Front. Electr. Electron. Eng. China 2011, 6(4): 567–574
DOI 10.1007/s11460-011-0158-7

RESEARCH ARTICLE

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Design and analysis of control system using neural network for regulated DC power supply

Abstract Conventional control systems used for regulated power supplies, including the proportional integral and derivation (PID) controller, have some serious disadvantages. The PID controller has a delayed feedback associated with the control action and requires a lot of mathematical derivations. This paper presents a novel controlling system based on the artificial neural network (ANN), which can be used to regulate the output voltage of the DC power supply. Using MATLAB™, the designed control system was tested and analyzed with two types of back-propagation algorithms. This paper presents the results of the simulation that includes sum-squared error (SSE) and mean-squared error (MSE), and gives a detailed comparison of these values for the two algorithms. Hardware verification of the new system, using RS232 interface and Microsoft Visual Basic 6.0, was implemented, showing very good consistency with the simulation results. The proposed control system, compared to PID and other conventional controllers, requires less mathematical derivation in design and it is easier to implement.

Keywords regulated power supply, neural network, proportional integral and derivation (PID) controller, multi-layer perceptron (MLP) network

1 Introduction

A power supply refers to a source of electrical power. A device or system that supplies electrical or other types of energy to an output load or group of loads is called a power supply unit (PSU). Regulated DC power supplies are needed for most analog and digital electronic systems. Virtually, every piece of electronic equipment, e.g., computers and their peripherals, calculators, TV and Hi-Fi equipment, and instruments, is powered from a DC power source, be it a battery or a DC power supply. Most of this equipment requires not only DC voltage but voltage that is also well filtered and regulated [1,2]. Power supplies for electronic devices can be broadly divided into linear and switching power supplies. The linear supply is a relatively simple design that becomes increasingly bulky and heavy for high current devices; voltage regulation in a linear supply can result in a low efficiency. A switched-mode supply of the same rating as a linear supply will be smaller, is usually more efficient, but will be more complex. Today, many types of power supplies are used for several applications, such as battery power supply, AC/DC supply, switched-mode power supply, programmable power supply, uninterruptible power supply, high-voltage power supply, voltage multipliers, etc. (http://www.silentpcreview.com/article28-page3.html).

Received March 2, 2010; accepted August 6, 2010

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2 Regulated power supplies

Despite the different types mentioned in the previous section, the constraints that commonly affect the performance of the power supplies are the amount of power they can supply, how long they can supply it without needing some kind of refueling or recharging, how stable their output voltage or current is under varying load conditions, and whether they provide continuous power or pulses [3].

Consequently, power supplies for many applications should be regulated. This requires in turn the design of an effective control system to perform this regulation. The regulation of power supplies is done by incorporating circuitry to tightly control the output voltage and/or current of the power supply to a specific value. The specific value is closely maintained despite variations in the load presented to the power supply's output, or any reasonable voltage variation at the power supply's input. This kind of regulation is commonly categorized as a stabilized power supply [4].

3 Problem formulation

As mentioned above, regardless of their various types, the power supplies for many applications should be regulated. Today, several methods and techniques to achieve this valuable aim are being implemented. Each of these methods and techniques has its advantages and disadvantages. One of the most common and effective methods is the regulation of the DC power supply by using the ID controller. Conventionally, most people and factories use the proportional integral and derivation (PID) controller for regulating the power supply. The PID control system has a feedback loop that combines all proportional, integral and derivative control mode. The parameters of the PID controller for applications are calculated by a variety of methods such as the Ziegler-Nichols method, etc. [2,3]. Figure 1 illustrates the operation of the PID control system. The actuation signal $v(t)$ is computed based on the rate at which the error is changing. The term has no effect on the steady-state performance, but for constant demand $c(t)$, it always tends to reduce the actuation signal and combats the tendency for the output to overshoot when recovering from a disturbance. An effect known as set point kick will be a further improvement in system stability.

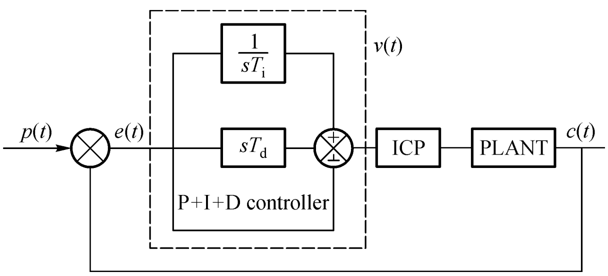

Fig. 1 Plant with P + I + D controller

3.1 PID controller equation

The PID controller can be expressed by [5]

$$v(t) = K_p\left(e(t) + \frac{1}{T_i}\int e(t)\mathrm{d}t + T_d\frac{\mathrm{d}e(t)}{\mathrm{d}t}\right), \tag{1}$$

where $v(t)$ is the actuation signal (controller output); K_p is the proportional gain (controller path gain); T_d is the derivative time constant; T_i is the integral time constant; e is the error signal; t is the time or instantaneous time. Taking into account that $K_i = K_p/T_i$, and $K_d = K_pT_d$, then Eq. (1) can be written as follows:

$$v(t) = K_pe(t) + K_i\int e(t)\mathrm{d}t + K_d\frac{\mathrm{d}e(t)}{\mathrm{d}t}, \tag{2}$$

where K_i is the integral gain of the controller, and K_d is the derivative gain of the controller. The transfer function of the controller is written using the Laplace form:

$$\begin{aligned}\frac{V(s)}{E(s)} &= K_p + \frac{K_i}{s} + K_ds \\ &= K_p + \frac{K_p}{T_is} + K_pT_ds \\ &= K_p\left(1 + \frac{1}{T_is} + T_ds\right) \\ &= \frac{K_p}{s}\left(s + \frac{1}{T_i} + T_ds^2\right) \\ &= \frac{K_pT_d}{s}\left(\frac{s}{T_d} + \frac{1}{T_iT_d} + s^2\right),\end{aligned} \tag{3}$$

where $V(s)$ and $E(s)$ are the output and input (error) signals of the controller using Laplace form, and $1/s$ is the error removing integration term.

It is appreciated that the error removing integration term, $1/s$, be present. The term T_d acts as a derivative time constant.

3.2 Disadvantages of PID control system

Normally, PID is considered as a traditional circuit that is used for monitoring the load current, load voltage and the input voltage that determine the parameters of PID. Despite the importance and many advantages that the PID controller has, there is a serious disadvantage incorporated with this dominant controller [2]. In fact, there is a limitation for the PID controller while controlling the DC power supply, that is, if the PID parameters are changing, it makes the controller become unstable against that condition. In addition to that, PID and most of the other conventional controllers require tedious mathematical derivations in design and simulation.

3.3 Proposed method

To overcome the above mentioned drawbacks of the PID controller, and consequently improve the whole performance of the regulated power supply, it is proposed to replace the PID controller with a new control system based on neural network. By replacing the PID controller with a neural network control system through the power supply, the problem of instability is overcome, and the tested power supply functions as an intelligent power supply. The function of the neural controller is to control the power supply according to its load voltage requirements. If the supply voltage of the power supply is lower or higher than the required level of the load, the neural controller will automatically decrease or increase the voltage in order to protect any type of load from being damaged because of the fluctuations in the voltage level or any other kind of electrical instability generated by the supply side. This will improve the steady-state and dynamic characteristics of the power supply. Using the neural network technique, a new control system for the regulated power supply based on the buck boost converter, was designed, simulated and implemented. The basic concept of the converter is to step down (buck) and step up (boost) the DC output voltage. Besides that, the DC input voltage is converted into DC output voltage. Consequently, we can say that the PID controller was successfully replaced by a new one. The neural control method needs no human intervention, and this is the major reason why the neural network has been chosen as the concept and became the main frame of the research conducted. In this paper, we preview such connectionist paradigm for creativity, which starts from the raw essential ingredients of simulated biologic neural nets, and artificial neurons (processing units) and synapses (connection weights) are specified.

4 Neural networks

Neural networks are composed of many simple elements operating in parallel. These elements are inspired by the biologic nervous system. The network function is determined largely by the connection between elements. Neural networks have been trained to perform complex functions in various fields of applications including pattern recognition, identification, classification, speech, vision, and control systems. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings [6]. Neural networks came from the desire to produce artificial systems capable of sophisticated, perhaps "intelligent", computations similar to those that the human brain routinely performs, and thereby possibly enhance our understanding of the human brain [7].

4.1 Artificial neural network

The artificial neural network (ANN) is a new information processing technique. It is a computer-based simulation of a living nervous system. It is biologically inspired and it is composed of elements that perform in a manner that is analogous to the most elementary functions of the biologic neuron. However, these elements are then organized in such a way that may or may not be related to the anatomy of the brain [6,7].

4.2 Neuron attributes

The basic attributes of neural networks may be divided into the architecture and the functional properties or neuro-dynamics. Architecture defines the network structure, that is, the number of artificial neurons in the network and their interconnectivity. A neural network consists of many interconnected neurons, with familiar characteristic, such as inputs, synaptic strength, activation, outputs and bias [8]. The arrangement of neurons into layers and the connection patterns within and between layers is called the net architecture. Neural is often classified as single-layer or multi-layer. In determining the number of layers, the input units are not counted as a layer because they perform no computation. The number of layers in the net can be defined to be the number of layers of weighted interconnected links between the slabs of neurons. The single-layer and multi-layer are shown in Figs. 2 and 3, respectively [7,8].

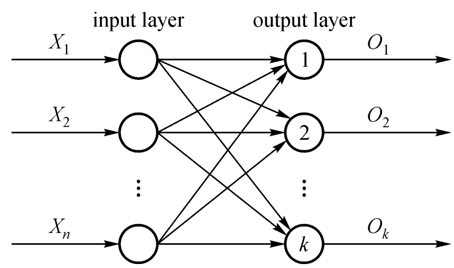

Fig. 2 Single-layer neural net

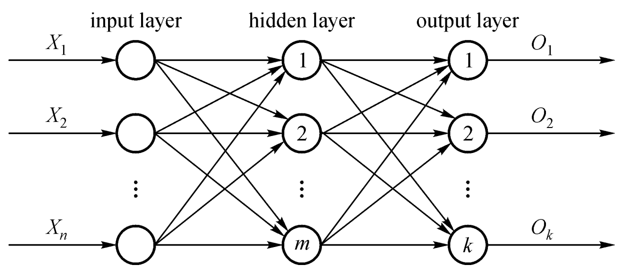

Fig. 3 Multi-layer neural net

4.3 Back-propagation learning algorithm

The back-propagation algorithm was developed by Paul Werbos in 1974 and rediscovered independently by Rumelhart and Parker [6]. Since its rediscovery, the back-propagation algorithm has been widely used as a learning algorithm in feed-forward multi-layer neural networks. The back-propagation is applied to feed-forward ANN with one or more hidden layers. The following information should be available when implementing back-propagation learning [6,7].

1) The set of tanning patterns, inputs, and the target;
2) A value of the learning rate, normally around 0.01;
3) A criterion that terminates the algorithm;
4) A methodology for updating weights;
5) The nonlinearity function, normally the sigmoid function is used;
6) Initial weight values, normally is small random value.

The simplest implementation of back-propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly, that is, the negative of the gradient. One of the iterations of this algorithm can be written as [6,7]

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \alpha_k \boldsymbol{g}_k, \tag{4}$$

where $\boldsymbol{x}_k$ is a vector of current weights and biases, $\boldsymbol{g}_k$ is the current gradient, and α_k is the learning rate.

There are two different ways in which this gradient descent algorithm can be implemented: incremental mode and batch mode. In the incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In the batch mode, all of the inputs are applied to the network before the weights are updated.

4.4 Levenberg-Marquardt algorithm (LM)

The error back-propagation (EBP) algorithm has been a significant improvement in neural networks research in the last few years [9]. The EBP performance index, $F(\boldsymbol{w})$, to be minimized is defined as the sum of squared errors between the target outputs and the network's simulated outputs, namely,

$$F(\boldsymbol{w}) = \boldsymbol{e}^{\mathrm{T}}\boldsymbol{e}, \tag{5}$$

where $\boldsymbol{w} = [w_1,w_2,...,w_N]$ consists of all weights of the network, $\boldsymbol{e}$ is the error vector comprising the error for all the training examples.

When training with the Levenberg-Marquardt (LM) method, the increment of weights $\Delta\boldsymbol{w}$ can be obtained as

$$\Delta\boldsymbol{w} = \boldsymbol{w}\left[\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} + \mu\boldsymbol{I}\right]\boldsymbol{J}^{-1}\boldsymbol{e}, \tag{6}$$

where $\boldsymbol{J}$ is the Jacobian matrix, μ is the learning rate, which is to be updated using the β depending on the outcome. In particular, μ is multiplied by decay rate β $(0<\beta<1)$ whenever $F(\boldsymbol{w})$ decreases, whereas μ is divided by β whenever $F(\boldsymbol{w})$ increases in a new step.

The standard LM training process can be illustrated in the following pseudo-codes.

1) Initialize the weights and parameter μ (μ = 0.01 is appropriate);

2) Compute the sum of the squared errors over all inputs $F(\boldsymbol{w})$;

3) Solve 2) to obtain the increment of weights $\Delta\boldsymbol{w}$;

4) Recomputed the sum of squared errors $F(\boldsymbol{w})$.

5 Design and simulation

As mentioned in Sect. 3, conventional control systems used for regulated power supplies, including the PID controller, have some serious disadvantages. The PID controller has delayed feedback associated with control action and requires a lot of mathematical derivations. Instead of using conventional control systems to regulate power supply voltage in a stabilized manner, neural network technique is implemented here. Relative to the conventional controllers, a neural network controller requires less mathematical derivation in design. In this way, an attempt is made to apply more like human thinking in the programming of computers. To perform this study, MATLAB software version 6.0 with its neural network toolbox was used. The neural network toolbox is a uniquely powerful tool in applications where formal analysis would be difficult or impossible, such as pattern recognition and nonlinear system identification and control. The block diagram shown in Fig. 4 illustrates how the system functions by sending signals to each stage. The general concept of this system deals with the closed-loop control system using the feedback concept to supply the extra signal back to the controller. The neural network show functions as a neural controller, which will search the voltage requirements of the load (v_l) and then sends a control signal to the power supply to increase or decrease the supply voltage (v_i) that supports the load.

Each time, while sending the output voltage to the load, the neural controller will set the feedback voltage (v_f) from the load and the input voltage (v_i) to compare with; the process will end at another new output (v_o). This operation will continue until the load receives its required voltage. Finally, the output voltage (v_o) across the regulated power supply will be stabilized.

5.1 Training of the algorithms

This paper discusses the performance of the ANN

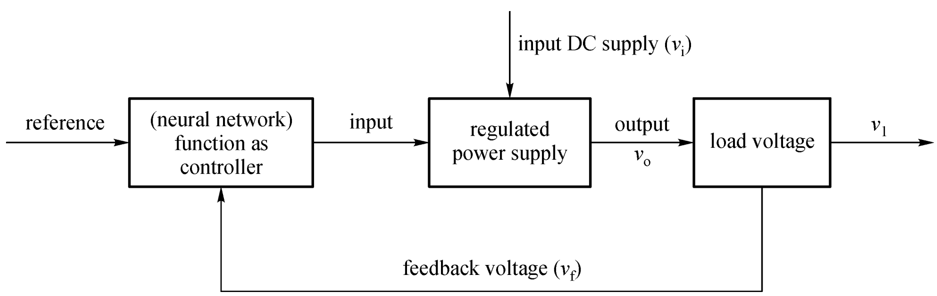

Fig. 4 Block diagram of regulated power supply using neural network

controller for all different conditions. The ANN system was trained by two different training algorithms; this is because the fastest training speed and minimum storage can be chosen between the algorithms. These algorithms were discussed in Sects. 4.4 and 4.3.

1) Levenberg-Marquardt back-propagation training (TRAINLM).

2) Resilient back-propagation training (TRAINRP).

5.2 Training steps and specification

The perceptron is a binary classifier that maps its input (normally a real-valued vector) to an output (normally a single binary) value. The multi-layer perceptron (MLP) is a hierarchical structure of several perceptrons and overcomes the shortcomings of the single-layer networks. The training steps for developing MLP networks can be summarized as below.

1) Define the inputs and outputs for input layer and output layer respectively;

2) Determine the number of neurons in the hidden layer;

3) Generate the record training data (input and target of the network);

4) Train the network with the generated data sets by using the back-propagation learning algorithm;

5) Check the performance of the training. If it is not satisfactory, increase the size of hidden layer and return to Step 4).

5.3 Simulating the performance of ANN controller

The network architecture for ANN has two inputs, namely, the "load voltage (v_l)" and "DC input voltage (v_i)" as shown in Fig. 5. The only output in the network is the output response (a_1). The network consists of a single hidden layer with hyperbolic tangent nonlinearity and an output with a linear transfer function. It was found that six neurons in the hidden layer can perform adequately, as depicted in Fig. 5.

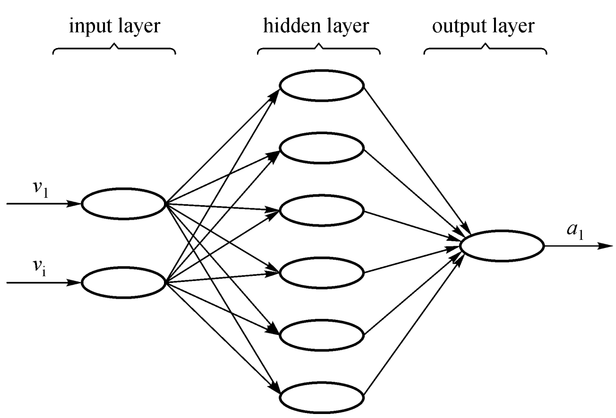

Fig. 5 MLP network

6 Results and analysis

6.1 TRAINLM

Because the training is based on the supervised learning of neural networks, the data set for training (inputs and targets) must be procurable. By using TRAINLM, the learning rate changes during the training process in order to keep the learning step size as large as possible while keeping the learning stable. Acting like a low pass filter, the Levenberg-Marquardt algorithm trains an MLP network 10 to 100 faster than the usual gradient descent back-propagation method. It will always compute the approximate Hessian matrix, which has dimensions of $n \times n$ [8].

6.1.1 Mean-squared error (MSE)

The ANN output is subtracted from the desired output, where the network gives the average squared error between the network outputs and the target outputs. The advantage of the MSE function is that its derivatives with respect to individual weights exist everywhere, in contrast to the count of the number of misclassifications [2]. The network is trained for the load voltage "12 V" and DC input voltage "24 V", where the training process is depicted below, and the error measuring trajectory is illustrated in Fig. 6.

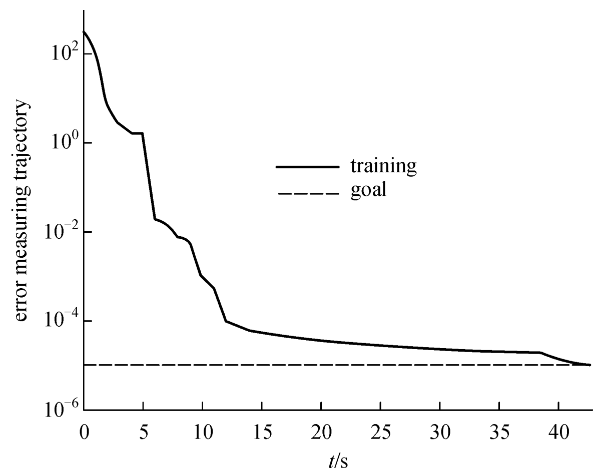

Fig. 6 Error measuring trajectory for TRAINLM using MSE

Pls key in 0 V to 25 V only
Load voltage: 12 V
DC input voltage: 24 V
ans = − 12 V feedback voltage
ans = 7.9059 V regulated output voltage

TRAINLM, Epoch 0/1000, MSE 487.618/1e-005, Gradient 1881.61/1e-010

TRAINLM, Epoch 30/1000, MSE 2.22942e-005/1e-005, Gradient 0.0809292/1e-010

TRAINLM, Epoch 43/1000, MSE 9.55734e-006/1e-

005, Gradient 0.879294/1e-010

TRAINLM, Performance goal met

a = 7.2562

Time elapsed for MLP network training [sec.] = 8.95

6.1.2 Sum-squared error (SSE)

The ANN output is subtracted from the desired output where the network minimizes the squared sum of the resulting errors in the training phase. The network is trained, where the training process is depicted below, and the error measuring trajectory is illustrated in Fig. 7.

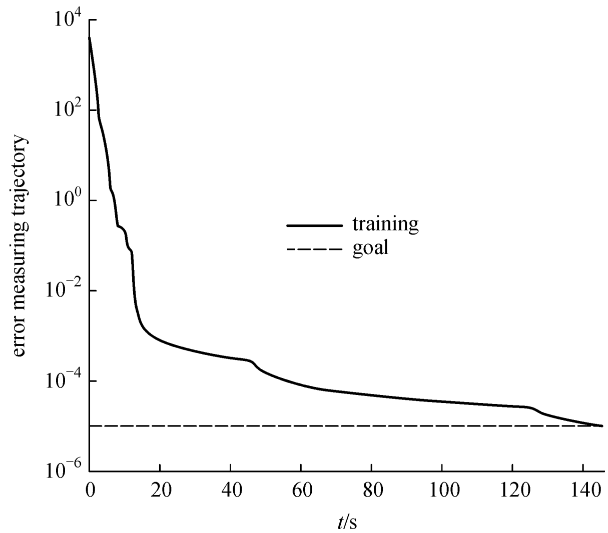

Fig. 7 Error measuring trajectory for TRAINLM using SSE

TRAINLM, Epoch 0/1000, SSE 5284.84/1e-005, Gradient 1628.93/1e-010

TRAINLM, Epoch 30/1000, SSE 0.00046951/1e-005, Gradient 0.17912/1e-010

TRAINLM, Epoch 60/1000, SSE 8.33784e-005/1e-005, Gradient 0.213039/1e-010

TRAINLM, Epoch 90/1000, SSE 3.96426e-005/1e-005, Gradient 0.0313761/1e-010

TRAINLM, Epoch 120/1000, SSE 2.73091e-005/1e-005, Gradient 0.0121674/1e-010

TRAINLM, Epoch 144/1000, SSE 9.83535e-006/1e-005, Gradient 0.0959647/1e-010

TRAINLM, Performance goal met

a = 6.7722

Time elapsed for MLP network training [sec.] = 11.42

6.2 TRAINRP

6.2.1 Mean-squared error (MSE)

The training process is depicted below, and the error measuring trajectory is illustrated in Fig. 8.

Fig. 8 Error measuring trajectory for TRAINRP using MSE

Pls key in 0 V to 25 V only

Load voltage: 24 V

DC input voltage: 7 V

ans = 17 V feedback voltage

ans = 15.8118 V repgulated output voltage

TRAINRP, Epoch 0/1000, MSE 87.4179/1e-005, Gradient 134.216/1e-006

TRAINRP, Epoch 47/1000, MSE 8.73852e-006/1e-005, Gradient 0.0751952/1e-006

TRAINRP, Performance goal met

a = 12.9924

Time elapsed for MLP network training [sec.] = 6.37

6.2.2 Sum-squared error (SSE)

The training process is depicted below, and the error measuring trajectory is illustrated in Fig. 9.

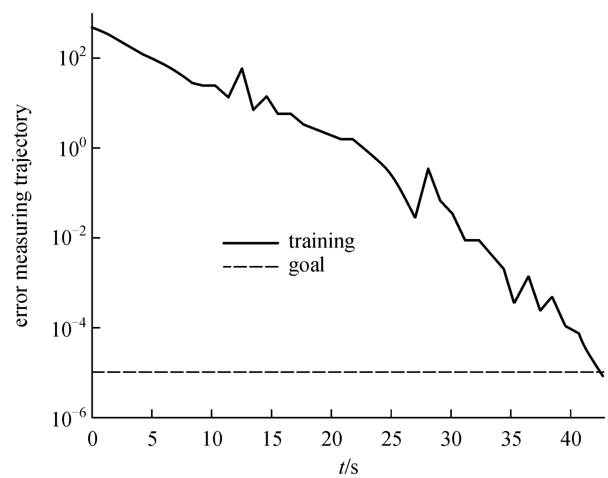

Fig. 9 Error measuring trajectory for TRAINRP using SSE

TRAINRP, Epoch 0/1000, SSE 501.889/1e-005, Gradient 701.121/1e-006

TRAINRP, Epoch 41/1000, SSE 8.20722e-006/1e-005, Gradient 0.131496/1e-006

TRAINRP, Performance goal met

$a = 12.9016$

Time elapsed for MLP network training [sec.] = 6.37

Analysis of the results obtained for the proposed system shows that, in all cases of the two different algorithms, the elapsing time of the error measured is in the acceptable range. This means that the difference between the voltage required by the load and the actual voltage is too small, less than 5%. Remembering that this difference is collapsing in a very short period of time, as results reveal (max period is 11.4 s), we can conclude that the voltage across the load is approximately constant and, consequently, the load voltage is stable enough. On the other hand, the comparison between the different algorithms implemented in this study demonstrates the effectiveness of using TRAINRP algorithm to reduce both the amplitude and the collapsing time of the error measured between the voltage required by the load and the actual one.

7 Hardware implementation and verification

An overview of the hardware implemented in this study is shown in Fig. 10. The hardware for the unit consists of an RS232 interface, a relay circuit, and a DC power supply. At the beginning, a Microsoft Visual Basic interface was developed, which functions as an intelligent controller that searches the voltage requirements of the load (v_l) and the input DC voltage. After the user keys in the voltage data (v_l) and (v_i), the computer will increase or decrease the supply voltage (v_i) until it can support the load. The control signal will be sent through the power supply by an RS232 cable.

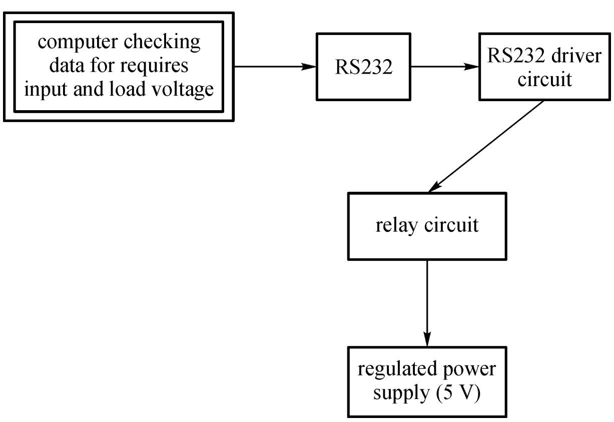

Fig. 10 Host unit hardware

While sending the data output voltage to the load, the Microsoft Visual Basic controller will set the data feedback voltage (v_f) from the load and the data input voltage (v_i) to compare with; the process ends at another new data output (v_o). This operation will continue until the load receives its required data voltage. The data will be sent through cable RS232 (pin3) to the RS232 driver circuit by applying Microsoft Visual Basic. After the driver circuit receives the data signal, pin12 will send the signal to the relay circuit and activate the regulated power supply.

- **RS232 interface**

To interface the host unit's microcontroller to the RS232 port of a personal computer, a chip must be present to convert the RS232 voltage levels to TTL and vice-versa. This is done in this study by using a garden-variety RS232 converter chip. MAX232CPE was chosen because it provides two converters RS232 to TTL and TTL to RS232, which is the exact number of converters needed for the host unit to communicate effectively with a personal computer. MAX232CPE is the cheapest chip that fits the conversion requirements. Although RS232 requires both a positive and negative voltage in order to communicate reliably, MAX232 requires only $a + 5$ V power supply to provide full RS232 compatibility. This is done by producing ± 10 V by means of an on-chip voltage converter. The converter portion requires four external capacitors. A general VCC to ground shunt capacitor is also needed. The circuit is shown in Fig. 11.

8 Conclusions

Conventionally, the most common methods used for regulating DC power supply are based on the PID controller. The PID controller has serious disadvantages, such as limitations incorporated with it while controlling the DC power supply, which results in instability of the system, and tedious mathematical derivations in its design and simulation. In this work, a novel controller is proposed based on the ANN. Using Matlab software and based on ANN, the performance of the regulated power supply was simulated. This paper describes the performance of the ANN under different conditions. The MLP is utilized. Back-propagation learning has emerged as the standard algorithm for the training of MLP. Two types of algorithms, namely, back-propagation algorithm and Levenberg-Marquardt back-propagation, were used. The SSE and MSE for both algorithms were measured. It was found that in all cases of the two algorithms, the elapsing time of the error measured is in the acceptable range. The difference between required voltage and the actual one is too small, $< 5\%$. Because this difference collapses in a very short time (max period is 11.4 s), the voltage across the load is approximately constant, and the load voltage is stable enough. A hardware verification of the proposed control system was done by using the RS232 interface and Microsoft Visual Basic 6.0, showing a very good consistency with the simulation results. By replacing the

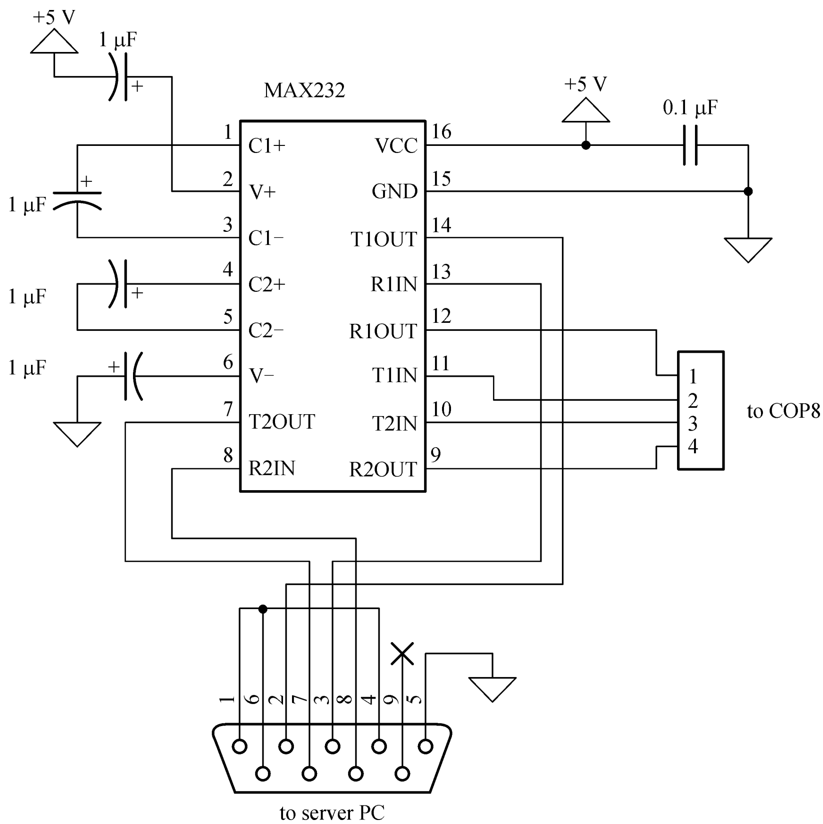

Fig. 11 RS232 interface

PID controller with a neural network control system, the problem of instability has been overcome, and the tested power supply works as an intelligent one. It controls the power supply according to its load voltage requirements, which will improve the steady-state and dynamic characteristics of the power supply. In addition, the neural network controller requires less mathematical derivation to be designed and is easier to implement.

References

1. Malmstadt H V, Enke C G, Crouch S R. Electronics and Instrumentation for Scientists. San Francisco: The Benjamin-Cummings Publishing Company, Inc., 1981
2. Ashan K J. PID Controllers. North Carolina: Instrument Society of America, 1995
3. Astrom K J, Hagglund T. Automatic tuning of simple regulators with specifications on phase and amplitude margins. Automatica, 1984, 20 (5): 645–651
4. Mohan N, Undeland T, Robbins W. Power Electronics. New York: John Wiley & Sons, 1995
5. Warwick K, Rees D. Industrial Digital Control System. London: Institution of Electrical Engineers, 1988
6. Rowe J, Partridge D. Creativity: A survey of AI approaches. Artificial Intelligence Review, 1993, 7(1): 43–70
7. Howard D, Mark B. Neural Network Toolbox for Use with Matlab. Natick: MathWorks, Inc., 1998
8. Fu L M. Neural Networks in Computer Intelligence. New York: McGraw-Hill, Inc., 1994
9. Suratgar A A, Tavakoli M B, Hoseinabadi A. Modified Levenberg-Marquardt method for neural networks training. World Academy of Science, Engineering and Technology, 2005, (6): 46–48