Application of Case Based Reasoning in Voltage Security Assessment

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Abstract—**In this paper case based reasoning (CBR) approach has been developed for voltage security assessment. In the CBR approach, probabilistic fuzzy decision tree (PFDT) is being trained in real time for getting solution of new cases. In case topology of the power system changes the PFDT models may not respond correctly and hence need retraining. CBR updates its case-base in real-time by learning new cases and use them in future. Also case-base of CBR can easily be modified for any change in topology of the power system. The proposed approach, classifies the power system operating states instantaneously into secure and insecure states with the desired accuracy**.

Keywords—voltage security assessment; Probabilistic fuzzy decision tree; case-based reasoning; CPF; Voltage Security Margin.

I. INTRODUCTION

The ever rising expansion of practical size inter-connected power systems and demand growing day by day. So the load is also increases on network. It is necessary to have high degree of security in day to day normal operations. Therefore, quick assessment of voltage security to provide reliable and secure delivery of electrical energy to customers is very important in the today's competitive environment. Providing information to the operating personals about the secure and insecure operating conditions of the power system during normal and contingent system is the prime objective of voltage security assessment, so as to initiate proper action within the safe time limit. Security assessment is the development of process to identify whether any violation of operating limit would lead to secure or insecure operation. Therefore it is very important to develop fast, accurate and efficient tools to assess the voltage security.

Power system experts and operators are accumulating valuable operational knowledge of the concern power systems over many years using artificial memories or their own memories. Real time data loggers can be used to store the operating states of the power system in real time, which consists of a set of power system parameters and corresponding voltage security status. By using this knowledge, the time of problem solving challenges could be curtailed and has led to many different approaches. One of the approaches is the case-based reasoning (CBR) where it uses experiences of solved problems for solving current problems and stored in case-base [1]. CBR is transparent system and all the shortcomings which are found in feed forward ANN are removed with use of CBR, like all the decisions can be verified by operators using rules generated by decision trees [2]. Case-based reasoning for real-time voltage security assessment of the power system is presented using Probabilistic Neural Network (PNN). PNN is used for similarity matching and solution of new cases using old cases of CBR system. An information gain based feature selection technique is used for selection of suitable input features for PNN, which reduces the input dimensionality so the process retrieval becomes faster [3]. After retrieval new case is adapted by CBR that is called case adaption. Case adaption improves the performance and application level of CBR [4]. CBR is a good approach for representing the data similar to some rules, logic and mathematical data in the form of case representation. It may provide theory support for the construction of prototype system. It enhances the ability of the past experience into the modernized auxiliary decision making [5, 6, 7]. In this paper a case based reasoning, a more accurate, efficient and fast algorithm is developed for voltage security assessment. In this approach the similarity matching for new cases has been avoided and real time training of PFDT is adopted to find solution of new cases using old cases in case base. Also indexing of case base is not required with PFDT. For every new case real time re-training of PFDT is provided therefore any change in topology of network or any new learning is easily adopted which further enhances prediction accuracy.

II. COMPONENTS OF CBR

Case-based reasoning is a problem-solving artificial intelligence methodology that uses past experiences to find out new problems. Whenever a new case crop up, CBR system retrained the PFDT (using old cases) from the case-base and solution of new case is assigned to the case base. Also the new case along with its solution is stored into the case-base for future use. Fig.1 shows the cycle of proposed CBR system.

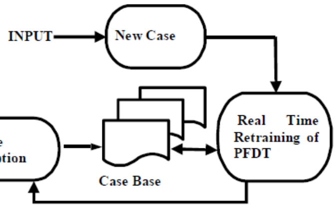

Fig. 1. Cycle of proposed CBR

A. Case representation

A case represents a knowledge of the system and it consists of the input attributes and an output attribute or variable. A good representation of cases will allow for sorting problems and use these solution for the clarification of decisions. Most of the CBR systems represent the cases as a plain structure composed of pairs of attribute value and corresponding class labeled to the case, as

$$X = [x_1, x_2, ..., x_n, x_c]$$

Where $x_1, x_2, ..., x_n$ are the input attributes (numeric or symbolic) and a solution x_c i.e. output attribute (class).

B. Case-base

In CBR, cases are the basis of system. The case-base or database is the essential and main part of CBR system. The case-base is the database or storage of solutions from previous operating conditions of power system.

C. Case adaptation

Case adaptation is the process of including new case to the case-base to form the solution of new case.

III. METHODOLOGY

Fig. 2 shows the overall voltage security framework. In the first stage case-base is generated by computer simulation. A load pattern, line outage number and corresponding security class characterize a case. In the second stage CBR system is developed, and in the last stage, CBR system is used for real-time voltage security assessment

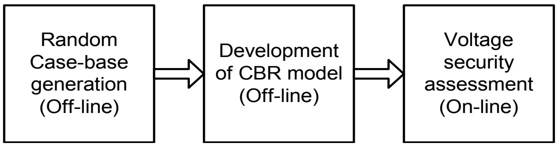

Fig. 2. Overall voltage security framework

1) Case-base generation

By using the computer simulation cases are generated for voltage security assessment to realize the effectiveness of the case-based reasoning. Database is generated by varying the real as well as reactive load (PQ load) randomly to include all the possible operating states to solve a particular task. Then Voltage Security Margin (VSM) is calculated corresponding to each pattern and under each single line outage. Continuation power flow (CPF) method is used to calculate VSM of the power system. VSMs mainly depend upon PQ load of the PQ buses, hence real and reactive loads of PQ buses and real load of PV buses are selected as input features and VSM (λ_m) is considered to be a output which is depending on input features. VSM corresponding to each pattern is divided as secure and insecure w.r.t. a critical value of λ_m as λ_{cr} so that if $\lambda_m \le \lambda_{cr}$ the operating state under a particular line outage will be insecure otherwise it will be a secure one. Thus *'X'* describes the case along with security status (class λ_k) as given below.

$$X = \left[P_1, P_2, ...P_{pq}, P_{pq+1}, P_{pq+2}, ..., P_{pq+pv}, Q_1, Q_2, ...Q_{pq}, L_n, \lambda_k, \lambda_m\right] \quad (1)$$

Where P_i and Q_i ($i = 1, 2, ..., pq$) are real and reactive loads respectively on i^{th} *PQ* bus, P_i ($i = pq+1, pq+2, …, pq+pv$) is real power demand of i^{th} *PV* bus, λ_k ($k = 1, 2$) is the output class.

2) Algorithm for Development of CBR

The algorithm to develop CBR model for voltage security assessment is given below.

Step 1: A load patterns were generated in large number, randomly by varying the real and reactive loads at all of the buses within the range of 50% to 150 % of base case values.

Step 2: Under each contingency CPF is performed for all the load patterns to calculate the VSM in terms of real power margins. Based on VSM, load patterns further divided into two categories namely 'secure' and 'insecure'

Step 3: Load bus and real load at PV buses are the actual real and reactive load (p.u.) of each cases, labeled with corresponding security class. A separate set of cases is generated under each contingency.

Step 4: To demonstrate the performance of CBR for new cases addition in future, 90% cases from case base is reserved for testing and initially 10% cases were used for training of PFDT. Now 20% cases were added as new cases in every new presentation of cases. After solving each of the new cases they are included in case base for future reference. Corresponding accuracy of prediction is calculated in every run of CBR using (2) given below.

Step 5: When all the cases were included in case base, the accuracy were plotted for every new addition of cases.

$$\%\,Accuracy\,(\eta) = \frac{Total\ No.of\ test\ cases\ \text{-}\ No.of\ Incorrectly\ clssified\ cases}{Total\ No.of\ test\ cases} \times 100 \quad (2)$$

IV. RESULT AND DISCUSSIONS

A total of 300 load patterns were randomly generated for each line outages, with load variation in the range of 50% to 150% of their base-case load. VSM (p.u.) are calculated for each load pattern under each contingency and each line outage. Post-contingent VSMs are classified into two classes as 'secure' and 'insecure' w.r.t. a threshold or critical value of VSM ($\lambda_{cr} = 0.3\ p.u.$). Out of 300 patterns for a particular contingency, 270 patterns are kept for testing every time. In first run, program considered 20% i.e. 60 patterns for training and 270 patterns for testing on PFDT. In second run, program took 40% it means 120 patterns for training and 270 patterns for testing on PFDT. In third run, program considered 60% it means 180 patterns for training and 270 patterns for testing on PFDT. In fourth run, now program considered 80% it means 240 patterns for training and 270 patterns for testing on PFDT. In fifth run, program took 100% it means 300 patterns for training and 270 patterns for testing on PFDT. The effectiveness of the proposed approach has been tested on IEEE-30 bus. Test result of the system is presented below.

IEEE-30 bus system

Out of 300 cases (patterns) under each severe contingency 270 cases were presented to the CBR system for testing, which are fixed for every run of CBR. These 300 patterns, which include testing patterns also, are presented in steps of 20% in every run of CBR cycle. In every run same set of test cases were tested.

In the testing set the percentage of secure and insecure cases are fixed because test cases are same every time. On every run 20% of new cases were added to case base therefore the percentage of secure and insecure cases varies in training patterns with every run of CBR cycle. Result shows the effect of accuracy of CBR system with addition of new operating states in the case base. Initially 20% of training cases were selected in first run and testing set is fixed at 90% of initial case base and kept constant for every run of CBR. In Table-I for line outage-1 show that 93% correctly classified cases when training patters were 20 %. In second run 97% correctly classified cases when training patters were 40 %. Similarly in third, fourth and fifth run accuracy is continue to enhance as the number of training patterns were increasing. Again from Table-I it is observed that percentage accuracy in under line outages goes on increasing with number of cases in case-base increases. From above, it is observed that every day some new kinds of states are expected to encounter, which can be recorded with their solution to solve the new events in future. This increases the accuracy and keeps the accuracy of classification at highest value always.

TABLE I. PERCENTAGE ACCURACY (η) OF LINE OUTAGES AT DIFFERENT LOAD PATTERNS

No. of Load Patterns in %	**% η Under Line Outage-1**	**% η Under Line Outage-2**	**% η Under Line Outage-4**	**% η Under Line Outage-5**	**% η Under Line Outage-36**
20	93	94	95	87	89
40	97	94	96	90	92
60	98	95	96	93	94
80	99	96	97	97	94
100	99	96	97	97	94

Fig.3 to Fig.7 reveals that as the number of cases increases in the case-base the accuracy is also enhancing. Sometimes it is found that for few cases accuracy may decreases due to weak relationship between inputs and an output but on and average accuracy always increases. This is happened due to less number of operating conditions considered in this research work which is generated by simulation, but in practical power system operating conditions, logged in the databases (case-based) are large in number i.e. in the range of 10,000 or more cases are available, which will have better and strong relationship between input attributes and an output therefore accuracy of predictions will have always increase with new cases added to case-base. Fig. 8 presented the highest accuracy of CBR after every 20% addition of cases under five number of line outages, which shows that if new cases continue to be adopted over the years, which will guaranteed the accuracy to be maintained at highest level.

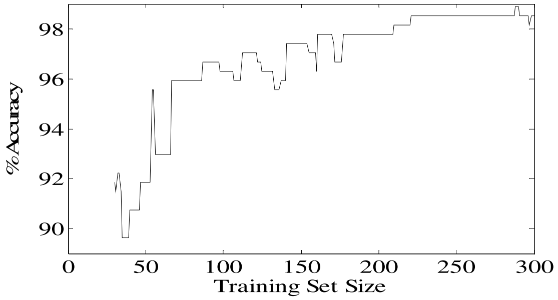

Fig. 3. Accuracy versus training set size of line outage-1.

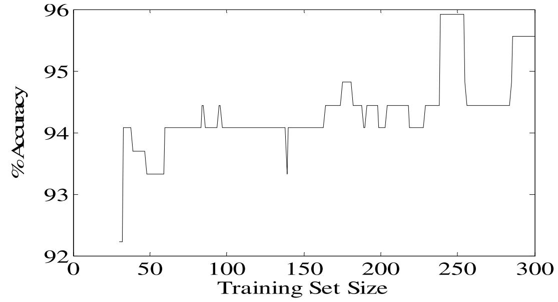

Fig. 4. Accuracy versus training set size of line outage-2.

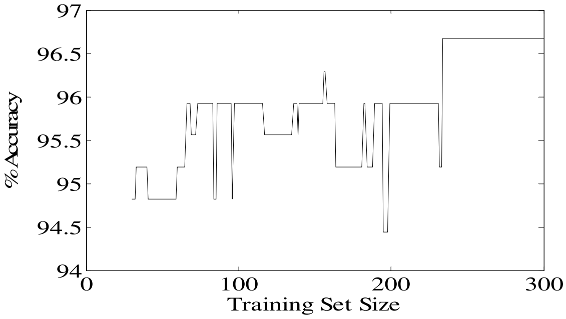

Fig. 5. Accuracy versus training set size of line outage-4

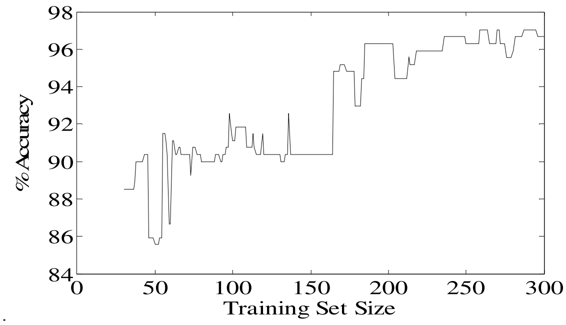

Fig. 6. Accuracy versus training set size of line outage-5

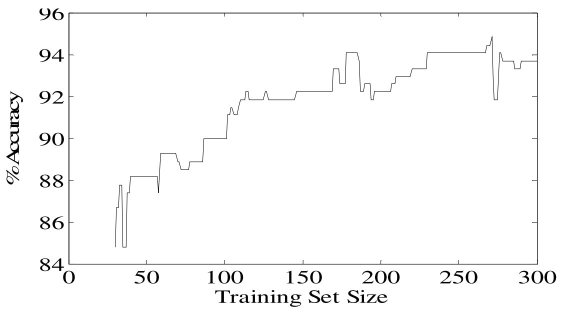

Fig. 7. Accuracy versus training set size of line outage-36

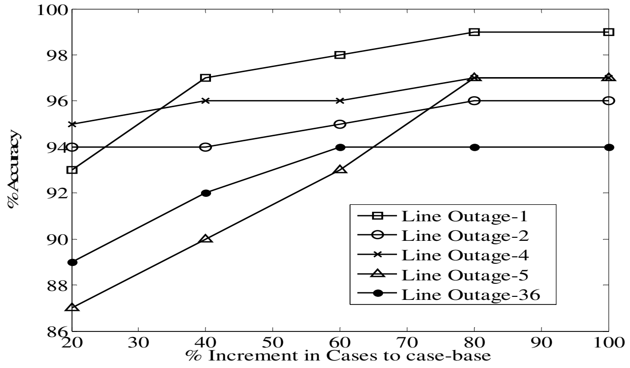

Fig. 8. Combined Accuracy of five different line outages

V. CONCLUSIONS

In this paper a case-based reasoning approach, is developed for real-time voltage security assessment of power systems. CBR is based on PFDTs which are being trained in real time for every new operating state of power system. PFDT is retrained before giving solution of new operating state every time. After solving the new case the solution of that new case is recorded into case base for future use. The proposed approach classifies the power system operating states instantaneously into secure and insecure states with the desired accuracy. Since PFDT is being trained in real time, any change in topology of power system can easily be updated. Also after solving the new cases, CBR include (learning) the new cases along with its solutions for future use, which guaranteed to maintain the accuracy of the system for typical operating conditions in future. CBR is fully transparent and comprehensible to the operators. Operator can easily understand the knowledge acquired by CBR system and incorporated at any intermediate stage. The computation of the VSM to assess the security of the system by traditional methods such as power flow/continuation power flow takes long time as it based on iterative process and it has to run for every change in load/generations. On the other hand CBR gives the information about the security of the unknown operating states of the system almost instantaneously and accurately. In energy management systems for on-line voltage security assessment, implementation of CBR technique is more appropriate.

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