Application of Neural Networks to the Optimization of the Thermal Treatment Process of Wood Materials

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Key Words: *Wood thermal treatment process; optimization; neural networks.*

Abstract. *In this paper, a software system for 2-dimensional and 3-dimensional modeling of frozen and not frozen logs and prismatic wood materials is used as a basis for optimization of the thermal treatment process of such materials. Then, the dependence of the optimal heating time on various parameters is approximated by means of neural networks. This would allow a fast real-time computation of the optimal heating time instead of performing extensive numerical simulations of the model comprised of partial differential equations.*

Introduction

A central objective in management, control and operation of the one of the most heat- and time-consuming processes in transforming the raw material into an industrial product – the wood thermal treatment process (TTP) – is increasing the competition, reducing the heat energy consumption, growing the capacity, and fulfilling the strict tight technological requirements.

Thermal treatment of wood materials comprises spatially distributed technological processes. They are described by partial differential equations (PDE). Various approaches have been developed during the last half century in order to overcome the numerous difficulties in modeling, simulation and control arising from the comparison with the lumped parameter systems (e.g. [1]). The academic-oriented research created principally new directions in transforming the infinite space presentation by finite dimension modeling in the linear case (e.g. [2]). The investigations have been enhanced towards nonlinear distributed parameter systems modeling and control [3,4].

During the last decade several intelligent techniques have been incorporated in modeling and model-predictive control of distributed parameter systems [5], and especially the implementation of artificial neural networks (NN) [6]. Though that wood thermal treatment processes were deeply studied in different technological aspects (e.g. [7]), only a few investigations are addressed to modeling and control of TTP using the listed above achievements in the area of distributed parameter systems. Available results are formed mainly in modeling [8,9].

In this paper, the earlier developed system for 2D and 3D modeling of frozen and not frozen logs and prismatic wood materials [10,11,12] is used as a basis for optimization of the thermal treatment process by means of neural networks.

Mathematical Modeling of the Thermal Treatment Process

TTP Principles and Peculiarities

The thermal treatment is a periodical process of wood material heating in order to reach a given average mass temperature of the charge subjected to prescribed requirements according to the admissible surface temperature and the internal temperature gradients. TTP is carried out in autoclaves with steam as a heating agent or in pits using hot water. The cross-section of a typical autoclave is presented in *figure 1.*

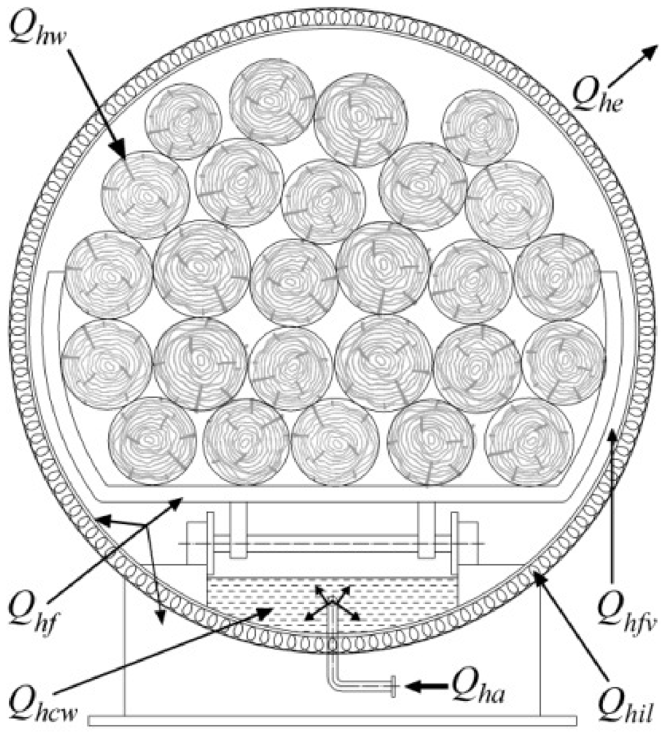

Figure 1. Autoclave cross-section

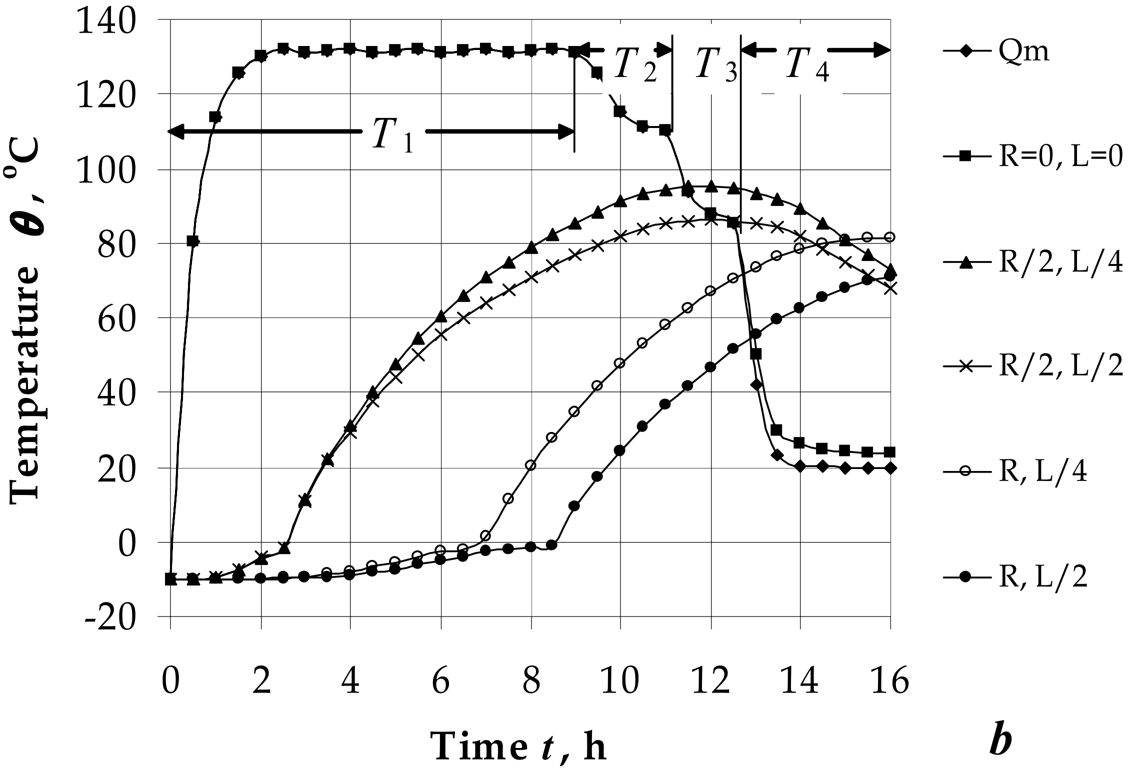

Figure 2. Temperature time profiles during TTP for frozen beech logs

The thermal treatment is a spatiotemporal nonlinear process. Typical temperature profiles for some characteristic points of the cross-section of beech logs with an initial temperature −10° C during their steaming in an autoclave with diameter of 2.4 mm and length of 9.0 m, obtained by computer simulation [12] are presented in *figure 2.* Two distinct heating processes can be observed in *figure 2*: (*i*) fast for the external heating medium temperature θ_m and (*ii*) slow for the internal points of the wood space.

The only temperature of the heating agent θ_m and the steam flow rate F_m can be measured on-line. Due this strong drawback the only model-based approaches are suitable for control systems design, state estimation, dispatching operations, and production scheduling. Unfortunately the lack of measurements provokes strong difficulties in the TTP management.

The operational conditions of each charge can be different because of the considerable variations of the initial conditions – wood specie, size, moisture content, temperature of the wood and aggregate state of the water in it at the beginning of TTP, and the relative loading of the autoclave as well. At the same time some of these initial charging parameters are immeasurable. Unfortunately they determine the parameters, the initial and boundary conditions necessary to solve the first-principle models based on partial differential equations (PDE) [10,11,12]. The attempt to use as model parameters some 'average' or operator's given values causes models fail and discredit all efforts for advanced control implementation in real industrial conditions.

The TTP has the following peculiarities:

- Only θ_m and F_m are on-line available as a secondary (indirect measurements).
- The values of θ_m and F_m are available only less than 20% of the whole TTP duration.
- The initial changing conditions are immeasurable.
- The accuracy of the PDE-based model considerably depends on the initial changing conditions.
- The TTP is strongly nonlinear distributed parameter system, especially in dependence of the frozen/unfrozen charged timber.
- The mathematical TTP modeling is highly time-consuming due to the nonlinearities and the space distribution. Thus adopting the on-line calculations as a part of the control algorithm cannot be a relevant strategy. More appropriate would be:
  – To develop models with reduced dimensionality;
  – The biggest part of the calculations to be carried out off-line;
  – To accept a strategy of suboptimal control.

The TTP is imposed on numerous constraints like [5]

$$\text{(1)}\qquad \frac{\partial\theta(x,y,z,t)}{\partial t} < \Gamma_1,\ \frac{\partial\theta(x,y,z,t)}{\partial n} < \Gamma_2,\ \theta(s) < \theta^{\max},$$

where $\theta\,(x, y, z, t)$ is the wood temperature in the point with coordinates (x, y, z), t – time, n – the normal vector, $\theta\,(s)$ – the surface temperature, s – the surface coordinates Γ_1, Γ_2, $\theta^{\max}$ – the technological requirements.

- The TTP control system constraints depend strongly on the model parameters.

In addition to the uncertainty due to the immeasurable initial charging parameters, the TTP is dependent on some specific bio- and morphological properties of the timber. They are immeasurable and stochastic [7].

Mathematical Modeling of TTP

A basic task in heat modeling, developing and managing the technologies and control of TTP is the determination of the temperature in certain points from the volume of the wood materials, at any moment from the process of their heating and further conditioning in aerial medium.

During the heating of the wood materials along with the purely thermal processes, a mass-exchange occurs between the heating medium and the wood. The values of the moisture diffusion of the different wood species cross sectional to their fibers are hundreds of times smaller than the values of their temperature conductivity. In a longitudinal to the fibers direction, the temperature conductivity exceeds the moisture diffusion by more than a hundred times.

These facts determine not so big change in the content of water in the materials during their TTP, which lags significantly from the distribution of heat in them. This allows during the creation of a mathematical model to disregard the exchange of mass between the wood and the heating medium and the change in temperature in the materials to be viewed as a result of a purely thermo-exchange process, where the heat in them is distributed only through thermo-conductivity.

The process of heating the subjected to TTP wood materials with prismatic form can be modeled with the help of the following equation:

$$
\begin{aligned}
& c\left(\Theta, w, w_{fsp}\right)\cdot\rho\left(\rho_b, w\right)\frac{\partial\Theta(x,y,z,t)}{\partial t} = \\
& \frac{\partial}{\partial x}\left[\lambda_x\left(\Theta, w, w_{fsp}, \rho_b\right)\frac{\partial\Theta(x,y,z,t)}{\partial x}\right] + \\
(2)\qquad & \frac{\partial}{\partial y}\left[\lambda_y\left(\Theta, w, w_{fsp}, \rho_b\right)\frac{\partial\Theta(x,y,z,t)}{\partial y}\right] + \\
& \frac{\partial}{\partial z}\left[\lambda_z\left(\Theta, w, w_{fsp}, \rho_b\right)\frac{\partial\Theta(x,y,z,t)}{\partial z}\right]
\end{aligned}
$$

with an initial condition

(3) $\Theta\,(x, y, z, 0) = \Theta_0$

and the following boundary conditions:

- during TTP:

(4) $\Theta\,(0, y, z, t) = \Theta\,(x, 0, z, t) = \Theta\,(x, y, 0, t) = \Theta_m\,(t)$

- during the conditioning in aerial medium of the heated materials:

$$(5)\qquad \frac{\partial\Theta(0,y,z,t)}{\partial x} = -\frac{\alpha_{sx}(0,y,z,t)}{\lambda_{sx}(0,y,z,t)}\left[\Theta(0,y,z,t)-\Theta_a\right];$$

$$(6)\qquad \frac{\partial\Theta(x,0,z,t)}{\partial y} = -\frac{\alpha_{sy}(x,0,z,t)}{\lambda_{sy}(x,0,z,t)}\left[\Theta(x,0,z,t)-\Theta_a\right];$$

$$(7)\qquad \frac{\partial\Theta(x,y,0,t)}{\partial z} = -\frac{\alpha_{sz}(x,y,0,t)}{\lambda_{sz}(x,y,0,t)}\left[\Theta(x,y,0,t)-\Theta_a\right],$$

where Θ, Θ_0, Θ_m, Θ_a, are the temperature, temperature of the wood at the beginning of TTP, temperature of the processing medium during TTP, and temperature of the aerial medium near the subjected to conditioning heated wood materials respectively, K. The meaning of the other notation is as follows:

c – specific heat capacity of the wood, J.kg^{-1}.K^{-1};

w – moisture content of the wood, kg.kg^{-1};

w_{fsp} – fiber saturation point of the wood specie, kg.kg^{-1};

λ_x, λ_y and λ_z – thermal conductivities of the wood in radial, tangential and longitudinal anatomical directions respectively, W.m^{-1}.K^{-1};

λ_{sx}, λ_{sy} and λ_{sz} – thermal conductivities on the surfaces of the wood materials in radial, tangential and longitudinal directions respectively, W.m^{-1}.K^{-1};

ρ – density of the wood, kg.m^{-3};

ρ_b – basic density of the wood, equal to the dry mass divided by green volume, kg·m^{-3};

α_{sx}, α_{sy} and α_{sz} – heat transfer coefficients between the respective surfaces (perpendicular to the coordinate axes x, y, z) of the subjected to TTP wood materials and the surrounding aerial medium, W.m^{-2}.K^{-1};

x – linear coordinate of each point from the thickness of the wood prism, m;

y – linear coordinate of each point from the width of the wood prism, m;

z – linear coordinate of each point from the length of the wood prism, m;

t – time, s.

For the solution of the created mathematical model a software package has been developed in the computing medium of Visual Fortran Professional. Through simulation of computer experiments this package allows to investigate the distribution of the temperature field in the volume of wood materials at different initial and boundary conditions and to form scientifically based technologies and control for TTP both in autoclaves and equipments, working under atmospheric pressure.

The vector p of immeasurable initial charging parameters has the following four components:

(8) $p = p\,(d, w_0, \theta_0, \gamma)$,

where d is the equivalent size, w_0, θ_0 are the initial moisture content and the temperature, g is the relative timber loading charged in the autoclave. All these components are arguments for the dynamic parameters λ_x, λ_y, λ_t, ρ, ρ_b, c in equation (2), the initial condition (3) and the boundary conditions (4)-(7). The heat accumulation in the autoclave can be presented in a semi-explicit form:

$$(9)\qquad \frac{d\theta_m(t)}{dt} = F_m\left(\theta_m(t), u(t), p, b\right),\ t < T_m,$$

where F_m is a nonlinear function, b is a known vector of physical constants and constructive parameters.

The variations of charging conditions represented by the parametric vector p influence the both interrelated TTP parts as shown in *figure 3*, where π is the wood specie.

The dynamic behavior of the medium temperature $\theta_m(t)$ must be defined by simultaneous solving this interconnected system of differential and algebraic equations. The solution in the time interval $0 \le t \le T_m$ strongly depends on the parameter-vector p values and it is the only available sensor information in real operations usable for the p reconstruction which we use in this research.

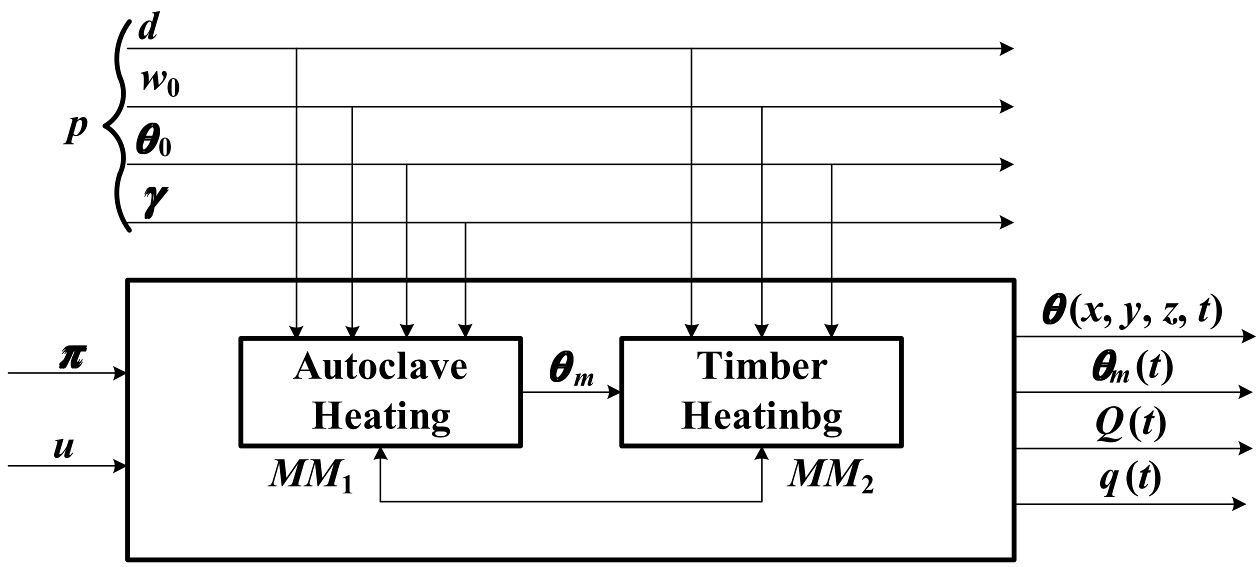

Figure 3. Scheme of unified TTP model

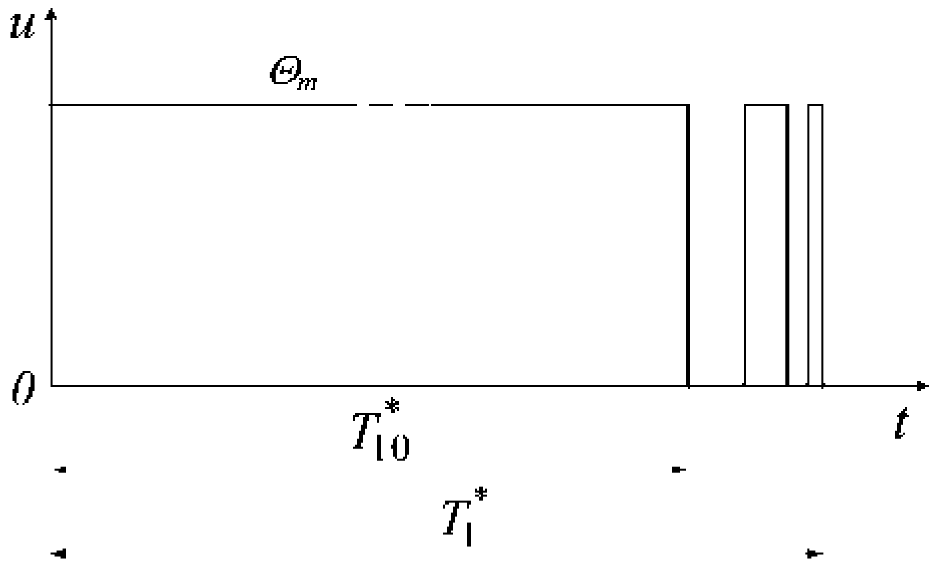

Figure 4. Minimum time control

Optimization of the TTP Process by Means of Neural Networks

In conformity with the basic investigations of the distributed-parameter-systems (DPS) time-optimal-control [13], the strict optimal control action has a form presented in *figure 4.*

As more than 95% of the time the temperature θ_m must be kept in the maximal available value $\theta_m^{\max}$ and it is impossible to fulfill the strict re-switching $\theta_m^{\max} - \theta_m^{\min} - \theta_{nn}^{\max}$ due to the cooling/heating inertness, there can be used a slightly suboptimal control with active heating during the time

(10) $T_1^* = 1.03T_{10}^*$,

where T_{10}^* is the first switching time in a strict time-optimal control [5]. For each vector parameter p there is a special value of π and the power u. Yet the value of the heating time T_1^* has been calculated during the initial off-line simulation,

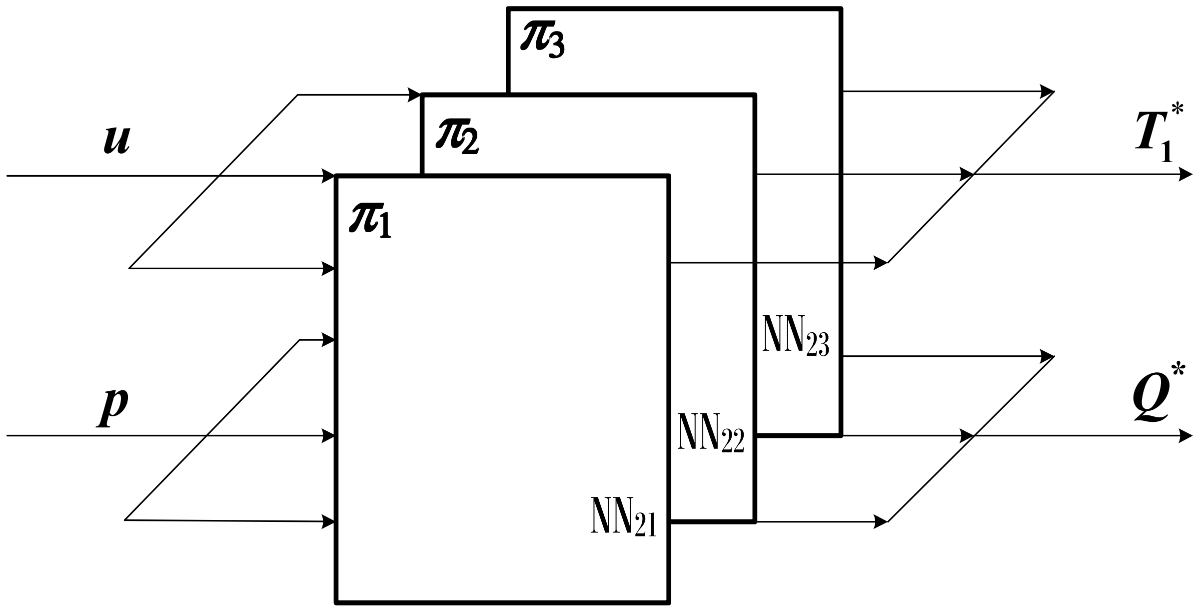

Figure 5. Static neural network NN_s

accomplishing the optimization procedures

(11) $T_1^* = T_1^*(\pi, u, p)$

using the set $T_1^*(\pi, u, p)$ and a static neural network NN_s (*figure 5*) has been learned. Here, Q^* is the total needed heat energy.

As the specific value of π and the power u^0 are prescribed, the only vector p_j represents the unknown input in the current autoclave j-run necessary to define the optimal heating time $T_1^*(p_j)$.

Following the proposed in [14] system for p_j identification, one of the values $\bar{p}(0)$ or $\bar{p}(l)$ will be available as the input to the neural network NN_s after finishing the estimation procedure. As the duration T_m of the first TTP stage is many times shorter than the expected whole heating time T, the derived from the neural network NN_s optimal value $T_1^*(p)$ will be accessible for the control system.

According to *figure 2*, the total operational time T considers four components:

(12) $T = T_1 + T_2 + T_3 + T_4$,

where T_1 is the heating time during the supply of steam from the heat generator, T_2 is the time for isochoric heating without supply of steam from the generator, T_3 and T_4 are the times of cooling timber up to an atmospheric pressure and of the air conditioning of the steamed materials respectively. All partial times T_i depend on the different components of the parameter vector p. When p is calculated, the values of $T_i(p)$ can be determined according to the results, represented in [12].

The neural network used to approximate the dependence of the optimal heating time T_1^* on the vector p ($p = (d, w_0, \theta_0, \gamma)$) is a two-layer perceptron with sigmoid activation function of the neurons in the hidden layer and linear activation function of the neuron in the output layer. A set of 28 data points related to the optimal thermal treatment of beech materials are used for training, validation and performance test of the network. This data set is obtained by solving numerically the minimum-time problem for the TTP process based on its model (2)-(7) with different values of p. The results for the mean squared prediction error of the neural network with 3 hidden neurons along the epochs are shown in *figure 6.*

In *figure 7*, it is shown how the optimal heating time depends on the thickness of the wood material. Each group of 7 data points have the same value of the thickness and within each group the change of the optimal heating time is due to the influence of the other 3 parameters (humidity of the material, its temperature and the load of the autoclave).

As it can be expected, the optimal heating time increases with the increase of the thickness. The accuracy of the neural network prediction is high as it can be observed by comparing the target and the predicted data (*figure 7*).

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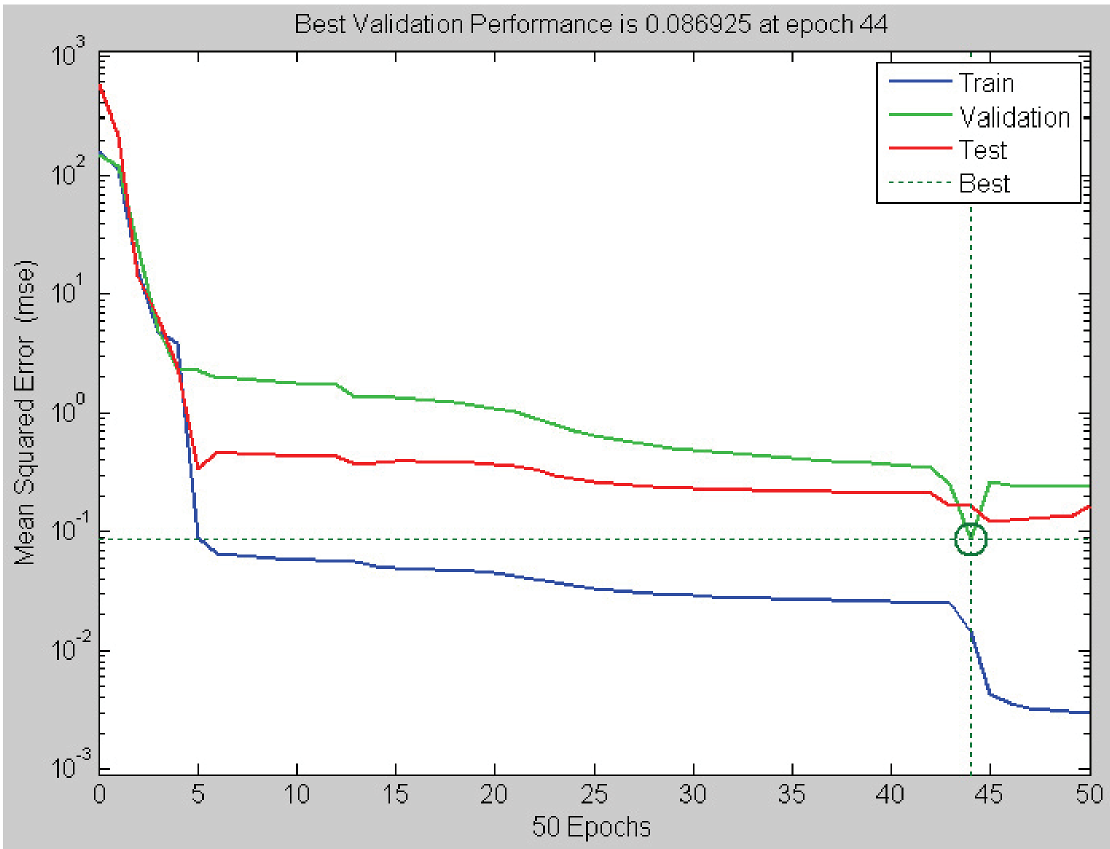

Figure 6. Mean squared prediction error along epochs

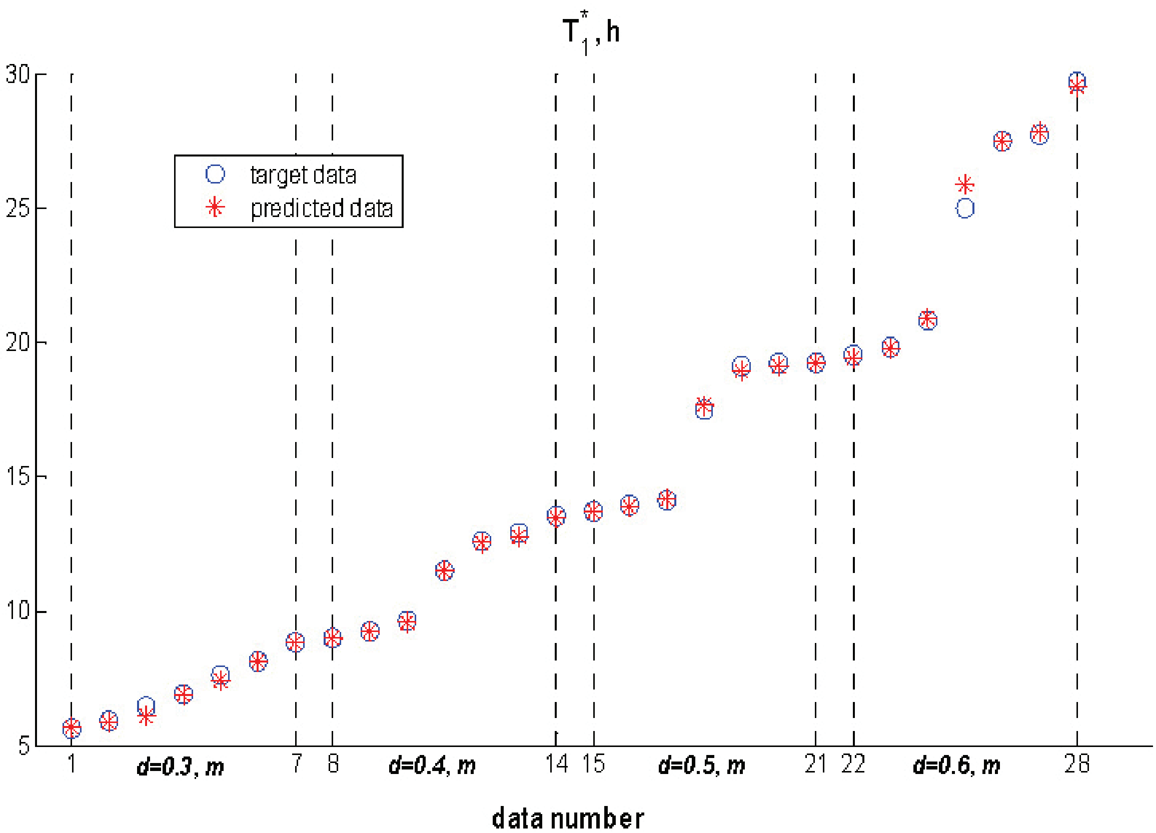

Figure 7. The dependence of the heating time on the thickness d of the wood material

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