A Levenberg-Marquardt backpropagation method for unsteady squeezing flow of heat and mass transfer behaviour between parallel plates

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Abstract
In this study, a new computing model by developing the strength of feed-forward neural networks with Levenberg-Marquardt Method (NN-BLMM) based backpropagation is used to find the solution of nonlinear system obtained from the governing equations of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates. The governing partial differential equations (PDEs) for unsteady squeezing flow of Heat and Mass transfer of viscous fluid are converting into ordinary differential equations (ODEs) with the help of a similarity transformation. A dataset for the proposed NN-BLMM is generated for different scenarios of the proposed model by variation of various embedding parameters squeeze Sq, Prandtl number Pr, Eckert number Ec, Schmidt number Sc and chemical-reaction-parameter $g$. Physical interpretation to various embedding parameters is assigned through graphs for squeeze Sq, Prandtl Pr, Eckert Ec, Schmidt Sc and chemical-reaction-parameter $g$. The processing of NN-BLMM training (T.R), Testing (T.S) and validation (V.L) is employed for various scenarios to compare the solutions with the reference results. For the fluidic system convergence analysis based on mean square error (MSE), error histogram (E.H) and regression (R.G) plots is considered for the proposed computing infrastructures performance in term of NN-BLMM. The results based on proposed and reference results match in term of convergence up to 10-02 to 10-08 proves the validity of NN-BLMM. The Optimal Homotopy Asymptotic Method (OHAM) is also used for comparison and to validate the results of NN-BLMM.

Keywords
NN-BLMM, unsteady squeezing flow, OHAM, heat transfer, mass transfer, neural networks

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Introduction
The unsteady squeezed flow between parallel plates is of great interest in hydromechanical machines. It has various applications in daily life, such as polymer handling, compression and injection models. The pioneering work was done by Stefan¹ to study squeezing flow under lubrication approximation. The steady Newtonian flow between two parallel plates was
studied by Ran et al. and Mustafa et al., and an exact solution is obtained. Khan et al. developed analytical solutions for the squeezing flow with entropy generation and velocity slip influence. Domain found an effective analytical solution to the turbulent squeezing flow of nanoparticles using a Duan-Rach technique. Hayat et al. studied the squeezed flow past a Riga plate. This experiment with doubly stratified fluid was studied by Ahmad et al. Hayat et al. and Ahmad et al. considered the Darcy effect and thermal radiation effects on the squeezing flow. The heat and mass transfer study is of great interest due to its broad applications in science and engineering such as fluid dynamic devices, polymer manufacturing, lubrication method, chemical manufacturing machinery, fog forming and dissipation, crop loss due to melting, food preparation and refining. The heat transfer (H.T.) occurs in condensation and evaporation, such as the vapour is used for evaporation in a chemical plant. Mass transfer (M.T.) includes the evaporation in a pond, blood purification in the liver. The H.T. influence on squeezing flows was studied by Duwairi. Mahmood et al. studied the H.T. in the squeezing flow with a porous medium. Vafai studied magnetohydrodynamics (MHD) effect on the H.T. and M.T. of squeezed flow. The effects of the suction/injection and stagnation point flow on H.T. and M.T. squeezing flow was presented by Tsai et al. and Muhamin et al. The H.T. and M.T. behaviour is studied at different nanofluid flow with certain conditions.

Several numerical methods have displayed a great perspective to solve the differential equations (D.E.s), such as collocation method (CM), Optimal Homotopy Asymptotic Method (OHAM), Multistage Optimal Homotopy Asymptotic Method (MOHAM), Adomian Decomposition Method (ADM), Homotopy Analysis Method (HAM), Homotopy Perturbation Method (HPM), Variational Iteration Method (VIM). These methods solved the D.E.s with some limitations and advantages when compared to some other methods. However, the Artificial Intelligence (A.I.) based numerical solver using soft computing looks promising for further research for D.E.s. The AI-based numerical techniques have been used for the solutions of D.E.s such as Van-der-Pol oscillatory nonlinear systems, nonlinear optics model, electrically conducting solids, nonlinear transport design, combustion-theory, mathematical Design of Carbon-nanotubes, astrophysics, circuit-theory, atomic-physics, lively heartbeat Design, HIV design, energy, wind-power and financial Design. According to the literature survey, no research has applied A.I. techniques through NN-BLMM to solve the unsteady squeezed flow with heat and mass transfer. So the purpose of this study to use the NN-BLMS in the heat and mass transfer of the squeezing flow, which is considered an essential item for industrial and engineering applications.

The critical aspect of the proposed computing paradigm is given as

- A new application based on Artificial Intelligence-based computing using neural network backpropagated with Levenberg-Marquardt is implemented to study the MHD boundary layer flow with a stretching sheet.
- The dataset for the NN-BLMS is generated for variations of Deborah and Magnetic parameters through the OHAM.
- The governing equations are transformed from a set of PDEs into ODE by using a similarity transformation.
- The processing of NN-BLMS means training, testing and validation in the boundary layer flow model for different scenarios to obtain the approximate solution and comparison with reference results.
- The convergence analysis based on the mean square, error histogram and regression plots are employed to ensure the performance of NN-BLMS for the detailed analysis of the boundary layer flow model.

The Mathematical modelling of the unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates model has been presented in Section II. The method for analysing unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates has been discussed in section III. The numerical and graphical results with discussion and comparison for the unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates through proposed technique NN-BLMM with numerical reference results are given in section IV. Finally, concluding remarks for the study on the proposed methodology for unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates is presented in section V.

**Mathematical modelling of the flow problem**

Consider the unsteady two-dimensional squeezing flow of an incompressible viscous flow between the infinite parallel plates with heat and mass transfer. The plates are placed at a distance \( z = \pm z_0 = h(t) \) from each other. The plates are squeezed until they reach \( z = \frac{h}{a} \) and for \( a \ll 0 \) the plates are separated. The generation of heat due to friction caused by shearing the flow is retained. This effect plays a significant role when the fluid is viscous mainly or flowing at high speed. This behaviour occurs at a high Eckert number. The mass
transfer with the chemical reaction of the time dependant rate is counted, and the flow considered is symmetric, as given in Figure 1.

The fundamental governing equations for mass, momentum, energy and heat transfer for the problem under consideration are given as $^3, ^7$

\[ u_x + v_y = 0, \quad u_t + uu_x + vv_y = - \frac{1}{\rho} P_x + v(u_{xx} + u_{yy}) \]

\[ v_t + uv_x + vv_y = - \frac{1}{\rho} P_y + v(u_{xx} + u_{yy}) \]

\[ T_t + uT_x + vT_y = \frac{k}{\rho C_p} (T_{xx} + T_{yy}) \]

\[ + \frac{\nu}{C_p} \left[ 4(u_y)^2 + (u_x + v_x)^2 \right], \]

\[ C_t + uC_x + vC_y = D(C_{xx} + C_{yy}) - K_1(t)C. \]

In equations (1)–(5) $u$ and $v$ are velocity components along $x$ and $y$ directions, $P$ is pressure, $\rho$ is density, $T$ is temperature and $C$ concentration, $\nu$ kinematic viscosity, $\kappa$ thermal conductivity, $D$ diffusion coefficient, $C_p$ specific heat.

The boundary conditions imposed are $^3$

\[ u = 0, \ v = v_w, \ v = \frac{dh}{dt}, \ C = C_H, \ T = T_H \ at \ y = h, \]

As $u_y = 0, \ T_y = 0, \ C_y = 0 \ at \ y = 0. \]

Using the transformation as given in equation (6)$^3, ^7$

\[ \eta = \frac{y}{\sqrt{1 - \alpha t}}, \ u = \frac{ax}{2(1 - \alpha t)} f'(\eta), \]

\[ v = \frac{\alpha l}{2\sqrt{1 - \alpha t}} f(\eta), \ \theta = \frac{T}{T_H}, \ \phi = \frac{C}{C_H}. \]

Using equation (6) into equations (1)–(6), we obtained the following system of equations

\[ f'''' - S(\eta f''' + 3 f'' + f'f'' - f f''') = 0, \]

\[ \theta'' + S Pr (\theta'' - \eta \theta') + Ec Pr (f'' + 4S\dot{\gamma}^2) = 0, \]

\[ \phi'' + SSc (\phi'' - \eta \phi') - \phi\gamma Sc = 0, \]

and

\[ \hat{f}(0) = 0, \ \hat{f}''(0) = 0, \]

\[ \theta'(0) = 0, \ \phi'(0) = 0, \]

\[ \hat{f}(1) = 1, \ \hat{f}''(1) = 0, \]

\[ \theta(1) = 1, \ \phi(1) = 1, \]

Prandtl $Pr$, squeeze $S$, Eckert $Ec$ and Schmidt number $Sc$ and $\gamma$ is the chemical reaction parameter. The above systems of ODEs are solved by the OHAM and neural network of the Levenberg Marquardt Approach, shown in section III.

Solution procedure

The proposed soft computing infrastructure based on NN-BLMS provided in the two neural representations, as shown in Figure 2. The proposed model depends on the framework of the fitting tool ‘nftool’ which is available in the neural networks toolbox in Matlab. The numerical attempt based on NN-BLMM is presented for unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates given in equations (8)–(11). The proposed NN-BLMM is performed for four scenarios by variation of parameters $S, Pr, Ec, \gamma, Sc$ with different cases for each scenario, as shown in Table 1. A summary of the proposed NN-BLMM workflow is presented in Figure 4. The supervised neural network in the NN-BLMM is used to obtain the output to get a more accurate calculation repeatedly. The interval’s step size is considered 1/100 between the interval [0, 1] created by using the OHAM$^{25, 26}$ for the
Analysis of the results

Solving unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates model using similarity transformation and required OHAM solves ODEs to get numbering data for \( f(\eta) \), \( \theta(\eta) \), \( \phi(\eta) \). The NN-BLMS results in all cases in working with performance and state are displayed in Figures 4 and 5 separately. Error Histogram are given in Figure 6, Fitting the results is shown in Figure 7, while regression analysis was presented in Figure 8 on all unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates cases. The effect of various physical parameters such as \( \text{Pr} \), \( S \), \( Ec \), \( Sc \), \( \gamma \) on \( f(\eta) \), \( \theta(\eta) \), \( \phi(\eta) \) along with absolute errors graphs are given in Figures 9 to 13. In addition, the control convergence constraints in terms of MSE, executed epochs, performance, backpropagation measures and time of execution are presented in Table 2. Subsections 4, MSE assembly of training, validation and testing procedures are presented for all cases of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates. One can see that the best P.F has been achieved at \( 7.7817 \times 10^{-8} \), \( 7.383 \times 10^{-11} \), \( 1.9542 \times 10^{-11} \), \( 6.149 \times 10^{-9} \) and \( 1.66 \times 10^{-10} \) are achieved at 1000, 37, 21, 542 and 64 epochs are given in Figure 4. Appropriate values for GD and step Mu size of back-propagation are \([9.952 \times 10^{-8}, 9.4848 \times 10^{-8}, 8.644 \times 10^{-8}, 9.6688 \times 10^{-8}, 1.7461 \times 10^{-8} \) and validation \( \mu \) are \([10^{-09}, 10^{-11}, 10^{-12}, 10^{-09}, 10^{-09}] \) and validation checks are 0, 0, 0, 0, 6 at epoch 157, 37, 21, 64 and 371 as shown in Figure 5(a) to (e). The results determine the correct and convergent P.F of NN-BLMM for each case. Error variability is also assessed with an error histogram for each input point, and the results are given in Figure 6. The maximum error achieved in the testing, performance and validation by the proposed NN-BLMM is less than \( 2.23 \times 10^{-5} \), \(-1.2 \times 10^{-7}\), \( 2.71 \times 10^{-7} \), \( 6.52 \times 10^{-7} \) and \( 3.36 \times 10^{-7} \) with 20 bins as given to Figure 7(a) to (e). The maximum error achieved is less than 1.0E-4, 9.0E-6, 8.2E-6, 8.3E-6 and 9.1E-6 in all cases of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates. The investigation over regression is given with the help of co-relation studies. The results of R.G. are given in Figure 8(a) to (e). Correlation R values invariably revolve around unity. NN-BLMS performance results of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates model cases are given in Table 2. NN-BLMM performance is approximately \( 10^{-09} \), \( 10^{-10} \) to \( 10^{-09} \), \( 10^{-09} \), \( 10^{-08} \), \( 10^{-08} \) and \( 10^{-08} \) for all scenarios with case 1 of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates. These results show the stable performance of NN-BLMS for each case of unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates model. The velocity temperature and concentration distributions, along with the comparison with numerical results, are plotted in Figures 9(a), (c) and (e), 10(a) and (c), 11(a) and (c), 12(a) and 13(a). The results of the NN-BLMM have been compared with OHAM solutions in each case; therefore, to achieve precision gauges, Absolute errors are determined from the reference solutions, and the results are shown in Figures 9(b), (d) and (h), 10(b) and (d), 11(b) and (d),

| Parameters | Variation | Physical quantities |
|------------|-----------|---------------------|
|            | \( S \)   | \( Pr \) | \( Ec \) | \( \gamma \) | \( Sc \) |
| 1          | 1         | 0.1     | 1       | 0.1     | 0.1   |
| 2          | 0.4       | 1       | 0.1     | 0.1     | 1     |
| 3          | 0.8       | 1       | 0.1     | 0.1     | 1     |
| 4          | 0.1       | 1       | 0.1     | 0.1     | 1     |
| 5          | 0.1       | 1       | 0.1     | 0.1     | 1     |

Table 1. Parameters with three variations for unsteady squeezing flow of heat and mass transfer behaviour between parallel plates.
Figure 3. (a–e) Phase configuration of the planned NN-BLMM for unsteady squeezing flow of heat and mass transfer behavior between parallel plates.

Figure 4. (a–e) Performance outcomes of NN-BLMM for Case (1–3) of parameters (1–5) Unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates.
Figure 5. (a–e) State transition outcomes of NN-BLMM of parameters (1–5) of unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates.
Figure 6. (a–e) Error histogram of NN-BLMM for parameters (1–5) of unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates.
Figure 7. Assessment of NN-BLMM outcomes with reference solution of parameters (1–5) unsteady squeezing flow of heat and mass transfer behavior between parallel plates.

Table 2. Results of NN-BLMM for all scenarios of unsteady squeezing flow of heat and mass transfer behavior between parallel plates.

|       | Mean square error | Performance | Gradient | Mu      | Epoch   | Time |
|-------|-------------------|-------------|----------|---------|---------|------|
|       | Training          | Validation  | Testing  |         |         |      |
| Sen 1 case |                   |             |          |         |         |      |
| 1     | 1.9425E-11        | 2.1312E-11 | 2.3963E-11 | 1.94E-11 | 9.18E-8 | 1.00E-12 | 17   |
| 2     | 1.2618E-11        | 1.95419E-11 | 1.3094E-11 | 1.26E-11 | 8.64E-8 | 1.00E-12 | 21   |
| 3     | 6.8152E-11        | 9.45050E-11 | 8.1724E-11 | 6.81E-11 | 9.04E-8 | 1.00E-11 | 25   |
| Sen 2 case |                   |             |          |         |         |      |
| 1     | 1.317E-10         | 2.557E-10  | 3.590E-10 | 3.84E-9 | 1.75E-6 | 1.00E-9  | 71   |
| 2     | 4.143E-10         | 1.1628E-9  | 3.5909E-10 | 2.69E-11 | 8.70E-8 | 1.00E-11 | 35   |
| 3     | 2.694E-11         | 4.456E-9   | 2.0693E-11 | 1.35E-10 | 9.72E-8 | 1.00E-10 | 44   |
| Sen 3 case |                   |             |          |         |         |      |
| 1     | 1.552E-10         | 3.228E-10  | 1.8842E-10 | 3.69E-11 | 9.67E-8 | 1.00E-10 | 470  |
| 2     | 3.6987E-11        | 1.660E-10  | 1.2185E-10 | 3.48E-11 | 9.48E-8 | 1.00E-11 | 492  |
| 3     | 1.850E-10         | 2.414E-8   | 3.5091E-8  | 3.19E-9 | 2.63E-06 | 1.00E-9  | 395  |
| Sen 4 case |                   |             |          |         |         |      |
| 1     | 3.48069E-11       | 7.3837E-11 | 7.3122E-11 | 1.27E-11 | 8.90E-8 | 1.00E-12 | 318  |
| 2     | 9.4528E-11        | 1.94737E-9 | 1.5072E-11 | 3.95E-10 | 9.96E-8 | 1.00E-11 | 493  |
| 3     | 3.3501E-8         | 1.86898E-8 | 1.6776E-7  | 4.35E-10 | 3.37E-8 | 1.00E-09 | 612  |
| Scen 5 case |                  |             |          |         |         |      |
| 1     | 7.73382E-9        | 7.7816E-08 | 6.7115E-11 | 1.35E-10 | 3.79E-8 | 1.00E-09 | 442  |
| 2     | 4.6489E-10        | 3.7641E-10 | 7.3569E-10 | 1.43E-10 | 8.75E-8 | 1.00E-09 | 498  |
| 3     | 3.84371E-9        | 7.6947E-10 | 1.48001E-9 | 4.35E-10 | 3.95E-8 | 1.00E-09 | 617  |
12(b) and 13(b) for case studies 1, respectively. One can note that absolute errors is almost \(10^{-2.3-10^{-2.5}}, 10^{-2.3-10^{-2.4}}, 10^{-2.3-10^{-2.06}}, 10^{-2.4-10^{-2.6}}, 10^{-3-10^{-2.5}}, 10^{-3-10^{-2.4}}, 10^{-5-10^{-2.6}}, 10^{-5-10^{-2.06}}, 10^{-5-10^{-2.7}}, 10^{-5-10^{-2.6}}\) in all cases respectively. These numerical and graphical diagrams ensure the precise, flexible and robust functionality of the NN-BLMM for unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates. As shown the outcomes for velocity temperature and concentration profiles for all parameters are determined in Figs. 9–13, of Unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates for variation of one parameter and all other parameters, are constant as shown in Table 1. For large values of S, significant reductions in the temperature field are reported shown in Figure 9. It is evident that when the plates are heading towards one another, the temperature is significantly higher. An improvement in S may be related to a reduction in kinematic viscosity, an improvement in the distance between plate’s and an improvement in the hurry at which the plate’s pass. The property of Ec and Pr are given in Figures 10 and 11, on increasing Pr and Ec, thermal boundary-layer thickness is observed to reduce. It is obvious that rise in Pr value greatly reduces thermal diffusivity, and thus decrease the thickness of the thermal boundary layer. The effects on the \(\phi(h)\) overall values of destructive chemical reaction parameters \((\gamma > 0)\), concentration drops rapidly shown in Figure 12. The effects of Sc on concentration gives significant enhancement in Sc is found to lead to the poorer diffusivity of molecules and the thinner boundary layer thickness, as given as in Figure 13. In addition, the control convergence constraints in terms of MSE, executed epochs, performance, backpropagation measures and time of execution are presented in Table 2. The validity and correctness of the proposed method are verified from Table 3 by comparing the results with the OHAM results. The absolute errors are optimized values when compared with the other method results given in Mustafa et al.²

Figure 8. (a)–(e) Regression plots of NN-BLMM outcomes of parameters (1–5) unsteady squeezing flow of Heat and Mass transfer behaviour between parallel plates.
Figure 9. (a–h) Numerical outcomes of squeeze number $S$ and its error graph in $f'(\eta)$, $f(\eta)$, $\theta(\eta)$, $\phi(\eta)$. of unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates. Differences of $S$ in $f'(\eta)$ (b) Error graph of $S$ in $f'(\eta)$ (c) Differences of $S$ in $f'(\eta)$ (d) Error graph of $S$ in $f'(\eta)$ (e) Differences of $S$ in $\theta(\eta)$ (f) Error graph of $S$ in $\theta(\eta)$ (g) Differences of $S$ in $\phi(\eta)$ (h) Error graph of $S$ in $\phi(\eta)$. 
Conclusions

Using Levenberg-Marquard Method with backpropagation neural networks, an advanced artificial intelligence based intelligent computing platform is provided to find a mathematical model solution describing chemical reactions and activation energy dynamics on the unsteady squeezing heat and mass transfer between two parallel plates. The equations obtained from the mathematical formulation of the flow problem are solved by OHAM progress the NN-BLMM combinations of various physical parameter. For NN-BLMM, 80%, 10% of the orientation data were used as practice, testing and validation. The near consistency between the application layer and the step 10-07 to 10-05 reference results verifies the system’s accuracy. This factor has been further confirmed by a graphical and numerical analysis of convergence graphs of MSE error-histograms and regression dynamics.

Table 3. Comparison of results of OHAM and NN-BLMM along with absolute errors.

| OHAM results | NN-BLMM results | Absolute errors |
|--------------|-----------------|-----------------|
| $\eta$ | $f(\eta)$ | $\theta(\eta)$ | $\phi(\eta)$ | $f(\eta)$ | $\theta(\eta)$ | $\phi(\eta)$ | |
| 0.0 | 0.0 | 1.02137 | 1.03872 | 0.0 | 1.02137 | 1.03872 | 1.002145E-15 |
| 0.1 | 0.143119 | 1.02136 | 1.03834 | 0.143119 | 1.02136 | 1.03834 | 2.145872E-15 |
| 0.2 | 0.283766 | 1.02129 | 1.03722 | 0.283766 | 1.02129 | 1.03722 | 3.001245E-15 |
| 0.3 | 0.419573 | 1.02098 | 1.03273 | 0.419573 | 1.02098 | 1.03273 | 1.02145E-15 |
| 0.4 | 0.548186 | 1.02021 | 1.02936 | 0.548186 | 1.02021 | 1.02936 | 1.02145E-15 |
| 0.5 | 0.667127 | 1.01874 | 1.02521 | 0.667127 | 1.01874 | 1.02521 | 1.02145E-15 |
| 0.6 | 0.773629 | 1.01642 | 1.02025 | 0.773629 | 1.01642 | 1.02025 | 2.000458E-16 |
| 0.7 | 0.864468 | 1.01319 | 1.01444 | 0.864468 | 1.01319 | 1.01444 | 1.003546E-17 |
| 0.8 | 0.935774 | 1.00920 | 1.00771 | 0.935774 | 1.00920 | 1.00771 | 1.879631E-17 |
| 0.9 | 0.982851 | 1.0047 | 1.00872 | 0.982851 | 1.0047 | 1.00872 | 5.124569E-18 |
| 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.021022E-19 |

Figure 10. Numerical outcomes of Prandtl number $Pr$ and its error graph in $\theta(\eta)$, $\phi(\eta)$ of Unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates. (a)Differences of $Pr$ in $\theta(\eta)$ (b) Error graph of $Pr$ in $\theta(\eta)$ (c) Differences of $Pr$ in $\phi(\eta)$ (d) Error graph of $Pr$ in $\phi(\eta)$. 

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Figure 11. Numerical outcomes of Eckert number Ec and its error graph in of $\theta(\eta)$, $\phi(\eta)$ unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates. (a) Differences of Ec in $\theta(\eta)$ (b) Error graph of Ec in $\theta(\eta)$ (c) Differences of Ec in $\phi(\eta)$ (d) Error graph of Ec in $\phi(\eta)$.

Figure 12. Numerical outcomes of chemical reaction parameter $\gamma$ and its error graph in $\phi(\eta)$ of Unsteady squeezing flow of Heat and Mass transfer behavior between parallel plates. (a) Differences of $\gamma$ in $\phi(\eta)$ (b) Error graph of $\gamma$ in $\phi(\eta)$. 
On increasing $S$, the velocity distribution increases while the temperature and concentration profiles decrease.

On increasing $Pr$ and $Ec$, thermal boundary-layer thickness and contraction profile are observed to reduce.

The effects $Pr$ on $f(h)$ for overall values of destructive chemical reaction parameters ($\gamma > 0$), the concentration drops rapidly.

The effects of $Sc$ on concentration gives significant enhancement in $Sc$ is found to lead to the poorer diffusivity of molecules and the thinner boundary layer thickness.

NN-BLMM is simple in applicability.

NN-BLMM has better P.F. as compared to other numerical methods.

NN-BLMM minimizes the absolute error.

The correctness of NN-BLMM is authenticated by MSC, E.H., A.E., P.F., T.S., T.R.

NN-BLMM uses 80%, 10% and 10% of the reference data as a T.R., T.S. and V.L.

New areas of interconnected AI-based intelligent systems will be conducted to solve the issues of fluid mechanics successfully.

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References
1. Stefan MJ. Versuch über die scheinbare adhesion. Sitzungsber Sächs Akad Wiss Wein, Math-Nat Wiss Kl 1874; 69: 713–721.
2. Ran XJ, Zhu QY and Li Y. An explicit series solution of the squeezing flow between two infinite plates by means of the homotopy analysis method. Commun Nonlinear Sci Numer Simul 2009; 14: 119–132.
3. Mustafa M, Hayat T and Obaidat S. On heat and mass transfer in the unsteady squeezing flow between parallel plates. Meccanica 2012; 47: 1581–1589.
4. Khan MI, Ahmad S, Hayat T, et al. Entropy Generation and Activation Energy Impact on Radiative Flow of Viscous Fluid in Presence of Binary Chemical Reaction. International Journal of Chemical Reactor Engineering 2018; 16(9): 20180045.
5. Domairry G and Aziz A. Approximate analysis of MHD squeeze flow between two parallel disks with suction or injection by homotopy perturbation method. Math Probl Eng 2009; 603916.
6. Hayat T, Khan M, Imtiaz M, et al. Squeezing flow past a Riga plate with chemical reaction and convective conditions. J Mol Liq 2017; 225: 569–576.
7. Ahmad S, Farooq M, Javed M, et al. Slip analysis of squeezing flow using doubly stratified fluid. Results Phys 2018; 9: 527–533.
8. Hayat T, Haider F, Muhammad T, et al. Darcy–Forchheimer squeezed flow of carbon nanotubes with thermal radiation. J Phys Chem Solids 2018; 120: 79–86.
9. Ahmad S, Farooq M, Javed M, et al. Double stratification effects in chemically reactive squeezed Sutterby fluid flow with thermal radiation and mixed convection. Results Phys 2018; 8: 1250–1259.
10. Duwairi HM, Tashtoush B, Damseh RA, et al. On heat transfer effects in a viscous fluid squeezed and extruded between two parallel plates. Heat Mass Transf 2004; 41: 112–117.
11. Mahmood M, Asghar S and Hossain MA. Hossain Squeezed flow and heat transfer over a porous surface for viscous fluid. Heat Mass Transf 2007; 44: 165–173.
12. Khaled AR and Vafai K. Hydromagnetic squeezed flow and heat transfer over a sensor surface. Int J Eng Sci 2009; 42: 509–519.
13. Tsai R and Huang JS. Heat and mass transfer for Soret and Dufour’s effects through porous medium onto a stretching surface. Int J Heat Mass Transf 2009; 52: 2399–2406.
14. Muhaimin I, Kandasamy R, Hashim I, et al. Effect of chemical reaction, heat and mass transfer on nonlinear boundary layer past a porous shrinking sheet in the presence of suction. Nucl Eng Des 2010; 240: 933–939.
15. Malvandi A, Safaei MR, Kaffash MH, et al. MHD mixed convection in a vertical annulus filled with Al2O3–water nanofluid considering nanoparticle migration. J Magn Magn Mater 2015; 382: 296–306.
16. Safaei MR, Safdari Shadloo M, Goodarzi MS, et al. A survey on experimental and numerical studies of convection heat transfer of nanofluids inside closed conduits. Adv Mech Eng 2016; 8(10): 1–14.
17. Wu H, Bagherzadeh SA, D’Orazio A, et al. Present a new multi objective optimization statistical pareto frontier method composed of artificial neural network and multi objective genetic algorithm to improve the pipe flow hydrodynamic and thermal properties such as pressure drop and heat transfer coefficient for non-Newtonian binary fluids. Physica A 2019; 535: 122409.
18. Karimipour A, Bagherzadeh SA, Goodarzi M, et al. Synthesized CuFe2O4/SiO2 nanocomposites added to Water/E.G.: Evaluation of the thermophysical properties beside sensitivity analysis & EANN. Int J Heat Mass Transf 2018; 127: 1169–1179.
19. Alrashed AAA, Gharibdousti MS, Goodarzi M, et al. Effects on thermophysical properties of carbon based nanofluids: experimental data, modelling using regression, ANFIS and ANN. Int J Heat Mass Transf 2018; 125: 920–932.
20. Bagherzadeh SA, D’Orazio A, Karimipour A, et al. A novel sensitivity analysis model of EANN for F-MWCNTs–Fe3O4/EG nanofluid thermal conductivity: outputs predicted analytically instead of numerically to more accuracy and less costs. Physica A 2019; 521: 406–415.
21. Bahrami M, Akbari M, Bagherzadeh SA, et al. Develop 24 dissimilar ANNs by suitable architectures & training algorithms via sensitivity analysis to better statistical presentation: measure MSEs between targets & ANN for Fe-CuO/Eg–water nanofluid. Physica A 2019; 519: 159–168.
22. Ghasemi A, Hassani M, Goodarzi M, et al. Appraising influence of COOH-MWCNTs on thermal conductivity of antifreeze using curve fitting and neural network. Physica A 2019; 514: 36–45.
23. Peng Y, Parsian A, Khodadadi H, et al. Develop optimal network topology of artificial neural network (AONN) to predict the hybrid nanofluids thermal conductivity according to the empirical data of Al2O3 – Cu nanoparticles dispersed in ethylene glycol. Physica A 2020; 549: 124015.
24. Deniez S. Comparison of solutions of systems of delay differential equations using Taylor collocation method, Lambert W function and variational iteration method. Sci Iran 2015; 22: 1052–1058.
25. Ullah H, Islam S, Idrees M, et al. Application of optimal homotopy asymptotic method to doubly wave solutions of the coupled Drinfel’d-Sokolov-Wilson equations. Math Probl Eng 2013; 2013: 1–8.
26. Ullah H, Islam S, Idrees M, et al. Solution of the differential-difference equations by optimal homotopy asymptotic method. Abstr Appl Anal 2014; 2014: 1–7.
27. Fiza M, Islam S, Ullah H, et al. Analytical solution of mhd viscous flow over a stretching sheet by multistage optimal homotopy asymptotic method. Int J Fluid Mech Res 2018; 45: 369–375.
28. Chowdhury SH. A comparison between the modified homotopy perturbation method and adomian decomposition method for solving nonlinear heat transfer equations. J Appl Sci 2011; 11: 1416–1420.
29. Liao SJ. The proposed homotopy analysis technique for the solution of nonlinear problems PhD Thes. Shan. 1992.
30. Fiza M, Alsuble A, Ullah H, et al. Three-Dimensional Rotating Flow of MHD Jeffrey Fluid Flow between Two Parallel Plates with Impact of Hall Current. Mathematical Problems in Engineering 2021; Article ID 6626411 2021: 9.
31. Ganji DD. The application of He’s homotopy perturbation method to nonlinear equations arising in heat transfer. Phys. Lett. A 2006; 355: 337–341.
32. Ganji DD, Afrouzi GA and Talarposhti RA. Application of variational iteration method and homotopy–perturbation method for nonlinear heat diffusion and heat transfer equations. Phys Lett A 2007; 368: 450–457.
33. Raja MAZ, Shah FH and Syam MI. Intelligent computing approach to solve the nonlinear Van der Pol system for heartbeat model. Neural Comput Appl 2018; 30: 3651–3675.
34. Khan JA, Raja MAZ, Syam MI, et al. Design and application of nature inspired computing approach for nonlinear stiff oscillatory problems. Neural Comput Appl 2015; 26: 1763–1780.
35. Ahmad I, Ahmad S, Awais M, et al. Neuro-evolutionary computing paradigm for painleve–equation-II in nonlinear optics. Eur Phys J Plus 2018; 133: 184.
36. Hassan A, Ahmad SU, Kamran M, et al. Design of cascade artificial neural networks optimized with the memetic computing paradigm for solving the nonlinear Bratu system. Eur Phys J Plus 2019; 134: 122.
37. Masood Z, Majeed K, Samar R, et al. Design of Mexican Hat Wavelet neural networks for solving Bratu type nonlinear systems. Neurocomputing 2017; 221: 1–14.
38. Ahmad I, Ilyas H, Urooj A, et al. Novel applications of intelligent computing paradigms for the analysis of nonlinear reactive transport model of the fluid in soft tissues and microvessels. Neural Comput Appl 2019; 31: 9041–9059.
39. Raja MAZ. Solution of the one-dimensional Bratu equation arising in the fuel ignition model using ANN optimised with PSO and SQP. Conn Sci 2014; 26: 195–214.
40. Raja MAZ, Ahmed T and Shah SM. Intelligent computing strategy to analyze the dynamics of convective heat transfer in MHD slip flow over stretching surface.
involving carbon nanotubes. *J Taiwan Inst Chem Eng* 2017; 80: 935–953.

41. Raja MAZ, Farooq U, Chaudhary NI, et al. Stochastic numerical solver for nanofluidic problems containing multi-walled carbon nanotubes. *Appl Soft Comput* 2016; 38: 561–586.

42. Sabir Z, Wahab HA, Umar M, et al. Novel design of Morlet wavelet neural network for solving second order Lane–Emden equation. *Math Comput Simul* 2020; 172: 1–14.

43. Ahmad I, Raja MAZ, Bilal M, et al. Neural network methods to solve the Lane–Emden type equations arising in thermodynamic studies of the spherical gas cloud model. *Neural Comput Appl* 2017; 28: 929–944.

44. Mehmood A, Zameer A, Ling SH, et al. Integrated computational intelligent paradigm for nonlinear electric circuit models using neural networks, genetic algorithms and sequential quadratic programming. *Neural Comput Appl* 2020; 32: 10337–10357.

45. Mehmood A, Zameer A, Aslam MS, et al. Design of nature-inspired heuristic paradigm for systems in nonlinear electrical circuits. *Neural Comput Appl* 2020; 32: 7121–7137.

46. Raja MAZ, Asma K and Aslam MS. Bio-inspired computational heuristics to study models of HIV infection of CD4 + T-cell. *Int J Biomath* 2018; 11: 1850019.

47. Jamal R, Men B, Khan NH, et al. Hybrid bio-inspired computational heuristic paradigm for integrated load dispatch problems involving stochastic wind. *Energies* 2019; 12: 2568.

48. Chouhdry ZU, Hasan KM and Raja MAZ. Design of reduced search space strategy based on integration of Nelder–Mead method and pattern search algorithm with application to economic load dispatch problem. *Neural Comput Appl* 2018; 30: 3693–3705.

49. Shahid F, Zameer A, Mehmood A, et al. A novel wave-nets long short term memory paradigm for wind power prediction. *Appl Energy* 2020; 269: 115098.

50. Zameer A, Arshad J, Khan A, et al. Intelligent and robust prediction of short term wind power using genetic programming based ensemble of neural networks. *Energy Convers Manag* 2017; 134: 361–372.