NEURO-ADAPTIVE BASED CONTROL OF WIND-DIESEL-REDOX FLOW BATTERY SYSTEM
5.1 INTRODUCTION

It is well known that the parameters of diesel engine units vary with operating conditions. The induction machines and synchronous machines are both non-linear devices. The parameters that describe their behaviour are a function of operating conditions [26]. Moreover, the power systems change due to planned expansion of the system. Some researchers have applied the variable structure control to power systems [5, 62] to make the controllers insensitive to the plant parameter changes. However, this method requires the information of the system state, which is not completely known generally. On the other hand self tuning [48] and neuro-adaptive controllers have the capability to cope up with the challenges on non-linearity and time varying nature of the controlled system. This type of control can maintain the consistent performance of the system in presence of unknown and time varying parameters of the controlled system.

The neuro-adaptive control is therefore, best suited for hybrid wind-diesel-RFB plant. In view of this, the use of neuro-adaptive control for active/ reactive power modulation of the RFB system inserted in a typical wind-diesel power system is proposed in this chapter. The proposed scheme is implemented through two control loops i.e. frequency control loop and voltage control loop. The control objective of loop 1 is to bring the frequency deviation at wind park bus to the desired value (i.e. zero). Loop 2 on the other hand aims at bringing the voltage deviation at wind park bus to its desired value (i.e. zero). Both the control loops make use of a pair of neural networks. One of the neural networks named as neural estimator is a two layered network which is used to estimate the cause-effect relationship. The well known Widrow-Hoff Delta Rule [75] is used as the learning algorithm for this network to minimize the difference between the actual
response and that predicted by the neural estimator. The optimal control law is then generated on-line by the second two layered network (called neural controller) so that the desired control objective is achieved. Proper adjustment of the parameters of neural controller in each control loop is made for optimal performance of the system. The performance of RFB unit controlled through adaptive neural controller is finally assessed for the various disturbances like wind power disconnection, load disturbance, turbulent wind, and step changes in wind power.

5.2 OVERVIEW OF NEURAL NETWORKS

Artificial intelligence (AI) basically aims at replacement of human intelligence with the computer network. In spite of the fact that the term AI was introduced around 1956, there is no standard definition. From the Oxford English Dictionary we can conclude:

Artificial: “produced by human art or effect rather than occurring naturally”

Intelligence: “the faculty of reasoning, knowing and thinking of a person or an animal”

Artificial intelligence: “the application of computers to areas normally regarded as requiring human intelligence”

A broader definition “the study of making computers do things that the human needs intelligence to do,” includes mimicking human thought processes and also the technologies that make computers accomplish intelligent tasks even if they do not necessarily simulate human thought processes.

Basically, there are three fundamentally different groups of AI

- Classical symbolic AI: knowledge-based (expert) system, logical reasoning, search techniques, natural language processing
• Biological model-based AI: neural networks, genetic algorithms (also known as evolutionary computing)

• Modern AI: fuzzy and rough sets theory, chaotic systems

Sometimes the areas of neural networks, genetic algorithms, fuzzy systems, rough sets, and chaotic systems are commonly referred to as soft computing, to stress an approximate computation (in contrast to precise computation, which is called hard computing) [t munata]

5.3 BASICS OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) have several important characteristics that are of interest to control and power system engineers:

• Modelling: Because of their ability to be trained using data records for the particular system of interest.

• Nonlinear systems: The nonlinear networks have the ability to learn nonlinear relationships

• Multivariable systems: Artificial neural networks, by their nature, have many inputs and many outputs and so can be easily applied to multivariable systems.

• Parallel structures: this feature implies very fast parallel processing, fault tolerance, and robustness.

5.3.1 Artificial Neuron Model

The elementary computational elements that create neural networks have many inputs and only one output. A typical neuron model and its symbol is shown in Fig. 5.1. These elements are inspired by biological neuron systems and, therefore, are called
neurons. The individual inputs \( x_j \) weighted by elements \( w_j \) are summed to form the weighted output signal:

\[
e = \sum_{j=0}^{N} w_j \cdot x_j \quad (5.1) \quad \text{and} \quad x_0 = 1 \quad (5.2)
\]

Where elements \( w_j \) are called synapse weights and can be modified during the learning process.

![Figure 5.1 Neuron Model](image)

The output of the neuron unit is defined as follows:

\[
y = F(e). \quad (5.3)
\]

Note that \( w_0 \) is adjustable bias and \( F \) is the activation function (also called transfer function). Thus the output, \( y \), is obtained by summing the weighted inputs and passing the results through a nonlinear (or linear) activation function \( F \). The activation function \( F \) maps, a weighted sum's \( e \) (possibly) infinite domain into a specified range. Although the
number of F functions is possibly infinite, five types are regularly applied in the majority of ANN: linear, step, bipolar, sigmoid, hyperbolic tangent. With the exception of the linear F function, all of these functions introduce nonlinearity in the network by bounding the output within a fixed range.

5.3.2 ANN Topologies

In the biological brain, a large number of neurons are interconnected to form the network and perform advanced intelligent activities. An artificial neural network is built by neuron models and in most cases consists of neuron layers interconnected by weighted connections. The arrangement of the neurons, connections, and patterns into a neural network is referred to as a topology or architecture.

5.3.2.1 The Layer of Neurons.

Neural networks are organized into layers of neurons. Within a layer, neurons are similar in two respects:

- The connections that feed the layer of neurons are from same source.
- The neurons in each layer utilize the same type of connections and activation function F.

A one layer network with N inputs and M neurons is shown in Fig 5.2. In this topology, each element of input vector X is connected to each neuron input through the weight matrix W. The sum of approximate weighted network inputs W*X is the argument of activation function F. Finally, the neuron layer outputs from a column vector Y. note that it is common for the number of inputs to be different from the number of neurons, i.e. \( N \neq M \).
5.3.2.2 Linear Filter

For the linear activation $F$ function, with unity positive scalar, the output of the neuron layer can be described by the matrix equation

$$Y = W_kX \quad (5.4)$$

Where

$$W_k = \begin{bmatrix}
  w_{11} & w_{21} & \cdots & w_{N1} \\
  \vdots & \vdots & & \vdots \\
  w_{1M} & w_{2M} & \cdots & w_{NM}
\end{bmatrix} \quad (5.5)$$

is the weight matrix.

Such a simple network can recognize $M$ different classes of patterns. The matrix $W_k$ defines linear transformation of the input signals $X \in \mathbb{R}^N$ into output signals $Y \in \mathbb{R}^M$. This linear transformation can have an arbitrary form (for example, Fourier transform). Therefore, such a network can be viewed as a linear filter.
5.3.2.3 Multilayer Neural Networks (MNN)

A neural network can have several layers. There are two types of connections applied in MNN:

- Intra-layer connections are connections between neurons in the same layer.
- Inter-layer connections are connections between neurons in different layers.

It is possible to build ANN that consists of one or both types of connections.

Organisation of the MNN is classified largely into two types:

- Feed forward networks
- Feedback (also called recurrent) networks.

When the MNN has connections that feed information in only one direction (e.g., input to output) without any feedback pathways in the network, it is feed forward MNN. But if the network has any feedback paths, where feedback is defined as any path through the network that would allow the same neurons to be visited twice, then it is called a feedback MNN.

5.3.3 Learning and Training of Feed forward ANN

One of the most important qualities of ANN is their ability to learn. Learning is defined as a change of connection weight values that result in the capture of information that can be recalled. Several algorithms are available for a learning process. Generally, the learning methods can be classified into two categories:

- Supervised Learning: It is a process that incorporates an external teacher and (or) global information as shown in Fig. 5.3. The supervised learning algorithms include error correction learning, reinforcement learning, and stochastic learning.
- Unsupervised Learning (also referred to as self-organisation): a process that incorporates no external teacher and relies upon local information during the entire learning process. Examples of unsupervised learning include Hebbian Learning, principal component learning, differential Hebbian learning, min-max learning, and competitive learning.

![Diagram of Supervised Learning](image)

**Fig 5.3 Supervised Learning**

Most learning techniques utilize off-line learning. When the entire pattern set is used to condition the connections prior to the use of the network, it is called off-line learning. For example, the back propagation training algorithm is used to adjust connections in multilayer feed forward ANN, but it requires thousands of cycles through all the pattern pairs until the desired performance of the network is achieved. Once the network is performing adequately the weights are stored and the resulting network is used
in recall mode thereafter. Off-line learning systems have the inherent requirement that all
the patterns have to be resident for training.

Not all networks perform off-line learning. Some networks can add new
information “on the fly” nondestructively. If a new pattern needs to be incorporated into
the network’s connection, it can be done immediately without any loss of prior stored
information. The advantage of off-line learning networks is that they usually provide
superior solutions in difficult problems such as nonlinear classifications, but on-line
learning allows ANN to learn during the system operation. In control and identification
systems mostly the feed forward ANN are applied.

5.4 NEURO-ADAPTIVE CONTROL OF THE REDOX FLOW BATTERY

The adaptive-neural control scheme is depicted in Fig. 5.4. There are two control
loops i.e. frequency control loop and voltage control loop. The control objective of loop 1
is to bring $y_1$ (the frequency deviation at wind-park bus) to zero. Similarly loop 2 aims at
bringing the controlled variable $y_2$ (which is the voltage deviation at wind park bus) to
zero. Each controller computes the control signal based on an optimal control law.

5.5 NEURAL ESTIMATORS

The relationship governing the dynamics between the frequency deviation and the active
power command for the RFB system at the wind park bus is modeled by a linear two-
layered neural network. The neural network learns the dynamic relationship using the
Widrow-Hoff delta rule. The input layer consists of $n+m$ elements [75]. The $n+m$ inputs
to the neural estimator comprise of active power commands and frequency deviations at
the previous sampling instants. The output layer has only one element whose output is the
predicted frequency deviation. The neural estimator for estimating the active power-
frequency deviation dynamic relationship is shown in Fig. 5.5. The weight vector at the sampling instant $k$ defined by

$$ W(k) = [w_1(k) \ w_2(k) \ ... \ \ w_n(k) \ \ w_{n+1}(k) \ ... \ \ w_{n+m}(k)]^T $$ (5.26)

is updated using Widrow-Hoff rule [75] as per the following:

Figure 5.4 Neuro-adaptive control scheme of the RFB integrated with a wind-diesel power system.
\[ W(k + 1) = W(k) + \frac{\alpha e(k + 1) X(k)}{\varepsilon + X^T(k)X(k)} \]  \hspace{1cm} (5.27)

Where \( X(k) \) is the neural network input vector which is given by:

\[ X(k) = [x_1(k) \ x_2(k) \ldots \ x_n(k) \ x_{n+1}(k) \ldots \ x_{n+m}(k)]^T \]

\[ = [-y(k) - y(k - 1) \ldots \ y(k - n + 1) \ u(k) \ldots \ u(k - m + 1)]^T \] \hspace{1cm} (5.28)

Where \( \alpha = (0, 2) \) is the reduction factor. The constant \( \varepsilon \) is chosen to be close to zero. In equation (5.28) \( y \) represents the output (frequency deviation) and \( u \) is the control signal (active power command to the RFB device). It is important to note that the estimation is performed on line in the presence of disturbances acting on the system and therefore no separate term \([75, 24]\) is required in the model.

The output predicted by the neural network can be calculated as:

\[ \hat{y}(k) = \sum_{i=1}^{n+m} W_i(k - 1) x_i(k - 1) \] \hspace{1cm} (5.29)

The adaption algorithm of equation (5.27) minimizes the error between the measured output, \( y(k) \) and the predicted output, \( \hat{y}(k) \).

The dynamic relationship between the voltage deviation at the wind park bus and the reactive power command for the RFB system is modeled by a similar neural-network.
The dynamics learnt by the neural estimators is used to adjust the connection weights of the neural controllers. Each neural controller consists of two-layered neural network with \(n+m-1\) elements in the input layer and one element in the output layer. The connection weight vector \(W'(k)\) associated with a neural controller is related to the connection weight vector \(W(k)\) of the corresponding neural estimator and the relationship is governed by the control strategy adopted. In this thesis we have proposed an optimal control strategy which minimizes the performance index of equation (5.30).

\[
J(k) = \hat{y}^2(k+1) + \lambda[u(k) - qu(k-1)]^2
\]  

(5.30)

The second term on the R. H. S. of eq. (5.30) ensures the prevention of excessive control action. \(\lambda\) is the weighing constant and \(q\) can assume a value of 1/0.
The control action which minimizes $J(k)$ can be derived by undergoing the following steps.

1) Obtain the expression for $\hat{y}(k+1)$ from the neural estimator model of equation (5.29).

2) Substitute the resulting expression of $\hat{y}(k+1)$ in equation (5.30).

3) Set $\frac{\partial J(k)}{\partial u(k)}$ to zero.

On following the above procedure a neural controller of Figure 5.6 is obtained.

From Eq. (5.29) we get the value of $\hat{y}(k+1)$ as given in Eq. (5.31)

$$\hat{y}(k+1) = \sum_{i=1}^{n+m} w_i(k) x_i(k) \quad (5.31)$$

This can be written in expanded form as

$$\hat{y}(k+1) = w_1(k) x_1(k) + w_2(k) x_2(k) + \ldots + w_n(k) x_n(k) +$$

$$w_{n+1}(k) x_{n+1}(k) + w_{n+2}(k) x_{n+2}(k) + \ldots + w_{n+m}(k) x_{n+m}(k) \quad (5.32)$$
Differentiate $J(k)$ in eqn. (5.30) with respect to $u(k)$ and set $\frac{\partial J(k)}{\partial u(k)}$ to zero, we get

$$\hat{y}(k+1) w_{n+1}(k) + \gamma [u(k) - qu(k - 1)] = 0 \quad (5.33)$$

Substitute the value of $\hat{y}(k+1)$ from Eq. (5.32) in Eq. (5.33) we obtain eqn. (5.34) for $u(k)$

$$u(k) = \frac{-w_{n+1}(k)}{w_{n+1}(k) + \gamma \left[ w_1(k)x_1(k) + w_2(k)x_2(k) + \ldots + w_n(k)x_n(k) \right]}$$

$$+ \frac{(w_{n+2}(k) - \lambda q)u(k - 1) + \ldots + w_{n+m}(k)u(k - m + 1)}{w_{n+1}(k) + \gamma \left[ w_1(k)x_1(k) + w_2(k)x_2(k) + \ldots + w_n(k)x_n(k) \right]}$$

The weight vector $W'(k)$ of the neural controller is thus related to the elements of weight vector $W(k)$ of the corresponding neural estimator through the following relation:

$$W'(k) = c_1[w_1(k) w_2(k) \ldots w_n(k)c_2 + w_{n+2}(k) \ldots w_{n+m}(k)]^T \quad (5.35)$$

Where $c_1 = \frac{w_{n+1}(k)}{w_{n+1}(k) + \gamma}$ and $c_2 = -\frac{\lambda q}{w_{n+1}(k)}$

5.7 SIMULATION MODEL

In order to carry out the simulation studies to investigate the effectiveness of the proposed scheme the detailed unified models are developed and the impact of intelligently controlled RFB system on the power quality is assessed using simulation studies. The RFB system is considered to be at wind park bus. However the simulation results are carried out for a converter rating of 50 kVA to explore the overload capacity of the RFB upto 40 kW.

5.8 CONTROL SCHEME

The sequence of actions for frequency control loop at instant $k$ is as follows:

1) Measure $y_1(k)$ i.e. the frequency deviation at wind park bus.

2) Use the neural network of Fig. 5.5 to compute the predicted value $\hat{y}_1(k)$. 

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3) Compute error $e_1(k) = \hat{y}_1(k) - y_1(k)$ and use delta rule to calculate new weights $W(k)$.

4) Compute the per unit control signal $u_1(k)$ as per equation (5.29) which represents the desired active power $P_{bat}$ to be exchanged between the wind park bus and the redox flow battery system.

The similar sequence of actions takes place for the voltage control loop. However keeping in view the different range of values for frequency and voltage deviations a scaling factor $[\text{Lim}]$ is introduced for voltage control. Thus in voltage control loop $y_2 = k_v \cdot$ voltage deviation at wind park bus. The control signal $u_2(k)$ represents the desired reactive power $Q_{bat}$ to be exchanged between the wind-park bus and the RFB system. As shown in Fig. 5.4 $P_{bat}$ and $Q_{bat}$ may have to be modified, keeping in view the converter rating and the RFB overload capacity constraints.

The exchange of desired active and reactive powers is exercised through the current controlled voltage source converter (CC- VSC) based on hysteresis current control, in a manner described in chapter 4. The parameters of the redox flow battery, converter and control parameters for the simulation study are expressed as under.

**Redox Flow Battery:**

RFB capacity = 15kW,

RFB equivalent circuit parameters:

$i_0 = 0.536 \, \text{A}, \, R_1 = 1.14 \, \Omega, \, R_2 = 0.15 \, \Omega, \, R_3 = 0.42 \, \Omega, \, C_o = 1333.33 \, \text{F}, \, C_1 = 20 \, \text{F}, \, C_2 = 142.86 \, \text{F}$

**Converter Parameters:**

$R_c = 0.025 \, \Omega, \, L_c = 1.2 \, \text{mH}, \, h_b = 0.03, \, C_{bus} = 5000 \, \mu\text{F}$ converter rating = 50 kVA

**Control Parameters**

Frequency control Loop: $\lambda = 5, \, e = 0.001, \, \alpha = 1, \, q = 0$
Voltage Control Loop: \( \lambda = 6.5 \), \( \varepsilon = 0.001 \), \( \alpha = 1 \), \( q = 1 \) \( K_v = 12 \)

5.9 TIME DOMAIN SIMULATION STUDIES

The various disturbances to which the wind diesel system under study is subjected to are wind power disconnection, active and reactive power load disturbance, turbulent wind and step/stochastic wind power. In all these case studies the system is assumed to be in steady state prior to the occurrence of a disturbance i.e. \( t < 0 \). The simulation results reported in the following subsections pertain to the adaptive neural controllers with the parameters given in section 5.8. These parameters were obtained by hit and trial method.

5.9.1 Wind Power Disconnection

In this case wind turbines are generating 100 kW of power and power system load is 312 kW/200 kVAR with the system frequency as 50 Hz. All the wind turbines are assumed to be disconnected along with their associated capacitor banks thereby deteriorating the power quality. Figure 5.7(a&b) which show the voltage and frequency deviations at the load bus when wind power is suddenly disconnected. The improvement in voltage and frequency by insertion of redox flow battery can be seen in the same figures. Figures 5.7 (c, d & e) show the battery voltage, active and reactive power supplied to the RFB.

5.9.2 Active/Reactive Power Load Disturbance

In this case wind power is assumed to remain at a constant level of 50 kW while as the load disturbance is allowed to come on the system in terms of change in active and reactive power at the load bus. Prior to disturbance the active/reactive power is 260 kW/182 kVAR which is now changed to 360 kW/200 kVAR. This change in load is modeled
as a change in topology of the network, resulting change in network admittance matrix.

Figs. 5.8 (a&b) show the positive impact of the RFB when such a load disturbance comes on the system. The voltage and frequency are kept within tolerable limits by RFB. Figures 5.8(c, d & e) show the battery voltage, active power and reactive power to be supplied to battery.

5.9.3 Turbulent Wind Disturbance

This mode of operation is very common for wind based power systems. The system is subjected to a rapidly varying turbulent wind. Prior to this the wind turbines are assumed to generate 50 kW and the load is at a level of 260 kW/182 kVAR. The nature of turbulent wind is same as shown in Fig. 3.11 of Chapter 3. Figures 5.9 (a&b) show the impact of RFB upon voltage and frequency when the system is subjected to turbulent wind. Figures 5.9 (c, d & e) respectively show the battery voltage, active power and reactive power supplied to the battery.

5.9.4 Step/Stochastic Wind Power Change

In this case the system is subjected to a wind disturbance of the pattern shown in Fig 3.12 in chapter 4. In this figure the wind power is comprised of two components. One is a simple step change in wind power upon which is superimposed another component of wind power which is stochastic in nature. This stochastic component of wind power is generated by using MATLAB/ SIMULINK tool box. For time t <0 the wind power generation is 50 kW. The simulation results are shown in Figs. 5.10(a, b, c, d & e).
Fig. 5.7 (a) Frequency deviation (Hz) due to wind power disconnection

Fig. 5.7 (b) Load Bus Voltage Deviation (%) due to wind power disconnection
Fig. 5.7(c) RFB Voltage (V)

Fig. 5.7 (d) Active Power (kW) supplied to RFB
Fig. 5.7 (e) Reactive Power (kVAR) supplied to RFB

Fig. 5.8 (a) Frequency deviation (Hz) due to load(PQ) disturbance
Fig. 5.8 (b) Load Bus voltage deviation (%) due to PQ load disturbance

Fig. 5.8 (c) RFB voltage (volts)
Fig. 5.8 (d) Active powers supplied to RFB due to load disturbance

Fig. 5.8 (e) Reactive power supplied to RFB due to load disturbance
Fig. 5.9 (a) Frequency deviation (Hz) due to turbulent wind

Fig. 5.9 (b) Load bus voltage deviation (%) due to turbulent wind
Fig. 5.9 (c) RFB voltage (volts)

Fig. 5.9 (d) Active power supplied to RFB due to turbulent wind
Fig. 5.9 (e) Reactive power supplied to RFB due to turbulent wind

Fig. 5.10(a) Frequency deviation (Hz) due to step wind
Fig. 5.10 (b) Voltage Deviation at Load Bus (%) due to step/stochastic wind disturbance

Fig. 5.10(c) Battery voltage due to step/stochastic wind
Fig. 5.10(d) Active power supplied to RFB

Fig. 5.10(e) Reactive power supplied to RFB
5.10 CONCLUSION

In this chapter impact of an intelligently controlled redox flow battery is studied on the power quality of wind-diesel system under various disturbances. The intelligent control scheme for RFB makes use of two decoupled neural adaptive controllers. The results obtained with the proposed scheme are comparable to those obtained in chapter 4 where control policy for RFB is based on fuzzy logic. However in some cases the results obtained are comparatively better.