Cumhuriyet Üniversitesi Fen Fakültesi
Fen Bilimleri Dergisi (CFD), Cilt:36, No: 6 Özel Sayı (2015)
ISSN: 1300-1949

Cumhuriyet University Faculty of Science
Science Journal (CSJ), Vol. 36, No: 6 Special Issue (2015)
ISSN: 1300-1949

Design of adaptive PI-like fuzzy logic controller for STATCOM using a hybrid meta-heuristic algorithm

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Received: 24.04.2015; Accepted: 09.07.2015

Abstract. The objective of this paper is to design an adaptive PI-like Fuzzy Logic Controller (FLC) based on sugeno method for a Static Synchronous Compensator (STATCOM) for improving voltage at the point of common coupling (PCC) of Doubly Fed Induction Generator (DFIG)-based wind farms with grid. A hybrid algorithm based on Genetic and Particle Swarm Optimization (GAPSO) has been utilized to train the parameters of the rules and Membership Functions (MFs) and output scaling factor of the fuzzy controller. Simulation results show that the STATCOM based PI-like FLC with tuning its parameters has the better performance than conventional PI controller and PI-like FLC in improving the voltage at the PCC.

Keywords: STATCOM, PI-like fuzzy logic controller, Particle Swarm Optimization, Genetic Algorithm, hybrid algorithm

Introduction

Wind power penetration to the existing power systems has been given a great concern especially with the worldwide trend to develop future smart grids and to generate electricity from renewable resources. Doubly Fed Induction Generator (DFIG) is, currently, the most employed wind generator due to its merits as; the higher efficiency and the capability of decoupling control of active power and reactive power for better grid integration [1]. However, by connecting stator windings directly to the power grid, a wind DFIG is extremely sensitive to grid faults.

In order to reduction of the negative influences of the power grid on DFIG-based wind farms, a Static Synchronous Compensator (STATCOM) is one of the good candidates. A STATCOM can generate more reactive power during voltage drops than other Flexible AC Transmission Systems (FACTS) devices like Static VAR Compensator (SVC). This is due to the fact that the maximum capacitive power generated by a STATCOM decreases only linearly with the bus voltage but it drops off as square of the bus voltage for an SVC. In addition, the STATCOM normally exhibits a faster response as it has no significant time delay associated with thyristor firing [2].

For voltage regulation Of Point of Common Coupling (PCC) under disturbance conditions, the PI controller gains of the STATCOM ac voltage regulator play a more important role than the other controllers [3]. In conventional methods, fixed gain PI controller is used that the dynamic response of the STATCOM was not satisfactory if there was a drastic change in the system configuration. Recently, self-tuning PI controllers are used that the controller gains are adopted with system conditions. Particle Swarm Optimization (PSO),

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Special Issue: International Conference on Non-Linear System & Optimization in Computer & Electrical Engineering

Artificial Neural Networks (ANNs), and fuzzy logic have been proposed to adapt the controller gains of the STATCOM [3,4], [5] and [6]. For many nonlinear systems with nonlinearities and uncertainties, the performance of PI controllers may not be satisfactory. The use of Fuzzy Logic Controller (FLC) to solve control problems has been increasing considerably in the past years. A STATCOM with FLC to compensate current harmonics and reactive power of nonlinear load current is proposed in ref. [7]. In [8] a PI-like FLC has used as control strategy for STATCOM, instead of conventional PI controller. However, the PI-like FLC performance depends on tuning of its parameters (i.e. Membership Functions (MFs), fuzzy rules and scaling factors). Therefore, the parameter tuning of the FLC can be formulated as an optimization problem. Optimizing MFs of a fuzzy system can be done using Particle Swarm Optimization (PSO) [9-11], Genetic Algorithm (GA) [12], Imperialist Competitive Algorithm (ICA) [13] and Hybrid Particle Swarm Optimizer with Mutation (HPSOM) [14].

This paper focuses on design of adaptive PI-like FLC for STATCOM in order to better voltage control of the PCC. In this paper, a strategy based on hybrid meta-heuristic algorithm GAPSO is presented to optimally choose the rules, MFs and output scaling factors simultaneously for the PI-like FLC.

I. System Description

Fig.1 shows the power system. A 9-MW DFIG wind farm (6×1.5 MW) connected to a 25-kV distribution feeder. An induction motor load with a 200-KW resistive load and a 3-MVA STATCOM are connected at the PCC bus. The parameters used for simulation are represented in Table I.

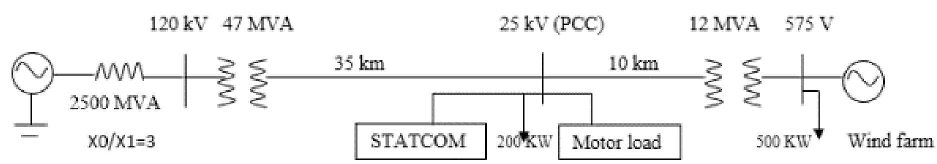


Figure 1. One-line diagram of the studied system.

Table I. The studied system data.

	Parameters of the DFIG	
Rotor and stator resistance	[0.005 0.00706]	P.U.
Rotor and stator inductance	[0.156 0.171]	P.U.
Magnetizing inductance	2.9	P.U.
Inertia constant	5.04	S
Wind speed	12	m/sec
Frequency	60	Hz
	Line data	
Resistance	0.1153	Ω/km
Inductance	1.05e-3	H$/km$
Capacitance	11.33e-009	F$/km$
	Induction motor load	
Nominal power and voltage	[1.68/0.93 2300]	[MW V]
Rotor and stator resistance	[0.007 0092]	P.U.
Rotor and stator inductance	[0.0717 0.0717]	P.U.
Mutual inductance	4.14	P.U.
Inertia constant	0.5	s

II. STATCOM Model

The equivalent circuit of the STATCOM is shown in Fig. 2. The R_s is resistance in series with the inverter, the L_s represents the leakage inductance of the transformer and the voltages e_{as}, e_{bs} and e_{cs} are the inverter ac side phase voltages suitably steped up. The STATCOM control block diagram is shown in Fig. 3. As shown in Fig. 3, the STATCOM is controlled to deliver either inductive or capacitive currents to the power system by varying its output voltages e_{as}, e_{bs} and e_{cs}. In the design of the STATCOM controller, the three-phase quantities u_{al}, u_{bl}, u_{cl}, e_{as}, e_{bs}, e_{cs}, i_{as}, i_{bs} and i_{cs} are first transformed to the quantities u_d, u_q, e_d, e_q, i_d and i_q in the synchronously rotating reference frame. Then, a current regulator is employed to reach decoupled current control [15]. In addition, an ac voltage controller is designed to regulate the PCC bus voltage through a PI controller. The ac voltage controller generates the desired reactive current reference $i_{q\,ref}$ for the current regulator.

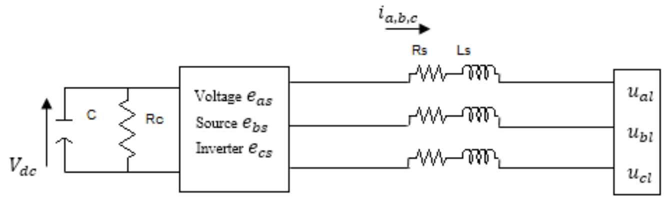


Figure 2. Equivalent circuit of STATCOM.

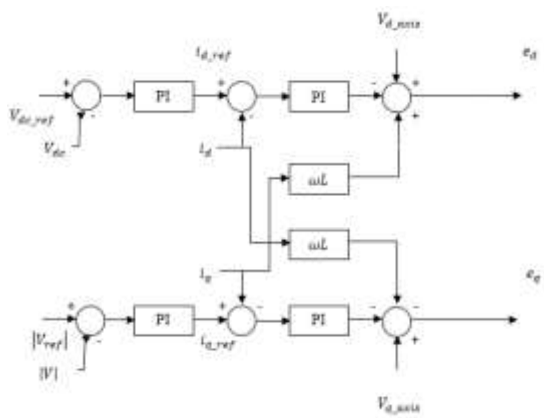


Figure 3. STATCOM control block diagram.

III. Conventional PI-like FLC for STATCOM

The STATCOM target is to maintain the PCC voltage at a steady level. For the PCC voltage regulation under disturbance conditions, the PI controller gains of the STATCOM ac voltage regulator play a more important role than the other controllers. Thus, only the ac voltage regulator is replaced by the PI-like FLC.

The block of PI-like FLC is shown in Fig. 4. The controller is implemented to enhance capability of voltage control of the STATCOM. The controller has two inputs and an output. Here, the error of PCC voltage $e(k)$ and derivative of error $\Delta e(k)$ are used to adjust the input variables $(E(k), \Delta E(k))$ by the scaling factors $(G_e, G_{\Delta e})$. The scaling factors play a role similar to that of the gains of a conventional controller [16]. The relationship between the scaling factors and the input and output variables of the FLC is $E = e \times G_e, \Delta E = \Delta e \times G_{\Delta e}$ and $\Delta u = \Delta U \times G_{\Delta u}$.

All MFs of the FLC inputs and the output, are defined on the common normalized domain [-1,1]. [17]. Here, the MFs of inputs are chosen the generalized bell-shape function as shown in Fig. 5. These bell-shaped functions have the following definition:

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

$$\mu_{Ai}(x) = exp\left\{-\left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}\right\} \tag{2}$$

Where, $\{a_i, b_i, c_i\}$ is the parameter set that changes the shape of the MF. The output MFs is considered constant. The collection of the rules is shown in Table II.

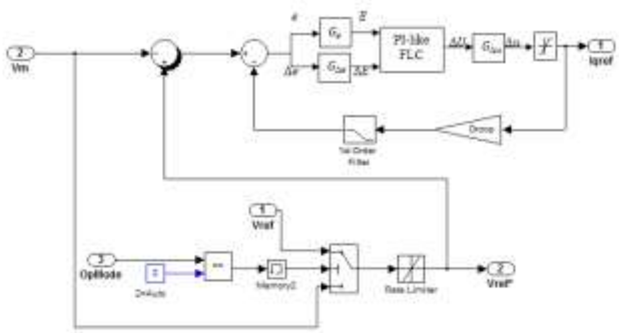


Figure 4. The STATCOM control system with PI-like FLC in MATLAB.

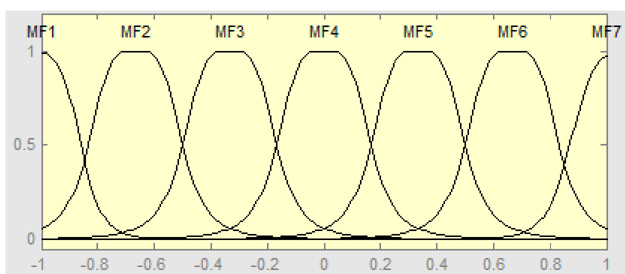


Figure 5. The initial MFs of inputs.

Table II. Initial fuzzy logic rules.

$\Delta E(k)$ / $E(k)$	**MF1**	**MF2**	**MF3**	**MF4**	**MF5**	**MF6**	**MF7**
MF1	-0.666	-0.666	-0.666	-0.334	0	0	0.334
MF2	-0.666	-0.334	-0.334	-0.334	0	0.334	0.666
MF3	-0.666	-0.334	0	0	0.334	0.666	1
MF4	-0.666	-0.334	0	0.3334	0.666	1	1.334
MF5	-0.334	0	0.334	0.666	0.666	1	1.334
MF6	0	0.334	0.666	1	1	1	1.334
MF7	0.334	0.666	0.666	1	1.334	1.334	1.334

IV. Adaptive PI-like Fuzzy Logic Controller

Conventional FLCs are designed based on expert knowledge in controlling various systems. Fuzzy rules and the fuzzy MFs are difficult to obtain from human experts. To overcome these difficulties, the GAPSO technique is proposed to automate the tuning process. The strategy of using a GAPSO algorithm for tuning of the MFs, the rules and the output scaling factor in FLC is depicted in Fig. 6.

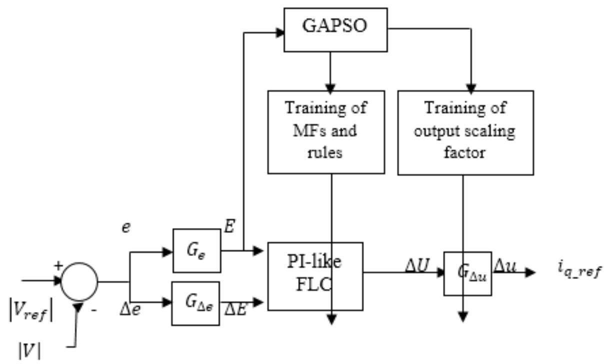


Figure 6. Block diagram of the proposed adaptive PI-like FLC.

A.Implementation of GAPSO

The idea of Genetic Algorithm (GA) is derived from biological evolution process which is an optimal searching algorithm based on the natural selecting principle of genetic mechanism and survival of the fitness. During iteration process, GA select chromosomes on the basis of adaption value such that chromosomes of better adaption can have more chances to reproduce. It mutate the chromosomes with certain probability, enriches the varieties of population and reduces the population precocity phenomena efficiently.

Particle Swarm Optimization (PSO) algorithm was proposed by American Dr. Kennedy in 1995 according to the foraging behavior of bird, similar to genetic algorithm belonged to evolutionary algorithm. It starts from a random solution, finds the optimal solution through iteration and evaluates the advantages and disadvantages of solutions through the fitness. In the search process, all particles fly at a certain degree of speed in accordance with its own flying experience and his companions', according to the current optimal value of the two to update their own, one is particle optimal value called individual extreme P_{best} and the other is optimal value obtained by the entire particle called global extreme G_{best} .The global optimal solution is obtained in the search space at last. The motion process of particle swarm of PSO is as follows:

Assuming that the dimension of searching space is n, let num be the particle total, $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$ be the position vector of the i^{th} particle, $V_i = (v_{i1}, v_{i2}, \dots, v_{in})$ be the velocity vector, $P_i = (p_{i1}, p_{i2}, \dots, p_{in})$ be the best position that particle has gone through, which can also be denoted as P_{ibest}, and g be the index numbers of best position that all particles have gone through, so $P_g = \left(p_{g1}, p_{g2}, \dots, p_{gn}\right)$, i.e. P_{gbest}.

During the iteration process of every particle in PSO, for every particle, the velocity and position are updated by the following two rules:

$$V_i^{k+1} = \omega \times V_i^k + C_1 \times r_1\left(P_i - X_i^k\right) + C_2 \times r_2\left(P_g - X_i^k\right) \quad (3)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{4}$$

Where k represents evolution times, ω inertia weight coefficient, C_1 and C_2 accelerating factor which are also called recognizing factor and social factor, r_1 and r_2 are random numbers in interval [0,1] To prevent the velocity of particle becoming too quick in the iteration, the velocity of particle should be restricted in interval [-1,1]. During motion process, particle swarm's shifting is attracted by both local optimal solution and global optimal solution, and converges to global optimal solution finally.

PSO has many disadvantages such as slow convergence rate, low accuracy, and early- maturing problem that always makes it impossible to get globally optimal solution. In GA, in spite of its capability of searching solution in parallel, crossover and mutation rates can subtly affect the convergence and also its ability to control convergence is less than PSO. In this paper, Hybrid algorithm comprising merits of both GA and PSO is used to get optimal parameters of generalized bell-shaped MFs i.e. $\{a_i, b_i, c_i\}$, rules and the output scaling factor i.e. $G_{\Delta u}$.

Algorithm used to design a GAPSO based FLC consists of following steps:

Step 1: Problem Definition

- Definite the cost function (Eq.7).
- Determine number of variables.

Step 2: Determination of the GA-PSO Parameters.

- Maximum number of iterations (It).
- Population size (P_S).
- Crossover and Mutation percentage.
- $\emptyset_1 = \emptyset_2 = 2.05, \emptyset = \emptyset_1 + \emptyset_2$.
- $x = \frac{2}{\emptyset - 2 + \sqrt{\emptyset^2 - 4\emptyset}}$.
- $C_1 = x.\emptyset_1,\ C_2 = x.\emptyset_2$.
- $\omega = x$.

Step 3: Initialization

- Create population, randomly.
- Initialize individuals of the population.
- Compute the cost function for each the individuals and rank of them on the base of the fitness values.

$GA\ Loop$:

- Apply crossover operator to produce new population.
- Choose two parents from the main population, randomly.
- Create two new offsprings according to following equation [18].

$$X_i(k+1) = \alpha_1.X_i(k) + (1-\alpha_1).X_j(k) \tag{5}$$

$$X_j(k+1) = (1-\alpha_1).X_i(k) + \alpha_1.X_j(k) \tag{6}$$

- Apply Gaussian mutation operator [18] to produce new population.

$PSO\ Loop$:

- Update velocity and position based on Eq.3 and Eq.4, respectively.
- Compute the cost function and obtain the best solution.
- Obtain the best cost function.
- Display the best solution.

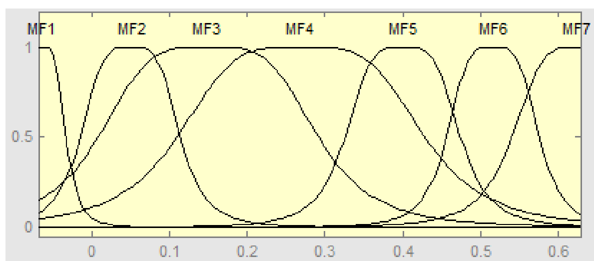
To evaluate the performance of the GAPSO algorithm with the aim of finding the smallest error, the equation of the Control Error (CE) is defined as:

$$f(CE(k)) = \sum_{k=0}^{T} (y(k) - \bar{y}(k))^2 \tag{7}$$

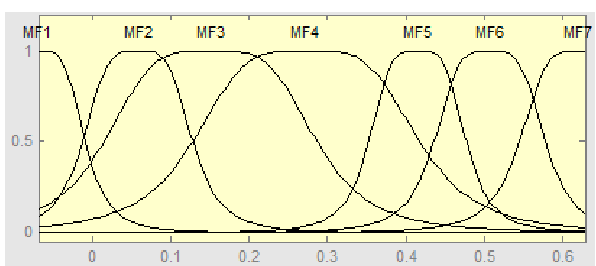
Where T is the sampling period. $y(k)$ and $\bar{y}(k)$ are current and reference values of a parameter, respectively.

V. Simulation Results

To examine the effectiveness of the proposed controller for the STATCOM, a PI controller and a PI-like FLC are used as a comparison base. The GAPSO parameters in this study are; total iteration number=50, population size=20, crossover percentage=0.7and mutation percentage=0.2. Where, there is a vector with 92 variables, the 42 variables represent the membership functions of the two inputs, and the 49 variables are the rules and a variable is the output scaling factor. A two-phase to ground fault is applied to the PCC bus at t=25 sec and is cleared at t=25.08 sec. the simulation results obtain using MATLAB/SIMULINK. At the completion of the GAPSO tuning, the MFs for the inputs of the adaptive PI-like FLC have been modified significantly. They are shown in Fig. 7. Table III shows the output parameters of the FLC after the GAPSO tuning process.



a. Error



b. Derivative of error

Figure 7. The tuned MFs for the FLC inputs at the final.

Figures 8-9 show the voltage curve at the PCC bus and the active power DFIG-based wind farm for the STATCOM with conventional PI controller, PI-like FLC and adaptive PI-like FLC. The proportional and integral gains of the ac voltage regulator are chosen $k_p = 0.5$ and $k_i = 8.1$ respectively. For both the two fuzzy controllers, the input scaling factors chosen here are $G_e = 1$ and $\Delta G_e = 2$. For the PI-like FLC, the output scaling factor is $\Delta G_u = 1.5$. . For the adaptive PI-like FLC, the output scaling factor is $\Delta G_u = 1.02$ at the final of the tuning process. It is clear that the adaptive PI-like FLC greatly improves the STATCOM response after clearing fault compared to PI controller and PI-like FLC.

Table III. The tuned output parameters of the FLC at the final.

$\Delta E(k)$ / $E(k)$	**MF1**	**MF2**	**MF3**	**MF4**	**MF5**	**MF6**	**MF7**
MF1	0.522	0.512	-0.399	-0.4	0.002	-0.0001	0.003
MF2	0.500	0.484	0.6216	1.339	0.061	-0.003	0.005
MF3	0.194	0.709	0.1807	0.724	0.737	0.0273	0.029
MF4	0.013	1.927	0.7669	0.767	0.698	0.144	0.141
MF5	0.017	0.161	0.6402	0.693	0.64	1.561	1.652
MF6	0.004	0.025	0.0429	1.148	1.986	-0.091	1.226
MF7	0.003	-0.012	0.037	0.161	2.66	1.382	1.243

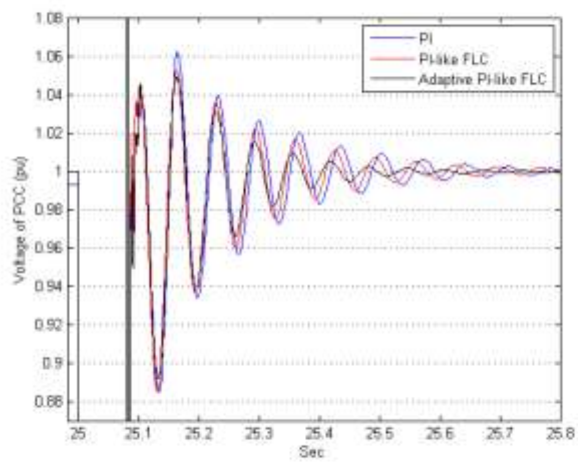


Figure 8. The voltage response at the PCC bus.

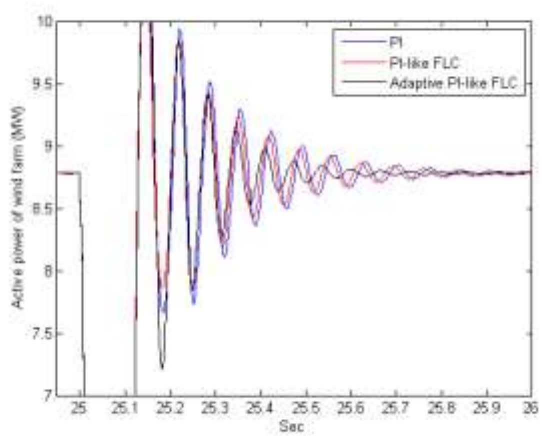


Figure 9. The active power of DFIG-based wind farm.

VI. Conclusion

In this paper, adaptive PI-like fuzzy logic controller is successfully designed for ac voltage regulator to control the STATCOM for improving voltage at the point of common coupling of DFIG-based wind farm with grid. A hybrid algorithm based on Genetic and Particle Swarm Optimization (GAPSO) has been utilized to train the parameters of the rules and MFs and output scaling factor of the fuzzy controller. The results have shown that STATCOM with the adaptive PI-like FLC is performing satisfactorily compared with conventional PI and PI-like FLC after clearing fault.

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