DESIGN OF ACTIVE HEAT DISSIPATION SYSTEM FOR ADAPTIVE WAVELET NEURAL NETWORK CONTROL

Yen-Bin Chen,[*] *Yung-Lung Lee*,[†] *Shou-Jen Hsu*,[‡] *Yi-wei Chen*[*]

Abstract: This paper develops an Adaptive Wavelet Neural Network Control (AWNNC) algorithm for radar active heat dissipation system. The radar core processor belongs to a highly precision component which consists of the electronic device of radio frequency integrated circuit (RFIC) with high power and high performance. The radar core processor should be operated in a narrowly closed environment without convection, which will increase the heat sink effect inside the core processor and further affect its reliability and life-time. The AWNNC comprises a wavelet neural network (WNN) controller and a robust compensator. The WNN controller is a principal tracking controller which is utilized to mimic an ideal controller; and the parameters of WNN are online tuned by the derived adaptation laws based on the gradient descent method. The robust compensator is designed to dispel the approximation error between the ideal controller and the WNN controller, thus the asymptotic stability of the closed–loop system can be achieved. Based on National Instruments-PCI extensions for Instrumentation (NI-PXI) system, combined the Thermo Electric Cooler (TEC) with a duct heater, active heat dissipation intelligent control system is designed to fix the problem of heat dissipation in long distance in a narrowly closed environment without convection. According to the amount of thermal source and thermal energy, the smart control system can help to adjust the rate of heat dissipation by taking advantage of an adaptive control so that the performance of heat dissipation may be accumulated by its numbers. Last but not least, compared the traditional analog circuit controller with adaptive wavelet neural network controller, the research proves that its proposed active heat dissipation intelligent control system can reach an excellent and accurate temperature control. Speaking more precisely, adaptive wavelet neural network controller can be easily adaptive to any environment. It is equipped with a good capability of tracking and searching; and in terms of the effect of temperature control, it never actually jitters due to an input of voltage saturation compared with traditional analog circuit controller. All these can make chips able to adjust its adaptive rate of heat dissipation in accordance with the thermal source of the chips in a narrowly closed environment without convection.

[*]Yen-Bin Chen – Corresponding Author, Yi-Wei Chen, School of Defense Science, C.C.I.T National Defense University, Taiwan, R.O.C. E-mail: `hank1832@gmail.com`, `1040510411@ndu.org.tw`

[†]Yung-Lung Lee, Department of Power Vehicle and Systems Engineering, C.C.I.T., National Defense University, Taiwan. R.O.C. E-mail: `dragonlee@ndu.edu.tw`

[‡]Shou-Jen Hsu, Electronic Systems Research Division, Chung-Shan Institute of Science and Technology, Taiwan, R.O.C. E-mail: `sj.hsu@msa.hinet.net`

Key words: *Thermoelectric cooling chip, wavelet neural network, adaptive control*

Received: February 20, 2014
Revised and accepted: August 16, 2014

DOI: 10.14311/NNW.2014.24.023

1. Introduction

During the past few years, neural network based on control technique has attracted increasing attentions, for it has provided an efficient and effective way for controlling the complex nonlinear or ill-defined systems. The key element to success is the approximation capabilities of the neural networks (NN). Hence, the parameterized NN can approximate any unknown system dynamics or the ideal tracking controller with arbitrarily accurate degree after learning. The basic concepts in neural network based on feedback control methods are to provide online learning algorithms that do not require preliminary offline tuning. Some of these online learning algorithms are based on the back propagation learning algorithm [3, 7], and some on the Lyapunov stability theorem [5, 8, 10, 11]. A number of researches have been done on the applications of wavelet neural networks (WNN) by combining the learning ability of NNs and the capability of wavelet decomposition [12]. Unlike the sigmoidal functions used in conventional neural networks, wavelet functions are spatially localized, so that the learning capability of WNN is more efficient than the conventional sigmoidal function neural network for system identification and control. The training algorithms for WNN typically converge in a smaller number of iterations than the conventional NNs [12]. Thus, WNN has been proved to be better than the other neural networks in that its structure can provide more potential for enriching the mapping relationship between inputs and outputs [12]. As a result, there has been considerable interest in exploring the applications of WNN to deal with the non-linearity and uncertainty of control systems [1,6]. Many experts and scholars value the neural network (NN) based on smart control strategy through promotion in recent years. NN mainly does not need an accurate mathematical model of the system. Meanwhile, it can be similar to any non-linear system with better efficiency. Among various wavelet artificial neural networks the excellent dynamic properties allow the structure to be widely used in a non-linear dynamic system for identification to assist in solving the control problem. The core idea of the research is to incorporate the wavelet theory into the traditional NN. The selection with the original NN excitation function shall be completed by a wavelet function so that it is more equipped with the capability similar to a better function. Compared with the S-excitation function, wavelet has more features shared with regional space properties. It can provide a copious input-output mapping. Therefore, it can be further applied to deal with system identification and control problem. In a non-linear ergonomic system model with time variance, the research introduces the adaptive property and learning abilities into the wavelet neural network. To build up the identification and control of a system, the research shows the input-output relation of a system so that it is believed that this method can help to improve the traditional way of identification of a system and to cut out the weakness found in control. It also allows many scholars to dedicate themselves in studying WNN. It is also a way to deal with the non-linear and uncertain properties found in the control system. The paper makes use of the wavelet neural network to construct a system. Hopefully, it can be a way to solve the non-linear heat transfer problem. Finally, a Rader Active Heat Dissipation system is performed to verify the effectiveness of the proposed control scheme. Results verify that the proposed AWNNC can achieve favorable tracking performance without any chattering phenomenon.

2. Build up a heat dissipation system combing heat pipe with TEC

Based on NI-PXI as the basic framework, the study combines heat pipe and TEC to establish an active cooling system which is divided into four systems: 1. Computer system (NI-PXI-8108, NI-PXI-6229, and NIPXI-4351); 2. Measurement system B3. Power system (Low power supply, High power supply, Amplifier module); and 4. Cooling system. The system hardware is shown in Fig. 1. The specifications of each hardware showed in Tab. I and Fig. 2 indicates the connections.

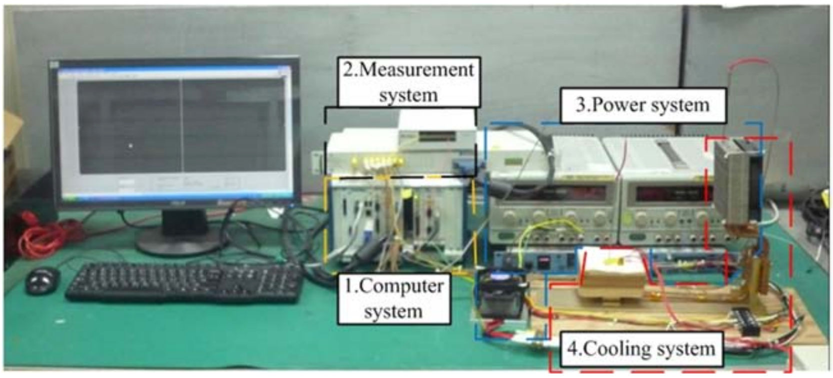

Fig. 1 *System hardware.*

NI-PXI-8108 computers including NI-PXI-6229, NI-PXI-4351 Temperature Sensor measurements are saved as Excel format in the terminal server (NI-PXI-8108). Voltage is output through NI-PXI 6229 to CONTROL I/P connection, passes operational amplifier, provides ± 15V with High Power supply, and uses O/P as output voltage connection to control TEC voltage (Fig. 3).

The cooling module (Item 8) shows in Fig. 4 whose numbers and names of components are the same as those in Table II. The heat source end is composed of Heat source and Heat distributor core plate (1); the thermal conductive interface is composed of Heat pipe (11) and Heat distributor core plate (3); the cooling end is composed of TEC (10), Side heat distributor plate (7), Six heat pipe module (8), Heat sink (9) and Fan (4); the cooling system supported structure is composed

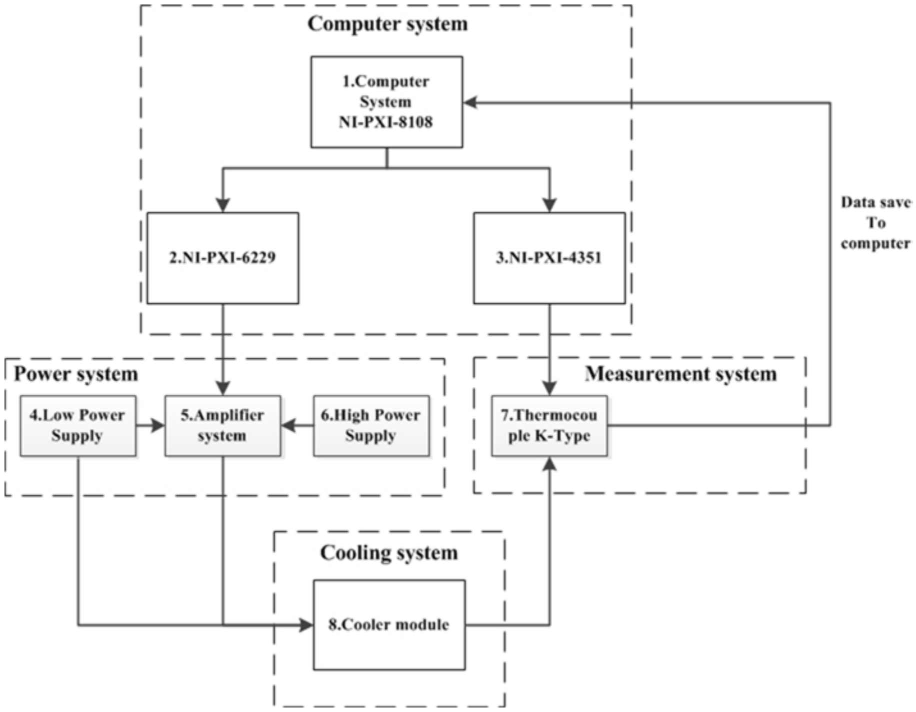

Fig. 2 *Indicates the connections.*

Hardware	Manufacturer	Type Specification
NI-PXI 8108	National Instruments	Inter Core 2 Duo 2.53GHz X2 2GRAM
NI-PXI-6229	National Instruments	DAQ16Bit, 250KS/s, 32AI, 4AO,48DIO
NI-PXI-4351	National Instruments	16-Channel, 15S/s/channel
Thermocouple	Thermocouple Technology	K-Type, 30A, 0.6X1.0mm, Max 260°
Hi Power Supply	EMS Power supply	DC 40V, 25A
Low Power Supply	GW Power supply	DC 18V, 5A
Heat Source	Hiintell igence	200W Dimensions 60X30mm, Copper
Heat source system	Hiintell igence	PID control, Input AC 220V
Amplifier system	MSK	Output 1∼10A, 0∼10V

Tab. I *The specifications of the hardware.*

of Heat distributor plate support (2), Floor support (5) and Contact interface hot insulation (6); among which Contact interface hot insulation (6) is an insulation material for isolating heat transfer.

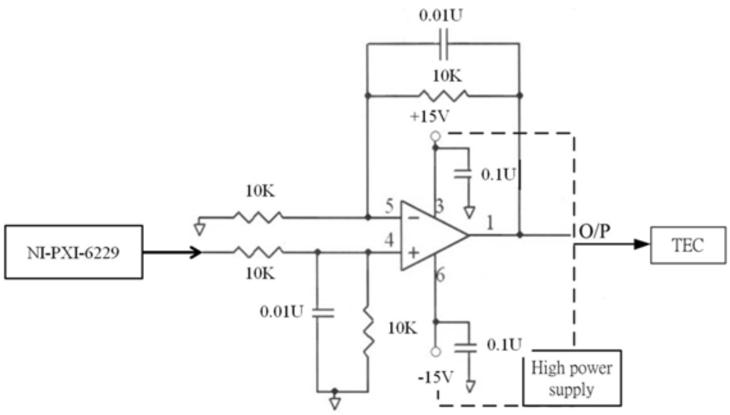

Fig. 3 *Amplification circuit.*

Item	Name	Function
1	Heat Source and Heat Distributor Core Plate	Link Heat Source
2	Heat Distributor Plate Support	Plate Support
3	Heat Distributor Core Plate	Core Plate
4	Fan	Cooling
5	Floor Support	Support
6	Contact Interface Hot Insulation	Heat Insulation
7	Side Heat Distributor Plate	Absorbs Heat Area
8	Six Heat Pipe Module	Transfer Heat
9	Heat Sink	Cooling
10	Thermoelectric Cooler (TEC)	Coolant Pump
11	Heat Pipe	Transfer Heat

Tab. II *Cooling module.*

3. Description of smart active heat dissipation system

First of all, assuming that the active heat dissipation system and the dynamic formula of its TEC output can be written down as follows, it is assumed that this formula looks like this.

$$\ddot{x}(t) = f(x,t) + u(t) + d(x,t) \tag{1}$$

In this formula, x indicates the temperature of the system while $f(x,t)$ indicating a non-linear dynamic formula, and $u(t)$ is the input of TEC control whereas $d(x,t)$ indicates the external jitters. Supposing that the temperature heat dissipation system and the parameters of its TEC featured as $f(x,t)$ and $d(x,t)$ are unknown functions, it is believed that it is hard to acquire a figure in fact.

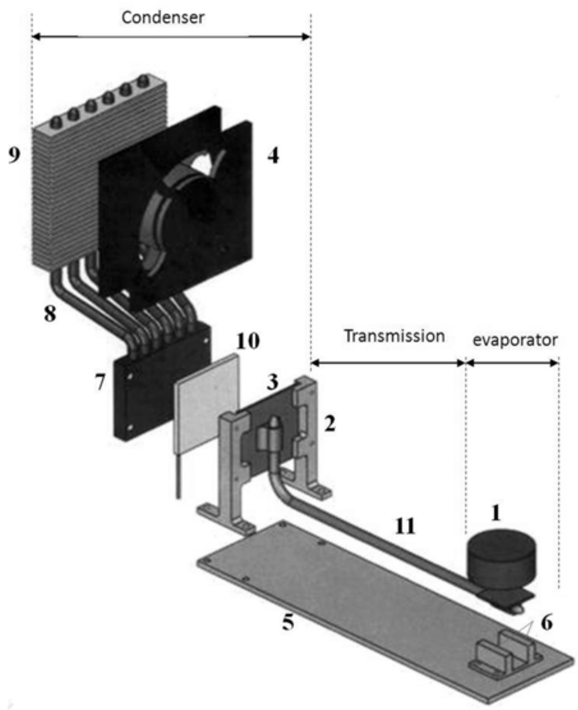

Fig. 4 *Active cooling system.*

3.1 Implementation of WNN

A WNN is proposed and shown in Fig. 5. This WNN is composed of input layer, mother wavelet layer, product layer, and output layer. The signal propagation and the basic function in each layer are introduced as follows.

(a) Input layer: For every node i in this layer, the net input and the net output are represented as

$$net_i^{(1)} = x_i^{(1)} \tag{2}$$

$$y_i^{(1)} = net_i^{(1)}, \text{ for } i = 1, 2, \ldots, n_i \tag{3}$$

where $x_i^{(1)}$ represents the i-th input to the node of input layer and n_i is the number of the input variables. The link weights at this layer are all set as unity.

(b) Other wavelet layer: Each node of this layer has a mother wavelet. The first derivative of a Gaussian function $\phi(\omega) = -\omega \exp((-1/2)\omega^2)$ is selected as a mother wavelet function, which has the universal approximation property [12]. Each node is derived from its mother wavelet. For the j-th node of the i-th input

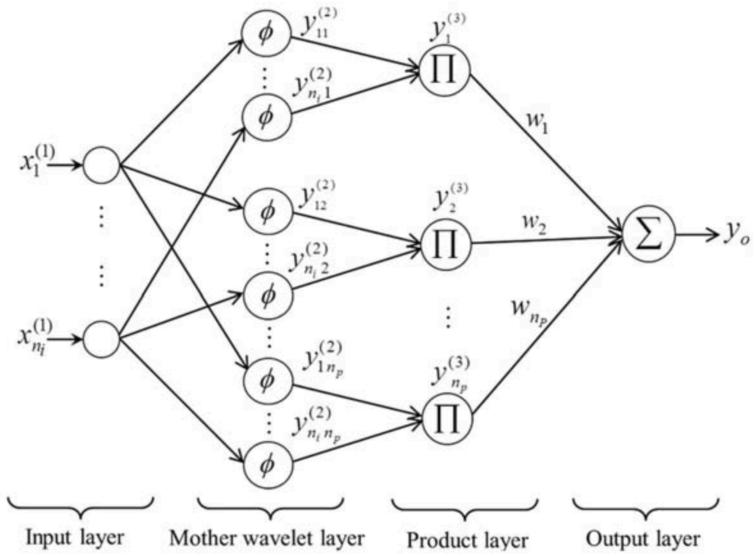

Fig. 5 *A structure chart of Wavelet Neural Network (WNN).*

$$net_{ij}^{(2)} = \frac{\left(x_i^{(2)} - c_{ij}\right)}{v_{ij}} = \frac{\left(y_i^{(1)} - c_{ij}\right)}{v_{ij}} \tag{4}$$

$$y_{ij}^{(2)} = \phi\left(net_{ij}^{(2)}\right), \text{ for } j = 1, 2, \ldots, n_p \tag{5}$$

where $x_i^{(2)}$ represents the i-th input to the node of mother wavelet layer, c_{ij} is the translation factor and σ_{ij} is the dilation factor of the mother wavelet node in the j-th term of the i-th input variable, respectively; σ_{ij} is the output of mother wavelet node; and n_p is the total number of the node in the product layer.

(c) Product layer: The node in this layer is given by the product of the mother wavelets as follows:

$$net_j^{(3)} = \prod_{i=1}^{n_i} x_i^{(3)} = \prod_{i=1}^{n_i} y_{ij}^{(2)} = \prod_{i=1}^{n_i} \left(\frac{-\left(y_i^{(1)} - c_{ij}\right)}{v_{ij}}\right) exp\left(-\frac{\left(y_i^{(1)} - c_{ij}\right)^2}{2v_{ij}^2}\right) \tag{6}$$

$$y_j^{(3)} = net_j^{(3)}, \text{ for } j = 1, 2, \ldots, n_p \tag{7}$$

where $x_i^{(3)}$ represents the i-th input to the node of product layer.

(d) Output layer: The output node in this layer is labeled as Σ, which computes the output as the summation of all incoming signals

$$net_o^{(4)} = \sum_{j=1}^{n_p} \theta_{jo} x_j^{(4)} = \sum_{j=1}^{n_p} \theta_{jo} y_j^{(3)} \tag{8}$$

$$y_j^{(4)} = net_j^{(4)}, \text{ for } o = 1, 2, \ldots, n_0 \tag{9}$$

where θ_{jo} is the connection weight between j-th product node and o-th output node and $x_j^{(4)}$ represents the j-th input to the node of output layer, $y_o^{(4)}$ is the output of the WNN, n_o is the number of the output node. The overall representation of the i-th input of $x_i^{(1)}$ and the o-th output $y_o^{(4)}$ is

$$y_o^{(4)} = \sum_{j=1}^{n_p} \theta_{jo} \sum_{i=1}^{n_i} \left(\frac{-\left(y_i^{(1)} - c_{ij}\right)}{v_{ij}} \right) \exp\left(\frac{-\left(y_i^{(1)} - c_{ij}\right)^2}{2v_{ij}^2} \right) \tag{10}$$

$$u_{WNNo} = y_o^{(4)} = \sum_{j=1}^{n_P} \theta_{jo} y_j^{(3)}(x_i^{(1)}, c_{ij}, v_{ij}) \tag{11}$$

The o-th output of WNN can be represented as Define the matrix and vectors $\mathbf{\Theta}$, $\mathbf{c}$ and $\mathbf{v}$ to collect all parameters of the connection weight and mother wavelets of WNN as

$$\mathbf{\Theta} = \begin{bmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1n_o} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2n_o} \\ \vdots & \vdots & \cdots & \vdots \\ \theta_{n_p1} & \theta_{n_p2} & \cdots & \theta_{n_pn_o} \end{bmatrix} \in \Re^{n_p \times n_o} \tag{12}$$

$$\mathbf{c} = [\ c_{11} \quad \cdots \quad c_{n_i1}, \quad c_{12} \quad \cdots \quad c_{n_i2}, \quad c_{1n_p} \quad \cdots \quad c_{n_in_p}\ ]^T \in \Re^{n_in_p} \tag{13}$$

$$\mathbf{v} = [\ v_{11} \quad \cdots \quad v_{n_i1}, \quad v_{12} \quad \cdots \quad v_{n_i2}, \quad v_{1n_p} \quad \cdots \quad v_{n_in_p}\ ]^T \in \Re^{n_in_p} \tag{14}$$

In summary, the outputs of WNN expresses in a vector notation as

$$\mathbf{u}_{WNN}(\mathbf{x}, \mathbf{c}, \mathbf{v}, \mathbf{\Theta}) = \mathbf{\Theta}^T \boldsymbol{\beta}(\mathbf{x}, \mathbf{c}, \mathbf{v}) \tag{15}$$

$$\mathbf{c} = [\ c_{11} \quad \cdots \quad c_{n_i1}, \quad c_{12} \quad \cdots \quad c_{n_i2}, \quad c_{1n_p} \quad \cdots \quad c_{n_in_p}\ ]^T \in \Re^{n_in_p}$$

$$\mathbf{v} = [\ v_{11} \quad \cdots \quad v_{n_i1}, \quad v_{12} \quad \cdots \quad v_{n_i2}, \quad v_{1n_p} \quad \cdots \quad v_{n_in_p}\ ]^T \in \Re^{n_in_p}$$

$$\mathbf{u}_{WNN} = [u_{WNN_1},\ u_{WNN_2},\ \cdots,\ u_{WNN_{n_o}}]^T$$

$$\mathbf{x} = [x_1^{(1)}, x_2^{(1)}, x_{n_i}^{(1)}]^T, \boldsymbol{\beta} = [y_1^{(3)}, y_2^{(3)}, y_{n_p}^{(3)}]^T$$

3.2 Online adaptation laws for WNN

In SMC, the sliding condition is derived as $\boldsymbol{\sigma}^T(t)\dot{\boldsymbol{\sigma}}(t) < 0$ such that the stability can be guaranteed for the closed-loop system [2]. In order to train the WNN effectively, the online parameter learning algorithm is a gradient descent method that aims to minimize $\boldsymbol{\sigma}^T(t)\dot{\boldsymbol{\sigma}}(t)$ for achieving fast convergence of $\boldsymbol{\sigma}(t)$. Therefore, $\boldsymbol{\sigma}^T(t)\dot{\boldsymbol{\sigma}}(t)$ is selected as the cost function. Taking the derivative of $\boldsymbol{\sigma}(t)$ and using Eq. (1), it can be obtained that

$$\dot{\boldsymbol{\sigma}}(t) = \ddot{\mathbf{e}} + \mathbf{K}_1\dot{\mathbf{e}} + \mathbf{K}_2\mathbf{e} = -\mathbf{f}(x,t) - \mathbf{u}(t) - \mathbf{d}(x,t) \tag{16}$$

Substituting Eq. (1) into Eq. (16) and multiplying both sides by $\boldsymbol{\sigma}^T(t)$, it is obtained

$$\boldsymbol{\sigma}^T(t)\dot{\boldsymbol{\sigma}}(t) = -\boldsymbol{\sigma}^T(t)\mathbf{f}(x,t) - \boldsymbol{\sigma}^T(t)\left[\mathbf{u}_{WNN}(t) + \mathbf{u}_{RC}(t)\right] \tag{17}$$

According to the gradient descent method, the connection weights are updated by the following equation:

$$\dot{\hat{\theta}}_{jo} = -\lambda_1 \frac{\partial \boldsymbol{\sigma}^T\dot{\boldsymbol{\sigma}}}{\partial \hat{\theta}_{jo}} = -\lambda_1 \frac{\partial \boldsymbol{\sigma}^T\dot{\boldsymbol{\sigma}}}{\partial u_{AWNCo}} \frac{\partial u_{AWNCo}}{\partial u_{WNNo}} \frac{\partial u_{WNNo}}{\partial \hat{\theta}_{jo}} = \lambda_1 \sigma_o(t) y_j^{(3)} \tag{18}$$

where u_{AWNCo} and u_{WNNo} are the o-th element of $\mathbf{u}_{AWNC}$ and $\mathbf{u}_{WNN}$, respectively. Selection of parameters for the translation factor and dilation factor of the mother wavelet functions will significantly affect the performance of WNN, and inappropriate mother wavelet functions will degrade the learning performance. Considering the mother wavelet functions, the adaptation laws of translation factor m_{ij} and the dilation factor σ_{ij} can also be derived via the gradient descent method as

$$\begin{aligned} \dot{\hat{c}}_{ij} &= -\lambda_2 \sum_{o=1}^{2} \frac{\partial \sigma^T\dot{\sigma}}{\partial u_{WNNo}} \frac{\partial u_{WNNo}}{\partial y_j^{(3)}} \frac{\partial y_j^{(3)}}{\partial y_{ij}^{(2)}} \frac{\partial y_{ij}^{(2)}}{\partial net_{ij}^{(2)}} \frac{\partial net_{ij}^{(2)}}{\partial \hat{c}_{ij}} = \\ &= \lambda_2 \sum_{o=1}^{2} \sigma_o(t)\hat{\theta}_{jo} \left(\prod_n y_{nj}^{(2)} \left| \begin{array}{l} if\, i = 1, \Rightarrow n = 2 \\ if\, i \neq 1, \Rightarrow n = 1,\ n \neq i \end{array} \right. \right) \\ &\quad exp\left(-\frac{1}{2} \frac{\left(y_i^{(1)} - \hat{c}_{ij}\right)^2}{\hat{v}_{ij}^2} \right) \left(\frac{1}{\hat{v}_{ij}} - \frac{\left(y_i^{(1)} - \hat{c}_{ij}\right)^2}{\hat{v}_{ij}^3} \right) \end{aligned} \tag{19}$$

$$\begin{aligned} \dot{\hat{v}}_{ij} &= -\lambda_3 \sum_{o=1}^{2} \frac{\partial \sigma^T\dot{\sigma}}{\partial u_{WNNo}} \frac{\partial u_{WNNo}}{\partial y_j^{(3)}} \frac{\partial y_j^{(3)}}{\partial y_{ij}^{(2)}} \frac{\partial y_{ij}^{(2)}}{\partial net_{ij}^{(2)}} \frac{\partial net_{ij}^{(2)}}{\partial \hat{v}_{ij}} = \\ &= \lambda_3 \sum_{o=1}^{2} \sigma_o(t)\hat{\theta}_{jo} \left(\prod_n y_{nj}^{(2)} \left| \begin{array}{l} if\, i = 1, \Rightarrow n = 2 \\ if\, i \neq 1, \Rightarrow n = 1, n \neq i \end{array} \right. \right) \\ &\quad exp\left(-\frac{1}{2} \frac{\left(y_i^{(1)} - \hat{c}_{ij}\right)^2}{\hat{v}_{ij}^2} \right) \left(\frac{\left(y_i^{(1)} - \hat{c}_{ij}\right)}{\hat{v}_{ij}^2} - \frac{\left(y_i^{(1)} - \hat{c}_{ij}\right)^3}{\hat{v}_{ij}^4} \right) \end{aligned} \tag{20}$$

This training scheme will increase the learning speed of WNN, where r_1, $r_2$the learning is rates with positive constants.

3.3 Control design of adaptive wavelet neural network

This research proposes a block diagram of adaptive wavelet neural network control as shown in Fig. 6. The aim of control is to find out a way to allow $x(t)$ being able to track the referential signal $x_d(t)$.

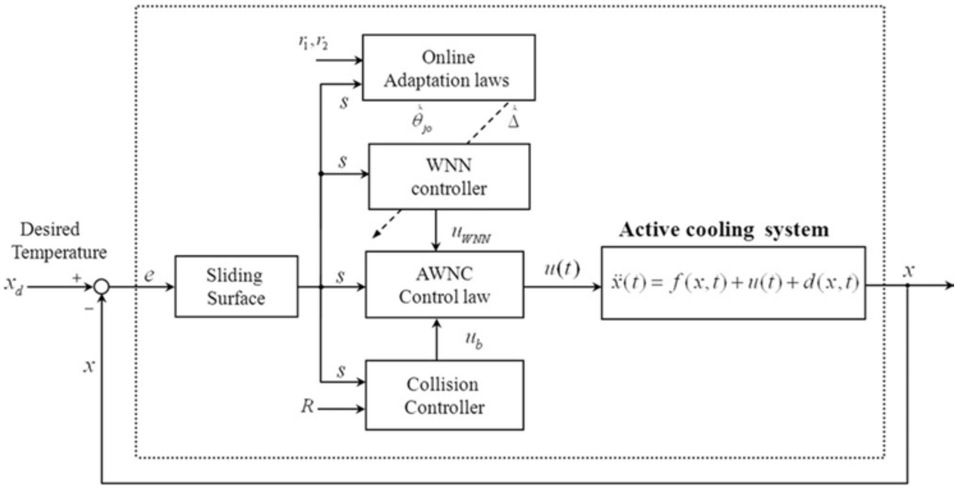

Fig. 6 *Active heat dissipation system applied to adaptive wavelet neural.*

To achieve the purpose of control, it is assumed that the tracking error must be defined at first.

$$e(t) = x_d(t) - x(t) \tag{21}$$

Next, a slide plane shall be defined in the following formula.

$$s(t) = \dot{e}(t) + ke(t) \tag{22}$$

In this formula, a fact that shows $k > 0$ shall be noted. Assuming that the dynamic function of controlled system, $f(x,t)$ and $d(x,t)$, are both known functions, it is believed that the best control can be acquired in the following formula.

$$u^*(t) = -f(x,t) - d(x,t) + \ddot{x}_d - k\dot{e}(t) \tag{23}$$

Provided that substituting Formula (18) into Formula (1), it is possible that a formula can be acquired as follows.

$$\ddot{e}(t) + k\dot{e}(t) = 0 = \dot{s}(t) \tag{24}$$

Furthermore, the above formula can acquire a result of $\lim_{t\to\infty} e(t) \to 0$ due to a fact that $k > 0$ to achieve the purpose of control. However, in actual system, $f(x,t)$ and

$d(x, t)$ are two unknown non-linear time variance functions. Thus, $u^*(t)$ in Formula (23) cannot be clearly defined. Accordingly, this research controls the system to perfect the best control $u^*(t)$ in a similar way.

First of all, Formula (1) can be written down in a simplified way and the following formula can be acquired.

$$\begin{aligned} \ddot{x}(t) &= f(x,t) + u(t) + d(x,t) \\ &= F(t) + u(t) \end{aligned} \tag{25}$$

In this formula, the non-linear time variance function written down as $F(t)$ cannot be clearly acquired in this formula $F(t) = f(x, t) + d(x, t)$. Thus, this research makes use of adaptive wavelet neural network system written down as $\hat{F}(x, c, v, \theta)$ to estimate approximation. In addition, it adds a collision control $u_b(t)$ to this formula conquer the approximation error of adaptive wavelet neural network system written down as $\hat{F}$ and actual non-linear time variance system written down as $F(t)$. The control by design is stated as follows.

$$u(t) = u_{WNN}(t) + u_b(t) \tag{26}$$

In this formula, $u_{WNN}(t)$ indicates the main control and $u_b(t)$ stands for the control force that keeps the track in the system on the slide plane. The main control is stated as follows.

$$u_{WNN}(t) = -\hat{F}(x, c, v, \theta) + \ddot{x}_d(t) + k\dot{e}(t) \tag{27}$$

Where

$$\hat{F}(x, c, v, \theta) = \mathbf{\Theta^T} \boldsymbol{\beta}(x, c, v) \tag{28}$$

In this formula, it shows the output of wavelet neural network system. At this point, x, c, v, θ indicates the adjustable variable vectors and $\hat{F}$ refers to the exciting vector of membership function. In this formula, $\mathbf{c}$ indicates connection weight values, and $\mathbf{v}$ indicates the parameter control of mother wavelet function. The definition is acquired and depicted as follows. A new formula is acquired by substituting Formula (26) and Formula (27) into Formula (25) by making use of Formula (22).

$$\dot{s}(t) = \left[\hat{F} - F(t)\right] - u_b(t) \tag{29}$$

Supposing that the best variable vector known as θ^* does exist, it is believed that $\hat{F}(x, c, v, \hat{\theta})$ can be extremely closed to a similar non-linear time variance function known as $F(t)$. And a small approximation error is defined as the following.

$$\omega_F = F(t) - \hat{F}(x, c, v, \hat{\theta}) \tag{30}$$

A new formula is thus acquired by substituting Formula (30) into Formula (29).

$$\dot{s}(t) = (\theta^{*T}\beta) + \omega_F - \hat{\theta}^T\beta + ub \tag{31}$$

Formula (32) can be written down in a simplified way.

$$\dot{s}(t) = (\tilde{\theta}^T\beta) + \omega_F + ub \tag{32}$$

In this formula, $\tilde{\theta} = \overset{*}{\theta} - \tilde{\theta}$ is defined as Lyapunov function.

$$V_1(t) = \frac{1}{2}\left(s^2 + \frac{1}{r_1}\tilde{\theta}^T\tilde{\theta}\right) \tag{33}$$

In this formula, r_1 indicates a positive constant. According to $V_1(t) > 0$ and $\dot{V}_1(t) < 0$ as defined in the Lyapunov Stability Criterion, it is possible that an adaptive law can be acquired through derivation.

$$\dot{\theta}_F = r_1 s(t)\beta(x, c, v) \tag{34}$$

$$u_b = -\Delta sgn(s(t)) \tag{35}$$

In this formula, it shows a fact that $\Delta > |\omega_F|_{\max}$. This boundary value of approximation error may have produced a Δ value that needs to be tested on a positive constant through selection in advance. The adaptive wavelet neural network system control in this research can be acquired in Formula (26). It consists of Formula (27) and Formula (34). Here, the adjustable parameter known as θ in the adaptive wavelet neural network system can be adjusted by using Formula (35). Consequently, it is assumed that Lyapunov Stability Criterion is able to assure the stability of its system.

4. Experimental method of active heat dissipation smart control system

Radar inner core processor belongs to a component with high precision. It means that the component consists of the Radio Frequency Integrated Circuit (RFIC) electronics with high-power and high-effect. Core processor needs to be worked in a narrow closed environment without convection, and dissipates heat problem in long distance of a narrow closed environment without convection by the simulate chip. While operate the chip, the highest temperature provides thermal source 20W to replace calorific value of the chip. The actual best controllable temperature is about 75°. The measuring Curie point distribution is drawn in Fig. 7.

No. 1 and No. 2 of the figure indicate a measuring the surface temperature of thermal source and heat pipe respectively. No. 1, 2, 3, 4, and No. 5 all refer to the temperature of the measuring heat pipe. No. 5 and No. 6 indicate the temperature of heat pipe at the bending point. No. 6 and No. 7 mean the surface temperature of measuring heat pipe and heat slug. To expect the design of active heat dissipation smart control system could achieve well and accurate temperature control. Through comparing in this experiment with traditional analogy circuit controller (contains relay, temperature switch, and control circuit) and adaptive wavelet neural network control. The temperature is controlled at the degree of 80°, 75°, and 70° respectively, and spaces at intervals about 1000 seconds for each. Settle the cooling system with wind sweeps at speeds 2300rpm, 24° for room temperature, input voltage section ranged from 0∼10V to 0∼10A, and heat the temperature to 4500 seconds. In this way, to prove the proposing of research that an active heat dissipation smart control system can achieve well and accurate function of lowing controllable temperature.

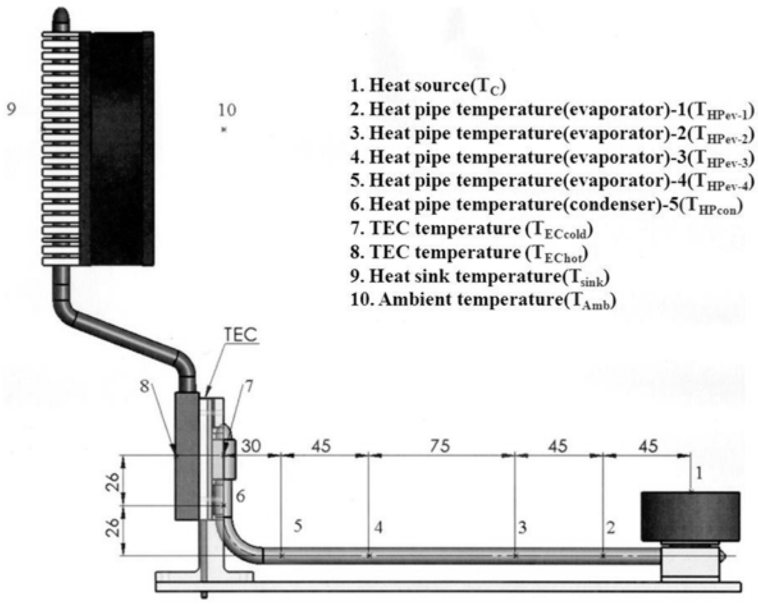

Fig. 7 *Temperature Points Distributed Measurement.*

5. Analysis of research findings

Fig. 8 displays the active heat dissipation system applied to a traditional analogy circuit controller. The temperature was settled at a degree of 80°, 75°, and 70° respectively. Assuming the actual temperature exceeds the set point, it is suggested that this research starts to provide voltage to cool down the temperature. It happens that voltage resulted in a frequent switch mode. It turns out to be a saturation voltage phenomenon. In addition, the response to control voltage reaction is not dealt with properly at once. Or perhaps, it may end up with an over control phenomenon, a decrease in voltage due to providing voltage, or the instability due to power supply for system use. Fig. 9 displays the active heat dissipation system application to adaptive wavelet neural network control. The temperature was settled at a degree of 80°, 75°, and 70° respectively. Assuming the actual temperature exceeds the set point, it is suggested that this research is capable of giving orders to tracking through good searching device. In addition, as far as the cooling effect is concerned, nothing does happen to this control compared to unlike the traditional analogy controller since no detect of frequent jitters while switching the control voltage input has occurred. It is possible to increase the heat dissipation effect according to chip thermal source by rendering adaptive, adjustable heat dissipation speed. It and can achieve the purpose to reach a good and accurate temperature control performance to deal with the heat dissipation problem in long distance where convection is not allowed.

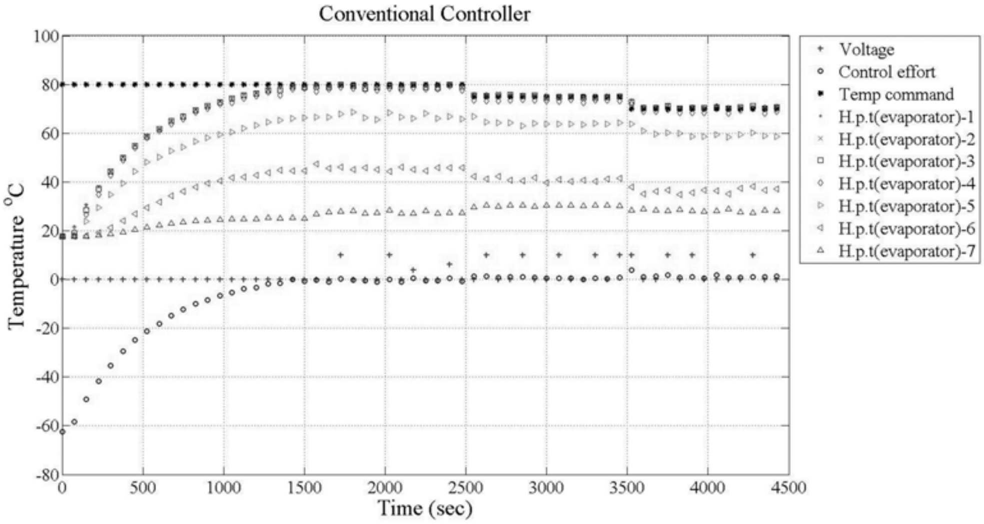

Fig. 8 *Coventional controller.*

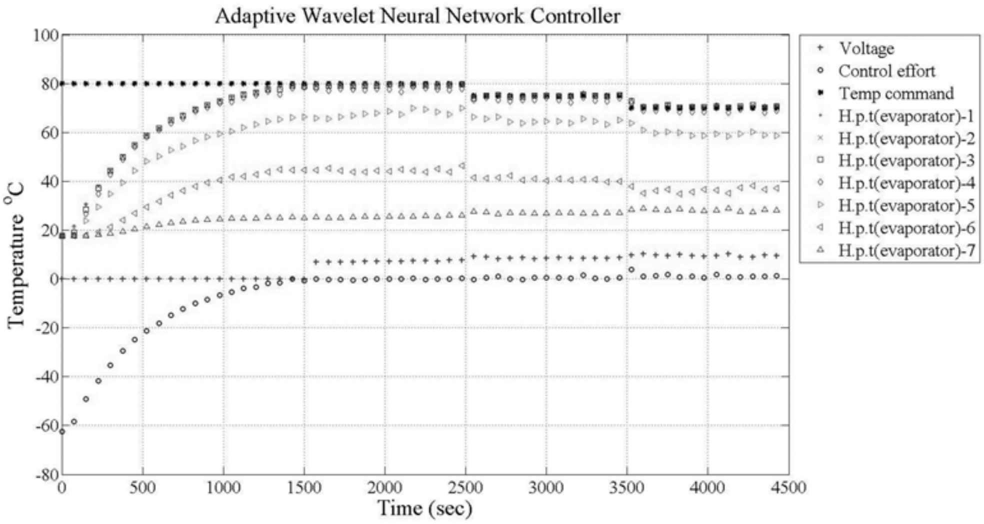

Fig. 9 *Active heat dissipation system applied to adaptive wavelet neural network control.*

6. Conclusion

This paper is based on NI-PXI system as the basic structure and combines TEC with heat pipe to work out a new active heat dissipation system so that the heat dissipation problem can be solved in long distance in a narrow closed environment without convection. To compare with an experiment of controller, this research adopts the adaptive wavelet neural network control and the traditional analogy controller. It proved that this research proposed an active heat dissipation smart control system which achieves a well accurate temperature control performance. Adaptive wavelet neural network control has the good capability of searching and tracking. In addition, its cooling control performance is far better than a traditional analogy circuit controller. There is nothing happened in a saturation voltage phenomenon while controlling the input of voltage. It ends up with a result that the chip can increase its heat dissipation effect in a narrow closed environment without convection according to the chip thermal source to give adaptive, adjustable heat dissipation speed. It helps to solve the heat dissipation problem in long distance without convection. It proves that this system is effective and practical. It also proved that the system can provide feasibility applied to a radar heat dissipation system with high power. Hopefully, the structure of the control can be provide d some solution to solve the key problems of the development of heat dissipation techniques in terms of livelihood, medical treatment, military affairs, and industry in the long run.

References

[1] CHEN C.H. Intelligent transportation control system design using wavelet neural network and PID type learning algorithms. *Expert Syst.* 2011, 38(6), pp. 6926–6939, doi: 10.1016/j.eswa.2010.12.031.

[2] DA F. Fuzzy neural network sliding mode control for long delay time systems based on fuzzy prediction. *Neural Computing and Applications.* 2008, 17(5–6), pp. 531–539, doi: 10.1007/s00521-007-0130-x.

[3] KHOH C.J., TAN K.K. Adaptive robust control for servo manipulators. *Neural Computing and Applications.* 2003, 12(3-4), pp. 178–184, doi: 10.1007/s00521-003-0380-1.

[4] KIM B.K., CHUNG W.K., CHOI H.T., SUH H., CHANG Y.H. Robust internal loop compensator design for motion control of precision linear motor. In: *Proceedings of the IEEE International Symposium on Industrial Electronics (ISIE'99). IEEE, 1999*, 3, pp. 1045–1050, doi: 10.1109/ISIE.1999.796773.

[5] LIN C.M., HSU C.F. Neural-network hybrid control for antilock braking systems. *IEEE Trans. Neural Netw.* 2003, 14(2), pp. 351–359, doi: 10.1109/TNN.2002.806950.

[6] LIN C.L., SHIEH N.C., TUNG P.C. Robust wavelet neuro control for linear brushless motors. *IEEE Trans. Aesop. Electron. Stys.* 2002, 38(3), pp. 918–932, doi: 10.1109/TAES.2002.1039408.

[7] NOURI K., DHAOUADI R., BENHADJ BRAIEK N. Adaptive control of a nonlinear dc motor drive using recurrent neural networks. *Applied Soft Computing.* 2008, 8(1), pp. 371–382, doi: 10.1016/j.asoc.2007.03.002.

[8] PARK J.H., HUH S.H., KIM S.H., SEO S.J., PARK G.T. Direct adaptive controller for nonaffine nonlinear systems using self-structuring neural networks. *IEEE Trans Neural Netw.* 2005, 16(2), pp. 414–422, doi: 10.1109/TNN.2004.841786.

[9] SLOTINE J.J.E., LI W.P. *Applied nonlinear control.* Englewood Cliffs, NJ: Prentice-Hall, 1991.

[10] WANG Z., ZHANG Y., FANG H. Neural adaptive control for a class of nonlinear systems with unknown dead zone. *Neural Computing and Applications.* 2008, 17(4), pp. 339–345, doi: 10.1007/s00521-007-0124-8.

[11] ZHAI J.Y., FEI S.M., MO X.H. Multiple models switching control based on recurrent neural networks. *Neural Computing and Applications.* 2008, 17(4), pp. 365–371.

[12] ZHANG Q. Using wavelet network in nonparametric estimation. *IEEE Trans. Neural Netw.* 1997, 8(2), pp. 227–236, doi: 10.1109/72.557660.

[13] ZHU H.A., HONG G.S., POO A.N. Internal model control with enhanced robustness. *International Journal of System Science*. 1995, 26(2), pp. 277–293, doi: 10.1080/00207729508929036.