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Distributed decision-making in electric power system transmission maintenance scheduling using Multi-Agent Systems (MAS)

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Distributed decision-making in electric power system transmission maintenance

scheduling using Multi-Agent Systems (MAS)

by

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A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Electrical Engineering

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Ames, Iowa

2004

UMI Number: 3145695

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For the Major Program

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1 INTRODUCTION

The electric power utilities around the world have been undergoing rapid changes in the past decades. The new deregulated environment forces individual utilities to reduce operating costs while maintaining the overall system reliability. One of the major costs of an electric utility is transmission maintenance. Some utilities are working proactively to address this issue by implementing efficient maintenance programs, such as condition-based maintenance, which requires utilization of a large volume of equipment condition data. In addition, the functional disaggregation of the once vertically integrated utility, together with the erosion of cooperative relations between major players, has resulted in authority fragmentation of a variety of decision-making problems, e.g., transmission maintenance scheduling, which now requires the coordination between various competing and autonomous entities across the entire system. It is evident that a good information integration and coordination mechanism among the self-interested entities is essential to achieving an optimal trade-off between the cost of maintenance and the system service reliability.

1.1 Characteristics of Equipment Condition Information

Sufficient equipment information is necessary to evaluate the operating conditions of the equipment and thus an effective maintenance program can be carried out. Over the past decades, the technologies employed for electrical equipment monitoring have been evolving from traditional periodic on-site examination and laboratory analysis to continuous, on-line monitoring. Recent technological advancements have made various sensors integrated with substation intelligent electronic devices (IEDs) available to monitor different parameters essential to the health of electrical equipment in operation. These monitoring systems monitor some critical equipment parameters continuously, in "real-time". Usually sampling is from several minutes to seconds. Therefore, a major aspect of these monitoring

technologies has been the accumulation of tremendous amount of equipment data at the field. Due to the physical and evolutionary nature of the electric power systems, these huge amount of equipment monitoring data contained in electric power systems, have some unique characteristics as following:

(a) *Spatial Distribution*: The power system is inherently spread across a wide geographical area. Intelligent electronic devices (IEDs) spread throughout the grid are rich repositories of equipment data, like currents, voltages, power factors, settings and various temperatures. Retrieving these data is a highly communication intensive activity, and it is also encumbered by the heterogeneity of the devices as well as associated software systems.

(b) *Heterogeneity*: Prior to the trend of deregulation in the power industry, rapid advances within the telecommunications sector together with the power sector's ever increasing need for information services have led utilities to use heterogeneous communication services, grouping together equipment from various manufacturers and technologies. The heterogeneity can involve one or more of the following facets: platforms, user interfaces, object definitions and communication protocols [Apostolov, 2001].

(c) *Time-Variance:* Electrical equipment's inevitable aging and gradually deterioration in operation, coupled with the inherent dynamic nature of the power system has made equipment condition information highly time-variant.

(d) *Proprietary Information:* Equipment data sources of interest are usually autonomously owned and operated. The information required for various analyses may need to be accessed from proprietary databases.

Currently, coordination of those highly dispersed equipment condition information requires significant human intervention since it is not easily accessed or generally available, because of information processing limitations, temporal barriers, tremendous volumes and proprietary constraints. The complexities of doing so make manual coordination incompatible with the maintenance need of today's transmission systems. Thus, in order to obtain and better utilize this useful information under such complex, data-intensive and

stressed scenarios, a sophisticated new paradigm is necessitated for comprehensive information accessing and integration in support of utilities' maintenance decision-makings.

1.2 Diversity of Decision Makers in Deregulated Electric Power System

In a vertically integrated system of the pre-deregulation era, decision-making authorities were strictly centralized, i.e., utilities centrally determined the need for power, the most economical choice to produce and deliver it, and how to maintain the system to ensure its reliability. Today, deregulation has created a more complex operation and maintenance (O&M) environment by creating new entities and defining new rights and responsibilities for these entities. The entities in such power systems can include power exchanges, utilities, ISOs, distribution companies, regulators, reliability councils, transmission owners, generation owners, scheduling coordinators and large industrial consumers. The functional disaggregation of the once vertically integrated utility, together with the erosion of cooperative relations between major players, has resulted in authority fragmentation of a variety of decision-making problems, such as transmission maintenance scheduling, which now requires the coordination between various competing and autonomous entities across the entire system.

1.3 Interdependence of Economic and Security

Reliability and economy are among the most important considerations in restructured power systems. The objective of competitive energy markets to obtain the highest overall system efficiencies can be viewed as a tradeoff problem between concerns for high market (economic) efficiency and the reliability of the system. In other words, it is the system reliability level that determines utility's flexibility in responding to the economic imperatives of the electric energy market. An optimized maintenance program can dramatically improve

system reliability in a cost-effective fashion. Reliability can be defined as the probability of a device or system performing its function adequately, for the period of time intended, under the operating condition intended [Endrenyi, 1978]. In order to develop an effective maintenance program and quantitatively evaluate the result of the maintenance activities in terms of system reliability enhancement, a prerequisite is to build models for estimating electric equipment time-dependent failure probability based on available equipment condition information.

1.4 Contributions of This Research Work

In transmission maintenance scheduling, given the competing nature of involved entities, dynamic and proprietary nature of equipment condition information available to these entities, there is a compelling need to look beyond the traditional centralized approaches. This work offers an alternative to traditional centralized maintenance practices by developing a multiagent negotiation-based framework for distributed decision support among various independent utilities. The most significant contributions of this work are summarized in what follows.

- An innovative risk-based transmission maintenance optimization procedure is introduced. This framework provides the ability to select and schedule maintenance tasks so as to utilize the available financial and human resources to optimize the risk-reduction achieved from them within a given budget cycle. Several models for linking condition monitoring information to the equipment's instantaneous failure probability are developed, which enable quantitative evaluation of the effectiveness of maintenance activities in terms of system cumulative risk reduction. Methodologies of statistical processing, equipment deterioration evaluation and time-dependent failure probability calculation are also described.

- A novel framework capable of facilitating distributed decision-making through multiagent negotiation is developed. A multiagent negotiation model is developed and

illustrated that accounts for uncertainty and enables social rationality. Some issues of multiagent negotiation convergence and scalability are discussed. The relationships between agent-based negotiation and auction systems are also identified.

▪ A four-step MAS design methodology for constructing multiagent systems for power system applications is presented. A generic multiagent negotiation system, capable of inter-agent communication and distributed decision support through inter-agent negotiations, is implemented.

▪ A multiagent system framework for facilitating the automated integration of condition monitoring information and maintenance scheduling for power transformers is developed. Simulations of multiagent negotiation-based maintenance scheduling among several independent utilities are provided. It is shown to be a viable alternative solution paradigm to the traditional centralized optimization approach in today's deregulated environment. This multiagent system framework not only facilitates the decision-making among competing power system entities, but also provides a tool to use in studying competitive industry relative to monopolistic industry.

1.5 Organization of This Thesis

The rest of this dissertation is organized as follows:

Chapter 2 presents a literature review related to this work. Different power system maintenance practices are summarized. Current industry efforts regarding standardization of communication protocols and information integration are identified. Then concepts of intelligent software agent and multiagent systems as well as their attractive attributes are introduced. Some MAS applications in electric power systems are also reviewed.

Chapter 3 first presents a risk-based transmission maintenance optimization procedure. We use power transformer as an example to illustrate our work. Different power transformer condition monitoring techniques as well as available condition information are

described. Various transformer failure modes are then identified. Based on condition monitoring information, different models of estimating equipment instantaneous failure probability are developed and illustrated. The estimation of equipment instantaneous failure probability enables the effective utilization of equipment condition information in related maintenance decisions, in order to enhance system reliability by performing appropriate maintenance activities subjected to various constraints.

Chapter 4 describes a distributed decision support framework through multiagent negotiation. The negotiation theory is extensively reviewed. A simple and easily implemented value function-based negotiation model is described. A utility function-based multiagent negotiation model, which accounts for uncertainty and enables social rationality, is developed. Some issues of multiagent negotiation convergence and scalability are discussed. The relationship between agent-based negotiations and auction systems is also identified.

Chapter 5 implements and illustrates a multiagent system framework for displacing centralized optimization with negotiated decision-making for maintenance scheduling. First, a four-step MAS design methodology for constructing multiagent systems for power system applications is described. Then the implementation of a multiagent negotiation system (MANS) is described. Based on this generic multiagent system platform, we further develop a multiagent framework for facilitating the automated integration of condition monitoring information and maintenance scheduling for power transformers. Simulations of multiagent negotiation-based maintenance scheduling among several independent utilities are also provided.

Chapter 6 presents conclusions, contributions and future work.

2 LITERATURE REVIEW

In this chapter, literature related to this work is reviewed. First, the traditional and state-of-the-art transmission system maintenance strategies are briefly described. Then current power industry efforts regarding standardization of communication protocols and information integration are outlined. The concepts of software agent and multiagent systems (MAS) technology, along with the characteristics of intelligent agent and multiagent systems are introduced. Finally, some MAS applications in electric power systems are also reviewed.

2.1 Transmission System Maintenance Strategies

According to [IEEE Std 902-1998], electrical equipment maintenance is the act of preserving or keeping in existence those conditions that are necessary in order for electrical equipment to operate as it was originally intended. Thus, the prime objective of maintenance is to keep the equipment in good working order and to maximize its lifetime productivity. There are different kinds of transmission maintenance strategies, which have been practiced in the industry. Here, the most frequently preformed maintenance strategies are reviewed [IEEE Std 902-1998; Harker, 1998; Okrasa, 1997; Endrenyi, 2001; Shahidehpour, 2000; Li, 2004].

2.1.1 Breakdown Maintenance

Those repair actions that are conducted after a failure in order to restore equipment or systems to an operational condition. This may also be referred to as corrective maintenance or reactive maintenance. Equipment is neither serviced on a regular scheduled basis, nor is it tested to determine its condition. With this approach, equipment is repaired or replaced only after a failure occurs. This is the most widely used approach in the past decades.

2.1.2 Preventive Maintenance

Preventive Maintenance is a program of routine equipment inspections, maintenance tasks and repairs that are scheduled to ensure that degradation of equipment is minimized. This is the maintenance that is carried out at predetermined intervals to reduce the likelihood of an item of equipment falling in service. In practice, the maintenance intervals are usually selected on the basis of long-time experience. A probabilistic model used to determine the mean time to preventive maintenance was described in [Sim, 1988]. A well-designed preventive maintenance program may slightly over-maintain equipment because the scheduling is designed for the worst case operating conditions. The overall objective is to prevent operating problems or failures, and ensure reliable operation of a facility. This approach is also frequently used in today's industry.

2.1.3 Predictive Maintenance

Predictive maintenance is the technique of regularly monitoring selected parameters of equipment operation to detect and correct a potential problem before it causes a failure. This is done by trending measured parameters, which allows a comparison of current parameters to historical data. From this comparison, qualified judgments about the need for corrective action can be made. This approach ensures that the right maintenance activities are performed at the right time.

2.1.4 Reliability-Centered Maintenance

Reliability-Centered Maintenance (RCM) is a systematic methodology that establishes initial preventive maintenance requirements or optimizes existing preventive maintenance requirements for equipment based upon the consequences of equipment failure. The failure consequences are determined by the application of the equipment in an operating system. In an RCM approach, various alternative maintenance policies can be compared and the one most cost-effective for sustaining equipment reliability selected. The most important

principle of RCM is to enhance or preserve the reliability level of the entire system through maintenance. Some general ideals of RCM for transmission system are presented in [Beehler, 1997]. However, it did not present any mathematical method to quantify transmission system reliability. A time-shift-based Monte Carlo simulation method was described in [Li, 2004], which quantifies the impact assessment of the planned outage on whole transmission system reliability. And reference [Shahidehpour, 2000] gives very detailed mathematical formations for generation and transmission maintenance scheduling problems considering the costs as optimization objectives while satisfying various constraints including system reliability.

2.1.5 Condition-Based Maintenance

Condition-Based Maintenance (CBM): Maintenance activities are carried out only when the condition-monitoring information of that equipment indicates a need. Obviously, this approach is heavily based on the assessment of equipment operating condition, where decisions with regard to the time and amount of maintenance are dependent on the actual condition (stage of deterioration) of the equipment. However, it may take a long time before enough equipment condition data are gathered for necessary analysis. Besides, this approach also requires rich field experience from maintenance personnel.

In the past, due to the lack of sufficient equipment condition information, most utilities employed the philosophy of age replacement or breakdown maintenance, i.e., a replacement is performed at a certain age or when the equipment actually fails, whenever comes first. It is easy to manage, however, now it is becoming more and more unacceptable, because of the possible high consequences associated with equipment failures in today's stressed network. Thus a more proactive attitude is taken by utilities to perform maintenance activities at a predetermined interval, such as one year regardless of actual operating condition of the equipment, i.e., preventive maintenance strategy. Obviously, this is not an optimal maintenance strategy in today's business environment, because there always be the situation that the equipment is in good condition and indeed needs no care, but actually

maintenance is performed according to predetermined schedule. So there is a room for costing saving by reducing the frequency of maintenance if possible. Fortunately, with the development of microcomputer and sensor technologies, various condition-monitoring techniques are now available for monitoring different key parameters of transmission equipment. This enables utilities to track the operating conditions of their equipment and detect any imminent failures. Thus utilities can perform some more efficient maintenance programs, such as reliability-centered maintenance and condition-based maintenance, to reduce their maintenance costs as well as sustain their equipment reliability.

As just mentioned above, in order to carry out more efficient maintenance strategies, such as RCM, it requires a large amount of equipment information to be collected and analyzed in a timely fashion. However, handling these condition data is extremely challenging due to its enormous size, high heterogeneity and physical distribution. In the next section, we will review some industry efforts, which are trying to deal with problems of this nature.

2.2 Current Efforts Regarding Standardization of Communications and Information Repository in Power Industry

Since the late 1980s, the emerging presence of computer and digital technologies has brought much greater efficiency and operational potential to the electric utilities. However, as both hardware and software vendors design systems suited to their own specific applications, the number of data storage platforms/formats and corresponding access/retrieval/interface methods have burgeoned. This has resulted in numerous and heterogeneous "information islands" at different levels throughout the power system, which are labor-intensive to identify, access, and integrate for a given purpose. In response, the power community has begun efforts to standardize communication protocols and information/data storage.

This section is organized as follows. First, current power industry efforts regarding standardization of communication protocols and information/data integration, e.g., *Utility Communication Architecture* (UCA), *Common Information Model* (CIM) are briefly introduced. Then some recent power system asset management tools are also reviewed.

2.2.1 Utility Communications Architecture

The *Utility Communications Architecture* (UCA) [EPRI, 1998a; EPRI, 1998b; CAP Tutorial 2001; UCA Forum] was developed under the sponsorship of the *Electric Power Research Institute* (EPRI) through a process of broad industry involvement since 1988. The objective has been to allow for seamless integration across the utility enterprise using off-the-shelf international standards to reduce costs. UCA is an architecture that provides communications solutions from simple devices to control centers all based upon compatible, standard and interoperable communications protocols and device object models.

The UCA Version 1.0 specification was issued in December 1991. While this specification supplied a great deal of functionality, industry adoption was limited, due to the lack of detailed specification of how the protocols would actually be used by applications. For example, the *Manufacturing Message Specification* (MMS) ISO/IEC 9506 protocol was specified for real time data exchange at many levels within a utility, but specific mappings to MMS for exchanging power system data and schedules or for communicating directly with substation or distribution feeder was lacking, resulting in continuing interoperability problems. Thus EPRI began the MMS Forum UCA 2.0 (now referred to as the UCA Forum) to define how MMS should be used in a utility environment. This definition formed much of the basis of UCA 2.0.

UCA 2.0 was concerned with defining the methods and language that would allow devices from different vendors to understand each other, or interoperate, in an electric utility substation. The UCA Version 2.0 incorporates a family of basic communications protocols to meet the requirements of a wide range of utility environments. The UCA protocols are

organized according to the *Open Systems Interconnection* (OSI) reference model. The UCA Version 2.0 includes profiles employing protocols from both the OSI and TCP/IP families of protocols.

The *Inter-Control Center Communications Protocol* (ICCP, also known as Telecontrol Application Service Element 2, TASE.2) defines a standardized use of MMS in UCA Version 2.0 compliant networks for real-time exchange of data within and between control centers, power plants, and SCADA masters. The *Generic Object Models for Substation and Feeder Equipment* (GOMSFE) contains detailed object models of common field devices, including definitions of their associated algorithms and communications behavior visible through the communication system. The device models developed within the UCA 2.0 effort make use of a common set of services to describe the communications behavior of the devices. A standard mapping of these services onto the UCA application layer protocol (MMS), when used in conjunction with the device models, completely specifies the detailed interoperable structure for utility field devices. The services and mapping to MMS are defined in UCA *Common Application Service Models* (CASM). CASM is the document that illustrates the step-by-step processes that must be followed for a communications service to be performed within UCA.

2.2.2 Common Information Model

Electric utility organizations have long needed to exchange system information with one another in order to construct simulation environments for power system economics and security analysis. Even though most *Energy Management Systems* (EMS) and *Distribution Management Systems* (DMS) are now supplied with standard operating systems on standard computer platform hardware, these systems are still built on proprietary databases. The consequences of this led to boundaries between different EMS systems and locked the user out of the environment.

Between 1993-1994, the *Electric Power Research Institute* (EPRI) Working Group on *Control Center Application Interfaces* (CCAPI) has as its objectives to publish a set of

guidelines for application interfaces, to develop associated support tools, and to promote the use of open software engineering approaches in EMS. The *Common Information Model* (CIM) [Lee, 1999; Podmore, 1999] is the foundation of the overall CCAPI framework. The CIM provides a standard for representing power system objects along with their attributes and relationships. The CIM facilitates the integration of EMS applications developed by different vendors; entire EMS systems developed by different vendors; or EMS systems and other systems concerned with different aspects of power system operations, such as generation or distribution management.

The CIM is partitioned into a number of submodels, or packages, for convenience: a Wires Model, SCADA Model, Load Model, Energy Scheduling Model and a Generation Model. The Wires Model represents physical equipment and the definition of how they are connected to each other. It includes information for transmission, subtransmission, substation, and distribution feeder equipment. This information is used by network status, state estimation, power flow, contingency analysis, and optimal power flow applications. The SCADA Model describes measurements, PTs, CTs, RTUs, scan blocks, and communication circuits. It supports operator control of equipment, telemetered data acquisition and alarming. The Load Model provides models for all load levels from customers to feeders to load areas to the system level. The load is modeled by time-varying curves that represent effects of different seasons and day-types. The voltage and frequency dependence of loads can also be modeled. The Energy Scheduling Model includes objects for schedules, companies, control areas, and tie lines. It handles scheduling transactions for energy, generation capacity, transmission, and ancillary services. The Generation Model includes objects for generators, prime movers, fuels, and heat rate curves. This information is used by unit commitment, economic dispatch, automatic generation control and operator training simulator applications.

2.2.3 Data Integration Needs for Asset Management

Recently there has been a great deal of investment in developing asset management tools. These tools may be classified by function. There are several which provide work-flow functions, work-order tracking, and data storage. Examples of these tools are *MAXIMO* [MAXIMO], *CASCADE* [CASCADE], and *Asset-Sentry* [ABB]. Typical data stored includes equipment data (nameplate), maintenance histories, and condition data. Some companies have several additional data repositories that house such information as outage schedules, operating histories (e.g., a process-information or PI-historian), and equipment-specific condition data (e.g., dissolved gas analysis results, tap changer temperatures). Because of the number and diversity of the asset management data repositories, EPRI also has developed *Maintenance Management Workstation* (MMW) that acts as a database integrator providing a number of functionalities among which is the ability to bring data from multiple sources to a consolidated data set.

2.3 An Alternative and Unifying Approach

UCA, CIM, and the asset management tools represent current efforts to facilitate communication needs and information processing needs within an information-intensive industry. An underlying, common theme is to *standardize* and *centralize* by defining and utilizing standard, interoperable communication protocols, by providing common object-models of power system data items, and by aggregating data into warehouses such as MMW. Therefore, the focus has been on aggregation of the data itself.

Intelligent agent and multi-agent systems represent an alternative where the focus is on the processing rather than on the data, leaving the data both heterogeneous and distributed. With intelligent agents distributed in the entire network, software agents can perform proactive as well as reactive information/data processing, communicate and coordinate with each other to solve complex problems. We believe that MAS represents within a single

technology a unified solution to the problems that drive the need for UCA, CIM, and many of the various asset management tools.

This section introduces the concepts of intelligent software agent and multiagent systems (MAS) technology used in this dissertation.

2.3.1 What is an Agent?

In the past decades, the term '*agent*' has been widely used to refer to software system, which may have attributes of intelligence, autonomy, perception or acting on behalf of a user. However, there is no agreed and widely understood definition of exactly what an agent is or what properties it should have. Various definitions from different disciplines have been proposed for the term over the past years. Below we introduce a few representative descriptions of agency [Franklin, 1996]:

Sankar Virdhagriswaran of Crystaliz, Inc., pointed out in an online white paper [Crystaliz], *"The term agent is used to represent two orthogonal concepts. The first is the agent's ability for autonomous execution. The second is the agent's ability to perform domain oriented reasoning."* In this definition, autonomous execution is clearly central to agency.

Russell and Norvig offered their definition [Russell, 1995], *"An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors."* The authors were interested in software agents embodying AI techniques. Clearly, this definition depends heavily on what we take as the environment, and on what sensing and acting mean.

Pattie Maes, of MIT's Media Lab, is one of the pioneers of agent research. She has coined the following definition of the term [Maes, 1995]. *"An agent is a computational system that inhabits a complex, dynamic environment. The agent can sense, and act on, its environment, and has a set of goals or motivations that it tries to achieve through these actions."* She adds a crucial element to her definition of an agent: agents must act autonomously so as to "realize a set of goals." Also, environments are restricted to being

complex and dynamic.

Barbara Hayes-Roth, of Stanford's Knowledge Systems Laboratory, provided her concept of agent in [Hayes, 1995]: *"Intelligent agents continuously perform three functions: perception of dynamic conditions in the environment; action to affect conditions in the environment; and reasoning to interpret perceptions, solve problems, draw inferences, and determine actions."* She insists that intelligent agents reason during the process of action selection.

This definition of IBM Agent from IBM's Intelligent Agent Strategy white paper [IBM], *"Intelligent agents are software entities that carry out some set of operations on behalf of a user or another program with some degree of independence or autonomy, and in so doing, employ some knowledge or representation of the user's goals or desires."* It views an intelligent agent as acting for another, with authority granted by the other entity.

FIPA (Foundation for Intelligent Physical Agents) uses a strawman definition of agent for all their specifications [FIPA]. They define an agent as: *"an entity that resides in environments where it interprets "sensor" data that reflect events in the environment and executes "motor" commands that produce effects in the environment. An agent can be purely software or hardware. In the latter case a considerable amount of software is needed to make the hardware an agent."*

Wooldridge and Jennings provides a weak notion of agency, which enjoys several properties, such as *autonomy, social ability, reactivity, proactivity,* [Wooldridge, 1995]. They said a simple way of conceptualizing an agent is thus as a kind of UNIX-like software process, that exhibits these above properties. This weak notion of agency has found currency with a surprisingly wide range of researchers.

Based on the examination of a list of agent definitions, Franklin and Graesser pointed out some requirements constituting the essence of being an agent and proposed a mathematical style definition of an autonomous agent which is widely accepted [Franklin, 1996]: *"An autonomous agent is a system situated within and a part of an environment that*

senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future."

The reason why it is so difficult to define precisely 'what an agent is', is that various attributes associated with agency are of different importance in different domains. While there is no universally accepted exact definition of the term 'agent', we provide our agent definition that captures most of the agent desiderata based on [Lind, 2001]: *"An agent is a software system that is situated in an environment and that operates in a continuous Perceive-Reason-Act (PRA) cycle, including communicating and coordinating actions with other agents in order to achieve global objectives that are consistent with individual goals",* as shown in Figure 2-1.
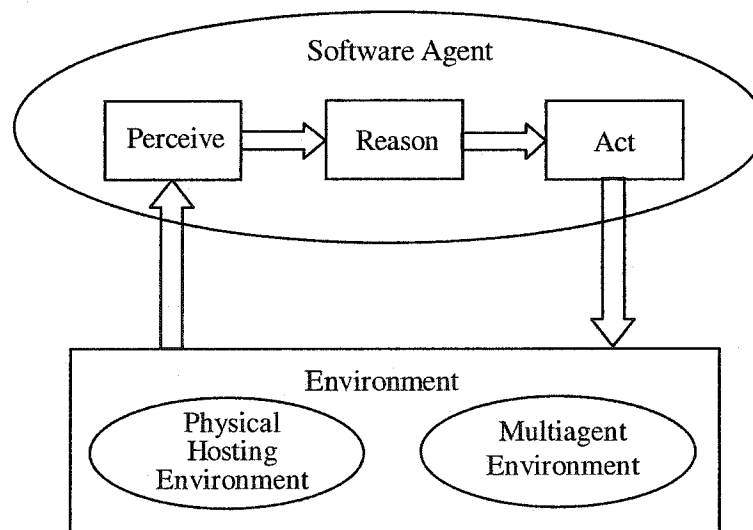
Figure 2-1: Software Agent Overview

Here the environment certainly includes both the *physical hosting environment,* such as an electric power system, and the *multiagent environment* consisting of other agents. The agent has the ability to persistently sense its environment. Based on the percepts from the environment and its own domain knowledge, the agent actively performs a reasoning process (decision-making) to determine the possible actions to best achieve the objectives. Then the agent autonomously carries out the selected set of actions, which in turn will change the

states of the environment.

2.3.2 Attributes of Intelligent Software Agent

As mentioned earlier, although there is no unanimously agreed definition of the term agent, an intelligent software agent may possess some characteristics, such as *autonomy*, *social ability, reactivity, and pro-activeness,* as shown in Figure 2-2. Some of those commonly identified agent attributes are described below.
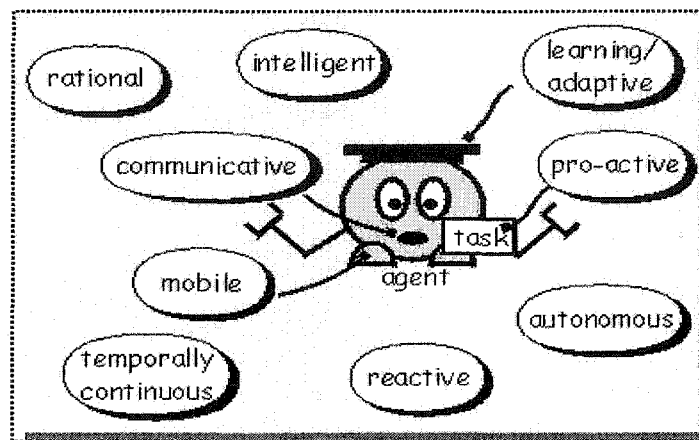
Figure 2-2: Properties of Intelligent Agent

- *Autonomy.* An agent can operate without direct intervention of humans or others, and have some kind of control over their actions and internal state [Castelfranchi, 1995]. This means that it should have some degree of autonomy from its user. A more autonomous agent can pursue an agenda independent of its user. This requires aspects of periodic action, spontaneous execution, and initiative, in that the agent must be able to take preemptive or independent actions that will eventually benefit the user [Foner, 1993].

- *Social Ability/Cooperation.* Agents can interact with other agents (and/or possibly humans) via some kind of *agent-communication language* (ACL) [Wooldridge, 1995]. Inter-agent cooperation is a mechanism by which agents exchange their knowledge, their beliefs and their plans to work together and solve larger problems, which are beyond their individual capabilities.

▪ *Reactivity*. Agents perceive their environment, (which may be the physical world, a user via a graphical user interface, a collection of other agents, the Internet, or perhaps all of these combined), and respond in a timely fashion to the changes that occur in it [Wooldridge, 1995].

▪ *Pro-activeness*. Agents do not simply act in response to changes in the environment; they are able to exhibit goal-directed behavior by taking the initiative [Wooldridge, 1995].

▪ *Mobility*. Agents can move {code, state} around an electronic network and continuously execute its actions [Wooldridge, 1995]. This ability could reduce data transfer while interacting with environment and help in controlling the information flow to alleviate network bandwidth saturation. For example, if data is distributed but bandwidth is costly, unreliable or temporary, then it may be better for the agent to move to where the data is and do its processing there.

▪ *Rationality*. Agent may be able to maintain a balance between individual and social responsibilities while it acts to achieve its goals.

▪ *Temporal Continuity*. Agents are continuously running processes, not "one shot" computations that terminate [Wooldridge, 1995].

▪ *Adaptivity*. Agents can continuously adapt to changes in the environment [Wooldridge, 1995].

▪ *Personizability*. The point of an agent is to enable people to do some task better. Since people don't do all the same tasks, and even those who share the same task do it in different ways, an agent must be educable in the task and how to do it. Ideally, there should be components of learning and memory [Wooldridge, 1995].

These above properties can be descriptive in distinguishing agents from ordinary software programs. However, it is not realistic to assume that the actual agents will satisfy all of these characteristics in their full sense.

2.3.3 Multiagent Systems

Multiagent Systems (MAS) are systems of multiple software agents which are essentially autonomous, distributed and maybe heterogeneous in nature. As pointed out by Durfee et al. [Durfee, 1989], usually several agents need to form *"a loosely coupled network, called a multiagent system, to work together to solve problems that are beyond their individual capabilities or knowledge of each entity"*, as shown in Figure 2-3.
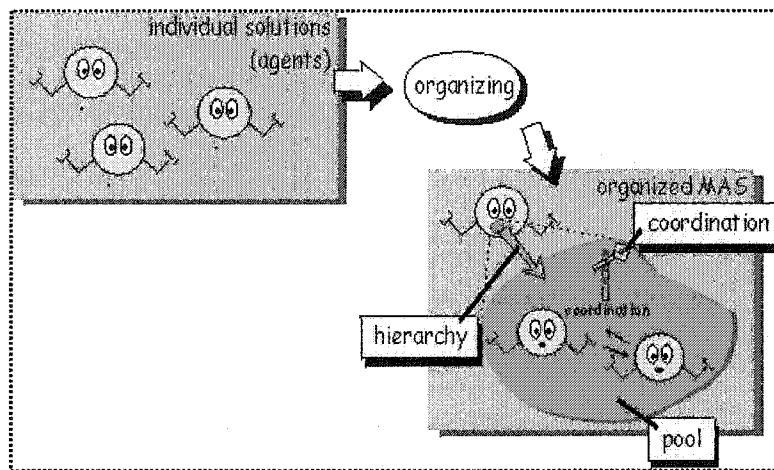
Figure 2-3: Multiagent Systems Overview

More recently, the term multiagent system has been given a more general meaning, and it is now used for all types of systems composed of multiple autonomous components showing the following characteristics [Jennings, 1998]:

- Each agent has incomplete capabilities to solve a problem

- There is no global system control

- Data is decentralized

- Computation is asynchronous

Multiagent system is regarded as a natural abstraction of the real world (a community of entities each with their own goals, communicating and often working together to achieve mutual benefit). In order to ensure satisfactory operation of multiagent systems, coordinated interaction among several autonomous entities is extremely important because no single

agent in a MAS has sufficient resources, intelligence, or competence to solve the problem on its own. Thus without coordination, all the benefits of decentralized problem solving provided by MAS will totally vanish. Successful application of multiagent systems needs to coordinate intelligent behaviors among agents – how they coordinate their knowledge, goals, skills, and plans jointly to take action or to solve problems.

Multiagent systems have proven to be an effective paradigm in a number of distributed networked applications that require information integration from multiple heterogeneous autonomous entities [Honavar, 1998; Yang, 1999; Caragea, 2001]. In [Müller, 1997], Müller proposes three requirements to be satisfied by the domain to ensure that multiagent systems can fruitfully be applied. First, the system should be characterized by *natural distributivity,* i.e. when mapping a distributed domain to a model, it is essential to keep up the distributivity, or the distributivity lies within the task structure. Second, the processes or objects, which should be implemented with the help of a multiagent system, are in need of *complex interactions,* e.g. they have to negotiate or exchange complex information. The third presupposition for the application of multiagent-systems is the demand for a *dynamic environment.* Dynamics does not only mean changing data of the environment but also changing the structure of the whole system. Surprisingly, our deregulated environment meets all the three requirements. Multiagent system is a promising paradigm for the information processing and decision support problems we are facing in deregulated power industry.

2.4 Applications of Agent-based Systems to Electric Power Systems

During the past years, software agents and multiagent systems have been used in an increasingly wide variety of domains, ranging from comparatively small systems such as email filters [Maes, 1994], information retrieval [Takahashi, 1997], to large and complex

mission-critical applications such as intrusion detection in communication networks [Helmer, 1998], air traffic control [Ljunberg, 1992] as well as electric power systems [McCalley, 2003a; Liu, 2000; Rehtanz, 2003; Gustavsson, 1999; Contreras, 1999]. It is always useful to do an extensive review of these agent applications. However, due to their variety nature and in order to focus on our problem, in what follows, we only describe some agent-based applications that actually utilize some of previously described agent-related desiderata, e.g., inter-agent communication and/or coordination, in various aspects of electric power system's operation and management.

2.4.1 Power Market Modeling and Simulation

Market-related applications of multiagent systems are being actively studied by the power systems community. Researchers have investigated strategic behavior of agents under congestive grid, design of market structures, design of auction mechanisms for power and ancillary services, market power analyses, application of machine learning algorithms to generate bidding strategies, and also to demonstrate loopholes in market designs. Recent representative work in this area includes [Seeley, 2000; Singh, 1998; Richter, 1999; Krishna, 1998; Lane, 2000]. Lane, D.W. etc. [Lane, 2000] proposed and developed a multi-agent based system to assist players, such as, owners of power generation stations, owners of transmission lines, and groups of consumers, in the same market to select partners to form coalitions. The system provides users with a cooperation plan and its associated cost allocation plan for the users to support their decision making process.

2.4.2 Transmission Planning

Transmission planning addresses the issue of increasing transmission capacity by adding new lines to serve the load without violating security constraints. Contreras and Wu [Contreras, 1999] have reported a novel application of distributed artificial intelligence concepts to this traditional problem. Specifically, the researchers apply coalition formation as

a framework to elicit negotiated transmission planning agreements. The investigators use a DC power flow for system analyses. For each coalition consisting of at least one load, one generator, and one transmission line, the following constraints must be satisfied: generators must meet the load demand, no thermal limit violations, and the network must be connected. Initial work by the researchers used the game theoretic notion of Bilateral Shapley Value to allocate the benefit of the coalition among the agents. Recent work by the researchers applies the game theoretic-concept of the "kernel" instead of the Shapley Value for better results [Contreras, 2000].

2.4.3 Power Systems Operations

"Asynchronous Teams" developed by Talukdar, et al [Talukdar, 1994a] are groups of distributed autonomous agents that cooperate to solve real-time and off-line control problems. The research reported in [Talukdar, 1994b] uses this concept to "agentize" the workhorse algorithm of power system operational planning, viz., the optimal power flow (OPF) algorithm. Wang, H.F. etc. [Wang, 2001], proposed a conceptual design for distributed control of the power system by intelligent agents operating locally with minimal supervisory control.

2.4.4 Strategic Power Infrastructure Defense

This research effort, jointly sponsored by EPRI and Department of Defense, to develop revolutionary technologies to reduce the vulnerability of the power system due to catastrophic and cascading events. Such an effort requires wide-area vulnerability assessment and coordination of several different actions. The notion of software agents and multiagent systems is the unifying thread of this project. The agents developed as part of this effort interact and take decisions using a three-layered architecture, viz., deliberative, coordination and reactive layers. The conceptual vision of this project and salient features of the design has been reported in [Liu, 2000; Amin, 2001; Liu, 2001].

2.5 Summary

This chapter reviews some literature pertained to this work. First, transmission system maintenance strategies, power industry efforts regarding standardization of communication protocols and information integration are briefly described. Then multiagent system technology, such as agent definitions, agent properties, concept of multiagent systems and their attributes are described. Multiagent system technology is now fascinating the power system community by offering a modular, extensible, flexible, and integrated approach to address the complex information processing and decision support problems.

In the following chapters, we will first introduce our risk-based transmission maintenance optimization problem. In order to coordinate the maintenance decisions among various independent entities for displacing centralized approaches, we will investigate the mechanism of multiagent negotiated decision-making, where autonomous distributed agents seek to achieve global objectives that are consistent with individual goals. A multiagent negotiation system will built in which software agents, armed with coded negotiation models, represent different decision-makers, and conflict resolution is achieved via inter-agent message exchange until agreement is reached.

3 TRANSMISSION SYSTEM MAINTENANCE OPTIMIZATION

3.1 Introduction

Most maintenance practices in transmission systems currently rely on time schedule or some other counters, such as number of operations and/or visual inspections. These existing maintenance approaches may be overly conservative and could result in maintenance being scheduled when none is required or deferred when it is critical. Innovative maintenance programs are needed in restructured power systems that would allow utilities to take proper steps to ensure reliability while controlling and, even lowering costs.

In this chapter, we first introduce such a program, a risk-based maintenance optimization system for transmission equipment [Jiang, 2003a; Jiang, 2003b]. This framework provides the ability to select and schedule maintenance tasks so as to utilize the available financial and human resources to optimize the risk-reduction achieved from them within a given budget cycle. It is important to observe the significance of this objective in that it differs from the traditional utility objective of minimizing costs subject to some constraint on minimal maintenance achievement. It also differs from the long-term objective of maximizing equipment life.

Although this approach is applicable to all transmission equipment, in order to limit our work, we will focus on power transformer in the rest this thesis. We will describe various transformer monitoring techniques, available condition data, as well as major failure modes. Then, we will develop several models for systematically utilizing available equipment condition/life data to provide a quantitative estimation of equipment's failure probability, which is a prerequisite for the implementation of our risk-based maintenance optimization system.

3.2 Risk-based Transmission Maintenance Optimization

Transmission equipment maintenance is costly but essential to ensuring transmission system reliability. Its effectiveness can vary dramatically depending on the target and timing of the maintenance activities. The state of the art in transmission maintenance practice goes by the term "reliability centered maintenance" (RCM) as descried before, which prioritizes maintenance activities based on quantification of likelihood and consequence of equipment failures.

The objective of the work reported in [Jiang, 2003a; Jiang, 2003b] is to develop a systematic methodology for transmission maintenance scheduling by achieving maximum cumulative system risk reduction, subject to constraints on economic resources, available maintenance crews, and restricted time intervals. We have developed such an optimization problem and solution algorithms, described in [Jiang, 2003a; Jiang, 2003b]. Here we just provide the attributes of this problem that are germane to the objective of this work.

The risk index for a single contingency is an expectation of severity, computed as the product of contingency $k's$ probability $p(k)$ with contingency severity $sev(k|m,t)$, where m indicates the mth maintenance task and thus the network configuration in terms of network topology and unit commitment, and t indicates the hour and thus the operating conditions in terms of loading and dispatch. The risk is given by $R(k,m,t)= p(k)*sev(k|m,t)$. A reference "basecase" network configuration (with no maintenance task) is denoted with $m=0$. The severity function $sev(k|m,t)$ comprises two parts: system related severity that captures the contingency severity in terms of overload, cascading overload, low voltage and voltage instability [Ni, 2003]; component damage severity that describes severity related to component damage and re-dispatch cost. The risk associated with any given network configuration and operating condition is computed by summing over the no-contingency condition ($k=0$) and all N contingencies. Cumulative risk assessment performs sequential, hourly simulation over a long term, e.g., 1 year. With some simplified assumptions as

discussed in [Jiang, 2003b], we can compute the cumulative-over-time risk reduction due to maintenance task m that reduces the contingency probability by $\Delta p(k,m)$, performed at time t_f as:

$$CRR(k,m,t_f) = \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,m,t)dt \qquad (3.1)$$

Let N be the number of maintainable transmission components and L_k be the number of maintenance *levels* for component k. Let $k = 1,...,N$ be the index over the set of transmission components, $m = 1,...,L_k$ be the index over the set of maintenance activities for transmission component k, and $t = 1,...,T$ be the index over the time periods. Define *Iselect(k,m,t)*=1 if the mth maintenance task for component k begins at time t, and 0 otherwise; *Iactive(k,m,t)*=1 if the mth task for component k is ongoing at time t, and 0 otherwise. Define $d(k,m)$ to be the duration of task m for component k, so that

$$Iactive(k,m,t) = \sum_{j=t-d(k,m)+1}^{t} Iselect(k,m,j), \forall (k,m,t) \qquad (3.2)$$

Equation (3.2) indicates that determination of whether the mth task for component k is active at time t is accomplished by searching the selection function over the duration of the task until t. Also, $cost(k,m)$ is the cost of the mth task for component k, and $CRR(k,m,t)$ is its cumulative risk reduction if it begins at time t. Let $Infeas(k,m)$ be the set of periods for which task m for component k cannot be performed. Each {component, task} combination (k,m) is tagged with a budget category $B(k,m)=b$. For example, $b \in 1, 2, 3, 4$, where 1=transformer maintenance, 2=tree-trimming, 3=insulator cleaning, and 4=circuit breaker maintenance. $Crew(k,m)$ is the required number of crews for m^{th} task for component k. $TotCrew(b,t)$ is the number of crews available for maintenance category b at time t. Then the objective function of our maintenance optimization can be expressed as:

$$Max\left\{ \sum_{k=1}^{N} \sum_{m=1}^{L_k} \sum_{t=1}^{T} CRR(k,m,t) \times Iselect(k,m,t) \right\} \qquad (3.3)$$

Subject to:

$$\sum_{m=1}^{L_k}\sum_{t=1}^{T} Iselect(k,m,t) \leq 1, \ k = 1,\cdots,N \tag{3.4}$$

$$Iactive(k,m,t) = 0, \forall t \in Infeas(k,m), \forall (k,m) \tag{3.5}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_k} Iactive(k,m,t) * Crew(k,m) < TotCrew(b,t), \forall t,b = 1,...4 \tag{3.6}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_k}\sum_{t=1}^{T} cost(k,m) * Iselect(k,m,t) < TotCost(b), b = 1,...,4 \tag{3.7}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_k} Iactive(k,m,t) * \Delta R(k,m,t) \leq \Delta Rmax(t), \forall t \tag{3.8}$$

$$Iselect(k,m,t) \in \{0,1\}, \forall (k,m,t) \tag{3.9}$$

In this optimization problem, the objective (3.3) is to maximize total cumulative risk reduction. Constraint (3.4) restricts each component to be maintained at most once. Constraint (3.5) requires each maintenance task be performed only within its feasible time period. Constraint (3.6) stipulates the number of maintenance tasks ongoing during any period is limited by crew constraints. Constraint (3.7) represents budget constraints. Constraint (3.8) ensures maintenance task (k,m) resulting in a risk increase of $\Delta R(k,m,t)$ due to outage of component k at time t does not exceed the maximum allowable risk increase for time t, $\Delta Rmax(t)$. The maximum allowable risk increase for time t is set so that no maintenance outage may cause a violation of reliability criteria. To solve this optimization problem is to determine $Iselect(k,m,t)$, which then determines $Iactive(k,m,t)$. The optimization problem is integer, with multiple constraints and high dimension and therefore is challenging to solve. We have tried three different solution methods: heuristic, branch and bound, and relaxed linear programming with dynamic programming/heuristic (RLP-DPH).

Obviously in the above approach, the transmission system maintenance scheduling is done centrally. The exclusive advantage of this centralized processing is that the solution

could optimize the reliability and operation cost of the entire system. However, in practice, this is often infeasible. In order to solve a problem centrally, one needs the complete information on the objective function as well as all the constraints. As electric utilities are heavily separated geographically and functionally, this information may be unattainable or prohibitively expensive to retrieve. More importantly, independent entities may be unwilling to share or report their private information, as it is not incentive to do so. Thus in order to optimize the maintenance schedule among various independent entities in a restructured power system, we must look beyond the traditional centralized approach. We will develop a multiagent framework in Chapter 4, to facilitate distributed decision-making among different autonomous entities through multiagent negotiations.

We assume that a maintenance activity, m, decreases the probability of a particular contingency k, which is triggered by failure of the associated equipment. In order to calculate the cumulative risk reduction by maintenance activities as expressed in (3.1), we need to determine the maintenance induced contingency probability reduction, i.e.,

$$\Delta p(k,m) = p_{bm} - p_{am}$$
(3.10)

where p_{bm} is the equipment failure probability before maintenance, p_{am} is the equipment failure probability after maintenance.

Calculation of the above maintenance induced contingency probability reduction is an extremely challenging problem. Because, unlike most reliability modeling which utilizes steady-state failure probabilities to capture average behavior over a large number of components and over an extended period of time, this asset management problem requires transient failure probabilities to capture instantaneous behavior for each specific component. As a result, failure probabilities cannot be computed from the number of failures of a population of components but rather from the most recent condition monitoring information available.

In the following sections, we will first review some equipment condition monitoring techniques, and then describe available condition data as well as major failure modes.

As pointed out before, although the above maintenance optimization approach is applicable to all transmission system equipment, in order to limit our work, we will focus on power transformer in the rest of this dissertation.

3.3 Various Transformer Condition Monitoring Techniques

The development in sensor, communication, computer, and data storage technologies has allowed the realization of a variety of condition monitoring systems for bulk transmission system equipment, e.g., power transformers, circuit breakers, transmission lines, and other related equipment, in order to utilize these capital-intensive transmission equipment in the optimal manner. Condition monitoring provides the surveillance of operating condition of the equipment in order to ensure proper performance and to detect any abnormalities indicative of approaching failures. For power transformers, monitoring can take many forms including manual inspections (periodic visual inspections), continuous monitoring with a change in status/condition alarm as the only output (low level alarm), periodic automated monitoring (connection of portable analysis instruments), or continuous on-line monitoring (full time measurement of parameters to assess condition while in service). Below we introduce some of these techniques, which monitor some power transformer key parameters, and provide crucial information for estimating the equipment failure probability [Chu, 1999; Bengtsson, 1996; Kirtley, 1996, Krieg, 2000].

3.3.1 Operating Condition Monitoring

Transformer operating condition is mainly determined by its load current and voltage. Maximum loading of transformers is restricted by the temperature to which the transformer and its accessories can be exposed without excessive loss of life. Continuous on-line monitoring of current and voltage at operating frequency coupled with temperature

measurements can provide a means to gauge thermal performance of the equipment.

3.3.2 Temperature Monitoring

Based on temperatures measured at different parts of transformer, e.g., oil temperature, winding temperature; thermal related faults could be identified. There is a direct correlation between winding temperature and normally expected service life of a transformer. The hottest spot temperature of the winding is one of the most important limiting factors for the load capability of power transformers. Insulation materials lose their mechanical strength with prolonged exposure to excessive heat. This can result in tearing and displacement of the paper and dielectric breakdown that will result in premature failures. Different kind of temperature sensors including fiber optic temperature sensor can be used to obtain on-line temperature measurements from various part of the equipment.

3.3.3 Dissolved Gas-in-oil Analysis

Dissolved Gas-in-oil Analysis (DGA) has proven to be a valuable and reliable diagnostic technique for the detection of incipient fault conditions with liquid-immersed transformers by detecting certain key gases. The gases involved are generally CO, CO_2, H_2, CH_4, C_2H_2, C_2H_4, C_2H_6. For any given oil sample, the absolute and relative concentrations of faults gas can be used to indicate the type, intensity and location of the fault. Table 3-1 summarized the key gas interpretation method [Pahlavanpour, 1997].

For a number of years, on-line sensors for detecting hydrogen (mainly indicative of partial discharge, but also of arcing) have been available on the market, e.g. the Hydran sensor from *Syprotec*. These sensors are most sensitive to hydrogen, but also measure other combustible gasses to a certain extent. Recently, efforts have been made to develop on-line sensors that measure individual concentrations of several gasses.

Table 3-1: Key Gas Interpretation

Key Gas	Characteristic Fault
H_2	Partial Discharge
C_2H_6	Thermal Fault $< 300°C$
C_2H_4	Thermal Fault $300°C \sim 700°C$
C_2H_2, C_2H_4	Thermal Fault $> 700°C$
C_2H_2, H_2	Discharge of Energy

3.3.4 Moisture-in-oil Monitoring

Moisture in the transformer reduces the insulation strength by decreasing the dielectric strength of the transformer's insulation system. The combination of moisture, heat and oxygen are the key conditions that indicate accelerated degradation of the cellulose. Excessive amounts of moisture can accelerate the degradation process of the cellulose and prematurely age the transformers' insulation system. The moisture level of the sample is evaluated at the sample temperature and at the winding temperature of the transformer. This data is vital in determining the relative saturation of moisture in the cellulose/liquid insulation complex that establishes the dielectric integrity of the transformer.

3.3.5 Partial Discharge Monitoring

Partial Discharges (PD) in the main insulation often poses a major threat to the function of the transformer. The major causes of the long-term degradation and ultimate failure of this insulation are erosion and tracking due to partial discharges. A significant increase either in the partial discharge level or in the rate of increase of partial discharge level can provide an early indication that changes are evolving inside the transformer. Localization of partial discharges is made acoustically using different methods for triangulation. This requires deep knowledge of wave propagation in different types of materials/liquids and is a task for highly qualified experts.

There are also some other types of monitoring methods available, e.g. insulation

power factor, static charge in oil, pump/fan monitoring. From the on-line monitoring information, developing transformer failure modes can be detected well before they could lead to possible catastrophic transformer/system failures.

3.3.6 Power Transformer Condition Data

These above condition monitoring techniques provide enormous amount of equipment condition data, which is a good indication of the equipment's operating condition. Typically the data includes:

- From testing (annual): insulation resistance, insulation power factor, winding resistance.

- Data from sampling (monthly to annual): gas-in-oil testing, moisture-in-oil.

- From inspections (monthly): conditions of transformer surface, oil levels, peak temperatures (top oil and windings), silica gel breathers, pressure gauge reading, pressure relief vents, cleanliness of bushings, condition of cooling fans.

- From real-time SCADA/EMS (every 3-5 minutes): loading, temperatures.

- From on-line condition monitoring (continuously): real-time current & voltage, temperatures, gas-in-oil contents, moisture content in oil, acoustic monitoring (partial discharge).

An important issue related to the accumulation of so much data is how to most effectively utilize it to optimize related maintenance activities. Due to the physical nature of the electric power systems and evolution of equipment condition monitoring techniques, the equipment information are highly heterogeneous, physically distributed, and enormous in size. Thus, the effective utilization of the equipment condition information presents great challenge in practice. Multiagent systems are capable of extracting and integrating information from heterogeneous, autonomous, and distributed data sources. And fortunately,

such a system, called INDUS [Reinoso-Castillo, 2002], has already been developed within our research team.

3.4 Typical Transformer Failure Modes

During the entire operation time, a power transformer has to withstand numerous stresses. These stresses are of thermal, electrical, chemical and mechanical nature and can result in various problems, which may eventually lead to a catastrophic failure if not corrected by maintenance in time. Based on an extensive review of literature and some other useful resources, we have summarized some typical failure modes, causes, effects as well as corresponding maintenance activities for power transformers, which is shown in Appendix A. These failure modes can be mainly grouped into four categories: general degradation, thermal related failures, dielectric related failures, and mechanical related failures [Bengtsson, 1996].

3.4.1 General Degradation

Degradation means a reduced insulation quality. The insulating materials used in the manufacture of power transformers, whether they are solid (paper, cellulose, pressboard) or liquid (oil), undergo a chemical alteration with time under the influence of heat and other factors such as oxygen and moisture [Hochart, 1987, p78]. The deterioration processes are accelerated by thermal and voltage stresses. The rate of decline in the strengths of an insulation system is a function of temperature, and is believed to follow the Arrhenius chemical reaction equation [Flanagan, 1992]. Various tests can be taken to determine the condition of the insulation system, including insulation resistance, insulation power factor, dielectric strength, interfacial tension (IFT), moisture content [IEEE Std C57.125-1991].

3.4.2 Thermal Related Failures

Overload, failures in the cooling system and high ambient temperatures are the main

causes of transformer thermal problems. Thermal stress is a leading factor that causes the insulation degradation. Exposed to prolonged excessive heat, insulation materials lose their mechanical strength and may lead to entire insulation breakdown. Decomposition products from breakdown of the oil, insulating paper or boards, glues, are transported through the transformer by the coolant oil. Some are low molecular weight gases dissolved in the oil and can be identified by gas chromatography. Dissolved Gas-in-oil Analysis (DGA) has proven to be a valuable and reliable diagnostic technique for the detection of incipient fault conditions with liquid-immersed transformers by detecting certain key gases. The gases involved are generally CO, CO_2, H_2, O_2, CH_4, C_2H_2, C_2H_4, C_2H_6. There is also a direct correlation between winding temperature and normally expected service life of a transformer [IEEE C57.115-1991]. The winding hottest spot temperature is also one of a number of limiting factors for the load capability of transformers [Chu, 1999].

3.4.3 Dielectric Related Failures

Partial discharge, corona, arcing, insulation tracking, static electrification of oil, are all forms of dielectric failure modes. Among them, partial discharge is the most common one. Reference [IEEE Std C57.127-2000] describes the instrumentation, test procedure and results interpretation for the acoustic emissions detection of partial discharges in power transformers. The dielectric breakdown of insulation will result in transformer failure.

3.4.4 Mechanical Related Failures

As a result of short circuit forces, or of possible vibration of supporting parts, mechanical related failures often occur in the active parts of the transformer. Resulting faults are deformations of the windings or of the cleat and leads [Bengtsson, 1996]. The most effective methods to detect any possible mechanical related failures include frequency response analysis (FRA) and leakage inductance.

Other failure modes include bushing contamination, earthing malfunctions, and

protection failures.

As summarized in Appendix A, if there is some abnormality in equipment condition information, corresponding failure mode(s) could be identified and appropriate maintenance activities should be performed to prevent possible equipment failures.

3.5 Instantaneous Equipment Failure Probability Estimation

The goal of this section is to develop some systematic and consistent approaches for associating to any maintenance task a quantitative evaluation of the reduction in probability of occurrence of the failure mode(s) the task is intended to affect. We assume a one-to-one mapping between a failure mode and a contingency k, so that there is no notational problem with denoting the desired probability reduction from maintenance m by $\Delta p(k,m)$. This assumption is easily lifted for a contingency that may be caused by multiple failure modes, as long as the failure modes are independent.

As indicated before, most probabilistic analyses for reliability focus on component average performance over long time periods and therefore average (or steady-state) probabilities are desirable to characterize the component behavior. But in order to quantify the component failure probability reduction from maintenance activity m, we need to estimate component instantaneous failure probability based on its available condition monitoring information. In the following sections, we will present several models for linking the equipment condition monitoring information to its time-dependent failure probability.

3.5.1 Hazard Function Models

We begin with some concepts in equipment reliability. Let T denote the time from the equipment is put into operation at time $t = 0$ until a failure occurs. The equipment may be either new or used when it is put into operation. In many cases the equipment will be re-put into operation after a refurbishment or a failure has been corrected. The uncertainties in the

time to failure, T, may be described by the distribution function $F(t) = \Pr(T \leq t)$, or the probability density function $f(t) = F'(t)$. The probability density function $f(t)$ may be expressed as:

$$f(t)\Delta t \approx P(t < T \leq t + \Delta t) \tag{3.11}$$

Hence, $f(t)\Delta t$ is approximately equal to the probability that the equipment will fail in the time interval $(t, t + \Delta t)$. The survivor function, which gives the probability that equipment will not fail up to time t, is given by:

$$R(t) = \Pr(T > t) \tag{3.12}$$

The equipment's life distribution is often most effectively characterized by the so-called failure rate, or hazard function $h(t)$, which is the conditional probability of failure. The failure rate function $h(t)$ may be expressed as:

$$h(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} \Pr[t < T \leq t + \Delta t \mid T > t] \tag{3.13}$$

If we consider the equipment that has survived the time interval $(0, t)$, i.e. $T > t$, then the probability that the equipment will fail in the time interval $(t, t + \Delta t)$ is approximately $h(t) * \Delta t$. It is only necessary to know one of the functions $h(t)$, $f(t)$, $R(t)$ in order to be able to deduce the other two, as illustrated in Figure 3-1 [Wolstenholme, 1999].

f(t)

-R'(t)

$$h(t)\exp[-\int\limits_{0}^{t}h(\tau)d\tau]$$

$$\frac{f(t)}{\int\limits_{t}^{\infty}f(\tau)d\tau}$$

$$\int\limits_{t}^{\infty}f(\tau)d\tau$$

-R'(t)/R(t)

R(t)

h(t)

$$\exp[-\int\limits_{0}^{t}h(\tau)d\tau]$$
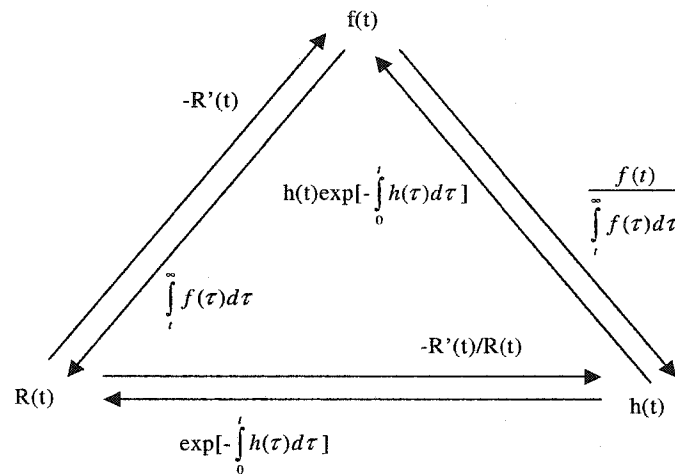
Figure 3-1: Relationships between h(t), f(t), and R(t)

The Weibull distribution is a widely used distribution to model equipment's time-to-failure. The Weibull probability density function is:

$$f_T(t) = \begin{cases} \dfrac{\beta t^{\beta-1}}{\alpha^\beta}\exp\left[-\left(\dfrac{t}{\alpha}\right)^\beta\right], & t,\alpha,\beta > 0 \\[2em] 0, \; otherwise \end{cases} \tag{3.14}$$

β is called the shape parameter because it determines the shape of the distribution. The parameter α is called the scale parameter because it determines the scale. Typically β is between 0.5 and 8.0. As β increases, the mean of the Weibull distribution approaches α and the variance approaches zero. Figure 3-2 illustrates the Weibull distribution with different shape and scale parameters.
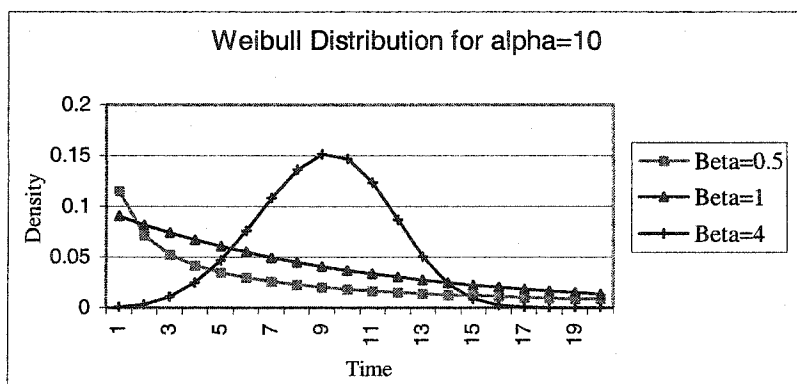
Figure 3-2: Weibull Distributions

The Weibull hazard function is:

$$h(t) = \frac{\beta\, t^{\beta-1}}{\alpha^{\beta}}, \quad t > 0 \tag{3.15}$$

If $\beta < 1$, the failure rate is decreasing; if $\beta = 1$, the failure rate is constant at a value of $1/\alpha$; if $\beta > 1$, the failure rate is increasing.

In order to estimate the hazard function $h(t)$ for power transformers, a procedure is described in [Kogan, 1988]. Suppose we record transformer life data for specific kinds of power transformers (make, model and voltage level), In interval $[t_i, t_{i+1})$[1], let N_i denotes the number of power transformers survived at t_i, F_i indicates how many transformers failed, and C_i is the number of power transformers that were censored. For censored transformers, they are treated as removed ones because we assume their exact times of failure or removal are known. It is clear that the number of power transformers surviving until t_{i+1} is:

$$N_{i+1} = N_i - F_i - C_i \tag{3.16}$$

---

[1] The time interval for estimating power transformer failure rates must be not include a time period in which some maintenance was performed, i.e., it must be between maintenance periods. Typically, it ranges from one to two years.

The "end of observation" time, t_{ij}, for the j-th transformer in interval $[t_i, t_{i+1})$ is defined as:

$$t_{ij} = \begin{cases} t_{ijf}, & \text{if jth transformer is observed to fail} \\ t_{ijc}, & \text{if jth transformer is removed (censored)} \\ t_{i+1}, & \text{if jth transformer survives till } t_{i+1} \end{cases} \tag{3.17}$$

Then the total amount of time of exposure to risk of all power transformers, TR_i, during interval $[t_i, t_{i+1})$ is clearly:

$$TR_i = \sum_{j=1}^{N_i} (t_{ij} - t_i) \tag{3.18}$$

Then the estimated central failure rate in interval $[t_i, t_{i+1})$ is defined as:

$$\tilde{h}_i = F_i / TR_i \tag{3.19}$$

If we do not know the exact time of failure or removal, it would be reasonable to assume that all failures and removals are expected at the middle of the interval $[t_i, t_{i+1})$. Then the estimated central failure rate in $[t_i, t_{i+1})$ can take the form:

$$\hat{h}_i = \frac{F_i}{(t_{i+1} - t_i)(N_i - (F_i - C_i)/2)} \tag{3.20}$$

Although expression (3.20) is not as precise as (3.19), it is more precise than the estimation frequently used in engineering applications for the failure rate:

$$\bar{h}_i = F_i / [(t_{i+1} - t_i)N_i] \tag{3.21}$$

With reasonable precision data of the failure or removal times of the power transformers, we can use either equations (3.19) or (3.20) to estimate the failure rate, h_i, as illustrated in Figure 3-3.
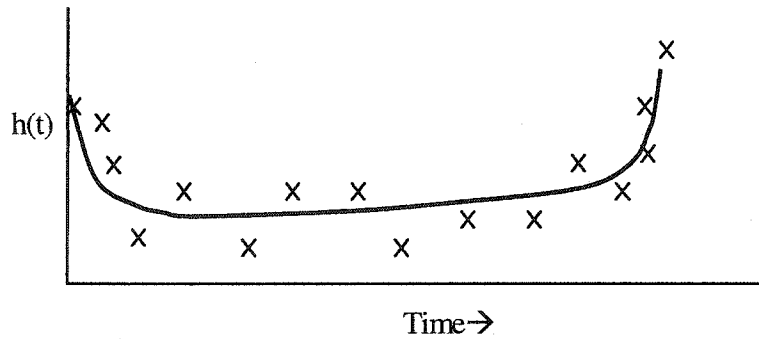
Figure 3-3: Bathtub Curve

Through experience and numerous data gathered by researchers and engineers, the transformer failure rate (hazard function, h_i) has been shown to follow the so-called "bathtub curve", as shown in Figure 3-3. The bathtub curve depicts equipment life in three stages. During the first stage, failure rate begins high and decreases rapidly with time. This stage is known as the infant-mortality period, and it has decreasing failure rate. The infant mortality is followed by nearly constant failure rate period, which is usually long. Finally, the curve ends with an increasing failure rate. This is the period of aging. This bathtub curve can be well modeled by the Mixture Weibull, comprising two or three Weibull distributions each of which have well-tuned and unique scale and shape parameters.

In a simplified method, called hazard function model 1 as shown in Figure 3-4, we utilize the equipment service time (component age) to get its time-dependent failure rate. Assume at time t_f , maintenance work m renews equipment condition back to t_0, then $\Delta p(k,m,t_f)$ can be easily obtained from the hazard function. As we can see from Figure 3-4, repeating a certain maintenance task will result in decreasing probability reduction.
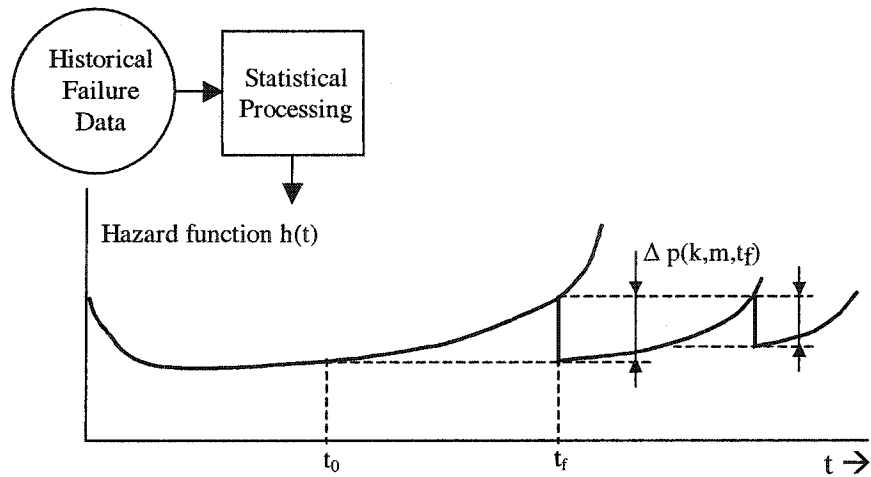
Figure 3-4: Hazard Function Model 1

Alternatively, in what we call hazard function model 2, we can divide the total transformer life cycle into several stages according to its condition, e.g. new, minor deterioration, major deterioration and failure, as illustrated in Figure 3-5. By evaluating the available equipment condition monitoring data, we can use the deterioration function $g(\underline{x})$, (which will be described in the next section), to determine the appropriate deterioration levels and then map the corresponding failure probabilities for both before maintenance, p_{bm}, and after maintenance, p_{am}, in order to calculate the maintenance induced contingency probability reduction.
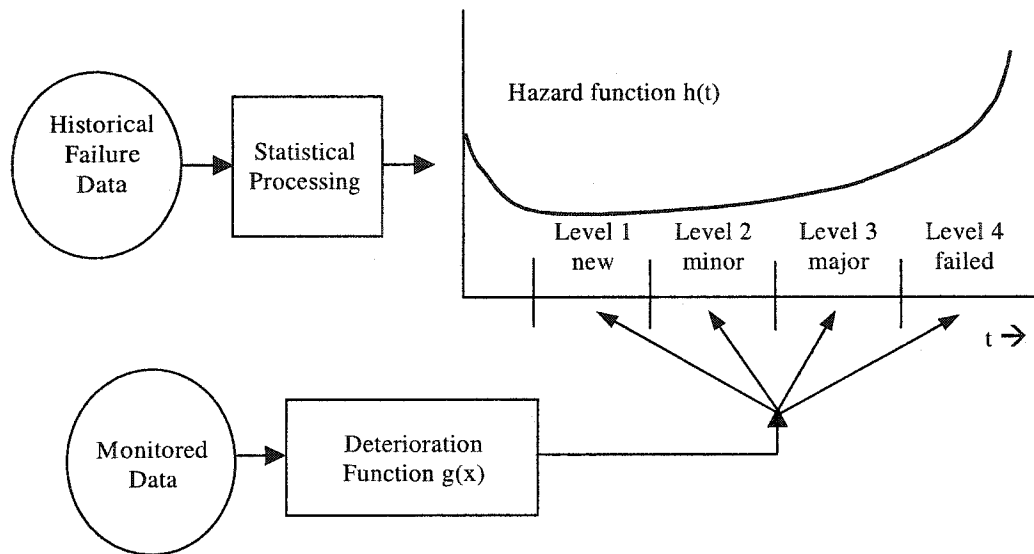
Figure 3-5: Hazard Function Model 2

In the above two hazard function models, the hazard function that captures the equipment life behavior remains constant. However, as more timely equipment condition information streams in, it can be used to update this function to reflect the equipment actual performance. We will introduce a Bayesian framework capable of updating equipment information based on newly acquired condition data in a later section.

3.5.2 Markov Model

Essential requirements for the approach are that we have at our disposal a set of condition measurements $\underline{x}(t)=[x_1(t),x_2(t),...,x_n(t)]$ for a number of similar components taken over an extended period of time $t=0,1,...,T$, and that it is possible to characterize boundary conditions that separate D states of deterioration, in terms of those measurements, via the deterioration function $g(\underline{x})$, such that deterioration level j is identified by $d_{j-1}<g(\underline{x})<d_j$, where the last state $j=D$ represents the *failed* state. It is important to note here that state D need not represent the rare "blue smoke" condition where the component has catastrophically failed (and for which very little data is typically available). Rather, state D may simply represent a set of measurement values for which engineering judgment would result in an action to

remove the component from service.
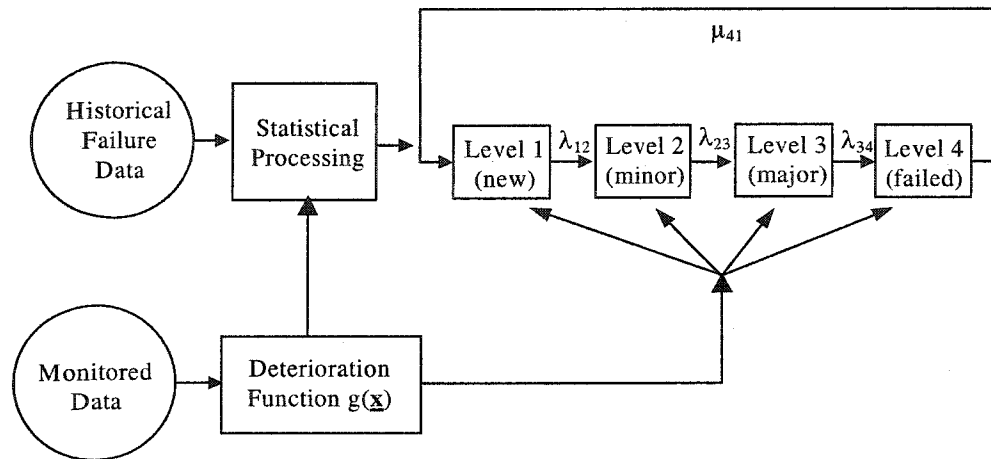
Figure 3-6: Markov Model

The approach is illustrated in Figure 3-6, based on a multi-state Markov model, where each of the D states is represented as a deterioration level. The particular representation of Figure 3-6 shows $D=4$ deterioration levels, and deterioration level j can be reached only from deterioration level $j-1$. However, the model is flexible so that any number of deterioration levels can be represented, and, if data indicates that transitions may occur between non-consecutive states (e.g., state 1 to state 3), the model can accommodate it. The transition from level 4 to level 1 stochastically represents the effects of maintenance, and since in our work, maintenance is a deterministic decision that results from the analysis, we would normally set $\mu_{41}=1$.

There are three main steps to implementing the approach: (a) Obtain the deterioration function $g(\underline{x})$. (b) Perform the statistical processing necessary to estimate the transition rates λ_{jk}. (c) Use the model to obtain the failure probability.

- *Deterioration function*: In both the above hazard function model 2 and Markov model, we need to use the equipment condition monitoring information data to determine its deterioration level. The deterioration function, denoted by $g(\underline{x})$, may be an analytical expression but in general would be a set of rules encoded as a program, likely consisting of a nested set of *if-then* statements that returns a scalar assessment value.

One method for monitoring the deterioration of transformer insulating material involves calculating the total volume of gas evolved. The total volume of evolved gas is an indicator of the magnitude of incipient faults. Identification of deterioration levels as a function of concentrations for separate gases as well as the total concentration of all combustible gases is provided in [IEEE Std C57.104-1991], as shown in Table 3-2. Here conditions 1, 2, 3, 4 correspond to the deterioration level 1, 2, 3, 4 in both the hazard function model 2 and the Markov model. Table 3-2 by itself represents only a first-order assessment criterion and must be supplemented with additional rules for interpreting DGA data for specific cases. For example, the rate of change of each gas concentration may be more informative of impending failures than the gas concentrations themselves.

Table 3-2: Determine the Transformer Condition based on DGA[2]

Status	Dissolved Key Gas Concentration Limits (ppm)							
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
Condition 1	100	120	35	50	65	350	2500	720
Condition 2	101-700	121-400	36-50	51-100	66-100	351-570	2500-4000	721-1920
Condition 3	701-1800	401-1000	51-80	101-200	101-150	571-1400	4001-10000	1921-4630
Condition 4	>1800	>1000	>80	>200	>150	>1400	>10000	>4630

For the model of Figure 3-6, the assessment value would be a deterioration level 1, 2, 3, or 4. EPRI has made significant effort in summarizing such rules, and most companies have expertise embedded in engineering personnel from which such rules may be developed. It is likely that such rules would depend not only on the condition measurements x but also the rates of change in such measurements. A challenging and worthy research problem for most equipment failure modes is to develop deterioration functions that return physical attributes characterizing the failure mode. Solution to this problem requires fundamental and

---

[2] TDCG: Total dissolved combustible gas. The TDCG value does not include CO_2, which is not a combustible gas.

complete understanding of the physical processes involved in the component deterioration. Although our overall approach readily admits such functions, they are not required.

• *Transition rates*: Once we decide how many deterioration levels to model and consequently how many Markov states are needed, (for example, 4, as shown in Figure 3-6), the transition intensities between these states can be obtained from life histories of multiple units of the same manufacturer and model. In the case of Figure 3-6, we would need to compute λ_{12}, λ_{23}, and λ_{34}. As indicated above, suppose we have a set of condition measurements $\underline{x}(t)=[x_1(t),x_2(t),...,x_n(t)]$ for N similar components taken over an extended period of time $t=0,1,...,T$. We use the deterioration function to compute the deterioration level for each component. For component i, this enables identification of the time it spends in deterioration level j, e.g., y_{ij}. For the same type of equipment population, the estimated time spent in state j would be the mean of these durations, which is,

$$\bar{y}_{ij} = \frac{1}{N} * \sum_{i=1}^{N} y_{ij}$$

(3.22)

The desired transition intensities are obtained by inverting these mean duration times. In this procedure, one must not use data across maintenance periods to compute mean duration times since a maintenance task inhibits the deterioration process being modeled.

• *Failure probability calculation*: For a particular set of transition rates, the transition probability matrix for the case represented by Figure 3-6 as:

$$\underline{P} = \begin{bmatrix} 1-\lambda_{12} & \lambda_{12} & 0 & 0 \\ 0 & 1-\lambda_{23} & \lambda_{23} & 0 \\ 0 & 0 & 1-\lambda_{34} & \lambda_{34} \\ \mu_{41} & 0 & 0 & 1-\mu_{41} \end{bmatrix}$$

(3.23)

The state probability vector gives the probability that a component is in any particular deterioration level at a given time, and is denoted by

$$\underline{p}(hT) = [p_1(hT) \quad p_2(hT) \quad p_3(hT) \quad p_4(hT)]$$

(3.24)

where $h=1,2,3,...,$ and T is the time step. If at time $t=0$, we know that the component resides in deterioration level j, then the initial state probability vector is comprised of all zeros except for element j, which is 1. For example, if we know that the component is in deterioration level 1 at $t=0$, then

$$\underline{p}(0) = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$$

(3.25)

The probability of finding the component in any deterioration level at time hT is then given by:

$$\underline{p}(hT) = \underline{p}(0)\underline{P}^h$$

(3.26)

Given that at any particular time (denoted by $t=0$) we know the component's deterioration level, then the last element of the 1×4 row vector in Eq. (3.26) provides the probability of residing in the failed state in any future time interval.

Eq. (3.26) is used to obtain the contingency probability for our long-term simulation, but we must also have a *deterioration assumption* that describes the levels of deterioration the component is expected to be in throughout the simulation period. The simplest deterioration assumption is that each component remains in the same deterioration level as characterized by the most recent condition measurement. In this case, we use $h=1$ in Eq. (3.26) and the obtained probability of residing in the failed state is the contingency probability used in each simulation time step. We might also assume that the component does in fact deteriorate throughout the year so that at certain times it moves from one deterioration level to another.

The contingency probability reduction from a maintenance task requires an assumption on the deterioration level resulting from the maintenance task. If we assume that a particular maintenance task results in renewing the component to deterioration level 1, then, if the component is in deterioration level 3 (for example), the contingency k probability

reduction for maintenance task m, $\Delta p(k,m)$, is given by the last element of the 1×4 row vector resulting from the calculation:

$$[0 \quad 0 \quad 1 \quad 0]\underline{P} - [1 \quad 0 \quad 0 \quad 0]\underline{P} = [-1 \quad 0 \quad 1 \quad 0]\underline{P}$$

(3.27)

As pointed out before, in the above procedure of calculate transition rates, one must not use data across maintenance periods to compute mean duration times since a maintenance task inhibits the deterioration process being modeled. However, at most of the time, the utility-recorded transmission equipment life data does include maintenance activities. One possible way to account for the maintenance effects on the transition rates is described as follows.

For a particular power transformer, suppose it takes the transformer y_{23} (years) to transit from state 2 to state 3. And during this period, there are m major maintenance and n minor maintenance activities has been carried out on this power transformer, then we normalize the time y_{23} for this transformer in the following way:

$$t_{23} = y_{23}/(1 + mk_1 + nk_2)$$

(3.28)

where, t_{23} is the normalized duration time;

y_{23} is the time it takes the transformer transiting from state 2 to state 3;

m, n are the numbers of major and minor maintenance activities respectively performed on this transformer during this time period;

k_1 and k_2 are weighing parameters for major and minor maintenance activities respectively, and $0 < k_2 < k_1 < 1$.

Then, for the similar equipment population, the estimated time spent in state j would be the mean of these normalized durations. And the desired transition intensities are obtained by inverting these mean duration times.

We have obtained some transmission equipment condition monitoring and maintenance history information from a US utility database. However, the information contained in the database is only for a very limited number of years. It is unrealistic for us to estimate the entire equipment life data from this database. It is desirable for us to use actual equipment life data to test our method, however without that, we can still give an illustrative example here. We speculate the durations of a population of power transformers (115 KV) spend in deterioration level j, e.g., y_{ij}, as shown in Table 3-3.

Table 3-3: Transition Rates of 115 KV Power Transformer

Transformer ID	Time to Transit between States (years)			Expected Life (years)
	y_{12}	y_{23}	y_{34}	
1	8.5	19.5	25	53
2	10.5	22	26	58.5
3	11	21.5	23.5	56
4	9.8	17.5	20	47.3
5	8.9	18.5	18.5	45.9
6	12	25	26.5	63.5
7	11.5	23	27	61.5
8	7.5	18.5	19.5	45.5
9	10.7	17	20.5	48.2
10	12	24.5	22.5	59
Mean Durations	10.24	20.7	22.9	53.84
Transition Intensities	0.0977	0.0483	0.0437	

Then the transition probability matrix is:

$$
\underline{P} = \begin{bmatrix} 1-\lambda_{12} & \lambda_{12} & 0 & 0 \\ 0 & 1-\lambda_{23} & \lambda_{23} & 0 \\ 0 & 0 & 1-\lambda_{34} & \lambda_{34} \\ \mu_{41} & 0 & 0 & 1-\mu_{41} \end{bmatrix} = \begin{bmatrix} 0.9023 & 0.0977 & 0 & 0 \\ 0 & 0.9517 & 0.0483 & 0 \\ 0 & 0 & 0.9563 & 0.0437 \\ 1 & 0 & 0 & 0 \end{bmatrix} \tag{3.29}
$$

As listed in Appendix B, based on the DGA results of a power transformer extracted from our database, we use [IEEE Std C57.104-1991] to identify the deterioration levels of the

transformer. Then we apply the above procedure to calculate the instantaneous failure probabilities of the power transformer. The results are shown in Table 3-4 and also plotted in Figure 3-7.

Table 3-4: Power Transformer Instantaneous Failure Probability Calculation

Time	TDCG	Deterioration Level	Failure Probability
12/15/1993	2528	3	0.0437
8/3/1994	2806	3	0.0437
10/10/1995	2763	3	0.0437
5/7/1996	2436	3	0.0437
7/14/1998	2280	3	0.0437
9/29/1998	5122	4	1
11/6/1998	4	1	0
7/27/2000	1124	2	0
10/8/2001	1443	2	0
3/21/2002	1346	2	0
3/31/2003	907	2	0
11/25/2003	892	2	0

As we can observe from Figure 3-7, there are two significant failure probability changes during Jul. 1998 and Nov. 1998. We have confirmed with the asset owner that the condition of this transformer deteriorated rapidly during that period (the failure probability increased to 1 at Sep. 1998), and then they had performed an oil change on this transformer (the failure probability decreased to 0 at Nov. 1998). We will also compare this failure probability estimation with that of Bayesian method in the next section.
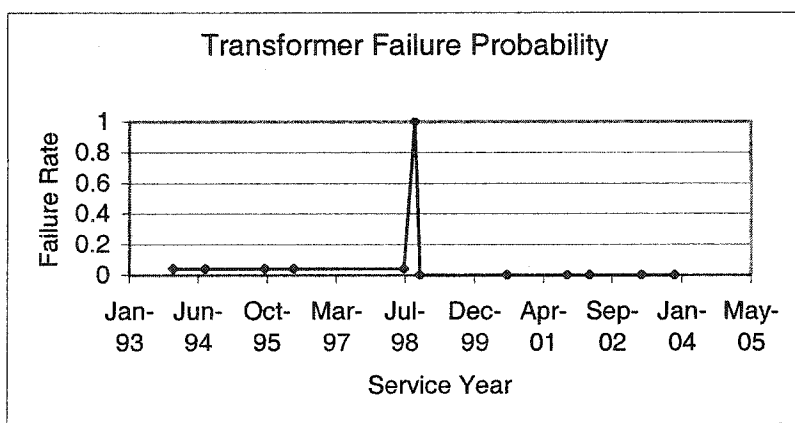
Figure 3-7: Transformer Instantaneous Failure Probabilities

In this Markov model, we first derive the transition rates from the equipment life history and then the transition rates remains unchanged. However, as time goes by, more equipment life data becomes available, and it can be used in updating the corresponding transition rates. A Bayesian method capable of doing so will be described in the next section.

3.5.3 Bayesian Approach

In this section, we develop a Bayesian approach as complementary of the previous methods for estimating the failure rate of power transformers. Because power transformer failures tend to be relatively rare events, empirical data for parameter estimation (e.g., the hazard function or the transition rates in Markov model) are generally spare. Thus, Bayesian method becomes a natural means to incorporate a wide variety of forms of information in the estimation process.

In the Bayesian framework, the uncertainties in the parameters due to lack of knowledge are expressed via probability distributions. This includes unknown distribution parameters. The Bayesian approach treats the unknown parameter, e.g., α or β in the Weibull characterization of the hazard function, or the transition rates in Markov model, as a random variable. Suppose τ is an unknown parameter in our probability model. We first define a distribution, $P(\tau)$, which generally aim to be as uninformative as possible. $P(\tau)$ is the prior distribution which represents uncertainty about τ based on prior knowledge, e.g.

historical information. Then, the posterior distribution of τ, given some observations of transformer condition monitoring data, is given by Bayes' Rule:

$$P(\tau|data) = \frac{P(data|\tau)P(\tau)}{P(data)} \qquad (3.30)$$

Here $P(data) = \int P(data|\tau)P(\tau)d\tau$. Suppose the obtained condition monitoring information includes: x_1, x_2, x_3, x_4, which may represent the DGA results, temperatures and other information. Then the conditional distribution $P(data|\tau)$ takes the form of $P(x_1,x_2,x_3,x_4|\tau)$, by the product rule of probability, which can be factored as:

$$P(x_1,x_2,x_3x_4|\tau) = P_{X_4}(x_4|x_1,x_2,x_3,\tau) \times P_{X_3}(x_3|x_1,x_2,\tau)$$
$$\times P_{X_2}(x_2|x_1,\tau) \times P_{X_1}(x_1|\tau) \qquad (3.31)$$

If x_1, x_2, x_3, x_4 are independently distributed, Eq. (3.23) can also be written as:

$$P(x_1,x_2,x_3,x_4|\tau) = P(x_1|\tau)P(x_2|\tau)P(x_3|\tau)P(x_4|\tau) \qquad (3.32)$$

The resulting posterior distribution in (3.30) is a conditional distribution, conditional upon observing equipment monitoring data. Thus, by using the above Bayesian approach, we can continuously update the equipment failure probability model based on available equipment condition monitoring information. A Bayesian framework of updating equipment hazard function is illustrated in Figure 3-8.
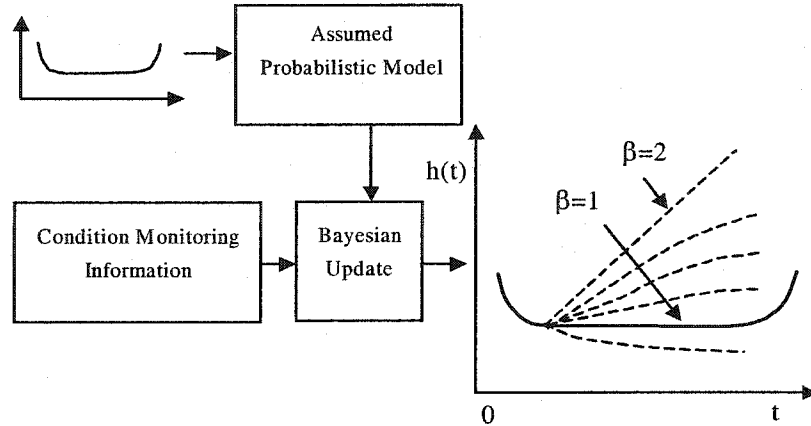
Figure 3-8: Bayesian Analysis of Equipment Failure Rate

We provide a Bayesian example for estimating transformer failure rate by updating the hazard function. Since the Weibull distribution shape parameter β determines whether the failure rate is increasing or decreasing, for simplicity, we assume scale parameter α is known and only model the uncertainty in the shape parameter β using a normal distribution with μ and γ^2 as its mean and standard deviation, i.e. $\beta \sim N(\mu, \gamma^2)$. We use available transformer DGA results to update this distribution by assuming that the amount of total dissolved combustible gases, G also follows a normal distribution, i.e. $G \sim N(\omega\beta + k_i, \omega^2\sigma^2)$, where $i = 1, 2, 3, 4$, corresponds to the conditions indicated by [IEEE Std C57.104-1991]; ω is a known parameter; k_i is the average amount of total dissolved combustible gases in condition i which can be obtained from [IEEE Std C57.104-1991] if no historical information is available. Then, by the linearity of normal distribution, we can get:

$$Gtemp = \frac{G - k_i}{\omega} \sim N(\beta, \sigma^2)$$ (3.33)

Using the above Bayesian update framework, we can get the posterior of β, which is still a normal distribution with mean and variance given by:

$$E(\beta|G) = \frac{\gamma^2}{\gamma^2 + \sigma^2} Gtemp + \frac{\sigma^2}{\gamma^2 + \sigma^2} \mu \qquad\qquad (3.34)$$

$$Var(\beta|G) = \frac{\gamma^2 \sigma^2}{\gamma^2 + \sigma^2} \qquad\qquad (3.35)$$

In this example, we also use a set of transformer DGA results obtained from a US utility, which is given in Appendix B. The data consist of the DGA results for a power transformer over a 10-year period. As stated before, our choice of the normal distribution to analyze this DGA data is for illustration purpose only. The values of these known parameters used in our example are: $\omega = 25$, $\gamma^2 = 2$, $\sigma^2 = 25$, $k_2 = 1200$ (for the period from Jul. 2000 to Nov. 2003), $k_3 = 2500$ (for the period from Dec. 1993 to Sep. 1998). And the initial value of μ is 1.5 (Dec. 1993). The evolution of means of the posterior distribution of shape parameter β is shown in Figure 3-9. We specify the scale parameter by taking advantage of empirical transformer failure rate is about 2% per year, i.e. α=50 if β=1. Based on the above expectations of the posterior distribution of the shape parameter, we can estimate power transformer failure rate using Eq. (3.15). The failure rate estimations based on both Markov model and Bayesian model are plotted in Figure 3-10.
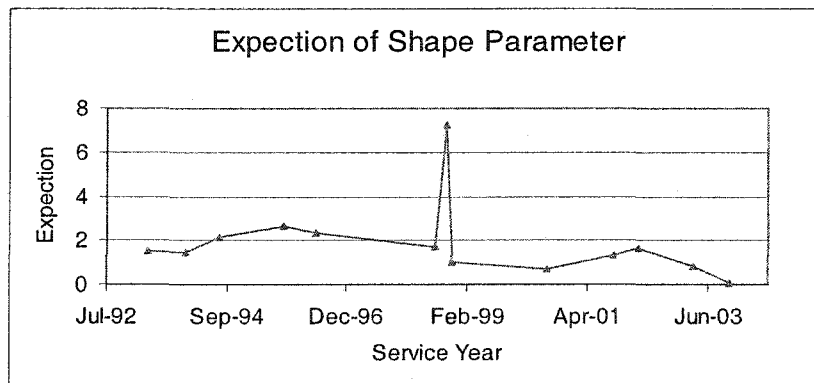
Figure 3-9: Expectation of Shape Parameter
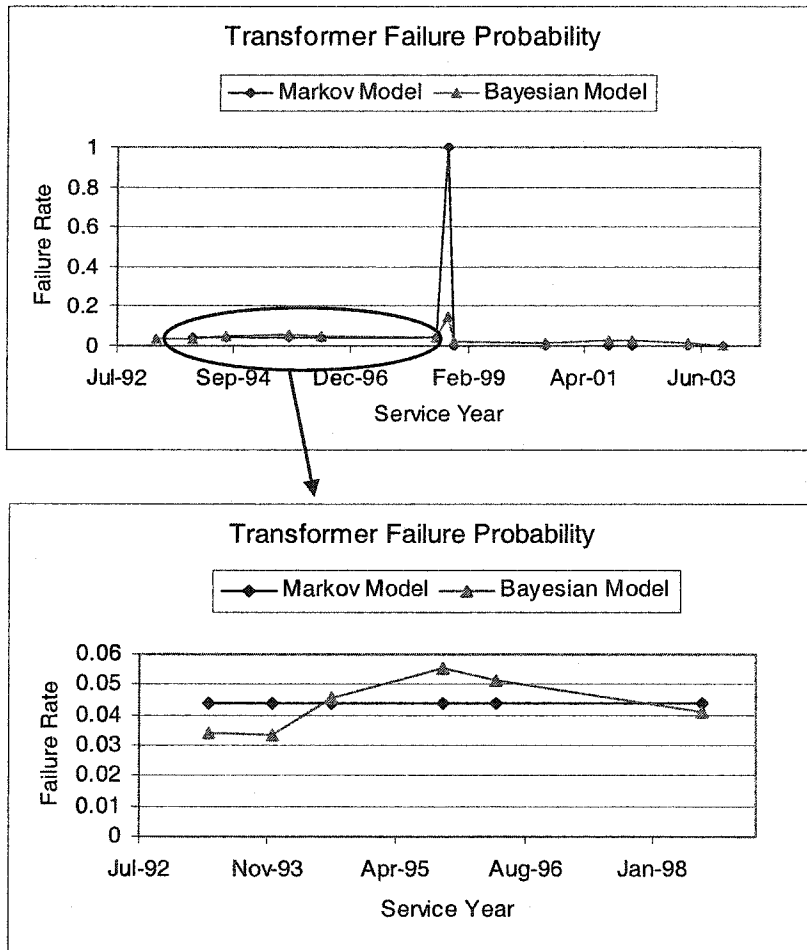
Figure 3-10: Transformer Failure Probability Estimations

From above Figure 3-10, we find that the overall shape of the two estimation curves fits each other. For Markov Model, the estimation is a step function, and could significantly change from one state to the next state, e.g., failure probability changes from 0.0437 (in state 3) to 1 (in state 4) and to 0 (in state 2); For Bayesian model, because new estimation is resulted from updating previous information, the Bayesian estimation is more continuous and consistent. However, the average Bayesian estimated failure probability during one state is very close to that of Markov model. This provides a validation for our models of estimating equipment instantaneous failure probability.

3.5.4 A Comparison between these Methods

We have described several methods for estimating the instantaneous failure probability for transmission equipment. A comparison between these methods is summarized in Table 3-5. The hazard function (Weibull function) models are the simplest and easiest to use. The Markov model is straightforward and flexible to accommodate different modeling needs. And the Bayesian method is mathematically stricter and thus requires more computation.

Table 3-5: A Comparison between These Methods

		Model	
		Weibull	Markov
Method	Deterioration Function $g(\underline{x})$	Constant model, update the "time"	Constant model, update the "state"
	Bayesian	Constant time, update the model	Update model, update the "state"

3.6 Summary

In this chapter, we first introduced an innovative program for transmission maintenance scheduling by achieving maximum cumulative system risk reduction, subject to constraints on economic resources, available maintenance crews, and restricted time intervals. Then various transformer condition-monitoring techniques, available monitoring information, and typical transformer failure modes as well as corresponding maintenance activities are presented. Several systematic methodologies of estimating instantaneous equipment failure probability based on equipment condition data are developed. They enable

quantitative evaluation of effectiveness of performing maintenance activities in terms of system cumulative risk reductions.

4 MULTIAGENT NEGOTIATION MODELS FOR POWER SYSTEM APPLICATIONS

4.1 Introduction

There are a wide range of power system decision problems, traditionally falling under one of the three categories of operations, maintenance, and planning, with the delineation between categories derived from the nature of the decision and the time horizon. Some of these decision problems include generation dispatching, fuel scheduling, control-room preventive and corrective actions, incident restoration, transmission service scheduling, unit commitment, transmission equipment maintenance, control system planning, and transmission upgrades. All of these share common attributes, among which are:

- Resulting decisions have system-wide impact and therefore require significant coordination of information among the various decision-makers;
- Higher system integrity is only achieved with greater allocation of financial resources;
- The essential decision variables are inherently uncertain;
- Uncertainty is reduced via acquisition and processing of information;
- Important information tends to be spatially dispersed;
- Complex and computationally intensive applications are required;

As a result, decision-making support aids require modeling of multiple objectives, application of significant computational resources, and use of flexible data access capability. Mathematical programming has been and continues to be a mainstay for such decision problems. However, traditional optimization tools, by their very nature, assume the existence of a single and benevolent decision-maker that has centralized access to all information, and coordination between decision makers is embedded in the processes and is generally of no threat to individuals carrying out those processes. Such was the case in the traditionally regulated world where ownership of all facilities, access to all information, and all authority

for decision rested within the single umbrella of the vertically integrated utility company. With the advent of industry restructuring and associated organizational disaggregation, however, facility ownership is heavily fragmented, and information access and decision-making authority is quite limited for any one particular organization. Even more, the various organizations comprising the industry are not necessarily cooperative one with another; in fact, many portions of the restructured industry are intentionally organized to be competitive. Yet the need for coordinated decision remains, as it is essential to the operational integrity of the system. This necessitates a new paradigm to build upon and ultimately replace the centralized decision approach, enabling optimized decisions in an environment of highly distributed information and a multiplicity of competing stakeholders.

The industry has attempted to retain decision-making ability using traditional optimization tools, but it has come at the expense of forming new, centralized and competitively neutral authorities such as independent system operators (ISOs) and reliability authorities (RAs) to coordinate system operations and issues related to system reliability. These organizations arbitrate those decisions where conflict between two or more parties may otherwise arise. For example, during operationally stressed conditions having excessive risk of load interruption, a centralized authority generally selects appropriate actions (e.g., emergency rating increase, load curtailment) in order to mitigate the risk. Another example is maintenance: given requests for simultaneous maintenance outage of multiple components (generators, transmission lines, and/or power transformers) such that network integrity is excessively compromised, a centralized authority generally determines the sequence and timing of the maintenance tasks. In both of these cases, a conflict (how much equipment rating should be increased or how much load should be curtailed in case 1 and which maintenance tasks to postpone in case 2) is settled by the arbitration of the central authority. The technology which motivates this work, multi-agent systems (MAS), may offer a viable alternative to this arrangement, or at least a useful complement, through the use of software agents equipped with negotiated decision-making capabilities operating within a MAS so as

to coordinate decision-making of competing stakeholders. In multi-agent negotiation systems, stakeholders, represented by agents, engage in negotiation, proposing and counter-proposing until an outcome is identified that is satisfactory to all.

It is important to clarify terms at the beginning. A *stakeholder* represents a human individual or human organization that has interest in the stated decision making problem would be one of the decision-makers if allowed to participate. Later, we use the term *player* and *party* to more explicitly refer to a stakeholder involved in a human-to-human negotiation. On the other hand, an *agent* is first and foremost a software entity, second, one that satisfies the usual criteria for agency (e.g., a computer system situated in some environment capable of autonomous action to meet its design objectives [Wooldridge, 1999]), and third, for our purposes here, one that has the essential social ability of communicating (sending and receiving messages). Thus, a stakeholder may be represented by a party, or by an agent. A party always represents a stakeholder. Although an agent does not necessarily have to represent a stakeholder (there may exist "functional" agents, for example), we assume in this chapter that an agent does. In effect then, within the domain of this chapter, "agent" is the software encapsulation of "party."

Here, a software agent, armed with a coded negotiation model, represents each stakeholder, and conflict resolution is achieved via inter-agent message exchange until agreement is reached. MAS is an essential enabling technology because it provides the necessary infrastructure in terms of model instantiation and maintenance together with the communication needs, including messaging, directory services, and communication protocols [Wooldridge, 1999].

The rest of this chapter is organized as follows. Section 4.2 reviews literature in terms of (a) negotiation theory and (b) computer-based negotiations. Section 4.3 describes two multiagent negotiation models. Section 4.4 discusses the issues of multiagent negotiation convergence and scalability. Section 4.5 describes the relationship between agent-based auction and negotiation. Section 4.6 concludes.

4.2 Negotiation Theory and Agents: a Review

Endowing agents with advanced social abilities, such as negotiation, for use within multiagent systems, has been of interest since the 1980's, but the study of negotiation as a fundamental form of human interaction has been ongoing throughout the 20th century, and an awareness of these developments is essential for understanding the recent and intimately related work in MANS. Section 4.2.1 focuses on literature from decision science, economics, and anthropology; more recent literature related to computer-based negotiation mechanisms is discussed in Section 4.2.2.

4.2.1 Basics of Negotiation Theory

Negotiation is a fundamental form of human interaction, and we see it in labour-management disputes, international diplomacy, governmental processes, business relations, and interpersonal relations. Despite its prevalence throughout all human history, it was not until the middle of the 20th century before development of a theory for negotiation was initiated. This effort had roots in a number of different disciplines, including decision science, economic bargaining theory, social psychology, political science, industrial sociology, and social anthropology [Gulliver, 1979]. We do not attempt a comprehensive literature review here but rather provide basic concepts on which we draw in instantiating negotiation models within agents.

There are two sub-disciplines within decision science that need particular attention in order to do justice to the field of negotiation theory. The first is multi-criteria decision-making (MCDM), because it is MCDM that provides a number of different decision approaches for multi-criteria decision problems. Some of these approaches include [Chankong, 1983; Hobbs, 2000] weighting methods such as analytical hierarchy process, Electre IV, goal programming, evidential theory, and utility-based approaches, where we typically search for efficient solutions y^*, i.e., those solutions for which there exist no other

solutions that can outperform y^* in all criteria. Of the various MCDM approaches, it is the utility-based approaches that have had particular influence on evolution of negotiation theory. A well-known and simple decision criterion is to choose the action which maximizes the expected value of benefit. Thus, if we can associate with each course of action A a set of outcomes characterized by their benefits c_1, c_2, ...c_n and corresponding probabilities p_1, p_2,...p_n, we desire to select the course of action that has the largest value of $\sum p_i c_i$. Bernoulli [Bernoulli, 1738], and later von Neumann and Morgenstern [Neumann, 1944] and others [Keeney, 1976; Tapan, 1997; Fishburn, 1982; Fishburn, 1988] argued that rather than using expected value, the rational way for people to evaluate decision problems is on the basis of expected utility $EU(A)=\sum p_i \, u(c_i)$ where $u(\bullet)$ is a utility function that characterizes the decision-makers preferences with respect to the possible benefits of each outcome.

The second sub-discipline that needs particular attention is the theory of *competitive problems* [Ackoff, 1968], characterized by decision scenarios where certain of the decision variables are controlled by two or more independent parties having different interests. This discipline, which has largely grown out of utility-based decision approaches, has formed the basis for much of the non-agent and agent-related work in negotiation theory. The most influential aspects of this work fall under the *theory of games* in which two or more *players* (i.e. parties) choose courses of action and in which the outcome is affected by the combination of choices taken collectively [Gulliver, 1979; Neumann, 1944; Keeney, 1976; Fishburn, 1982; Fishburn, 1988; Tapan, 1997; Ackoff, 1968]. A key assumption is that players behave *rationally*, where rational behavior is characterized by action selection, by each party, so as to maximize individual expected utility. Additional assumptions include (a) there is a fixed set of rules that specify what courses of action can be chosen; (b) there are well-defined end-states that terminate the game; (c) associated with each end-state are player-specific payoffs; (d) all players have perfect knowledge with regard to the rules, the range of outcomes, probabilities, and payoffs, and each player's preferences; (e) there is no interference or influence from the outside world. The central question addressed is: for a

specified game, under assumptions a-e, what will be the utility vector on which the players will agree? The most well-known example of such a game is the so-called prisoners' dilemma whereby the district attorney has two robbers in different cells. If both confess, both get 8 years jail time; if neither confesses, both get 5 years, and if one confesses and the other does not, the confessor gets 2 years and the other 10. Game theory provides several different models for studying player decisions.

A simple game-theoretic model is identified by Raiffa in [Raiffa, 1982], where it is assumed that by analysing the consequences of no agreement, each party can establish a threshold value to be used for decision. Define x^* as the final-contract value, the sellers reservation price s that represents the very minimum price for which the seller will sell, the buyers reservation price b that represents the very maximum price for which the buyer will buy. Then the zone of agreement is the interval (s, b), assuming $s<b$. If $b<s$, then agreement is not possible. The buyer's surplus is $b-x^*$, the sellers surplus is x^*-s, and both buyer and seller try to maximize their surplus.

One limitation to game theory is that it is pre-occupied with outcome, discussed in terms of equilibria (e.g., Nash, perfect, dominant), rather than the process (or mechanism) used to arrive at that outcome. This point is central to the goal of automating multi-party decision-making because we need the capability of implementing the mechanism to achieve this goal. Thus, we turn to the closely related negotiation theory.

There are at least six different mechanisms of reaching a collective decision among two or more parties, including persuading, educating, manipulating, coercing, appealing to an authority, and negotiation [Strauss, 1978]. Of these, the last two, arbitration and negotiation, are two distinctive forms of identifying agreements between two or more parties that have significantly more formality and structure. Arbitration provides a mechanism which selects a single outcome as the point of agreement between the parties. Judges often assume this role in legal disputes, so do certain kinds of power system decision-making authorities. In arbitration, the parties direct their communication towards a third party, but not to each other.

Arbitration, with only a single decision-maker, is most effective when parties seek to agree over values, norms, and the assessment of facts. Negotiation, on the other hand, is the *joint-decision* process of forming and revising offers, by each involved party, whereby offers are made with the intention to converge to an agreement, without the presence of a third-party decision-maker. ([Gulliver, 1979] argues that this definition applies more appropriately to *bargaining* with a broader definition used for negotiation that includes the initiation and recognition of the motivating need, the process, the final outcome, and the execution of that outcome). In negotiation, the focus of communication is (are) the other party (parties). Generally, negotiation is performed as a result of a conflict or dispute between two or more parties, and the negotiation objective is to resolve the dispute. Negotiation is most effective in a situation of scarcity when parties seek the same resources without there being enough to satisfy both [Gulliver, 1979]. These types of negotiations have been characterized as either *strident antagonist* or *cooperative antagonist* [Raiffa, 1982]. The former is characterized by completely distrustful and malevolent (towards one another) parties, as would be the case when authorities negotiate with kidnappers or airline hijackers. The latter is characterized by entirely self-interested and disputing parties but ones that recognize and abide by whatever rules exist. A third type of negotiation is called *fully cooperative* [Raiffa, 1982], where the parties have different needs, values, and opinions, but they share information, expect total honesty, perform no strategic posturing, and think of themselves as a cohesive entity with intention to arrive at the best decision for the entity, as would be the case for a happily married couple. We are interested here in the two different levels of cooperative negotiations, since they better typify the various types of power system decisions problems. For example, a negotiation involving two transmission owners over equipment maintenance schedules is a good example of cooperative antagonists. A negotiation involving two ISOs sharing responsibility for operational integrity of different portions of the network in the same interconnection, over equipment maintenance schedules, is a good example of a fully cooperative negotiation. Some negotiations are also

characterized by the presence of a mediator, where an impartial outsider has the role of helping the parties find a compromise solution. Although often useful, this refinement offers no fundamental change to negotiation models, and we do not address it further.

There are at least two main phases to any negotiation. These are:

1. Information exchange:

- Pre-bargaining, including identification of the issues, establishing maximal limits to the issues, and agreeing on the rules

- Issue iterations (offers and counteroffers)

2. Arriving at the outcome:

- convergence on a final contract value,

- retention of the status quo (no change) via a walk-out by one party.

Characterizing features of negotiations have been set forth in a number of works, including [Gulliver, 1979; Cross, 1969; Raiffa, 1982; Bartos, 1974]. Of these, a key attribute is whether the negotiation involves 2 parties (bilateral) or more (multi-lateral). Multi-party negotiations have complexity that significantly exceeds that of bilateral negotiations, as players may form any of a number of different coalitions. Even in the simplest of cases, the three-party negotiation (A, B, C), one must account for any of four scenarios: no coalition, or coalition of AB, AC, or BC. One obvious approach is to abandon negotiation altogether and utilize, for example, voting, some form of arbitration such as an auction, or perform the multi-party negotiation as a sequence of independent bilateral negotiations. Another approach, which maintains the essence of the multi-party negotiation, suggested in [Rubenstein, 1982] and described further in [Kraus, 2001], called Rubenstein's model of alternating offers, formulates the negotiation rules to explicitly disallow coalitions. Here, when one of the agents makes an offer, all other agents respond, with each agent accepting, rejecting, or cancelling (walking out). The negotiation terminates if all agents accept the offer (an agreement) or if one of them cancels. If the negotiation does not terminate, the negotiation proceeds to the next time period, another agent makes an offer, and the process repeats.

Coalitions are prevented by disallowing inter-party communication. In addition, it is important to ensure that no party knows others' responses until the round is complete (otherwise parties have incentive to wait, to gain more information). The order in which parties can offer is randomized. In addition to avoiding coalitions, Rubenstein's model is also attractive because it is general; it works just as well for bilateral negotiations as it does for multi-lateral negotiations.

A second key attribute is the number of issues, i.e., the substances over which the negotiation occurs; there may be one (single issue) or more (multi-issue). The ability to handle multi-issue negotiations lies in the way each party evaluates an offer. Some method of normalizing among different issues is required, and expected utility provides for this. Other features of most negotiation models are whether or not they represent the influence of time, learning, strategic behaviour, and a pre-bargaining phase.

In reading the negotiation literature, it is important to recognize whether the author's perspective is *descriptive* or *prescriptive*. Descriptive models describe how negotiating parties actually behave, whereas prescriptive models prescribe how the parties should behave. For example, Gulliver in his well-known text [Gulliver, 1979] argues strongly against the use of utility theory in negotiation models because, he feels, it does not represent how people actually think (no one, he argues, actually decides based on quantification of their own and others' probabilities and preferences for various outcomes) and instead proposes two other models that capture the *cycling* and *developmental* features of negotiation, respectively. Considering Gulliver's criticism in the context of MANS, one may argue that MANS provides a degree of information accessibility and modelling power that was not available when Gulliver wrote, so that many of the complexities of how humans decide may now be effectively addressed. However true, this response neglects to recognize that MANS is not concerned with describing how humans negotiate (although it may be useful to build into MANS certain features of how humans negotiate). Rather, MANS is concerned with providing humans with decision-support, i.e., prescribing how humans should decide.

Therefore, the implementation mechanism is important only insofar as it provides us with desirable outcomes. In this sense, then, MANS has the same function that mathematical programming has had, except that MANS accommodates the feature of distributed decision-making that is now prevalent in the electric power industry.

4.2.2 Computer-based Negotiation Systems

There is a large and growing body of literature on computer-based negotiation systems, including MANS. We limit ourselves here to three important texts, published in 1994 [Rosenschein, 1994], 1999 [Huhns, 1999], and 2001 [Kraus, 2001] that well-capture the state of the art at those times, together with a survey of some very recent literature published in a journal dedicated to the topic [Holsapple, 1996; Ehtamo, 2001; Kersten, 2001; Tajima, 2001; Weigand, 2003; Lomuscio, 2003] that can be conveniently found on-line at http://journals.kluweronline.com/.

Rosenschein and Zlotkin [Rosenschein, 1994] make a strong case that "game theory is the right tool in the right place for the design of automated interactions", arguing that despite its shortcomings in capturing human interactions, automated societies are perfectly amenable to the assumptions on which game theoretic models rest. They provide a list of attributes associated with machine interaction, including efficiency (outcomes should be Pareto Optimal), stability (no agent should have incentive to deviate from the agreed-upon available strategies), simplicity (low computational and communication requirements), distributedness (interaction rules should not require a centralized entity), and symmetry (the interaction mechanism should not arbitrarily favour one agent more than another). The work rests on the standard assumptions of game theory (rationality based on utility) together with a few more reminiscent of Rubenstein's model, including: (a) each negotiation is independent of past or future negotiations; (b) agent-specific utility calculations may be transformed into common "system" units; (c) all functionalities (abilities) are equally accessible to all agents; (d) public agreements are binding; (e) no utility (in the form of money, for example) is

explicitly transferred from one agent to another. They make the important clarification that their work is about design of machine negotiation protocols, where protocols are not about the low-level issue of how machines communicate (it is assumed that they do), but rather about a higher-level issue regarding the public rules by which machines come to agreement, such as Rubenstein's model described above. Thus, they proceed to identify different problem domains and specify various protocols appropriate for that domain. For example, the task-oriented domain is one in which an agent's activity can be defined in terms of a set of tasks that it has to achieve (in contrast to domains where agents are concerned with moving its environment from one state to another, or where agents assign a worth to states and select the best state in which to move). Given a protocol, the remaining attributes necessary to characterize a negotiation are the space of possible deals, the negotiation process, and the negotiation strategy. They utilize standard game theoretic models (e.g., Zeuthen's) to analyze the influence of different strategies on outcomes.

Huhns and Stephens [Huhns, 1999] also emphasize the importance of protocols, and they distinguish between communication protocols (e.g., KQML, KIF) and "interaction" protocols. They classify the different interaction protocols into coordination, cooperation, contract net, blackboard systems, negotiation, and market mechanisms. Their overview of each provides a useful taxonomy for more broadly understanding negotiation protocols.

Kraus [Kraus, 2001] clearly distinguishes efforts in the area of designing agent *interaction* (i.e., coordination and cooperation) from that of designing agent *architecture*. Her efforts, relating to the former, integrates game theory with economic techniques and artificial intelligence heuristics to develop a strategic-negotiation model patterned after that of Rubenstein under assumptions similar to those of Rosenschein and Zlotkin. The importance of this work is in its detailed treatment of illustrating the generality of the proposed negotiation model in a diverse array of applications, including negotiations about data allocation, resource allocation, task distribution, pollution reduction, and hostage crises.

Reference [Holsapple, 1996] proposes a theory of negotiation developed with the

intent of understanding negotiation support systems as computer-based decision systems, predicated on the idea that there are 8 different features that must be identified in order for a negotiation to be properly understood. These features are issues to be negotiated, entities involved, the acceptance region of the entities in the space of issues, the current location of the entities within that space, the strategies and movements of the entities, and negotiation rules, and the level and nature of assistance from an intervener (arbitrator or mediator). A long list of computer-based support functionalities is provided for each of the features, and a classification framework is provided in terms of the kind of entity set for which the system is used (group/peer-to-peer or organization/hierarchical) and the nature of the system's participation in the negotiation (assistance/support or autonomous negotiator). Reference [Ehtamo, 2001] identifies 5 negotiation activities where mathematical modelling can provide prescriptive decision aid, and focuses on one of them, the search for agreement and improvements, in showing how it can be formalized as a MCDM gradient search problem or as a constraint proposal problem. Reference [Kersten, 2001] identifies characterizing features of distributive and integrative negotiations, terms first articulated by [Walton, 1965] to distinguish between "fixed-pie" negotiations where parties are inherently in conflict and compete over scarce resources such that when one party gets more, the other gets less (distributed) and win-win negotiations where some settlements can be better for both parties. Although integrative negotiations are generally multi-issued, they do not have to be as illustrated in the classic case where two sisters argue over an orange, one needing the juice and the other the peel. It is distributed as long as they do not know each other's needs but immediately becomes integrative when they do. Integrative negotiations generally lead to better solutions, and the authors conclude that auctions should be considered when distributive negotiation cannot be converted to integrative, but auctions are not applicable where it is possible to for parties to learn about one another to determine opportunities and establish relationships. This theme is extended in [Tajima, 2001] which purposes logrolling, an algorithmic method for multi-issued integrative negotiations that produces Pareto-optimal

solutions through jointly improving exchange of issues such that loss in some issues is traded for gain in others resulting in overall gain for all parties. Reference [Weigand, 2003], in focusing on computer-based business-to-business negotiations, also distinguishes between distributive and integrative negotiations and their relation to auction as in [Kersten, 2001] and goes on to also compare norm and goal orientations in designing negotiation protocols. Reference [Lomuscio, 2003] further addresses automated negotiation in the context of e-commerce applications, providing a useful negotiation taxonomy that collectively incorporates many of the attributes discussed piecemeal in the literature to date. Within this taxonomy, the parameters of the negotiation space include: cardinality (number of agents, number of issues), agent characteristics (role, rationality, knowledge, strategy), environment (static or dynamic), goods (public or private), and parameters related to offers, information, and allocation. It also describes a number of proposed negotiation models and locates them in its taxonomy.

4.3 Multiagent Negotiation Models

We conceive of a society of agents organized as the electric power industry is organized, i.e., there are agents corresponding to *load-serving entities*, *generation owners*, *transmission owners*, and whatever centralized organizations that may exist such as *Independent System Operaters* (ISOs), *reliability authorities*, and *power exchanges*. Decisions are made as a result of different inter-agent negotiations. Our negotiation models may be applied to decisions with or without incorporation of uncertainty. We begin by describing the model in terms of bilateral, multi-issued negotiation, without uncertainty, as it both general and simple. By avoiding the need to model uncertainty, agent decisions are made based on assessment of *utility* (or value), rather than *expected utility* (or expected value).

4.3.1 Negotiation Model for Individual Rationality

This is a basic model for *two parties, many issues* negotiations. As described in [Faratin, 1997], let a represents the negotiating agent in a multi-agent system S (i.e. $a \in \{S\}$), and $X_a = \{x_1, x_2, ..., x_n\}$ be the set of issues about which agent a want to negotiate, each taking values in the range specified in the set:

$$range(X_a) = \{[\min(x_1), \max(x_1)], ..., [\min(x_n), \max(x_n)]\} \tag{4.1}$$

The set X_a is termed as *negotiation set*. The agent uses a non-decreasing or non-increasing scoring function $V(x)$ to score the value of each issue between 0 and 1, i.e., for each negotiation issue x_j ($j \in \{1, 2, ..., n\}$):

$$V_j : [\min(x_j), \max(x_j)] \rightarrow [0,1] \tag{4.2}$$

This enables the agent a to assign a value of issue x_j in the range of its acceptable values. For convenience, scores are kept in the interval [0, 1]. Such functions are sufficient to model transitive preference structures. If the agent prefers an outcome x' to x'' for a single issue, then $V(x') > V(x'')$; if the agent is indifferent between two outcomes x' and x'', then $V(x') = V(x'')$. For example, an agent can use the value function defined on the domain $[\min(x), \max(x)]$:

$$V(x) = [(x - \min(x))/(\max(x) - \min(x))]^k, \quad k > 0 \tag{4.3}$$

The next element of the model is using additive value functions to get the net value of a negotiation set. The agent assigns relative importance (weight) to each issue in the negotiation set; w_j is the relative importance of issue x_j to the agent, and we assume that the weights are normalized:

$$\sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0 \tag{4.4}$$

Then the agent a's scoring function for the negotiation set X_a is defined as:

$$V^a(X_a) = \sum_{j=1}^{n} w_j * V(x_j) \tag{4.5}$$

The additive scoring function as defined above is the simplest multi-issued value function. However, to achieve flexibility in the negotiation, negotiating agents may change their ratings of the importance (w_j's) over time, allowing them adopt different negotiation tactics. For example, remaining time may become more important than imitation of the other's behaviors as it approaches the time by which an agreement must in place.

One of the most important advantages of the above bilateral negotiation model is its simplicity and easy to be implemented. However, the main disadvantage of this model is that it does not count for the social influence of agent's actions and precludes the possibility of modeling any uncertainty.

4.3.2 Embedding Agents with Social Rationality

In this section, we develop an expected utility-based model for multiagent rational decision-making, which is capable of enabling each agent to balance between its social behavior and self-interest as well as dealing with uncertainty.

As pointed out in [Vishwanathan, 2001], the value function based multiagent negotiation model oversimplifies the preference and attitude of the agent and precludes the possibility of modeling any uncertainty in the outcome of an action. However in practice, agents do face uncertainties in the consequences of their actions. While the expected utility theory has been widely adopted as the quintessential paradigm for decision-making in the face of uncertainty [Biswas, 1997; Fishburn, 1988], the predominant view of the agent's decision-making function has been solipsistic in nature and based upon the principle of

maximizing the individual expected utility [Hogg, 1997a] given the probability of reaching a desired state and the desirability of that state. Although this is intuitively and formally appealing, it lacks applicability in real systems consisting of multitude of interacting agents.

Given the importance of power system integrity, when designing a system in which multiple agents need to interact (coordinate) in order to achieve both individual (e.g. maximize individual entity's revenues) and system (e.g. minimize the system risk level) goals, we hold that neither egoism nor altruism are the best means to achieve globally optimal system states, but rather a good combination of these two aspects of interaction can yield the best global results. Because of the inherent interdependencies between agents, an agent's decision affects not only itself, but also other agents in the multiagent system environment. It is therefore important to equip the agents within a multiagent system with a mix of self-interest and social consciousness that allows them to value the performance of the entire society as well as their individual performance. An agent's decision should depend on not only its individual utilities, but also social utilities (utilities afforded to other agents in the MAS) of all possible actions while determining which action to perform. This is more appropriate for application to power systems where entity-represented agents are interdependent. If an agent places more emphasis on its individual utility, it is selfish in nature. On the other hand, an altruistic agent pays more attention to social utilities. A socially rational agent tries to maintain a balance between individual and social responsibilities [Hogg, 1997b].

Due to its intuitive and formal treatment of making decisions from a set of alternatives under uncertainty, we use the aforementioned expected utilities of the agent's actions to describe a dynamic utility calculating framework, which provides agents with a more descriptive notion of choice within a multi-agent environment. In our MAS, a particular agent may work in a group with a small number of agents, a loose confederation with a larger number of agents and hardly at all with the remaining agents. Thus, the calculation of social utility (includes individual utility) can be further distinguished by differentiating between the

different social relationships in which an agent is engaged. To account for this, we define R as the agents' *Social Relationship Matrix* in our MAS [Zhang, 2002]:

$$R = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n-1} & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n-1} & r_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ r_{n-1,1} & r_{n-1,2} & \cdots & r_{n-1,n-1} & r_{n-1,n} \\ r_{n,1} & r_{n,2} & \cdots & r_{n,n-1} & r_{n,n} \end{bmatrix}, \quad \sum_{j=1}^{n} r_{i j} = 1, \quad r_{ij} \geq 0 \tag{4.6}$$

R is a $n \times n$ matrix (n is the number of agents within the multiagent system); each row or column corresponds to an agent. The value of $r_{i,j}$ indicates agent i's attitude toward the social relationship between itself and agent j. This means that each agent can quantitatively weight all social relationships with respect to the influence of its possible actions within the multiagent system. While different agents may have different social perspectives, the value of $r_{i,j}$ is not necessarily equal to $r_{j,i}$. Therefore, in general the social relationship matrix R is not symmetric. Each agent can retrieve its own social relationship information from matrix R using its *Identification Matrix* I. For instance, for the k-th agent, its identification matrix is a vector in the form of:

$$I = [i_1 \quad i_2 \quad \cdots \quad i_j \quad \cdots \quad i_n] \tag{4.7}$$

where $i_j = 1$, if and only if $j = k$; otherwise $i_j = 0$.

Supposing the k-th agent executes a possible action A, from its perspective, the utilities afforded to each agent in the multiagent system by A can be denoted as:

$$U_A = \begin{bmatrix} SU_{k,1} \\ \vdots \\ IU_{k,k} \\ \vdots \\ SU_{k,n} \end{bmatrix} \tag{4.8}$$

where $IU_{k,k}$ represents the individual utility to the k-th agent by that action, and all others are social utilities[3]. Then we can compute the expected utility for k-th agent if it carries out action A by the following equation:

$$EU(A) = I_k * R * U_A \qquad (4.9)$$

By trying to maximize the above combined expected utility, agents can naturally take both individual and social utilities into the consideration of their decisions. The above mechanism equips the agents within multiagent systems with a mix of self-interest and social consciousness that allows them to rationally evaluate their individual performance over the entire society. In addition, by varying the corresponding values in the relationship matrix R (if $r_{i,j}$ is set to zero, that means agent i either neglects the social relationship ($i \neq j$) between the two agents or totally removes its personal benefits from its decisions ($i = j$).), each agent can dynamically determine the way that it combines the individual and social utilities of all possible actions in order to make a rational decision.

4.4 Negotiation Convergence and Scalability

During each round of negotiation, an agent will have three choices: accept the offer, propose counter-offer, or drop out of the negotiation. In our negotiation protocol (which will be described in the next chapter), agent is designed to first evaluate the received offer (calculate its expected utility), then decide to accept (if the expected utility of the received offer is no less than its own expected utility) or counter offer or drop out. In our system, all agents are supposed to be rational (i.e., no malicious agent involved), that means agents are willing to make concession during negotiation in order to reach a global solution as long as its expected social utility is no less than that when it drops out of the negotiation. Thus,

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[3] In a cooperative environment, when agent k executes a possible action A, we assume that each agent would let agent k know its utility offered by action A. This is simple and enable agent to avoid modeling other agents in the system.

dropping out of the negotiation is the last resort of the agent, which would lead to a negotiation failure. To prevent this from happening, we can impose a penalty on the agent's utility when an agent chooses to drop out of the negotiation. So, if an agent is not satisfied with the received offer, it will try to propose its counter-offer. Because our agents have not been equipped with learning capabilities during the negotiation, they just gradually increase or decrease their offers until coming into a global agreement. This coincides with the notion of Nash equilibrium [Kraus, 2001], i.e., each agent is trying to make an optimal choice, given the choices that other agents are making. Thus, there are several assumptions, which guarantees the convergence of our agent negotiation: (a) all negotiating agents are rational; (b) the time for negotiation is longer enough; (c) all negotiating agents are willing to make concessions; (d) the negotiation parameters can be changed smaller enough in each negotiation step; (e) all negotiating agents have enough computing power to finish evaluating offers and construction counter-offers in a timely manner.

In this chapter, we have developed two multiagent negotiation models. As we see, they are capable of evaluating offers from multiple parties. In other words, they are able to support multilateral inter-agent negotiations. However, when the number of agents involved in negotiation grows very big (e.g., more than a dozen), the computation burden of each agent (because it needs to evaluate the received offers) will be increasing dramatically and thus it will slow the negotiation process. Being aware of this, we intend to illustrate the merit of multiagent negotiated decision-making without involving too much programming complexity. Thus our implementation of negotiation protocol and communication protocol (which will be described in the next chapter) is based on the most simple scenario, i.e., only two agents involved in a negotiation. So our multiagent system framework can facilitate bilateral, sequential inter-agent negotiations. However, it is not expected there is too much difficulty in enhancing the protocol implementation to accommodate multilateral inter-agent negotiations. One possible way of doing so is to adopt broadcast communication, where one agent can physically broadcast the message to all the agents in the system. However

considering the confidentiality of the negotiation content, it is also desirable to implement a hybrid approach by using broadcast communication to convey non-sensitive information, e.g., negotiation purpose, involved parties and issues, identities and addresses of agents in the negotiation; and then use direct communication to exchange information of agents' offers during in the negotiation iteration. This is a mechanism very similar to an auction system where one auctioneer interacts with multiple bidders to determine one issue, e.g., price of a piece of goods in the auction. We will discuss the relationship between agent-based auction and negotiation in the next section.

4.5 Comparison between Agent-based Auction and Negotiation

Agent-based auctions have been successfully applied in various power market-related applications [Richter, 1999; Lane, 2000], e.g., purchasing of active power and ancillary services. The most important and appealing features of these agent-based auction systems are process efficiency, ease of use, and their ability to simultaneously manage very large numbers of bidders. Auctions also have very small information and coordination costs. Auctions focus on determining the value of products, e.g., price of MW power, through a process that is managed only by one side.

In contrast, agent-based negotiation is a process that is managed by all the participants who cooperate to create values. Auctions mainly deal with known and well-defined objects (e.g., MW power), while negotiations are about defining these objects and modifying the participants' own perceptions and preferences. This allows for ill-defined and difficult issues to be negotiated (e.g., where and how much load should be curtailed in a stressed system condition; when and which maintenance activity should be performed if there is not enough resource to carry them out all). Thus, a negotiation is a process that is typically more costly than an auction in terms of time and effort required to achieve a solution from the participants. Moreover, since not all potential participants may be involved, negotiation is also prone to inefficient solutions in terms of market efficiency.

However, these are not sufficient reasons for replacing negotiations with auctions. The two mechanisms are complementary, and negotiations are used in many situations in which auctions should not or cannot be used. As just mentioned, when an issue is not well defined and requires rich communication and proactive coordination among involved participants, agent-based negotiation will be more appropriate to use than simple auctions. Agent-based negotiations may also accommodate machine learning, construction of alternatives and modification of constraints. Thus the outcome of a negotiation is often more than the negotiated product or service, the parties may establish a lasting relationship and engage in other transactions afterwards.

4.6 Summary

In this chapter, various aspects of multiagent system negotiated decision-making: including basics of negotiation theory, negotiation models as well as negotiation convergence and scalability issues are described. The relationship between agent-based auction and negotiation is also discussed. Multiagent system technology is now mature enough to support negotiation as a decision paradigm among different autonomous entities. As such, it is very attractive for use in addressing a fundamental difficulty inherent to operating today's power systems where we see different stakeholders simultaneously required to compete and cooperate.

In the next chapter, we will first develop a generic multiagent system platform that have most of the desiderata of software agents including inter-agent communication and handling inter-agent negotiations. Then a multiagent framework of integrated condition monitoring and maintenance scheduling for transmission equipment will be presented by extending the generic agents. We will also demonstrate the application of multiagent-based negotiated decision-making in transmission equipment maintenance scheduling.

5 A MAS FRAMEWORK OF INTEGRATED CONDITION MONITORING AND MAINTENANCE SCHEDULING SYSTEM

5.1 Introduction

The trend toward a deregulated electricity market has put the utilities under severe stress to reduce costs in order to be competitive in today's challenging business climate. One of the largest costs of an electric utility is the operation and maintenance of energy delivery systems. In this context, transmission maintenance has attracted considerable attention in the past decades. By performing efficient transmission maintenance practice, developing faults can be detected before costly outages and/or equipment failures occur, thus cost saving can be realized through a delay in the procurement of transmission equipment and reduction in maintenance effort.

As described in Chapter 3, we have developed an innovative risk-based transmission maintenance scheduling optimization procedure. This framework provides the ability to centrally select and schedule maintenance tasks so as to utilize the available financial and human resources to maximize the risk-reduction within a given budget cycle. In order to solve this problem centrally, one needs the complete information on the objective function as well as all the constraints. From the arguments put forth, however, this is often impossible in practice. The restructuring of electric power industry has resulted in unbundling a multitude of services provided by different self-interested entities, such as power generators (GENCOs), transmission providers (TRANSCOs), distribution company (DISCOs), and a host of others. As these entities move toward restructured market-based operation, new decision-making paradigm must be prepared to evaluate the impact of competition. The choice must take into account coordination between these self-interested entities. As developed in Chapter 4, multiagent negotiated decision-making is a novel framework which can be built upon and

ultimately replace the centralized decision approach, enabling optimized decisions in an environment of highly distributed information and a multiplicity of competing entities.

In this chapter, we intend to develop and implement a multiagent system framework, which provides the basis for displacing centralized optimization with negotiated decision-making for transmission maintenance scheduling. The rest of this chapter is organized as follows. First, a four-step MAS design methodology for constructing multiagent systems for power system applications is presented in section 5.2. Section 5.3 describes the implementation of a generic multiagent negotiation system. Based on this platform, in section 5.4, two security-economy decision-making scenarios will be illustrated using multiagent negotiations. In section 5.5, the framework of multiagent-based transformer condition monitoring and maintenance scheduling system is presented. The scheme of system-wide transmission maintenance scheduling through multiagent negotiations is described in section 5.6. Simulations of multiagent negotiation-based maintenance scheduling among several independent utilities are provided in section 5.7. Section 5.8 summaries.

5.2 Multiagent System Methodology

MAS is a relatively new field and as yet has not converged on a universally accepted design methodology. Several MAS paradigms and methodologies have been proposed in the literature, e.g. MASSIVE [Lind, 2001], DESIRE [Brazier, 1997], Gaia [Wooldridge, 2000] and MaSE [Wood, 2000], based on different notions of agents and multi-agent organizations. We feel it is appropriate to use a 4-stage methodology for constructing MAS for power systems applications: *Analysis, Design, Implementation, and Deployment,* as shown in Figure 5-1.

5.2.1 Analysis: Environment and Tasks

This is the first stage which identifies the application domain, overall problem, objectives, MAS application environment, i.e., information that will be available to an agent,

actions required of the agents, and operational (e.g., security) and performance constraints. Task decomposition is performed to determine what the system is supposed to do (and not how it is supposed to do it) to achieve overall MAS objectives.
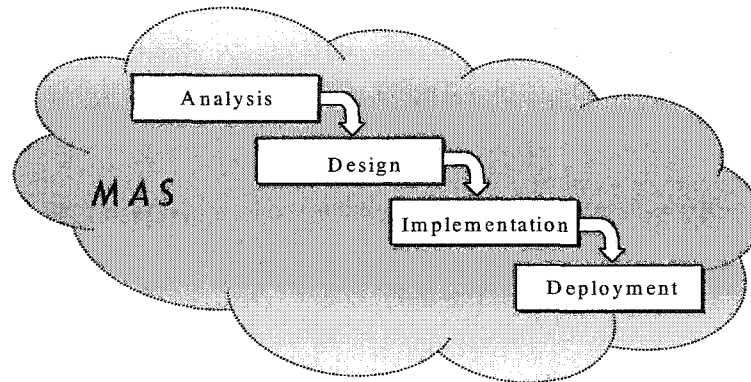
Figure 5-1: MAS Design Methodology

5.2.2 Design: Roles, Interactions, and Organizations

Having decomposed the problem into constituent tasks, the next stage is to identify the agents required to effectively perform the tasks in terms of (a) definition of agent roles (data, functional, decision, mediator, facilitator) linking domain-dependent application features to appropriate agent technology, and specifying services to be associated with each agent; (b) identifying the types of interactions needed between different agents in order to achieve individual or joint goals; and (c) specifying the organization of the different agents in terms of a society of agents that is consistent with the various defined roles and that achieves the overall objectives.

5.2.3 Implementation: Architecture

A key requirement for implementing a MAS is the selection of system and agent architectures. System architecture includes such aspects as multi-agent organization (e.g., hierarchical versus flat), agent management, and coordination mechanisms, including such things as directory services (or yellow pages) that enable each agent to know the capabilities and location of other agents, and the Agent Communication Language (ACL) that provides

the common basis for inter-agent communication. The most common ACLs include Knowledge Query and Manipulation Language (KQML) [Genereth, 1994] and Foundation for Intelligent Physical Agents (FIPA) ACL [FIPA]. There are a number of available agent platforms for implementing MAS including Voyager [Voyager], Concordia [Concordia], Aglets [Aglets] and SMART [Wong, 2001]. Based on an agent platform, individual agents can be extended with abilities to process specific messages and communicate with other agents. In order to enable inter-agent communication, besides ACL, it is also essential to define an appropriate ontology, or vocabulary, for the MAS that specify all possible message contents. In addition, some kind of inter-agent coordination strategy must be in place.

A broad range of architectures for agents (including reactive, deliberative, adaptive, communicative) have been studied in artificial intelligence. Properties that distinguish the various agent architectures include reasoning capabilities, resource limitations, control flow, knowledge handling, autonomy, user interaction, temporal context, and decision making.

5.2.4 Deployment

Here, actual agents are instantiated to cooperatively solve the problem. Testing is done to validate the model.

5.3 Multiagent System Implementation

Based on previously described MAS methodology, we intend to first develop generic agents that have most of the desiderata of software agents, including persistent interaction with environment, composing and interpreting messages, handling multiple conversations and so on. Then software agents with specific functionalities can be implemented by extending the generic agent. We use object-oriented software design method to develop agents representing different power system entities, e.g., suppliers, transmission owners, system operators, and delivery companies.

We have built a platform independent, object-oriented software infrastructure, called

MASPower [Vishwanathan, 2001] on top of the commercial distributed computing platform *Voyager ORB* [Voyager] to instantiate agents and multiagent systems for eliciting coordinated and negotiated decision-making from power system decision-makers. Voyager supports dynamic proxy generation, naming services, synchronous and asynchronous messaging, management of multiple concurrent tasks and multiple conversation protocols, and preceptors for accessing local and remote percept sources for distributed MAS.

The developed software can be used to instantiate generic software agent that has most of the functionalities of software agent, including managing multiple tasks, managing multiple conversation threads, perceptors for accessing local and remote environmental sources. The software platform is organized into the following eight packages:

- *edu.iastate.maspower.agents*: This package contains the basic and collaborative agent classes which can be used to implement agents with different functionalities together with other supporting classes.

- *edu.iastate.maspower.agents.gui*: This package contains the classes for the graphical user interface (GUI) for the agent.

- *edu.iastate.maspower.agents.task*: Activities carried out by the agent are abstracted as "tasks". Such tasks are instantiated by inheriting the functionalities provided by classes in this package.

- *edu.iastate.maspower.acl*: This package contains the functionalities for enabling communication between different agents using inter-agent messages following an agent communication language.

- *edu.iastate.maspower.acl.conversa*tions: This package contains functionalities for managing multiagent conversations including enforcing conversation protocols.

- *edu.iastate.maspower.mas* and *edu.iastate.maspower.mas.directories*: These packages contain the classes and interfaces for enabling the existence of the multiagent system including directory services and distributed computing support for inter-agent messaging.

- *edu.iastate.maspower.negotiations*: This package contains classes for agents to negotiate with other agents.

Individual agents may reside on any CPU within a network as long as the CPU is running *MASPower* on top of Voyager. The distributed computing components of *MASPower* are engineered by using the functionalities provided by Voyager ORB.

We extended the federated directory service implementation of Voyager ORB to provide the ability to maintain names of currently active agents together with keywords to identify the agent's area of expertise. *MASPower* stores the directory location as an XML document, read by every newly created agent, to avoid the need to recompile a program every time the directory location is changed.

Agent communication is performed using inter-agent messaging with message interpretation being private to each agent, providing the ability to interpret the same message differently under different agent internal states. Structural elements of an inter-agent message are per FIPA-2000 recommendations [FIPA]. Multiagent conversations are managed using thread, tagged by unique conversation identifiers generated by the agent initiating the conversation. Conversation protocols were designed as finite state machines (FSM) following the COOL notations [Barbuceanu, 1999]. The FSM for a conversation protocol is characterized by a START state, END state, FAIL state, and a variable number of intermediate states. Transition between one state to another occurs by either sending or receiving a message with a particular performative. For example, the FIPA recommendation for the contract net protocol [Smith, 1980; Smith, 1983] can be encoded as the FSM in Figure 5-2. This protocol is useful for automated contracts in environments where all agents cooperatively work toward the same goal. The manager proposes a task, announces it, and potential contractors evaluate it (together with other announcements from other managers) and then submit bids on the tasks for which they are able to perform.
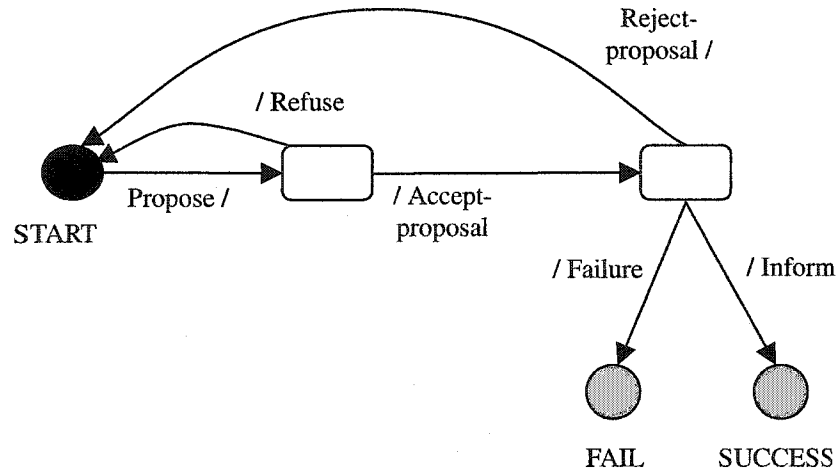
Figure 5-2: FSM of Contract Net Protocol

The FSM to be used by an agent depends on the role that the agent is playing in the conversation: the FSM in Figure 5-2 is used by the agent responding to the initiating agent. The initiating agent uses the same FSM except that "send" and "receive" labels are interchanged for all transitions.

Each activity that can be undertaken by an agent in its lifetime is organized as tasks. Whenever a new task instance is created, the object registers with the agent's task manager. A key attribute of *MASPower* is that many tasks can run concurrently within the agent.

An agent that initiates the negotiation process is termed *initiator*, and one or more responding agents are termed *responder(s)*. The FSM of our implemented negotiation protocol is illustrated in Figure 5-3.

It is important to keep in mind that the above multiagent system implementation as well as the multiagent negotiation models developed in Chapter 4, are all general and not confined to any particular application. The rationale behind this approach is that instead of only focusing on a particular decision-making context, we intend to first develop this general framework and then use some decision-making scenarios as specific instances of this framework. We will present some example applications of MAS negotiated decision-making

in the following sections of this chapter, including security-economy decision-making in stressed power system and system-wide maintenance scheduling problem.
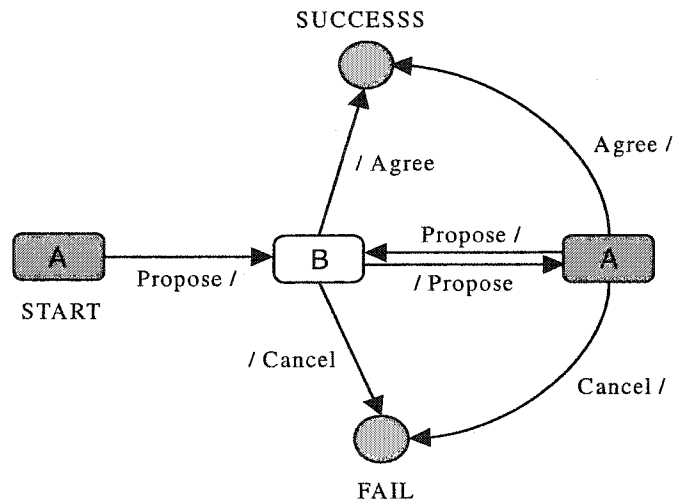
Figure 5-3: Negotiation Protocol

5.4 Illustrative System Security-Economy Decision-makings

During stressed operating conditions, there is an excessive risk of system collapse and massive load interruption. Thus coordination among different involved entities, such as transmission owners (TOs), load serving entities (LSEs), independent system operator (ISO) is needed to take the most appropriate actions to mitigate the problem. In this section we present two illustrative security-economy negotiated decision-making scenarios, employing the two negotiation models described in section 4.3 respectively within our multiagent system.

In simulation one, we use the IEEE Reliability Test System [IEEE, 1999] under stressed operating conditions, with the following decision required: *Determine by how much to operate a transmission circuit in excess of its identified rating?* In the traditional vertically integrated energy industry, this decision was made by a single organization, the utility company, because it both owned and operated the transmission system. However these two functions are now separated, with the ISO responsible for system operations and

implementing the market based dispatch insofar as system security limits allow. A transmission owner is responsible for the physical integrity of the circuit, including the specification of the circuit rating, and in addition, the transmission owner receives revenues for use of the circuit in proportion to the flow. We have simulated a negotiation between the ISO-Agent and the Transco-Agent over the increase in circuit rating and pro-rata compensation for the transmission service. Both agents employ the value-function based negotiation model as discussed in section 4.3.1. The negotiation issues are *circuit rating increase* and *monetary compensation*. The resources used by the agents are *equipment life* (only for the Transco), *money*, and *negotiation time*. Figure 5-4 illustrates the progress of the negotiation. The negotiation concluded after 54 iterations, taking 282 seconds, when the ISO accepts an offer of 4.62 MW rating increase at $13.13 for each MW of transmission service. A second simulation (not shown) repeated the first, except that the negotiation time resource for the Transco was decreased from 600 sec to 240 seconds, resulting in agreement after 42 iterations taking 225 seconds, at 5.54 MW rating increase at $11.76 for each MW of transmission service.
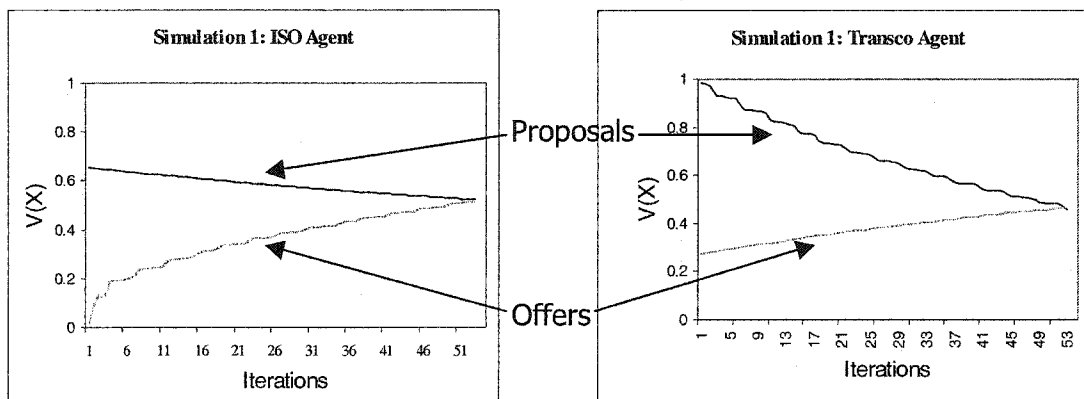
Figure 5-4: Negotiation between ISO-Agent and Transco-Agent

We also completed another system security related inter-agent negotiation simulation using the rational negotiation model as described in section 4.3.2. In order to construct a security-constrained case, we first apply several modifications to the IEEE Reliability Test

System [IEEE, 1999]:

- Line 11~13 is removed;

- Set terminal voltage of the Bus 23 generator to 1.012pu;

- Shift 480 MW of load from buses 14, 15, 19, 20 to bus 13; (Bus 14: 40 MW, Bus 15: 190 MW, Bus 19: 150 MW, Bus 20: 100 MW)

- Add generation capacity at buses 1 (100 MW unit), 7 (100 MW unit), 15 (100 MW unit, 155 MW unit), 23 (155 MW unit).

- Change the outage rate of Line 12~23, 13-23, 11-14 to 0.1 1,5, 10, respectively, so their outage rates have significant difference.

Area 1: bus 1 ~ 10.
Area 2: bus 12, 13, 23.
Area 3: the rest buses
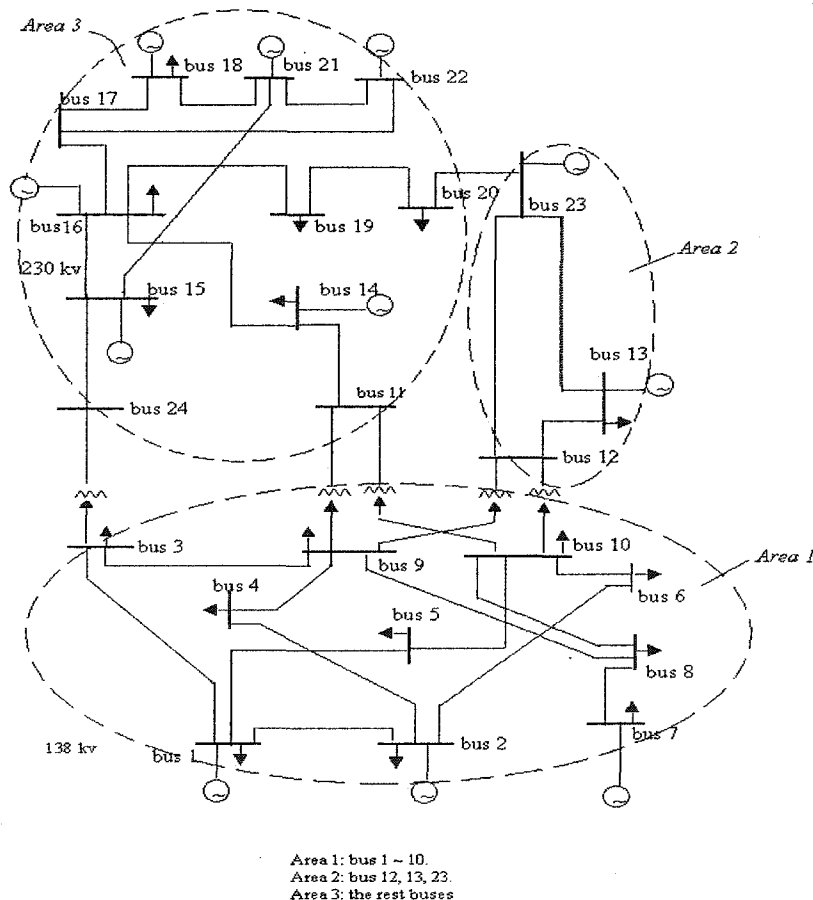
Figure 5-5: Modified RTS-96 System

Because of large amount of load shifted to bus 13, the modified test system has a

severe overflow problem in line 16 (from bus 23 to bus 13), which results in system high overload risk (23.0665). Traditionally this problem will be resolved solely by the system operator without coordinating with other entities in the system. But under the deregulated environment, all the entities in power system now become autonomous and independent. Thus resolving this kind of problem now needs the coordination of all related entities instead of mandatory actions. The MAS paradigm of distributed decision support through inter-agent negotiation is an ideal solution approach for this problem. Below we will illustrate this through the negotiation of entity-representing agents using the socially rational negotiation model based on expected utility.

In order to simplify the negotiation process, we will just focus on the overload risk of the test system. Representing the independent system operator, the ISO-Agent is in charge of the overall system security and periodically examines the system risk values calculated by RBSA-Agent. When it detects the high system overload risk, it immediately initiates negotiation with the Load-Agent representing the load entity at bus 13. The negotiation issues include *load curtailment* by the Load-Agent, and *compensating money* offered by the ISO-Agent. During the negotiation, the Load-Agent has to analyze the tradeoff between the monetary compensation proposed by ISO-Agent and the expected loss due to its load curtailment. Each agent fist evaluate the received offer (calculate its expected utility), then decide to accept (if the expected utility of the received offer is larger than its own expected utility) or counteroffer or reject. Here in our simulation, we assume that agents should have common interest in reaching an agreement over the negotiation issues, so there is no brutal rejection. If an agent will not accept the received offer, it will try to propose its counteroffer. They gradually increase or decrease its offer until both of them come into an agreement.

The simulation results are shown in Figure 5-6. The system overload risk significantly decreases as the Load-Agent agrees to shed more and more load at bus 13, and eventually when the two agents come to agreement that the Load-agent sheds 700MW load, the system overload risk drops to zero. The expected utilities of the two agents both mainly

increase as the negotiation processes. This is because both agents use socially rational negotiation models: the system security level influences the ISO-Agent as well as the Load-Agent. Figure 5-6 also illustrates how the compensated money evolves during the negotiation process, finally resulting in agreement between the two agents on $58,974 for 700MWh load curtailment.
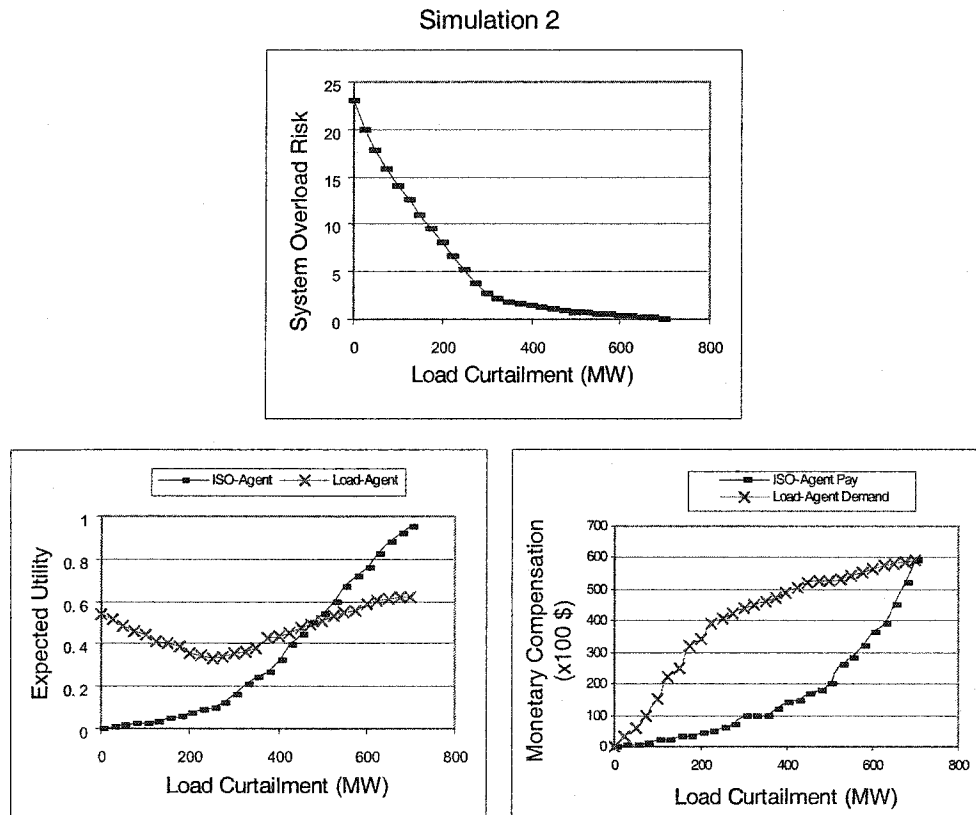
Figure 5-6: Negotiation Between ISO and Load Agents

The above two simulations are illustrative examples of resolving system stressed scenarios through negotiations between several agent-represented entities. The MAS paradigm of distributed decision support through inter-agent negotiation facilitates the coordination among different independent entities to resolve these type of problems, once resolved solely by the system operator without coordinating with other entities in the system. This is an innovative paradigm to build upon and ultimately replace the centralized decision approach, enabling more satisfactory solution to all involved parties.

5.5 Multiagent-based Transformer Condition Monitoring and Maintenance System

We have developed a platform-independent, object-oriented software infrastructure, *MASPower*, as described in Section 5.3. It could be used to rapidly instantiate software agents and multiagent systems for eliciting complex information processing and negotiated decision-making scenarios. Based on this software agent infrastructure, we further implement a multiagent based condition monitoring and maintenance system (MCMMS) for power transformer. The framework of MCMMS is shown in Figure 5-7.
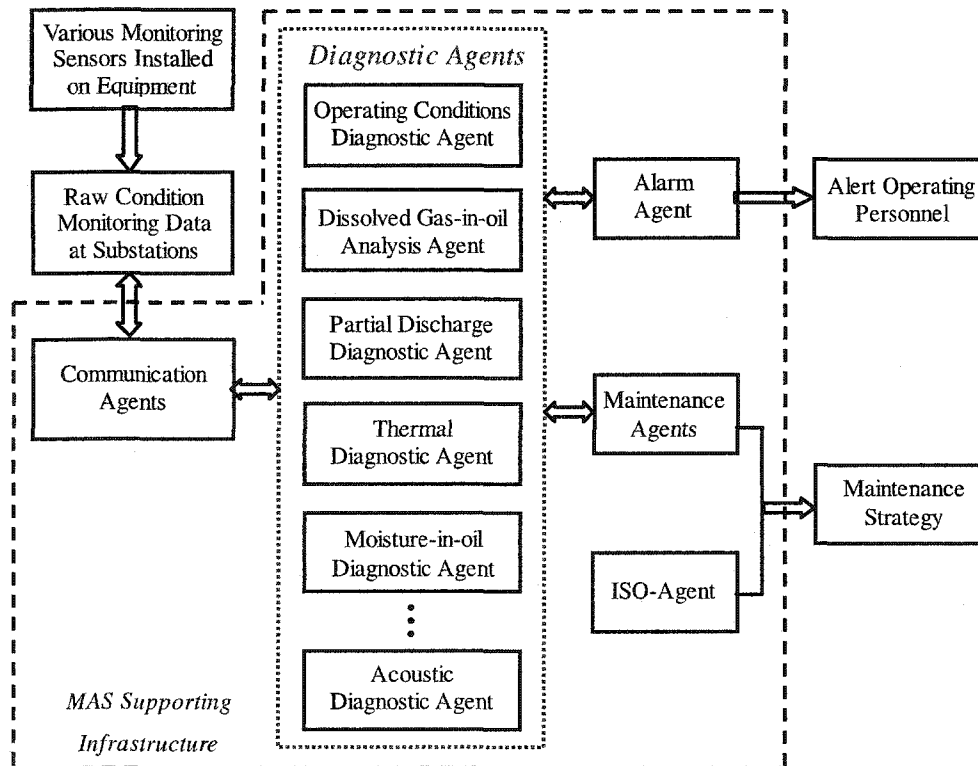
Figure 5-7: Multiagent based Condition Monitoring and Maintenance System (MCMMS)

5.5.1 Model of Communication Agent

Large amounts of equipment monitoring data are gathered at monitoring equipment, operational hardware, software systems and databases that are not easily accessed or

generally available. Based the application described in [Reinoso-Castillo, 2002], the intelligent communication agent is capable of accessing distributed, heterogeneous, proprietary data sources, and extracting all related transformer condition monitoring information. It can also communicate with diagnostic agents using ACL. The model of communication agent is shown in Figure 5-8.
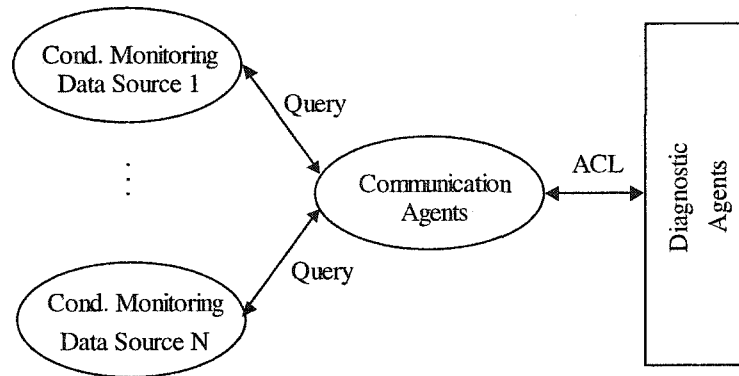
Figure 5-8: Model of Communication Agent

5.5.2 Model of Diagnostic Agent

The model of diagnostic agent is shown in Figure 5-9. Diagnostic agents possess knowledge of the necessary monitoring techniques as previously described. Based on the queried monitoring data, diagnostic agents can cooperatively perform diagnostic functions. Because monitoring systems continuously collect real-time data, the amount of data is enormous, and the diagnosis can be data and computation intensive. MAS architecture enables diagnostic agents to cooperatively detect abnormal situations and identify any possible transformer failure modes as summarized in Appendix A. Once certain predefined operating thresholds have been violated, the alarm agent alerts the operating personnel at a central control room.
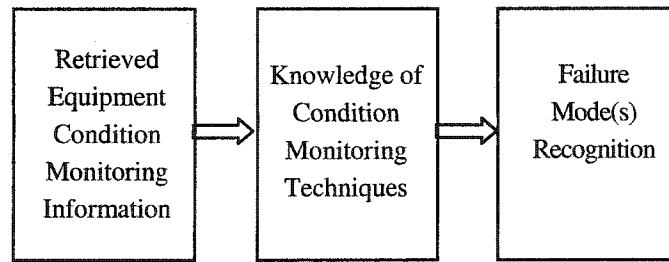
Figure 5-9: Model of Diagnostic Agent

5.5.3 Model of Maintenance Agent

The model of maintenance agent is shown in Figure 5-10. Based on detected possible failure modes, the maintenance agent will recommend appropriate maintenance activities as listed in Appendix A for the equipment. And the instantaneous transmission equipment failure probabilities will also be estimated based on recently acquired condition monitoring information, using the methods described in Section 3.5. Then each maintenance agent, representing independent utility, performs the centralized maintenance scheduling optimization in its own territory, using the *Integrated Maintenance Selector and Scheduler* (IMSS) as described in [Jiang, 2003a]. They can further be engaged in inter-agent negotiations with other maintenance agents representing different utilities to reach an acceptable system-wide maintenance schedule.
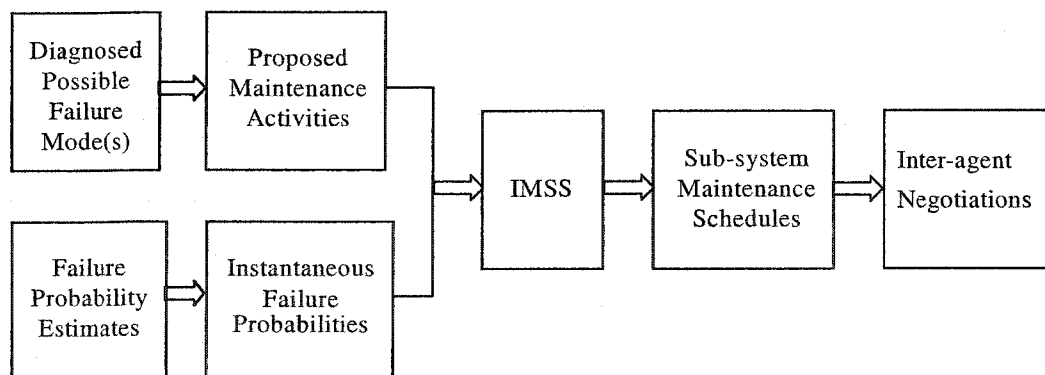
Figure 5-10: Model of Maintenance Agents

5.6 System-wide Maintenance Scheduling through MAS Negotiations

In Section 3.2, we have described a system-wide centralized maintenance scheduling optimization procedure by maximizing cumulative risk reduction. In principle, one may consider to solve this large-scale mathematical problem centrally using currently available computing power and solution techniques [Jiang, 2003a; Jiang, 2003b]. However, with recent organizational disaggregation and functional balkanization in the industry, facility ownership is heavily fragmented, and information access and decision-making authority is quite limited for any one particular organization. Decision problems, such as maintenance scheduling, once solved using centralized optimization algorithms are now more difficult due to distributed information and the multiplicity of competing stakeholders. We have developed a multiagent negotiation system [McCalley, 2003a] in which software agents, armed with coded negotiation models, represent different decision-makers, and conflict resolution is achieved via inter-agent message exchange until agreement is reached. It is more appropriate to employ multiagent negotiation to solve this maintenance-scheduling problem. The multiagent socially rational negotiation model developed in Section 4.3.2 is suitable in this situation, because maintenance activities would not only save cost for each utility (by avoiding costly equipment failures and extend the life of electrical equipment), but also significantly improve reliability of the entire system.

Different maintenance software agents are coded to represent different independent utilities. Each maintenance agent can perform the centralized maintenance scheduling optimization as described in Section 3.2 in its own footprint first, and comes up with its own maintenance schedule. Agents communicate with each other using communication protocol specified in the design of our multi-agent system platform as described in Section 5.3. Conflicts among the maintenance schedules of different utilities, e.g., more than one utility

want to schedule a major power transformer maintenance during the same time period, are then resolved via inter-agent negotiations according to the overall system security constraints imposed by the ISO-Agent. The scheme is shown in Figure 5-11.

: ISO-Agent   : Maintenance Agent
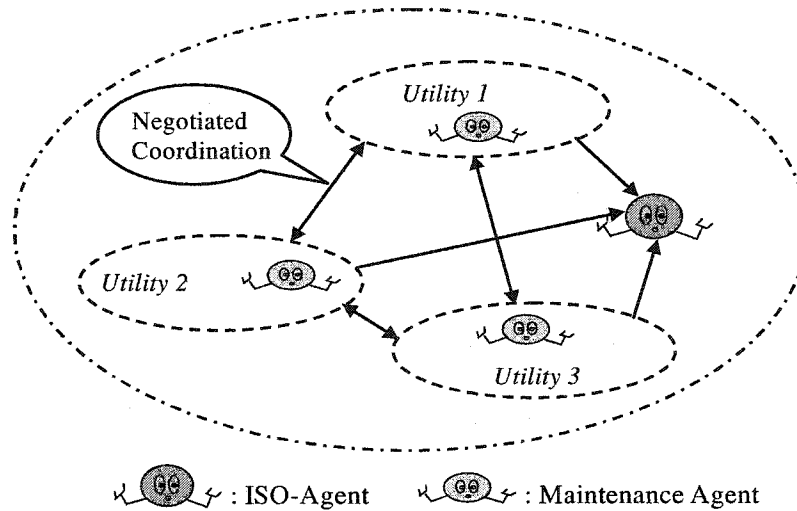
Figure 5-11: Maintenance Scheduling through MAS Negotiations

5.7 System Maintenance Scheduling Simulations through Multiagent Negotiation

To illustrate our agent negotiation-based method for maintenance scheduling, we use a model of an actual electric power system but with hypothetical maintenance activities. The system has 36 generators, 566 buses, 561 transmission lines and 115 transformers [McCalley, 2003b]. We divide the entire system into three subsystems, and stipulate that each of them belongs to a different utility. And three different software agents are coded to represent the three different utilities respectively. In the following simulations, we apply the multi-agent negotiation in transformer maintenance scheduling. The three subsystems, A, B and C, first use the centralized optimization method [Jiang, 2003a; McCalley, 2003b] to schedule their proposed power transformer maintenance activities individually. The resulted maintenance

schedules (only for major transformer maintenance) of the three individual subsystems are listed in Table 5-1.

Table 5-1: Transmission Maintenance Schedules for Three Sub-systems

Periods (week)	XFMR major maintenance schedule for sub-system A	XFMR major maintenance schedule for sub-system B	XFMR major maintenance schedule for sub-system C
1-3	Xrmj5	Xrmj13	Xrmj16
4-6	Xrmj7	Xrmj15	Xrmj19
7-9	Xrmj6	Xrmj14	Xrmj17
10-12	Xrmj2	Xrmj9	Xrmj18
13-15	Xrmj4	Xrmj11	Xrmj20
16-18	Xrmj1	Xrmj12	
19-21	Xrmj3	Xrmj8	
22-24		Xrmi10	
25-52			
# schedules	7	8	5
CRR	0.162061	0.283093	0.129787

In our simulations, we assume that there is a security constraints posed by the ISO-Agent: only one major transformer maintenance is allowed during the same time period in the entire system. From the above maintenance schedules, we can observe that there are many conflicts among the three individual maintenance schedules of the sub-systems. We need to resolve these conflicts through coordination of these three maintenance agents. For these agents, which are responsible for the corresponding sub-systems' maintenance scheduling, they will initiate negotiations among themselves regarding the sequence of maintenance activities they take. The negotiation issue is who will take this *maintenance spot*. The resources used by the negotiating agents include *system cumulative risk reduction* (CRR), and *compensated money* (CM). Each maintenance agent employs a linear utility function in the form of:

$$U_i = k_{i1} * CRR_i + k_{i2} * CM_i \quad , \quad \sum_{j=1}^{2} k_{ij} = 1 \quad , \quad k_{ij} > 0 \quad , \quad j = 1, 2$$

(5.1)

Each maintenance agent may also have different social prospective: i.e., have different r_{ij}'s

as described in Section 4.3.2.

Maintenance Scheduling Simulation
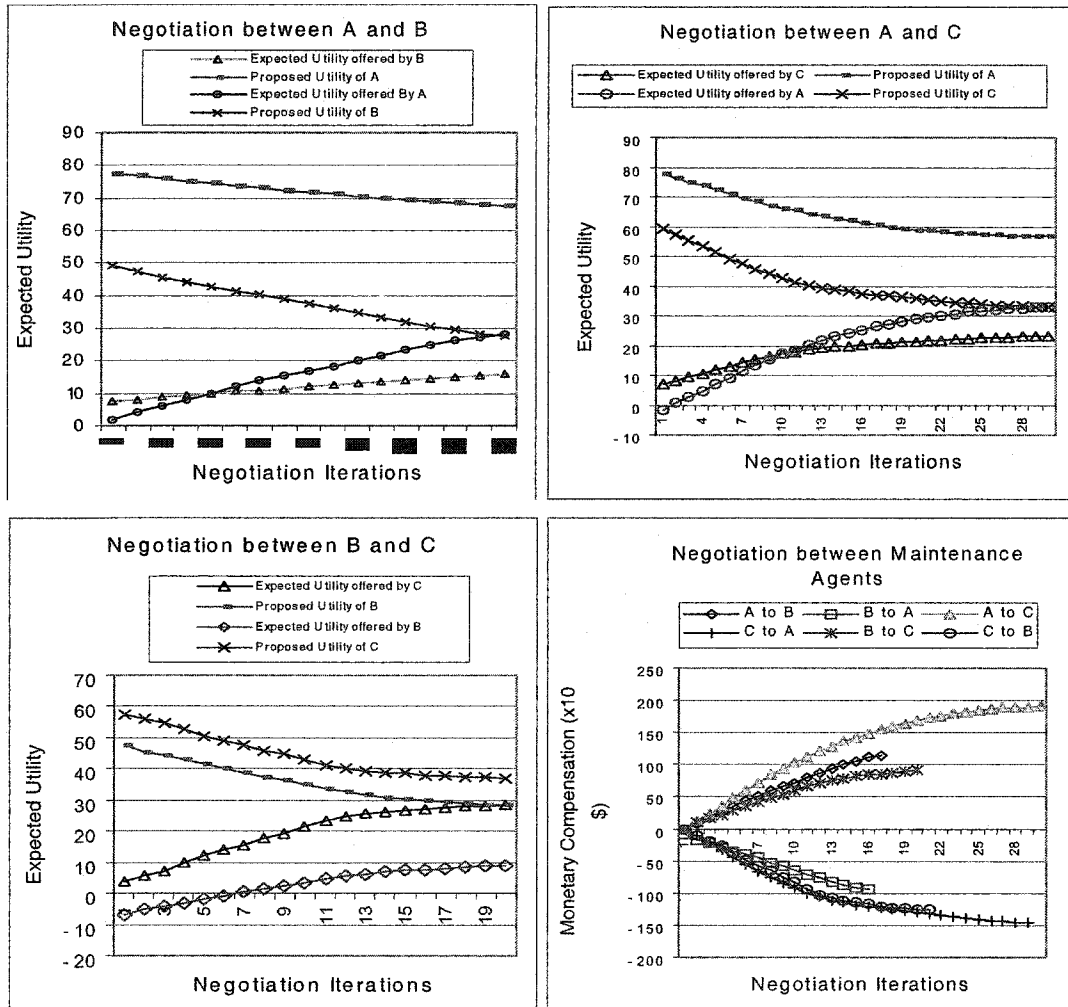
Figure 5-12: Maintenance Scheduling Simulation through Negotiation

At every round of negotiation, in order to determine who will take the *maintenance*

spot, each maintenance agent first evaluates the expected utility of its opponent's offer. If this

expected utility is no less than the utility of its own proposal, the agent will accept the offer;

otherwise, it will try to counteroffer. A bilateral sequential negotiation among the three

maintenance agents, A, B and C, is illustrated in Figure 5-12. In this round of negotiation, B

accepts A's offer with the agreement of 1140 $ monetary compensation from A in exchange of scheduling A's maintenance work ahead of B's. Similarly, B accepts C's offer with the agreement of 1260 $ monetary compensation in exchange of scheduling C's maintenance work ahead of B's; C accepts A's offer with the agreement of 1910 $ monetary compensation in exchange of scheduling A's maintenance work ahead of C's.

In our simulation scenario 1, we first consider that all the three maintenance agents are totally socially rational, i.e., social utilities are equivalent to their own individual utilities when all r_{ij}'s are equal to 1/3. The simulation result is shown in Table 5-2. The total number of schedules for the entire system is 17. The numbers of maintenance schedules for the three subsystems are 6, 8, and 3 respectively. And the system cumulative risk reduction is 0.4013.

Table 5-2: Transformer Maintenance Scheduling Simulation 1

Week	XFMR major maintenance		
	XFMR NO.	Sub-system	CRR
1-3	Xrmj15	B	0.050577
4-6	Xrmj13	B	0.046665
7-9	Xrmj14	B	0.042179
10-12	Xrmj16	C	0.040515
13-15	Xrmj9	B	0.032109
16-18	Xrmj12	B	0.030683
19-21	Xrmj11	B	0.029439
22-24	Xrmj10	B	0.024004
25-27	Xrmj8	B	0.021771
28-30	Xrmj7	A	0.020942
31-33	Xrmj5	A	0.020365
34-36	Xrmj6	A	0.017662
37-39	Xrmj2	A	0.010409
40-42	Xrmj1	A	0.006546
43-45	Xrmj19	C	0.004381
46-48	Xrmj4	A	0.001998
49-51	Xrmj18	C	0.001037
52			
# schedules	17		
Total CRR	0.4013		

In our simulation scenario 2, maintenance agent A is more selfish: e.g., $r_{11} = 0.5$,

$r_{12} = r_{13} = 0.25$. And the other two agents are still rational, i.e., $r_{21} = r_{22} = r_{23} = 1/3$,

$r_{31} = r_{32} = r_{33} = 1/3$. Clearly, the negotiation result will be in favor of maintenance agent A.

The simulation result is shown in Table 5-3. The total number of maintenance schedules for

the entire system is 17. The numbers of maintenance schedules for the three subsystems are 8,

8, and 1 respectively. And the system cumulative risk reduction is 0.3960.

Table 5-3: Transformer Maintenance Scheduling Simulation 2

Week	XFMR major maintenance		
	XFMR NO.	Sub-system	CRR
1-3	Xrmj15	B	0.050577
4-6	Xrmj13	B	0.046665
7-9	Xrmj14	B	0.042179
10-12	Xrmj7	A	0.025854
13-15	Xrmj16	C	0.039058
16-18	Xrmj12	B	0.030683
19-21	Xrmj5	A	0.023595
22-24	Xrmj9	B	0.023387
25-27	Xrmj11	B	0.027039
28-30	Xrmj6	A	0.020578
31-33	Xrmj10	B	0.023525
34-36	Xrmj2	A	0.014133
37-39	Xrmj8	B	0.013038
40-42	Xrmj5	A	0.007142
43-45	Xrmj6	A	0.005457
46-48	Xrmj2	A	0.002004
49-51	Xrmj4	A	0.001039
52			
# schedules	17		
Total CRR	0.3960		

In our simulation scenario 3, maintenance agent B is more unselfish: e.g., $r_{22} = 0.2$,

$r_{21} = r_{23} = 0.4$. And the other two agents are still socially rational, i.e., $r_{11} = r_{12} = r_{13} = 1/3$,

$r_{31} = r_{32} = r_{33} = 1/3$. Clearly, the negotiation result will be in favor of maintenance agent 1 and 3. The simulation result is shown in Table 5-4. The total number of maintenance schedules for the entire system is 17. The numbers of maintenance schedules for the three subsystems are 7, 5, and 5 respectively. And the system cumulative risk reduction is 0.3494.

Table 5-4: Transformer Maintenance Scheduling Simulation 3

Week	XFMR major maintenance		
	XFMR NO.	Sub-system	CRR
1-3	Xrmj15	B	0.050577
4-6	Xrmj16	C	0.043825
7-9	Xrmj15	B	0.047312
10-12	Xrmj7	A	0.026559
13-15	Xrmj6	A	0.025270
16-18	Xrmj5	A	0.024579
19-21	Xrmj1	A	0.019173
22-24	Xrmj2	A	0.017854
25-27	Xrmj19	C	0.017055
28-30	Xrmj18	C	0.016416
31-33	Xrmj4	A	0.015619
34-36	Xrmj3	A	0.014453
37-39	Xrmj17	C	0.010309
40-42	Xrmj20	C	0.006286
43-45	Xrmj13	B	0.008611
46-48	Xrmj14	B	0.003889
49-51	Xrmj9	B	0.001646
52			
# schedules	17		
Total CRR	0.3494		

We also have done a simulation for entire system maintenance scheduling using the centralized optimization method as described in [Jiang, 2003b]. The simulation result is shown in Table 5-5.

Table 5-5: Transformer Maintenance Scheduling Simulation 4

Week	XFMR major maintenance		
	XFMR NO.	Sub-system	CRR
1-3	Xrmj15	B	0.050577
4-6	Xrmj13	B	0.046665
7-9	Xrmj14	B	0.042179
10-12	Xrmj16	C	0.040515
13-15	Xrmj9	B	0.032109
16-18	Xrmj12	B	0.030683
19-21	Xrmj11	B	0.029439
22-24	Xrmj10	B	0.024004
25-27	Xrmj8	B	0.021771
28-30	Xrmj7	A	0.020942
31-33	Xrmj5	A	0.020365
34-36	Xrmj6	A	0.017662
37-39	Xrmj2	A	0.010409
40-42	Xrmj1	A	0.006546
43-45	Xrmj19	C	0.004381
46-48	Xrmj4	A	0.001998
49-51	Xrmj18	C	0.001037
52			
# schedules	17		
Total CRR	0.4013		

A comparison between the three multiagent negotiation-based maintenance simulation results and the centralized optimization result is shown in Table 5-6. From the simulation results, we can easily find that the result of agent negotiation simulation 1 is exactly the same as that of our centralized optimization simulation. The reason is because, in this negotiation simulation, all the maintenance agents are totally rational and they also utilize the system-wide information of cumulative risk reduction (CRR). Thus whichever maintenance activity can achieve larger system accumulative risk reduction, it will be scheduled ahead of others. And when some of the maintenance agents deviate from totally rational (either selfish or unselfish as in our simulation 2 and 3), then the simulation results would become sub-optimal.

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Table 5-6: A comparison between the Maintenance Simulations

	Total Schedules	Schedules for sub-system A	Schedules for sub-system B	Schedules for sub-system B	Cumulative Risk Reduction
Negotiation Simulation 1	17	6	8	3	0.4013
Negotiation Simulation 2	17	8	8	1	0.3960
Negotiation Simulation 3	17	7	5	5	0.3494
Centralized Optimization Simulation 4	17	6	8	3	0.4013

Here, we can see two advantages by using the MAS negotiated decision-making. One is that it can actually be implemented to facilitate the decision-making among a multiplicity of distributed decision-makers. Different entities represented by software agents with coded negotiation models, can coordinate with each other to resolve problems, such as maintenance scheduling, once handled by a centralized organization. The rationale of this distributed decision-making paradigm through multiagent negotiation is not only to reflect the true picture of the deregulated environment, but also enable solutions in a more satisfactory manner to all involved parties. The other is that it is a tool to use in comparing distributed decision-making relative to centralized decision-making. The centralized solution is optimal if all relevant information is available. However, in today's restructured environment, this is not always the case, because either required information for decision is proprietary and not fully accessible, or decision-making authority is highly fragmented and need coordination among all entities. The paradigm of distributed decision-making through multiagent negotiation provides a way to achieve solutions with varying levels of cooperation and information among all parties. It offers different levels of centralization in decision-making, i.e., negotiated decision-making allows simulation and study of decision quality as the

decision framework moves from being highly centralized (i.e., vertically integrated utilities) to entirely distributed (i.e., restructured power industry).

5.8 Summary

In this chapter, we developed and implemented an innovative multiagent system distributed decision-making framework, which provides the basis for displacing centralized optimization with inter-agent negotiation. We illustrated this framework for transmission maintenance scheduling. The multiagent design methodology was introduced. Different implementation issues of our multiagent system, including directory service, inter-agent communication protocol and negotiation protocol were described. Based on this generic multiagent platform, a multiagent system framework for integrated condition monitoring and maintenance scheduling system for power transformer was described. Simulations of resolving the maintenance-scheduling problem through multi-agent negotiations were presented. We conclude that multiagent negotiated decision-making provides a viable alternative solution procedure, which is more attractive in a deregulated environment.

In next chapter, we summarize the major contributions of this work and pave the way for further research efforts in this direction.

6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this work, motivated by the need to coordinate transmission maintenance scheduling among a multiplicity of self-interested entities in restructured power industry, we have developed a distributed decision support framework based on multiagent negotiation systems (MANS). In the first chapter, we described the need of decision coordination among competing power system entities for a variety of decision-making problems, such as system-wide transmission maintenance scheduling. In chapter 2, literature related to this work was reviewed. Different transmission system maintenance practices were summarized. Current industry efforts regarding standardization of communication protocols and information integration were identified. Then concepts of intelligent software agent and multiagent systems as well as their attractive attributes were introduced. In chapter 3, we first presented an innovative risk-based transmission maintenance optimization procedure. In order to best enhance system reliability by performing appropriate maintenance activities, we need evaluate the condition of aging transmission equipment. We used power transformer as an example to illustrate our work. Different power transformer condition monitoring techniques along with available condition data were described. Various transformer failure modes were also identified. Based on condition monitoring information, different models for estimating equipment instantaneous failure probability were developed and illustrated. The quantification of equipment instantaneous failure probability enables the effective utilization of equipment condition information in related maintenance decisions. In chapter 4, we again motivated the need of a new paradigm for distributed decision coordination among competing entities in deregulated power industry. The basics of negotiation theory were reviewed. Two multi-agent negotiation models were described. Some issues of multiagent negotiation convergence and scalability were discussed. The relationship between

agent-based negotiations and auction systems was also identified. In chapter 5, we first described a four-step MAS design methodology for constructing multiagent systems for power system applications. Then the implementation of a multiagent negotiation system (MANS) was described. Based on this generic multiagent system platform, we further developed a multiagent system framework for facilitating the integration of condition monitoring information and maintenance scheduling for power transformers. Simulations of multiagent negotiation-based maintenance scheduling among several independent utilities were also provided.

6.2 Contributions and Significance of This Work

Some decision-making problems in today's deregulated power industry, like transmission maintenance scheduling, necessitate a new paradigm to build upon and ultimately replace the centralized decision approach, enabling optimized decisions in an environment of highly distributed information and a multiplicity of competing entities. This work offers an alternative to traditional centralized maintenance practice by developing a multiagent negotiation-based framework for coordination of maintenance decisions among independent utilities. The most significant contributions of this work are summarized in what follows.

▪ An innovative risk-based transmission maintenance optimization procedure was introduced. This framework provides the ability to centrally select and schedule maintenance tasks so as to utilize the available financial and human resources to optimize the risk-reduction achieved from them within a given budget cycle. Several models for linking condition monitoring information to the equipment's instantaneous failure probability were developed. They enable quantitative evaluation of the effectiveness of maintenance activities in terms of system cumulative risk reduction. These models include straightforward, easily implemented hazard function models; and a strict, flexible Markov model as well as a

complementary Bayesian model. Methodologies of statistical processing, equipment deterioration level evaluation and time-dependent failure probability calculations were also described.

- A novel framework capable of facilitating distributed decision-making through multiagent-based negotiation was developed. A multiagent negotiation model was developed and illustrated that accounts for uncertainty and enables social rationality. Some issues of multiagent negotiation convergence and scalability were discussed. The relationship between agent-based negotiations and auction systems was also identified.

- A four-step MAS design methodology for constructing multiagent systems for power system applications was presented. A generic multiagent negotiation system, capable of inter-agent communication and distributed decision support through inter-agent negotiation, was implemented.

- A multiagent system framework for facilitating the integration of condition monitoring information and maintenance scheduling for power transformers was developed. Simulations of multiagent negotiation-based maintenance scheduling among several independent utilities were provided. It is a viable alternative solution paradigm to the traditional centralized optimization approach in today's deregulated environment.

The distributed decision-making paradigm through multiagent negotiation presented in this thesis has a number of explicit and implicit significance to the restructured power industry. Here we are not intend to enumerate all of them, but try to describe several most representative ones:

- *Knowledge-level Communication Capability*: Within a multiagent system, agents can communicate with each other using *agent communication language* (ACLs), which resembles human-like speech actions more than typical symbol-level program-to-program communication protocols. This capability enables agents to distill useful knowledge from voluminous heterogeneous information sources and communicate with each other on the

basis of which they coordinate their actions. By enabling performance of computation where computing resources and data are located, and allowing for flexible communication of relevant results to relevant entities as needed, MAS offer significant new communication capabilities to power systems, which have for so long depended on various forms of expensive telemetry to satisfy most communication needs.

- *Distributed Data Access and Processing*: Recall that in power system industry, it presents a great challenge to gather, analyze and integrate a wide variety of information/data on multiple, geographically distributed, heterogeneous and often autonomously owned operational hardware and software systems in support of distributed problem solving and decision making. The benefits offered by MAS with the distribution of multiple, more or less autonomous agents across a network could lead to solve this problem. Software agents may have different levels of intelligence, ranging from data agents and functional agents to decision agents (corresponding to what were termed data view, function view, and dynamics view in [Lind, 2001]). Special agents can be designed to extract, transform and assimilate relevant information from heterogeneous and proprietary data sources, such as the application described in [Reinoso-Castillo, 2002]. This application uses a three-layer architecture consisting of the physical layer, the ontological layer, and the user-interface layer. The physical layer allows the system to communicate with the distributed information sources. The ontological layer automatically bridges the syntactic and semantic mismatches among the heterogeneous data sources. Finally, the user interface layer enables users to interact with the system, define ontologies, post queries and receive answers. Because each agent is designed to perform a specific role, with associated knowledge and skills, distributed and heterogeneous information can be efficiently processed locally and utilized in a coordinated fashion in distributed knowledge networks [Honavar, 1998], resulting in reduced information processing time and network bandwidth consumption in comparison to that of more traditional centralized schemes in current power industry.

- *Integratability*: The power industry maintains a rich plethora of power system software applications, developed in many different computer languages, intended for use on many different platforms. Extending old applications or developing new ones usually involves integrating legacy systems, and doing so is cumbersome and labor-intensive. Within MAS, this problem can be largely overcome by wrapping agent functionality, mainly the communication mechanism, around the existing legacy systems to provide them with highly flexible interoperability.

- *Scalability*: Each agent can be identified as an independent entity and thus help in incremental growth and flexible expansion of the entire system. The advantage of scalability is provided as each agent can join a system, start working with other agents, or just leave a system it was engaged in after it has finished a plan, without affecting the overall function of the system. Because there may be several agents that are capable of doing the same thing, if one is unavailable or not properly working, another can do the job. This feature makes MAS highly robust and maintainable. In addition, MAS naturally facilitate the dissemination of new and more powerful functionality; as a new function becomes available, it is not simply limited to the particular self-contained system in which it is deployed but rather to the entire society of agents.

- *Distributed Decision Support*: Design of complex systems in general, in order to be feasible, often requires modular design, which involves the decomposition of the overall task into more manageable subtasks. Multiagent system offers a natural task decomposition approach to problem solving through interaction among agents. This is facilitated by the ability of different agents to coordinate behavior through cooperation (agents have established and mutually agreeable objectives), negotiation (agents negotiate until agreement is reached as described I this thesis), or mediation (agents resolve conflicts that cannot be resolved by negotiation by appeal to a third, neutral agent) [Lind, 2001]. In this sense, MAS provides an innovative distributed decision support paradigm in contrast to the traditionally

centralized approaches. Each of these coordination mechanisms will certainly find ubiquitous applications in power systems.

From the arguments put forth in favor of multiagent systems and distributed decision making through agent-based negotiations, we conclude that there are at least two distinct ways in which the power industry will benefit from successful implementation of this multi-agent negotiation framework: better decisions and better models. Better decisions may be expected because: (a) The ability to perform computer-evaluation of relevant issues, including accessing complex, distributed data, is inherent to the negotiation itself. This is in contrast to human-based negotiation where obtaining additional information or performing additional processing is typically done outside the time and space given to the negotiation process. (b) The negotiation speed is significantly increased. In contrast to human-based negotiation where negotiation speed depends on the limitations of the human negotiators, computer-based negotiated decisions may be reached as fast as network bandwidth and computer processing power allow. This not only provides for enhancing existing negotiated decision-making scenarios but also introducing negotiated decision-making where it was previously thought to be untenable. For example, networked negotiation enables consideration of negotiated decision making between control centers, even between individual generation and/or transmission companies, following outages when typically decision-time is quite short.

The second way in which the power industry will benefit is that multi-agent negotiated decision-making offers a modeling framework that enables study of important power industry characteristics for which good models are not presently available. One of these characteristics is the level of centralization in decision-making, i.e., negotiated decision-making allows simulation and study of decision quality as the decision framework moves from being highly centralized (i.e., vertically integrated utilities) to entirely distributed (i.e., restructured power industry).

6.3 Future Work

The research described in this dissertation lays out the framework of multiagent system as an integrated approach to complex information integration and distributed decision support for a lot of problems in deregulated power system environment, such as transmission maintenance scheduling. This work offers an alternative to traditional centralized approaches by coordination among agent-represented decision entities. However, before this framework could be fruitfully deployed in a physical system, there are still many related issues worthy of investigation. Some of them are discussed as follows:

- *Different kind of inter-agent coordination techniques*: As described before, except negotiation, there are some other kind of inter-agent coordination techniques, such as mediation, auctions, voting and bargaining [Sandholm, 1999]. We have studied inter-agent negotiation mechanism, which we feel is the most appropriate coordination mechanism needed for a multiplicity of competing entities in deregulated power system environment. However, those other coordination techniques also need to be investigated, as they may be more suitable than negotiation in some application scenarios.

- *Multilateral inter-agent negotiations:* As described in section 4.4, we have implemented a multiagent negotiation system capable of enabling bilateral, sequential inter-agent negotiations. It is desirable to do some enhancement with the software implementation to enabling multilateral inter-agent negotiations. The negotiation models developed in this dissertation are capable of multilateral inter-agent negotiations, but the negotiation protocol need to be somehow modified. One possible way of doing so is to adopt broadcasting communication as discussed in section 4.4.

- *Equip software agents with learning mechanisms:* Learning from experiences is an essential ingredient in human decision-making. Integrating machine learning algorithms [Bui, 1996; Arai, 2000; Chajewska, 2000; Ng, 2000] within the agents' decision-making process enables the agents to learn the characteristics of their opponent and environment,

thus enables faster, more intelligent decisions, and enables the agents to exhibit more autonomous behavior.

- *Integration with power system databases:* So far, we have obtained limited amount of transmission equipment condition data from the industry. We are planning to acquire more information, such as, different transmission equipment life history data, failure data, different kind of condition monitoring data, test data, maintenance records and histories. We will test our agent software system [Reinoso-Castillo, 2002] for facilitating distributed, heterogeneous data integration and distributed decision support.

- *Study different kind of application scenarios in power system:* In this work, we have investigated the application of distributed decision-making through multiagent negotiation in the area of transmission maintenance scheduling. There are a lot of other potential domains where this innovative decision support paradigm could also be fruitfully applied, such as: power market operation, demand (load) management, load forecasting, cascading outage prevention, remote device setting adjustment, system reconfiguration and re-dispatching, system restoration, energy system coordination.

Appendix A. Transformer Failure Modes and Maintenance Activities

Components	Dominant Failure mode(s)	Failure cause(s)	Failure effect	Maintenance Activity
Transformer oil	Oil deterioration	Oxidization of oil	Cause corrosion of the various metals within the transformer	Oil tests, oil level checking.
		Thermal decomposition of oil	Carbon formation, sludge and insulation deterioration	
		Contamination from moisture	Corrosion, deterioration of insulation	
Conservator	Loss of sealing	Moisture ingress & oxidization	Leakage of oil	External examination for leaks
Pressure relief device	Pressure relief device block	Mating surface sticks	Cannot release the pressure during internal fault, may cause substantial damage to the tank	Visual inspection
Winding	Resistance not in range	Fault, wrong settings	Helpful during fault investigation	Winding resistance testing
	Winding overheat	Excessive overloading, failure of cooling system	Winding resistance increase. Damage of winding	Inspection of cooling system. Winding temp. Device test
	Fails to transform voltage	Turn to turn short, open winding, loose internal bolted/compression connection	Upset customers. System instability.	Oil analysis, vibration analysis
Coordinating gaps	Flashover	Painting deteriorated by pollution, burned by arcing	Shortage	Gaps cleaning, painting or replacing
Insulator	Flashover	Pollution, moisture ingress, aging	Insulation failure	Greasing, cleaning, replacing
Fans and pumps	Malfunction	Block, wrong direction, deterioration	Overheat, insulation failure	Test, replacement
Neutral earthing	Earthing malfunction	Earthing disconnected with earth or resistance too large	Induced circulating currents	Check on the integrity of earthing
Surge protection	Malfunction	Lightening	Facility damage	Inspection, testing
Breather system	Malfunction	Block or cannot filtrate moisture or other contamination	Oil deterioration, overheat	Checking, testing
Seals	Loss of Sealing ability	Moisture ingress leading to dielectric failure	Loss of sealing ability leading to increased demand on, and the early failure of system equipment	Inspection, monitoring, replacement
Bushings	Insulation failure	Loss of oil, pollution, moisture ingress	Endanger personnel	Visual inspection, power factor test, replacing

Appendix B. Transformer Oil Test Results

Company: Alliant Energy
Manufacturer: Allis-Chalmers
Location: Marshalltown, IA
MFG Date: 1/1/1960
EquipNum: 10120267341
Primary kV: 115
Second kV: 13.2
Phase: 3

Sample Date	H_2	CO	CO_2	CH_4	C_2H_2	C_2H_4	C_2H_6	TDCG*
12/15/1993	199	2053	3921	266	0	1	9	2528
8/3/1994	601	1867	18036	279	0	5	54	2806
10/10/1995	810	1662	30360	236	0	8	47	2763
5/7/1996	509	1585	30859	283	0	8	51	2436
7/14/1998	908	1233	19292	111	0	12	16	2280
9/29/1998	2432	2396	28506	225	0	35	34	5122
11/6/1998	0	4	24	0	0	0	0	4
7/27/2000	249	753	20845	80	0	13	29	1124
10/8/2001	556	746	24479	84	0	21	36	1443
3/21/2002	200	960	30435	118	0	14	54	1346
3/31/2003	26	690	19092	120	0	23	48	907
11/25/2003	28	673	19062	116	0	26	49	892

*TDCG: Total dissolved combustible gases. It does not include CO_2, which is non-combustible.

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ACKNOWLEDGEMENTS

I would like to take this opportunity to express my great thankfulness to those who helped me with various aspects of conducting research and writing of this dissertation. First and foremost I offer my sincerest gratitude to my advisor, Dr. James D. McCalley, for his guidance, patience and support throughout this research and the writing of this dissertation. His care and encouragement on both my research and my life have made all of my achievements at Iowa State University possible.

Special thanks also go to the members of my Program of Study (POS) committee, Dr. S. S. (Mani) Venkata, Dr. Vasant Honavar, Dr. Manimaran Govindarasu and Dr. Glenn R. Luecke, for their kindly help and advice on this work. This work could not be completed without their valuable inputs.

Gratitude beyond my expression is sent to my family, who supports me so much, and trusts me a lot during this period of studying. I also thank all my old and new friends, especially all the members of the electric power group at Iowa State University, who support me personally during the past three years.