Approximation of Heat Transfer Coefficients by using AI techniques

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The knowledge of the heat transfer coefficient plays a crucial role in evaluating coolants utilized for immersion quenching of steels. This coefficient effectively characterizes the heat exchange occurring between the immersed workpiece and the liquid coolant. The calculation of the heat transfer coefficient involves solving an inverse heat transfer problem, typically addressed using stochastic optimization algorithms. These algorithms rely on iterative processes and are computationally intensive, often requiring hundreds or even thousands of iterations to obtain a solution. To alleviate the computational burden, this paper introduces an initialization technique based on a non-iterative approach for solving the inverse heat transfer problem. The proposed method utilizes an artificial neural network to solve the problem. Specifically, a multi-layer feedforward neural network is utilized, trained using the backpropagation algorithm. In order to train the network, a synthetic database containing 150,000 records of heat transfer coefficients is created. The coefficient is determined as a function of temperature, with an unconventional utilization of the Fourier transform of the cooling curve as input for the inference system. Furthermore, the performance of the neural network is compared with other conventional learning algorithms. It is observed that when combined with stochastic algorithms, the network achieves comparable solutions in a shorter timeframe.

Keywords: *inverse heat conduction, immersion quenching, heat transfer coefficient, mlp, afwa*

1. Introduction

In the industrial sector, the post-production process of steel and alloys involves subjecting them to a heat treatment regimen. This entails heating the workpiece to a specified temperature and maintaining it at that temperature until the desired structural transformation occurs within the material. Subsequently, controlled cooling is applied to the workpiece. The primary objective of this process[1)] is to enhance the mechanical, physical, and chemical properties of the product by inducing structural changes. In heat treatment programs, precise control of the cooling rate is crucial, as it directly influences the resulting structures. The heat transfer coefficient governs the rate at which the coolant effectively dissipates heat from the workpiece. The complexity of fluid dynamics and mechanical flow during the cooling process affects the magnitude of this coefficient. Consequently, determining the coefficient necessitates a combination of technical examinations, experimental measurements, and theoretical calculations. Previous studies[2-3)] have demonstrated the feasibility of approximating the heat transfer coefficient by employing inverse methods and utilizing measurements. However, bio-inspired heuristic algorithms utilized for this purpose exhibit a high level of predictability, these algorithms are computationally intensive, often requiring over 10 hours to complete. Additionally, prior to initiating these calculations, the user must specify the locations at which the nominal functions, derived from measurements, are to be compared with the functions obtained from the inverse algorithm. Failure to set these points correctly may result in incomprehensible outcomes that are only evident after several hours of simulation. To mitigate unnecessary and erroneous simulations, it is desirable to develop a rapid estimation method that can provide users with nearly instantaneous feedback on the results. Moreover, this method can be executed even before using bio-inspired heuristic algorithms, allowing successful heuristics to be initiated based on the initial estimation. The aim of this research is to develop a method that is suitable for approximating the heat transfer coefficient function in an environment where accuracy is not that important, but the speed is in focus. Application of the method is, for example, incorporation into a hybrid algorithm. In previous research, the application of deep neural networks has already been demonstrated to be efficient in solving complex problems, such as assessment and disease diagnosis[5-6)]. This precedent underscores the suitability of employing a neural network to address the present heat transfer coefficient approximation problem.

2. Methodology

2.1 Heat transfer model

As part of the numerical method a heat transfer model was applied, which is described by the following differential equation, assuming central-symmetric heat transfer conditions for a cylinder with finite length of L:

$$\nabla \cdot (\lambda(\boldsymbol{r}, T) \cdot \nabla T) + Q(T, \boldsymbol{r}, t) = C_p(\boldsymbol{r}, T)\rho(\boldsymbol{r}, T) \cdot \frac{\partial T}{\partial t} \quad (1)$$

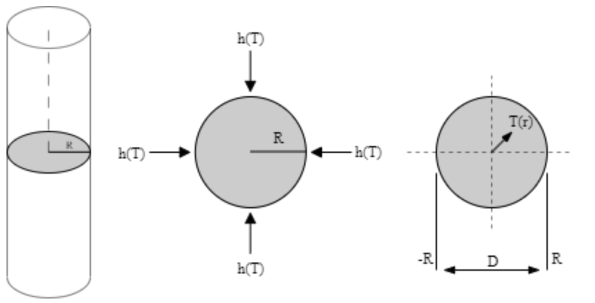
where r is the coordinate along the radius, t is time, T is temperature, λ is thermal conductivity, C_p is heat capacity, ρ is density, Q is latent heat (its value is zero during the entire heat transfer process). The initial condition is described by the following equation:

$$T(\boldsymbol{r}, t=0) = T_a(\boldsymbol{r}) \quad (2)$$

where T_a is the initial temperature of the domain. The boundary conditions are described by the following equations:

$$\begin{aligned} -\lambda \frac{\partial T}{\partial r} &= h_1(T)(T(\boldsymbol{r}, t) - T_{am}) \\ &\cdots \\ -\lambda \frac{\partial T}{\partial r} &= h_p(T)(T(\boldsymbol{r}, t) - T_{am}) \end{aligned} \quad (3)$$

where T_{am} is the coolant temperature, h_i is i. heat transfer coefficient for the rim.



1. Figure - Axismmetric cylindrical geometry

The edges of the cylinder are marked as Γ, and the conditions $\Gamma_1 \cup \Gamma_2 \cup .. \Gamma_p = \Gamma$ and $\Gamma_1 \cap \Gamma_2 \cap .. \Gamma_p = \emptyset$ hold true for these edges. Each edge Γ possesses a temperature-dependent heat transfer coefficient $h_i(T)$. The heat transfer coefficient function is implemented using (T, h) data pairs, with the coefficient value determined through linear interpolation between the points. In the case of an axisymmetric cylinder, three edges are considered: the curved surface and the two bases, as depicted in Figure 1. However, if the heat transfer calculations are limited to the inner circle of an infinitely long cylinder, only the curved surface edge remains. Consequently, in this study, one-dimensional heat transfer analysis is performed, with a single edge defined at the coordinate *r=R*. The temperature distribution along the radius is calculated at *Nx* points. To solve the differential equation, the Smith's[7)] explicit finite difference method is employed.

2.2 Inverse Heat Conduction Problem

The specimen's temperature was measured at p points within the boundary. Following the thermal field calculation, T_i^C is obtained and utilized to compute the difference between T_i^C and T_i^M as defined in ¥ref{eq:cost}. equation. The solution to the inverse heat conduction problem[7)] can be achieved by minimizing this objective function.

$$S = \sum_{i=1}^{p} (T_i^C - T_i^M)^2 \quad (4)$$

2.3 Initialization strategy

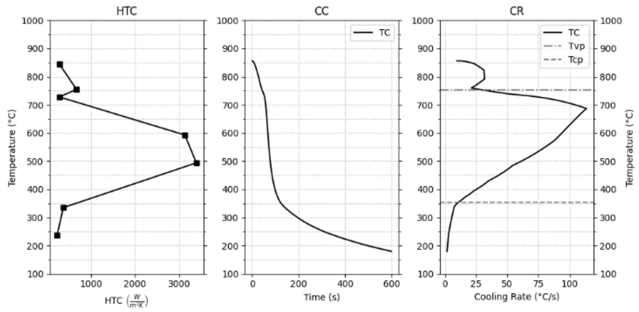
A robust optimization method is recommended to solve the inverse problem, ensuring avoidance of local extreme values. Bio-inspired heuristic algorithms[3-4)] are well-suited for this purpose. By exploring global extreme values at multiple calculation points instead of a single point, these algorithms prevent getting trapped in local optima. In a previous study, the author[8)] used the Adaptive Fireworks Algorithm (AFWA), a variant of the Fireworks Algorithm, to address this specific problem. Computational efficiency comparisons were made between AFWA and the Genetic Algorithm. Numerical tests demonstrated that AFWA can estimate heat transfer coefficients; however, it exhibits significant computational intensity. When dealing with a higher number of dimensions, obtaining results from AFWA can take several hours. To mitigate this weakness, learning algorithms offer a viable solution as they do not operate iteratively. For instance, artificial neural networks, which fall under the category of learning algorithms, require considerable training time (the iterative phase); however, once the model is trained, heat transfer coefficient estimations can be quickly obtained. Although the accuracy may not be on par with swarm-based algorithms, leveraging these initial results can significantly reduce the overall running time. This approach is referred to as an initialization strategy, and it allows for the creation of hybrid methods by combining learning algorithms with swarm-based optimization algorithms.

2.4 Artificial Neural Network

The Universal Approximation Theorem[9)] states that any function can be approximated with an artificial neural network with the appropriate number of neurons. An artificial neural network is a learning-based model that (partially) mimics the biological processes of the human brain. It has already been demonstrated in previous research[10)] that the artificial neural network can be used to solve the inverse heat transfer problem. The utilized model is a feed-forward artificial neural network. Each neuron in a layer is connected to all neurons in the adjacent layers. The input layer of the model consists of 15 neurons, corresponding to the number of Fourier coefficients, while the output layer comprises 14 neurons, representing the control points of the heat transfer coefficient. A total of 14 (T, HTC) data pairs are used, resulting in the derivation of 7 control points. The network incorporates a single hidden layer, consisting of 100 neurons. Sigmoid activation functions are applied to the neurons in the hidden layer, while the input and output layers use linear activation functions.

2.5 Dataset

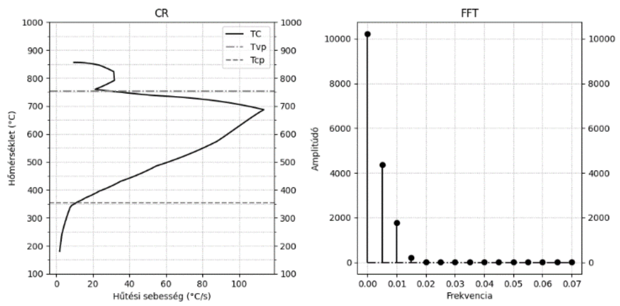
The dataset was generated by recording the cooling curve of a 12.5 mm diameter cylinder composed of Inconel 600 alloy at a specific location along the axis during immersion hardening. For the purpose of heat transfer analysis, a one-dimensional heat transfer assumption is made, considering the cylinder to have infinite length, which will be simulated later. Subsequently, the heat transfer coefficient functions were reconstructed using a well-established Inverse Heat Conduction Problem (IHCP) algorithm. The heat transfer coefficient functions were encoded with 7 control points, representing the (temperature - HTC) pairs. By averaging the heat transfer coefficient functions, a single average heat transfer coefficient function was obtained. To introduce variability, 150,000 heat transfer coefficient functions were randomly generated around the control points of the mean function, with a standard deviation.



2. Figure - Generated heat transfer coefficient and the associated drop curve and its derivative

2.6 Preprocessing

The data preprocessing steps were carried out during the dataset creation process. The first step involved numerically deriving the cooling curve, resulting in the CR cooling rate. To determine the Tvp and Tcp points that define the source section, the cooling curve was analyzed. By identifying the maximum point and subsequently moving left and right until reaching the inflection points, the Tvp and Tcp points were determined. In the second preprocessing step, the Tvp - Tcp range of the cooling curve was isolated for further analysis, and this range was saved as CR_TvpTcp in a file.



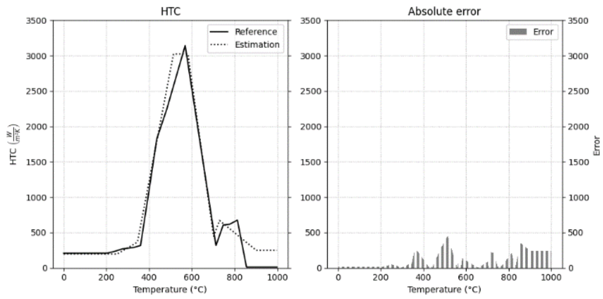
3. Figure - Fourier transformed applied on Cooling Rate

The final preprocessing step aimed to remove the time dependency of the cooling curve. This was achieved by transforming the cooling curve into the frequency domain using the Fourier transformation. By encoding the curve with its Fourier coefficients, the cooling curve could be represented with significantly fewer numbers. This process was applied to the CR_TvpTcp curve, as depicted in Figure 3. where the negative range was omitted due to symmetry. The one-dimensional discrete Fast Fourier Transformation algorithm was utilized to perform the Fourier transform on the CR_TvpTcp curve.

2.7 Evaluation

2.7.1 Result

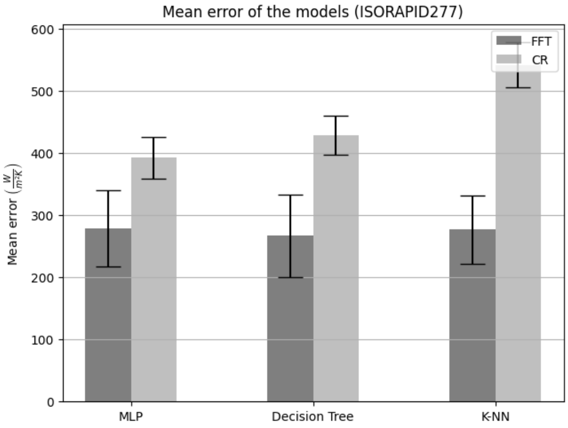
Upon completion of pre-processing, the heat transfer coefficient was estimated using a trained feed-forward artificial neural network (MLP). It should be noted that the expected output heat transfer coefficient of the test dataset is encoded with 32 control points, whereas the MLP can estimate only 7 control points. Hence, a direct comparison between the two is not feasible. To enable comparison, the heat transfer values in the temperature range of 0-1000 °C were calculated via linear interpolation between the control points of both HTC functions. Subsequently, the two functions were compared at 1000 temperature points, with the absolute error between them computed and presented in the right side of Figure 4. On the left side of the figure, the two HTCs are depicted. It can be observed that the maximum error does not exceed 500. While it is challenging for a function encoded with 7 points to precisely approximate the original function encoded with 32 points, the MLP model provides a suitable approximation from which another optimization algorithm can be initiated. Furthermore, by increasing the number of search dimensions, additional control points can be interpolated between the existing ones, facilitating a closer approximation to the original function. Additionally, it is worth noting that the MLP achieved a satisfactory estimate of the function within 1 second, whereas an iterative optimization algorithm would have required thousands of iterations to achieve a comparable result.



4. Figure - Estimation

2.7.2 Comparison with conventional learning algorithms

The performance evaluation of the algorithms was conducted using average error and standard deviation metrics. The average error and standard deviation were calculated for all the curves in the test dataset. The results, including the average error and error standard deviation, are presented in Figure 5. The artificial neural network is denoted as MLP, the decision tree as Decision Tree[11)] and the K-nearest neighbors algorithm[12)] as K-NN. The heat transfer coefficient was estimated using each model with the preprocessed data as described earlier. Additionally, to demonstrate the importance of preprocessing, the heat transfer coefficient was estimated based solely on the cooling rate and without any preprocessing. The average error of the estimates made on preprocessed inputs is indicated with the label FFT, while the error of the estimate based on the unprocessed cooling rate is indicated with the label CR.

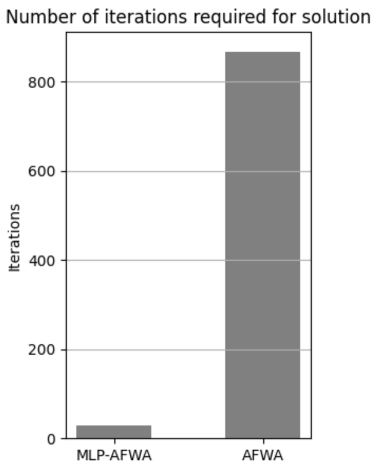


5. Figure - Comparison of learning algorithms

From the figure, it is evident that the learning algorithms achieve significantly improved performance with Fourier transformed data, with the average error of the FFT models being nearly half compared to the CR models. Furthermore, the diagram reveals that MLP, Decision Tree, and K-NN yield similar estimation results, exhibiting almost identical error levels. Consequently, it can be inferred that all three learning algorithms can be utilized interchangeably for heat transfer coefficient estimation.

2.7.3 Hybrid solution

In the first scenario, the presented initialization strategy was employed, where the heat transfer coefficient function was approximated using an artificial neural network. Subsequently, the Adaptive Fireworks Algorithm (AFWA) was initialized based on the obtained approximation. The search was initiated from these points, considering the swarm-based nature of AFWA. To prevent the algorithm from converging to a single point, the points were initialized around the approximation.



6. Figure - Number of total iterations

In the second scenario, AFWA was executed independently without the neural network initialization. The results of both optimizations are displayed in Figure 6. Both methods were terminated based on the same stopping condition. It is noteworthy that the AFWA initialized with MLP required only 28 iterations to reach the solution, whereas the standalone AFWA necessitated over 900 iterations to achieve the same outcome. Consequently, employing this hybrid approach significantly reduces the optimization runtime, as demonstrated by the results.

2.8 Conclusion

The aim of this research was to develop a robust method for estimating the heat transfer coefficient using an artificial neural network, specifically designed for time-independent analysis in a one-dimensional heat transfer domain. To train the neural network, a dataset comprising 150,000 records was generated based on filtered measurements using predefined rules. Prior to training, the dataset was Fourier transformed to transition the data from the time domain to the frequency domain. This preprocessing step ensured that the trained network was not reliant on the duration of the entire cooling process. The network was then trained on this preprocessed dataset and validated using a separate test dataset. The Fourier transform of the trained artificial neural network enabled the estimation of the heat transfer coefficient function from the cooling curve. Additionally, estimations were performed on unprocessed cooling curves and with alternative learning algorithms such as Decision Trees and K-nearest neighbors. Results indicated that superior estimations could be achieved using Fourier transformed inputs, and all the considered learning algorithms could perform the estimation. Thus, each model can be utilized within the initialization strategy. Subsequently, a heat transfer coefficient function was reconstructed using the Adaptive Fireworks Algorithm. The initial points of the algorithm were initialized based on the results obtained from the artificial neural network. The algorithm was then executed independently. Notably, the network-initialized optimization required significantly fewer iterations to converge to the same solution. It is important to note that the network estimation is applicable exclusively to one-dimensional heat transfer models but has the potential for extension to two-dimensional models.

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