A SPECULATIVE FRAMEWORK FOR THE APPLICATION OF ARTIFICIAL INTELLIGENCE TO LARGE SCALE INTERCONNECTED POWER SYSTEMS

By

Nadipuram R. Prasad
Satish J. Ranade
Electrical Engineering
Department

Eric Dietrich
Roger T. Hartley
Computer Research
Laboratory

New Mexico State University
Las Cruces, New Mexico
USA

Prem. K. Kalra
Electrical Engineering
Department
Montana State Univ.
Bozeman, Montana
USA

ABSTRACT

This paper addresses broad issues relating the application of artificial intelligence (AI) technologies to the operation and control of large scale interconnected electric power systems. A fundamental issue discussed in this paper is the control structure of power systems. An evaluation of the control structure yields the characteristic requirements of knowledge-based systems and can indicate a means of integrating "intelligent" control with "algorithmic" control systems. As a result the nature of an overall knowledge-based philosophy can be speculated.

The paper presents a hypothesis that the structure of knowledge, in a knowledge-based system, should evolve as the structure of the power system evolves in real-time. This hypothesis is explored in terms of the distributed and centralized power system control structures, and the hierarchies that exist in the control structures. The hierarchical nature of the control structures suggest a hierarchical structure in the knowledge-based system. Parallelism between the power system. control structure and the structure of knowledge, in the knowledge-based system, is conjectured as a fundamental requirement of the information processing (IP) system. The evolution of knowledge then is speculated to occur through a process involving lea

Keywords: artificial intelligence, expert systems, knowledgebased systems, power systems control.

INTRODUCTION

There is a growing interest in the power industry in examining artificial intelligence (AI) techniques toward the integration of knowledge-based systems in energy management system (EMS) environments. The interest stems from the fact that, at times, there is either too much or too little information regarding the power system response which makes it difficult for the operator and the state-of-the-art algorithms to respond in a cost-effective and secure manner [1]. It is important to take note that, in real-time system operations, the function of a system operator in the overall control loop is to be able to evaluate and implement necessary control actions. These control actions may include strategic, tactical, and emergency control measures that allow power system security to be maintained. Failure to provide the system operator with clear and concise information of the system requirements (in terms of either long-term or short-term control actions), especially during system emergencies, may result in degraded system performance. Consequently, there is a need to develop high level information processing systems that allow better interfacing between the operator and the system.

At the present time the development of expert systems has become commonplace in the power industry. Such expert systems can potentially monitor and control a number of imp

ortant power system functions. Noteworthy contributions, [1-71, have been made. Yet there seems to be no framework within which the fundamental concepts of AI and their application to overall control can be examined. An early attempt towards such a framework is presented in [8]. The ideas presented in [8] are discussed in this paper in a manner that allows a concept ualization of the overall structure of knowledge-based systems in a power system EMS environment.

The objective in the operation and control of power systems is to steer the power system through various normal and abnormal operating states in a secure and reliable manner. However, breakdowns do occur (as in the case of any physical system) for which restorative knowledge is required to return the system to its normal state. The goal, then, in the application of AI, to power systems, is to develop machine intelligence to an extent that the information generated by a power system can be analyzed and interpreted in a manner that will allow human interaction with the system in achieving more effective operation and control.

In this paper we discuss the current status of AI applications to power systems including its limitations in a decision making environment. A discussion outlining the requirements of an information processing system, towards the speculation of an overall framework, is presented. The paper provides a general description of the problem-solving environment in power systems in which various issues of intelligent control are discussed in an evolutionary sense. The nature of the problem-solving environment is discussed in terms of the power system control structure, and time scales over which control is actuated. Hierarchies that naturally exist in the control structure leads to a conceptualization of the structure of knowledge-based systems. Within this Structure we speculate the coexistential requirements for reasoning, learning, and inferencing (decision making)' systems. As such a speculative framework for the application of AI to large scale interconnected power systems is proposed.

AI TECHNOLOGY IN POWER SYSTEMS

Current technology in AI applications to power systems has brought up on us a perception that human knowledge about the behavior of a process, sets of processes, or the overall complex physical system, can be described in terms of rules, sets of rules, and knowledge about the rules. This has resulted in the development of rule-based expert systems.

The development of expert systems constitutes the first major thrust in an attempt to build intelligent systems. These expert systems are designed such that they attempt to simulate the expertise of humans in diagnosing and analyzing a variety of power system problems [The performance of an expert system can be judged on the basis of how well it can interpret or reason the physical system behavior. Hence, metaknowledge, or knowledge about the knowledge represented in the system, is used to enhance the expert system performance. The incorporation of such formalisms in the rule-based structure has been shown to prune the solution search space in an effective manner [10]. While such development is necessary a major short-coming of rule-based expert systems is that they tend to fail if all conceivable rules included do not cover unexpected contingencies [111. Consequently it is difficult, in the application of AI, to perceive that rule-based expert systems alone can ever be developed to achieve overall integrated control.

Since expert systems are task oriented their use as a decision tool is limited to those functions for which clearly defined answers or solutions exist. Sutherland [12] examines the contribution of AI to decision technologies. Among other observations he concludes that no amount of heuristics in association with axiomatic constructs can allow inference operations that stochastic decision exercises demand. While decision theory has deep rooted mathematical foundations it is plausible that the resources generated by both decision theory and AI concepts can be effectively integrated.

Current practice in the control of large-scale power systems involves developing a real-time topological model of the system. This coincides with the notion that parallelism between the structure of the physical system and that of the IP system is essential. However, one can argue that the real-time model is at best an approximation of the actual system on account of uncertainties and the fact that the model only represents a subset of the entire state space. Nevertheless, such a model is used in estimating, predicting, and generating control actions. The uncertainty in the structure of the physical system and limitations in the modeling structure creates a tendency for isolated rule-based systems to degrade in performance.

There is no doubt that expert systems are required. They serve a specific function in assimilating raw information and a means for providing immediate corrective control. Known abnormalities can be easily detected at a very early stage for which, if a solution exists, the appropriate control action or strategy may be implemented. The inherent limitations, however, allow one to perceive expert systems in an environment where many expert systems interacting with one another at best provide some of the knowledge required for other higher level decision making elements. This implies a parallel structure should exist between the interacting nature of processes that comprise the power system and the interaction of knowledge about the system, in the knowledge-based system [1] in order to render control. It is necessary therefore to consider the application of expert systems within a broader framework of *knowledge-based systems.* By knowledge-based systems we mean systems that should exhibit a hierarchical structure in which learning, reasoning, and higher level decision support systems serve to maintain the performance of expert systems.

TOWARDS A FRAMEWORK

In this paper we outline a conceptual framework for the application of AI to the operation and control environment of large-scale interconnected power systems. The speculation that the structure of knowledge, in a knowledge-based system, should replicate the information flow in the physical system is conjectured as a fundamental requirement of high-level information processing (IP) systems. Such a requirement naturally leads to a d nition of the structural abilities of an IP system.

Information processing, in an EMS environment, requires:

(a) the ability to ensure relevance in the topological structure of the modeled power system (system identification)
(b) the ability to interpret system behavior in the presence of vast amount of uncertain and uncorrelated data (definition of control structure)
(c) the ability to estimate and predict system behavior (trajectory assessment)
(d) the ability to generate control strategies (prioritization of control)
(e) the ability to interact with a human operator in selecting,

These properties define a processing structure of the IP system and reflect the heirarchical nature of the knowledge-based system in the operation and control environment.

In the context of the above discussion this paper explores several notions of intelligent behavior with the goal of replicating such behavioral characteristics to the operation and control environment of large-scale interconnected power systems. Exploring such notions provide a means to:

- uncover information flow in the physical system;
- establish the control structure
- allow formulation of a knowledge-based control structure
- identify issues relating to the integration of knowledge-based systems
- identify the structure of the problem solving environment as a whole,

POWER SYSTEM PROBLEM-SOLVING ENVIRONMENT

Overview:

We begin our discussion with certain notions about the problem-solving environment and later expand upon the possible structure(s) of knowledge required. In a problem-solving environment generating answers or solutions to problems, in general,

- some level of algorithmic computation based on static and dynamic models (i.e., power flow analysis, state estimation, transient stability, etc.).
- interpretation of algorithmic results and model verification (i.e., time derivatives, evaluation of system trajectories, hypothesis testing, etc.)
- qualitative analysis - reasoning by which an assessment of the power system response can be made - (i.e., a qualitative measure of present system behavior in terms of line/ transformer loadings, generator limits, transfer limits etc., and the potential effects on future behavior).
- decision making in which a choice of control strategies or control actions can be made from a set of available alternatives (i.e., control actions that will maintain normal steady-state operation).

While all of the above are currently being done in an EMS environment the question that naturally arises is - how and in what aspects can the application of AI concepts benefit the overall operation and control functions in an Energy Management Systems (EMS) environment?

Wollenberg and Sakaguchi [1] discuss various issues relating to real-time control, operations planning, and operator training.

- Alarm Processing
- Switching_ Operations
- Voltage Control
- Restoration Control
- Contingency Analysis
- Unit Commitment
- Operator Training
- Scenario Building

The benefits in the application of AI are both tangible and intangible. Quasi stand-alone functions such as long-term unit commitment, contract compliance, and off-line operator training provide tangible (economic) benefits. Other applications provide more security. It should be noted, for example, that the restoration control function, in the IP system, cannot be treated independently. Restorative control includes switching operations, voltage control, unit commitment, scenario building, contingency analysis, and alarm processing. While alarm processing is independently required to generate a comprehensible sequence of system operations, the need to consider the alarm processing function in an integrated environment is evident. These functions should serve a means of assisting the system operator to steer the system to a satisfactory operating state and also serve a means of on-line operator training, if necessary.

[1] Intelligent control in the power systems environment can be thought of as the ability of the information processing system to develop and suggest control strategies, evaluate operator selected actions, recommend alternatives (if necessary), and actuate the most effective control strategy.

Issues in Intelligent Control:

At the outset, the notion that intelligence is non-algorithmic (at least for the most part) is accepted. Intelligence represents the ability to combine (organize), process, analyze, and understand information or data towards making decisions. When large dynamic systems are involved, available information may be insufficient or have redundancies, be conflicting or just too voluminous that decision making can become extremely complicated and time consuming. The tendency, therefore, may be to intelligently hypothesize system behavior despite the lack of ordered or consistent information.

Several issues then that need to be addressed are:

1) How can the intelligence, or the knowledge required to process information, be represented?
2) What is the structure in the knowledge) representation?
3 How does the hierarchy in the physical system (i.e., power system) relate to the hierarchy in the structure of knowledge?
4) Can the structure of knowledge in an IP system dynamically evolve along with the structure of information flow in the physical system?

Knowledge representation, the structure of knowledge, and the hierarchy in the structure of knowledge are all critical issues. While substantial work has been reported in the area of knowledge representation [10,13,14,151 much work remains to be done that will allow the qualitative behavioral representation of large-scale dynamical systems.

Smith [16] presents a ***Knowledge Representation*** hypothesis2 which states:

> Any mechanically embodied intelligent process will be comprised of structural ingredients that a) we as external observers naturally take to represent a propositional account of the knowledge that the overall process exhibits, and b) independent of such external semantical attribution, play a formal but causal and essential role in engendering the behavior that manifests that knowledge.

On the basis of this hypothesis it is observed3 that the two major properties which the structures in knowlege-based systems should satisfy include:

1. Propositions which can be interpreted as those representing the overall knowledge of the system.
2. The symbolic structure within a knowledge-based system which must play a causal role in the behavior of that system.

These properties which form the primary requirements of any knowledge representation scheme does not indicate, with any specificity, the dynamics associated with knowledge evolution.

On the basis of the proposition' that: "knowledge does not depend on a fixed model, but can be applied in new ways to novel situations," it is conjectured that the structure of knowledge should exhibit evolutionary chan es to satisfy the overall requirements of knowledge-based systems. Consequently, the issue of dynamical evolution of knowledge is central to the development, integration, and application of knowledge-based systems to power system operation and control.

In this context, it is hypothesized that:

> ***the information processing system should be considered an environment for simulating and interpreting the structures of information (or more form4lly - the structures of knowledge) that evolve as the structure of the power system evolves in real-time***

The acquisition of qualitative knowledge by way of qualitative reasoning represents how humans perceive the behavior of physical systems. The ability to qualitatively describe process behavior without the need for quantitative estimates constitutes knowledge about the process and the interaction between processes. Research in this area of knowledge representation has shown promise when applied to small systems [17].

Govindaraj [181 discusses several modeling approaches in an effort to define a methodology using qualitative approximation. He states:

> "Qualitative approximation is based on a hierarchical description of dynamic systems, where the primitives that approximate the function of the components are at the lowest level. The primitives provide the qualitative states that describe the evolution of the system."

He concludes that the methodology is suitable for simulating the qualitative behavior of any dynamical system. While such development in the application methodology is required the intent in this paper is not to suggest the use of a specific methodology or a programming environment but to emphasize the need to consider a broader perspective of the operation and control environment in power systems towards the development of knowledge-based systems.

Conceptual Architecture for an Intelligent Control System

The application of AI, as a means to assist in the operation and control of large scale interconnected power systems, is to provide the ability to derive consistent intelligent machine generated solutions to problems that are encountered in the operation of the physical system. Where excellent algorithms exist to compute system control variables that subsequently affect system response, the application of AI to generate such control variables is obviously not desirable. Consequently, one tends to believe AI is primarily non-algorithmic as well, can act upon data structures to provide qualitative interpretations, and allow interaction with a human operator.As such

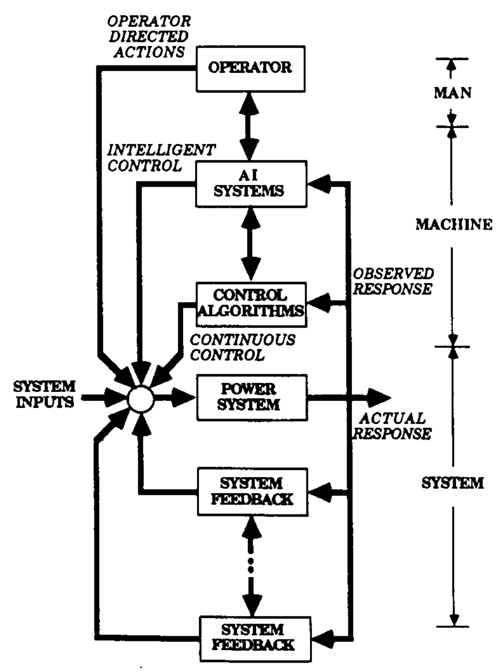

Figure 1. Conceptual Structure of Machine Intelligence

2,3 Levesque and Brachman provide an indepth analysis of Knowledge Representation issues in "A Fundamental Tradeoff in Knowlege Representation and Reasoning," Readings in Knowledge Representation, Morgan Kaufmann Publishers, Inc., CA, 1985, pp. 42-70. (cf. [151 in this paper).

4 Sowa , J. F., Conceptual Structures, Addison-Wesley, Reading, . MA, 1984 . (cf. [12] in this paper).

architecture which personifies the hierarchy in the structure of machine intelligence emerges and is conceptually presented in Figure 1. Figure 1 highlights a parallel structure between what constitutes inherent system feedback and that provided by the man/machine system. Without higher level decision making elements, in a practical sense, it would be fortuitous to assume that the software driven machine response is identical to the hardware produced feedback response. Consequently, one may view the algorithm/AI based feedback control as an interacting system where the intelligence derived from high level decision support systems to actuate control attempts to replicate the interactive nature of the actual system feedback. Hierarchically, in such an architecture it is apparent that knowledge-based AI systems would act as the interpreter, serve as the primary interface between the operator and the power system, and through control algorithms aid in "tracking" the system control structure. In this context a discussion of the control structure in the operational environment of power systems is presented.

CONTROL STRUCTURE

Present day operation and control of large-scale interconnected power systems incorporates control structures which are both distributed as well as centralized. They differ from one another in the fact that distributed control tends to be hardware based while centralized control is primarily algorithm (software) based. Figure 2 illustrates a conceptual diagram of the integrated control structure in power systems. Control

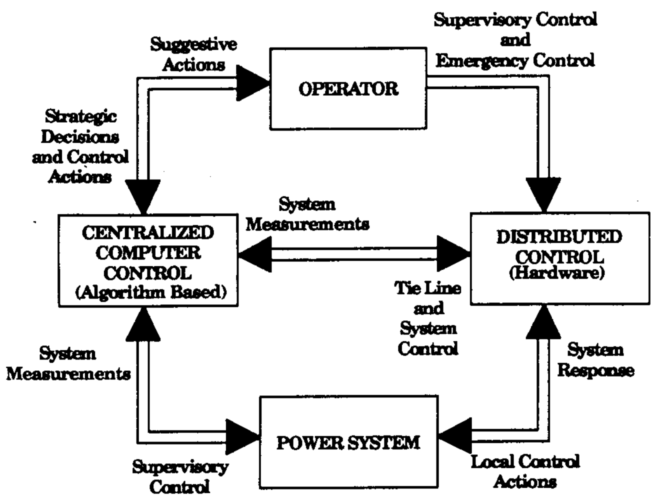

Figure 2. Operations and Control Environment in Power Systems

actions developed by the centralized algorithm-based system affect distributed control hardware via communication channels. As a result, local control actions on the power system produce a system response which in the presence of sensors yields a set of system measurements. While the algorithm-based control actions serve a means of short-term continuous system and tie-line control, longer-term control strategies and supervisory control actions can be actuated independently by the operator and/or with the aid of on-line and off-line algorithms.

Distributed Control

Distributed control involves primary control functions to regulate frequency and voltage in the power system. In the normal steady-state operation, while both frequency and voltage are locally regulated by speed-control and excitation-control functions at generating facilities, maintaining system voltages require additional control via the use of synchronous condensers, static VAR systems, and automatic transformer tap changing on-load. Other control functions, that include switched capacitors, switched reactors, and manual transformer tap changing are required as supplementary measures to regulate system voltages and to attain satisfactory voltage profiles. These supplementary control functions are implemented, when necessary, under the direction of the system operator in the form of supervisory control actions.

The control functions, in a distributed control environment, can be divided in to those which are susceptible to direct supervisory control and those which are indirectly affected. An example of this might be a network reconfiguration which can result in poor voltages and the subsequent switching in of capacitor banks to restore system voltages. It is noted that there is direct supervisory control over network switching components that indirectly control system voltages. This interaction suggests a natural flow of information that occurs through the distributed control structure.

Distributed control may be further described as a means of affecting the control structure. Changes in the control structure can occur without any change in system topology. From a control theory viewpoint this corresponds to changes in feedforward and feedback filter gains and time constants. As a result, similar topological structures can produce dissimilar control structures.

The question then is - how can the distributed control agents regulate their control functions such that some global criterion set forth by centralized control functions is satisfied?

While it is conceivable that every system measurement can be obtained the task of assimilating such vast amounts of system data (information) in a centralized system would be impossible even with the most powerful computer systems. Consequently, the distributed nature of the equipment (system hardware) and the need to coordinate distributed control activities in a hierarchical manner suggest consideration of a comprehensive *distriibuted* information processing system. The distributed structures of knowledge then, in a distributed knowledge-based IP system, can be speculated as a means to identify an evolving control structure.

Centralized Control

In the centralized control structure it is possible to delineate the control actions generated by EMS algorithms in to three distinct categories. The first of these categories is the load/frequency control function, the second category is the economic dispatch function, and the third category is the operator-in-the-loop function. It is important to note that in totality the function of centralized control is to provide automatic generation control actions besides serving as a source of supervisory actions. The distinction between the delineated control actions is that the load/frequency control function constitutes immediate corrective control actions to regulate frequency whereas the economic dispatch control function merely readjusts generation across the system to meet economic criteria. These control actions reflect time scales over which control is actuated.

Current US practices include scanning the power system every 2 - 3 seconds for generator outputs, tie-line power flows, and frequency. This sampling interval allows data filtering and load/frequency control computations to be carried out at reasonable rates. Economic dispatch, which in principle must use results from state-estimation, power-flow, and penalty-factor computations, occurs within 3 minute intervals. Longer-term control comprising operator requested actions, maintaining unit commitment schedules, and other supervisory control usually range upwards of 10 minutes. Consequently, centralized control exhibits a hierarchical control structure in which both fast acting control (i.e., continuous control attempting to track load) and slow acting control (i.e., strategic control attempting to redispatch generation and/or long-term unit commitment, supervisory control) are present.

Overall Control Structure

The overall control structure in a power system is an integration of both centralized and distributed control structures. While distributed control represents the inherent control actions resulting in system response, centralized control is primarily a simulated environment where system response is postulated for a given set of control actions. Regardless, it is the goal in an EMS environment to observe the system response closely enough such that control actions will regulate system behavior. Hence a systematic analysis of the information flow is required if knowledge-based systems were to be used in the operation and control of power systems.

STRUCTURE OF KNOWLEDGE-BASED SYSTEMS

It is self-evident in AI to define an intelligent system as one that can invoke relevant knowledge appropriately to solve complex tasks. Knowledge involves the ability to generate relevant action or information to achieve a particular goal [19]. This implies that the system must have not only the knowledge necessary to accomplish the task, but also a structure to fulfill the task in art effective manner. In this context, it is important to consider the structural requirements at both the micro and macro level descriptions such that time scales in the operation and control of power systems can be satisfied.

In some instances the solution to a specific task may require minimal interpretation (or reasoning). Other tasks may require substantial analysis/ reasoning fore any action can result. Consequently, it is believed that a hierarchy in the structure of knowledge-based systems should exist to accommodate both time scale requirements and problem solving abilities. To achieve this structure it is necessary to consider a framework in which the reasoning abilities required to address problem-solving tasks and time scale issues are comparable to those perceived of the human reasoning system.

In [201, Sage presents a hypothesis that describes human reasoning in a problem-solving environment. The hypothesis delineates human perceptive reasoning into three distinct, yet interacting, capabilities namely, formal reasoning, rule-based (with heuristics) reasoning, and skill-based reasoning. Within this framework of reasoning, learning is hypothesized to occur either directly or indirectly as a feedback. It is inferred that skill-based knowledge is an accumulation of knowledge from formal and rule-based reasoning through a learning process.

Sage's hypothesis presents interesting possibilities and seems quite apropos to speculating a framework for knowledge-based systems in a power system environment. In this context, we present a discussion of how human problem--solving skills may potentially map in the domain of control systems that incorporate knowledge-based systems.

Reasoning:

Formaj reasoning implies the ability to explain the behavior of systems by virtue of the nature of physical actions and interactions between processes. In a sense it is a way of hypothesizing system behavior without much need for factual system data. In humans such reasoning could be intuitive, analogical, etc., constituting extensive wholistic information processing capabilities. The question, however, is - how can such formalisms be adopted in machine environments?

An important step in developing a basis for formal reasoning is to uncover an underlying model of the process which can be described in a qualitative manner. If there is a mathematical model underlying part of the conceptual structure it may provide enough problem solving abilities or may serve to justify consistency among qualitatively defined relationships. In this context formal reasoning may constitute the analysis of system behavior based on the results of both qualitative and algorithmic approaches to an actual or hypothesized system structure (e.g., contingency analysis).

Rule-based reasoning, which has been interpreted and implemented in the form of expert systems that incorporate expertise similar to humans, has received wide attention. The ability of ex ert systems as the decision making tool has been criticized [12]. However, they do serve a place in the overall knowledge-based environment to gather and process factual information for which causal relationships exist. Interaction with mathematical models may be required to substantiate inconsistent factual data or to support the inferencing of results from on-line or off-line algorithmic analysis.

Skill-based reasoning, in a power system environment, can be related closely to the required operator skills in adopting or implementing specific operating functions within the operating guidelines. These guidelines represent both normal -and emergency operating criteria that are generic in nature. Consequently, while such guidelines can direct the operator to a particular set of operating functions, dependence on algorithmic models for a pre--evaluation of the operator directed actions cannot be precluded (e.g., system restoration)

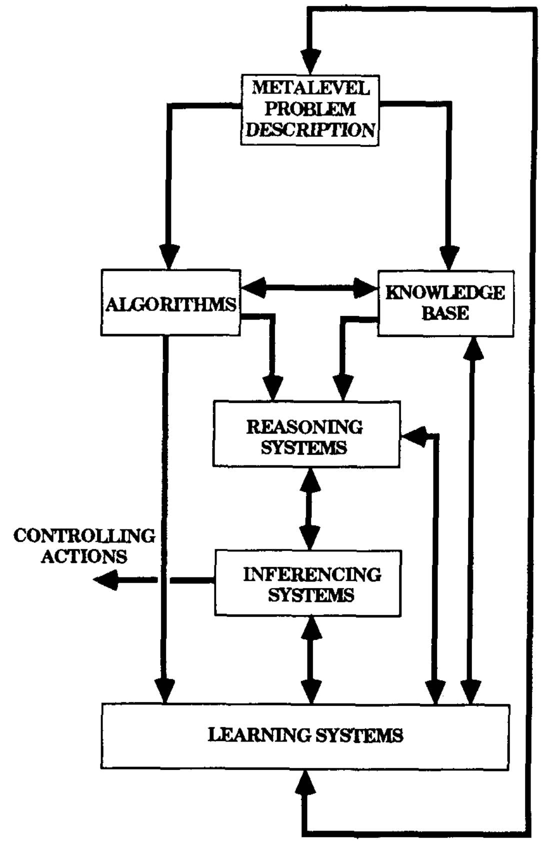

Figure 3. Conceptual Framework of the Problem–Solving Environment

As a result of the above discussion, Figure 3 illustrates a concept ualization of the structure of knowledge-based systems required in dynamic problern--solving environments'. The metalevel problem description can be perceived as the highest level of decision making ("deciding how to decide" [201) in the problem-solving environment. This decision process includes human interaction, when required. Consequently, a decision-to-control task structure' is formed by interacting systems (reasoning, inferencing, and learning systems interacting with algorithmic-based systems) within the overall structure.

For example, a system voltage problem mi ht require a rapid acquisition of facts from the knowledge base (system data base) such that a basis to evaluate the problem task structure can be formed. The formulation of such a task structure is dependent upon the ability of the reasoning system to justify the need for an algorithmic evaluation, if necessary, and/or the ability of the inferencing systems to generate, or suggest, the required control actions: Learning, therefore, can be speculated to occur within an environment defined by the metalevel problem description,

[5]In Figure 3, as well as other figures in this paper, the uni-, and bi-directional arrows merely illustrate potential information flow among various processing units. An exact determination of such information flow (communication within the structure of knowledge-based systems) is a subject for further research.

[6]Task structure implies structure of knowledge. It defines the hierarchical structure of the various processing elements in the IP system. That is, depending on the nature of the problem solving, the interaction among the processing elements is speculated to reflect an evolving control structure.

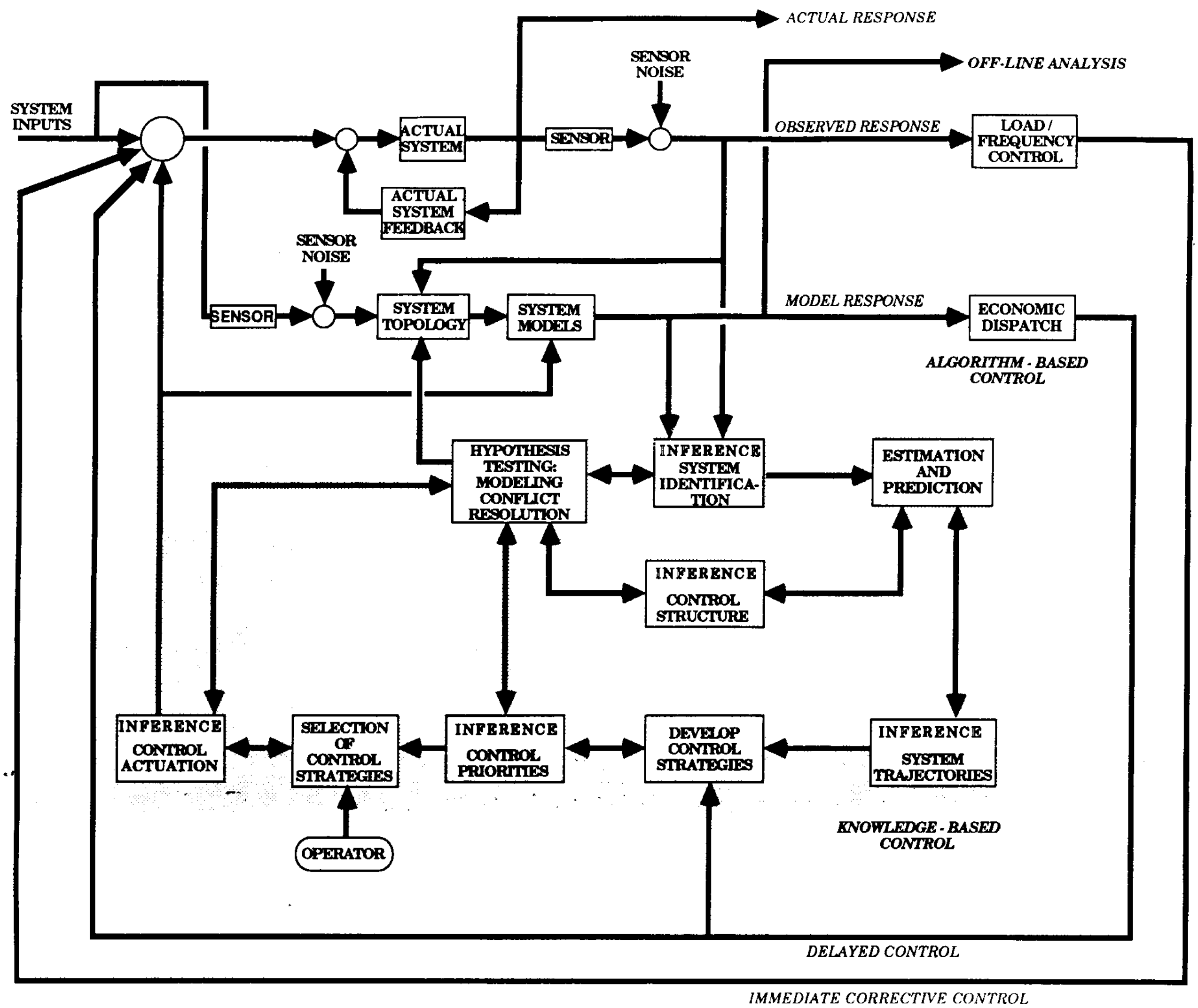

Figure 4. Conceptual Algorithm/Knowledge Based Integrated Control Structure

the knowledge base, reasoning, and inferencing systems. In this framework of problem solving the capability should also exist, within the task structure, to request an algorithmic processing structure for more complex system operations (as in restorative control).

Inferencing:

Inferencing is an essential element to problem solving. While a complete diagnosis of the problem and subsequent remedial action might not be possible by machine encoded knowledge, human intervention in the inferencing process can result in machine learning. Consequently, an important step in the development of knowledge-based systems for EMS environments is the identification of potential inference mechanisms within the infrastructure of the overall control loop.

In Figure 4 we illustrate an information flow diagram highlighting areas where inferencing could potentially occur in the closed loop control structure. Customarily, the system is modeled on the basis of breaker/switch status indicators to represent the topological nature of the actual system. The observed set of real system parameters are then used to generate (from the modeled system) a vector set of parameters from which appropriate control actions are derived. It is necessary in the control process to examine the validity of the model response in relation to the observed response. This is typically done in the state-estimation algorithms in terms of bad-data estimation (hypothesis testing). With regard to the knowledge-based control, it was previously stated that the structure of knowledge in a knowledge-based system should exhibit the ability to:

- identify the system structure
- define the control structure
- assess system trajectories
- generate control priorities
- actuate intelligent control

These inferencing abilities which form a closed loop within the infrastructure of the knowledge-based system in fact represents a parallel structure to the algorithmic control structure.

Figure 5 expands upon the properties on an IP system described above in illustrating the hierarchy of knowledge in a centralized knowledge-based system. The figure distinguishes between traditional expert systems and those systems required for learning, reasoning and decision making.

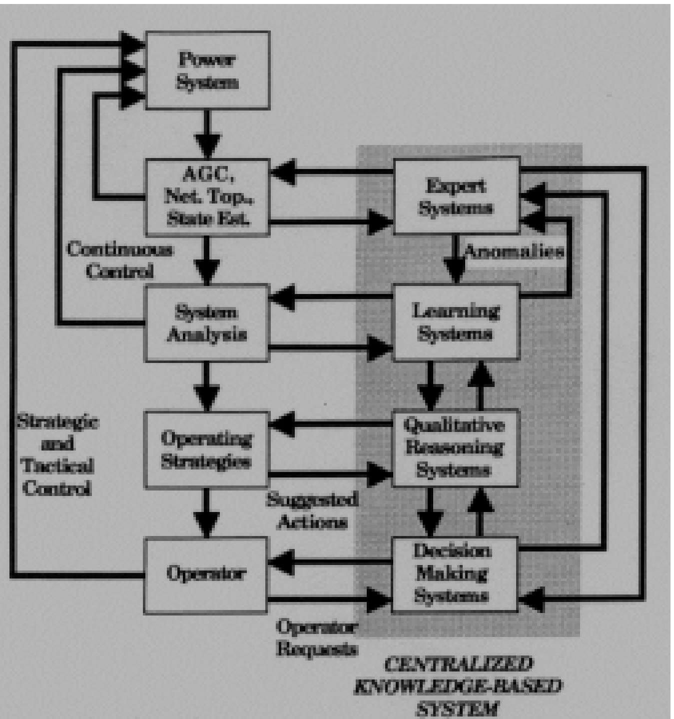

Figure 5. Conceptual Centralized Knowledge–Based System Hierarchy

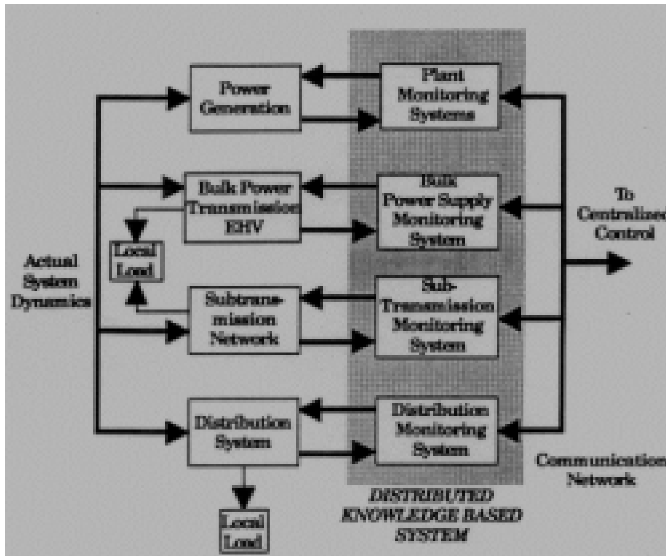

Figure 6. Conceptual Distributed Knowledge–Based System

Learning:

One of the most fundamental aspects of intelli ent behavior is the process of learning. Learning is based on observations and the subsequent effects of the observables on the response of the system. Such a process may either be direct or a feedback in the physical system [20].

Since a power system operates in a continuously evolving environment the ability to make accurate generalizations from few scattered facts or to identify behavior patterns from a large set of system observations is crucial to the reliable operation of the power system. The synthesis of knowledge through pattern recognition and event covering techniques has been discussed [21,22]. Automated construction of knowledge bases through a process of inductive learning has been proposed [231. In this paper a cursory review of the learning paradigm is presented in an attempt to describe the framework for the application of AI to large scale interconnected power systems. Much work has been reported [24,25] which has its origins in mathematically based adaptive control and learning theory. Many issues of decentralized control, which arise in the control of large dynamical systems, have been exposed. Narendra and Wheeler [25] argue that an automaton approach has the greatest potential in problems involving many decision makers interacting in a decentralized manner. On the basis of extensive applications to problems in communication traffic routing they contend that the problem must possess certain specific characteristics if **control algorithms are** to be most effective. The specific characteristics required are:

a) the system is sufficiently complex, involves larger number of uncertainties, for which an adequate model does not exist.
b) the system inherently possesses decentralized control functions which by virtue of their dispersed nature are small in number at each location.
c) that feedback to every decentralized controller is provided by some realization of control actions based on a global performance criterion.

These **characteristics, in principle, apply** directly to the power system environment as well.

Figure 6 illustrates a conceptual diagram of the distributed control system and a speculative illustration of the corresponding knowledge-based system. The concept of distributed intelligence, in a large scale distributed control system, suggests that information sharing is one of the many features required if the system is considered amenable to control [8,18]. While such information sharing occurs naturally in a physical system via machine/ network /load interactions (i.e., system dynamics), explicit communication links are required in the IF’ system. This communication between knowledge bases establishes a parallel control structure which has the tendency to replicate the structure of system dynamics or more precisely the structure of the set of system variables that produce a specific dynamic response. Davis and Smith [261 discuss the concept of a "contract net" towards integrating distributed knowledge systems. The fundamental idea in their concept is to establish communication between knowledge sources such that information at each processor is available on a need-only basis.

In light of the discussions presented in this paper it is possible then to conceptualize an intelligent environment for power systems- as illustrated in Figure 7. The figure shows parallelism between the structure of knowledge-based systems and that of algor t hm / hardware- based systems (See Figure 2).

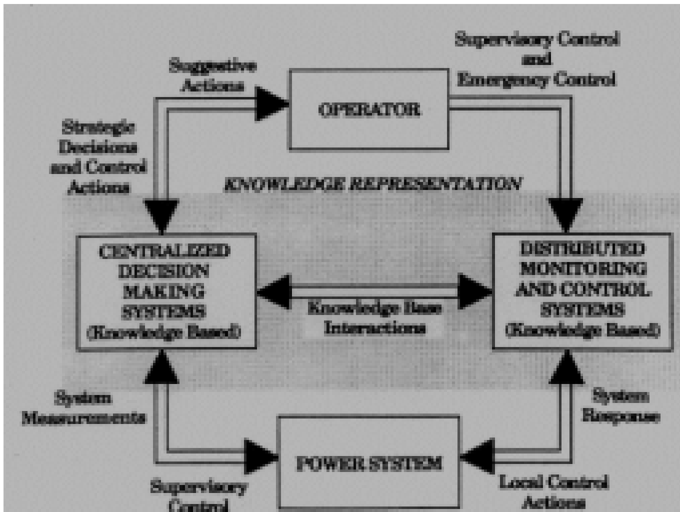

Figure 7. Conceptual Framework for an Integrated Knowledge–Based System

CONCLUSIONS

The paper presents several important issues to be considered in the application of artificial intelligence to the operational environment of power systems. Parallelism between the structure of knowledge in the information processing system and the control structure of the power system is emphasized as the key issue. The need for incorporating learning, reasoning, and decision making systems in a hierarchical structure is recognized. The fact that expert systems alone are incapable of making complex decisions is emphasized.

While expert systems per se are static models, knowledge evolution in a hierarchical system is speculated to occur through learning, reasoning, and decision making. Along with development of isolated and/or cooperating expert systems that address specific static problem-solving, attention should be focussed on broader issues of knowledge-based systems that culminate in providing effective, integrated, intelligent control.

With emerging technologies in computing machinery, the concepts being explored in our research seem to hold a place in the future of real-time operation and control of power systems. Much work remains to be done even before examining issues relating to the feasibility of implementation. In this context, this paper provides a speculative framework for the application of AI to large scale interconnected power systems.

ACKNOWLEDGEMENTS

We thank the sponsoring companies of the Electric Utility Management Program at New Mexico State University , Professor W. H. Kersting, and Dr. J. D. Morgan for their active support of our endeavors. Special thanks go to Ms. Martha Mendoza for her relentless efforts in the preparation of this document.

REFERENCES

[1] Wollenberg, B. F. and Sakaguchi, T., "Artificial Intelligence in Power System Operations," Proceedings of the IEEE, Vol. 75, No. 12, December 1987.

[2] Sakaguchi, T. and Matsumoto, K., "Development of a Knowledge-Based System for Power Systems Restoration," IEEE Trans., PAS, Vol. PAS-102, No. 2, pp. 320-329, Feb. 1983.

[3] Wollenberg, B. F., "Feasibility Study for an Energy Management System Intelligent Alarm Processor,' Proc. 1985 Power Industry Computer Applications Conf., pp. 249-254, May 1985.

[4] Mokhtari, S., Singh, J., and Wollenberg, B. F., "A Unit Commitment Expert System," Proc. 1987 Power Industry Computer Applications Conference, May 1987.

[5] Talukdar, S. N., and Cardozo, E., "Artificial Intelligence Technologies for Power System Operations," Rep EL-4323, Electric Power Research Institute, Jan 1986.

[6] Lui, C. C., and Tomsovic, K., "An Expert System Assisting Decision-Making of Reactive Power/Voltage Control," Proc. 1985 Power Industry Computer Applications Conf., pp. 242-248, May 1985.

[7] Fuki, C., and Kawakami, J., "An Expert System for Fault Section Estimation Using Information from Protective Relays and Circuit Breakers," IEEE Trans. Power Delivery, Vol. PWRD-1, No. 4, pp. 83-90, October 1986.

[8] Prasad, N. R., Ranade, S. J., Dietrich, E., and Hartley, R.T., "Speculation on the Nature of Knowledge-Based Systems in a Power Systems Environment," Proc. of the 19th Annual North American Power Symposium, October 1987, pp 323-332.

[9] Gonzalez, A. J., and Osborne, R. L., "An Expert System for On-Line Diagnosis of Turbine Generators," CIGRE Paper 11-07 1986 Session.

[10] Aiello, L., Cecchi, C., Sartini, D., "Representation and Use of Metaknowledge," Proceedings of the IEEE, Vol. 74 No. 10, October 1986, pp. 1304-1321.

[11] Stanfill, C., and Waltz, D., "Toward Memory-Based Reasoning," Comm. of the ACM, Vol. 29, No. 12, December 1986.

[12] S utherland, J. W., "Assessing the Artificial Intelligence Contribution to Decision Technology," IEEE Trans. Syst. Man Cybern., Vol. SMC-16, No. 1, pp 3-20, Jan/Feb. 1986.

[131 Woods, W.A., "Important Issues in Knowledge Representation," Proceedings of the IEEE, Vol. 74, No. 10, October 1986, pp 1322-1334.

[14] Georgeff, M.P., and Lansky, A.L., "Procedural Knowledge," _ ibid., pp 1383-1398.

[15] Brachmann, R. J. and Levesque, H. J., (eds.), <u>Readings in Knowledge Representation,</u> Morgan Kaufmann Publishers, Inc., CA, 1985.

[161 Smith, B. C., Reflections and Semantics in a Procedural Lan uage, Ph.D. Thesis and Tech. Report MIT/LN/TR-272, MIT, Camb id e MA 1982. ri Qualitative

[17] Bobrow, D. G., (ed.) "Special Volume on Reasoning About Physical Systems," Artificial

[18] Intelligence, 20 1-3), 1984. Govindraj, T., 'Qualitative Approximation Methodology for Modeling and Simulation of Large Dynamic Systems: Applications to a Marine Steam Power Plant," IEEE Trans. Syst Man Cybern., Vol. SMC-17, No.6, Nov/Dec 1987.

[19] Newell, A., "The Knowledge Level," Artificial Intelligence, Vol. 18, pp. 87-127, 1982.

[20] Sage, A. P., "Information Systems Engineering for Distributed Decision making," IEEE Trans. Syst. Man Cybern., Vol. SMC-17, No. 6, pp 920-936, Nov/Dec.1987.

[21] Chin, D.K.Y., and Wong, A.K.C., "Synthesizing Knowledge: A Cluster Analysis Approach Using Event Covering," IEEE Trans. Syst. Man Cybern., Vol. SMC-16, No.2, Mar/Apr 1986.

[221 Hein, F., "Expert System Using Pattern Recognition By Real-Time Signals," CIGRE Paper 39-10, 1986 Session.

[23] Michalski, R. S., "A Theory and Methodology of Inductive] Learning' " Artificial Intelligence, 20 (2), February 1983.

[24 Narendra, K.S., and Thathachar, M.A.L., "Learning Automata: A Survey," IEEE Trans. Syst. Man Cybern., Vol. SMC-4, 1974 323-334.

(25] Narendra, K.S., <u>(ed), Adaptive and Learning Systems: Theorv and Applications,</u> Plenum press, New York, NY, 1986, pp. 197-211.