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Intuitionistic fuzzy estimation of a model of a thermoelectric cooling system, presented by neural network

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Abstract: Neural networks are the tools that can be used for the modelling for many systems. Thermoelectric cooling systems (TCS), generated on the basis of Peltier elements, are very widely used in the military industry and computing, which require smooth but precise thermostating of objects and volumes. For the estimations between these two systems we use intuitionistic fuzzy set.
Keywords: Intuitionistic fuzzy set, Thermoelectric cooling systems, Neural networks.
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1 Introduction

Thermoelectric cooling systems

In the devices and systems used for cooling and thermostating of objects and volumes, the thermoelectric energy converters are becoming more and more widely used [9, 11]. In recent years, a growth in the study, design and manufacture of thermoelectric modules (TEM) has been observed, driven by the increased demand for thermoelectric devices (TED), both for specialized and general use. Compared to other cooling systems, TEDs have the following advantages: high reliability; no moving parts; unlimited service life, independent of their orientation in space; harmless to the environment, etc.

Thermoelectric cooling systems (TCS), generated on the basis of Peltier elements, are very widely used in the military industry and computing [5, 10], which require smooth but precise

thermostating of objects and volumes. The need for thermoelectric intelligent systems which respond adequately to the rapidly changing processes and working conditions is getting bigger and bigger.

The purpose of this paper is to create a model of intelligent TCS with the help of a neural network based on real experimental test results. An experimental setup (Fig. 1) is implemented, by which the working mode of Peltier TEM is studied.

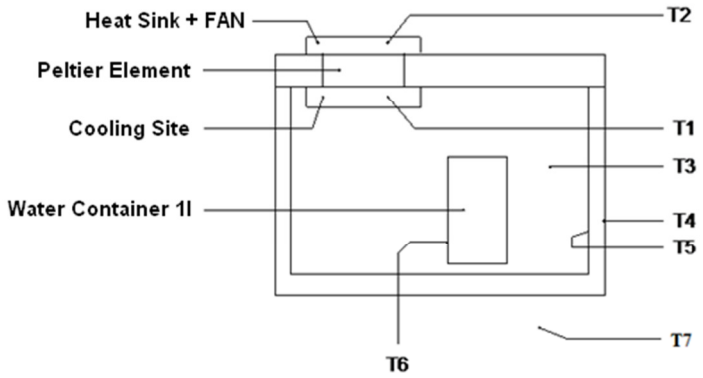

Figure 1. Thermoelectric cooling system, where $T_1 = T_c$ – temperature of the cold radiator; $T_2 = T_h$ – temperature of the hot radiator; $T_3 = T_v$ – temperature in the casing volume; T_4 – temperature of the outer wall of the casing; T_5 – temperature of the inner wall of the casing; T_6 – temperature of the outside wall of the water container; T_7 – ambient temperature (air in the room).

The constructed TCS provides the necessary thermostabilization. It consists of thermoelectric battery and thermostatic casing, composed of double walls, between which a thermal insulation layer is integrated. In the casing, it is relied only on natural convection and there is no additional ventilation.

A fundamental unit of TCS is the thermoelectric battery in which a thermoelectric energy converter – Peltier module - is integrated [4, 7].

For the normal operation of TEM, it is necessary to ensure an efficient heat transfer between its hot and cold side.

In a preliminary experiment has been found the optimal current I_{opt} at which maximum cold production is reached. Therefore, in the conducted measurements the following direct current mode is used:

$$I_{opt} = 8A\,;\; U_{cc} = 11V$$

The synthesized thermoelectric battery uses Peltier TEM: TEC1-12712 YK-0458. The catalog data items of the element are presented in Table 1.

Type	U_{max} (V)	I_{max} (A)	ΔT_{max} (C)	Q_{max} (W)	*L/W/H* (mm)	*R* (Ω)
TEC1-12712	15,5	12	55	40,1	40×40×4,6	1,2

Table 1. Catalog data items of element TEC1–12712

Artificial Neural Networks

The artificial neural networks [2, 5] are one of the tools that can be used for object recognition and identification. In the first step it have to be learned and after that we can use for the recognitions and for predictions of the properties of the materials. Fig. 2 shows in abbreviated notation a classic two-layered neural network.

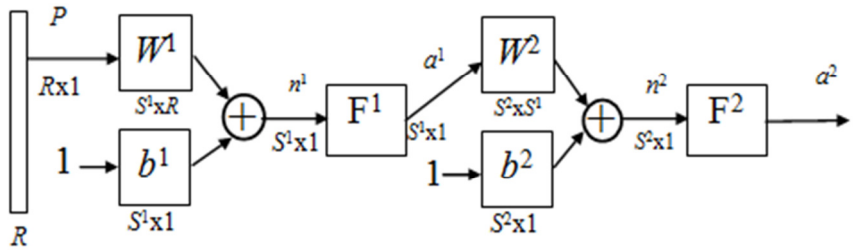

Figure 2. Abbreviated notation of a two layer Multi-Layer Perceptron

In the two-layered neural networks, one layer's outputs become inputs for the next one. The equations describing this operation are:

$$a^2 = f^2(w^2 f^1(w^1 p + b^1) + b^2),$$

where:

- a^m is the output of the m-th layer of the neural network for $m = 1, 2$;
- w^m is a matrix of the weight coefficients of the each of the inputs of the m-th layer;
- b is neuron's input bias;
- f^1 is the transfer function of the 1-st layer;
- f^2 is the transfer function of the 2-nd layer.

The neuron in the first layer receives outside inputs p. The neurons' outputs from the last layer determine the neural network's outputs a.

Since it belongs to the learning–with–teacher methods, to the algorithm are submitted training set (an input value and a target on the network's output)

$$\{p_1, t_1\}, \{p_2, t_2\}, ..., \{p_Q, t_Q\},$$

where $Q \in (1, ..., n)$, n is the subsequent number of the learning couple, where p_Q is the input value (on the network input), and t_Q is the output's value corresponding to the target. Every network's input is preliminary established and constant, and the output have to corresponding to the target. The difference between the input values and the target is the error $e = t - a$.

The "back propagation" algorithm [5, 8] uses mean-quarter error:

$$\hat{F} = (t - a)^2 = e^2.$$

In learning the neural network, the algorithm recalculates network's parameters (W and b) so to achieve mean-square error.

The "back propagation" algorithm for i-neuron, for $k + 1$ iteration use equations:

$$w_i^m(k+1) = w_i^m(k) - \alpha \frac{\partial \hat{F}}{\partial w_i^m};$$

$$b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial \hat{F}}{\partial b_i^m},$$

where:

- α - learning rate for neural network;
- $\frac{\partial \hat{F}}{\partial w_i^m}$ - relation between changes of square error and changes of the weights;
- $\frac{\partial \hat{F}}{\partial b_i^m}$ - relation between changes of square error and changes of the biases.

The overfitting [3] appears in different situations, which effect over trained parameters and make worsen output results as shown in Fig. 2.

There are different methods that can reduce the overfitting – "Early Stopping" and "Regularization". Here we will use Early Stopping [3].

When the multilayer neural network is trained, usually the available data has to be divided into three subsets. The first subset, named "Training set", is used for computing the gradient and updating the network weighs and biases. The second subset is named "Validation set". The error of the validation set is monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. Sometimes, when the network begins to overfit the data, the error of the validation set typically begins to rise. When the validation error increases for a specified number of iterations, the training stops, and the weights and biases at the minimum of the validation error are returned [6]. The last subset is named "test set". The sum of these three sets has to be 100% of the learning couples.

When the validation error e_V increases (the amendment de_V have positive value) the neural network learning stops when:

$$de_V > 0.$$

The classic condition for the learned network is when

$$e^2 < E_{\max},$$

where $E_{\max}$ is the maximum square error.

2 Intuitionistic fuzzy sets

Intuitionistic fuzzy sets (IFS, [1]) are sets whose elements have degrees of belonging and not belonging. They are defined by Krassimir Atanassov (1983) as an extension of fuzzy sets of Lotfi A. Zadeh. In the classical theory, element belongs or does not belong to the summary. Zadeh defines membership in the interval [0, 1]. The theory of intuitionistic fuzzy sets extends above concepts by comparing belonging and not belonging real numbers in the interval [0,1] and the sum of these numbers must also belongs to the interval [0,1].

Let the universe is *E*. Let *A* be a subset of *E*. Let us construct the set

$$A^* = \{< x, \mu_A(x), \nu_A(x) > | x \in E\}$$

where $0 \le \mu_A(x) + \nu_A(x) \le 1$. We will call *A** an IFS. The functions $\mu_A : E \to [0,1]$ and $\nu_A : E \to [0,1]$ set degree of membership and non-membership. The function $\pi_A : E \to [0,1]$ is defined through $\pi(x) = 1 - \mu\ (x) + \nu\ (x)$, corresponding to the degree of uncertainty.

3 Discussion

For the preparation, we use MATLAB and neural network structure 6:5:1 (6 inputs, 5 neurons in hidden layer and one output (Fig. 3). For the inputs data we use T_c,˚C, T_h,˚C, T_4,˚C, T_5,˚C, T_6,˚C and T_7,˚C. For the output we use T_v,˚C. The target data and output data are shown in Fig. 4.

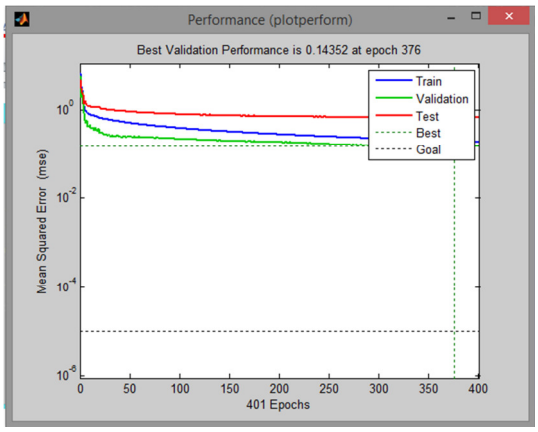

Figure 2: The learning process

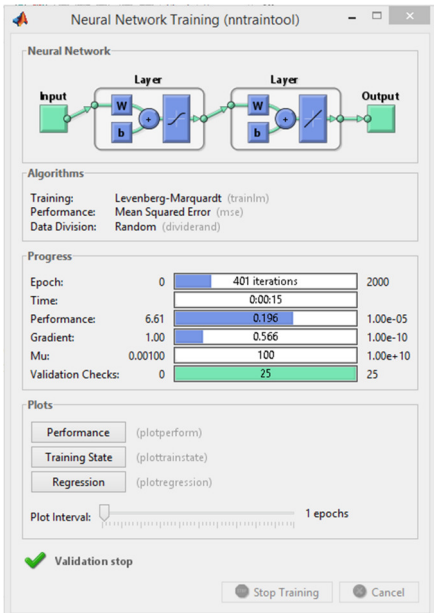

Figure 3: The neural network structure

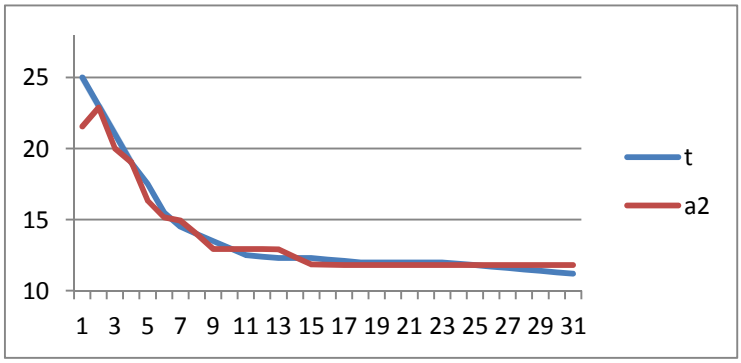

Figure 4. Target and output data

Every measurement system has the error *Err*. In this paper we also introduce intuitionistic fuzzy assessment of the comparison of the data in Fig. 4.

If $a - t > Err$, the assessment belongs to degree of the affiliations (μ). If $a - t < Err$, the assessment belongs to degree of the nonaffiliations (ν). The estimation belong to the uncertainty (π) when the difference between a and t are [$-Err$, $+Err$]. The obtained information, are represented by ordered pairs $\langle \mu, \nu \rangle$ of real numbers from the set $[0,1] \times [0,1]$.

The degree of uncertainty also represents as a $\pi = 1 - \mu - \nu$.

At the beginning is done statistics of the 31 values (Table 2.) that we used for learning the neural network. Initially when still no information has been obtained, all estimations are given initial values of $\langle 0, 0\rangle$. When $k \geq 0$, the current $(k+1)$-st estimation is calculated on the basis of the previous estimations according to the recurrence relation

$$\langle \mu_{k+1}, \nu_{k+1}\rangle = \left\langle \frac{\mu_k k + m}{k+1}, \frac{\nu_k k + n}{k+1} \right\rangle,$$

where $\langle \mu_k, \nu_k\rangle$ is the previous estimation, and $\langle \mu, \nu\rangle$ is the estimation of the latest measurement, for $m, n \in [0, 1]$ and $m + n \leq 1$.

t. min	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**	**20**
Tc,˚C	25	10	2,5	–0,5	–3,5	–5	–6	–6,5	–7	–7,1	–7,2
Th,˚C	25	36	36,1	36,2	36,3	36,4	36,5	36,5	36,5	36,5	36,6
Tv,˚C	25	23	21	19	17,5	15,5	14,5	14	13,5	13	12,5
T4,˚C	25	25	25	25	25	25	25	25	25	25	25
T5,˚C	25	23,5	21,5	21	20	19	18	17	16,5	16	15,7
T6,˚C	25	25	25	25	25	25	25	25	25	25	25
T7,˚C	25	25	25	25	25	25	25	25	25	25	25
t. min	**22**	**24**	**26**	**28**	**30**	**32**	**34**	**36**	**38**	**40**	**42**
Tc,˚C	–7,3	–7,4	–7,5	–7,6	–7,7	–7,8	–7,9	–8	–8	–8	–8
Th,˚C	36,7	36,8	36,9	37	37	37	37	37	37	37	37
Tv,˚C	12,4	12,3	12,3	12,3	12,2	12,1	12	12	12	12	12
T4,˚C	25	25	25	25	25	25	25	25	25	25	25
T5,˚C	15,5	15,3	15,1	15	15	15	15	15	15	15	15
T6,˚C	25	25	25	24,8	24,7	24,6	24,5	24,4	24,3	24,2	24,1
T7,˚C	25	25	25	25	25	25	25	25	25	25	25
t. min	**44**	**46**	**48**	**50**	**52**	**54**	**56**	**58**	**60**		
Tc,˚C	–8	–8	–8	–8	–8	–8	–8	–8	–8		
Th,˚C	37	37	37	37	37	37	37	37	37		
Tv,˚C	12	11,9	11,8	11,7	11,6	11,5	11,4	11,3	11,2		
T4,˚C	25	25	25	25	25	25	25	25	25		
T5,˚C	15	15	15	15	15	15	15	15	15		
T6,˚C	24	24	24	24	24	24	24	24	24		
T7,˚C	25	25	25	25	25	25	25	25	25		

Table 2. Experimental data from the thermoelectric cooling system

4 Conclusion

The main goal of the paper is to prepare neural network for modelling the thermoelectric cooling systems with Peltier element. We also introduced intuitionistic fuzzy estimation that can give us the quality estimation between the output of the neural network and the thermoelectric cooling systems. The real experimental data are shown.

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