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Application of neural network for computing heat performance in axisymmetric viscoelastic transport: Hybrid meta heuristic techniques

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ABSTRACT

Background and Objectives: Genetic algorithm and Interior point algorithms individually can have reliable and effective approaches to tackle physical flow problems. However, hybrid heuristic algorithms GA-IPA has been discovered an efficient and accurate solver than GA and IPA algorithms.
Methodology: Mathematical development and governing equations under the channel boundaries is developed and explore with mechanism of thermal deposition. Moreover, Genetic Algorithm (GA) and Interior Point Algorithm (IPA) are explored in a hybrid arrangement for the weights optimization of ANN which optimized the performance of thermal deposition in axisymmetric viscoelastic transport phenomena. Additionally, we incorporate artificial neural networks (ANNs) architecture Schematic and workflow diagram for experimental explanation of proposed design scheme.
Significances: A universal function approximation technique which is known as Artificial Neural Network (ANN) has been applied in the various field of practical importance. Among these fields are control systems, system identification, time series forecasting and decision support systems. For the purpose of ANN modeling, the weights optimization is required in a supervised manner to model the desired function.
Conclusions: Artificial Neural Network is a stable and provide accurate and reliable solutions. For the validation purpose,we provide error graphs against number of runs.

Introduction

In beginning, model a problem has become admired popularity for characteristic of machine learning, signal processing and computer vision. Traditional models based on numerical and programming techniques have been discovered. These methods include lambda iteration method, Lagrangian relaxation algorithm, gradient method, dynamic programming and many more [1,2]. All above said tools are flexible and appropriate for linear problems [3]. Moreover, use of artificial neural network models proves supremacy on classical algorithms [4]. However, while using neural network model, parameters adjustment in complex constraints during learning is a major issue. This can be overcome by employing metaheuristic techniques like hill climbing, swarm intelligence, ant/bee colony and Hopfield optimizations [5,6]. Optimization especially mathematical optimization is a basis for solving various problems in computer revelation. Noticeable fact can be observed quick look into incredible contributions in computer vision.

A wide range of research work exercises optimization algorithms. Nonlinear optimization problems arise in computer visualization such as alignment of image, motion structure, optical flow and camera calibration. A number of approaches used to solve nonlinear optimization problems. Floudas and Visweswaran [7] introduces global optimization approach in 1993 and Aguilera-Venegas et al. [8] set up accelerated time simulation based on machine learning for airport terminal in 2014. Numerical algorithms have been applied broadly to find solution of dynamical systems based on highly nonlinear equations by many researchers [9,10]. Moreover, Baris [11] analyzed steady flow of Oldroyd 8 constant fluid in convergent channel. MHD flow of Oldroyd 8 constant fluid is solved numerically by Khan et al. [12]. Very recently, Ali et al. [13] carried out a study to inspect heat transfer in peristaltic flow of Oldroyd 8 constant fluid in a curved channel in which they considered negligible effects of inertial and streamline-curvature. Built-in approximation capabilities of universal function are associated with artificial neural networks (ANNs). Physical flow problems have been broadly modeled through ANN such as optimal control problems [14], Vander Pol oscillators [15] and Painleve Équation-I [16]. A traditional optimization control approximation is widely used in last decade on flow problems. Raja and Samar [17] used MHD Jeffrey-Hamel flow problem and computational techniques have been utilized using different feed forward ANN trained by employing interior point method. In another attempt

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Nomenclature

V, u	Velocity vector and com ponent of velocity
r, θ, z	Cylinderical Coordinates
σ, S, A_1	Cauchy stress, extra stress and first Rivilin-Ericksen tensors
T	Fluid temperature
T_m, T_w	Maximum and wall temperatures
α_1, α_2	Rheological fluid parameters
Br, R	Brinkman number, Radius of cylinder
μ, λ_i	Material constants
C_p	Specific heat
k	Thermal conductivity
p	Pressure
β, w, b	Unknown weight vectors
$h(x)$	Activation function
m	Number of neurons
e_i	Mean square errors
e	Fitness function
Dimentionless parameters	
f	Dimensionless velocity
θ	Dimensionless temperature
ξ	Dimensionless variable
Abbreviations	
ANNs	Artificial Neural Networks
GAs	Genatic Algorithms
IPA	Interior Point Algorithms
PSO	Particle Swarm Optimization
ASM	Active Set Method
MHD	Magnetohydrodynamics

[18] they used stochastic technique by ANN training with particle swarm optimization (PSO) and active set method (ASM) to solve the problem. Physical flow problem arising in electromagnetic theory is solved by neural network modeling by Khan et al. [19]. Very recently, Masood et al. [20] worked on Bratu type equation with help of Mexican Hat Wavelet based neural network design. An energy function is constructed first time in an unsupervised manner by them. Hybrid approach is used to solve nonlinear Bratu type equation using genetic algorithms and sequential quadratic programming to find best weights.

In recent years, the heat transfer mechanism has been a topic of extensive research due to its increasing demand in many industrial processes such as cooling of electronic devices, reactor insolation, home ventilation and solar collector etc. Some interesting contributions are cited in Refs. [21–24]. Additionally artificial neural networks are accomplished for applying to problems which arise in heat transfer, fluid flow and renewal of energy system etc. (see Refs. [25–27]).

Present work is an attempt to address steepest decent approximation method, namely, GA-IPA based on echolocation performance of genetic algorithm and interior point algorithm. Oldroyd 8 constant fluid is modeled through neural network modeling. They are combined to define an unsupervised error for problem which is reduced by optimizing weights using a tool for global search method namely genetic algorithm. Moreover, the method is hybridized with local search method interior point algorithm. This hybridization has no requirement of starting points and capable to determine global optimum solution to Oldroyd 8 constant flow for ranges of constraints and objective functions.

Physical problem development and governing equations

We suppose that an incompressible Oldroyd 8- constant fluid is flowing in a circular pipe of radius R. Here the flow is because of an applied pressure gradient in the z direction which is taken as the axis of flow. A constant temperature is provided to the pipe and heat transfer is taken into account. The governing equations may be put in the form

$$\nabla \cdot \mathbf{V} = 0, \tag{1}$$

$$\rho \frac{d\mathbf{V}}{dt} = \text{div}\,\boldsymbol{\sigma}, \tag{2}$$

$$\boldsymbol{\sigma} \cdot \mathbf{L} + k\nabla^2 T = \rho C_p \frac{dT}{dt}, \tag{3}$$

$$\boldsymbol{\sigma} = -p\mathbf{I} + \mathbf{S}, \tag{4}$$

$$\mathbf{S} + \lambda_1 \frac{D\mathbf{S}}{Dt} + \frac{\lambda_3}{2}(\mathbf{S}\mathbf{A}_1 + \mathbf{A}_1\mathbf{S}) + \frac{\lambda_5}{2}(tr\mathbf{S})\mathbf{A}_1 + \frac{\lambda_6}{2}[tr(\mathbf{S}\mathbf{A}_1)]\mathbf{I} = \mu\left[\mathbf{A}_1 + \lambda_2 \frac{D\mathbf{A}_1}{Dt} + \lambda_4 \mathbf{A}_1^2 + \frac{\lambda_7}{2}\left[tr\left(\mathbf{A}_1^2\right)\right]\mathbf{I}\right], \tag{5}$$

$$\mathbf{A}_1 = \mathbf{L} + \mathbf{L}^*, \tag{6}$$

$$\mathbf{L} = \text{grad}(\mathbf{V}), \tag{7}$$

in which $\mathbf{V}$ designates the velocity vector, $\boldsymbol{\sigma}$ represents the Cauchy stress tensor, $-p\mathbf{I}$ is the indeterminate part of the stress due to the constraint of incompressibility, $\mathbf{S}$ is an extra stress tensor, T is the temperature, C_p is the specific heat, d/dt is the material derivative and k is the thermal conductivity, $\mathbf{A}_1$ is the first Rivilin-Ericksen tensor and μ and λ_i $(i = 1, 2, \ldots, 7)$ are the material constants of the fluid. Moreover, radiation effects and body forces are neglected. The contravariant convected derivative D/Dt is defined as

$$\frac{D\mathbf{S}}{Dt} = \frac{d\mathbf{S}}{dt} - \mathbf{L}\mathbf{S} - \mathbf{S}\mathbf{L}^*, \tag{8}$$

where $(*)$ is the matrix transpose. Considering $\mathbf{V} = (0, 0, u(r))$, Eq. (1) is identically satisfied and Eqs. (2)–(7) give

$$\frac{\partial p}{\partial r} = \frac{1}{r}\frac{d}{dr}(rS_{rr}) - \frac{S_{\theta\theta}}{r}, \tag{9}$$

$$\frac{\partial p}{\partial \theta} = 0, \tag{10}$$

$$\frac{\partial p}{\partial z} = \frac{1}{r}\frac{d}{dr}(rS_{rz}), \tag{11}$$

$$S_{rr} = \frac{\mu(\lambda_4 + \lambda_7 - \lambda_3 - \lambda_6)\left(\frac{du}{dr}\right)^2 + \mu[(\lambda_4 + \lambda_7)\alpha_2 - (\lambda_3 + \lambda_6)\alpha_1]\left(\frac{du}{dr}\right)^4}{1 + \alpha_2\left(\frac{du}{dr}\right)^2}, \tag{12}$$

$$S_{rz} = \frac{\mu\frac{du}{dr} + \mu\alpha_1\left(\frac{du}{dr}\right)^3}{1 + \alpha_2\left(\frac{du}{dr}\right)^2}, \tag{13}$$

$$S_{\theta\theta} = \frac{\mu(\lambda_7 - \lambda_6)\left(\frac{du}{dr}\right)^2 + \mu(\lambda_7\alpha_2 - \lambda_6\alpha_1)\left(\frac{du}{dr}\right)^4}{1 + \alpha_2\left(\frac{du}{dr}\right)^2}, \tag{14}$$