ICIT & MPT 2014

Ljubljana, Slovenia, April 9th - 11th 2014

Conference Proceedings

Edited by

Aleš Hančič,
Janez Grum,
Gašper Gantar,
Irena Pulko

TECOS - SLOVENIAN TOOL AND DIE
DEVELOPMENT CENTRE

INDEX OF CONTENTS

General

Polymer Technologies

Heat Treatment and Surface Engineering

Metal Working

SLOVENIAN TOOL AND DIE
DEVELOPMENT CENTRE

ICIT&MPT 2014

9th International Conference on Industrial Tools and Material Processing Technologies

Slovenia, Ljubljana, October 9th - 11th 2014

INVITED PAPER

ESTIMATION OF HEAT TRANSFER COEFFICIENTS BY USING HYBRID OPTIMIZATION TECHNIQUES

Imre Felde[a]

[a]Faculty of Informatics, Óbuda University, Budapest, Hungary

Abstract

The estimation of thermal boundary conditions occurring during heat treatment processes is an essential requirement for characterization of heat transfer phenomena. In this work, the performance of five optimization techniques is studied. These models are the Conjugate Gradient Method, the Levenberg-Marquardt Method, the Simplex method, the NSGA II algorithm and a hybrid approach based on the NSGA II and Levenberg-Marquardt Method sequence. The models are used to estimate the heat transfer coefficient in 2D axis symmetrical case during transient heat transfer. The performance of the optimization methods is demonstrated using numerical experiments.

Keywords: *quenching ,inverse heat conduction problem, ,hybrid optimization*

1. Introduction

Immersion quenching is widely applied in the industry to change materials properties under high temperatures and high rates of cooling, a condition in which the heat transfer can be dominated by the cooling characteristics o the cooling media. To attain the required heat transfer conditions conditions, exactly known thermal loads must be supplied on the material surface, namely design surface, and thus both the temperature and the heat flux are prescribed. The problem consists of determining the specifications for the heat exchange to achieve the desired conditions on the design surface. Performing inverse heat conduction problem (IHCP) analysis [1-4] the required information for the heat transfer process can be achieved.

The IHCP of immersion quenching has been usually tackled by either implicit or explicit formulation. In the implicit approach, the problem is formulated as a multivariable optimization problem, while the explicit formulation attempts to determine directly the unknown parameters with the use of regularization techniques to solve the resulting system of equations. There are two distinct groups of optimization techniques: the deterministic methods (Conjugate Gradient [3], Levenberg-Marquardt [4], Simplex [5], etc) and the stochastic approaches (genetic algorithms [6], particle swarm optimization [7,8] etc.).

In general, deterministic methods are faster than stochastic methods, although they are more prone to converge to a local instead of the global minima or maxima. On the other hand, stochastic algorithms, despite being more likely to converge to the global minima or maxima, are in general expensive computationally. Various optimization techniques have been applied to estimate the heat transfer during quenching process as well.

This study is focusing on a hybrid solution that combines two approaches: the stochastic method, by which the global extremum in the search space can be localized and the deterministic formulation, which is for the swift find the global optimum.

2. The heat conduction model

The mathematical formulation of the transient heat transfer for a homogeneous isotropic domain (Ω) is defined as follows:

$$\nabla \cdot \left(k(\mathbf{r},T) \cdot \nabla T\right) + Q(T,\mathbf{r},t) = C_p(\mathbf{r},T)\rho(\mathbf{r},t)\frac{\partial T}{\partial t} \quad (1)$$

where rεΩ is the spatial vector, t is the time, k is the thermal conductivity, T is the temperature, C_p is the specific heat, ρ is the density and Q is the latent heat. The initial condition is

$$\mathrm{T}(\mathbf{r}, \mathrm{t}=0) = \mathrm{T}_0(\mathbf{r}) \quad (2)$$

where T_0 is the initial temperature of the domain. The boundary conditions are expressed by:

$$-k\frac{\partial T}{\partial \mathbf{r}} = h_i\left(T(\mathbf{r},t) - T_{am}\right)$$

in Γ_i i= 1 …p (3)

where hi are the heat transfer coefficients corresponding to different portions of the boundary ($\Gamma_1 \frown \Gamma_2 \ldots \smile \Gamma_p = \Gamma$ and $\Gamma_1 \frown \Gamma_2 \ldots \frown \Gamma p = \varnothing$) and T_{am} is the ambient temperature.

3. The inverse heat conduction model

Assuming that the temperature inside the work piece and/or on its surface is measured during the heat transfer process, it is possible to solve the inverse heat conduction problem by determining the time / or temperature variations of the thermal boundary conditions [1-3]. Each one of domain boundary zones Γ, is considered to have a time dependent heat transfer coefficient, $h_i(t)$. The time dependence of the heat transfer coefficient can be approximated by polynomial functions, each one defined by a set of parameters $h_i^{(r)}$ = (r=1…p; i=1…q), according to Fig. 1. The unknown design parameters can be expressed by the vector of m (m= p*q), components $\tau = (\tau^1,\ldots,\tau_m) = (h_1^{(1)}, \ldots, h_q^{(1)}, h_1^{(2)}, \ldots, h_q^{(2)}, \ldots, h_1^{(p)}, \ldots, h_q^{(p)})$. The temperature at different times is given by measurements at n points in the solid region, located at r_k, (k=1…n). On calling T_k^m, the measured temperatures, and T_k^c, the calculated temperature at those points, one can pose the problem of obtaining the values of the heat transfer coefficients τ_i that minimize the cost function, S:

$$S = S(\tau_1,\ldots,\tau_m) = \sum_{k=1}^{n}\left(T_k^m - T_k^c\right)^2 = \min \tag{4}$$

where n is the total number of measured temperatures, i.e., the number of points multiplied the number of measurements at each point.

4. Hybrid formulation

The solution of the the inverse parameter estimation problems is based on the minimization of equation (4). The following optimization approaches have applied used to minimize the value of S:

1. Simplex (Simplex) search method is based on the Nelder–Mead algorithm [5]
2. Levenberg-Marquardt Method (LMM) [4]
3. Conjugate Gradient Method (CGM) [3,4,9],
4. The Non-dominated Sorting Genetic Algorithm (NSGA II) [10-12]
5. Hybrid method using (NSGA II) and (LMM) is sequentially

According to Fig.1., the iterative computational procedure for the estimation of HTC can be summarized as follows:

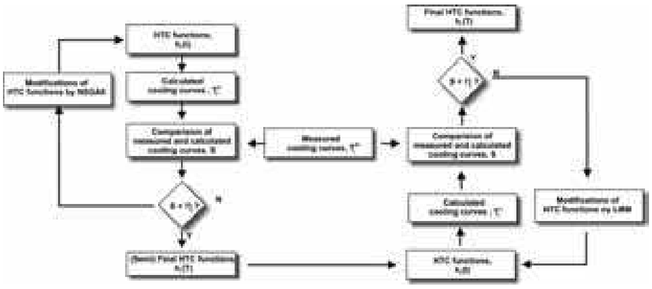

Figure 1 The iterative procedure for the determination of thermal boundary conditions

The following steps are obtained by using the optimization methods if they used by their own (Simplex, LMM, CGM and NSGAII):

1. During the initial iteration, the components of the vector τ are initialized to some values
2. The values of $h_i(t)$ functions are set
3. The cooling curves (T_k^c) are calculated based on numerical simulation
4. The difference between the measured (T_k^m) and the calculated (T_k^c) time-temperature signals are characterized by calculating S
5. If the value of S is greater than a desired tolerance value (η) then the $h_i(t)$ functions are modified by using the optimization algorithm and a new iteration is started at Step 2. If S is less than η then the iteration stops.

The Hybrid approach is also based on the Steps 1-5 while the output results of Step 5 will be the input data for the temperature field computations. The Hybrid method requires the following additional steps:

6. The cooling curves (T_k^c) are calculated based on numerical simulation
7. The difference between the measured (T_k^m) and the calculated (T_k^c) time-temperature signals are characterized by calculating S
8. If the value of S is greater than a desired tolerance value (η) then the $h_i(t)$ functions are modified by using the LMM algorithm and a new iteration is started at Step 6. If it is so than the final estimated $h_i(t)$ functions are estimated

5. Numerical example and discussion

In order to compare the performance of the optimization algorithms on the prediction of thermal boundary conditions, two numerical experiments for the quenching process have been performed. In the analysis, there was no physical set-up to directly measure the temperature T_k^m. Instead, we assume theoretical heat transfer coefficient functions, $h_i(T)$ and substitute them directly into the equations (1)–(3) to calculate the temperatures at each location for the thermocouples (TC). The results are used in the computed temperature Tkm curves. Due to this concept the T_k^m curves have been assumed to be error-free samples. The following concepts have been used for the computational investigations:

- The theoretical $h_i(T)$ functions have been determined
- The Tkm temperature signals have been generated by obtaining simulations on the basis of $h_i(T)$ functions
- Inverse computations have been carried out by applying each optimization method, in order to reconstruct the original $h_i(T)$ functions
- The computational results were analysed

The quenching process for a cylindrical work piece, mounted with 5 TC's was investigated. A 2D axis-symmetric heat transfer model was applied to calculate the temperature distribution during the cooling process. The physical properties of Inconel 600 alloy were assigned to the workpiece. The thermocouples were assumed to be mounted at 1 mm below the side surface of the rod. The location of the TC's (the distances from the bottom of the cylinder) and the parameters used for the calculations are summarized in Table 1.

RADIUS, R	25 MM
Length, L	200 mm
Initial temperature, T_0	850 C⁰
Ambient temperature, T_{am}	50 C⁰
Locations of TC 1-5 below the surface	r=R-1
TC 1	z = 0 mm
TC 2	z = 50 mm
TC 3	z = 100 mm
TC 4	z = 150 mm
TC 5	z = 200 mm

Table 1. Parameters applied for the computational example

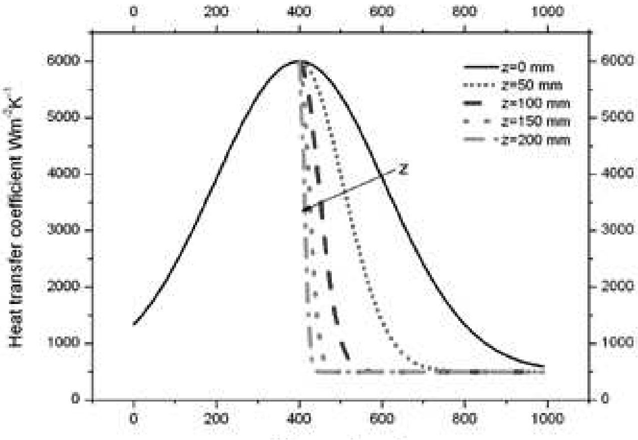

Figure 2. The theoretical heat transfer coefficient function applied

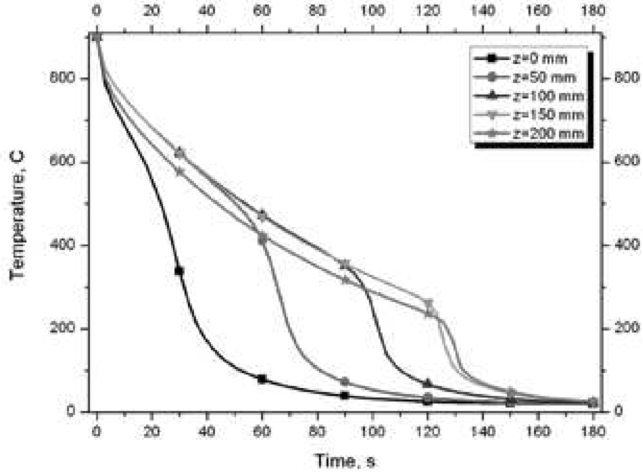

Figure 3. The predicted cooling curves obtained at the TC locations in direction of axis "z"

The effect of wetting front kinematics that occurs during immersion quenching, is taken into consideration, by defining the heat transfer coefficient [14,15] $h_i(T,z)$, which is assumed to be dependent on temperature and the vertical local coordinate, equation (5). The theoretical $h_i(T,z)$ as predefined, is represented at Fig. 2., while the cooling curves obtained at the TC locations are shown at Fig. 3. The $h_i(T,z)$ is used for all the surfaces of the work piece including the top and the bottom faces as well. For the inverse calculations 100 components of the vector τ have been applied, while the initial estimate of $h_i(T,z)$ was set to 100 $Wm^{-2}K^{-1}$. The population size was defined to 100, for the NSGA II method.

$$h_i(T,z)=\begin{cases}5500 * e^{-e^{-1.34*(T-400)^2+500}} & T \le 400°C \\ 5500 * e^{-e^{(-1.34+0.0606*z-2.653*10^{-4}*z^2)*(T-400)^2+500}} & T > 400°C\end{cases} \tag{5}$$

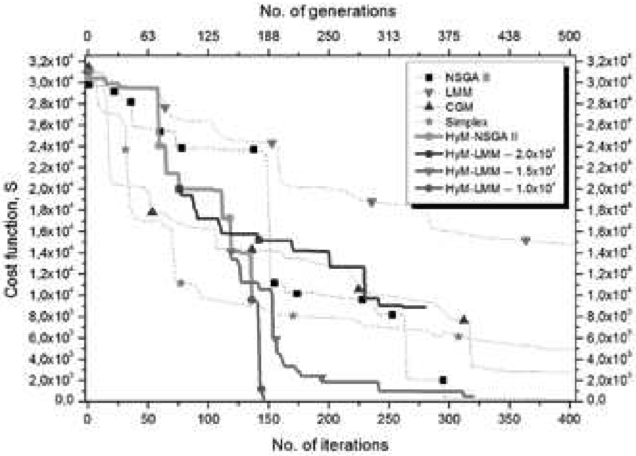

Figure 4. The evolution of cost function (S), as functions of iterations and generations

In order to reconstruct the thermal boundary conditions 500 generations were investigated by the NSGA II model and 400 iterations were performed by the LMM, CGM and Simplex models (Fig. 4.). The concept of using the Hybrid approach was to perform the generations until the cost function exceeds 2.0*104, or 1.5*104, 1.0*104 and then the iteration was continued by means of LMM. Then the LMM calculations were carried out till the S was lower than 100 or the number of LMM iterations exceed 150.

The results obtained by Simplex, LMM and CGM showed a limited accuracy for the inverse estimation. The discrepancy of the predicted heat transfer coefficient were still unacceptable huge after the 400 iterations. Very good agreement between the original and recovered HTC functions was given by using the NSGAII algorithm. However, at least 300 generations had to be built to achieve the desired output. The fastest convergence with the highest recovery performance was given by using the hybrid optimization sequence when the NSGAII method was used until the value of S was lower than 1.0*104. Similar results but slower convergence obtained in the case of LMM --1.5*104, while rather big S belongs to LMM -- 2.0*104.

The reason for the poor agreement between the measured (pre-calculated) and estimated temperature curves is due to the complexity of the heat transfer phenomena, where the boundary conditions of the third type varied with the surface temperature, as well as, the distance measured from the bottom of the work piece. These results point out that the inverse heat transfer calculations applied for sophisticated thermal problems needs robust numerical methods to achieve a desirable outcome.

6. Summary

In this work, the performance of five different optimization models for the estimation of heat transfer coefficients during an immersion quenching process have been compared. An automatic optimization procedure based on a process simulator, cost function and various numerical optimization techniques was used. The optimizations methods applied were the Simplex, Conjugate Gradient Method, Levenberg-Marquardt Method, NSGAII method and a hybrid approach based on a NSGAII-LMM sequence. The performance of the optimization algorithms is compared using on a numerical test, where the thermal boundary condition of the third type was functions of surface temperatures and local coordinates. The best prediction was given by the hybrid method as well as the NSGAII algorithm, however the later one required more computational efforts. It must be noted that the results performed by using LMM, CGM and Simplex techniques are strongly depend on the initial set of parameters [6,7]. The more smaller the difference between the initial guess functions and the HTC functions to be estimated the more faster convergence of the cost function and more accurate prediction of boundary conditions can be performed. However, our investigation is based on the concept that no any preliminary knowledge has been given about the HTC functions. These assumptions comprise the parameter intervals and isolation of the search space. With finer isolations, the applied methods would most likely perform differently. Testing the methods on different isolations remains a task for further investigation.

Acknowledgement

We acknowledge the financial support of this work by the Hungarian State and the European Union under the TÁMOP-4.2.2/A-11/1-KONV-2012-0029 project.

References

[1] J.V. Beck, B. Blackwell, C.R. St Clair Jr., Inverse Heat Conduction, Wiley, New York, 1985.
[2] A.N. Tikhonov, V.Y. Arsenin, Solution of Ill-posed Problems, Winston, Washington, DC, 1977.
[3] O.M. Alifanov, Inverse Heat Transfer Problems, Springer, Berlin/Heidelberg, 1994.
[4] M.N. Özisik, H.R.B. Orlande, Inverse Heat Transfer: Fundamentals and Applications, Taylor & Francis, New York, 2000.
[5] J.A. Nelder, R. Mead, A simplex method for function minimization, Comput. J. 7 (4) (1965) 308–313.
[6] J.C. Lagarias, J.A. Reeds, M.H. Wright, P.E. Wright, Convergence properties of the Nelder–Mead simplex method in low dimensions, SIAM J. Optimiz. 9 (1) (1996) 112–147.
[7] R. Das: A simplex search method for a conductive–convective fin with variable conductivity, International Journal of Heat and Mass Transfer 54 (2011) 5001–5009
[8] O. Nelles, Nonlinear system identification, Springer-Verlag, Berlin, 2001.
[9] Fletcher, R. and Reeves C. M., "Function Minimization by Conjugate Gradients," Computer J., 7, 149-1 54, 1964.
[10] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197.
[11] K. Deb, Multi-objective Optimization Using Evolutionary Algorithms, Wiley, Chichester, UK, 2001.
[12] D.A.V. Veldhuizen, G.B. Lamont, Multi-objective evolutionary algorithms: analyzing the state-of-the-art, Evolutionary Computation 8 (2) (2000) 125–147.
[13] J. Clark and R. Tye: "Thermophysical properties reference data for some key engineering alloys". High temperatures – high pressures, 2003/2004, Vol. 35/36. pp 1-14.
[14] A. Majorek, B. Scholtes, H. Müller, E. Macherauch: Influence of heat transfer on development of residual stresses in quenched steel cylinders, 1994, Steel research No. 4, p. 146-151
[15] H. M. Tensi, A. Stick : Martens hardening of steel - Prediction of temperature distribution and surface hardness, Materials Science Forum Vols. 102-104 (1992) p. 741-75