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Earth Station Neural Network Control Methodology and Simulation

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***Abstract*—**Renewable energy resources are inexhaustible, clean as compared with conventional resources. Also, it is used to supply regions with no grid, no telephone lines, and often with difficult accessibility by common transport. Satellite earth stations which located in remote areas are the most important application of renewable energy. Neural control is a branch of the general field of intelligent control, which is based on the concept of artificial intelligence. This paper presents the mathematical modeling of satellite earth station power system which is required for simulating the system.Aswan is selected to be the site under consideration because it is a rich region with solar energy. The complete power system is simulated using MATLAB–SIMULINK.An artificial neural network (ANN) based model has been developed for the optimum operation of earth station power system. An ANN is trained using a back propagation with Levenberg–Marquardt algorithm. The best validation performance is obtained for minimum mean square error. The regression between the network output and the corresponding target is equal to 96% which means a high accuracy. Neural network controller architecture gives satisfactory results with small number of neurons, hence better in terms of memory and time are required for NNC implementation. The results indicate that the proposed control unit using ANN can be successfully used for controlling the satellite earth station power system.

***Keywords*—**Satellite; Neural network; MATLAB; Power system

I. INTRODUCTION

GROUND system consists of ground station and control centers working together to support the spacecraft and the data user. Earth station consists of major subsystems, transmitter, receiver, antenna, tracking equipment, and terrestrial interface equipment and power supply. Power subsystem is an important subsystem that required for supplying the earth station with electrical power to continuously communicating with its remote sensing satellite [1, 2].

In the last three decades, numerous alternative control techniques, such as neural networks have been proposed instead of conventional classical techniques to solve complicated practical problems in various areas and are becoming more popular nowadays.

Development of ANN's theory has inspired new resources for possible implementation of better and more efficient control. ANN's have capability of learning the dynamical systems that estimated input-output functions [3]. On the other hand, before used for control purposes, ANN's have to be trained and they need some information (not based on mathematical model but sometimes taken measurement from plant) about the plant [4].

In order to simulate the final power system of the earth station, it is required to find the mathematical model for each subsystem. This paper develops the mathematical models for the proposed power system. The neural network control methodology is introduced. This technique is applied to manage the earth station power system. Also, the MATLAB simulation results are presented.

II. EARTH STATION POWER SYSTEM ARCHITECTURE

PV systems are most effective at remote sites off the electrical grid. In this system, a storage battery is needed. Excess energy produced during times with no or low loads which charges the battery, while at times with no or too low solar radiation the loads are met by discharging it. A charge controller supervises the charge/discharge process in order to ensure a long battery lifetime. Figure 1 represents the main components of stand alone PV system. By virtue of the variable nature of the energy source sun, one of the most expensive aspects of a PV power system is the necessity to build in system autonomy. Autonomy is required to provide reliable power during "worst case" situations, which are usually periods of adverse weather, seasonally low radiation values or unpredicted increased demand for power. The addition of autonomy could be accomplished by over sizing the PV array and greatly enlarging the battery storage bank-generally the two most costly system components. An additional benefit of this approach is the added system reliability provided by the incorporation of the back-up energy source [5, 6]. Aswan is selected to be the site under consideration because it is a rich region with solar energy.

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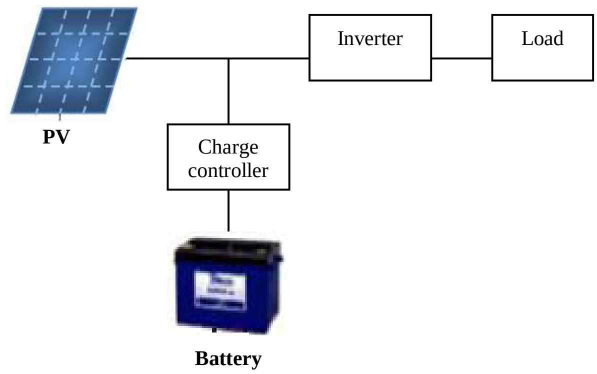

Fig. 1 Earth station power system architecture

III. PV Generator Model

The I-V characteristics of a solar array are given by the following equation [7]:

$$I_o = I_{ph} - I_{rs}\left(e^{qV_o/kTA} - 1\right) \quad (1)$$

Where I_o is the PV array output current (A); V_o is the PV array output voltage (V); q is the charge of an electron, k is the Boltzmann's constant in J/K; A is the p–n junction ideality factor; T is the cell temperature (K); and I_{rs} is the cell reverse saturation current; The factor A determines the cell deviation from the ideal p–n junction characteristics. The ideal value ranges between 1 and 5 [8].

The photocurrent I_{ph} depends on the solar radiation and the cell temperature as stated in the following equation:

$$I_{ph} = (I_{scr} + k_i(T - T_r))\frac{S}{S_t} \quad (2)$$

Where I_{scr} is the PV array short circuit current at reference temperature and radiation (A); k_i is the short circuit current temperature coefficient (A/K); S_t is the standard solar radiation; and S is the incident solar radiation (W/m^2).

The reverse saturation current I_{rs} varies with temperature according to the following equation:

$$I_{rs} = I_{rr}\left(\frac{T}{T_r}\right)^3 e^{\left(E_o/K'A\right)\left(\left(1/T_r\right)-\left(1/T\right)\right)} \quad (3)$$

Where T_r is the cell reference temperature; I_{rr} is the reverse saturation current at T_r; k' is the Boltzmann's constant in eV/K; and E_{go} is the band gap energy of the semiconductor used in the cell.

Finally, Eq. (4) was used in the computer simulations to obtain the open circuit voltage of the PV array:

$$V_{oc} = \frac{AkT}{q} ln\left(\frac{I_{ph} + I_{rs}}{I_{rs}}\right) \quad (4)$$

From Eqs. (2) to (4), the reverse saturation current can be obtained as follows:

$$I_{rr} = \frac{(I_{scr} + k_i(T - T_r))\frac{S}{S_t}}{e^{V_{oc}q/AkT} - 1}\left(\frac{T_r}{T}\right)^3 e^{-\left(E_o/K'A\right)\left(\left(1/T_r\right)-\left(1/T\right)\right)} \quad (5)$$

Eqs. (1) to (5) are used in the development of the simulations of the solar array. The MATLAB SIMULINK is used.

IV. Battery Bank Model

At any hour the state of battery is related to the previous state of charge and to the energy production and consumption situation of the system during the time from (t-1) to (t). During the charging process, when the total output of PV and wind generators is greater than the load demand, the available battery bank capacity at hour (t) can be described by [9, 10]:

$$C_{bat}(t) = C_{bat}(t-1).(1-\sigma) + \left(E_{PV}(t) - \frac{E_L(t)}{\eta_{inv}}\right)\eta_{bat} \quad (6)$$

On the other hand, when the load demand is greater than the available energy generated, the battery bank is in discharging state. Therefore, the available battery bank capacity at hour (t) can be expressed as:

$$C_{bat}(t) = C_{bat}(t-1).(1-\sigma) + \left(\frac{E_L(t)}{\eta_{inv}} - E_{PV}(t)\right) \quad (7)$$

Where $C_{bat}(t)$ and $C_{bat}(t-1)$ are the available battery bank capacity (Wh) at hour (t) and (t-1) respectively; η_{bat} is the battery efficiency (during discharging process, the battery discharging efficiency was set equal to 1 and during charging, the efficiency is 0.65 to 0.85 depending on the charging current); σ is self-discharge rate of the battery bank; $E_{PV}(t)$ is the energy generated by PV; $E_L(t)$ is the load demand at hour (t); and η_{inv} is the inverter efficiency.

V. Artificial Neural Network

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. As indicated in Fig. 2, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function [11, 12].

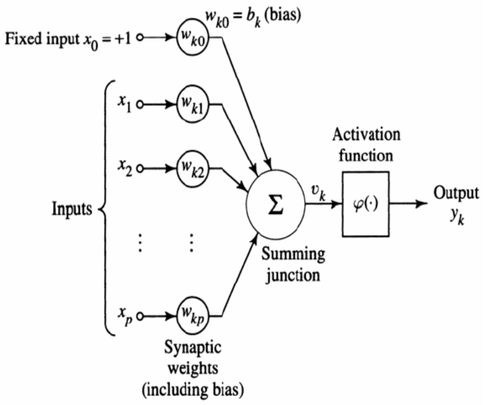

Fig. 2 Nonlinear model of a neuron

The main advantages of the neural network technique are:

- Nonlinearity;
- Mapping input signals to desired response;
- Adaptivity;
- Evidential response: confidence level improves classification;
- Contextual information: Knowledge is represented by the very structure and activation;
- Fault tolerent: graceful degradation of performance if damaged;
- Uniformity of analysis and design;
- Neurobiological analogy.

The total synaptic input, *u*, to the neuron is given by the inner product of the input and weight vectors:

$$u = \sum_{i=1}^{I} w_i x_i \tag{8}$$

The output activation, *y*, is given by:

$$y = \phi(u) \tag{9}$$

VI. Earth Station Power System Control Methodology

Stand alone PV system for earth station is controlled using neural network. Figure 3 indicates the proposed power system controller for earth station. As depicted in Fig. 3, NN controller controls the battery charge current. The proposed controller has two inputs, the error signal, and the ambient temperature.

The structure of the Multi Layer Perceptron (MLP) proposed for controlling the charge current of battery bank subsystem is shown in Fig. 4. Different tests have been done in order to choose the number of neurons and the actual number selected which produced the best results. It consists of three layers. The first one or input layer has two inputs as follows:

Error: error signal between the generated current and load current.

T_{air}: ambient temperature.

The second layer, also called the hidden layer, has two neurons or nodes. Finally, the last layer is called the output layer, has only one node. It represents the value of change in battery charge current. The training is done by the Levenberg-Marquart back propagation algorithm.

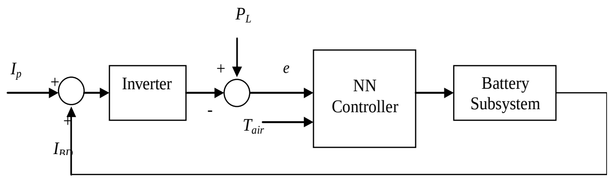

Fig. 3 Block diagram of proposed NNC for earth station power system

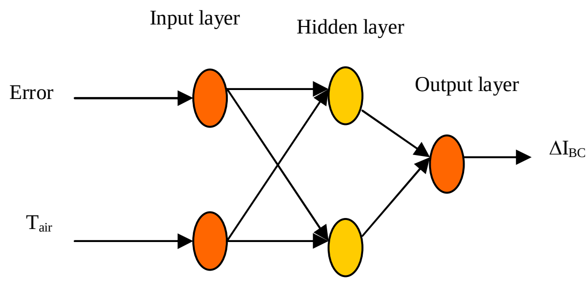

Fig. 4 The architecture of the NN controller for earth station power system

VII. MATLAB Simulation

Figure 5 indicates the MATLAB-SIMULINK of power system architecture of earth station. The global system of earth station consists of PV, battery, and control subsystem.

As depicted in Fig. 6, the inputs to the PV subsystem are insolation and temperature variables of Aswan, while the outputs are the PV current and power. SIMULINK model of the lead acid battery subsystem is described in Fig. 7.

A control system, which includes the NNC is developed for achieving the coordination between the components of stand alone power system as well as control the energy flow. After many trials, the developed NNC eventually employed a 2-neuron input, a 2-neuron hidden layer, and one neuron output layer. The input network parameters are; the ambient temperature and the error signal while the output is the change in battery charge current (ΔI_{BC}) as shown in Fig. 8. The NNC layer1 and its weights can be obtained using Fig. 9 & Fig. 10 respectively. Also NNC layer2 and its weights are described in Fig. 11 & Fig. 12.

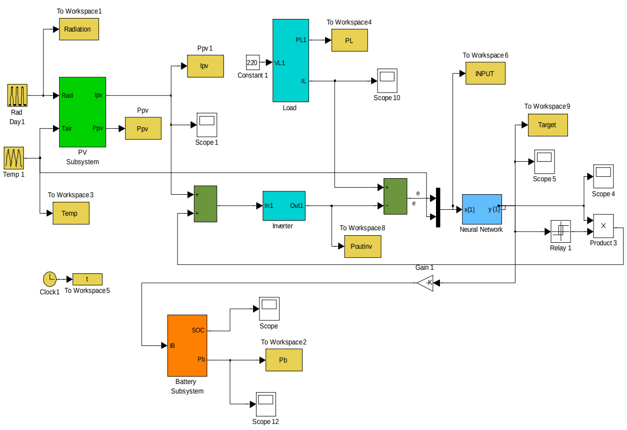

Fig. 5 Simulink block diagram of the earth station power system using NN

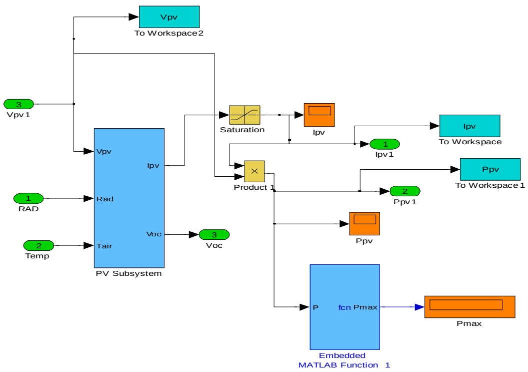

Fig. 6 Simulink block diagram of the earth station PV subsystem

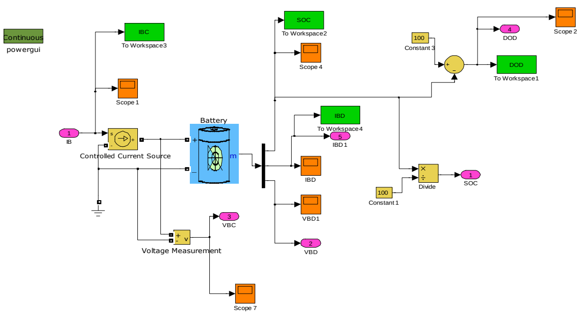

Fig. 7 The lead acid battery subsystem

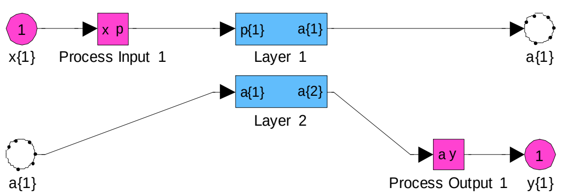

Fig. 8 Simulink block diagram of the earth station NNC

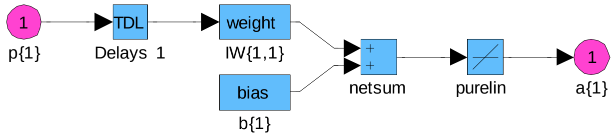

Fig. 9 Simulink Block Diagram of the layer1 of earth station NNC

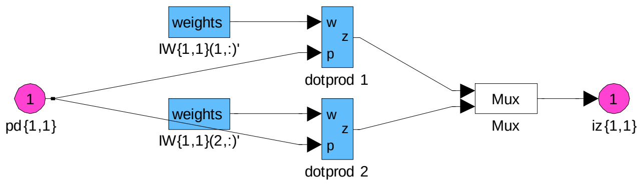

Fig. 10 Simulink block diagram of the IW{1,1}(1,:)' in Layer1 of earth station NNC

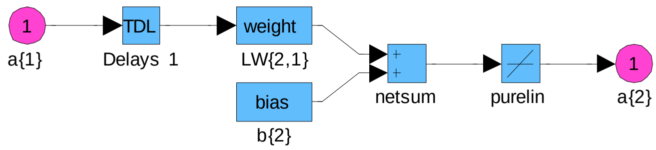

Fig. 11 Simulink Block Diagram of the layer2 of earth station NNC

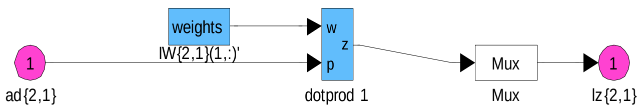

Fig. 12 Simulink Block Diagram of the LW{2,1} of Layer2 of earth station NNC

VIII. MATLAB-SIMULINK RESULTS

In order to run the simulation for the earth station power system, the solar insolation and air temperature data are needed. The variation of the hourly solar insolation and air temperature (the ambient temperature) are shown in Fig. 13 and Fig. 14 respectively. The average annual solar insolation during the year has a peak value of 900 W/m^2 at 12:00 p.m while the ambient temperature changes between 20 ^{o}C to 34 ^{o}C.

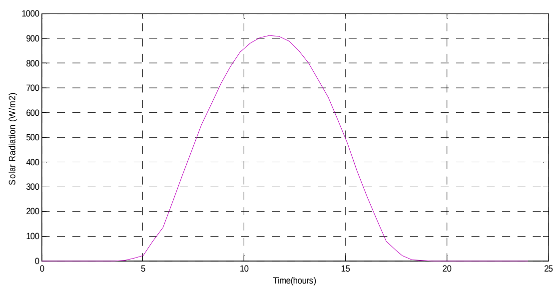

Fig. 13 Average annual solar insolation data in Aswan

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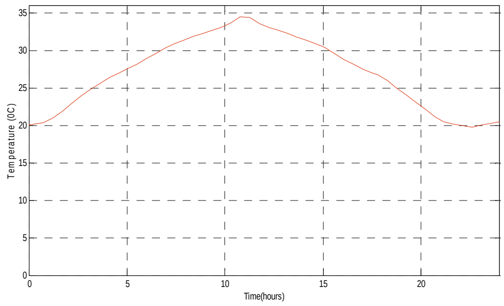

Fig. 14 Air temperature in Aswan

Solar radiation data are very important and essential for design, sizing, and simulation of PV power systems. The PV array output power is shown in Fig. 15. The variation of the output power follows the variation in solar insolation. The PV cell temperature varies between 20 ^{o}C to 61 ^{o}C over the 24 hour simulation period as indicated in Fig. 16. Figure 17 indicates the battery power profile. The battery delivers the required power to load during night periods while it charges in sunny periods.

PV power, battery power, and load power are indicated from Fig. 18. During the night, the power generated from PV is none and there is power generating from the battery (negative battery power means a discharge state) to feed the required load. While during day light at sufficient amount of solar insolation, the generated electrical power from the PV is greater than that of load demand. In this case, the energy surplus is stored in the battery and the battery is in charge state and the battery power is positive.

Neural network controller is used to control whether the system in night or in eclipse conditions comparing the solar array current with the load current, the change in battery charge current is considered as the difference between them. The results of ANN are compared to actual results. The trained model is assumed to be successful if the model gives good results for that test set. To insure that, ANN models provide correct prediction, the prediction results produced by ANN models can be validated against expert predictions for the same cases or it can be validated with the results of other computer programs.

After the network is trained successfully, the next step is to test the network in order to judge its performance and to determine whether the predicted results confirm with the actual results.

Figure 19 depicts the mean square error which can be defined as the average squared difference between the output and the target. It is clear from the figure that the results is reasonable because of small mean square error can be obtained from NNC, the test set error and the validation set error have approximately similar characteristics. The best performance is obtained at epoch 4. The network response analysis is indicated in Fig. 20. It indicates the regression (R) which measures the correlation between output and target. The value of (R) is nearly 0.96 % which means that the output tracks the targets very well for training, testing, and validation.

From the simulated network, the weights and bias are obtained. The weights of the hidden layer 1 are W {1, 1} = [–1.434 –0.14598; –0.34777 –0.93983]. The weights of the hidden layer 2 are W {2, 1} = [–0.59126 0.084595]. The bias to layer 1 is b {1} = [0.13203; –0.17087]. The bias to layer 2 is b {2} = [–0.1142].

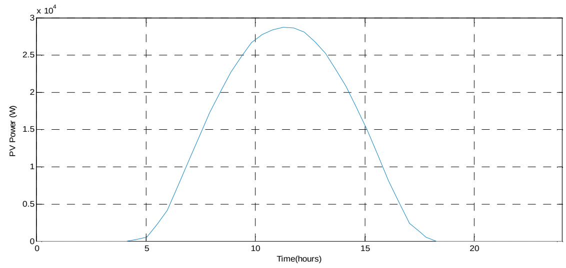

Fig. 15 PV array output power

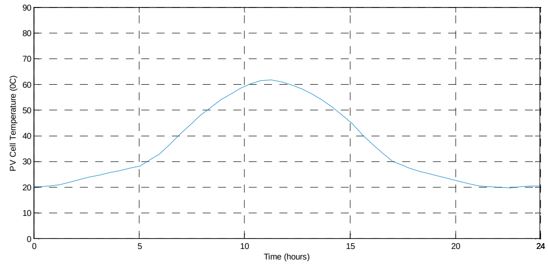

Fig. 16 PV cell temperature

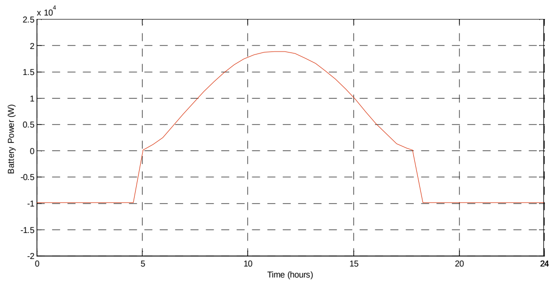

Fig. 17 Battery power

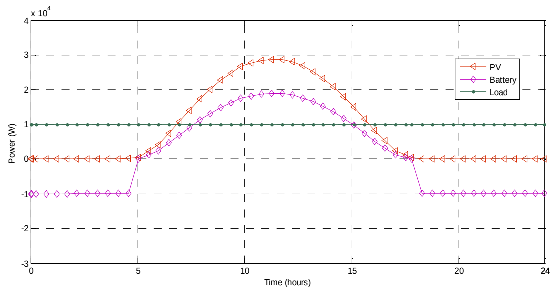

Fig. 18 Total system performance

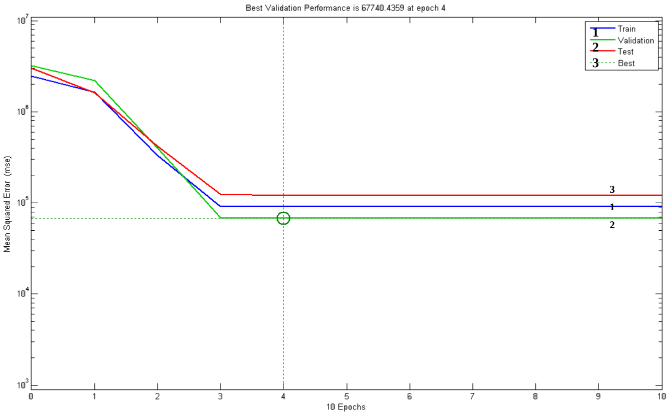

Fig. 19 Mean square error of NN

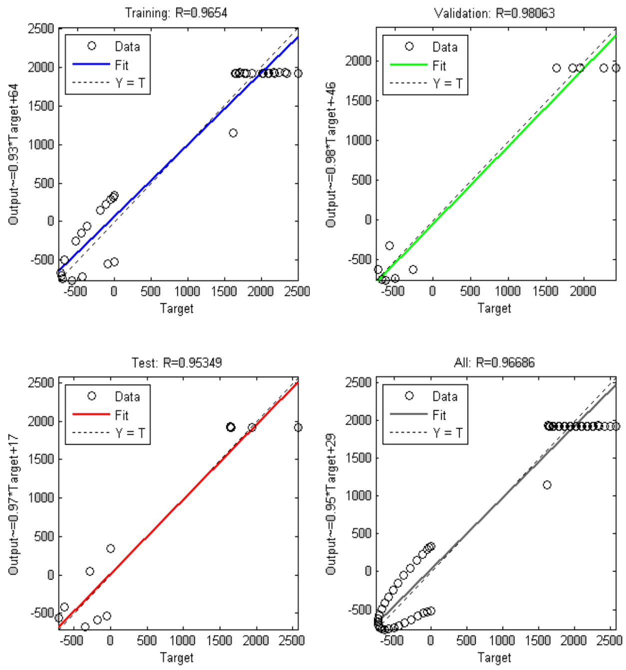

Fig. 20 NN Regression

IX. Conclusions

In this paper, the mathematical model of earth station power system components was introduced in order to investigate the dynamic behavior of each subsystem. AI techniques are becoming useful as alternate approaches to conventional techniques such as neural network. Nowadays, considerable attention has been focused on use of ANN on system modeling and control applications. Therefore, the proposed control technique of earth station power system is presented. The global system of earth station power system was explored using MATLAB-SIMULINK.

ANN is used to control the operation of the earth station power system as a result of its ability to handle large and complex systems with many interrelated parameters. Also, it can map nonlinearity and it has generalization capability, therefore it can interpolate data. ANN is trained using a back propagation with Levenberg–Marquardt algorithm using MATLAB–SIMULINK. A 2-2-1 feed forward neural network is obtained by MATLAB-SIMULINK for the earth station power system controller. Results obtained clearly demonstrate that an ANN can be used with high degree of confidence for control strategy. The results show that, the proposed ANN introduces a good accurate prediction for the change in the battery charge current for the earth station power system.

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