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FRT capability enhancement of wind turbine based on DFIG using machine learning

Makine öğrenimi kullanarak ÇBAG'a dayalı rüzgâr türbininin FRT yeteneğinin iyileştirilmesi

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Abstract

The doubly fed induction generator (DFIG) is very sensitive to the high voltage and current harmful effects that occur during the grid fault. A capacitive bridge type fault current limiter (CBFCL) based on the support vector machine (SVM), which is one of the machine learning (ML) methods, is presented to improve the fault ride-through (FRT) performance of in three phase-to-ground (3LG) symmetric grid fault that may occur in a wind turbine based on DFIG working under normal operating conditions in this study. The machine learning algorithm based on SVM has been implemented in both the control systems of DFIG converters and a control system of CBFCL. Four different SVM classifier algorithms are applied to generate the switching signals of electronic switching elements used in rotor side, grid side converter, and circuit topology of CBFCL. Fine Gaussian, Quadratic, Cubic and Linear kernel functions are preferred in the training of SVM classifiers. The developed SVMs have been suitably trained to true predict and decide behaviours of converters during normal and grid fault conditions. The performance of Fine Gaussian and Linear types of SVM is compared to the effectiveness of training efficiency for a wind turbine based on DFIG. The accuracy rate of the Fine Gaussian of SVM is 100 %, while the accuracy rate of Linear SVM is 22 %. The simulation results show that the Fine Gaussian SVM protects more efficiently from the harmful effects of 3LG grid fault compared to the Linear SVM for a wind turbine based on DFIG.

Keywords: Doubly fed induction generator (DFIG), Machine learning (ML), Capacitive bridge type fault current limiter (CBFCL), Wind turbine (WT),

Öz

Çift beslemeli asenkron generatörü (ÇBAG), şebeke arızası sırasında meydana gelen yüksek gerilimin ve akımın zararlı etkilerine karşı çok hassastır. Makine öğrenmesi (ML) yöntemlerinden biri olan destek vektör makineye (DVM) dayalı bir kapasitif köprü tipi arıza akım sınırlayıcısı (KKTAAS), üç fazlı arızada geçiş (FRT) performansını iyileştirmek için önerilmiştir. Bu çalışmada, normal şebeke koşullarında çalışan ÇBAG tabanlı bir rüzgâr türbininde oluşabilecek faz-toprak (3LG) simetrik şebeke hatası DVM' ye dayalı makine öğrenimi algoritması hem ÇBAG dönüştürücülerin kontrol sistemlerinde hem de KKTAAS' in bir kontrol sisteminde uygulanmıştır. Rotor tarafında, şebeke tarafında dönüştürücüde ve KKTAAS' in devre topolojisinde kullanılan elektronik anahtarlama elemanlarının anahtarlama sinyallerini üretmek için dört farklı DVM sınıflandırıcı algoritması uygulanmıştır. DVM sınıflandırıcılarının eğitiminde İnce Gauss, Kuadratik, Kübik ve Doğrusal kernel fonksiyonları tercih edilmiştir. Geliştirilen DVM' ler, normal ve şebeke arızası koşulları sırasında dönüştürücülerin davranışlarını doğru tahmin etmek ve karar vermek için uygun şekilde eğitilmiştir. İnce gauss ve Doğrusal DVM türlerinin performansı, ÇBAG' ye dayalı bir rüzgâr türbini için eğitim verimliliğinin etkinliği ile karşılaştırılmıştır. DVM' in İnce Gaussian' in doğruluk oranı %100'dür, Doğrusal DVM' in doğruluk oranı ise %22'dir. Simülasyon sonuçları, İnce Gaussian DVM' in, ÇBAG tabanlı bir rüzgâr türbini için Doğrusal DVM' ye kıyasla 3LG şebeke hatasının zararlı etkilerinden daha verimli bir şekilde koruduğunu göstermektedir.

Anahtar kelimeler: Çift beslemeli asenkron generatör (ÇBAG), Makine öğrenmesi (ML), Kapasitif köprü tipi arıza akım sınırlayıcı (KKTAAS), Rüzgâr türbini (RT),

1 Introduction

In recent years, due to the fluctuations in oil prices, the importance of wind power plants has increased day by day. Several generator types are used in wind power plants such as direct current, permanent magnet synchronous, and double feed induction generator (DFIG) [1,2].

Grid code is a technical specification, which must meet to ensure proper operation, defining parameters like the electrical system is safe, secure, and economical. All countries have not a common grid code and each country has a different grid code [3]. Requirements of the grid code are divided into two categories as dynamic and static requirements. All electricity generating facilities, including independent energy producers such as wind turbines and photovoltaic power plants, must comply with the grid code [4]. A grid code will determine the required behaviour of a connected generator during grid faults. These include reactive power supply, power factor limits, and voltage regulation [5]. In literature, there have been many studies that electricity-generating facilities and consumers remain

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continuously connected to the electrical power grid system during grid fault such as the crowbar system [6-8], static synchronous compensator (STATCOM) [9,10], static VAR compensator (SVC) [11], series dynamic braking resistor (SDBR) [12], dynamic voltage restorer (DVR) [13,14]. Recently, new modified [15] and new structure [16] models have been proposed for the bridge type fault current limiter (BFCL). The capacitive-BFCL (CBFCL) method has started to be used among the stability methods of electrical power grid systems. The CBFCL produces a practical solution to protect the wind tribune system from the harmful effects of high-level fault currents [17]. The CBFCL has zero impedance in the normal operation of the power grid and high impedance in the case of a grid fault. There is no power loss o grid system during normal operation due to CBFCL. In addition, CBFCL has superior features compared to other methods such as rapid recovery after fault elimination and operating immediately after the fault occurs [18].

According to a literature review, traditional control methods are predominantly used in control systems of the CBFCL and WT. Traditional control methods provide a performance suited to a given output. However, traditional control systems remain weak in solving complex systems such as WT based on DFIG compared to machine learning (ML). Recently, ML control system has been applied in many renewable energy fields such as wind energy [19], solar energy [20-24], and power grid [25,26]. However, the ML algorithms have been carried out in a limited number of studies in wind turbine protection systems, especially for grid faults. Some studies presented in the literature have been carried out for the WT's protection system based on ML algorithms. Yun et al. [27] proposed the ice detection of WT using a novel adaptive inductive transfer learning. This study applied the 5 methods, which are the most general classification methods. These methods are Fully-connected Neural Networks, Random Forest, AdaBoost, Quadratic, and k-Nearest Neighbors (kNN) classifiers. The accuracy value of Autoencoder and TrAdaBoost is 0.94. This value is near the normal operating value. Hsu et al. [28] applied a statistical program control to define the four faults of a WT using two machine learning algorithms, such as hydraulic oil systems, generators, gearboxes, and rotary blades. The data of WT are obtained from normal and abnormal conditions of the wind turbine operation. The accuracy rate of the machine learning algorithm is higher than 92%. Zhang et al. [29] implemented the diagnosis method of the gearbox bearing fault of WT using deep learning methods. The bearing fault diagnosis method consists of a support vector machine (SVM) classifier and a one-dimensional convolutional neural network. The above methods in the literature have been suggested for different protection systems of WT such as ice detection, and gearbox bearing fault. Also, these studies are related to outdoor working conditions and the reduction of mechanical negative effects. However, indoor working conditions of wind turbine based on DFIG have a more complex structure than outdoor working conditions. Therefore, a CBFCL based on an ML system is proposed to protect DFIG from the harmful effects of grid fault in this study. In this respect, the subject dealt with is quite different and original from the related literature studies.

This paper introduces a novelty control algorithm using machine learning to performance enhance DFIG based on WT during 3LG grid fault. A machine learning method based on the SVM classifier algorithm is designed to enhance the FRT capability of the DFIG based on WT during normal and fault operation conditions. SVM has advantages such as being productive in multidimensional data analysis, solving complex problems with kernel solution functions, and producing optimum output even if there is not enough information data. Due to these advantages, a performance analysis of various SVM techniques has been made to protect more efficiently from the harmful effects of 3LG grid fault of WT based on DFIG in this study. The main contributions of the article work can be summarized as:

1) Unlike previous studies in the literature, a machine learning algorithm is implemented in the control systems of both CBFCL and DFIG converters.

2) Proposed machine learning algorithm has been suitably trained to true predict and decide behaviours of converters during normal and fault operation conditions.

3) The accuracy rate of Fine Gaussian of SVM is 100 %, while the accuracy rate of Linear SVM is 22 %.

4) The Fine Gaussian of SVM more efficiently protects DFIG based on WT from the harmful effect of 3LG grid fault compared to Linear SVM.

2 Wind turbine and mathematical model of DFIG

WT is a device that converts wind energy into electrical energy. WT is designed considering factors such as cost, energy output, and low fatigue life. A wind turbine needs to achieve the maximum theoretical power output in order to effectively generate electrical power. It has been emphasized that the different parameters of a WT have different effects on the output power of WT in literature studies. If a wind speed is represented by v, the conversion coefficient is represented C_p, the air density is represented ρ, and the swept area is represented by A, the output power of the WT is obtained in Equation 1 [30].

$$P_m = \frac{1}{2}\rho A C_p(\lambda,\beta)v^3 \tag{1}$$

If the wind speed is depicted by v and an angular velocity of a WT is represented by ω_m, λ is obtained as the type speed ratio in Equation 2 [30].

$$\lambda = \frac{\omega_m R}{v} \tag{2}$$

where, λ depict a rate between wind speed and angular speed of WT. R depict the radius of wind turbine blade in Equation 2 [30].

DFIG is the most commonly used type of generator in WT due to its flexibility and ability to control reactive and active power. A mathematical model of DFIG is stated to be very useful for analyzing its electrical properties under both normal and fault conditions. The general and widely used mathematical model of DFIG has been obtained using the transformation model of the Park model. The rotor and stator voltages of DFIG are given in a suitable d-q reference frame as follows [31,32]:

$$v_s = R_s i_s + \frac{d\psi_s}{dt} + j\omega_e \psi_s \tag{3}$$

$$v_r = R_r i_r + \frac{d\psi_r}{dt} + j(\omega_e - \omega_r)\psi_r \tag{4}$$

where, v_r and v_s are the voltages of the rotor and stator, respectively. R_s and R_r depict resistances of rotor and stator, respectively. L_r and L_s depict inductances of the rotor and stator, respectively. ω_e and ω_r depict the electrical angular velocity and the angular velocity of the rotor, respectively. ψ_r and ψ_s depict the inductances of the rotor and stator, respectively. The flux components of rotor and stator are expressed by [31,32]:

$$\psi_s = L_s i_s + L_m i_r \tag{5}$$

$$\psi_r = L_r i_r + L_m i_s \tag{6}$$

where, L_r and L_s depict inductances of rotor and stator, respectively. i_r and i_s depict currents of rotor and stator, respectively [31,32].

3 The design of the proposed system

A single-line diagram of WT based on DFIG is illustrated in Figure 1. Rotor side converter regulates reactive and active power of the generator by means of IGBT gate signals, while grid side converter regulates DC Link voltage amplitude (V_{dc}) by means of IGBT gate signals. A proportional-integral (PI) controller is usually used to obtain the control signal of the IGBT gate signal in the literature. The PI controller generates optimum output for a given operating condition. The conventional control systems are not capable of dealing with some challenges in complex systems such as WT based on DFIG. The PI control system does not give effective results in varying operating conditions such as grid fault due to the fact that its parameters have been fixed. The PI has difficulty controlling a WT with uncertain operating conditions. However, the proposed control technique has overcome the uncertainties of a WT based on the DFIG system [33]. Therefore, the machine learning control system has been applied separately for grid and rotor side converter control systems in the study. Machine learning, which is considered a part of artificial intelligence, is defined as a computer algorithm that improves automatically with the use of data and experience. The machine learning algorithm has different types due to the fact that each system has a different type of task and data or the solve methods of problem. The machine learning algorithm has two methods: classifying data according to the developed models and making predictions for future results based on these models. Machine learning algorithm has several types of learning methods such as reinforcement, unsupervised and supervised learning.

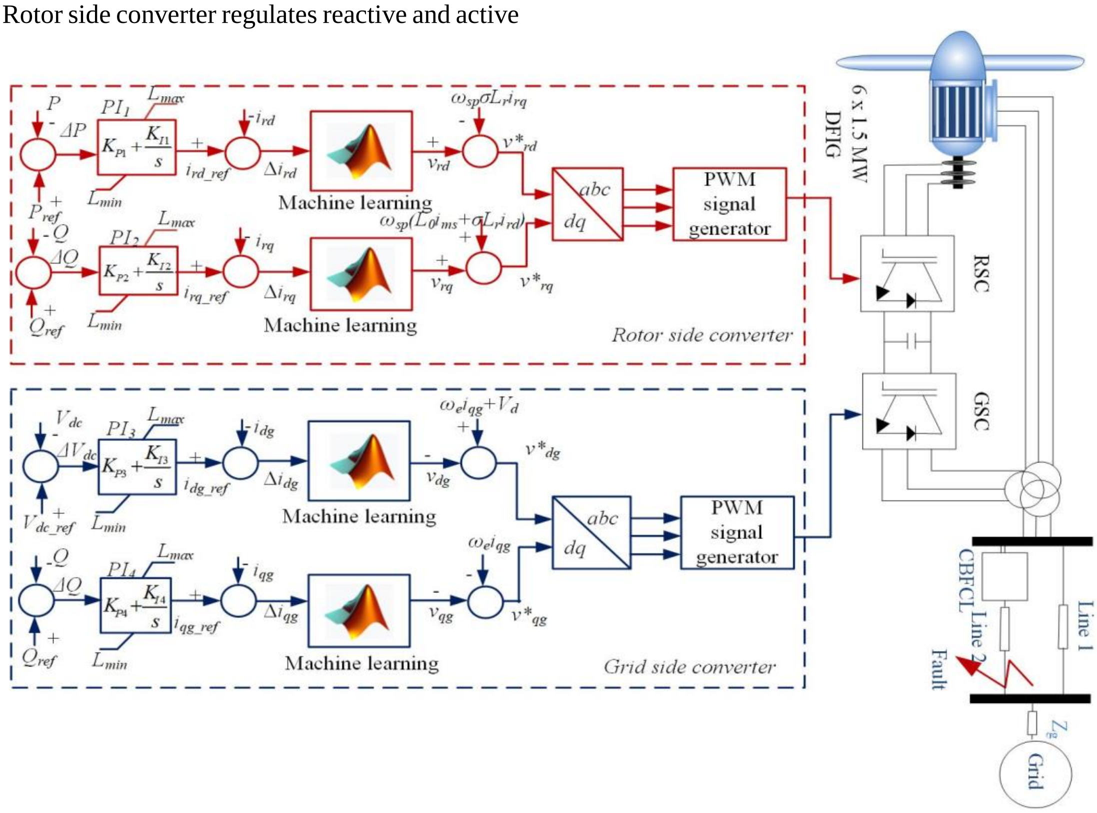

Figure 1. A single line diagram of WT based on DFIG using machine learning.

Classification Learner Toolbox in Matlab has various classifier types such as SVM, kNN, and ensemble. SVM is one of several classification algorithms in the machine learning models and is one of the most widely used in the supervised learning models that analyze for classification and regression. The classifier techniques of the SVM are Coarse Gaussian, Medium Gaussian, Fine Gaussian, Cubic, Quadratic, and Linear in the Matlab. A support vector machine, which is a supervised learning model, is used in this study [19].

4 Capacitive bridge type fault current limiter based on machine learning control

The circuit topology of the CBFCL based on machine learning control is given in Figure 2. CBFCL consists of two parts, called the bridge and shunt parts. A shunt part includes of Capacitor (C_{sh}) and resistor (R_{sh}). A shunt part has a high impedance. In this study, the best results of the system are obtained by choosing the values of capacitance and resistance as $C_{sh} = 50\ \mu F$ and $R_{sh} = 10\Omega$. The bridge part consists of four bridge diodes, a small resistor, an inductor and a freewheeling diode. The resistor (R_{dc}) and inductor (L_{dc}) are connected in series and this is called dc reactor. Dc reactor is in the middle of four bridge diodes. In this study, the best results of the system are obtained by choosing the values of inductor and resistance as $L_{dc} = 0.015\ H$ and $R_{dc} = 0.015\ \Omega$. A freewheeling diode discharges the energy stored in the DC reactor when the IGBT switching signal turns on [2].

5 Simulation Results

The model of WT based on DFIG is simulated in the Matlab/Simulink. Machine learning control method is implemented to control system of a 9-MW, 690V DFIG based on WT. The wind speed is 15 m/s and DC Link voltage is 1150 V. CBFCL based on ML system is applied to protect from the harmful effects of overcurrent during a grid fault.

A comparison of four SVM classification methods is given in Table 1. The accuracy rates of Cubic SVM, Quadratic SVM, and Fine Gaussian SVM are 100 %. This value of the proposed system indicates that the model is more effective in classifying the wind turbine. The accuracy rate of Linear SVM is 22%. Each type of SVM has 1000 test samples in the test set. However, 10 of these test examples are given in the confusion matrix in Figure 3.

Table 1. Comparison of different SVM classification methods

SVM Classification Method	Accuracy Rate (%)
Fine Gaussian SVM	100%
Quadratic SVM	100%
Cubic SVM	100%
Linear SVM	22%

The 3LG grid fault, which is called a symmetrical grid fault, is the most serious type of grid fault. Therefore, it is vital to control this type of grid fault. The 3LG grid fault is applied at t = 4 s and cleared after 4.5 s in the study.

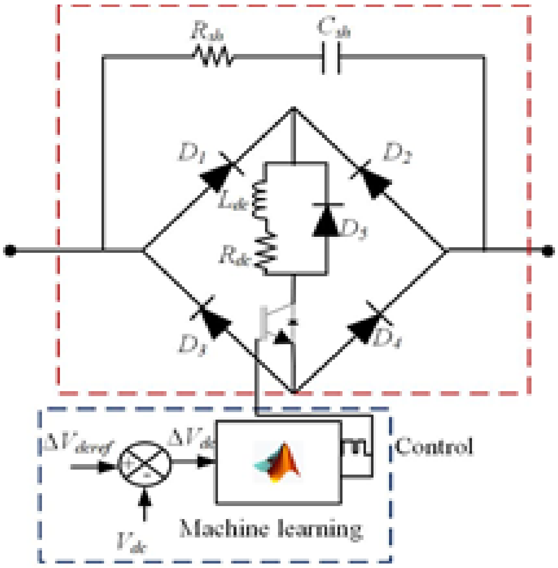

Figure 2. Circuit topology of the CBFCL based on machine learning control.

Table 2. Comparison of tracking the performance of two SVM methods for the 3LG grid fault in time t=4.5

Signal	Method	Peak value	Lowest value	Settling time	Steady state error
P(MW)	Fine Gaussian SVM	9.717	8.78	4.75	0.002
	Linear SVM	12.73	1.058	7	0.3
Q(MVAR)	Fine Gaussian SVM	0.393	-0.24	4.8	0.001
	Linear SVM	3.535	-2.22	4.9	0.39
Vdc(V)	Fine Gaussian SVM	1171	1145	4.605	0.02
	Linear SVM	1343	1107	4.62	4
Te (p.u.)	Fine Gaussian SVM	-0.616	-0.95	4.65	0
	Linear SVM	0.3	-2.7	7	0.06
PCC (p.u.)	Fine Gaussian SVM	1	0.91	4.75	0
	Linear SVM	1.0125	0.18	4.9	0.01

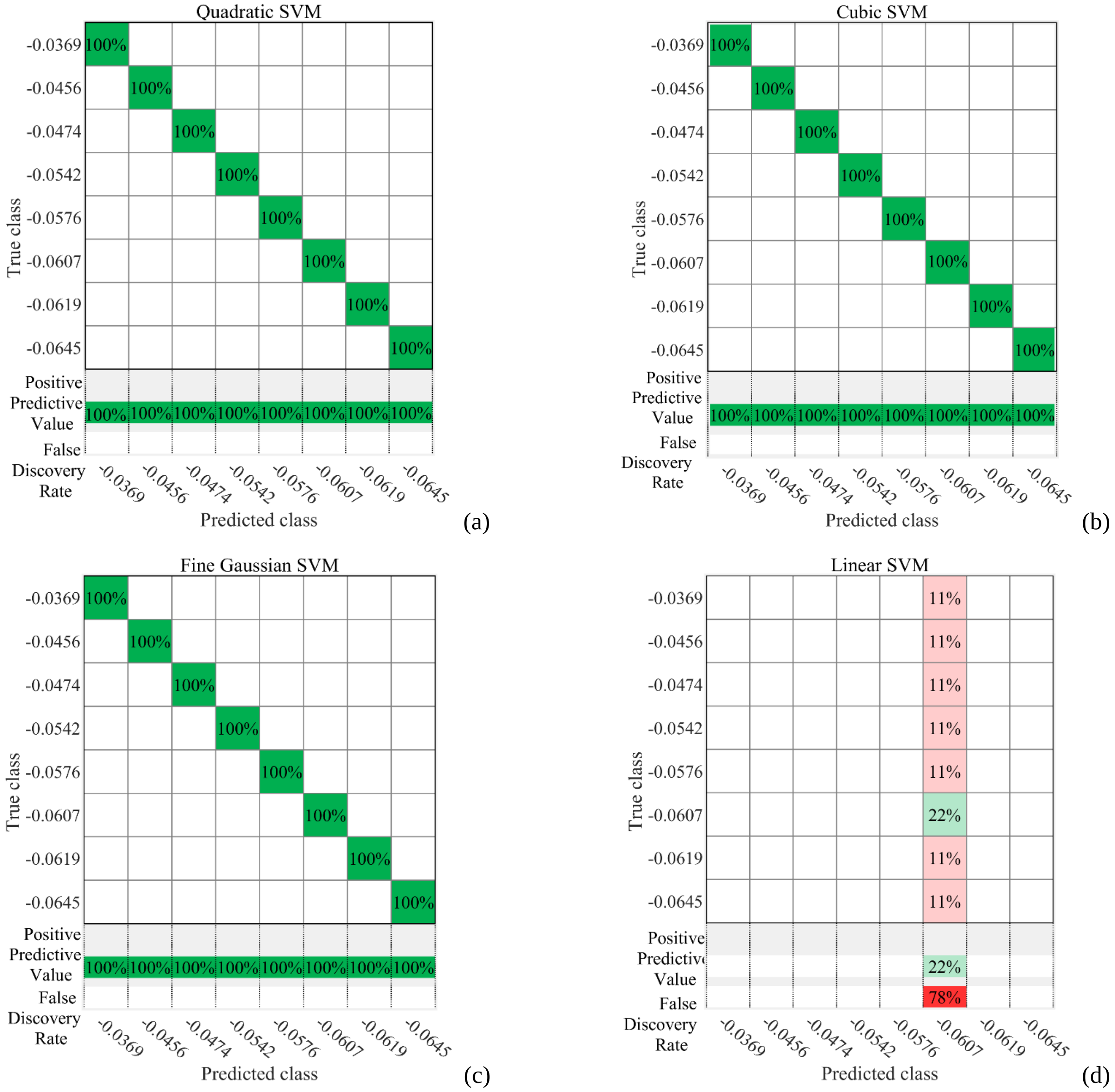

Figure 3. Confusion matrix of different SVM models

The numerical results in terms of peak value, lowest value settling time, and steady-state error are illustrated in Table 2. Figure 4(a) illustrates the variations in active power of WT with both protection methods. The active power peak value of WT with the proposed control algorithm is 9.717 MW and the active power lowest value of WT with the proposed control algorithm is 8.78 MW during the 3LG grid fault. Settling time and steady-state error of power of WT with the proposed control algorithm are very low compared to Linear SVM control algorithm results. Figure 4(b) illustrates the variations in the reactive power value of WT. The rated value of reactive power is 0 MVAR during normal operation. The settling time of the Linear SVM is 0.1 s longer than presented control system and then value of reactive power returns to the rated value nearly. However, the steady-state error of the Linear SVM is 0.39. Figure 4(c) illustrates the variations in DC link voltage of WT with both protection methods. The rated value of DC link voltage is 1150V during normal operation. The peak value of DC link voltage with the Linear SVM is 1343 V. The electronic switching elements can be damaged due to the fact that this value is more than the nominal value. Figure 4(d) and (e) illustrate the variations in the electromagnetic torque (p.u.) and voltage (p.u.) of the PCC, respectively. The lowest value voltage of the PCC with the Linear SVM algorithm is 0.18 p.u. The wind turbine cannot stay connected with the grid during 3LG grid fault because the voltage value of PCC with the Linear system is significantly reduced. According to simulation results, the proposed method is fully capable of controlling to 3LG grid fault.

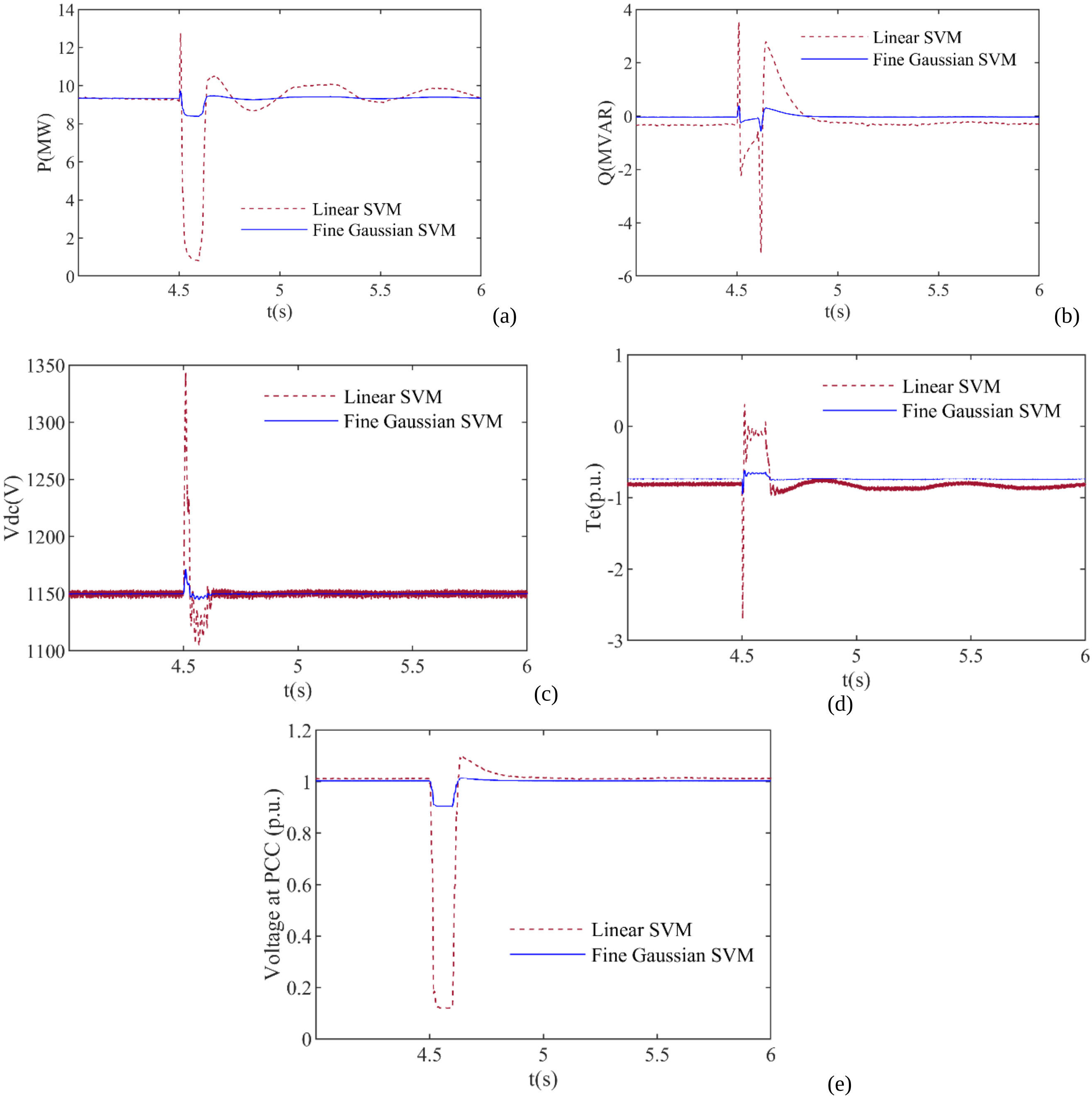

Figure 4. Dynamic response of a 9MW DFIG with machine learning methods during a 3LG symmetrical fault.

6 Conclusion

The model of wind turbine based on DFIG is simulated in Matlab/Simulink. The simulation results are obtained in real-time. In this paper, a CBFCL based on a machine learning algorithm is presented to enhance the FRT capability of the wind turbine based on DFIG during normal operation conditions and grid fault. The machine learning control method is applied to both the control systems of DFIG converters and the control system of the CBFCL.

Fine Gaussian SVM, Quadratic SVM, Cubic SVM, and Linear SVM are applied to generate the switching signals of electronic switching elements used in the rotor side, grid side converter, and circuit topology of the CBFCL. The performance of these types of SVM is compared to the effectiveness of training efficiency for a wind turbine. The accuracy rates of Cubic SVM, Quadratic SVM, and Fine Gaussian SVM are 100 % in Table 1. This value of the proposed system indicates that the model is more effective in classifying the wind turbine. Peak value, lowest value, settling time and steady-state error values of WT with the proposed control algorithm are very low compared to Linear SVM control algorithm results during the 3LG grid fault. WT with presented control system can stay connected with the grid during the 3LG grid fault due to the fact that the voltage value of the PCC with the proposed control system is reduced to an acceptable range. According to simulation results, the proposed method has fully capable of controlling the 3LG grid fault. The simulation results show that presented type of SVM is more efficiently protects the DFIG based on wind turbine from the harmful effect of 3LG grid fault compared to the other types.

Conflict of interest

The authors declare that there is no conflict of interest.

Similarity rate (iThenticate): %14

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