Comparison of different artificial neural network (ANN) training algorithms to predict the atmospheric temperature in Tabuk, Saudi Arabia

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ABSTRACT Use of Artificial neural network (ANN) models to predict weather parameters has become important over the years. ANN models give more accurate results in weather and climate forecasting among many other methods. However, different models require different data and these data have to be handled accordingly, but carefully. In addition, most of these data are from non-linear processes and therefore, the prediction models are usually complex. Nevertheless, neural networks perform well for non-linear data and produce well acceptable results. Therefore, this study was carried out to compare different ANN models to predict the minimum atmospheric temperature and maximum atmospheric temperature in Tabuk, Saudi Arabia. ANN models were trained using eight different training algorithms. BFGS Quasi Newton (BFG), Conjugate gradient with Powell-Beale restarts (CGB), Levenberg-Marquardi (LM), Scalled Conjugate Gradient (SCG), Fletcher-Reeves update Conjugate Gradient algorithm (CGF), One Step Secant (OSS), Polak-Ribierrre update Conjugate Gradient (CGP) and Resilient Back-Propagation (RP) training algorithms were fed to the climatic data in Tabuk, Saudi Arabia. The performance of the different training algorithms to train ANN models were evaluated using Mean Squared Error (MSE) and correlation coefficient (R). The evaluation shows that training algorithms BFG, LM and SCG have outperformed others while OSS training algorithm has the lowest performance in comparison to other algorithms used.

Key words – Artificial neural network, Atmospheric temperature, Prediction, Tabuk, Training algorithms.

1. Introduction

Interest in use of Artificial Neural Networks (ANNs) for developing climate change prediction models has increased in recent years due to ever changing climate patterns in the world (Yadav and Chandel, 2013; Acharya et al., 2014; Belayneh et al., 2014; Hashim et al., 2017; Moghim and Bras, 2017; Mishra et al., 2018). ANNs are computer systems inspired by biological neural networks to model relationships between independent and...
dependent variables. They are capable of modelling complex non-linear relationships from raw data sets to find relationships among variables (Betiku et al., 2015; Emeko et al., 2015; Ebrahim and Rajaei, 2017; Ravansalar et al., 2017). Unlike traditional statistical techniques, ANNs do not require the transformation of raw data prior to model generation. Furthermore, pre-assumption of the nature of relationship between input and output variables is not required in ANNs (Agatonovic-Kustrin and Beresford, 2000; Ibić et al., 2003). Literature gives different ANN algorithms and applied to many real-world events predicting future scenarios. In addition, these different ANN training algorithms were tested for their performance while comparing them each other (Kisi, 2004; Nayak et al., 2004; Wang et al., 2018). Climate change is such a real-world scenario which ANN was heavily used by many researchers.

The climate change, which is heavily influenced by the human activities has become a vital topic for discussion in the present world (Field et al., 2015). Emissions from burning fossil fuel is one of the major factors for the climate change and climate variability, where gases like carbon dioxide (CO₂), methane (CH₄), ozone (O₃), etc., are emitted through these fossil fuels (Karl, 2003; Quadrelli and Peterson, 2007). Not only human life, but also other living species like plants and animals have been badly affected through the climate change and climate variability (Vorbsmarty et al., 2000; Hughes et al., 2003; Barnett and Adger, 2007; Harvell et al., 2014; Patz et al., 2016; Azamathulla et al., 2018; Friedrich et al., 2018).

Among the other climatic factors, atmospheric temperature is a key factor in defining the climate change and a slightest change in temperature could trigger the changes in people’s daily routines (Kalkstein and Smoyer, 1993). Thus, prediction of atmospheric temperature using various research methods can be increasingly found in literature (Rotstayn et al., 2014; Simmons et al., 2014; Mears and Wentz, 2017).

Kisi and Uncuoglu (2005) studied on the use of three back propagation training algorithms, Levenberg-Marquadt (LM), resilient Back-Propagation (BP) and conjugate gradient for two case studies, stream-flow forecasting and to determine the lateral stress in cohesion-less soils. Based on their comparisons of convergence velocities in training and testing performance, they found that LM algorithm is faster and has better performance than other algorithms in training. However, results showed that Resilient Back-Propagation algorithm has the best accuracy during training. Ghaffari et al. (2006) tested five training algorithms, Incremental Back-Propagation (IBP) and Batch Back-Propagation (BBP) under gradient descent, Levenberg-Marquadt, Quick Propagation (QP) and Genetic Algorithm (GA) for their ability in predicting the effect of coating weight gain and pectin-chitosan amount in the coating solution for drug delivery. The performance was tested using the effect of two factors, coating weight gain and amount of pectin-chitosan in the coating solution on the in-vitro release profile of theophylline for biomedical drug delivery. No significant difference was observed between the performances of IBP and BBP, although, the convergence speed of BBP was found to be three-to-four-fold higher than IBP. In addition, they found that the predicting ability precision based on the performance was in the order of IBP, BBP >LM >QP >GA. However, Pham and Sagiroglu (2001) showed that the BP is the best training algorithm out of tested algorithms, (BP), QP, Delta-Bar-Delta (DBD) and Extended-Delta-bar-Delta (EBDB). These training algorithms were used to learn ANN to recognize control chart patterns and classify wood veneer defects. Kisi (2007) studied on the use of four different ANN training algorithms, BP, conjugate gradient (CG), cascade correlation (CC) and LM to forecast streamflow in the North Platte river in the United States. He found that LM gave the best flow forecasts and faster results compared to other training algorithms. In addition, his results showed that CG and CC models produced more satisfactory predictions than BP. Therefore, several studies illustrate different algorithms to reach the best prediction.

However, further studies have used different training algorithms in ANN to forecast various climatic parameters such as rainfall (Lee et al., 1998; Hall et al., 1999), evaporation (Shiri et al., 2014a), dew point temperature (Shiri et al., 2014b), solar radiation (Landeras et al., 2012), daily reference evapotranspiration (Guven and Gunal, 2008; Izadifar and Elshorbagy, 2010), etc. Azamathulla et al. (2018) presented a study to predict the atmospheric temperature in Tabuk, Saudi Arabia using gene expression techniques and compared that to the ANN model. However, no proper study has carried out to predict the minimum and maximum atmospheric temperature in Tabuk using different ANN algorithms and then to compare their performance. Therefore, identifying that research gap, we developed eight different ANN models to predict the atmospheric temperature of Tabuk, Saudi Arabia using other climatic factors. The results from eight different training algorithms including, Levenberg-Marquadt (LM), BFGS Quasi Newton, Resilient Back-Propagation, scaled conjugate gradient, Conjugate gradient with Powell-Beale restarts, Fletcher-Powell conjugate gradient, Polak-Ribiere conjugate gradient and One step secant are promising. Prediction of minimum and maximum atmospheric temperatures which are two most important climatic parameters to the dwellers in Tabuk is the major novelty of the presented paper.
2. Artificial Neural Networks (ANNs) training algorithms

As it was stated in the introduction section, artificial neural networks are popular among researchers and planners these days to predict real world scenarios. These ANN algorithms use local or global non-linear optimization methods for optimizing the feed-forward neural networks weights. The local searches are limited to local solutions whereas, global searches avoid this limitation (Ilonen and Kamarainen, 2003). The training performance varies based on the objective function of optimization process and the underlying error surface for a given problem and the network configuration. The most popular optimization methods are variants of gradient based back-propagation algorithms. This is because the gradient information of error surface is available in these algorithms. The widely used methods are Levenberg-Marquadt (LM), BFGS Quasi Newton, Resilient Back-Propagation, Scaled conjugate gradient, Conjugate gradient with Powell-Beale restarts, Fletcher-Powell conjugate gradient, Polak-Ribiere conjugate gradient, One step secant (Hagan and Menhaj, 1994; Liang et al., 1994; Martin, 1997; Japkowicz and Hanson, 1999) The objective of the training process in an ANN is to reduce the global error \( E \) and the error is defined as follows in Equation (1) (Kişi, 2007).

\[
E = \frac{1}{P} \sum_{p=1}^{P} E_p
\]

where, \( P \) is the total no of training patterns and \( E_p \) is the error for training pattern \( P \). \( E_p \) is calculated using the following Equation (2).

\[
E_p = \frac{1}{2} \sum_{k=1}^{N} \left( O_k - t_k \right)
\]

where, \( N \) is the total number of output nodes, \( O_k \) is the network output at the \( k^{th} \) output node and \( t_k \) is the target output at the \( k^{th} \) output node. The global error is reduced by adjusting the weights and biases in the training algorithm (Kişi, 2007). The following subsections present the widely used algorithms for training the neural networks.

2.1. Levenberg-Marquadt (LM) algorithm

The Levenberg-Marquadt (LM) optimization algorithm is identified to be more powerful than the conventional gradient descent techniques (Lera and Pinzolas, 2002; Lourakis, 2005; Kişi, 2007). It is the most widely used optimization algorithm and designed to approach the second-order training speed without computing the Hessian Matrix (Moré, 1978). The Hessian Matrix can be approximated when the performance function is in the form of sum of squares and given in Equation (3).

\[
H = J^T J
\]

where, \( J \) is the Jacobian matrix, containing the first derivatives of the network errors with respect to the weights and biases.

The standard back-propagation technique is used to compute the Jacobian matrix, which is less complex than computing the Hessian matrix. Equation 4 gives the Newton-like update used in the LM algorithm. When \( \mu = 0 \), this is the Newton’s method, using the approximate Hessian matrix.

\[
x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e
\]

where, \( e \) is a vector of network errors, \( \mu \) is a scalar quantity, \( x_{k+1} \) is the predicted minimizer and \( x_k \) is the current point.

2.2. BFGS Quasi Newton Back-Propagation (BFG) algorithm

The BFGS Quasi Newton algorithm was independently developed by C. G. Broyden, D. Goldfarb, R. Fletcher and D. F. Shanno (Nocedal and Wright, 1999). The basic step in the Newton’s method given in equation (5), where, \( H^{-1} \) is the Hessian matrix of the performance index at the current values of the weights and biases (usual notations are used here).

\[
x_{k+1} = x_k - H^{-1} g
\]

BFGS method does not calculate the \( 2^{nd} \) derivatives. However, an approximate Hessian matrix is updated in each iteration of the algorithm. This update is calculated as a function of the gradient. Super linear convergence rate is observed in BFGS method on most practical problems, even though the algorithm requires more computations and storage in each of the iterations performed (Nocedal, 1980; Nocedal and Wright, 1999; Schraudolph et al., 2018).

2.3. Resilient Back-Propagation (RP) algorithm

Resilient Back-Propagation is an algorithm which directly adapts weights based on local gradient. In this learning scheme, adaptation is not blurred by the behaviour of the gradient. For this to happen, an
individual update value $\Delta_{ij}$ is given for each weight to
determine the size of the weight update. $\Delta_{ij}$ evolves
during the learning process depending on its sight on local
error function $F$, governed by the learning rule given in the
equation (6):

$$
\begin{align*}
\Delta_{ij}^{(t)} &= \eta^{+} \times \Delta_{ij}^{(t-1)}, \text{ if } \frac{\partial F^{(t)}}{\partial a_{ij}} \times \frac{\partial F^{(t-1)}}{\partial a_{ij}} > 0 \\
\Delta_{ij}^{(t-1)}, \text{ if } \frac{\partial F^{(t)}}{\partial a_{ij}} \times \frac{\partial F^{(t-1)}}{\partial a_{ij}} < 0 \\
\Delta_{ij}^{(t-1)}, \text{ else }
\end{align*}
$$

(6)

where, $0 < \eta^- < 1 < \eta^+$; $\eta$ is update value factor
and $\omega$ is corresponding weight. More details on this
algorithm can be found in Saini (2008).

2.4. Scaled Conjugate Gradient Back-Propagation (SCG) algorithm

Usually, line search is required at each iteration in
conjugate gradient algorithms. However, scaled
conjugate gradient algorithm developed by Moller (1993)
abandons the time consumption in line search. The model
trust region approach used in the LM algorithm is
combined with conjugate gradient approach in this
algorithm. Scaled Conjugate Gradient Back-Propagation
algorithm requires more iterations to converge than other
algorithms. But, computations in each iteration are
significantly less compared to others since line search is
not performed (Moller, 1993; Andrei, 2007; Cetisli and
Barkana, 2010).

2.5. Conjugate Gradient with Powell-Beale Restarts (CGB) algorithm

The search direction is periodically reset to the
negative gradient in conjugate gradient algorithms. The
standard reset point has occurred when number of
iterations is equal to the number of network
parameters. Powell (1977) proposed a reset method
based on the earlier method proposed by Beale
(1967) to improve the efficiency of the training.
According to this technique, restart is set if a little
orthogonality is left between current and previous
gradients and this is tested using the inequality given in
the equation (7) (Colaco and Orlande, 1999; Saini and
Son, 2002).

$$\left| g^T_{k-1}g_k \right| \geq 0.2 g_k^2$$

(7)

where, $g^T_{k-1}$ is the norm squared of the previous
gradient and $g_k$ is the current gradient.

2.6. Fletcher-Reeves (CGF) and Polak-Ribiere (CGP) conjugate gradient algorithm

Fletcher-Reeves and Polak-Ribiere introduced two
equations to calculate $\beta_k$ positive scalar to find the $P_{n0}$
search vector in this algorithm. Equation 8 presents the $\beta_k$
for Fletcher-Reeves method whereas Equation 9 presents it
for the Polak-Ribiere method (Colaco and Orlande, 1999;
Saini and Son, 2002; Shaheed, 2004).

$$\beta_k = \frac{g^T_k g_k}{g^T_{k-1}g_{k-1}}$$

(8)

$$\beta_k = \frac{\Delta g^T_{k} g_{k}}{g^T_{k-1}g_{k-1}}$$

(9)

where, $\beta_k$ is the ratio of the norm squared of the
current gradient to the norm squared of the previous
gradient and it is a positive scalar.

2.7. One step secant (OSS) algorithm

The one-step-secant (OSS) algorithm is an approach in
bridging the gap between the quasi-Newton approach
and the conjugate gradient algorithm. This approach does
not store the complete Hessian matrix, instead it was
assumed at each iteration. OSS also has the advantage of
calculating the new search direction without computing an
inverse matrix. However, OSS requires more computation
in each iteration and more storage than conjugate gradient
methods (Constantinescu et al., 2008; Upadhyay, 2013).

3. Methodology

MATLAB installed in a personal computer (Intel(R)
Core (TM) i7-7700HQ CPU @ 2.80 GHz. 16 GB RAM)
was used to develop the above stated algorithms to predict
the monthly minimum and maximum atmospheric
temperature in Tabuk, Saudi Arabia. The input variables
of the algorithms were monthly rainfalls, minimum
monthly relative humidity, maximum monthly relative
humidity, minimum monthly air pressure, maximum
monthly air pressure and monthly average wind speed. In
addition, minimum monthly atmospheric temperatures and
maximum monthly atmospheric temperatures were also
ded to the algorithms to calibrate and test the ANN
algorithms. The developed ANN models are used to
predict $y(t)$ (are dependent variables of the model; the
minimum and maximum atmospheric temperatures) with
d past values of $y(t)$ and $x(t)$, where $y(t)$ is a parameter
depending on different $x(t)$ parameters for set of time
steps, $x(t)$ is the independent parameter for different time
steps (are the monthly rainfalls, minimum monthly
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Fig. 1. Conceptual diagram of ANN

relative humidity, maximum monthly relative humidity, minimum monthly air pressure, maximum monthly air pressure and monthly average wind speed) and $d$ is the available past values for $x(t)$ parameters.

The ANN was trained with 70% of target time steps while 15% each of target time steps were used to validate and test. In addition, 10 hidden neurons and 2 delays were used in the network. The details are shown in the Fig. 1. Performance of each training algorithm in predicting the atmospheric temperatures was evaluated using the Mean Squared Error (MSE) and the correlation coefficient (R). The simulation times for all algorithms were around 1-3 seconds from the above stated personal computer.

4. Case study application – Tabuk, Saudi Arabia

Tabuk city is in Saudi Arabia in its north western part as shown in the Fig. 2 and it has an area of 139,000 km². Tabuk province is bound by Saudi-Jordan country boundary from north, Red sea from south and west and Hufa depression from the eastern side. The city is located at an average altitude of 770 m from the mean sea level. Tabuk province is classified as a hyper-arid catchment and experiences a shorter winter season and a longer summer season (Abushandi and Alatawi, 2015). Monthly weather data were collected for 30 years from 1986 to 2015 from the Saudi General Authority of Meteorology and Environment Protection and fed to the developed ANN algorithms to predict the minimum and maximum atmospheric temperatures in Tabuk.

5. Results and discussion

Figs. 3(a-h) clearly shows that training algorithms BFGS Quasi Newton (BFG) and Conjugate gradient with Powell-Beale restarts (CGB) perform better with R values closer to 1 (>0.97). However, in general, other algorithms also result higher R values.

Figs. 4(a&b) present the results from the ANN models for BFG and CGB algorithms against the target. Even though BFG and CGB give the better
performance in R values [Figs. 3(a-h)], they have slightly lower gradients compared to the target [Figs. 4(a&b)]. Therefore, the minimum atmospheric temperature values for Tabuk, Saudi Arabia are under-predicting as per training algorithms BFG and CGB. Nevertheless, it is not a significant reduction as the gradients are 0.93 and 0.94, respectively to the two algorithms.
Fig. 4(a&b). Best fits to the target for the ANN results for minimum atmospheric temperature.

Fig. 5(a-h). Validation performance for different ANN algorithms for minimum temperature.
Figs. 5(a-h) gives the Mean Squared Error (MSE) values for different algorithms in ANN. CGB and SCG algorithms have shown the lowest MSE values at convergence point. However, these two algorithms have taken more epochs to converge to the least MSE when compared to other training algorithms. Nevertheless, algorithm LM has only taken 17 epochs to reach 5.5387 of MSE. The CGB algorithm has also performed averagely
well in the validation process. It reached the convergence at 20 epochs while reaching a considerable low MSE (~4). However, the OSS algorithm has taken the greatest number of epochs (77) and it has the highest MSE (~7) at the convergence. Therefore, OSS was outperformed by the other algorithms. Therefore, the results show that the BFG algorithm has a better approach when compared to the others in predicting the minimum atmospheric temperature in Tabuk, Saudi Arabia. Nevertheless, CGB and SCG algorithms can also be considered alternative better approaches.

6. Maximum atmospheric temperature

Correlation coefficients for performance of ANN models in predicting the maximum temperature in Tabuk are shown in Figs. 6(a-h). However, slight reductions can be seen in the correlation coefficients of Figs. 6(a-h) when compared to those of at Figs. 3(a-h) (for minimum atmospheric temperature). The maximum value of R value in minimum temperature prediction ANN is around 0.98; however, it is lower in the maximum temperature prediction. A similar observation can be seen for the minimum R values. The minimum atmospheric temperature prediction algorithms have the minimum R value of 0.935 while it is 0.865 in the maximum atmospheric temperature prediction algorithms. Therefore, this observation indicates that the regression plot of ANN models for predicting minimum atmospheric temperature are less scattered compared to that of in maximum atmospheric temperature. It can be clearly seen that the Figs. 6(a-h) give similar R values except in the OSS algorithm. OSS algorithm has shown lowered R values. However, among the others, LM and CGF algorithms have good performances.

Figs. 7(a-h) present the MSE values for the validation process of the different algorithms in maximum
atmospheric temperature prediction. Similar to the Fig. 5(a), LM algorithm shows the lowest number of epochs in convergence (9 epochs) in the maximum atmospheric temperature prediction. However, it also has the lower MSE value (~4) among the other algorithms. In addition, SCG (~3) and CGF (~4) algorithms have lower MSE values; however, they used greater number of epochs for the convergences (38 and 61, respectively). OSS algorithm converged faster compared to the other algorithms; however, it has the highest MSE value. Therefore, similar conclusions can be drawn in maximum atmospheric temperature prediction for OSS algorithm (similar to the minimum atmospheric temperature prediction). The OSS algorithm was outperformed by the other algorithms. Therefore, in general LM and CGF algorithms have performed well to predict the maximum atmospheric temperature for Tabuk, Saudi Arabia.

7. Conclusions

Eight different ANN algorithms were developed to predict the atmospheric temperature in Tabuk, Saudi Arabia. The algorithms used several weather parameters including, rainfall, relative humidity, wind speed, air pressure and atmospheric temperature. Results revealed that, in general, two different ANN algorithms have performed better for predicting minimum and maximum atmospheric temperature in Tabuk. They are BFG for minimum temperature and LM for maximum temperature. However, one common algorithm also performed better in minimum and maximum temperature prediction and that is SCG algorithm. Nevertheless, results show that all eight training algorithms have performed to an acceptable level because, all the correlation coefficients are greater than 0.85 and have acceptable MSE values for the validation processes. Therefore, it can be concluded herein that the atmospheric temperature forecasting process in Tabuk can be reliably done using the artificial neural networks. In addition, the weather forecasters have a choice of different algorithms to use in prediction. Among the other algorithms, LM, BFG and SCG algorithms are proposed as the preferred algorithms for the prediction.

Furthermore, the models are based on the real measured data. Therefore, they are applicable in the real-world cases. Not only applicable in real world cases, but also the models can be used to predict the future minimum and maximum atmospheric temperatures based on the various climate models’ driven independent variables.

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