Chemical and MHD Effects on Mixed Oscillatory Flow Dynamics: A Neural Network Study

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Abstract: - This paper investigates in detail the thermal and chemical effects of an unstable magnetohydrodynamic (MHD) mixed oscillatory flow. The temperature, velocity, and concentration profiles can be investigated in detail by transforming the governing equations into a dimensionless system. These equations are solved using the perturbation method, which reveals details about the significant effects and connections between the variables being examined. The velocity, temperature, and concentration are found to decrease as the magnetic field, heat radiation, and chemical reaction rise. Additionally, artificial neural network (ANN) approaches are applied to these ordinary differential equations (ODEs), and the outcomes are contrasted with numerical simulations. This work illustrates the ANN model's capacity to produce extremely precise heat transfer rate forecasts from an engineering standpoint. This method improves knowledge of complex fluid magnetohydrodynamics and porous medium flows by incorporating artificial intelligence.

Key-Words: - MHD, Chemical reaction, Thermal reaction, Oscillatory flow, ANN, Porous medium, Perturbation method.

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1 Introduction

Application of industrial processes such as nuclear reactors, geothermal energy extraction, and advanced material processing, the combined impact of chemical and magnetic effects are very much essential. The study of MHD fluid is used in energy storage technologies, plasma physics, and metal casting. MHD flows exhibit complex nonlinear dynamics when coupled with chemical interactions, making it challenging to evaluate them with usual mathematical methods. Consequently, data-driven methods – specifically, artificial neural networks, or ANNs have gained attention for simulating and predicting the behavior of these systems.

Neural networks' capacity to discover complicated patterns in datasets and approximate nonlinear functions has made them extremely effective tools for tackling fluid flow problems in recent years. Neural network-based models are more capable of handling large-scale simulations, adapting to dynamic boundary conditions, and optimizing predicted accuracy than traditional numerical or analytical approaches. Artificial Neural Networks (ANNs) are essential for both scientific and industrial breakthroughs since they use deep learning techniques to improve the accuracy of fluid dynamics studies and aid in real-time forecasts.

[1] showed how ANN models can accurately represent complex thermal and entropy behaviors in cavities containing nanomaterials, which are frequently seen in energy storage devices, heat exchangers, and microelectronics. [2] used Artificial Neural Networks (ANNs) to estimate the temperature and the rate of heat transfer to analyze the thermal effects in MHD flows. Their research showed how well ANNs performed in forecasting the thermal behavior of intricate MHD flows, [3] investigated the influence of chemical processes on MHD flows in a more sophisticated ANN application. They demonstrated how well ANNs performed in mimicking the combined impacts of fluid motion, magnetic fields, and chemical processes. [4] included in their analysis of the application of ANN in fluid dynamics and MHD flows. They elaborated on other ANN architectures and training procedures necessary for flow pattern design. [5] in their study for unsteady oscillatory MHD flows in 2017 employed ANNs to predict the flow field's nonsteady behavior. In general, their studies have shown that ANNs can accurately model the nonsteady behavior of MHD flows.

According to their research, artificial neural networks (ANNs) effectively capture the time-dependent characteristics of unstable magnetohydrodynamic (MHD) flows. [6] explored the use of ANNs in simulating heat and mass transfer within chemically reacting MHD flows, emphasizing their ability to generate precise predictions for complex MHD systems. [7] further studied the combined effects of chemical and thermal factors on MHD flows using ANNs, showcasing their capability to handle multi-parameter challenges and provide insights into the interplay of various physical processes.

[8] looked at modeling MHD slip-flow over a porous stretched surface using ANNs, demonstrating how well neural networks capture intricate flow patterns. [9] concentrated on creating a predictive artificial neural network (ANN) model that can precisely estimate the heat transfer properties of electrically conducting fluids. [10] studied MHD heat and mass transfer in an oscillating fluid over a permeable plate, as well as the impact of chemical processes and magnetic fields.

In this study, artificial neural networks (ANNs) are employed to model and analyze the impact of thermal and chemical factors on unsteady MHD mixed oscillatory flows. The primary goal is to convert the governing equations of MHD flow into a dimensionless system. Using the perturbation method, an analytical solution is derived from the dimensionless equations. Subsequently, an ANN model is developed to investigate the system in greater detail and compare its results with those obtained from the analytical simulation.

2 Problem Formulation

Consider the oscillatory flow of a magnetohydrodynamic (MHD) fluid characterized by electrical conductivity and chemical reactivity through a porous medium. The flow occurs in a channel with the **X-axis** aligned vertically and the **Y-axis** oriented perpendicular to the plates of the channel. The following assumptions are made to simplify the analysis:

- **Unsteady and Oscillatory Flow:** The flow is unsteady and exhibits oscillatory behavior, driven by an oscillating pressure gradient applied at the channel's ends.
- **Negligible Induced Magnetic Field:** The induced magnetic field is considered negligible and is therefore not included in the analysis.
- **Porous Media Resistance:** The effects of viscous resistance and Darcy's law are accounted for, assuming the porous medium has constant permeability.
- **Boussinesq Approximation:** The governing equations for the flow are derived under the standard Boussinesq approximation, simplifying the analysis by treating density variations only in terms of buoyancy effects.

The governing equations for this MHD oscillatory flow are presented as follows:

$$\frac{\partial v^*}{\partial y^*} = 0$$

$$\frac{\partial U^*}{\partial t^*} = -\frac{1}{\rho}\frac{\partial P^*}{\partial x^*} + \gamma\frac{\partial^2 u}{\partial y^2} + \frac{\sigma B_0^2}{\rho}U^* + v^*\frac{\partial U^*}{\partial y^*} + g\beta(T - T_1) + g\beta^*(C - C_1) - \frac{v}{k}U^*$$

$$\frac{\partial T^*}{\partial t^*} = \frac{K}{\rho C_P}\frac{\partial^2 T^*}{\partial y^{*2}} - \frac{1}{\rho}\frac{\partial q^*}{\partial y^*} + \frac{Q(T-T_1)}{\rho C_p}$$

$$\frac{\partial C^*}{\partial t^*} = \frac{\partial^2 C^*}{\partial y^{*2}} + \frac{K_1^{'}(C-C_1)}{d} - v^*\frac{\partial C^*}{\partial y^*} + \frac{D_m}{T}\frac{\partial^2 T^*}{\partial y^2}$$

where $v' = -v_0\left(1+\varepsilon e^{inx}\right)$ is suction velocity.
With boundary conditions,
$U^* = L_1 \frac{\partial u^*}{\partial y^*}, T^* = T_1^* + \frac{\partial T^*}{\partial y^*}, C^* = T_1^* + \frac{\partial C'}{\partial y'}$ at $y = 0$

The non-dimensionless parameters:
$x = \frac{x^*}{d}, y = \frac{y}{d}, P = \frac{dp^*}{\mu U_0}, \theta = \frac{T^*-T_1^*}{T_2^*-T_1}, \phi = \frac{C^*-C_1^*}{C_2^*-C_1}$

$$t = \frac{U_0 t^*}{d}, R_e = \frac{U_0 d}{v}, \gamma = \frac{k}{d^2}, M = \frac{\sigma B_0^2 d^2}{\mu}, G_r = \frac{g\beta(T_2 - T_1)d^2}{vU_0}$$

$G_c = \frac{g\beta'(C_2-C_1)d^2}{vU_0}, R = \frac{U_0 d^2}{\mu}, P_e = \frac{\rho C_p U_0 d}{K}, S_c = \frac{D}{Ud}$
$K' = \frac{Kd^2}{v}, S_r = \frac{D_k}{T}\frac{(T_\infty - T_\infty)}{(C_\infty - C_\infty)}$

The above equations can be written as:

$$Re\frac{\partial U}{\partial t} = -\frac{\partial P}{\partial x} + \frac{\partial^2 U}{\partial y^2} + \lambda_1 \frac{\partial U}{\partial y} + G_r\theta + G_c\phi + \left(M + \frac{1}{K}\right)U$$

$$Pe\frac{\partial \theta}{\partial t} = \frac{\partial^2\theta}{\partial y^2} + (Q_1)\theta$$

$$\frac{\partial \phi}{\partial t} = S_C\frac{\partial^2 \phi}{\partial y^2} + K_r\phi + S_r\frac{\partial^2\theta}{\partial y^2}$$

And the boundary conditions become:

$$U_0 = \gamma\frac{\partial U_0}{\partial y}, \theta_0 = d_2\frac{\partial \theta_0}{\theta_0 y}, \phi_0 = 1 + d_1\frac{\partial \phi_0}{\partial y}\ at\ y = 0$$

3 Solution to the Problem

The above equations are modified using the below equations:

$$U(y,t) = U_0(y) + \epsilon U_1(y)e^{i\omega t}$$
$$\theta(y,t) = \theta_0(y) + \epsilon\theta_1(y)e^{i\omega t}$$
$$\phi(y,t) = \phi_0(y) + \epsilon\phi_1 e^{i\omega t}$$
$$-\frac{\partial P}{\partial x} = e^{i\omega t}$$

Substitute into Governing Equations:
Zeroth order:

$$\frac{\partial^2 U_0}{\partial y^2} + MU_0 = 0$$
$$\frac{\partial^2 \theta_0}{\partial y^2} + Q_1\theta_0 = 0$$
$$Sc\frac{\partial^2 \varphi_0}{\partial y^2} + Kr\varphi_0 = 0$$

First Order:

$$\frac{\partial^2 U_1}{\partial y^2} + MU_1 = -i\omega ReU_1 + Gr\vartheta_1 + Gc\varphi_1 + \lambda_1\frac{\partial U_1}{\partial y}$$
$$\frac{\partial^2 \theta_1}{\partial y^2} + Q_1\theta_1 = -i\omega Pe\theta_1$$
$$Sc\frac{\partial^2 \varphi_1}{\partial y^2} + Kr\varphi_1 = -i\omega\varphi_1 + Sr\frac{\partial^2 \theta_1}{\partial y^2}$$

General solutions are:

$$U_0(y) = C_1\, e^{-\sqrt{M}y} + C_2\, e^{\sqrt{M}y}$$
$$\theta_0(y) = D_1\, e^{-\sqrt{Q_1}y} + D_2\, e^{\sqrt{Q_1}y}$$
$$\varphi_0(y) = E_1\, e^{-\sqrt{\frac{Kr}{Sc}}y} + E_2\, e^{\sqrt{\frac{Kr}{Sc}}y}$$

With the boundary condition:

$$U_0 = \gamma u_0', \theta_0 = d_2\theta_0', \phi_0 = d_1\phi_0' at y = 0$$

4 Results and Discussion

The effect of the magnetic field (represented by M, the magnetic parameter) on velocity profiles in an unstable magnetohydrodynamic (MHD) mixed oscillatory flow can vary depending on the fluid's composition and flow circumstances as shown in Figure 1. In most MHD investigations, a rise in the magnetic field causes a magnetic drag, sometimes referred to as the Lorentz force, which frequently causes a velocity drop. The relationship may, however, vary in some circumstances, such as when the fluid characteristics exhibit particular behavior or when other factors such as temperature or chemical impacts predominate.
In this scenario, velocity decreases as the magnetic parameter, M, rises. The following are some possible causes of this:

- When a conducting fluid flows in the presence of a magnetic field, it experiences a Lorentz force that opposes the motion of the fluid. This force acts as a resistive drag. The Lorentz force is proportional to the magnetic field strength and opposes the fluid motion. As M increases, the Lorentz force becomes stronger, which suppresses the velocity of the fluid.
- The magnetic field introduces a damping effect on the fluid motion. This is beneficial in processes where controlling turbulence or stabilizing fluid flow is desired.
- The work done against the Lorentz force converts the kinetic energy of the fluid into heat, leading to energy dissipation.

Figure 2, shows the relationship between the temperature profile for different thermal radiation parameters. Temperature profile decreases when thermal radiation increases. The relationship between thermal radiation and the temperature profile can be understood in the context of heat transfer and the Stefan-Boltzmann law. Here's an explanation:

- As an object or surface temperature increases, it emits more radiation according to the Stefan-Boltzmann law, which states that the power radiated per unit area of a body is proportional to the fourth power of its temperature:
  $Q=\sigma T^4$
  where:
  - Q is the radiative heat flux (power per unit area),
  - σis the Stefan-Boltzmann constant,
  - T is the temperature of the object in Kelvin.

  So, when thermal radiation increases (due to higher temperature), more heat is radiated away from the system.
- In a system where heat is transferred, the temperature profile refers to how the temperature varies across the system or medium. If thermal radiation increases significantly, more heat is lost to the surroundings, leading to a cooling effect in the system. As a result, the temperature at different points in the system may decrease.
- When thermal radiation increases, the object loses heat more quickly, which can cause a reduction in its temperature. If this heat loss is not compensated by another form of heat input, the overall temperature of the system will decrease, causing the temperature profile to lower.

When the **chemical reaction parameter** increases, concentration tends to decrease which is shown in Figure 3. This phenomenon can be understood by considering the following factors:
This can be explained through the principles of reaction kinetics. Here's the reasoning behind why an increase in the chemical reaction parameter (like reaction rate constant) leads to a decrease in concentration:

- The rate of a chemical reaction is typically governed by the reaction rate constant (k) and the concentration of reactants. According to the rate law, the rate of the reaction is generally proportional to the concentration of the reactants raised to a certain power (which can be determined by the order of the reaction).
  For a general reaction:
  $A \rightarrow B$
  The rate of reaction 'r' can be written as:
  $r=k[A]^n$
  where:
  - r is the rate of the reaction,
  - k is the rate constant,
  - [A] is the concentration of reactant A,
  - n is the order of the reaction (which depends on the specific reaction).
- When the reaction rate constant k increases (for example, due to higher temperature, catalyst presence, or other factors), the reaction proceeds more quickly. This means that the reactant is consumed faster.
- As the reaction progresses and the rate constant increases, the reactant A is converted into product B at a faster rate. This leads to a more rapid decrease in the concentration of A over time.

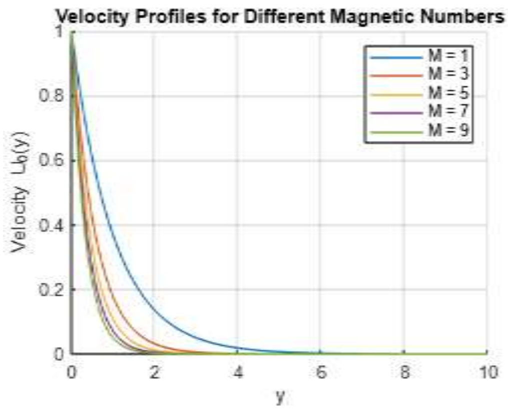

Fig. 1: Velocity profiles for distinct values of M

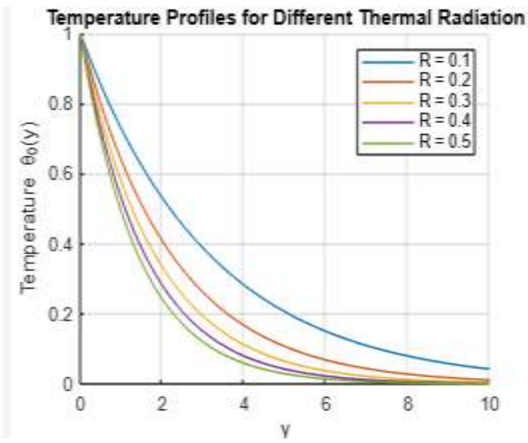

Fig. 2: Temperature profiles for different values of R

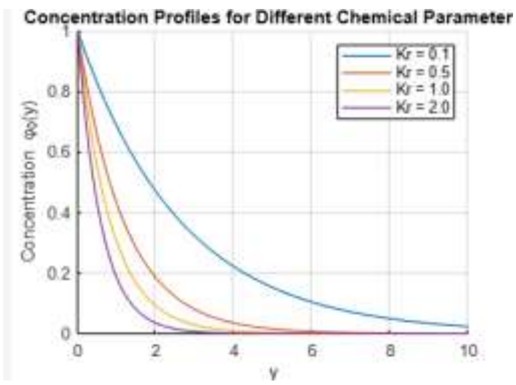

Fig. 3: Concentration profile for different values of Kr

5 Modeling - Artificial Neural Network

The artificial neural network concept is applied to the context of exploring the impact of thermal and chemical factors on unsteady magnetohydrodynamic (MHD) mixed oscillatory flow.

The basic units of an ANN are neurons, which process input data and pass the information through the network. Each neuron receives input, applies a weight to each input, sums them, applies an activation function, and produces an output.

- ANNs are composed of multiple layers of neurons. These include:
  - **Input Layer:** Receives the initial data.
  - **Hidden Layers:** Intermediate layers that process inputs from the previous layer.
  - **Output Layer:** Produces the final output of the network.

In our recent study, we used a multi-layer feed-forward artificial neural network combined with the Back Propagation development algorithm. Multi-layer perception consists of at least three layers: an input layer, an output layer, and one or more hidden layers. To close the gap between expected and actual results, weights are modified using the Back Propagation training method. ANN structures were developed and trained in MATLAB for this project. Back propagation training was carried out in feed-forward mode with one hidden layer. 70% of the total data set was utilized for training, 15% for validation, and 15% for evaluating the model's results.

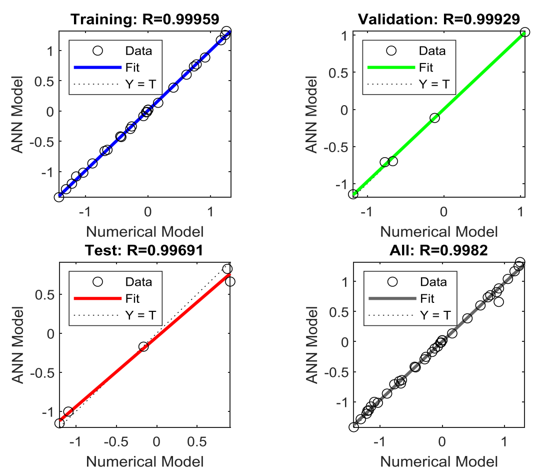

Fig.: 4 Graphical representation of skin friction

Figure 4 and Figure 5 depict the training state of the ANN for "skin friction coefficient, rate of heat transfer". This training stage teaches the neural network to map predictors to continuous responses. Figure 4 and Figure 5 compare the projected and actual experimental values of the test data for skin friction and HT rate, respectively. These graphs demonstrate that the ANN model fits the dataset fairly well. The model performance has increased. The test dataset yielded an accuracy of more than 99%.

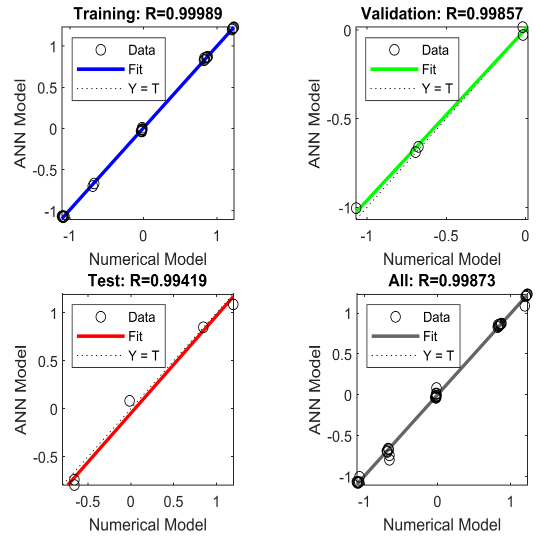

Fig. 5: Graphical representation of Nusselt number

6 Conclusion

Artificial Neural Networks are an effective tool for investigating the impacts of temperature and chemical changes on unsteady magnetohydrodynamic mixed oscillatory flow. Because of their ability to simulate nonlinear interactions, forecast system behavior, and enhance performance, artificial neural networks are essential in current engineering and scientific research. As technology progresses and computing capabilities expand, ANNs will play an increasingly important role in enhancing our understanding and application of MHD systems, paving the path for novel solutions in the energy, manufacturing, and environmental sectors.

In conclusion, including ANNs in MHD research not only improves forecast accuracy but also promotes a deeper knowledge of complicated fluid dynamics, resulting in more efficient and sustainable engineering techniques.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilized artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Conflict of Interest

The authors have no conflicts of interest to declare