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Computational Intelligence for Mitigation of Blackouts

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Abstract

Using intelligent computing will make the blackout prevention easy and fast for the power operators. This will improve assessment efficiency and increase power systems stability. Voltage profiles show no abnormality prior to undergoing voltage collapse because of load variations. Operators may observe no advance warning signals until sudden significant changes in voltage magnitude result in action of protective equipment crash the network. Therefore, an artificial intelligent tool can provide timely evaluation of blackout of the system under the diversified operating conditions. ANN application also applied on 6-bus system

1. INTRODUCTION

A system enters in the state of voltage instability when a disturbance, increase in load demand, or change in system condition causes progressive and uncontrollable drop in voltage. The main factor causing instability is the inability of the power system to meet the demand of reactive power [1]. The heart of the problem is usually the voltage drop that occurs when active power and reactive power flow through inductive reactance associated with the transmission network. Intelligent computing suits application to voltage stability studies because of endless number of system configurations, making each voltage stability problem unique in its characteristics and diagnosis. Distributed monitoring system that gathers a huge amount of data, which is infeasible for a human expert to handle. Serious imprecision of data making conventional programs fail to identify voltage stability problem. Lack of synchronization between monitors adds to the dispersion of the data. Voltage stability diagnosis requires expertise in variety of power topics [2]. This work demonstrates the use of the Artificial Neural Networks for voltage stability assessment of a sample power system. Artificial intelligence is the science of making machines to do things that would require intelligence if done by humans. The artificial intelligence is used to shed light on the human variety of intelligence by attempting to model it with computers, make computers easier to use by making them operate more like human user and solve complex problems that traditional programming methods can not solve efficiently. Applicability of artificial intelligence is also shown in various papers for power engineering power operators. Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. In effect, the role model for soft computing is the human mind. In coming years, the presence of intelligent systems is certain to have a reflective impact on the ways in which man-made systems are conceived, designed, manufactured, employed and interacted with. This is the perspective in which the basic issues relating to soft computing and intelligent systems are addressed. As power systems become increasingly complex, there is a critical need to make available improved tools for training power system engineers and analysts. A criterion for voltage stability is that, at a given operating condition for every bus in the system, the voltage magnitude increases as the reactive power injection at the same bus is increased. A system is voltage unstable if, for at least one bus in the system, the bus voltage magnitude (V) decreases as the reactive power injection (Q) at the same bus is increased. The QV curves obtained using neural networks and compared with conventional methods [4]. At different loading conditions of the sample system results are obtained. Records of major disturbances indicate that the initial system faults have been cleared in milliseconds, and systems have separated into unbalanced load and generation subsystems several seconds later. Blackouts have taken place several minutes after the separations, and the power systems have been restored several hours after the blackouts. Most of these power outages have been of extended duration. For instance, as found in a review covering 24 recent power failures, seven have lasted more than 6 hours. The U.S.-Canada report on the 14 August 2003 blackout cites seven major power disturbances with the greatest impact, lasting between 10–50 hours. These failures clearly indicate a need for renewed emphasis on developing restoration intelligent methodologies and implementation plans. Sustained operation of power systems is impossible unless generator frequencies and bus voltages are kept within strict limits. During normal operation, these requirements are met by automatic control loops under operator supervision. During restoration, when individual generators are being brought up to speed and large blocks of load are being reconnected, perturbations outside the range of automatic controls are expected; hence, hands-on control by system operators is necessary. "System" frequency is the mean frequency of all the machines that are online, and deviations by individual machines must be strictly minimized to avoid mechanical damage to the generator and disruption of the entire system. This is generally accomplished by picking up loads in increments that can be accommodated by the inertia and response of the restored and synchronized generators. Smaller radial loads should be restored prior to larger loads while maintaining a reasonably constant real-to-reactive power ratio. Above all the combinations of reactive power sources for stable and secure power systems need an intelligent arrangement with quick solutions. Presently available conventional methods are unable to avoid collapses. In this paper we will be using the Artificial Neural Network approach to reduce these unwanted situations up to the optimum level. MATLAB based neural network solution for the trained network will be applied to maintain the stability between the generation and the load point.

2. THE VOLTAGE BLACKOUT PROBLEM

A power transmission network has an inherent limit as to how much power it can deliver to loads. When this limit is exceeded, the voltages experienced by loads become too low to be practically useful. In many cases, the voltages will go straight from normal to zero in a matter of a few seconds or minutes. This process is called voltage collapse. Massive voltage collapses across several interconnected power systems are not unusual. For example, at the summer of 1996, two voltage collapses occurred in the west coast Canada-US-Mexico interconnected system, causing blackouts for millions of customers. The capability of a transmission network can be loosely visualized as the size of a pipe or the number of parallel pipes. The power transfer capability of this system would be affected if one or more pipes (transmission lines) were lost. Loss of transmission lines or other supporting components such as shunt capacitors will cause the reduction of system capability. When system capability is reduced, loads have to be shed. Otherwise the demand and supply cannot match and voltage collapse will occur. The simplest form of voltage stability assessment involves the determination of a network's power transfer capability. This capability must be greater than the anticipated load. The network capability will change if some of its components are not available due to failure or maintenance. The capability assessment therefore needs to be conducted for number contingency scenarios. PV and QV curves are two most commonly used techniques to assess the capability of a network. These curves show the voltages of selected buses as functions of increased system load. The "nose points" of these curves are the system limit.

3. NECESSITY OF ARTIFICIAL INTELLIGENCE

Given the high stakes and intense competition within all areas of industry, intelligent business decisions are more important than ever. Data analysis plays an important role as a critical strategic weapon in business. The inherent limitations of existing statistical technology makes normal data analysis a very tedious and often costly process - requiring assumptions, rigid rules, force fitting of data, as well as extensive trial and error experimentation and programming. Interpreted errors, biases and mistakes are introduced. Valuable competitive insights are lost. There are a range of AI technologies available now - each with their own strengths and weaknesses: Expert systems, Fuzzy Logic, Case-Based Reasoning, Neural Networks and Genetic Algorithms [3].

4. EXPERT SYSTEMS

Expert systems (ES) are probably the most established form of AI technique. They attempt to embody human knowledge in a computer program through the creation of a set of "rules" that describe the behavior and thought processes of the human expert concerned. This capture of human knowledge is achieved by interviewing or monitoring human experts and then representing this information in the form of a (typically large) set of IF-THEN-ELSE rules.

The main strength of expert systems is that they store and use knowledge in a transparent way that is easy for an expert to modify or an operator to interpret; their rule-based nature provides a convenient mechanism for explaining decisions or predictions. This, of course, is only true for small rule-bases, with 1000's of rules it is quite a different picture.

The main disadvantage of expert systems is that human experts often find it hard to explain clearly the processes they use when performing a task, making the generation of clear, logical rules very difficult. Even when it is possible to devise rules, it is often a very expensive and time-consuming task, requiring a high degree of skill, both in terms of the developers and the experts concerned. The performance of the system is dependent upon the skill of the human expert and how this is interpreted into the computer. Experts are often subjective and only deal with a limited number of variables. The precise, inflexible nature of the rules themselves, leads to poor performance when the data contains errors, contradictions, or missing values. Finally, most expert systems lack any form of automated learning and cannot adapt to follow changes in the business environment; any changes have to be implemented manually and are typically expensive to perform. As the rule-base grows it becomes hard to maintain and requires considerable computing power to run.

5. FUZZY LOGIC

Fuzzy logic (FL) is a more generalized form of conventional rule-based system. It introduces an element of "fuzziness" or imprecision into both the specification of the rules and the description of the data, thereby emulating the imprecise nature of human reasoning and interpretation. Whereas in traditional Boolean logic, statements are considered to be either "true" or "false", in fuzzy logic, they can be partially true or partially false. The degree to which they are true (or false) is represented by a numeric value between zero and unity. These fuzzy values can also be used to describe the degree to which data belongs to various categories. In fuzzy logic, the standard Boolean operation AND and OR are replaced by the binary operators MIN and MAX, respectively. Fuzzy rules are constructed by combining these operators into statements. Fuzzy expert systems are rule-based systems that utilize fuzzy rules, instead of Boolean logic, to reason about data. Owing to the fuzzy nature of the rules, many different rules may be activated in response to a new input to the system. Fuzzy systems make decisions using the combined contribution of all the activated rules, rather than relying on the outcome of a single, precisely matched rule as in conventional expert systems. This makes them inherently more robust to noisy or incomplete data. Like rule-based systems, knowledge is stored in a transparent way, making it relatively easy for experts to adjust the knowledge base to improve or modify functionality. This also provides a mechanism for generating explanations about how individual decisions are generated. However, the essentially rule-based nature of these systems means that a human expert is still required to specify the processes used to perform a task. This elicitation of knowledge is a highly skilled and time-consuming process making these systems expensive to construct and maintain. In some situations, where little is known about the processes required to perform a task, it may even prove impossible to construct an appropriate set of rules. Finally, the lack of an automated learning element makes it difficult for these systems to adapt and follow changes in the business environment.

6. CASE-BASED REASONING

Case-based reasoning (CR) takes a slightly different approach to using expert knowledge to solve problems. Rather than formulate specific rules to describe the processes used to perform a task, historical data is accumulated. When new problems arise, the most similar previous historical cases are used to develop a solution to the current problem. The new solution is then added to the historical cases. In the simplest case, the input data might represent a list of attributes for a particular problem and the output, the decision of an expert. When a new input is applied to the system, the most similar historical cases are retrieved and the new output determined by a majority vote of the historical responses. In general, case-based reasoning systems are much more complex than this simple example, but the principle is the same: historical data on a problem is stored and later recalled to help determine a solution to a new problem. The advantages of case-based reasoning systems over rule-based expert systems is that the processes needed to solve the problem need not be known in advance; knowledge is embodied in the historical data and the processes that make use of this data. This feature also makes it easy to automate these systems and allows them to adapt to changes in the business environment. Their main disadvantage is that they are not very efficient in their operation. A large number of historic examples are typically needed to replace a single rule in a rule-based system. As the complexity of the problem grows, the number of historical examples increases dramatically, leading to large computational and storage overheads in operational use. Furthermore, while they are more robust to noisy or imprecise data than expert systems, their performance is significantly degraded when there is only a limited amount of data or the expert responses are contradictory.

7. NEURAL NETWORKS

Neural Networks (NN) are based upon the biological processes of the brain and can learn. "Brain-like", "massively parallel", "learning machines" and "revolutionary" have all been used to describe neural computing. Neural networks are trained on historical data, using a learning algorithm. The learning algorithm changes the functionality of the network to suit the problem by modifying the values of the connection weights between processing elements. Once trained, the network interprets new data in a way that is consistent with the experience gathered during training. Neural networks can provide highly accurate and robust solutions for complex non-linear tasks such as fraud detection, business lapse/churn analysis, risk analysis and data mining. One of their main benefits is that the method for performing a task need not be known in advance; instead, it is automatically inferred from the data. Once learned, the method can be quickly and easily adjusted to track changes in the business environment. A further advantage of neural networks once trained, they are far more efficient in their storage requirements and operation; a single mathematical function can replace a large number of rules.

8. GENETIC ALGORITHMS

Genetic algorithms (GA) are search algorithms based on the mechanics of natural selection and natural genetics. The process begins with a population of candidate solutions to a problem. These candidates are represented using a variety of encoding schemes equivalent to genetic chromosomes. Information is typically encoded in the form of a binary string. Having been randomly initialized, the performance of each candidate is evaluated using a fitness function. Once fitness values have been obtained, the fitter candidates (better solutions) are allowed to "breed" while others are "killed off" by a process of selection. A process of mutation augments this reproduction process, where small random changes are introduced into members of the population. Many of the mutants will not perform well and will perish; however, some will do well and survive. Genetic algorithms can be used to search for solutions to classification, prediction, and optimization problems. Their main strength lies in their ability to find globally optimal solutions to a problem, even when the global optimum is hidden among many, poorer, local optima. However, the evolutionary process is very time-consuming, requiring large amounts of computing resource. Another, more serious disadvantage, relates to the expertise required in encoding the candidate solutions and setting up the fitness function. This means that the initial development process is both highly skilled and extremely costly.

Various Artificial Intelligence technologies have been reviewed as below:

Table 1:

Property	ES	FL	CR	NN	GA
No programming required (method for performing a task need not be known in advance)	×	×	✓	✓✓	✓✓
Robust to noisy, imprecise or incomplete data	×	✓✓	✓	✓✓	✓✓
Automated learning procedure	×	×	✓✓	✓✓	✓✓
Compactness of representation / efficiency of operation	✓	✓	×	✓✓	✓✓
Transparency of operation / availability of explanatory information	✓✓	✓✓	✓	✓	✓
No expert setup required for each new application	×	×	✓	✓	×

9. ANN APPLICATION

The proposed method has been tested using a 6-bus system shown in Fig. 1

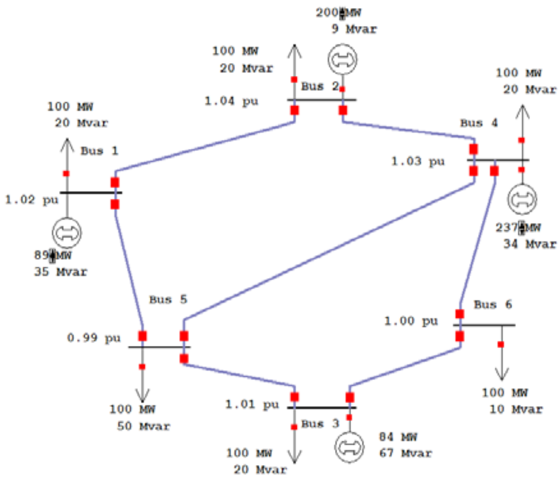

Fig. 1: Six Bus sample power system

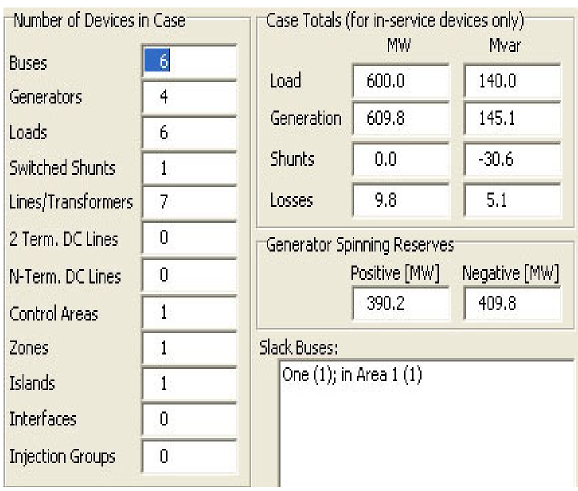

Fig. 2: Case information

The input/output training patterns used for the learning phase of the ANN are total of 15 patterns at bus 3 are used for training the network. The switch able shunt is kept on bus 3 and the load at bus 3 is increased. The learning data input/output patterns are presented to the ANN during the learning phase. ANN adopts a function corresponding to these input values as shown in Fig 3.

Commercially available ANN toolbox from MATLAB, implementing the radial basis (exact fit) method, is used. The neural network has 15 inputs, 15 hidden neurons and outputs. After continuous increase of reactive load, a point comes where voltage blackout for complete power system occurs. When the shunt is kept at bus 3, collapse occurs at 225 MVAr giving normal operation but on the verge of collapse. This point of collapse is a shifted point because of the insertion of a switched shunt.

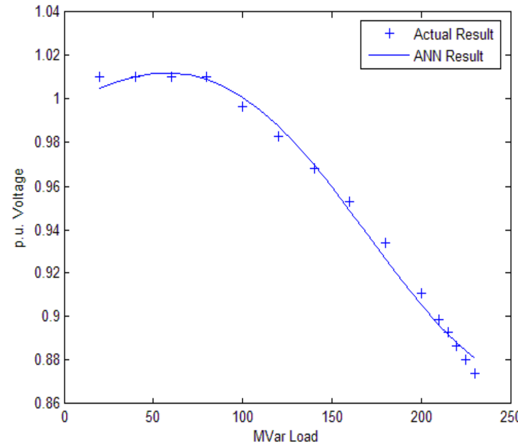

Fig. 3: ANN Adapted Function and Actual Loading Plot

Comparison between ANN adopted function and actual loading plot as shown in Figure 3, shows that the collapse point in studied case 0.8802 (p.u. voltage) is taken as indicator boundary for system collapse. Comparison between ANN adopted function and actual loading plot as shown in Figure 3 shows that the collapse point in studied case 0.8875 (p.u. voltage) is taken as indicator boundary for system collapse.

10. CONCLUSION

In the present paper necessity of computational intelligence for mitigation of power system blackout discussed. Using intelligent computing will make the blackout prevention easy and fast for the power operators. The use of artificial neural network for reactive power balancing between generation and demand points has been presented in this paper. The trained ANN has been tested with input data not previously seen by the ANN. The trained ANN provides reasonable results in an extremely short time (almost instantaneously) when compared with other existing methods utilizing successive power flow or optimization. The inputs/outputs for training are easily obtained via successive power flows and do not require extensive computation when compare with certain other energy based methods.

REFERENCES:

1. P. Kundur, "*Power System Stability and Control*", New York: McGraw-Hill . 1994
2. F. A. Shaikh, "Neural Networks Technique Applicability for Voltage Stability of Power Systems", *IEEE International Conference on Systems, Man & Cybernetics October 5-8, 2003*, Washington, D.C., USA.

3. S. Rajasekaran and G.A. Vijalakshmi Pai, "*Neural Networks, Fuzzy Logic, and Genetic Algorithms*, PHI, New Delhi, 2006.

4. F. A. Shaikh, A. Tripathi, S. Shukla, "Neural Network Based Reliability Analysis of Power Systems", *International Conference on Recent Advancements and Application of Computer in Electrical Engineering*, Bikaner, Rajasthan, India, March 24-25, 2007.