Transient Stability Analysis of Ocean Wave Energy Fed to a Power Grid Using a SSSC

Kai-Hung Lu¹,², Qiangqiang Xu¹,²,* and Ziwen Chen¹,²,*

¹ School of Information Technology, Beijing Institute of Technology, Zhuhai. No.6 Jinfeng Road, Zhuhai City, China
² Zhuhai Key Laboratory of smart grid and new energy technology. No.6 Jinfeng Road, Zhuhai City, China

* Correspondence: khluphd@163.com

Abstract. This paper proposes the design of a closed-loop vector control structure based on Recurrent Functional Link based Elman Neural Network (RFLENN) for a Static Synchronous Series Compensator (SSSC), linking to a Seashore Wave Energy System (SWES) driven Doubly-Fed Induction Generator (DFIG) is connected. A RFLENN controller for a SSSC in order to reduce the power fluctuations, voltage support and damping for a hybrid power system. The proposed RFLENN is a functional link-based recurrent Elman Neural Network. Analysis of the performance of the proposed controller shows that it can achieve better damping characteristics. The internal power fluctuations to the power system can effectively stabilize the network under unstable conditions. This paper presents a closed-loop vector control structure based on RFLENN for a grid-connected SWES driven DFIG. This paper presents the transient stability improvement and power-flow control results of a DFIG-based SWES connected to a SSSC connected in series with one of two parallel transmission lines.

1. Introduction
Ocean wave energy is gaining interest as renewable and clean power sources. Various strategies have been proposed to control the speed of wind turbines and seashore wave energy systems. In recent years, ocean wave power farms have been evaluated and are now in commercial operation. Offshore wave farms are being evaluated and developed in the seas around Western Europe and the United Kingdom [1]. New offshore ocean wave power is being built and hence there are more opportunities to include other offshore renewable energy technologies such as wave energy converters and Wells turbines. There are main aspects to the integration of wave energy [2].

The ocean wave energy industry is currently developing rapidly, although there is only limited information about large-scale wave energy conversion system performance. A Well-designed and properly controlled electrical drive for the Wells turbine can operate at low values of air velocity to reduce the average power generated, and such a performance is undesirable [3]. However, the economic performance of the SWES is still far from competitive and significant scope exists for the improvement of the capacity factor using the intelligent control systems [4]. Three-phase doubly-fed induction generators (DFIG) are widely used for generating power from renewable energy sources, such as wave, wind and small hydro for standalone and grid-connected applications.

The Static Synchronous Series Compensator (SSSC) proposed by Gyugyi and Hingorani, is the most versatile and powerful FACTS device [5-7]. It can increase the system security by raising the...
transient stability limit, limiting short circuit currents and overloads, blackouts and damping oscillations of power systems. In recent years, several studies have proposed control methods for SSSC to improve the damping of the low frequency power oscillations in power systems, such as the use of nonlinear voltage control loops, state feedback control techniques, or Adaptive critic designs [8-10]. However, the complexity of the renewable energy systems to which the SSSC is connected means that the control schemes become less efficient with regard to mitigating SSR, thus reduce the control performance. Some studies have proposed external controllers using intelligent control schemes, such as fuzzy logic controllers, neuro-fuzzy external controllers and a Gray-Based Genetic algorithm method [11-13].

The Elman neural network (ENN) is a partially recurrent network model that was first proposed by Elman in 1990 [14]. The dynamic characteristics of an Elman network are given using internal connections, and the state of the system does no need to be used as an input or training signal. The ENN is better than a static feed-forward network, and thus is widely applied with dynamic systems, although its convergence and training speed are usually very slow. In order to improve the ability to identify complex dynamic systems, a functional-link neural network (FLNN) is adopted in this paper to improve the performance of the ENN. This improved performance is because the input variables are linearly independent trigonometric basis functions which are used for a functional expansion of the FLNN in the extended space for classification. Moreover, the FLNN can capture the nonlinear input–output relationships among a suitable set of polynomial inputs, since the high-order effects are incorporated in the input variables into higher dimensions of the input space. The FLNN can thus effectively approximate a nonlinear function [15-16], and so it is suitable to be applied in complex power system applications, such as the one examined in this work.

This paper proposed a RFLENN for a SSSC to damp power system oscillations. The proposed RFLENN consists of the Functional Link based Elman Neural Network and a feedback path. The RFLENN for the SSSC damping controller is developed to achieve improvements in transient stability. An integrated DFIG-based wave energy system is studied under the condition of changes in wave speed, with a focus on a three-phase short circuit fault and the transient responses of the system. The performance of conventional controllers degrades under such changes, and thus these need to be retuned to give the desired performance, a weakness the RFLENN approach overcomes.

2. Modeling of the Studied System
Fig. 1 shows the configuration of the system studied in this paper. The SG is connected to a single-machine infinite-bus through a transformer T1 and two parallel transmission lines; where line 2 contains the proposed SSSC located near Bus S. The aggregated SWES containing 200MW DFIG-based Wells turbine generators is connected to Bus S through a T2 transformer. The SWES represented by a large equivalent aggregated DFIG is driven by an equivalent aggregated Wells turbine through the gearbox. The employed capacity of the proposed SSSC is 80 MVA, and its series voltage is added to Bus S (voltage V3), by the series connected transformer T3.

![Figure 1](image1.png)  
**Figure 1** Configuration of a SSSC system with the studied power system of a SWES

![Figure 2](image2.png)  
**Figure 2** Schematic diagram of the studied wave energy power generation system

2.1. System Configuration
Fig. 2 shows the system configuration of the proposed block diagram of the power circuit and control strategy for DFIG converting power from the wave to deliver power into the electric grid with constant frequency and the AC line voltage for a large range of wave variation. The proposed AC/DC converter is designed to convert the variable-frequency variable-voltage power generated by the DFIG AC power to regulated DC power. The variation of the wave speed of the turbine or when changing the load, there is provided an effective method of control based on RFLENN control system of the dc link voltage. This method is used to control the electrical torque of the DFIG driven by a variable speed wave turbine, where different forms of wave speed variation effect taken into consideration.

2.2 Wells Turbine Model
The capture mechanical torque from wave \( T_t \), torque coefficient \( C_t \), and the angle of incidence of air on the turbine blade \( \alpha \) of the studied Wells turbine can be expressed by the following equations, respectively [17]

\[
T_t = kC_t \left( V_A^2 + V_P^2 \right)
\]

\[
C_t = C_1 + \frac{C_2 \alpha^2 - C_3 \alpha^2 + C_4 \alpha - C_5}{C_6 \alpha^2 + C_7 \alpha - C_8}
\]

\[
\alpha = \tan^{-1}\left( \frac{V_A}{V_P} \right)
\]

where \( V_A \) is the axial velocity in m/s, \( V_P \) is the blade tip speed in m/s, \( k \) is the coefficient of the employed Wells turbine, \( C_1 - C_8 \) are constant, and \( \alpha \) is defined as the arctangent of the ratio of \( V_A \) to \( V_P \). The torque \( (T_t) \) produced from the axial velocity \( V_A \) of the Wells turbine is delivered to the shaft of the DFIG. The DFIG’s rotational speed must be higher synchronous speed to make sure that the generated active power of the DFIG can be delivered to the grid.

2.3. Doubly Fed Induction Generator
The wind generator is chosen as a three-phase DFIG. The mechanical torque \( (T_m) \) and electrical torque \( (T_e) \) can be expressed as

\[
T_m = \frac{P_m}{\omega}
\]

\[
T_e = \frac{P_e}{\omega} = \frac{P_r}{\omega}
\]

In general, the mechanical dynamic equation of a DFIG is given by

\[
J \frac{d\omega}{dt} = T_m - B\omega_e - T_e
\]

where \( \omega_e \) is electrical angular frequency, \( J \) is the inertia moment of WTG, \( B \) is the friction coefficient of the generator.

2.4 SSSC
The SSSC can supply both the capacitive and the inductive compensation to support the bus voltage \( V_s \) by independently controlling its output current. The real current is responsible for controlling the real power, while there active current is used to control the reactive power and the power system. It is also capable of improving the power system stability. The SSSC is controlled by external damping controller to damp the reference signal of the dc voltage. The control block of the traditions external damping controller for SSSC is shown in Figure 3.

Real power of line 2 \( P_L \) can be controlled by its series voltage of SSSC. Under the synchronous reference frame, the d-q axis components of the simple PI controllers are used to generate the direct and quadrature components of the modulated voltages. The direct and quadrature components of the
voltages are then used to generate the modulation index and phase shift for the PWM module. $P_L^*$ is reference signals for the real power flows through the transmission line. $V_s^*$ is reference signal for the sending voltage and dc link voltage of the SSSC. $K_{p1}$, $K_{p2}$, $K_{i1}$, and $K_{i2}$ are the proportional and integral gains for the series PI controllers. $V_{S(0)}$ and $V_{S(o)}$ are the initial values for the d-q axis voltages at the synchronous reference frame. The modulation index $m$ and phase shift $\alpha$ are provided to the PWM generator, which generates the gating signals for the power electronic switches in the SSSC.

![Figure 3](image)

**Figure 3** The control block of the SSSC with damping controller

3 **Recurrent Functional Link based Elman Neural Network (RFLENN)**

The designed RFLENN produce the variation gains values $\Delta K_P$ and $\Delta K_I$ of PI controller of the SSSC to improve the SWES system stability.

3.1 **Structure of RFLENN**

Fig. 4 shows the design of the RFLENN. It has an input layer, a hidden layer with a sigmoid function $S(x)=1/(1+e^{-x})$, a context layer, and an output layer that is connected with an FLNN. The context layer is fed back to itself with a time delay $z^{-1}$. The FLNN uses a feedforward neural network structure to generate a set of linearly independent functions, and functionally expands the elements of the input variables. The trigonometric function is used in the FLNN, since it can be computed more quickly than the Gaussian, sine and cosine functions. Moreover, it also provides better performance results when the outer product term is taken into account in the function expansion [16]. The input vector $X=\{X_1, X_2\}^T$, which is a functional expansion that uses a trigonometric polynomial basis function, can be written in the enhanced space as $\psi=[\psi_1, \psi_2, \ldots, \psi_p]=\{1, \sin(\pi X_1), \cos(\pi X_1), X_2, \sin(\pi X_2), \cos(\pi X_2), X_1 X_2\}$, where $X_1 X_2$ is the outer product term. Furthermore, the FLNN output is expressed by a linear sum of the yth node, as follows:

$$
\hat{y}_j(k) = \theta \left( \sum \psi_{E} (x_i) \cdot w_{Ey} \right) = \theta \left( w_{Ey} \cdot \psi_{E}(X) \right)
$$

where $\hat{y}_j$ is the outer product term. $w_{Ey}$ is the connective weight, and $\psi_{E}$ is the function expansion output. $\theta$ is a set of basic functions.

The RFLENN input $X=[\Delta \theta_{in}, \Delta V_z]^T$ is used by the power system to directly transmit the numerical inputs to the next layer in this study. The context neurons of RFLENN serve as memory units, as they store the hidden layer output signal. Therefore, the RFLENN can employ the context neurons to increase dynamic characteristics of the network. The node output of the each layer of the RFLENN and the superscripts present the layer-number of the output $O$, while the subscripts present the signal number of the related output, and these are given as follows.

$$
O_i^{(1)}(t) = \prod x_1^i (t) \cdot \phi_1 \cdot O_i^{(5)}(t - 1)
$$

$$
O_j^{(2)}(t) = \sum_i O_i^{(1)}(t) \cdot w_{ij} + \sum_i O_i^{(3)} \cdot w_{rj}
$$

$$
O_r^{(3)}(t) = \alpha O_r^{(3)}(t - 1) + O_j^{(2)}(t - 1)
$$

$$
O_m^{(4)}(t) = \hat{y}_j \prod_{y=1}^{p} O_j^{(2)}(k) \cdot w_{fy}
$$
\[ O^{(5)}(t) = \sum_j O^{(4)}(k) \cdot w_o \]  

where the \( w_{ij} \) is the connecting weights of the input layer to the hidden layer, while \( w_{rj} \) is the connecting weights of the context layer to the hidden layer. \( \alpha \) is the self-connecting feedback gain (0~1) of context neurons, and \( w_{jy} \) is the connecting weight between the hidden layer and multiplication layer. The link weight \( w_o \) at output layer is unity. The objective of the FLENN controller is to train the parameters \( w_{ij}, w_{rj}, w_{jy} \) and \( w_{Ey} \) to make the best match with regard to the control signal \( O^{(5)} = \Delta K_P \) and \( \Delta K_I \).

**Figure 4** FLENN controller

### 3.2 The training process of FLENN

The gradient of the error function is the direction to which the function increases. Therefore, searching the opposite side of the gradient can force the cost-to-go function to be minimized. The gradient descent algorithm with the mean squared error function as the error function \( E \) can be defined by

\[ E = \frac{1}{2} \left[ J^*(t) - J(t) \right]^2 \]  

where the \( J^*(t) \) is the reference value of the cost-to-go function, which in the case of dealing with deviation signals is zero.

The backpropagation algorithm (BP) changes in direct proportion to the amount that weights vector \( W_{\text{FLENN}} \) are modified, and can be used to produce the instantaneous estimates of the negative gradient. In order to use an online algorithm for proposed FLENN, the gradient based on the chain rule can be represented as (14). The formulae for adjusting the weights \( W_{\text{FLENN}} \) of FLENN are shown in by (15). More details of the training procedure can be found in an earlier work [1].

\[ \frac{\partial E}{\partial W_{\text{FLENN}}} = \frac{\partial E}{\partial f_j} \cdot \frac{\partial f_j}{\partial o^{(5)}} \cdot \frac{\partial o^{(5)}}{\partial W_{\text{FLENN}}} \]  

\[ W_{\text{FLENN}}(t + 1) = W_{\text{FLENN}}(t) - \eta_{\text{FL}} \cdot \frac{\partial E(t)}{W_{\text{FLENN}}(t)} \]  

where \( W_{\text{FLENN}} = [w_{ij}, w_{rj}, w_{jy}, w_{Ey}, \varphi_i] \), and \( \eta_{\text{FL}} = [\eta_{ij}, \eta_{rj}, \eta_{jy}, \eta_{Ey}, \eta_{\varphi}] \) are the learning rates of \( W_{\text{FLENN}} \).

### 4. Simulation Results

The simulation case in this paper, a sudden three-phase short-circuit fault in the power grid is simulated at \( t=2 \) s for a duration of 0.2 s, the transient response of the studied system is shown in Figures 5-7. Figure 5(a) shows that the SSSC with a PI controller can have better damping
performance with regard to the real power on Line 1 than the system without SSSC. It can be also seen that the proposed RFLENN for SSSC has the best damping effect and a faster convergence than others on the transient stability. Similar stability improvements can be also found from the transient stability of the real power of Line 1 shown in Figure 5 (b).

The fault cases large fluctuations in the temporary voltage. Figure 6 shows that RFLENN can effectively improve the voltage transient stability of Bus S. It can be seen that the AC bus voltages drop to 0.42 pu, for the lowest of without SSSC. The voltage response of the SSSC with a PI has the longest recovery time of approximately 3s to recovery, although slight oscillations can still be observed. It can be also seen that the proposed RFLENN has the best effect and a faster voltage recovery is achieved bus voltage. Figure 7 shows that the rotor speed of the DFIG can recover more quickly to steady states.

![Figure 5](image) (a) The real power of Line 1. (b) The real power of Line 2.

![Figure 6](image) The voltage response of Bus S.  

![Figure 7](image) The rotor speed of the DFIG.

5. Conclusion
This study has successfully demonstrated the effectiveness of the proposed RFLENN controller for use in a SSSC and wave power system in order to improve the transient stability of the grid. The transient responses of the system when subjected to three-phase short-circuit fault show the effectiveness of the proposed control scheme. The control performance shows that this method can effectively stabilize the grid under unstable conditions. The transient stability of the studied wave power generation system under three-phase fault can be obtained systematically. The simulation results indicate the effectiveness and robustness of the proposed technique and showed that it was superior to PI and RFLENN in terms of the performance of the wave energy systems. Therefore, the performance comparison shows that our proposed algorithm is robust and provides outstanding performance.

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