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Analysis of Thermal Transient Processes by Means of Neural Network Technique

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1. Introduction

Particularly in the past decade, a very large effort has been expended in developing numerical methods for solving complex multidimensional problems in area of engineering processes. In the last few years the complex behaviour of biological, chemical and industrial systems has been explained in terms of dynamic analysis and many techniques to obtain predictions have been developed. The dynamic investigations of a various processes have focused attention on the problem of the mathematical description. In principle, this knowledge may be obtained by many computational modelling. As an easier alternative, the experimental data may be used to find out a black-box model or an empirical correlation defining the system behaviour. The limitation of this approach is that it requires assumption of the functional form of the proposed correlation.
The popular approach to analyse the unsteady and steady heat transfer problems is associated with the availability of non-linear empirical modelling methodologies, such as neural networks, inspired by the biological network of neurons in the brain (Hussain, 1999; Ou & Achenie, 2005). Authors (Liau & Chen, 2006) proposed this methodology to model optimal concentrations of reactants for preparing sub-micron silica particles. Different sets of the reactant concentrations were selected within an operating range and were designed to evaluate the PSD data. The relationship between the reactant concentration and resultant PSD can be evaluated by means of the ANN modelling approach. The neural network models can be successfully used to compute PSD of particles with different shapes in highly concentred suspensions from laser diffraction measurements (Nascimento et al., 1997; Guardani et al. 2002). The ANN pattern recognition (ANNPR) approach has also been proposed for fed-batch cultivation processes of *Escherichia coli* (Duan et al., 2006). A novel data mining macro-kinetic approach based on ANN was proposed to develop the macro-kinetic model of oxidation of *p*-xylene to terephthalic acid in a industrial type of continuous stirred tank reactor (Yan, 2007). Authors (Liu & Kim, 2008) used the purely mathematic and mechanical model with ANN to model membrane filtration process. As a tool of modelling, neural network technique has been used by (Jones et al., 1999) to magnetic inverse problem of determining the anisotropy field distribution from experimental transverse susceptibility data. Approximation models such as artificial neural networks (ANNs) are powerful and reliable in predicting the complex conditions such as nonlinear and time-variant biological

processes (Liu et al., 2008). Consequently, this approach has been used to predict hold-up in slurry pipelines (Lahiri & Ghanta, 2008), for mapping the structure of a liquid spray (Heinlein et al., 2007), for analysis of heat and mass transfer (Kahrs & Marquardt, 2007).
The dynamic investigations of the unsteady heat transfer process has focused attention on the problem of the mathematical description. In principle, this knowledge can be obtained by many computational modelling. As an easier alternative, the experimental data may be used to find out a black-box model or an empirical correlation defining the system behaviour. The limitation of this approach is that it requires assumption of the functional form of the proposed correlation. The popular approach to analyse the unsteady and steady heat transfer problems is associated with the availability of non-linear empirical modelling methodologies, such as neural networks, inspired by the biological network of neurons in the brain. The implementation of ANN technique in heat transfer science literature is limited. For the identification or analysis of heat transfer problems a neural network approach has been attempted by authors (Thibault & Grandjean, 1991; Christtofindes, 2001; Alotaibi et al., 2004; Zdaniuk, 2006; Ashforth-Frost et al.,1995 and Yilmaz & Atik,2007). In the relevant thermal scientific literature is most concerned with the performance prediction and control of heat exchangers (Islamoglu, 2003; Diaz et al., 2001; Pacheco-Vega et al. 2001).
In the present work, an attempt has been made to use ANN to model the thermal transient process and the thermal behaviour of reciprocating mixer. We believe that this modelling approach is considerably interesting than the more conventional empirical correlation approach. This encouraged us to investigate the problem which is presented in this chapter.

2. Experimental details

The investigations of the temperature transient processes were made using the experimental set-up shown in Figure 1. The experimental investigations were performed using a vertical cylindrical vessel of 0.248 m in inside diameter and 0.678 m in height. The mixing was varied out with a single perforated plates agitators with the different degree of perforation (ratio of hole-to-solid area of plate) oriented horizontally were reciprocating in a vertical direction. The agitator was always placed at half of the liquid height in the vessel and the diameter is equal to 0.241 m. An electric a.c. motor coupled through a variable gear and V-belt transmission turned a flywheel. A vertical oscillating shaft with a single plate perforated and a hardened steel ring through a sufficiently long crankshaft were articulated eccentrically to the flywheel. This system were used to generate reciprocating movements of agitator. The water was used as the mixed liquid as well as cooling medium. The flow rates of municipal water continuously flowing through the mixer and jacket surrounding internal tubular vessel were established and controlled by means of flow meters. The temporal variations of temperature as a transient thermal processes were measured by using the microprocessor sensors. Therefore, these processes were obtained by means of the thermal-response technique. This method is very flexible and may be applied to large scale systems but it required very sensitivity measuring sensors. The measured electronic signals proportional to the temperature were passed through converter and system of temperature sequential sampling to personal computer where the temperature transient processes may be easily analytically recorded and formed the database including the characteristic quantities of this process. These processes were generated by the thermal disturbance of the cold water stream introducing on the free surface of the mixer vessel by means of centrally mounted perforated distributor. This loading device was protected against premature penetration of cold bulk liquid in the mixer vessel

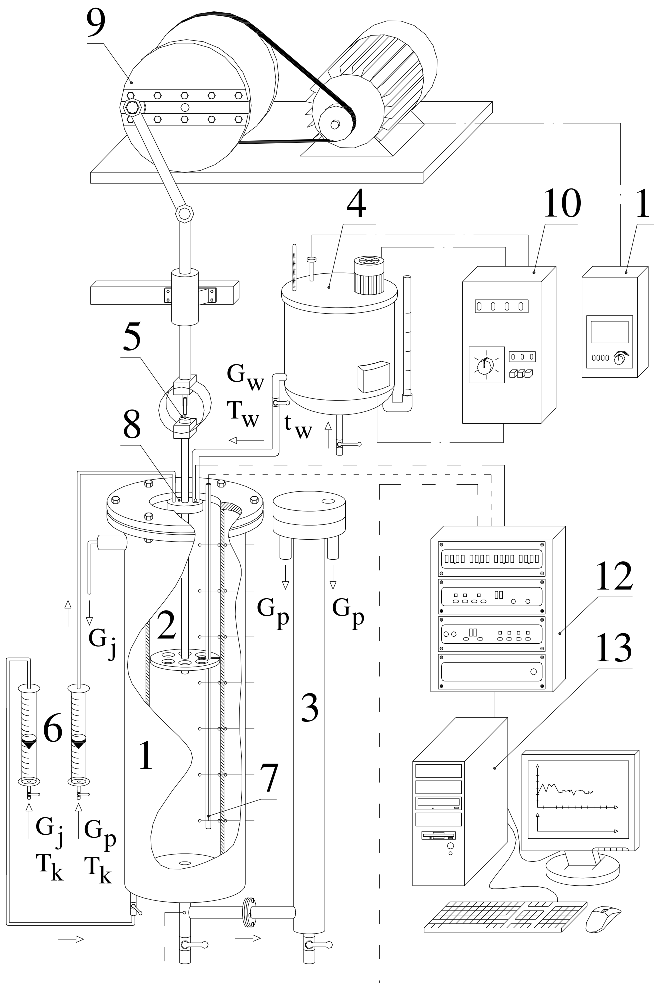

Fig. 1. Experimental set-up: 1 - tubular vessel, 2 - perforated plate agitator, 3 - external overflow, 4 - generator of input temperature signal and hot liquid feeder,
5 - hardened ring with inductive transducer, 6 – flow meters, 7 - temperature sensors,
8 - distributor of cold liquid, 9 - electromechanical eccentric drive,
10 - power cube, 11 - controller of motor speed, 12 - system of temperature sequential sampling, 13 - personal computer

The thermal disturbance as the pulse temperature input signal was the volume of hot liquid described by parameters G_w, T_w and t_w. Before the experimental measurements the mixer bulk was mixed to constant field temperature inside the mixed and flowing water. This field was controlled by the set of movable temperature sensors. Next the hot water was injected to the stream of cold water and the temperature transient process was recorded simultaneously. The transient process was regarded as a complete when the temperature variation in the stream flowing out the mixer vessel did not change with time. Then the transient response curve is asymptotic to the time axis. As mentioned above, experimental studies of the thermal transient processes were conducted in the reciprocating mixer and the databases included the operational parameters, such as: perforation degree of the reciprocating plate agitator - ψ, amplitude of reciprocating motion - Γ, frequency of reciprocating motion - ω, mass flow rate of water in mixer vessel - G_p, mass flow rate in cooling jacket - G_j, mass of hot water introduced into the steam of the water flowing through the mixed vessel - G_w, time duration of the thermal impulse signal - t_w, temperature of hot water - T_w and temperature of the mixed water - T_k are collected in Table 1.

parameter	$\psi\left[m^2\cdot m^{-2}\right]$	$\Gamma[m]$	$\omega\left[s^{-1}\right]$	$G_p\left[kg\cdot s^{-1}\right]$	$G_j\left[kg\cdot s^{-1}\right]$	$G_w\left[kg\cdot s^{-1}\right]$	$t_w[s]$	$T_w\left[^oC\right]$	$T_k\left[^oC\right]$
minimal value	0.05	0.01	0.028	0.02778	0.0692	1	5	32.1	3.2
maximal value	0.45	0.14	2.5	0.1667	0.1528	6	120	92.9	10

Table 1. The range of operational parameters

Such programming of the experimental investigations enables to explore many aspects of the unsteady heat transfer realised by using the mixed vessel equipped with the reciprocating agitator. The results of the experiments for the various set of the operational parameters may be graphically presented as a dependence of the output temperature response on the time duration of the temperature variation. Figure 2 illustrates the typical example of transient response curve. The response curves obtained for the different combination of the operational parameters were similar to the typical example of thermal response curve (see Figure 2).

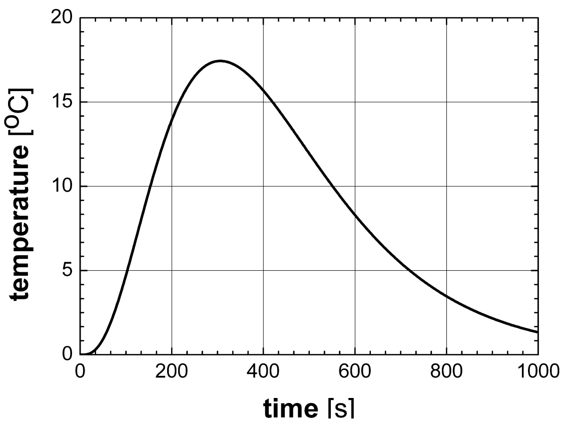

Fig. 2. Typical example of thermal-response curve

The influence of the operational parameters on the transient process may be assessed by the analytically approximated of transient curves or characterized in the more simple way using the specially chosen characteristic quantities of these curves. As follows from the comparison of these thermal transient process for the different sets of operational parameters, it may be found that these thermal-response curves should be defined by means of the five characteristic parameters such as: the time lag of thermal process - t_0, the maximal value of temperature - T_{max}, the time of the achievement of maximal value of temperature - t_{max}, the time duration of thermal process - t_p and the quantity of area between the thermal response of transient process and the time axis - A.
The typical example of thermal response curve with the marked characteristic quantities is graphically presented in Figure 3.

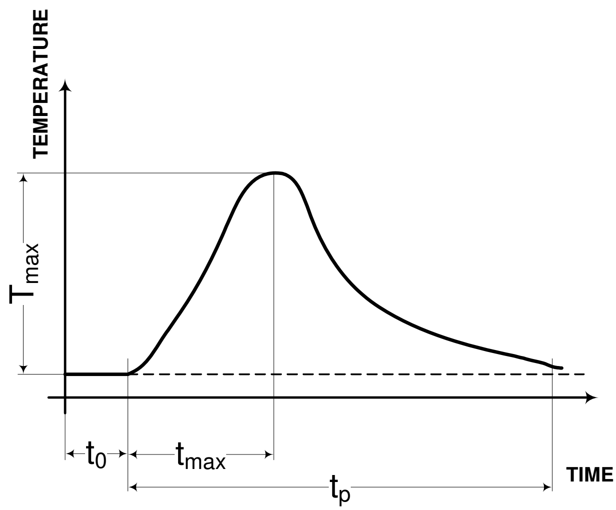

Fig. 3. Typical example of thermal-response curve with the marked characteristic quantities

The series of the 3000 experimental values of the five characteristic quantities were obtained for the various sets of operational parameters. Recent approaches to building mathematical description have been based on the statistical or numerical modelling of experimental database. In the case of the absence of accurate theoretical models, regression methods have been employed to find an approximate functional form that can best describe the relationship between the independent variables and the observed dependent parameters. Artificial neural networks (ANN) are an attempt to predict the effect of changing input data on the dependent variables. Earlier experimental works have reported from the use of the various types of networks to analysis the number of engineering problems. The produce ANN model estimates the five characteristic parameters with respect to the establish values of operational condition. The great advantage of the proposed methodology is that the complex mathematical relationship for the non-linear unsteady heat transfer processes is omitted. Consequently, the computational time required to solve the classical mathematical models is significantly reduced and the description of the dynamic behaviour of thermal transient process with various effects under constantly changing conditions is possible.

3. Results and discussion

3.1 Predictions of operational characteristics value by using the ANN model

The nature of obtained databases is permitted to analyse and describe the experimental results applying the statistical or numerical modelling. In the case of the absence of accurate theoretical models, regression methods should be exploded to find an approximate functional form for description of the relationship between the independent variables and the observed dependent quantities. Artificial neural networks have offered of the splendid attempt to predict the effect of changing input data on the dependent variables. The produce ANN model estimates the power characteristics for the novel construction of static mixer with respect to the establish values of operational parameters. The great advantage of the proposed methodology is that the computational time required to solve the classical mathematical models is significantly reduced and the description of the operational behaviour of the static mixer under constantly changing conditions is possible.

Traditionally, ANN has been used to model complex non-linear systems and appeared to be a good alternative to traditional empirical, phenomenological or statistical correlations. The ANN models are more powerful and can manipulate non-linear input-output relationships more successfully than available literature conventional correlations.

The critical step in building a robust ANN is to create an architecture, which should be as simple as possible and has a fast capacity for learning of the data set. The choice of the input variables is the key to insure complete description of the analysed systems, whereas the experimental data set have a tremendous impact on the reliability and performance of the ANN model. This type of model provides a non-linear mapping between input and output variables and is also useful in providing cross correlation among these variables. The ANN is a very useful tool in rapid predictions such as steady-state or transient process flow sheet simulations, on-line process optimization and visualisation and parameter estimation.

The experimental database are processed using ANN models. The neural network approach was thus carried out by means of the Statistica Neural Network software. The multi layer perceptron (MLP) networks consist of three layers, namely the input layer, the hidden layer and the output layer. For practical application, the RBF network is structured so that it can approximate the five characteristic quantities of thermal-transient curves (transient processes) and estimate the dynamic behaviour of temperature at unsteady heat transfer in the reciprocating mixer. To achieve this, the input layer of the analysed network is formulated so that it contains the input parameters as follows:

$$\bar{x} = \left[\psi \ \Gamma \ \omega \ G_p \ G_j \ G_w \ t_w \ T_w \ T_k \right]^T \tag{1}$$

The neural network output is the estimation of the five characteristic parameters of the thermal-transient processes, which are calculated as a weighted sum of the responses of the hidden layer nodes. Figure 4 presents the structure of the MLP network used to model the thermal-transient processes.

It should be noticed that the training a MLP network is conducted by the minimal deviation between the predicted and the true values of the output variables over the set of the available experimental database. As follows from the realised analysis, the MLP model consisting of 11 nodes in the hidden layers. This number of nodes is caused by the

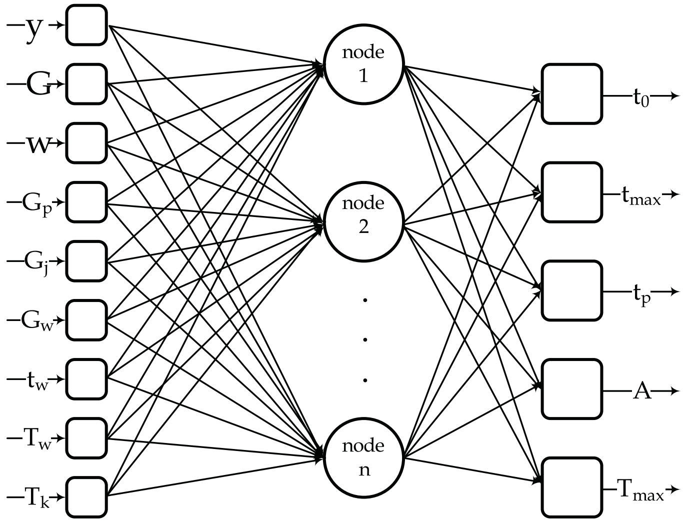

Fig. 4. The MLP neural network architecture for the characteristic quantities of the thermal transient process

complexity of the analysed heat transfer problem and the non-linear relationship between the input vector of the operational parameters and the approximated values of output parameters. As follows from the analysis of the proposed ANN architecture model, the values of qualitative coefficients for the training, validating and testing sets are amount to 0.991136, 0.987181 and 0.989819, respectively. Moreover, the operational parameters (input parameters) may be reorganised from the most to the least important parameter for the proposed architecture of the MLP model as follows:

$$\bar{x} = \left[t_w \; G_p \; \psi \; T_k \; \Gamma \; \omega \; T_w \; G_w \; G_j \right]^T \tag{2}$$

Figure 5 gives the generalization result, by plotting the power characteristics for the novel type of static mixer calculated by using the ANN model as a function of the experimental investigations.

The first conclusion drawn from the inspection of these graphs is that the proposed neural network is predicted the analysed experimental data very well. Therefore, these results suggest that the characteristic parameters for the novel type of static mixer my be successfully approximated by means of the ANN methods.

Moreover, the radial basic function (RBF) network was used to model the thermal-transient curves. Figure 6 presents the values of time duration of thermal-transient process, t_p, obtained from the RBF model and the values measured from experiments. Almost all the results lay in the limits of the ±30% maximal error. As follows form the analysis of the obtained results, the MLP model is shown to be superior to the RBF network approach.

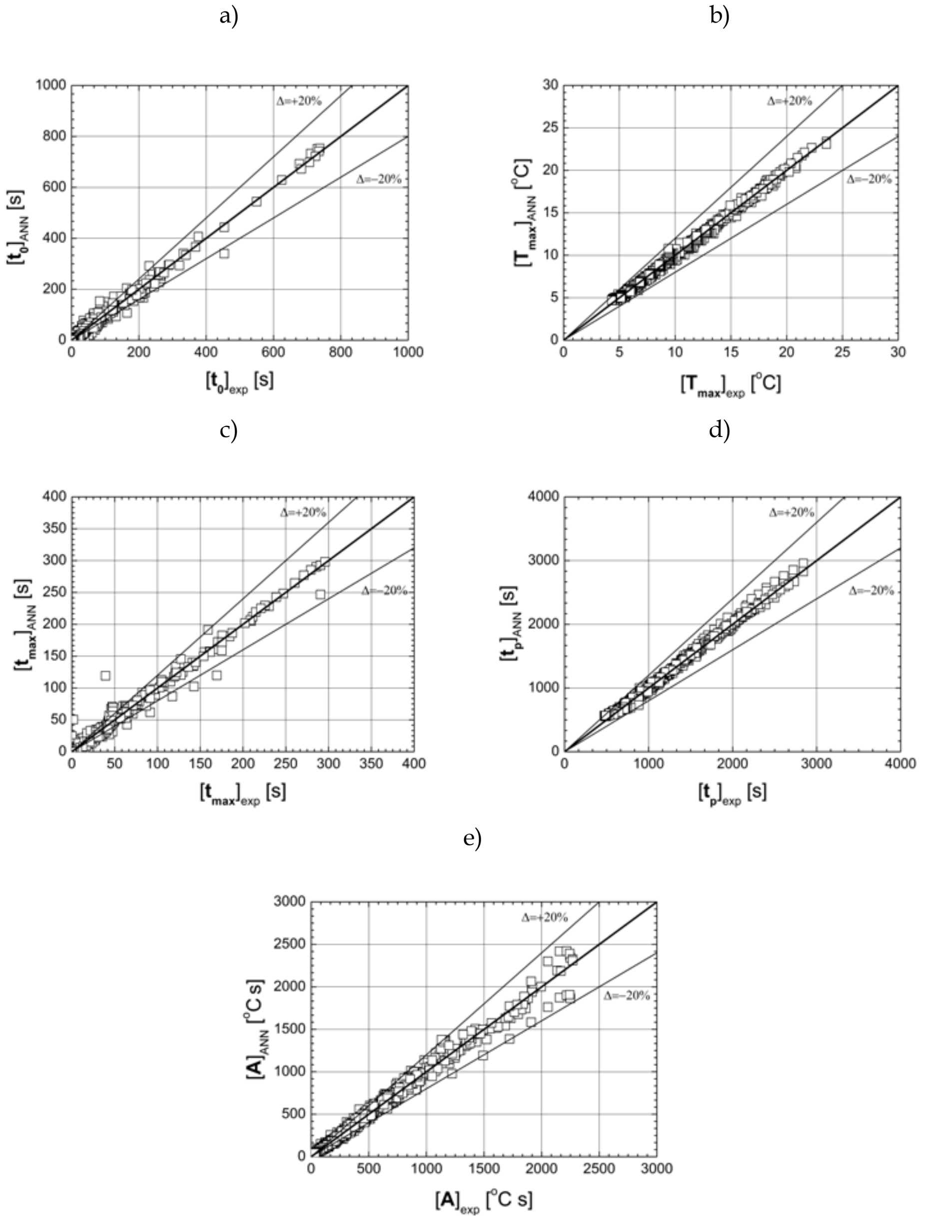

Fig. 5. The graphical comparison of values of characteristic quantities for results obtained experimentally and using ANN model: a) the time lag of thermal process - t_0, b) the maximal value of temperature - T_{max}, c) the time of the achievement of maximal value of temperature - t_{max} d) the time duration of thermal process - t_p and the e) quantity of area between the thermal response of transient process and the time axis - A

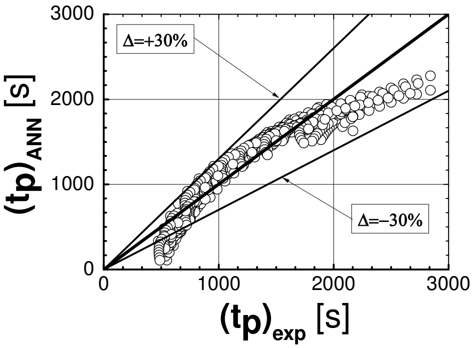

Fig. 6. The graphical comparison of the experimental and predicted values of the time lag of thermal process (t_0) for the RBF network model

3.2 Effects of operational parameters on characteristic quantities of thermal transient process

The practical utility of the results presented here is to illustrate the effects of operational parameters on the characteristic quantities for the realized transient process in the reciprocating mixing system. In recognition this fact, the three-dimensional response surfaces were generated and used to study the liquid properties and operating conditions on characteristic quantities.

Figure 7 illustrate the effect of the selected operational parameters on the time lag of thermal transient process (t_0). As it can be observed in Figure 7, this parameter depends significantly on the operational conditions.

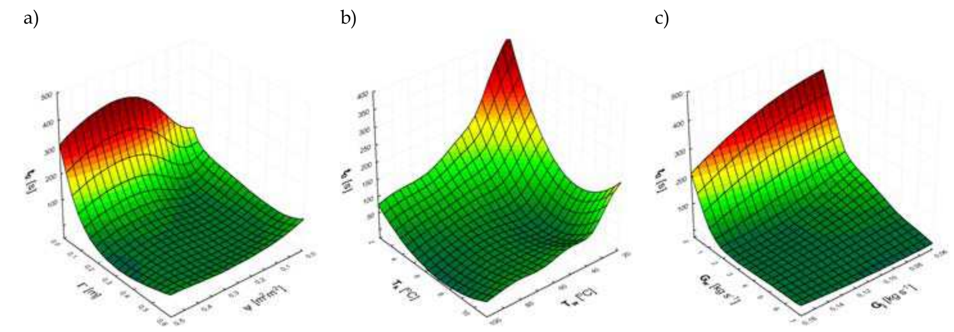

Fig. 7. The effect of selected operational parameters on the time lag of thermal transient process (t_0)

Figure 7a shows the effect of the parameter connected with the reciprocating mixer on on the time lag of thermal transient process (t_0) as an attempt to simulate the effect of changing the perforation degree of the reciprocating plate agitator (ψ) and the amplitude of reciprocating motion (Γ). It was found that, t_0 values seem to decrease with increasing the amplitude of reciprocating motion of the tested mixer. Moreover, this figure shows that the obtained t_0 values increase with increasing amplitude of reciprocating motion. In this study, the effect of the temperature of hot water (impulse temperature - T_w) appears to be stronger than the mixed water temperature (T_k) leading to an increase of the time lag of thermal transient process (t_0), as can be seen in Fig.6b. In analyzed reciprocating mixer, the lag time values were found to change with the mass flow rate in cooling jacket (G_j) and mass of hot water introduced into the steam of the water flowing through the mixed vessel (G_w). Therefore, the Figures 7a-c indicate that the time lag of thermal transient process (t_0) is considerably changed with variation of operational conditions.

As follows from the realized simulations, the complicated hydrodynamics in the tested reciprocating mixer may successfully described by means of the ANN technique. The non-linear relationship between the input vector of the operational parameters and the approximated values of output parameters is approximated. The appropriate design, scale-up and optimization of industrial processes is depended on the description of influence of operating conditions on the characteristics parameters of the thermal transient process.

Figures 8a-c shows the effect of operational conditions on the maximal value of temperature (T_{max}). As can be observed in this figure, the maximal value of temperature (T_{max}) seem to increase with increasing the operational parameters $(\Gamma, \psi, T_k, T_w, G_w, G_j)$.

a) b) c)

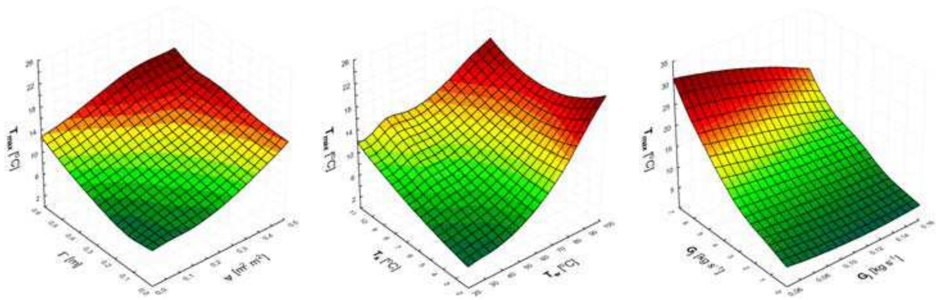

Fig. 8. The effect of selected operational parameters on the maximal value of temperature (T_{max})

Figures 9a-c presents the effect of operational conditions on the time of the achievement of maximal value of temperature (t_{max}), and as can been seen, this parameter appears to

a) b) c)

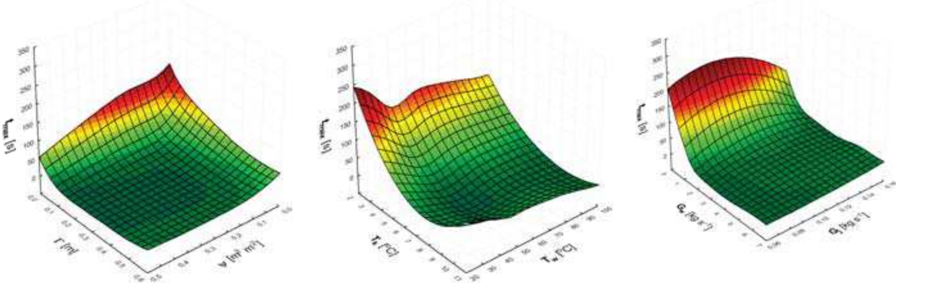

Fig. 9. The effect of selected operational parameters on the time of the achievement of maximal value of temperature (t_{max})

decrease with the changes of operational parameters range, which is in agreement with the realized experimental works.

Figure 10 depict the effect of operational conditions on the time duration of thermal process (t_p). In agreement with the realized experimental investigations, this parameter was found to decrease with the operational conditions. This figure may be used to speculate the effect of mixing device on the mixing time in industrial applications. From practical point of view, this parameter may treated as an important criterion in analysis of the mixing process. Moreover, this magnitude may be used in the selection of the suitable agitator or the mixing manner for the homogenisation process. The most importance of costs of production which should be depends on the time duration of mixing process. The operational costs of the production process are obviously an important element in the economic design. The capital costs will be comprised of the expenditure on the driving units and the employed of suitable mixing device. Longer mixing time will inevitable demand a higher cost of production. In the case of this experimental investigations, the time duration of mixing process progressively decreases with increasing of the operational conditions.

a) b) c)

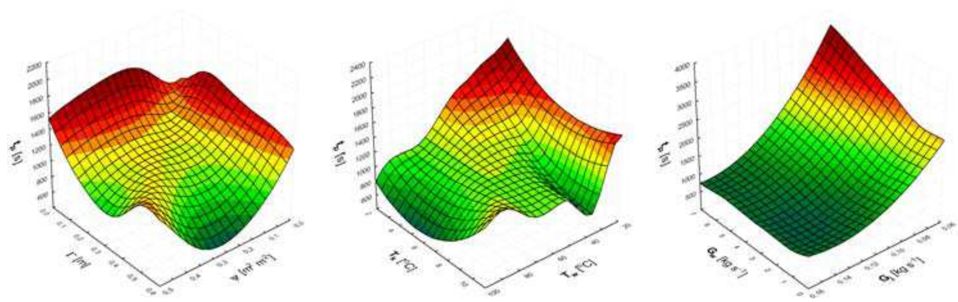

Fig. 10. The effect of selected operational parameters on the time duration of thermal process (t_p)

Figure 11 depicts the effect of operational conditions on the the quantity of area between the thermal response of transient process and the time axis (A).

a) b) c)

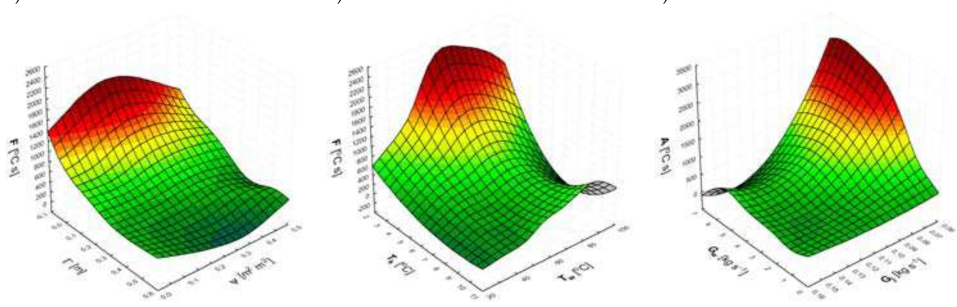

Fig. 11. The effect of selected operational parameters on the quantity of area between the thermal response of transient process and the time axis (A)

It should be noticed that the MLP model successfully captures different thermal-transient curves. Therefore, the unsteady heat transfer processes as given by this ANN model have been developed. According to the realized analysis, the time duration of the thermal impulse signal, t_w, and the mass flow rate of water in mixer vessel, G_p, are mostly influenced on the output parameters of the MLP model (see Equation 2). Therefore, three different cases have been considered: the first one concerns small values of operational parameters (variant I). In the second, the values of these parameters are maximum (variant III). In order to have a accurate analysis of thermal-transient processes, a middle values of operational parameters is obviously required in the ANN model (variant II). A procedure was followed with the time duration of the thermal impulse signal, t_w, and the mass flow rate of water in mixer vessel, G_p, taking values between 5÷120°C and 0.02778÷0.1667 kg·s^{-1}, respectively. The performance of the produced MLP neural network model with respect to the values of operational parameters collected in table 2.

parameter	$\psi\left[m^2 \cdot m^{-2}\right]$	$\Gamma[m]$	$\omega\left[s^{-1}\right]$	$G_p\left[kg \cdot s^{-1}\right]$	$G_j\left[kg \cdot s^{-1}\right]$	$G_w\left[kg \cdot s^{-1}\right]$	$t_w[s]$	$T_w\left[{}^oC\right]$	$T_k\left[{}^oC\right]$
variant I	0.05	0.01	0.028	0.02778 ÷ 0.1667	0.0692	1	5÷ 120	32.1	3.2
variant II	0.255	0.07	1.25		0.0764	3		60,5	6,6
variant III	0.45	0.14	2.5		0.1528	6		92.9	10

Table 2. The set of operational parameters for the analysis of the performance of the produced RBF neural network model

Figures 12 and 13 have been drawn using the successfully produced MLP model of the unsteady heat transfer in the reciprocating mixer to depict the effect of the operational parameters on the five characteristic quantities of thermal-transient curve while t_w and G_p parameters are varied in the established range. Some of the presented figures reveal interesting aspects. These figures show that the values of five characteristic quantities for the selected arbitrary sets of the operational parameters (variant I, II and III) may be predicted by MLP model.

As gives in this figures, the operational parameters affects significantly the values of characteristic quantities. It can be noticed that the differences between the values for the various variants of the operational parameters are significant. The effect of the operational parameters on the characteristics quantities of thermal-transient processes was examined by increasing the operational parameters from the minimal values up to the maximal values (see Table 2) for which the variation of these quantities are observed.

Figures 12 and 13 may be used to obtain the values of the characteristic parameters of thermal-transient process without the complicated analysis of the experimental curve. The dynamic behaviour of the tested reciprocating mixer may be predicted by means of the analysed thermal transient process. The dynamic response of the investigated system may be predicted by means of the five characteristic parameters (see figure 3). The obtained

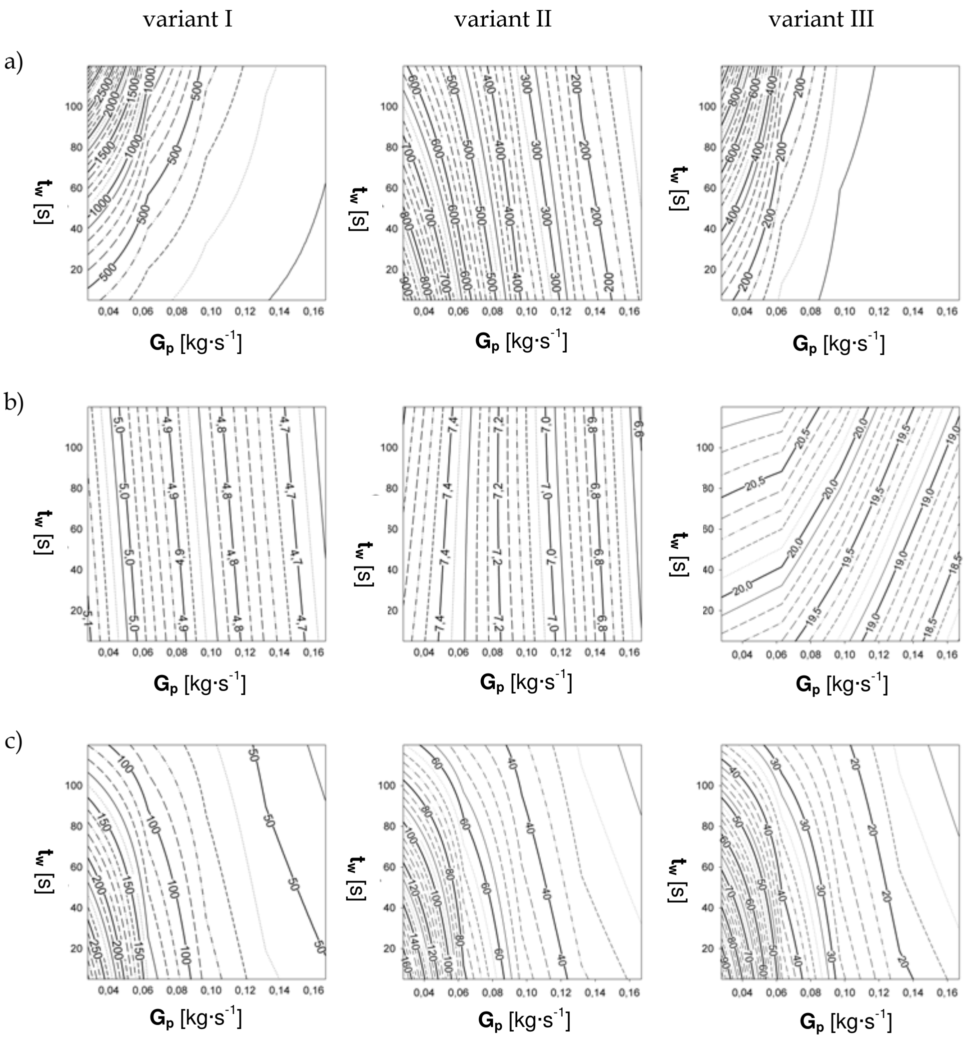

Fig. 12. Predictions of the time lag of thermal process (a), the maximal value of temperature (b) and the time of the achievement of maximal value of temperature (c) depending on the time duration of the thermal impulse signal (t_w) and the mass flow rate of water in mixer vessel (G_p)

results suggest significant influence of the operational conditions (especially the time duration of the thermal impulse signal and the mass flow rate of water in mixer vessel) on the obtained parameters of the thermal response curves. Referring to the graphical presentation of the reliable simulation results, it is observed that the different configuration of operational parameters has been reported to change the turbulences at the mixed liquid leading to a variation of the thermal-transient response curves.

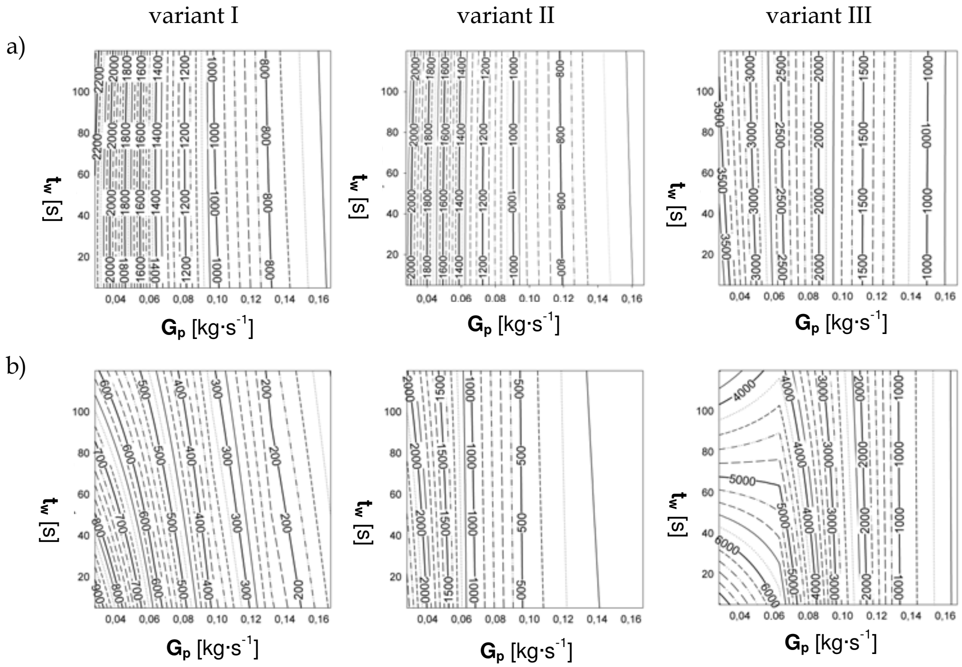

Fig. 13. Predictions of the time duration of thermal process (a) and the quantity of area between the thermal response of transient process and the time axis (b) depending on the time duration of the thermal impulse signal (t_w) and the mass flow rate of water in mixer vessel (G_p)

4. Conclusion

The main aim of this paper is to present the application of artificial neural network (ANN) technique for the development of a mathematical description of thermal-transient processes for a mixer equipped with reciprocating agitator. The proposed ANN model, describing the thermal behavior of this type mixer, is developed and compared with the experimental measurements.

Unsteady heat transfer process prediction of the reciprocating mixer by using MLP model is investigated. The simulation results indicate that the MLP network model can appropriately predict the characteristic quantities of thermal transient processes (the time lag of thermal process, the maximal value of temperature, the time of the achievement of maximal value of temperature, the time duration of thermal process and the quantity of area between the thermal response of transient process and the time axis) by using the set of input operational parameters. The predictions obtained by computational simulation are very good agreement with experimental data. This good agreement leading to the conclusion that ANN technique is a powerful tool for modeling parametrical sensitivity in the dynamic investigations of the heat transfer phenomena for the realized mixing process. Therefore, neural network can be an alternative approach to assessment of the thermal-transient processes without the nonlinear sequential estimation of the shape of transient curves.

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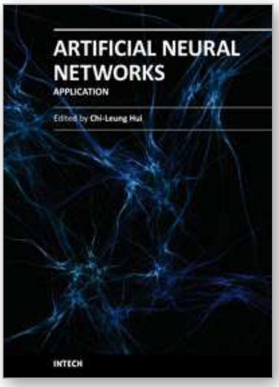

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