A R C H I V E S O F M E T A L L U R G Y A N D M A T E R I A L S
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THE MATHEMATICAL-PHYSICAL MODELS AND THE NEURAL NETWORK EXPLOITATION FOR TIME PREDICTION OF COOLING DOWN LOW RANGE SPECIMEN

MATEMATYCZNO-FIZYCZNE MODELE ORAZ WYKORZYSTANIE SIECI NEURONOWYCH DO PROGNOZOWANIA CZASU OCHŁADZANIA PRÓBEK O ZRÓŻNICOWANYCH WYMIARACH

The method exploits sufficient similarity between cooling down curves of individual specimens from the same material but when specimens vary in geometric shape. Time scale altering for individual specimens leads from practical point of view to coincidence of all curves with so called "general curve" for given material which is calculated from measured values by means of statistic methods. This operation can be denoted as a definition of time transformation coefficient (TTC) (for known specimens). If an artificial neural network learns itself to assign time transformation coefficient to known dimensions of specimens, it is then with sufficient accuracy able to determine time transformation coefficient even for specimens with different shapes, for which it has not been learnt. By backward time transformation is then possible to predict probable time course of the cooling down curve and accordingly also the moment of accomplishment of given temperature. To obtain more general results, when above mentioned exploration of TCC, coupling with the numerical solutions of partial differential equations of the heat fields together with their initial and boundary conditions solutions can be used. The initial conditions in the most cases are unique or they can be with the sufficient precision determined, whereas the boundary conditions of heat transfer equations are usually wary hard to set. So some potential methods of boundary conditions determining and some difficulties by their time behavior settings can be illustrated, too. The advantages of both methods can be mixed and sufficient speedy and accuracy solution may be got.

Keywords: cooling down of materials, temperature prediction, artificial neural network, boundary condition, numerical heat transfer equation

Zaprezentowana metoda wykorzystuje podobieństwo pomiędzy krzywymi chłodzenia dla próbek z tego samego materiału, różniących się cechami geometrycznymi. Dopasowanie skali czasu dla poszczególnych próbek prowadzi do zbieżności z tzw. „ogólną krzywą" dla danego materiału, którą można wyznaczyć metodami statystycznymi. Ta operacja jest określana jako definiowanie współczynnika przekształcenia czasu TTC dla próbek o określonych kształtach (wymiarach), to będzie możliwe wyznaczenie z wystarczającą dokładnością współczynnika TTC dla próbek o odmiennych kształtach (wymiarach). Umożliwi to, poprzez przekształcenie odwrotne czasu, przewidywanie prawdopodobnego przebiegu krzywej chłodzenia, a także czasu osiągnięcia zadanej temperatury. W celu osiągnięcia bardziej ogólnych wyników wspomnianą wcześniej metodą TTC połączono z analizą numeryczną cząstkowych równań różniczkowych opisujących pole temperatury z uwzględnieniem warunków początkowych i brzegowych. Warunki początkowe w większości przypadków są jednoznacznie określone lub mogą być określone z zadawalającą dokładnością, natomiast warunki brzegowe wymiany ciepła są zwykle trudne do ustalenia. Przedstawione zostały wybrane metody określenia warunków brzegowych oraz trudności związane z określeniem charakterystyk czasowych. Zalety obu metod mogą być łączone w celu osiągnięcia zadawalającej szybkości i dokładności rozwiązania.

1. The neural network approach

Artificial neural networks (ANN) have been nowadays more and more exploited in technical praxis [1], [2]. The goal was to verify the ability of artificial neural networks exploitation for prediction of the moment of accomplishment a priori defined temperature of the laboratory specimens surface of various geometric shapes and chemical composition within the process of natural cooling down before rolling in laboratories of Institute of Modelling and Control of

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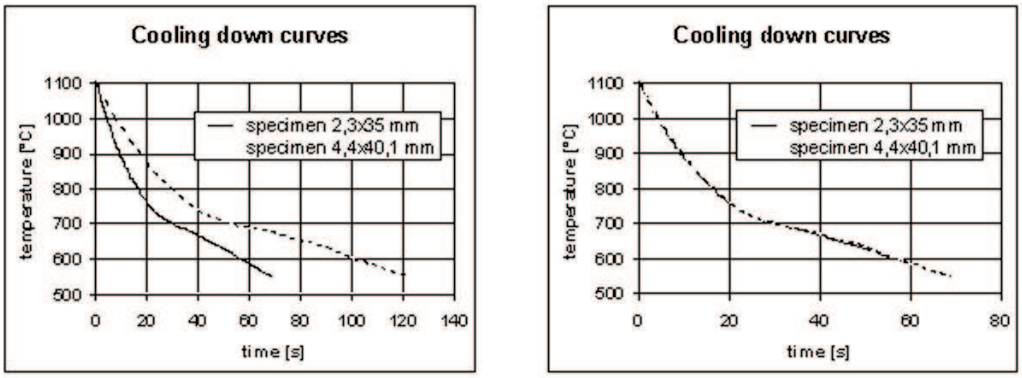

a) measured cooling down curves   b) transformed cooling down curves

Fig. 1. Example of time transformation of cooling down curves of two specimens

Forming Process at VŠB – Technical University of Ostrava. Manipulation with specimens has to be exactly timed while thanks to its relatively small dimensions they very quickly cool down. Based on measured temperature cooling down curves of the surface of representative number of various dimension specimens on time is apparent that graphic flows for particular specimens of the same brand are geometrically similar (see Fig.1.a) which denotes that by means of appropriate time scale change practically changes of time scales are expressed by time transformation coefficient for every kind of specimen (TTC). Particular identical graphical flows of cooling down curves (see Fig 1.b) are acquired. In the picture because of transparency, only two cool down curves are used. Theirs parameters are stated in Tab.1. TTC values are then expedient to define by statistic calculation in iteration cycles with criterion of minimal error attainment between flows of cooling down curves of all specimens and so called "general curve" for given material. General curve could e.g. be the one from measured cooling down curves against it after time transformation all other curves show the least square error. As the general curve in the picture, temperature curve of cooling down specimen with dimensions 2.3×35 mm was used and for obtaining the curve with time transformation of the other specimen with dimensions 4.4×40.1 mm, the value TTC = 0.56 was assigned.

TABLE 1

Parameters of specimens

Specimens parameters	specimen 1	specimen 2
Material of specimen	St37	St37
Height of specimen	2.3 mm	4.4 mm
Width of specimen	35 mm	40.1 mm
Length of specimen	110 mm	110 mm

The relationship between specimen dimensions and time transformation coefficient can from measured data be profitably acquired by artificial neural network applying. Artificial neural network learns itself to define TTC value from the training data set, where as input data of geometric shapes of measured specimens (h – height, l – length, w – width) is used, whereas correctness of learning process can favourably be influenced by pre-calculated width and height ratio and height and width product values of the specimen inputs adding [4] which good characterize temperature-caloric parameters of the specimens. The output of artificial neural network is then in the learning process compared with appropriate TTC value which for known specimens was defined by graphic flows of cooling down processes analysis. Topology of the mentioned artificial neural network is shown in Fig. 2. Learned neural network (in this case by means of Back Propagation method) [3] than thanks to its capacity to generalize and involvement of non linear relationships between inputs and output estimates coefficient values of time transformation even for cases which were not the part of training data set, therefore neural network did not work with this data in the learning process.

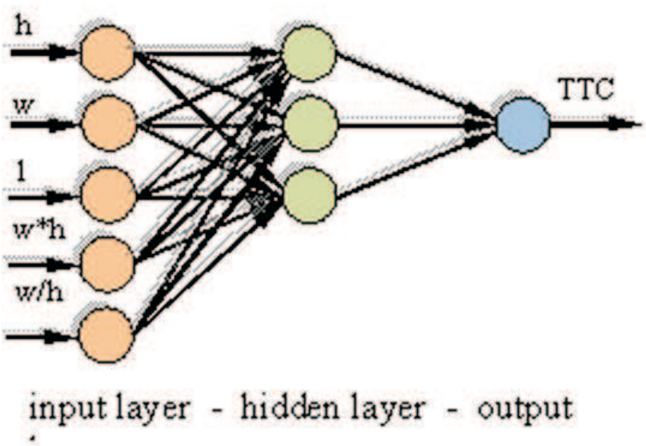

Fig. 2. ANN topology

If the data about dimensions of the specimen and appropriate pre-calculated values is now brought to the input neurons of the learned artificial neural

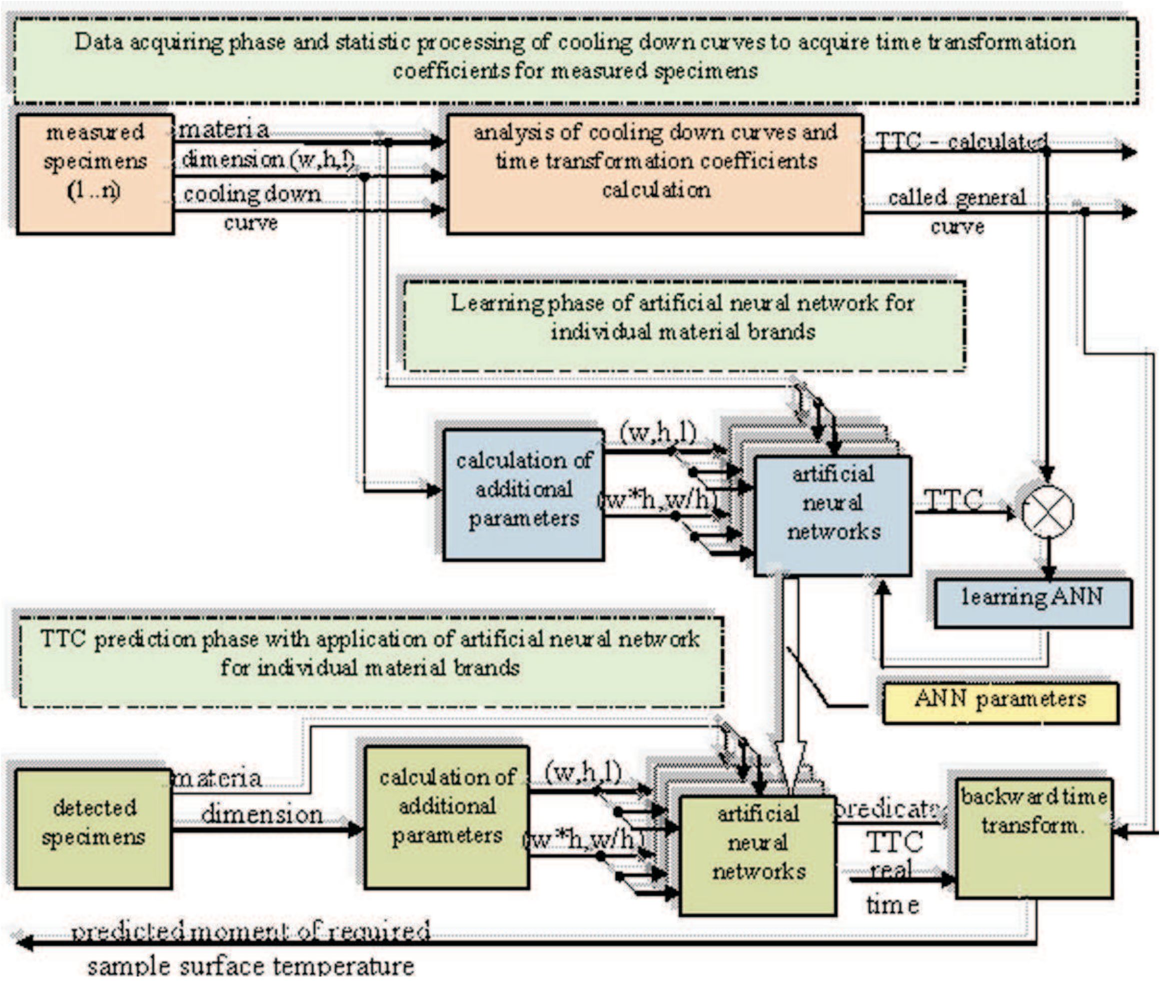

Fig. 3. Calculation diagram of the moment of required sample surface temperature achievement with ANN

network input level, the TTC value of the given specimen is the output of the neural network. Knowing TTC value of random specimen with known geometric dimensions enables the execution of backward time transformation, when time values of general curve are divided by TTC value.

A probable flow of cooling down curve of monitored specimen and in this way also the moment in which the desired temperature of its surface is reached, is acquired. Calculation diagram of the moment of required sample surface temperature achievement with ANN is illustrated in Fig. 3. Errors between measured and calculated curves with artificial neural network exploitation in this case did not exceed value of 15°C, of which is apparent that TTC calculation with artificial neural network exploitation enables with sufficient correctness to predict temperatures of specimen surfaces during the cooling down process. The correctness of detection TTC value and thereby also the prediction of the moment of reaching given temperature of the specimen surface by neural network is based on the count and representatives of measured temperature cooling down specimen curves, correctness of specimen surfaces temperature measurement, the way of TTC defining value from measured data and also generally on the quality of learnt artificial neural network [8].

2. The mathematical description of specimens cooling

Field of temperature trace specimen is determined by Fourier's heat conduction partial differential equation. Out of the problem kind we have to know its initial conditions and its border conditions. Initial conditions determine character of the temperature distribution at the beginning solution; boundary conditions determine state on border of investigated system, in our case body on the body surface. The whole algorithm is shown on Fig. 4. Initial conditions we suppose in form of homogeneous temperature distribution. This premise is correct in case sufficiently long specimens warming - up when temperature field inside the specimen is homogenized [7]. Cooling border conditions it is possible to describe by:

1. temperature trace on the body surface,
2. value of heat flow from the body surface,

3. trace of body surrounding temperature at distance where this temperature is not influenced by the temperature of proper body anymore.

In the third case, for determination of border condition, it is not sufficient only to know environment temperature trace but we have to know also amount of summary heat-transfer coefficient from heated body to surrounding space. In our case the heat flow is certainly from warmer body to surrounding space.

Let´s suppose that summary heat-transfer coefficient is function of body surface temperature. In our case it does concern neither solving of heat convection direct problem nor purely solving inverse problem. The heat thermal characteristics of the specimens are defined from literature [4, 5]. In first case the trace particular quantities are taken as temperature functions, in second case the harrow tabular values are taken for given temperatures, parameter value among tabbed values is set by linear interpolation. Entire calculation proceeds iteratively in particular steps.

2.1. Initialization step

To be able to execute the computation of the specimen temperature field during the following steps the initialize values of trace of the summary heat-transfer coefficient like a function of the body surface temperature has to know.. In this step for each time interval homogenous temperature distribution in body will be reflected. The middle part of bodies like perpendicular excision – prism will be choose, whose two dimensions are identical to corresponding two dimensions of investigated body and the third dimension we'll reflect as unitary. As the homogeneous temperature field is supposed, the heat flux will be zero through cutting sides. Then heat balance is given by area formed by body surface, by coefficient heat transfer, by temperature difference of surface and of surrounding space and by sample temperature variation in time. Surrounding temperature is constant and surface temperature is known, so that we are able to determine heat flux from body into surrounding environment. Heat flux during specific time period has to be equal to heat decrease in the sample during the same time.

2.2. The numerical solution

Although the dependence of the specific thermal capacity in carbon steels is a nonlinear function of the temperature, for small temperature changes we do not commit essential mistakes if we consider the behaviour for given temperature and its close surrounding as a linear function. On the basis of this premise rough estimation of complex heat-transfer coefficient size as the function of the surface body temperature is able to determine.

For calculations it is necessary either to choose relatively big time period or to filter rigorously the measured data. From accessible numerical filters the filter filtfilt seemed to be as more suitable within MATLAB simulator environment. This is non-causal filter which has on his output the zero phase distortion. Filter satisfactorily coverers the step changes of temperature, which from physical point of view are impossible in this case, because temperature gradient in time should change only slowly.

2.3. The iteration computation

Following calculations will be executed as long, as the results of two subsequent steps differentiate less than value of error stated in advance. The calculation in itself will be very complicated because the substance of calculation is built on base of discretization of heat convection partial differential equations by their differential equivalents, namely as in three – dimensional coordinates as in time coordinates. This exercise can be solved either as the implicit scheme, then a system of equations given by differential scheme is solved, or as explicit scheme, when time step of temperature inside the body we study in times t – dt and t, time step of the border temperature we study in times t + dt. For each time step new temperature associating with selected point is determined and compared with really measured temperature. Difference of these two data serves for the correction of the complex heat-transfer coefficient.

To keep the numerical stability of the calculation the newly calculated value is considering certain weight less than one. Value of this weight is changed depending, if the deviation between measured and calculated temperatures has in the following calculation steps the same sign or if the deviation sign changes. The aspiration of the algorithm is to put on the numerical solution to the steady oscillation state when the sign of deviations periodically changes. So far as the preset threshold deviation value is exceeded at sign change the weight is decreased in case it does not cross in advance defined maximum or minimum value. To reach inquired "instability", the value of the weight is determined also by sum of deviations between measured and calculated temperature value. Values already in this way defined the total heat-transfer coefficient are taken also for calculation of the heat flux from surface places with lower temperature. Value of coefficient for higher temperatures does not change anymore. Values are saved like a function of temperature, whereas the mean average of all calculated values it's taken into

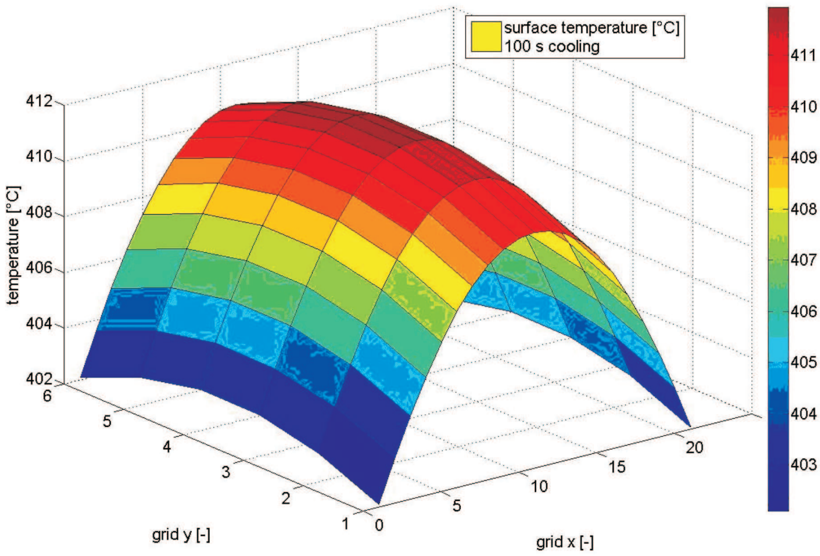

Fig. 4. The surface temperature of the specimen – 100 s freezing

account. New average is then re – counted for next lower temperature. Explicit algorithm will provide the temperature values in selected node points of the body, so that the time flow of temperature field of cooling body is considered as next result of calculation. The example of surface temperature of the specimen is shown on Fig. 4.

Due to temperature surface measuring inaccuracies caused partly by sampling period and partly by measurement errors as well as by pyrometer resolution abilities the determination of the total heat-transfer coefficient is assigned not only from a single sample, but within the second and higher iterations as an average value of the heat-transfer coefficient of all specimens. Owing to above mentioned inaccuracies in temperature measuring the errors on assessment heat-transfer coefficient values are various for separate specimens and differs in time. Therefore their average value and standard deviation are calculated by the selection of valid values, and if this standard deviation exceeds stated limit, the values with the greatest deviations of average value are eliminated.

2.4. Authentication

As the last step the single specimens cooling trace testing simulation calculated as heat convection straight forward exercise is performed.

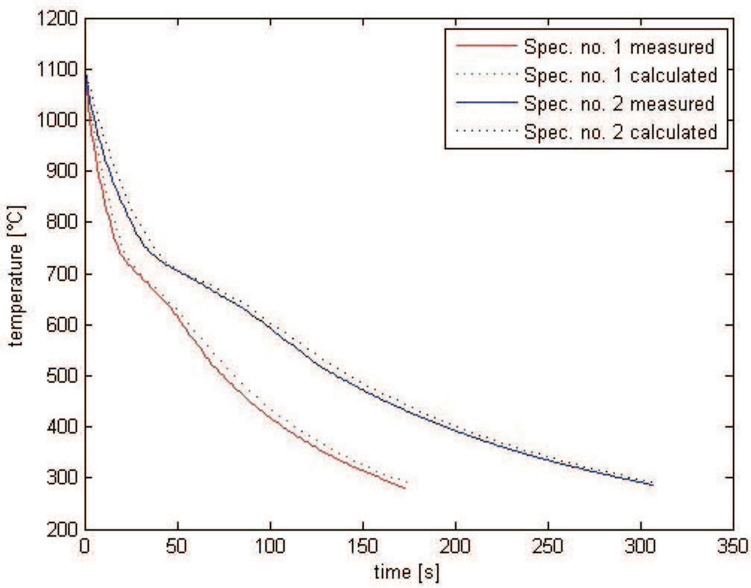

Fig. 5. Results of cooling simulation

From comparing of measured and calculated cooling curves it is evident that the initial premise, it means dependence assessment of total coefficient of heat-transfer from specimen to the environment, is fulfilled and it is possible to use it also for calculation for specimens of other sizes than those ones which were used for measurement. It is possible to suppose that the time dependence of thermal field will sufficiently accurate even for specimens of bigger or smaller sizes. Accuracy of enumeration can be influenced especially by the surface characteristics different for separate specimens and by non-performance of their preferably the same orientation in space during cooling process. On the other hand the fact that if the value of the calculating heat transfer coefficient varies from real value in percentage, then computation error of temperature time flow is even in tens of percents arises from performed simulations. Surface temperatures in time are shown on Fig. 5.

3. Conclusion

The correctness of detection TTC value and thereby also the prediction of the moment of reaching given temperature of the specimen surface by neural network is based on the count and representatives of measured temperature cooling down specimen curves. The TCC method can give only temperature on one point of exploring body. The second method based on the numerical identification of temperature dependence of all over heat transfer coefficient can propagate the complex temperature filed cross all points of body and so the minimum, average and maximum temperature of body in the time can be determined. The neural network model advantage depends on promptness by TCC determination and so on promptness of the true time of the selected temperature reaching. This method disadvantage is that only the range of goods using for ANN learning is applicable. The method accuracy depends on number of specimens (measurements number), which for ANN learning was used. On the opposite the mathematical-physical model can be used universally for any specimen dimensions (even those outside the range of having measurement). Next advantage is the knowledge of temperature field over all the dimension. On the other hand a low speed of computing improper for real time control is its disadvantage. The mix of both methods enables sufficient powerful and accuracy solution even if a lot of measurements is available. The values for ANN learning are generated using mathematical physical model using non limited intervals and the learned ANN can be used for rapid predefined temperature computing.

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