TWO INPUT PID FUZZY C MEANS POWER SYSTEM STABILIZER

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Abstract

Power System Stabilizer (PSS) must be capable of providing appropriate stabilization signals over a broad range of operating conditions and disturbances. Traditional power system stabilizers rely on linear design methods. In the present paper, a novel approach for design of PSS using Fuzzy C Means is presented. The proposed Fuzzy C Means PSS (FCMPSS) is trained with the pre-designed two input PID fuzzy logic PSS(FLPSS). The simulation results of the proposed FCMPSS are compared to those of conventional stabilizers and the pre-designed Fuzzy PSS for a Single Machine Infinite Bus (SMIB) system. The effect of system parameter variations on the proposed stabilizer performance is also examined. The results show the Robustness of the proposed FCMPSS and its ability to enhance system damping over a wide range of operating conditions and system parameter variations.

Keywords: Fuzzy C Means , Power system stabilizer, Dynamic stability.

1. INTRODUCTION

The basic function of a PSS is to extend stability limits which are characterized by lightly damped or spontaneously growing oscillations in the 0.2 to 2.5 Hz frequency range [1]. This is accomplished via excitation control to contribute damping to the system modes of oscillation. Consequently, it is the stabilizer's ability to enhance damping under least stable condition. A PSS can be most effectively applied if it is tuned with the understanding of the characteristics of the power system associated. Considerable efforts have been directed towards developing an adaptive PSS. Machine Learning is considered as a subfield of Artificial Intelligence and it is concerned with the development of techniques and methods which enable the computer to learn. In simple terms development of algorithms which enable the machine to learn and perform tasks and activities. Machine learning overlaps with statistics in many ways. Over the period of time many techniques and methodologies were developed for the design of PSS using machine learning tasks[1]-[4].

The fuzzy logic approach is emerging as a compliment to the conventional approach. The most important advantages of fuzzy controller is that there is a very little mathematical computation [5][[6][7] involved in this method and this control method will not increase the order of the system. It is realized that this method of control can perform very effectively when the operating conditions change rapidly and also when the system nonlinearities are significant. These features make very attractive for power system applications. One of the hallmarks of fuzzy logic is that it allows nonlinear input/output relationships to be expressed by a set of qualitative "if – then rules." Nonlinear control and process models may all be expressed in the form of fuzzy rules. Most fuzzy systems are hand crafted by human expert to capture some desired input/output relationships that the expert has in mind. However often an expert cannot express his or her knowledge explicitly and for many applications, an expert may not even exist. Hence there is considerable interest in being able to extract fuzzy rules from experimental input/output data. The motivation for capturing data behavior in the form of fuzzy rules is easy to understand. An expert can check the rules for completeness and fine-tune or extend the system by editing the rule base. Obviously, it is difficult for human experts to examine all the input/output data from complex system to find the number of proper rules for fuzzy system. To cope with this difficulty, much research effort has been devoted to develop alternative design methods. Recently, methods for extracting fuzzy rules have incorporated clustering techniques.

A common concept of more or less all the clustering techniques is that they are prototype based that are characterized by clustering prototypes Ci. ,i=1,2,….c. Prototypes are used to capture the distribution of data in each cluster. The cluster center ci is instantiation of the attribution utilized to illustrate the domain. The various applications of the unsupervised learning based data clustering can be summarized as:

- It can group data with no label.
- It can be applied for fuzzy and neural modelling as well as to real time modelling
- It can be easily applied for detection of faults and its isolation.
- It is helpful in learning the parameters and structure both in fuzzy and neuro-fuzzy model

2. CLUSTERING:

Clustering is the unsupervised classification[8][9] of patterns (objects, data items or future vectors) into groups (clusters). The main aim of clustering is to divide data set in a way that the data belonging to one cluster is as similar as possible. The idea is to identify the number of sub classes 'c' of clusters in a universe 'x' composed of 'n' data samples and divide 'x' into 'c' clusters. One of the easiest method is the distance between the observed data and if one is able to measure the distance between the all observed data then it can be expected that the distance between the points in the same cluster will be less when compared to the distance between the points indifferent clusters. Based on the requirements the user can decide the number of clusters needed that can be best suit the given purpose.

2.1 BASIC CLUSTERING ALGORITHMS:

The idea to define an objective function and to minimize it for achieving clustering is being used universally for a long time. Apart from basic cluster algorithms many developments, modifications and proposals have been given that aims at improving the performance of the existing cluster algorithms related to a particular problem The basic forms of clustering are crisp or Hard C-Mean (HCM) clustering and soft or Fuzzy C-Mean (FCM) clustering.

2.1.1 Hard C-mean Clustering (HCM)(or) K-Means:

Bezdek developed a powerful classification method for accommodating fuzzy data popularly known as Hard C-Mean (HCM) or K-means clustering, is an algorithm based on finding data clusters in a data set such that an objection function of dissimilarity (or distance) measure is minimized. In most cases this dissimilarity measure is chosen as the Euclidean distance.

A set of n vectors xj , j =1,2.., n , are to be partitioned into c groups Gi, i =1,2,..c . The objective function, based on the uclidean distance between a vector xk in group j and the corresponding cluster center ci , can be defined by

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\left(\sum_{k.x_k \in G_i} \|x_k - c_i\|^2 \right) \qquad \text{------(1)}$$

Where $J_i = \sum_{k.x_k \in G_i} \|x_k - c_i\|^2$ is the objective function within group i .

The partitioned groups are defined by a cXn binary membership matrix U, where the element uij is 1 if the jth data point xj belongs to group i , and 0 otherwise. Once the cluster centers ci are fixed, the minimizing uij for equation (1) can be derived as

$$u_{ij} = \begin{cases} 1 \cdots if \ \|x_j - c_i\|^2 \le \|x_j - c_k\|^2, \ foreach, k \ne i \\ 0 \cdots otherwise. \end{cases} \qquad \text{------(2)}$$

This means that xj belongs to group i, if ci is the closest center among all centers.

On the other hand, if the membership matrix is fixed, i.e. if uij is fixed, then the optimal center ci that minimizing equation (1) is the mean of all vectors in group i :

$$c_i = \frac{1}{|G_i|} \sum_{k.x_k \in G_i} x_k \qquad \text{------(3)}$$

where $|G_i|$ is the size of G_i or $|G_i| = \sum_{j=1}^{n} u_{ij}$.

The algorithm is presented with a data set xi =1,2,.. n ; it then determines the cluster centers ci and the membership matrix U iteratively using the following steps:

Step 1: Initialize the cluster center, ci , i=1,2,.. c. This is typically done by randomly selecting c points from among all of the data points.

Step 2: Determine the membership matrix U by Equation (2).

Step 3: Compute the objective function according to Equation (1). Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.

Step 4: Update the cluster centers according to Equation (3). Go to step 2.

The performance of the HCM algorithm depends on the initial positions of the cluster centers, thus it is advisable to run the algorithm several times, each with a different set of initial cluster centers.

Strengths and Weaknesses:

K-means is simple and can be used for a wide variety of data types. It is also quite efficient, even though multiple runs are often performed. Some variants, including bisecting K-means, are even more efficient, and are less susceptible to initialization problems. K-means is not suitable for all types of data however. It cannot handle non-globular clusters or clusters of different sizes and densities, although it can typically find pure sub clusters if a large enough number of clusters is specified. K-means also has trouble clustering data that contains outliers. Outlier detection and removal can help significantly in such situations. Finally, K-means is restricted to data for which there is a notion of a center (centroid).

2.1.2 Fuzzy C-Mean Clustering (FCM):

The main disadvantage of HCM is that it has to assign each data point to exactly one and only one cluster. Also the points which can belong partially to several clusters should be assigned to one cluster only. This drawback is overcome by using FCM clustering. Fuzzy cluster analysis allows gradual membership of data points to clusters measured as degrees in [0,1]. This gives the flexibility to express that the data points can belong to more than one cluster. However, FCM still uses an objective function that is to be minimized while trying to partition the data set. The membership matrix U is allowed to have elements with values between 0 and 1. However, the summation of degrees of belongingness of a data point to all clusters is always equal to unity:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, 2..., n \qquad \text{------(4)}$$

The objective function for FCM is a generalization of Equation (1):

$$J(U, c_1, c_2 ... c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \qquad \text{------(5)}$$

Where uij is between 0 and 1; ci is the cluster center of fuzzy group i .

$d_{ij} = \left\| c_i - x_j \right\|$ is the Euclidean distance between the ith cluster center and the jth data point; and $m \in [1, \infty)$ is a weighting exponent.

The necessary conditions for Equation (5) to reach its minimum are

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \quad \text{and} \qquad \text{------(6)}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad \text{------(7)}$$

The algorithm works iteratively through the preceding two conditions until the no more improvement is noticed. In a batch mode operation, FCM determines the cluster centers ci and the membership matrix U using the following steps:

Step 1: Initialize the membership matrix U with random values between 0 and 1 such that the constraints in Equation (4) are satisfied.

Step 2: Calculate c fuzzy cluster centers, 1, , ci i=1,2….c , using Equation (6).

Step 3: Compute the objective function according to Equation (5). Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.

Step 4: Compute a new U using Equation (7).Go to step 2.

3. SYSTEM MODEL

The small perturbation block diagram of a synchronous machine connected to infinite bus system [2] is considered. The exciter is assumed to be of the thyristor type. Amortisseur effects, armature resistance, armature pψ terms and saturation are neglected. The linearized model parameters K1 to K6 vary with operating conditions with the exception of K3. The stabilization problem is to design a stabilizer, which provides supplementary stabilizing signals to increase the damping torque of the system.

An infinite bus is a source of constant frequency and voltage either in magnitude and angle. A schematic representation of this system is shown in fig 1.

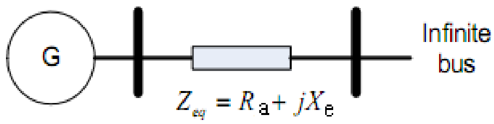

Fig1 Single Machine Connected to infinite busbar

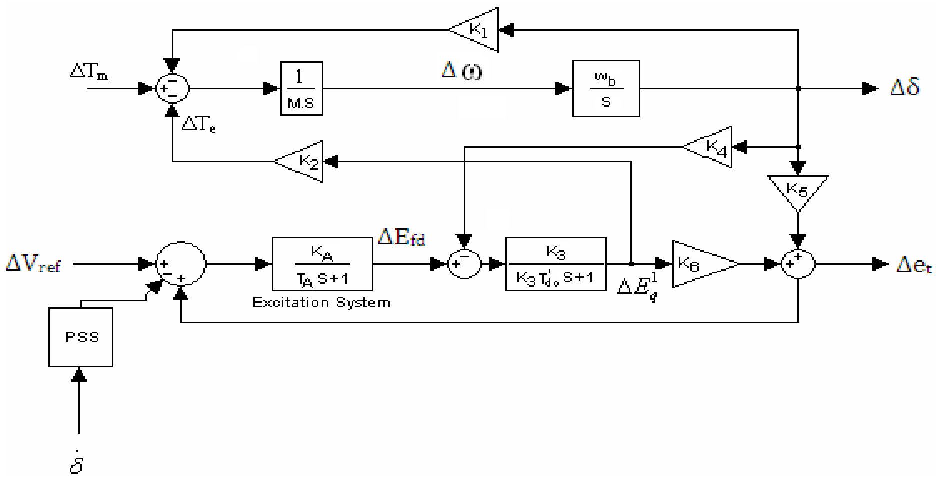

Fig.2 Block diagram representation of the system

4. THE DESIGN OF THE PROPOSED FUZZY CONTROLLER:

Step 1: The Normal Fuzzy controller is designed heuristically with rules shown in Table -4.1

Step 2: The Fuzzy C-Means PSS is tuned to the pre-designed fuzzy PSS .

Step 3: The input space is divided into desired number of clusters using Fuzzy C-Means and the cluster centers are identified. These centers represent the rules of the proposed FCMPSS.

Step 4: The FCMPSS is designed. The designed FCMPSS is tested for a single machine infinite bus system for different operating conditions.

Rule 1	If $X(\dot{\delta})$ is N and $X(\ddot{\delta})$ is N then output is PB
Rule 2	If $X(\dot{\delta})$ is N and $X(\ddot{\delta})$ is Z then output is PS
Rule 3	If $X(\dot{\delta})$ is N and $X(\ddot{\delta})$ is P then output is Z
Rule 4	If $X(\dot{\delta})$ is Z and $X(\ddot{\delta})$ is N then output is PS
Rule 5	If $X(\dot{\delta})$ is Z and $X(\ddot{\delta})$ is Z then output is Z
Rule 6	If $X(\dot{\delta})$ is Z and $X(\ddot{\delta})$ is P then output is NS
Rule 7	If $X(\dot{\delta})$ is P and $X(\ddot{\delta})$ is N then output is Z
Rule 8	If $X(\dot{\delta})$ is P and $X(\ddot{\delta})$ is Z then output is NS
Rule 9	If $X(\dot{\delta})$ is P and $X(\ddot{\delta})$ is P then output is NB

5. NUMERICAL SIMULATION:

In the small signal model the parameters K1-K6 except K3 are functions of the operating condition. K3 is the impedance factor and it is constant. The data as in [21] as follows

xd=1.6 , x'd=0.32 , xq=1.55 ,T'do=6 s, H=5 s, Ta=0.05, Ka=100 ,wb=377 rad/s ,xe =0.4, Re=0.0. All resistances and reactances are in Per unit and time constants are in seconds.

Operating condition	Constants					
	k_1	k_2	k_3	k_4	k_5	k_6
1+j0	1.174	1.468	0.36	1.879	-0.117	0.3011
1+j0.5	1.01	1.149	0.36	1.47	-0.097	0.4184
1-j0.5	1.566	1.729	0.36	2.21	-0.1006	0.798
0.5+j0	0.942	1.07	0.36	1.37	0.5448	0.4391

Table 4.1 k_1 to k_6 Constants at different operating conditions

4.2.1 Simulation Results: The dynamic response of the system with the proposed Two input Single out put PSS, FLPSS and CPSS for 0.05 step change in ΔVref is shown in figures 4.2 to 4.5.

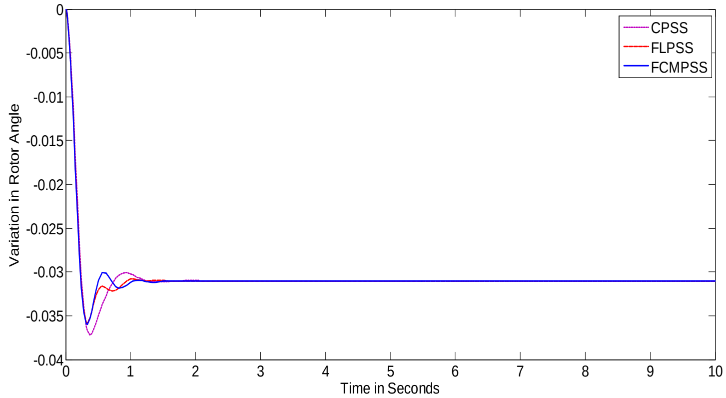

Figure 4.1 (a) Response with CPSS, FLPSS, and FCMPSS for the operating point 1+j0

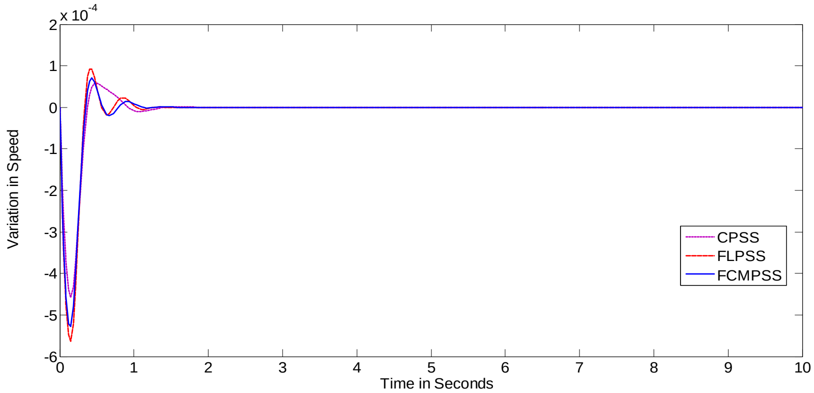

Figure 4.1(b) Response with CPSS, FLPSS, and FCMPSS for the operating point 1+j0

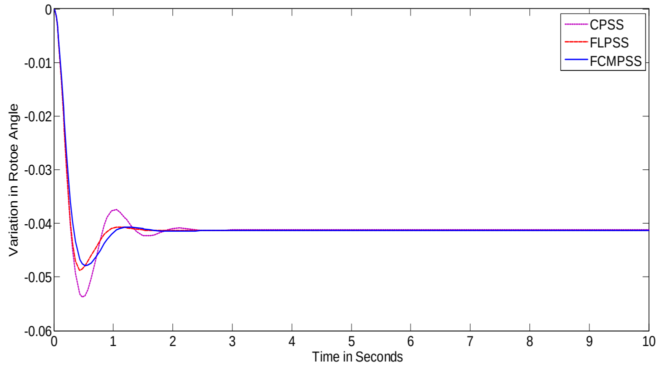

Figure 4.2(a) Response with CPSS, FLPSS, and FCMPSS for the operating point 1+j0.5

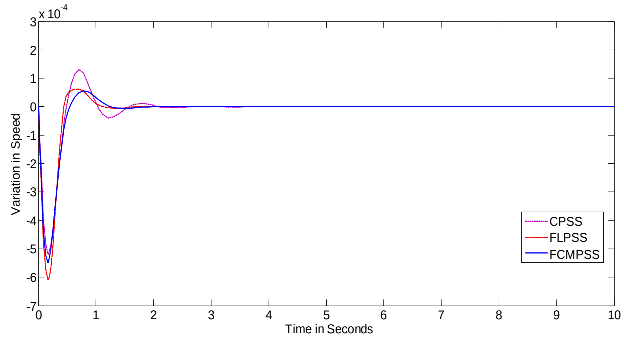

Figure 4.2(b) Response with CPSS, FLPSS, and FCMPSS for the operating point 1+j0.5

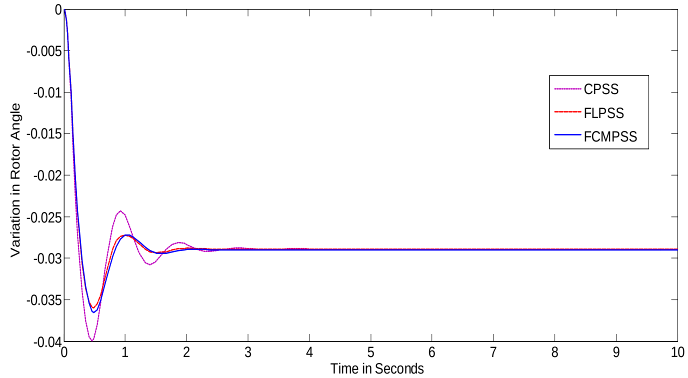

Figure 4.3(a) Response with CPSS, FLPSS, and FCMPSS for the operating point 1-j0.5

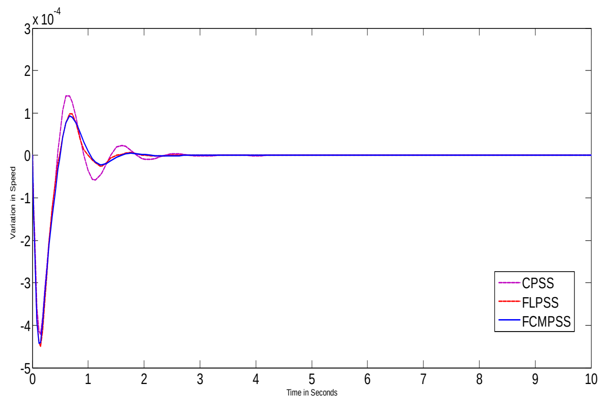

Figure 4.4(b) Response with CPSS, FLPSS, and FCMPSS for the operating point 1-j0.5

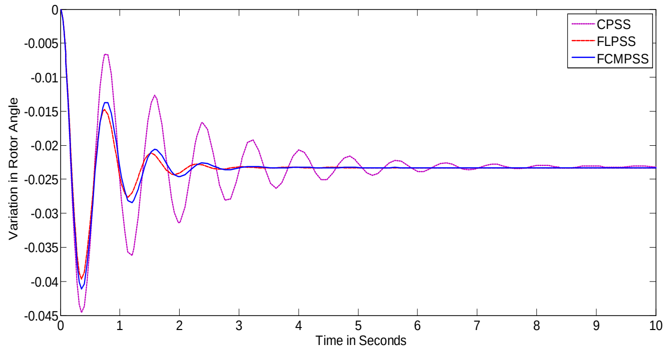

Figure 4.5(a) Response with CPSS, FLPSS, and FCMPSS for the operating point 0.5+j0

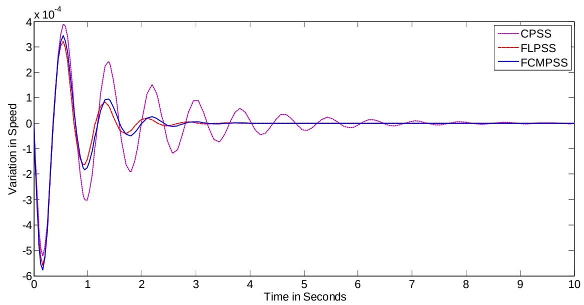

Figure 4.5(b) Response with CPSS, FLPSS, and FCMPSS for the operating point 0.5+j0

5. CONCLUSIONS:

In this study FCM based Power System Stabilizer (FCMPSS) is presented to adapt the PSS parameters to improve power system dynamic stability. Time domain simulations of the system with FCMPSS given a good speed deviation and change in rotor angle response at different type of loading condition. The results show that the performance of the FCMPSS parameters yields the less settling time and less overshoots as compared with conventional PSS parameters.

ACKNOWLEDGMENT:

This work was supported by grants from the All India Council for Technical Education (AICTE) project under RPS Scheme under file No. F.No.8023/BOR/RID/RPS- 94/2008-09.

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