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RBF NN Based Marine Diesel Engine Generator Modeling

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Abstract—**For building a real time marine power system simulator, models of fast calculation and high precision of marine power system are needed. Because there are abilities of learning and batch operation with artificial neural networks (ANN), it is fit for using ANN to build a real time marine diesel generator model for marine power system simulator. In this paper, radial basis function neural networks (RBF NN) was used for building model of marine diesel engine generator. RBF NN is universal approximation neural network. There is ability to approximate a nonlinear function with RBF NN. According to working principles of diesel generator, parameters of excitation current/voltage and diesel engine mechanical torque are as inputs of RBF NN, parameters of terminal voltage current and frequency of generator are as outputs for RBF NN training. The type of supervised learning of center selection strategy was used for the RBF NN learning method. An approximated model of marine diesel generator is built in high precision result with 99 hidden neurons of RBF NN.**

I. Introduction

ACCORDING to STCW78/95 international convention, established by the International Maritime Organization (IMO), marine engineers on automatic ocean-ships must be advance through marine power system simulator training. Marine power system is different with shore power system because the generator is drove by large capacity diesel engine. For building a real time marine power system simulator, mathematical model of marine diesel generator is needed. Two factors about the real time model are considered. One factor is calculation speed of model. Another factor is precision of model. The factors are important to response characteristics of real time marine power system simulator. Because theory model of electrical generator is so complex, it is not fit for simulator calculating by DSP. ANN provides opportunity for improving the precision and fast calculation speed to real time marine diesel generator model. Radial basis function neural network (RBF NN) is broad to uniformly approximate any continuous function [4]. There is ability to approximate nonlinear model with RBF NN. In the paper, RBF NN was used for marine diesel generator modeling of real time power system simulator.

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II. Neuron Model and Network Architecture of RBF NN

Neuron model of RBF NN is showed in Fig.1 with **p** inputs. Here R is number of elements in input vector. The "‖dist‖" box in this figure accepts the input vector **p** and the single row input weight matrix, and produces the dot product of the two [1]. The net input to the transfer function is the vector distance between its weight vector **w** and the input vector **p**, multiplied by bias b. The relationship between input and output is:

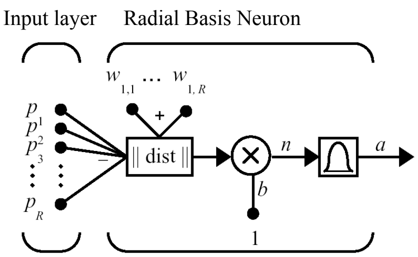

Fig. 1. Neuron model of RBF NN

$$\mathbf{p} = [p_1 \; p_2 \; p_3 \ldots\ldots p_R]$$
$$\mathbf{w} = [w_{1,1} \; w_{1,2} \; w_{1,3} \ldots\ldots w_{1,R}]$$
$$a = f_1[(\|\mathbf{w} - \mathbf{p}\| \times b)]$$

Select Gaussian function as transfer function. The function for a radial basis neuron is:

$$f_1(n) = e^{-n^2} \qquad (1)$$

The output of a is:

$$a = exp[-(\|\mathbf{w} - \mathbf{p}\| \times b)^2]$$

$$b = \frac{m_1}{d_{max}^2}$$

Here, m_1 is the number of centers and d_{max} is the maximum distance between the chosen centers.

RBF NN consists of three layers include input layer with networks. Fig.2 shows network architecture of radial basis networks. The input layer is made up of source nodes that

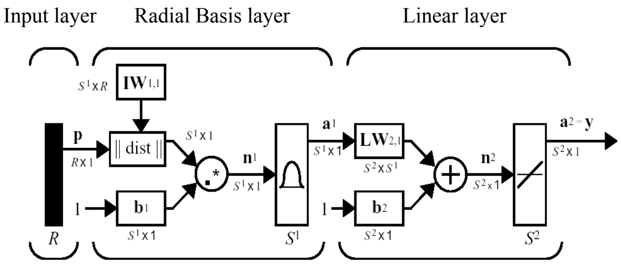

Fig. 2. Network architecture of RBF NN

connect the network to its environment. The second layer, the only hidden layer, it is radial basis layer of S^1 neurons. Here S^1 is number of neurons in hidden layer. It applies a nonlinear transformation from the input space to the hidden space, in most applications the hidden space is of high dimensionality. The "‖dist‖" box in this figure accepts the input vector **p** and the input weight matrix $\mathbf{IW}_{1,1}$ and produces a vector having S^1 elements. The elements are the distances between the input vector and vector $\mathbf{IW}_{1,1}$ formed from the rows of the input weight matrix [1]. And another is output linear layer of S^2 neurons. The output layer is linear layer.

According to network architecture of RBF NN in Fig.2, the output of radial basis layer and linear layer can be calculate as:

$$a_i^1 = \exp[-(\|{}_i\mathbf{IW}_{1,1} - \mathbf{p}\| \times b_i^1)^2]$$

$$\mathbf{y} = \mathbf{a}^2 = f_2(\mathbf{LW}_{2,1}\mathbf{a}^1 + \mathbf{b}^2)$$

In Fig.2, R is number of elements in input vector, S^1 is number of neurons in radial basis layer, S^2 is number of neurons in linear layer. a_i^1 is the ith element of $\mathbf{a}^1$. ${}_i\mathbf{IW}_{1,1}$ is a vector made of the ith row of $\mathbf{IW}_{1,1}$. f_2 is a linear function.

An important point is the fact that the dimension of the hidden space is directly related to the capacity of the network to approximate a smooth input-output mapping; the higher the dimension of the hidden space, the more accurate the approximation will be [3].

III. MARINE ELECTRIC POWER SYSTEM INTRODUCE

The power supply and control system are becoming more complex now the electrical capacity of automated ocean-going ships is growing larger. Fig. 3 shows the configuration of electric power system of a large marine container ship. This is an AC440V (3-Φ60Hz) power network system. The capacity of each diesel generator is 2850kVA, 3657A. There is an emergency diesel generator (325kVA, 417A) with the system. About electric loads, there are side-thruster (2200kW, 465A), steering gear, refrigerated container and so on. The dynamic characteristic of marine power system depends on the diesel

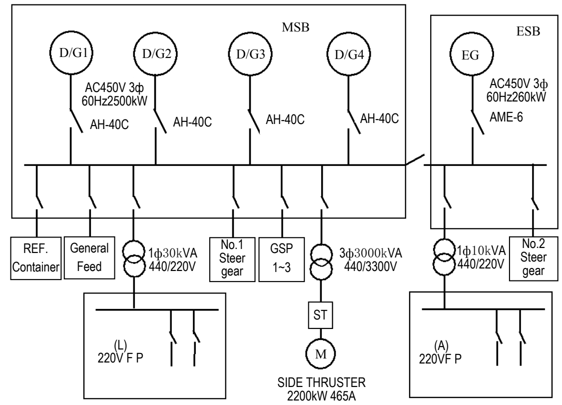

Fig. 3 Configuration of the electric power system

engine generator. For power system simulator, model of the diesel engine generator is the most important section.

IV. MARINE DIESEL ENGINE GENERATOR MODELING BASED ON RBF NN

A. Diesel Generator Modeling Method

Three layers networks were formed with one input layer one hidden layer and one output layer as Fig. 2. The neural networks based model of generator depends on the weights between neural elements. Supervised learning is used in the system training. We can train a neural network by adjusting the values of the weights according to error. After that an input tend to a specific target output.

A supervised neural network was pursued in a variety of weights. The supervised training of the neural networks can be viewed as a curve-fitting process. For approach to the marine diesel generator model, a configuration diagram of RBF NN of diesel generator modeling and training is shown in Fig. 4. First step is to select input and output parameters of generator. We selected that the input parameters are excitation current/voltage (v_t) and diesel engine mechanical torque (P_m). The output parameters are terminal voltage (v), current (i) and frequency (f) of generator. Through measuring and recording, a set of data will be obtained as sampling data for training. The measured data vector is **x**.

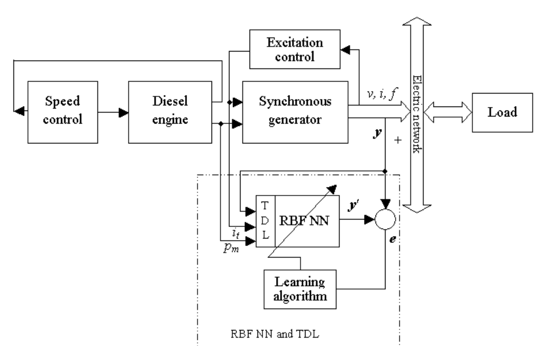

Fig. 4. Configuration diagram of RBF NN training

The input **p** connected to RBF NN through a tapped delay line. The input vector **p** of RBF NN is:

$$\mathbf{p} = [v_t \ P_m \ v' \ i' \ f']$$

The output vector **y** of RBF NN is:

$$\mathbf{y} = [v_1 \ i_1 \ f_1]$$

Such input value and desire value pair vectors were used for training a network in supervised learning. The network is adjusted, based on error of output vector $\mathbf{y} = [v_1 \ i_1 \ f_1]$ and desired response vector $\mathbf{d} = [v \ i \ f]$, until the network output matches the desired response. So the number of elements in input vector (R) is five. The number of neurons in linear layer (S^2) is three.

B. Learning Strategies of RBF NN

There are different learning strategies that we can follow in training of a RBF NN, depending on how the centers of the radial-basis functions of the network are specified. Here supervised selection of centers learning strategies was used. The centers of the radial basis functions and other parameters of the network in supervised learning process. We define the value of cost function as:

$$\varepsilon = \frac{1}{2}\sum_{j=1}^{N} e_j^2 \tag{2}$$

Here N is the size of the training sample used to do the learning, and e_j is the error defined by:

$$e_j = d_j - y_j = d_j - F^*(\mathbf{p}_j) = d_j - \sum_{i=1}^{S^2} w_i G\left(\left\| \mathbf{p}_j - \mathbf{t}_i \right\|_{C_i} \right) \tag{3}$$

The requirement is to find the parameters w_i, $\mathbf{t}_i$, and $\mathbf{\Sigma}_i^{-1}$ (the latter being related to the norm-weighting matrix $\boldsymbol{C}_i$) so as to minimize ε. Here, w_i is linear weights, $\mathbf{t}_i$ is positions of centers of a radial-basis function, $\mathbf{\Sigma}_i^{-1}$ is spread of centers. The results of this minimization are summarized as follow:

(1) Linear weights (output layer)

$$\frac{\partial \varepsilon(n)}{\partial w_i(n)} = \sum_{j=1}^{N} e_j(n)\varphi(\left\|\mathbf{p}_j - \mathbf{t}_i(n)\right\|_{C_i}) \tag{4}$$

$$w_i(n+1) = w_i(n) - \eta_1 \frac{\partial \varepsilon(n)}{\partial w_i(n)}, \qquad i = 1,2,\cdots,S^1 \tag{5}$$

(2) Positions of centers (hidden layer)

$$\frac{\partial \varepsilon(n)}{\partial \mathbf{t}_i(n)} = 2w_i(n)\sum_{j=1}^{N} e_j(n)\varphi'(\left\|\mathbf{p}_j - \mathbf{t}_i(n)\right\|_{C_i})\sum\nolimits_i^{-1}(n)[\mathbf{p}_i - \mathbf{t}_i(n)] \tag{6}$$

$$t_i(n+1) = t_i(n) - \eta_2 \frac{\partial \varepsilon(n)}{\partial \mathbf{t}_i(n)}, \qquad i = 1,2,\cdots,S^1 \tag{7}$$

(3) Spreads of centers (hidden layer)

$$\frac{\partial \varepsilon(n)}{\partial \sum_i^{-1}(n)} = -w_i(n)\sum_{j=1}^{N} e_j(n)\varphi'(\left\|\mathbf{p}_j - \mathbf{t}_i(n)\right\|_{C_i})Q_{ji}(n) \tag{8}$$

$$Q_{ji}(n) = [\mathbf{p}_j - \mathbf{t}_i(n)][\mathbf{p}_j - \mathbf{t}_i(n)]^{\mathrm{T}} \tag{9}$$

$$\sum\nolimits_i^{-1}(n+1) = \sum\nolimits_i^{-1}(n) - \eta_3 \frac{\partial \varepsilon(n)}{\partial \sum_i^{-1}(n)} \tag{10}$$

Here, n is steps number of iteration. $e_j(n)$ is the error signal of output unit j at step n. The $\varphi'(\cdot)$ is first derivative of the Green's function $\varphi(\cdot)$ with respect to its argument. The η_1, η_2 and η_3 are three coefficients of learning. The learning-rates were depended on the value of them respectively.

The training process of RBF NN modeling as follow:

(1) Endow with initial values to all weights and bias.
(2) Present input and output sample data for RBF NN training.
(3) Calculate the outputs of RBF NN according to inputs, weight and bias. When the value of cost function between sample data to output of RBF NN is little than permission value, the training process finishes. Otherwise shift to step (4).
(4) According to difference between RBF NN output value and expectation value, the weights and bias will be adjusted.
(5) Go back to step (2).

C. Modeling Results of Marine Diesel Generator

The parameters of input and output were measured as sampling data, and used for RBF NN offline training. We selected some different running states of marine power system, such as diesel engine generator starting, a general pump (240kW, 440V) of power system running, a side-thruster (2200kW, 3300V) starting and three-phases short circuit ground fault.

After training, the diesel engine generator model of RBF NN was built in network weights function. There are 99 (S^1) hidden neurons with one RBF NN model for normal operating model. As example, terminal voltage parameter of generator is selected to demonstrate the precision of model in normal operating. The parameter of terminal voltage is per unit value in diagram. The error is desired value minus output value of RBF NN model. The axis of horizontal is time (t). It is a relationship between period time (T) of sampling and size (N) of the training samples. There is $t = T \times N$. Some approximated results were obtained. The first approximated result is diesel engine starting. Fig. 5 shows voltage of generator and its error between desired value and output value of RBF NN model when diesel engine generator starting. Fig. 6 shows terminal voltage of generator and error when lubrication pump is starting. Fig. 7 shows terminal voltage of generator and error when side-thruster motor is starting. For power system three-phases short circuit ground fault, the fault process likes this. A ground fault occurs from a general pump. A large overload current was produced, and terminal voltage of generator was full down. After that the protection unit cut off this general pump because of overload current. In the end, the terminal voltage of generator was recovered. Fig. 8 shows terminal voltage of generator and error with RBF NN model when three-phase grounded fault happened. From the recorded data and error curve all above, the error value is limited in 5×10^{-4}. So the diesel engine generator model approximated by RBF NN with high precision results.

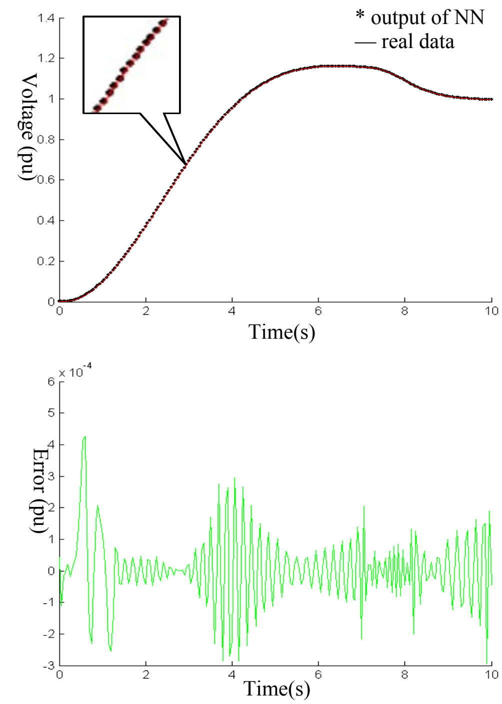

Fig. 5. Voltage and its error with RBF NN model when diesel engine generator is starting

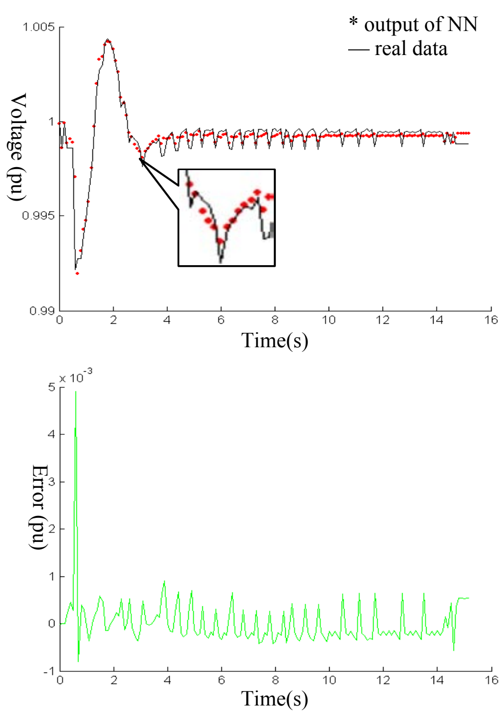

Fig. 6. Voltage and its error with RBF NN model when lubrication pump is starting

V. Application of Marine Diesel Engine Generator Model to a Real Time Simulator

For building a real time marine power system simulator, ANN model of synchronous generator has been obtained.

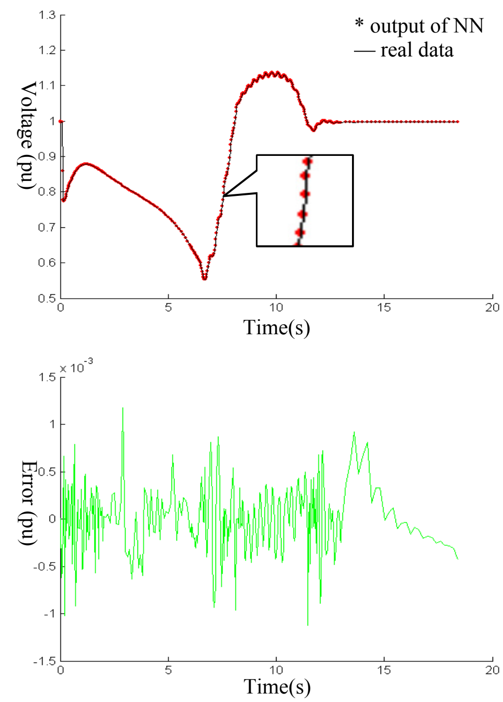

Fig. 7. Voltage and its error with RBF NN model when side-thruster motor is starting

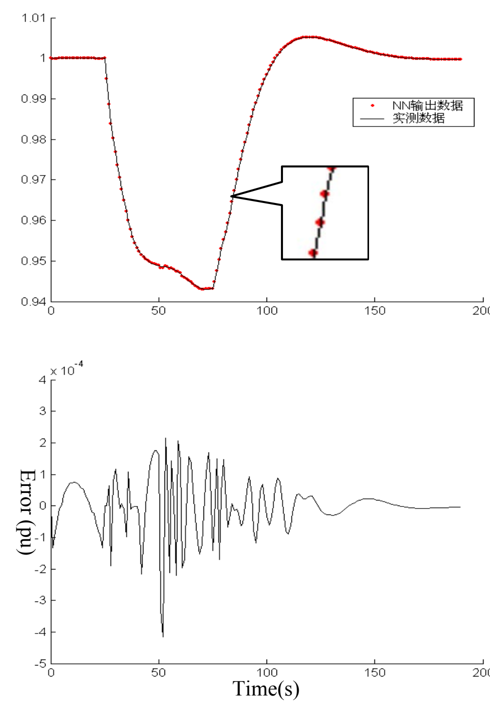

Fig. 8. Voltage and its error with RBF NN model when three-phase grounded fault happened

After that the model operation program is downloaded to a digital signal processor (DSP). Fig. 9 shows a part of configuration between controller and models for real time marine power system simulator. Logical controller is used for diesel engine starting and stopping. Speed controller is used for constant value control of diesel engine rotational

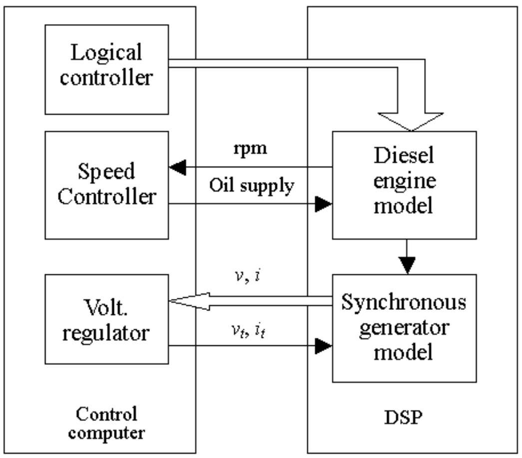

Fig. 9. Part structure of real time simulator

speed. Voltage regulator is used for terminal voltage control of generator. Generally the rule of regulators are PID controllers. Through testing by TMS320LF2407 DSP (30MIPS), the operating period time of model is little than 158 microseconds with 99 hidden neural nodes of RBF NN.

In the real time marine power system simulator system, the control computer was an industrial microcomputer. A data acquisition and control system is used for signals input and output. Generally the input signals are rotational speed (rpm) of diesel engine, voltage (V) and current (A) of generator. The output signals are oil supply, excitation voltage or current. The RBF NN generator model produces voltage signal and current signal to voltage regulator. All parameters were display through control computer.

VI. Conclusion

Because generator system is a nonlinear system, the RBF NN was used for marine diesel engine generator modeling, the model approximated with good precision. The calculation speed is satisfactory using RBF NN generator model. The advantage of using RBF NN to build a marine generator model is that the algorithm is simple and fast. It is fit for DSP calculating. The disadvantage of the method is that the generalization of system is not so satisfactory. The ability of RBF NN generalization is not enough for all status of generator in one model especially for failure running state of generator. In normal operating mode and fault operating mode of real time power system simulator, we had to use two different models. One model is used for normal operating. Other model is used for fault operating.

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