RESILIENT CONTROL STRATEGY AND ANALYSIS FOR POWER SYSTEMS USING (N, K)-STAR TOPOLOGY

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ABSTRACT

This research focuses on developing novel approaches in load balancing and restoration problems in electrical power distribution systems. The first approach introduces an inter-connected network topology, referred to as (n, k)-star topology. While power distribution systems can be constructed in different communication network topologies, the performance and fault assessment of the networked systems can be challenging to analyze. The (n, k)-star topologies have well defined performance and stability analysis metrics. Typically, these metrics are defined based on: i) degree, ii) diameter, and iii) conditional diagnosability of a faulty node. These parameters could be evaluated and assessed before a physical (n, k)-star topology power distribution system is constructed. Moreover, in the second approach, we evaluate load balancing problems by using a decentralized algorithm, *i.e.*, the *Multi-Agent System* (MAS) based consensus algorithm on an (n, k)-star power topology. With aforementioned research approaches, an (n, k)-star power distribution system can be assessed with proposed metrics and assessed with encouraging results compared to other topology networked systems. Other encouraging results are found in efficiency and performance enhancement during information exchange using the decentralized algorithm. It has been proven that a load balance solution is convergent and asymptotically stable with a simple gain controller. The analysis can be achieved without constructing a physical network to help evaluate the design. Using the (n, k)-star topology and MAS, the load balancing/restoration problems can be solved much more quickly and accurately compared to other approaches shown in the literature.

To my parents,

Qin & Ping

my parents-in-law,

Xinfeng & Jie

my wife and my son,

Carina & William

I would give my deepest love to all my families, who always support me unconditionally all these years. I dedicate this work to you all.

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CHAPTER 1

INTRODUCTION AND BACKGROUND

There has been tremendous research investigating load balancing and power restoration problems in power and energy systems. Particularly, decentralized methods to solve load balancing and power restoration problems are attracting attentions from researchers. Load balancing is one of the major challenging problems to solve by applying decentralized methods. Due to the dynamic nature of power supply and demands, the goal is to balance the power supply to meet the load demands. To keep the power demand balanced, efficient decentralized control algorithms must be designed to rapidly respond to the information change and dynamically assign power allocation to loads even under priority needs of the loads and possible system failures. Consequently, the *Multi-Agent System* (MAS) framework enables loads to have power restoration ability to restore to their optimal states when there is a fault. The fault of a power system can be, *e.g.*, power shortage, generator failure and power link failure. However, the current decentralized control algorithms still need to be optimized. The main reason is that, under the control of these algorithms, MAS may experience uncertainty to fulfill the demand of all the power loads. There are three challenges to solve load balancing and power restoration problems, and these include:

1. optimizing the decentralized control algorithm;

2. ensuring the reliability/resilience; and

3. lack of sufficient metrics for adequate evaluation of MAS network

These are the main challenges solved by the proposed methodologies. This dissertation presents a novel approach to utilize an interconnected network topology, called (n, k)-star, to model with a power distribution topology. It is a MAS based distributed framework. In reference [21], researchers have proven that an (n, k)-star topology has its advantages in reducing communication cost. Also, it has higher reliability compared to other communication network topologies [8]. Thus, in this dissertation, (n, k)-star interconnected network topologies are integrated into power distribution systems' interconnected network. Then, the metrics of these systems can be formulated based on the properties of (n, k)-star topologies. These metrics will solve the challenge of insufficient observations and measurements to evaluate a MAS based control algorithm. Furthermore, a method based on the analysis of MAS consensus control algorithms is introduced to solve the other two challenges. Based on this approach, the stability analysis of consensus control algorithms is applied to the design process. The purpose is to optimize the performance and ensure the stability and resilience of power distribution systems.

This dissertation offers the following insights. The networked system is able to make rapid, robust and reliable decisions within a complex, dynamical and possibly unknown environment after integrating the (n, k)-star power topology and utilizing the proposed consensus control algorithm into the power distribution system. To better demonstrate the approaches, we evaluate several standard testbeds, namely the standard 16-bus power system [34, 51], IEEE 39-bus power system [39], and IEEE 162-bus power system [35].

Moreover, this dissertation introduces a novel *Item Response Theory* (IRT) based assessment approach to evaluate the resilience of power distribution systems. By introducing this methodology, it is possible to estimate the resilience of system in different application domains. Consequently, appropriate decisions can be made according to priorities of system maintenance based on resilience under events of the system failure.

1.1 Background

Power outages and faults are considered as significant problems that occur in interconnected power networked systems due to information propagation delays. Technologies exist that address power system diagnosis and estimation can diagnose or estimate faults of a power system. These, however, are implemented after the design process or offline. There is still a high risk for power outages or failures that were not known before a load balance/restoration decision can be made effectively. These critical information includes human operation error, control system failures, cyber-attacks and likely hardware failures due to poor weather conditions [42]. Thus, many modern control methods [53] are proposed to solve these problems in real time. For example, there are heuristic search based methods [9, 11] and Artificial Intelligence (AI) based algorithms [3, 10, 56]. Also, one fuzzy logic approach [27] was derived recently using the AI based algorithms. These solutions can provide relatively efficient and effective approaches in simulation only, but they are computationally expensive so they could not be utilized in real-time fault diagnosis in system reconfiguration or discovery when a fault occurs [43]. MAS has been widely studied in recent years, with an increasing number of applications in highly flexible power restoration problems. Among the approaches, the *Belief-Desire-Intent* (BDI) MAS model is one of the basic MAS models that are applied in this dissertation. BDI MAS was used to reconfigure power grids and to solve the power load balance and restoration problems in a distributed manner [23, 24, 28, 32, 46]. However, one major drawback of BDI MAS based approaches is that the performance varies when applied to different interconnected topology network architectures. Some topologies, especially interconnected networks such as ring and mesh structures, have exhibited constraints when scaled to large ones. Recently, a fully distributed multi-agent based load restoration algorithm [51] was proposed with any network topologies (radial, mesh, or mixed). However, this algorithm took too much computation time to make distributed systems reach a convergent state for a large network with multiple nodes. In particular, the conclusion can be reached that even the algorithm itself is independent in topology structures, the constraints related to the properties of the graph (topology) still affect the performance of the system. This influence exists in both the process of system establishment and the process of network reconfiguration due to a variety of faults. Due to the distributed nature of the MAS approach, nodes (loads and generators) in a power system will be grouped into multiple subsystems [49] with balanced power. When a severe fault occurs, a multi-agent node cannot discover the fault within its own subsystem. In other words, the node may take much longer time to discover the fault. More often than not, a suboptimal solution may be obtained. Even worse, a solution can cause cascade effects for loads and generators to shut down.

Another known issue is that power transmission topology, different from communication network topologies, can inevitably cause troubles in power restoration/load balance processes [55]. Recently, communication topology approaches have gained popularity to address and solve issues in power systems for quick information discovery. Topologies, studied generically in graph theory, have some well-known properties that can offer insights in scalability and computation complexity of power restoration process. These properties of a topology are:

1. connectivity, which is known as degree in graph theories, is defined as the number of edges that are incident to the vertices [21];

2. diameter, that can represent how much computation time it will take to balance the system;

3. diagnosability, addresses the fault tolerance and resilience for a system.

The goal of this dissertation is to investigate the properties of power load balance/restoration network topologies. With these known properties, we can implement a better solution with higher scalability and full fault tolerance in power systems. Furthermore, a distributed power topology model is fully investigated for performing effective power branching.

In MASs, agents can independently communicate to each other. Ideally, an agent in a distributed system can always make decisions without communicating with all other agents. Thus, MAS modeling becomes an ideal approach to solve consensus problems since information can propagate through an agent's neighbors. In the past, MAS was studied in the area of distributed consensus control. Consensus algorithms were designed and investigated in problems such as flocking birds, synchronized coupling of oscillators, vehicle formation and team robot task assignment [13, 33, 36, 48, 54]. Multi-agent consensus is defined as each agent reaches a common goal depending on the state of its neighboring agents [13]. A consensus algorithm is an interactive rule that specifies the information exchange between an agent and all of its neighbors on the network. In order to perform a consensus algorithm, the system must be distributed and all of its agents must have dynamic status. The great merit of this consensus algorithm is that it limits the cost of communication. The leader-follower problem was studied and considered as the first introduction of consensus control of networked dynamic systems [33]. Leader-follower problems share a lot of similarity with the power supply problems. Particularly, in a power supply system, the relationship between a generator and a load is the same as that of a leader to a follower. Thus, as the research field of smart grids attracts more and more attentions, the control of smart grids was then widely investigated as consensus problems. MAS and consensus control have been widely applied to load balancing and restoration of distributed power systems [18, 43, 51]. The algorithms introduced by these works can solve load restoration problems in a distributed way. Another study was also focused on the MAS approach for power grid supply balancing process [19]. However, there are not sufficient studies practically analyzing the fundamental aspects of consensus control algorithms on power systems [31]. These aspects include the stability analysis, proof of solution possibilities and ensurance of system reliability.

Moreover, system resilience has been introduced by researchers to represent the ability of a system to adjust its system status during failure. However, without any precise metric for quantifying the resilience, the solution to address system failure varies in different application domains. In the field of engineering, a resilient system cannot be accurately measured in various domains. These domains include public infrastructures, communication networks, image/video processing and logistic networks [20, 30, 50]. Furthermore, each domain is classified into subdomains which can be subdomains of other domains. As a result, the approaches to evaluate resilience are difficult to categorize. *i.e.,* different resilience were defined in public infrastructure systems, water distribution networks, smart power grids and traffic control systems [2, 17, 22]. Each of these systems has to apply a specific assessment approach in order to quantify its resilience. This is due to the different characteristics in each sub-system. Meanwhile, for these systems, the assessment of resilience becomes a complex problem because of the lack in formulation and quantification of resilience [22]. Thus, resilience of a man-made system is an intrinsic property that is difficult to be evaluated and is a concealed characteristic that is difficult to quantify. To address this problem, in this dissertation, a resilience definition is defined by using IRT, so its intrinsic property can be quantified.

1.2 Challenges

While novel works have been conducted to address the issues of load balance on power distribution systems using MAS [43, 51], most works still utilize centralized approaches [19]. These centralized algorithms succeed in addressing both load balancing and power restoration processes. However, these algorithms require information broadcasting so that redundant communication cost is added. The algorithms would not fully utilize the benefits of MAS. Thus, the performance of control algorithms on MAS would be significantly optimized if were performed in a distributed manner. Meanwhile, the evaluation of power systems is based on the iterations each of them takes to fulfill the goal. Thus, most of works still apply the discrete time consensus algorithm, which is widely studied but is in need to be practically investigated in continuous time [52]. The research in this dissertation mainly focuses on implementing algorithms that are both distributed and continuous in time. It also focuses on introducing the (n, k)-star interconnected network topology to better analyze power distribution systems. The following challenges are addressed in this dissertation.

1.2.1 Metrics and Measurements

For a MAS algorithm with many approaches, one major drawback is the variability of performance when applied to different interconnected power architectures. A second drawback is that there is not a specific metric besides the number of iterations to evaluate the performance of the power distribution system. The lack of metrics makes it difficult to compare the performance among different algorithms. Therefore, metrics and evaluation methods are important. They are developed to predict the system performance before the system is physically implemented. The analysis of properties of power distribution systems can be investigated and compared. Therefore, the design of the algorithms will be more reliable when the controls of the metrics are under consideration. Since load balancing problems vary on different power topologies, there are common properties that can be derived from graph theory to better analyze the processes. Ideally, the metrics derived from interconnected network topologies should be universal to most of MAS power topologies.

1.2.2 Consensus Control

Although consensus control has been widely studied and improved, it has not been carefully applied to power distribution systems or smart grids. In consensus control for power systems, most decision-making algorithms control power flow in a centralized manner. It makes the structure of the power system not as scalable as it should be [43, 44]. Also the stability is not guaranteed in these approaches. Recently, there has been a surge of interest among control scientists in consensus problems due to the work of Olfati-Saber and Murray [13, 48]. Following their cooperative alignment method for consensus control, more studies have successfully implemented a consensus agent based algorithm for power distribution systems [52]. However, it has been investigated in a discrete time manner assuming the power exchanged by the agents is net power. Because practically power flow is continuous in time, this discrete-time algorithm still lies behind the reality which makes it difficult to be implemented on real power systems. Thus, it is challenging for the design of the algorithm considers the continuous-time case, which makes it more realistic.

1.2.3 Resilience Evaluation

Evaluation of resilience to an engineering system is very important as it can predict the status of the system; thus actions can be taken to prevent the system from failures. Most of the evaluation approaches are based on a probabilistic framework in failure detection [13], which are derived from the modeling of the failure estimation equations. However, these probabilistic approaches are only accurate when the system failure position is predefined clearly so that the system objective function is easily modeled. In order to overcome this problem, statistic approaches have been widely investigated to assess the resilience of an engineering system. The common statistical method is to formulate the system resilience as a measure of the ability of a network to maintain service under failure conditions. Researchers have tried to use parameters of physical significance to analyze the system objective function [47]. These approaches evaluate systems using diagnostic scenarios and are based on the sample size. However, a common constraint of these approaches is that the combination of possible failure scenarios grows exponentially as the system becomes larger [4]. For an NP-hard problem, the increasing number of parameters involved in the assessment equation adds significant complexity to the assessment process.

1.3 Contributions

The primary contributions of this research are:

1. modeling of (n, k)-star power topology provides metrics to power distribution systems;
2. a decentralized consensus control method that optimizes the process of load balancing and power restoration; and
3. a novel IRT based resilience assessment tool to evaluate a power distribution system.

The specific research achievements are listed as follows:

Contribution 1:

(n, k)-star power topology model, which is a novel topology model extended from (n, k)-graph interconnected power systems is introduced to address the load balancing and power restoration problems. Three types of power agents: 1) producer (generator) agents, 2) consumer (load) agents and 3) phantom power agents, are defined and assigned with different BDI tasks accordingly. A set of metrics are defined and studied from the (n, k)-star power distribution topology, such as communication cost and power branching penalty.

Contribution 2:

A generalized power agent model, which can be universally applied to both consumer and producer agents in power distribution systems, is investigated. On top of this novel proposed power agent model, the decentralized consensus algorithm with cooperation is designed and the stability of the system is addressed accordingly. Its stability is analyzed theoretically in order to prove the existence and uniqueness of the solution.

Contribution 3:

The IRT based resilience evaluation approach contains three processes: 1) *Item Characteristic Curve* (ICC) modeling, 2) parameter calibration and 3) resilience estimation. It can successfully quantify the intrinsic property of a system, such as resilience. This approach is implemented on a micro power distribution system; however, the concept easily extends to other resilient engineering systems such as other power networks, fluid flow systems, communication networks and onchip networks.

We compare (n, k)-star power topology to other three standard power distributions, and the results show that (n, k)-star power topology is faster in load balancing process (with lower communication cost), and costs less in the process of power restoration (with lower power restoration penalty) compared to standard multi-bus systems. With these contributions, it becomes possible to predict or monitor crucial measurements such as communication cost or power restoration penalty for a certain power distribution system. Thus quantifying the potential threats or current status of the load balancing and power restoration processes becomes possible. Also, with the development of the decentralized consensus control algorithm, it is demonstrated that the stability of the system is ensured. The system can always receive a consensus convergent status as all the demands of the loads are fulfilled. Furthermore, the IRT based evaluation approach is simulated to demonstrate the process of quantifying the resilience. It is discussed that this method can be used to compare the resilience of different systems or the different application domains of the same system.

1.4 Possible Applications

This research idea was first applied on naval shipboard electrical systems, which was funded by the *Office of Naval Research* (ONR) through the *Computer Fusion Laboratory* (CFL) at Temple University. The purpose is to utilize and harvest the shipboard low-power device computation. The methodology investigated in this dissertation offers a rapid and robust decision making system for the shipboard electrical systems within a complex and dynamical environment. In order to fully utilize the advantage of (n, k)-star power topology, standard power systems, including standard 16-bus system, IEEE standard 39-bus system and IEEE standard 162-bus system, are selected as applications and testbeds for proposed the methodologies [35]. The standard 16-bus system is initially provided by the *Power System Test Case Archive* (PSTCA) developed at University of Washington. The IEEE 39-bus system and IEEE 162-bus system are proposed by IEEE. With applying these multi-bus systems as simulation platforms, the approach in this dissertation can be generalized to standard problems with known benchmarks that are widely studied.

The proposed decentralized consensus control algorithm and its stability analysis can be easily extended to any homogeneous systems similar but not limited to multi-bus power systems. Load balancing and power restoration problems can also be generalized as information discovery and system reconfiguration problems. So the proposed consensus algorithm can also be applied to the engineering systems that require communication and is capable to reconfigure.

Moreover, the applications of the proposed IRT based assessment methodology can be more widely applied to engineering systems. With the ability to quantify the intrinsic properties such as resilience, reliability, and cyber-security, researchers are able to consider the priority of the maintenance proactively to the system failure. Also, it is valuable that since the calibration process requires a significant number of test scenarios, this methodology can be easily converted to a big data approach for applications other than ones in statistical field.

1.5 Organization of this Dissertation

The rest of this dissertation is organized as follows. Chapter 2 describes the problem definition and modeling of the (n, k)-star power topology. The measurements and centralized control algorithms are introduced as well. Chapter 3 gives the development of the decentralized consensus control algorithm, including its stability analysis and the modeling of general power agents. Chapter 4 offers the novel methodology of IRT resilience assessment using IRT. Experimental design and data discussions are provided in Chapter 5. Chapter 6 presents the concluding remarks, future plans and potential impacts.

CHAPTER 2

POWER TOPOLOGY MODEL USING (N, K)-STAR

This chapter presents the modeling of (n, k)-star power topology and properties derived from (n, k)-star interconnected network. Then, it introduces novel defined metrics on (n, k)-star power topology. Centralized algorithms are described to solve the load balancing and power restoration problems. The problem definition is discussed at the beginning of the chapter to clarify the design objectives.

2.1 Problem Definition

Assuming a power network is connected by a set of buses, generators and loads, *Kirchhoff's Current Law* (KCL) must be satisfied for all the buses. KCL ensures that the total outflow power should be equal to the total inflow power at a bus connecting all the lines. In Figure 2.1, four lines are connected to bus i, where two are inflows and the other two are outflows. Bus i can be denoted as $i = \{m, j, k, l\}$. Its power can be represented as $P_i = P_m + P_j + P_l + P_k$, where $P_j, P_k > 0$ indicates the power lines j and k are inflows and $P_m, P_l < 0$ means the other two power lines are outflows. If the total inflow power on Bus i is 100MW, where 60MW from line j and 40MW from line k, the total outflow power must be 100MW (70MW and 30MW from lines m and l, respectively). So the overall power at Bus i is 0MW.

In order to illustrate how a bus switches on and off connections to achieve the total power,

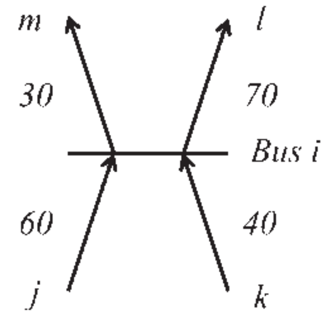


Figure 2.1: KCL for an arbitrary bus (unit: MW)

Figure 2.2 shows the connection switches inside the 4-bus system. Without considering the power loss on transmission lines, power generators should fully satisfy the power demand from loads. The power for each bus is denoted as follows:

$$
\begin{aligned}
P(B_1) &= 400MW, B_1 \in S \\
P(B_2) &= 100MW, B_2 \in S \\
P(B_3) &= 300MW, B_3 \in R \\
P(B_4) &= 200MW, B_4 \in R
\end{aligned}
\tag{2.1}
$$

where the notation B_i indicates the Bus i; S is generator set and R is load set, which means Buses 1 and 2 are supplying power while Buses 3 and 4 are demanding power.

In Figure 2.2, the connection between each bus shows if it is connected to another bus. In this example, Bus 2 is disconnected from Bus 4 is because Bus 4 has more demand than Bus 2 can supply. Thus Bus 2 has to switch to connect with Bus 1 to add both power together. The arrows at Buses 2 and 1 show how the power flows on the connections. Then, Bus 1 makes the decision to switch to Buses 3 and 4 to supply both loads. There is no connection between Buses 3 and 4 since there is no action in between. Therefore, the total generated power is 500MW and is equal to the total demanded power. More specifically, for each bus,

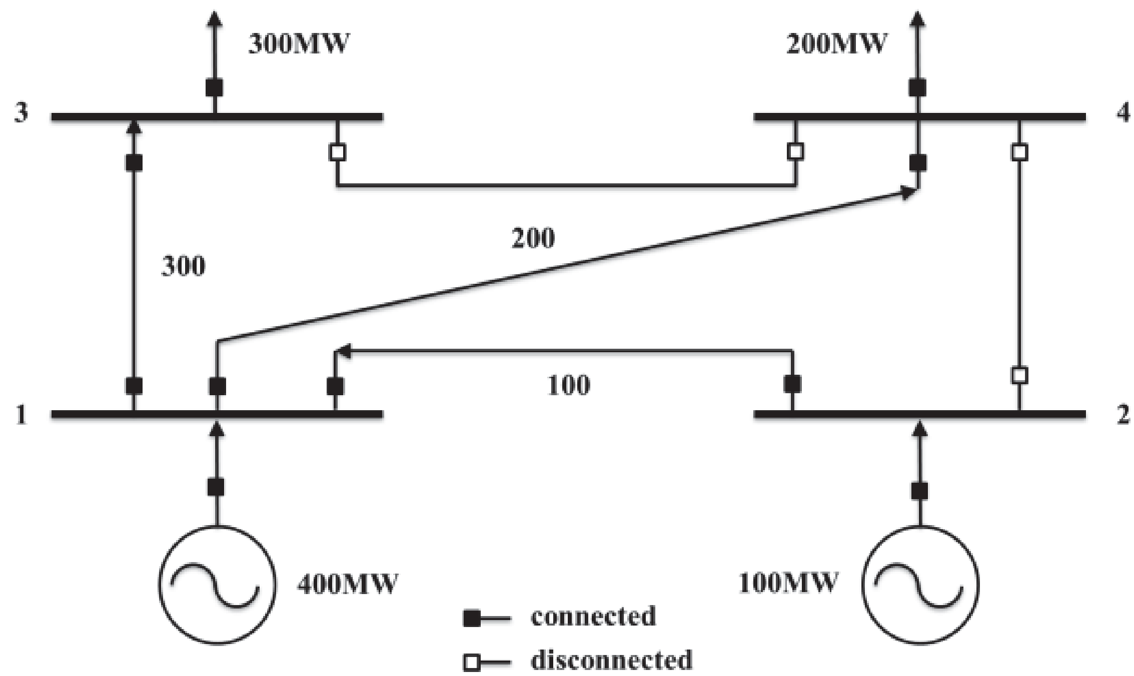


Figure 2.2: 4-bus power distribution system

the total inflow power is equal to the total outflow power. For example, for Bus 1 the power inflows are 400MW from the generator and 100MW from Bus 2 and the power outflows are 300MW to bus 3 and 200MW to Bus 4.

By extending this concept, several standard bus systems were developed. They can be used as test beds or simulation platforms [25, 37, 38]. In this dissertation, a standard 16-bus system is used as a case study for the load balancing and power restoration problems, and then the methodology is extended to IEEE standard 39-bus system as well as IEEE standard 162-bus system. The 16-bus system has two different categories of buses: generator agents (buses connected to generators) and load agents (buses connected to loads) as is shown on Figure 2.3. These two types are also respectively known as producer agents and consumer agents, which will be discussed as main components for a market based MAS architecture in the following subsection. These two types of agents are categorized based

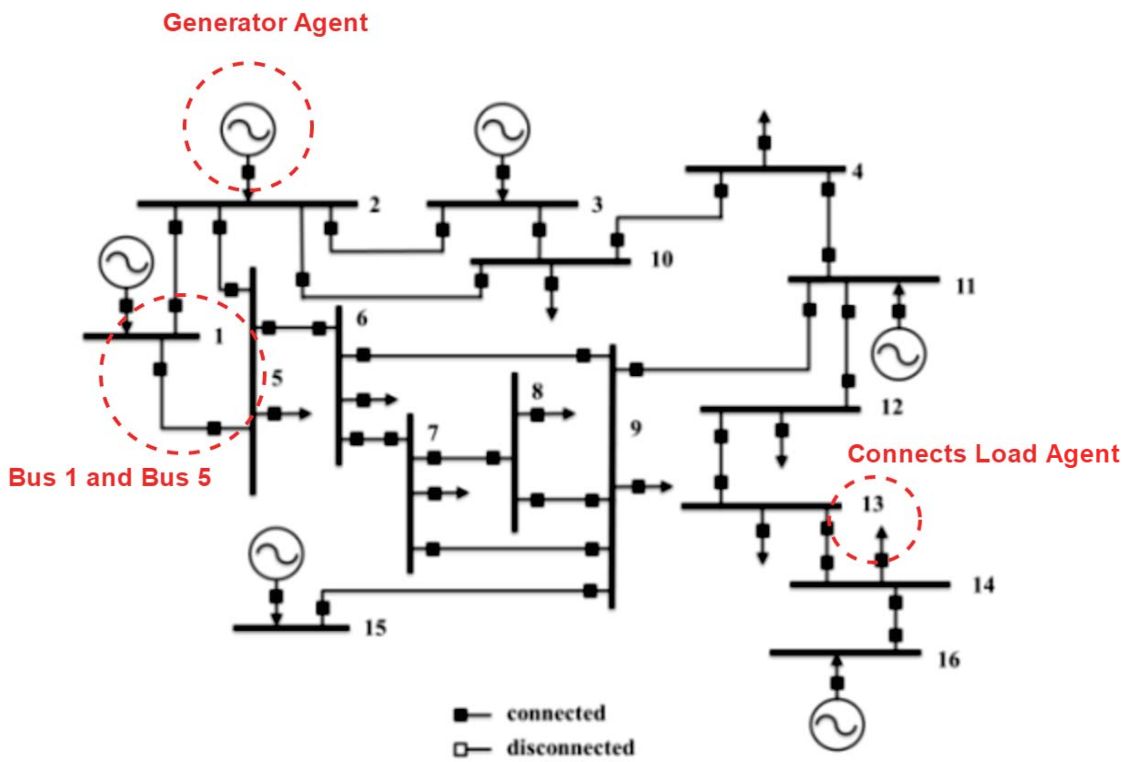


Figure 2.3: Standard 16-bus Power System Test Case

on the method of numerical representation of the power generated and power consumed. When buses are connected to generators, the total power is positive, and it is negative when buses are connected to loads, according to Table 2.1. This representation transferred the load balancing problem to a numerical computing problem. With these fundamental definitions, the goal of this research is to design an algorithm to discover the power supply route of the bus system ensuring *as many as possible loads are being served* while *the total net power is minimized*.

The following constraint is to ensure load balancing for the proposed market based MAS power grid structure:

Constraint 1: The total net power for the producers should be greater than or equal to the

Table 2.1: Standard 16-bus Power System Agent Net Power and Parameters

Agent	Role	Power Demand/Supply (MW)	Neighbor Agents	Priority
1	1	40	[2,5]	-
2	1	40	[1,3,5,10]	-
3	1	50	[2,10]	-
4	0	-25	[10,11]	L_{p_2}
5	0	-35	[1,2,6]	L_{p_2}
6	0	-20	[5,7,9]	L_{p_1}
7	0	-15	[6,8,9]	L_{p_2}
8	0	-25	[7,9]	L_{p_1}
9	0	-5	[6,7,8,11,15]	L_{p_1}
10	0	-30	[2,3,4]	L_{p_2}
11	1	40	[4,9,12]	-
12	0	-45	[11,13]	L_{p_1}
13	0	-10	[12,14]	L_{p_2}
14	0	-40	[13,16]	L_{p_2}
15	1	30	[9]	-
16	1	50	[14]	-

total net power of consumers, which is represented as:

$$\sum_{s \in S} P_s \geq \sum_{r \in R} (-P_r). \tag{2.2}$$

where R is the consumer (load) agent set, S is the producer (generator) agent set, r and s are the elements in consumer agent set R and producer agent set s accordingly. The total consumption of the net power should always be less than or equal to the total production of the net power. This constraint ensures that if the load balancing algorithm is designed properly, the loads in a distribution system would be fully supplied. It is a necessary condition of load balancing but not a sufficient condition because the final status of the loads depends on how the power is distributed mechanically as switch open or close. Table 2.1 shows the net power for each agent in 16-bus power system. The total power for all the agents is 0, which makes this 16-bus power system as a standard test case. It is one sufficient condition that the system will receive balancing status for all the agents. However, whether the system will reach the balancing goal is depending on control algorithms.

Therefore, one of the research goals for this dissertation is to design an algorithm to discover the power supply route of the bus system. By doing so, it is necessary to optimize as many loads as possible to be served and the total net power is minimized, allowing loads with higher priorities to be served first. Thus the objective function can be derived as following:

$$\begin{cases} \max \left\{ \frac{1}{\sum_{r_1 \in P_{L_{p_1}}} x_{r_1} P_{r_1} + \sum_{r_2 \in P_{L_{p_2}}} x_{r_2} P_{r_2} + G} \right\} \\ \max \left\{ \left(\sum_{r_1 \in P_{L_{p_1}}} x_{r_1} \right) \right\} \end{cases} \tag{2.3}$$

where $(r_1, r_2) \in R$ are the agents from producer agent set R. L_{p_1} and L_{p_2} are the constants representing the priority of a producer agent, which have the relationship $L_{p_1} > L_{p_2}$. The lower number it is, the higher priority the agent will be. $x_{r_1}, x_{r_2} \in 0, 1$ are the connection booleans that indicate whether there is a connection from the load to the agent. L_{p_1} is the level 1 load set and L_{p_2} is the level 2 load set. In equation (2.3) the level 1 load is considered as higher priority to be supplied with power. The goal is to ensure as many as high priority loads to be supplied before any of the level 2 loads being supplied. The standard multi-bus systems we discuss in this dissertation consider two-level priority settings. However, the objective function can be easily extended to multiple-level priority system settings. Thus, equation (2.3) is the mathematical formulation representing the goal of the load balancing problem and is considered as the common objective function for all the methodological goals achieved in this dissertation.

2.2 Belief-Desire-Intent Agents

In order to solve the load balancing and power restoration problems, it is necessary to establish an environment that is suitable for power systems. This environment should systematically host a feasible, understandable, and accessible platform. It will allow each component on this platform to independently communicate with each other in order to achieve a common goal. Researchers have investigated a coupled tank system as a market, where the agents are characterized as producers and consumers [45]. Noticeably, the agents can either play the role of the producer or the consumer depending on the water level of the tank. The researchers applied this idea on a water supply system. Experiment results have shown that how water level can indicate the role of the virtual agents: if it is higher than a threshold, the agents can take the producer role to do certain tasks; otherwise they will be consumers that can do some other tasks. It is demonstrated that market based agent system is one of the solutions to solve a resource allocation problem. The equilibrium price the experiment achieved at the end can be extended to any balancing status of a system. The outstanding aspect of the solution is that through the simple interactions of trading among individual agents a desirable global goal can be achieved.

This dissertation utilizes the market-based MAS approach and investigates its performance. More specifically, the power scheduling platform is treated as the market. An agent can be delegated on each bus. Bus agents are either producers or consumers depending its role: it is a producer agent if $P_i > 0$ and is connected to power, otherwise it is treated as a consumer agent. During the communication, the agents can maintain their local status to balance the power exchange dynamically. When a fault occurs in the system, the agents can still maintain the global goal once there is a power restoration algorithm for each agent in a distributed manner.

A BDI agent is a computational virtual unit that simulates rational attributes of *Belief, Desire and Intention* (BDI). Beliefs represent information that an agent obtains from sensing its environment and the agent's internal states. Desires, also known as goals, and represent the agent's motivation and direct the actions of the agent. Intentions are courses of action of deliberating which refers to the agent's commitments to its goals. Intentions involve beliefs and desires. Thus, in MAS environment, an agent acts towards some of the environmental states it desires to be true and believes to be possible. Their actions are only caused by desires other than cognitions or emotions. Their intentions are consistent and are achieved by executing plans. These attitudes together determine the agents' behavior and they are critical for achieving optimal goals. BDI agents are usually utilized to solve resource allocation problems when agents are defined with limited time and limited computational power. The BDI model was initially proposed by Rao and Georgeff in 1995 [40]; however, the notion of the BDI model was officially conceived in Michael Bratman's brilliant book as a theory of human practical reasoning, where Bratman makes remarkable progresses in the theory of human action and unintentionally enhances our knowledge of the foundations of human beings [5]. In 1999, according to Martha Pollack [15], the BDI model could be further considered as a general model for practical reasoning. A BDI MAS is the multi-agent system that composed of multiple interacting BDI agents. It is a natural and efficient way to decompose complex systems into distributed, autonomous sub-systems as agent, with asynchronous or synchronous processing in real-time.

Therefore, BDI MAS system is introduced in this dissertation as a basic platform for power distribution systems. There are three reasons to use the BDI agent platform for solving load balancing and power restoration problems:

1. In MAS, autonomous action and interaction are inherent capabilities of agents. Agents can sense their environment through given beliefs, and accomplish delegated goals through actions or plans. Their actions as outputs can modify the environment. The outputs may also update beliefs or goals. BDI agents have different beliefs about their environment and different goals to be achieved.

2. BDI agents can work together effectively in a fully distributed and dynamic environment. BDI agents can be designed and modeled with their own beliefs and goals, so they can update their status dynamically with a distributed manner. Agents can communicate to each other and act strategically in order to achieve the goals they want. These communications and actions may be synchronous or asynchronous in real-time, so the agents have to act autonomously. *i.e.*, agents can make decisions about what to do at run-time, rather than have all decisions hardwired in upon design time in traditional distributed and concurrent systems.

According to the problem definitions and to represent the bus agents of the power distribution in this dissertation, we need to define three sub-types of agents: generator agents, load agents and phantom agents. These agents are all derived from bus agents that exist in the power distribution models in this dissertation. Each of them performs as a bus agent with its own BDI properties to help the whole power system make decisions.

2.3 (n, k)-star Power Topology

The BDI Agents approach requires the load balancing and power restoration algorithms control the agents to mechanically switch connections on and off to reach the desires. Thus, the performance of the algorithms varies when the communication strategies are different. In order to optimize the communication procedure of MAS based power systems, we introduced an interconnected network topology, named (n, k)-star, to power system to solve load balancing and power restoration problems. In large-scale power distribution systems and smart grids, solving both load balancing and the power restoration problems requires agent communication in a distributed and fast way. Thus, the decision-making procedure for a power distribution system can be treated as a communication problem. In order to optimize a communication process for large-scale networks, one of the research trends is based on network topologies. The (n, k)-star interconnected network topology is utilized in this dissertation to represent the standard multi-bus power system. With applying the advantages of the properties and metrics derived from (n, k)-star topology, we are able to create theoretical metric models for (n, k)-star electric power grids. In this section, well defined metrics, such as communication cost and power branching penalty, are described. Compared to the related study [51], the (n, k)-star topology outperforms the original multi-bus topology with the advantages of lower communication cost and lower power restoration penalty. Simulation results will be provided in Chapter 5 to demonstrate the metrics and the performance evaluated from these metrics.

2.3.1 Definition

The basic definition and terminology can be found in [6, 7, 57]. An (n,k)-star graph $S_{n,k}$ with $1 \leq k < n$ is denoted by the two parameters n and k. For simplicity, $\langle n \rangle$ is

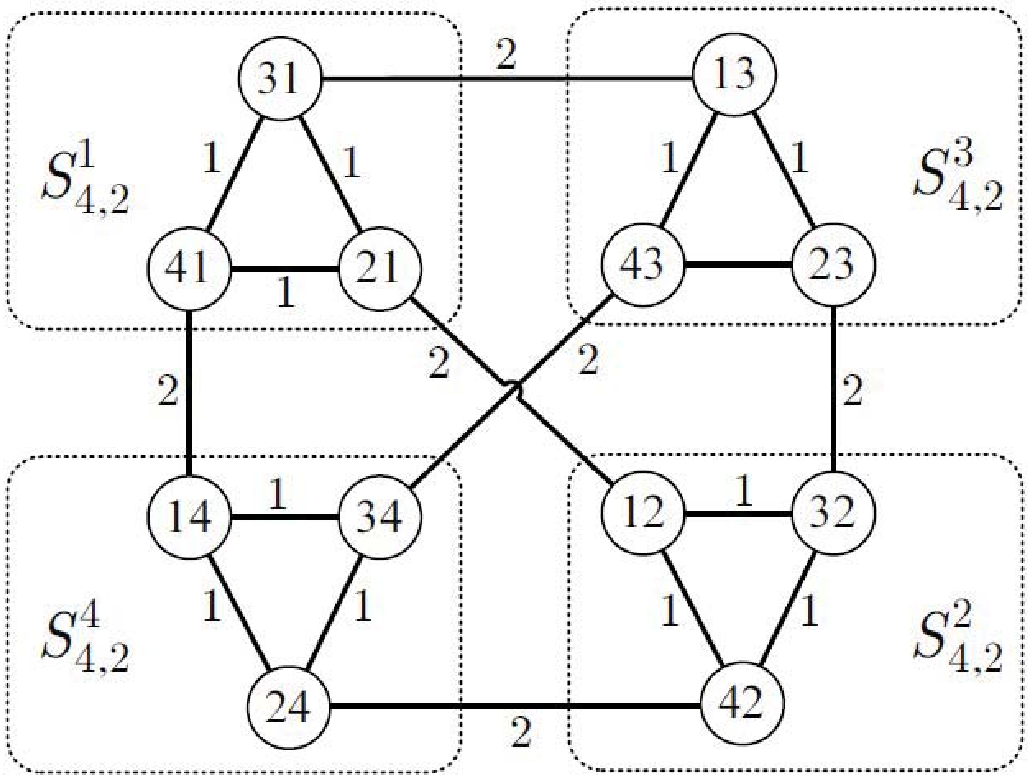


Figure 2.4: (4,2)-star topology. By applying Definition 2 the diameter is 3

used to denote a set of nodes, *i.e.,* $\{1,2,\ldots,n\}$. The vertex set of $S_{n,k}$ is denoted by $\{v(S_n,k) = \{p_1, p_2, \ldots, p_k \mid p_i \in \langle n \rangle$ and $p_i \neq p_j$ for $i \neq j\}$. The edge set of $S_{n,k}$ is defined as follows: A vertex $p_1, p_2, \ldots p_i, \ldots p_k$ is adjacent to:

1. The vertex $p_i p_2 \ldots p_1 \ldots p_k$ through an edge of dimension i, where $2 \leq i \leq k$ (*i.e.*, exchange p_1 and p_i);

2. The vertex $x p_2 \ldots p_k$ through an edge of dimension 1, where $x \in \langle n \rangle \setminus \{p_1, p_2, \ldots, p_k\}$, is a selected starting number.

According to the definition above, an $S_{n,k}$-star graph is $(n-1)$-regular and contains $\frac{n!}{(n-k)!}$ vertices. The edges of type (1) are referred to as *i-edges*, whereas the edges of type (2) are referred to as *1-edges*. Figure 2.4 shows an example of $S_{4,2}$. Specifically, an $(n-1)$-regular graph is defined as a graph that has the same degrees for all the nodes. That means once n and k of a certain (n,k)-star is chosen, its degree and node number are all fixed because they can both be represented as a function of n and k. Moreover, the following two definitions demonstrate that the conditional diagnosability and diameter of an (n, k)-star graph can also be represented as a function of n and k.

The $S_{n,k}$, where $2 \leq k \leq n$, can be constructed by interconnecting n number of $S_{n-1,k-1}$ components. As is proven in [7], one of the most important properties related to scalability is that $S_{n,k}$ can be decomposed into n vertex-disjoint $S_{n-1,k-1}$ components over any dimension i by fixing one symbol in any position i, where $2 \leq i \leq k$. If the subgraph of $S_{n,k}$ is represented by $S^i_{n,k}$, it has been proven that $S^i_{n,k} \cong S_{n-1,k-1}$. Thus, because of the property that an $S_{n,k}$-star graph is $(n-1)$-regular, which means the degree of $S_{n,k}$ is $deg(S_{n,k}) = n-1$, there is an important property that a $S_{n,k}$-star graph is $(n-1)$-connected. There is an assumption that conditional diagnosability of an $S_{n,k}$-star graph must be greater than $n-1$. Then, this property makes an (n, k)-star graph competitive with other interconnected power system topologies. It is the main focus of this dissertation to migrate this topology to examine the diagnosability and the fault tolerance for agent communication in power network restoration. Figure 2.4 shows an example to construct a (4,2)-star topology using the above definition. When $n = 4$ and $k = 2$, the number of vertices is $\frac{n!}{(n-k)!} = 12$. These twelve nodes are assigned with different notations and form the set $V = \{12,13,14,21,23,24,31,32,34,41,42,44\}$. This step follows the definition of vertices of (n,k)-star topology, which is $\{v(S_n,k) = \{p_1, p_2, \dots p_k \mid p_i \in \langle n \rangle$. Then, the connections are constructed by following the two steps of definition for neighbor formation. In the first step, agents connect each other through connection type 1 (Figure 2.4). This is also known as intra-connection of neighbors. Then, the agents follow the second step to connect each other through connection type 2. These connections connect the sub-networks generated by the first step so it is recognized as the inter-connection of neighbors. Figure 2.5 shows another example which is an (8, 4)-star construction. It follows the same three steps:

1. node construction: k numbers are selected from a set of all n numbers, which is $\{1, 2, \ldots, n\}$. In this case $k = 4$ and $n = 4$ so that 4 numbers are selected from the set of 8 numbers ($\{1, 2, 3, 4\}$). The sub-networks are formed by grouping the nodes with the same ending number together. For example, the nodes in the upper left sub-network are $\{1234, 2134, 3124, 1324, 2314, 3214\}$. They form the same sub-network because they have the same ending number 4.

2. neighbor construction by switching node: connection (step1): exchanging p_1 with p_k will get three connections for each node. For example, node 1234 will connect to three nodes. They are 2134 (exchanging 1 and 2), 3214 (exchanging 1 and 3) and 4231 (exchanging 1 and 4) respectively.

3. neighbor construction by replacing first one with ones do not appear (step2): there are none of the connections in this type since $\langle n \rangle \setminus \{p_1, p_2, \ldots, p_k\}$ is ϕ.

The definitions in the following subsection explain the properties that are useful for distributed MAS based algorithm.

2.3.2 Related Properties

(n, k)-star graph topology has been proven to be a highly fault-tolerant topology in the area of graph theories [57]. It is derived from n-dimensional star graph model with additional redundancy and reliability. Among all the properties of (n, k)-star graph topology, fault-tolerance can be especially important for communication of interconnected networks. Since each component in the network may fail and cause the whole system a failure, the

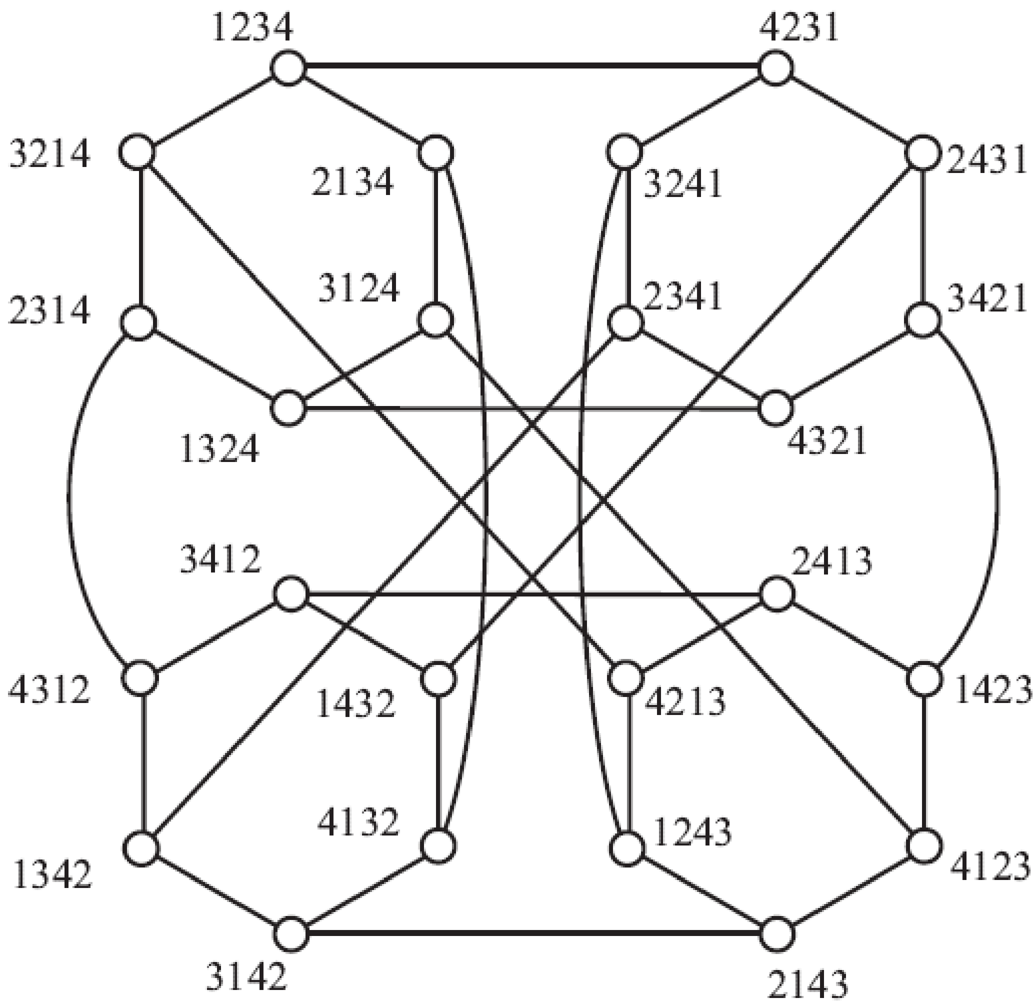


Figure 2.5: (4,4)-star topology example

definition diagnosability is introduced to general network topologies to provide one of the metrics of system faults [6]. The diagnosability, denoted by $t(G)$, is described as the maximal number of faulty nodes that can be diagnosed by the system. For example, a system is t-diagnosable if all faulty nodes can be identified without a replacement, provided that the number of occurring faults does not exceed t. Then, Conditional Diagnosability is first proposed by Lai et al. [26]. In reality, it is common that if all neighbors of a node u

in the interconnected networking system are faulty simultaneously, u cannot be tested as faulty or fault-free; thus, it is impossible for traditional system diagnosability to be more than its minimum node degree. Thus, other than strong diagnosability [58], they introduced conditional diagnosability which is based on the assumption that all neighbors of any node in a multnode system cannot be faulty simultaneously. Particularly, the authors of [6, 18] provided us with a definition of an (n,k)-star graph topology on fault tolerance:

Definition 1 *The conditional diagnosability of the (n,k)-star graph $S_{n,k}$ is given by the following:*

$$t_c(S_{n,k}) = \begin{cases} 0, & \text{if } n = 3, k = 1; \\ \lceil \frac{n}{2} \rceil - 1, & \text{if } n \geq 4, k = 1; \\ n + 2k - 5, & \text{if } n \geq 4 \text{ and } 2 \leq k \leq n-1; \\ 3n - 7, & \text{if } n \geq 4 \text{ and } k = n. \end{cases}$$

where $\lceil \frac{n}{2} \rceil$ is defined as the smallest integer greater than or equal to $\frac{n}{2}$.

This definition describes the outstanding property of an (n, k)-star power system topology. To a power distribution system, the conditional diagnosability represents the number of critical nodes in the system. The number $t(G)$, defined as the diagnosability for graph G, is the minimum number of nodes that can go to faults before making the whole system branching into two sub-systems. In addition to the application of fault-tolerant algorithms to power distribution architecture, an (n, k)-star is able to provide relatively high conditional diagnosability, which can ensure the system resilience on hard faults of a power network agent node. Therefore, in comparison to other traditional topologies, such as radios and rings, the (n, k)-star topology model is a good candidate model for practical resilient power restorations in the sense of fault tolerance. Moreover, the researchers of [21] provided us with another definition on diameter of nodes in (n, k)-star topology, which is the longest distance between two arbitrary nodes:

Definition 2 *The diameter $D(S_{n,k})$ of (n, k)-star graph is formulated as:*

$$D(S_{n,k}) = \begin{cases} 2k-1, & \text{if } 1 \leq k \leq \lfloor \frac{n}{2} \rfloor; \\ \lfloor \frac{n-1}{2} \rfloor - 1, & \text{if } \lfloor \frac{n}{2} \rfloor \leq k < n. \end{cases}$$

where $\lfloor \frac{n-1}{2} \rfloor$ is defined as the largest integer less than or equal to $\frac{n-1}{2}$.

It is obvious that the diameter of an (n, k)-star topology is smaller than other former interconnected network topologies. Definitions 1 and 2 proved that (n, k)-star topology is suitable for power grid design in the advantages of fault tolerance and discovery cost. Overall, the (n,k)-star topology is provided in this section with:

1. Relatively high degree, which gives the (n,k)-star topology redundancies for power rerouting. The architecture is more fault tolerant as the degree is high.

2. Relatively high diagnosability. It adds hardware fault tolerance to power network restorations.

3. Relatively low diameters. This ensures the communication cost to be minimal for (n,k)-star agent based communication.

2.3.3 Topology Model

There has been rising trend of research works on MAS approaches for power restoration. This dissertation presents a novel way to utilize market based MAS on power distribution systems and design centralized and decentralized algorithms. In this dissertation, our approach is initialized with establishing the power agents (including consumer and producer agents), which are constructed as power components in the system [43]. Upon the initialization of the system, the structured MAS is considered as a blind marketplace to all agents. In this marketplace, some agents are defined as consumers and some as producers. Each consumer agent has no global knowledge of the power supply in the market: what it has is the BDI model from itself and the information from its adjacent agents. After the initialization, consumer agents start to explore the market by looking for producers in the producer set. Since the global goal of the market is to satisfy the total demand of power, the desired system condition is that the total supply and demand are balanced. This goal should be a time-varying one because the power system is a dynamic system and maintenance of stability is needed in the network at all times. *Finding a producer* plan is consequently executed to achieve the *finding a producer goal*. The plan is to access the belief set, which contains all the initial status of BDI agents, visit all the adjacent agents whose roles are producers, and retrieve the net power. Then, the plan is on pending status until a trading goal is achieved. A trading plan is triggered by the trading goal and it is represented for the consumer i as:

$$p_j^{k+1} = p_i^{k+1} = \max_{j \in N_i} \alpha(p_i^k + p_j^k)\, for\, i \,=\, 1, 2, \ldots, n \tag{2.4}$$

where n is the number of buses; α_{ij} is the coefficient that indicates the connection between producer j and consumer i. If producer j and consumer i are connected then α_{ij} is 1, otherwise 0; p_i^k and p_i^{k+1} are the net power of consumer i at iteration k and $(k+1)$ respectively.

The modeling of (n,k)-star power topology is only taking place on the communication system. The physical connections for the multi-bus system remain the same. The communication system is proposed as a computational system [18] that is commanding the physical system by sending commands from a control algorithm. This communication system is powered by the power from the physical power systems. Therefore, a power

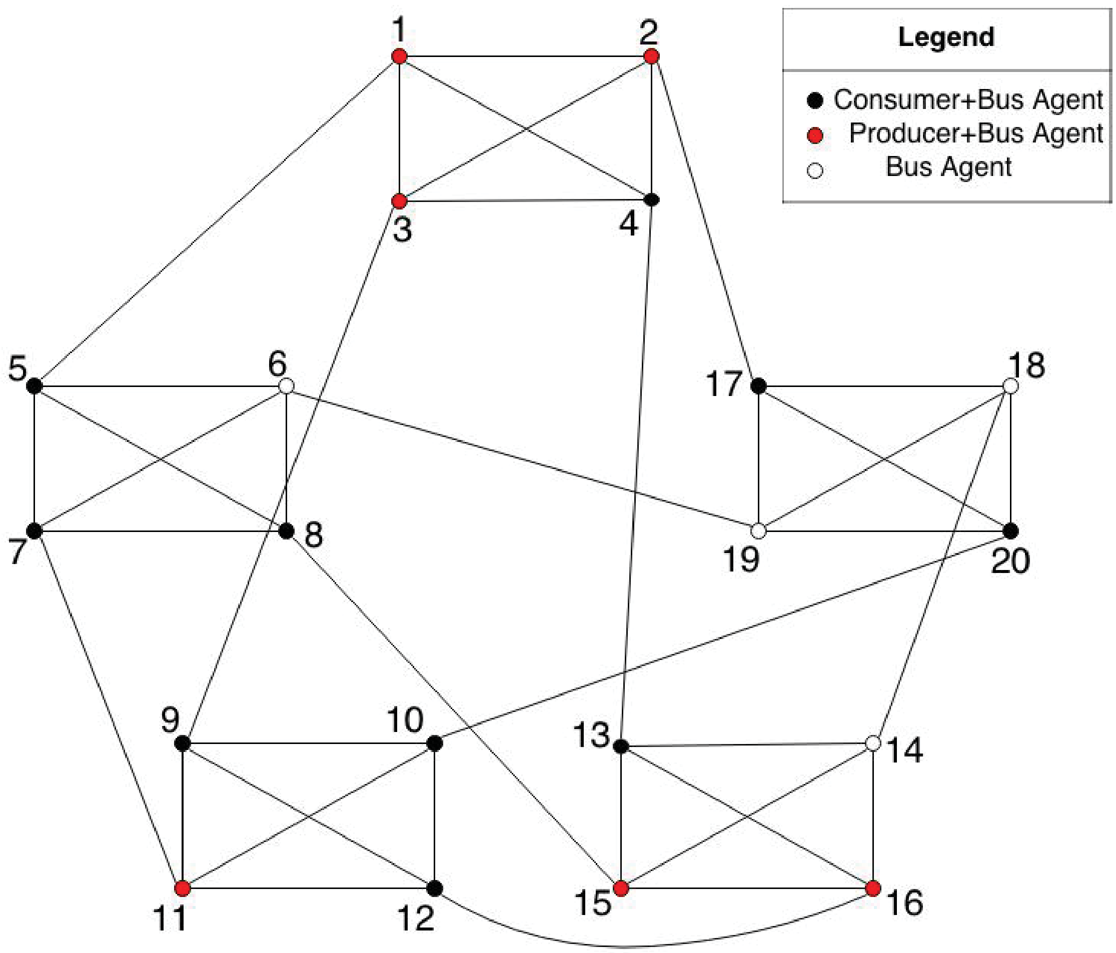


Figure 2.6: MAS based $(5,2)$-star topology implementing standard 16-bus power system with extra bus agents

shortage on the physical system will result in the communication agent shut down in the communication network. However, the communication link shortage would not affect the power flow on the physical power systems. In this dissertation, we studied on the three multi-bus physical power systems, which are the 16-bus, 39-bus and 162-bus systems respectively. The modeling of (n,k)-star topology systems is on top of the according physical systems. For example, Table 2.3 shows how (5,2)-star power topology is constructed. In this table, the last two columns show the connection to the physical agents, and their neighbors

Table 2.2: (n, k)-star Bus System Modeling Table

Bus Systems	(n, k)-Star	Number of Nodes	Extra Nodes	Degree	Diameter
16-Bus	$S_{5,2}$	20	4	4	3
39-Bus	$S_{7,2}$	42	3	6	3
162-Bus	$S_{7,3}$	210	48	6	5

accordingly. Thus, the structure of our proposed modeling of (n,k)-star power topology is a hybrid system with two layers, one is physical systems (multi-bus systems) and the other is communication systems ((n,k)-star power topology).

In our preliminary studies, the MAS approach was presented for power network restoration algorithms [43, 44], in which an agent is defined as a BDI module to act as a bus for the power system. In this dissertation, we mapped the agents in the power network system to the (n, k)-star graph model. The agents would be performing as bus agents (categorized as BDI consumer/producer power agents) in the proposed (n, k)-star power system model.

As defined in the last section, the number of nodes in the (n,k)-star graph topology can be expressed linearly by n and k. The combination of numbers n and k generates a limit selection of total agent number for a (n, k)-star system. The number of nodes is fixed once the numbers n and k are chosen. That means that, in order to construct an (n, k)-star power distribution system for an existing multi-bus system, some constraints should be designed to map the difference of number of nodes between two systems. Thus for the standard bus system test cases studied in [44, 51], the number of nodes in the (n, k)-star topology must be greater than but closest to the number of nodes in bus systems. Therefore, instead of having only bus agents in the system, there will be one more type of agents that needs to be designed. Bus agents that play the role of orchestrating switching and routing decisions when necessary are defined as Phantom Agents. Phantom Agents are agents that are not initialized with any beliefs, desires or intents, but they are in the process to transfer powers from adjacent producer agents to adjacent consumer agents. Phantom nodes are virtual nodes that only participate in communication. Ideally, they do not consume any power and the communication cost is zero. Thus in the 16-bus power system, as shown in Figure 2.6 the phantom bus agents implement the same intra and inter connections in the system to make an (n, k)-star topology. The number of phantom agents is the difference of components between the standard multi-bus power system and the (n, k)-star power topology. These phantom agents are randomly located in the (n, k)-star topology. Table 2.2 shows the value of n and k selected for standard multi-bus systems [46]. The total number of agents for the (n, k)-star power topology representing the 16-bus power system, 39-bus power system and 162-bus power system is 20, 42 and 210 accordingly. For example, when $n = 5$ and $k = 2$ are selected for a 16-bus power system, the number of phantom agents is 4 out of a total number of 20 agents. In this case there will be 16 components to perform as power and bus agents in the architecture illustrated in Figure 2.6. The other 4 components are phantom bus agents that are randomly located to the topology.

2.3.4 Metrics

Considering the BDI MAS control system as a distributed decision making system, the proposed (n, k)-star power model implements the agent based control scheme to solve load balancing and power restoration problems. According to the trading plan equation (2.4), the consumer agent in the load balancing process will be initially requesting through all the neighboring producer agents for net power to fulfill the initial demand. If no neighbors are producer agents, the algorithm iterates over all its second hierarchy neighbors (its neighbor's neighbor) until it reaches the producer and is supplied with net power. Objectively, we define each communication action as an iteration. Therefore, the maximum number of iterations for the whole system to get every consumer agent's goal fulfilled is represented by the *Communication Cost* of the whole distributed power system. Then the following theorem and corollary are derived from Definitions 1 and 2 for the *Communication Cost* of (n,k)-star power model:

Theorem 1 *For (n,k)-star power system, the upper boundary for Communication Cost is the sum of the diameter and the degree:*

$$D(S_{n,k}) + deg(S_{n,k}) = \begin{cases} n+2k-2, & \text{if } 1 \leq k \leq \lfloor \frac{n}{2} \rfloor; \\ n + \lfloor \frac{n-1}{2} \rfloor - 2, & \text{if } \lfloor \frac{n}{2} \rfloor \leq k < n. \end{cases}$$

Proof. The key to prove this theorem is to find the worst case *Communication Cost* scenario among all configurations of (n, k)-star topologies. The following two scenarios must occur when it is recognized as the worst case scenario for Communication Cost for a certain system configuration:

1. A *consumer agent* must exist in the topology where none of its neighbors are not *producer agents*.
2. All of the neighbors of that *consumer agent* are *consumer agents* and they have the longest distance, which equals to the diameter of the graph, from the nearest *producer agent*.

Once these constraints are fulfilled, it is obvious that this exemplifies the highest communication cost for this consumer agent to communicate to the nearest *producer agent*. Therefore, respectively, if the first constraint is fulfilled, the communication cost is exactly how many neighbors each node has, which equals to the degree of the (n, k)-star topology; if the second scenario occurs, the communication cost is the number of agents included in the longest path of the topology, which is identical to the value of the diameter. ■

Moreover, if the number of degree is represented as $d(S_{n,k})$ and the diameter is $D(S_{n,k})$, the following corollary defines the time complexity of the route discovery algorithm of the MAS approach:

Corollary 1 *Time complexity of the route discovery algorithm for load balancing process on the (n,k)-star distributed power network topology is $O(d(S_{n,k})+D(S_{n,k}))$.*

The communication cost is one of the novel proposed metrics in this dissertation. It is derived from the communication properties in communication networks. It provides with a direct way to observe and evaluate the load balancing process and its algorithms. This metric is important and novel to our investigation into evaluating power topology systems and comparing them to other system architectures. The second metric we propose in this dissertation is the power restoration penalty. The idea of indicating the complexities of algorithms is also borrowed to define this metric. As is defined previously, power restoration processes may break the system into several sub-systems. There are two circumstances where a system branching will happen: the shutdown agents would separate some of the consumer agents from reaching their producers or the system reconfiguration runs an algorithm and forms several sub-systems, where each agent is supplied locally. These two circumstances may occur separately or jointly. Thus, the number of branches the new systems break into is defined as the Power Restoration Penalty in this dissertation. The global scope after a certain power restoration algorithm is always preferred. It is because the more branches the system breaks into, the less resilience would each sub-system have since there would be fewer producer agents locally. Thus, the power restoration penalty is the direct metric to represent the performance of a power restoration algorithm. There are two factors that will affect the power restoration penalty of a power restoration algorithm. The first one is the number of degree of the power distribution system. The more degree a power system has, the more neighboring agents an agent can reach. So if there is a system fault on a certain component, the more degree it has, the more redundant routes it can pick to restore the system. The second factor is the conditional diagnosability, which represents the number of critical nodes of a topological system. More conditional diagnosability contributes more resilience to the system and will better prevent the system from branching, especially when multiple faults occur. It is given in the definition of (n,k)-star topology that the degree is $(n-1)$ and in Definition 1 that the *Conditional Diagnosability* is in terms of selected n and k. It can be concluded that the relatively high degree gives redundancy to the system so that the restoration may happen less frequently compared to the original *Standard Bus Architecture*. The relatively high *Conditional Diagnosability* would lead the proposed (n,k)-star topology to a more stable architecture when multiple faults occur.

A set of simulation scenarios is also provided to illustrate the relationship between the metrics and algorithm performance. More specifically, the properties of optimized communication cost during load balancing and advantages when power restoration are illustrated by the experiments described in Chapter 5. The possible factors that affects power branching penalty are also listed in Chapter 5 of this dissertation.

2.4 Load Balancing and Power Restoration Algorithms

2.4.1 System Configuration Example

In order to show a clear view of the algorithms for an (n, k)-star power topology, a (5,2)-star power topology representing a 16-bus power system is shown as an example [44]. The

Table 2.3: Configuration of (5,2)-star Power System Representing 16-bus System

Agent	Role	Power	Neighbors	Priority	Physical Agent	Physical Neighbors
G1	1	40	2,3,4,5	-	1	2,5
G2	1	40	1,3,4,15	-	2	1,3,5,10
G3	1	50	1,2,4,20	-	3	2,10
L4	0	-25	1,2,3,12	L_{p2}	4	10,11
L5	0	-35	6,7,17,1	L_{p2}	5	1,2,6
E6	2	0	5,7,10,17	-	-	-
L7	0	-20	5,6,9,17	L_{p1}	6	5,7,9
L8	0	-15	9,10,11,17	L_{p2}	7	6,8,9
L9	0	-25	8,10,11,16	L_{p1}	8	7,9
L10	0	-5	6,8,9,11	L_{p1}	9	6,7,8,11,15
G11	1	40	8,9,10,14	-	11	4,9,12
L12	0	-30	4,13,14,18	L_{p2}	10	2,3,4
L13	0	-45	12,14,18,19	L_{p1}	12	11,13
E14	2	0	11,12,13,18	-	-	-
G15	1	30	2,16,19,20	-	15	9
G16	1	50	9,15,19,20	-	16	14
L17	0	-10	5,6,7,8	L_{p2}	13	12,14
E18	2	0	9,12,13,14	-	-	-
E19	2	0	13,15,16,20	-	-	-
L20	0	-40	3,15,16,19	L_{p2}	14	13,16

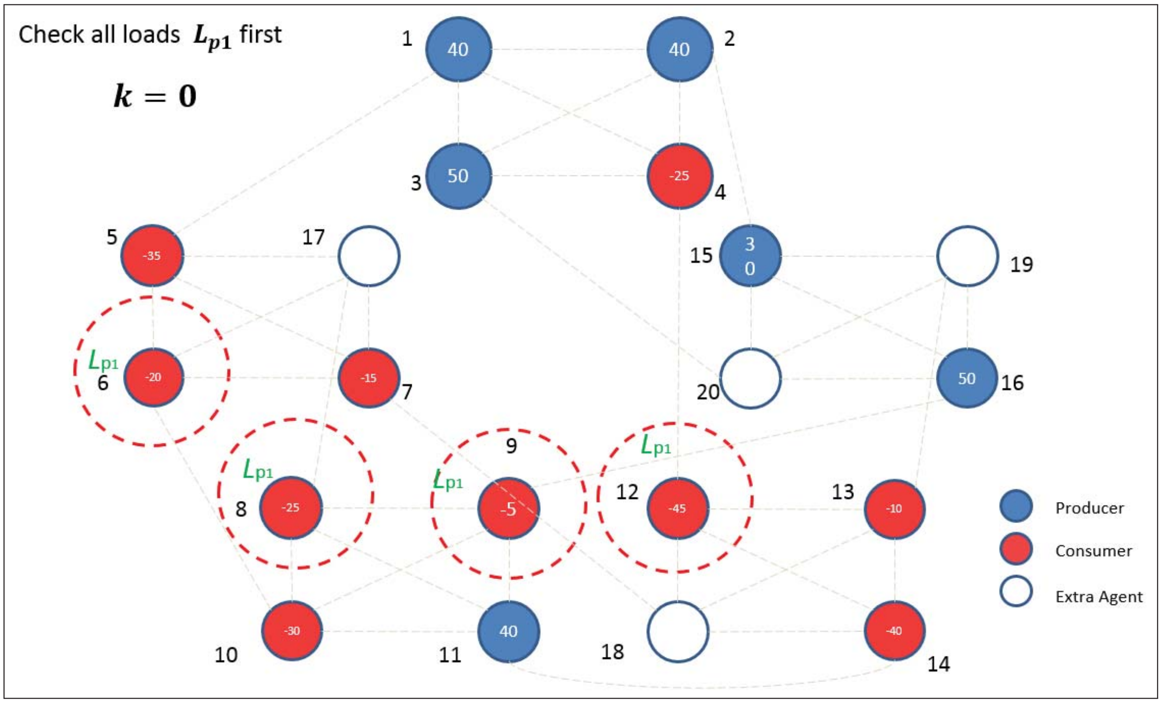
configuration for (5,2)-star power distribution system is shown in Table 2.3. In the table, the agent role is selected form a set $\{0,1,2\}$, where 0 represents the consumer, 1 represents the producer and 2 represents the phantom node. The number of each type of agent is exactly following the settings from standard 16-bus system. The fourth column, labeled as Neighbors, is the neighbor index connecting to the agent on each row. The initial net power for each agent also matches the initial net power of standard 16-bus system.

2.4.2 Centralized Control Algorithm

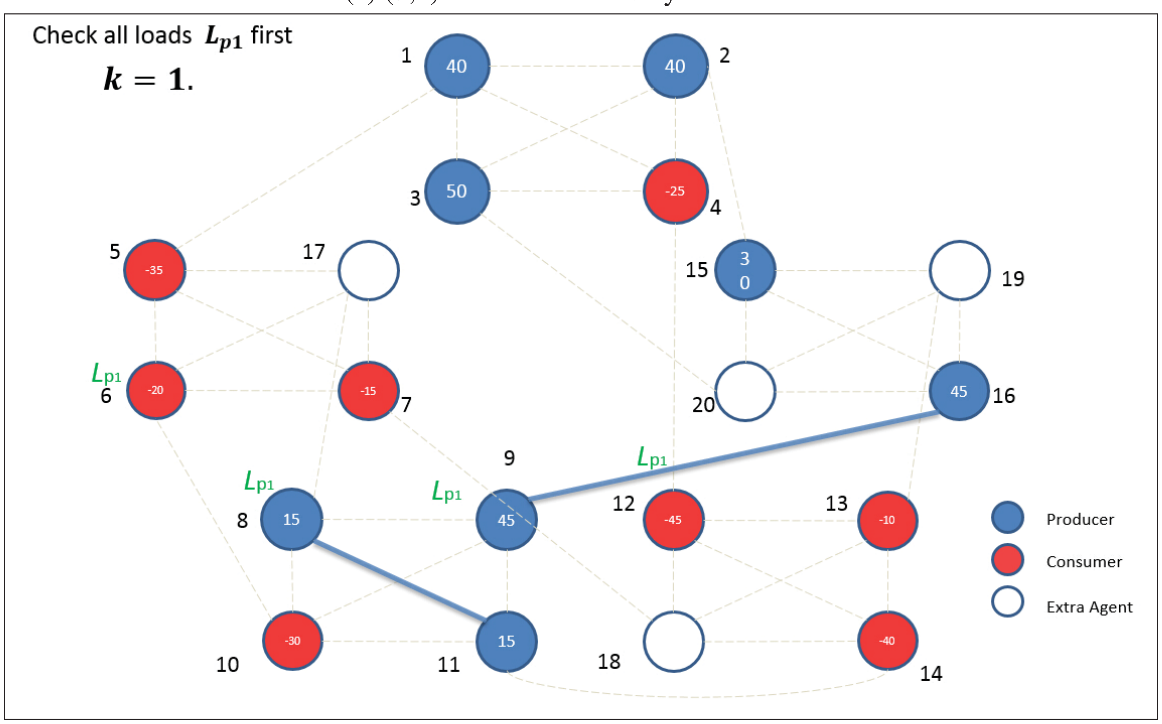
The centralized control algorithm we proposed for an (n, k)-star power topology is derived from the consensus control method from [51]. It improved the communication procedure in order to minimize the communication cost of load balancing. This algorithm is proposed in [43] and is applied to the (n, k)-star power topology to investigate the performance by measuring the designed metrics. The algorithm is formulated into the following equation:

$$p_i^{k+1} = p_j^{k+1} = \begin{cases} \max\limits_{\substack{j \in N_i \\ p_j > 0}} a_{ij} \left(p_j^k + p_i^k \right) & p_i < 0 \\ \\ \min\limits_{\substack{j \in N_i \\ p_j < 0}} a_{ij} \left(p_j^k + p_i^k \right) & p_i > 0 \end{cases} \tag{2.5}$$

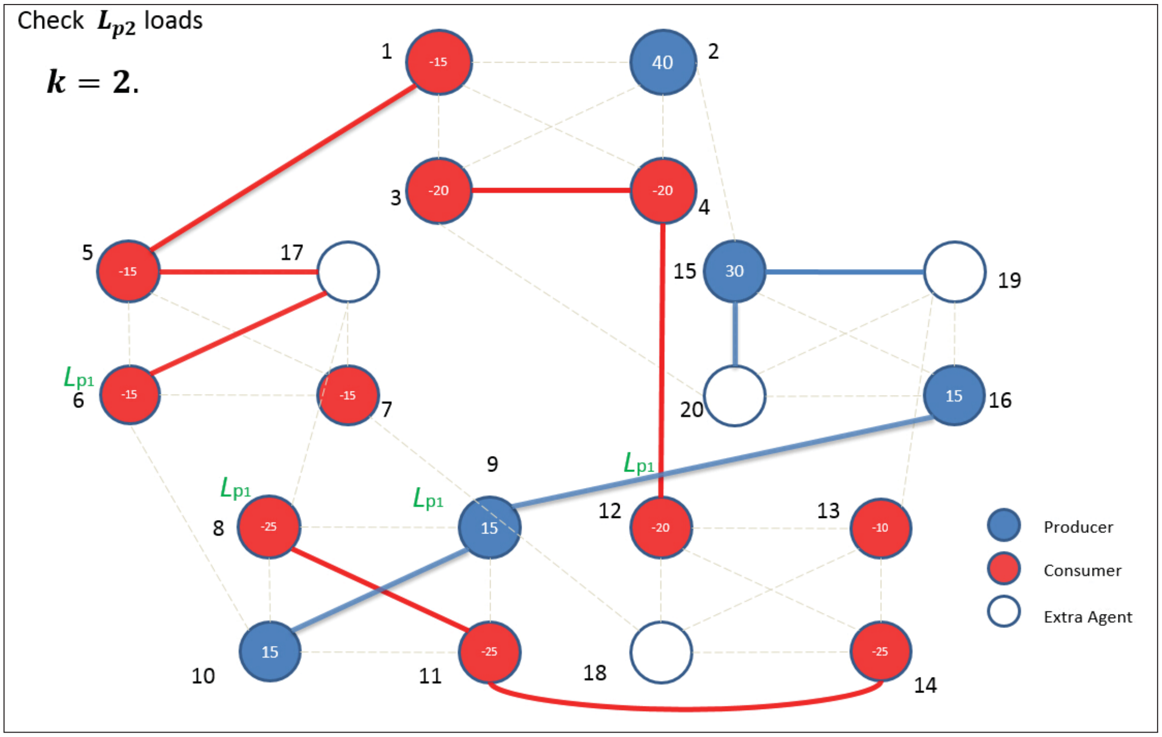
where p_i^{k+1} and p_j^{k+1} are the net power of agents i and j at the $(k+1)$th iteration. They are identical at the $(k+1)$th iteration and both equal to the exchange of the net power state from the last iteration. The right hand side of the equation shows that the current agent always adds the net power of an agent that maximizes its net power if it currently lacks power; otherwise it adds the net power of an agent that minimizes its net power if it currently has sufficient power. This equation defines the communication process of this centralized control algorithm. The goal is to make the final net power converge to zero.



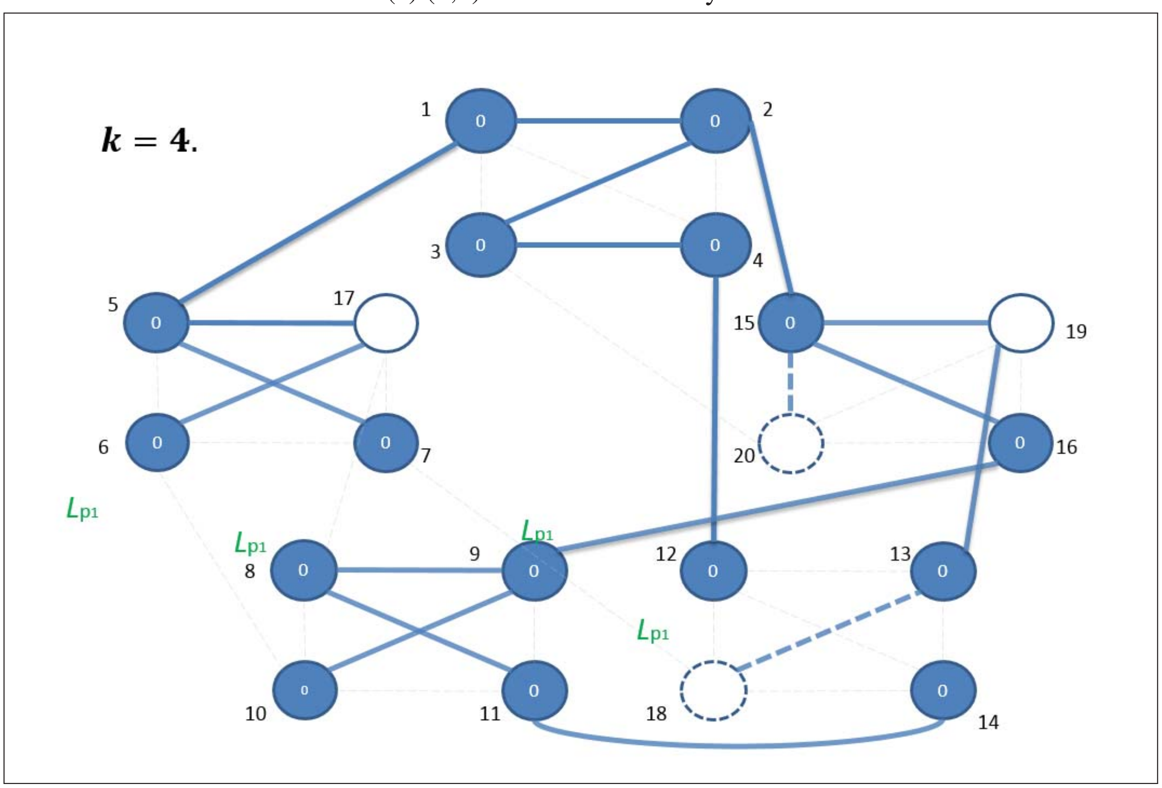
(a) (5,2)-star route discovery initial state



(b) (5,2)-star route discovery k=1



(c) (5,2)-star route discovery k=2



(d) (5,2)-star route discovery final state

Figure 2.7: The route discovery algorithm running on (5,2)-star power distribution system, where k is the number of iterations

This approach is based on BDI MAS. To illustrate it we show the (5,2)-star power topology study case as an example. The step-by-step status for each agent per iteration is shown in Figure 2.7. The status at iteration equals 1, as shown in Figure 2.7a, is the initial stage of the system. The dashed lines represent the physical connections between agents. In the Figure, the red colored circles denote the role of an agent. Producers are in blue and consumers are in red. The number in the circles indicate the initial net power at a certain iteration, p_i^k. At the stage when iteration equals to 1 (notified by k), as shown in Figure 2.7b, consumers with a higher priority start to trade power with the adjacent producers at first. It can be observed that even agent 6 is a consumer with the highest priority L_{p1}. Agent 6 makes no action since there is no producer connected directly. It is the same situation for L_{p1} consumer agent 12. Therefore, only agent 8 and agent 9 can make trades with their neighbors respectively. The decisions are made from the algorithm equation (2.5). Agent 8 is supplied by agent 11 and agent 9 is supplied by agent 16 because agents 11 and 16 are the suitable generator agents that maximize the net power. After trading with agent 11 and 16, both agents changed their role to producers because the summation turned out to be both positive. At the end of this stage two branches are established. At the stage when iteration equals 2, consumers with a lower priority start to trade power with the adjacent producers. The equation of the algorithm in equation (2.5) is performed again. At the end of the stage when the iteration equals 2, there are four branches established in total. Two of them are balanced while the other two are not, as shown in Figure 2.7c. By repeating the processes at iteration equals 1 and 2 on the new status of agents, eventually the BDI MAS will reach stage at iteration equals 4, the final stage. Finally the common net power reaches 0 for all the agents, and the system is branched into a whole interconnected system.

All the experiments extended from this example is actually following the process described above, with randomly locating the agents inside a certain (n, k)-star power distribution system. The other two IEEE standard multi-bus systems are also configured to be represented by related (n, k)-star power topology as well. Certain repeated experiments are done respectively as the locations of the agents are randomly assigned. At the end, the iteration number at convergence is recorded for each (n, k)-star power distribution system to calculate the communication cost metric.

The performance of this algorithm will be discussed in Chapter 5 when the simulation results are provided. Nonetheless, although this algorithm is an optimized one derived from a consensus algorithm, it loses its decentralized property when introducing the priority settings. The information of agent priority has to be broadcasted to every agent in case they can behave based on a certain priority order. This information is also necessary to be updated in real time to avoid the disorder of power exchange. Thus, the control of the system became centralized since there must be an overall controller to inform the priority information. That means the agent cannot be independent. This is considered the main issue of this method and the reason to develop the decentralized consensus control algorithm in this dissertation, which will be described in the following chapter.

2.4.3 Power Restoration Algorithm

The communication system on top of a physical system is powered by the generators in the physical system. Therefore, a power shortage on the physical system will result in the communication agent shut down in the communication network. However, the communication link shortage would not affect the power flow on the physical power systems.In this dissertation, we define the power restoration for a communication system as the communication channel reconfiguration due to the faults on agents that are connecting to a physical generator.

After the system is in the balanced mode and all the power agents are supplied, the

Algorithm 1 Algorithm for 0/1 Knapsack power restoration problem

Input: Topology, Initial net power, Current status, Faulty agent
Output: Shutdown agent(s)
  Detect the single power fault
  LOOP Process
  while $(p_{S_r} + p_{A^0_{w_3}} \leq 0)||w_3 == \phi$ **do**
    $w_1 = \arg_{i j \in N_i} A_i \in V_r$
    $w_2 = \arg_{j \in w1} \max_{A_j \in b_r} \text{priority}(A_j)$
    $w_3 = \arg_{j \in w_2} \min_{A_j \in b_r} (p^0_{A_j})$
    $V_r = S_r + A_{w_1}$
    $S_r = S_r \cup A_{w_3}$
  end while
  $b_r = b_r \backslash \{A_{w_3}\}$
  return w_3

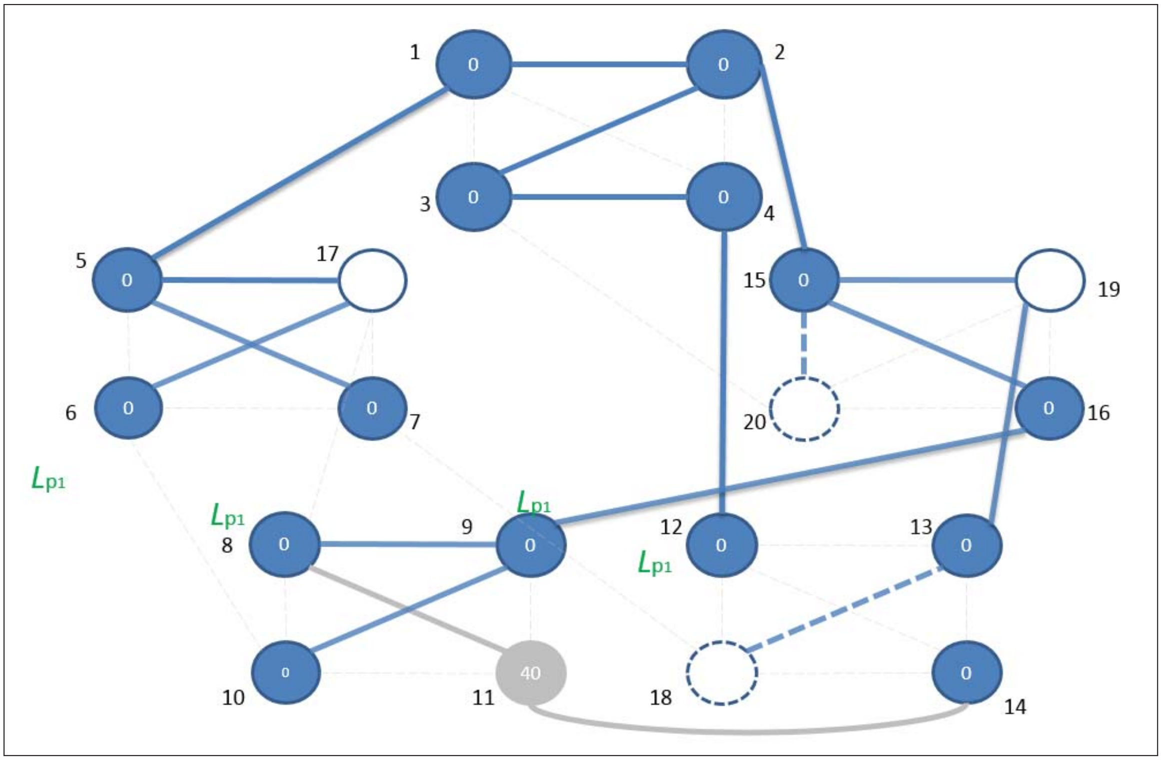
system is monitored by a centralized power restoration algorithm. This algorithm deals with the failure of an agent if a fault occurs. The algorithm's objective is to maintain the balancing state of the system when fault occurs. It re-iterates through the agents and shuts down the consumer agents if it cannot be supplied; or branches the system into several sub branches in order to maximize the number of supplied load agents. This algorithm is based on a 0/1 Knapsack Problem which is one of the optimal algorithms for resource allocation. The algorithm is described in algorithm 1.

In Algorithm 1, w_1 is initialized as the faulty node. S_r is the adjacent neighbors of that node. w_1 is the shutdown node set. Within the while loop, if the initial net power of the current shutdown nodes can not fulfill its neighbors or the shutdown set is empty, the agent loops over its neighbors. In the same loop it looks for the consumer agents from lowest priority to highest for the minimum initial net power. The loop stops once the summation of the net power for visited set S_r is positive. This final state will have all the agents that can not be supplied shut down. Meanwhile the other agents will be fully supplied. This system may break into multiple branches depending on the resilience of the system and number of faulty agents. This algorithm ensures that the lowest priority load agent with the highest initial demand will be shut down to make sure the system balance is maintained.

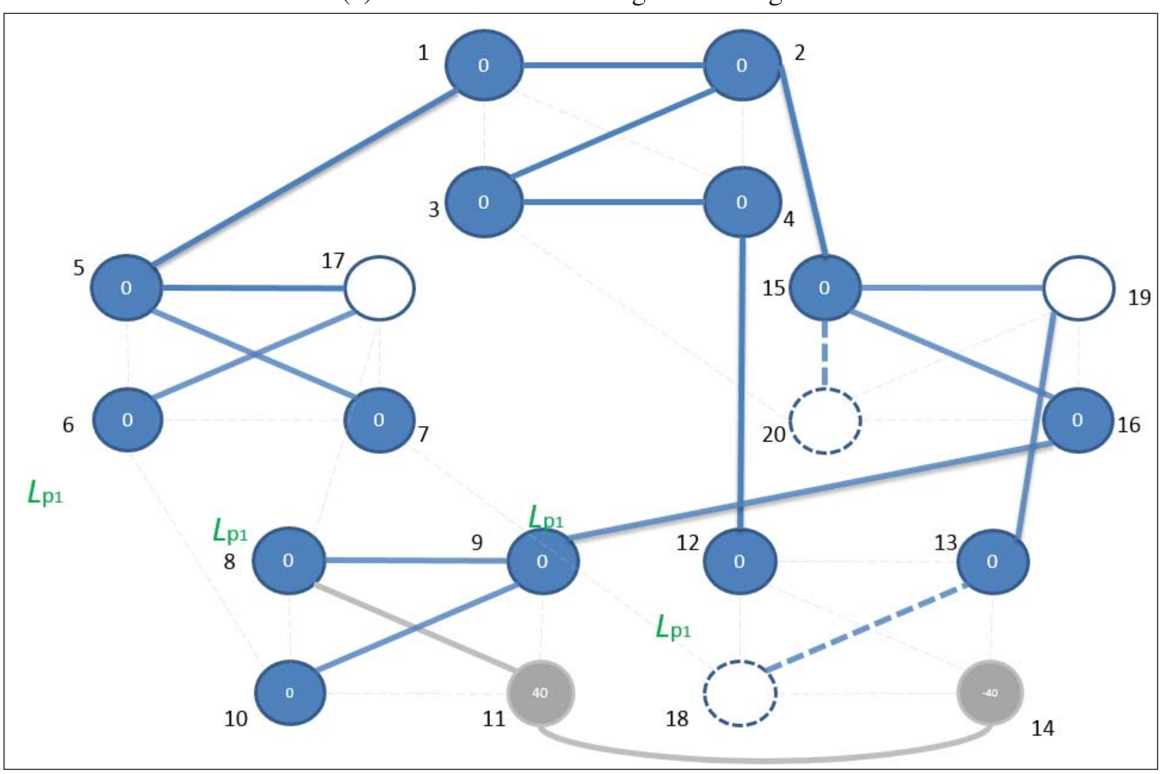
Assuming that the producer agent 11 suddenly goes in faulty state and loses the supplied power totally. The post-fault system is illustrated in Figure 2.8a, which is also treated as the initial state of the power restoration process. Producer agent 11, shown in grey, is in a fault state. From Table 2.3, we can see that G11 has the net power 40. After the fault occurs, agent 11 is not able to supply any power to the system. Therefore, the consumers need to find another producer as supplier. The algorithm for power restoration is executed and checked every agent in the branch for a suitable consumer agent that meets the Algorithm 1. At the end, agent 14 is recognized as the lowest priority load that can maximize the summation to the initial net power of faulty agent.

2.5 Limitations

Both the load balancing and power restoration algorithms are dynamic but still have their limitations. Both algorithms have to share the status of each agent at the end of each iteration, and the status of the higher priority agents needs to be broadcasted to the ones with lower priority. Thus, a centralized communication scheme to notify each agent is necessary, which results in the centralized manner for the algorithms. Centralized algorithms are always fast in reaction but is not optimal for large-scale control tasks. It will increase the communication costs therefore is not practical. Moreover, since the power restoration algorithm may branch the system into several sub-systems, the global optimal solution is not guaranteed in centralized algorithm designs.



(a) Power Restoration Algorithm Stage 1



(b) Power Restoration Algorithm Stage 2

Figure 2.8: The process for power restoration algorithm when agent 11 had a fault and shutdown nodes are agent 11 and 14

2.6 Summary

The proposed (n, k)-star power topology is a novel approach to solve load balancing and power restoration problems in MAS based power distribution systems. It brings all the metrics existing in communication network technology into power engineering. These metrics help evaluate power distribution systems and their control algorithms. The centralized algorithms for multi-bus power distribution systems meet the original objectives of load balancing and power restoration. However, a decentralized control method is in need to be designed to ensure the global optimal solution and reduce the communication costs. The following chapter will present this algorithm with its stability analysis.

CHAPTER 3

DECENTRALIZED CONSENSUS CONTROL

The proposed centralized control algorithm has its disadvantages when concerning the balancing speed. The broadcast status of each agent helped the system to know a better scope of the whole power system but it resulted in slow convergence time for load balancing process. Thus, the centralized control strategy does not fully utilize the advantages from MAS based approach. It adds communication cost so that the agents are not independently making decisions as they are designed to be. However, decentralized algorithms can control the agents in a distributed manner. Each agent can communicate with its neighbors with consistent information exchange. With less redundant communication cost, decentralized algorithms enable fast load balancing and consistence of each agent's status.

In this chapter, the decentralized consensus control algorithm is presented. It is developed to address the above issues of centralized algorithms. The stability of this algorithm is analyzed so that under certain conditions the balancing status is always reached. The condition is depending on the gain of the controller for each agent. Moreover, the algorithm is in decentralized continuous-time manner. The general power agent model and related Graph Theory are introduced as well to support the investigation of the algorithm.

3.1 Graph Theory

Necessary notations are briefly introduced in this section before introducing the algorithm. If the interaction topology of a networked power grid is represented using a directed graph $G = (V,E)$ with the set of nodes $V = 1,2,\dots,n$ and edges $E \in V \times V$, and the neighbors of an agent i are denoted by $N_i = \{j \in V : (i,j) \in E\}$, the graph Laplacian of the topology can be defined as follows:

$$L = [l_{ij}] \text{ where } l_{ij} = \begin{cases} -1, & j \in N_i \\ |N_i|, & j = i. \end{cases}$$

Here, $|N_i|$ denotes the number of neighbors of node i (or the degree of node i).

According to Gershgorin Theorem [16], the eigenvalues for the graph Laplacian of an undirected (n, k)-star graph are upper bounded by the Laplacian Spectrum $\lambda^* = 2deg(S_{n,k})$ where deg is the degree of the certain topology. The following two definitions are derived from the research in [29, 36] that prove the stability and the consensus property of a graph topology with its graph Laplacian.

Definition 3 *A local controller stabilizes the formation dynamics in a dynamic system topology if and only if it simultaneously stabilizes the set of N systems*

$$\begin{aligned} \dot{x}_i &= P_A x_i + P_B u_i, \\ y_i &= P_{C_1} x_i, \\ z_i &= \lambda_i P_{C_2} x_i \end{aligned} \tag{3.1}$$

where λ_i are the eigenvalues of graph Laplacian L.

Definition 4 *If the eigenvalues of a specific system* $L_{22} + \boldsymbol{1}_{N-1} \cdot \alpha^T$ *are* $\lambda_2, \ldots, \lambda_N$*. Thus, there exists an invertible matrix* T *such that* $L_{22} + \boldsymbol{1}_{N-1} \cdot \alpha^T$ *is similar to a Jordan canonical matrix*

$$T^{-1}(L_{22} + \boldsymbol{1}_{N-1} \cdot \alpha^T)T = J = diag(J_1, \ldots, J_s) \tag{3.2}$$

where J_k *are upper triangular Jordan blocks, whose principal diagonal elements consist of* λ_i*. Therefore,* T *is an upper triangular block matrix, which together with the properties of Kronecker product, implies that the eigenvalues of* $L_{22} + \boldsymbol{1}_{N-1} \cdot \alpha^T$ *are in the open left half plane.*

The two definitions above are applied later to prove the consensus and stability of the proposed model. The Kronecker product of matrices $A \in R^{m \times n}$ and $B \in R^{p \times q}$ is defined as

$$A \otimes B = \begin{bmatrix} a_{11}B & \ldots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \ldots & a_{mn}B \end{bmatrix}$$

which satisfies the following properties:

$$(A \otimes B)(C \otimes D) = (AC) \otimes (BD)$$

$$(A \otimes B)^T = A^T \otimes B^T$$

$$A \otimes B + A \otimes C = A \otimes (B + C)$$

3.2 Definition of Consensus

This dissertation investigates consensus of linear systems using a leader-follower concept. In the leader-follower consensus system, any arbitrary subsystem can take the role of a leader, and the other subsystems are expected to follow the leader. First, we introduce the basic notion of consensus for distributed systems: a) *Mean Square Consensus*; b) *Weak Mean Square Consensus*; and c) *Collective Weak Mean Square Consensus*. Three equations are shown as follows:

1. *Mean Square Consensus* definition for a MAS distribution system is:

$$\lim_{t\to\infty} E\{\|x_i(t) - x_j(t)\|\}^2 = 0, \text{ for any } i \neq j \tag{3.3}$$

2. *Weak Mean Square Consensus* definition for a MAS distribution system is:

$$\lim_{t\to\infty} E\{\|x_i(t) - x_j(t)\|\}^2 = \varepsilon, \text{ for any } i \neq j \tag{3.4}$$

   where $\varepsilon > 0$ is small.

3. *Collective Weak Mean Square Consensus* definition for a MAS distribution system is:

$$\lim_{t\to\infty} E\{\sum_{i=1}^{N} \|x_i(t) - x_j(t)\|\}^2 = \varepsilon, \text{ for any } j \tag{3.5}$$

   where $\varepsilon > 0$ is small.

The mean square consensus means that the subsystem trajectory will track that of the leader with zero mean square error, whereas weak mean square consensus implies that the subsystem state will be only within ε-neighborhood of that of the leader. Since the system evolves in a continuous-time manner, it is not expected that the state error will converge to zero. Rather the best one can hope for is that the state error between the subsystems will remain within a small bound, which is defined as error tolerance, denoted as ε. Collective mean square consensus is weaker than mean square consensus since it defines consensus of the subsystems as a group rather than for each individual subsystem. In this dissertation it is presented the stability analysis based on week mean square consensus.

3.3 Power Agent Model

The nodes in the standard multi-bus systems have been previously represented by the power agents. They are specified as producer and consumer agents [19]. Since the the above investigations of this dissertation focused on the properties of the topology, the power agents were designed to be stationary. Therefore, generator (producer) agents can supply the load (consumer) agents discontinuously from iteration to iteration. Their status cannot change based upon the status of the neighboring load agents. Thus the control process cannot happen in continuous-time. This is considered the main issue from the previous proposed centralized approach. When considering the real-time control algorithm and its applicability on physical power systems, we need to improve the design of the agents. In order to make reactive changes upon the status of power flow, a novel power agent model is proposed. It is derived from *Automatic Generation Controller* (AGV) from the real-time power system. This agent model can be universally applied to all the components in power distribution systems, even for smart grid components like RGs, ESSs, SGs as well as loads. Figure 3.1 shows the components in an IEEE 5 bus system. Each component in that system can be represented by and implemented as one power agent model.

In Figure 3.2 the supplementary controller is the core module of this power agent model. It has the *Agent Control Error* (ACE) as the input, which is the sum of the feedback

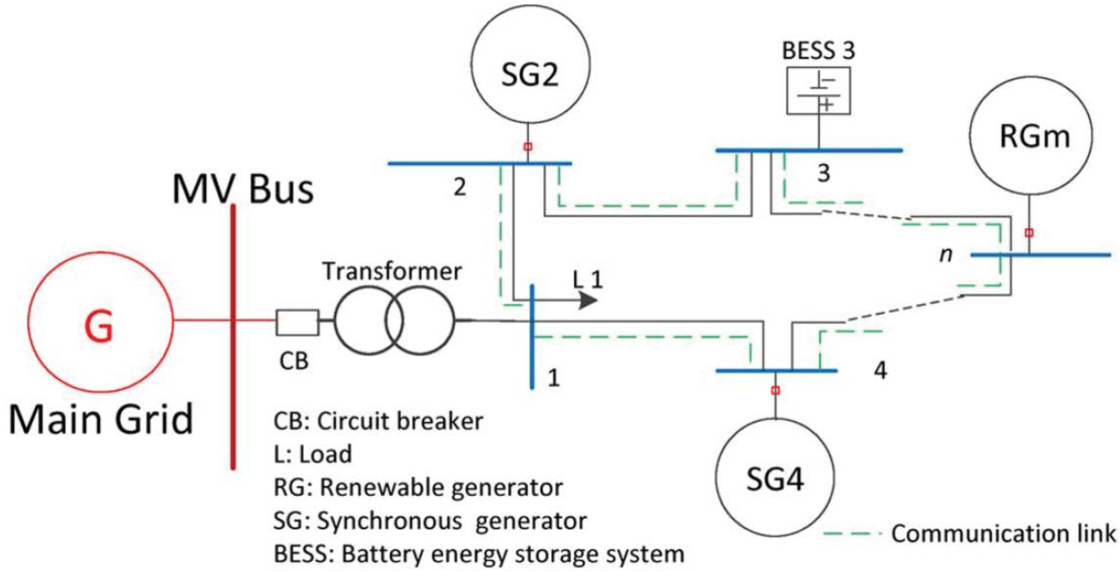


Figure 3.1: IEEE 5 Bus Power Distribution Topology

frequency deviation multiplied by a frequency-bias factor B, and the power flow deviation from the neighboring agents. The ACE can be formulated as:

$$ACE = \Delta P_{load} + B\Delta f \tag{3.6}$$

Therefore, each power agent that participates in the power distribution system has a supplementary controller that receives the ACE as the input, shown in Figure 3.2. The controller outputs regulation feedbacks and leads the reactions of the generator and load. Depending on the output, either the generator turbine will change its steam valve position or the load change the power it consumes. Specifically, the module $\frac{1}{R}$ in the figure causes the reaction. It is a regulator with R as the Speed Regulation, which has a positive value:

$$R = -\frac{\Delta f}{\Delta P_{load}} \tag{3.7}$$

where both R and f are percentage values. This means the slope of the load-frequency

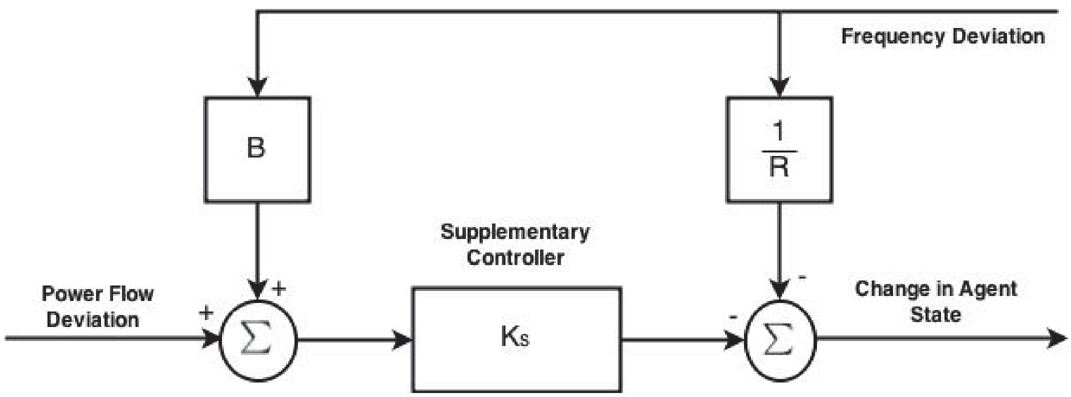


Figure 3.2: Real-time Power Flow Generator Agent Model with Automatic Generation Control

control characteristic is $(-R)$. For example, regulation R equal to 3% implies that a 0.1 per unit change in the electrical neighbor loads corresponds to 0.3% change in the base frequency. Thus, the output of this model, as shown in Figure 3.2, is connected to the turbine, which performs the steam valve adjustment at the turbine. The output voltage of the generator agent will be changed accordingly. The supplementary controller here in the model can be any Proportional-Integral-Derivative (PID) controller widely used in industrial control systems. In this dissertation, we pick the simplest gain controller K_s as the supplementary controller.

In order to make this supplementary controller act in continuous-time, and be universal to all the components in power distribution systems, a definition of agent dynamic should be given as:

$$x_i = sgn(P_i)|P_i| \text{ where} \tag{3.8}$$

$$sgn(P_i) = \begin{cases} -1, & i \in R \text{ and } R \text{ is load agent set} \\ 1, & i \in S \text{ and } S \text{ is generator agent set} \\ 0, & \text{otherwise.} \end{cases}$$

Then the power flow deviation in supplementary controller can be defined from the above definition:

$$x_i - x_j = \begin{cases} -(|P_i| + |P_j|), & \text{if } i, j \in R \\ |P_i| + |P_j|, & \text{if } i, j \in S \\ |P_i| - |P_j|, & \text{if } i \in S \text{ and } j \in R \\ |P_j| - |P_i|, & \text{if } i \in R \text{ and } j \in S \end{cases}$$

where the $x_i - x_j$ is the state error between agents and in the dynamics of agents in the next section.

In this way the power agent model is finally applicable to represent and control for all the types of agents in the power distribution system. To express this controller in practical terms, upper and lower limits are assigned to the agents so that both generator (producer) and load (consumer) agents can dynamically control their states based on the demand. The power flow deviation is controlled within these boundaries. Thus, the notion $P_i^m in$ and $P_i^m ax$ are defined as the lower and upper limits to power agent and are assigned their own dynamics $P_i^m in(t)$ and $P_i^m ax(t)$ as the demand changes during time. Practically, the upper limit for a generator agent is the maximum power it can generate; the lower limit for a load agent is the least amount of power it may consume. The output of this supplementary controller controls the power flow to be dynamically changing within these two boundaries. This controller is the core part for the power agent modeling in continuous-time using common dynamics. This power agent model is reactive to power shortages from the neighboring agents in continuous time. The reactive and active power of the power agent is adjusted due to the output of the model. The main merit of this model is that it brings independent dynamic control to each generator agent. The whole system can be controlled independently in a continuous-time manner. This matches the concept of MAS control and consensus communication. It is considered as a sufficient condition for the centralized or decentralized power distribution systems to be stable and consensus.

3.4 Consensus Control Stability Analysis

This section presents the decentralized consensus control algorithm and its stability analysis. According to Definition 3 [29, 36], an arbitrary power agent can be selected as a leader. Then, the whole system is considered a leader-follower consensus problem by assigning the selected power agent as the leader node in the networked subsystem. We assume the randomly selected leader node is x_1, then the set of $N-1$ power agents is considered the follower set. The state error (disagreement) between neighboring power agent i and the leader agent is:

$$\hat{x}_i = x_i - x_1, \text{for } 2 \leq i \leq N, i \in \mathbb{Z} \tag{3.9}$$

Given the dynamics of a the proposed power agent model, the system can be represented as:

$$\begin{aligned} \dot{x}_i &= P_A x_i + P_B u_i, \\ y_i &= P_C x_i, \\ u_i &= K \sum_{j=1}^{N} a_{ij}(y_j - y_i) \end{aligned} \tag{3.10}$$

where $x_i \in R^n$ is the state vector, $u_i \in R^m$ is the control input, $\dot{x}_i$ is the first order derivative of input state, and $y_i \in R^r$ is the measured output. The system matrices P_A and P_B are the control matrices derived from the supplementary controller in the power agent model. When subjecting the dynamic equation (3.9) into (3.10), it can be derived that:

$$\begin{aligned} \dot{x}_1 &= P_A x_1 + P_B K P_C \sum_{j=1}^{N} a_{1j}\hat{x}_j \\ \dot{\hat{x}}_i &= P_A \hat{x}_i + P_B K P_C \sum_{j=1}^{N} a_{ij}(\hat{x}_j - \hat{x}_i) - P_B K P_C \sum_{j=1}^{N} a_{1j}\hat{x}_j \end{aligned} \tag{3.11}$$

Then from of the disagreement definition in equation (3.9), it can be stated that all the disagreement equations for each load agent into a vector $\hat{x}$:

$$\hat{x} = [\hat{x}_2\ \hat{x}_3\ \dots\ \hat{x}_N]^T \tag{3.12}$$

Then, every element in equation (3.12) is replaced with equation (3.11) so that the leader-follower system (3.10) can be described as:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{\hat{x}} \end{bmatrix} = \begin{bmatrix} P_A & -L_{12} \otimes P_B K P_C \\ 0_{N-1} & (I_{N-1} \otimes P_A) - (L_{22} - 1_{N-1} L_{12} \otimes P_B K P_C) \end{bmatrix} \begin{bmatrix} x_1 \\ \hat{x} \end{bmatrix} \tag{3.13}$$

Next, the disagreement dynamic can be expressed by a first order differential equation:

$$d\hat{x} = \hat{P}_A \hat{x} dt \tag{3.14}$$

where, $\hat{P}_A$ is $(I_{N-1} \otimes P_A) - (L_{22} - 1_{N-1} L_{12} \otimes P_B K P_C)$.

It has been provided in Definition 4 [29] that the MAS maintains a weak mean square consensus if there exists a gain matrix K so that $\hat{P}_A$ is a negative definite matrix. Following this definition a transformation matrix $T \otimes I_n$ can be selected that satisfies:

$$\begin{aligned}&(T \otimes I_n)^{-1}[(I_{N-1} \otimes P_A) - (L_{22} - 1_{N-1}L_{12} \otimes P_B K P_C](T \otimes I_n)\\&= I_{N-1} \otimes P_A - J \otimes P_B K P_C\end{aligned} \tag{3.15}$$

This is an upper triangular matrix with the eigenvalues $P_A - \lambda_i P_B K P_C$, where $i = 2, 3, \dots, N$ and all the λ are the eigenvalues of L_{22}. Thus, the gain controller can be chosen from $\hat{K} = \lambda^* K$, which gives the gain $K = \frac{\hat{K}}{\lambda^*}$. Here λ^* is defined by Gershgorin Theorem [16] so that all the eigenvalues are bounded in λ^*. This K guarantees the stability of the system $A - \lambda_i P_B K P_C$ which is equivalent to the system $(I_{N-1} \otimes A) - (L_{22} - 1_{N-1}L_{12} \otimes P_B K P_C)$ and is convergent and asymptotically stable.

3.5 Example

In order to address the stability of an (n, k)-star power topology with the consensus algorithm, (5,2)-star power topology system is shown as an example. There are 20 nodes in this topology so that 20 power agents can be represented. This topology is then designed with a specific number of generator agents and load agents according to the standard 16-bus system settings. In this (5,2)-star system, there are 4 phantom agents. The modeling of phantom nodes inherits from the preliminary work [19]. Figure 3.3 shows the graph Laplacian of the (5,2)-star topology. The eigenvalues are then calculated as $\lambda = \{0,1,1,1,1,4,4,4,4,4,5,5,5,5,6,6,6,6,6,6\}$ and the upper bound of the spectrum of the graph Laplacian is calculated as $\lambda^* = 8$. To make it a simple case, P_A and P_B are selected

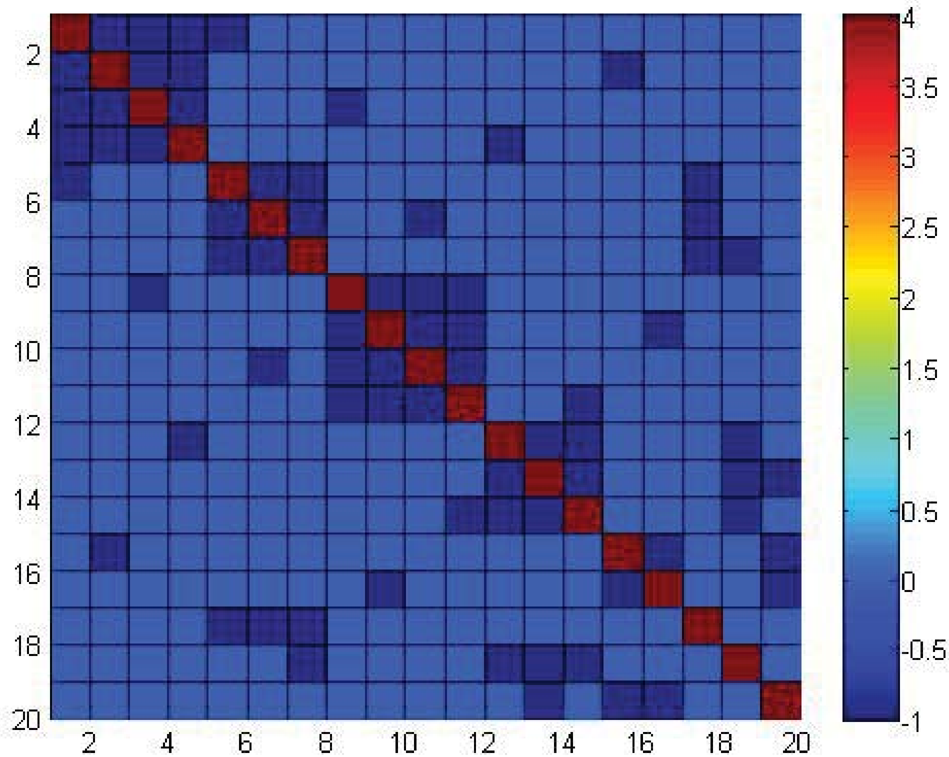


Figure 3.3: $(5,2)$-star topology graph Laplacian. The values -1, 0 and 4 are represented by dark blue, blue and red blocks.

from a simple supplementary controller as

$$P_A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, P_B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, P_C = [0,1]$$

Thus, for the gain, when $0 < K < 4$ the matrix of $P_A - \lambda_i P_B K P_C$ will be negative definite. Then the gain value is picked as $K = 1$ so that the system is consensus and stable according to the analysis in the above section. That means the (5,2)-star power grid topology can always have a converging consensus solution if the gain controller K is 1.

3.6 Summary

It is important to introduce the decentralized consensus control method to the study of an MAS based load balancing problem. The goal is to ensure how quickly information discovery can converge to the true state value of the system. Without a consensus algorithm, divergence of observed state and true state can be drastically different. As a consequence, the failure of distributed system became non-invertible. The analysis of stability proves the possibility of a solution to the system. All of the investigations in this chapter can be considered as the analyzing process for the power topology design before physical implementation, which is one of the main contributions in this dissertation.

CHAPTER 4

RESILIENCE ASSESSMENT USING IRT

The investigations in this dissertation on power restoration enable the ability of fault-tolerance. By implementing the proposed algorithms, power systems can be reconfigured after a system failure. As a result, the systems are fault-tolerant. However, among all the different system topologies, it is difficult to determine which system is more fault-tolerant. There are not enough metrics that can help evaluate the system fault-tolerance. Moreover, other than the system fault-tolerance, there are more properties that are related to stability but are difficult to be measured, such as reliability, security, etc. Thus, we define resilience as an intrinsic property that can represent stability related properties for a system. It is an intrinsic property that can be specified in multiple domains. Therefore, to evaluate resilience of a system in a domain will enable the possibility to compare different systems or topologies. Then, researchers can determine which system is better in a domain before physical construction and benchmarks.

IRT is a psychometric theory and family of associated mathematical models that relate latent trait (observable manifestations of hypothesized properties, constructs, or attributes) of interest to the probability of responses to items on the assessment [12]. In order to utilize this IRT assessment methodology, the system must meet the following assumptions:

1. *Unidimensionality*: states that the test measures only one construct, which is resilience in this case;

2. *Local Independence*: assumes that item responses are independent given a subject's

latent trait value;

3. *Nature of ICC*: for dichotomously scored test items, logistic functions are used to model the probability of success

This chapter presents a novel statistical approach to determine the resilience of a reconfigurable engineering system, especially for (n, k)-star power distribution systems. In addition to known probabilistic methods of estimating resilience in terms of system redundancy and reliability, IRT is applied to assess the resilience. IRT methodology is based on the measurements and observations of the system to determine the overall score of the resilience in a certain domain. The observation of whether the system will fail is collected through different diagnostic processes as the input data of the method. Then the resilience of the system is estimated through three processes: a) *Item Characteristic Curve* (ICC) modeling, b) parameter calibration and c) resilience estimation. The main results on a simulated microgrid power system are presented as well. However, the concept easily extends to other resilient engineering systems such as smart grids, fluid flow systems, communication networks and onchip networks. Experiments demonstrated that the rating scale can differentiate the resilience on different domains and can be a good evaluation method to extend the practical uses of IRT to the engineering field.

To better present the methodology of this IRT based approach, the IEEE 5-bus power grid (illustrated in the previous chapter) is introduced as an example. This section is to introduce the three main procedures of proposed assessment approach based on the example of IEEE 5-bus power grid. These three procedures are ICC modeling, parameter calibration and resilience estimation. These procedures are derived from traditional IRT and are slightly modified to evaluate power distribution systems. This section makes it clear that this approach can be easily extended to large scale power distribution systems as well as other reconfigurable resilient engineering systems.

4.1 Physical Resilience Model on Power Grids

The IEEE standard multi-bus systems are widely used as test cases for smart grids. They have been investigated to explore the fault-tolerance in power restoration [18, 19, 51]. The 5-bus system has a load, a renewable generator, two synchronous generators and a battery energy storage system as is shown in Figure 3.2. All these components are interconnected following the topology of the 5-bus power system. It is set up that each component has a probability to be failure. If there is a failure in one of the components, the system is able to reconfigure to reach a stable state. Here the stable state for a power system is that the load remains being supplied by the generators or power storage modules. The power system is considered to be nonfunctional if the load cannot be fully supplied by the other components. In order to assess the system, we assume that the system can be diagnosed by different diagnostic tests. These tests are usually conducted before the system evaluation to observe whether the system is functioning. Therefore, the parameter calibration and resilience estimation are taking the data from diagnostic tests as inputs. Moreover, the resilience of a power system can be defined as the ability of a power system to maintain and adapt its power supply strategy in the face of failure conditions on its components. This definition is the foundation of IRT resilience assessment. In this dissertation, the system resilience is the intrinsic property that is to be assessed.

4.2 Methodology

Since resilience of power systems is defined, this section introduces the IRT based assessment approach. The approach is described in three procedures as follows.

4.2.1 ICC Modeling

The Item Characteristic Curve is the model that can represent the item response function. It is initially designed in IRT to relate the probability that the person answers a question correctly to the person's actual level of knowledge. In our proposed methodology the same characteristic curve model is constructed. We utilize this model to reflect the relationship between the probability of system functioning and the system resilience. The item in this proposed method is each of the diagnostic tests. More specifically, these diagnostic tests are carefully designed to address different physical threats to a power system. These threats may cause a physical damage to a specific component which may cause the system failure. Examples of the tests are system behavior tests on different levels of wind strength, different geographical locations, and different environment conditions. In traditional ICC for IRT, there are different models depending on the number of parameters. There are two-parameter logistic (2PL) model, three-parameter logistic (3PL) model and four-parameter logistic (4PL) model. The 2PL model is selected as an example to describe the approach. Then, the ICC to represent the probability of system functioning on system resilience is:

$$P_i(\theta) = \frac{1}{1 + e^{-a_i(\theta - b_i)}} \tag{4.1}$$

where θ is the quantified resilience of the system, and is the one intrinsic property to be assessed; i is in the range from 1 to N representing the index of the diagnosis test; p_i is the probability that the system is functioning, based on the resilience, and is 1 when it has highest probability of a functional system; a_i and b_i are constant parameters for this ICC model. a_i is defined as the differentiability of the diagnostic test, which means the higher a_i is, the easier for this test scenario to differentiate resilience levels. b_i is defined as the degree of the damage for a certain diagnostic test, which means the higher degree of damage, the lower the probability of keeping the system functioning. These two parameters are derived from the original *Item Response Function* (IRF) where a_i is the level of discrimination and b_i is the difficulty of an item. As is shown in Figure 4.1.(a), different values for a give different slopes on certain θ value. For a specific θ value range, *e.g.,* from -1 to 1, the slope of the blue curve is always greater. This means the blue curve, with the highest differentiability $a = 2$, is the most capable to differentiate the resilience level of a system. Meanwhile, as is shown in Figure 4.1.(b), the differences between degrees of damage reflect the how bad the damage is for a certain test. The higher the degree of damage is, the lower probability there will be for system maintaining its status. The second procedure, which is the parameter calibration procedure, describes how these two parameters are calibrated based on a series of diagnostic tests.

4.2.2 Parameter Calibration

The calibration of the parameters of a 2PL model of an ICC is based on the diagnostic tests of systems in which resilience levels are known. The responses of the tests are defined as:

$$U_i \ni u_{ij} = \begin{cases} 1, & \text{system remains functioning} \\ 0, & \text{system goes to failure} \end{cases} \tag{4.2}$$

where $j \in N$ is the index number of the systems, and $i \in n$ is the index number of the items. Thus, the conditional probability given the known resilience θ can be represented as:

$$P(U|\theta_j) = \begin{cases} P(\theta_j), & \text{if } u_j = 1 \\ 1 - P(\theta_j) = Q(\theta_j), & \text{if } u_j = 0 \end{cases} \tag{4.3}$$

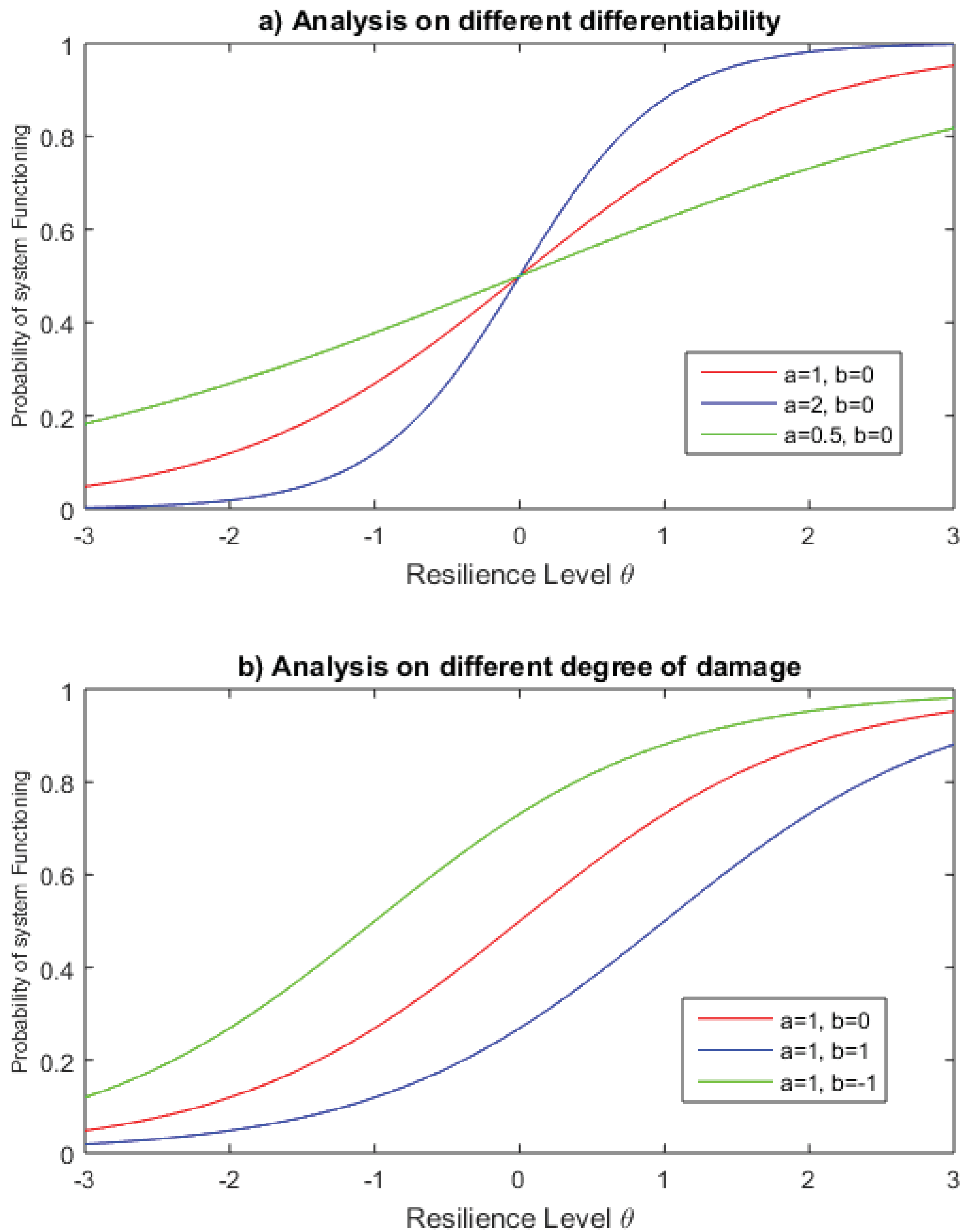


Figure 4.1: Item Response Function represents ICC and analysis on different differentiability and degree of damage

So equation (4.3) can be simplified as:

$$P(U|\theta_j) = P_j^{u_j} Q_j^{1-u_j} \tag{4.4}$$

where P_j is $P(\theta_j)$ and Q_j is $Q(\theta_j)$.

The next step is to apply all the test scenarios to all the resilience-known systems, and then substitute the resilience level θ_j to find the combination of the conditional probability listed below:

$$\begin{aligned} & P(U_1, U_2, \ldots, U_N | \theta_1, \theta_2, \ldots, \theta_N) \\ =& P(U_1|\theta_1) P(U_2|\theta_2) \ldots P(U_N|\theta_N) \\ =& \prod_{j=1}^{N} P_j^{u_j} Q_j^{1-u_j} \end{aligned} \tag{4.5}$$

So the product of the conditional probabilities given the resilience level is listed in equation (4.5). The summation of each item in the product needs to be as large as possible so that a and b can be calibrated to the most likely test scenario [41]. Then a logarithm function is given to estimate the parameters:

$$\begin{aligned} L =& lnP(U_1, U_2, \ldots, U_N | \theta_1, \theta_2, \ldots, \theta_N) \\ =& \sum_{j=1}^{N} (lnP_j^{u_j} + lnQ_j^{1-u_j}) \\ =& \sum_{j=1}^{N} (u_j lnP_j + (1-u_j) lnQ_j) \end{aligned} \tag{4.6}$$

Finally, with substituting equation (4.1) and equation (4.2), the above equation becomes a function of parameters a and b. Then the selected value a and b that make the function L

maximum value are the calibrated parameters. Generally, the calibration process is to treat the resilience levels of pre-selected systems as inputs to calculate the parameters a and b. According to the IRT definition and equation (4.5), the systems with known resilience should be independent to each other to ensure accuracy. The more of these systems there are, the more accurate the calibrated parameters will be. This calibration process is called *Maximum Likelihood Estimation* (MLE) [1]. It is the original estimation method for both parameter calibration and ability estimation for IRT. There are plenty of other estimation methods such as *Joint Maximum Likelihood Estimation* and *Maximum-Likelihood-Like Estimation*, which are left as future work.

4.2.3 Resilience Estimation

The resilience estimation process with MLE is the opposite process of the parameter calibration procedure. It assumes that the parameters for each test scenario are already given by the calibration process. The test response function can be rewritten as:

$$U_j \ni u_{ij} = \begin{cases} 1, & \text{system remains functioning} \\ 0, & \text{system goes to failure} \end{cases} \tag{4.7}$$

where $i \in n$ is the index number of the tests and $j \in N$ is the index number of systems. Thus, for a certain system, the conditional probability given the known resilience θ can be represented similar to equation (4.4):

$$P(U|\theta) = P_i^{u_i} Q_i^{1-u_i} \tag{4.8}$$

Accordingly, the total conditional probability can be calculated as:

$$\begin{aligned}
&P(U_1, U_2, \ldots, U_n|\theta) \\
=&P(U_1|\theta)P(U_2|\theta)\ldots P(U_n|\theta) \\
=&\prod_{i=1}^{n} P_i^{u_i} Q_i^{1-u_i}
\end{aligned} \tag{4.9}$$

And this is under the assumption that all the test scenarios are locally independent to each other. Similar to the steps from the calibration process, the logarithm function is derived to form the likelihood equation:

$$\begin{aligned}
L =&lnP(U_1, U_2, \ldots, U_n|\theta) \\
=&\sum_{i=1}^{N}(lnP_i^{u_i} + lnQ_i^{1-u_i}) \\
=&\sum_{i=1}^{N}(u_i lnP_i + (1-u_i)lnQ_i)
\end{aligned} \tag{4.10}$$

Finally, the estimated resilience can be derived as the maximum value of the likelihood function equation (4.10). Then,

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} L \tag{4.11}$$

This is named as the continuous Maximum Likelihood estimation process for IRT. It meets the objective of estimating and quantifying the intrinsic property of the power system, which is the resilience. The estimation is only accurate when the number of test scenarios is large.

So far, there are three advantages for this IRT based approach that can be summarized:

1. It is suitable for any system assessment that is targeted to quantify an intrinsic concealed property;

2. The estimation of the target property can vary for different application domains, if

and only if it fulfills the assumptions;

3. It is easily applied to any engineering systems, no matter if they are small-scale or large-scale.

4.3 Application Extension

It has been concluded that this methodology is independent on different application domains. It means that the method can be extended to other applications or different domains of the same application. Thus, for the following section, simulation has been done using this assessment approach on the IEEE standard 5-bus system on different domains. This resulted in another practical use of the IRT based assessment method: to compare resilience of two areas of the same system in order to consider which maintenance plan is more urgent.

Since the resilience is defined as the ability of a system to spring back into shape in front of any threats, we can extend the application of this proposed IRT based methodology to assess the resilience of the power systems. With known resilience assessments that have been done in related research, we can construct items that are unidirectional to express system resilience; while ensuring the independence among each item. Thus we can construct calibrated parameters and estimate the resilience for power distribution systems. However, future works must be done before this methodology is ready to be applied, they are listed as follows:

1. resilience needs to be precisely defined and the items should be selected based on the definition;

2. IRT assumptions should meet or the items; and

3. calibration set should be sufficiently large to ensure correctness of calibrated

parameters.

4.4 Summary

In this chapter, a statistical method to assess the resilience of an engineering system was proposed. This chapter also described how this method was derived and modified from IRT. The methodology details for modeling on an example of a resilient power grid were also presented. The approach itself is a novel approach to statistically evaluate the resilience. And since resilience of an engineering system is always intrinsic and can be different on different domains, this IRT based approach has provided a way to quantify the resilience before physical implementation.

CHAPTER 5

SIMULATION RESULTS

The first set of experiments was the evaluation of (n, k)-star power topology using the proposed metrics. In this set of experiments, we constructed the (n, k)-star power topology and the standard bus systems. The proposed metrics were observed during this set of experiments and were shown statistically to evaluate the system and algorithm performance. The second set of experiments was designed in MATLAB/Simulink environment to simulate the proposed decentralized consensus control algorithm. (n, k)-star power topology was configured as the platform for this algorithm. The average iteration number was recorded and compared to the centralized algorithm in order to address the performance enhancement and convergence of the methodology.

Experimental results are presented in this chapter. The results include:

1. performance evaluation of (n, k)-star power topology;

2. validation results on metrics design of (n, k)-star power topology; and

3. the numeric proof of the stability analysis; and

Overall, these results demonstrate the efficiency and performance enhancement when migrating the (n, k)-star topology from interconnected network studies into power distribution systems. (n, k)-star power topology is proven to be a solution for the load balancing and power restoration problems. The effectiveness of the algorithms and methodologies are also demonstrated by analyzing the results.

5.1 Evaluation of (n, k)-star Power Topology

In order to evaluate the performance of the proposed (n, k)-star power topology, a simulation program was developed in MATLAB. Similar to the simulation studies in [43, 51], A set of power distributions, including (n, k)-star power topology systems and standard multi-bus power systems, was simulated. The results are compared to related studies in order to illustrate the advantages of the proposed topology model.

5.1.1 Load Balancing Experiments on Single Fault

First, a set of experiments was simulated on all of the three (n, k)-star power model representing the 16, 39 and 162 multi-bus power systems. This set of experiments was assumed with a single fault scenario. The experiments included two parts:

1. the first part is the load balancing process running on each system using the centralized control algorithm;

2. the second part is the power restoration process by introducing single fault to each system.

Each of the components in the system was selected as a faulty agent to perform one test scenario. Therefore, the experiment for the (5,2)-star system was performed 20 times, the one for the (7,2)-star system was performed 42 times and the one for the (7,3)-star system was performed 210 times. The number of repeated times equals to the number of agents. In each case, the phantom agents were randomly located in the system. Each experiment ran the proposed centralized load control algorithm until the load balancing goal was achieved: all the load agents' net power was fully supplied by the generator agents. Then the 0/1 Knapsack power restoration algorithm was performed until one or some agents shut down

Table 5.1: Load Balancing Average Communication Cost Compared to Estimated Limit

(n,k)-star Graph	Simulation Iterations	Estimated Cost Limit
$(5,2)$-star	4	7
$(7,2)$-star	3	9
$(7,3)$-star	4	11

to maintain the balance status for the system.

During the load balancing process, the number of iterations for each bus system was recorded as a measurement of the *Communication Cost*. Table 5.1 illustrates the average number of iterations, which reflects the communication cost of each system. In the table, it is addressed that the average number of iterations is always smaller than the estimated communication cost (the sum of *Diameter* and *Degree* of the related (n,k)-star power system). This demonstrates the proposed theorem that the Communication Cost limit is predictable once the (n, k)-star power architecture is constructed.

Figure 5.1, 5.2, 5.3 are the selected experimental scenarios showing the results graphically to better present the load balancing process. They respectively show the changes of net power for each agent over the number of iterations. It is observed that the average net power converges to zero for most of the nodes (different color indicates different agent numbers). It illustrates that all of the agents' goals have been fulfilled once the algorithm is finished. It is observed as well that some of the agents' net power is not zero at the end. This is because the objective function in equation (2.3), which shows that the net power is non-negative value. In other words, power generated is greater than power being consumed.

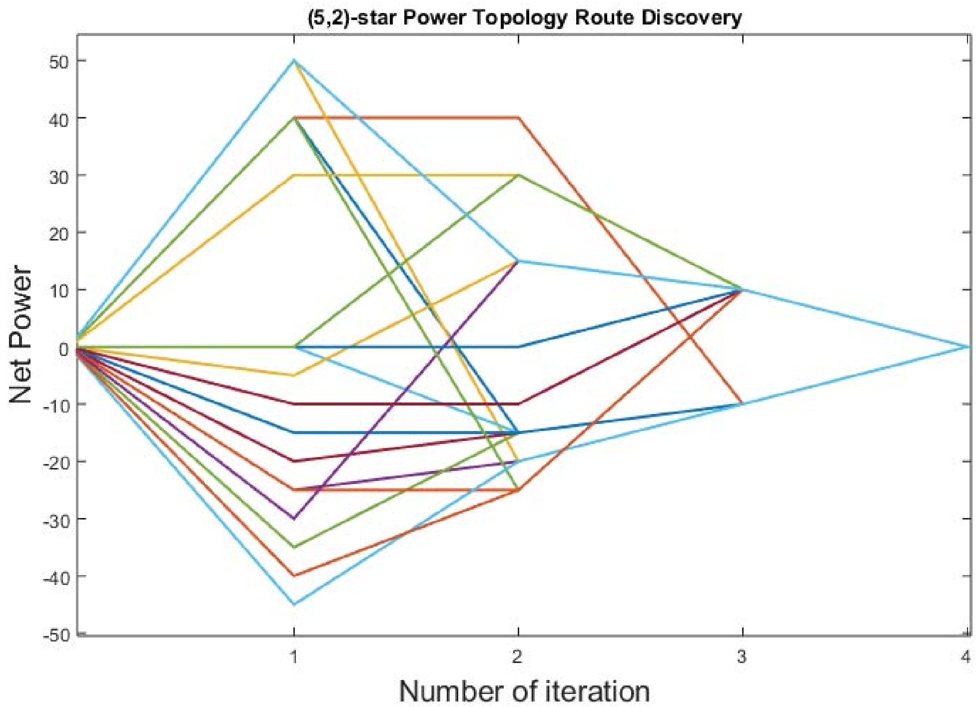


Figure 5.1: MAS based $(5,2)$-Star Power Topology Implementing Standard 16-Bus Power System with Redundant Phantom Bus Agents

5.1.2 *Power Restoration Experiments on Single Fault*

In the second part, the single fault power restoration process for each test case was simulated. The result was compared to standard multi-bus systems. For all test scenarios, one single fault was injected randomly in power systems at a time when the load balancing was completed. For each experiment, one agent was injected with fault so that it would not be

Table 5.2: Number of Average Shutdown Node due to Single Fault Power Restoration (Compared to Standard Bus System)

$(5,2)$-star	16-Bus System	$(7,2)$-star	39-Bus System	$(7,3)$-star	162-Bus System
1.45	1.5	1.2143	1.2821	1.0381	1.0617

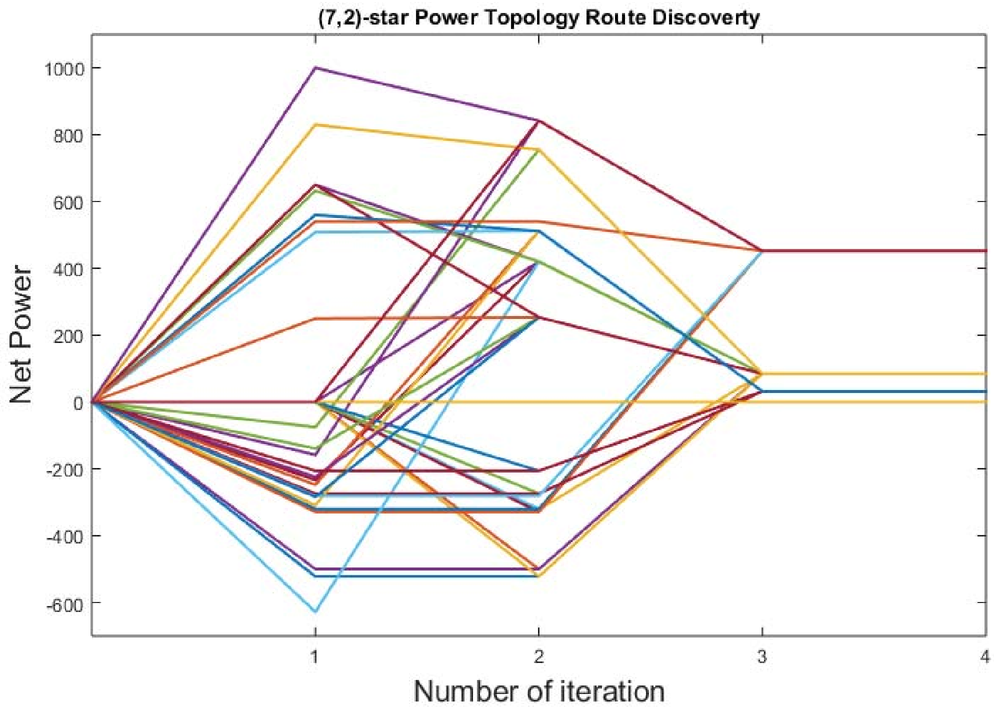


Figure 5.2: MAS based $(7,2)$-star Power Topology Implementing IEEE Standard 39-Bus Power System with Redundant Phantom Bus Agents

able to communicate with other agents. The system performed the 0/1 Knapsack algorithm to do the power restoration, as is shown in Algorithm 1. The system would terminate some agents, branch into sub-systems to maintain load balancing in whole power network. The average value of power restoration penalty was observed to show the performance. For (n, k)-star power topology systems, 20 tests were simulated for (5,2)-star power system; 42 tests were simulated for (7,2)-star power system and 210 tests were simulated respectively to (7,3)-star topology model. From Table 5.2 it is observed that the average number of shutdown agents due to power restoration is listed for both (n, k)-star and standard multi-bus power systems. It is concluded that for single fault power branching, (n, k)-star has lower number of shutdown nodes due to power restoration than the standard multi-bus system. Particularly for (7,3)-star and 162-bus system, the numbers are close to 1 because both of

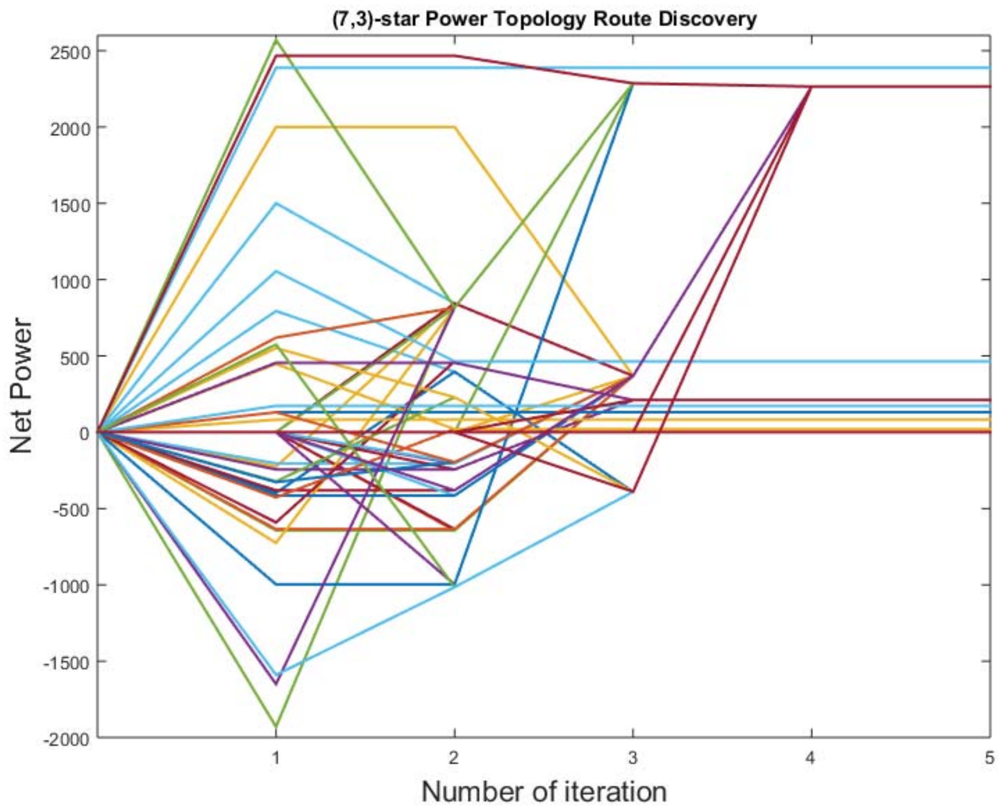


Figure 5.3: MAS based $(7,3)$-star Power Topology Implementing IEEE Standard 162-Bus Power System with Redundant Phantom Bus Agents

them have sparse number of agents and the redundancies are both high.

5.1.3 Power Restoration Experiments on Multiple Faults

After demonstrating the performance enhancement for (n, k)-star power topology on load balancing and single fault restoration, the set of experiments with multiple faults was conducted to better prove the advantages of (n, k)-star power topology. The system configurations for both standard multi-bus systems and (n, k)-star power distributions kept the same as in the single-fault scenario. The same phantom agents were constructed to implement the (n, k)-star power topology (numbers and locations were duplicated from previous experiments). After the accomplishment of load balancing procedure, multiple agent faults were generated to the power system. For each power distribution, number of faulty agents iterated from 2 to 6. According to each fault count, N number of experiments were executed. Table 5.3 shows the number N for each test scenario. This number is selected upon the complexity of the simulation. For small sets of simulation scenarios, all the possible fault agent combinations were simulated. But for large sets of the simulation scenarios, the execution time would be too long if all the scenarios are simulated. Thus, for these experiments with large number of faults, *i.e.*, number of faults greater than 4 for (5,2)-star power system, a random number selector was created to generate 10000 combinations of faulty agents. Therefore, the example where the fault agents number is 4 for (5,2)-star power system will select 10000 cases from all the possible combinations of 2 fault agents out of 20. So the number N for each fault number per system was calculated according to the equation below:

$$N = \begin{cases} \binom{|V|}{f}, & \text{if } \binom{|V|}{f} < 10000, \\ 10000, & \text{if } \binom{|V|}{f} \geq 10000 \end{cases} \tag{5.1}$$

where V is the vertex set for any graph G. The graph can be either the standard multi-bus systems or the (n, k)-star power distribution systems. So $|V|$ is the number of vertexes, which is the number of the agents in this case. f here represents the number of faults and varies on different simulation scenarios. This simulation setup enables that the simulation time will not be too long while the quality and reliability of the output data are ensured since the simulation set is large enough.

The purpose of this power restoration simulation on multiple faults is to provide the proof of advantages for (n, k)-star power topology, especially in resilience in terms of 0/1 Knapsack power restoration algorithm after the sysrem is fully balanced by the centralized

Table 5.3: Number of tests for multiple fault scenario for both Standard Multi-Bus Systems and (n, k)-star Power Distributions

Number of Faults	2	3	4	5	6
16-Bus System	120	560	1820	4368	8008
(5,2)-star	190	1140	4845	10000*	10000*
39-Bus System	741	9139	10000*	10000*	10000*
(7,2)-star	861	10000*	10000*	10000*	10000*
39-Bus System	10000*	10000*	10000*	10000*	10000*
(7,3)-star	10000*	10000*	10000*	10000*	10000*

Note*: if the number of possible fault agent combination is greater than 10000, the number of tests will then be 10000, in which case the faulty agents are randomly selected

load balancing algorithm. The predefined metric power restoration penalty was recorded for each simulation. All the results are listed in Table 5.4 to show the performance of each power distribution system. The number of faults for each systems was set from 2 to 6. The upper limit was set to 6 because it was the minimum number of the total number of generator agents. *i.e.*, both the standard 16-bus system and (5,2)-star power distribution system have 6 generator agents. Once there are more than 6 faulty agents in either system, there will be a possible scenario that all the generator agents shut down due to the faults and all the agents will be shut down. This particular scenario adds the complexity to interpret the simulation result thus the upper limit of 6 faulty agents is selected to ensure correctness of the conclusion.

Table 5.4: Average Power Restoration Penalty on Multiple Faults using 0/1 Knapsack Power Restoration Algorithm

Number of Faults	16-Bus	$(5,2)$-star	39-Bus	$(7,2)$-star	162-Bus	$(7,3)$-star
2	2.9167	2.6917	2.5304	3.0310	2.1222	2.1087
3	4.2536	3.9518	3.7477	4.4800	3.1808	3.1554
4	5.5143	5.1571	4.8148	5.7226	4.2349	4.2042
5	6.7024	6.3095	5.8737	6.9723	5.2890	5.2525
6	7.8214	7.4107	6.9291	8.1973	6.3326	6.2915

According to Table 5.4 the number showing on each cell is the average power restoration penalty, which is the count of the total number of shutdown agents due to system faults. It is shown graphically in Figure 5.4 the change of average power restoration penalty on increasing number of faults. It can be observed on the figure that the average number of shutdown agents is almost linear to the number of faults for both types of systems. The figure also shows that the (5,2)-star and (7,3)-star system perform more resilient behavior than the 16-bus and 162-bus systems respectively, which is expected. This has proven that the communication advantages brought by the properties of (n, k)-star power topology adds resilience to power systems when experiencing multiple system faults.

However, the average power restoration penalty for the (7,2)-star power system is more than the one for the 39-bus system. To better investigate the reason for this, the average number of degrees for standard multi-bus systems and (n, k)-star power distribution systems are collected before and after the information discovery process is collected and shown on Table 5.5. The second and third columns in Table 5.5 show the average number of degrees of all the generator agents before and after the information discovery respectively.

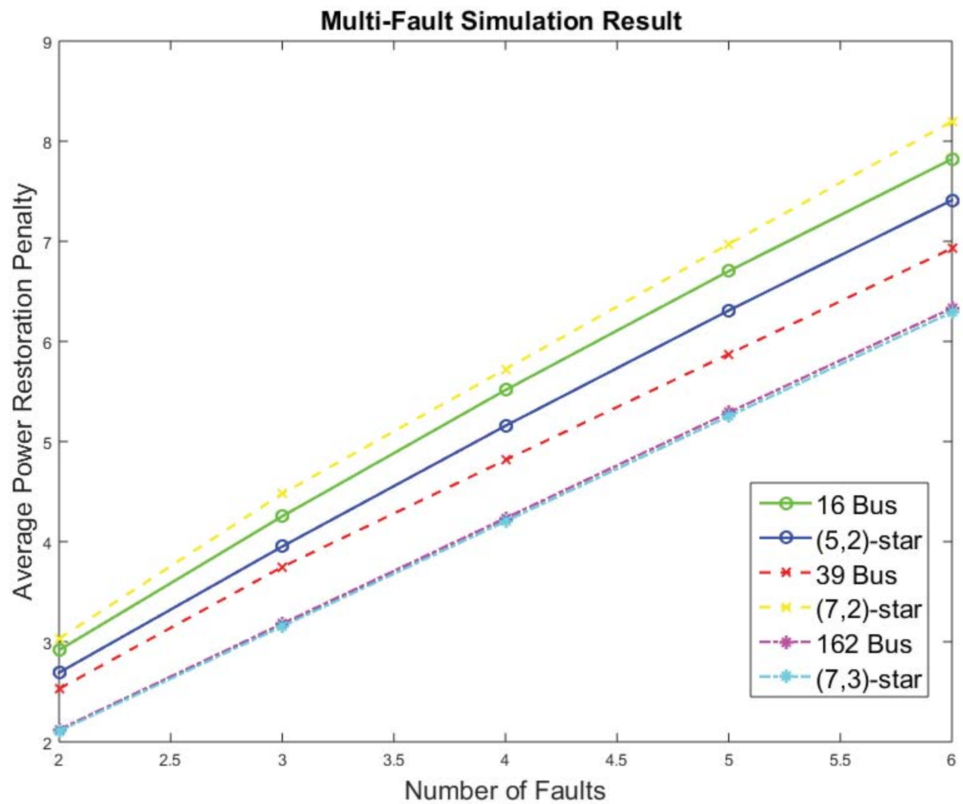


Figure 5.4: Average Power Restoration Penalty on Multiple Faults for Different Power Systems

It can be observed for the simulated (n, k)-star power distribution systems, the average available degree, which is the number of unoccupied links, is always greater than the average initial degree of the system. This provides the reason why most of the (n, k)-star power topology systems are more resilient due to multiple system faults: the greater number of average available degrees enables the generator agents to be able to reroute to supply more insufficiently supplied loads. Nonetheless, both the numbers of average initial and available degrees make the 39-bus system become a special case. It is 1.1111 for the initial degree and 0 for the available degree, which means most of the generators in 39-bus power system has week connectivity to its neighbors and after the load balancing process, all the links

Table 5.5: Average Available Degree for Generator Agents before and after Information Discovery

System	Average Initial Degree	Average Available Degree
16-Bus	2.1667	0.6667
(5,2)-star	4	1.8333
39-Bus	1.1111	0
(7,2)-star	6	4.2222
162-Bus	3.4118	2.8235
(7,3)-star	6	4.7059

from the generators are occupied so the average available degree becomes 0. Then, it results in two consequences: a) each generator in the end constructs its own local branch since its initial degree is low; b) the fault on generator will not affect many loads but only the ones in its local branch. Therefore, the 39-bus becomes a special case that it has less shutdown agents due to multiple faults and outperforms the resiliency experiments for (7,2)-star power distribution system.

5.2 Evaluation of Decentralized Consensus Control Algorithm

In this section the experiments were designed and executed to evaluate the decentralized consensus control algorithm designed for (n, k)-star power distribution systems. The experiments were based on a MATLAB/Simulink program which can generate the Simulink configurations for (n, k)-star power distribution systems. The consensus control algorithm was implemented on each agent so that the simulation can be performed in a decentralized

Table 5.6: Parameters of the Agents for Decentralized Consensus Algorithm in (5,2)-star System

Agent	Power Demand/Supply	Upper Bound	Lower Bound
G1	40	30	60
G2	40	30	60
G3	50	40	65
L4	-25	-15	-40
L5	-35	-25	-50
E6	0	-	-
L7	-20	-15	-30
L8	-15	-5	-20
L9	-25	-15	-40
L10	-5	0	-15
G11	40	30	50
L12	-30	-20	-40
L13	-45	-40	-55
E14	0	-	-
G15	30	25	40
G16	50	40	65
L17	-10	-5	-15
E18	0	-	-
E19	0	-	-
L20	-40	-30	-50

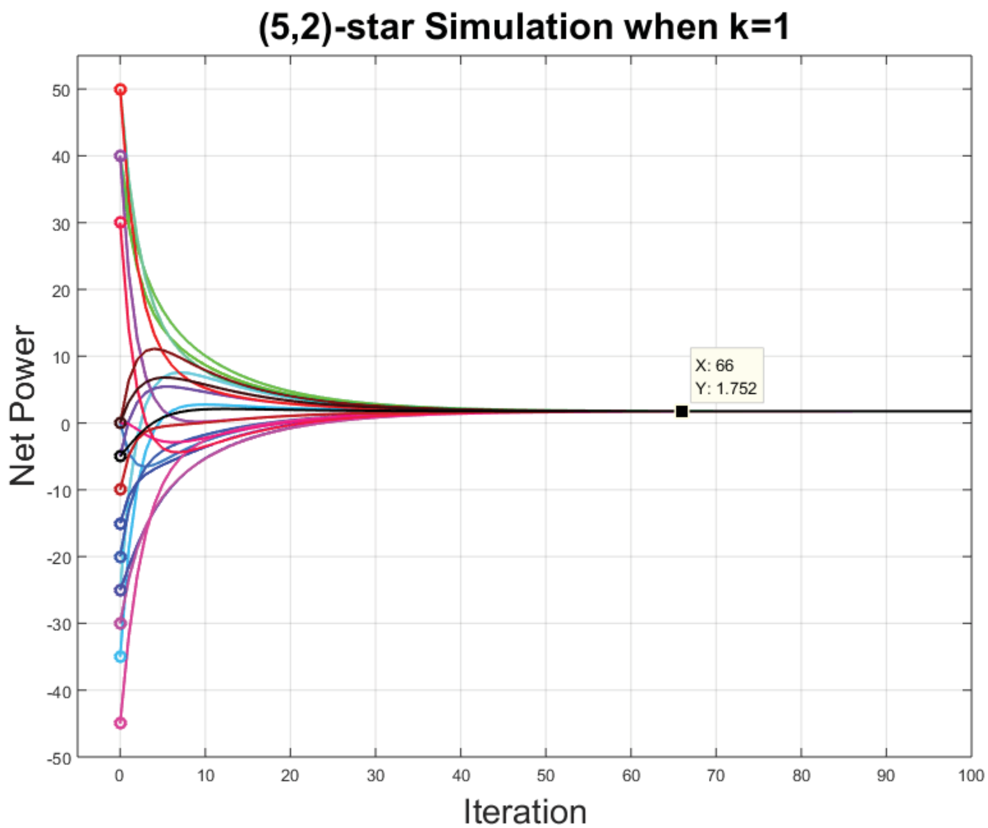


Figure 5.5: (5,2)-star Decentralized Consensus Algorithm Simulation

manner. In order to compare the result to the related work on discrete-time consensus microgrids [51, 52], the number of simulation iteration for each experiment set was recorded. The evaluation of the proposed decentralized algorithm was performed in two sets of experiments: a) Simulations on different (n, k)-star power distributions with same gain value K; b) Simulations on the same (n, k)-star power distributions with different controller gain.

Simulations on Different Distributions

The first set of simulation was executed by mapping the standard 16-bus power system to the (5,2)-star power distribution system, IEEE standard 39-bus power system to the (7,2)-star power distribution system and IEEE standard 162-bus power system to the (7,3)-star power

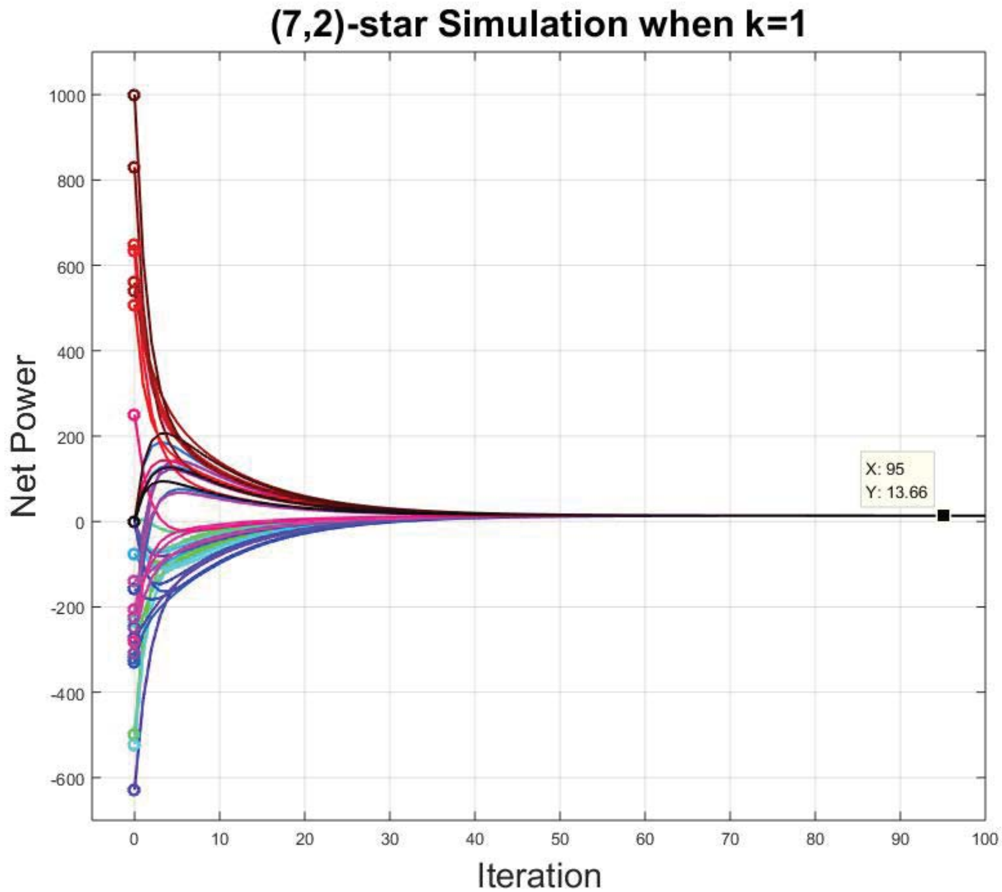


Figure 5.6: (7,2)-star Decentralized Consensus Algorithm Simulation

distribution system. All the power agents used in the system were defined with the power agent model with the supplementary controller proposed in Chapter 3. The phantom agents were randomly constructed in the simulation program on the three (n, k)-star power distribution systems. The initial status of the agents for (5,2)-star power distribution system is given in Table 5.6 as an example. Therefore, with the dynamics of each agent specified in Matlab/Simulink model, the simulation for the (5,2)-star, (7,2)-star and (7,3)-star power topologies with randomly selected leader agents were conducted. Figures 5.5 and 5.6 are shown to illustrate how the values of net power change during the consensus process. Figure 5.5, which contains 20 power agents, follows the leader agent to reach a stable state with

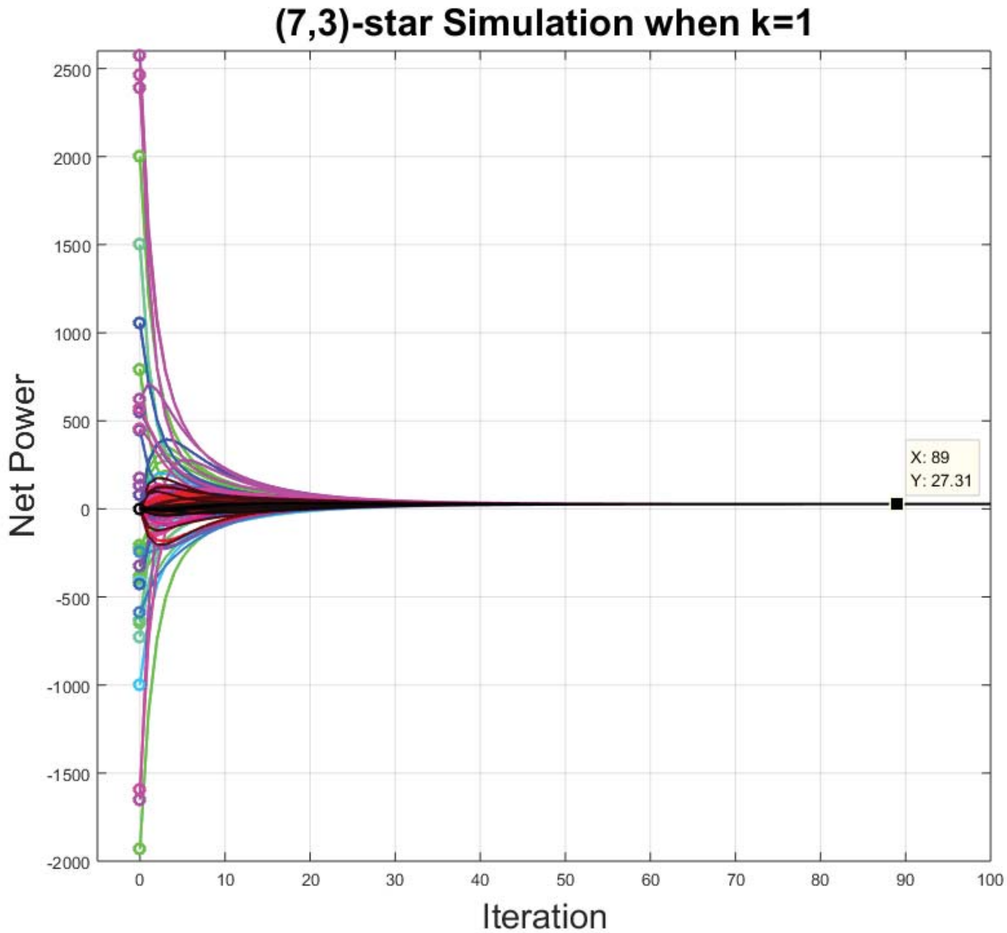
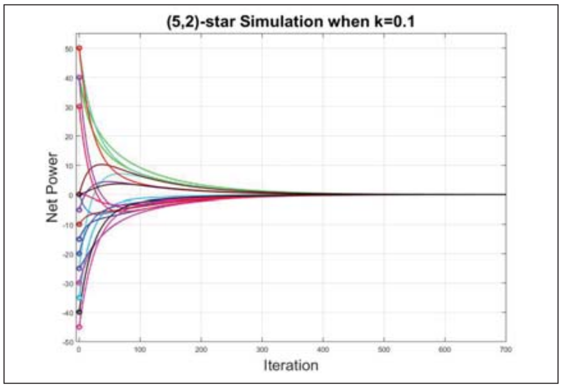
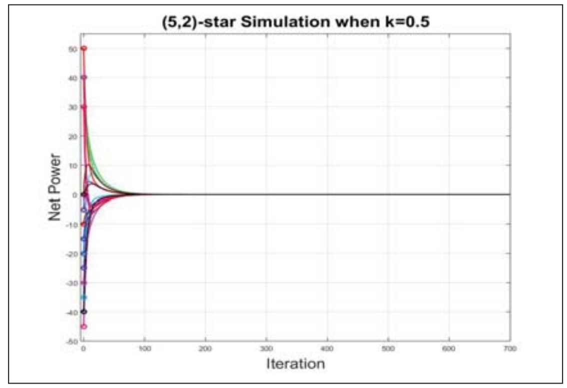


Figure 5.7: (7,3)-star Decentralized Consensus Algorithm Simulation

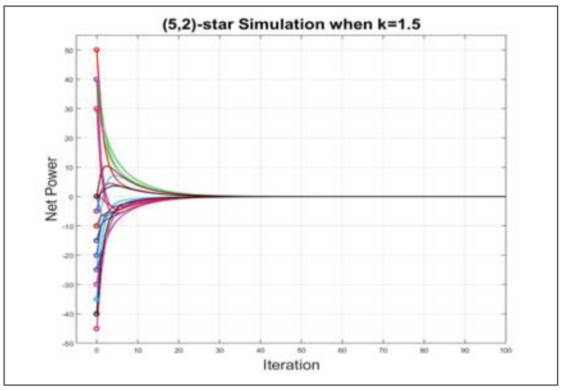
the power equal to 1.752 for one of the agent. The variance of every agent is limited in a certain value so the system is considered as convergent. In every scenario of this set of experiments, the threshold for variance was set to be 0.0001. It is shown in the figure the simulation took 66 iterations for all the agents to reach a net power set that the variance was less than 0.0001. The other experiment, which was simulating the process for (7,2)-star power topology, reached its consensus status at the 95th iteration when each agent had the power around 13.66. The simulation for (7,3)-star power topology reached its convergence state at simulation iteration equaled to 89 with each agent net power equal to 27.31. This set



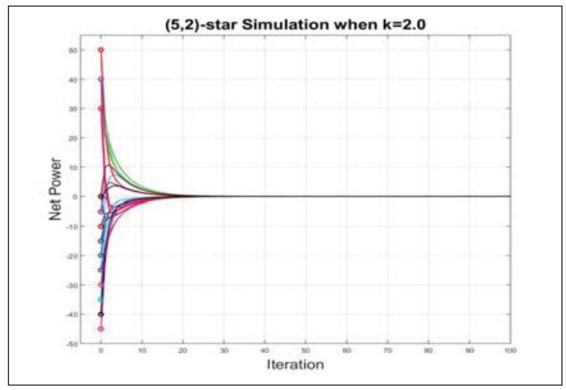
(a) k=0.1, Iteration of Convergence is about 600



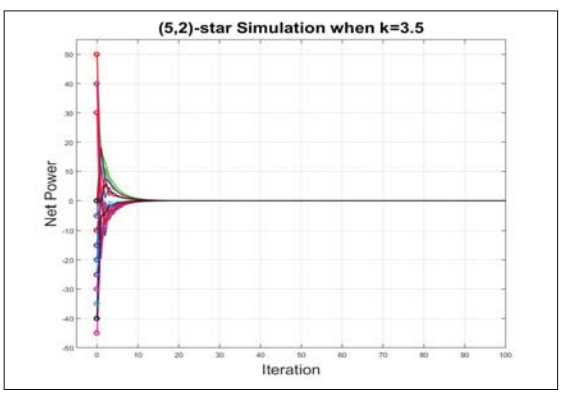
(b) k=0.5, Iteration of Convergence is about 200



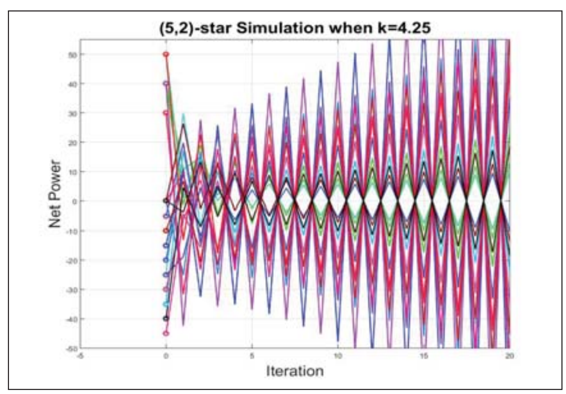
(c) k=1.5, Iteration of Convergence is about 80



(d) k=2.0, Iteration of Convergence is about 20



(e) k=3.5, IoC is about 10 but with Overshoot



(f) k=4.25, system is unstable

Figure 5.8: The Decentralized Consensus Control Algorithm on (5,2)-star Power Distribution Topology Representing Standard 16-Bus System Simulation Result when Varying k

Table 5.7: Discrete-time Information Discovery Algorithm Performance on Standard Bus System

System	Number of Iterations
16-Bus	71
39-Bus	143
162-Bus	165

of experiments demonstrated that the modeling of power agents and the stability analysis both worked as expected for (n, k)-star power distribution systems if a proper gain controller was assigned.

Furthermore, in order to better illustrate the advantage of the proposed decentralized consensus control algorithm, the results were compared to the results achieved by related studies [51]. In their study, the researchers designed their consensus control algorithm in a discrete time manner and tested it on standard multi-bus systems, which were the same standard multi-bus systems we utilized in this dissertation.

Table 5.7 shows the simulation iteration for the discrete-time consensus control algorithm. The error tolerance for this set of simulation is 0.03, which means the upper limit of the standard deviation for each agent's net power is 0.03. In the simulation set performed in this dissertation, an error tolerance value of 0.01 is selected, which means the standard deviation of the net power outputs for all the agents would always be less than or equal to 0.01. Table 5.8 shows the iteration counts for the proposed algorithm in this dissertation. It is clear that with a smaller error tolerance, the continuous-time consensus control algorithm takes shorter time in terms of simulation iterations other than the time spent on the discrete-time consensus control algorithm.

Table 5.8: Continuous-time Load Balancing Algorithm Performance on (n, k)-star Power Distributions

System	Number of Iterations
(5,2)-star	66
(7,2)-star	95
(7,3)-star	89

Simulations with Different Gain Value

The other set of simulation experiments were then designed for (5,2)-star power distribution topology. In this set of experiments, the initial status and leader agent was kept the same for all the test cases. The only difference was the change of the value of the gain controller k. The purpose is to investigate the influence on performance, which is represented by the number of iteration of convergence. This is also the experiment that proves the proposed theorem of stability analysis.

According to Figure 5.8, as the number for the gain controller k changes, the number of iteration for convergence changes accordingly. As k equals 0.1, it spends about 600 iterations to reach the consensus status. As k changes from 0.1 to 3.75, the number of iteration for convergence decreases to 10. It does not mean that the more value the gain k is the better performance the system achieves. For example, in Figure 5.8e when $k = 3.75$, the value of k is approaching the limit $k = 4$. Thus the system converges to the consensus status too fast so that the netpower of the agent overshoots in several iterations. So it shows significant noise when k is approaching the upper limit. For the simulation scenario in Figure 5.8f, when k exceeds the upper limit, the system behaves in an unstable manner and it never reaches its consensus status. This proved that the gain controller must be designed properly according the theorem in Chapter 3 so that the system is stable.

All of the simulations in this section proved the convergence and stability of the proposed theorem in Chapter 3. The final total net power also met the original goal of the load balancing control. The results provided by this set of simulations also demonstrated that the speed of the convergence of net power can also be controlled by the gain k. However, the k value must be properly chosen that the matrix $P_A - \lambda_i P_B k P_C$ was negative definite. The value of k can be sufficiently close to the upper limit to make the convergence process faster. But in practical use, the k value must depend on the hardware so it sometimes cannot be too close to the upper limit.

5.3 Summary

The practical merit of the (n, k)-star power topology on a power distribution system is provided by these experimental results. The proposed metric models can evaluate and measure a (n, k)-star topology power distribution system before physically constructed.

In the second set of the experiments, the (n, k)-star power topology is implemented in continuous-time with a distributed way. This ensures the algorithm to be a fully decentralized consensus control strategy. Thus, the agents can only make the decision based on the states of their neighbors. This makes the system more resilient.

The simulation is implemented on a MATLAB/Simulink environment. The dynamics of the algorithm specified in chapter 3 are implemented in a Simulink block to represent the continuous-time load balancing. The total number of iterations is recorded as metrics in order to compare to the discrete-time algorithms. In this chapter the results for the experiments are provided, including the evaluation of the (n, k)-star interconnected network topology, metrics on (n, k)-star power topology and continuous-time consensus analysis on (n, k)-star power topology. The results of these experiments directly demonstrated the functionality of the proposed methodologies and algorithms. However, future work needs to be done to better demonstrate the design.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of Research

Power distribution systems, such as large-scale power grids and wind/solar based micro grids, are the most promising energy systems in our daily life. However, impacts of variability and uncertainty of such power, cause a sudden loss of power component which leads to a load balancing problem. It is noticeable that the active net power exchange is theoretically considered as a communication process. Therefore, an interconnected network topology, like (n, k)-star, has its advantages in addressing the communication issues of a certain power distribution system before physical implementation.

In this dissertation, the properties of the (n, k)-star power distribution model with metrics were investigated. The evaluation definitions for an (n, k)-star power topology were designed as well. Then, a novel consensus load balancing algorithm on an (n, k)-star power distribution system was presented. This power distribution topology model can be used to optimize the performance of load balancing and power restoration problems, with the performance evaluation offered by the novel proposed metrics. The stability analysis for the (n, k)-power grid on (n, k)-star power systems was then proposed. It was proven step by step that if a proper gain controller is chosen, the system can be collectively consensus and stable. The load balancing process on an (n, k)-star will converge to a certain stable status. Thus, the loads from the system can always reach their common goal. Also, in this research, two sets of experiments were designed and conducted to further demonstrate the proposed methodologies.

In the experiments, results showed the improved performance in communication cost for the information discovery process on an (n, k)-star power topology. The experiment results have shown enhancement in the power restoration, with both single-fault and multiple-fault scenarios. Moreover, the decentralized consensus algorithm was simulated on all three (n, k)-star power distribution systems, with analysis and comparison to related research.

The proposed fundamental research is sufficient to theoretically address the load balance and power restoration problem for any common power distribution systems. With applying these proposed methodologies, more reliable decisions can be made before the physical construction of the power distribution systems. The metrics, stability analysis, existence of the solution and the assessed resilience can be achieved in modeling and analysis. Thus, the possible applications for these methodologies could include large-scale power grids, microgrids, or embedded electrical power systems.

6.2 Future Work

Based on the presented research, there are two research directions that can be done in the future. First, the approach of the decentralized consensus control algorithm can be extended to switching topology power systems. Second, the IRT based assessment tool should be further applied to practical uses to prove its functionality.

6.2.1 Power Restoration using Switching Topology Consensus

Networked systems with a dynamic topology are commonly known as switching networks. A switching network can be modeled using a dynamic graph $G_{s(t)}$ parameterized with a switching signal $s(t)$. The consensus mechanism on a power network with a variable topology becomes a linear switching system.

$$\dot{x} = -L(G_k)x \tag{6.1}$$

That means that, if we treat the single fault agent or multiple fault agents as the switching state of the topology, the system can be formulated in to a control system with dynamic of the component.

Accordingly, it has been provided in [14, 48] the consensus and convergence analysis of such a system. Stochastic process analysis is applied to prove the existence of the solution. Thus, the future work of this study will be focused on the fundamental research of this consensus problem switching topology. Once the stability is analyzed, the performance of the algorithm will be evaluated again on single and multiple failure scenarios. The results will also be compared to the centralized power restoration algorithm in [43] and the discrete-time consensus power restoration algorithm proposed in [51]. It is expected that the result will outperform both approaches in terms of communication cost and power restoration penalty.

6.2.2 Apply IRT Model to Practical Tests

In this dissertation, we presented a prof of concept for assessing resilience of an engineering system. The example we illustrated for (n,k)-star power topologies were utilizing four systems as calibration set and a total number of eight items. However, in practical use, a 2PL model IRT methodology should apply to a sufficiently large set of calibration systems and many predefined items. These are left as future work. The calibration set should be well selected fulfilling the assumption that all the systems are measuring the same construct; while the items should be well defined to be locally independent.

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