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

T.Eswaran[1], V.Suresh Kumar[2]

[1]Research scholar, [2]Associate Professor

Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

eswaranthangaraju@gmail.com

Abstract

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

Keywords: Power Quality, DSTATCOM, Fuzzy C-Means Clustering, Proportional-Integral, Fuzzy logic.

1. Introduction

The power quality problems such as voltage sag, swell, neutral current compensation, voltage instability etc. have been focused by many researchers. These issues lead to slower response time, reduction in power flow limits and system collapse [1]. All these things have made a situation to develop a new device for improving the 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 such as low cost, generates less harmonics, compact size and low loss compared to other devices [3]. The specific quality of DSTATCOM is capability of fast and continuous nonstop inductive or capacitive compensation. To meet the specification of the utility connection total demand, the DSTATCOM injects required amount of leading or lagging compensation current based on the given load. These kinds of injection made DSTATCOMs play a vital role in the radial distribution system [4].

In recent years, these kinds of DSTATCOM controllers are used in induction generator mainly to support reactive compensation. In any application, the performance of DSTATCOM normally depends on the control algorithm. In the Ref. [5], the authors have discussed 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 is designed for DSTATCOM connected to a distribution network with distributed generation discussed in the literature [6].

The authors in the Ref. [7] developed a control algorithm for a DSTATCOM by using self tuning filters with instantaneous reactive power theory. Some of the researchers have used DSTATCOM not only for the control of reactive power exchange but also used to provide damping support to the system. For the control of DSTATCOM, reference values are usually obtained from the PI controllers mainly'd' and 'q' axes currents.

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

Recently, an alternate fuzzy logic controller and artificial neural network have been used instead of conventional linear and nonlinear controllers for controlling DSTATCOM. [12-14] have 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 and it is the 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 distinguishes them from the traditional linear controller. The performance of the controller can be enhanced even better with the choice of inputs to the controller and it is a good task which has been addressed by this paper in a better way.

Considering all these issues, Fuzzy c-means clustering has been proposed along with fuzzy PI controller for controlling DSTATCOM 'd' and Q-axes. Fuzzy logic generalized from fuzzy set theory has appeared to offer a better solution to various control problems [15]. They are capable of handling complex, nonlinear and mathematically in tangible dynamic systems and these activities have undoubtedly attracted the researchers to use fuzzy logic in designing the controllers. However, obtaining an appropriate set of membership functions and rules is not an easy task.

In almost all applications, based on fuzzy controller, the membership functions and the rules are developed by human experts only. But, it needs lot of experiences and skills and even a time which all are tedious design and tuning fuzzy exercise that may not be optimal too. There have been many researches going on for the development of membership functions and rule in fuzzy logic controller design. The authors in Ref. [16] proposed a technique to extract fuzzy rules directly from the available numeric for the development of fuzzy logic control. In this paper, fuzzy c-means clustering is used for extracting membership function and fuzzy rules and this method is used by pre-specifying the number of rules per number of membership function per input features. These features are set with initial values for adjusting the parameters.

The quality of the solutions is improved by choosing appropriate initial values. The authors in Ref. [17] discussed the use of clustering for the development of membership function and rules along with the issues related with proper domain and validation of the cluster algorithm. The authors in Ref. [18] developed an algorithm for direct extraction of regular fuzzy system from data by fuzzy c-elliptotype clustering algorithm. The authors in Ref. [19] presented a fuzzy rule extraction technique for both pattern classification and function approximation. By estimating the cluster in the data, the algorithm is developed and in which, each cluster is obtained corresponding to a fuzzy rule which is straightaway related to the region in the space of both input and output. The proposed controller is implemented, simulated and compared with conventionally designed controller. The proposed technique gives better characteristics.

The rest of paper has been organized as follows: section 2 deals with the mathematical modeling of DSTATCOM. Section 3 handles fuzzy logic controllers and section 4 presents the design of fuzzy logic controllers by fuzzy c-means clustering. The results are compared and discussed in section 5 and the conclusion is given in section 6.

2. Modelling of DSTATCOM

2.1. Resource assessment

To improve the load voltage, a 3 MVAR DSTATCOM is connected in parallel with the load at B3 as shown in Fig.1. The power, that is generated, passes through B1, B2 and B3, via 21 km feeder and 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 used. To carry out the study, both variable and fixed loads are connected in B3 via 25/0.6 step down distribution transformer.

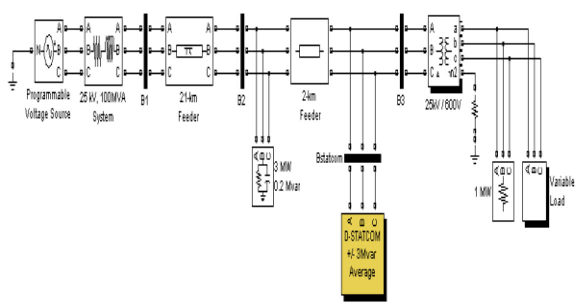

Fig. 1. System configuration of a distribution system

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 and at the same time, it acts as a capacitor by generating reactive power, if the secondary voltage is higher than the bus voltage [20]. In table 1, the quantities taken for study for a source voltage, line voltage, fixed and variable loads are described.

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	11.33 NF/km
Frequency	60 Hz
Fixed load at bus 2	3 MVA, pf = 0.998
Fixed load	1MVA, pf = 1
Variable Load	1.8 MVA, pf = 0.9 1.2 MVA with Mod. freq of 5Hz
Capacitor of DC bus	10000 mF
Reference voltage of DC bus	2400 V

3. Fuzzy logic

Any application done by Fuzzy Logic Controller (FLC) comprises four main components like fuzzification , knowledge base , decision logic and defuzzification [21].The knowledge base will have all information about the input and output along with the term set and membership functions by defining the input and output variables to rule-base system. In fuzzification, the crisp values of inputs signal are converted to fuzzy variable and they are composed with decision variables. Based on the inference engine, the choice of fuzzification is done. The complete information about the plant will be handled by knowledge base which provides necessary data base for the fuzzifcation process. Rule base, which is a control method, is usually taken from the expert knowledge as a set of IF - ITHEN rules, which are all based on the inference. Here, Mamadani fuzzy system is used, as it is suitable for the system that faces slow changes. In this, the defuzzification output, which is done through center of gravity method, is used to control the STATCOM in particular for firing the thyristors present in the STATCOM.

4. Fuzzy C-means clustering

4.1 Cluster estimation

Fuzzy C-means clustering (FCM) technique is one of the best techniques to frame rules and membership functions even when the input-output data have cluster substructure or not. It is always possible by FCM to partition the data into a number of subsets and thereby, they 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 and it 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 [22]. The equations (1) is 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 {x1, x2…….xn}.

$$P_i = \sum_{j=1}^{n} e^{-\alpha\|x_i - x_j\|^2} \quad (1)$$

Where $\alpha = 4/r_a^2$. The Euclidean distance is represented as $\|.\|$, and r_a is a positive constant. The chances for high potential value depend normally for data available with many neighboring data points. The neighboring data are 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. By this, for a data point of X_i, the revised formula for estimating potential value is shown in equations (3).

$$P_i \leftarrow P_i - P_1^k e^{-\beta\|x_i - x_1^*\|^2} \quad (2)$$

Where $\beta = 4/r_b^2$, and for the generalized case is shown in equation (3).

$$P_i \leftarrow P_i - P_k^* e^{-\beta\|x_i - x_k^*\|^2} \quad (3)$$

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 [23].

4.2. Extraction of membership functions and rules

First step in the extraction of rules is the data separation, in which the data are grouped according to their respective classes. Then, clustering is 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 rules. So, the fuzzy rules are formed by translation from each cluster center for identifying the classes. This can be understood even better by this that is when clustering is applied to specific group of data for class, then cluster center $\boldsymbol{x}_i^*$ is found in that group of data for class C_1 and from this, the cluster center provides the rule such as

Rule I: IF { $x\ is\ near\ x_i^*$} then class is C_1

The degree of fulfillment of this class can be defined as shown in equation (4).

$$\boldsymbol{\mu_i = e^{-\propto\|x_i - x_1^*\|^2}} \quad (4)$$

Where 'α is the constant. Mostly, AND operator is used to compute the degree of fulfillment. The rules developed by this technique can be combined to form the overall rule base of the classifier with the highest degree of fulfillment for an output class.

5. Result and discussion

5.1. Fuzzy – PI controller

The well established classical control system, which has been often used as a replacement for other types of controllers, is nothing but a linear PI controller. As per the name, this controller is a linear controller which is not suitable for a system dealing with nonlinearity. As an alternate, fuzzy logic controller has been used for a non linear system. This fuzzy logic controller doesn't require mathematical model for controlling any system and hence, it has been widely used in the system with complex structure. The structure of this fuzzy-PI is shown in Fig 2.

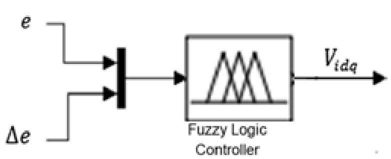

Fig. 2. Fuzzy-PI controller

Here, output is a pulse modulation index 'm' of the DSTATCOM voltages. To carry out this process further, triangular functions are chosen as membership function for inputs and outputs as shown from Fig. 3 to Fig. 5.

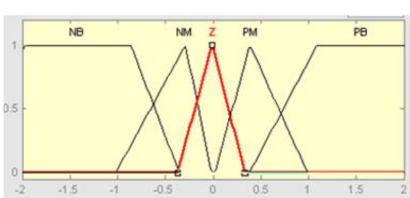

Fig. 3. Input variable (e)

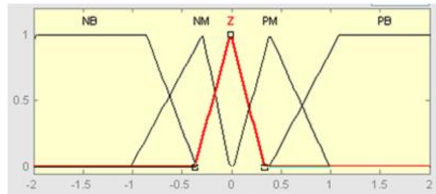

Fig.4 Input variable (Δe)

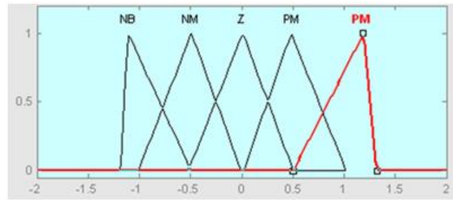

Fig.5 Output variable

The following linguistic variables Positive Big (PB), Positive Medium (PM), Zero (Z), Negative Medium (NM) and Negative Big (NB) are chosen and it can be seen in the membership of input and output by relating the input to the output. A set of rules is developed such as IF "e" is negative big and (Δe) is negative big, the output, which is going to control, will also be negative big. For 'N' variables, there will be 'N^2' possible combinations and they are shown in Table 2.

Table 2. Decision table

e/(Δe)	**NB**	**NM**	**Z**	**PM**	**PB**
NB	NB	NB	NB	NB	NM
NM	NB	NB	NM	MN	Z
Z	NB	NM	Z	PM	PB
PM	NM	NM	Z	PM	PB
PB	NM	Z	PM	PB	PB

Finally, defuzzification is carried out to convert fuzzy outputs in to classical output by using centre of gravity method. These outputs are used to stabilize a power system.

5.2. Fuzzy logic controller by fuzzy C-means clustering

To carry out this process, the set of two-dimensional input and output vectors, which are error and change in error with the output generated by operating the model over its full range of operation, is used. The samplings of input variables, that are error and change in errors, are done uniformly based on the output. After the generation of data, the rules and membership function are generated automatically by this method. It is shown in Fig. 6. Based on the influence of radius 'r_a', the rules, which are generated, also depend on the ranges of the membership function. In this task, by using the clustering algorithm, the number of extracted membership functions for both the input and outputs is restricted to 5. Also, the clustering technique, which is generated the prams for both input and output along with type of membership function, could be appropriate for the specific task and it is depicted in Table 3.

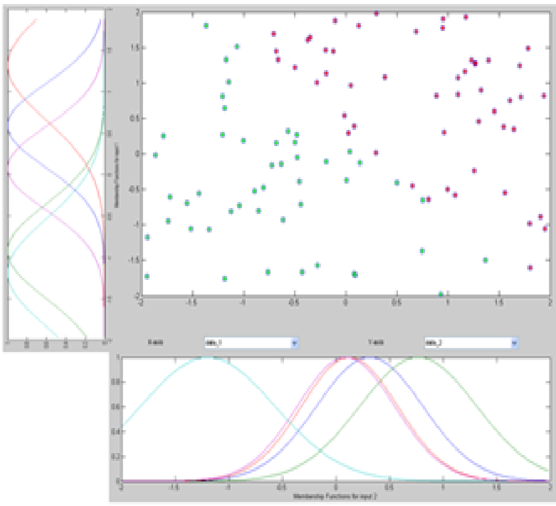

Fig. 6. Membership function

Table. 3. Simulated params by FCM

MFs	Params			Membership function Type		
	Input1	Input2	Output	In.1	In.2	Output
Ranges	[-1.964 1.878]	[-1.996 1.988]	-1.999 1.97			
MF1	[0.5057 0.5934 0 0]	[0.4961 0.3155 0 0]	[0.727 1.246 0 0]			
MF2	[0.5671 -0.9234 0 0]	[0.5458 0.7688 0 0]	[0.5841 -1.214 0 0]		gaussmf	
MF3	[0.6578 1.321 0 0]	[0.4491 0.1268 0 0]	[0.6037 -1.283 0 0]			
MF4	[0.6446 -1.182 0 0]	[0.6264 -1.194 0 0]	. [0.6494 0.8038 0 0]			
MF5	[0.5024 0.07876 0 0]	[0.4542 0.09415 0 0]	[0.5959 -1.196 0 0]			

With this information, as usual the fuzzy logic analyses are carried out by developing input and output membership functions from the fuzzy MATLAB toolbox. Based on the generation and by the clustering algorithm for the rules of Antecedent, Consequent, Rule weight and Rule connection, the final output is estimated and it is shown from Fig.7 to Fig.11.

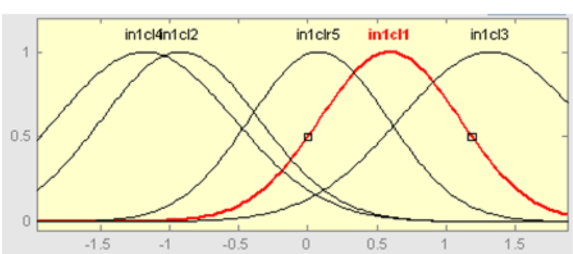

Fig.7 Input variable (e) generated by clustering technique

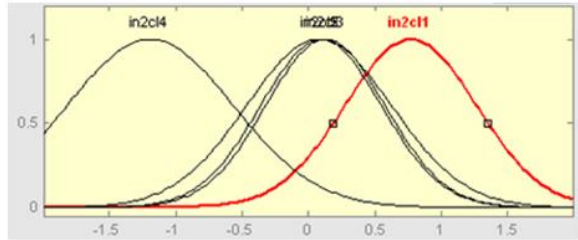

Fig.8 Input variable (Δe) generated by clustering technique

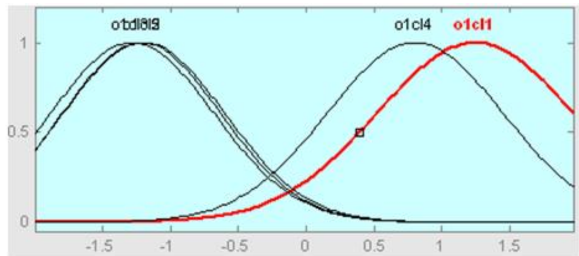

Fig.9. Output variable generated by clustering technique

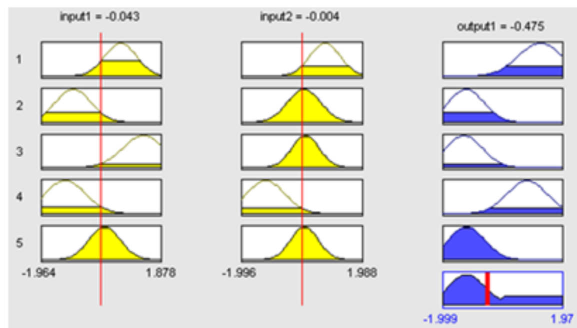

Fig.10 Implemented fuzzy rule for I/O data

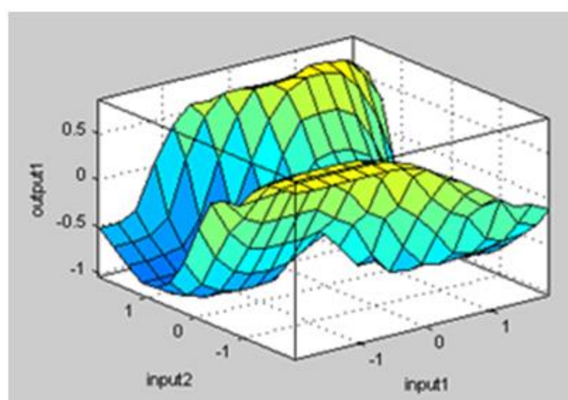

Fig.11 Surface view of the FCM results

The outputs, that are estimated by this controller, are replaced with PI controller which has been used to control of ‘d’ and ‘q’-axes current.

The simulation results of PI-controller, fuzzy–PI controller and fuzzy logic controller by

FCM for the variation of I_q and I_{qref} are shown from Fig. 12 to Fig.14.

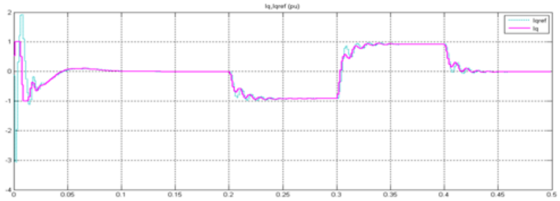

Fig. 12. Simulation result of PI controller for variation of Iq and Iq_{ref}

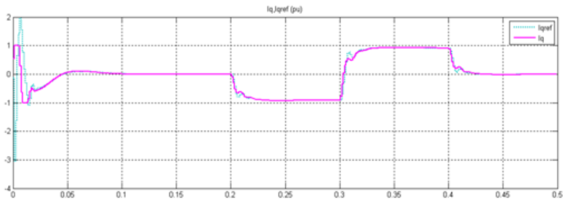

Fig. 13. Simulation result of Fuzzy- PI controller for variation of Iq and Iq_{ref}

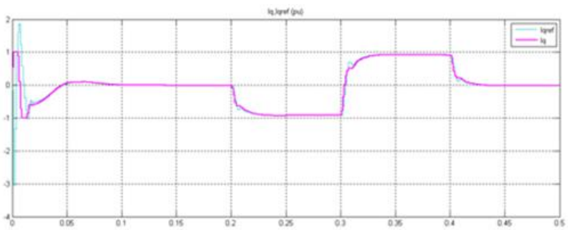

Fig. 14. Simulation result of fuzzy–FCM controller for variation of Iq and Iq_{ref}

From the results, while comparing the PI and fuzzy controller, the overshoot between Iq and Iq_{ref} is less with fuzzy logic controller designed with FCM. The variations of average dc voltage of all the three techniques are shown from Fig. 15 to Fig. 17. From which for the parameter given, it is clear that the rise time and peak time of FCM technique are somewhat slightly higher than the other two techniques.

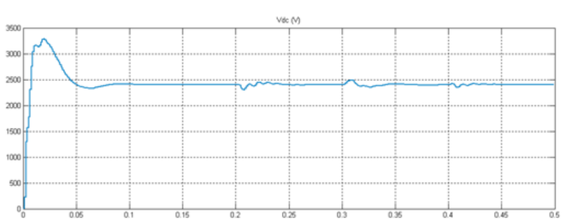

Fig. 15. Variation of average DC voltage with PI controller

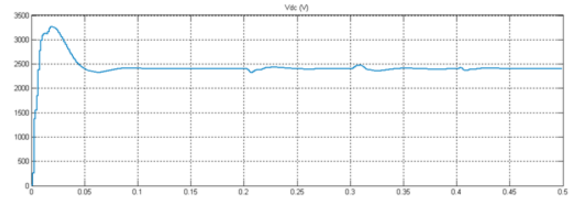

Fig. 16. Variation of average DC voltage with Fuzzy-PI controller

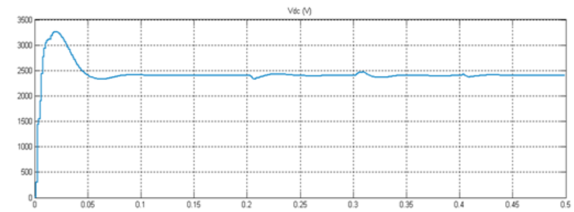

Fig. 17. Variation of average DC voltage with Fuzzy-FCM controller

6. Conclusion

This paper has presented the design of fuzzy logic controller by fuzzy c-means clustering for the DSTATCOM to improve the 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 fuzzy-PI controller. From the comparison results, it is clear that the fuzzy logic controller developed with FCM provides better responses in change of reference reactive current over other conventional techniques.

Further, the proposed controller’s overshoot between Iq and Iqref is very less and for the parameter given, the rise time and peak time are somewhat slightly higher. From this, it is evident that the technique proves itself as the best alternative than the other conventional techniques for solving complex task such as task with complex mathematical model. In the case of power system, this technique can be employed to have better performance and it can also be employed for power quality improvement problems.

Reference

1. T. Yuvaraj, K. Ravi, K.R. Devabalaji, “DSTATCOM allocation in distribution networks considering load variations using bat algorithm”, In Ain Shams Engineering Journal, vol. 8, no. 3, pp. 391-403, 2017.
2. A. Ghosh and A. Joshi, "The concept and operating principles of a mini custom power park," in IEEE Transactions on Power Delivery, vol. 19, no. 4, pp. 1766-1774, 2004.

3. S. Jazebi, S.H. Hosseinian, B. Vahidi, "DSTATCOM allocation in distribution networks considering reconfiguration using differential evolution algorithm", Energy Conversion and Management, vol. 52, no. 7, pp.2777-83, 2011.
4. O.P. Mahela, A.G. Shaik, "A review of distribution static compensator, In Renewable and Sustainable Energy Reviews", vol. 50, pp. 531-546, 2015.
5. T. Zaveri, B. Bhalja, N. Zaveri, "Comparison of control strategies for DSTATCOM in three-phase, four-wire distribution system for power quality improvement under various source voltage and load conditions", International Journal of Electrical Power & Energy Systems, vol. 43, no. 1, pp. 582-594, 2012.
6. M.A. Mahmud, H.R. Pota and M.J. Hossain, "Nonlinear DSTATCOM controller design for distribution network with distributed generation to enhance voltage stability", Electrical Power and Energy Systems, vol. 53, pp. 974–979, 2013.
7. B. Singh, S.K. Dube and S.R. Arya, "An improved control algorithm of DSTATCOM for power quality improvement," Electrical Power and Energy Systems, vol. 64, pp. 493–504, 2015.
8. N.G. Hingorani, L. Gyugyi, "Understanding FACTS, concepts and technology of flexible AC transmission systems" New York: IEEE; 1999. ISBN 0-7803-3455-8.
9. C. Resul, D. Besir, A.T.A. Fikret., "Fuzzy-PI current controlled DSTATCOM", Gazi Univ J Sci, vol. 24, no. 1 pp. 91–9. 2014.
10. D. Masand, S. Jain, G. Agnihotri. "Control strategies for distribution static compensator for power quality improvement", IETE J Res, vol. 54, no. 6, pp. 421–8, 2008.
11. B. Singh, A.P. Mittal, J.R.P. Gupta. "Modelling and control of DSTATCOM for three phase, four- wire distribution systems", In: Industry applications conference, 14th IAS annual meeting, conference record of the 2005, vol. 4, pp. 2428–34, 2005.
12. G.K. Venayagamoorthy, R.G. Harley. "Computational intelligence techniques for control of FACTS devices", In: Applied mathematics for restructured electric power systems optimization, control and computational intelligence, pp. 201–37, 2005.
13. D. Amoozegar, "DSTATCOM modelling for voltage stability with fuzzy logic PI current controller," Electrical Power and Energy Systems, vol.76, pp. 129–135, 2016.
14. L.A. Zadeh, "Fuzzy Sets", Information and Control, vol. 8, pp.3, 38-3531, 965.
15. S. Abe, and M.S. Lan. "A Method for Fuzzy Rules Extraction Directly from Numerical Data and Its Application to Pattern Classification", EEE Trans. Fuzzy Systems, vol.3, no.1, pp.18-28, 1995.
16. F. Klawonn, and R. Kruse., "Automatic Generation of Fuzzy Controllers by Fuzzy Clustering", Proc. IEEE Inter. Conf. on Syst. Man and Cyber., pp. 2040-2045, 1995.
17. R. Nikhil, K. Pal, J.C. Bezdek, and T.A. Runkler., "Some issues in system identification using clustering," Proc. of International Conference on Neural Networks, vol. 4, pp. 2524-2529, 1997.
18. T. A. Runkler and R.H. Palm, "Identification of nonlinear systems using regular fuzzy celliptotype clustering", Proc. of the Fifth IEEE International Conference on Fuzzy Systems, vol. 2, pp.1026-1030, 1996.
19. S.L. Chiu, "Extracting fuzzy rules from data for function approximation and pattern classification", Chapter 9 in Fuzzy Set Methods in Information Engineering: Book- A Guided Tour of Applications, D. Dubois, H. Prade, and R.Yager, ed., John Wiley, 1997.
20. The MathWorks, SimPowerSystems User's Guide, MatlabR2009b.
21. S.M. Reza, O. Pooria, K.M. Hassan. "Robust control strategy for electrically driven robot manipulators: adaptive fuzzy sliding mode", IET Sci Meas Technol, vol. 9, no. 3, pp. 322–34, 2014.
22. F. Klawonn and R. Kruse, "Constructing a fuzzy controller from data", Fuzzy Sets and Systems, vol. 85, pp. 177-193, 1997.
23. S. L. Chiu, "Extracting fuzzy rules from data for function approximation and pattern classification", Fuzzy Set Methods in Information Engineering: Book- A Guided Tour of Applications, D. Dubois, H. Prade, and R.Yager, ed., John Wiley, 1997.