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MOHAMMAD MEHDI KARAMI

AKBAR ITAMI

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Implementation of SVC based on grey theory and fuzzy logic to improve LVRT capability of wind distributed generations

Mohammad Mehdi KARAMI[1,*], **Akbar ITAMI**[2]
[1]Department of Electrical Engineering, Islamic Azad University, Saveh Branch, Saveh, Iran
[2]Department of Electrical Engineering, Islamic Azad University, Lahijan Branch, Lahijan, Iran

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Abstract: Due to the great absorption of reactive power after voltage drops caused by faults in network, the low-voltage ride through (LVRT) capability of squirrel cage induction generators (SCIGs) in wind farms is a great challenge. If a static VAR compensator (SVC) is installed at the point of common coupling (PCC) of a wind farm with a main network, it can improve the wind generation's LVRT capability with reactive power compensation. In the voltage control loop of a conventional SVC, the voltage actual value of the PCC is compared with the reference voltage value. This paper presents a method for implementation of a SVC based on grey theory and fuzzy logic to improve the LVRT capability of SCIG wind turbines. In this method, instead of the voltage actual value of the PCC, the voltage of the PCC is predicted by the GM (1,1) grey model. Predicted voltage is then compared with reference voltage. After obtaining voltage error, a fuzzy controller with a PI controller in the SVC voltage control loop controls the SVC output. The simulation results are compared for a conventional SVC, fuzzy SVC and fuzzy-grey SVC. These results show the superiority of the fuzzy-grey controller for the SVC in improving the LVRT capability of wind farms with SCIGs.

Key words: Low-voltage ride through, static VAR compensator, fuzzy control, grey system

1. Introduction

Today, due to environmental issues and reduction of fossil fuels, renewable energy sources are taken into consideration. Wind distributed generation resources are one of the most important resources producing electric power at the voltage level of distribution systems. Thus, the investigation of their effects on power systems is very important. One of the most important issues of wind generation integration to a network is voltage instability due to occurrence of disturbances in the power system. Thus, the low-voltage ride through (LVRT) capability of wind turbines is one of the most important requirements of their integration to a network. LVRT means that wind turbines remain in circuit during voltage drops due to faults and deliver their power to the network [1,2].

Fixed speed wind turbines have great advantages including simple construction, low cost, and high reliability, but they cannot control the reactive power. Wind turbines of the squirrel cage induction generator (SCIG) type work at super-synchronous speed. These generators absorb reactive power from the power system or any reactive power compensator at steady mode. During network faults, the reactive power demand of these turbines is increased. Thus, the LVRT capability of SCIG turbines is very weak [3].

Based on the behavior of induction generators used in wind turbines during voltage drop, various methods

*Correspondence: mehdi4rasht@yahoo.com

are used to improve the LVRT capability of SCIG turbines, such as blade angle control to control input mechanical torque and reactive power compensation. After the fault is cleared, wind generations apply much reactive power and prevent voltage returning to the initial value before fault occurrence. By installing controlled reactive current devices such as a static synchronous compensator (STATCOM), static VAR compensator (SVC) [4–7], and unified power flow controller (UPFC) [8], we can provide the required reactive power for the induction generators.

The SVC belongs to the flexible AC transmission systems (FACTS) family and can present reactive power rapidly and continually. The SVC voltage regulator uses a PI controller. Increasing integral gain reduces or omits the steady-state error but this reduction occurs with the reduction of system response speed. Thus, satisfactory control results cannot be obtained by traditional control strategy. To improve the SVC performance, a fuzzy logic control method is suitable. According to references [9,10], a fuzzy controller for SVCs was used to improve system damping. Reference [11] proposed a fuzzy controller to control the firing angle of thyristors. In reference [12], to improve SVC performance, a fuzzy controller was used instead of a PI controller in the voltage regulator loop. Reference [13] applied the combination of fuzzy and PI controllers to improve transient stability and damping of system fluctuations. Reference [14] proposed an adaptive fuzzy controller for SVCs. In this method, an online identifier is applied by the recursive least squares method to update fuzzy controller parameters.

The present study presents a method for implementation of SVCs based on grey theory and fuzzy logic to improve the LVRT capability of SCIG wind turbines. Compared to artificial intelligence techniques needing much effort and time to define the parameters and modeling, the grey prediction model is most practical and simple. In the grey prediction model, a differential equation is used to describe an indefinite system with fewer data. The proposed method in this paper has already been used in the control of a nonlinear system in reference [15]. This study applied a combination of the grey prediction method with a PID type fuzzy controller. The result of this combination is low overshoot and omitting of steady-state error. In the present paper, instead of the voltage actual value of the PCC, the predicted voltage of the PCC by grey theory of the GM model (1,1) is compared with reference voltage in the SVC voltage control loop. Then voltage error $(e(k))$ and the derivative of voltage error $(\dot{e}(k))$ signals are considered as input for the fuzzy logic controller. The fuzzy controller with a PI controller in the SVC voltage control loop controls the SVC output (susceptance). Simulation results are compared for performance of a conventional SVC, fuzzy SVC, and fuzzy-grey SVC. These results show the superiority of the fuzzy-grey controller for SVCs in improving the capability of LVRT of SCIG wind farms.

2. SCIG wind turbines' performance under network fault

Induction generators used in wind units of SCIG are squirrel cages. These generators absorb reactive power from the power system or any reactive power compensator at steady mode. When a grid fault occurs, system voltage is dropped with wind terminal voltage within a short time. According to Eq. (1), the electromagnetic torque also drops instantaneously since it is proportional to the square of the terminal voltage, while the mechanical torque remains unchanged at the same time. Thus, imbalance occurs between input mechanical torque and output electromagnetic torque. Based on accelerating torque in Eq. (2), $T_e < T_m$, accelerating torque is positive and it accelerates the rotor of generator [16,17].

$$T_e = \frac{3}{\omega_S} \cdot \frac{U^2}{\left(R_1 + \frac{R_2'}{S}\right)^2 + \left(X_1 + X_2'\right)^2} \cdot \frac{R_2'}{S} \tag{1}$$

$$T_a = T_m - T_e \tag{2}$$

Here, U is voltage of the induction generator (V). R_1 is stator resistance (Ω), $R_2^{'}$ is resistance of the rotor referred to the stator (Ω), X_1 is stator leakage reactance (Ω), $X_2^{'}$ is rotor leakage reactance referred to the stator (Ω), S is induction generator slip, ω_S is synchronous speed $\left({}^{rad}/_{s} \right)$, T_a is accelerating torque, T_m is mechanical torque, and T_e is electromagnetic torque $\left({}^{N}/_{m} \right)$.

After clearing the fault, the generator has high speed and slip. The high slip leads to an increase in reactive power consumption; therefore, the terminal voltage and active power production capability are reduced. As a result, the rotor of the generator continues to accelerate and the system is unable to recover [18].

3. Conventional SVC

The SVC is a shunt device of the FACTS family using power electronics to control power flow and improve transient stability on power grids. The SVC regulates voltage at its terminals by controlling the amount of reactive power injected into or absorbed from the power system. When system voltage is low, the SVC generates reactive power (SVC capacitive). When system voltage is high, it absorbs reactive power (SVC inductive). The variation of reactive power is performed by switching three-phase capacitor banks and inductor banks connected on the secondary side of a coupling transformer. Each capacitor bank is switched on and off by three thyristor switches (thyristor switched capacitor, TSC). Reactors are either switched on-off (thyristor switched reactor, TSR) or phase-controlled (thyristor controlled reactor, TCR). Figure 1 shows the SVC's structure. It consists of a step down transformer, voltage regulator calculating susceptance (B), TCR unit, TSC units, distribution unit calculating firing angle (α) for TCR and TSC switching, and a phase locked loop (PLL) for synchronization of secondary voltage. SVC susceptance (B_{SVC}) is obtained with the following [9]:

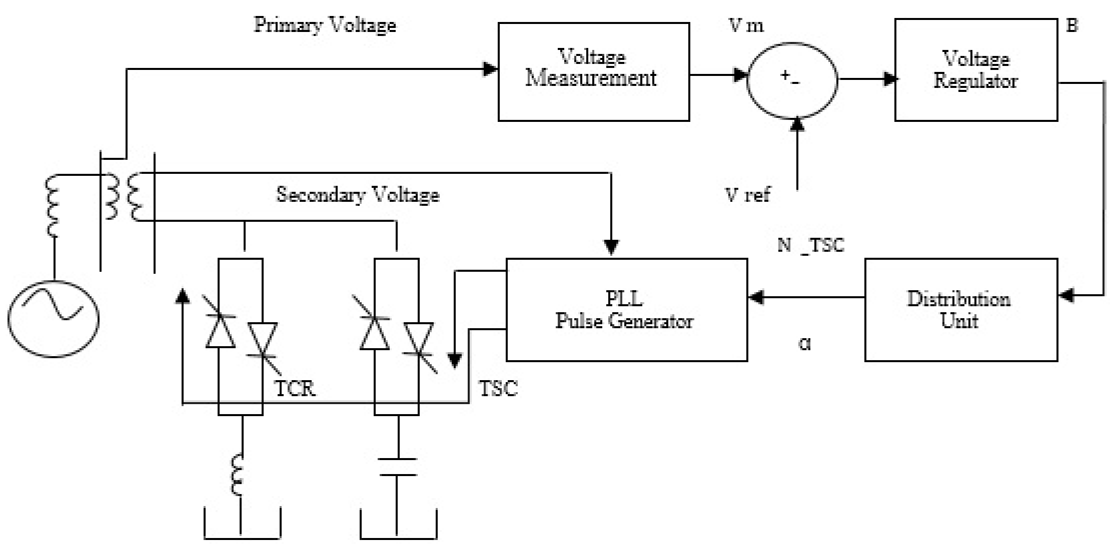

Figure 1. SVC compensator structure.

$$B_{SVC} = -\frac{1}{X_C X_L}\left\{ X_L - \frac{X_C}{\pi}\left[2\pi - 2\alpha + \sin 2\alpha\right] \right\} \tag{3}$$

Here, X_C and X_L are capacitive and inductive reactance, respectively.

4. The concepts of grey system theory and GM (1,1) model

Deng [20] proposed grey systems theory. Grey models can predict the next outputs of a system without knowing the mathematical model of an actual system with high precision. In other words, like fuzzy theory, grey theory is an effective math model to solve indefinite problems. In grey systems theory, GM (n,m) denotes a grey model in which ‘n’ is the rank and ‘m’ the number of variables of a differential equation.

GM (1,1) is first-order one-variable grey model that is used in various fields. This model renews the new data. Differential equation GM (1,1) by n steps solves the predicted value of the system. Finally, using the predicted value, the inverse accumulating generation operation (IAGO) is applied to find the predicted values of original data [15].

If $X^{(0)}$ is a nonnegative main series with n samples, we have

$$X^{(0)}=\left(X^{(0)}(1),X^{(0)}(2),\ldots..,X^{(0)}(n)\right),\ n\geq 4 \tag{4}$$

When this sequence is subjected to the accumulated generation operation (AGO), the following sequence, $X^{(1)}$, is obtained.

$$X^{(1)}=\left(X^{(1)}(1),X^{(1)}(2),\ldots..,X^{(1)}(n)\right),\ n\geq 4 \tag{5}$$

Where:

$$X^{(1)}(k)=\sum_{i=1}^{k}X^{(0)}(i),\ k=1,2,\ldots,n \tag{6}$$

The generated mean sequence $Z^{(1)}$ of $X^{(1)}$ is defined as:

$$Z^{(1)}=\left(Z^{(1)}(1),Z^{(1)}(2),\ldots..,Z^{(1)}(n)\right) \tag{7}$$

Here $Z^{1}(k)$ is the mean value of adjacent data, i.e.

$$Z^{(1)}(k)=\frac{1}{2}X^{(1)}(k)+\frac{1}{2}X^{(1)}(k-1),\ k=2,3,\ldots,n \tag{8}$$

The least square estimate sequence of the grey difference equation of GM (1,1) is defined as follows:

$$X^{(0)}(k)+az^{(1)}(k)=b \tag{9}$$

The whitening equation is therefore as follows:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{10}$$

In the above, $[a,b]^{T}$ is a sequence of parameters that can be found as follows:

$$[a\,b]^{T}=\left(B^{T}B\right)^{-1}B^{T}Y \tag{11}$$

Where:

$$Y=\left[X^{(0)}(2),X^{(0)}(3),\ldots,X^{(0)}(n)\right]^{T} \tag{12}$$

$$B=\begin{bmatrix} -Z^{(1)} & (2) & 1 \\ -Z^{(1)} & (3) & 1 \\ . & & . \\ . & & . \\ -Z^{(1)} & (n) & 1 \end{bmatrix} \tag{13}$$

According to Eq. (10), the solution of $x^{(1)}\,(t)$ at time k is:

$$x_p^{(1)}\,(k{+}1) = \left[X^{(0)}\,(1) - \frac{b}{a}\right] e^{-\,ak} + \frac{b}{a} \tag{14}$$

To obtain the predicted value of the primitive data at time (k + H), the IAGO is used to establish the following grey model [15].

$$x_p^{(0)}\,(k{+}H) = \left[X^{(0)}\,(1) - \frac{b}{a}\right] e^{-a(k+H-1)}\,(1{-}e^{a}) \tag{15}$$

5. The design of a fuzzy-grey controller for SVC

In this study, a method is presented for implementation of a SVC based on grey theory and fuzzy logic to improve the LVRT capability of SCIG wind turbines. In this method, instead of the voltage actual value of the PCC, voltage of the PCC is predicted by grey algorithm and then is compared with the reference voltage value in the SVC voltage regulator. Then the voltage error signal and its derivative signal are considered as input of a fuzzy logic controller. The fuzzy controller with a PI controller in the voltage control loop of the SVC regulates the SVC output (susceptance). Figure 2 shows a diagram of the proposed controller in the Simulink/MATLAB environment.

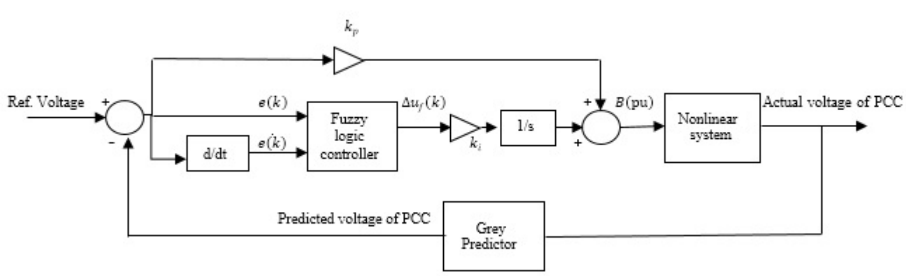

Figure 2. Fuzzy-grey controller modeled in Simulink/MATLAB.

According to Figures 1–3, the methodology can be expressed as follows:

Step 1. Actual voltage data of PCC are generated by simulation.

Step 2. Actual voltage data of PCC are defined as primitive data for the grey algorithm. Then the grey algorithm produces the predicted voltage of PCC based on the flowchart in Figure 3.

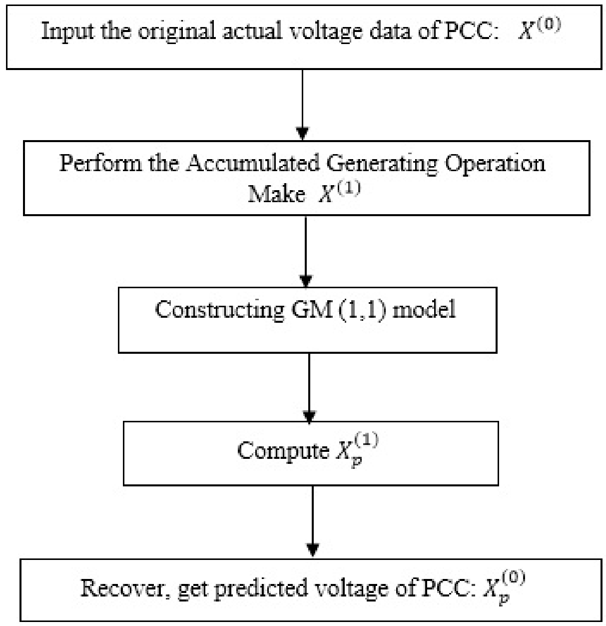

Figure 3. Basic processing model of GM (1,1).

Step 3. The predicted voltage of PCC by grey algorithm is compared with the voltage reference value (i.e. 1 P.U.) and then the voltage error, $e(k)$, is obtained.

Step 4. Voltage error $e(k)$ and derivative of voltage error $\dot{e}(k)$ are applied as inputs to the fuzzy controller. Fuzzy controller output is applied to the integral term of the PI controller for reduction or elimination of voltage error.

Step 5. The SVC susceptance is determined by voltage regulator. A distribution unit determines the firing angle (α) of TCRs. A synchronizing system using a PLL synchronized on the secondary voltages and a pulse generator sends appropriate pulses to the thyristors.

The fuzzy logic controller design details are explained below.

5.1. Designing the fuzzy logic controller

Fuzzy logic control (FLC) is one of the best methods among expert control strategies and it is one of the important tools to control nonlinear, complex systems. This control method is a compatible control based on linguistic variables by innovative rules and previous experiences of operators. Implementation of this control method consists of translating input variables to linguistic variables such as large positive, large negative, zero, etc.

In this paper, FLC is used in place of the integral term while the proportional term is kept unchanged. The fuzzy logic controller design process is explained as follows.

5.1.1. Fuzzification step

The fuzzification step is an entrance step in which input variables to the controller are translated via membership functions to linguistic variables. A fuzzy set is an extension of a classical set. If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs. Thus, in the mathematical equation we have:

$$A = \{x, \mu_A(x) \,|\, x \in X\} \tag{16}$$

where $\mu_A(x)$ is called the MF of x in A. MF is a curve defining how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

In this study, the fuzzy controller consists of two inputs and one output. Input variables are the error between reference voltage and predicted voltage by grey algorithm, $e(k)$, and its derivative, $\dot{e}(k)$. Input membership functions are triangular. Inputs are described by 7 fuzzy sets: large negative (LN), medium negative (MN), small negative (SN), zero (ZO), small positive (SP), medium positive (MP), and large positive (LP) (Figure 4). Output membership functions are linear, as is fuzzy controller output, and the same input fuzzy sets are used. Both the input and output of fuzzy logic are normalized in the interval [–1,1].

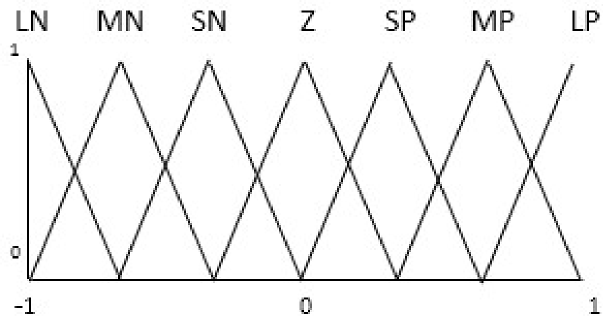

Figure 4. Input and output membership functions.

5.1.2. Rule-based system and inference

For the fuzzy controller, the Takagi–Sugeno fuzzy inference method is used. The relationship between inputs and output of fuzzy logic is defined by 49 rules. The Table shows fuzzy rules. The typical rules are:

Table. Rule-based fuzzy controller.

$\dot{e}(k)$								
LP	MP	SP	ZO	SN	MN	LN	$\Delta u_f(k)$	
ZO	SN	MN	LN	LN	LN	LN	LN	$e(k)$
SP	ZO	SN	MN	LN	LN	LN	MN	
MP	SP	ZO	SN	MN	LN	LN	SN	
LP	MP	SP	ZO	SN	MN	LN	ZO	
LP	LP	MP	SP	ZO	SN	MN	SP	
LP	LP	LP	MP	SP	ZO	SN	MP	
LP	LP	LP	LP	MP	SP	ZO	LP	

Rule 1: If voltage error $e(k)$ is LN AND derivative of voltage error $\dot{e}(k)$ is LN, then the output, $\Delta u_f(k)$, is LN.

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Rule 49: If voltage error $e(k)$ is LP AND derivative of voltage error $\dot{e}(k)$ is LP, then the output, $\Delta u_f(k)$, is LP.

5.1.3. Defuzzification step

In this step, the fuzzy output should be turned into a number. The method used for final fuzzy output is the weight average calculation of all output rules [19].

$$\Delta u_f(k) = \frac{\sum_{i=1}^{9} w_i (u_f)_i}{\sum_{i=1}^{9} w_i} \tag{17}$$

Here, w_i is the firing strength of the rule that weighted the output level. For this controller, w_i is set to 1.

6. Test system and simulation results

6.1. System description

To evaluate the proposed controller's accuracy to improve LVRT, a test system that consists of a SCIG wind farm of 9 MW (6×1.5 MW) linked to a 25-kV distribution network is considered. The 120-kV network is linked via a 35-km, 25-kV feeder to the distribution network. Reactive power absorbed by the IGs is partly compensated by capacitor banks connected at each wind turbine low voltage bus (400 kVAR for each pair of 1.5-MW turbines). To keep PCC voltage at about 1 P.U., a SVC of 3 MVAR is used. The test system is shown in Figure 5. The complete information of the system is shown in the Appendix.

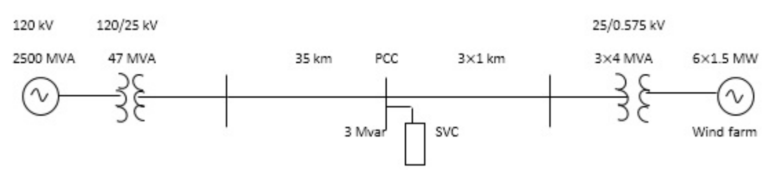

Figure 5. Single-line diagram of test system.

6.2. Transient analysis of the wind farm for a three-phase fault

This section will be devoted to studying the performance of the SCIG wind farm with a conventional SVC for a three-phase fault to ground on the 25-kV system, which starts at t = 15 sec and lasts 0.082 s. As shown in Figure 6, the wind terminal voltage level (575 V) is 0.98 before the fault. The voltage drops to about zero during the fault. At this moment, because of imbalance between the electromagnetic and mechanical torque of the induction generator, the rotor speed increases. After removal of the fault at t = 15.082 s, the wind terminal voltage returns to 0.8, which is lower than the prefault value. In order for the wind turbine to be able to deliver its nominal active power, the wind terminal current increases. Additionally, the rotor speed will not return to the prefault value. As a result, the voltage will continue to drop until 0.75 at t = 16.64. This voltage dropping continues until t = 16.74, and the wind terminal voltage is 0.744. As regards the delay time of the undervoltage relay, which is 0.1 s, it takes out all of the wind turbines in t = 16.74 from the circuit for protection.

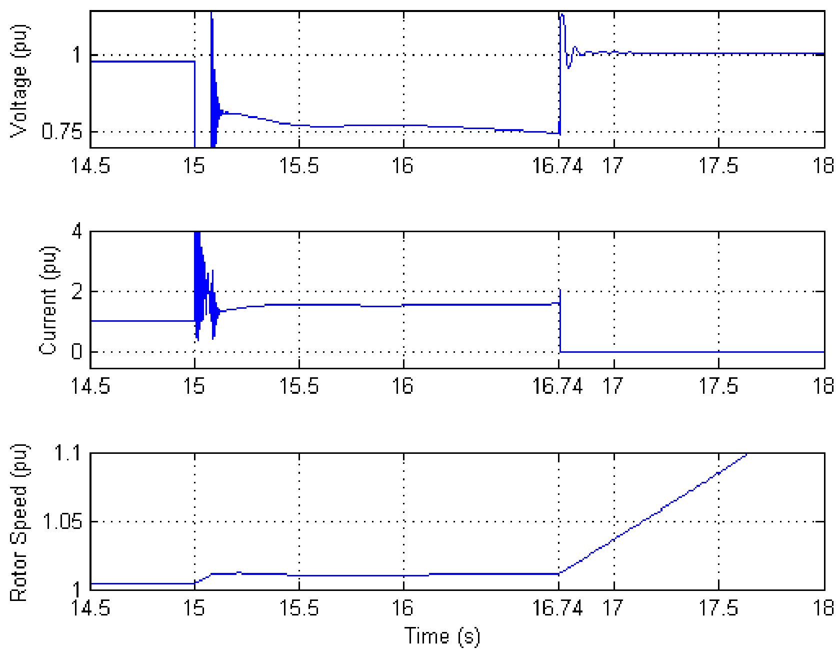

Figure 6. The voltage, current, and speed curve of one of the wind turbines (575 V), with conventional SVC.

6.3. Results for SVC with fuzzy and fuzzy-grey controller

In most control applications, the control signal is based on the present error of the system in the previous time. Error signal is the difference between the actual value and reference value. In grey systems theory, the GM (1,1) model can only be used for positive data sequences [20]. The wind terminal voltage curve is considered in this paper as a data sequence. It is obvious that the voltage value is never negative and the GM (1,1) model can be used to predict voltage curve.

This section investigates the results of performance of the SVC with fuzzy and fuzzy-grey controllers in the improvement of LVRT of the SCIG wind turbines for the same fault as in Section 6.2. As seen in Figure 7, when the conventional SVC is used, the wind terminal voltage (575 V) will continue to drop after fault clearing, until t = 16.74 s, the wind terminal voltage being 0.744 and undervoltage relay taking out all of the wind turbines from the circuit for protection. Based on this figure, SVCs with fuzzy and fuzzy-grey controllers can return the wind voltage to nominal value without taking the turbines out of the circuit, although the voltage return is faster with the fuzzy-grey controller for the SVC. In this work, the prediction horizon of the grey algorithm (i.e. H in Eq. (15)) is considered as 15.

Figure 8 shows the voltage curve of the PCC (25 kV). It is shown that with the conventional SVC, the voltage of the PCC reduces after fault clearing. After that, at t = 16.74, all the wind turbines exit the circuit, and the SVC rapidly returns the voltage to the nominal value. However, the SVC with fuzzy and fuzzy-grey controllers can return the voltage to the nominal value without taking the turbines out of circuit. In the SVC with fuzzy controller, the voltage is returned to its nominal value at t = 18.65, while with the fuzzy-grey controller, the voltage recovery time to the nominal value is reduced to t = 18.34. As a result, the SVC reaction for the voltage recovery is faster.

Figure 9 shows the SVC reactive power curve with the conventional SVC, fuzzy SVC, and fuzzy-grey SVC. As is shown, after the fault clearing, because the conventional SVC cannot meet the demand of reactive power of the wind farm correctly, they are being taken out of circuit by the undervoltage relay. Under these conditions, SVC output is about zero. With the fuzzy and fuzzy-grey controllers, the SVC can quickly provide adequate reactive power for the wind farm.

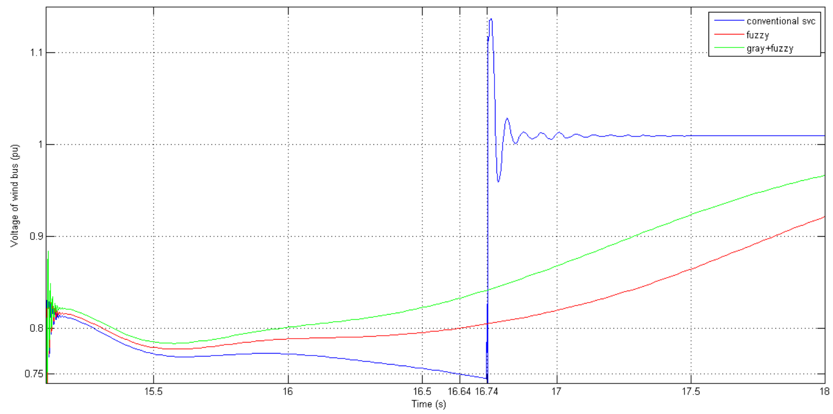

Figure 7. The wind terminal voltage (575 V) with conventional SVC, fuzzy SVC, and fuzzy-grey SVC.

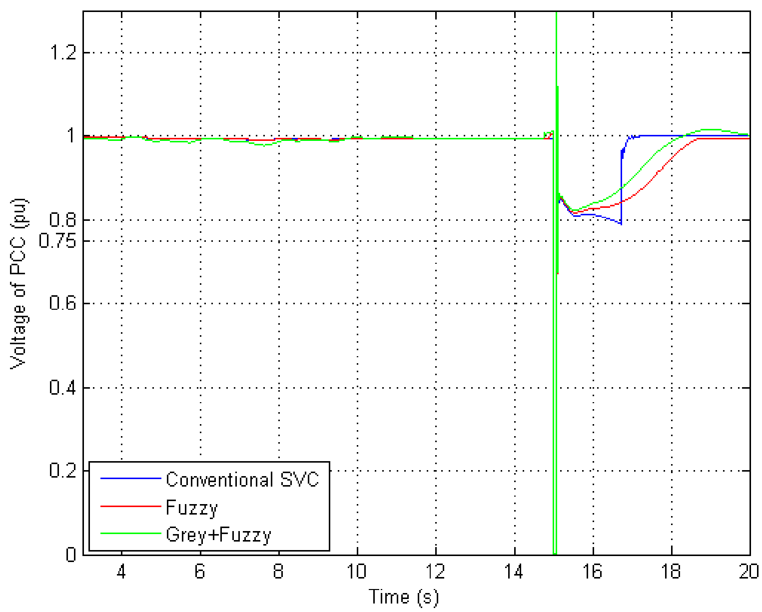

Figure 8. PCC voltage curve (25 kV) with conventional SVC, fuzzy SVC, and fuzzy-grey SVC.

The active power curve of the wind farm is shown in Figure 10. It can be said that with the proposed controller, the output active power profile of the wind farm after the fault clearing rapidly achieves its nominal value.

7. Conclusion

The present study presents a method for implementation of a SVC based on a combination of grey theory and fuzzy logic to improve the LVRT capability of SCIG wind turbines. In the proposed method, instead of the actual value of voltage in the PCC, the predicted voltage value by grey theory of the GM (1,1) model is compared with the reference voltage value. Then the voltage error and derivative of voltage error signal are considered as input for the fuzzy logic controller. The fuzzy controller with a PI controller in the voltage

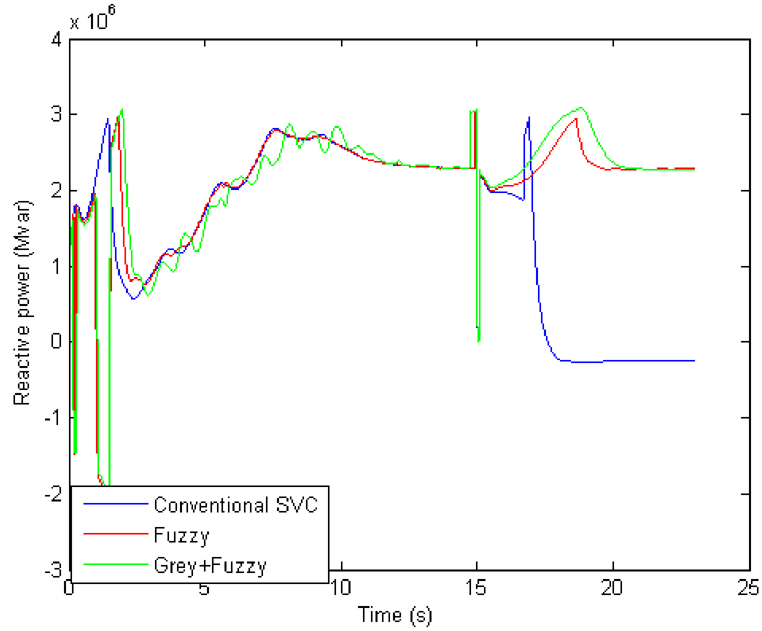

Figure 9. SVC reactive power curve with conventional SVC, fuzzy SVC, and fuzzy-grey SVC.

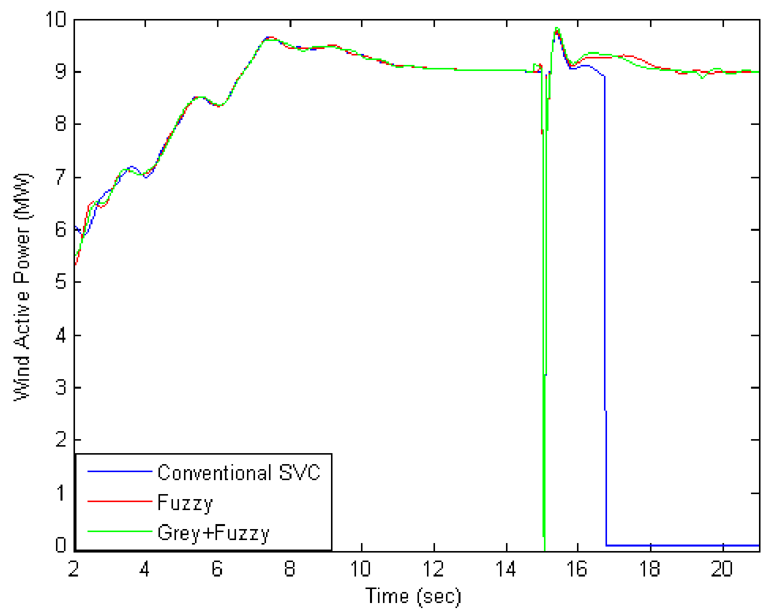

Figure 10. Wind farm active power curve with conventional SVC, fuzzy SVC, and fuzzy-grey SVC.

control loop of the SVC regulates the SVC output (susceptance). The results of simulation show the suitable performance of the SVC combined with a fuzzy controller and grey theory in improvement of LVRT capability of SCIG wind generation compared to the conventional SVC and SVC with fuzzy controller. This means that due to prediction of the terminal voltage curve of the PCC by the grey system the next time, the SVC can deliver the reactive power rapidly and voltage recovery is done rapidly.

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Appendix. System information.

Data of each wind turbine	
575 (V)	Nom. voltage
1.5 (MW)	Nom. power
0.9 (lag)	Power factor
[0.0048 0.1248] (P.U.)	Stator [R_s,L_s]
[0.00437 0.179] (P.U.)	Rotor [R_r,L_r]
6.77 (P.U.)	L_m
9 (m/s)	Base wind speed
Voltage relay data	
1.1 (P.U.)	Upper limit voltage
0.75 (P.U.)	Under limit voltage
0.1 s	Delay time
SVC data	
25 (kV)	Nom. voltage
3 (MVAR)	Reactive power
0.03	Droop X_s
[0, 300]	[K_p,K_i]
Distribution feeder data	
[0.1153, 0.413] (Ω/km)	[R_1,R_0]
[1.05e-3, 3.32e-3] (H/km)	[L_1,L_0]
[11.3e-9, 5.01e-9] (F/km)	[C_1,C_0]
35 (km)	Length
Main grid data	
60 (Hz)	Frequency
120 (kV)	Nom. voltage
2500 (MVA)	Base MVA
3	X_0/X_1