Application of Genetic Algorithm for Evaluation of Quenching Test by Inverse Task with Unknown Time Constant of Sensor

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Abstract

The rapidly growing need for defining and solving inverse problems has become apparent during the last two decades in industrial and academic engineering. Simultaneously with the development of traditional deterministic methods, new approaches based on methodology from artificial intelligence appear to have overcome some the limitations of deterministic methods. In this paper, an application of a genetic algorithm to solve an Inverse Heat Conduction Problem (IHCP) is presented. First, a number of numerical tests have been performed and the results used as a the basis for understanding how to set up a genetic algorithm for solving such a difficult problem in the shortest possible time. In the second step, the genetic algorithm which had been set up was applied to the evaluation of a quenching test in the area of continuous casting. The results presented confirm that the genetic algorithm determined the heat transfer coefficient (HTC) history and the sensor time constant with a satisfactory level of accuracy and are thus promising for future applications of genetic algorithms in inverse problems.

1 Introduction

Genetic algorithms are receiving increased attention in the difficult problems of search optimization and machine learning, and the list of successful solutions has increased considerably in recent years, Goldberg [4]. Such complex problems undoubtedly include inverse tasks. The multi-disciplinary filed of inverse problems has become on of great interest to many researchers and engineers in various fields of science and engineering. In recent years, in order to overcome some of the limitations of deterministic methods, research interest has focused on different approaches, which are based on the methods of artificial intelligence. One can find applications of Evolutionary algorithms, Expert systems as well as Neural networks, Dumek [2].

In this paper, we present the application of GAs to one typical engineering problem, i.e. the inverse determination of boundary conditions in heat transfer problems. Beck defined two major groups of inverse problems, Beck [3]: parameter-specification and functional-specification. In this problem, thermal material parameters such as thermal conductivity, thermal capacity and density can be considered to be unknown in the first group. For the second group, it is normal to search for a heat transfer coefficient history or the surface heat flux history. In this paper, a search for an unknown heat transfer coefficient history, based on the given observation of the temperature history at one of the interior points of a steel plate is presented. In addition, the actual time constant of the thermocouple used for the temperature history measurements has to be identified.

In regards to problem definition, GA has been found to be a promising approach to overcome some of the limitations of the deterministic methods, which are normally used. As a stochastic, large-memory dynamic system, which enables solutions to 'evolve' based on the principle of 'survival of the best', genetic algorithms can be used to operate on potentially stochastic, non-stationary problems of infinite variety, and high dimension and complexity, Goldberg [1]. Because of that, GAs or other evolutionary algorithms can reliably solve a range of inverse problems with sufficient accuracy and speed, or at least can be involved in the solution when combined with other techniques. Thus, the results presented may inspire or help in solving a variety of problems in diverse areas of inverse problematics.

We start by defining the problem to be solved and briefly reviewing the principles and modifications of GAs. We continue by describing the numerical test and discussing the final results with regard to GA setup. Theoretical predictions and empirical results are then used for a practical evaluation of the quenching test in the area of continuous casting. The paper concludes by discussing the advantages and limitations of the approach used and by outlining a further research focus.

2 The inverse heat conduction problem

Following the generally considered definition of inverse problems, the inverse heat conduction problem can be specified as the determination of unknown surface boundary conditions based on internaly measured temperature histories.

In other words: given the one-dimensional heat conduction equation, constant, known coefficients and a complete description of the action at one end of the domain and measurements of the temperatures at some known location inside the domain, determine the unknown action at the second boundary, Krejsa [4]. Specifically, we have to determine the heat transfer coefficient history, and in addition, the actual time constant of the thermocouple used for the temperature history measurements. The actual time constant in a given experiment can be quite different from the time constant indicated by the thermocouple producer and has to be considered as an inherent parameter of the experiment arrangement.

The mathematical model describing the physical behavior of the system considering a one-dimensional problem can be covered by the partial differential equation:

$$\frac{\partial^2 T}{\partial x^2} = \frac{1}{a}\frac{\partial T}{\partial t} \quad , \tag{1}$$

where T is temperature, x the spatial coordinates, a the thermal diffusity and t time.

To solve Eg.1, one has to know the initial temperature field and the boundary conditions involved in the equation:

$$h_{(0,t)}(T_{0,t} - T_{\infty,t}) = -k\frac{\partial T}{\partial x}\Big|_{0,t} = f(t) \quad , \tag{2}$$

where the time dependent boundary conditions are imposed on the surface of the body in $x=0$ and the surface in $x=1$ is adiabatic. The HTC is introduced by h and k denotes thermal conductivity. The boundary conditions are described by the ambient temperature T_∞ and the heat transfer coefficient. The ambient temperature is known and the HTC history has to be found by the inverse task.

As already stated, the unknown sensor time constant has to be incorporated into the inverse task as well. The dynamic behavior of thermocouple can be described as follows:

$$\frac{dY_t}{dt} = \frac{h_m A}{\rho c_p V}(T_m - Y_t) = \frac{1}{\tau}(T_m - Y_t) \quad , \tag{3}$$

where Y_t represents the temperature readings of the thermocouple, h_m is the contact heat transfer coefficient, A is the surface area, V is the volume, ρ is the density and c_p the specific heat. T_m denotes the temperature of the material in sensor location and τ is the time constant of the thermocouple.

Apparently, introducing the sensor time constant into the parameters and functions to be found, makes the already quite difficult inverse problem even more complicated.

While the computation of the direct task (temperature fields) is routine, solving the inverse problem deals with a ill-posed unstable problem. Thus, all IHCP approaches must be concerned with the stability question.

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3 Genetic Algorithms

GAs have become widely used random search strategies, which use partially random methods to 'evolve' solutions to optimal or near-optimal ones. GAs are one of the techniques which deal with a group of solutions called a population. This search strategy allows for the generation of a new population in each particular step. This population is better or at a minimum not worse than the previous generations. The composition of a population in a particular generation depends on probabilities of the population of the previous generations. To obtain such a new population, a couple of operators such as crossover and mutation are applied to selected solutions. The selection procedure distinguishes between good and bad solutions based on an objective function that returns a numerical value representing fitness.

Thus, the backbone of a genetic algorithm is the selection procedure and crossover and mutation operators. The crossover swaps some elements (genes) between individuals and mutation changes some of them at random to explore solutions other than those which have been presented. However, these operators are limited in their abilities to explore the solution space. Since, after a greater number of new generations, the population is composed of nearly identical individuals, the crossover yields individuals similar or identical to the parent strings. Apparently the crossover cannot reintroduce the needed diversity to the population of solutions, Goldberg [1]. In such a situation, only mutation can reintroduce diversity, which can potentially explore the full solution space. One the other hand, a mutation range which is too high can lead to a more random search procedure which is of very little use in solving difficult problems in the shortest possible time. By introducing a mutation range which is too narrow at the beginning of the run, GA can only operate on a small part of the solution space and remains at a local optima for a long time.

To decrease this limitation, a scheduled decreasing of the mutation range is incorporated in the GA along with the mutation operator. Assuming real-value strings (individuals) in the population, GA starts with a high mutation range covering 100 % of the search space and decreases this range following a given schedule during the generating of new populations. Different types of schedules can be used depending on the problem. We have used the simple linear schedule, lowering the range upon the number of repeated non-changed best fitness in following generations. The described property of GA to focus on a particular part of the search space according to the actual stage and results of the search can be understood as an adaptive behavior and so an adaptive genetic algorithm (AGA).

GA used in this particular application for IHCP proceeds as follows. First, let X be a vector of the inputs to the system and let H be the transfer function that produces a vector of the outputs $Y=H(X)$. Second, let H^{-1} be the inverse transfer function $X=H^{-1}(Y)$. To solve the inverse problems usually means either finding the inverse transfer function H^{-1} or searching for an input vector X that gives a known output vector Y, $Y=H(X)$. Herein a GA is used to find such input vector X fitting the best to a given $Y_G=H(X)$. Given a population P composed of a set of instances of genetic strings S and a mapping M that describes the predefinied context of the input vector X_i and genetic strings S_i so that the computed response vector Y_c is:

$$Y_{Ci} = H(X_i), \quad X_i = M(S_i), \quad S_i \in P \tag{4}$$

Given a desired value Y_G and a fitness function f ,which evaluates the differences between the computed solution Y_{ci} and the desired values Y_{gi}. Then the fitness functions can be defined as follows:

$$f = -\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{Ci} - Y_{Gi})^2} \quad , \tag{5}$$

where N is the number of the elements of vector Y_{Ci}, resp. Y_{Gi}.

Using the above definition GA starts by mapping M that maps genetic strings S to input vectors X and setting all elements of the genetic strings to the initial random values. Then GA repeats following steps:

1. Computation of the response vector Y_{ci} and evaluation of the fitness function for each individual S_i of the population P.
2. Selection procedure, which in our simplest way, assigns each individual S_i either to the group of good solutions or to the group of the bad solutions.
3. Substitution of bad individuals with new individuals generated probabilistically using crossover and mutation operators. Crossover allows the swapping of two randomly chosen parents from the group of good solutions at any number of points and positions. Mutation operator substitute randomly chosen newly generated elements of individuals by new values g_i according to the mutation range. The mutation range is gradually decreased following the linear schedule:

$$g_i \in \begin{cases} < R_{Li}; R_{Hi} > & i_N < I_{\max} \\ < R_{Li} + s; R_{Hi} - s > & i_N \geq I_{\max} \end{cases} \quad , \tag{6}$$

where R_{Li} , resp. R_{Hi} is the lower resp. upper range boundary. i_N represents the actual number of repeated non-changed fitness in following generations. I_{max} introduces he highest value of i_N , when the range is decreased by the reduction number s.

Steps 1,2 and 3 are then repeated until a acceptable solution is find.

4 Numerical tests

The effective convergence of GAs can be affected seriously by different approaches with different selection procedures and crossover and mutation operators. Thus first, the laboratory quenching test was simplified a little bit and simulated numerically in a number of numerical tests, incorporated into the GA. The results obtained were used as a prior knowledge of how to set up a final genetic algorithm to evaluate the real quenching test later in the shortest time.

In these simulation studies, the steel plate was uniformly heated to an initial temperature of 1 (-). The body was cooled in $x=0$ and the surface in $x=1$ was adiabatic. The ambient temperature was known. Assuming the thermocouple with known time constant, placed inside the plate ($x=0.3$), and the distribution of

HTC is known, one can easily compute the temperature history by a numerical method. In our case, the unknown time constant was set to 2 s and the HTC history was sinusoidal to compute the desired temperature history in the time period of 12 time steps. The temperature field (Fig.1) derived by Eq.3 was obtained by 1D direct task based on the control volume method. In the simulated inverse task, the time constant is unknown and varies in range 0-5 s. The unknown HTC varies from 0 to 20000 W/m^{2}K.

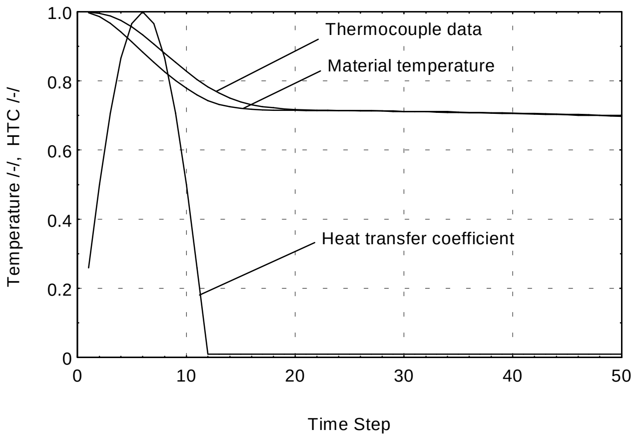

Figure 1: Inputs and outputs of 1D direct task.

Using the mathematical denomination, the input vector X contains the first 11 time step values of HTC and the thermocouple time constant t. The response vector Y contains 50 values of the temperature T. The transfer function H, $Y=H(X)$ is the solution of the Fourier partial differential equations of the heat conduction. The vector Y_G is obtained by numerical simulations as the pattern temperatures $T_{m.}$ The inverse task is defined to find X_{opt}, which suits to the equation $Y_G=H(X_{opt})$. Hence, GAs explore the search space to find such a vector X that produces the response Y_G , for which the fitness function f (Eq.5) reaches the global maximum.

After couple of computational experiments with various GAs population sizes, a population of 32 genetic strings of 12 genes each (11 for HTC, 1 for the time constant) was used and initial values of the vector X were chosen at random from a given range. The range for HTC varying from 0 to 20000 and for the time constant from 0 to 5 were mapped using the linear M function to range from 0 to 1000.

In order to prevent oscillations of the heat transfer coef. history, which appeared in the first experiments, the following simple smooth condition f_s was incorporated into the final fitness function:

$$f_s = -\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(\frac{x_i + x_{i+2}}{2} - x_{i+1}\right)^2} \tag{7}$$

To deal with this multiple objectives a simple approach based on a linear combination (weighted sum) of multiple attributes was used. Then the final fitness function can be expressed as:

$$f = -\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{Ci} - Y_{Gi})^2} \; - \alpha\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(\frac{x_i + x_{i+2}}{2} - x_{i+1}\right)^2} \quad , \qquad (8)$$

where α represents the weight for the linear combination of attributes values. Figure 2 shows tree typical HTC curves, each founded by GA for a different weight of α. As one can see, the best results were obtained for α =0.02.

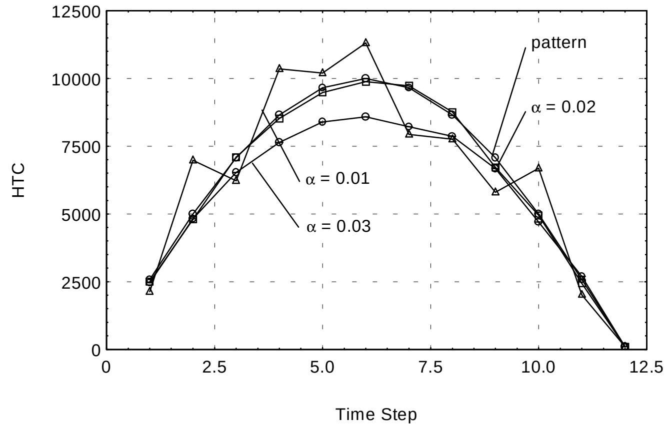

Figure 2: Influence of differently weighted smouth condition on HTC curves.

Further experiments were focused mainly on the scheduled decreasing of the mutation range. As expected, the different types of schedules seriously affect the speed of convergence. In the chosen simple way, GA decreases the mutation range of each parameter by a constant value s in the time instance, when a number of repeated non-changed best fitness i_N in following generations achieve a given value I_{max}..

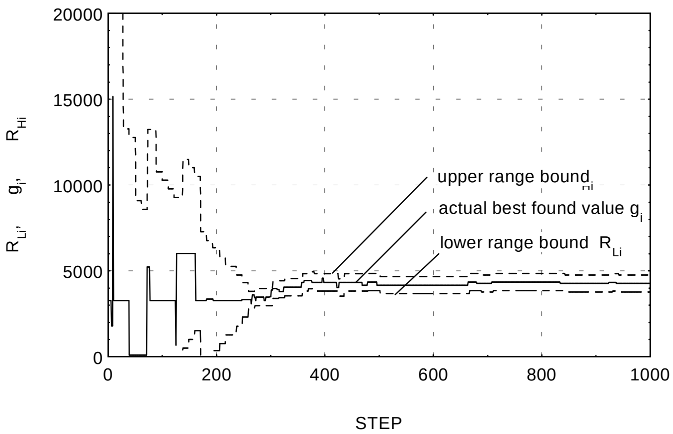

Figure 3: Scheduled decreasing of the mutation range of one of the parametrs.

In Fig.3 one can see an example of the scheduled decreasing of the range of one parameter. Moreover, one can recognize the movement of range following the best found solution.

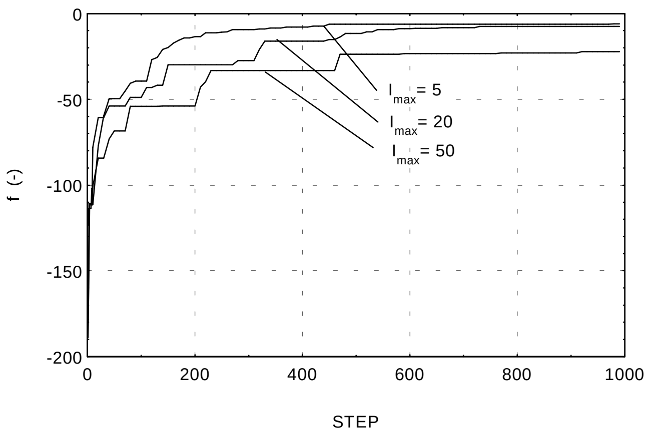

Figure 4: The influence of the setting I_{max} on the convergence speed.

The influence of the setting I_{max} on the convergence speed is demonstrated in Fig.4. One can see, that the lower I_{max} is used, the faster GA converge to the global optima. On the other hand, too small a value I_{max} simultaneously with too small a value s can fix the GA at a local maxima.

5 Quenching test

Theoretical predictions and empirical results leading to the final set up of the GA described in previous sections, were used for the practical evaluation of the quenching test in the area of the continuous casting. The process of continuous casting was simplified to enable us to perform experimental studies of the process using experimental devices in our lab. Regardless of the process simplifications, the results obtained from the experimental studies with emphasis on the heat transfer process were reliable and useful for evaluation of such a test by the inverse task.

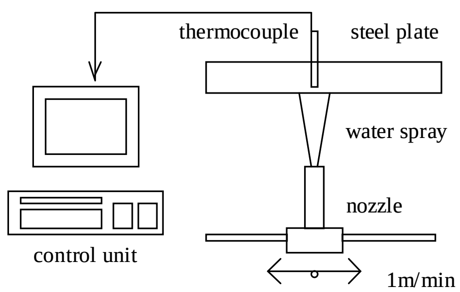

Figure 5: Experimental apparatus.

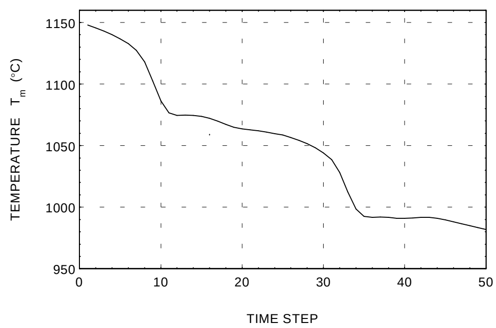

Figure 6: Measured temperature history.

The arrangement of the experimental apparatus is shown in Fig.5. The steel plate embedded with thermocouples is uniformly heated to an initial temperature of 1150°C and the water cooling nozzle is set to the initial position at the left side of the plate. The procedure of the experiment starts by opening of the cooling nozzle and moving the spraying nozzle under the plate at a constant distance and constant velocity of 1 $m.min^{-1}$. When the nozzle reaches the right side of the plate, the spraying is closed and the nozzle moves back to the initial position and again repeats the cooling process. The temperature history in the measured point in duration of 100 seconds using the 2 seconds time step is given in Fig.6.

This temperature history was used as the pattern temperatures T_m in the inverse task. Instead of the 11 unknown values of the HTC history in previous numerical test, 50 unknown values of the heat transfer coefficient had to be found to evaluate this quenching test. The higher number of unknown values makes the problem more difficult for the GA. Nonetheless, the GA was able to converge to a global or near-global optima. The resulting heat transfer history presented in Fig.7 satisfies well given requirements for the evaluation of such a test. The minimized average distance between the pattern temperatures T_m and the temperatures computed using the found HTC history by the GA was less then +/- 1 degree Celsius.

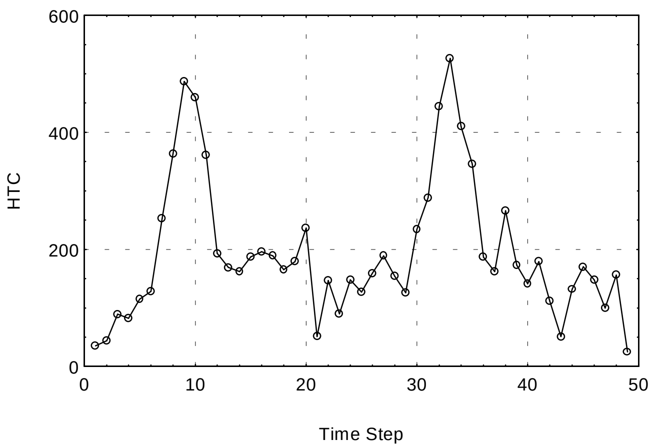

Figure 7: The resulting heat transfer history.

The real time constant was near zero, and so at the lower end of the search range, what is different comparatively with the numerical tests. The reason for that comes from the physical background of the heat transfer process resulting in only slight differences between the temperatures in the case of a small time constant of the thermocouple. Despite that, the GA converged reliably to a zero value of the time constant and the simultaneous identification of the thermocouple time constant in the quenching test can be also considered to be successful.

6 Conclusions

Although the GAs like any algorithms that includes a random element can be treated with suspicion by those, who wish to understand the solution procedure, they are of a real benefit in solving of highly complex problems, where the limitations of the traditional approaches cannot be easily overcome. One of these complex problems is undoubtedly also the inverse heat transfer problem demonstrated in the numerical and following quenching test. Despite the use of a simple type of GA, the resulting heat transfer coefficient histories and the time constants of thermocouple well satisfies the given requirements. The successful application was demonstrated in the numerical tests, and in addition verified using experimental data obtained from the quenching test. Further investigations will be focused on other mechanisms and methods such as a different selection procedure or scheduled decreasing of the mutation range, which may help improve convergence, Goldberg [5]. Besides the general methods used to speed up the simple GA, a different approaches to deal with the multiple objectives based on the niching mechanism, Horn [6], can be also introduced in the GA in the future.

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Key words: genetic algorithm, heat transfer, inverse problem

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