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Computational analysis of magnetohydrodynamic natural convection in a square cavity with a thin fin



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HIGHLIGHTS

GRAPHICAL ABSTRACT

- Magnetohydrodynamic laminar natural convection in a square cavity with a fin is examined.
- Three numerical approaches of AN-FIS, ANN and CFD are used in the investigation.
- ANFIS and ANN accurately predict the cavity's thermal performance in less time.
- Magnetic field affects natural convection especially at higher Rayleigh numbers.
- Fin's length and position significantly affect the heat transfer rate of the cavity.

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ABSTRACT

A numerical study of laminar natural convection in a square cavity with a thin fin that is under the influence of a uniform magnetic field is presented. The side walls of the cavity are kept at different temperatures and the horizontal walls are thermally insulated. An Adaptive Network-based Fuzzy Inference System (ANFIS) approach and an Artificial Neural Network (ANN) approach are developed, trained and validated using the results of Computational Fluid Dynamics (CFD) analysis. The effects of pertinent parameters on fluid flow and heat transfer characteristics are studied. Among these parameters are the Rayleigh number ($10^3 \le Ra \le 10^6$), the Hartmann number ($0 \le Ha \le 100$), the position of the thin fin ($0.1 \le Y_p \le 0.9$) and the length of the thin fin ($0 \le L_p \le 0.8$). The results show that ANFIS and ANN can successfully predict the fluid flow and heat transfer behaviour within the cavity in less time without compromising accuracy. In most cases, ANFIS can predict the results more accurately than ANN. © 2014 Elsevier Masson SAS. All rights reserved.

1. Introduction

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http://dx.doi.org/10.1016/j.euromechflu.2014.03.002 0997-7546/© 2014 Elsevier Masson SAS. All rights reserved. There is an increasing level of interest among the researchers in understanding the flow behaviour and the heat transfer mechanism of electrically conducting fluids in cavities that are located Nomenclature

B_0	magnetic field strength
C_n	specific heat, $I \text{ kg}^{-1} \text{ K}^{-1}$
σ	gravitational acceleration m s^{-2}
о На	Hartmann number $(B_0 I_1 \sqrt{\sigma / \rho v})$
k	thermal conductivity $W m^{-1} K^{-1}$
к I	length of the cavity m
	length of the fin m
	length of the fill, in
L_p	dimensionless length of the late set (E_f/L)
N	the number of data in the data set (Eq. (9))
Nu	local Nusselt number
р	fluid pressure, Pa
\overline{p}	modified pressure $(p + \rho_c gy)$
Р	dimensionless pressure $(\overline{p}L^2/\rho\alpha^2)$
Pr	Prandtl number (ν/α)
Ra	Rayleigh number $(g\beta L^3(T_h - T_c)/\nu\alpha)$
S_{n}	dimensionless vertical distance of the fin from the
P	top wall $(1 - Y_P)$
Т	temperature. K
- 11 v	velocity components in x and y directions m s ⁻¹
	dimensionless velocity components (uI/α , vI/α)
0, V V V	Cartesian coordinates m
л, у И-	vertical distance of the fin from the bottom wall m
y _f V V	dimensionless coordinates $(y/L, y/L)$
л, I V	unification of the second sec
••	duppopulation local transformation of the tup thomas the
I p	dimensionless vertical distance of the fin from the
Ip	dimensionless vertical distance of the fin from the bottom wall (y_f/L)
Ip Creation	dimensionless vertical distance of the fin from the bottom wall (y_f/L)
r _p Greek sys	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols
r _p Greek sys	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity. m ² s ⁻¹ (k/oC _n)
r _p Greek sy α	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ $(k/\rho C_p)$ thermal expansion coefficient K^{-1}
r _p Greek sy α β	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ $(k/\rho C_p)$ thermal expansion coefficient, K ⁻¹ duramic viscocity. N c m ⁻²
$Greek system \alpha$ β μ	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ $(k/\rho C_p)$ thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻²
r _p Greek sy α β μ θ	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ $(k/\rho C_p)$ thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$
r _p Greek sys α β μ θ ρ	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³
r _p Greek syn α β μ θ ρ σ	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm
r _p Greek syn α β μ θ ρ σ ν	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ)
r _p Greek syn α β μ θ ρ σ ν ω	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from
r _p Greek syn α β μ θ ρ σ ν ω	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD
r _p Greek syn α β μ θ ρ σ ν ω ω ω	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω
F_p $Greek syn \alpha\beta\mu\theta\rho\sigma\nu\omega\omega_m\omega_p$	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from
F_p $Greek syn \alpha\beta\mu\theta\rho\sigma\nu\omega\omega_m\omega_p$	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN
F_p $Greek syn \alpha\beta\mu\theta\rho\sigma\nu\omega\omega_m\omega_p\psi$	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function
F_p Greek sy. α β μ θ ρ σ ν ω ω ω_m ω_p ψ	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function
r_p $Greek system \alpha\beta\mu\theta\rho\sigma\nu\omega\omega_m\omega_p\psiSubscript$	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function
r_p $Greek system \alpha\beta\mu\theta\rho\sigmav\omega\omega_m\omega_p\psiSubscript$	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function
r _p Greek sy α β μ θ ρ σ ν ω ω ω ω φ Σubscrip	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ (k/ ρC_p) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function ts cold wall
r _p Greek sy α β μ θ ρ σ ν ω ω ω ω φ Σubscrip c f	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function ts cold wall fin
r _p Greek sy α β μ θ ρ σ ν ω ω ω ω ψ Subscrip c f h	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ (k/ ρC_p) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function ts cold wall fin hot wall
r _p Greek sy α β μ θ ρ σ ν ω ω ω ω ω ψ Subscrip c f h m	dimensionless vertical distance of the fin from the bottom wall (y_f/L) mbols thermal diffusivity, m ² s ⁻¹ ($k/\rho C_p$) thermal expansion coefficient, K ⁻¹ dynamic viscosity, N s m ⁻² dimensionless temperature $(T - T_c)/(T_h - T_c)$ density, kg m ⁻³ electrical conductivity, μ S/cm kinematic viscosity, m ² s ⁻¹ (μ/ρ) the calculated value of the parameter obtained from CFD the average of ω the predicted value of the parameter obtained from ANFIS or ANN stream function ts cold wall fin hot wall average

in magnetic fields [1–6]. Information related to this could be applied to many engineering problems, such as those involving the crystal growth in fluids, the metal casting, the fusion reactors and the geothermal energy extractions. The common finding of previous studies in this field is that the convective heat transfer is influenced by the magnetic field. It has also been found that the orientation and the aspect ratio of the cavity, as well as the strength and direction of the magnetic field, all affect the flow and temperature fields [7–12]. These studies have simulated the heat transfer in various geometries using Computational Fluid Dynamics (CFD), which in turn requires long computational times and large memory allocations.

Recently, numerical modelling techniques such as artificial intelligence systems have demonstrated an ability to deal with non-linear engineering problems and to reduce the cost and time of the analysis. An Artificial Neural Network (ANN) system is an information-processing paradigm that operates like a biological nervous system and simulates the neural activities in the human brain [13,14]. ANN simulations generally draw from experimental findings, observations and records of engineering problems. However, some studies reported in the literature use the data obtained from the numerical modellings to train and test the ANN simulations and to expand the numerical results [15,16].

Mahmoud and Ben-Nakhi [17] studied the feasibility of using ANN networks to predict the complete thermal and flow characteristics of natural convection in a portioned cavity. They trained and tested the ANN architectures using the results of CFD simulations. They demonstrated that ANN could accurately predict the natural convection parameters with a significant reduction in the analysis time and effort. Sudhakar et al. [18] also employed ANN to examine the influence of positioning of five discrete heat sources on the wall of a three-dimensional vertical duct in which the heat transfer was due to mixed convection. They used the temperature database, which was developed from CFD simulations, to train the neural network. They concluded that the trained neural network could predict the temperature of the heat sources very accurately; it was also much faster than the CFD analysis. In another study, Ozsunar et al. [19] trained and tested a neural network approach using the results of CFD simulations in order to find suitable thickness levels and materials for a chip subjected to a constant heat power. They concluded that ANN was an efficient and time-saving method compared to the CFD analysis.

ANNs have self-learning and non-linear estimation abilities, but they lack the ability to infer. This means an ANN requires massive quantities of training data, the inputting of which is an intensive and time-consuming process. The Fuzzy Logic Inference System (FIS), on the other hand, is a fast approach to solving fuzzy and uncertain problems. However, it is basically dependent on the experience of experts; it is particularly challenging to produce forecasting results when the information provided is insufficient. The Adaptive Network-Based Fuzzy Inference System (ANFIS) proved to be a robust approach, as it has the superior capabilities of ANN and FIS. It achieves more accurate modelling than the conventional time series and regression methods [20,21].

Varol et al. [22] presented a comparison study of the results of ANN, ANFIS and CFD when analysing the natural convection characteristics in a triangular enclosure. They claimed that ANN and ANFIS were both capable of accurately predicting the flow and thermal behaviour within the enclosure, and that the results obtained from ANFIS were more accurate than ANN. In a similar study, Varol et al. [23] showed that ANFIS could significantly reduce the computation time and memory space required for the analysis of a buoyancy-induced flow field in a triangular enclosure without sacrificing the accuracy of the results.

The present study is motivated by the need to develop a fast and accurate solution for the heat transfer problem in a square cavity with a thin fin that is under the influence of a magnetic field. This study focuses on examining the effects of the length and position of the fin on the heat transfer performance of the cavity by using the ANN and ANFIS techniques. As such, a CFD simulation is carried out and the CFD results are used to train and test the ANN and ANFIS analyses. A comparison study of the accuracy and the computation time of these methods is also presented.

2. Mathematical formulation

Fig. 1 shows the schematic diagram of a two-dimensional square cavity with a thin fin that is considered in this study. The left vertical wall of the cavity is at a relatively high temperature (T_h) ,

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