CHAPTER 6

ARTIFICIAL NEURAL NETWORK CONTROLLER BASED POWER MANAGEMENT SYSTEM

6.1 ARTIFICIAL NEURAL NETWORK

The term neural network (NN) was traditionally used to refer to a network or circuit of biological neurons. The modern usage of the term often refers to artificial neural networks (ANN), which are composed of artificial neurons or nodes. Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons) and their importance lie in the capacity to represent or emulate human knowledge, with it, to memorize, acquire knowledge, perceive and take intelligent decisions.

Artificial neural networks may be used to solve the problems like system identification, process control, prediction and diagnosis, etc. without necessarily creating the model of a real biological system. In the area of power electronics, insulating materials diagnostics for high voltage engineering, and especially in the area of non-conventional sources based power generation systems, the application of ANN has achieved great improvements, and the future looks promising.

6.2 FEED FORWARD NEURAL NETWORK

In a feed forward neural network (FF NN), the information moves in only one direction, forward, from the input nodes, through the hidden
nodes, and to the output nodes. There are no cycles or loops in the network. This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has direct connections to the neurons of the subsequent layer. The common structural representation of a FF NN, i.e., multi-layer perceptron neural network (MLP NN) is shown in Figure 6.1.

![Figure 6.1 Structure of feed forward neural network](image)

**6.3 ANN BASED POWER MANAGEMENT SYSTEM**

ANN based PMS is proposed and designed for an SA-HPS (Recep Yumurtaci 2013) to coordinate the sharing of power among the non-conventional energy sources (based on its availability) for any LD. The block diagram representation of the proposed ANN controller based PMS for an SA-HPS is shown in Figure 6.2.
The control structure of proposed ANN based PMS for an SA-HPS is developed with three levels of control as shown in Figure 6.3. The proposed control architecture is termed as the ‘centralized control paradigm’ which
encloses a central controller and two local controllers for each of the IBC connected to a RES to handle instantaneous power flow control.

![Centralized Controller Diagram]

**Figure 6.3** Centralized control paradigm based hierarchical control structure

### 6.4.1 Centralized Control Paradigm

In a centralized control paradigm (Hajizadeh & Golkar 2007), the centralized controller acts as a supervisory controller, which makes the primary decisions. The main objective of using a central controller is to implement the hierarchy in utilization of the sources or to optimize energy use among the various energy sources of the system.

The central controller receives various measured signals such as LD, $P_S$, $P_W$, Maximum deliverable power of the fuel cell, present SOC of the battery, and the actual current delivered from the sources such as $I_{solar}$, $I_{wind}$, $I_{fuel}$, $I_{batD}$, $I_{batCH}$ and $I_{Load}$. The central controller executes the priority in
utilization of the sources and delivers the control signals such as \( SP, WP, FP, BCHP, BDCHP \) and \( LOAD \) pulse that connects / disconnects the sources from PCC. It also calculates and delivers various control signals for the local controllers such as \( V_{s\_ref}, V_{w\_ref}, V_{f\_ref}, V_{bd\_ref} \) and \( V_{bc\_ref} \) for the ‘local controller 1’ for voltage control and voltage dependent current control and the control signals such as \( I_{s\_ref}, I_{w\_ref}, I_{f\_ref}, I_{bd\_ref}, \) and \( I_{bc\_ref} \) for the ‘local controller 2’ for current fine-tuning.

The control variables are then sent to the corresponding local controllers (ANN), which in turn optimize the duty cycles for the corresponding IBC’s. The advantage of this ‘Centralized control paradigm’ structure is that the multi-objective energy management system can achieve global optimization based on all available information. In the hierarchical control, the EC is proposed to perform the functions of a centralized controller and ANN controllers to function as the local controllers to optimize the duty cycle for each of the IBC’s to

1) maintain a constant voltage at the PCC to limit the circulating current between the sources,

2) regulate the power flow between the sources and load with voltage dependent current control (VDCC) technique, and

3) fine-tune the actual current flow exactly equal to the reference current magnitude.

The ANN is preferred as the local controllers as it accurately optimizes the duty cycle at faster execution speed. For the continuously varying instantaneous reference values that is estimated by the EC, the ANN’s connected to all the IBC should instantaneously, continuously and concurrently optimize the duty cycle to perform the above stated functions to manage the power flow in an instantaneous basis.
6.5 REALIZATION OF THE MLPN NN SYSTEM

The most useful ANN in function approximation is the MLP NN. The first step in building an MLP NN by MATLAB coding starts with collecting the input data of the problem, which essentially contains a predefined set of input and target vectors. The input data (P) are arranged as a set of ‘n’ input vectors as columns in a matrix. Then the target data (T), which are the set of ‘n’ target vectors (the correct output vectors for each of the input vectors), are arranged in the second matrix. For example,

\[
P = \begin{bmatrix}
\end{bmatrix}
\]

\[
T = \begin{bmatrix}
-0.2699 & -0.2305 & -0.1602 & -0.0995 & -0.0466 & -0.0359 & -0.0337 & -0.0315 & -0.0293 & -0.027 & -0.0247 & -0.0223 & -0.02 & -0.0176 & -0.01519 & -0.0127 & -0.0102 & -0.00774 & -0.00519 & -0.00261 & 0.00265 & 0.00532 & 0.00804 & 0.0108 & 0.0136 & 0.0164 & 0.0192 & 0.0222 & 0.0251 & 0.0281 & 0.0311 & 0.0342 & 0.0373 & 0.04044 & 0.0436 & 0.0603 & 0.0976 & 0.1935 & 0.4318
\end{bmatrix}
\]

The input data are then defined into the toolbox as the input data and target data of the proposed control process, the next step in training a network is to create the neural network object. FF NN often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Hence ‘tansig’ transfer function is used in the hidden layer and ‘purelin’ transfer function is used in the output layer. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between the input and output vectors. This arrangement can be used as a general function approximator. It can approximate any function with a finite number of discontinuities, arbitrarily well, given sufficient neurons in the hidden layer. The training of the network is done based on the Levenberg-Marquardt optimization.
The developed ANN controller in the form of a Simulink block can be connected to the individual IBC’s in an HPS to perform both the voltage and voltage dependent current control. The structure of the FFNN developed for doing the task is shown in Figure 6.4 and its subsystems are shown in Figures 6.5 (a), 6.5 (b), 6.5 (c), 6.5 (d) and 6.5 (e).

Figure 6.4 Developed neural network block

(a) Feed forward neural network

(b) Subsystem of layer 1

(c) Subsystem of W{2.1}

Figure 6.5 (Continued)
When multiple sources connected together in parallel are sharing a common LD, the power delivery of a source can be raised by increasing the current delivery of that source as the output voltage is fixed. The current output of the source is increased by fractionally incrementing the voltage beyond 156V by marginally adjusting the duty cycle. As the output voltage of the IBC increases marginally, the converter brings in more current into the
load circuit than the rest of the converters. This ‘voltage dependent current control’ technique is implemented in the proposed ANN based PMS to regulate the power flow.

Based on the instantaneous power delivered by the sources and LD, the central controller decides any one mode, out of the possible 25 modes of operation in an SA-HPS (discussed in section 5.2.7) and suitably delivers the ‘control pulses’ pertaining to that mode to connect the sources to the PCC to satisfy the LD. Also the central controller aptly delivers the control signals to all the local controllers which in turn optimize the duty cycle for the IBCs in the HPS to regulate the power flow and also to accommodate the instantaneous variations in the PM.

6.6.1 Voltage Control and VDCC using MLPN Neural Network

The I-V characteristics of the all the sources in HPS are different. Hence a dedicated ANN controller is designed based on the characteristics of each source and is connected to the IBC as shown in Figure 6.6 to carry out voltage control, VDCC and finite current control. The output voltage of all the IBCs connected to the PCC can be controlled to convey a magnitude of 156V by continuously adjusting the duty cycle ‘α’ as in the Equation (6.1)

\[
V_o = V_i \left( \frac{I}{I-\alpha} \right)
\]  

(6.1)

It is highly imperative to calculate the value of ‘\(V_{s_{ref}}\)’ which basically behave as one of the vital parameters of the ANN controller based on which the controller optimizes the duty cycle. The ‘\(V_{s_{ref}}\)’ is one of the inputs of the ‘sum’ block which generates the ‘error voltage’ which is the input of the ANN controller. The other inputs of the ‘sum’ block are the ‘\(V_{ref_{pcc}}\)’, i.e., 156V and the actual output voltage of the PCC. The ‘sum’ block
works on ‘++-’ logic and generates the ‘error voltage’ as given in Equation (6.2).

\[
\text{error voltage} = V_{\text{ref}_{-\text{pcc}}} \ (i.e., 156) + V_{s_{-\text{ref}}} - V_{os_{-\text{pcc}}} \quad (6.2)
\]

**Figure 6.6** ANN controller for voltage control and VDCC in IBC connected to SPV panel

where ‘\(V_{os_{-\text{pcc}}}\)’ is the instantaneous actual output voltage of IBC connected to SPV panel at PCC, ‘\(V_{s_{-\text{ref}}}\)’ is the cumulative voltage component that includes the magnitude of voltage to re-establish the ‘\(V_{\text{ref}_{-\text{pcc}}}\)’ and the voltage component proportional to the instantaneous reference current of the source to establish it as the actual current by VDCC technique. The instantaneous magnitude of the parameter ‘\(V_{s_{-\text{ref}}}\)’ is estimated using the Equation (6.3) and (6.4)

\[
\alpha_s = 0.5897 + \left[ \left( I_{s_{-\text{ref}}} - I_o \right) / \left( 156 \times I_{s_{-\text{ref}}} \right) \right] \quad (6.3)
\]
The controller computes duty cycle ‘\( \alpha_s \)’ which essentially consists of two parts. 1) To develop and maintain a constant DC voltage at PCC, i.e., 156V, and 2) the VDCC component of the duty cycle adjusts the current delivery of the IBC proportional to the instantaneous power delivered by that source. The first component of ‘\( \alpha_s \)’, i.e., the duty cycle magnitude ‘0.5897’ is calculated as in the Equation (6.7) and is responsible for generating 156V at the output of the IBC. The second component of ‘\( \alpha_s \)’ is proposed to realize VDCC in the IBC and is designed following the basics of the boost converter \([(I_{s\_ref} - I_{so})/(156*I_{s\_ref})]\). The magnitude ‘156’ in the denominator of the equation (6.3) normalizes the duty cycle in relevance to the output voltage of the IBC. For any change in the ‘\( I_{s\_ref} \)’, the second part of the equation marginally increments / decrements the overall duty cycle by a thin margin, which in turn increments / decrements the ‘\( V_{s\_ref} \)’ in the Equation (6.4),

\[
V_{s\_ref} = \left[ \frac{64}{(1 - \alpha_s)} \right]^{-156}
\]

(6.4)

where 64V is the terminal voltage of the SPV panel, which basically forms the input voltage of the IBC while 156V is the desired output voltage. The parameter ‘\( V_{s\_ref} \)’ at the input of the voltage controller behaves as a proportional gain constant and helps in achieving the steady state conditions quickly. The ANN controller continuously reduces the steady state error by suitably delivering the ‘\( \Delta \alpha \)’ which is the change in duty cycle required to re-establish the required voltage.

For example, consider that the actual current ‘\( I_{so} \)’ delivered at the output of the IBC connected to the SPV panel is 5A. If the instantaneous current reference ‘\( I_{s\_ref} \)’ of the SPV panel changes to 3A, then the parameter ‘\( V_{s\_ref} \)’ is calculated as -1.6245V from the Equations (6.5) and (6.6).

\[
\alpha_s = 0.5897 + \left[ \frac{(3-5)}{(156*3)} \right]
\]

(6.5)
\[ \alpha_s = [0.5897 + (-0.00427)] = 0.585426 \]

and,

\[ V_{s\_ref} = \left[ \frac{64}{(1 - 0.585426)} \right]^{-156} = -1.6245V \] (6.6)

The training data (input data and the target data) of the ANN designed for voltage control and VDCC technique are the error voltage (deviation from a reference voltage with inherent current control) and the change in duty cycle ‘Δα’ necessary to reinstate the reference voltage and current. In the event of any load variations (increase/decrease), the actual output voltage and current of the IBC can be higher or lower than the reference voltage and current. Hence the training data of the ANN are considered for both the cases, i.e., for positive and negative error voltages.

In the SA-HPS, a 64V/1kW SPV panel is used. The training data of the proposed ANN for voltage and VDCC are determined by performing an open loop experimental investigation on the IBC being supplied from 64V SPV panel. Under normal irradiance and load conditions, the duty cycle of the IBC is adjusted to deliver 156V and is recorded, and also it can be estimated using the Equation (6.7). By varying the load (increase / decrease) and source conditions the changes in the output voltage (drop / increase) which are considered to be the ‘error voltage’ are noted. The magnitude of duty cycle varied to bring back the 156V at the output with inherent current control is also noted. For example, consider the output voltage of the IBC changes to 166V due to loss of load, the change in duty cycle required to re-establish 156V can be calculated using the Equations (6.7), (6.8) and (6.9).

\[ \alpha_{156} = \frac{V_o - V_{in}}{V_o} = \frac{156 - 64}{156} = 0.58974 \] (6.7)

\[ \alpha_{166} = \frac{V_o - V_{in}}{V_o} = \frac{166 - 64}{166} = 0.61445 \] (6.8)
\[ \Delta \alpha = \alpha_{156} - \alpha_{166} = 0.58974 - 0.61445 = -0.0247 \quad (6.9) \]

Likewise 40 different variations on both sides of 156V are estimated which form the training data of the ANN controller and is shown in Table 6.1. The proposed ANN for voltage control and VDCC is developed by M-file coding as delineated in chapter 6.5. The magnitude of duty cycle ‘\( \alpha \)’ at the (\( k-1 \)) instant is calculated externally from the input and output voltage of the IBC at the (\( k-1 \)) instant using the ‘sum’ and ‘product’ blocks following the Equation (6.10), which can be seen in Figure 6.6.

**Table 6.1 Training data of the ANN controller connected to SPV panel fed IBC for voltage control and VDCC**

<table>
<thead>
<tr>
<th>INPUT: ( P )</th>
<th>([-300 -200 -100 -50 -20 -15 -14 -12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 20 30 50 80])</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET: ( T )</td>
<td>([-0.2699 -0.2305 -0.1602 -0.0995 -0.0466 -0.0359 -0.0337 -0.0315 -0.0293 -0.027 -0.0247 -0.0223 -0.0206 -0.0176 -0.01519 -0.0127 -0.0102 -0.00774 -0.00519 -0.00261 0 0.00265 0.00532 0.00804 0.0108 0.0136 0.0164 0.0192 0.0222 0.0251 0.0281 0.0311 0.0342 0.0373 0.04044 0.0436 0.0603 0.0976 0.1935 0.4318])</td>
</tr>
</tbody>
</table>

\[ \alpha_{k-1} = \frac{V_o - V_{in}}{V_{in}} \quad (k-1) \]

\[ \alpha_k = \alpha_{k-1} + \Delta \alpha \quad (6.11) \]

Based on the ‘error voltage’, the ANN controller optimizes the change in duty cycle ‘\( \Delta \alpha \)’ required to reinstate the reference value which is to be added with the ‘\( \alpha_{k-1} \)’ to nullify the error voltage. Hence ‘\( \alpha \)’ at instant ‘\( k \)’ is given by the Equation (6.11).
The relationship between the input and target data established by the developed ANN for voltage control and VDCC is shown in Figure 6.7. The training performance of the proposed ANN controller is shown in Figure 6.8 and the best training performance is 2.8831e-08 and it is achieved in 40 epochs. The regression plot of the ANN controller gives an idea of how close the output of the model is to the actual target values as ‘R’ value is 1. It indicates that there is an exact linear relationship between outputs and targets. The regression plot of the proposed ANN is shown in Figure 6.9.

Figure 6.7 Relationship developed by the proposed ANN controller between the input and target data

Figure 6.8 Training performance of the proposed ANN controller

Figure 6.9 Regression plot of the proposed ANN controller
6.6.2 ANN based Current Fine-Tuning in SPV Panel fed IBC

When the duty cycle is optimized separately for voltage control and current control, each controller gives out duty cycle separately to minimize its error value, and its cumulative effect results in instability, hence in the proposed ANN based PMS, the VDCC is realized. In the VDCC technique, a small variation in the output voltage of the IBC beyond 156V causes extreme variations in the current output as the system is connected in parallel with other systems. Therefore, the VDCC technique has the inherent advantage of good dynamic performance as it enables faster reaching of the actual current flow to the reference current value. When the gap between the actual and reference current is large, it enables faster accomplishment of the actual current flow to the reference current. But when the actual current doesn’t exactly settle at the reference current, it causes dynamic oscillations of actual current flow around the reference current magnitude. Hence another ANN controller with very diminutive duty cycle variation is integrated along with the VDCC to enable exact settling of the actual to the reference current value.

The training data (input data and target data) of the ANN controller developed for finite actual current adjustment are the instantaneous reference current of the source ‘$I_{s, \text{ref}}$’ and very tiny duty cycle values respectively. Based on the instantaneous reference current, the controller outputs a fractional change in duty cycle, which suitably increases the voltage by a very thin margin to set the actual current flow exactly equal to the reference current. For an instantaneous reference current ranging from ‘0’A to 11A, the number of training data and the interval between the training data is arbitrarily chosen, and the target data is obtained by performing the simulation analysis. The proposed ANN controller is trained with 16 different values of reference current and its corresponding duty cycle that should be added along with the present duty cycle to reinstate the reference current. The training data of the proposed ANN based current controller are given in Table 6.2.
Table 6.2 Training data of the ANN controller connected to SPV panel fed IBC for current control

| INPUT: | P = [0 0.0156 0.0312 0.156 0.312 1.56 3.12 3.9 5.2 7.8 8.21 8.67 9.176 9.75 10.4 11] |
| TARGET: | T = [0 0.00025 0.000526 0.001319 0.00215 0.002715 0.00379 0.00459 0.00677 0.00979 0.0103 0.0109 0.01146 0.01202 0.0125 0.013] |

6.6.3 ANN based Voltage Control and VDCC in WTG fed IBC

In the SA-HPS, a 400 Watts WTG is used. The output voltage of the MPPT controller connected to the WTG varies continuously which can be seen in Figure 6.10. Also the power output of the WTG is proportional to the cube of the wind velocity and even a small change in the wind velocity causes a large change in the power output which fundamentally results in a varying voltage and current, hence a voltage controller is necessary.

Figure 6.10 Output voltage of the MPPT system connected to WTG

The output of WTG is rectified and filtered with a capacitive filter to remove the ripple on the rectified output. The magnitude of the filtered output stands at 97.8V. The duty cycle ‘α’ required to put up 156V at the output of the IBC from the nominal input voltage of 97.8V is estimated as in
the Equation (6.7), which essentially forms the base value of the training data. All the processes in building the ANN controller such as estimating the magnitude of ‘\( \alpha_w \)’ and ‘\( V_{w,ref} \)’ are similar to that in the Equations (6.3) and (6.4).

The maximum possible voltage deviations on either side of the 156V are presumed and their corresponding change in duty cycle ‘\( \Delta \alpha \)’ necessary to reinstate the reference voltage and carry out VDCC is calculated theoretically similar to that of the SPV system. In the similar way, 54 different voltages on both sides of 156V are considered and their corresponding change in duty cycle ‘\( \Delta \alpha \)’ are calculated to make up the training data of the ANN controller and it is shown in Table 6.3.

Table 6.3 Training data of the ANN controller connected to WTG for voltage control and VDCC

| INPUT: P = [-600 -500 -400 -350 -300 -260 -230 -200 -180 -160 -140 -120 -100 -90 -80 -70 -60 -50 -40 -30 -20 -15 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 12 15 17 20 25 30 35 40 45 50 55] |
|TARGET: T = [-0.4985 -0.4788 -0.4519 -0.4345 -0.4132 -0.3926 -0.3743 -0.3529 -0.3365 -0.3181 -0.297 -0.273 -0.2454 -0.2298 -0.2129 -0.1945 -0.1745 -0.1524 -0.1282 -0.1013 -0.07138 -0.0551 -0.03777 -0.03426 -0.0306 -0.0269 -0.02326 -0.0195 -0.0157 -0.0118 -0.00795 -0.00401 0 0.00405 0.00815 0.0123 0.01653 0.0208 0.02512 0.0295 0.03395 0.03846 0.04302 0.05235 0.0668 0.07683 0.09238 0.1198 0.1495 0.1817 0.2166 0.2546 0.2963 0.342] |

6.6.4 ANN based Current Fine-tuning in WTG fed IBC

The training data of the ANN for minute current control in the WTG fed IBC are estimated by performing an open loop experiment on an
arrangement similar to that of the actual system. For the various magnitude of ‘\( I_{w,\text{ref}} \),’ minor deviations in the actual current with respect to the reference current are created by adjusting the load parameters and minute duty cycle variations required to achieve the reference current are noted and it is given as input and target data of the ANN controller. The training data are shown in Table 6.4 and it shall be noticed that, the duty cycle parameter of the training data is very fractional in nature.

<table>
<thead>
<tr>
<th>Table 6.4 Training data of the ANN controller connected to WTG fed IBC for minute current control</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>INPUT:</strong></td>
</tr>
<tr>
<td><strong>TARGET:</strong></td>
</tr>
</tbody>
</table>

### 6.6.5 ANN based Voltage Control and VDCC in Fuel cell fed IBC

The training data of the ANN for voltage control, VDCC and current fine-tuning are estimated by performing simulation analysis on a 1kW PEM fuel cell with the nominal voltage and current of 64.96V and 15.3945A respectively. The I-V characteristics of the fuel cell shown in Figure 6.11 are highly nonlinear and the terminal voltage of the fuel cell drops with an increase in the power output. Hence, a dedicated controller is required to maintain a constant voltage at PCC and also to realize the power flow control a steadfast current control technique is required.

Similar to that of the SPV panel and WTG, it is imperative to calculate the value of ‘\( V_{f,\text{ref}} \’ \) (collective component for voltage control and VDCC) following the Equation (6.12) and (6.13) which are one of the inputs of the ‘sum’ block.
\[ \alpha_f = 0.5835 + \left[ \frac{(I_{f_{\text{ref}}}-I_{f_0})}{156 \times I_{f_{\text{ref}}}} \right] \]  
\hspace{1cm} (6.12)

and,

\[ V_{f_{\text{ref}}} = \left[ \frac{64.96}{1 - \alpha_f} \right]^{-156} \]  
\hspace{1cm} (6.13)

The other inputs are the ‘\(V_{\text{ref, pcc}}\)’, i.e., 156V and the actual output voltage of the IBC. The ‘sum’ block works on ‘++-’ logic and it generates the ‘error voltage’ as in the Equation (6.14).

\[ \text{error voltage} = V_{\text{ref, pcc}} (i.e., 156) + V_{f_{\text{ref}}} - V_{o_{\text{pcc}}} \]  
\hspace{1cm} (6.14)

An assortment of training data, i.e., 24 different ‘error voltages’ on either side of the reference voltage, and its corresponding target data are estimated from the open loop simulation analysis and used as the training data of the ANN controller.
Table 6.5 Training data of the ANN controller connected to fuel cell fed IBC for voltage control and VDCC

<table>
<thead>
<tr>
<th>INPUT:</th>
<th>P = [-200 -100 -50 -25 -10 -5 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 20 30 50 80]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET:</td>
<td>T = [-0.234 -0.1627 -0.1011 -0.057 -0.02509 -0.0129 -0.00265 0 0.00268 0.00541 0.008167 0.01096 0.01379 0.01666 0.01956 0.0225 0.0255 0.0285 0.031599 0.0347 0.03786 0.04106 0.0612 0.09917 0.1964 0.4384]</td>
</tr>
</tbody>
</table>

6.6.6 ANN based Current Fine-tuning in Fuel cell fed IBC

The training data of the ANN for finite current control are obtained by performing simulation analysis on the system similar to that of the actual system. Very small deviations in the actual current delivered with respect to the reference current ‘I_{ref}’ are created by changing the load parameters for various reference currents. Slight duty cycle corrections required to build the actual current equal to the reference current are given as the training data for the proposed ANN which generally functions as the correction factor. The training data of the proposed ANN for minor current adjustments are shown in Table 6.6.

Table 6.6 Training data of the ANN controller connected to fuel cell fed IBC for minute current control

<table>
<thead>
<tr>
<th>INPUT:</th>
<th>P = [0 0.0156 0.0312 0.156 0.312 1.56 3.12 3.9 5.2 7.8 8.21 8.67 9.176 9.75 10.4 11]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET:</td>
<td>T = [0 0.00025 0.000526 0.001319 0.00265 0.003715 0.00479 0.00559 0.00777 0.01079 0.0113 0.0119 0.01246 0.01302 0.0135 0.014];</td>
</tr>
</tbody>
</table>
6.6.7 ANN based Voltage Control, VDCC and Current Fine-Tuning in Battery fed IBC

The nominal discharge characteristics of a 100V, 150Ah battery are shown in Figure 6.12 and it is noticeable that the terminal voltage depends on the SOC and discharge current of the battery which is continually varying while the battery is discharging.

![Nominal Current Discharge Characteristic at 0.1C (15A)](image)

Figure 6.12 Nominal discharge characteristics of a 100V, 150Ah lead-acid battery

A similar condition holds while the battery is charging as well. Hence, to maintain a constant voltage and regulate the current flow an ANN controller is planned. The input of the ANN controller is the ‘error voltage’ which is fed from a ‘sum’ block and follows the ‘++-’ logic to its input and is given in the Equation (6.15)

\[
\text{error voltage} = V_{ref\_pcc} \quad (i.e., 156) \quad + \quad V_{bd\_ref} \quad - \quad V_{o\_bd} \quad \quad (6.15)
\]
The \( V_{bd\_ref} \) is calculated as in Equations (6.16) and (6.17)

\[
\alpha_{bd} = 0.2654 + \left[ \frac{(I_{bd\_ref} - I_{bo})}{156 \times I_{bd\_ref}} \right] \quad (6.16)
\]

The first component, i.e., ‘0.2654’ is the duty cycle required to maintain the 156V at the output while the second is for VDCC. The \( V_{bd\_ref} \) required to realize the VDCC is calculated using the Equation (6.17)

\[
V_{bd\_ref} = \left[ \frac{114.6}{(1 - \alpha_{bd})} \right] - 156 \quad (6.17)
\]

The training data of the ANN are estimated by performing the open loop experimental investigations. The terminals of the battery are connected to the IBC and the duty cycle is adjusted to deliver 156V at its output. Under these conditions, the load and source parameters are varied to realize various ‘error voltage’ on either side of reference voltage and 28 No’s of training data, such as the ‘error voltage’ and the combined duty cycle variations required to carry out voltage control and VDCC for diverse \( I_{bd\_ref} \) are estimated and shown in Table 6.7.

Table 6.7 Training data of the ANN connected to battery fed IBC for voltage control and VDCC

<table>
<thead>
<tr>
<th>INPUT:</th>
<th>P = [-300 -200 -100 -50 -20 -10 -5 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 20 30 50 80]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET:</td>
<td>T = [-0.483 -0.4127 -0.2869 -0.1783 -0.08347 -0.04425 -0.0228 -0.004679 0 0.004739 0.00954 0.0144 0.01933 0.0243 0.02938 0.0345 0.0397 0.04497 0.05032 0.0557 0.0612 0.06678 0.0724 0.07815 0.108 0.1749 0.3465 0.7732]</td>
</tr>
</tbody>
</table>
The first ANN controller applies voltage control and VDCC in the IBC in which the controller largely increases / decreases the current delivery to match the reference current. Any fractional deviation from the reference current is corrected by the second ANN which increments / decrements the duty cycle by a very fractional magnitude. It behaves as a correction factor in making the actual current equal to that of the reference current and the training data of the ANN are given in Table 6.8.

Table 6.8 Training data of the ANN connected to battery fed IBC for current fine-tuning

<table>
<thead>
<tr>
<th>INPUT:</th>
<th>P = [0 0.0156 0.0312 0.156 0.312 1.56 3.12 3.9 5.2 7.8 8.21 8.67 9.176 9.75 10.4 11]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET:</td>
<td>T= [0 0.00028 0.000536 0.001329 0.00205 0.002415 0.00342 0.0042 0.00577 0.00979 0.0103 0.0109 0.01146 0.01202 0.013 0.014]</td>
</tr>
</tbody>
</table>

6.7 ANN CONTROLLER BASED PMS FOR GI-HPS

The instantaneous current reference scheme based PMS for a GI-HPS is designed using ANN controller and the block diagram representation of the proposed ANN controller based PMS is shown in Figure 6.13. Based on the instantaneous LD, P_s, P_W, P_Fmax and SOC of the battery, the proposed PMS coordinates the sharing of power among the SPV panel, WTG, fuel cell and battery along with AC grid in any one of the possible 28 modes to satisfy the LD (delineated in chapter 5.3.4).

In ANN based PMS for a GI-HPS, in addition to the various signals used in the SA-HPS, the EC calculates and uses the control variables pertaining to the AC grid such as ‘I_{ac, ref}’ and ‘I_{ac}’ the instantaneous reference current and the actual current flow of the AC grid respectively and ‘V_{ac, ref}’ the voltage component that accomplishes the voltage control and VDCC.
Figure 6.13 GI-HPS with ANN controller based power management system

The input and output voltage of the IBC connected to the SPV panel, WTG, fuel cell and battery are the same as that of the SA system. Hence, the same ANN controllers developed for the SA-HPS are used in the
GI-HPS as well. As the AC grid is used as one of the inputs in the GI-HPS, a set of ANN for voltage control, VDCC and current fine-tuning is developed.

### 6.7.1 Voltage Control and VDCC using MLPN NN in AC Grid fed IBC

The AC grid is the strongest source compared to other sources in the GI-HPS. Hence a stringent control is very much essential as the AC supply has the capability to give out large magnitude of circulating current. A dedicated ANN controller is developed for the IBC connected to AC supply is shown in Figure 6.14.

The input of the ANN controller is the ‘error voltage’ computed as in the Equation (6.18)

\[
error \text{ voltage} = V_{\text{ref}_pcc} (i.e., 156) + V_{\text{ac}_\text{ref}} - V_{\text{oac}_pcc} \quad (6.18)
\]

While ‘\(V_{\text{oac}_pcc}\)’ is the instantaneous actual output voltage of IBC connected to the AC supply, ‘\(V_{\text{ac}_\text{ref}}\)’ is the cumulative voltage component that includes the voltage control and VDCC. The instantaneous magnitude of ‘\(V_{\text{ac}_\text{ref}}\)’ is estimated using the Equation (6.19) and (6.20)

\[
\alpha_s = 0.37307 + \left[ \frac{(I_{\text{ac}_\text{ref}} - I_{\text{oac}})}{(156 \times I_{\text{ac}_\text{ref}})} \right] \quad (6.19)
\]

and,

\[
V_{s\_ref} = \left[ \frac{97.8}{(1 - \alpha_s)} \right]^{156} \quad (6.20)
\]

While ‘\(\alpha_s\)’ is the duty cycle component concerned to voltage control and VDCC, ‘\(I_{\text{ac}_\text{ref}} \)’ and ‘\(I_{\text{oac}} \)’ are the instantaneous reference current and actual output current of IBC connected to the AC supply. The magnitude ‘0.37307’
is the duty cycle component pertaining to voltage control at the PCC and '97.8V' is the input voltage of the IBC connected to the AC supply.

Figure 6.14 ANN controllers for voltage control, VDCC and current fine-tuning in IBC connected to AC grid

The training data for the proposed ANN are devised by performing an open loop experimental investigation on the IBC supplied from a 100V, 50Hz AC supply. A system similar to that of the actual HPS is developed by
connecting two IBC in parallel and the duty cycle of the IBCs is adjusted to deliver 156V. The load and the source parameters of the AC grid fed IBC is varied to realize various ‘error voltage’ conditions at the output on either side of the reference voltage. Also the voltage variation and the change in duty cycle required to vary the current from the minimum to the maximum possible value of \(I_{ac,ref}\) in a parallel connected system are studied, and verified with the theoretical calculations. A total of 51 sets, which form the training data of the proposed ANN intended for voltage control and VDCC is given in Table 6.9.

The rapport established by the ANN between the input and target data proposed for voltage control and VDCC is shown in Figure 6.15. The training performance of the proposed ANN controller is shown in Figure 6.16 and the best training performance is 2.7999e-08 and it is achieved in 62 epochs. The value of ‘R’ as ‘1’ in the regression plot indicates a linear relationship between outputs and targets. The regression plot of the proposed ANN is shown in Figure 6.17.

**Table 6.9 Training data of the proposed ANN controller connected to AC supply fed IBC for voltage control and VDCC**

| INPUT: | P = [-350 -300 -260 -230 -200 -180 -160 -140 -120 -100 -90 -80 -70 -60 -50 -40 -30 -20 -15 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 12 15 17 20 25 30 35 40 45 50 55] |
| TARGET: | T = [0.4345 -0.4132 -0.3926 -0.3743 -0.3529 -0.3365 -0.3181 -0.297 -0.273 -0.2454 -0.2298 -0.2129 -0.1945 -0.1745 -0.1524 -0.1282 -0.1013 \textbf{-0.07125} -0.0551 -0.03777 -0.03426 -0.0306 -0.0269 -0.02326 -0.0195 -0.0157 -0.0118 -0.00795 -0.00401 \textbf{0} 0.00405 0.00815 0.0123 0.01653 0.0208 0.02512 0.0295 0.03395 0.03846 0.04302 0.05235 0.0668 0.07683 0.09238 0.1198 0.1495 0.1817 0.2166 0.2546 0.2963 0.342] |
6.7.2 ANN based Current Fine-tuning in AC Grid fed IBC

An ANN with diminutive duty cycle variation is integrated along with VDCC to enable exact settling of the actual current to the reference value which improves the steady state performance of the system. Training data of the ANN for current fine-tuning are obtained by performing simulation.
analysis. Very small deviations in the actual output current ‘I_{oa,c}’ to that of the reference current are created by changing the load parameters, and the minute duty cycle variations required to restore the actual output current ‘I_{oa,c}’ are noted. Similarly, many such deviations in the actual current flow is created and duty cycle corrections required to put back the reference current are noted and given as the training data for the proposed ANN which functions as the correction factor and it is given in Table 6.10.

Table 6.10  Training data of the ANN connected to AC supply for minute current control

<table>
<thead>
<tr>
<th>INPUT:</th>
<th>P = [0  0.0156  0.0312  0.156  0.312  1.56  3.12  3.9  5.2  7.8 8.21  8.67  9.176  9.75  10.4  11]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET:</td>
<td>T = [0  0.00035  0.000576  0.001519  0.00285  0.003215 0.00399  0.00429  0.00627  0.00979  0.0103  0.0109  0.01186 0.01202  0.0125  0.0136]</td>
</tr>
</tbody>
</table>

6.8  PERFORMANCE OF THE PROPOSED ANN BASED PMS DEVELOPED FOR SA AND GI-HPS

A constrained source and load data are fed as the input to the SA and GI-HPS to validate the performance of the ANN based PMS on managing the power flow from sources to load. The simulation response for various modes of operation is presented to portray the efficiency of the proposed PMS.

6.8.1  Modes of Operation of the SA-HPS

When the LD>P_{S}+P_{W} and if LD<P_{S}+P_{W}+P_{B}, the ANN based PMS connects SPV panel, WTG and battery to the PCC and optimizes the duty cycle for each of IBC to harvest all of P_{S}, P_{W} and supply the remaining power deficit from the battery. Simulation response of the proposed ANN based
PMS for such a constrained input is shown in Figure 6.18. Based on the $P_S$ and $P_W$, the EC computes $I_{S,\text{ref}}$ and $I_{W,\text{ref}}$ and then the reference signals for the LC’s. The ‘LC1’ optimizes the cumulative ‘change in duty cycle’ for voltage control and VDCC and the ‘LC2’ optimizes for current fine-tuning, which is very tiny to exactly settle the actual current flow to the reference current value, which can be noticed in Figures 6.19 and 6.20. The competence of the ANN in making the actual current flow to follow the reference current can be evidenced from the comparison of actual current flow to the reference current value, shown in Figure 6.21.

![Figure 6.18](image)

**Figure 6.18**  ANN based PMS extracts all of $P_S$, $P_W$ and duly discharges the battery to supply the LD.

The simulation results for a few other modes of operation, such as mode 12, mode 15, mode 20 and mode 23 are presented in Figures 6.22, 6.23, 6.24 and 6.25 respectively to authenticate the efficacy of the proposed ANN based PMS developed for the SA and GI-HPS.
Figure 6.19 Change in duty cycle for voltage control, VDCC, and current fine-tuning in SPV panel fed IBC (Mode 10)

Figure 6.20 Change in duty cycle for voltage control, VDCC, and current fine-tuning in WTG fed IBC (Mode 10)
Figure 6.21  Reference vs actual current flow in an ANN controller based PMS (Mode 10)

Figure 6.22  Utilizing all of $P_S$, the ANN based PMS duly discharges the battery to supply the remaining deficit.
Figure 6.23 $P_S$, $P_W$ is zero and $LD<P_B$, the ANN based PMS duly discharges the battery to supply the load.

Figure 6.24 PMS extracts all of $P_S$, $P_W$, $P_{B(max)}$ and supplies the remaining power deficit from FC.
Figure 6.25  PMS extracts all of $P_S$, $P_W$ to supply the LD and delivers the remaining deficit from FC.

6.8.2  Mode of Operation of the GI-HPS

The proposed ANN based PMS is tested in all the modes of operation of the GI-HPS, and the simulation output of mode 8 is presented to show its effectiveness in managing the power flow. $P_S$ is dominant while $P_W$ is zero, also battery SOC<40% and the fuel cell cannot produce power. Under these conditions, if the LD>$P_S$, the ANN based PMS optimizes the duty cycle for the IBC’s to extract all of $P_S$ and to supply the remaining power deficit from the AC grid as other sources are not available. The PMS charges the battery at its rated charging current (5% of ampacity) as shown in Figure 6.26.
Figure 6.26 PMS uses all of $P_S$, connects AC grid to supply the remaining deficit and to charge the battery