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Intelligent Backpropagated Neural Networks for numerical computations for MHD squeezing fluid suspended by nanoparticles between two parallel plates

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Abstract:

In the present research, artificial intelligence based backpropagated neural networks with Levenberg-Marquardt algorithm (BNN-LMA) are utilized to interpret the numerical computation for squeezing 2D magneto-hydrodynamic (MHD) nanofluid flow between two parallel plates. The non-linear system of ODEs represents the magneto-hydrodynamic, squeezing nanofluidic flow model (MHD-SNFM). A reference dataset for BNN-LMA is formulated by utilizing Adam numerical solver for different scenarios of MHD-SNFM by variation of squeezing number, Hartmann Number and heat source parameter. The validation, testing and training processes of BNN-LMA are exploited to analyze the approximate solution of MHD-SNFM for different scenarios and correctness of proposed BNN-LMA is verified by comparison of reference outcomes. The performance of BNN-LMA to solve the MHD-SNFM is validated through regression analysis, histogram studies and mean square error (MSE).

Keywords- MHD nanofluid, artificial intelligence based numerical computation, Levenberg Marquardt algorithm, backpropagated neural network, squeezing 2D flow.

1. Introduction:

The squeezing flow, first explored by Josef Stefen, is the form of flow in which flow is squeezed, deformed or pressed out between two parallel plates or disks. Moreover, it demonstrates the movement of fluid particles, its contact with the surface of plates and effects of other parameters such as temperature, viscosity and heat source parameter etc. In this research we are dealing with nanofluid squeezed between two parallel particles, nanofluid comprises of nanoparticles mixed base fluids. These nanoparticles are metal oxides, metals or carbon nanotubes.

In the recent years, most of the literature has been done on study of nano-particles and nanofluids. Nanofluids, first named by Choi [1], are basically nanoparticles suspended in base fluids. T Hayat et. al [2] have studied the behavior of parameters on velocity, temperature and concentration profiles, also computed and analyzed the heat and mass transfer. The fluid flow and heat transfer characteristics are analyzed by Mehmood et al. [3]. Siddique et al. [4] analyses the MHD squeezing flow between two parallel surfaces. Shoaib et al. [5] investigated the heat and mass transfer in 3-D MHD radiative flow of of hybrid nanofluid. If one nanoparticle is mixed with base fluid, it is mono nanofluid while if two or more nanoparticles are added then it is hybrid nanofluid. Ali Imran et al. [6] theoretically investigate the heat transfer of nanofluid flow in ciliated channel.

Azimi et al. [7] have discussed MHD squeezing flow of nanofluid between parallel plates and compared the analytical and numerical results. The heat transfer in unsteady nanofluid flow between two moveable parallel plates is investigated by Ganji DD et al. [8], and analyzed the effects of various parameters. The chemical reactions, velocity slip, thermal radiation and Brownian motion in 3-D flow of Casson nanofluid has been studied by M Umar et al. [9]. Babazadeh et al. [10] have studied the effects of thermophoresis, magnetic forces on nanoparticles squeezed between two plates. Noor et al. [11-12] have analyzed the unsteady MHD squeezing flow of Jeffery fluid in a porous medium and effects of viscous dissipation and chemical reaction on MHD squeezing flow of Casson nanofluid between parallel plates in a porous medium. Many of other researchers [13-21] have contributed their work on squeezing flow of nanofluids including hybrid nanofluids and Casson nanofluid.

In most of the engineering problems, the system of PDEs representing mathematical relations of the problem are transformed into ODEs. In many cases, the solution to scientific problems does not admitted analytically, this leads to the equation to be solved by using special techniques. One of the methods are reconstruction of variational iteration method [22], homotopy perturbation method [23] and other [24-25]. Later many other researchers worked on other techniques, including Jadoonet al. [26] and Oyang et al. [27] and many other [28-34] to solve the many problems.

The optimization procedures including evolutionary computation techniques are utilized in stochastic numerical computing solvers connected with neural networks for determining the results/ solutions of linear or non-linear differential equations representing different models of the problem. Recently, the implementation of these techniques include thermodynamics [35],

atomic physics [36-37], magneto-hydrodynamics [38-39], fluid dynamics [40-41] and nanotechnology [42-43].

Although above cited literature on nanofluid flows containing nanoparticles for different fluidic systems, mostly on squeezing flows by using various traditional numerical and analytical methods; but stochastic numerical techniques are required to exploit for squeezing flow problems due to their worth, effectiveness and robustness. The stochastic numerical methods are already implemented for various research problems by the research workers [44-49]. Some most recent artificial intelligence based techniques are Emden–Fowler Model [50], nonlinear unipolar electro hydrodynamic pump flow model [51], non-linear corneal shape model [52] and COVID-19 Models [53-54]. These soft computing infrastructures are inspiring factors for the authors source of motivation to exploit an accurate and reliable alternate framework based on soft computing infrastructure for the solution of heat generation in mixed convected Williamson fluid stretching flow problem by conducting a parametric study to examine the effects or various physical quantities on the velocity, concentration and temperature profiles. Mathematica and MATLAB software are utilized for numerical treatment.

The experimental insights of computing simulation are highlighted as follows:

- Intelligent computation is presented by Levenberg-Marquardt algorithm based backpropagated neural networks to study the MHD squeezing nanofluid flow between two parallel plates.
- The designed BNN-LMA coupled with PDEs for the MHD-SNFM, which are then converted into system of ODEs.
- Adams numerical techniques is used to interpret the dataset for designed BNN-LMA for the variants of MHD-SNFM on the basis of squeezing number, Hartmann Number and heat source parameter.
- The training, validation and testing processes of BNN-LMA are utilized by modelling MHD squeezing nanofluid flow model for different scenarios.
  The performance of designed BNN-LMA validated through convergence plots of MSE, error histograms, regression and fitness function.

1. Problem Formulation of MHD-SNFM:

In this research, numerical computation for the analysis of 2D unsteady, incompressible, squeezing nanofluid flow between two parallel plates having distance $z = \pm l\sqrt{1-at} = \pm h(t)$ has been interpreted, where l is the distance between the plates at $t = 0$, and a is squeezed parameter, when $a > 0$ the plates are squeezed but when $a < 0$ and $t = \frac{1}{a}$ the plates are separated. The magnetic field's variation with time t is defined as $B = B_0(1-at)$, heat generation is neglected due to viscous dissipation effect in the flow. There is nanofluid flow flowing between the plates have following assumption: radiative heat transfer is neglected, no chemical reaction and no-slip condition occurs. The nanoparticles and base flow that is incompressible are in thermal equilibrium. Figure 1 shows the geometry of the given problem.

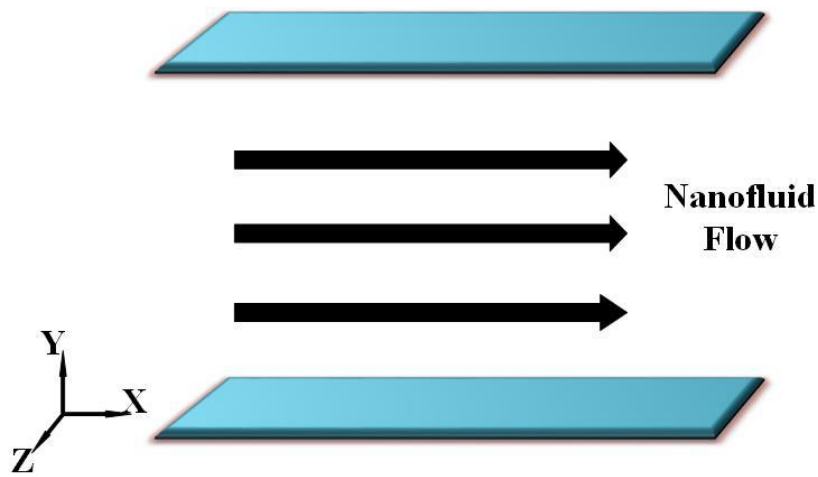


Figure 1: MHD Squeezing fluid flow between two parallel plates

The governing equations of conservation of momentum and energy are given as [55]:

$$\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}=0, \tag{1}$$

$$\rho_{hnf}\left(\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}\right)=-\frac{\partial p}{\partial x}+\mu_{hnf}\left(\frac{\partial^2 u}{\partial x^2}+\frac{\partial^2 u}{\partial y^2}\right)-\sigma_{hnf}B^2u, \tag{2}$$

$$\rho_{hnf}\left(\frac{\partial v}{\partial t}+u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}\right)=-\frac{\partial p}{\partial y}+\mu_{hnf}\left(\frac{\partial^2 v}{\partial x^2}+\frac{\partial^2 v}{\partial y^2}\right), \tag{3}$$

$$\frac{\partial T}{\partial t}+u\frac{\partial T}{\partial x}+v\frac{\partial T}{\partial y}=\frac{k_{hnf}}{\left(\rho C_p\right)_{hnf}}\left(\frac{\partial^2 T}{\partial x^2}+\frac{\partial^2 T}{\partial y^2}\right)+\frac{Q}{\left(\rho C_p\right)_{hnf}}T. \tag{4}$$

Where u and v are velocity components, T is temperature, p pressure, Q is function of heat source, ρ_{hnf} effective density, $\left(\rho C_p\right)_{hnf}$ effective heat capacity and σ_{hnf} is electrical conductivity of nanofluid. The boundary conditions are:

$$v=v_w=\frac{dh}{dt},\quad T=T_H,\quad y=h(t),$$

$$v=\frac{\partial u}{\partial y}=\frac{\partial t}{\partial y}=0y=0. \tag{5}$$

Now by using some parameters given below:

$$\eta=\frac{y}{l\sqrt{1-at}},\qquad u=\frac{ax}{l(1-at)}f'(\eta),\qquad v=\frac{al}{l\sqrt{1-at}},\quad \theta=\frac{T}{T_H}, \tag{6}$$

The system of PDEs are transformed into system of ODEs as follows:

$$f^{iv} - S\left(\frac{A_1}{A_4}\right)\left(\eta f''' + 3f'' + f'f'' - ff'''\right) - Ha^2\left(\frac{A_5}{A_4}\right)f'' = 0, \tag{7}$$

$$\theta'' + PrS\left(\frac{A_2}{A_3}\right)(f\theta' - \eta\theta') + \frac{Hs}{A_3}\theta = 0, \tag{8}$$

And the boundary conditions are:

$$f(0) = 0, \qquad f'(0) = 0,$$

$$f(1) = 1, \qquad f'(1) = 0,$$

$$\theta'(0) = 0, \qquad \theta(1) = 1. \tag{9}$$

Where S is squeezing number, Ha is Hartmann Number, Pr is Prandtl number and Hs is heat source parameter and A_1, A_2, A_3, A_4 and A_5 are dimensional constants.

2. Solution Methodology:

The nftool, an effective algorithm in artificial based neural networks (NNs) toolbox in MATLAB software package is utilized to execute the designed backpropagated neural network with Levenberg Marquardt Algorithm (BNN-LMA). The solution methodology consists of essential description for dataset and implementation procedure for implementation of designed BNN-LMA. The designed neural network for BNN-LMA is shown in Figure 2 and flow chart of methodology presented in Figure 3.

Table 1. Depiction of scenarios for MHD-SNFM

Scenarios	Cases	Physical Quantities		
		S	Ha	Hs
Scenario 1	1	1	0	-1
	2	3	0	-1
	3	5	0	-1
	4	7	0	-1
Scenario 2	1	1	0	-1
	2	1	2	-1
	3	1	3	-1
	4	1	4	-1
Scenario 3	1	1	0	-1
	2	1	0	-3
	3	1	0	-5
	4	1	0	-7

Mathematical relation of MHD-SNFM model (7-9) is presented for case 1 of scenario 1.

$$f^{iv} - 2\left(\eta f''' + 3f'' + f'f'' - ff'''\right) = 0, \tag{10}$$

$$\theta'' + 0.625(f\theta' - \eta\theta') - 0.312\theta = 0, \tag{11}$$

And the boundary conditions are:

$$f(0) = 0, \qquad f'(0) = 0,$$

$$f(1) = 1, \qquad f'(1) = 0,$$

$$\theta'(0) = 0, \qquad \theta(1) = 1. \tag{12}$$

Similarly, we can obtain mathematical relations for different cases of all the scenarios in designed MHD-SNFM.

The reference dataset of designed BNN-LMA is created for inputs between 0 and 1 with time interval of 0.01 by utilizing Adam numerical solver through "NDSolve" in Mathematica software package by variation of squeezing number, Hartmann Number and heat source parameter in MHD-SNFM as listed below in the Table 1.

3. Interpretation of Results:

The possible outcomes of numerical computation for the designed neural networks backpropagated with Levenberg Marquardt algorithm is exploited for the proposed MHD-SNFM as presented in equations (7-9). The three scenarios of MHD-SNFM by variation of squeezing number S, Hartmann Number Ha and heat source parameter Hs are formulated for four different cases for both velocity and temperature parameters of MHD squeezing nanofluidic flow model as mentioned in Table 1.

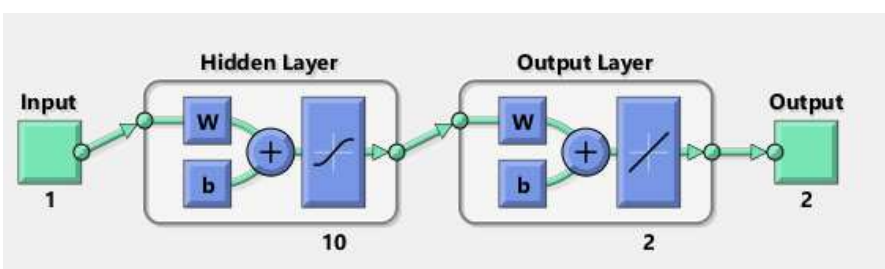


Figure 2 Neural Network for designed BNN-LMA of MHD-SNFM

The reference dataset for $f(\eta)$ and $\theta(\eta)$ of designed BNN-LMA are determined by utilizing Adams numerical method for η between 0 and 1, with step size of 0.01 for all the four cases of three different scenarios of BNN-LMA of MHD-SNFM. The obtained dataset in terms of $f(\eta)$ and $\theta(\eta)$ is then utilized as reference outcome in this presented research.

The designed BNN-LMA is exploited to determine the solution of squeezing, nanofluidic flow model in between two parallel plates by utilizing nftool in MATLAB software package. The reference dataset for velocity and temperature profiles (f and θ) is created for 101 input points in

which 80% are utilized for training, 10 % each for validation and testing respectively for BNN-LMA using the neural network as presented in Figure 3.

The solutions of BNN-LMA for second case of each scenario in terms of performance and state transition is represented in Figures 4-5 and function fitness with error histogram plots are demonstrated in Figure 6 for second case of each scenario while regression plots are depicted in Figure 7. Moreover, the convergence in terms of MSE for performance of training, testing and validation, performance, epochs, backpropagated operator i-e., Mu and time taken are presented in Tables 2-4.

In the subfigures 4(a), 4(b), 4(c), the convergence of MSE for training, testing and validation curves are depicted for second case of all the scenarios of MHD-SNFM. The most excellent execution is accomplished at 134, 127 and 166 epochs with MSE around $10^{-11}, 10^{-11}$ and 10^{-09} respectively. The gradient and Mu parameter of Levenberg Marquardt backpropagation are [9.84E-08, 9.88E-08 and 9.91E-08] and [1.00E-10, 1.00E-10 and 1.00E-09] as demonstrated in subfigures 5(a), 5(b) and 5(c). The correctness and convergent efficiency of BNN-LMA for each case of MHD-SNFM has been proved by outcomes.

The efficiency of results of BNN-LMA is observed with matching outcomes of Adam numerical solver for all the three scenarios of MHD-SNFM as shown in Figure 6 which is further endorsed by error plots. The investigation through regression analysis is carried out by co-relation studies. Figure 7 shows the results of regression outcomes of respective three variants of MHD-SNFM. One may see that the value of correlation R close to unity indicates perfect modeling, in terms of training, testing and validation certified the correctness of BNN-LMA for the designed MHD-SNFM.

Additionally, the corresponding numerical values listed in Tables 2-4 for all the three scenarios of both velocity and temperature profiles of designed MHD-SNFM demonstrated the performance on MSE around E-11 to E-12, E-11 to E-12 and E-09 to E-11. The consistent and accurate performance of BNN-LMA is authenticated by all the numerical illustrations in Tables 2-4 for solving each variant of MHD-SNFM.

Consequently, the solutions of BNN-LMA are executed for the velocity profile $f(\eta)$ for all the three scenarios of MHD-SNFM, demonstrated in subfigures 8(a), 8(c) and 8(e), while the solutions for $\theta(\eta)$ are depicted in 9(a), 9(c) and 9(e). One can witness that Absolute Error achieved for $f(\eta)$ are about 10^{-4} to 10^{-09}, 10^{-4} to 10^{-08} and 10^{-3} to 10^{-08} of scenario 1, scenario 2 and scenario 3 respectively, as shown in 8(b), 8(d) and 8(f). And the Absolute Error achieved for $\theta(\eta)$ are about 10^{-5} to 10^{-08}, 10^{-5} to 10^{-08} and 10^{-4} to 10^{-09} of scenario 1, scenario 2 and scenario 3 respectively, as shown in 9(b), 9(d) and 9(f). Moreover, one can observe from subfigures 8(a), 8(c) and 8(e), the velocity profile increases with the increase in squeeze number and decreases with increase in Hartmann number, while subfigures 9(a), 9(c) and 9(e), the temperature profile decreases with the increase in squeeze number and Hartmann number.

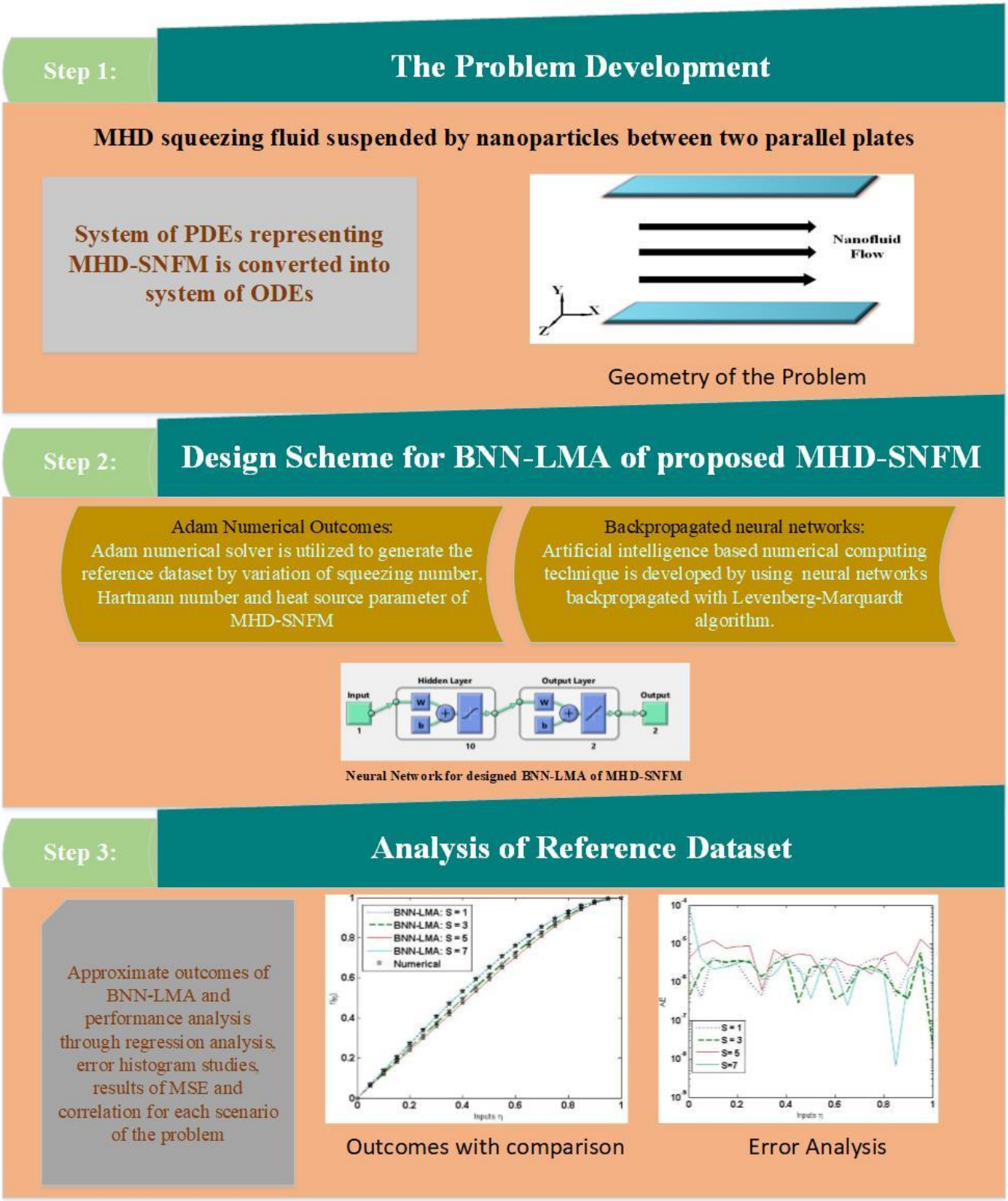
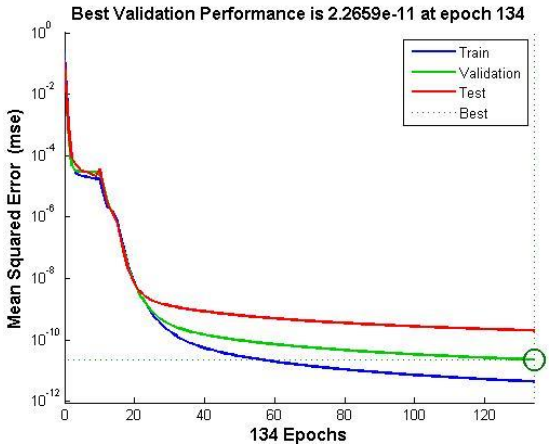
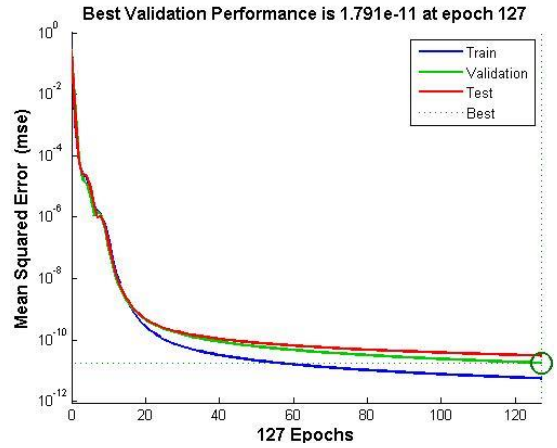


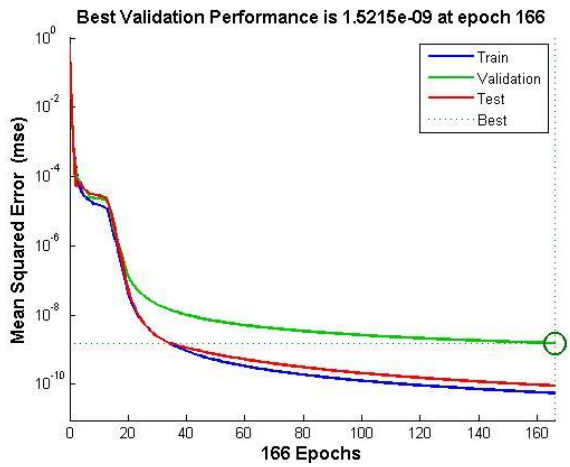
Figure 3 Flow Chart of MHD Squeezing fluid flow model



a) Results of MSE for Case 2 of Scenario 1



b) Results of MSE for Case 2 of Scenario 2

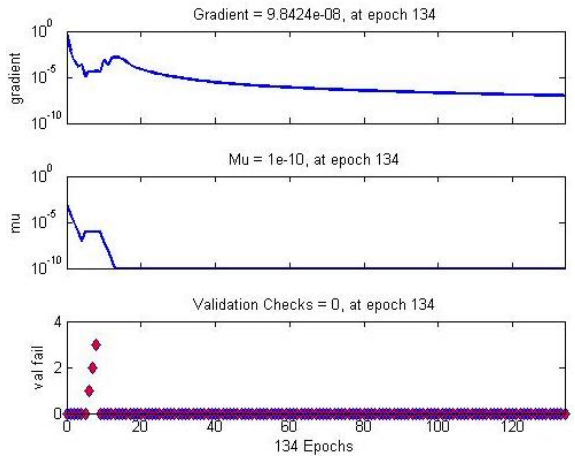


c) Results of MSE for Case 2 of Scenario 3

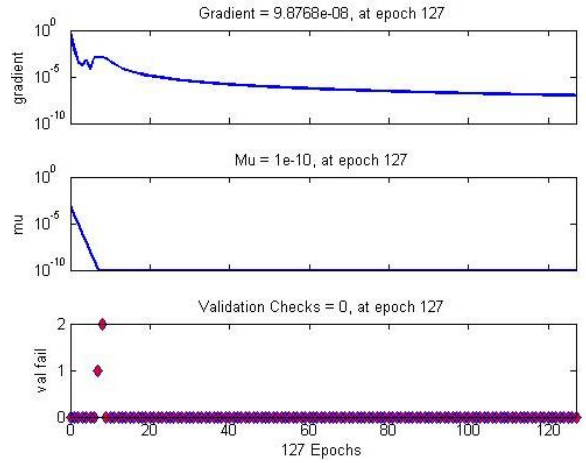
Figure 4: Performance on MSE of designed BNN-LMA of case 2 of all the scenarios of MHD-SNFM

Table 2: Outcomes of BNN-LMA for Scenario 1 of MHD-SNFM

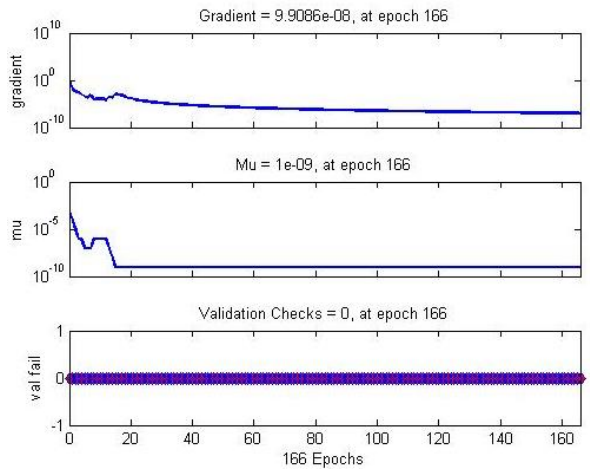
Case	Hidden neurons	MSE			Performance	Grad	Mu	Epochs	Time
		Training	Validation	Testing					
1	10	6.69E-12	1.60E-11	2.22E-11	6.70E-12	9.95E-08	1.00E-10	117	3s
2	10	4.36E-11	2.27E-11	2.00E-10	4.36E-12	9.84E-08	1.00E-10	134	1s
3	10	3.44E-11	1.27E-10	5.84E-11	3.44E-11	9.96E-08	1.00E-09	201	2s
4	10	4.65E-12	6.69E-12	4.88E-10	4.65E-12	9.93E-08	1.00E-10	143	1s



a) Training State of Case 2 of Scenario 1



b) Training State of Case 2 of Scenario 2

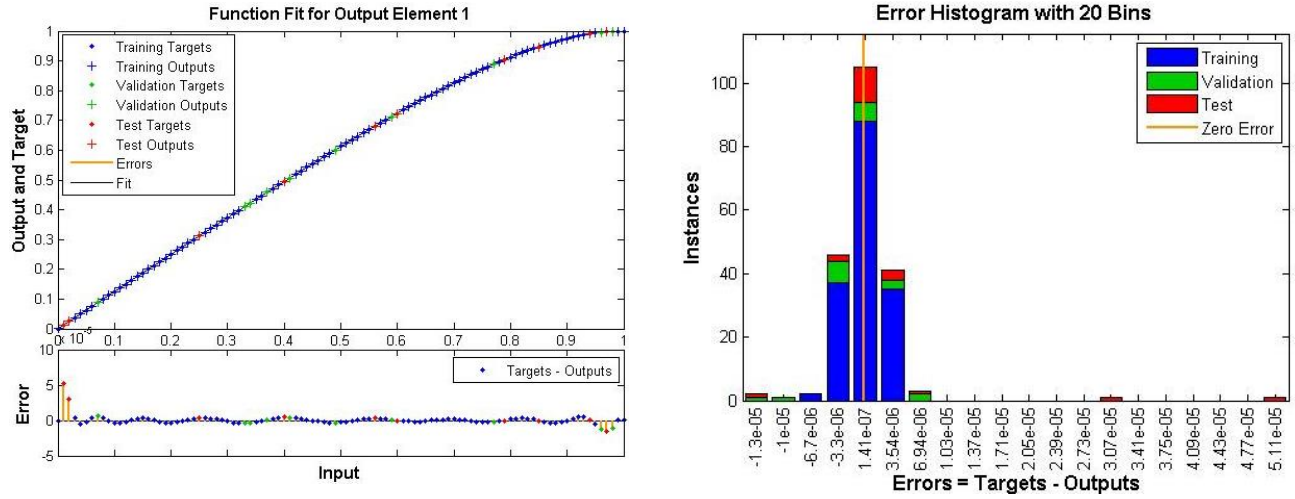


c) Training State of Case 2 of Scenario 3

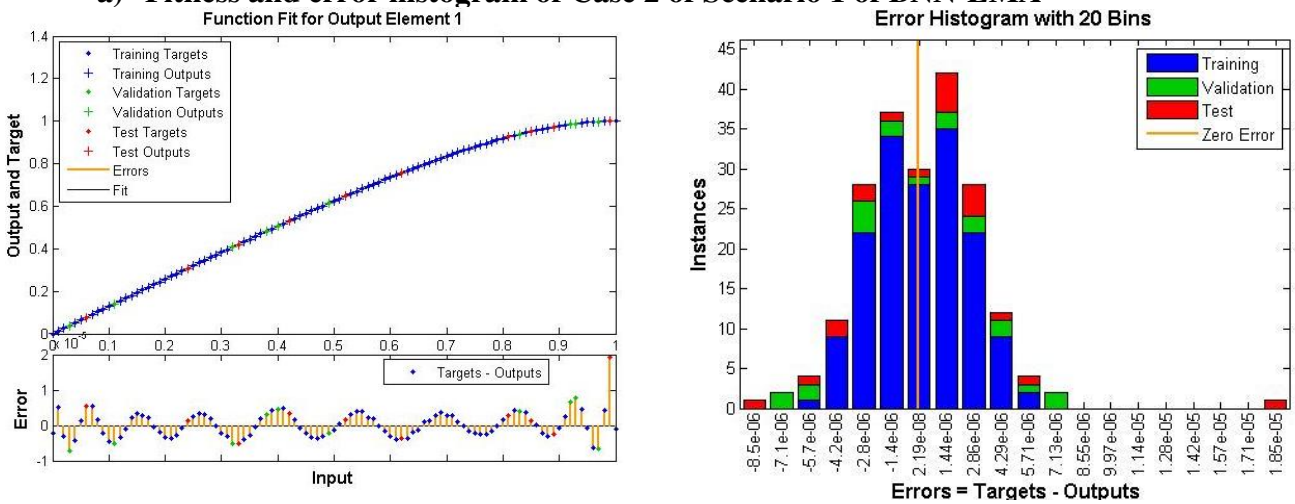
Figure 5: Transition State of designed BNN-LMA of Case 2 of all the three scenarios of MHD-SNFM

Table 3: Outcomes of BNN-LMA for Scenario 2 of MHD-SNFM

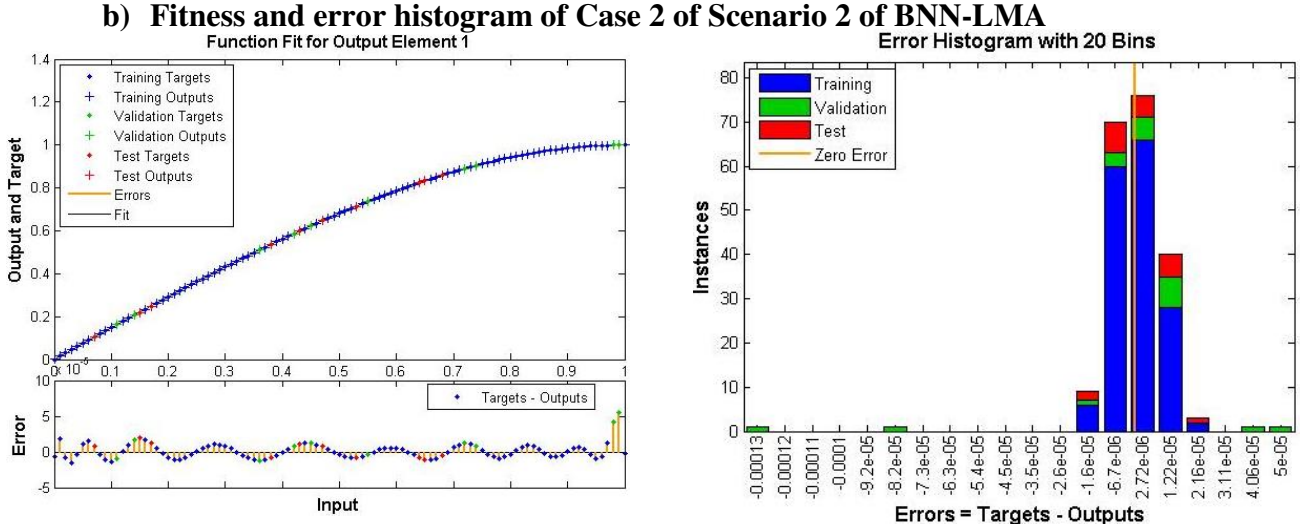
Case	Hidden neurons	MSE			Performance	Grad	Mu	Epochs	Time
		Training	Validation	Testing					
1	10	5.58E-12	1.39E-10	7.72E-12	5.58E-12	9.87E-08	1.00E-10	131	1s
2	10	5.58E-12	1.79E-11	3.08E-11	5.58E-12	9.88E-08	1.00E-10	127	2s
3	10	2.72E-12	1.47E-11	9.83E-11	2.72E-12	9.90E-09	1.00E-10	217	2s
4	10	4.29E-11	1.85E-10	1.00E-10	4.29E-11	9.98E-08	1.00E-09	182	1s



a) Fitness and error histogram of Case 2 of Scenario 1 of BNN-LMA

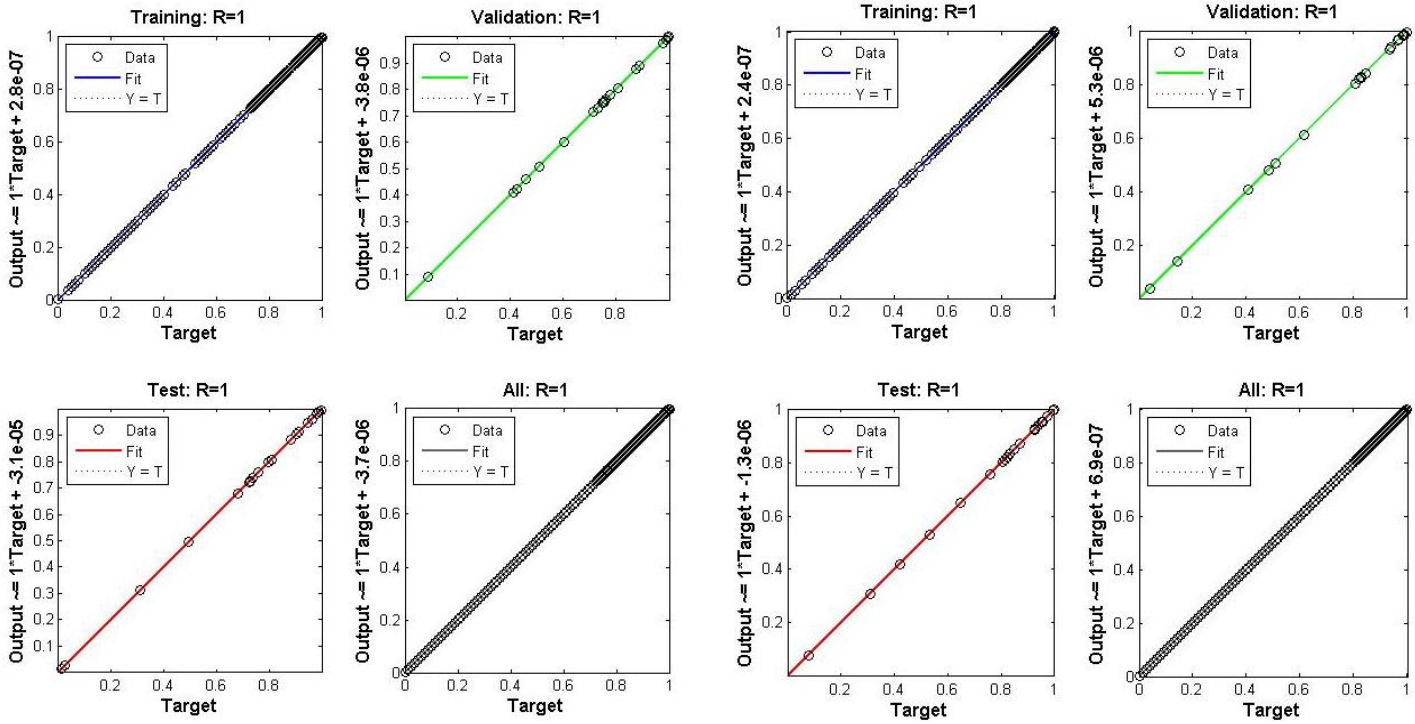


b) Fitness and error histogram of Case 2 of Scenario 2 of BNN-LMA



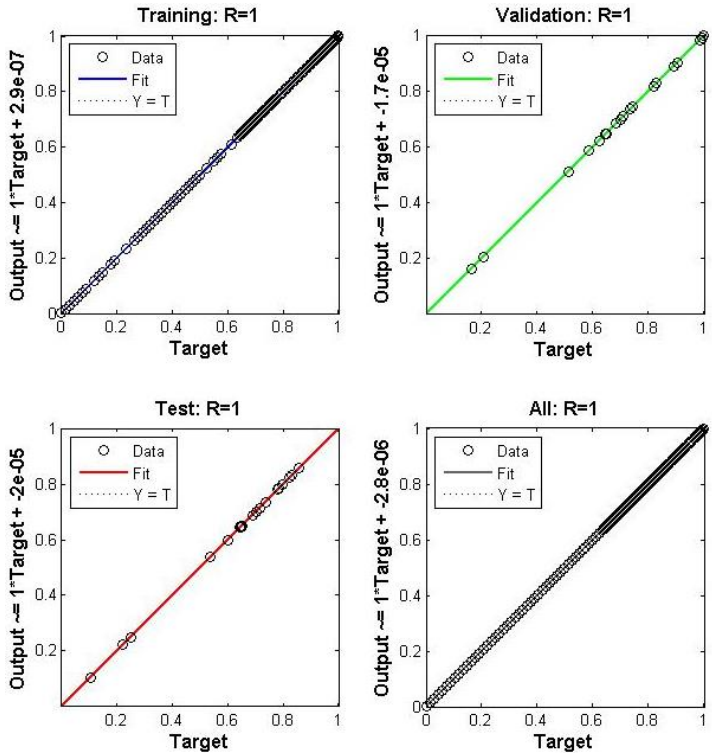
c) Fitness and error histogram of Case 2 of Scenario 3 of BNN-LMA

Figure 6: Function Fitness and error histogram studies of designed BNN-LMA of MHD-SNFM



a) Regression of Case 2 of Scenario

b) Regression of Case 2 of Scenario2

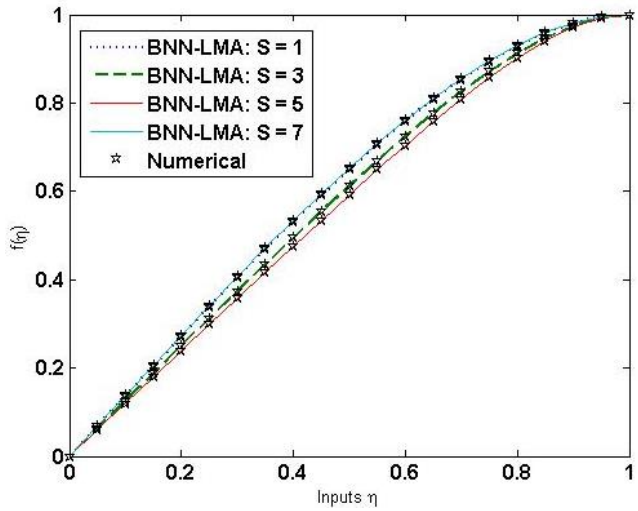


c) Regression of Case 2 of Scenario 3

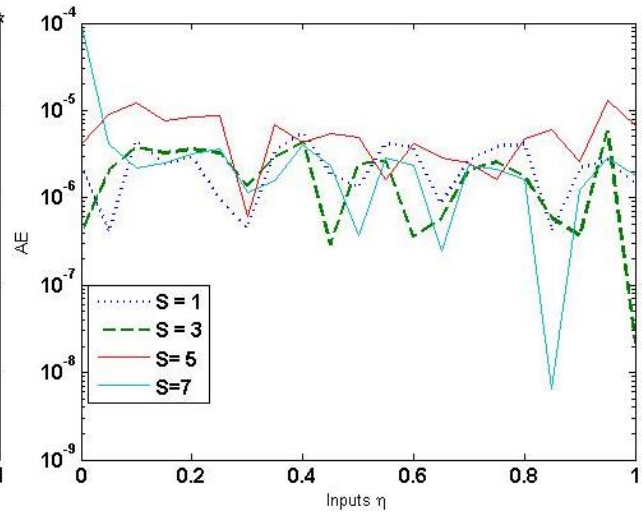
Figure 7: Regression presentations of BNN-LMA for case 2 of all the Scenarios of MHD-SNFM

Table 4: Outcomes of BNN-LMA for Scenario 3 of MHD-SNFM

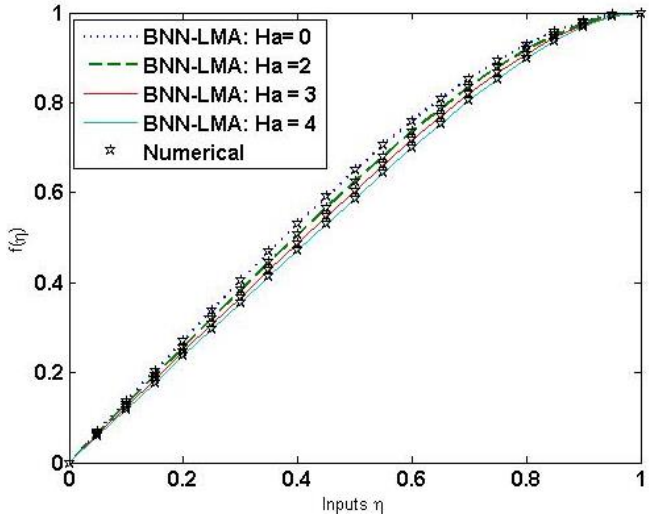
Case	Hidden neurons	MSE			Performance	Grad	Mu	Epochs	Time
		Training	Validation	Testing					
1	10	3.95E-12	6.28E-12	5.44E-10	3.95E-12	9.89E-08	1.00E-10	153	1s
2	10	5.49E-11	1.52E-09	8.98E-11	5.49E-11	9.91E-08	1.00E-09	166	1s
3	10	4.92E-12	7.40E-12	5.11E-12	4.92E-12	9.93E-09	1.00E-10	127	1s
4	10	4.67E-11	7.30E-11	4.81E-11	4.67E-11	9.92E-08	1.00E-09	158	1s



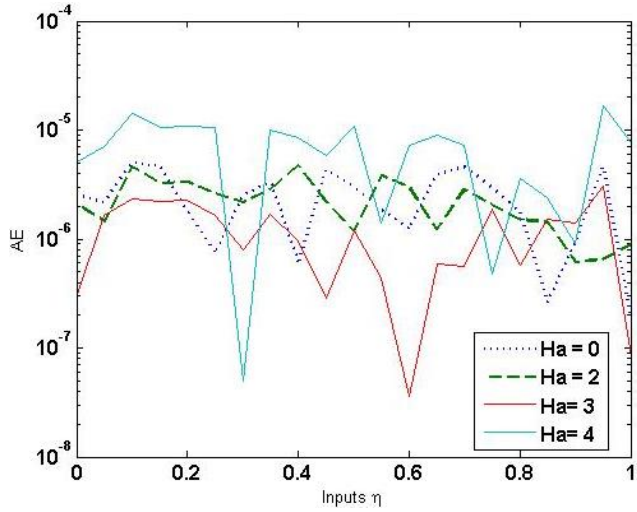
a) **Variation of S for f**



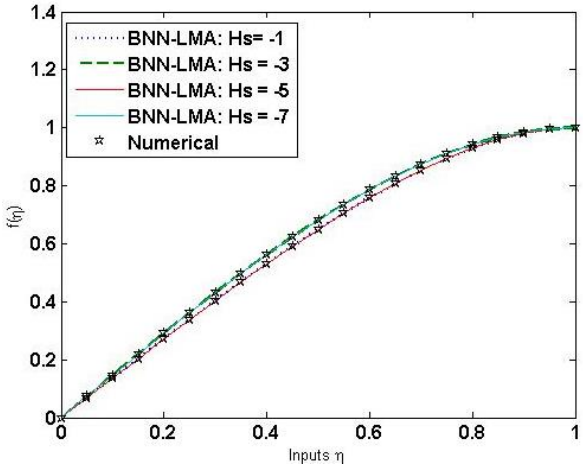
b) **Analysis of AE in variation of S for f**



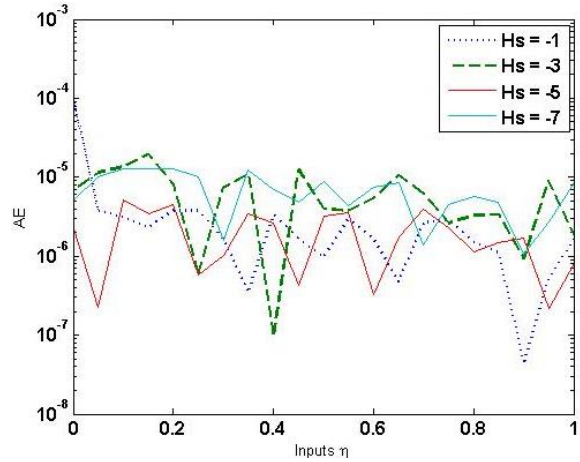
c) **Variation of Ha for f**



c) **Analysis of AE in variation of Ha for f**

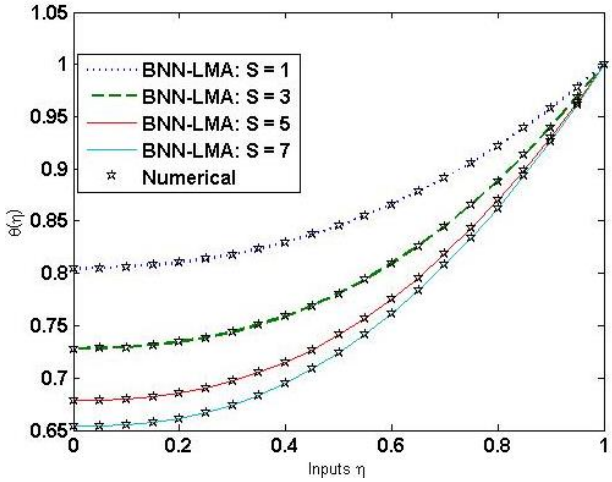


e) Variation of Hs for f

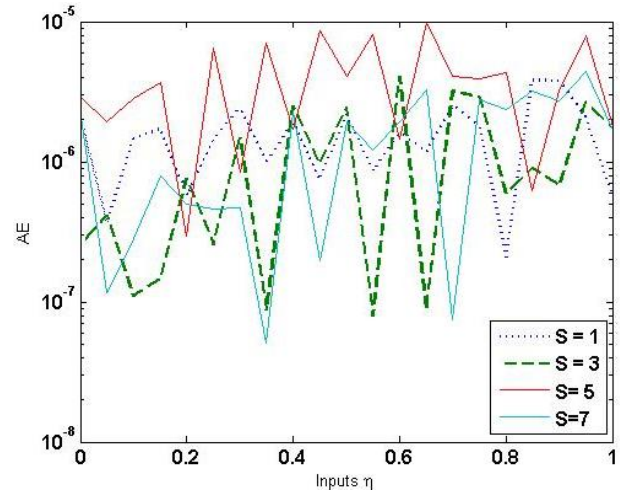


f) Analysis of AE in variation of Hs for f

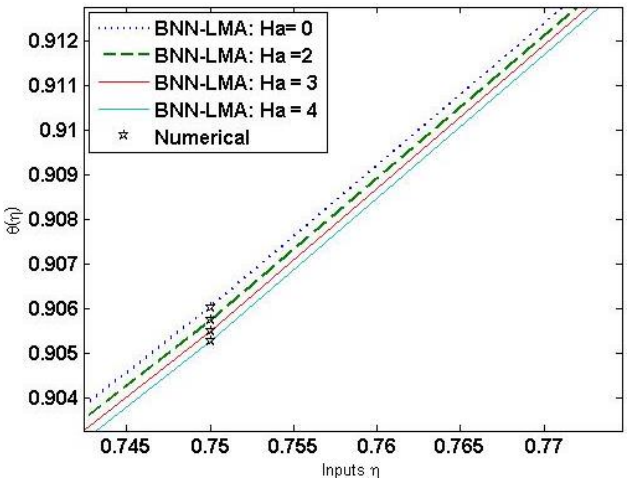
Figure 8: Assessment of BNN-LMA with reference dataset for f of MHD-SNFM



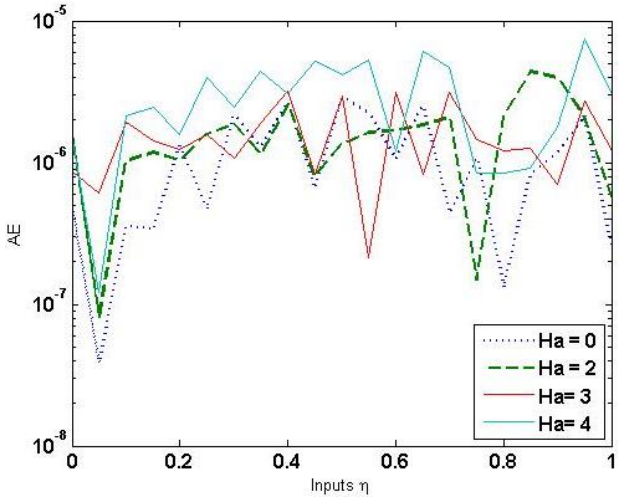
a) Variation of S for θ



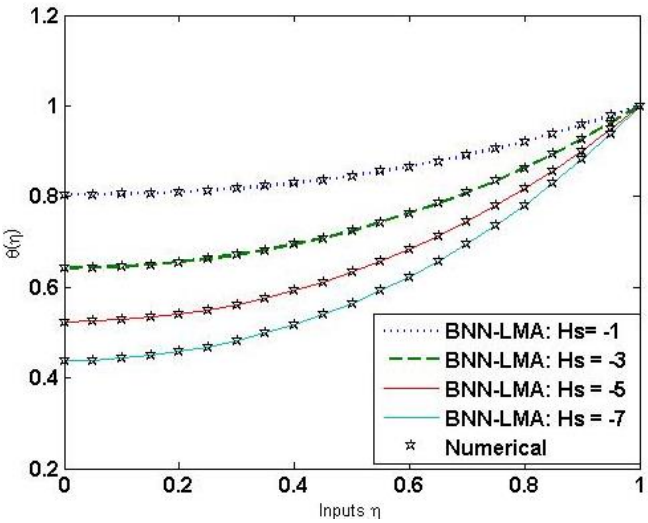
b) Analysis of AE in variation of S for θ



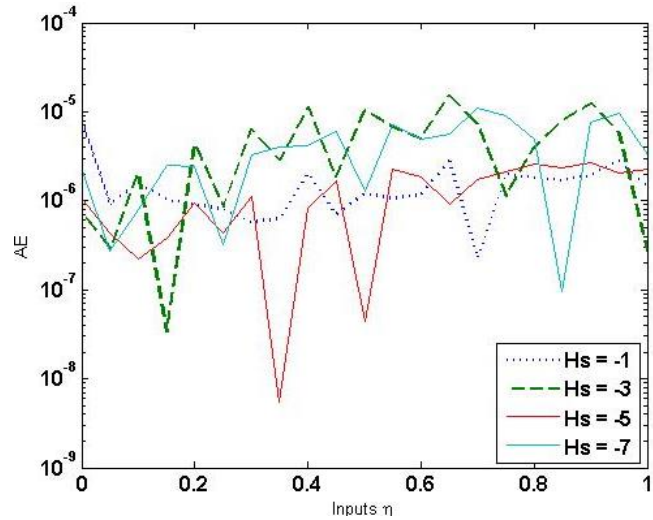
c) Variation of Ha for θ



d) Analysis of AE in variation of Ha for θ



e) Variation of Hs for θ



f) Analysis of AE in variation of Hs for θ

Figure 9: Assessment of BNN-LMA with reference dataset for θ of MHD-SNFM

4. Conclusion:

The artificial intelligence based backpropagated neural networks with Levenberg-Marquardt algorithm (BNN-LMA) are utilized to interpret the solution of mathematical model of squeezing 2D magneto-hydrodynamic (MHD) nanofluid flow between two parallel plates for different scenarios by variation of squeezing number, Hartmann Number and heat source parameter. The PDEs of MHD squeezing nanofluid flow model are transformed into equivalent ODEs by using similarity variables. Adam numerical solver is utilized to generate the reference dataset of MHD-SNFM by variation of different variants. The 80%, 10% and 10% of the reference data are utilized for training, testing and validation for BNN-LMA. The proposed and reference outcomes verify the correctness of the technique and is further justified through numerical and graphical illustrations of convergence plots of MSE, regression and correlation analysis, and histogram studies.

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Author Contributions

M.S, M.A.Z.R and P.K modeled and solved the problem. M.S and I.F wrote the manuscript. Z.S, M.A.Z.R and P.K contributed in the numerical computations and plotting the graphical results. All authors finalized the manuscript after its internal evaluation.

Additional Information

Competing Interests: The authors declare no competing interests

Figures

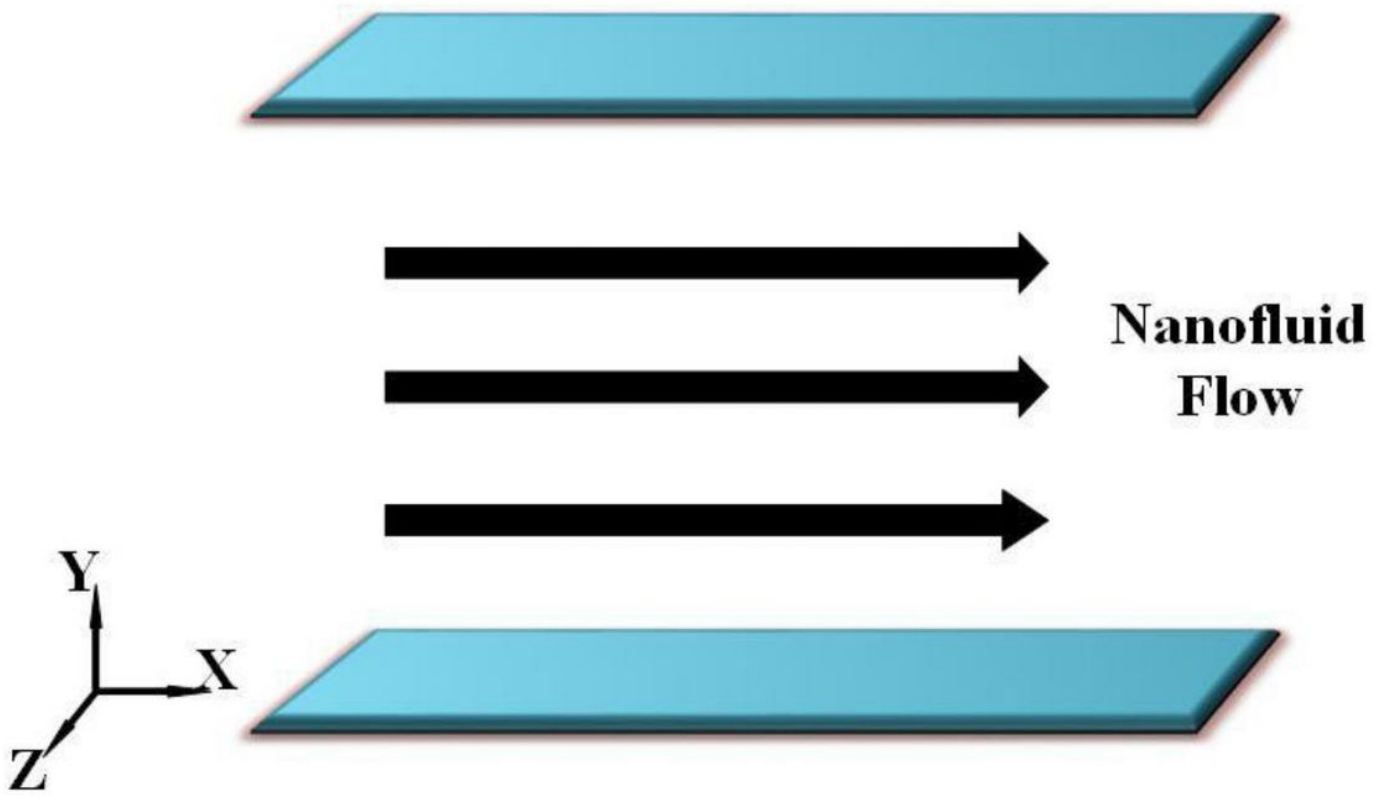


Figure 1

MHD Squeezing fluid flow between two parallel plates

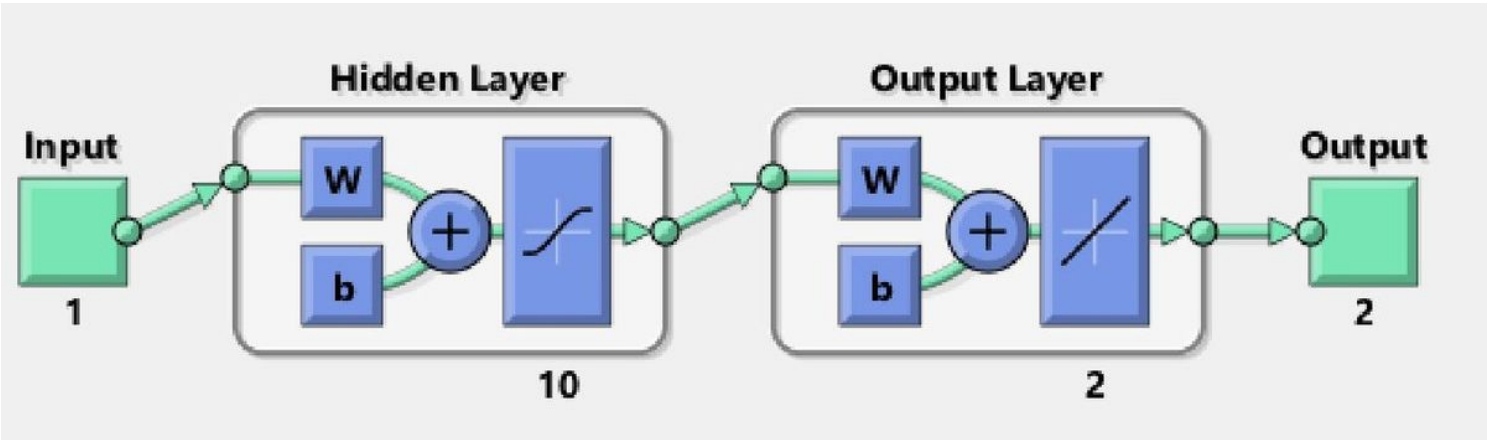


Figure 2

Neural Network for designed BNN-LMA of MHD-SNFM

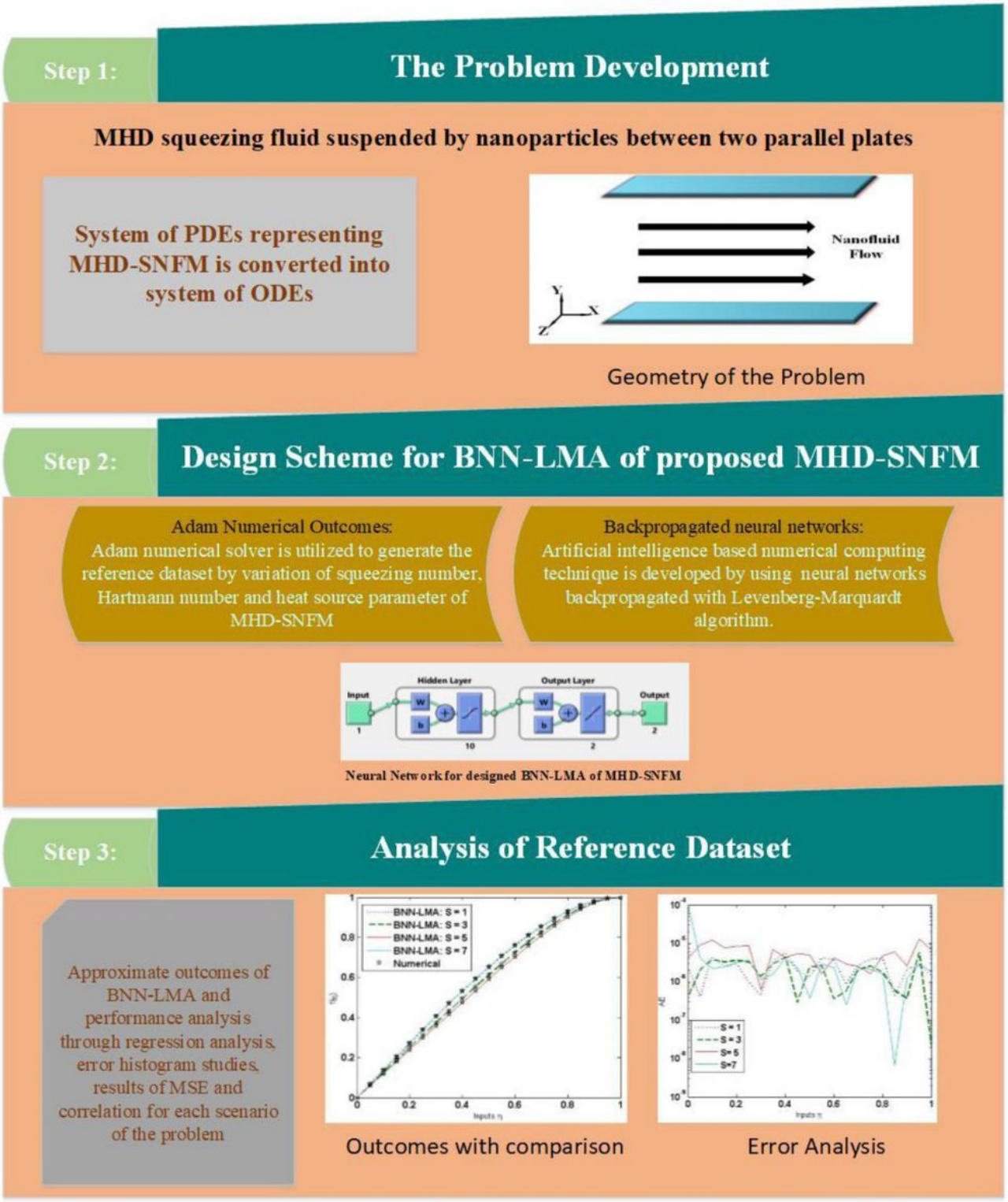


Figure 3

Flow Chart of MHD Squeezing fluid flow model

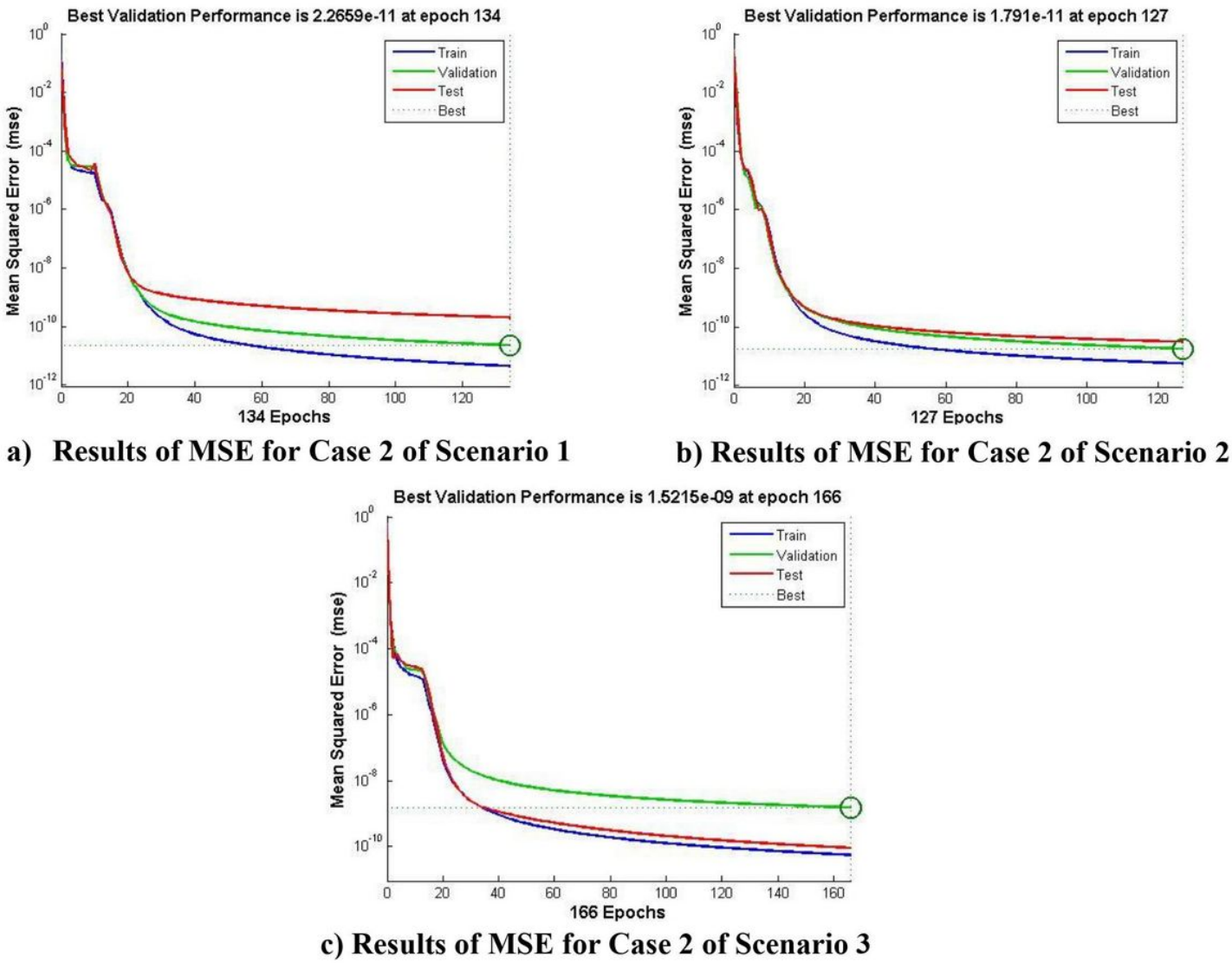


Figure 4

Performance on MSE of designed BNN-LMA of case 2 of all the scenarios of MHD-SNFM

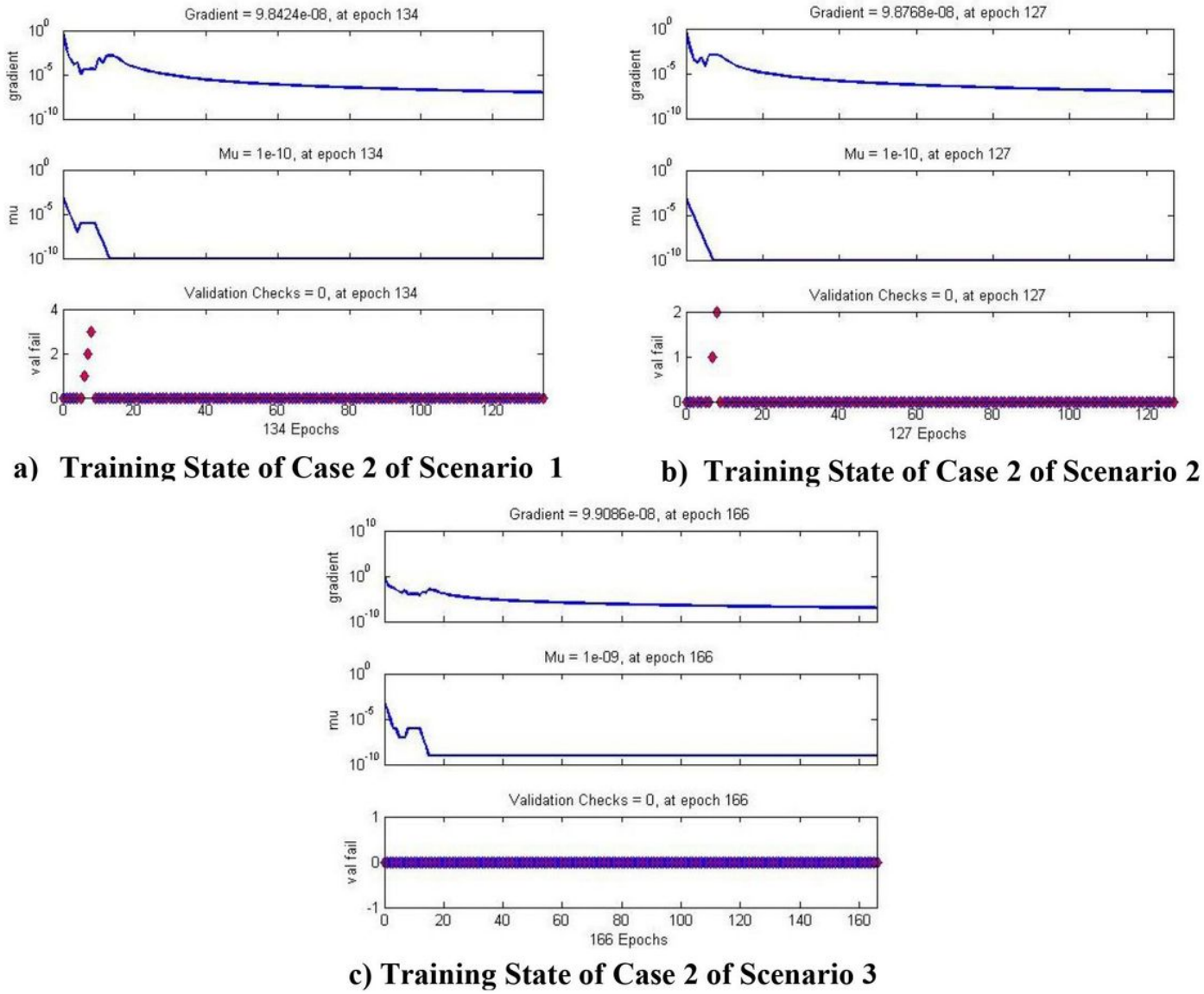
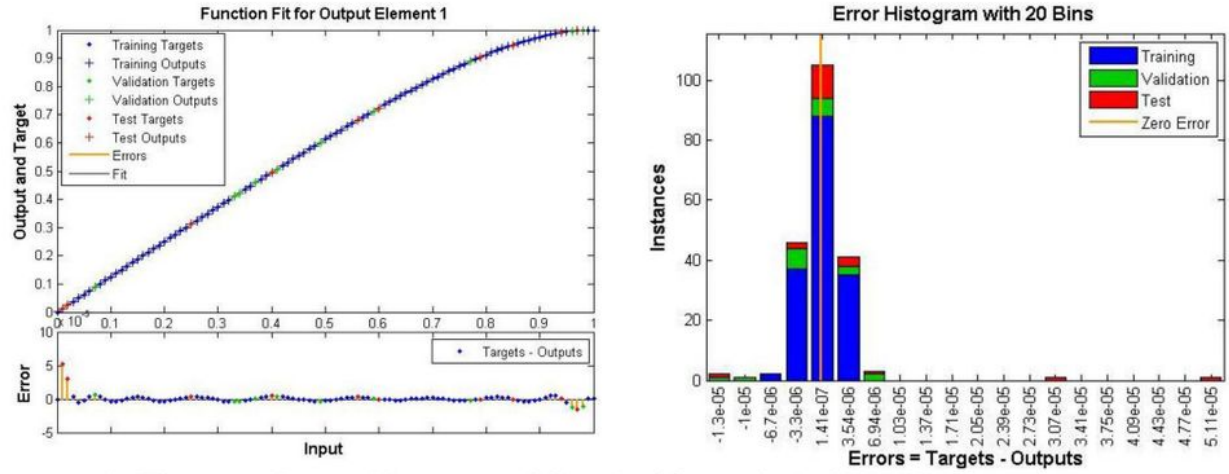
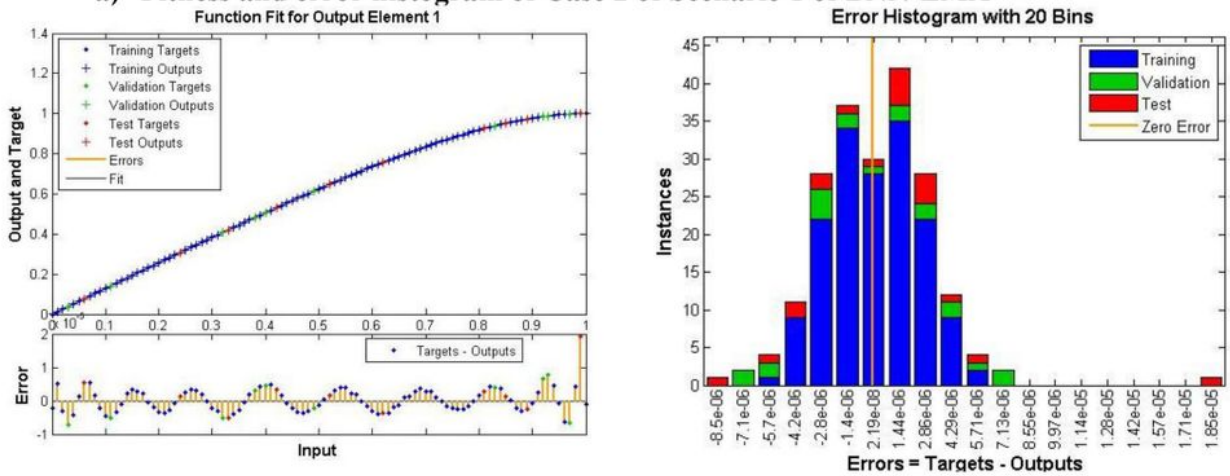


Figure 5

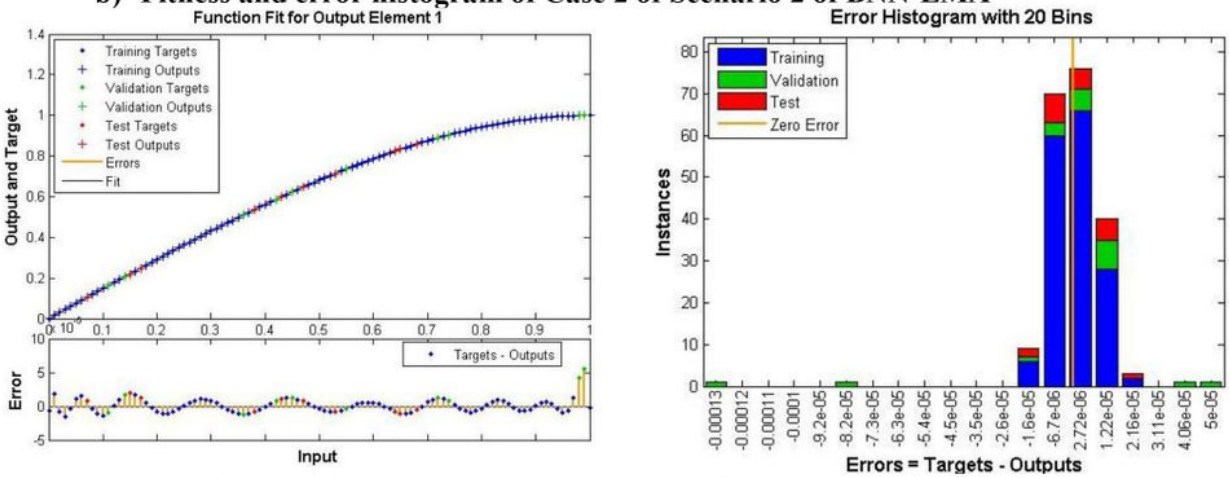
Transition State of designed BNN-LMA of Case 2 of all the three scenarios of MHD-SNFM



a) Fitness and error histogram of Case 2 of Scenario 1 of BNN-LMA



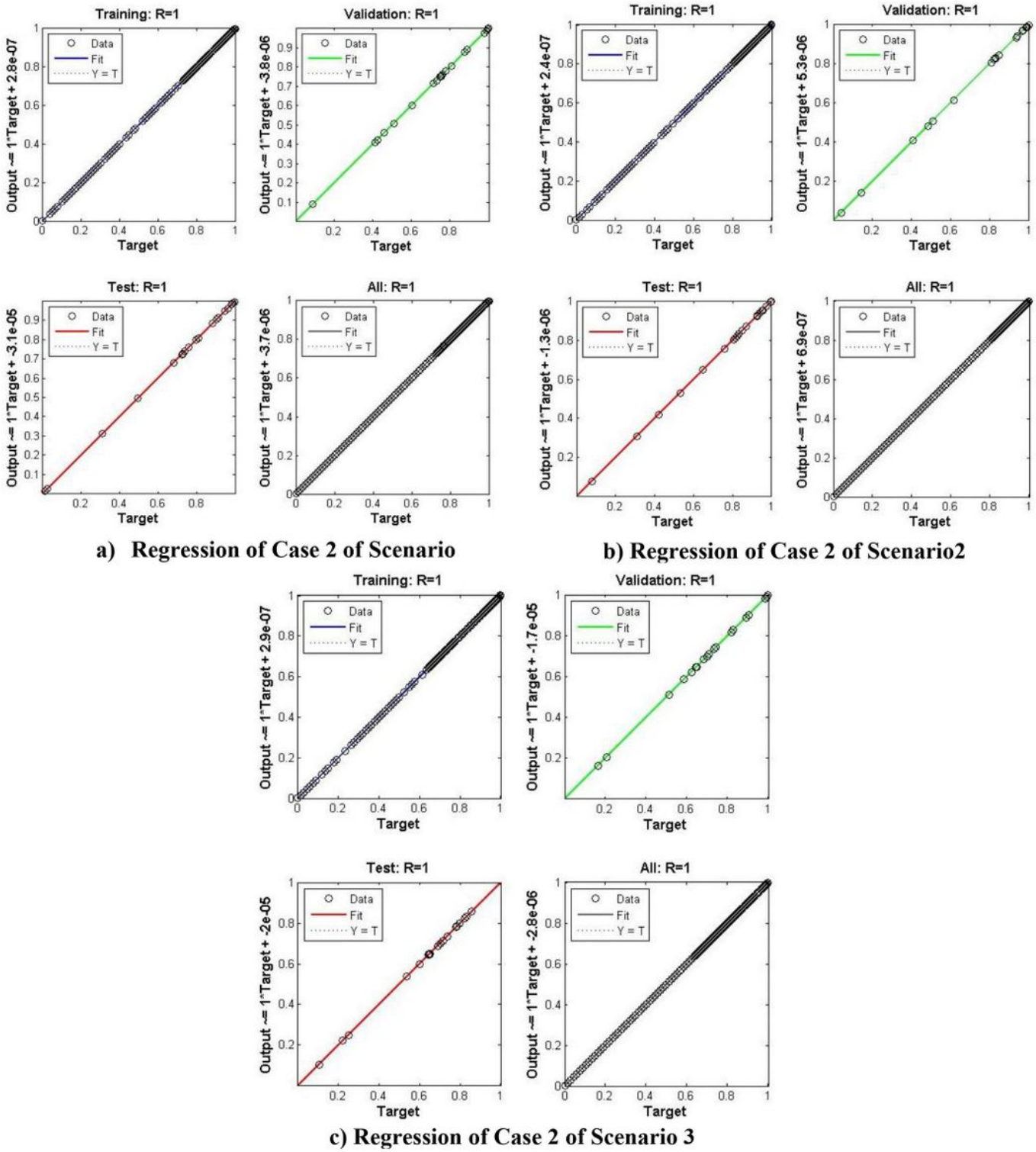
b) Fitness and error histogram of Case 2 of Scenario 2 of BNN-LMA



c) Fitness and error histogram of Case 2 of Scenario 3 of BNN-LMA

Figure 6

Function Fitness and error histogram studies of designed BNN-LMA of MHD-SNFM



a) Regression of Case 2 of Scenario

b) Regression of Case 2 of Scenario2

c) Regression of Case 2 of Scenario 3

Figure 7

Regression presentations of BNN-LMA for case 2 of all the Scenarios of MHD-SNFM

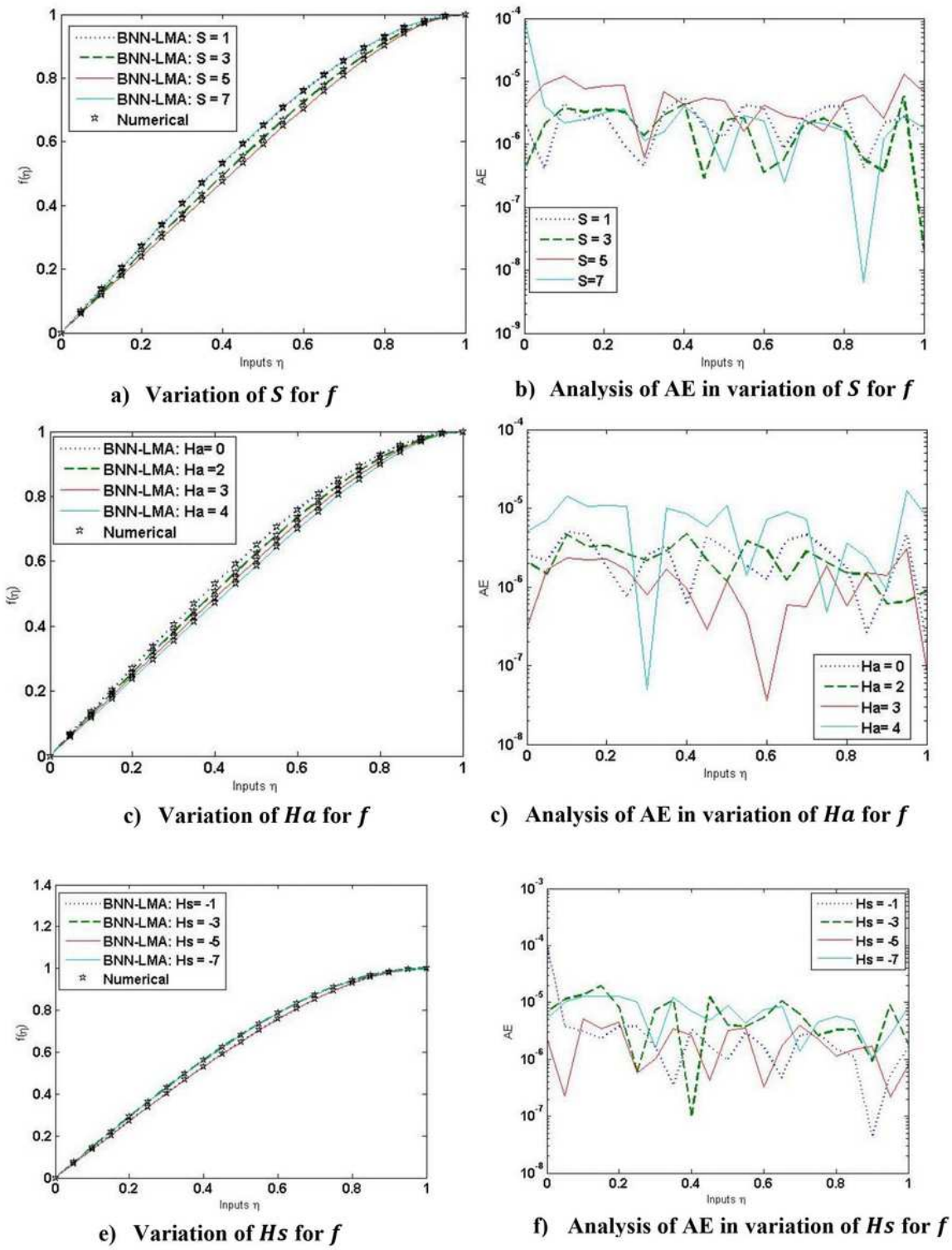


Figure 8

Assessment of BNN-LMA with reference dataset for f of MHD-SNFM

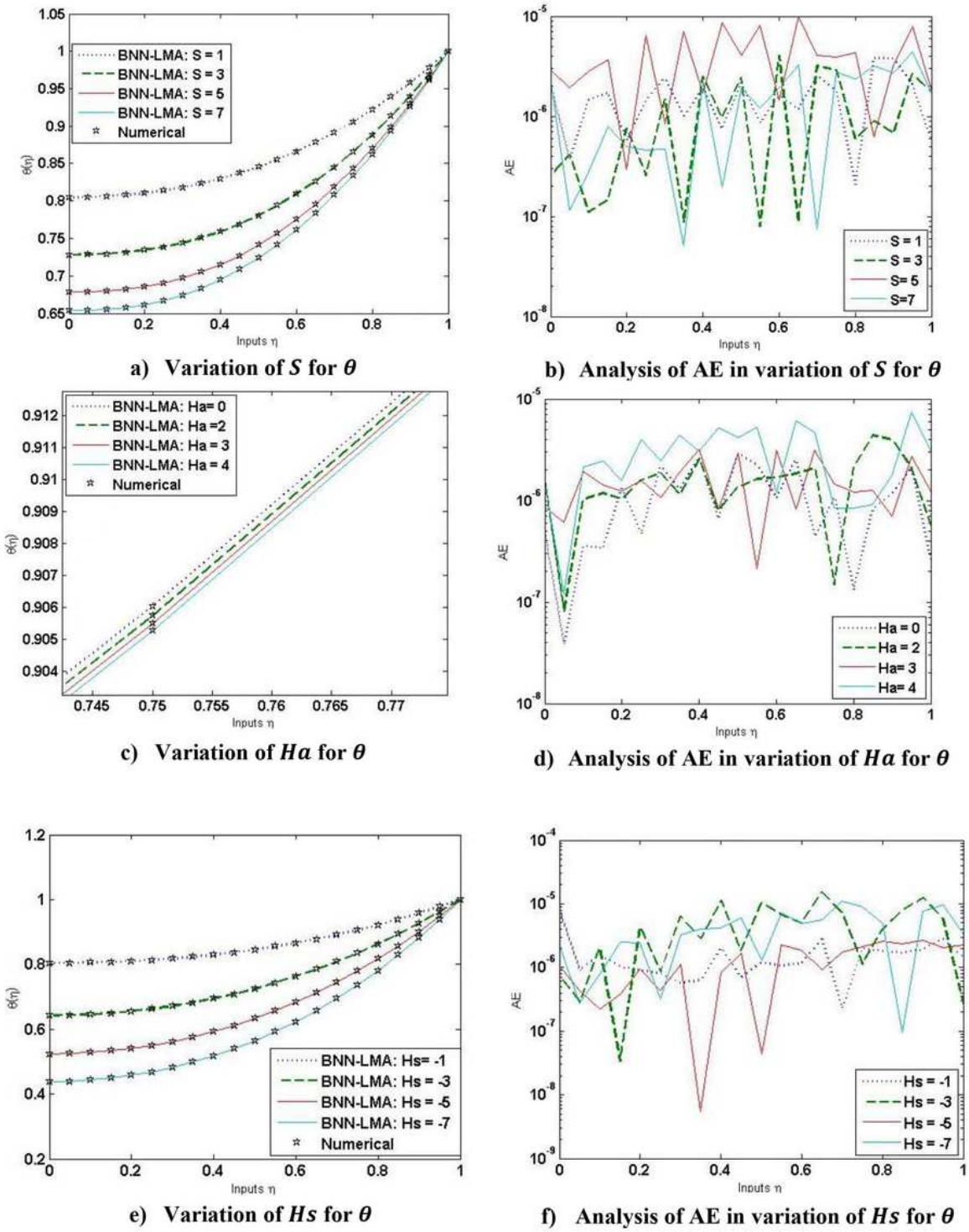


Figure 9

Assessment of BNN-LMA with reference dataset for θ of MHD-SNFM