An artificial intelligence-based prediction way to describe flowing a Newtonian liquid/gas on a permeable flat surface

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Abstract

The purpose of this study is to utilize artificial neural network (ANN), as one of the most powerful artificial intelligence methods, for modeling stream function (f) and the dimensionless temperature (θ) for the considered problem. The problem that is investigated here is flowing a Newtonian fluid on a permeable flat surface. The Homotopy Perturbation Method (HPM) recently developed by the authors for this problem is utilized to provide enough number of the input data. The best ANN is found for each of the two indicated outputs. Then, the best ANN model for each output is utilized to investigate the impact of changing the similarity variable in the range 0.0 to 10.0 on prediction error of the two mentioned outputs. Four values for porosity, which are 0.2, 0.5, 0.8, and 1.0, are investigated. According to the findings, an almost quadratic relation for changes prediction error of f as a function of η is seen, whereas after a sudden drop, the error in prediction of θ declines linearly. Moreover, for the whole range, and for both outputs, the error remains in an acceptable range, which verifies the good accuracy of ANN.

Keywords: Artifcial neural network · Error analysis · Fluid fow simulation · Heat transfer modeling · Porous media

Abbreviations

b : Bias of a neuron in ANN

f : Stream function

U : Free stream velocity (m s^{-1})

w : Mass of a neuron in ANN

x : Dimension alongside *x* axis

y : Dimension alongside *y* axis

ϑ : Dimensionless temperature

v : Kinematic viscosity ($m^2 s^{-1}$)

ANN: Artificial neural network

HPM: Homotopy Perturbation Method

Introduction

Life of human on the planet has been changed considerably compared to the past [1,2,3,4,5]. The dramatic progress in the technologies human beings use has led to developing more efficient materials for better functionality [6,7,8,9,10,11], including heat and mass transfer phenomena [12,13,14,15,16], and taken this point into the consideration, much efficient porous (permeable) materials have been constructed and utilized during the past years [17,18,19]. Porous media are found in different shapes and sizes [20,21,22], and they have been used in a variety of applications [23,24,25,26].

In order to analyze the performance of a porous medium, different simulation approaches have been employed [27, 28]. They include numerical approaches, including finite element and finite difference, mathematical approaches, including Homotopy Perturbation Method (HPM), and so on [29, 30]. In addition to those approaches, artificial intelligence methods, especially artificial neural network (ANN), is another means for modeling which is increasingly becoming favorite [31, 32].

ANN has been utilized to provide a prediction way to estimate different parameters in various problems in the porous media field. The investigation done by Santos et al. [33] could be given as an example, where flowing a fluid through a permeable material was simulated using neural network. Moreover, Mohebbi Najm Abad et al. [34] determined the transport phenomena for the interaction of a nanofluid and a porous medium by means of neural network. Ebadi et al. [35] also provided an alternative way to obtaining Jacobian matrix and the inverse of that using ANN, which led to save both time and computational cost.

In another study, Alizadeh et al. [36] presented a radial basis function ANN to determine the transport properties for flowing fluid through porous media around a cylinder. Furthermore, a special type of neural network, called Auto-Encoder, was utilized by Shams et al. [37] for reconstructing the structure a porous material. Moreover, Babakhani et al. [38] estimated transport behavior of nanoparticles in a permeable material using ANN in which 493 series of the experimental data was employed as the input for modeling.

Additionally, ANN was used for predicting the thermal behavior of a permeable material located in a square cavity by Ahmad et al. [39], where a good agreement between the estimation of ANN and the results found in the literature was reported. For a cone which was made of a permeable material, Athani et al. [40] proposed an ANN model to describe the heat transfer properties. A “quite accurate” performance was reported based on the obtained results.

The conducted literature review demonstrates that the despite great investigations which have been done up to now, a number of gaps should still be addressed. One of the most significant items, which is trying to be fulfilled here, is that to the best of authors’ knowledge, the error values have been given for the whole range as one value, while the prediction error for a range of effective parameters has not been investigated in details. As a result, this study is performed, which aims at estimating stream function (*f*) and the dimensionless temperature (θ) for flowing a Newtonian fluid on a permeable plate. ANN is utilized for this purpose, while the data generated by analytical solution of Homotopy Perturbation Method (HPM) is used as the input data. Having verified ANN model, it is used to find the impact of the similarity variable (η) on changing prediction error for different values of porosity (k^*).

In this study, after introduction, i.e., the current section, the methodology is presented in Sect. 2. After that, in Sect. 3, the obtained findings are given and discussion about them is carried out. Finally, the most remarkable results are listed in Sect. 4 of this paper, which entitles conclusion.

Methodology

This section shares information about the investigated problem, as well as the working principle of ANN. They are presented in Sects. 2.1 and 2.2, respectively.

The investigated problem

Figure 1 gives a schematic description of the problem that was investigated in this study. This is the problem of flowing a Newtonian fluid on a flat porous plate. In order to analyze this problem, the continuity and incompressibility assumptions are considered. Moreover, the properties are assumed to be constant. In addition, the flow is considered to be both laminar, single phase and steady.

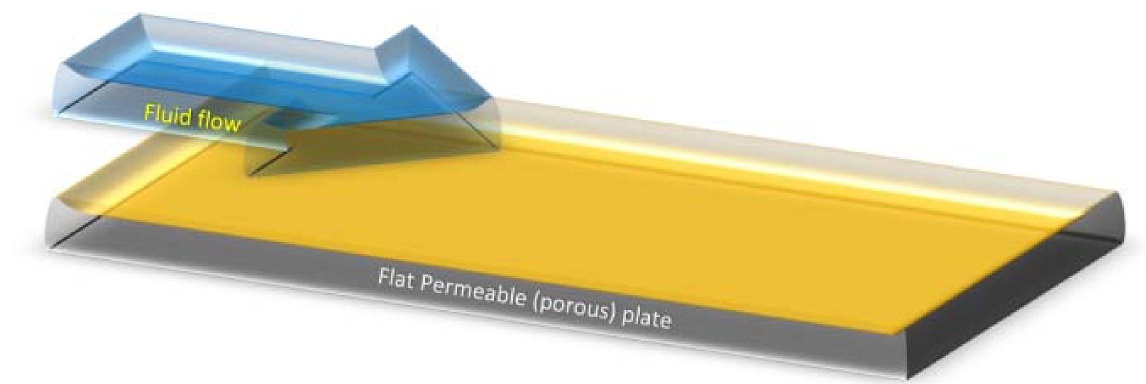


Fig. 1. Description of the problem that was investigated in this study

Here, enough number of data should be extracted to feed into the modeling procedure as the input data. Moreover, they are needed for validation purposes. Considering these points, the solution obtained for this problem by Homotopy Perturbation Method (HPM) in the recent study of the authors [41] is utilized. HPM was initially proposed by He [42], and it is taken into account as a powerful way to obtain analytical solutions for various problems [43,44,45], including the one considered in this study. Since all the employed equations and other details about HPM for solving this problem have been completely found in the previous publication of the authors [41], for not getting the paper lengthy, that reference is given for further read.

Artificial neural network

As indicated previously, in this study, using the data obtained from HPM, both stream function and the dimensionless temperature are simulated by artificial neural network (ANN). Compared to other techniques, including solving governing equations, or numerical modeling, ANN has big advantages. One of the most important items is that using it does not need any knowledge or background about the governing equations or numerical modeling, and only a general information about the problem is enough. Moreover, it enjoys a fast speed of calculation, especially compared to numerical modeling technique. However, it needs to gain information about working ANN, while compared to other statistical tools, it has an almost complex structure, which makes its using without a computer extremely hard [46,47,48]. By having the enough number of data and following the stages introduce in the continue, an ANN could be built [49]:

1. At the beginning, the tuning parameters are adjusted. The tuning parameters cover number of neurons in each layer, the net and transform function for neurons, number of layers, type of the network, learning algorithm, stopping criteria, and so on.

2. Then, using the training data, finding the mass and biases of each neuron in the structure is done in a way the value of one error-related criterion gets optimized. Mean square error (MSE), coefficient of determination (R^2), and sum square error (SSE) are the three most-widely considered error-related criteria for this purpose.

3. Next, the developed ANN model is compared with the preceding one by means of the validation data. If the error for the currently developed ANN is lower than the previously found one, it is a successful epoch; otherwise, it is not

4. After that, the stopping criteria are checked. If one or more than one of them are met, the algorithm terminates by introducing the best obtained network; otherwise, the process is continued from the stage #2.

It is also worth mentioning that stream function and the dimensionless temperature are considered as the output of ANN modeling. For each item, a separate ANN is obtained, while the input parameters are the same as the ones taken into account in [41]. Moreover, like HPM, more details about ANN could be found in the previous cited studies of the authors, in addition to the reference books about that, like [50,51,52]. Moreover, by taking advantage of the written codes in MATLAB software program, developing ANN models was done.

Results and discussion

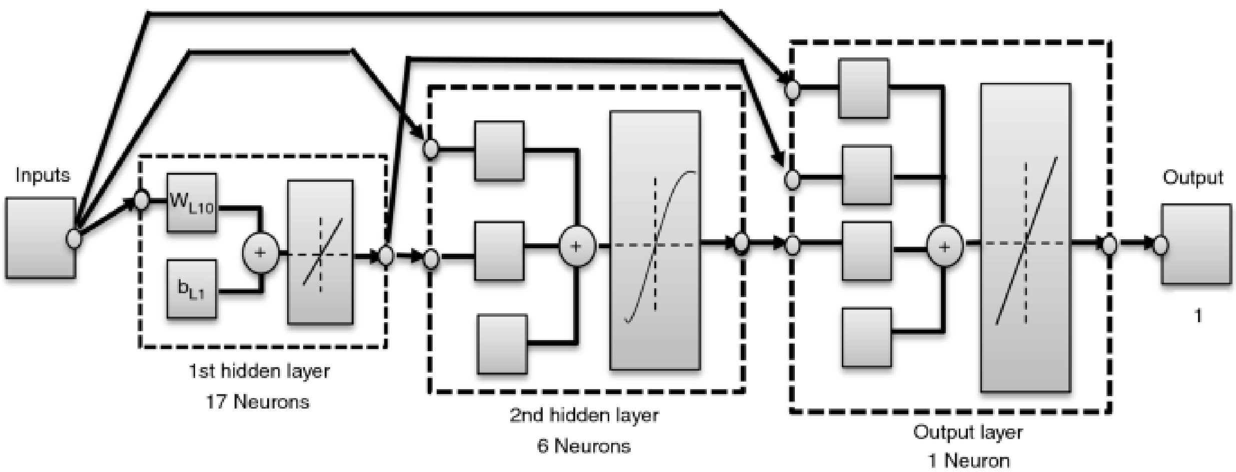
The results of this investigation are given and discussed in this part. This part contains introducing and validation of the developed ANN model in Sect. 3.1, and a parametric study in Sect. 3.2. The parametric study is done with the aim of comparing the error in prediction of ANN for a range of η and k^*. As indicated, η is the similarity variable, which is obtained from Eq. (1):

$$\eta = y\sqrt{\frac{U}{\nu x}} \qquad (1)$$

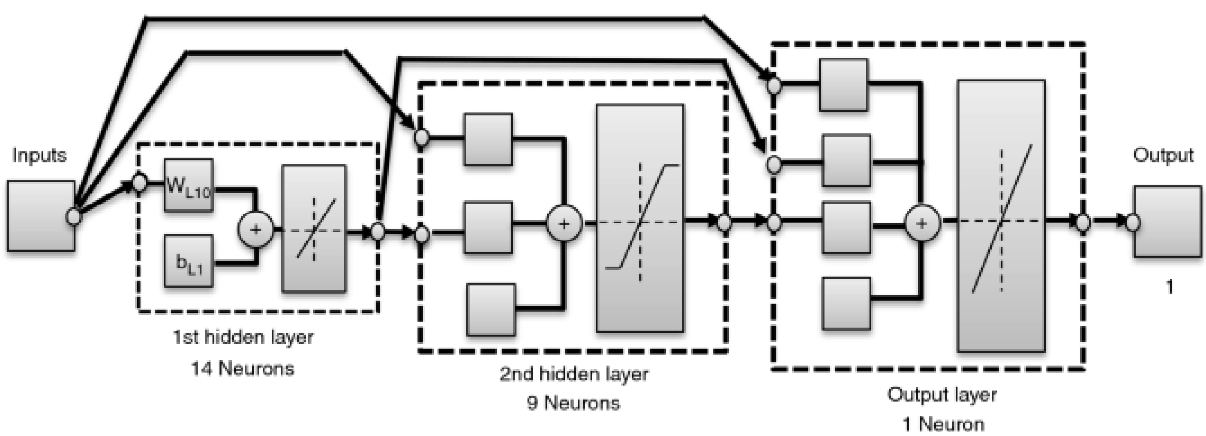
Introduction and validation of the developed ANN

Following the same fashion as the previously done investigation in the field of developing ANN models for different systems like [46, 47, 49], several networks were built, and then, by taking mean absolute error (MAE) and coefficient of determination (R^2) for 40 series of data which has not been utilized to create the models, the best ANN is chosen.

Evaluation of different obtained networks shows that ANN models with the forms shown in Fig. 2a and b are the best one to predict f and θ, respectively. The values of MAE for them are 3.19 and 2.83%, while they have R^2 of 0.988364 and 0.989091, respectively.



(a)



(b)

Fig. 2. A schematic showing the structure of the best ANN models obtained to predict **a** f; **b** θ

After finding the best ANN models for f and θ, double-checking is done by comparing the results with prediction of HPM method for this problem, which was originally presented in [41]. Figure 3a and b demonstrates the results, where a provided good accuracy by ANN compared to HPM is observed. Consequently, double-checking is also found successful. It should be noted that the validation condition here is exactly the same as the one used in [41].

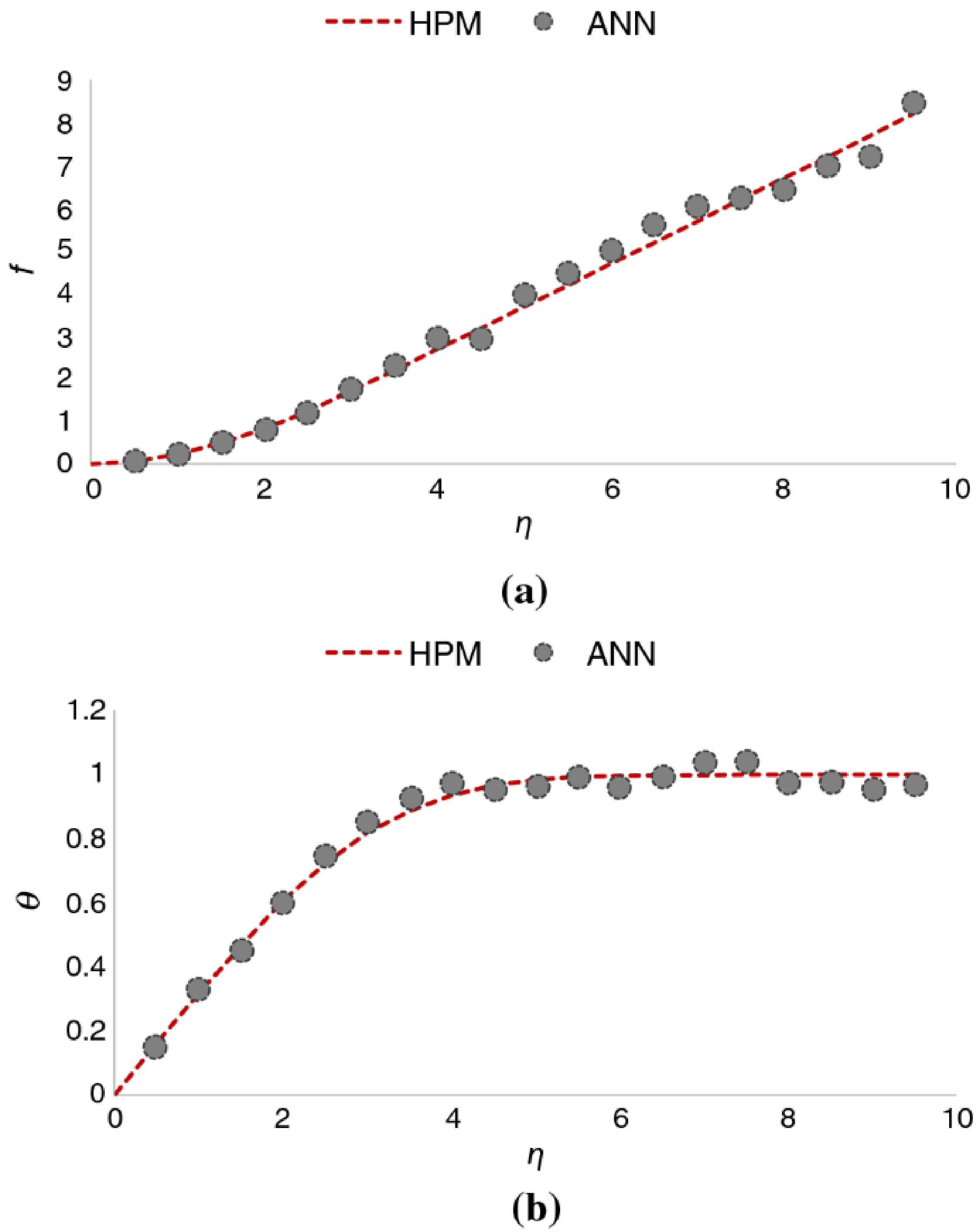


Fig. 3. Double-checking the prediction accuracy of the best ANN models in comparison with HPM, which was originally presented in [41] **a** f; **b** θ

Parametric study of error variation

In this part, the prediction ability of the best ANN models to estimate f and θ is evaluated for various values of porosity, shown by k^*. Sections and provide the results for f and θ, respectively.

Stream function

As seen in Fig. 4, for four values of k^*, i.e., 0.2, 0.5, 0.8, and 1.0, f is obtained in the η range of 0 to 10 by means of the best ANN. Then, the error in prediction is computed using the found analytical solution of reference [41].

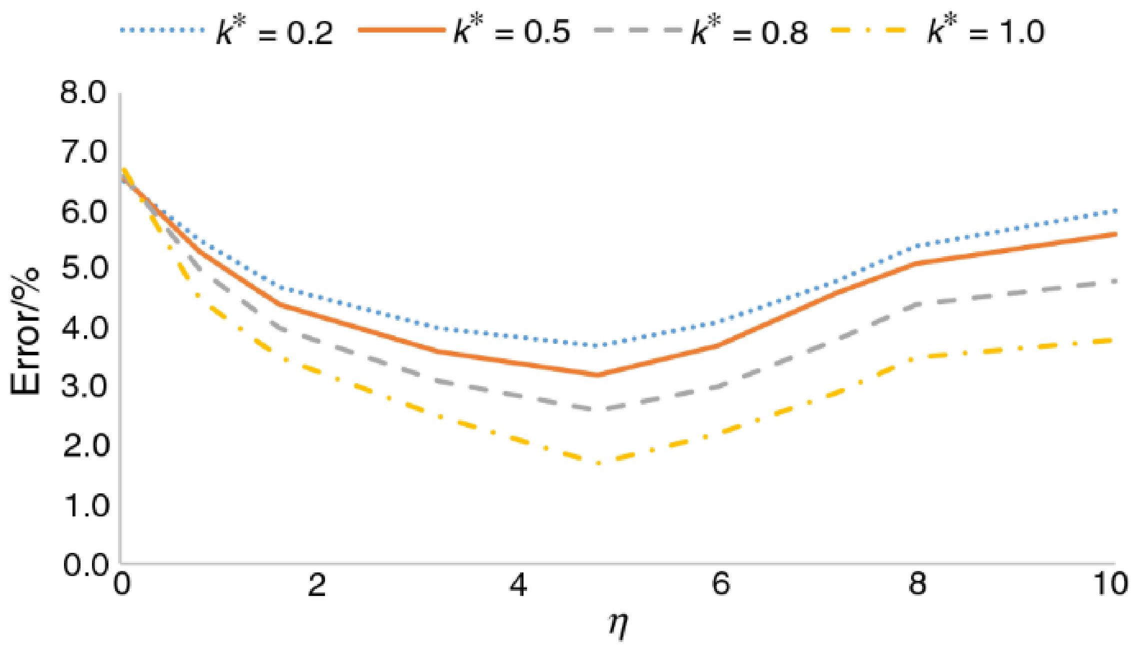


Fig. 4. Variation of error in the prediction of the best ANN to predict the stream function, i.e., f for 4 values of k^*, which are 0.2, 0.5, 0.8, and 1.0

Based on Fig. 4, when $\eta = 0$, the error values in prediction of f are almost equal for all the cases. However, by increasing k^*, prediction error declines and reaches a minimum level for all the investigated conditions, and then, it goes up. The minimum error occurs around η of 4.7. The higher k^* is, the greater minimum error is observed. For k^* of 0.2, 0.5, 0.8, and 1.0, the minimum values of error are 3.7, 3.2, 2.6, and 1.7%, respectively.

As mentioned, when the minimum passes, the error has an upward trend. Nonetheless, the rate of growth afterwards is lower than the rate of decline before, and for that reason, the error in prediction at the end of the investigated range of η does not reach the value at the beginning. Moreover, an almost quadratic behavior could be detected for variation of error as a function of the error range stays in acceptable range for all the studied k^* levels. The ranges between 3.7 and 6.6% for $k^* = 0.2$, 3.2 and 6.6% for $k^* = 0.5$, 2.6 and 6.6% for $k^* = 0.8$, and 1.7 to 6.6% for $k^* = 1.0$ are obtained. It highlights the fact that the best ANN model to predict f has enough accuracy in a wide range of η.

Dimensionless temperature

Similar to f, the error in prediction of θ using the best ANN is computed and compared in Fig. 5 for four conditions of k^*, which are 0.2, 0.5, 0.8, and 1.0 presents the results. Like f, for this case, the same error for $\eta = 0$ is seen. However, the variation trend is not the same as f, and here, a decrease in error in the whole range of η is observed for all k^* values.

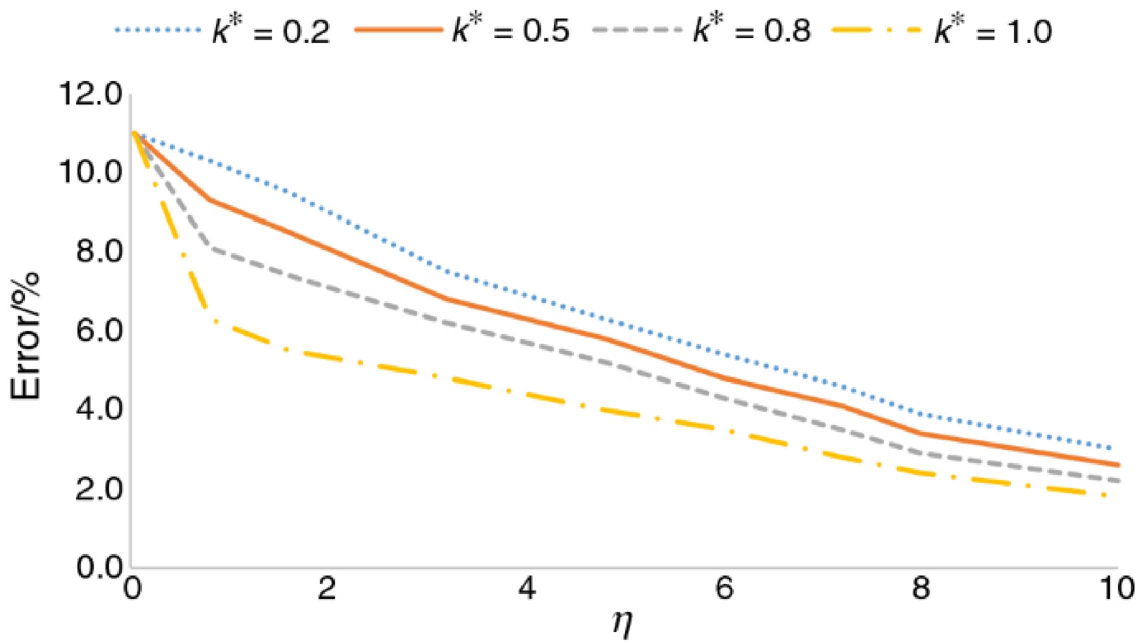


Fig. 5. Variation of error in the prediction of the best ANN to predict the dimensionless temperature, i.e., f for 4 values of k^*, which are 0.2, 0.5, 0.8, and 1.0

The declination trend of prediction error could be divided into two parts. The first part is a sudden drop at the beginning of η range, which is accompanied by a linear reduction after that. The higher k^* is the more severely the error in prediction of θ drops. For $k^* = 0.8$, the decrease in prediction error from $\eta = 0$ to $\eta = 0.8$ is 2.9%, whereas by reaching $k^* = 1.0$, it becomes 62% more, i.e., 4.7%.

After η around 0.8, the trend gets linear in a way that the error in prediction of θ at different conditions of k^*becomes very close together at the end of the investigated range. Although differences between error values for k^* of 0.2 and 0.5, 0.5 and 0.8, and 0.8 and 1.0 are 1.0, 1.1, and 1.9% at $\eta = 0.8$, they get all 0.4 when $\eta = 10$. Additionally, the average error of 6.3, 5.8, 5.2, and 4.0% for the four indicated k^* values reveals that the best ANN has a robust prediction tool for this case too.

Conclusions

The present study revealed that ANN was able to successfully predict both stream function and the dimensionless temperature. Moreover, the detailed error analysis in a wide range of similarity variable changes demonstrated that the error in prediction of both indicated outputs remained acceptable for different conditions of porosity. The maximum error was a bit above 10%, which indicated that an acceptable level of accuracy could be offered by ANN. Moreover, it was found that the relation between similarity variable and error in prediction of the stream function was almost quadratic. Nonetheless, after a sudden drop, a linear decrease was observed for error in prediction of the dimensionless temperature by increasing the similarity variable.

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