A Neural Controller for Electron Beam Welding Power Supply Unit

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Abstract
Welding is an unavoidable unit practically for every manufacturing industry. Electron Beam welding (EBW) are very important unit of some specific manufacturing processes where high degree of accuracy and flawless welding is highly desirable like aerospace engineering. The power supply unit (PSU) used for EBW are very important unit, for which high degree of stability is a must. Since EBW is absolutely non-linear system, for better performance, adopting non-linear control methods could be a good solution. In the current study a robust adaptive controller based on multi-layer feed-forward neural network is developed for real-time voltage regulation. Simulation shows a better characteristic in terms of maximum overshoot and maximum undershoot for the neural controller compared to that of a conventional PI controller based on Ziegler Nichols [1,2,3,4] frequency response tuning method. The controller has the unique advantages of nonlinear mapping and adaptive learning.

Index Terms: Artificial Neural Network (ANN), Error back propagation algorithm, EBW.

Introduction
Electron Beam Welding (EBW) is widely used in industry, most notable for manufacture of aero engines. The equipment consists of a vacuum chamber, work piece manipulator and electron gun. The gun typically operated in the range of few kilovolts to several hundreds of kilovolts, which will accelerate the electron beam to increase the kinetic energy. In the advancement of the high voltage solid state device SMPS are used to produce such a high voltage for electron gun. The primary design requirements for the power supply are

- To produce a stable, low ripple accelerating voltage (DC) at the gun
- To be able to adjust that voltage over the working range
- To maintain the voltage from virtually no load to full load
- To reduce the stored energy at output filter elements

EBW system is a complex nonlinear system due to flash over and sparks occurs inside welding chamber. Due to its strong nonlinear behavior, the problem of identification and control of EBW power supply is always a challenging task for control systems engineer. Usually in the industries EBW power supplies are controlled using linear PI control configurations and the tuning of controller parameters is based on the Linearization of the models of the PSU in a small neighborhood around the stationary operating points. If the process is subjected to larger disturbance or it operates at conditions of higher state sensitivity, the state trajectory can considerably deviate from the aforementioned neighborhood and consequently deteriorates the performance of the controller.

PSU design for operation in the area of its higher state sensitivity and in some cases at the borders of its stability is important, even in the vicinity of an unstable stationary point that might have induced the periodic oscillations. As a result, the nonlinear nature of the PSU acquires more relevance in control systems and creates difficult control problems. If severe nonlinearity is involved in the controlled process, a nonlinear control scheme will be more useful. Nowadays, neural networks have been proved to be a promising approach to solve complex nonlinear control problems.

The use of neural networks in EBW field offers potentially effective means of handling three difficult problems: Complexity, non-linearity and uncertainties. The variety of available neural network architectures permits us to deal with a wide range of process control problems in comparison to other empirical models. Neural networks are relatively less sensitive to noise and incomplete information and deal with higher levels of uncertainty when applied in process control problems. The multilayer feed forward neural networks offer interesting possibilities for modeling any nonlinear process without a priori knowledge. Thus, self-learning ability of neural networks eliminates the use of complex and difficult mathematical analyses, which is dominant in traditional modeling methods.

A DC–DC converter is an integral part of EBW PSU, where low voltage unregulated DC is regulated by a high frequency DC-DC converter. Then regulated DC is converted to quasi square wave AC by means of an inverter and stepped UP to high voltage by a high frequency transformer. Finally,
high frequency high voltage square wave is rectified and filtered to high voltage regulated DC. Pulse-width modulation (PWM) is often employed to control the DC output voltage by modulating the duty cycle via electronic switching circuits. To improve the power efficiency, many different switching circuit topologies have been proposed [9-14]. In conventional controller design, it is assumed that all the circuit components are ideal with no performance degradation and power loss and the circuit is operated at a stable bias point so that it can be modeled by a set of linear equations. However, in practice, the switching network is highly nonlinear and an accurate mathematical model is very difficult to obtain. In addition, the supply voltage and load current may also fluctuate over a wide range. Thus, real-time adaptive control is necessary to improve the system performance. Recently, artificial neural networks (ANN) have been applied to improve the performance of DC–DC converters to dynamical system changes refer [8, 15]. However, no prior work has yet been reported to control EBW using a neural network approach. Simulation circuit used to test the performance of the EBW is shown in (Fig.1). The block diagram of the EBW with controller is shown in (fig.2).

![Fig. 1. Simulation circuit, test the performance of the EBW](image)

![Fig. 2. System block diagram showing Neural controller](image)

**Error Back-Propagation Neural Networks and Back-Propagation algorithms**

Artificial neural network [5-7] is usually defined as a network composed of a large number of processing units (neurons) that are massively inter connected, operate in parallel and learn from experience (examples). In recent years, ANN has become more popular because of its ease of operation moreover its accuracy in prediction can be improved through a good training process. The robustness of a well-trained network is excellent.

Back-Propagation Neural Networks are a kind of widely used Neural Networks nowadays. It is a multilayer feedforward neural based on error back propagation algorithm [16, 17]. The model of BP Neural Networks is composed of three parts, input layer, output layer and hidden layer. Sigmoid-type function is usually used in the neurons of hidden layer. Activation function for the output layer depends on the output nature of the concern problem. Calculation accuracy must be concerned to determine the quantity of hidden layer. The standard BP Neural Networks adopt step-transform based on Widrow-Hoff rule. The following aspects should be considered when designing the BP Neural Networks, the layer-number of the networks, the number of the nerve cell in each layer and activation function, initial value, learning rate.

BP algorithm is composed of two parts, forward transfer of the working signal and reverse transfer of the error signal. The mean square error $F(x)$ is used as the performance function in multi-layer networks BP algorithm. The input of the algorithm is the combining of the sample with correct network behaviour $\{p_1, t_1\}, \{p_2, t_2\}... \{p_q, t_q\}$. Once a sample is input, network output is compared to target outputs, and the weights of the networks are adjusted by BP algorithm to minimize the mean square error $F(x)$.

$$F(x) = E[e^2] = E[(t-y)^2(t-y)]$$

In this formula, $x$ is the vector of weights in the networks, and $y$ is the output vector. $F(x)$ is used to calculate mean square error approximately, replacing the expected value of the mean square error with the mean square error after $k$-th iteration.

$$F(x) = [t(k) - y(k)]^T [t(k) - y(k)] = e^T(k)e(k)$$

The steepest descent method to approximate mean square error is

$$W_{ij}^{m}(k+1) = W_{ij}^{m}(k) - \alpha \frac{dF}{dW_{ij}^{m}}(k)$$

In these formulas, $\alpha$ is the learning rate. $W_{ij}^{m}$ is the weight value of the $j$-th nerve cell is for the $i$-th nerve cell on the $m$-th element. Theoretically, the model of the BP Neural Networks precisely depends on the training data provided. So the structure of the Neural Networks should be selected reasonable, and obtaining the model of high precision with few training data.

**Neural Network model for the Controller**

A three layer neural network (Fig.3) was designed with 10 numbers of hidden neurons. The input layer contains 2 neurons corresponding to two input parameters supply voltage and instantaneous output load current. A single output neuron at the network output corresponding to the control voltage. Uni-polar sigmoid function has been chosen as the activation function for both hidden layer and output layer neurons. The
training and testing data were taken from the simulation model with PI as the controller. Data set were normalized to train the network in the non-linear region of the sigmoid function avoiding the saturation area. An adaptive learning rate was chosen with initial value 0.9 and decremented by a factor of 10% when stuck in the local minima. Initial high value for learning rate was chosen due to the large error at the starting of training. A small momentum value of 0.2 was chosen. Mean absolute error (MAE) was chosen as the performance criteria for the network and training was done with an iteration limited approach.

Simulation Results
MATLAB Simulink models were developed for both PI controller based on Ziegler Nichols frequency response tuning method and the neural controller. Current and voltage waveforms were traced. Performance of the neural controller is compared with that of PI controller. Other performance parameters have been calculated (Table I) to verify the better characteristics of neural controller in comparison to conventional PI controller. Fig. 4 shows comparison between output voltage for PI and Neural controller. Fig. 5-6 shows output current waveforms for PI and Neural controllers respectively.

<table>
<thead>
<tr>
<th>Performance Parameters</th>
<th>PI Controller</th>
<th>Neural Controller</th>
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<tr>
<td>%Over Shoot</td>
<td>15</td>
<td>4.95</td>
</tr>
<tr>
<td>%Under Shoot</td>
<td>2.245</td>
<td>1.4</td>
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<tr>
<td>Delay Time (T_d) (10^{-5}s)</td>
<td>1.31</td>
<td>1.4</td>
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<tr>
<td>Rise Time (T_r) (10^{-5}s)</td>
<td>3.25</td>
<td>4.25</td>
</tr>
<tr>
<td>Settling Time (T_s) (10^{-3}s)</td>
<td>1.16</td>
<td>1.4</td>
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<tr>
<td>Average Integral Absolute Error (AIAE)</td>
<td>0.0773</td>
<td>0.0758</td>
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<tr>
<td>Integral Squared Error (ISE)</td>
<td>1.5252x10^4</td>
<td>1.119x10^4</td>
</tr>
<tr>
<td>Average Integral Squared Error (AISE)</td>
<td>0.1768</td>
<td>0.1138</td>
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Summary and Conclusions
In this paper the proposed neural network controller gives a better performance in comparison to the PI controller in terms of maximum overshoot and maximum undershoot fig.4. Other factors like AIAE, ISE and AISE also verify the better performance of neural controller over the PI controller.
References


Authors Biography
Jagannath Malik is pursuing Integrated Dual Degree (Bachelors/ Masters) in Electronics & Computer Engineering with specialization in Wireless Communication at Indian Institute of Technology (IIT) Roorkee, India. His research interest includes soft computing techniques, artificial neural networks (ANNs), optimization algorithms, image processing, millimeter-wave engineering, metamaterial, microstrip antennas for communications, RF and microwave designs. He has published a number of papers in the fields of ANN and microstrip antennas.

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