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Control of Power System Management in Spacecraft using Adaptive RBF

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Abstract

In this paper, modeling of various subsystem integrated under spacecraft power system has been presented. A control mechanism has been developed to provide the proper coordination among different sub system available in the spacecraft system using the adaptive radial basis function neural network. Strategy has also defined to maintain the energy flow from power resources to load in optimum manner. Performance evaluations of adaptivenss in radial basis function neural network are compared with static form of radial basis function architecture as well as multilayer perceptron architecture.

Keywords: Spacecraft, Spacecraft power system, neural network, Radial basis function and Photovoltaic array.

INTRODUCTION

In space craft system the power system plays the central role to decide the life span furthermore different desired functional operations. Any type of failure or faults in power system will reason for fatal outcomes which might cause of failure of mission permanently or temporarily. Hence, rather than conventional control strategy within the power management system, an intelligent control is that the more sensible choice that might have higher adaptiveness to handle the situation on demand. Neural network has capability to learn by examples to acquire the knowledge, which helps to design the control system more precisely. Photovoltaic conversion of the sun's energy is the commonest source of electrical power in space. A typical solar panel–battery power system is shown in Fig1.

A photovoltaic cell thought-about as a p–n semiconductor junction diode that transforms the energy of solar light into electricity. During a simplified model (neglecting the series resistance) of solar cell, the I-V nonlinear relationship represented by an eq. (1)

$$I_o = I_{ph} - I_{rs}\left(e^{qV_O/KTA} - 1\right) - {V_O}/{R_{Sh}} \quad \ldots\ldots\ldots \quad (1)$$

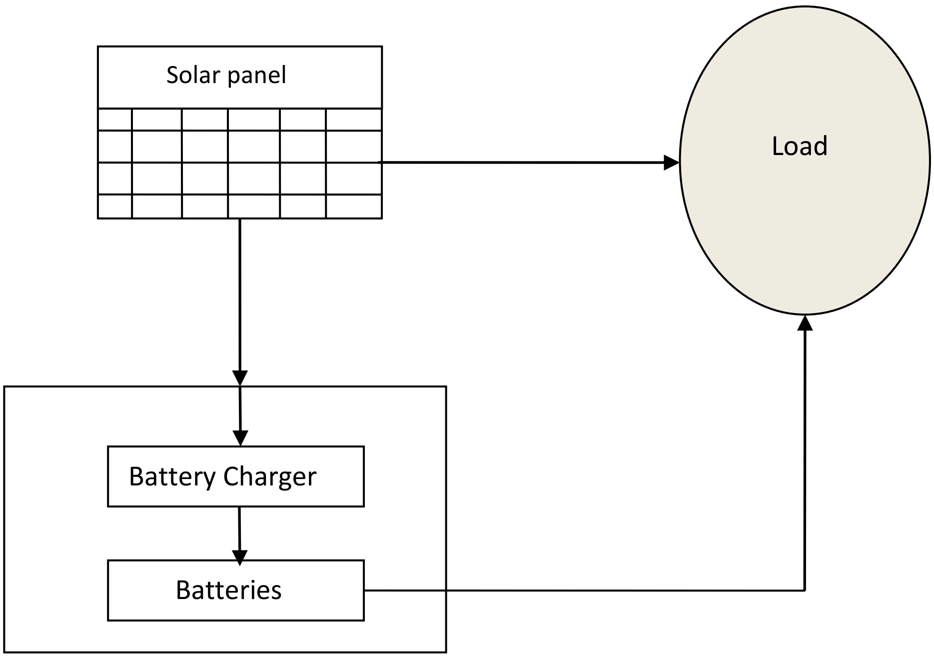

Figure 1. Simple representation of power connectivity in spacecraft

Where, I_0 is the PV array output current (A), V_0 is that the PV array output voltage (V), q is that the charge of an electron, k is that the Boltzmann's constant in J/K, A is that the P–N junction ideality factor, T is the cell temperature (K), and Irs is the cell reverse saturation current(A). The photocurrent I_{ph} is function of solar radiation and therefore the cell temperature and defined by an eq. (2)

$$I_{Ph} = \left(I_{scr} + K_i(T - T_r)\right)\frac{s}{1353} \quad (2)$$

Where I_{scr} is the PV array short circuit current (A) at reference temperature and radiation, T_r is the cell reference temperature, k_i the short circuit current temperature coefficient (A/K) and S is that the solar radiation (W/m2).

In [1] review of how artificial neural networks are utilized in the renewable energy field normally and additional specifically within the solar energy field has conferred. This review has conjointly enclosed applications of artificial neural networks within the photovoltaic (PV) and in the solar radiation fields. Detail analysis and design of spacecraft mission has presented in [2]. In general, satellite electrical power system plays a vital role in its mission performance. To perform the mission with success, the satellite ought to be supplied with the adequate power till end-of-life (EOL). To provide the adequate power, it's hard to install a larger power generation and storage source with power control units on satellite. The varied technologies are developed to cut back the satellite power sizing and to design power efficiently. The peak power tracking (PPT) technique has been developed for spacecraft power system to use maximum available power of solar array [3].The power system configuration depends on numerous factors such as quantity of power required, kind of orbit, period of the mission, constraints on mass volume, and the impact of the system's hardware on the spacecraft design. Power system encompasses power generation, energy storage and power process. The organization of control and management circuits to carry out these functionalities is termed as Power Control and Management (PCM). Choice of an applicable PCM is must for achieving the required mission goal. Thus a set performance metrics which might serve as benchmark has been elaborated in [4]. Ever changing operating conditions in space creates difficulties for supplying reliable power to spacecraft. A property of biological systems, homeostasis, will resolve challenges by using multi-alternative principles: Multi-level structure and control, functions diversity and partition, and structure modularity [5]. So as to estimate and forecast the solar radiation, it's important to trace sun's orbit, weather conditions and dissipation of rays. The function of solar photovoltaic systems is to convert solar energy into electric power. The output power depends on approaching radiation and few features of the supposed solar panel. Currently, photovoltaic power is generated in larger amounts, it's necessary that the forecasted knowledge may be efficiently used for controlling and running electricity gauze and to merchandise solar power. In [6], ANNs are accustomed to formulate the solar radiation prediction models. Power management and distribution (PMAD) models were developed to model candidate architectures for numerous Space Exploration Initiative (SEI) missions [7]

OVERVIEW OF RADIAL BASIS FUNCTION (RBF) NETWORKS

RBF networks have 3 layers input layer, hidden layer & output layer. Sometimes RBF is employed or derived from function approximation i.e. their output may be a real value. One neuron in the input layer corresponds to every predictor variable. Each neuron within the hidden layer consists of a radial basis function for example Gaussian function and this function is centered on a point with a similar dimension as the predictor variables. The output layer has a weighted total of outputs from the hidden layer to make the network outputs.

RBF network performs Non-Linear Transformation over a input vector before input vectors are fed for classification, by using such non-linear transformation, it is doable to converge linearly non-separable problem to a linearly separable problem. The essential plan is that a predicated target value of an item is probably going to be concerning identical as different things that have close values of the predicator variables. A RBF network positions one or more RBF neurons in the space described by predictor variables. This space has as many dimensions as there are predictor variables. Then Euclidian distance is computed from the point being evaluated to the middle of every neuron and RBF (kernel function) is applied to the distance to compute the weights (influence) for every neuron. Additionally a neuron is from some extent being evaluated it's less influence. The radial function is so named because the radial distance is that the argument to the function.

By viewing the detail structure at RBF neural network it has a input layer having neuron and a hidden layer having one or a lot of neurons, each having a RBF transfer function as an instance, Gaussian function and output of these hidden layer will become input to output layer i.e. weighted inputs to output layer. The output is the weighted sum of the inputs. The inputs are outputs of hidden layer and each of them for hidden layer the transfer function is Gaussian function. The Gaussian function has 2 parameters the center c and radius r. For each neuron in the hidden layer, requires finding those distances and related weights.

Functional approach of RBF

In observe, the supervise training of the neural network is thought of because the curve fitting process. The network is conferred with training pairs, and each consisting of a vector from an input space and a desired network response. Though a defined learning algorithm, the network performs the adjustments of its weights so that error between the actual and desired response is of its weights so that the error between the actual and desired response is minimized relative to some optimization criteria. Once trained, the network performs the interpolation within the output vector space. A non linear mapping between the input and therefore the output vector spaces is achieved with radial basis function.

The architecture of the RBF-NN consists of three layers as shown in Fig1: An input layer, a single layer of nonlinear processing neurons and the output layer. The output of RBF-NN is calculated according to Eq (3).

$$y_i = f_i(x) = \sum_{k=1}^{N} W_{ik}\phi_k(x, c_k) = \sum_{k=1}^{N} W_{ik}\phi_k\left(\left\|x - c_k\right\|_2\right) \qquad \text{i=1,2,….m} \tag{3}$$

Where $x \in \Re^{n\times 1}$ is an input vector, $\phi_k(.)$ is a function from $\Re^{+}$ to $\Re$, $\|.\|_2$ denotes the Euclidean norm, W_{ik} are the weights in the output layer. N is the number of neurons within the hidden layer, and $c_k \in \Re^{n\times 1}$ is the RBF center in the output space. For every neuron in the hidden layer, the Euclidean distance between its associated centers and therefore the input to the network is computed. The output of the neuron in a hidden layer is a nonlinear function of the distance. Finally the output of the network is computed as a weighted total of the hidden layer outputs. The functional form of $\phi_k(.)$ is assumed to have given and principally Gaussian function as given by Eq. (4)

$$\phi(x) = \exp\left(-x^2/\sigma^2\right) \tag{4}$$

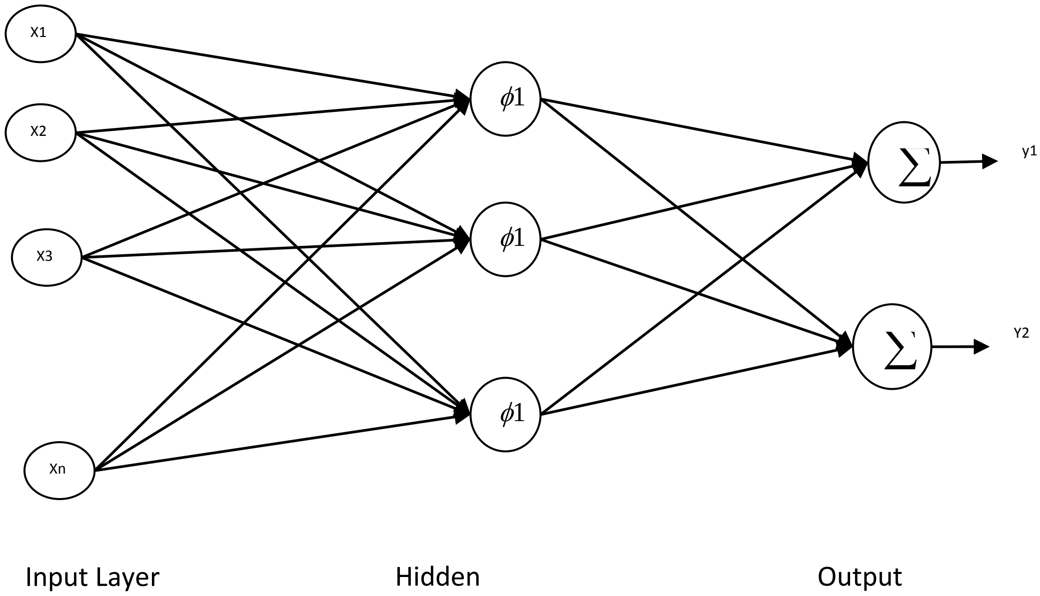

Figure 2. RBF NN architecture

Where σ is a parameter which control the "width" of RBF and is generally referred as spread parameter. The centers are defined points that are assumed to perform an adequate sampling of the input vector space. They are usually preferred as a subset of the input data. In the case of the Gaussian RBF, the spread parameter σ is usually set according to the following heuristic relationship

$$\sigma = \frac{d_{\max}}{\sqrt{k}} \tag{5}$$

Where $d_{\max}$ is the maximum euclidean distance between the selected centers. K is the number of the centers. Using Eq. (6) the RBF of a neuron in the hidden layer of the network is given by

$$\phi(x, c_k) = \exp\left(-\frac{k}{d_{\max}^2}\left\|x - c_k\right\|^2\right) \tag{6}$$

Conventionally the middle values are randomly sampled from the data set and the standard deviation is measured using the present Euclidean distance. This approach is suitable only when there is extremely concentrated information set available as very little variation exists. The performance be able to enhance by providing the optimal value of centers and corresponding customary deviations. The training of the parameters may be a critical part. Every parameter is updated based on the error in the output. Approach supported gradient mechanism is applied for updating, throughout every iteration.

Adaptive RBF NN

In the fixed centers based RBF NN, there's only 1 adjustable parameter of network is on the market and its weights of the output layer. This approach is simple, but to perform adequate sampling of the input, an outsized variety of centers should be chosen from the input file set. This can produces a comparatively terribly giant network.

In projected technique there are possibilities to regulate all the 3 set of network parameters that's weights, position of the RBF centers and also the breadth of the RBF. Therefore, together with the weights within the output layer, each the position of the centers moreover because the spread parameter for each process unit in the hidden layer undergoes the method of supervised training. The primary step within the development is to outline instant error cost function as

$$J(n)=\frac{1}{2}|e(n)|^2=\frac{1}{2}\left[y_d(n)-\sum_{k=1}^{N}w_k(n)\phi\{x(n),c_k(n)\}\right]^2 \quad (7)$$

Through the selected RBF is Gaussian, Eq.10 become

$$J(n)=\frac{1}{2}\left[y_d(n)-\sum_{k=1}^{N}w_k(n)\exp\left(-\frac{\|x(n)-c_k(n)\|_2^2}{\sigma_k^2(n)}\right)\right]^2 \quad (8)$$

The revised equation for the network parameters are specified by Eq.12 to Eq.14

$$w(n+1)=w(n)-\mu_c\frac{\partial}{\partial w}J(n)\ \rangle_{w=w(n)} \quad (9)$$

$$c_k(n+1)=c_k(n)-\mu_c\frac{\partial}{\partial c_k}J(n)\ \rangle_{c_k=c_k(n)} \quad (10)$$

$$\sigma_k(n+1)=\sigma_k(n)-\mu_k\frac{\partial}{\partial c_k}J(n)\ \rangle_{\sigma_k=\sigma_k(n)} \quad (11)$$

CONTROL STRATEGY

The control unit defines the control over supply of the power resources under condition of spacecraft in solar peak power or in the condition of eclipse by comparison of solar current within load current. The distinction is the deciding factor in the change of battery charge current. Neural network has given the off line training that has been obtained through the simulation. The matlab software package has given for simulation of system like PV array, battery storage and also the control system and shown in Fig.3.Through the system, coordination has outlined between poser subsystem and control over the distribution of energy. Within the simulation the inputs to the PV subsystem are taken as insolation and temperature variables for one orbital amount, while, the outputs are the PV current and power. The battery element has thought-about with one input, the charge current as a result of the temperature is assumed to be constant throughout the operation as a result of its isolation from the space environment. The profile of solar insolation and the temperature have shown in Fig4 and in Fig 5. ARBF has acquired the learning using gradient method for all the 3 parameters in design and the obtained best lead to terms of mean square was 8.3427 x 10-11. The required varieties of iteration were 583. There have been size architecture as two input nodes, three hidden nodes and one output node. The load current and error signal have thought-about as inputs whereas the amendment within the battery current has considered as output.

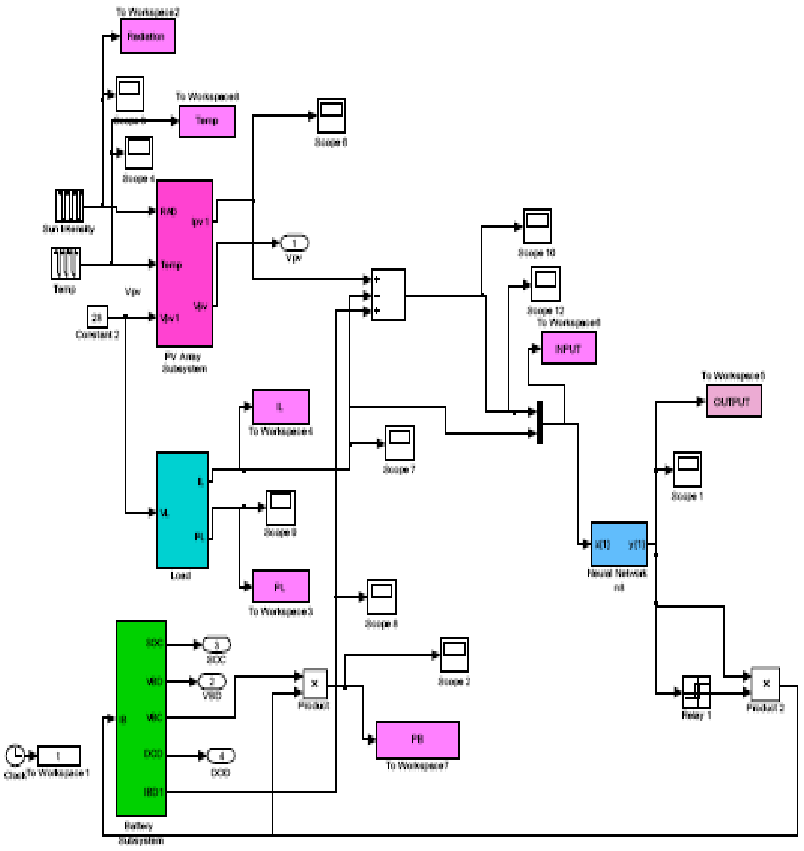

Figure 3. Simulation of spacecraft system with ARBF

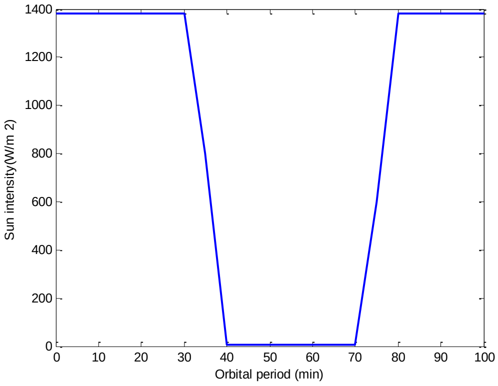

Figure 4. Solar insolation profile

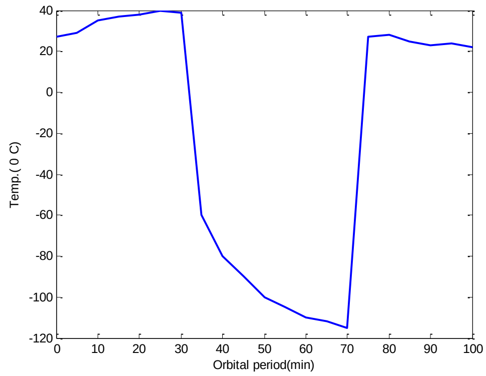

Figure 5. Temperature profile

The behavior of PV array system has shown in Fig.6 wherever it will observe that variation in PV current is according to the intensity of solar energy. Once there's is eclipse period, PV system unable to satisfy the demand of load that indicates that there's would like of a storage system that may offer sufficient energy once desired.

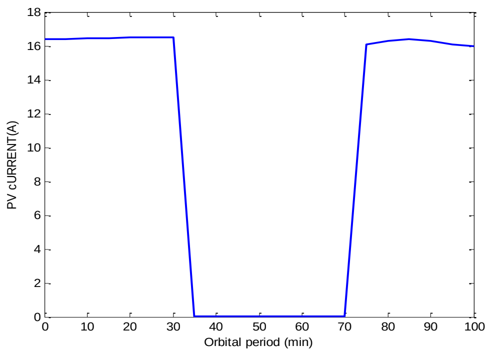

Figure 6. The typical PV current

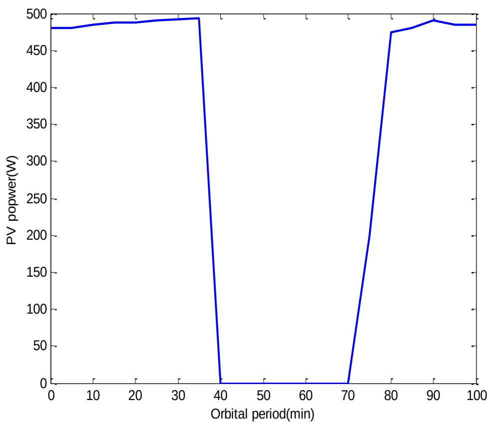

Figure 7. PV power profile obtained using ARBF controller

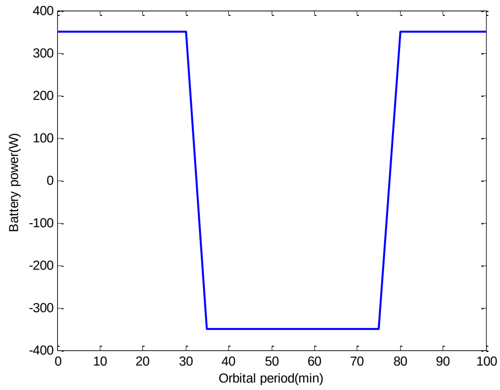

Figure 8. Battery power profile obtained using ARBF controller

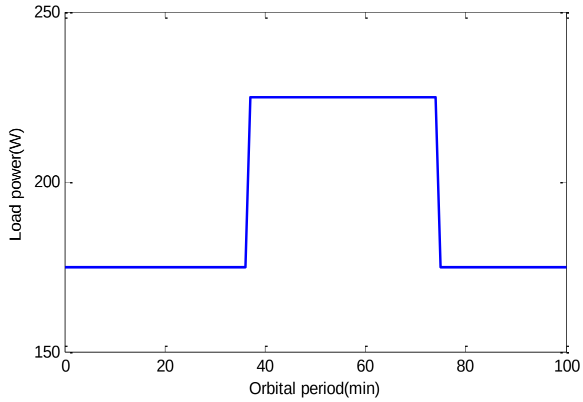

Figure 9. Load power profile obtained using ARBF controller

Using ARBF, the PV output power, the battery power, and therefore the load power profile are shown in Fig. 7 to Fig.9.It is clear that once there's enough solar power out there, PV system provides the power to the load directly and additional power used to charge the battery system. Once there's eclipsed section, PV array might fulfill the power demand of load and battery system takes the control to produce the specified power. The Positive values within the battery profile show the charging status while the negative values ensure the status of discharging. The control output power generation using ARBF has shown in Fig.10 and it's clear there is terribly little error within the generation and load and setting time is additionally terribly less.

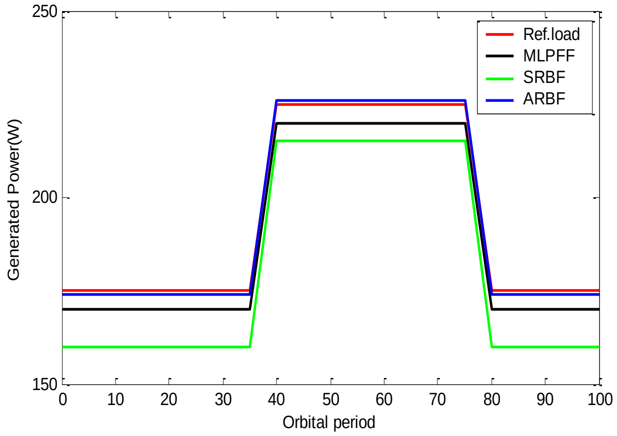

Figure 10. Comparative performance between, MLP Feedforward architecture, static RBF and adaptive RBF

It is also observed that in the case of static RBF the performances way deviated from needed reference load, it all happens due to learning wasn't correct (because only weights were available to acquire the knowledge). It's conjointly ascertained that MLP feed forward design shown improvement this regard.

But overall has the critical situation obtainable with the spacecraft the fulfillment of reference load is extremely necessary, thus the maximum amount as possible error ought to suppose to be the minimum, which has been provided by the adaptive RBF technique as it's shown in Fig. 10.

CONCLUSION

Adaptive radial basis function based control system for power management in spacecraft has bestowed. For simulation power system in low every orbit has selected. Planned resolution has delivered very optimal way the power demand in eclipsed condition and there is terribly less settling time needed. Proposed solution needed less size of memory and computational cost. Because of its efficiency and simplicity it can be considered as applicable module in space applications.

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