23rd International Federation of Heat Treatment and Surface Engineering Congress (IFHTSE2016), Savannah, 2016, pp. 348-353.

Parallel PSO method for estimation Heat Transfer Coefficients

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Abstract

The methodology based on the Particle Swarm Optimization (PSO) method, as a recent stochastic optimization technique to solve complex inverse heat transfer problems is outlined. The temporospatial Heat Transfer coefficient obtained on the surfaces of a cylindrical work piece is reconstructed by solving the inverse heat conduction problem. The fitness function to be minimized by the PSO approach is defined by the deviation of the measurements and the calculated temperatures is minimized. The PSO algorithm has been parallelized and implemented on a GPGPU architecture. Numerical results are demonstrated that the determination of Heat Transfer Coefficient functions can be performed by using the PSO method, as well as, the GPU implementation; provide a less time consuming and accurate estimation.

Introduction

Inverse Heat Conduction Problems (IHCP) are known as “reverse engineering” problems, due to the reversal of a cause-effect sequence, in the field of heat transfer analysis. An inverse problem means that some of the initial, boundary conditions or material properties are not fully specified as determined from the measured temperature profiles at some specific locations. The inverse problems in most situations are likely to be ill-posed [1]. Solutions of the inverse problem are very sensitive to measurement errors, i.e. small errors in the measured data values can produce very large errors in solutions. In general, the exclusivity and stability of an inverse problem solution is not guaranteed. In recent years, the inverse problems have been studied extensively due to their applications in various engineering disciplines.

The most of the methods approach the inverse heat conduction problem, as an optimization problem, i.e. the problem is defined as the minimization of a cost function or a fitness function measuring the distance between measurements and predictions [2,3]. With the improvement of computer capability, a variety of numerical techniques and computational methods have been developed to provide accurate solutions for IHCP in the last decade. Among these methods, stochastic optimization methods have become a popular means of solving inverse problems, due to their capability of finding the global optimal result without computing the complicated gradient of the objective function

The introduction contains the opening text for the main body of the manuscript. It should include a statement of the problem or situation and the approach taken to resolve it. This first section may also contain a summary of the past developments and background of what is already known and/or published elsewhere. This is best summarized in your own paper, with references to other publications containing more-extensive discussions of this background information. All references are placed at the end of the paper.

Genetic algorithms [4,5] are applied successfully for solving many types inverse heat transfer problem. The quantitative evaluation of different numerical optimization techniques showed [6] that stochastic methods could serve more accurate results for IHCP than gradient approaches in recovering complex thermal boundary conditions. The Particle Swarm Optimization (PSO) algorithm became popular in the recent years due to its ability of maintaining a good balance between the convergence and diversity. Applications of PSO algorithms in the field of heat transfer are still limited. An inverse application of boundary elements method to estimate the thermal conductivity and the shape of an inclusion was implemented [7]. Qi et al. [8] applied the multi-phase PSO method to solve the inverse radiation problem. The proposed method applied the benefits of both two-group PSO and multi-start PSO algorithms. The effectiveness and efficiency of Particle Swarm Optimization technique in inverse heat conduction analysis were analysed by Vakili and Gadala [9]. Three variations of the PSO method, i.e. basic PSO, repulsive PSO, and complete repulsive PSO, were performed to solve the boundary inverse heat conduction problem, in one, two and three dimensions. The results showed that PSO can reduce the stability problems of the classical methods, for solving the inverse heat conduction problems.

In this work, an inverse analysis for the reconstruction of local coordinate and a time-varying Heat Transfer Coefficient, in two-dimensional cylindrical coordinates is investigated. The inverse heat conduction analysis is based on the application of a PSO technique. Transient temperature measurements at multi-locations in the body of the work piece, obtained by the solution of the direct heat transfer problem, served as the virtual experimental data required to solve the inverse analysis. The fitness function which is defined by the quadratic residual between the measurements and the calculated temperatures is minimized. The PSO algorithm has been parallelized and implemented on a GPU architecture. Numerical results are demonstrated that the determination of Heat Transfer Coefficient functions can be performed by using the PSO method, as well as, the GPU implementation; provide a less time consuming and accurate estimation.

The Heat Transfer Model

The determination of the Heat Transfer Coefficient is an important issue of the IHCP and has been extensively studied. Improvements and adaptations of the numerical algorithms on the applications are still an active area of research for obtaining stable and reliable results. A two-dimensional axis-symmetrical heat conduction model is considered to estimate the temperature distribution in a cylindrical work piece (the radius and length of the cylinder is noted by R and Z). The cylinder is subjected to a longitudinal local coordinate and time varying Heat Transfer Coefficient HTC(z,t) on all its surfaces. Both the thermal conductivity and the heat capacity are varying with the temperature, k(T) and C_p(T). The dimensional mathematical formulation of this nonlinear transient heat conduction problem can be described as follows:

$$\frac{\partial}{\partial r}\left(k\frac{\partial T}{\partial r}\right)+\frac{k}{r}\frac{\partial T}{\partial r}+\frac{\partial}{\partial z}\left(k\frac{\partial T}{\partial z}\right)+q_v=\rho C_p\frac{\partial T}{\partial t} \quad (1)$$

with the initial and the boundary conditions

$$T(r,z,0)=T_0 \quad (2)$$

$$k\frac{\partial T}{\partial z}\bigg|_{\substack{0\le z\le Z\\ r=R}}=HTC(z,t)\left[T_q-T(r,z,t)\right] \quad (3)$$

where r and z is the local coordinate, t is the time, ρ is the density, T_0 is the initial temperature and Tq is the temperature of the cooling medium. In this work, the weighted Schmidt explicit finite difference method is used to discretize the Eqs. (1-3) and solve the direct problem.

The Inverse Heat Transfer 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 [1,2,3]. 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, the solution of the present inverse problem can be obtained by minimizing the following fitness function

$$S=\sum_{k=1}^{n}\left(T_k^m-T_k^c\right)^2=\min \quad (4)$$

where *n* is the total number of measured temperatures, i.e., the number of points multiplied the number of measurements at each point. The inverse problem is recast as an optimization problem. A variety of numerical and analytical techniques have been developed to solve the optimization problems.

The particle swarm optimization algorithm

The Particle Swarm Optimization (PSO) algorithm introduced by Kennedy and Eberhart [10] in 1995 is a stochastic optimization technique which draws inspiration from the social behavior of a flock of birds or the collective intelligence of a group of social insects with limited individual capabilities. The basic PSO model consists of a swarm of M particles moving in a problem search space. Each particle is a potential solution of the global optimum over a given domain D. For a N-dimensional search space, the position of the i^{th} particle is represented as $X_i = (x_{i1},x_{i2}, . . . ,x_{iN})$. At each generation, the new particle position is found by adding a displacement to the current position where the displacement is the particle velocity multiplied by a time step of one as shown in Eq. (5)

$$X_i^{n+1} = X_i^n + V_i^{n+1} \quad (5)$$

In Eq. (5), X_i^n and X_i^{n+1} represent the current and previous positions of particle i, V_i^{n+1} i is the current velocity of particle i and is represented as $V_i^{n+1}= (v_{i1},v_{i2}, . . . ,v_{iN})$. The velocity of each particle is also updated at each generation and is given by:

$$V_i^{n+1} = V_i^n +c_1r_1(P_{best,i} - X_i^n) +c_2r_2(G_{best} - X_i^n) \quad (6)$$

where V_i^n and V_i^{n+1} are the current and previous velocities of the particle i, respectively. Each particle maintains a memory of its previous best position, say $P_{best,i} = (p_{i1}, p_{i2}, . . . ,p_{iN})$, where the position giving the best fitness function value. The best one among all the particles in the swarm is represented as the global best position, say $G_{best} = (p_{g1},p_{g2}, . . . ,p_{gN})$. The new velocity in Eq. (6) can be seen as the sum of three parts. The first part of Eq. (6) represents the previous velocity and is called the momentum part. The second part of the Eq. (6) represents the tracking of best position for individual particle and is called the cognition part. The third part of the Eq. (6) represents the cooperation among particles in the swarm and is called the social component. The cognitive learning coefficient c_1 and social learning coefficient c_2 are known as accelerating factors, and r_1 and r_2 are two random numbers generated by the uniform distribution within 0 and 1. The relative sizes of these components determine their contribution to the new particle velocity. The most common setting for c_1 and c_2 are 2.0 for the standard PSO algorithm.

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One difficulty encountered in the standard PSO algorithm is that it could easily fall into local optimum in many optimization problems. Better selection of the inertial weight provides a balance between global and local exploration and exploitation. Therefore, less iteration is needed to find the optimal solution and improve the performance of the algorithm. A constriction factor was incorporated into the PSO algorithm by Clerc's suggestion [11] to insure the convergence of the algorithm (PSOC). The velocity term was update as follows:

$$V_i^{n+1} = C_3(V_i^n + c_1 r_1 (P_{best,i} - X_i^n) + c_2 r_2 (G_{best} - X_i^n)) \quad (7)$$

When Clerc's constriction method is used, the constant multiplier C_3 is approximately equal to 0.7298 and the two coefficients c_1 and c_2 are 2.05. The Clerc's approach has been used for the determination of Heat Transfer Coefficients.

Computation procedure for the PSO algorithm

The aim of the inverse analysis is to iteratively estimate the unknown HTCs using the PSO procedure which results a negligible difference between measurements taken at the given locations of the work piece and temperatures computed from the numerical model. The fitness functions value of each particle at the nth iteration is given by the difference between the measured and calculated temperature curves, Eq (4) at the position X_i^n. The computational steps of the PSO algorithm described above are given as follows:

- Step 1: Generate the initial particles in a swarm by randomly generating the position and velocity for each particle.
- Step 2:Evaluate the fitness function of each particle.
- Step 3: Update the $P_{best,i}$ for each particle, if its fitness is smaller than the fitness of its previous best position ($P_{best,i}$).
- Step 4: Update the G_{best}, if the fitness function of a particle is smaller than the fitness of the best position of all particles (G_{best}).
- Step 5: Update each particle according to Eqs. (5) and (7).
- Step 6: Repeat the loop until the stopping criteria or a predefined number of generations is reached.

It is strongly advised to parallelize the computational jobs in Step 2 due to the fact that there are no interferences between the iterations as well as there is no communication between the particles in a given iteration. Therefore, these parts are executable in a data parallel fashion, which is ideal for GPU implementation [12,13]. We used the following configurations for the tests:

- Graphics accelerator: NVIDIA Tesla K40c
- Architecture: Kepler (GK110B)
- Number of shades: 2880
- SMX Count: 15
- Memory: 12GB GDDR5

Verification of the proposed method

The Heat Transfer Coefficients obtained during immersion quenching of a cylindrical bar have been estimated by using the proposed approach.

A cylindrical rod was produced from X8NiCrS18-9 austenitic steel 1.4305 (chemical composition is in Table 1, while physical properties is summarized in Table 2) in the IWT - Stiftung Institut für Werkstofftechnik (Bremen, Germany). The work piece have been equipped with 10 TCs which were located various distances from the top surface and 1 mm under the vertical surface of the cylinder (Fig 1.). The diameter of the cylinder was 50 mm while the length was 100 mm.

C%	Si%	Mn%	P%	S%	Cr%	N%	Ni%	Cu%
<0.1	<1.0	2.0	0.045	0.2	0.18	0.11	8.0	1.0

Table 1. Chemical composition of X8NiCrS18-9 steel grade

Temperature, °C	Specific heat, J/kgK	Conductivity, W/mK	Density, Kg/m³
0	443.3	14.6	7920
200	530.9	17.14	7832
400	568.5	19.68	7865
600	591.5	22.22	7660
800	627.1	24.76	7570
1000	985.3	27.30	7480

Table 2. Physical properties of X8NiCrS18-9 steel grade

The rod has been heated up to 860°C and immersed in oil (Isorapid 277) without agitation at 80°C temperature. The signals of the TCs have been recorded during the cooling process. Fig 2. represents the cooling curves acquisited during the quenching process.

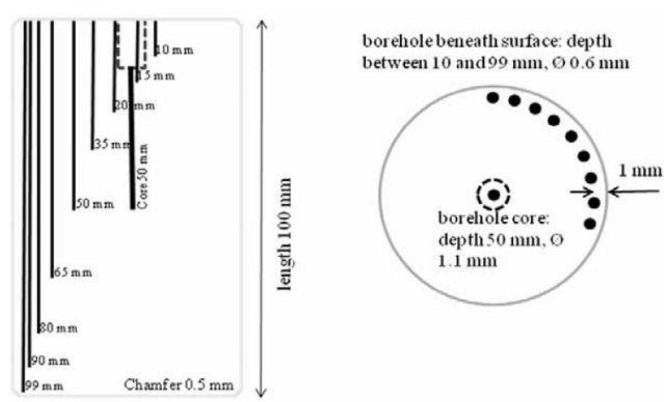

Figure 1. Locations of TCs mounted in the cylindrical work piece (produced in the IWT - Stiftung Institut für Werkstofftechnik)

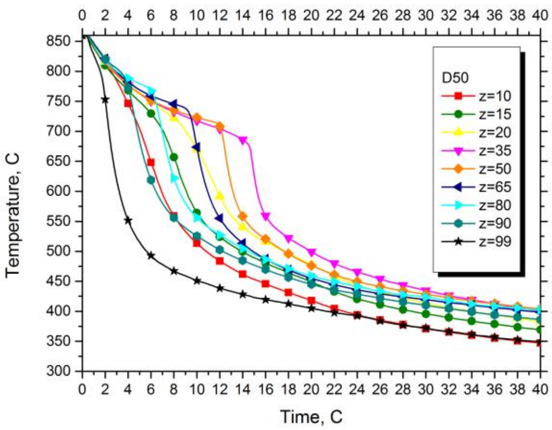

Figure 2. The cooling curves recorded during quenching of the cylindrical probe

A 2D axis-symmetric heat transfer model was applied to calculate the temperature distribution during the cooling process. The physical properties of stainless steel (Table 2) were was assigned to the virtual work piece.

Inverse computations have been carried out by including PSO algorithm, in order to predict the HTC(z,t) functions. The Heat Transfer Coefficient function was defined by a matrix where the rows stood for the local coordinates "z" given by the locations of the thermos couples. The columns of the matrix included the time instances. In the recent investigation 10 vectors (HTC(t)) consisted the matrix. The exact values of the HTC(z,t) function was calculated by the bilinear interpolation procedure.

A hybrid approach is applied to estimate the Heat Transfer Coefficient function: four calculation cycles of PSO and one calculation cycle of Levenberg-Marquardt Method [14] (LMM, a gradient optimization technique) has been used. A swarm size was set to 3000 particles for each computational steps. The concept of the sequential hybrid estimation is based on the following assumptions:

1. In PSO Step 1, the HTC(t) vectors for each TC locations have been determined by 5 time instances (Fig 3, "PSO Step 1" chart).
2. Extra 2 time instances are given to the HTC(t) vectors in PSO Step 2 ((Fig 3, "PSO Step 2" chart). The HTC(z,t) matrix included 10x7=70 elements.
3. In PSO Step 3, 3 new time instances added again to the HTC(t) vectors. The total number of elements in the HTC(z,t) matrix was 100.
4. In PSO Step 3, the number of time instances was increased to 14. The HTC(z,t) matrix included 10x14=140 elements.
5. In the last calculation step, the LMM was applied.

The calculation process in each PSO and LMM Steps stopped when the relative deviation of the fitness function between the former and the recent iteration step was less than 10%.

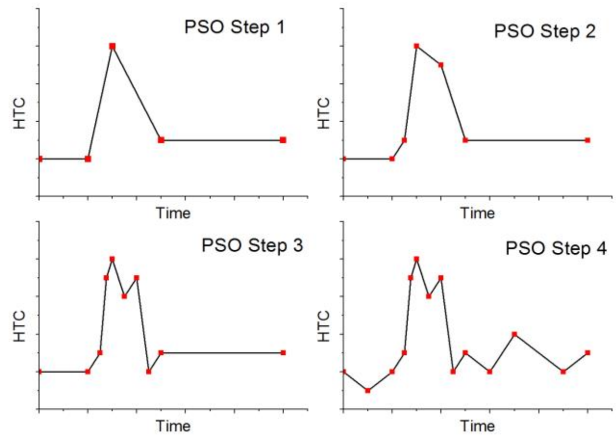

Figure 3. The concept of the sequential hybrid estimation process

The measured T_k^m, and the reconstructed T_k^c cooling curves at the locations of the TCs (k=1,2...10) are shown in Fig 4.

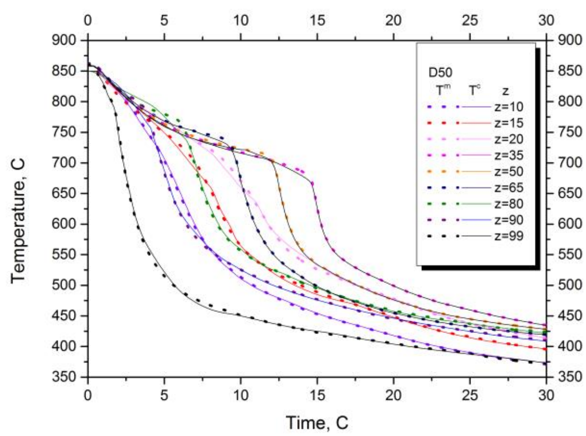

Figure 4. The measured T_k^m, and the reconstructed T_k^c cooling curves at the locations of the TCs (k=1,2,..10)

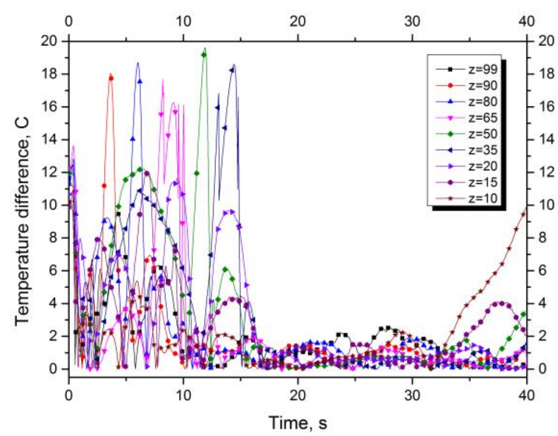

Figure 5. Difference between measured and calculated cooling curves at the locations of the TCs (k=1,2,..10) as a function of time

Satisfactory agreement of original and predicted cooling curves can be observed. The difference between the measured and estimated samples as a function of time for each TC positions is shown in Fig. 5.

In order to quantify the magnitude of deviation between the measured and the recovered temperature samples the mean, standard deviation and maximum value of the difference of cooling curves in each positions were calculated (Table 3). The highest value of temperature difference (19.60°C) was given at the middle of cylinder's length (z = 50 mm). The standard deviation were given in the range of 1.88 to 3.39 while the mean of value the differences was between 2.15 and 4.39. The reason of relatively high maximum deviations could be originated to the fact that the proper time instances needed to reconstruct the Heat Transfer Coefficient have not been found exactly by PSO algorithm. Due to the low value of differences the hybrid PSO approach applied to estimate the complex Heat Transfer Coefficient in a two dimensional axis-symmetrical model seems to be a feasible approach providing an acceptable accuracy.

TC location, mm	Mean, °C	Standard deviation, °C	Maximum deviation, °C
10	2.22	2.29	10.60
15	2.65	2.60	11.96
20	2.74	3.32	11.65
35	3.34	4.39	18.58
50	3.39	4.31	19.60
65	2.06	3.55	17.68
80	2.22	3.30	18.71
90	1.88	2.88	18.09
99	1.91	2.15	10.18

Table 3. The statistical information of deviations between measured T_k^m*, and the reconstructed* T_k^c *cooling curves*

The predicted Heat Transfer Coefficient function obtained by the PSO technique is shown in Fig. 6.

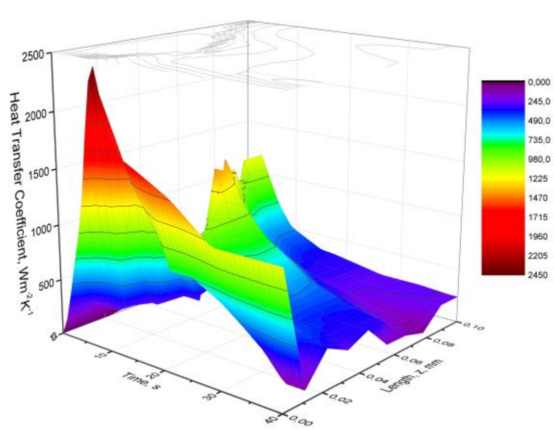

Figure 6. The estimated HTC(z,t) function

It is important to report the results of the computational time required for PSO based estimation. The calculations have been made in:

1. Sequential processing (the fitness value of each particle has been estimated one after another in the swarm in one generation)
2. Multi-tier processing (8 parallel computation of particles at the same time)
3. Full parallelization on GPU architecture

The implementation of version 1 and 2 a PC hardware setup (Processor: Intelr CoreTM i7-2600, Architecture: Sandy Bridge, Number of cores: 4, Memory: 16GB DDR2) has been applied while for version 3 the GPU setup is used mentioned earlier. The time measured during performing the inverse estimations are summarized in Table 4. The parameters show the solution performed on the GPU architecture provides a significant acceleration of calculation time.

PSO Implementation	Calculation time, h
Sequential processing	27.01
Multi-tier processing	11.73
GPU processing	0.81

Table 4. The calculation times (in hours) required for HTC estimations

Conclusions

An inverse analysis using a sequential approach of Particle Swarm Optimization algorithm and of Levenberg-Marquardt Method has been presented to reconstruct the Heat Transfer Coefficient in a two dimensional heat conduction problem. The Heat Transfer Coefficient obtained on the surfaces of a cylindrical probe was considered as functions of local coordinates and time. The temperature samples applied as measured cooling curves were acquisited during immersion quenching experiment. The obtained results underline the feasibility of the procedure and the capabilities for the PSO technique to reconstruct a complex surface Heat Transfer Coefficient without using any prior information of the unknown transient functions. The PSO algorithm has been carried out in high performance GPU configuration using the CUDA environment. The GPU implementation of the inverse heat conduction problem provides significant acceleration of the prediction compared to sequential or multi-tier computation used on a personal computer.

Acknowledgments

We acknowledge the financial support of this work by the Mexican-Hungarian S&T bilateral project TÉT MX -1-2013-0001 and „Cooperative research on control of heat treatment stress and distortion for high value added machinery products" (2014DFG72020) projects. The authors would like to express the acknowledgement for Dr. Thomas Lübben (IWT - Stiftung Institut für Werkstofftechnik) for supporting the experimental part of this work.

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References

[1] Beck J. V; Blackwell B; St Clair Jr. C.R: Inverse Heat Conduction, Wiley, New York, 1985.

[2] Alifanov O.M.: Inverse Heat Transfer Problems, Springer, Berlin/Heidelberg, 1994.

[3] Özisik M.N.; Orlande H.R.B.: Inverse Heat Transfer: Fundamentals and Applications, Taylor & Francis, New York, 2000

[4] Verma S.; Balaji C: Multi-parameter estimation in combined conductione radiation from a plane parallel participating medium using genetic algorithms, International Journal of Heat and Mass Transfer 50, 1706-1714., 2007

[5] Kim K.W.; S.W. Baek: Inverse surface radiation analysis in an axisymmetric cylindrical enclosure using a hybrid genetic algorithm, Numerical Heat Transfer Part A e Applications 46 (4) 367-381., 2004

[6] Felde I.: Estimation of Thermal Boundary Conditions by Gradient Based and Genetic Algorythms, MATERIALS SCIENCE FORUM 729: pp. 144-149. (2012)

[7] Ardakani M.D.; Khodadad M.: Identification of thermal conductivity and the shape of an inclusion using the boundary elements method and the particle swarm optimization algorithm, Inverse Problems in Science and Engineering 17 (7), 855-870., 2009

[8] Qi H.; Ruan L.M; Shi ; An W.; Tan H.P.: Application of multi-phase particle Swarm Optimization Technique to inverse radiation problem, Journal of Quantitative Spectroscopy & Radiative Heat Transfer 109, 476–493. 2008

[9] Vakili S.; Gadala M.S.: Effectiveness and efficiency of Particle Swarm Optimization technique in inverse heat conduction analysis, Numerical Heat Transfer Part B: Fundamentals 56 (2), 119–141., 2009

[10] Kennedy J.; Eberhart R.C.: Particle Swarm Optimization, in: Proceedings of the IEEE International Conference on Neural Networks, 1942–1948. , 1995

[11] Clerc M.: The swarm and the queen: Towards a deterministic and adaptive Particle Swarm Optimization, in: Proceedings of the Congress on Evolutionary Computation, 1951–1957., 1999

[12] Szénási S.; Felde I.; Kovács I.: Solving One-dimensional IHCP with Particle Swarm Optimization using Graphics Accelerators, Proceedings of the 10th IEEE International Symposium on Applied Computational Intelligence and Informatics, Timisoara, Románia, 365-369., 2015

[13] Kirk D. B.; Hwu W. W.: Programming Massively Parallel Processors: A Hands-on Approach, 1st ed. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2010.

[14] M.N. Özisik, H.R.B. Orlande, Inverse Heat Transfer: Fundamentals and Applications, Taylor & Francis, New York, 2000Downey, D. F. *et al.*, Ion Implantation Technology, Prentice-Hall (New York, 1993), pp. 65-67. [A book reference …]