MED'04

12TH Mediterranean Conference on Control and Automation

CONFERENCE PROGRAM



Sponsored by:
Mediterranean Control Association (MCA)

Organized by:
Mechatronics Res. and Application Center,
Boğaziçi University, Turkey

June 6-9, 2004
Kuşadası, Aydın - Turkey
Korumar Hotel

IEEE

Control Systems Society

Table of Contents

Table of Contents 1

A Message from General Chair 3

A Foreword of Thanks and Welcome 4

Organization 5

Committees 5

Acknowledment 6

General Information 6

Session Coding 7

Important Events 7

Conference Schedule 8

Pleanary Sessions 10

PleS1 : Human-Centered Robotics 10

PleS2 : A map of the World of Learning and Optimization 10

PleS3 : Intelligent Control of Unmanned Aerial Vehicles for Improved Autonomy and Reliability 11

PleS4 : TerraMax: The Autonomous, Off-Road Vehicle 11

Special Sessions : 12

MoM1-C : SS on Computational Methods for CACSD – 1 12

MoA1-D : SS on Mobile Robots 13

MoA2-C : SS on Computational Methods for CACSD – 2 15

TuA1-D : SS on Positive Systems 16

Regular Sessions : 17

MoM1-A : Mobile Robots 17

MoM1-B : Linear Control 1 18

MoM2-A : Environmental & Energy Systems 19

MoM2-B : Linear Control 2 20

MoM2-C : Fuzzy Control 21

MoA1-A : Stability 23

MoA1-B : Aerospace Control 24

MoA1-C : Process Control 25

MoA2-A : System Identification 26

From the Technical Program Committee

Dear MED'04 participants,

I welcome you to Kusadasi, host of this year's Mediterranean Conference on Control and Automation - MED'04, the latest of a series of annual Conferences co-sponsored by the IEEE Control Systems Society and the Mediterranean Control Association. I hope that the Conference will be rewarding not only for its technical program but also for the opportunity to forge personal relationships among colleagues in the Region.

During the past half century or so, Control and Automation has evolved into major discipline that involves diverse fields from Industrial Automation to Robotics, all seeking solutions using common Systems methodologies. The famous gap between theory and practice cannot but close a little through technical Conferences like MED where colleagues from all over the world converge even for a few intensive days to share ideas, knowledge and experience and learn of research activities in the field in countries in the Region and further afield. I like to view MED'04 as a bazaar, an Eastern Mediterranean tradition, where ideas are traded, research partners are found and lasting friendships are made over endless cups of sweet Turkish coffee and tea ... while viewing the sunset over the Aegean.

This year's Mediterranean Conference on Control and Automation Conference follows in the footsteps of earlier MED Conferences in nearby countries. Over 260 papers were submitted to the Conference and some 170 will be presented. The Technical Program Committee and the International Program Committee worked hard to assemble a technical program that portrays the state of the art of our field. In addition to the four Plenary Sessions presented by speakers of international renown, four Special Sessions that focus on current research activity in our field have been programmed. The social events are but a sample of the unexcelled hospitality of the host country General Chairman Okyay Kaynak.

It is indeed most gratifying that this year's Conference has contributions from more than 45 countries from as far as the USA, Japan and China. In addition to providing a forum for technical discussion, the Conference satisfies the equally weighted objective of exposing participants from the various countries to the culture, traditions and history of the host country.

On behalf of the
MED'04 Technical Program Committee
Robert E. King

Frisch scheme–based algorithms for EIV identification

Roberto Diversi[1], Roberto Guidorzi[1], Umberto Soverini[1]
[1]*Universit`a di Bologna, Italy*

In many practical situations the process data are affected by noise on both inputs and outputs. In these contexts, errors–in–variables (EIV) models can be the best choice for identification purposes and several approaches based on these representation are present in the literature. This work refers to one of these methods, the so–called dynamic Frisch scheme. In particular, two different Frisch scheme– based algorithms are analyzed and compared by means of Monte Carlo simulations.

Implementation of Identification Algorithms in Systems with Reduced Computational Resources

Anastasios Mourikis[1], Anthony Tzes[1]
[1]*University of Patras, Greece*

In this paper, the implementation of a classical identification technique with medium computational complexity over a system with limited computing capability, is addressed. As a testbed, the Frequency-Domain Least Mean Squares (FD-LMS) algorithm [1] is implemented with fixed--point (finite wordlength) rather than floating--point routines. The fundamental issue of faster sampling at a reduced wordlength, compared to the case of a slower sampling rate with increased accuracy (smaller roundoff errors) is investigated in the ensuing simulation studies. This problem is typical in embedded systems (controllers) with limited number crunching capabilities, where their computational power significantly limits the maximum number of operations (multiplications and additions) that can be executed within a time interval. The results of this study point towards the need of jointly optimizing the sampling rate, the wordlength size and the complexity of the assumed filter (model) in system identification cases.

Two MOESP Type Recursive Subspace Identification Algorithms

Catarina J. M. Delgado[1], P. Lopes dos Santos[1], J.L. Martins de Carvalho[1]
[1]*Instituto de Sistemas e Robotica - Porto, Portugal*

In this paper two recursive algorithms are presented, based on MOESP type subspace identification. The main idea was to show that subspace identification methods can be represented as sequences of least squares problems and implemented through sequences of modified Householder algorithms. Therefore, it is possible to develop iterative algorithms with most of the advantages of this kind of methods, and still improve the numerical efficiency, in order to deal with real-time applications and minimize the computational burden.

MoA2-B — Monday, June 7, 18:15-19:30 @ Room B
Neural Control
Session Chairman : Mehmet Akar

Adaptive Beam Controlling for Smart Antennas Using Autoregressive and Adaline Neural Network Modeling

Halil Yigit[1], Adnan Kavak[1], H. Metin Ertunc[1]
[1]*Kocaeli University, Turkey*

In Time Division Duplex (TDD) mode wireless communications, downlink beamforming performance of a smart antenna system at the base station can be degraded due to variation of spatial signature vectors of an antenna array especially in fast fading scenarios. To mitigate this, downlink beams must be controlled by properly adjusting their weight vectors in response to changing propagation dynamics. This can be achieved by modeling the spatial signature vectors in the uplink period and then predicting them for the new mobile position in the downlink transmission period. In this paper, we show that linear prediction of spatial signature vectors using autoregressive (AR) and ADALINE (ADAptive LInear NEuron) network modeling provide certain level of performance improvement compared to conventional beamforming method under varying channel (mobile speed) and filter (delay) order conditions. ADALINE structure outperforms AR modeling in terms of downlink SNR improvement and relative error improvement.

Development of a Neural Control Program to Reduce Uncertainty in the Measurements of DC HV Resistive Dividers

Serhat Yilmaz[1], Hasan Dincer[1]
[1]*Kocaeli University, Turkey*

In this study, a control program devised for increasing precision in measurement of a resistive voltage divider system is described. The system includes two controllers which are regulating the factors that cause to errors in measurement. Due the system contains non-linear elements, a knowledge based control approach is suggested and used in the system to match the best fitted controller outputs and inputs. Corporate neural training and neural control programs have been developed for covering these requirements. Major aim of this paper is focused on development stages of the control program.

DEVELOPMENT OF A NEURAL CONTROL PROGRAM TO REDUCE UNCERTAINTY IN THE MEASUREMENTS OF DC HV RESISTIVE DIVIDERS

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Abstract

In this study, a control program devised for increasing precision in measurement of a resistive voltage divider system is described. The system includes two controllers which are regulating the factors that cause to errors in measurement. Due the system contains non-linear elements, a knowledge based control approach is suggested and used in the system to match the best fitted controller outputs and inputs. Corporate neural training and neural control programs have been developed for covering these requirements. Major aim of this paper is focused on development stages of the control program.

1. Introduction

Accurate measurements of DC voltages at values above 10V and calibrating other measurement devices are achieved by standard voltage dividers. As to the effects of self heating of the resistors, chaotic distribution of this heat, leakage currents and corona effects are caused to error in measurements. Uncertainties arisen from the last two effects may be reduced by arrangements in design and construction of voltage divider systems. However, the self heating of the resistors and any vertical temperature gradient along the resistor column are keeping to be the major error sources in precise measurements [1].

The temperature of such a system has to be kept in some certain degree and temperature gradient should be approximated to insignificant values. In this purpose, a dc voltage divider system which includes a control process to regulate these variables, is realised. The divider is designed for precise measurements up to 5 kV. The control process is consist of computer aided heat and heat gradient controllers.

Experimental observations indicates that, responses of the plant to the control signals are not linear and depends on several variables. Besides, complex structure of the system's heat dispersion (conduction and convection) could affect performance of the control process. Dependent and independent input variables and their effects to the control process are determined by these observations. A suitable training set of inputs and outputs is derived from the actual observation results. Parameters of the controllers are trained by neural networks by means of the training set. And afterwards, the trained networks carried out the control process. In this purpose, neural training and neural control programs are developed [2]. This paper describes the programs and gives briefly the preparation stages, algorithm and experimental results of the control program.

2. Structural features of the 5kV DC voltage divider system

The divider's features are given: Maximum input voltage is 5 kV, total resistance is 5 MΩ and it is consist of 4x1 MΩ+9x100 KΩ+10x10KΩ resistors [3]. Voltage division ratio is 1 000:1 and the maximum output voltage is 5V.

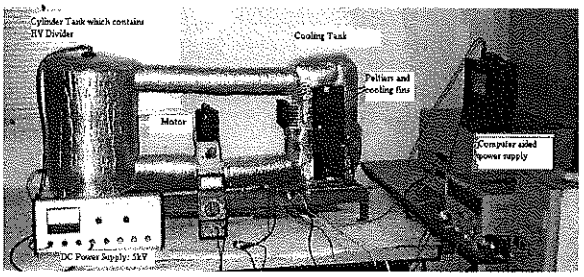


Fig.1. Heat controlled HV divider mechanism.

A closed mechanism which contains a pair of tanks is used for heat control of DC HV Resistive Divider. A polyamide cylinder which conserves the resistive divider is located in the left. An aluminium cooling tank which removes the heat produced by the resistors, is located in the right. The oil is used as a fluid heat convection element between the tanks, by means of a circulation pump.

The transmission tubes are isolated against the heat transfer. The heat is absorbed from one side of the peltier effect thermoelectric elements to the other side and it is removed to the outer ambience by the air forced cooling fans [4].

3. Determining structure of the neural controllers

In this application, two neural controllers are used. The first determines current of the power supply which drives the peltiers to fix temperature of the system while the second adjusts speed of the circulation motor to reduce T_{upper}-T_{lower} heat gradient along the resistors column. The training program, trains and tests the neural controller parameters according to training and testing sets of inputs and outputs. The control program carries out regulating the self heating and heat gradient errors during the control process according to the trained control parameters.

3.1. Building the structure of NN which trains parameters of the temperature controller

The first neural controller adjusts cooling rate of the peltier according to E and η_c where;

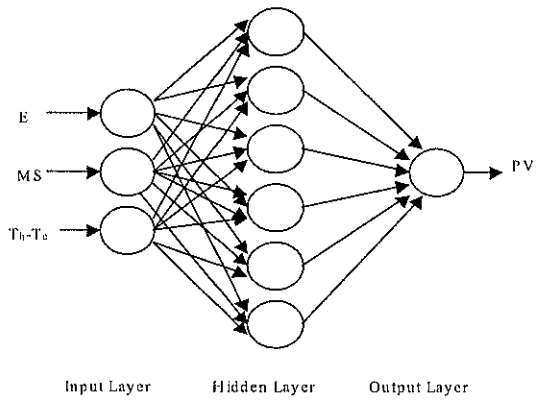


Fig.2. Structure of NN used for the temperature control.

E : Error between the real and the required temp. values

η_c : Cooling efficiency of the peltiers which depends on motor speed which is represented by the motor voltage (MV) and T_h-T_c (Temperature difference between hot and cold side of the peltier cooling elements).

The relation between inputs (η_c = f (MV, T_h-T_c) , E) and control output (PV: Peltier Voltage) is derived from experimental results [2] and they are represented by a set of sample inputs and their matching outputs, called training set. Due the system contains 3 inputs and 1 output, structure of the network is selected in (3x6x1) form as shown in Figure.2

3.2. Building the structure of NN which trains parameters of the gradient controller

Similarly, the second neural controller drives the voltage that adjusts the motor speed according to T_{upper}-T_{lower} heat gradient and its derivative, to reduce the temperature gradient which occurs along the resistor column. The training set of the gradient controller is also derived from experimental results. Training process aims to match the best fitting between the inputs (T_{upper}-T_{lower} , Δ (T_{upper}-T_{lower}) and control output (MV). Structure of the second network is selected in (2x4x1) form as shown in Figure.3

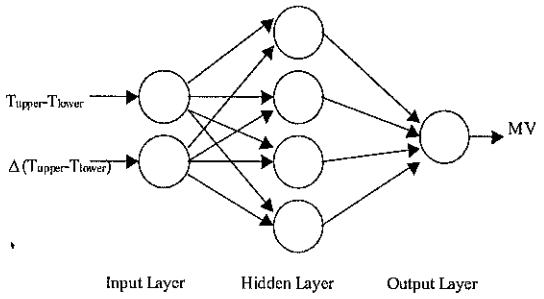


Fig.3. Structure of the NN used in the T_{upper}-T_{lower} vertical temperature gradient control.

3.3. Methodology of the training program

Controller parameters are weights of connections between the neurones and their threshold values. Methods and training steps of the network weights are identical for both controllers. The weights are updated according to back propagation method during the training stage. The method depends on minimising a cost function of errors, by means of iterative evaluating gradient descents of the function versus each weight. A coefficient matrix consist of weights is updated along the iterations (Eq.1)

$$w_{ij}^{k}(next) = w_{ij}^{k}(previous) + \Delta w_{ij}^{k} \quad (1)$$

$$\Delta w_{ij}^{k} = \eta \, \delta_{i}^{k+1} o_{j}^{k} \quad (2)$$

δ_i^{k+1} represents delta value of the (i^{th}) neurone in the next ($k+1^{th}$) layer. Delta values contain information about changes in the cost function according to total inputs of each neurone. Its' formulation is varied in the program with respect to its' location whether it is in hidden layer or in output layer.

o_j^k represents output of the (j^{th}) neurone in the current (k^{th}) layer. It contains information about effects of weights to total inputs of neurones in the following layer[5].

4. Programs developed for the system

The training and the control programs are prepared in Delphi 5.0 [6]. The first program trains, tests and stores optimum control parameters. The next program loads and uses these parameters during the control process.

4.1. Training Program

The training program and its' flow chart is considered in details in reference[7] After the training process initialises, desired training outputs are graphed in the order of sample sequence number (Figure.4, upper left). Actual outputs may be graphed together by means of option buttons. In the lower left side, actual outputs of the NN for the subsequent iterations are shown. Error of the set is represented by a cost function as shown in the right. Error reduces parallel to progression of training epochs.

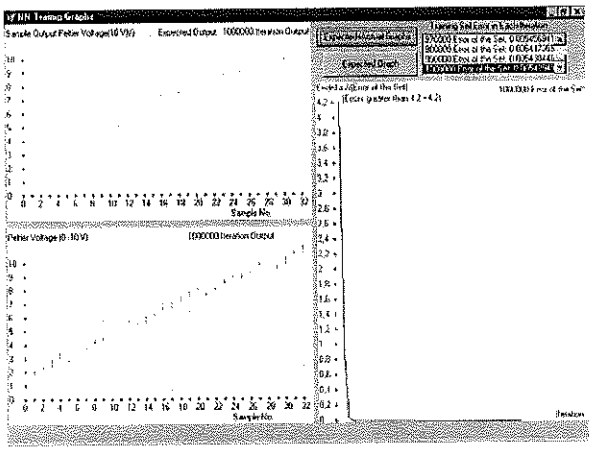


Fig.4. Graphs of the training NN for heat control

Parameters of trained network, such as weights and thresholds, number of neurones, layers are saved to file.

4.2. Neural Control Program and Control Results

The control program is prepared due to the characteristics and structures of the controllers described above. Main menu interface of prepared neural control program is shown in Figure.5. Under title "Analog I/O Card Reports", reports are given about the situation of ADC card. The menu also reports dates and starting time of the experiments. Title "Control Information" represents the knowledge about controls of both peltier cooling rate and motor speed.

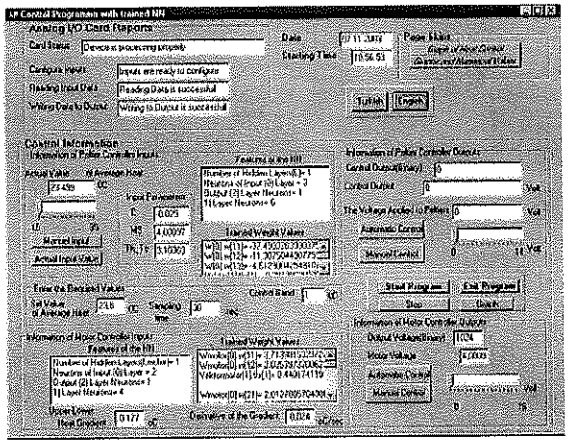


Fig 5. Neural control interface

Fig. 6 reports the average temperature (Eq.3) of the cylinder tank in the left side of the system, versus time.

$$T_{avg} = \frac{T_{upper} + T_{lower}}{2} \qquad (3)$$

The dashed line represents the required temperature value, called set value. The box in the left shows the temperature value which belongs to current sampling time. The box in the right stores previous values by 1 minute intervals. They are recorded to a file while the program is closed.

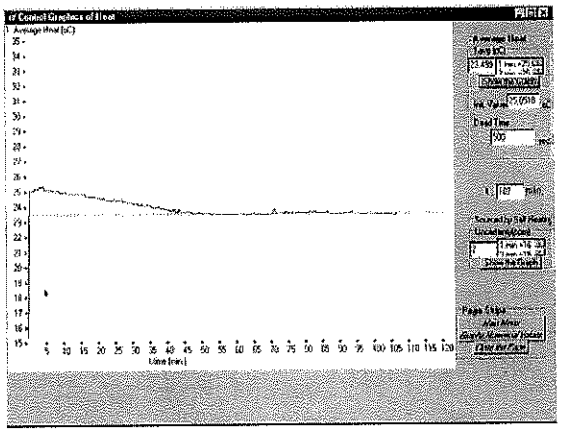


Fig 6. Average temperature value of the fluid in the tank .

These data are used to calculate the transient state criteria such as max. overshoot, delay , settling and rise times etc.

The second controller which regulates the motor speed keeps the T_{upper}-T_{lower} heat gradient close to zero as shown in Figure.7.

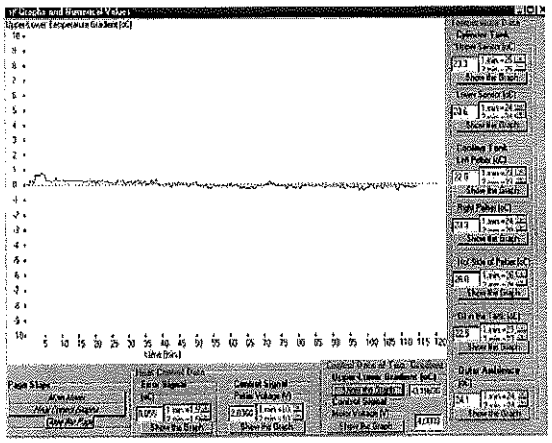


Fig 7. Upper-Lower heat gradient.

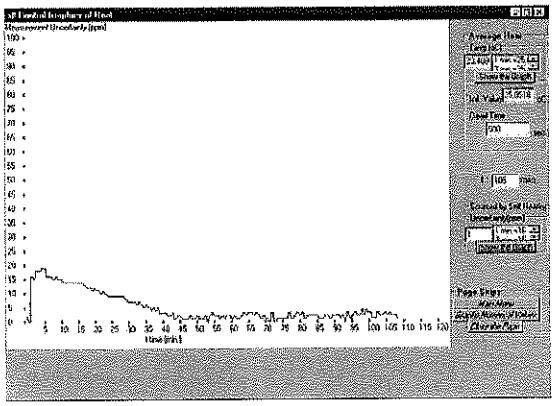


Fig.8. Measurement uncertainty sourced by the heat

Similarly, measurement uncertainty which is sourced by the heat is graphed as shown in Fig.8. It represents bounds of uncertainty that could be occurred by the changes in resistor values caused by heat according to their thermal coefficients. It is a square cost function derived from combination of T_{set}-T_{avg} heat gradient and T_{upper}-T_{lower} heat gradient (Shown in Figure.6 and Figure.7 respectively). Here, max. overshoot is 4ppm and rise time is 38 min.

4.2.1.Graphs and Data about Temp. in Certain Points

In this section, temperature data acquired from upper and lower sensors, from the sensors located to hot and cold side of the peltier elements, from the sensor which is plunged in the liquid inside the cooling tank, and the data acquired from the ambient is graphed versus time. These graphs are used to observe the delay times and the effects of peltier control voltage in various points.

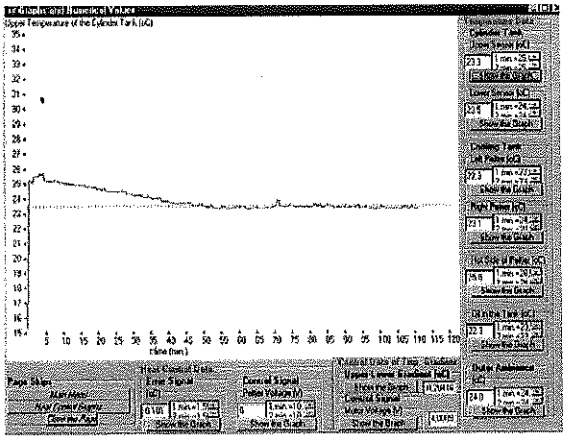


Fig.9. Upper temperature of the tank which resistors exist

In the temperature graph which belongs to the upper sensor, it is shown that ripples are greater than the lower one. Self heating of the resistors in the cylinder tank warms the liquid. Warmer liquid is arisen upwards of the cylinder tank by means of natural convection. Cooler liquid in the cooling tank is subjected to a forced convection in opposite direction by means of the circulation motor. First conflicting is occurred and caused to a turbulence on the point where upper sensor is located. T_h-T_c is used for calculating cooling efficiency of peltiers.

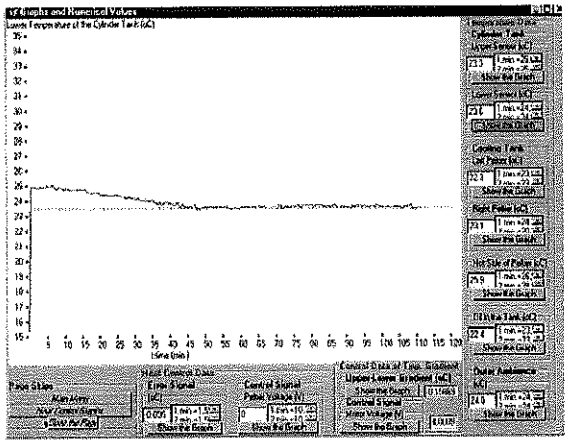


Fig.10. Lower Temperature of the tank which resistors exist

Cold side sensors are located to a position on surface of the tank which is close to cold side of peltiers. Along a certain transient time, peltiers rapidly cool body of the cooling tank. That's why, in the transient time, a rapid decrease in the temperature is observed. Then, the cooling is spreaded to the liquid in the tank. Refer to the temperature difference between the cooling tank and the liquid, temperature of the cold side begins to rising until it settles around a certain stable degree which is close to degree of the liquid shown in Fig.13. After settling to an

equilibrium state, cold side temperatures of the peltiers varies according to control voltage for directing temperature of the liquid (shown in Fig.13) to a desired

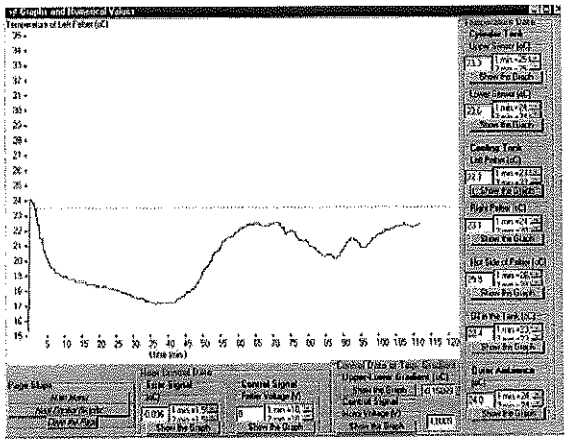


Fig.11. Cold side of the peltier in the left of cooling tank.

temperature (Fig.11). Hot side of a peltier is deviated refer to control voltage as shown Fig.12.

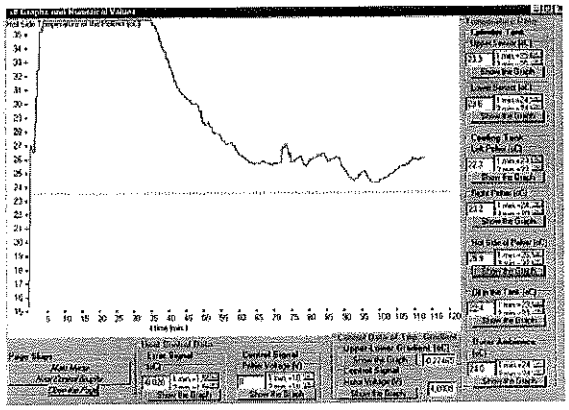


Fig.12. Hot side of the peltier in the left of cooling tank.

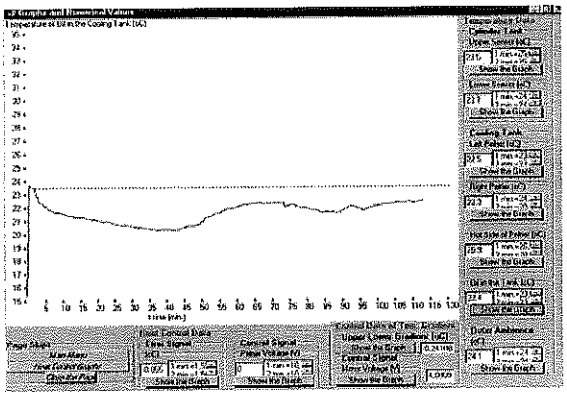


Fig.13. Temperature of liquid in the cooling tank

Fig.14, indicates temperature of the outer ambience which is an independent input variable that effects the control process by changing T_h [8] , consequently η_c .

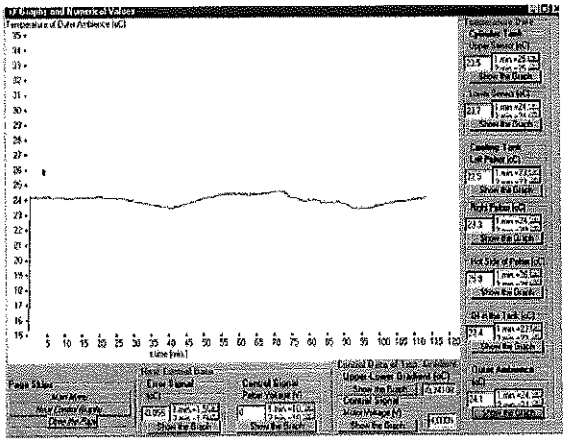


Fig.14. Temperature of the outer ambience

4.2.2. Graphs and Data about the Control Process

Input values of the controllers are derived and graphed by means of the temperature data described in the previous section. For example the error data which is an input of the neural temperature controller is derived from temperature difference between set value and actual value of the average temperature as shown in Fig.15. Similarly, Upper-Lower Heat Gradient data which is an input of the neural vertical gradient controller is derived from temperature difference between upper and lower temperatures of the cylinder tank in the left (Fig.7).

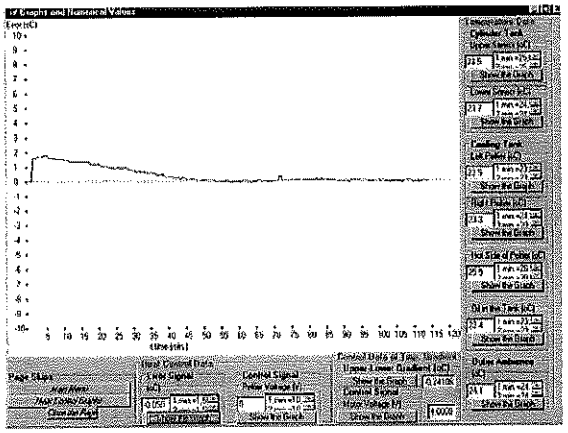


Fig.15. Temperature difference between set value and actual value of the average temperature

The corresponding control output values are graphed in Fig.16 and Fig.17 respectively. They are the voltages applied to peltiers and to motor.

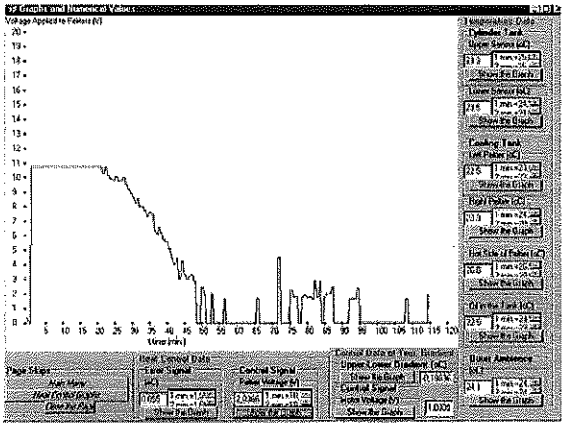


Fig.16. Neural control voltage applied to peltiers.

Control voltage, applied to peltiers follows a decreasing trend in general, parallel to reduction in the error. Appropriate control voltage is also determined by NN control parameters which are trained according to consideration of the other input variables.

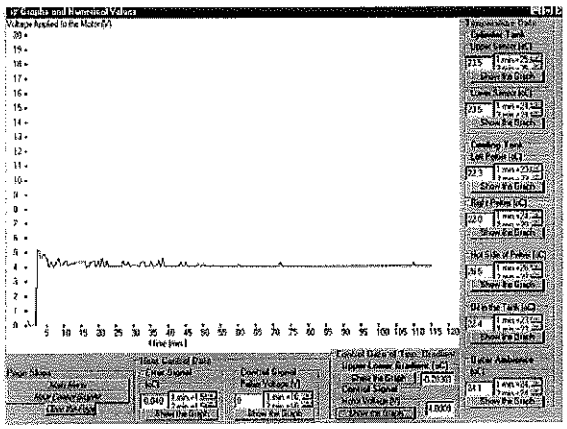


Fig.17. Neural control voltage applied to motor

Reason of non-linear and discontinuous transitions in the voltage is originated by this non linear character of the training set.

In initialisation, a T_{upper}-T_{lower} error trend is shown in positive direction which proves the natural convection (Figure.7) . Motor control signal shown in Figure.17, prevents further increase and in addition it reduces the error.

5. Conclusions

In this study, a neural control program which has been devised for carrying out of temperature and vertical temperature gradient control processes is considered. The controllers reduce uncertainty of the system. The temperature controller has fixed the temperature arround the required value. The gradient controller has kept the temperature gradient close to zero.

Another investigation that concentrates on the neural training program together with the control program and their algorithms in details may strengthen expressions of this study. Different control approaches may be suggested for the system or performance comparison with the other methods [9,10] may be considered in the future works.

Acknowledgement: Authors thanks to Hasan KARABAY, Mustafa SEÇİLMİŞ, Erdal ASLAN, Engin GEÇER, Okan YILMAZ, Yakup GÜLMEZ, Saliha S. TURHAN and Ahmet MEREV for their contributions.

References

[1] WU, S.L. and SCHON K., 1987. Investigation into The Self-Heating Effect of HV DC Dividers. Fifth International Symposium on High Voltage Engineering, 73.05, 1-4, Braunschweig.

[2] YILMAZ, S., 2003. DA YG Dirençsel Bölücülerde Ölçüm Belirsizliğinin Azaltılması için Yeni Yaklaşımlar. Doktora Tezi, KOÜ Fen Bilimleri Enstitüsü, 76-100, Kocaeli

[3] J.H. Park, "Special Shielded Resistor for High-Voltage D-C Measurements", Journal of Research of the National Bureau of Standards-C. Engineering and Instrum,Jan.1962, pp.19-24

[4] INCROPERA, F. P. and DEWITT, D. P.,2001. Isı ve Kütle Geçişinin Temelleri. 4. Basımdan Çeviri, Literatür Yayınları, 1-369, İstanbul.

[5] EFE, M. Ö. ve KAYNAK, O., 2000. Yapay Sinir Ağları ve Uygulamaları. Boğaziçi Ün. Yayınları, 1-141, İstanbul.

[6] CALVER, C., 1997. Delphi Unleashed. Sams Publishing / Sistem Yayıncılık, 1-230, İstanbul.

[7] YILMAZ, S., DINCER,H., "Development of a Neural Training Program which is used for Improvement in the Measurements of DC HV Resistive Dividers", NEU-CEE 2004 2nd Int. Symp on Electrical, Electronic and Computer Engineering, Proc., pp.132-137, March 2004, Lefkoşa.

[8] http://www.tellurex.com/cthermo.html

[9] YILMAZ, S., DİNÇER,H., "DA Yüksek Gerilim Bölücülerde Ölçüm Belirsizliğini Azaltmak İçin Geliştirilen PID Denetim Programı", Elektrik-Elektronik-Bilgisayar Mühendisliği 10. Ulusal Kongresi, Bildiriler Kitabı, s.232-235, Eylül 2003-İstanbul

[10] YILMAZ, S., DİNÇER, H., "Development of a Fuzzy Control Program to Reduce Uncertainty in the Measurement of DC HV Resistive Dividers" ELECO'2003 The third International Conference on Electrical and Electronics Engineering, Proceedings, pp.310-314, December 2003, Bursa.

Author Index

Abdalla, Babiker K. TuM1-B
Abd-Elgeliel, M. TuA1-C
Abdessemed, Foudil MoM1-A
Abu-Khalaf, Murad MoA2-C
Afkhami, Saman TuM1-B
Ailer, P. MoA1-A
Akar, Mehmet TuM1-B
Akin, Ozkan MoM2-C
Alan, Irfan MoM2-C
Alavi, S. M. Mahdi MoM1-B
Alci, Musa MoM2-C
Alci, Musa TuM2-D
Alexandridis, A.T. WeM1-A
Allgower, F. MoA2-C
Al-Naemi, Mohammed TuM1-B
Antonelli, Gianluca TuM1-A
Antoniou, E.N. MoM1-C
Antoniou, E.N. MoM1-C
Antsaklis, Panos J. TuA1-C
Arampatzis, Th. WeM1-B
Arantes, Filipe TuA1-C
Arcak, Murat TuA1-B
Arogeti, Shai TuM1-A
Ashokaraji, Immanuel MoM1-A
Athans, Michael WeM1-A
Avanzini, Giulio WeM1-A
Bagheri, S. MoM1-A
Banyasz, Cs. TuM2-B
Barbu, Gheorghe MoM2-A
Barbu, Marian MoM2-A
Barbu, Marian TuA1-A
Barnes, Laura E. TuA1-C
Bashkirov, S. MoA1-D
Batur, Celal TuM1-D
Bayrak, Coskun TuA1-A
Becerikli, Yasar TuM1-D
Benghanme, M. MoM2-C
Berman, Nadav TuM1-A
Bicchi, Antonio TuM1-A
Bingul, Zafer TuM1-A
Bitsoris, George TuM1-B
Bitsoris, George TuM2-B
Blomqvist, Eva WeM1-B
Bogdan, Stjepan MoA1-C
Bokor, Jozsef MoM1-B
Bokor, Jozsef TuA1-A
Bouchoucha, Mouloud MoM2-C
Boudellioua, Mohamed S. MoM2-B
Braiek, N. Ben Hadj TuM1-B
Brlecic, Zdenko MoA1-C
Bru, Rafael TuA1-D
Bruns, Torsten TuA1-A
Bujorianu, Manuela L. MoA1-C
Buslowicz, Mikolaj TuA1-D
Cai, Jianfeng MoM1-C
Canto, Rafael TuA1-D
Caraman, Sergiu TuA1-A
Carari, Sorin MoA1-C
Carvalho, Joao B. MoA2-C
Casalino, Giuseppe MoM1-A
Ceanga, Emil MoM2-A
Ceanga, Emil TuA1-A
Celentano, G. WeM1-B
Cevik, M. K. Kulmiz TuM2-C
Chadli, Mohammed TuM2-D
Chen, Xin TuM1-D
Chiaverini, Stefano TuM1-A
Christodoulou, M.A. MoA1-B
Christodoulou, Manolis MoA1-B
Christova, Nikolinka TuA1-B
Chrysostomou, C. MoM2-C
Chu, Yun-Chun MoA1-B
Chuang, Chih-Ying MoA1-D
Cong, Shuang WeM1-A
Costoulakis, Constantinos MoA1-B
Crane III, Carl D. WeM1-A
Dahleh, Munther A. MoA1-A
Dahleh, Munther A. TuA1-A
Dal, Mehmet TuM2-B
Danesi, Antonio TuM1-A
Dang, Pritpal TuM2-C
Datta, Biswa Nath MoA2-C
Davison, Edward J. TuA1-A
Davison, Edward Joseph MoM2-B
Davrazos, Gregory MoA1-A
De Carvalho, J.L. Martins MoA2-A
De Keyser, Robin WeM1-B
De Santis, Elena TuM2-C
Dede, Mehmet Ismet Can MoA1-C
Delgado, Catarina J. M. MoA2-A
Deligiannis, Vasileios WeM1-B
Demircioglu, Huseyin TuM1-C
Derdouche, Abd El Kader MoM2-C
Di Benedetto, Maria Domenica TuM2-C
Dias, Flavio TuA1-C
Dincer, Hasan MoA2-B
Dionisio, R.V. TuM2-A
Diversi, Roberto MoA2-A
Djezzar, Salah MoM2-B
Dos Santos, P. Lopes MoA2-A
Dourado, A. MoA2-B
Duarte-Ramos, H. MoA2-B
Economou, John MoM1-A
Eksin, Ibrahim TuM1-C