# A Brief History of Application of Artificial Intelligence to Power Systems

Chen-Ching Liu and Anjan Bose

*Abstract*—**This paper tries to summarize the attempts to apply artificial intelligence (AI) to power systems, particularly power system planning and operations which require significant computer analysis. Although the term AI was coined earlier, this paper considers the beginning to be in the 1980s when the first expert systems were applied to power engineering. Of course, many of the analytical techniques applied can be traced to earlier statistical analysis and pattern recognition. The concept of expert systems was very much in line with the concept of AI. The various methods for applying AI to power systems are traced here. The historical journey in this paper closes with the great explosion of AI applications in the last decade when almost all power system analysis is trying to utilize AI techniques to help the transformation of the power system into a more efficient and carbon-free system. This proliferation of research in the application of AI is covered in the other papers in this series.**

*Index Terms*—**Artificial intelligence, expert system, knowledge-based system, artificial neural network.**

## I. Introduction

FOR decades, the concept of artificial intelligence (AI) has been envisioned for many disciplines. The development of expert systems or knowledge-based systems was widely known in the 1970s, e.g., Feiggenbaum's application in medicine diagnosis at Stanford University, USA. AI and other related applications, such as pattern recognition, have been proposed earlier; however, the application of expert systems to power systems began to emerge in early 1980s. An updated collection of AI applications to power systems is documented in a comprehensive book [1], where applications of intelligent system techniques are discussed, including expert systems, artificial neural networks (ANNs), fuzzy systems, decision trees, genetic algorithms, multi-agent systems, heuristic optimization, and unsupervised learning and hybrid methods.

A notable event that was followed by a series of activities was a well-attended panel session at 1985 IEEE Power Industry Computer Application (PICA) Conference on AI applications to power systems, where technical subjects including alarm processing, power system restoration, and reactive power/voltage control were discussed [2] - [4]. In 1986, a workshop on system operations was organized by CIGRE in Paris, France. Encouraged by the high level of interest, a new series of symposia on expert system applications to power (ESAP) System was inaugurated in 1988. As ANNs began to capture the attention of the industry and research communities, the workshop on ANN applications to Power System (ANNPS) was established in 1991. To facilitate the synergy of AI technologies and communities, ESAP and ANNPS were integrated in 1994 to form the current Intelligent System Applications to Power (ISAP) System symposia. According to the papers presented at ISAP 1994, 60 papers were applications for expert systems, 35 papers for ANNs, 20 papers for fuzzy sets, and an additional 6 papers for heuristic search. The techniques in these papers were applied to real time control, operation, operation planning, and system planning in power systems. Since then, ISAP has been organized about every 2 years. The last ISAP took place in Budapest, Hungary, in 2024. In 1996, IEEE PES created a permanent base of activities for the AI-related applications under the Subcommittee on Intelligent System Applications as part of the then newly formed Technical Committee on Power System Analysis, Computing, and Economics (PSACE).

## II. Expert Systems and Knowledge-based Systems

The ultimate goal of an expert system is to clone a human expert on a specialized subject. The knowledge captured from the human expert can be represented in various forms such as rules, logic, study cases, and models. Thus, an expert system performs reasoning based on its knowledge base and the inference procedure. As an example, a rule-based system has a rule base and an inference procedure to search through the If-Then structures to reach a conclusion driven by the available data and information. The motivation of expert system development for power system applications is to capture and store the knowledge of experienced system operators or planners. Thus, the knowledge learned from years of experience and lessons learned will not be lost as experts move or retire. Power system analysis often requires computational algorithms, such as power flow and dynamic simulations. A rule-based system interfaced with numeric algorithms is referred to as a knowledge-based system.

Early applications of knowledge-based system applications

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to power systems can be found in [5]. Among various ESAP systems, the more established area for real-world deployment is probably power system restoration. Distribution service restoration is one of the pioneering areas of expert system applications. The restorative actions used by distribution system operators using remote-controlled switches include fault isolation, service restoration, and load transfer among available feeders. For safety, the service restoration plan developed by the expert system and distribution power flow tools need to be approved by distribution system operators. The concept and algorithm development evolved, over about 20 years, from a Ph. D. dissertation at the University of Washington, USA to a large-scale implementation and deployment at all distribution operation centers of the Korean Electric Power Company, Korea [6], [7]. With extensive availability of remote-controlled switches or smart switches, on the Korean distribution feeders, the knowledge-based system demonstrated significant reduction of the service restoration time and improved reliability indices such as system average interruption duration index (SAIDI).

The application at the transmission level of power system restoration started as a knowledge-based system that incorporates power system dispatchers' knowledge and experience concerning actions and constraints in a power system restoration scenario. To adapt the restoration strategy to diverse system configurations and resource availability, a set of generic restoration building blocks and restoration actions was designed that can be tailored and integrated for various power systems and restoration strategies. Setting the targets during the different stages of power system restoration is a critical and complex task. The methodology of restoration milestones is the key concept to allow the targets and associated restorative actions to be determined [8]-[10]. The computational tools of Power System Restoration, Optimal Blackstart Capability (OBC v10.0), and System Restoration Navigator (SRN v13) have been developed with support from Electric Power Research Institute (EPRI), USA, and distributed to electric power industry for about 10 years.

As mentioned earlier, voltage/var control is one of the early application areas for expert systems or rule-based systems [4]. The reactive power/voltage control problem is complex and nonlinear that involves continuous controls, e.g., generator excitation system, and discrete control devices, e.g., transformer tap changers. Empirical rules of power system operators play a significant role in the operational environment of power grids. Although heuristic rules can best be captured in a rule base, it is also necessary to integrate the optimization tools to handle the computational tasks [11].

Alarm processing is also one of the early AI applications [3]. Alarms are created by the energy management systems (EMSs) to alert system operators concerning the power system condition, e.g., breaker operations, violations of voltage or line flow limits, and changes in the remote terminal unit (RTU) communication status. Numerous alarms can be triggered by a severe event on the power system, making it challenging for system operators to respond to the alarms. Practical ideas, such as setting the priority or use of visualization tools, have been integrated in modern EMSs. A model-based method considering the cause-effect relationship of physical devices, such as transformers, can be used to synthesize alarms, increasing the information content [12].

Fault diagnosis is the task to identify the fault type(s) and location(s) as well as possible malfunctioning of protective devices. The design of proactive relays is logic-based, e.g., if the primary protection relays on two sides of a line are triggered, then the fault is located within the line. Hence, logic reasoning based on the protective and switching devices is a natural tool for fault diagnosis. An expert system for fault diagnosis using information from protection and switching devices has been developed and implemented [13]. Also, at the substation level, an advanced guidance system has been developed and deployed in an advanced 500 kV substation [14]. For the sub-transmission lines with automatic switching devices, a logic-based system serves as a decision support tool to identify the fault location and restorative actions for customers served from the lines [15].

There are several stages in the development of expert system applications: proof of concept, prototyping, implementation, field test, and practical use. Most of the applications in the literature are in the proof of concept and prototyping stages. Verification and validation are critical steps in the development and maintenance of a knowledge-based system. As the power system conditions and scenarios vary, it is necessary to modify the knowledge base to ensure that the system performances, i. e., accuracy and computational speed, meet the practical requirements. This task could be time-consuming and there is no assurance that the knowledge base will be able to handle any scenario that may emerge. An incomplete knowledge base may cause the knowledge-based system to be brittle in the sense that, it is not able to provide a proper conclusion even if the change of scenarios is modest. The other hurdle of practicality is the use of specialized software tools for the knowledge base (including rule base) implementation. The maintenance of these special tools requires expertise that is not available in the existing skill set of power grids.

## III. ANNs

ANNs are computational models of neural nets that perform perception and other related tasks. This is in contrast with a logic reasoning task that depends on the available knowledge and data. Various ANN models exist, including multi-layered perceptron (MLP), Hopfield neural networks, and Kohonen's self-organizing feature map. A collection of ANNPS is available in [16]. Possibly, the most popular ANN model is that of an MLP. An MLP consists of the input nodes, output nodes, and the hidden layers (one or more) of neurons between the inputs and outputs. Each neuron in the hidden layer has an activation function. The connections between inputs and the hidden layer as well as the hidden layer and outputs are weighted. These weights are determined by the training procedure. As the training proceeds with a set of training cases, the weights are adjusted iteratively until the training process is complete based on the training set. The widely adopted back propagation algorithm is used to reduce the discrepancies between the predicted output and actual output, resulting in a set of weights minimizing the errors. Mathematically, the MLP can be viewed as a tool to model nonlinear relationships between the inputs and outputs.

Hopfield neural networks can be visualized as a dynamic system with a number of neurons, each of which has a state variable [17]. Each pair of neurons is connected by a synaptic connection with a weight. Neurons receive sensory or other inputs. The classic Hopfield neural networks have neurons with binary state values, while the extended models have continuous state values with upper and lower bounds. Starting with given initial state values of the neurons, a Hopfield neural network behaves like a dynamic system with time varying state values. The dynamic system has a Lyapunov function that guides the network dynamics to converge to a local minimum (which may or may not be global), in a manner similar to a dynamic system converging to a stable equilibrium point. The optimization model of a Hopfield neural network provides opportunities for applications in power systems. An example is to determine the optimal configuration of a large number of feeders following an outage. This is a combinatorial optimization problem where, for each feeder connected between two substations on two sides of the line, the problem is to determine which substation should be used to serve the feeder load while maintaining a radial configuration of the distribution system [18].

Kohonen's self-organizing feature map is a tool for learning-classification tasks. The basic function of a Kohonen net is to map an *N*-dimensional vector to a 2-dimensional neural network while preserving the topological property. The mapping from an *N*-dimensional input vectors to a simpler 2-dimensional lattice neural networks provides clusters of neurons on the map that help to visualize different patterns embedded in the input vectors. The applicability is best illustrated by the application to power system security analysis based on acquired measurements [19]. A power system operating condition is secure if no violations of the operating limits will occur for each and every contingency in a pre-specified list of events; and insure otherwise. With extensive computation offline, it is possible to determine the anticipated measurements such as line power flows and bus voltages. These results serve as a training set for the Kohonen's self-organizing feature map. With adequate training, the 2-dimensoinal neural network will display various patterns of insecurity for an input vector, which may or may not be part of the training set. An example of a cluster of neurons indicating insecurity is one that represents overload of specific line and/or load that cannot be met within the operating constraints. The power industry has long computed and utilized the nomograms that provide the boundaries of power system security for critical measurements based on numerous simulations of steady state and dynamic operating conditions. The neural network provides a systematic method to provide the critical security information in a different setting.

A well-established ANNPS is short term load forecasting [20]. Various ANN methods have been proposed over the 1990s. A practical ANN tool that has been developed and adopted for practical use by the power industry is the ANN short term load forecaster (ANNSTLF), sponsored by EPRI [21]. This tool provides the forecasted base load as well as the change of load. Humidity and wind speed are also considered in the development. The methodology is a multi-layer feedforward perceptron. The activation function of the hidden layer neuron as well as the output layer is a sigmoid function, which is a nonlinear transfer function. The weights are initially determined by training with back propagation. The weights are adaptive in the sense that they are updated on a daily basis. With test results from a good number of utility systems, the tool is able to achieve an average load forecasting error within 2%-3%.

Although ANN can be very computationally efficient and it does not require an explicit knowledge base, a common hurdle for practical deployment is the lack of an explanation of the conclusions reached, which is important for power system operational tasks where safety and security are critical requirements. The other consideration is whether the training set is sufficient, such that the ANN will provide reliable results for the scenarios that are not encountered in training.

## IV. Other Intelligent System Techniques

### *A. Fuzzy Logic*

Fuzzy logic is a mathematical technique to handle uncertainty or imprecision. A simple example is the description of "high" or "low" in daily language. Although the term appears to be binary or crisp, the reality is that there is a gradual transition between high and low. The use of a fuzzy membership function provides a continuous function that bridges high and low. The fuzzy set concepts can be applied to logic reasoning. Functional relations are available to combine fuzzy membership functions describing different quantities. It is typical to combine fuzzy membership functions and use the maximum or minimum operator to derive a conclusion with an integrated fuzzy membership function. It is also possible to defuzzify the conclusion by taking the center of gravity of the fuzzy set for conclusion and then use the maximum value of the membership as the crisp conclusion.

Further techniques are available to extend the fuzzy concepts for the study of possibility or necessity. These techniques allow the fuzzy sets to be used to derive whether one event is possible (or a necessity) given the status of another event. A fuzzy inference system is the one that can be deployed to generate the fuzzy rules based on a training set. The fuzzy inference system is particularly important when the number of fuzzy variables is large and the logic between various fuzzy variables cannot be easily identified [22].

Fuzzy set is a fundamental technique to handle uncertainties that has been incorporated in various applications to power systems with other modeling and computational techniques [23]. Computational tools are widely available in computational software packages. Fuzzy load and generation levels are incorporated in an optimal power flow method to determine the range of distribution for the uncertain line flows [24]. Fuzzy techniques have been used to combine various indicators of transformers to determine the belief and plausibility based on dissolved gas analysis and other techniques [25]. The fuzzy inference system has been proposed as a tool for electricity market price forecasting [26]. A fuzzy rule base is generated for forecasting based on training cases. A desirable feature of the fuzzy inference system is that it provides an interpretation of how the results are obtained. This is in contrast to a traditional algorithm such as least-squared estimation where no explanation is provided.

### *B. Multi-agent System*

The concept of an "agent" has existed for decades as part of the AI literature. Probably, the most important feature of an agent-based system is that an agent is designed with the ability to act autonomously and not rely on a central command. A multi-agent system has multiple agents that may or may not be cooperative, i. e., agents may be competing to serve their individual interest, e. g., agents in a competitive electricity market. On the other hand, multiple agents working to maintain power system security would be cooperative. They collaborate to handle different aspects of the overall technical objective.

To achieve a high level of productivity, a well-known mechanism to facilitate the agent communication is the average consensus algorithm, where agents communicate with their adjacent agents as the agents work toward a consensus strategy. These agent-based algorithms have been developed for control and communications based on system theoretic methods. Agent-based standards have been developed by the Software Standard Organization, Foundation for Intelligent Physical Agents (FIPA). Various agent specifications, e. g., agent communication language, have been created using the FIPA standard.

Multi-agent-based systems have been applied to various areas of power system engineering [27], [28]. An application to transformer diagnosis has an architecture with the information layer, corroboration layer, interpretation layer, and data layer [29]. Several agents are designed for the diagnostic tasks, including the transfer diagnosis agent, backpropagation neural agent, *K*-means clustering agent, and feature vector extraction agent, monitoring the partial discharge activities of the transformer. Another application to physical security monitoring of the substations is based on remote monitored and controllable video cameras installed at the substation. These pan, tilt, and zoom (PTZ) video cameras serve as multi-agents that perform detection and identification of an intruder at a substation based on image processing. Then, these agents collaborate to track the movement of the intruder and conduct the impact analysis of potential actions of the intruder. The multi-agent-based technology was demonstrated at a major transmission substation in Europe [30].

### *C. Genetic Algorithms and Decision Trees*

Genetic algorithms are heuristic search methods to deal with a combinatorial explosion of the search space for large-scale optimization problems. The basic method is to generate candidate solutions referred to as chromosomes, analogous to the genetic information encoded by DNA. A new chromosome is formed from an old one by mutation, through which a small random change is made to the old one. Another technique is crossover, in which two existing chromosomes are split at some dividing point and the pieces are rearranged to form two new chromosomes, each with a piece from one of the original chromosomes. Each string has a fitness value. The higher the fitness value is, the more copies the string will have in a mating pool. Strings in the pool are grouped in couples. Each couple of strings in the pool can swap their bits in the crossover procedure. The search procedure may converge to an optimum point, which may be local or global. Generally, there is no guarantee for genetic algorithms to find the global optimal solution. However, there are search techniques that help to escape from the convergence to a local optimum so that further search will be performed to find improved optimum points. Beyond the basic genetic algorithms, there are other heuristic search methods such as evolutionary strategies, simulated annealing, particle swarm optimization, artificial bee colony, and tabu search. They have been applied to various power system topics including unit commitment, economic dispatch, forecasting tasks in power system operation and planning [31].

A genetic algorithm has been developed for distribution network planning [32]. The multi-stage planning, which is a combinatorial search problem, is to determine a list of upgrades for the distribution network based on the load growth. As the genetic algorithm proceeds with mutation and crossover, each candidate solution is evaluated by a fitness function, which incorporates the cost of upgrades, electrical losses, reliability, and voltage drops. As a result, the infeasible candidate solutions will be removed in the search process. The result of the heuristic search is a set of feasible options of the distribution network planning. The other application is the use of tabu search for distribution feeder loss minimization [33], which is a combinatorial problem as it involves the on/off status of manual or remote-controlled switches on the feeders in the distribution system. The key concept of the tabu search is to maintain a prohibited list to help escape from the trap of a local optimum, thereby enhancing the hill climbing search. Parallel tabu search increases the computational performance and accuracy.

A decision tree represents the conditions under which decision options are applicable. Decision trees can be constructed by statistical or machine learning techniques. A tutorial with example applications can be found in [34]. A well-known technique is "learning from examples", in which learning samples are classified into groups based on the "entropy" of each group such that each group is as "pure" as possible. A good application area is that of transient stability assessment, which is a complex task that currently requires extensive computation of the system dynamics. On-line transient stability depends on the construction of decision trees with the most relevant attributes. The application in [35] uses the attribute of critical clearing time, which is the maximum operating time for breakers to clear the fault before transient instability occurs.

## V. Lessons Learned

Among the many proposed AI applications to power systems, relatively few have reached the stage of practical deployment in real-world power systems. Although control center vendors have developed some applications and some power companies have deployed locally developed applications, no AI application has become commonly-used standard practice in the power industry. However, the research experience as noted above has been positive and the recent explosion of AI applications especially in large language modeling and computer vision in other fields has increased research efforts in the application of AI to power systems.

Today, the field of AI has spawned many sub-fields that are rapidly growing in their capability and applicability. Probably, the sub-field that is of the most research interest is machine learning (or deep learning). This is a direct follow-on from the work mentioned in Section III on ANN (with the "deep" referring to the multiple levels of neural networks). Just as the previous ANN applications showed promise in predictions, the machine learning applications being researched now are also powerful techniques in predicting not just load demand but also solar generation, wind generation, and battery charging.

The application of expert systems in the past (Section II) had not yielded widespread deployment in power systems because of difficulties in constructing the knowledge base and developing the inference engine. However, in recent years, the sub-field of expert systems has made major strides in applying to other fields like health and medicine. One problem was the difficulty of gathering the expertise of power system operators from interviews by experts. Today, this could be augmented by data bases of collected relay and control center data from real-time recordings, but this remains a major hurdle. More control operations can certainly be automated, but the idea of completely eliminating the human operator is still far off.

The ability to handle natural languages has been an important sub-field of AI. This is a subject that has rarely been explored in power system applications. An example is the AI system that was developed to analyze a high volume of numerical results from testing of various relays and write a concise evaluation report in natural language for the engineers and managers. Given the highly capable AI natural language platforms available today, it will be beneficial to look into applications in the power industry environment.

There are other sub-fields of AI that can be useful to power companies in work areas other than power system planning and operation. For example, computer vision (image recognition) can be quite useful for asset maintenance and management and are already being deployed in limited ways. Another sub-field, robotics, has seen huge advances in many areas, especially manufacturing, and crawling robots for transmission line monitoring have been proposed.

Any successful deployment of AI applications in a practical environment will rely on the supporting power system infrastructure, including personnel, software, hardware, field testing, and maintenance. As an example, a successful implementation of an AI system to support decision making of distribution service restoration [6], [7] requires the distribution systems to have a high-level deployment of smart switches, which is usually the case in densely populated urban areas with a high level of distribution automation.

In cases where specialized AI development tools, such as a rule-based inference engine or neural network models, are utilized, the expertise has to be available in the industry environment to support the maintenance, upgrading, and training functions. As in other sophisticated computer-based tools, e.g., EMS or distribution management system, the AI tools will require power company personnel to have the expertise needed for applying and maintaining these tools.

## VI. Conclusion

In this paper, a brief overview of the application of AI to power system planning and operation is presented. It provides a broad brush coverage of the research efforts in the 1980s and 1990s when the term AI was not commonly used. The application of two fields, i.e., expert system/knowledge-based system and ANN, to power systems is covered in more detail than the application of fuzzy logic, multi-agent systems, genetic algorithms, and other techniques which were also tried by some researchers. The choice of these topics to include in this paper was made on the promising results shown in these research applications even though none of them went beyond prototypes and field implementations to widely-adopted commercial applications. Moreover, these techniques and methods have fed directly, if not inspired, the present explosion today into the application of AI in power systems.

## References


[1] M. Eremia, C.-C. Liu, and A. Edris, *Advanced Solutions in Power Systems: HVDC, FACTS, and Artificial Intelligence*. Hoboken: Wiley-IEEE, 2016.

[2] T. Sakaguchi and K. Matsumoto, "Development of a knowledge based system for power system restoration," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-102, no. 2, pp. 320-329, Feb. 1983.

[3] B. F. Wollenberg, "Feasibility study for an energy management system intelligent alarm processor," *IEEE Transactions on Power Systems*, vol. 1, no. 2, pp. 241-246, Mar. 1986.

[4] C.-C. Liu and K. Tomsovic, "An expert system assisting decision-making of reactive power/voltage control," *IEEE Transactions on Power Systems*, vol. 1, no. 3, pp. 195-201, May 1986.

[5] C.-C. Liu, "Knowledge-based systems in power systems," *Proceedings of the IEEE*, vol. 80, no. 5, p. 1, May 1992.

[6] C.-C. Liu, S. J. Lee, and S. S. Venkata, "An expert system operational aid for restoration and loss reduction of distribution systems," *IEEE Transactions on Power Systems*, vol. 3, no. 2, pp. 619-626, May 1988.

[7] S. J. Lee, S. I. Lim, and B. S. Ahn, "Service restoration of primary distribution systems based on fuzzy evaluation of multi-criteria," *IEEE Transactions on Power Systems*, vol. 13, no. 3, pp. 1156-1163, Mar. 1998.

[8] C.-C. Liu, K. Liou, R. Chu *et al.*, "Generation capability dispatch for bulk power system restoration: a knowledge-based approach," *IEEE Transactions on Power Systems*, vol. 8, no. 1, pp. 316-325, Jan. 1993.

[9] Y. Jiang, S. Chen, C.-C. Liu *et al.*, "Blackstart capability planning for power systems restoration," *International Journal of Electrical Power and Energy Systems*, vol. 86, no. 3, pp. 127-137, Mar. 2017.

[10] Y. Hou, C.-C. Liu, K. Sun *et al.*, "Computation of milestones for decision support during system restoration," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1399-1409, Aug. 2011.

[11] J. L. M. Ramos, A. G. Exposito, J. C. Cerezo *et al.*, "A hybrid tool to assist the operator in reactive power/voltage control and optimization," *IEEE Transactions on Power Systems*, vol. 10, no. 2, pp. 760-768, May 1995.

[12] R. Dahlgren, G. Rosenwald, C.-C. Liu *et al*., "Model-based synthesis and suppression of transformer alarms in a control center environment," *IEEE Transactions on Power Delivery*, vol. 13, no. 3, pp. 843-848, Jul. 1998.
[13] T. Minakawa, Y. Ichikawa, M. Kunugi *et al*., "Development and implementation of a power system fault diagnosis expert system," *IEEE Transactions on Power Systems*, vol. 10, no. 2, pp. 932-940, May 1995.
[14] S. Ito, I. Hata, T. Hasegawa *et al*., "Advanced operation guidance system for 500 kV substation," *International Journal of Electrical Power & Energy Systems*, vol. 14, no. 2, pp. 114-121, Apr. 1992.
[15] K. Tomsovic, C.-C. Liu, P. Ackerman *et al*., "An expert system as a dispatcher's aid for the isolation of line section faults," *IEEE Transactions on Power Delivery*, vol. 2, no. 3, pp. 736-743, May 1987.
[16] T. Dillon and D. Niebur. *Neural Net Applications in Power Systems*. London: CRL Publishing Ltd., 1996.
[17] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 79, no. 8, pp. 2554-2558, Aug. 1982.
[18] Y. Hayashi, S. Iwamoto, S. Furuya *et al*., "Efficient determination of optimal radial power system structure using Hopfield neural network with constrained noise," *IEEE Transactions on Power Delivery*, vol. 11, no. 3, pp. 1529-1535, Jul. 1996.
[19] D. Niebur and A. J. Germond, "Unsupervised neural net classification of power system static security states," *International Journal of Electrical Power & Energy Systems*, vol. 14, no. 2, pp. 233-242, Apr. 1992.
[20] D. C. Park, M. A. El-Sharkawi, R. J. Marks *et al*., "Electric load forecasting using an artificial neural network," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 442-449, May 1991.
[21] A. Khotanzad, R. Afkhami-Rohani, and D. Maratukulam, "ANNSTLF-artificial neural network short-term load forecaster-generation three," *IEEE Transactions on Power Systems*, vol. 13, no. 4, pp. 1413-1422, Jul. 1998.
[22] T. Hiyama and K. Tomsovic, "Current status of fuzzy system applications in power systems," in *Proceedings of 1999 IEEE International Conference on Systems, Man, and Cybernetics*, Tokyo, Japan, Jun. 1999, pp. 527-532.
[23] L. Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 22, no. 6, pp. 1414-1427, Dec. 1992.
[24] V. Miranda and J. P. Saraiva, "Fuzzy modelling of power system optimal load flow," *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 843-849, Mar. 1992.
[25] K. Tomsovic, M. Tapper, and T. Ingvarsson, "A fuzzy information approach to integrating different transformer diagnostic methods," *IEEE Transactions on Power Delivery*, vol. 8, no. 3, pp. 1638-1646, May 1993.
[26] G. Li, C.-C. Liu, C. Mattson *et al*., "Day-ahead electricity price forecasting in a grid environment," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 266-274, Jan. 2007.
[27] S. D. J. McArthur, E. M. Davidson, V. M. Catterson *et al*., "Multi-agent systems for power engineering applications: part I: concepts, approaches, and technical challenges," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1743-1752, Jul. 2007.
[28] S. D. J. McArthur, E. M. Davidson, V. M. Catterson *et al*., "Multi-agent systems for power engineering applications: part II: technologies, standards, and tools for building multi-agent systems," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1753-1759, Jul. 2007.
[29] S. D. J. McArthur, S. M. Strachan, and G. Jahn, "The design of a multi-agent transformer condition monitoring system," *IEEE Transactions on Power Systems*, vol. 19, no. 4, pp. 1845-1852, Jul. 2004.
[30] J. Xie, A. Stefanov, and C.-C. Liu, "Physical and cyber security in a smart grid environment," *WIREs Energy and Environment*, vol. 5, no. 5, pp. 519-542, Sept. 2016.
[31] K. Y. Lee and Z. A. Vale, *Heuristic Optimization Methods in Power and Energy Systems*. New York: Wiley-IEEE, 2020.
[32] V. Miranda, J. V. Ranito, and L. M. Proenca, "Genetic algorithms in optimal multi-stage distribution network planning," *IEEE Transactions on Power Systems*, vol. 9, no. 4, pp. 1927-1933, Jul. 1994.
[33] H. Mori and Y. Ogita, "A parallel tabu search based method for reconfiguration of distribution systems," in *Proceedings of IEEE PES Summer Meeting*, Seattle, USA, Jul. 2000, pp. 1-6.
[34] C. Bulac and A. Bulac, "Decision trees," in *Advanced Solutions in Power Systems: HVDC, FACTS, and Artificial Intelligence*. New York: Wiley-IEEE, 2016, pp. 819-844.
[35] L. Wehenkel, M. Pavella, E. Euxibie *et al*., "Decision tree based transient stability method a case study," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 459-469, Jan. 1994.

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