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Energy Conversion and Management 47 (2006) 2361–2370

ENERGY CONVERSION & MANAGEMENT

www.elsevier.com/locate/enconman

Predictions of temperature distributions on layered metal plates using artificial neural networks

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Received 7 June 2005; accepted 28 November 2005

Abstract

The temperature distribution influences the amount of energy needed to heat a body. The benefits of using multi-layered metal plates (MMP) are due to the requirement of a regular temperature distribution on the opposite side with one side heated irregularly. The factors that affect the regular distribution of the temperature in such a structure are the thickness of the layers and the materials themselves, since for different materials, heat conduction coefficients, density and specific heat values change.

In this study, the main objective is to find a neural network solution for the problem of the non-regular distribution of temperature on the non-heated side of an irregularly heated MMP consisting of two layers of Cu/CrNi and Al/CrNi in order to obtain the optimum thickness levels for the layers. To achieve this aim, the results of the finite elements method (FEM) produced by the program package ANSYS have been used to train and test the network. They are the coefficient of heat conduction (K), specific heat (C), density (D), temperature (T) and layer thickness (L), which are used as the input layer, while the outputs are the maximum, minimum and mean temperature values of the materials.

The back propagation learning algorithm with three different variants, single layer and logistic sigmoid transfer function have been used in the network. By using the weights of the network, formulations have been given for each output. The network has yielded R^2 values of 0.999 and the mean percent errors are smaller than 0.8 for the training data, while the R^2 values are about 0.999 and the mean percent errors are smaller than 0.7 for the test data. The analysis has been extended for different materials and for the different temperature values that have been applied. The Al/CrNi laminated plate has a lower temperature gradient distribution on the upper (or non-heated) surface due to its lesser heat conductivity compared to the Cu/CrNi steel. The thickness of 8 mm provides the best results among the alloys that have been considered.

Keywords: Artificial neural network; Heat conduction; Layered plate; Temperature distribution

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0196-8904/$ - see front matter
doi:10.1016/j.enconman.2005.11.023

Nomenclature

ANN	artificial neural network
C	specific heat (kJ/kg K)
D	density (kg/m^3)
K	thermal conductivity coefficient (W/m K)
L	layer thickness (mm)
LM	Levenberg–Marquardt
MMP	multi-layered metal plate
R^2	fraction of variance
RMS	root mean square
SCG	scaled conjugate gradient
T	temperature (°C)
x, y, z	rectangular coordinates

1. Introduction

MMPs are used in several places. Kitchens are one of the places where we use them daily as the base for saucepans. In the past, they were mainly made of aluminum or pure steel. However, the need to have a uniform distribution inside the saucepan has led to the development of multi-layered bottoms for them. This was mainly due to the requirement for an even distribution of surface temperature during the cooking process.

In the case of multi-layered metal bottoms used in cooking kitchenware, the producers use either copper or aluminum in addition to a CrNi layer. As stated earlier, whether bi-layer or multi-layer, we expect these products to provide a regular temperature distribution at the opposite side even when they are heated irregularly from one side [1,2]. New, composite multi-layered metal structures have been introduced to confirm this expectation [3]. Optimisation techniques to obtain the best possible temperature distribution on such MMPs have also been developed [4].

Because of the fact that different materials behave differently when heated, because of their different heat conduction coefficients, density and specific heat values, in the production stage of multi-layered plates, usually the thickness of the main material (i.e. CrNi) is kept constant, and the thickness of the additional layer (i.e. copper or aluminum) is varied. For the time being, this is a common exercise, and it seems to be the most appropriate solution. This naturally leads to the requirement of several analyses to find the best level of thicknesses for the additional layers. Naturally, this means that several experiments, sometimes based on the trial error method, need to be conducted to find the best thickness level for the additional layer.

As used in several application areas, artificial neural networks (ANN) may also be used in predicting the temperatures of the different materials. For example, in Ref. [5], the authors use an ANN to predict the thermal stress of metal steel bars calculated by the finite element method, while another study [6] focused on estimating the daily and annual temperature variations of soil using ANNs.

In this study, we have used ANSYS to calculate the temperature distributions of highly conductive materials where the heat disperses easily away from the heat source and less conductive materials where the heat does not disperse easily away from the heat source, which are used in such MMP structures. Here, the aim was to determine whether we could train an ANN with a number of thickness levels and afterwards get predictions from it for varying thickness levels of similar materials, thereby saving us from doing several analyses or experiments for different materials and different thickness levels.

The following section provides a mathematical background and preparation of the data used in our analysis. Section 3 concerns the ANN and its data sets, while Section 4 provides the primary results and evaluation of this study. Finally, Section 5 concludes this paper.