Modelling of DSTATCOM for Improving Power Quality using ANN Controller by Fuzzy C-Means Clustering

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***Abstract:* -** In recent years for reactive power compensation an inverter based conditioners have been used due to their faster response. To improve the quality of power in a distribution system, Distribution Static Synchronous compensator (DSTATCOM) which is a inverter based device which is been used broadly. To control these kind of devices, Proportional-Integral (PI) controller is been used with certain prespecified fixed parameters. Nowadays these kind of controllers performance are not up to the expectation due to the nonlinearity of the system .In this paper, the (Artificial Neural Network) ANN controller is described with the use of Fuzzy C-Means clustering (FCM) algorithm to generate appropriate weight to control direct and quadrature axes currents of DSTATCOMs. Simulations on wide range of processes are carried out by using MATLAB/Simulink software and responses are observed by changing the reference reactive current. The results are compared between the controllers in terms of several performance measures, in which the DSTATCOM improves the damping of a power system by proposed schemes.

***Key-Words:* -** Radial Basis Function Neural Network , Fuzzy C-Means Clustering, Proportional-Integral, DSTATCOM, Power Quality.

1 Introduction

The power quality problems such as voltage sag, swell, neutral current compensation, voltage instability etc... were all focused by many researchers .These issues leads to slower response time , reduction in power flow limits and system collapse [1]. All these things made a situation to develop a new device for improving power quality, that too particularly in the customer's side. DSTATCOM which is a power electronic device tries to improve the quality of power both at the load and source side of the distribution system [2]. DSTATCOM has many features compared with other devices such as low cost , generates less harmonics , compact size and low loss [3] .The specific benefits that the DSTATCOM has is the capability of fast and continuous nonstop inductive or capacitive compensation. To meet the specification for the utility connection total demand, the DSTATCOM injects required amount of leading or lagging compensation current based on the given load. This kind of injection made DSTATCOM to play a vital role in the radial distribution system [4].
In recent years these kind of DSTATCOM controller are used in induction generator mainly to support reactive compensation. In any application, the performance of DSTATCOM normally depends on the control algorithm.[5] discussed about the control of DSTATCOM by PI controller with fixed parameters and presented three control strategies to produce reference currents components. To regulate the line voltage, a nonlinear controller was designed for DSTATCOM connected to a distribution network with distributed generation [6]. [7] developed a control algorithm for a DSTATCOM by using self-tuning filters with instantaneous reactive power theory. Some of the researchers used not only for control of reactive power exchange but also used to provide damping support to system. For the control of DSTATCOM, reference values are usually obtained from PI controllers mainly 'd' and 'q' axes currents. The data extraction is normally

done in linear controller which requires mathematical model [8-10] in which the parameters are tuned to obtain best results for a particular region with restricted conditions. These kind of controllers developed by linear mathematical model fails to perform satisfactorily under nonlinear dynamics of the system particularly variation in parameters and load disturbance[11].Till now linearized models have been used to control the DSTATCOM, also the use of some nonlinear control strategies with limited advantages have also been reported .Some researchers used complex Lyapunove procedure for developing nonlinear controller for simple power system models, which cannot be generalized for all application.

Recently, as an alternate fuzzy logic controller and artificial neural network is been used instead of conventional linear and nonlinear controller in controlling DSTATCOM.[12-14] discussed the importance and benefits of fuzzy logic and neural network based controllers in the grid system. The controllers design with expert system doesn't require any mathematical model which is a major advantage to have a timely response without any delay. With this kind of controller, there is a possibility of wide range of system operating conditions irrespective of complexity of the task, which distinguished them from the traditional linear controller. The performance of controller can be enhanced even better with the choice of inputs to the controller which really matters, which is been addressed by this paper in a better way.

Considering all these issues, Fuzzy c-means clustering is been proposed along with ANN-PI controller for controlling DSTATCOM'd' and q-axes. ANN has appeared to offer a better solution to various control problems .They are capable of handling complex, nonlinear and mathematically in tangible dynamic's systems which are undoubtedly attracted the researchers to use ANN in designing the controllers. However, obtaining an appropriate weight and change in weight is not an easy task. In almost all applications, based on ANN controller the adjustment of weights is developed by human experts only. But it needs lot of experience, skills, even a time which all are tedious design and tuning weight exercise that may not be optimal too. There have been many research going around on the estimation of appropriate weight required for a controller design In this paper fuzzy c-means clustering is used for extracting weight, this method is used by prespecifying the weight function per input features. These features are set with initial values for adjusting the parameters.

By estimating the cluster in the data, the algorithm were developed in which each cluster obtained corresponds to weight which straightaway relates the region in the space of both input and output. The proposed controller implemented, simulated and compared to conventionally designed controller, the proposed technique gives better characteristics.

To summarize, the paper deals first with mathematical modeling of DSTATCOM, then the work handles with ANN-PI then with design of ANN controllers by fuzzy c-means clustering. The results were compared to show the performance of the proposed technique from the conventional technique.

2 Modeling of DSTATCOM

To improve the load voltage, a 3Mvar DSTATCOM is connected in parallel with the load at B3 as shown in Fig.1. The power that is generated, pass through B1, B2 and B3, via 21km feeder the voltage sources are connected directly to B1, B2 and B3. In this, to make a connection between B2 and B3 a 2 km feeder is been used. To carry out the study both variable and fixed loads are connected in B3 via 25/0.6 step down distribution transformer. The purpose of load particularly, variable load is to fluctuate in the current and voltage waveform at bus B3.At bus B3 the DSTATCOM regulates the voltage by absorbing or generating reactive power. This reactive power transfer is done in the network side by generating a secondary voltage in phase with the primary voltage with the help of leakage reactance of the coupling transformer. The voltage support is done by voltage-source PWM inverter present in the DSTATCOM. The DSATCOM acts like an inductor by absorbing reactive power, whenever the secondary voltage gets lower than the bus voltage of the system at the same time it acts a capacitor by generating reactive power if secondary voltage is higher than the bus voltage [15]. In table 1 the quantities taken for study for a source voltage, line voltage, fixed and variable loads etc… are shown

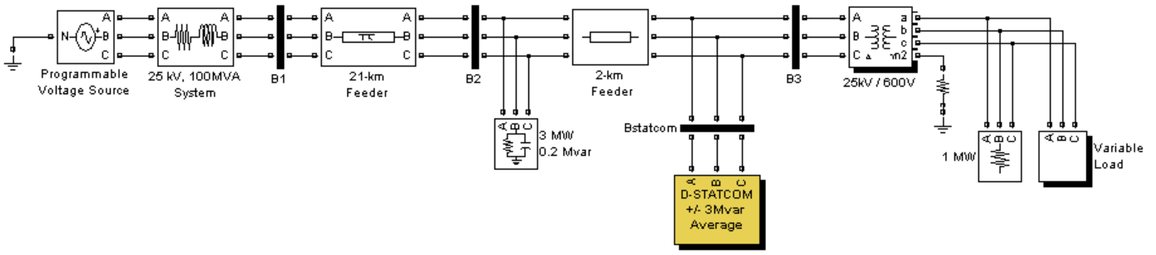

Fig.1.System configuration of a distribution system [15]

Table .1 System parameters

System Quantities	Values
Source Voltage	25000 v
Line voltage	25000 v
Feeder resistance R	0.1153 ohms/ km
Feeder inductance L	1.048 MH/km
Feeder capacitance C	11.33NF/km
Frequency	60hz
Fixed load at bus 2	3MVA ,pf = 0.998
Fixed load	1MVA, pf = 1
Variable Load	1.8 MVA, pf = 0.9 1.2MVA with Mod.freq of 5Hz
Capacitor of DC bus	10000 micro farad
Reference voltage of DC bus	2400 v

3. Radial Basis Function Neural Network

Assume Radial basis function neural network consists of a network similar to back propagation network as shown in Figure 2 with a single hidden layer. RBFNN proves to be best for classification task from the investigation result presented.Each hidden layer consists of smoothing factor and centroids. The distance between the input and the centroid are normally computed by the neurons.

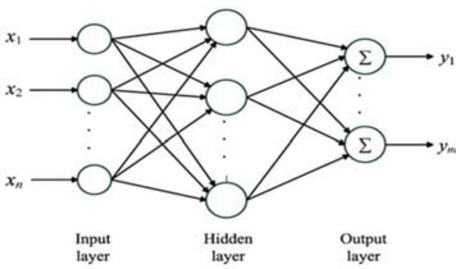

Fig. 2 Architecture of NN

The outputs are a radial symmetrical function of the distance .When it is close to value the output will be a strong one.
The real mapping function f_m in general form is expressed in equation (1).

$$f_m(x) = \sum_{i=1}^{M} w_i\, k[\, (x_i - c_i\,)/\,\sigma_i \qquad (1)$$

The function k is a radial symmetrical kernel function computed by M kernel units.
The Gaussian exponential function used in RBF is expressed in equation (2).

$$f(x) = \beta \exp(-\sum_i [\, (x_i - c_i\,)/\,\sigma_i]^2\,) \qquad (2)$$

According to the training data set, centroid and constant have to be chosen.

4. Fuzzy C-means Clustering

4.1 Cluster Estimation

Fuzzy c-means clustering (FCM) technique is one of the best techniques to frame a rules and membership functions even when the input-output data has cluster substructure or not. It is always possible by FCM to partition the data into a number of subsets and thereby can be converted in to rule from each subset. The number of rules is decided by the hyper spherical cluster that is , if the data indeed has hyper spherical cluster then the number of rules will be always smaller. With this clustering the rules can be framed even if the input-output relations are linear which normally won't have any cluster structure, yet this kind of data can also be grouped to generate a set of rules to predict the linearity of the system that is by having small number of hyper spherical clusters to data taken in to account for the analysis [16]. The equation 3 and 4 are used to estimate the measure of potential for a data point which is a function of its distance to all other data points from the collection of 'n' data points {x_1, x_2…….x_n}.

$$P_i = \sum_{j=1}^{n} e^{-\propto\|x_i - x_j\|^2} \tag{3}$$

$$\text{Where}\alpha = 4/r_a^2 \tag{4}$$

$\|.\|$ represents the Euclidean distance , r_a is a positive constant. The chances for high potential value depend normally for a data available with many neighboring data points. The neighboring data is usually defined by r_a the radius. In the process after computing the potential of every data, the data with highest potential is selected as the first cluster center. Let P_1^* and X_1^* be the location of the first center and potential value of cluster.So by this, for a data point of X_i , the revised formula for estimating potential value is shown in equation 5 and 6.

$$P_i \leftarrow P_i - P_1^k \, e^{-\beta\|x_i - x_1^*\|^2} \tag{5}$$

$$\text{Where}\beta = 4/r_b^2 \tag{6}$$

And for the generalized case is shown in equation 7.

$$P_i \leftarrow P_i - P_k^* \, e^{-\beta\|x_i - x_k^*\|^2} \tag{7}$$

Where P_k^* the potential is value and x_k^* is the k^{th} cluster center location.

Until estimating the remaining potential of all data points that falls below the threshold of the potential of the first cluster center P_1^* , the process is been repeated to acquire new cluster center on applying revising potentials [17].

4.2 Extraction of Appropriate Weights

First step in extraction of weight, is the data separation, in which the data is grouped according to their respective classes, then clustering is been done to the input space of all groups of data separately for identifying each class of data. Whenever the cluster found in the available data of a specified group identifies the region in the input space that usually mapped in to weights. So the weights are formed by translation from each cluster center for identifying the classes. This can be understood even better by this , that is when clustering was applied to specific group of data for class then cluster center x_i^* was found in that group of data for class C_1 from this the cluster center provides the rule such as

The degree of fulfillment of this class can be defined as shown in equation 8.

$$\mu_i = e^{-\propto\|x_i - x_1^*\|^2} \tag{8}$$

Where 'α is the constant.

The weights are developed by this technique can be combined to form the overall weight of the classifier with the highest degree of fulfillment for a output class.

5 Results and Discussion

5.1 RBFNN – PI Controller

The well-established classical control system which is been often used as a replacement against the other types of controllers was nothing other than linear PI controller. As from the name this controller is a linear controller which is not suitable for a system dealing with nonlinearity. As an alternate, ANN controller is been used for a nonlinear system. As this ANN controller doesn't required mathematical model for controlling any system, so it's been widely used in system with complex structure. The structure of this ANN-PI is shown in Figure 3.

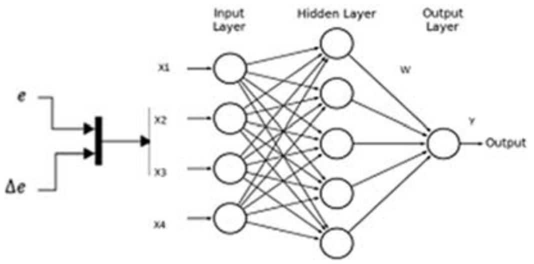

Fig.3.ANN-PI controller

In which output is a pulse modulation index 'm' of the DSTATCOM voltages. To carry out this process further. Input signals for training are selected randomly at a time. The training is set for learning rate 0.01 and target error 0.001. Each network is trained with 15 input data, of each class and 30 data of each class are considered for testing. Weights are updated in each and every iteration , in this way new training input is given to the network. The randomly selected parameters from 30 samples are used to test the RBFNN. The validation performance of RBFNN were shown in Figure 4.

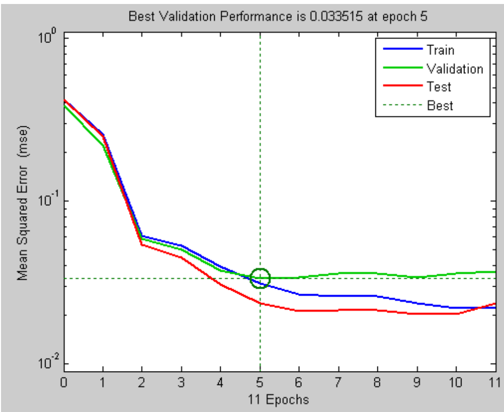

Fig 4 Validation performance using RBFNN

5.2 RBFNN controller by Fuzzy C-Means Clustering

To carry out this process the set of two-dimensional input and outputs vector which are error and change in error with the output generated by operating the model over its full range of the operation are used. The sampling of input variables that is error and change in errors were done uniformly based on the output. After the generation of data the weights were generated automatically by this method which is shown in figure 5. Based on the influence of radius 'ra' the weights are generated which are also depends on the ranges of the weight function. In this by using the clustering algorithm the number of extracted weights for both the input and outputs are restricted to the fixed thresholds.

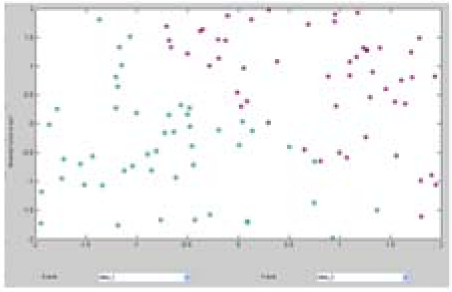

Fig.5.Generated Weights by Clusters

With this information as usual the ANN analysis were carried out by developing input and output weight with MATLAB toolbox. The outputs that is output estimated by this controller is replaced with PI controller which is been used to control of'd' and 'q'-axes current. The simulation results of PI-controller, ANN-PI controller and RBFNN controller by FCM for variation of Iq and Iqref are shown in figure 6 to figure 8.

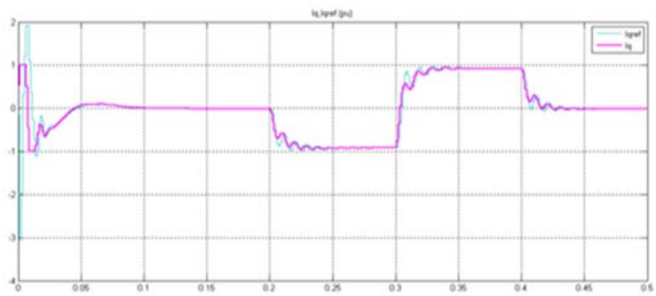

Fig.6 Simulation result of PI controller for variation of Iq and Iq_{ref}

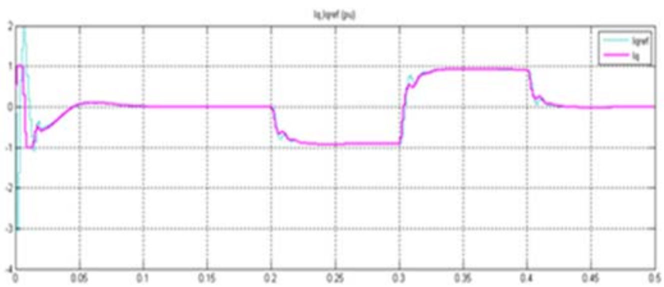

Fig.7 Simulation result of ANN- PI controller for variation of Iq and Iq_{ref}

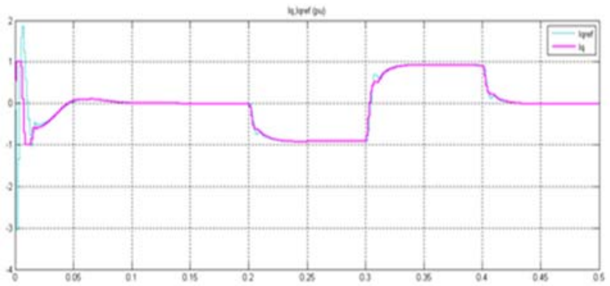

Fig.8 Simulation result of RBFNN –FCM controller for variation of Iq and Iq_{ref}

From the results while comparing to PI and ANN controller the overshoot between Iq and Iq_{ref} is less with RBFNN controller designed with FCM. Variations of average dc voltage of all the three technique were shown in figure 9 to figure 11 from which for the parameter given, the rise time and peak time of FCM technique was somewhat slightly higher than with other two techniques.

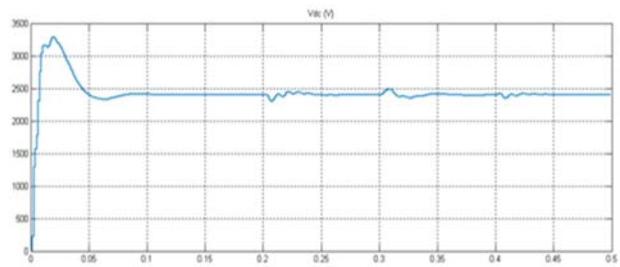

Fig. 9 Variation of average dc voltage with PI controller

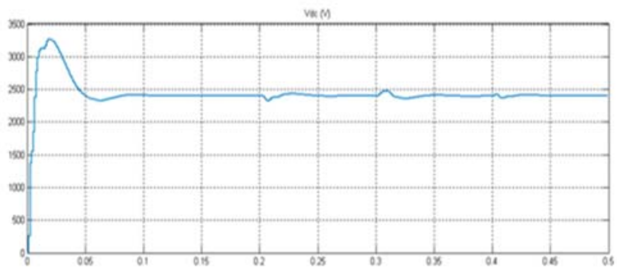

Fig.10 Variation of average dc voltage with RBFNN-PI controller

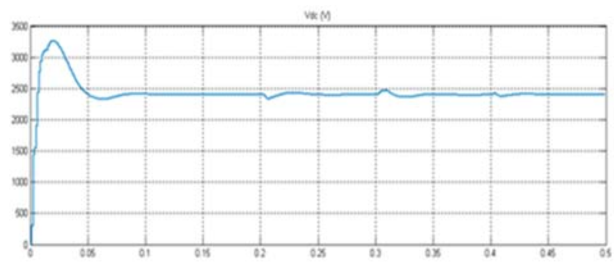

Fig. 11 Variation of average dc voltage with RBFNN-FCM controller

6 Conclusion

This paper has presented the design of RBFNN controller by fuzzy c-means clustering for the DSTATCOM to improve voltage stability and power quality of a distribution system. The entire work is realized in MATLAB/SIMULINK platform. The results have been compared with traditional PI controller and RBFNN-PI controller. From the comparison, the results show that RBFNN controller developed with FCM provides better responses in change of reference reactive current over other conventional techniques. The proposed controller, overshoots between Iq and Iqref is very less and for the parameter given, the rise time and peak time was somewhat slightly higher. From this, the technique proves itself as best alternative for other conventional technique for solving complex task such as task with complex mathematical modeling. For the power system this technique can be employed to have better performance in any power quality improvement problems.

7 References

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