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Using artificial neural network to predict velocity of sound in liquid water as a function of ambient temperature, electrical and magnetic fields

Hashem Nowruzi*, Hassan Ghassemi

Department of Ocean Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

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Abstract

One of the main thermophysical properties of liquid water is velocity of sound. However, the effect of different externalities on velocity of sound in liquid water is not well known. Therefore, in current study, by designing an artificial neural network (ANN) velocity of sound in liquid water under different externalities is predicted. Selected externalities are ambient temperature from 272.65 K to 348.43 K, different electrical fields in range of 0 V/m to 4.03E + 9 V/m and magnetic fields in range of 0–10.0594 T. To prepare of reference dataset for entry to ANN, numerical and experimental data as macroscopic reference data are extracted from microscopic characteristic of water HB strength. In order to achieve an appropriate ANN, ANN architecture sensitivity analysis is conducted by using an iterative algorithm. Learning procedure in the selected feed-forward back propagation ANN is done by hyperbolic transfer functions. Also, Levenberg–Marquardt algorithm is utilized for the optimization process. ANNs output showed that the maximum MSE in prediction of velocity of sound is 0.00066. Also, the minimum of correlation coefficient in prediction of velocity of sound is 0.99131. Based on the ANNs outputs, weights and bias, an equation to predict of velocity of sound in liquid water under intended externalities is proposed. Also, according to weight sensitivity analysis input of electrical fields with 63% relative importance percentage has a grater impression on the response variable of velocity of sound in liquid water.
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Keywords: Artificial neural network; Electrical field; Magnetic field; Velocity of sound; Temperature.

1. Introduction

The most abundant and vital liquid on our planet is water. So, it has been studied more than any other liquid by scholars. However, weird properties of water resulted to being a ‘‘complex fluid’’ with a lot of anomalies [1–3]. On the other hand, according to comprehensive application of liquid water at microscopic and macroscopic scales, it is necessary to understand of liquid water properties. Therefore, several numerical and experimental studies are conducted to cognition of liquid water properties in recent decade [4–7]. However, there are a lot of issues in field of liquid water properties which are not well known.

In this regard, environmental conditions are effective on liquid water properties. Ambient temperature, electrical field and magnetic field are some of the most important externalities which are impressive on liquid water properties. Several works related to study the effects of externalities on water are done by scholars [8–12]. While, these papers are only focused on effects of externalities on the hydrogen bonding (HB) strength of water in a restrict interval of their considered externalities. Hence, lack of study related to impression of different externalities on the thermophysical properties of liquid water is observable. Velocity of sound in liquid water is one of the important thermophysical properties in liquid water. So, velocity of sound in liquid water under different externalities is studied in the current paper. It is notable that, to access the velocity of sound in liquid water under different externalities, a lot of experiments or numerical simulations must be done, which are time consuming and expensive. Also, velocities of sound in liquid water under different externalities are complex and non-linear problem. Therefore, forecasting method according to available information such as soft computing

* Corresponding author. Fax: +98 21 66412495.
E-mail address: h.nowruzi@aut.ac.ir (H. Nowruzi).

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and artificial intelligence tools including neural networks are proposed.

Although, there is no study in order to predict of velocity of sound in liquid water by using artificial neural network, however, there are several studies related to using soft computing (e.g. artificial neural networks) in context of acoustic and hydro-acoustic [13–17]. In this regard, Luo et al. [18] offered an artificial intelligent method to build a neural network model of multi-parameter sound velocity prediction. They focused sound velocity of marine sediment and showed an appropriate accordance of predicted and experimental data. Liu et al. [19] presented a more general predicting method to estimate of sound absorption coefficients at six central frequencies of a sandwich structure nonwoven absorber. They conducted their study by using general regression neural network (GRNN) as an estimation model to bridge the gap between the measured structural parameters of each absorber and its sound absorption coefficient. Novel biologically inspired method to classify of sound event that combines spike coding with a spiking neural network (SNN) is proposed by Dennis et al. [20]. They showed the superiority of spiking neural network versus conventional cross-entropy neural networks. Recently, Zhang et al. [21] in paper titled as "Sound quality prediction of vehicle interior noise and mathematical modeling using a back propagation neural network (BPNN) based on particle swarm optimization (PSO)" solve the complex non-linear problem between the subjective sound quality evaluation results by using a back propagation neural network.

Based on cited literature, lack of study related to predict of velocity of sound in liquid water under different externalities and necessity of study in this context is detectable. As a result, novelty of present paper is study and prediction of velocity of sound in liquid water under different externalities by using artificial neural network (ANN). To this accomplishment, influence of different electrical fields, magnetic fields and different ambient temperatures on velocity of sound in liquid water are predicted.

The following sections are organized as follows. Influences of external fields on water HB and velocity of sound in liquid water vs. water HB strength are reviewed in Section 2. Then, in Section 3, theoretical and computational procedures based on ANN architectures are provided. The results of ANN training procedure and predicted results are presented and discussed in Section 4. Finally, Section 5 is given for the conclusions.

2. Influences of external fields on water HB

Gases, liquid and solid are three phases of water. Water environmental condition (e.g. ambient temperature and pressure) and external fields have key role in existence of these different phases. So that, these factors are impressive on the molecular structure of water, especially on the average number of hydrogen bonding (nHB) and strength of HB in water. It is also notable that, according to continuum models of water, it has a space-filling hydrogen bond network. The strength of covalent bonding between oxygen-hydrogen bonding in an individual water molecule in liquid phase at 298.15 K is 492 kJ mol$^{-1,}$ while the hydrogen bonding between one molecule oxygen atoms to hydrogen atom of another water molecule has an averaged strength of 23.3 kJ mol^{-1} [22,23].

These are different definition for strength of HB in water. In this regard, one of the useful definitions for strength of HB in liquid water is the energy required to break and completely separate of bond as sum of maximum four hydrogen bonds per molecule [22]. We use this dentition to determine of strength of HB in liquid water in the current study. So that, averaged number of hydrogen bonding (n_{HB}) of each an individual water molecule is multiply by its related strength is intended as HB strength of an individual water molecule.

On the other hand, length and angle of HB are two affective parameters on the HB strength. These parameters are dependent on polarization shifts in different hydrogen-bonded environments. Small change of HB length and angle resulted to significant variations in strength of HB. On the other words, stronger HB is predicted under lower HB length. Therefore, it can be conclude that, external fields are impressive on HB strength by change of HB length and angle and consequently, are effective on the strength of donor and acceptor atom in HB.

Ambient temperature is one of the most important effective externalities on the water molecules. Water molecules clusters and strength of HB are under influence of temperature difference. So that super-cooled water, ambient water, supercritical water and gaseous water are obtainable. In the present paper, we are interested on the ambient water. Ambient water is ubiquitous phase of water which forms in temperature interval of 273.15–373.15 K. Importance of ambient water resulted to several theoretical and experimental studies related to investigate of impression of temperature difference on the strength of HB [24–26]. In these studies, scholars used X-ray Raman spectroscopy (XRS) and X-ray absorption spectroscopy (XAS) to study the effects of temperature difference on the HB strength [27,28]. On the other hand, average number of hydrogen bonding (n_{HB}) is another efficient parameter to study the change of one water molecules due to its surrounding effects. In this regards, several studies related to the influence of temperature on the n_{HB} by using molecular simulations are conducted [8,9,23]. According to these studies, one can be concluded that, tendency of individual water molecules to enhancement of n_{HB} is decreased by water temperature increment.

On the other hand, bipolar structure of water molecules and delocalization of electrons between water molecules resulted to capability of water interaction with external field including magnetic, electric and electromagnetic fields. Enhancement of HB strength in direction of external electrical field is predictable [29]. The reason of this fact is related to polarizability of water molecule. In addition, increase of HB and diminish of water cluster size with impose of electrical filed is detectable [30,31]. However, Suresh et al. [10] indicated that electrical fields can only enhance the HB structure

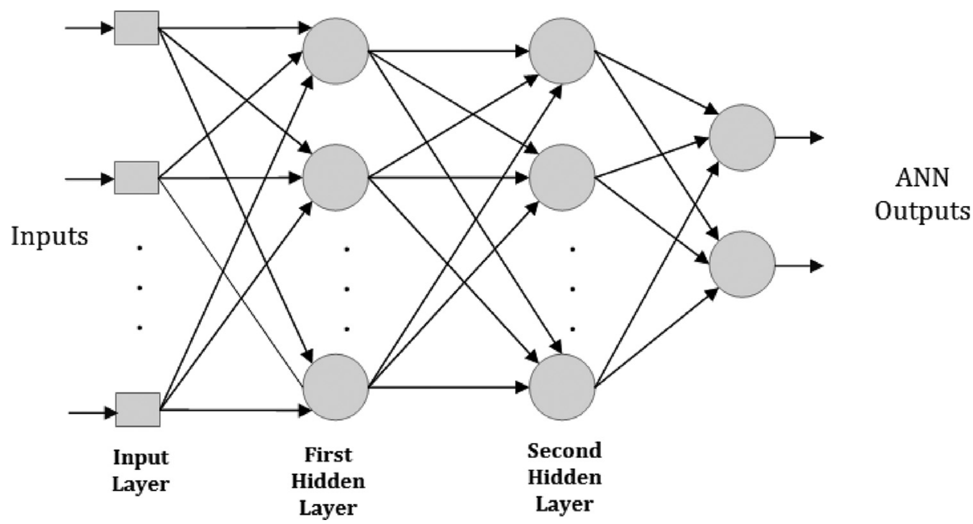

Fig. 1. Architecture of multilayer perceptron (MLP) neural network.

of water, not disrupt it at any of the practically attainable field strengths. Therefore, it is visible that, the influences of electrical field on water cluster are dependent on the strength of electrical field.

Other externality which is effective on water molecules and structure is magnetic field. Magnetic field impressions on the water structure are interesting issue which is studied by scholars [11,12]. The balance between HB and van der Waals force will be disturbed by magnetic fields. This happen resulted to increase of HB bond [32]. In this regard, Zhou et al. [11] showed decrease of n_{HB} of water under entering magnetic field by using Monte Carlo (MC) simulation. While, Chang and Weng [33] in a MD simulation study relate to effect of magnetic field in range of 0–10 T at 300 K on the n_{HB}, indicated an increment of n_{HB} by increase of magnetic field strength. Also, Cai et al. [34] showed higher activation energy and slower rotational dynamics of magnetized water. Consequently, increase of the average size of water clusters in magnetized water is predictable.

On the other hand, microscopic strength of water HB is a key role to change the thermophysical properties of water at macroscopic scale. In other words, decrease and increase of HB strengthening has significant effect on velocity of sound in liquid water [22]. In this regards, mediocre change in velocity of sound is detectable by HB strength variations. It's also is notable that, such small change velocity of sound in liquid water has remarkable effect on some processes [22].

As a result, based on the above discussion, the necessity of study to predict of velocity of sound in liquid water under different externalities is visible. On the other hand, velocity of sound in liquid water under different externalities is a black box, which must be predicted as a complex system. So, in the next section, we faced with this complex system by implement of artificial neural networks.

Indeed, from multi-scale phenomenological aspect of liquid water, variation of HB strength at microscopic scale is able to change of velocity of sound in liquid water at macroscopic scale. In addition, as discussed before, different externalities are impressive on HB strength and respectively on the velocity of sound in liquid water. Now, we can produce an ANN to predict of velocity of sound in liquid water under different externalities by using reference data. This reference data are experimental data that are representative of relation between HB strength and velocity of sound in liquid water and are extracted from scientific publications and presented in Section 3.1.

3. Theoretical and computational procedure

3.1. Artificial neural network structures

Estimate of complex system output with different impressive input parameters is capability of artificial intelligence system such as artificial neural networks (ANNs) system. ANNs are composed from interconnected integrated process units (i.e. neurons) which are placed in three different layers. Input layer, hidden layers, and an output layer are these three layers that are shown in Fig. 1. On the other hand, feed-forward back-propagation neural network is one of the popular deep learning supervised ANN model which is used in the present study.

Process of feed-forward back-propagation neural networks is that, outside evidences will be received by input layer. Afterward, by using identity transfer function, these inputs are transferred to input variables. Then, they entered to the hidden layers through the interconnection between input layer and hidden layer neurons. By interconnected weights between the neurons of hidden layers, the principle computation of ANNs implemented in these layers. So that, in neurons of hidden layer, summations of outputs of previous layer is weighted. Then they are adding with bias. Afterward, this sum will be passed via a transfer function. Hyperbolic Tangent sigmoid transfer function is implemented for neuron in hidden layer by

$$n_j = \frac{2}{1+e^{-2Z}} - 1 \quad (1)$$

Where, n_j is the jth neuron output and Z will be determined as following

$$Z = \sum_{i=1}^{r} \omega_{ij} p_i + b_j \quad (2)$$

Here, ω_{ij} are interconnection weights of ith neuron in previous layer to the jth neuron and p_i is output of ith neuron. In addition, r is the number of previous layer neurons and b_j is the bias.

At the end, the results will be sent to the output layer. So, the output variable will be achieved by output layer. In the present paper, linear transfer function (λ) is applied in output layer as,

$$g = \lambda(\omega_L.Z + b_o) \quad (3)$$

Where, ω_L are interconnection weights between last hidden layer and output layer. Also, b_o is the output layer bias.

On the other hand, in feed-forward back-propagation neural networks, learning algorithm is based on three steps. Feed-forward of training of the inputs, back-propagation of the associated errors, and adjustment of the weights and bias by transfer of error from the previous layer are these steps. This learning method is back-propagation algorithm which is proposed by Rumelhart et al. [35]. So that, in this algorithm, the error function will be minimized by using a nonlinear optimization. Also, we used Marquardt–Levenberg algorithm to optimize of our ANN, where methods of setting network parameters (i.e. connection weights and bias neurons) and initial random values were intended.

In BP neural network, backward propagation of errors is a learning algorithm. For this purpose, stochastic gradient descend method is used for learning procedure. In this method, each propagation is conformed instantly by update of weights. In addition, in our BP ANN, we used offline training by using Levenberg–Marquardt algorithm (LMA) as damped least-squares (DLS) method.

Different uncertainty resulted to errors in ANN prediction. To assessment the suitability of predicting methods, different error definitions are proposed by scholars [36,37].

To evaluate the performance efficiency of our selected ANNs, we implemented two different statistical methods. Mean square errors (MSE) and correlation Coefficient (R) are these two error evaluation factors which can be define as following

$$MSE = \frac{\sum_{i=1}^{N} (O_i - y_{desired})^2}{N} \quad (4)$$

$$R = 1 - \frac{\sum_{i=1}^{N} (O_i - y_{desired})}{\sum_{i=1}^{N} (O_i - \bar{y}_{desired})} \quad (5)$$

Here, N, $y_{desired}$, O_i and $\bar{y}_{desired}$ are number of evidence data, reference data as desired values, predicted results as actual values and average of desired values, respectively.

Table 1
Limit values of input and output variables for ANN.

	Limit values	Units
Input variables		
Temperature (T)	272.65–348.43	K
Electrical field (E)	0–4.03E+9	V/m
Magnetic field (M)	0–10.0594	T
Output variable		
Velocity of sound in liquid water (c)	1184.6688–1545.0431	m/s

It is also notable that, proximity of R value to 1 is representative of better prediction in different ANNs. While, lower MSE indicates a proper prediction in different ANNs.

Databases of present paper are composed from the numerical and experimental data. Indeed, the numerical and experimental results as macroscopic reference data were extracted from microscopic characteristic of water HB strength. We extract 112 reference data from different scientific publications [10,22,33,38–40] for n_{HB} and strength of the HB. Then, by using this 112 reference data and according to Chaplin [22] study and reference data source of velocity of sound in liquid water [41–43], our inputs–outputs data (i.e. reference data) are prepared for entry into ANNs. So that, three input variables of temperature *(T)*, electrical field *(E)*, magnetic field (M) will be entered to ANN and output parameter is velocity of sound in liquid water (c).

Inputs–outputs of our reference data are classified in three randomly groups of train data, validation data and test data. In the present paper, 60% of data are used as train data. Also, 20% of inputs–outputs of evidence are intended for each of validation data and test data.

In training procedure on train data, weight and biases of each neuron will be created. Then, by validating data in training procedure, adjustment of ANN classifier will be performed.

Limit values of input and output variables for ANN is presented in Table 1.

Since we have different magnitude of input variables, normalization procedure in interval of [0.1–0.9] is done on our input–output data based on Khataee and Kasiri [44] study as following

$$\phi_n = 0.8 \times \left[\frac{\phi - \min(\phi)}{\max(\phi) - \min(\phi)} \right] + 0.1 \quad (6)$$

Where, ϕ_n is the normalized input. In the normalization step, initially we normalized all of our 112 input–output data (i.e. including three input vector of temperature, electrical and magnetic field and output vector of velocity of sound in liquid water) by using Eq. (6) in range of [0.1–0.9]. Afterward, this normalized matrix is submitted into our ANN.

To select of proper ANN to predict of velocity of sound in liquid water, an iterative algorithm is proposed as can be seen in Fig. 2. In this algorithm, in step 1, initially our strong database (i.e. reference data) randomly divided in training, validation and test data sets. Afterward, in step 2, in iterative procedure, optimal artificial neural networks are developed to predict of velocity of sound in liquid water. It is notable that,

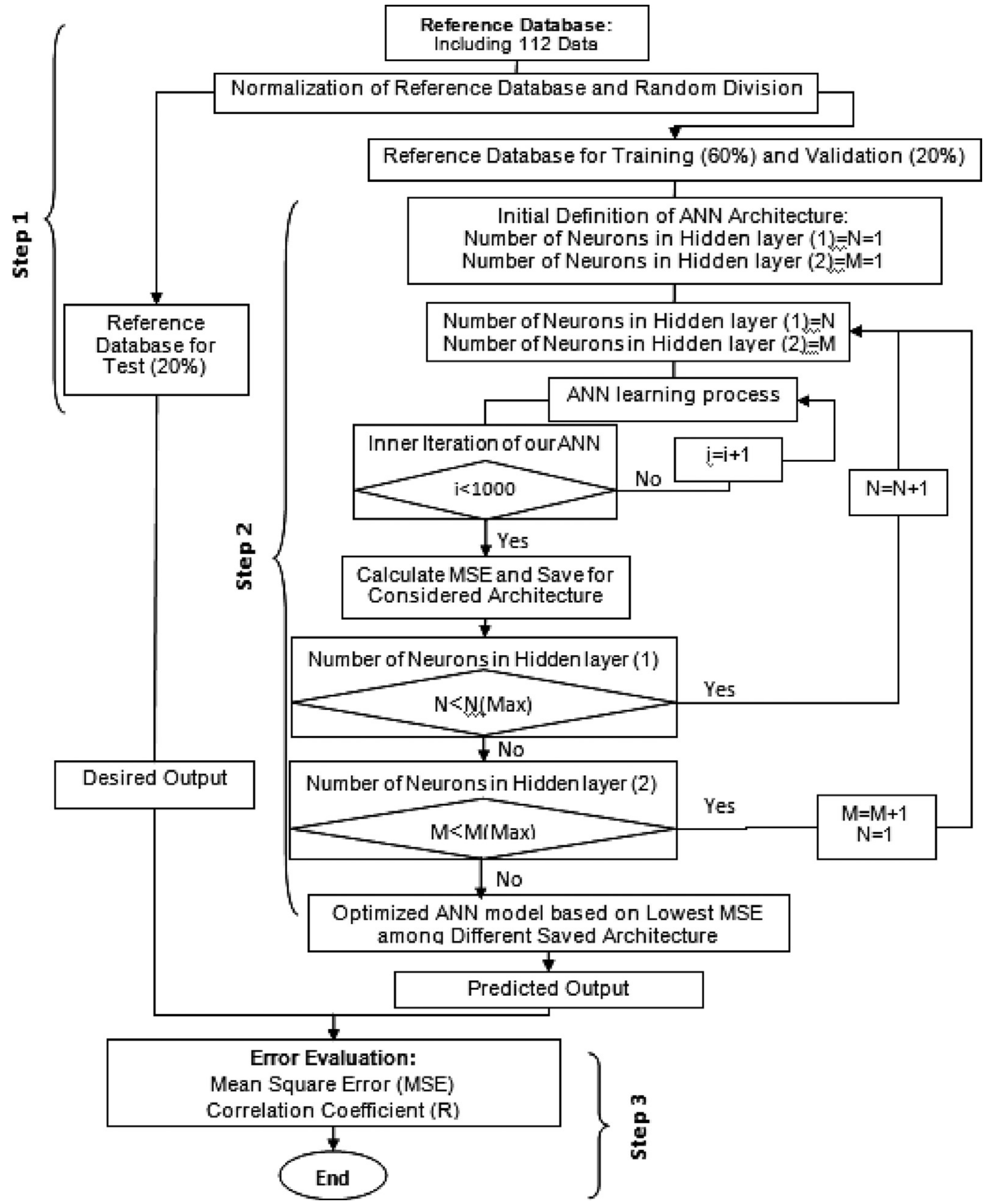

Fig. 2. Iterative algorithm to select of optimal ANN.

to select an appropriate ANN architecture, two different scenario of single hidden layer and two hidden layer architecture are evaluated.

Finally, in step 3, a comparative study is performed between predicted variables and reference data. Continued, According to this iterative algorithm, neural network architectures sensitivity analysis is studied to select optimal neural networks to predict of velocity of sound in liquid water.

3.2. Neural network architectures sensitivity analysis

According Fig. 2, various architectures can be implemented for ANN. For this purpose, two neural network architectures including single and two hidden layer is evaluated. In one hidden layer scenario, $N = 1$ to N (max) $=30$ neurons and $M = 0$ (based on Fig. 2) is studied. In addition, in scenario of two hidden layer, for each of layers, 1 to 10 neurons (N (max) $=10$ and N (max) $=10$) is used. Afterward, these different ANNs are tested based on Fig. 2 and our optimal architectures according to lowest MSE are selected. Also, to investigate of the impression of using normalized reference data instead of real input–output value, all architectures are tested for both of normalized and real input-output values.

The optimal ANN for different scenarios which obtained from iterative algorithm is illustrated in Table 2. It is notable that, our optimal ANN architectures are selected from 260 different structures. In all cases to predict of velocity of sound

Table 2
ANNs architecture sensitivity analysis.

Output	ANN architecture	MSE
One hidden layer real input–output values		
Velocity of sound in liquid water (c)	3:22:1	0.003
One hidden layer normalized input–output values		
Velocity of sound in liquid water (c)	3:7:1	1.528e−4
Two hidden layer real input–output values		
Velocity of sound in liquid water (c)	3:9:7:1	0.568
Two hidden layer normalized input–output values		
Velocity of sound in liquid water (c)	3:6:8:1	1.685e−4

in liquid water, input layer has three neuron of temperature (T), electrical field (E), and magnetic field (M) neurons.

According to Table 2, in scenario of one hidden layer, MSE is diminished by use of real value instead of normalized value for all cases. On the other hand, MSE is increased by use of scenario of two hidden layer instead of one hidden layer. Consequently, according to analysis of Table 2, selected optimal ANN architecture to predict of velocity of sound in liquid water is 3:7:1 in scenario of one hidden layer and use of normalized input–output reference data.

In the next section, the result of selected ANN to predict of velocity of sound in liquid water under different externalities are presented and discussed.

4. Results and discussion

This section is divided into three parts. Correlation diagram between used data and predicted value for training, testing, validating and all data set is presented at first part. Then, an equation to estimate of velocity of sound under different externalities based on extracted weights and bias is proposed at second part. Finally, in third part, weight sensitivity analysis to show the relative importance of each input variables on the velocity of sound in liquid water is conducted.

4.1. ANN for velocity of sound in water

Velocity of sound in liquid water under different temperatures and different imposed electrical and magnetic fields is predicted based on ANN with architecture of 3:7:1.

To investigate of correlation between used data values and predicted velocity of sound in liquid water for training data set, validation data set, test data set and all data set, Fig. 3 is presented. As shown in Fig. 3, the data are on the bisector or in its vicinity which representative an appropriate correlation between reference data and predicted output. On the other words, this figure indicates closeness between the referenced data and the predicted outputs. The maximum of mean square error (MSE) and lowest value for correlation coefficient from Fig. 3 are 0.00066 and 0.99131, respectively.

4.2. Equation to predict of velocity of sound in liquid water under different externalities

Based on previous section, it is observable that, our selected ANN is able to estimate the velocity of sound in liquid water with high accuracy. Indeed, small error value in prediction of velocity of sound in liquid water is obtained. As a result, due to lack of an equation to predict of velocity of sound in liquid water under different temperature, electrical and magnetic fields, a predictive equation is proposed in Eq. (7). This equation is based on ANN outputs and inputs variables of temperature (T), electrical field (E) and magnetic field (M). Also, it can be used in temperature ranging from 272.65 K to 348.43 K, electrical fields in range of 0 V/m to 4.03E+9 V/m and magnetic fields range of 0–10.0594 T.

It is also notable that, as mentioned before, Hyperbolic Tangent sigmoid transfer function is used for neurons in hidden layer (see Eqs. (1) and (2)). Therefore, we can present a predictive equation for velocity of sound in liquid water under considered externalities by implement of our ANN weights and bias in Eqs. (7) and (8) which are representative of Eqs. (1) and (2).

$$\text{Velocity of sound} = C = \frac{2}{1+exp(-2.K)} - 1 \quad \begin{array}{c} 272.65\ \text{K} < T < 348.43\text{K} \\ 0 < E < 4.03E+9\ \text{V/m} \\ 0 < M < 10.0594\ \ \text{Tesla} \end{array} \tag{7}$$

where

$$K = \left(\sum_{i=1}^{7} \omega_{iO}\cdot\left(\frac{2}{1+\exp\left(-2.[(T.\omega_{Ti}+E.\omega_{Ei}+M.\omega_{Mi})+b_i]\right)} - 1\right)\right) + b_O \tag{8}$$

The constant values for Eq. (8), is tabulated in Table 3.

To verify our proposed equation, results of used data (reference data) and predicted outputs from proposed equation are compared for all data set in Fig. 4. According to Fig. 4, proper agreement between used data and predicted results is observable.

4.3. Weight sensitivity analysis

Weight sensitivity analysis is another analysis which can be applied on the ANNs. Matrixes of the weights as numerical parameters that are adjusted by a learning algorithm are utilized to study the relative importance of each input variable on the output value in our ANN. Partitioning the ANN weights method which presented by Garson [45] is used to calculate of inputs relative importance analysis, as following

$$I_j = \frac{\sum_{m=1}^{m=Nh}\left(\frac{\left|\omega_{jm}^{ih}\right|}{\sum_{k=1}^{N_i}\left|\omega_{km}^{ih}\right|}\cdot\left|\omega_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\frac{\left|\omega_{km}^{ih}\right|}{\sum_{k=1}^{N_i}\left|\omega_{km}^{ih}\right|}\cdot\left|\omega_{mn}^{ho}\right|\right)\right\}} \tag{9}$$

Here, I_j is the relative importance of the input on output variable. Moreover, N_i and N_h are the number of inputs and

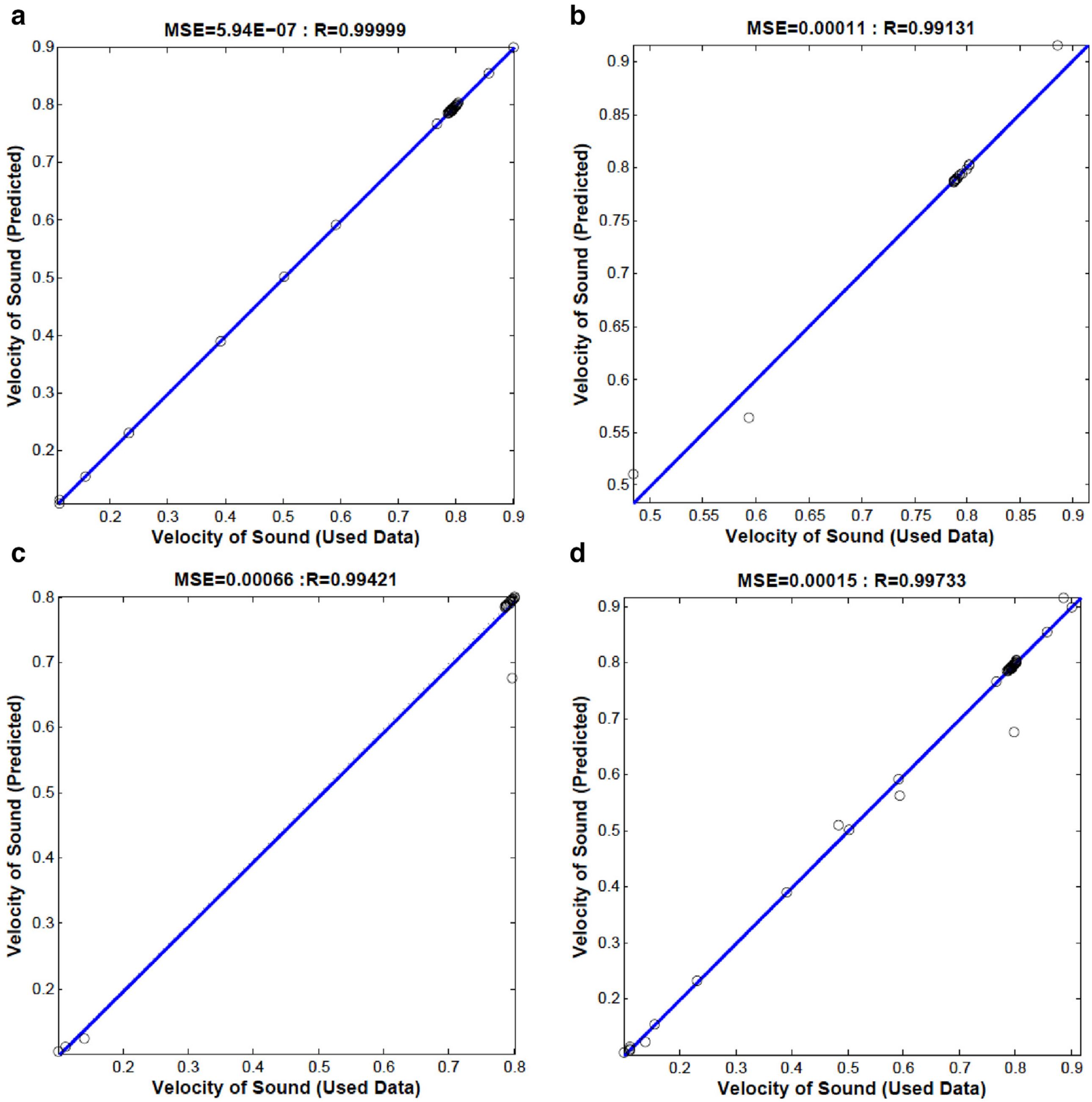

Fig. 3. Correlation between used data values and predicted outputs for velocity of sound in liquid water, (a) training data set, (b) validation data set, (c) test data set, (d) all data set.

Table 3
Constant values of proposed correlation to estimate the velocity of sound in water.

i	ω_{iO}	b_i	ω_{Ti}	ω_{Ei}	ω_{Mi}	b_O
1	0.7746	−1.9700	1.4070	−1.9500	−0.9871	−0.1420
2	0.7617	3.0299	−2.2367	−1.4062	−1.6669	
3	−0.1159	0.2640	0.2661	2.1189	−2.8071	
4	0.0313	0.3721	−0.8709	−0.0046	−3.2448	
5	6.0097	1.3110	−1.6238	13.9640	−3.2120	
6	6.2407	−1.1598	5.1547	−8.9066	0.3779	
7	−0.5204	2.0585	0.6607	1.9598	−1.3451	

neurons in the hidden layer and ω is the connection weight. Superscripts 'i', 'h' and 'o' refer to the input, hidden, and output layers, respectively. In addition, the subscripts 'k','m' and 'n' are related to input, hidden and output neurons, respectively. Relative importance of the input variables on the velocity of sound in liquid water value is illustrated in Fig. 5.

According to Fig. 5, an electrical field with relative importance percentage of 63% has a significant greater effect on the response variable of velocity of sound in liquid water compared to two other inputs of magnetic field and temperature. Also, lower impression on the response variable of velocity

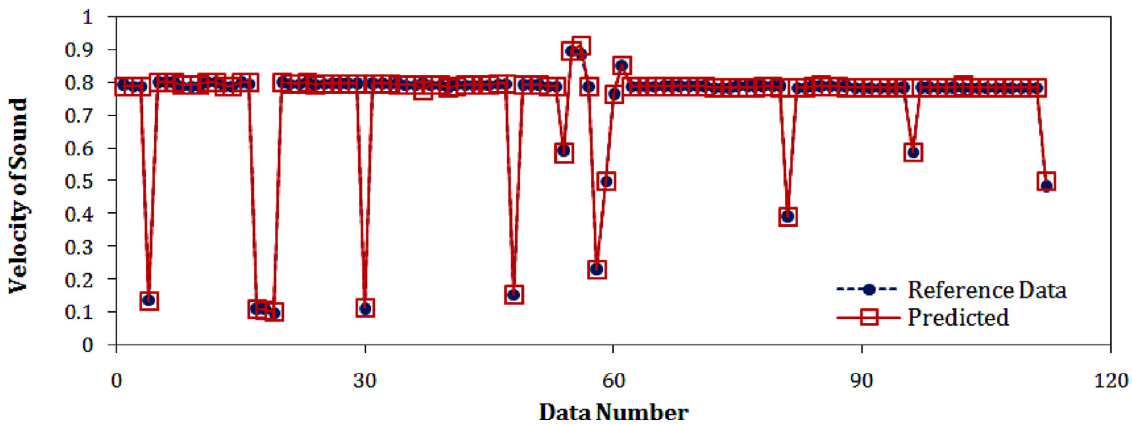

Fig. 4. Comparison between used data results and predicted outputs from proposed equation for velocity of sound in liquid water for all data set.

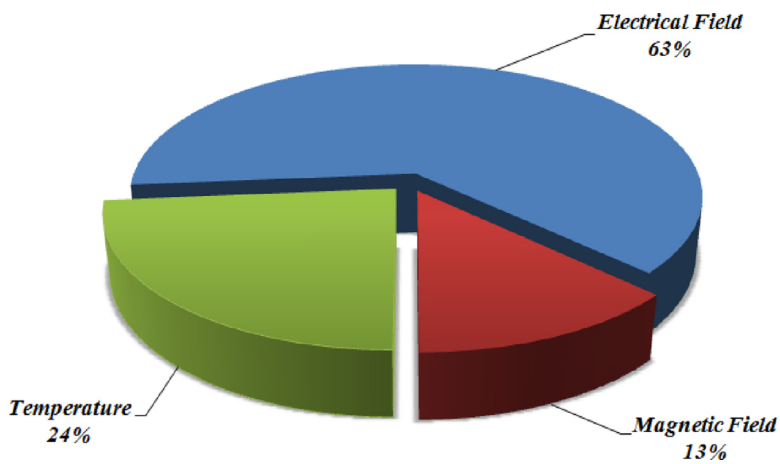

Fig. 5. Relative importance of the input variables (temperature, electrical and magnetic fields) on the response variable of velocity of sound in liquid water.

of sound in liquid water is obtained for input variable of magnetic field.

5. Conclusion

Water is a vital liquid on earth. Velocity of sound is one of the most important properties in liquid water. On the other hand, this property is affective by strength of HB. In addition, different externalities are impressive on the strength of liquid water HB strength and consequently on its velocity of sound. Therefore, the necessity of study on the velocity of sound of liquid water under different externalities is visible. However, this issue is not well-known. So, in the present study, velocity of sound in liquid water under different externalities is predicted by using optimal artificial neural network. Different temperature in range of from 272.65 K to 348.43 K, different imposed electrical fields in range of 0 V/m to 4.03E + 9 V/m and magnetic fields range of 0–10.0594 T are considered as externalities. To select optimal ANN, according to iterative algorithm, ANN architecture sensitivity analysis is conducted. To this accomplishment, 1–30 neurons for scenario of one hidden layer architectures and two hidden layer structure with each layers 1–10 neurons are studied. Hence, our optimal ANN is selected among 260 different ANNs architectures. Feed-forward back propagation ANN is implemented. Moreover, transfer functions of tangent hyperbolic sigmoid and linear are applied for hidden layer and output layer, respectively. Also, Marquardt–Levenberg algorithm is utilized to optimize of neural network. Afterward, ANN is trained and validated. Among the most important finding from present study can be referred to following:

(1) For velocity of sound in liquid water, the comparison between used data and predicted values showed correlation coefficients in the range of 0.99131–0.99999; with an MSE of 5.94E−07–0.00066.
(2) To predict of velocity of sound in liquid water, a predictive equation based on extracted bias and weights is proposed to estimate them under considered externalities. The comparison between reference data and predicted output from proposed equation, indicates an appropriate accordance between them.
(3) Based on weight sensitivity analysis, input of electrical field with 63% relative importance percentage, has higher impression on the response variable of velocity of sound in liquid water compared to other input variables.

Finally, capability of an appropriate ANN model to estimate of velocity of sound in liquid water under different externalities is detected.

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