in G^u, t \in \tau, \tag{2.12}$$

where G^u is the set of generators in power grid supported by node u in water supply network, and $\sum_{t' \in t} p_{gt'}$ denotes the generation amount of g in all periods $t' \in t$. Here we assume the water demand for generator g is totally supplied by its connected water node u.

Over operation period $t' \in t$ of power grid, the water or wastewater treatment facility node u connected to bus i has energy demand $\sum_{t' \in t} D^w_{it'u}$ for energy is used in operation period t of water supply network. Thus, we have the following energy demand constraint for water or wastewater treatment:

$$\sum_{t'\in t} D^{w}_{it'u} = \beta_u \sum_{\{v:(u,v)\in A\}} q_{uvt}, \quad \forall u \in N^i_T, t \in \tau. \tag{2.13}$$

where N^i_T is the set of water or wastewater treatment facilities in water supply network supported by bus i in power grid. Here we assume the energy demand for water node u is totally supplied by its connected energy generator g.

Over all operation periods $t' \in t$ of power grid, the water pumping arc (u, v) connected to bus i has demand $\sum_{t'\in t} D^{w}_{it'uv}$ for energy is used in operation period t of water supply network. Thus, we have the following energy demand constraint for water pumping:

$$\sum_{t'\in t} D^{w}_{it'uv} = \gamma_{uv} q_{uvt}, \quad \forall (u,v) \in A^i_P, t \in \tau. \tag{2.14}$$

where A^i_P is the set of pumps in water supply network supported by bus i in power grid. Here we assume the energy demand for water arc (u, v) is totally supplied by its connected energy generator g.

2.2.5 Coordinated planning and operations

The objective function in this model is to minimize the cost of planning and operations for both systems. In water system, the cost is divided into expenses for building storage facilities in planning period $\sum_{u\in N_S}\sum_{\tau\in\mathcal{T}} c^S_{u\tau} x^S_{u\tau}$, building treatment facilities in planning period $\sum_{u\in N_T}\sum_{\tau\in\mathcal{T}} c^T_{u\tau} x^T_{u\tau}$, and total operating cost for water flow in long-term period $\sum_{(u,v)\in A}\sum_{t\in\tau\in\mathcal{T}} c_{uvt} q_{uvt}$.

In energy system, the cost consists of expenses for adding new generators in planning period $\sum_{g\in G}\sum_{\tau\in\mathcal{T}} c^G_{g\tau} x^G_{g\tau}$, and adding new transmission lines in planning period

$\sum_{(i,j)\in E}\sum_{\tau\in\mathcal{T}} c^E_{ij,\tau}x^E_{ij,\tau}$, and total operating cost for power generation in long-term period $\sum_{g\in G}\sum_{t'\in t\in\tau\in\mathcal{T}} c_{gt'}p_{gt'}$.

Therefore, the whole model to indicate coordinated planning of these two systems is shown as

$$\begin{aligned}
\min & \sum_{u\in N_S}\sum_{\tau\in\mathcal{T}} c^S_{u\tau}x^S_{u\tau} + \sum_{u\in N_T}\sum_{\tau\in\mathcal{T}} c^T_{u\tau}x^T_{u\tau} + \\
& \sum_{g\in G}\sum_{\tau\in\mathcal{T}} c^G_{g\tau}x^G_{g\tau} + \sum_{(i,j)\in E}\sum_{\tau\in\mathcal{T}} c^E_{ij,\tau}x^E_{ij,\tau} + \\
& \sigma_1 \sum_{(u,v)\in A}\sum_{t\in\tau\in\mathcal{T}} c_{uvt}q_{uvt} + \sigma_2 \sum_{g\in G}\sum_{t'\in t\in\tau\in\mathcal{T}} c_{gt'}p_{gt'} \\
s.t.\ & (2.1) - (2.14),
\end{aligned}$$

where σ_1 and σ_2 are positive constants to adjust the costs between planning and operations.

This optimization model represents the coordinated planning of interdependent water and energy systems because of the same sharing timeline and the mutually supporting relationship between the two systems. For both water and energy system, no matter the unit time is monthly or daily, finally they are all considered into several years period. And also, part of the demands in one system is needed by part of the supplies in another system. Instead of making planning decision separately, this proposed model requires the consideration of supply and demand of one system from the other one.

2.3 Solution Approach

The proposed MIP problem has a large number of variables and constraints that grow rapidly with the increasing number of nodes, arcs and time periods. For large energy and water interdependent systems with a long planning horizon, the model can quickly become computationally intractable. In this section, the Benders Decomposition

(BD) method is developed to solve the MIP problem.

Now write the original model as master problem, which is pure integer problem (no continuous variables are involved), and subproblem, which is a dual linear programming problem.

Here, $x^T_{u\tau}, x^S_{u\tau}, x^E_{ij\tau}, x^G_{g\tau}$ are fixed to a feasible integer configuration, the resulting subproblem model (PSP) to solve is:

$$\begin{aligned} &\min\ \sigma_1 \sum_{(u,v)\in A} \sum_{t\in\tau\in\mathcal{T}} c_{uvt} q_{uvt} + \sigma_2 \sum_{g\in G} \sum_{t'\in t\in\tau\in\mathcal{T}} c_{gt'} p_{gt'} \\ &s.t.\ (2.4) - (2.14). \end{aligned}$$

The dual of the inner LP subproblem (DSP) can be found accordingly, and the complete minimization master problem (MP) can therefore be written as:

$$\begin{aligned} \min_{(2.1)-(2.3)} &\sum_{u\in N_S} \sum_{\tau\in\mathcal{T}} c^S_{u\tau} x^S_{u\tau} + \sum_{u\in N_T} \sum_{\tau\in\mathcal{T}} c^T_{u\tau} x^T_{u\tau} + \\ &\sum_{g\in G} \sum_{\tau\in\mathcal{T}} c^G_{g\tau} x^G_{g\tau} + \sum_{(i,j)\in E} \sum_{\tau\in\mathcal{T}} c^E_{ij,\tau} x^E_{ij,\tau} + min\{ \\ &\sigma_1 \sum_{(u,v)\in A} \sum_{t\in\tau\in\mathcal{T}} c_{uvt} q_{uvt} + \sigma_2 \sum_{g\in G} \sum_{t'\in t\in\tau\in\mathcal{T}} c_{gt'} p_{gt'}\ :\ (2.4) - (2.14)\}. \end{aligned}$$

The solutions for the PSP is feasible if and only if the dual problem is bounded.

So the feasibility conditions can be defined as follows,

$$
\begin{aligned}
&\sum_{u\in N_{NS}}\sum_{t\in\tau}(\sum_{g\in G^u} d^e_{utg} - b_{ut})\delta_{ut} + \sum_{u\in N}\sum_{t\in\tau} P_{ut}\varepsilon_{ut} + \\
&\sum_{u\in N}\sum_{t\in\tau}(R_{ut} + WT_{ut}x^T_{u\tau})\zeta_{ut} + \sum_{(u,v)\in A}\sum_{t\in\tau} Q_{uvt}\xi_{uvt} + \\
&\sum_{i\in B}\sum_{t'\in t\in\tau}(D_{it'} + \sum_{u\in N^i_T} D^w_{it'u} + \sum_{(u,v)\in A^i_P} D^w_{it'uv})\vartheta_{it'} + \\
&\sum_{(i,j)\in E}\sum_{t'\in t\in\tau} F_{ij}x^E_{ij,\tau}\kappa_{ijt'} + \sum_{(i,j)\in E}\sum_{t'\in t\in\tau} F_{ij}x^E_{ij,\tau}\lambda_{ijt'} + \\
&\sum_{g\in G}\sum_{t'\in t\in\tau} P_{gt'}x^G_{g\tau}\mu_{gt'} + \sum_{u\in N_{NS}}\sum_{g\in G^u}\sum_{t\in\tau} d^e_{utg}\nu_{ugt} + \\
&\sum_{u\in N^i_T}\sum_{i\in B}\sum_{t\in\tau}(\sum_{t'\in t} D^w_{it'u})\pi_{uit} \\
&+ \sum_{(u,v)\in A^i_P}\sum_{i\in B}\sum_{t\in\tau}(\sum_{t'\in t} D^w_{it'uv})\sigma_{uvit} \leq 0
\end{aligned}
\tag{2.15}
$$

The Benders Decomposition algorithm can be stated in Algorithm 1.

Algorithm 1 Benders Decomposition Algorithm

```
1: t ← 0
2: solve MP
3: if MP is infeasible then
4:     EXIT
5: else
6:     Let X^t be the optimal solution to MP
7:     for t ∈ τ do
8:         solve DSP, let z^t be the objective value
9:         if z^t > 0 then
10:            Add feasibility cut (15) to MP
11:        end if
12:    end for
13:    if no feasibility cut added in step 10 then
14:        X^t is optimal, EXIT
15:    else
16:        t ← t + 1, go to step 2
17:    end if
18: end if
```

2.4 Numerical Experiments

The proposed optimization model is implemented in C++ and solved using CPLEX 12.3 via ILOG Concert Technology 2.9 callable library. All computations were performed on a Linux workstation with 4 Intel(R) Xeon(TM) CPU 3.60GHz processors and 32 GB RAM. We tested the proposed model and algorithm in two cases.

In planning period, we collect the data about budgets for building storage and water or wastewater treatment facilities in water supply network, and adding generators and transmission lines in power grid. In operational periods, we need the detailed information for existing nodes and pipelines in water network, the data for existing power grid buses, generators and transmission lines, and also the connection structure between these two networks. The last but not the least is the coefficients which are used to coupling interdependent systems.

Because the unit of collected data in energy network is Megawatt, we need to transfer it to Megawatt hour to keep the power unit the same in whole system. The calculation equation for one year is $1MWh = 1MW \times \text{efficiency} \times 24hours \times 365days$. And the relevant efficiencies for solar, wind, coal, hydro, nuclear, natural gas, and oil energy are separately 0.80, 0.32, 0.59, 0.95, 0.91, 0.5 and 0.38 (Mai et al., 2012).

Water is used for energy generation stations. For different kinds of generation energy, water consumption rates keep changing with different techniques. The coefficient α_g = 25 Gal/MWh for solar energy, and α_g = 5 Gal/MWh for wind energy. These two coefficients are used in simulating the following examples. On the other hand, energy usually is used for pumping, water and wastewater treatment. In pumping station, γ_{ij} could be calculated through the equation: $P_{h(kW)} = q\rho gh/(3.6 \times 10^6)$, here, $P_{h(kW)}$ is hydraulic power (kW), q is flow capacity (m^3/h), ρ is density of fluid (kg/m^3), g is gravity $9.81m/s^2$, h is differential head (m) (CottonInfo, 2015). In these examples, the pump lifted the water 100 feet, $\gamma_{ij} = 5.7 \times 10^{-7}$ MWh/gal. In water or wastewater treatment plant, coefficient β_i could ranges from 700-1800 kWh/million gallon (Reliance, 2009; Energy Star, 2015). In these examples, water and wastewater treatment facilities apply the coefficient $\beta_i = 1.3 \times 10^{-6}$ MWh/gal.

It is the time to consider the potential building cost in water supply network and power grid. If the capacity of water or wastewater treatment facility is 1000 gallons, its cost is estimated as \$5,412. If the capacity of water storage facility is 1000 gallons, its cost is estimated as \$1,839. The cost for energy transmission line is estimated as \$1,002/m. The cost for 10 MW solar energy generator is estimated as $\$2.025 \times 10^7$. The cost for 16 MW wind energy generator is estimated as $\$3.7536 \times 10^7$.

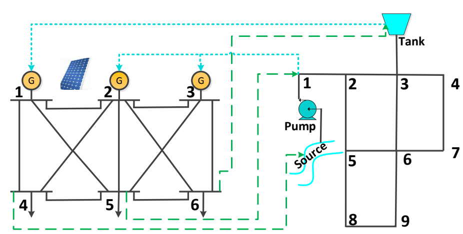


Figure 2.1: IEEE 6-bus power system and 1-tank-1-pump water system

2.4.1 Test for IEEE 6-bus power system and 1-tank-1-pump water system

As shown in Fig. 2.1, this interdependent network consists of IEEE 6-bus power system and 1-tank-1-pump water system. Now we plan to apply the data of this system in the proposed optimization model, and then get the optimal 3-year and 10-year planning results.

Firstly, let us see the data that will be used in both 3-year planning and 10-year planning projects in this example.

Table 2.1 and Table 2.2 are the data for power grid. This is IEEE 6-bus power testing system, cited from Ankaliki (2014). Table 2.3 and Table 2.4 are the data for water supply network. This is Net1_Rossman2000 example, from Open Water Analytics (Net1, 2017). Table 2.5 is the interlinks between water and energy system. These interlinks connect these two system as interdependency.

Table 2.1: Energy network generator data — IEEE 6-bus power system

Bus	Generator	Cost	Demand	Generating Capacity
1	1	20	0	50-200
2	2	25	0	37.5-150
3	3	30	0	45-180
4	0	0	20	0
5	0	0	40	0
6	0	0	30	0

Table 2.2: Energy network transmission data — IEEE 6-bus power system

Transmission	Susceptance	Flow Capacity
(1,2)	0.02	40
(1,4)	0.02	60
(1,5)	0.03	50
(2,3)	0.03	40
(2,4)	0.01	70
(2,5)	0.02	30
(2,6)	0.025	90
(3,5)	0.025	70
(3,6)	0.01	80
(4,5)	0.04	20
(5,6)	0.03	40

Table 2.3: Water network node data — 1-tank-1-pump water system

Node	Supply	Demand
S	800	0
1	0	10
2	0	30
3	0	10
4	0	20
5	0	30
6	0	40
7	0	20
8	0	30
9	0	90
T	120	0

Table 2.4: Water network pipeline data — 1-tank-1-pump water system

Pipeline	Capacity	Multiplier	Cost	Pumping
(1,2)	300	0.9	124	0
(2,3)	200	0.85	165	0
(3,4)	300	0.7	97	0
(S,1)	300	0.95	274.59	540
(T,3)	300	0.97	285.58	0
(2,5)	300	0.83	153	0
(3,6)	100	0.86	115	0
(4,7)	300	0.8	147	0
(5,6)	200	0.82	180	0
(6,7)	200	0.94	167	0
(5,8)	300	0.77	186	0
(6,9)	200	0.9	74	0
(8,9)	200	0.72	141	0

Table 2.5: Interlinks data

Energy $\longrightarrow$ Water	Water $\longrightarrow$ Energy
bus 4 $\longrightarrow$ node S	node T $\longrightarrow$ bus 1
bus 5 $\longrightarrow$ node 1	node S $\longrightarrow$ bus 2
bus 6 $\longrightarrow$ node T	node S $\longrightarrow$ bus 3

Secondly, the yearly budget is different between 3-year planning and 10-year planning. Also put the planning results here through simulating different time periods.

(1) The yearly budget for water facilities 3-year planning is assumed as \$4,000, \$8,000, \$8,000. The yearly budget for energy network 3-year planning is assumed as $\$8 \times 10^7$, $\$8 \times 10^7$, $\$4 \times 10^7$.

The 3-year planning result for IEEE 6-bus power system and 1-tank-1-pump water system is shown in Fig 2.2. The schedule is in first year, building a new storage facility in node 7, adding one generator at bus 1 and one at bus 3; in second year, building a new treatment facility in node 9; in third year, adding a generator at bus 2.

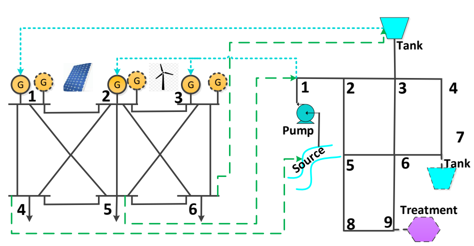


Figure 2.2: 3-year planning results

(2) The yearly budget for water facilities 10-year planning is assumed as \$4,000, \$8,000, \$8,000, \$4,000, \$4,000, \$4,000, \$8,000, \$4,000, \$4,000, \$4,000. The yearly budget for energy network 10-year planning is assumed as $\$8\times10^7$, $\$8\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$, $\$4\times10^7$.

The 10-year planning result for IEEE 6-bus power system and 1-tank-1-pump water system is shown in Fig 2.3. The schedule is in first year, building a new storage facility in node 4, adding one generator at bus 3; in second year, building a new treatment facility in bus 9; in third year, adding one generator at bus 2; in fourth year, adding a transmission line between bus 1 and bus 6; in fifth year, building a new storage facility in node 5; in sixth year, adding one generator at bus 1; in seventh year, building a new storage facility in node 8 and a new treatment facility is node 6, adding one generator at bus 5; in ninth year, adding a transmission line between bus 4 and bus 6.

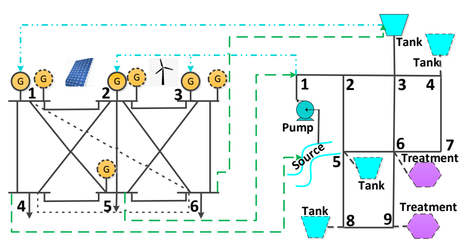


Figure 2.3: 10-year planning results

2.4.2 Test for IEEE RTS-96 power system and 3-tank-2-pump water system

This interdependent network consists of IEEE Reliability Test System 96 (IEEE RTS-96) and 3-tank-2-pump water system. Now we plan to apply the data of this system in the proposed optimization model, and then get the optimal 3-year and 10-year planning results.

Firstly, let us see the data that will be used in both 3-year planning and 10-year planning projects in this example.

Table 2.6 and Table 2.7 are the data for power grid. This is IEEE RTS-96 power system, cited from UWEE Power Systems Test Case Archive (RTS, 1996). Table 2.8, Table 2.9 and Table 2.10 are the data for water supply network. This is Net3_Rossman2000 example, cited from Open Water Analytics (Net3, 2017). Table 2.11 is the interlinks between water and energy system. These interlinks connect these two system as interdependency.

Table 2.6: Energy network generator data — IEEE RTS-96 power system

Bus	Generator	Cost	Demand	Generating Capacity
1	1	240	71.5	86.3
2	2	500	73.7	87.8
3	/	0	80.6	/
4	/	0	72.9	/
5	/	0	70.5	/
6	/	0	81.6	/
7	3	400	85.6	97
8	/	0	72.7	/
9	/	0	90	/
10	/	0	89.6	/
11	/	0	0	/
12	/	0	0	/
13	4	100	75.4	74.4
14	5	800	75	87
15	6	1000	72.1	85.6
16	7	1500	80	88
17	/	0	0	/
18	8	900	90	94.2
19	/	0	71.5	/
20	/	0	75.4	/
21	9	700	0	90.9
22	10	800	0	97
23	11	680	0	88
24	/	0	0	/

Table 2.7: Energy network transmission data — IEEE RTS-96 power system

Transmission	Susceptance	Flow Capacity
0	0.02	90
2	0.02	90
3	0.02	90
4	0.03	70
5	0.02	80
6	0.035	60
7	0.025	100
8	0.02	70
9	0.04	70
10	0.01	90
11	0.01	100
12	0.01	80
13	0.023	70
14	0.018	90
15	0.02	100
16	0.02	90
17	0.02	90
18	0.02	60
19	0.02	50
20	0.03	60
21	0.027	60
22	0.025	70
23	0.02	60
24	0.01	60
25	0.02	80
26	0.02	80
27	0.015	70
28	0.015	90
29	0.015	70
30	0.01	100
31	0.02	80
32	0.02	60
33	0.02	100
34	0.03	70
35	0.025	90
36	0.02	90
37	0.02	80
38	0.02	100

Table 2.8: Water network node data — 3-tank-2-pump water system

Node	Supply	Demand
S1	800	0
S2	900	0
T1	140	0
T2	260	0
T3	190	0
1	0	20
2	0	10
3	0	30
4	0	60
5	0	60
6	0	10
7	0	10
8	0	50
9	0	80
10	0	60
11	0	60
12	0	40
13	0	10
14	0	60
15	0	40
16	0	40
17	0	30
18	0	70
19	0	90
20	0	110
21	0	40
22	0	30
23	0	70
24	0	20
25	0	80
26	0	50
27	0	60
28	0	50
29	0	30
30	0	30
31	0	70
32	0	60
33	0	60
34	0	60
35	0	60
36	0	10
37	0	10
38	0	50
39	0	90
40	0	100
41	0	20
42	0	90
43	0	40

Node	Supply	Demand
44	0	40
45	0	10
46	0	10
47	0	50
48	0	50
49	0	50
50	0	50
51	0	50
52	0	70
53	0	50
54	0	80
55	0	20
56	0	20
57	0	70
58	0	20
59	0	20
60	0	30
61	0	20
62	0	50
63	0	80
64	0	10
65	0	10
66	0	20
67	0	40
68	0	110
69	0	80
70	0	40
71	0	40
72	0	50
73	0	40
74	0	40
75	0	30
76	0	70
77	0	60
78	0	40
79	0	60
80	0	20
81	0	20
82	0	20
83	0	20
84	0	20
85	0	20
86	0	20
87	0	40
88	0	40
89	0	40
90	0	30
91	0	20
92	0	30

Table 2.9: Water network pipeline data — 3-tank-2-pump water system

Pipeline	Capacity	Multiplier	Cost	Pumping
(S1,1)	600	0.95	178	540
(1,11)	500	0.95	167	0
(11,13)	500	0.92	145	0
(11,12)	500	0.87	168	0
(12,14)	500	0.7	123	0
(14,34)	500	0.71	100	0
(13,15)	300	0.96	100	0
(15,33)	400	0.84	134	0
(13,17)	300	0.83	178	0
(17,16)	300	0.83	193	0
(16,32)	300	0.83	188	0
(17,18)	300	0.76	165	0
(18,19)	300	0.82	80	0
(16,19)	300	0.77	80	0
(19,21)	400	0.74	163	0
(21,32)	200	0.83	199	0
(32,33)	600	0.91	89	0
(21,31)	200	0.9	205	0
(10,21)	200	0.99	232	0
(10,31)	100	0.94	167	0
(S2,3)	600	0.89	80	0
(3,2)	200	0.89	88	260
(3,4)	200	0.73	164	0
(4,2)	200	0.77	155	0
(2,5)	200	0.69	207	0
(5,10)	200	0.99	79	0
(10,9)	200	0.91	90	0
(9,8)	400	0.94	151	0
(8,7)	400	0.83	132	0
(T1,8)	500	0.87	200	0
(7,6)	400	0.71	79	0
(7,23)	400	0.81	144	0
(23,26)	400	0.85	169	0
(26,25)	300	0.85	176	0
(25,24)	300	0.92	183	0
(26,27)	100	0.94	169	0
(27,28)	400	0.94	100	0
(28,29)	400	0.94	207	0
(29,30)	400	0.94	94	0
(30,31)	300	0.98	97	0
(30,22)	200	0.78	150	0
(9,22)	200	0.79	169	0
(31,37)	200	0.97	148	0
(37,38)	200	0.82	170	0
(33,34)	200	0.85	270	0
(33,36)	500	0.84	200	0
(34,36)	200	0.84	281	0
(34,35)	200	0.84	178	0
(35,43)	200	0.84	98	0
(36,45)	400	0.91	94	0
(45,44)	200	0.9	204	0
(44,42)	200	0.94	205	0
(38,42)	200	0.84	109	0
(43,45)	300	0.94	159	0
(45,46)	200	0.77	166	0
(46,53)	200	0.81	186	0
(46,47)	500	0.95	139	0
(42,41)	200	0.91	164	0

Table 2.10: (Cont'd)Water network pipeline data — 3-tank-2-pump water system

Pipeline	Capacity	Multiplier	Cost	Pumping
(41,40)	400	0.9	105	0
(40,39)	100	0.9	169	0
(41,47)	300	0.9	140	0
(43,52)	300	0.88	142	0
(47,49)	300	0.9	97	0
(49,48)	300	0.9	140	0
(49,50)	300	0.9	85	0
(50,53)	500	0.94	170	0
(53,52)	300	0.83	150	0
(52,51)	300	0.83	192	0
(51,62)	200	0.85	153	0
(53,61)	300	0.85	184	0
(50,56)	300	0.85	205	0
(49,57)	300	0.85	208	0
(62,63)	200	0.85	190	0
(62,61)	300	0.85	94	0
(60,64)	300	0.9	237	0
(64,T2)	300	0.9	236	0
(60,59)	300	0.92	176	0
(55,54)	100	0.92	271	0
(55,56)	100	0.93	91	0
(56,57)	200	0.99	87	0
(57,58)	100	0.87	159	0
(58,59)	100	0.79	170	0
(55,59)	200	0.86	139	0
(59,65)	200	0.89	156	0
(63,70)	200	0.81	175	0
(65,67)	200	0.9	164	0
(67,66)	400	0.8	166	0
(67,68)	200	0.81	142	0
(65,69)	200	0.71	131	0
(68,69)	500	0.76	123	0
(69,70)	200	0.76	121	0
(68,71)	200	0.77	186	0
(70,71)	300	0.77	201	0
(71,72)	300	0.92	180	0
(72,73)	300	0.92	98	0
(73,74)	300	0.95	99	0
(74,80)	200	0.95	153	0
(79,80)	200	0.88	145	0
(78,79)	200	0.88	146	0
(77,78)	400	0.86	155	0
(77,75)	400	0.9	186	0
(77,76)	400	0.9	187	0
(80,81)	400	0.87	130	0
(79,82)	500	0.87	129	0
(81,82)	400	0.89	116	0
(82,83)	400	0.93	222	0
(81,86)	400	0.96	115	0
(85,86)	200	0.96	184	0
(85,84)	400	0.85	149	0
(85,89)	300	0.79	140	0
(86,87)	200	0.9	130	0
(87,88)	300	0.92	159	0
(88,90)	300	0.93	204	0
(89,90)	300	0.92	200	0
(90,91)	500	0.95	175	0
(T3,91)	300	0.87	125	0
(90,92)	300	0.88	182	0

Table 2.11: Interlinks data

Energy $\longrightarrow$ Water	Water $\longrightarrow$ Energy
bus 7 $\longrightarrow$ node T2	node 8 $\longrightarrow$ bus 15
bus 7 $\longrightarrow$ node T3	node 11 $\longrightarrow$ bus 18
bus 13 $\longrightarrow$ node T1	node 23 $\longrightarrow$ bus 22
bus 21 $\longrightarrow$ node 1	node 27 $\longrightarrow$ bus 13
bus 23 $\longrightarrow$ node 3	node 32 $\longrightarrow$ bus 21
-	node 38 $\longrightarrow$ bus 14
-	node 48 $\longrightarrow$ bus 23
-	node 64 $\longrightarrow$ bus 16
-	node 77 $\longrightarrow$ bus 7
-	node 85 $\longrightarrow$ bus 2
-	node 91 $\longrightarrow$ bus 1

Secondly, the yearly budget is different between 3-year planning and 10-year planning. Also put the planning results here through simulating different time periods.

(1) The yearly budget for water facilities 3-year planning is assumed as \$30,000. The yearly budget for energy network 3-year planning is assumed as $\$8 \times 10^7$.

The 3-year planning result for IEEE RTS-96 power system and 3-tank-2-pump water system is shown in Table 2.12.

Table 2.12: 3-year planning results

Year	Storage	Treatment	Transmission Line	Generator
1	21,33,50	34,78	(12,24)	19
2	81	-	(3,23)	5
3	43	11,50,82	-	-

(2) The yearly budget for water facilities 10-year planning is assumed as \$30,000.

The yearly budget for energy network 10-year planning is assumed as $\$8 \times 10^7$.

The 10-year planning result for IEEE RTS-96 power system and 3-tank-2-pump water system is shown in Table 2.13.

Table 2.13: 10-year planning results

Year	Storage	Treatment	Transmission Line	Generator
1	22,70	7,85	-	19
2	-	34	-	10
3	-	61	(11,18),(7,24)	9,20
4	31,59,69	74	(10,24)	-
5	44,74	-	-	-
6	-	-	-	7,14
7	71	62,64	-	5
8	-	32	(5,11)	-
9	-	-	-	-
10	16	-	(10,23)	3

2.4.3 Running time

The results for solving the above examples through original optimization model and Benders Decomposition algorithm have been listed in Table 2.14. The running time (counting in seconds) of Benders is compared with the approach before improved. The test systems are relevant to 3-year planning and 10-year planning for interdependent IEEE 6-bus power system and 1-tank-1-pump water network, as well as 3-year planning and 10-year planning for interdependent IEEE RTS-96 power system and 3-tank-2-pump water network.

Table 2.14: Run time for different solution approaches to the examples

Test System	By Original Model	By BD (second)
3-Year IEEE 6-Bus	324	43
10-Year IEEE 6-Bus	726	236
3-Year RTS-96	1,272	308
10-Year RTS-96	3,444	894

2.5 Conclusions

This chapter proposes a coordinate planning and operations model for interdependent energy and water system. In this optimization model, we analyze the long-term planning period and the operation or management period. Here, the long-term planning is coordinated because the consideration of the interdependency during operations between the two systems. We present some interlinks between them two to show the interdependence. Some efficiency coefficients occur with interlinks, which represent how water usage is related with energy generation, and how energy usage is relevant to water pumping and distribution. We test the model in two interdependent systems. One consists of IEEE 6-bus power system and 1-tank-1-pump water system, and the other comprises IEEE RTS-96 power system and 3-tank-2-pump water system. The details and final decisions made for these two examples could be found in numerical experiment section. Benders decomposition algorithm is applied to solve the proposed model with high efficiency. For future research, the post-contingency analysis among the two systems should be considered for the reliability and resilience of the two interdependent systems.

Chapter 3

Optimization of power system operations with renewable energy integration and water limitations

In this chapter, we consider the optimization of power system operations, consisting of the unit commitment problem and the optimal power flow problem as economic dispatch with renewable energy integration and water limitations for electricity power production. The unit commitment problem in electrical power production is one of the fundamental problems in power system management and simulation, because there are many variants and it needs to be solved within time limits. It is a mathematical optimization problem where the production of the generators is coordinated to match the energy demand with minimum cost or receive the maximum revenue from energy production. In recent years, the production from intermittent renewable energy sources has significantly increased, and it introduces the uncertainty issues to the system. It is necessary to take uncertainty into account through appropriate mathematical modeling techniques, such as robust optimization approaches. In the operation of the power system, water is the vital important resource used in production processes. Thermal power plants typically require a large amount of cooling water whose evaporation is regarded to be consumed. Hydropower plants result in evaporative water loss from the large surface areas of the storing reservoirs. With the development of new technologies and their integration to the conventional power grid, the smart grid with the capacity of satisfying power demand by large amount of renewable energy is emerging (Ruiz Duarte and Fan, 2018), and the renewable energy production also needs the water supply, such as concentrated solar power plants. The electricity power generation process of different energy resources, such as coal, gas, solar, and wind, could not leave the water supply. The total water supply amount may be strictly limited in some areas, as a result of restricted water availability. The water availability will affect the total cost of the power system operations. Thus the decision-making in power system operations should consider both renewable energy integration and water limitations.

The remainder of this chapter is organized as follows. Chapter 3.1 introduces the background and motivation of this research. In Chapter 3.2, the mixed integer programming model is explained. The uncertainty concern of renewable energy and the water limitation in the electricity power production processed are both included. The numerical experiments are performed on two test cases, and the results are shown in Chapter 3.3. The conclusions are presented in Chapter 3.4.

3.1 Introduction

The problem of optimal power flow (OPF) has been marked as one of the most operational needs. Many utilities paid much attention to the OPF problem. The solutions of this problem aim to optimize an objective function via optimal adjustment of the power system control variables. The constraints in the OPF problem consist of equality constraints and inequality constraints. The equality constraints are the power flow equations, and the inequality constraints are the operating limits on system variables.

About how to solve the OPF problem, some researchers put forward different approaches. Lai et al. (1997) present an improved genetic algorithm for optimal power flow under both normal and contingent operation states, and Bakirtzis and Biskas (2002) present an enhanced genetic algorithm. The solution techniques such as Newton-based (Momoh, El-Hawary, and Adapa, 1999), linear programming, non-linear programming, interior point methods and evolutionary programming are applied to the OPF problem (Yuryevich and Wong, 1999). An efficient and reliable evolutionary-based approach which employs particle swarm optimization algorithm is used to optimal set the control variables (Abido, 2002). Besides the traditional OPF problem, Geidl and Andersson (2007) present an approach for combined optimization of coupled power flows of different energy infrastructures such as electricity, gas, and district heating systems. An optimal management mechanism for grid connected photovoltaic systems with storage and the structure of a power supervisor based on an optimal predictive power scheduling algorithm are performed using dynamic programming (Riffonneau et al., 2011). When the energy sources refer to the renewable energy, the optimal power flow model needs to consider the renewable energy integration. Renewable energy sources tend to be variable in supply with no correlation to changes in demand (Richardson, 2013).

The use of renewable energy is increasing as a supplement and an alternative to large conventional central power stations. Carrasco et al. (2006) present new trends in power electronics for the integration of wind and photovoltaic power generators, also introduces the appropriate storage-system technology used for the integration of intermittent renewable energy sources. High accuracy forecast systems are required for multiple time horizons that are associated with regulation, dispatching, scheduling and unit commitment. The solar forecasting methods are useful for both the solar resource and the power output of solar plants at the utility scale level (Inman, Pedro, and Coimbra, 2013). A number of possible optimisation criteria for the design of energy systems with large shares of fluctuating renewable energy sources are listed as reserving capacity requirement, using of import and export, condensing mode operation, primary energy consumption or fuel use, renewable energy shares, and so on (Østergaard, 2009). Besides these optimisation criteria, there are some different computer tools which could be used to analyse the integration of renewable energy. Connolly et al. (2010) provide the information necessary to identify a suitable energy tool for analysing the integration of renewable energy into various energy-systems under different objectives.

Water is en essential resource for most electric power generation technologies (Lee et al., 2018). In professional power plants, water is commonly used in many industrial processes including cooling systems (Regucki, Engler, and Szeliga, 2016). Water consumption to satisfy the growing demand for energy will increase. Georgia Power's Plant Scherer is one of the largest coal-fired thermoelectric power-production facilities in the United States. It is a coal-fired facility that provides electricity for Georgia. The capacity of the plant is around 3,520,000 kilowatt. For the 530-foot tall cooling towers, each of them circulates 268,000 gallons of water per minute. About 8,000 gallons water are lost to evaporation per minute (Georgia Power, 2016).

3.2 Robust Optimization for Power System Operations with Renewable Energy Integration

In this chapter, we consider the operations of the power system with renewable energy integration. First we list the index sets and indices, parameters, and decision variables for the operation of the power system.

Sets and Indices:

- $\mathcal{T}$: set of time periods, indexed by t ($T = \mathcal{T}$);
- $\mathcal{I}$: set of buses, indexed by i;
- $\mathcal{G}$: set of generators, indexed by g ($i_g \in \mathcal{I}$);
- $\mathcal{E}$: set of transmission lines, indexed by e ($e = (i_e, j_e)$);
- Y: set of renewable energy generators, indexed by y;

Parameters:

- P_g^{min}, P_g^{max}: lower and upper power output limits of generation unit $g \in \mathcal{G}$;
- T_g^{d0}, T_g^{u0}: minimum initially offline and online time periods of generation unit $g \in \mathcal{G}$;
- T_g^d, T_g^u: minimum offline and online time periods of generation unit $g \in \mathcal{G}$ once it is shut down/started up;
- R_g^d, R_g^u: maximum ramp-down and ramp-up rate of generation unit $g \in \mathcal{G}$ between adjacent time periods;
- $\tilde{R}_g^d, \tilde{R}_g^u$: maximum shutdown/startup ramp rate of generation unit $g \in \mathcal{G}$ when it is turned off/on;
- F_e: capacity of transmission line $e \in \mathcal{E}$;
- B_e: susceptance of transmission line $e \in \mathcal{E}$;
- $D_{i,t}$: energy demand for load at bus $i \in \mathcal{I}$ at time $t \in \mathcal{T}$;
- C_g^u, C_g^d: fixed startup/shutdown cost of generation unit $g \in \mathcal{G}$;
- C_g^p: production cost function of generation unit $g \in \mathcal{G}$;
- $C_{i,t}^s$: cost of shedding one unit of power on bus $i \in \mathcal{I}$ at time $t \in \mathcal{T}$;

Decision Variables:

- $x_{g,t} \in \{0, 1\}$: binary variable indicating if generation unit $g \in \mathcal{G}$ is committed or not at time $t \in \mathcal{T}$;
- $c_{g,t}^u, c_{g,t}^d$: incurred startup/shutdown cost of generation unit $g \in \mathcal{G}$ at time $t \in \mathcal{T}$;

- $p_{g,t}$: power generation of generation unit $g \in \mathcal{G}$ at time $t \in \mathcal{T}$;
- $f_{e,t}$: power flow on transmission line $e \in \mathcal{E}$ at time $t \in \mathcal{T}$;
- $z_{e,t} \in \{0,1\}$: transmission line $e \in \mathcal{E}$ is switched on or off at time $t \in \mathcal{T}$;
- $\theta_{i_e,t}$: voltage angle of bus $i \in \mathcal{I}$ on transmission line $e \in \mathcal{E}$ at time $t \in \mathcal{T}$;
- $q_{i,t}$: amount of load shedding at bus $i \in \mathcal{I}$ at time $t \in \mathcal{T}$;
- $P_{y,t}$: power generation of renewable energy generation unit $y \in Y$ at time $t \in \mathcal{T}$.

3.2.1 Unit commitment

The following set of constraints is related to the generation capacity of each generator and to the decisions of shutting down or starting up the generators. These are corresponding to the operational planning period decisions.

$$\sum_{t=1}^{T_g^{u0}}(1 - x_{g,t}) = 0, \ \forall g \in \mathcal{G}; \tag{3.1}$$

$$\sum_{t=1}^{T_g^{d0}} x_{g,t} = 0, \ \forall g \in \mathcal{G}; \tag{3.2}$$

These two constraints represent the initial online and offline time periods requirements for each generator $g \in \mathcal{G}$.

$$\sum_{t'=t}^{t+T_g^u-1} x_{g,t'} \geq T_g^u(x_{g,t} - x_{g,t-1}), \ \forall g \in \mathcal{G}, t \in \{T_g^{u0}+1, \cdots, T - T_g^u + 1\}; \tag{3.3}$$

$$\sum_{t'=t}^{t+T_g^d-1} (1 - x_{g,t'}) \geq T_g^d(x_{g,t-1} - x_{g,t}), \ \forall g \in \mathcal{G}, t \in \{T_g^{d0}+1, \cdots, T - T_g^d + 1\}; \tag{3.4}$$

These two constraints represent the minimum number of time periods that the generator must remain online/offline after the minimum initial online/offline required time.

$$\sum_{t'=t}^{T}(x_{g,t'} - (x_{g,t} - x_{g,t-1})) \geq 0, \ \forall g \in \mathcal{G}, t \in \{T - T_g^u + 2, \cdots, T\}; \tag{3.5}$$

$$\sum_{t'=t}^{T}((1 - x_{g,t'}) - (x_{g,t-1} - x_{g,t})) \geq 0, \ \forall g \in \mathcal{G}, t \in \{T - T_g^d + 2, \cdots, T\}; \tag{3.6}$$

These two constraints restrict the minimum number of time periods the generator must remain online/offline.

$$c_{g,t}^u \geq C_g^u(x_{g,t} - x_{g,t-1}), \ \forall g \in \mathcal{G}, t \in \mathcal{T}; \tag{3.7}$$

$$c_{g,t}^d \geq C_g^d(x_{g,t-1} - x_{g,t}), \ \forall g \in \mathcal{G}, t \in \mathcal{T}; \tag{3.8}$$

These two constraints represent the start up and shut down cost.

$$c_{g,t}^u \geq 0, c_{g,t}^d \geq 0, x_{g,t} \in \{0, 1\}, \ \forall g \in \mathcal{G}, t \in \mathcal{T}. \tag{3.9}$$

These constraints are the restrictions of the decision variables.

3.2.2 Optimal power flow model

This set of constraints are corresponding to the optimal power flow in power systems operation process. They exist in the economic dispatch for normal state operations.

$$P_g^{min} x_{g,t} \leq p_{g,t} \leq P_g^{max} x_{g,t}, \ \forall g \in \mathcal{G}, t \in \mathcal{T}; \tag{3.10}$$

This constraint means a generator could supply power only if it is online, and the supply amount has limitations.

$$p_{g,t} - p_{g,t-1} \leq R_g^u x_{g,t-1} + \tilde{R}_g^u(x_{g,t} - x_{g,t-1}) + P_g^{max}(1 - x_{g,t}), \ \forall g \in \mathcal{G}, t \in \mathcal{T}; \tag{3.11}$$

$$p_{g,t-1} - p_{g,t} \leq R_g^d x_{g,t} + \tilde{R}_g^d (x_{g,t-1} - x_{g,t}) + P_g^{max}(1 - x_{g,t-1}),\ \forall g \in \mathcal{G}, t \in \mathcal{T}; \quad (3.12)$$

These two constraints describe the generator status and the ramping rate could determine the power supply amount.

$$-F_e z_{e,t} \leq f_{e,t} \leq F_e z_{e,t},\ \forall e \in \mathcal{E}, t \in \mathcal{T}; \quad (3.13)$$

This constraint limits the flow going through transmission lines, with consideration of transmission line switching.

$$f_{e,t} = B_e(\theta_{i_e,t} - \theta_{j_e,t}) z_{e,t},\ \forall e \in \mathcal{E}, t \in \mathcal{T}; \quad (3.14)$$

This constraint shows the relation among the flow on transmission line, susceptance, phase angle difference and line switching status.

$$\sum_{e:j_e=i} f_{e,t} + \sum_{g:i_g=i} p_{g,t} + \sum_{y \in Y} P_{y,t} = (D_{i,t} - q_{i,t}) + \sum_{e:i_e=i} f_{e,t},\ \forall i \in \mathcal{I}, t \in \mathcal{T}; \quad (3.15)$$

This constraint represents the power flow balance, which means the inflow and the generation amounts are equal to the outflow and the demand amounts.

$$0 \leq q_{i,t} \leq D_{i,t},\ \forall i \in \mathcal{I}, t \in \mathcal{T}; \quad (3.16)$$

This constraint means the load shedding is limited by the demand.

$$p_{g,t} \geq 0, z_{e,t} \in \{0, 1\},\ \forall g \in \mathcal{G}, e \in \mathcal{E}, t \in \mathcal{T}. \quad (3.17)$$

This constraint is the restriction of the decision variables.

3.2.3 Water limitations

In the power generation process, water is used in several phases, such as cooling system. In this optimal power flow with renewable energy integration model, we try to include the water limitations as one constraint. Both the conventional energy resources and the renewable energy resources need water as the required supply in the electricity power generation process. The water availability varies by time and locations. Some areas are lack of groundwater, lakes, reservoirs, and rivers. The electricity power generation industry is limited by water supply in these areas. So the water sensitivity analysis corresponding to the total water supply amount for a power production system should be done.

On the other hand, the coefficient of the water usage varies as the different energy resources. α_g is the coefficient to represent how much water is needed to generate 1 megawatt hour electricity power by generator $g \in \mathcal{G}$. β_y is the coefficient to represent how much water is needed to generate 1 megawatt hour electricity power by renewable energy generator $y \in Y$. As the technologies develop, these efficiency coefficients should become smaller and smaller.

$$\sum_{t \in \mathcal{T}} \sum_{g: i_g = i} \alpha_g p_{g,t} + \sum_{t \in T} \sum_{y \in Y} \beta_y P_{y,t} \leq W. \tag{3.18}$$

In this constraint, the α_g and β_y are different numbers with different types of energy resource. For coal energy, $\alpha_g = 515$ gal/MWh. For solar energy, $\beta_y = 25$ gal/MWh. We refer to Chapters 2.2.4 and 2.4 for more details of these coefficients. The constant W are given as data. Here, through this constraint, we could test how the water limitation affects the power generation and the total cost in the whole system. Additionally, as technology advances, the water amount to be used for energy generation can decrease, and a sensitivity analysis about how the water usage amount in the electricity power production processes will change in the future.

3.2.4 Objective function without uncertainty renewable energy

For the operations of the power network, the total cost consists of power generation cost, decision costs about starting up and shutting down the generators, and load shedding related cost. The objective function could be formulated as the minimum total cost. Therefore, the whole optimal power flow model with renewable energy integration could be shown completely as (3.19):

$$\begin{aligned} \min \; & \sum_{t\in\mathcal{T}} \Big(\sum_{g\in\mathcal{G}} (C^p_g p_{g,t} + c^u_{g,t} + c^d_{g,t}) + \sum_{i\in\mathcal{I}} C^s_{i,t} q_{i,t} \Big) \\ s.t. \; & (3.1) - (3.18). \end{aligned} \tag{3.19}$$

3.2.5 Renewable energy uncertainty

As the renewable energy are intermittent, the electricity power generation amounts by renewable energy generators are uncertainty. The generation schedule of a generator over the time horizon could be changed within an interval. This interval could be written as an uncertainty set $\mathcal{Y}_y$ corresponding to the generator $y \in Y$. The uncertainty set, expressing the generator $y \in Y$ in time periods $t \in \mathcal{T}$, is expressed by the mean value and standard deviation of generation amount by the generator:

$$\mathbf{P}_y \in \mathcal{Y}_y = \bigcup_{t\in\mathcal{T}} [max\{P^{mean}_{y,t} - a_{y,t}\sigma_{y,t}, 0\}, min\{P^{mean}_{y,t} + b_{y,t}\sigma_{y,t}, \overline{P_y}\}], \; \forall y \in Y,$$

where P_y is a vector of $P_{y,t}$ for all $t \in \mathcal{T}$; $P^{mean}_{y,t}$ and $\sigma_{y,t}$ denote the expected value and the standard deviation of power generation by renewable energy generator $y \in Y$ in time period $t \in \mathcal{T}$, respectively. $\overline{P_y}$, a vector represents the power generation capacities over all $t \in \mathcal{T}$ of renewable energy generator $y \in Y$. For the nonnegative multipliers $a_{y,t}$ and $b_{y,t}$, we apply the uncertainty budget, constant Γ, to bound them as $\sum_{y\in Y}\sum_{t\in\mathcal{T}}(a_{y,t} + b_{y,t}) \leq \Gamma$. The constant Γ could be chosen as any number in the set $[0, |\mathcal{T}||Y|]$.

If we consider the objective function for the operations of the power system with renewable energy integration, the robust optimization model should be formulated. In the robust optimization model, we need to consider the worst-case scenario related to the uncertain factors, which are renewable energy power generations. It means when we try to minimize the total operating costs, there is another entity tries to maximum it by optimizing the uncertainty factors. The problem could be formulated as a two-stage robust model as (3.20):

$$\begin{aligned} \max_{\mathbf{P}_y \in \mathcal{Y}_y : y \in Y} \min_{\mathbf{b},\mathbf{p}} \quad & \mathbf{c}^T \mathbf{p} \\ s.t. \quad & \mathbf{A}\mathbf{b} \leq \mathbf{g} \\ & \mathbf{D}\mathbf{p} - \mathbf{K}\mathbf{b} \leq \mathbf{h} - \mathbf{J} \cdot \mathbf{P}_y \\ & \mathbf{b} \in \{0, 1\} \\ & \mathbf{p} \geq \mathbf{0} \end{aligned} \tag{3.20}$$

where $\mathbf{c}, \mathbf{g}, \mathbf{h}, \mathbf{A}, \mathbf{D}, \mathbf{J}$, and $\mathbf{K}$ are the corresponding vectors or matrices of the model coefficients, $\mathbf{b}, \mathbf{p}, \mathbf{P}_y$ separately represents the vector of binary variables, the vector of continuous variables, the uncertainty variables. The first set of constraints in (3.20) refer to constraints (3.1)-(3.6). The second set of constraints correspond to (3.7)-(3.9) and (3.10)-(3.18). The third set of constraints correspond to the binary variables. The fourth set of constraints correspond to the nonnegative variables.

3.3 Solution Approach and Numerical Experiments

The compact model (3.20) is hard to solve. We try to isolate the binary variables from the objective function to get a tri-level model. The objective has been changed as the formulation as shown in (3.21). And the constraints keep the same.

$$\max_{\mathbf{P}_y \in \mathcal{Y}_y : y \in Y} \min_{\mathbf{b}} \min_{\mathbf{p}} \ \mathbf{c}^T \mathbf{p} \tag{3.21}$$

If the uncertainty variables (renewable energy generation $\hat{\mathbf{P}}_y$) and the binary variables (unit commitment states $\hat{\mathbf{x}}$ and line switching decisions $\hat{\mathbf{z}}$) are fixed, the third level model corresponding to the decision variables $\mathbf{p}$ is pure linear programming. We could write down the compact form of the primal and dual problems.

$$\begin{aligned} \min_{\mathbf{p}} \ & \mathbf{c}^T\mathbf{p} \\ s.t. \ & \mathbf{D}\mathbf{p} \leq \mathbf{h} + \mathbf{K}\hat{\mathbf{b}} - \mathbf{J}\cdot\hat{\mathbf{P}}_y \\ & \mathbf{p} \geq \mathbf{0} \end{aligned} \tag{3.22}$$

$$\begin{aligned} \max_{\alpha} \ & (\mathbf{h} + \mathbf{K}\hat{\mathbf{b}} - \mathbf{J}\cdot\hat{\mathbf{P}}_y)^T\alpha \\ s.t. \ & \mathbf{D}^T\alpha \leq \mathbf{c} \\ & \alpha \leq \mathbf{0} \end{aligned} \tag{3.23}$$

The comprehensive expression of the primal problem and the corresponding dual variables are shown in the follow model:

$$\begin{aligned} \min \ & \sum_{t\in\mathcal{T}}\Big(\sum_{g\in\mathcal{G}}(C_g^p p_{g,t} + c_{g,t}^u + c_{g,t}^d) + \sum_{i\in\mathcal{I}} C_{i,t}^{sh} q_{i,t}\Big) \\ s.t. \ & (\alpha_{g,t}) \quad -c_{g,t}^u \leq -C_g^u\big(\hat{x}_{g,t} - \hat{x}_{g,t-1}\big), \quad \forall g\in\mathcal{G}, t\in\{2,\ldots,T\} \\ & (\alpha'_{g,t}) \quad -c_{g,t}^d \leq -C_g^d\big(\hat{x}_{g,t-1} - \hat{x}_{g,t}\big), \quad \forall g\in\mathcal{G}, t\in\{2,\ldots,T\} \\ & (\alpha_{g,t}) \quad -c_{g,1}^u \leq -C_g^u\big(\hat{x}_{g,1} - \overline{x}_{g,0}\big), \quad \forall g\in\mathcal{G} \\ & (\alpha'_{g,t}) \quad -c_{g,1}^d \leq -C_g^d\big(\overline{x}_{g,0} - \hat{x}_{g,1}\big), \quad \forall g\in\mathcal{G} \\ & (\beta_{g,t}) \quad -p_{g,t} \leq -\hat{x}_{g,t}P_g^{min}, \quad \forall g\in\mathcal{G}, t\in\mathcal{T} \\ & (\beta'_{g,t}) \quad p_{g,t} \leq \hat{x}_{g,t}P_g^{max}, \quad \forall g\in\mathcal{G}, t\in\mathcal{T} \\ & (\gamma_{g,t}) \quad p_{g,t} - p_{g,t-1} \leq R_g^u\hat{x}_{g,t-1} + \tilde{R}_g^u\big(\hat{x}_{g,t} - \hat{x}_{g,t-1}\big) + P_g^{max}\big(1 - \hat{x}_{g,t}\big), \\ & \qquad\qquad \forall g\in\mathcal{G}, t\in\{2,\ldots,T\} \\ & (\gamma'_{g,t}) \quad p_{g,t-1} - p_{g,t} \leq R_g^d\hat{x}_{g,t} + \tilde{R}_g^d\big(\hat{x}_{g,t-1} - \hat{x}_{g,t}\big) + P_g^{max}\big(1 - \hat{x}_{g,t-1}\big), \\ & \qquad\qquad \forall g\in\mathcal{G}, t\in\{2,\ldots,T\} \end{aligned}$$

$$(\gamma_{g,t}) \quad p_{g,1} \leq \overline{p}_{g,0} + R_g^u\overline{x}_{g,0} + \tilde{R}_g^u\big(\hat{x}_{g,1} - \overline{x}_{g,0}\big) + P_g^{max}\big(1 - \hat{x}_{g,1}\big), \quad \forall g\in\mathcal{G}$$

$$(\gamma'_{g,t}) \quad -p_{g,1} \leq -\overline{p}_{g,0} + R^d_g \hat{x}_{g,1} + \tilde{R}^d_g\big(\overline{x}_{g,0} - \hat{x}_{g,1}\big) + P^{max}_g\big(1 - \overline{x}_{g,0}\big), \quad \forall g \in \mathcal{G}$$

$$(\delta_{e,t}) \quad -f_{e,t} \leq \hat{z}_{e,t} F_e, \quad \forall e \in \mathcal{E}, t \in \mathcal{T}$$

$$(\delta'_{e,t}) \quad f_{e,t} \leq \hat{z}_{e,t} F_e, \quad \forall e \in \mathcal{E}, t \in \mathcal{T}$$

$$(\zeta_{e,t}) \quad -f_{e,t} + B_e(\theta_{i_e} - \theta_{j_e}) \leq (1 - \hat{z}_{e,t}) M_e, \quad \forall e \in \mathcal{E}, t \in \mathcal{T}$$

$$(\zeta'_{e,t}) \quad f_{e,t} - B_e(\theta_{i_e} - \theta_{j_e}) \leq (1 - \hat{z}_{e,t}) M_e, \quad \forall e \in \mathcal{E}, t \in \mathcal{T}$$

$$(\iota_{i,t}) \quad \sum_{e:j_e=i} f_e + \sum_{g:i_g=i} p_{g,t} + q_{i,t} - \sum_{e:i_e=i} f_e = D_{i,t} - \sum_{y:i_y=i} \hat{P}_{y,t}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}$$

$$(\kappa_{i,t}) \quad q_{i,t} \leq D_{i,t}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}$$

$$(\lambda) \quad \sum_{t\in T}\sum_{g\in G} \alpha_g p_{g,t} \leq W - \sum_{t\in T}\sum_{y\in Y} \beta_y \hat{P}_{y,t},$$

$$p_{g,t}, c^u_{g,t}, c^d_{g,t} \geq 0, \quad \forall g \in \mathcal{G}, t \in \mathcal{T}$$

$$q_{i,t} \geq 0, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}$$

The dual problem of the current primal problem could be written as:

$$\begin{aligned}
\max_{\alpha,\gamma,\beta,\delta,\zeta,\iota,\kappa,\lambda} \quad & \sum_g \Big(\alpha_{g,1}\big(-C^u_g\big(\hat{x}_{g,1} - \overline{x}_{g,0}\big)\big) + \alpha'_{g,1}(-C^d_g\big(\overline{x}_{g,0} - \hat{x}_{g,1}\big))\Big) \\
& + \sum_g \sum_{t=2}^{T} \Big(\alpha_{g,t}\big(-C^u_g\big(\hat{x}_{g,t} - \hat{x}_{g,t-1}\big)\big) \\
& + \alpha'_{g,t}\big(-C^d_g\big(\hat{x}_{g,t-1} - \hat{x}_{g,t}\big)\big)\Big) \\
& + \sum_g \Big(\gamma_{g,1}\big(\overline{p}_{g,0} + R^u_g \overline{x}_{g,0} + \tilde{R}^u_g\big(\hat{x}_{g,1} - \overline{x}_{g,0}\big) + P^{max}_g\big(1 - \hat{x}_{g,1}\big)\big) \\
& + \gamma'_{g,1}\big(-\overline{p}_{g,0} + R^d_g \hat{x}_{g,1} + \tilde{R}^d_g\big(\overline{x}_{g,0} - \hat{x}_{g,1}\big) + P^{max}_g\big(1 - \overline{x}_{g,0}\big)\big)\Big) \\
& + \sum_g \sum_{t=2}^{T} \Big(\gamma_{g,t}\big(R^u_g \hat{x}_{g,t-1} + \tilde{R}^u_g\big(\hat{x}_{g,t} - \hat{x}_{g,t-1}\big) + P^{max}_g\big(1 - \hat{x}_{g,t}\big)\big) \\
& + \gamma'_{g,t}\big(R^d_g \hat{x}_{g,t} + \tilde{R}^d_g\big(\hat{x}_{g,t-1} - \hat{x}_{g,t}\big) + P^{max}_g\big(1 - \hat{x}_{g,t-1}\big)\big)\Big) \\
& + \sum_g \sum_t (-\beta_{g,t} \hat{x}_{g,t} P^{min}_g + \beta'_{g,t} \hat{x}_{g,t} P^{max}_g) \\
& + \sum_e \sum_t (\hat{z}_{e,t} F_e(\delta_{e,t} + \delta'_{e,t})) + \sum_{e\notin\mathcal{E}'} \sum_t (1 - \hat{z}_{e,t}) M_e(\zeta_{e,t} + \zeta'_{e,t})
\end{aligned}$$

$$
\begin{aligned}
&+\sum_i\sum_t(\kappa_{i,t}D_{i,t})+\sum_i\sum_t(\iota_{i,t})(D_{i,t}-\sum_{y:i_y=i}\hat{p}_{y,t})+\lambda(W-\sum_{t\in T}\sum_{y\in Y}\sigma_y\hat{p}_{y,t})\\
s.t.\ &-\alpha_{g,t}\le 1,\quad \forall g\in\mathcal{G},t\in\mathcal{T}\\
&-\alpha'_{g,t}\le 1,\quad \forall g\in\mathcal{G},t\in\mathcal{T}\\
&-\beta_{g,t}+\beta'_{g,t}+\gamma_{g,t}-\gamma'_{g,t}-\gamma_{g,t+1}+\gamma'_{g,t+1}+\iota_{i_g=i,t}+\sigma_g\lambda\\
&\qquad\qquad\le C^p_g,\quad \forall g\in\mathcal{G},t\in\{1,\ldots,T-1\}\\
&-\beta_{g,T}+\beta'_{g,T}+\gamma_{g,T}-\gamma'_{g,T}+\iota_{i_g=i,T}+\sigma_g\lambda\le C^p_g,\quad \forall g\in\mathcal{G}\\
&-\delta_{e,t}+\delta'_{e,t}-\zeta_{e,t}+\zeta'_{e,t}+\iota_{j_e=i,t}-\iota_{i_e=i,t}=0,\quad \forall e\in\mathcal{E},t\in\mathcal{T}\\
&\sum_{i:e_i=i}B_e(\zeta_{e,t}-\zeta'_{e,t})-\sum_{i:e_j=i}B_e(\zeta_{e,t}-\zeta'_{e,t})=0,\quad \forall i\in\mathcal{I},t\in\mathcal{T}\\
&\iota_{i,t}+\kappa_{i,t}\le C^{sh}_{i,t},\quad \forall i\in\mathcal{I},t\in\mathcal{T}\\
&\alpha_{g,t},\alpha'_{g,t},\gamma_{g,t},\gamma'_{g,t},\beta_{g,t},\beta'_{g,t}\le 0,\quad \forall g\in\mathcal{G},t\in\mathcal{T}\\
&\delta_{e,t},\delta'_{e,t},\zeta_{e,t},\zeta'_{e,t}\le 0,\quad \forall e\in\mathcal{E},t\in\mathcal{T}\\
&\kappa_{i,t}\le 0,\forall\ \ i\in\mathcal{I},t\in\mathcal{T}\\
&\iota_{i,t}\ u.r.s,\forall\ \ i\in\mathcal{I},t\in\mathcal{T}\\
&\lambda\le 0
\end{aligned}
$$

From the strong duality theory, we could determine the optimal solutions of the primal problem are the same as the optimal solutions of the dual problem, if the problem is linear programming model. Thus, we could replace the original third level problem by its dual formulation with the dual variables α, and the current robust model could be written as (3.24):

$$
\begin{aligned}
\max_{\mathbf{P}_y\in\mathcal{Y}_y:y\in Y}\min_{\mathbf{b}}\max_{\alpha}\ &(\mathbf{h}+\mathbf{K}\mathbf{b}-\mathbf{J}\cdot\mathbf{P}_y)^T\alpha\\
s.t.\ &\mathbf{A}\mathbf{b}\le\mathbf{g}\\
&\mathbf{D}^T\alpha\le\mathbf{c}\\
&\mathbf{b}\in\{0,1\}\\
&\alpha\le\mathbf{0}
\end{aligned}
\tag{3.24}
$$

Now we could consider how to deal with the decision variables $\mathbf{b}$. For the current tri-level model, if we could introduce a new index to express the formulation related to $\mathbf{b}$, the model could be simplified. We propose to change the objective function into the following form, as shown in (3.25).

$$\max_{\mathbf{P}_y \in \mathcal{Y}_y : y \in Y, \Theta} \{\Theta | \Theta \leq \min_{\mathbf{b}} \max_{\alpha} (\mathbf{h} + \mathbf{K}\mathbf{b} - \mathbf{J} \cdot \mathbf{P}_y)^T \alpha\} \tag{3.25}$$

For any given subset of variables $\hat{\mathbf{b}}^{(\omega)}, \omega = 0, \ldots, |\mathcal{C}|$, which are feasible to (3.20), the current problem could be solved. We could delete the constraints about the binary variables. Here $\mathcal{C}$ represents the set of all possible combinations of binary decision variables $\mathbf{b}$. We also know that the value of α is corresponding to $\omega \in \mathcal{C}$, so $\alpha^{(\omega)}$ could be regarded as decision variables. For the two max in the objective function, we could merge them, and put the inequality to restrict the Θ as a constraint. After linearizing the nonlinear term $(\mathbf{J} \cdot \mathbf{P}_y)^T \alpha^{(\omega)}$, the new variable $\mathbf{U}^{(\omega)}$ is introduced in the model. The current model becomes (3.26).

$$\begin{aligned}
\max_{\mathbf{U}^{(\omega)}, \mathbf{P}_y \in \mathcal{Y}_y : y \in Y, \alpha^{(\omega)}, \Theta} \quad & \Theta \\
s.t. \quad & \Theta \leq (\mathbf{h} + \mathbf{K}\hat{\mathbf{b}}^{(\omega)})^T \alpha^{(\omega)} - \mathbf{J}^T \mathbf{U}^{(\omega)} \\
& \mathbf{D}^T \alpha^{(\omega)} \leq \mathbf{c} \\
& \hat{\mathbf{b}}^{(\omega)} \in \mathcal{C} \\
& \alpha^{(\omega)} \leq \mathbf{0}
\end{aligned} \tag{3.26}$$

If we plan to reformulate the original optimization model in a master problem and a subproblem, the subproblem should be able to generate one combination of $\hat{\mathbf{b}}^{(\omega)} \in \mathcal{C}$, and this combination could be applied in the master problem to get the solution of $\mathbf{P}_y \in \mathcal{Y}_y$ in each iteration. To obtain this goal, we discover that (3.26) could be the master problem, and then, the subproblem could be defined as (3.27).

$$
\begin{aligned}
\min_{\mathbf{b},\mathbf{p}} \ & \mathbf{c}^T\mathbf{p} \\
s.t. \ & \mathbf{Ab} \leq \mathbf{g} \\
& \mathbf{Dp} - \mathbf{Kb} \leq \mathbf{h} - \mathbf{J} \cdot \hat{\mathbf{P}}_y \\
& \mathbf{b} \in \{0, 1\} \\
& \mathbf{p} \geq \mathbf{0}
\end{aligned}
\tag{3.27}
$$

The column-and-constraint generation (C&CG) algorithm is presented in Algorithm 2, which presents how to solve the problem with a subset of combinations of $\hat{\mathbf{b}}^{(\omega)} \in \mathcal{C}$. It has been proven to converge in finite number of iterations as shown in Zeng and Zhao (2013).

Algorithm 2 C&CG Algorithm

```
Set LB = −∞, UB = ∞, ω = 1, b̂^(ω) = b_0, C = {1}
while UB − LB > ϵ do
    Solve master problem (MP) defined in (3.26)
    Let U*(ω), P*_y, α*(ω) and Θ* be MP optimal solution
    Update UB = Θ*
    Solve subproblem (SP) defined in (3.27), with P̂_y = P*_y
    Update LB = max{LB, Obj*(SP)}
    Let b* and p* be SP optimal solution
    Let ω = ω + 1
    Update C = C ∪ {ω}
    Set b̂^(ω) = b*
end while
Obtain optimal scheduling plan from SP
End
```

The proposed formulations and algorithm are all implemented in C++ and using CPLEX 12.8 via ILOG Concert Technology 2.9, and all computations are performed on a Linux machine with 4 Intel(R) Xeon(TM) CPU 3.60 GHz processors and 32GB RAM. For the IEEE 6-bus power testing system, the data taken from Chen et al.

(2017) was used. There are three conventional generators, one solar generator at bus 1, and some demand loads from three buses in this power generation and operation system. In the numerical experiments, the values for $a_{y,t}, b_{y,t}$ are randomly chosen following the range requirements.

We consider the water limitations in the optimal power flow model because the water availability is limited in some regions. If the supply water is in shortage for the system, part of the demand will not be satisfied, which means the load shedding exist. In the objective function, there is penalty cost from load shedding. In this case, we could analyze the relation between the water supply amount and the total cost of the power generation and operation. In Figure 3.1, we could find that water needed amount in this system to satisfy all demands should be 2,180,410 gallons. With this amount of water, there will be no load shedding. When the water supply amount is larger than this number (the right hand side of 2,180,410 on the x axis of the coordinated system), the total cost will keep the same due to no changes showing in the objective function. But when the water supply amount is less than this number (the left hand side of 2,180,410 on the x axis of the coordinated system), the load shedding occurs, and the penalty cost from the load shedding will affect the total cost in the whole power system operating.

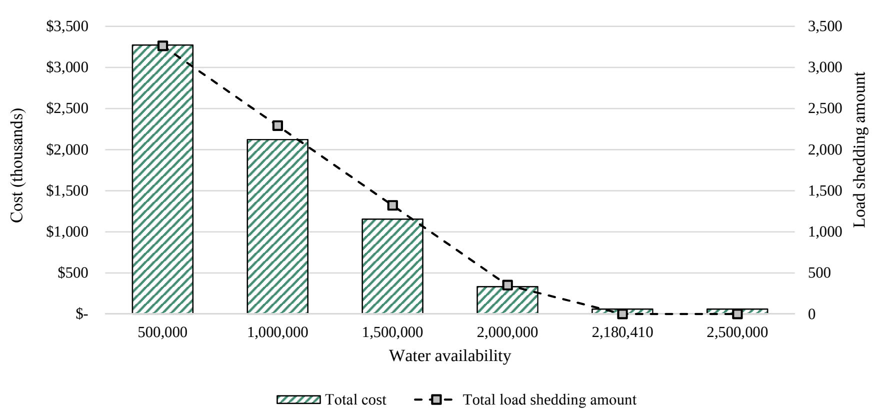


Figure 3.1: Water usage analysis in IEEE 6-bus system

As the technology develops, the coefficients, which are used to express how much water will be used to generate per unit electricity power by a generator, should be smaller and smaller. This fact could be applied for both conventional energy sources and renewable energy sources. In Figure 3.2 where RES denotes the renewable energy systems., we could find how the coefficients will affect the water usage amount in the IEEE 6-bus power system. The percentage numbers on x axis represent the efficiency coefficients will be decreased to partial of their original values. If the efficiency coefficients of generators decrease, the water usage amount in the power generation system used to satisfy the electricity power demands will be less. The solid line in the figure shows that the total water usage amount in all electricity power generators keeps decreasing with respect to the smaller and smaller efficiency coefficients of conventional energy generators, represented by α_g in constraint (3.18). In this case, we make coal generators as typical conventional energy generators. The dashed line in the same figure expresses that the water used by renewable energy generators will become less with decreasing efficiency coefficients of renewable energy generators, indexed by β_y in constraint (3.18). In this case, we regard solar generators as typical renewable energy generators.

In the IEEE 30-bus power testing system, there are 6 conventional electricity power generators, and 2 solar generators. One of the solar generators is located in bus 3 and another one is located in bus 6. In Figure 3.3, we could observe that water needed amount in this system to satisfy all demands should be 2,196,050 gallons. With this number of supply water, there will be no load shedding. When the water supply amount is larger than this number (the right hand side of 2,196,050 on the x axis of the coordinated system), the total cost will keep the same due to no changes

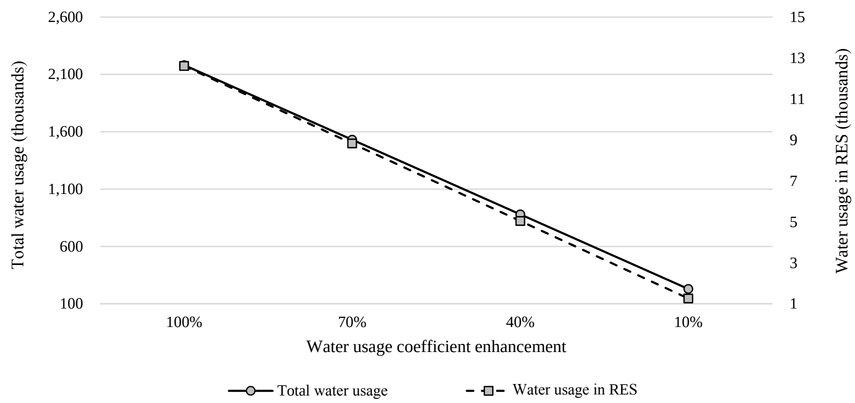


Figure 3.2: Sensitivity analysis of water coefficients in IEEE 6-bus system

showning in the objective function. But when the water supply amount is less than this number (the left hand side of 2,196,050 on the x axis of the coordinated system), the load shedding occurs, and the penalty cost from the load shedding will affect the total cost in the system operations.

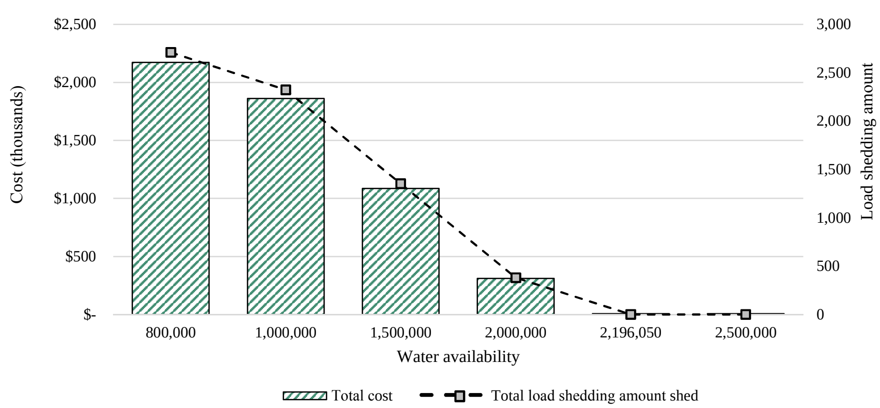


Figure 3.3: Water usage analysis in IEEE 30-bus system

In Figure 3.4, we could find how the efficiency coefficients will affect the water usage amount in the IEEE 30-bus power system. The solid line in the figure shows that the total water usage amount in all electricity power generators keep decreasing with respect to the smaller and smaller efficiency coefficients of conventional power generators, represented by α_g in constraint (3.18). In this case, we make coal generators as typical conventional energy generators. The dashed line in the same figure expresses that the water used by renewable energy generators will become less with the deceasing efficiency coefficients of renewable energy generators, indexed by β_y in constraint (3.18). In this case, we regard solar generators as typical renewable energy generators.

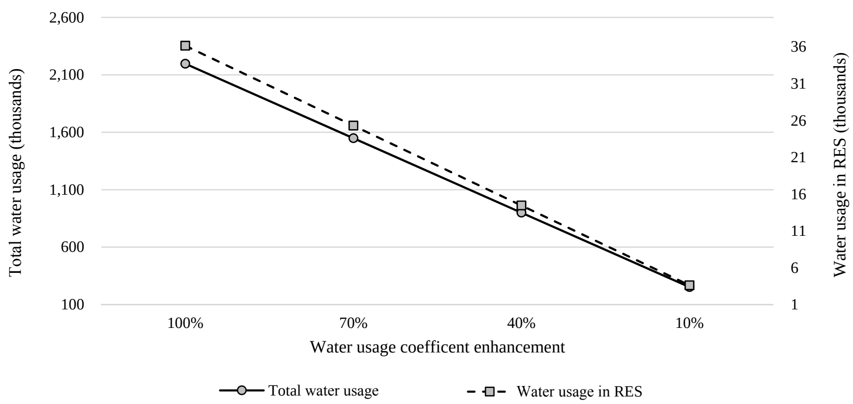


Figure 3.4: Sensitivity analysis of water coefficients in IEEE 30-bus system

3.4 Conclusions

In this chapter, we discuss a mixed integer programming model to simulate the operational planning period and normal operational period of power system. The unit commitment, optimal power flow problem, renewable energy integration and water limitations are included in the optimization process of the power system operations. In this optimization model, we consider the generator states scheduling, transmission line switching decisions, and uncertainty issue of renewable energy generation.

Because the renewable energy sources are intermittent and the percentage of the renewable energy sources in electricity power production processes are increasing, the uncertainty issues will affect the optimal solutions. We select the robust optimization framework to manage the uncertainty factors. In the numerical experiments, we apply the C&CG algorithm to solve the model, and test on both IEEE 6-bus power system and IEEE 30-bus power system. Based on the testing results, we could find with different water supply amounts, the total cost for the power system operating will be changed. It is corresponding to the load shedding amount. This kind of water sensitivity analysis represents how the water supply amount will affect the electricity power generation and the whole power system operation. In different types of power generators, the water amount used to generate per unit electricity power is up to the sort of energy sources. We could check how efficiency coefficients can impact the water usage amount in the power system.

Chapter 4
Vulnerability analysis for power grid and its control communication network

In this chapter, we propose the integer programming approaches to model the cascading failure process in interdependent networks consisting of two networks (for example, power grid and communication network). The goal is to identify the k most vulnerable nodes or edges in power grid, whose removal can mostly trigger the failures. We develop the stage idea to model the cascading failure process and apply the percolation theory (Herega, 2015) to indicate that only nodes belong to the largest connected component (LCC) could survive. The size of the resulting mutually connected component (MCC) in the steady state after cascading failure process is used to measure the resilience. Thus, the removal of most vulnerable nodes or edges will lead to the least size of MCC. To solve the proposed mixed integer nonlinear programming models, some reformulation techniques are applied. For comparison purpose, the sizes of resulting nodes in power grid and communication network are also used as measurements for resilience of the interdependent network.

The remainder of this chapter is organized as follows. Chapter 4.1 introduces the background and motivation of this research. In Chapter 4.2, two examples are introduced to explain the cascading failure process. The modeling stages and the steady state are also discussed. Chapter 4.3 presents the integer programming formulations for identification of the most vulnerable nodes and edges in the interdependent network. The numerical experiments are performed in Chapter 4.4, and the results are concluded in Chapter 4.5.

4.1 Introduction

On September 28, 2003, several nodes of the power grid failed in Italy, and caused failures of the control communication network, which, in turn, caused a further breakdown of power grid. The failures eventually led to a large-scale blackout affecting the whole Italian Peninsula, and the full restoration took almost 19 hours (see an overview in Sforna and Delfanti, 2007). The analysis of this incident suggests that higher level coordinated operations of the interconnected systems are needed in case of unpredictable failures. The management of power grid requires the control of communication network, while the operations of communication network needs electricity supply from power grid. Such interconnections and the two systems present an example of the interdependent networks.

In interdependent networks, one network depends on another to be functional. Additionally, failures in one will affect not only itself but also the ones dependent on it. Interdependence models these kinds of relationships and the mutual reliance between networks (Buldyrev et al., 2010). There are many examples of interdependent networks, especially for modeling critical infrastructures. Some examples include water and energy systems (Stokes-Draut et al., 2017), water and its control system (Zhang, Yang, and Lall, 2016), airport and seaport systems (Cision, 2017), signal and traffic systems (US DOT, 2015). As explained above, the failure in one network may cause the failure in another and lead to cascading failure (Yang and Motter, 2017). A cascading failure is defined as a process in interdependent networks in which the failure of one or a few parts can trigger the failure of other parts. There exist some cases that a failure of a very small fraction of nodes or edges in one network may lead to the complete failure of the whole interdependent network (e.g., Dueñas-Osorio and Vemuru, 2009).

Therefore, for better coordinated operations or to improve the planning phase, a vulnerability analysis is necessary to define, identify, and classify the vulnerabilities in interdependent networks. In the past decade, the study of vulnerability analysis has consisted of centrality measures (Wang, Scaglione, and Thomas, 2010), link importance and the site exposure idea (Jenelius, Petersen, and Mattsson, 2005), a developed reflection metric (Abedin et al., 2006), and the topology extraction method (Wang et al., 2013). However, these methods lack the efficiency to manage the results, and are only suitable for special cases. The approach of identifying the k most vulnerable nodes in the network, presented by Sen et al. (Sen et al., 2014), performs better than the previous approaches for vulnerability analysis. To identify the vulnerable or critical nodes, there are some developed techniques, such as the interdependent power network disrupter optimization problem, to identify the nodes to access the vulnerability of the networks (Nguyen, Shen, and Thai, 2013). The techniques include the network controllability model (Li et al., 2015), a specific method based on 0-1 formulation (Veremyev, Boginski, and Pasiliao, 2013), an exact optimization-based approach with 0-1 formulation (Veremyev et al., 2014), the interdiction-based approach (Nguyen and Sharkey, 2016), and the study of supply node connectivity (Zhang and Modiano, 2017). Besides the behavior of vulnerable nodes, that of the vulnerable or critical edges should be considered as a possible element on which to perform the vulnerability analysis. The searching method based on electric betweenness entropy (Yu et al., 2016), the active power flow betweenness indicator (Sun, Zhang, and Zhang, 2016), the amount of optimal load shedding under the consideration of risk theory (Liu et al., 2017), and the first performance measure (Qiang and Nagurney, 2007) are the state-of-the-art approaches used to determine the vulnerable edges. However, the current vulnerable node and edge identification methods have been developed primarily for independent power grids, not for interdependent networks. The generating function approach (Buldyrev et al., 2010), (Gao et al., 2012) and two-phase control policy (Parandehgheibi, Modiano, and Hay, 2014) both capture the phenomenon of the cascading failures. These methods reveal that considering the minimum number of the initial failed nodes or edges needed to trigger the complete failure of the interdependent network should be the main problem to be considered when studying vulnerability (Parandehgheibi and Modiano, 2013). The problem is that these approaches applied to simulate the cascading failure are usually hard to solve. Additionally, there is lack of research on integer programming approaches to exactly model the cascading failure process and identify the most vulnerable nodes and edges in the interdependent networks.

4.2 Cascading Failure Process and Steady State

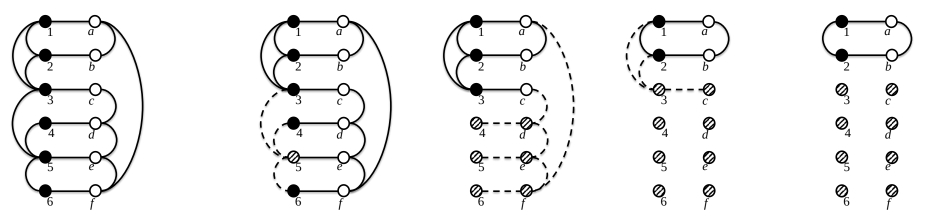
In this section, we illustrate the cascading failure process on two interdependent networks as examples to explain the proposed stage idea in Chapter 4.3. Then, the steady state after the cascading failure process is explicitly defined, and will be used as a measurement of the vulnerability of the network.

4.2.1 Cascading failure

The cascading failure process starts with the failure of one or a few parts of the power grid, and can trigger the failure of other parts in the power grid as well as the communication network through interdependency links. Then some of these communication network failures will cascade back to the power grid because of interdependency. Continuing this process, eventually there will be a state where the process terminates. To illustrate this process, we begin with an example where the links between two systems have bidirectional dependency.

The interdependent network shown in Fig. 4.1(a) (case from Buldyrev et al., 2010) consists of 6 nodes $\{1,2,3,4,5,6\}$ and 6 edges $\{(1,2),(1,3),(2,3),(3,5),(4,5),(5,6)\}$ in the power grid. Additionally, there are 6 nodes $\{a,b,c,d,e,f\}$ and 5 edges

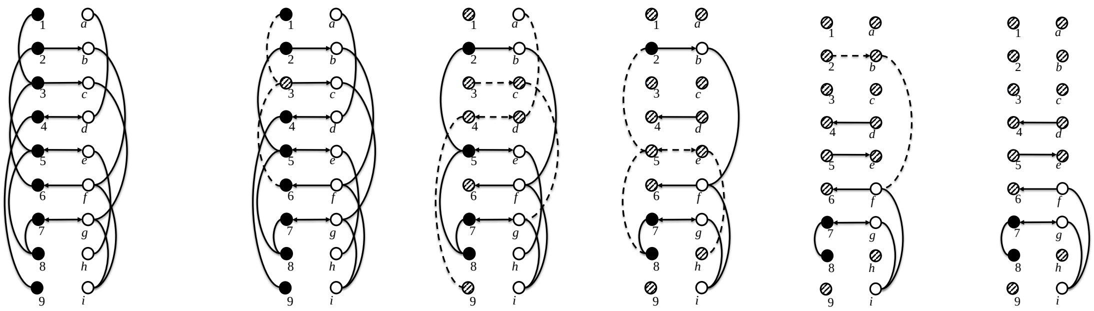
$\{(a,b),(a,f),(c,d),(d,e),(e,f)\}$ in the communication network. There are also 6 bidirectional interdependency links between the power grid and communication network, $\{(1,a),(2,b),(3,c),(4,d),(5,e),(6,f)\}$. To begin, assume that the node 5 is removed initially. When this occurs, the incident edges $\{(3,5)$, $(4,5)$, $(5,6)\}$ will fail (stage 0, as shown in Fig. 4.1(b)). Except the LCC with nodes $\{1,2,3\}$ in power grid, the two others $\{4\}$, $\{6\}$ will be failed according to the percolation theory. The related interdependency links $\{(4,d),(5,e),(6,f)\}$and connected nodes $\{d,e,f\}$ will fail, as well as the incident edges $\{(c,d),(d,e),(e,f),(a,f)\}$ in the communication network (stage 1, as shown in Fig. 4.1(c)). The larger one with nodes $\{a,b\}$ of the resulted two connected components can keep working and the node c fails, which results the failure of interdependency link $(3,c)$, node 3, and edges incident to node 3 (stage 2, as shown in Fig. 4.1(d)). Finally, there is only one connected component in power grid with nodes $\{1,2\}$, and also another connected one in communication network with nodes $\{a,b\}$. The cascading process terminates to a steady state with the MCC having nodes $\{1,2,a,b\}$ (stage 3, as shown in Fig. 4.1(e)).



(a) Original network (b) Stage 0 (c) Stage 1 (d) Stage 2 (e) Stage 3

Figure 4.1: Interdependent network with bidirectional interdependency links and cascading failures

In the previous example, failure of either end of a bidirectional interdependency link can cause the failure of the other. In the following example, the interdependency link is associated with a direction. For example, the failure of node 2 can cause failure of node b in Fig. 4.2 through link $(2,b)$, but it cannot be influenced in the other direction.



(a) Original network (b) Stage 0 (c) Stage 1 (d) Stage 2 (e) Stage 3 (f) Stage 4

Figure 4.2: Interdependent network with directional interdependency links and cascading failures

The interdependent network shown in Fig. 4.2(a) (case from Wang et al., 2013) consists of 9 nodes $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ and 6 edges $\{(1, 3), (2, 5), (3, 6), (4, 9), (5, 8), (7, 7)\}$ in the power grid, and 9 nodes $\{a, b, c, d, e, f, g, h, i\}$ and 6 edges $\{(a, d), (b, f), (c, g), (e, h), (f, i), (g, i)\}$ in the communication network. Additionally, there are 9 directional interdependency links between the power grid and communication network, $\{(2, b), (3, c), (4, d), (d, 4), (5, e), (e, 5), (f, 6), (7, g), (g, 7)\}$. To begin, assume that the node 3 is removed initially, the incident edges $\{(1, 3), (3, 6)\}$ are failed (stage 0, as shown in Fig. 4.2(b)). Aside from the LCC with nodes $\{2, 5, 7, 8\}$ in the power grid, the three others $\{1\}, \{4, 9\}, \{6\}$ will fail according to percolation theory. The related interdependency links $\{(3, c),\ (4, d)\}$ and connected nodes $\{c, d\}$ in the communication network will fail, as well as the incident edges $\{(a, d), (c, g)\}$ in the communication network (stage 1, as shown in Fig. 4.2(c)). The larger one with nodes $\{b, f, g, i\}$ of the resulted three connected components will continue to work while nodes $\{a, e, h\}$ will fail, resulting in the failure of interdependency link $(e, 5)$, node 5, and edges incident to node 5 (stage 2, as shown in Fig. 4.2(d)). The larger one with nodes $\{7, 8\}$ of the resulted two connected components can keep work and the node 2 fails, which results the failure of interdependency link $(2, b)$, node b, and the edges incident to node b (stage 3, as shown in Fig. 4.2(e)). Finally, there remains only one connected component in the communication network with nodes $\{f, g, i\}$, and a connected one in the power grid with nodes $\{7, 8\}$. The cascading process terminates in a steady state with a MCC of nodes $\{7, 8, f, g, i\}$ (stage 4, as shown in Fig. 4.2(f)).

As illustrated in the above two examples, in this paper we model the cascading failure process by stages, beginning by identifying the LCC in all stages except for stage 0, which contains the initial failures in the power grid. In each stage, after identifying the LCC, the other, smaller, connected components and their incident components will be failed according to percolation theory.

4.2.2 Steady state and assumptions

The cascading failure process terminates in a state, called the steady state, where no more failure will occur as time goes on. In this paper, we consider the MCC as a measure of resilience, as only mutually connected clusters can be potentially functional after failures (see Buldyrev, Shere, and Cwilich, 2011).

In an interdependent network, a MCC is a connected subgraph, consisting of nodes from both networks, and interdependency links in both directions. It is usually used to denote the remaining subgraph after the cascading failures among its networks (see Bianconi, Dorogovtsev, and Mendes, 2015; Hwang et al., 2015). In the following section, we utilize the size of the largest MCC after a cascading failure process as a resilience measure to identify the most vulnerable nodes or edges in a power grid.

4.3 Integer Programming Formulations for Vulnerability Analysis

In this section, we present the integer programming formulations for the vulnerability analysis problem to identify the vulnerable nodes and edges of the interdependent network. We start with the definitions of parameters used for modeling and also the stages utilized to capture the cascading failures. Based on these definitions, the constraints and objectives of the integer programming models are presented for vulnerability analysis of interdependent networks.

4.3.1 Parameters and decision variables

Let $\mathcal{I}(G_s, G_c, E_{sc})$ denote an interdependent network, consisting of two networks $G_s = (V_s, E_s)$ and $G_c = (V_c, E_c)$, where V_s, V_c are the corresponding node sets with cardinalities $m = |V_s|, n = |V_c|$ and E_s, E_c are the corresponding edge sets, respectively for G_s and G_c. In this paper, G_s denotes the power grid and G_c denotes its control communication network.

For the interdependency links in E_{sc} between G_s and G_c, two cases will be discussed in this chapter:

(i) Each link in E_{sc} has a direction to indicate the dependency between two networks. An example is shown in Fig. 4.2. To distinguish the direction, we use $(i, f) \in E_{sc}$ to denote that node $f \in V_c$ is depending on $i \in V_s$ (flow from G_s to G_c), and $(f, i) \in E_{sc}$ to denote that node $i \in V_s$ is depending on $f \in V_c$ (flow from G_c to G_s).

(ii) Each link $(i, f) \in E_{sc}$ is bidirectional, where $i \in V_s, f \in V_c$. Therefore, the bidirectional link (i, f) can be considered as two directional links (i, f) and (f, i). An example is shown in Fig. 4.1.

Additionally, we assume each node $i \in V_s$ has at most one dependency node in V_c, and similarly each node $f \in V_c$ has at most one dependency node in V_s. The failures always start within nodes in G_s.

The *vulnerability analysis problem of the interdependent network* is stated as follows: Given an integer k, we want to find a subset of nodes in V_s with cardinality k, such that the size of the largest MCC (i.e., the number of nodes in both power grid and communication network in the MCC), after the cascading failures by initially removing these k nodes, is minimized.

Let t denote the stage (as defined in the following) of the cascading failure process. We define the following decision variables:

$$x_i(t) = \begin{cases} 1, & \text{if node } i \in V_s \text{ is failed at stage } t,\ \forall i \in V_s \\ 0, & \text{otherwise} \end{cases}$$

$$y_f(t) = \begin{cases} 1, & \text{if node } f \in V_c \text{ is failed at stage } t,\ \forall f \in V_c \\ 0, & \text{otherwise} \end{cases}$$

$$u_{ij}(t) = \begin{cases} 1, & \text{if edge } (i,j) \in E_s \text{ is failed at stage } t,\ \forall (i,j) \in E_s \\ 0, & \text{otherwise} \end{cases}$$

$$v_{fg}(t) = \begin{cases} 1, & \text{if edge } (f,g) \in E_c \text{ is failed at stage } t,\ \forall (f,g) \in E_c \\ 0, & \text{otherwise} \end{cases}$$

$$w_{if}(t) = \begin{cases} 1, & \text{if interdependent link } (i,f) \in E_{sc} \text{ is failed at stage } t,\ \forall (i,f) \in E_{sc} \\ 0, & \text{otherwise} \end{cases}$$

4.3.2 Cascading failure process

As the bidirectional case can be converted to the directional case, in the following we use the directional interdependency to explain the cascading failure process by stages (the variables in the brackets will be used to indicate the failures):

- **Stage 0**. We initially remove k nodes in V_s [$x_i(0)$] and thus edges in E_s incident to these k nodes will be all failed [$u_{ij}(0)$];

- **Stage** t (t is odd, i.e., $t = 1, 3, 5, \cdots$). The cascading failures in G_s and related failures include:

– nodes/edges in the resulted network of G_s not in LCC are all failed $[x_i(t), u_{ij}(t)]$,

– links in E_{sc} incident to above failed nodes $[w_{if}(t)]$,

– the dependency nodes in V_c after removal of interdependency links $[y_f(t)]$, and

– the incident edges to above failed nodes in E_c $[v_{fg}(t)]$;

- **Stage** $t+1$ (t is odd, i.e., $t = 1, 3, 5, \cdots$). The cascading failures in G_c and related failures include:

  – nodes/edges in the resulted G_c not in LCC $[y_f(t+1), v_{fg}(t+1)]$,

  – links in E_{sc} incident to new failed nodes of G_c $[w_{fi}(t+1)]$,

  – dependency nodes in V_s after removal of interdependency links $[x_i(t+1)]$, and

  – the incident edges to above failed nodes in E_s $[u_{ij}(t+1)]$.

If there occur two or more connected components with the same largest size in the cascading failure process, we assume the algorithm will randomly select one of them to survive. The maximum number T of stages should be $m+n-k-1$, as the stage 0 removes k nodes and one node is removed at each stage in the worst case. In practice, the cascading failure process mostly stops earlier, and the proposed model will treat the following stages before T as copies of the stopping one. Thus, the t value mentioned above is an odd number between 1 and $T = m+n-k-1$. Thus, the steady state and its corresponding t are dependent on the values of m, n, k. This is discussed in the section titled as "Stage $T = m+n-k-1$ constraints".

Based on the idea of stages, we present the following integer programming constraints to model the cascading failure process:

Stage 0 constraints in G_s. To perform the vulnerability analysis to find the most vulnerable nodes in power grid, we initially remove k nodes in stage 0, and the corresponding constraint is shown in (4.1a).

$$\sum_{i \in V_s} x_i(0) = k \tag{4.1a}$$

$$\frac{x_i(0)+x_j(0)}{2} \le u_{ij}(0) \le x_i(0)+x_j(0),\ \forall (i,j)\in E_s \tag{4.1b}$$

For any edge $(i,j)\in E_s$, if one of its ends is failed, it will be failed as well. That is $1-u_{ij}(0)=(1-x_i(0))(1-x_j(0))$, which can be equivalently formulated as a linear constraint in (4.1b) because of binary choices of $u_{ij}(0), x_i(0), x_j(0)$.

Stage t (t is odd) constraints in G_s. From stage 0 to stage 1, the initial failures in network G_s will disconnect the network G_s. According to percolation theory, only the LCC in the resulting network will survive. Similar situations happen from stage $t-1$ to stage t when t is even. Therefore, we present the general constraints for capturing failures in stage t.

The resulted network of G_s from $t-1$ has node set $\{i\in V_s : x_i(t-1)=0\}$, and edge set $\{(i,j)\in E_s : u_{ij}(t-1)=0\}$. There are at most $|V_s|=m$ connected components in this resulted network, and we use G_{sl} with node set V_{sl} to denote the connected components ($l=1,2,\cdots,m$). There may be some empty connected components under this notation, as we do not know the exact number of components. To determine the LCC in this resulting network and the failures (indicated by $x_i(t), u_{ij}(t)$), we introduce more decision variables for stage t (t is odd):

$$r_{ij}(t)=\begin{cases}1, & \text{if nodes } i,j \text{ are in the same connected component at stage } t,\\ 0, & \text{otherwise,}\end{cases}$$
$$\forall i,j\in V_s,$$

$$s_{il}(t)=\begin{cases}1, & \text{if node } i \text{ is in set } V_{sl} \text{ of component } G_{sl} \text{ at stage } t,\\ 0, & \text{otherwise,}\end{cases}$$
$$\forall i\in V_s, l=1,\dots,m,$$

$$\delta_l(t)=\begin{cases}1, & \text{if the connected component } l \text{ is the largest one at stage } t,\\ 0, & \text{otherwise,}\end{cases}$$
$$l=1,\dots,m.$$

With these decision variables, we use the following set of constraints to find the LCC in the resulted network of G_s.

$$r_{ij}(t) = (1 - u_{ij}(t-1))(1 - x_i(t-1))(1 - x_j(t-1)),\ \forall (i,j) \in E_s \tag{4.2a}$$

$$\begin{cases} r_{i_1 i_2}(t) + r_{i_2 i_3}(t) - r_{i_1 i_3}(t) \leq 1 \\ r_{i_1 i_2}(t) - r_{i_2 i_3}(t) + r_{i_1 i_3}(t) \leq 1 \qquad \forall \text{ triplets } i_1, i_2, i_3 \in V_s \\ -r_{i_1 i_2}(t) + r_{i_2 i_3}(t) + r_{i_1 i_3}(t) \leq 1 \end{cases} \tag{4.2b}$$

$$r_{ij}(t) = \sum_{l=1}^{m} s_{il}(t) s_{jl}(t),\ \forall i,j \in V_s, i \neq j \tag{4.2c}$$

$$\sum_{l=1}^{m} s_{il}(t) = 1 - x_i(t-1),\ \forall i \in V_s \tag{4.2d}$$

$$LG_s(t) = \max\{\sum_{i \in V_s} s_{il}(t),\ l = 1, \ldots, m\} \tag{4.2e}$$

$$\delta_l(t) \sum_{i \in V_s} s_{il}(t) = 0 \text{ or } LG_s(t),\ l = 1, \ldots, m \tag{4.2f}$$

$$\sum_{l=1}^{m} \delta_l(t) = 1 \tag{4.2g}$$

$$x_i(t) = \sum_{l=1}^{m} (1 - \delta_l(t)) s_{il}(t) + x_i(t-1),\ \forall i \in V_s \tag{4.2h}$$

$$1 - u_{ij}(t) = (1 - x_i(t))(1 - x_j(t)),\ \forall (i,j) \in E_s \tag{4.2i}$$

$$r_{ij}(t), s_{il}(t), \delta_l(t) \in \{0,1\},\ \forall i,j \in V_s, l = 1, \ldots, m \tag{4.2j}$$

For all surviving nodes in G_s from the previous stage $t-1$, if there is an edge between two nodes, they belong to the same component in this stage (4.2a). For all surviving nodes from stage $t-1$, if the first node and the second node are in the same component, and the second node and the third node are in the same component, then these three nodes are in the same component in the resulting network (4.2b). Through constraints (4.2c) and (4.2d), the connected nodes will be assigned to some component, and every surviving node must belong to only one component. Through constraints (4.2e) and (4.2f), the number of nodes in different connected components are compared to find the largest one. The notation $LG_s(t)$ represents the size of the

LCC in the power grid in stage t. There is only one LCC determined by $\delta_l(t) = 1$ by constraint (4.2g). For all surviving nodes coming from the previous stage $t-1$, only the nodes in the LCC can survive in this stage, and the other nodes will all fail, as shown in constraints (4.2h). Only those edges, where both the tail and the head survive, will survive (see constraints (4.2i). Constraints (4.2j) state the binary requirements.

Besides these constraints, there are other valid constraints. For example, if a node fails in stage $t-1$, it does not belong to any component; or if a node survives from a previous stage, it belongs to just one component in this stage. That is

$$0 \leq s_{il}(t) \leq 1 - x_i(t-1), \quad \forall i \in V_s, l = 1, \ldots, m. \tag{4.3}$$

Following failures in the power grid, the interdependency links connected to the failed nodes in power grid G_s will fail, and thus the nodes in the communication network connected to the failed interdependency links will fail as well. The other interdependency links and nodes in the communication network still survive in this stage. These failures are reflected in constraints (4.4a).

$$x_i(t) = w_{if}(t) = y_f(t), \ \forall (i, f) \in E_{sc} \tag{4.4a}$$

$$\frac{y_f(t) + y_g(t)}{2} \leq v_{fg}(t) \leq y_f(t) + y_g(t), \ \forall (f, g) \in E_c \tag{4.4b}$$

For the communication network, if one end of an edge $(f, g) \in E_c$ is failed, this edge will be failed, which can be formulated as $1 - v_{fg}(t) = (1 - y_f(t))(1 - y_g(t))$, or equivalently as (4.4b).

Stage $t+1$ (t is odd) constraints in G_c. The resulting network of G_c from stage t has node set $\{f \in V_c : y_f(t) = 0\}$, and edge set $\{(f, g) \in E_c : v_{fg}(t) = 0\}$. Similarly to the last stage, we need to find the LCC in this resulting network and simulate cascading failures (indicated by $y_f(t+1), v_{fg}(t+1)$). As in the last stage, we will also define more decision variables for stage $t+1$ (t is odd):

$$p_{fg}(t+1) = \begin{cases} 1, & \text{if nodes } f, g \text{ are in the same connected component at stage } t+1, \\ 0, & \text{otherwise,} \end{cases}$$

$$\forall f, g \in V_c,$$

$$q_{fh}(t+1) = \begin{cases} 1, & \text{if node } f \text{ is in set } V_{ch} \text{ of component } G_{ch} \text{ at stage } t+1, \\ 0, & \text{otherwise,} \end{cases}$$

$$\forall f \in V_c, h = 1, \ldots, n,$$

$$\epsilon_h(t+1) = \begin{cases} 1, & \text{if the connected component } h \text{ is the largest one at stage } t+1, \\ 0, & \text{otherwise,} \end{cases}$$

$$h = 1, \ldots, n.$$

Through these decision variables, similarly, we use following sets of constraints (4.5a)-(4.5j) in stage t+1 to find the LCC in the resulted network of G_c by $\epsilon_h(t{+}1) = 1$. The notation $LG_c(t{+}1)$ represents the size of the LCC in the communication network in stage $t+1$.

$$p_{fg}(t+1) = (1 - v_{fg}(t))(1 - y_f(t))(1 - y_g(t)),\ \forall (f,g) \in E_c \tag{4.5a}$$

$$\begin{cases} p_{f_1 f_2}(t+1) + p_{f_2 f_3}(t+1) - p_{f_1 f_3}(t+1) \leq 1, \\ p_{f_1 f_2}(t+1) - p_{f_2 f_3}(t+1) + p_{f_1 f_3}(t+1) \leq 1, & \forall \text{ triplets } f_1, f_2, f_3 \in V_c \\ -p_{f_1 f_2}(t+1) + p_{f_2 f_3}(t+1) + p_{f_1 f_3}(t+1) \leq 1, \end{cases} \tag{4.5b}$$

$$p_{fg}(t+1) = \sum_{h=1}^{n} q_{fh}(t+1) q_{gh}(t+1),\ \forall f, g \in V_c, f \neq g \tag{4.5c}$$

$$\sum_{h=1}^{n} q_{fh}(t+1) = 1 - y_f(t),\ \forall f \in V_c \tag{4.5d}$$

$$LG_c(t+1) = \max\{\sum_{f \in V_c} q_{fh}(t+1),\ h = 1, \ldots, n\} \tag{4.5e}$$

$$\epsilon_h(t+1) \sum_{f \in V_c} q_{fh}(t+1) = 0 \text{ or } LG_c(t+1),\ h = 1, \ldots, n \tag{4.5f}$$

$$\sum_{h=1}^{n} \epsilon_h(t+1) = 1 \tag{4.5g}$$

$$y_f(t+1) = \sum_{h=1}^{n} (1 - \epsilon_h(t+1)) q_{fh}(t+1) + y_f(t),\ \forall f \in V_c \tag{4.5h}$$

$$1 - v_{fg}(t+1) = (1 - y_f(t+1))(1 - y_g(t+1)),\ \forall (f,g) \in E_c \tag{4.5i}$$

$$p_{fg}(t+1), q_{fh}(t+1), \epsilon_h(t+1) \in \{0,1\},\ \forall f,g \in V_c, h = 1,\dots,n \tag{4.5j}$$

Besides these constraints, we have the following additional ones. If the node $f \in V_c$ is failed in previous odd stage, it does not belong to any component in the resulted network of G_c; if the node $f \in V_c$ is survived from previous odd stage, it belongs to one component in the resulted network. That is

$$0 \le q_{fh}(t+1) \le 1 - y_f(t),\ \forall f \in V_c, h = 1,\dots,n \tag{4.6}$$

The interdependency links connected to the failed nodes in the communication network will fail. The nodes in power grid connected to the failed interdependency links will then fail as well. The other interdependency links and nodes in power grid will still survive in this stage. These limitations are reflected in constraints (4.7a).

$$y_f(t+1) = w_{fi}(t+1) = x_i(t+1),\ \forall (f,i) \in E_{sc} \tag{4.7a}$$

$$\frac{x_i(t+1) + x_j(t+1)}{2} \le u_{ij}(t+1) \le x_i(t+1) + x_j(t+1),\ \forall (i,j) \in E_s \tag{4.7b}$$

For the power grid, if one end of the edge is failed, the edge will be failed, too. That can be constrained by $1 - u_{ij}(t+1) = (1 - x_i(t+1))(1 - x_j(t+1))$, or equivalently as (4.7b).

Stage $T = n + m - k - 1$ constraints. In order to identify the LCC in the steady state, we consider the different cases for the numbers m, n, k and the objectives discussed in Chapter 4.3.3 can be expressed differently under different inputs m, n, k:

i) $T = m + n - k - 1$ is odd. This will occur when (i1) m is even, n is even and k is even; (i2) m is even, n is odd and k is odd; (i3) m is odd, n is even and k is odd; or (i4) m is odd, n is odd and k is even. The last stage happens in the power grid G_s, and it will follow all constraints in stage t (t is odd).

- if the objective function is to find the MCC in the resulted interdependent network of the steady state (expressed as $LG(T)$ in Chapter 4.3.3), it can be identified in stage $m+n-k-2$ and $m+n-k-1$, like stage $t-1$ and t.
- if the objective function is to find the LCC in power grid of the steady state (i.e., $LG_s(T)$), it can be identified in stage $m+n-k-1$, like stage t.
- if the objective function is to find the LCC in communication network of the steady state (i.e., $LG_c(T)$), it can be identified in stage $m+n-k-2$, like stage $t-1$.

ii) $T = m+n-k-1$ is even. This will occur when (ii1) m is even, n is even and k is odd; (ii2) m is even, n is odd and k is even; (ii3) m is odd, n is even and k is even; or (ii4) m is odd, n is odd and k is odd. The last stage happens in the communication network G_c and it will follow all constraints in stage $t+1$ (t is odd).

- if the objective function is to find the MCC in the resulted interdependent network of the steady state (i.e., $LG(T)$), it can be identified in stage $m+n-k-2$ and $m+n-k-1$, like stage t and $t+1$.
- if the objective function is to find the LCC in power grid of the steady state (i.e., $LG_s(T)$), it can be identified in stage $m+n-k-2$, like stage t.
- if the objective function is to find the LCC in communication network of the steady state (i.e., $LG_c(T)$), it can be identified in stage $m+n-k-1$, like stage $t+1$.

Once the LCC is identified either in power grid or communication network, the corresponding MCC formed by the LCC in the steady state can be found. Regarding the MCC, there are two cases: (i) There exists an MCC after the cascading failure in stage T, i.e., at least one surviving node in G_s, at least one surviving node in G_c, and at least one link in both directions connecting the corresponding two components containing two nodes, respectively; (ii) There is no MCC after cascading failure in stage T, i.e., no bidirectional link between the two networks (there might be some nodes in either G_s or G_c, but the resulting component will not be functional). We model these two cases in the following set of constraints:

$$\begin{cases} a \le \sum_{(i,f)\in E_{sc}} w_{if}(n+m-k-1) \le Ma \\ b \le \sum_{(f,i)\in E_{sc}} w_{fi}(n+m-k-1) \le Mb \\ a, b \in \{0,1\} \end{cases} \tag{4.8}$$

where $ab = 1$ indicates the case (i), $ab = 0$ indicates the case (ii), and M is a big positive constant. If the connected component contains at least one link from a node in the power grid to one in the communication network ($a = 1$), and at least one link from the node in communication network to that in power grid ($b = 1$), the MCC exists. The objective in Chapter 4.3.3 will be to determine the size of the component. If the connected component could not satisfy these conditions, no MCC exists. The objective in Chapter 4.3.3 will be affected to be 0. Also in this case, the corresponding nodes in $LG_s(T)$ or $LG_c(T)$ cannot be functional, and their values would be 0 as well.

Constraints between stage t and $t+1$. For all the nodes and edges, once they have failed, they will continue to be failed forever. A set of constraints to express the relations between two stages can be stated as follows:

$$x_i(t+1) \ge x_i(t),\ \forall i \in V_s \tag{4.9a}$$

$$y_f(t+1) \ge y_f(t),\ \forall f \in V_c \tag{4.9b}$$

$$w_{ab}(t+1) \ge w_{ab}(t),\ \forall (a,b) \in E_{sc} \tag{4.9c}$$

$$u_{ij}(t+1) \ge u_{ij}(t),\ \forall (i,j) \in E_s \tag{4.9d}$$

$$v_{fg}(t+1) \ge v_{fg}(t),\ \forall (f,g) \in E_c \tag{4.9e}$$

The model we have just explained is for the directional interdependent case. It is also useful for bidirectional examples, but the difference is the interlinks between the two interdependent networks have both directions. We model this as $w_{if} = w_{fi}$.

4.3.3 Integer programming model for vulnerable node identification

The goal of this study is to find the most vulnerable nodes in the interdependent networks, which means that if these k nodes are removed, the cascading failure will be the most severe, and the possible number of failed nodes will be maximized. By identifying these nodes, we could better protect the whole system. As described above, the final surviving nodes should be mutually connected. The size $LG(T)$ of largest MCC is the summation of the cardinality of the resulting nodes in V_s and V_c in the largest MCC. Therefore, the objective function and constraints of the proposed problem can be expressed in the following integer program when $T = m + n - k - 1$ is odd:

$$\begin{aligned} \mathit{min} \quad & LG(T) \qquad (4.10) \\ \mathit{s.t.} \quad & LG(T) = a \cdot b \ \max\{\sum_{i \in V_s} s_{il}(T) + \sum_{f \in V_c} q_{fh}(T),\ l = 1, \ldots, m, h = 1, \ldots, n\} \\ & \text{Constraints } (4.1), (4.8) \\ & \text{Constraints } (4.2) - (4.4),\ t = 1, 3, 5, \cdots, T \\ & \text{Constraints } (4.5) - (4.7), (4.9),\ t = 1, 3, 5, \cdots, T - 2 \end{aligned}$$

When T is even, the t index for constraints (4.2)-(4.7),(4.9) will be $t = 1, 3, \cdots, T-1$, and the rest constraints will be the same.

The objective $LG(T) = a \cdot b \ \max\{\sum_{i \in V_s} s_{il}(T) + \sum_{f \in V_c} q_{fh}(T),\ l = 1, \ldots, m, h = 1, \ldots, n\}$, expressed as the first constraint in (4.10) is nonlinear and it can be linearized as follows

$$\begin{cases} \sum_{i\in V_s} s_{il}(T) + \sum_{f\in V_c} q_{fh}(T) \le w,\ l=1,\cdots,m,\ h=1,\cdots,n \\ \sum_{i\in V_s} s_{il}(T) + \sum_{f\in V_c} q_{fh}(T) \ge w-(1-z_{lh})M,\ l=1,\cdots,m,\ h=1,\cdots,n \\ \sum_{l=1,\ldots,m}\sum_{h=1,\ldots,n} z_{lh}=1 \\ LG(T)\ge 0,\ LG(T)\le Md,\ LG(T)\ge w-M(1-d),\ LG(T)\le w \\ d\le a,\ d\le b,\ d\ge a+b-1,\ d\ge 0 \\ a,b,\ z_{lh}\in\{0,1\},\ l=1,\ldots,m, h=1,\ldots,n \end{cases}$$

where a, b, w, z_{lh} are newly added decision variables.

Constraints (4.2a), (4.2c), (4.2e), (4.2f), (4.2h), and (4.2i) have nonlinear terms and they can be linearized as follows:

$$\begin{cases} 1-u_{ij}(t-1)-x_i(t-1)-x_j(t-1)\le r_{ij}(t)\le \\ \qquad \frac{3-u_{ij}(t-1)-x_i(t-1)-x_j(t-1)}{3},\ \forall (i,j)\in E_s; \\ r_{ij}(t)=\sum_{l=1}^m a_{ijl}(t), s_{il}(t)+s_{jl}(t)-1\le a_{ijl}(t)\le \\ \qquad \frac{s_{il}(t)+s_{jl}(t)}{2},\ \forall i,j\in V_s, i\ne j, l=1,\ldots,m; \\ a_{ijl}(t)\in\{0,1\}, \forall i,j\in V_s, i\ne j, l=1,\ldots,m; \\ LG_s(t)\ge \sum_{i\in V_s} s_{il}(t),\ l=1,\ldots,m; \\ LG_s(t)\le \sum_{i\in V_s} s_{il}(t)+M(1-\delta_l(t)),\ l=1,\ldots,m; \\ x_i(t)=\sum_{l=1}^m c_{il}(t)+x_i(t-1), s_{il}(t)-\delta_l(t)\le c_{il}(t)\le \\ \qquad \frac{1-\delta_l(t)+s_{il}(t)}{2},\ \forall i\in V_s, l=1,\ldots,m; \\ c_{il}(t)\in\{0,1\},\ \forall i\in V_s, l=1,\ldots,m; \\ \frac{x_i(t)+x_j(t)}{2}\le u_{ij}(t)\le x_i(t)+x_j(t),\ \forall (i,j)\in E_s. \end{cases}$$

Similarly, constraints (4.5a), (4.5c), (4.5e), (4.5f), (4.5h), and (4.5i) can be linearized as follows:

$$\begin{cases} 1 - v_{fg}(t) - y_f(t) - y_g(t) \le p_{fg}(t+1) \le \frac{3 - v_{fg}(t) - y_f(t) - y_g(t)}{3}, \ \forall (f,g) \in E_c; \\ p_{fg}(t+1) = \sum_{h=1}^{n} b_{fgh}(t+1), q_{fh}(t+1) + q_{gh}(t+1) - 1 \le b_{fgh}(t+1) \le \\ \qquad \frac{q_{fh}(t+1) + q_{gh}(t+1)}{2}, \ \forall f, g \in V_c, f \ne g, h = 1, \dots, n; \\ b_{fgh}(t+1) \in \{0,1\}, \ \forall f, g \in V_c, f \ne g, h = 1, \dots, n; \\ LG_c(t+1) \ge \sum_{f \in V_c} q_{fh}(t+1), \ h = 1, \dots, n; \\ LG_c(t+1) \le \sum_{f \in V_c} q_{fh}(t+1) + M(1 - \epsilon_h(t+1)), \ h = 1, \dots, n; \\ y_f(t+1) = \sum_{h=1}^{n} d_{fh}(t+1) + y_f(t), q_{fh}(t+1) - \epsilon_h(t+1) \le d_{fh}(t+1) \le \\ \qquad \frac{1 - \epsilon_h(t+1) + q_{fh}(t+1)}{2}, \ \forall f \in V_c, h = 1, \dots, n; \\ d_{fh} \in \{0,1\}, \ \forall f \in V_c, h = 1, \dots, n; \\ \frac{y_f(t+1) + y_g(t+1)}{2} \le v_{fg}(t+1) \le y_f(t+1) + y_g(t+1), \ \forall (f,g) \in E_c. \end{cases}$$

By replacing the corresponding constraints by these linearizations, the integer programming model (4.10) can be reformulated as a mixed integer linear program (MILP). Additionally, for comparison purposes, we also use the size $LG_s(T)$ of the component containing the resulting nodes of V_s in the largest MCC, and the size $LG_c(T)$ of the component containing the resulting nodes of V_c as objectives. They can be expressed respectively by

$$LG_s(T) = a \cdot b \ \max\{\sum_{i \in V_s} s_{il}(T), \ l = 1, \dots, m\}$$
$$LG_c(T) = a \cdot b \ \max\{\sum_{f \in V_c} q_{fh}(T), \ h = 1, \dots, n\}$$

More specifically, if T is odd, the cascading failure will stop in the power grid. In this case, if we select $LG_c(T)$ as the objective, it represents the number of resulting nodes in the communication network. If T is even, the cascading failure will stop in the communication network. In this case, if we select $LG_s(T)$ as the objective, it represents the number of resulting nodes in the power grid.

4.3.4 Integer programming model for vulnerable edge identification

In this subsection, we present the integer programming formulations to identify the most vulnerable edges in power grid. The definitions of the parameters used for modeling are the same as those in Chapter 4.3.1. The constraints utilized to capture the cascading failures triggered by edge removal are slightly different from those used to describe the failures triggered by node removal. Aside from stage 0, the other stages in the cascading failure process are the same as shown in Chapter 4.3.2. In stage 0, we should switch to initially remove k edges in E_s $[u_{ij}(0)]$, as a new goal now is to identify the vulnerable edges. Therefore, the constraint in stage 0 should be

$$\sum_{(i,j)\in E_s} u_{ij}(0) = k \tag{4.11}$$

Because we do not remove any nodes initially, and assume that at least one node fails in each stage, the maximum number of stages is $m+n$. In practice, the cascading failure may stop much earlier than $m+n$ stages. Once it stops, the rest of the stages will be the same as the last one before stopping. We discuss $T = m+n$ is odd if one of m and n is odd, and the other one is even, T is even if both of them are even or odd. When T is odd, we know the cascading failure stops in G_s, and otherwise, it stops in G_c. The constraints in stage $T = m+n$ should be

$$\begin{cases} a \leq \sum_{(i,f)\in E_{sc}} w_{if}(m+n) \leq Ma \\ b \leq \sum_{(f,i)\in E_{sc}} w_{fi}(m+n) \leq Mb \\ a, b \in \{0,1\} \end{cases} \tag{4.12}$$

This guarantees that the final surviving nodes are mutually connected. The size $LG(T)$ of largest MCC is the summation of the cardinality of the resulting nodes in V_s and V_c in the largest MCC. Therefore, the objective function and constraints of the proposed problem can be expressed as in the following integer program when

$T = m + n$ is odd:

$$
\begin{aligned}
min \quad & LG(T) && (4.13)\\
s.t. \quad & LG(T) = a \cdot b \ \max\{\sum_{i \in V_s} s_{il}(T) + \sum_{f \in V_c} q_{fh}(T),\ l = 1, \ldots, m, h = 1, \ldots, n\} \\
& \text{Constraints } (4.11), (4.12) \\
& \text{Constraints } (4.2) - (4.4),\ t = 1, 3, 5, \cdots, T \\
& \text{Constraints } (4.5) - (4.7), (4.9),\ t = 1, 3, 5, \cdots, T-2
\end{aligned}
$$

When T is even, the t index for constraints (4.2)-(4.7),(4.9) will be $t = 1, 3, \cdots, T-1$, and the rest constraints will be the same. Similarly, the reformulations in Chapter 4.3.3 can be applied to obtain the equivalent MILP.

4.4 Numerical Experiments

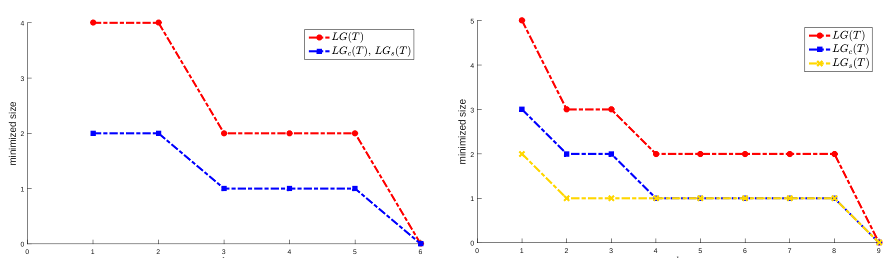
The proposed integer programming models are all implemented in C++ and solved using CPLEX 12.3 via ILOG Concert Technology 2.9, and all computations were performed on a Linux workstation with 4 Intel(R) Xeon(TM) CPU 3.60GHz processors and 32GB RAM.

In order to identify the most vulnerable nodes and edges in interdependent networks, in addition to the examples presented in Chapter 4.2, we construct some interdependent networks based on the power grid and its communication networks, formed by phase measurement units (PMUs). The interconnections between buses (nodes) in the power grid and PMUs are from results in Fan and Watson (2015). The PMUs are nodes in the communication network, and links among them are randomly selected and assumed to be in different density levels as shown in the following. Under any density level, all PMUs in the communication network will be connected. For example, in the IEEE 14-bus system, the PMUs are placed in buses 2,6,9 (with bidirectional links between bus 2 and 1st PMU, bus 6 and 2nd PMU, bus 9 and 3rd PMU), and then these three PMUs are connected to form the communication network.

4.4.1 Identification of vulnerable nodes

Under different objectives shown in Chapter 4.3.3, the most vulnerable nodes may be different. In the following, we present the corresponding different objective values (i.e., $\min\ LG(T), \min\ LG_s(T), \min\ LG_c(T)$) under different values of k.

Fig. 4.3(a) shows the results for the interdependent network of Fig. 4.1(a). Under three different objectives, the identified most vulnerable nodes in power grid are the same: {4}, {4,5}, {1,4,5}, {1,2,4,5}, {1,2,3,4,5}, and all nodes in power grid, when $k = 1, \cdots, 6$. Here we notice that the minimized size of the LCC is the same whether we use the objective $\min\ LG_s(T)$ or $\min\ LG_c(T)$. Fig. 4.3(b) shows the results for the interdependent network of Fig. 4.2(a). Under the three different objectives, the identified most vulnerable nodes in power grid are the same: {3}, {3,8}, {1,3,8}, {1,2,3,8}, {1,2,3,4,8}, {1,2,3,4,7,8}, {1,2,3,4,6,7,8}, {1,2,3,4,6,7,8,9}, and all nodes in power grid, when $k = 1, 2, 3, \cdots, 9$. In both cases, observe that $\min\ LG(T) = \min\ LG_s(T) + \min\ LG_c(T)$ for different values of k.



(a) Example in Fig. 4.1(a) (b) Example in Fig. 4.2(a)

Figure 4.3: Vulnerable nodes in interdependent networks

Fig. 4.4 shows the results related to the IEEE 14-bus system and its communication network formed by 3 PMUs. Here we assume that the 3 PMUs are fully connected, i.e., there are three edges within the communication network. If the objective is min $LG(T)$, the most vulnerable nodes are node {6}, {2,6}, {2,6,13}, {2,6,9,11}, {2,3,6,9,11}, {2,3,5,6,9,11}, {1,4,5,6,9,10,12} when $k = 1, \cdots, 7$, respectively. However, with objective min $LG_c(T)$, the most vulnerable nodes are {6}, {5,6}, {2,6,13}, {2,6,9,11}, {2,3,6,9,11}, {2,3,5,6,9,11}, {1,4,5,6,9,10,12}, and with objective min $LG_s(T)$, the most vulnerable nodes are {6}, {2,6}, {2,6,13}, {2,6,9,11}, {2,5,6,10,14}, {2,3,5,6,9,10}, {1,4,5,6,9,10,12}, when $k = 1, \cdots, 7$. Additionally, it is observed that min $LG(T) =$ min $LG_s(T) +$ min $LG_c(T)$ for $k = 1, 3, 4, 6, 7, \cdots, 14$, and min $LG(T) >$ min $LG_s(T) +$ min $LG_c(T)$ for $k = 2, 5$. When using the $LG_s(T)$ as the objective, the corresponding sizes of MCC when $k = 2, 5$ are 7,3, respectively. When using the $LG_c(T)$ as the objective, the corresponding sizes of MCC when $k = 2, 5$ are 6,4, respectively. But with the objective $LG(T)$, the corresponding sizes of MCC when $k = 2, 5$ are 6,3, respectively. From this case, it can be observed that the objective min $LG(T)$ would best help identify k most vulnerable nodes.

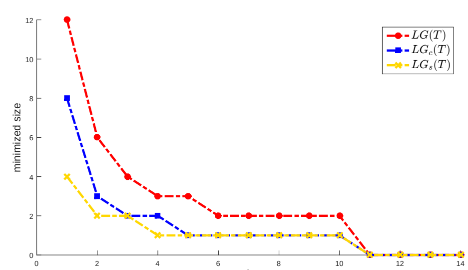
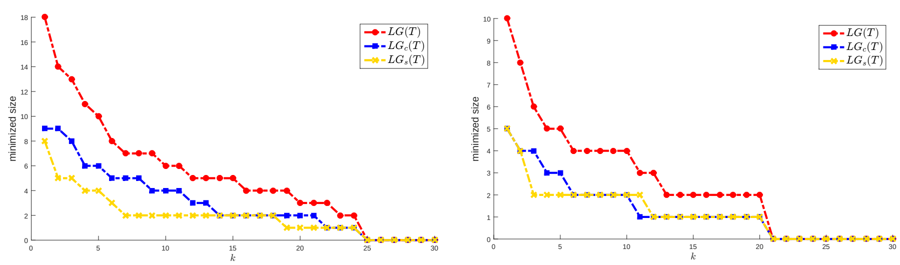


Figure 4.4: Vulnerable nodes in interdependent network based on IEEE 14-bus system

Next, we perform vulnerability analysis of interdependent networks consisting of the same power grid and different connection levels (expressed by densities) for the PMUs in the communication network. The density of the communication network is the fraction of edges over all possible edges within the system. Fig. 4.5

(a) and (b) show the minimized sizes with the objectives $LG(T), LG_s(T), LG_c(T)$ in IEEE 30-bus system with two different density levels. In the interdependent network with density 1, it is observed that min $LG(T) >$ min $LG_s(T) +$ min $LG_c(T)$ for $k = 1, 4, 9, 14, 15, 19, 22$, and min $LG(T) =$ min $LG_s(T) +$ min $LG_c(T)$ for others. In the interdependent network with density 0.5, it is observed that min $LG(T) >$ min $LG_s(T) +$min $LG_c(T)$ for $k = 12$, and min $LG(T) =$ min $LG_s(T) +$min $LG_c(T)$ for others. For the IEEE 30-bus system with density 1, when using the min $LG_s(T)$ as the objective, the corresponding sizes of MCC when $k = 1, 4, 9, 14, 15, 19, 22$ are 19,13,7,6,5,4,4, respectively. When using the min $LG_c(T)$ as the objective, the corresponding sizes of MCC when $k = 1, 4, 9, 14, 15, 19, 22$ are 18,12,7,5,5,5,3, respectively. But with the objective min $LG(T)$, the corresponding sizes of MCC when $k = 1, 4, 9, 14, 15, 19, 22$ are 18,11,7,5,5,4,3, respectively. From this case, it can be observed that the objective min $LG(T)$ would help best identify k most vulnerable nodes.



(a) Density = 1 (b) Density = 0.5

Figure 4.5: Vulnerable nodes in interdependent network based on IEEE 30-bus system

The four curves in Fig. 4.6 respectively represent the minimized sizes of $LG(T)$ in IEEE 30-bus system and communication networks with densities 1, 0.75, 0.5 and 0.33. They indicate that the number of the final surviving nodes keeps increasing as the density of the communication network becomes larger. If the same number of nodes are initially removed, the minimum MCC after cascading failure performs better in the interdependent network with a larger communication network density.

This means that the system will be much harder to fail if its communication network density could be improved.

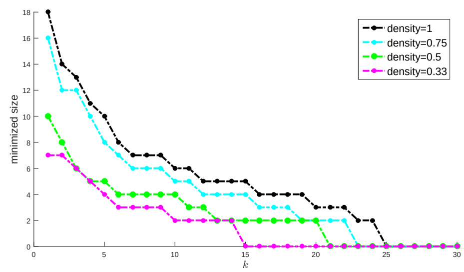


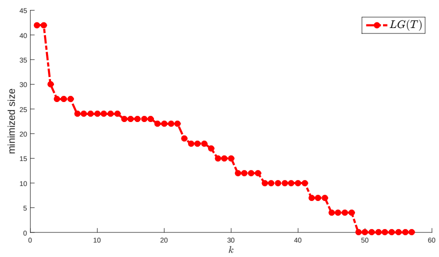
Figure 4.6: Vulnerable nodes in interdependent network based on IEEE 30-bus system and communication network with different densities

In Fig. 4.7, the vulnerable nodes in several different interdependent networks are identified with the objective min $LG(T)$. Fig. 4.7(a) is relevant to the IEEE 57-bus system and its communication network consisting of 11 PMUs (with density 0.7). Fig. 4.7(b) refers to the IEEE 118-bus system and its communication network consisting of 28 PMUs (with density 0.2). Fig. 4.7(c) reflects the IEEE 300-bus system and its communication network consisting of 68 PMUs (with density 0.03). In these three cases, as observed in the ones above, as the number of nodes removed initially increases, the sizes of the MCC will be monotonically decreasing.

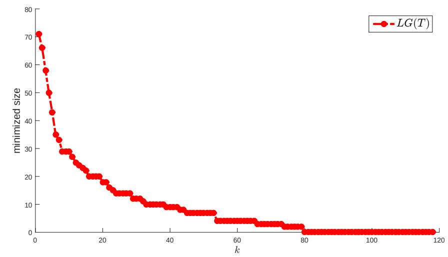
4.4.2 Identification of vulnerable edges

In Chapter 4.4.1, we focused on the most vulnerable nodes in the power grid that could lead to the most severe cascading failures. The following results are related to the optimization model stated in Chapter 4.3.4, that identifies the most vulnerable edges in power grid.

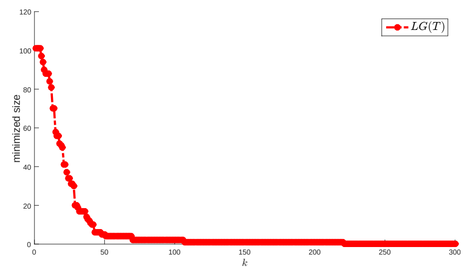
In Fig. 4.8, the vulnerable edges in several different interdependent networks are identified with the objective min $LG(T)$. Fig. 4.8(a) shows the minimized size of the



(a) based on IEEE 57-bus system



(b) based on IEEE 118-bus system



(c) based on IEEE 300-bus system

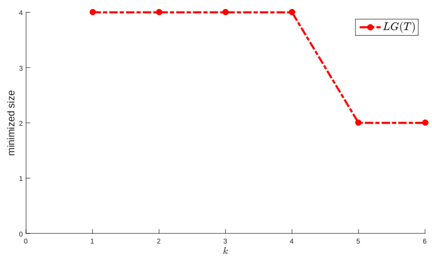
Figure 4.7: Vulnerable nodes in interdependent networks

MCC in the interdependent network of Fig. 4.1(a). The initially removed k edges in the power grid are identified as edges {(3,5)}, {(3,5),(4,5)}, {(3,5),(4,5),(5,6)}, {(1,2),(3,5),(4,5),(5,6)}, {(1,2),(2,3),(3,5),(4,5),(5,6)}, and all of the nodes in the power grid. Fig. 4.8(b) shows the minimized size of the MCC in the interdependent network of Fig. 4.2(a). The initially removed k edges in the power grid are identified as edges {(5,8)}, {(2,5),(5,8)}, {(2,5),(5,8),(7,8)}, {(1,3),(2,5),(5,8),(7,8)}, {(1,3),(2,5),(3,6),(5,8),(7,8)}, and all of the nodes in the power grid. Fig. 4.8(c) shows the results with the IEEE 14-bus system and its communication network formed by 3 PMUs (with density 1). Fig. 4.8(d) represents the IEEE 30-bus system and its communication network with 7 PMUs (with density 0.5). Fig. 4.8(e) presents the minimized size MCC in the IEEE 57-bus system and its communication network consisting of 11 PMUs (with density 0.7). Fig. 4.8(f) refers to the IEEE 118-bus system and its communication network consisting of 28 PMUs (with density 0.2). Fig. 4.8(g) reflects the cascading failure results in the IEEE

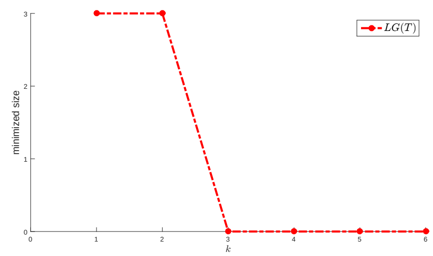
300-bus system and its communication network consisting of 68 PMUs (with density 0.03). It is also observed that as the number of initially removed edges increases, the size of the MCC in the steady state is monotonically decreasing. However, compared with the corresponding node removal, the effects of removing the same number of edges will cause less severe cascading failures.

4.5 Conclusions

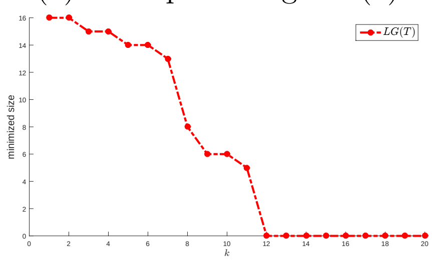
Vulnerability analysis of interdependent networks has become increasing important as the number of the applications for complex interconnected networks in critical infrastructures and cyber-physical systems has grown. In this paper, integer programming approaches are proposed to model the process of cascading failure and to identify the most vulnerable nodes and edges. The modeling is based on the stage idea, and can be extended to other similar interdependent networks, or networks consisting of more than two networks. We observe that the least MCC measurement in the interdependent network is most useful when I identify the most vulnerable nodes, the number of final surviving nodes increases with larger system density, and that removing nodes affects the system more than removing edges. For applications, the identified nodes and edges can inform the strategy for protecting critical infrastructures and cyber-physical systems during both planning and operations. A limitation of the current approaches is that they do not consider the probability or fraction of failures of nodes and edges. Future research can address this issue and work to identify vulnerable network elements based on percolation theory and random graph properties.



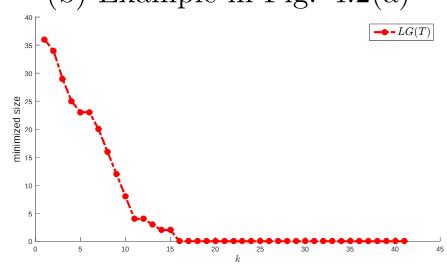
(a) Example in Fig. 4.1(a)



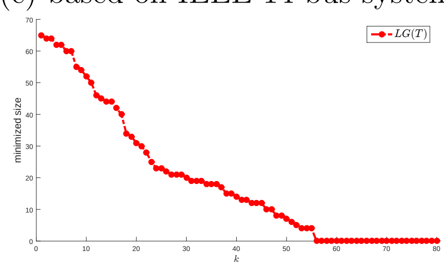
(b) Example in Fig. 4.2(a)



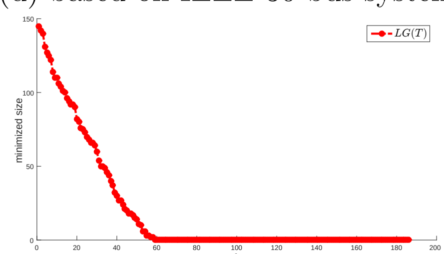
(c) based on IEEE 14-bus system



(d) based on IEEE 30-bus system



(e) based on IEEE 57-bus system



(f) based on IEEE 118-bus system

(g) based on IEEE 300-bus system

Figure 4.8: Vulnerable edges in interdependent networks

Chapter 5
Conclusions and Future Work

In this dissertation, we focus on the application of multilevel optimization to address the vulnerability analysis, planning and operations issues of multiple interdependent infrastructures, including energy systems, water systems and communication control networks. In this chapter, we first summarize the contributions of the dissertation, and then we discuss some future research directions.

Conclusions. The dissertation covers three topics, coordinated long-term planning for interdependent energy and water systems, optimization of power system operations with renewable energy integration and water limitations, vulnerability analysis for power grid and its control communication network. The main idea is about the interdependent infrastructures, of that one infrastructure system's operations need supports from another system. Models to connect different infrastructures with different flows, and influences of failures from each other are challenging. In the dissertation, efforts are taken to resolve this issue. As shown and validated in the numerical experiments of each topic, the proposed approaches can efficiently and effectively address the issues in planning and operations of multiple interdependent infrastructures. Additionally, under the multilevel optimization framework, the intermittent renewable energy resources are added to achieve sustainable infrastructures. On the solution methodologies, Benders decomposition, and column-and-constraint generation algorithms are utilized to solve the proposed complex optimization models. In the summary, the dissertation takes efforts in several aspects to achieve the resilience and sustainability of multiple interdependent infrastructures.

Future Research Directions. For future research, there are several directions can be extended based on the work of this dissertation:

- Extension the work of vulnerability analysis of modeling cascading failures in two interdependent infrastructures to interdependent network formed by multiple infrastructures. In Chapter 4, integer programming formulation following the idea of multiple stages is proposed to model the cascading failure process between two infrastructure networks. The interdependent network formed by multiple infrastructures, such as water-energy-agriculture (food supply chain network), energy-gas-water, etc., will require detailed analysis and extended models and algorithms to perform the vulnerability analysis.

- Development of the models and algorithms for water-energy nexus to additional levels of decisions. In Chapter 2, the planning level and operational level are considered in both water and energy systems. In Chapter 3, the operational planning level (unit commitment) and operational level is considered in energy system with renewable energy integration and water limitations. However, the operations of either energy system or water system include the post-failure operations. The future research can consider additional levels and study how they can impact the operations or planning decisions of infrastructures. Apply the multilevel optimization framework, which is proposed in the dissertation, to continuously model such kind of problems.

- Algorithm development for multilevel optimization. In Chapters 2, 3 and 4, although some algorithms, such as Benders decomposition and constraint-and-column-generation algorithms, are applied to study large-scale infrastructure systems, it still needs additional efforts to design efficient algorithms if more uncertainties and additional levels are considered.

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