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On-Line Dynamic Security Assessment of Power Systems Utilizing Case-Based Reasoning Approach

Abstract: - Online dynamic security of power system is one of the main issues of reliable operation of power system due to increasing stress on power system network and operating of systems near their stability limits. Dynamic security is the ability of power system to maintain its synchronism among system's machines during and following contingencies and disturbances. This work shows effectiveness of Case-Based Reasoning (CBR) technique for dynamic security analysis. CBR is a type of machine learning method that falls within the broader domain of artificial intelligence. The principle behind CBR involves utilizing solutions from past problems and adapting them to estimate solutions for new problems by making necessary modifications. This technique is applied to dynamic security analysis of a standard IEEE 9 bus system, that is a highly nonlinear task. For creating initial data, the system was modeled in ETAP program and transient analysis is executed for different load-generation conditions of power system. Security level of power system is determined by calculating critical clearing time of a fault (CCT). To check robustness and efficiency of CBR technique, it is compared with the performance of Artificial Neural Network (ANN) for dynamic security assessment.

Keywords: Dynamic Security, Case Based Reasoning, Artificial Neutal Networks, Similarity Index, Long-term Transient Stability

I. INTRODUCTION

Dynamic security assessment (DSA) is a long-term study of transient stability of power system. Detailed modeling of power system along with its generation control system parameters have to be considered. Conventionally, DSA was conducted offline using enumerative forecasting and comprehensive contingency simulations. However, because of continual changes in power systems, conventional off-line DSA become inadequate and uneconomical. Thus, there is high need for on-line DSA assessments, to continuously monitor system dynamic security condition and reduce the risk of dynamic insecurity to prevent cascading blackouts.

Power system security analysis encompasses power system stability, modeling of power system and security analysis. The concepts of power system stability are taken from [1-4]. In [5], power system voltage stability has been elucidated with all details like reactive power compensation and control. An in-depth discussion about power system stability and modeling has been given in [6] focusing in stability and in [7] focusing in modeling.

An overview about power system security & stability, state estimation and contingency analysis can be found in [8,9]. Conventional method for power system security analysis was time-domain simulation (TDS) with detailed machine modeling for all credible contingencies, as this approach requires enormous computational time and found infeasible for real time security analysis of large-scale power networks various work has been done to propose new robust method especially to transient and dynamic security analysis. In recent years, many techniques like multilayer feed forward network [10], self-organizing feature map [11]], fuzzy logic combined with neural network [12] help in reducing the short comings of the traditional method. In [2] different Intelligent system (IS) for security analysis has been discussed and subsequently Extreme learning machine (ELM) has been developed for real-time dynamic security analysis for a system with large integration of wind resources.

Recent work has been focused on on-line dynamic security analysis using IS systems. Different technics like Pattern Recognition (PR), Decision Tree (DT), Artificial Neural Network (ANN) and Extreme learning machine (ELM) have been proposed, in [1] Case Based Reasoning (CBR) is a new method that depends on Intelligent Systems, that has been designed to address DSA where there is a large integration of wind power. This method uses inferences from the previous solutions to build up accurate estimates. In this work CBR system is designed for an IEEE power system of 9 buses with three machines, and an ANN system is made for the same system and dynamic security analysis results of both systems has been compared.

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II. ON-LINE DYNAMIC SECURITY ASSESSMENT:

On-line DSA updates off-line DSA by considering current operation condition of power system. Generally, the process has two major steps;

1. Finding credible contingency by contingency screening then contingency ranking
2. Conducting security analysis by mean of Artificial intelligent system (AIS)

During security analysis it takes measurement of current condition by different means like SCADA, PMUs etc., does analytical work in real-time and communicates the same to control system to take preventive or corrective control action. The AIS is built off-line so that in real time the time for any computations is drastically reduced. From the database of all the cases, AIS can identify the state of the system from the input gathered. The schematic of AIS system is illustrated in Figure 1.

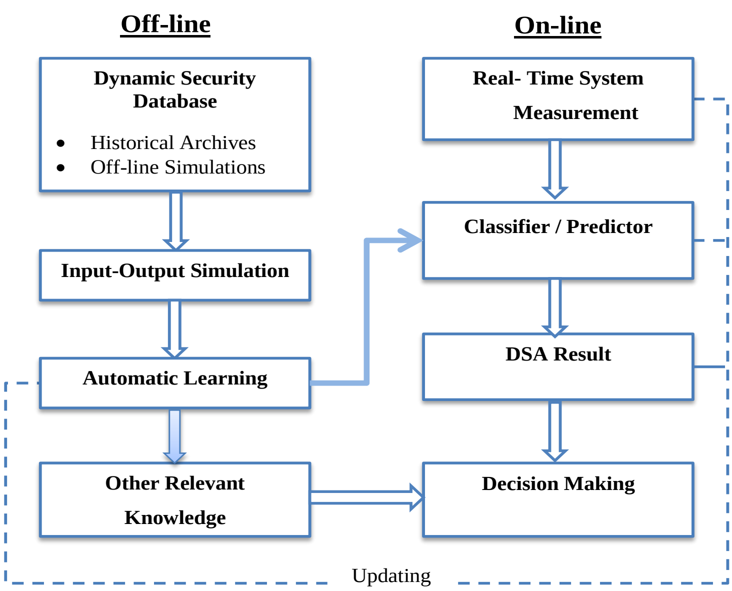

Figure 1. Schematic of an Artificial Intelligent System (AIS)

Important factors in developing a successful Intelligent Systems (IS) for security analysis are:

- Input & Output Variables
- Database Generation
- IS training Algorithm

2.1 Input & Output Variables:

There are two different types of power system variables are static and dynamic, that belong to pre-and post-fault conditions respectively. Some general variables that have been commonly used in literature are static variables like system load, generation, voltage and flows and dynamic variables like rotor angles, angular velocities, and dynamic voltage profiles etc.

2.2 Database Generation:

A sufficient database is important to the IS or else the output of assessment goes wrong. The database is developed by considering ample operating conditions, whose analysis is performed and their corresponding result stored. Historical data is also stored in the database. Nevertheless, the quantum of data in the database becomes in adequate in certain cases owing to market conditions and sources irregularities. In such situations, various statistical measures are considered to obtain the accurate solution.

2.3 IS learning Algorithm:

The learning algorithm forms the heart of the AIS. Different algorithms such as Case Based Reasoning CBR, Artificial Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM) Techniques, and sophisticated data-mining techniques, etc. are some of the examples. Each technique has its advantages and draw

backs. Each algorithm has unique features, but the choice of algorithm is made on some key factors like fastness, robustness, correctness, adaptiveness, and efficiency.
Case Based Reasoning approach (CBR) will be used in the following work.

2.4 Case Based Reasoning Algorithm CBR:

Case-Based Reasoning (CBR) is most recent and popular one among learning algorithms. It is based on the principle that past experience becomes useful on estimating the solution of the future situation. It is applicable man fields and works on a memory-based concept similar to human interpretation of learned aspects, rather than solving mathematical formulations.
The methodology of CBR can be explained as follows. The measured input for a particular operating condition is compared to the instances present in the memory for similarity, more similar solutions are extracted from the data base and presented as solution. This is further reviewed by the subject expert and modified if required according to the experience of expert.
This new solution will now become a part of the database or memory, which has a new operating condition and corresponding result. This can now be treated as a new case and is reserved in the database. Main stages of CBR cycle are illustrated in Figure 2, the individual task in the cycle is known as “4 REs”.

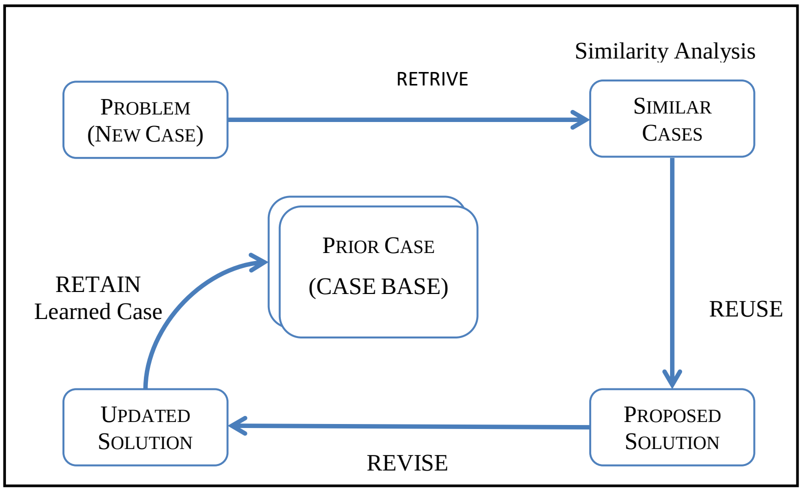

Figure 2. Case Based Reasoning method working cycle

Most CBR used K-Nearest Neighborhood Algorithm for retrieving most similar case; this algorithm will be used during case study in this work as well. In the K-NN Algorithm each case will have a value in a multidimensional axes graph. Number axes are based on number of input attributes. Then for retrieving K similar cases for the new case, distance between new case and every case in memory will be calculated and the k nearest cases will be retrieved. Distance between two cases can be calculated by using Euclidean space formula for finding distance between two points as shown in (1).

$$\boldsymbol{Similarity}(\boldsymbol{T},\boldsymbol{S}) = \sum_{i=1}^{n} \boldsymbol{f}(\boldsymbol{T}_i - \boldsymbol{S}_i) * \boldsymbol{w}_i \qquad (1)$$

Where,

T is the target case
S is the source case
(n) is number of attributes in each case
(i) is an individual function for attribute (i) in cases T and S
(w) is the importance weighting factor of attribute (i)

2.5 Algorithm to Develop CBR for DSA:

1. A large number of operating conditions called old cases are generated randomly. Input attributes to the system can be real and reactive power injection for generators, real and reactive power of load, generator angles, power flow of lines and the output can be Critical Clearing time. These operating conditions can be generated by modeling the system and running transient security analysis in any time domain simulation software.

2. Credible contingencies are specified, power flow and transient stability analysis is executed for every operating condition. Results can be selected as CCT and it should be recorded
3. Case library is organized in several groups for every contingency. Each group represents the cases belonging to a particular contingency.
4. When a new case is presented to the CBR system, it is directed to the respective group of cases into the case library based of contingency indexing.
5. The most similar case from case library is retrieved using (2)

$$SI_{\,nj} = \frac{\sum_{i=1}^{p} W_i \left[1 - \left(\frac{a_{ij} - b_{in}}{Max_{\,(ai)} - Min_{\,bi}} \right)^2 \right]}{\sum_{i=1}^{p} W_i} \qquad (2)$$

Where,

($SI_{\,ni}$) is similarity index computed between new case (n) and retrieved case (j)
(a_{ij}) is the attribute values of features (i) of the retrieved case (j)
(a_{in}) is the attribute values of features (i) of the new case (n)
(W_i) is the weighting factor of feature (i)
(Max_{ai}) and (Min_{bi}) are the maximum and minimum attributes of feature (i) respectively.

6. If the new case is completely same as the retrieved one, then solution of the retrieved case is the same as the new case.
7. If the new case is slightly different then the retrieved case, solution of retrieved case if adapted to new case using (3)

$$CCT_{e(n)} = CCT_{rj} + \sum_{i=1}^{P} \alpha_i \, e^{(\beta_i\,(\,b_{in} - a_{ij})} \qquad (3)$$

Where,

$CCT_{e(n)}$: Is the estimated solution of the new case n
CCT_{rj}: Is the solution of the retrieved case j
α_i & β_i: Are weighting coefficients of feature i
a_{ij}: Is the attribute values of feature i of the retrieved case j
b_{in}: Is the attribute values of feature i of the new case n.

III. CASE STUDY& RESULTS

Case Based Reasoning (CBR) to dynamic security assessment has been applied to a standard IEEE 9 bus system which has three synchronous generators, three transformers, and three loads. For comparison purpose an Artificial Neural Network (ANN) for dynamic security assessment of the same system has also been made and the result of dynamic security assessment using both systems CBR and ANN has been compared. As both method belongs to artificial intelligent systems, thus the must be trained. In order to create data for training these systems, aforementioned power system has been modeled using Electrical Transient Analysis Program (ETAP). Thus this case study has three main steps:

1. Modeling power system using ETAP and creating different load-generation conditions to gather initial training and testing data.
2. Creating a Case Based Reasoning system using MATLAB-programing for dynamic security assessment. The initial training data that has been created in first step will be stored as *case-base* or *library* for this system. Then the system will be tested using testing data created in first step.
3. Building an Artificial Neural Network using MATLAB-Programing and MATLAB NN-toolbox for dynamic security assessment. There also, the network will be trained using initial training data created in first step. Then the network is applied on the testing data, and the result is compared with the result of CBR system.

3.1 IEEE 9 bus system modeling Using ETAP and data creation

Standard IEEE 9 bus system which consists of three synchronous generators, 6 lines, and three transformers has been modeled using ETAP software. The system is show in Figure 3.

As the study purpose in dynamic security assessment, equivalent model of synchronous generator has been used with excitation, automatic voltage regulator (AVR) and governor system. For this model, R_{eq} and X_{eq} are defined as ($R_{eq} = R_a$ & $X_{eq} = X_q$) and the following differential equations describe it:

$$\frac{dE_q'}{dt} = \frac{1}{T_{do}'} * \left(E_{fd} - E_i\right) \qquad (4)$$

$$E_q \ = \ E_q' + j\left(X_q - X_d'\right) * \ I_d \qquad \text{(III5)}$$

$$E_t \ = \ E_q - \left(R_a + jX_q\right) * I_t \qquad \text{III} \qquad (6)$$

$$E_i = E_t + \ R_a * I_t + j\left(X_d I_d + X_q I_q\right) + f\left(E_q'\right) \qquad (7)$$

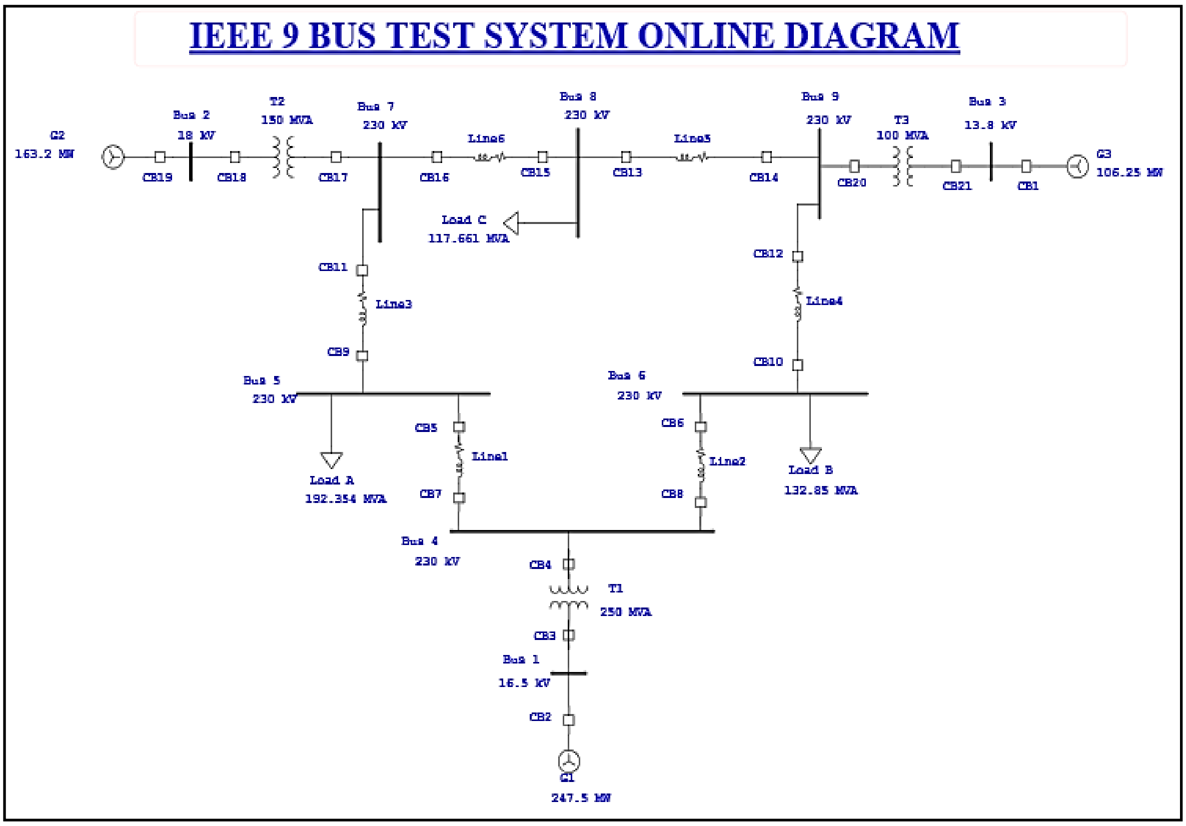

Figure 3. IEEE 9 bus system diagram

3.2 System data:

System data is taken from [7]. Generation unit one is a hydro-generation with salient-pole generator and is chosen as swing generator and two other generation units are round-rotor steam generators.

Table 1. Sample Selected power system Generation and Load condition

Load Condition			**Generation Condition**		
Load A	Load B	Load C	Generation 1	Generation 2	Generation 3
MVA	MVA	MVA	MVA	MVA	MVA
153.88	106.28	94.13	103.19	164.33	108.03
Total Load		**354.29**	**Total Generation**		**375.55**
		Maximum Generation Capacity			**516.95**

This procedure is conducted for around 166 different conditions of power system (cases), every case have six input that are loads and generations and one output that is critical clearing time for the corresponding condition. This computed data is used for training and testing of Case based reasoning CBR and artificial neural network ANN systems. These cases are separated into two parts, first part contains 120 cases and it will be used to train aforementioned IS systems; in these cases, both inputs and output will be given to the system. Second part has 56 cases and these will be used for testing them and only inputs will be given to IS systems and output of IS systems will be check with actual output. For testing IS systems, a third group of cases is also selected from the training.

For the selected power system dynamic security analysis case-based reasoning script has been written using MATLAB Programing. Training cases that were calculated through ETAP software is used as case-base (library) of the system. The system will calculate similarity index (SI) of every new case with every case in case-base using (9). Every case will have six inputs containing 3 loads value and 3 generation value, and one output that is critical clearing time of fault.

$$[Case] = \ [MVA_{Load\ A}\ , MVA_{Load\ B}\ , MVA_{Load\ C}\ , MVA_{Gen\ A}\ , MVA_{Gen\ B}\ , MVA_{Gen\ C}, CCT] \tag{8}$$

$$\boldsymbol{SI_{nj}} = \frac{\sum_{i=1}^{p} \boldsymbol{W_i} \left[\mathbf{1} - \left(\frac{\boldsymbol{a_{ij} - b_{in}}}{\boldsymbol{Max_{(ai)} - Min_{bi}}} \right)^{\mathbf{2}} \right]}{\sum_{i=1}^{p} \boldsymbol{W_i}} \tag{9}$$

Where,

(SI_{nj}) is similarity index computed between new case (n) and retrieved case (j)
(a_{ij}) is the attribute values of features (i) of the retrieved case (j)
(a_{in}) is the attribute values of features (i) of the new case (n)
(W_i) is the weighting factor of feature (i)
(Max_{ai}) and (Min_{bi}) are the maximum and minimum attributes of feature (i) respectively.

Weighting for every input attributes are calculating based on their sensitivity on the resulting critical clearing time; they are shown in Table 2.

Table 2. Weighting factor for input attributes

Weighting Factor					
W1	**W2**	**W3**	**W4**	**W5**	**W6**
Load A	**Load B**	**Load C**	**Gen A**	**Gen B**	**Gen C**
0.20	0.05	0.15	0.15	0.25	0.20

The highest value of SI indicates best similarity between new case and corresponding library case, and that library case will be retrieved for further analysis. If the new case is completely similar to the retrieved case, result of the retrieve case will be used for this new case as well; otherwise result of retrieved case will be adapted using (10) to take care of the differences between retrieved case and the new case.

$$\boldsymbol{CCT_{e(n)}} = \boldsymbol{CCT_{rj}} + \sum_{i=1}^{P} \boldsymbol{\alpha_i\, e^{(\beta_i\,(b_{in} - a_{ij})}} \tag{10}$$

Where

CCT_{rj}: Is the solution of the retrieved case j
α_i & β_i: Are weighting coefficients of feature i
a_{ij}: Is the attribute values of feature i of the retrieved case j
b_{in}: Is the attribute values of feature i of the new case n.

Weighting coefficient for every attribute value of inputs is calculated by multiple exponential regression technique. For calculating these coefficients, a MATLAB code is written that initially calculated difference of 9 specific cases input attributes and output with all other cases in the library. Then, based on multiple exponential regression method, it calculates weighting coefficients for each one of these 9 cases. Lastly, for getting more accurate values, it takes average of every coefficient from all these 9 bases. The resulting values are shown in Table 3.

3.3 Comparison between ANN and CBR approaches to DSA:

As both Case based reasoning and artificial neural network systems has been built using same training cases and test with same lists of cases, result of them are compared with each other and with the actual critical clearing time which have been gathered using time domain simulation through ETAP software. Both systems' results have been compared for two list of new cases as mentioned before,

As illustrated in tables, both systems' results are accurate enough. CBR error for cases that are included in library is zero. In the classification process of both systems, CBR had one misclassified state while ANN had two misclassified state of power system. Error of dynamic security analysis using both ANN and CBR has been compared using graph and is illustrated in Figure 5. As the graph shows result of case-based reasoning approach to dynamic security assessment is more accurate than neural network system. Besides, computational time for dynamic security analysis of CBR system is much less than CBR.

Table 3. Weighting coefficient for all attributes of input cases

Weighting Coefficient					
Load A	Load B	Load C	Gen A	Gen B	Gen C
α1	α2	α3	α4	α5	α6
0.0004220	0.0004420	0.0004980	0.0004020	0.0003230	0.0004780
Ɓ1	Ɓ2	Ɓ3	Ɓ4	Ɓ5	Ɓ6
0.00930	0.01170	0.0010	0.00900	0.05220	0.00460

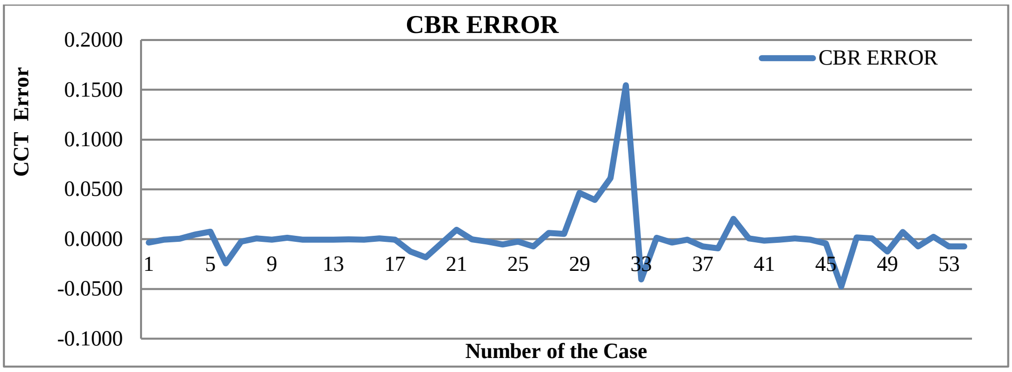

Figure 4. Error of CCT calculated using CBR with respect to actual CCT

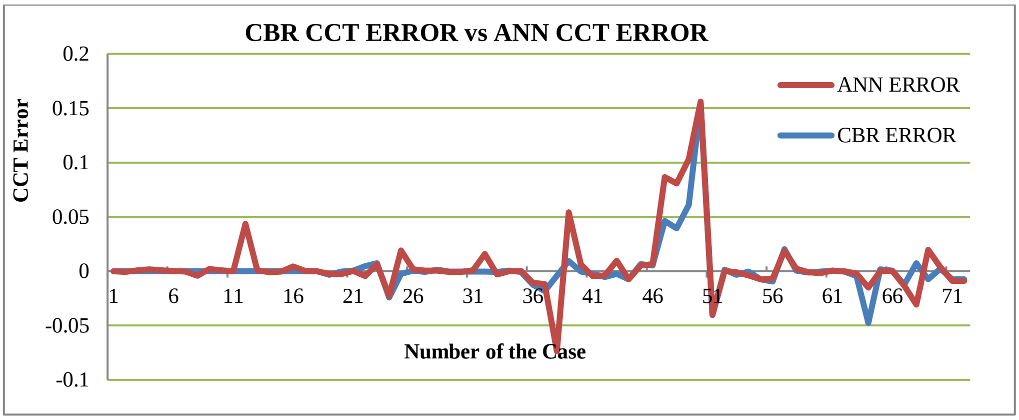

Figure 5. Comparison graph of DSA errors of both systems (ANN & CBR)

IV. Conclusion

This work shows effectiveness of an alternative artificial intelligence system for online dynamic security assessment of multi-machine power system called case-based reasoning (CBR). It is used for classification of power system condition. Security level of power system is determined by critical clearing time (CCT) which is the maximum time that the system can maintain synchronism while subjected to disturbances. If the CCT of power system for a specific operating condition is greater than actual clearing time of circuit breaker the system is secure otherwise it is insecure.

Case-based reasoning system to assess dynamic security of power system is built to study dynamic security assessment of standard IEEE 9 bus system in MATLAB programing. In first step to create enough data for library of CBR, IEEE 9 bus system was modeled in ETAP software for transient stability analysis. By changing load-generation condition of the power system 170 cases generated for one contingency in the form of three-phase short-circuit in middle of line three are clearing this fault by removing the line. Their stability level is determined by critical clearing time (CCT). 120 cases from this list were used as case base of CBR and then it was executed with remaining cases. CBR system determines CCT of every case, besides it classify every case into secure or insecure. For classification purpose, calculated CCT is compared with clearing time of cricket breaker, where clearing time of circuit breaker is selected 0.44 sec for a 50 Hz system.

This work focal point is long-term transient stability analysis. Modeling of power system has been discussed for long-term transient stability analysis and different method of calculation for long-term transient stability analysis has been presented. Besides, basics of security analysis have been discussed and more focus has been paid to dynamic security analysis and online-dynamic security analysis. Different method of online-dynamic security analysis has been presented namely time-domains simulation and artificial intelligent methods.

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