Artificial neural networks for infectious diarrhea prediction using meteorological factors in Shanghai

Yongming Wang
Department of Computer Science & Technology
East China Normal University
Shanghai, China
ymwang819@gmail.com

Junzhong Gu
Department of Computer Science & Technology
East China Normal University
Shanghai, China
jzgu@ica.stc.sh.cn

Zili Zhou
Department of Computer Science & Technology
East China Normal University
Shanghai, China
zlzhou@ica.stc.sh.cn

***Abstract*—Infectious diarrhea is an important public health problem around the world. Meteorological factors have been strongly linked to the incidence of infectious diarrhea. Therefore, accurately forecast the number of infectious diarrhea under the effect of meteorological factors is critical to control efforts. In this paper, a three layered feed-forward back-propagation artificial neural network model (FFBPNN) are developed to predict the weekly number of infectious diarrhea by using meteorological factors as input variable. The meteorological factors were chosen based on the strongly relativity with infectious diarrhea. Also, as a comparison study, the multivariate linear regression (MLR) also was applied as prediction model using the same dataset. Further, since one of the drawbacks of FFBPNN model is the interpretation of the final model in terms of the importance of variables, a sensitivity analysis is performed to determine the parametric influence on the model outputs. The simulation results obtained from the neural network confirms the feasibility of this model in terms of applicability and shows better agreement with the actual data, compared to those from the regression models. The FFBPNN model, described in this paper, is an efficient quantitative tool to evaluate and predict the infectious diarrhea using meteorological factors.**

Keywords-artificial neural networks; forecasting model; infectious diarrhea; multivariate linear regression; sensitivity analysis; meteorological factors

I. INTRODUCTION

As a kind of common and important infectious disease, infectious diarrhea has a serious threat to human health and leads to one billion disease episodes and 1.8 million deaths each year (WHO, 2008). Infectious diarrhea in young children is a killer illness, especially in developing countries [1, 2]. In Shanghai of China which is the biggest developing country, the incidence of infectious diarrhea has significant seasonality throughout the year and is particularly high in the summer and autumn of recent years. Hence, a robust short-term (week-ahead) forecasting model for infectious diarrhea incidence is necessary for decision-making in policy and public health.

Infectious diseases have a closely relation with meteorological factors [3] and can affect infectious diseases in a linear or nonlinear fashion [4]. In recent years, there has been a large scientific and public debate on climate change and its direct as well as indirect effects on human health [5]. The effects of meteorological factors, such as temperature and rainfall, on diarrhea diseases incidence have got much more concerning recently. As far as we are concerned with the prediction of diarrhea diseases in literature, many forecasting models based on statistical methods for diarrhea diseases forecasting have been reported. Zhao N et al. [6] establish multiple regression model rolling forecast of daily incidence of infectious diarrhea in Beijing. Chou WC et al. [7] applied a climate variation-guided Poisson regression model to predict the dynamics of diarrhea-associated morbidity. The results indicated that the maximum temperature and extreme rainfall days were strongly related to diarrhea-associated morbidity. Lloyd SJ et al. [8] undertook a global cross-sectional study of diarrhea incidence in children under 5, and assessed the association with climate variables (temperature and rainfall) by linear regression method.

With regard to the fact that number of meteorological factor that effect infectious diarrhea are too much and the inter-relation among them is also very complicated, prediction models based on statistics methods may not be fully suitable for such type of problems. Nowadays, artificial neural networks (ANNs) are considered to be one of the intelligent tools to understand the complex problems and have been widely used in the medical and health field [9, 10, 11]. To the best knowledge of the authors, there is no works has been carried out to utilize the ANNs method in predicting diarrhea disease. In this paper, an attempt has been made to establish a new ANNs model (FFBPNN) to predict infectious diarrhea in Shanghai with a set of meteorological factors as predictors. Also, as a comparison, a multivariate linear regression (MLR) model was developed for the same purpose using the same dataset. Finally, since one of the drawbacks of ANNs is the interpretation of the final model in terms of the importance of input variables, the calculation is performed using sensitivity analysis.

The rest of this paper is organized as follow. Study area and dataset are briefly described in Sect. II. The prediction method and performance evaluation criterias (PECs) which are used in this paper are introduced in Sect. III. The FFBPNN and MLR models are developed and training results are reported in Sect. IV and Sect. V, respectively. In order to investigate the performance of the established model, the prediction results of the FFBPNN model are reported in comparison with the MLR model as discussed in Sect. VI. Sect. VII illustrated the sensitivity analysis, and conclusions of this paper are concluded in Sect. VIII.

II. STUDY AREA AND DATASET

A. Study area

Shanghai is located in the eastern part of China, and the city has a mild subtropical climate with four distinct seasons and abundant rainfalls. It is the most populous city in China comprising urban/suburban districts and counties, with a total area of 6,340.5 square kilometers. Since the study population was relatively stationary during the time period from 2005 to 2008 with the annual growth rate below 1%, the trend of incidence during that time period could be similarly prescribed by the trend of disease cases number. Hence we used the number of infectious diarrhea instead of incidence as the response variable in our models.

B. Dataset

The daily data of the infectious diarrhea cases for the period 2005.1.3-2009.1.4 were collected from National Disease Supervision Information Management System. The cases were all clinical or laboratory-confirmed cases and reported by hospital diagnostic. The daily meteorological factors data (including temperature, relative humidity, rainfall, atmospheric pressure, wind speed, and sunshine duration) in Shanghai for same time period were selected and collected from the Shanghai Meteorological Bureau of City Environmental Meteorological Center.

A total of 209 weeks experimental data pairs (infections diarrhea cases vs. nine meteorological factors) were obtained by daily records for constructing the FFBPNN and MLR models. The statistical descriptions of the input and output parameters show that the range of data can cover the various values of input and output parameters and all the dataset are bearing almost similar statistical properties. Description of the input (meteorological factors) and output (the weekly number of infectious diarrhea) parameters for constructing the FFBPNN and MLR models have been given in Table I.

TABLE I. DESCRIPTION OF INPUT AND OUTPUT PARAMETERS

Input/Output	Weekly Parameter (Unit)	Symbol
Meteorological factors	Maximum temperature (℃)	T_{max}
	Minimum temperature (℃)	T_{min}
	Average temperature (℃)	T_{avg}
	Minimum relative humidity (%)	RH_{min}
	Average relative humidity (%)	RH_{avg}
	Average atmospheric pressure (hPa)	AP_{avg}
	Sunshine duration (h)	SD
	Average wind speed (m/h)	WS_{avg}
	Rainfall (mm)	R
Infectious diarrhea	Number of infectious diarrhea	$WNID$

III. THE PREDICTION METHOD AND PERFORMANCE METRICS

In this section, the modeling approach of the FFBPNN for forecasting is briefly reviewed. Then, the performance evaluation criterias of the prediction model are presented.

A. Feed-forward back-propagation neural network

ANNs which consist of a large number of simple and highly interconnected computing components, called nodes or neurons are a branch of artificial intelligence methods. ANNs are organized into layers, called input layer, hidden layers, and output layer. These layers further include interconnections between the nodes of successive layers through the weights. The internal weights of the network are adjusted by an iterative process termed training and the algorithm used for this purpose called training algorithm. ANNs have a lot of important capabilities including learning from data, generalization and working with unlimited number of variable. ANNs, with their remarkable ability to derive meaning from complicated or imprecise data, are usually used to model complex relationships between inputs and outputs or to extract patterns in dataset.

The multilayer perception, trained by the standard back-propagation (BP) learning algorithm, is generally known as the FFBPNN. The BP learning algorithm is composed by the forward spread of the data stream and the reverse spread of the error signal. Among the most of different ANNs architectures, the FFBPNN is one of the most commonly and widely used for the purpose of prediction problems [12]. Apart from an input layer receiving inputs from the environment and an output layer generating the network's response, one or more intermediate hidden layers also exist. The typical topology structure of single hidden layer FFBPNN (Fig. 1) is the most widely used model form for forecasting.

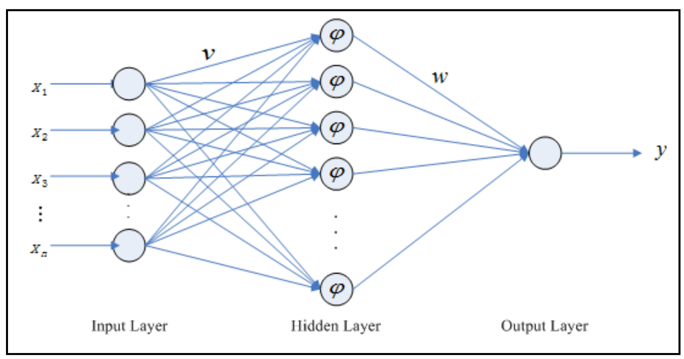

Figure 1. The typical topology structure of FFBPNN

The relationship between the output (y) and the inputs ($x_1,x_2,...,x_n$) has the following mathematical representation:

$$y = f(x_i) = w_0 + \sum_{j=1}^{m} w_j \varphi\left(\sum_{i=1}^{n}(v_{ij}x_i - b_j)\right) - b \tag{1}$$

Where m denotes the number of hidden nodes, w_j, denotes the weight between the j-th hidden node and the output node, v_{ij} denotes the weight between the i-th input node, x_i, and the j-th hidden node, b_j and b, denote the biases for the j-th hidden nodes and the output node respectively, φ is the transfer function of the hidden set in which the sigmoid function is used.

B. Evaluation criteria for model performance

To date, there is no single performance measure has been recognized as the universal standard. As a result, we need to assess the performance based on multiple metrics, and it is interesting to see if different metrics will give the same performance ranking for the models to be tested [21]. Among of PECs, the mean absolute error (MAE), the root mean square error (RMSE), the mean absolute percentage error (MAPE), the correlation coefficient (R) and the coefficient of determination (R^2) are the most widely used performance evaluation criterias and will be used in this study. The models with the smallest RMSE, MAE and MAPE and the largest R and R^2 are considered to be the best models.

IV. DEVELOPMENT OF FFBPNN MODEL

The FFBPNN modeling consists of two steps: the first step is to train the network using training dataset which are used for adjusting the model parameters; the second step is to test the network with testing dataset, which are not used in training step and are used to estimate the generalization error of trained networks. A model is considered good if the error of out-of-sample testing is the lowest compared with the other models. FFBPNN models were trained and tested by means of the Neural Network Toolbox of the MATLAB R2012b.

In this study, the dataset were chosen and segregated in time order. In other words, the dataset of the earlier period were used for training and the dataset of the latest time period were used for testing. From the collected dataset, the dataset form 2005 to 2007 were selected for the development of the FFBPNN models, the remaining dataset (2008) were used to verify the generalization capability of the established FFBPNN model. RMSE value for the testing period was considered for performance evaluation and all testing stage estimates were plotted in the form of hydrograph

A. Model input and output parameters

Input parameters selection is an important task before the neural network modeling, whether to choose a set of input variables which can best reflect the reason for desired output changes is directly related to the performance of neural network prediction. In this study, the input parameters affecting the infections diarrhea are weekly values of nine meteorological factors. The output parameter is the weekly number of infections diarrhea.

B. Data pre-processing and post-processing

It was noticed that the range of input and output parameters were different. In order to improve the efficiency and generalization of neural network models, the dataset should firstly be normalized. Because of the use of sigmoid functions in the FFBPNN model, the dataset are normalized between 0.05 and 0.95 rather than between 0 and 1 to avoid saturation of the sigmoid function leading to slow or no learning. The normalized values for each row of input and output parameters were calculated using (2):

$$x_{ij} = 0.9 \times \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} + 0.05 \tag{2}$$

Where x_{ij} is the normalized input/output value, X_{ij} is the actual input/output value, $\max(X_i)$ is the maximum input/output value, $\min(X_i)$ is the minimum input/output value. After the modeling and prediction, a reverse of this procedure is performed, transforming the output data back to the original scale, then these data can be applied to the estimate of the model performance, the comparison between the predicted and the actual values, and the appreciation of the accuracy.

C. Determination of optimum network and parameters

In the development of FFBPNN model, determination of an appropriate architecture for a particular problem is an important issue as the network topology directly affects its computational complexity and its generalization capability [13]. There is no unified approach for determination of an optimal FFBPNN architecture [14]. The number of input-output layer nodes is determined according the modeling problem being tackled, and in this study the input layer has nine neurons and one neuron in the output layer.

For the number of hidden layer, Hecht-Neilsen [15] indicated that a single-hidden layer FFBPNN is sufficient to approximate the corresponding desired outputs arbitrarily close. Therefore, one hidden layer was preferred in this study. However, the number of neurons is the most critical task in the FFBPNN structure. In this study, the number of neurons in the hidden layer has to be decided based on a series of trial-and-error experiments and it was determined by gradually increasing the number of neurons and observing their effect on the predicted value.

As demonstrated in Fig. 2, various network architectures with respect to hidden node numbers were trained and tested in order to obtain the best model architecture. The network with 9-4-1 was found to be the optimum model architecture for the *WNID* prediction (See Fig. 3) because of its minimum network error (RMSE) values for the training and testing dataset (For each number of hidden neurons, network was trained for 20 times to overcome the randomness of choosing initial weights and biases of neurons).

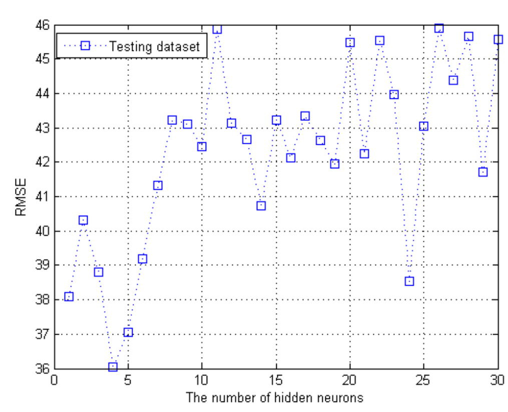

Figure 2. Hidden neurons and network errors for FFBPNN models

A back-propagation learning algorithm was utilized in a FFBPNN trained using the Levenberg-Marquardt (LM) algorithm [16]. An S-shaped nonlinear hyperbolic tangent sigmoid activation function $f(x)=(1-e^{-x})/(1+e^{-x})$ was used in the hidden layer and a linear activation function (Purelin) was used in the output layer, respectively. In order to develop the FFBPNN model, a very large number of trials with varying number of other network control parameters like learning rate and momentum rate were performed using training dataset through multiple iterations. The optimum architecture of the network and effective number of parameters used in developed FFBPNN model are shown in Table II.

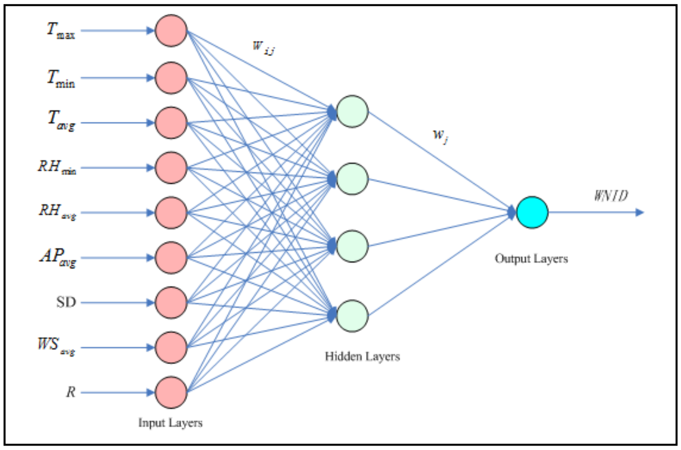

Figure 3. FFBPNN architecture for infections diarrhea predicting

TABLE II. THE NETWORK ARCHITECTURE AND PARAMETERS USED IN OPTIMUM NETWORK ARCHITECTURE

Parameters	FFBPNN
Number of input layer units	9
Number of hidden layer	1
Number of hidden layer units	4
Number of output layer units	1
Momentum rate	0.9
Learning rate	0.74
Error after learning	1e-6
Learning cycle	1500 epoch
Transfer function in hidden layer	Tansig
Transfer function in output layer	Purelin
Training function	TRAINGDM

V. DEVELOPMENT OF MLR MODEL

In order to compare the results of FFBPNN model with an empirical model, we also developed MLR model for *WNID* forecasting using the same dataset. The *WNID* values were selected as the dependent variable, and the meteorological factors variables were selected as independent variables. MLR is carried out to find out the relationship of several independent variables with a dependent variable. The software Matlab version R2012b was used to calculate the values of these coefficients. MLR was carried out on training dataset to determine the mathematical expressions for the *WNID*. The MLR model by using multiple linear regressions for prediction of the *WNID* is derived as presented by the following mathematical equation:

$$\begin{aligned} WNID &= -1972.7903 - 10.9619T_{\max} \\ &+ 20.8158T_{\min} - 2.6208T_{avg} - 1.6506RH_{\min} \\ &+ 0.2993RH_{avg} + 2.0902AP_{avg} + 5.7734SD \\ &- 15.7205WS_{avg} + 1.6048R \end{aligned} \tag{3}$$

VI. RESULTS AND DISCUSSION

In this section, the results by using the FFBPNN and MLR models for predicting *WNID* are presented. The optimal structure for ANN model often results in different networks, dependent on the initial random values of the synaptic weights. Therefore, the outcome will, in general, not be the same in two different trials even if the same training data have been used. In this article, we have only presented the best result obtained after 20 trials with the same input-output dataset for different models. The model outputs were transformed back to the original range, and then five key PECs were calculated and compared between actual and predicted values for training and testing dataset.

The prediction performance statistical values of building FFBPNN and MLR models for both the training and testing dataset have been depicted in Table III. By comparing the results, it is clear that the models considered in this study show acceptable prediction accuracy and higher coefficient of determination values with R^2 (R^2 > 0.90 for FFBPNN model and R^2 > 0.80 for MLR model). The MAPE of prediction were always lower than 0.5 in testing dataset for all the models. It is also clear that when the performance measurements are compared for MLR and FFBPNN models, the performance of FFBPNN models in terms of those PECs consistently outperforms MLR model. Therefore, the predicting performance of the FFBPNN model is better than that of the MLR model.

TABLE III. THE RESULTS OF FFBPNN AND MLR MODELS FOR TRAINING AND TESTING DATASET

PECs	Models			
	FFBPNN		***MLR***	
	Training	***Testing***	***Training***	***Testing***
MAE	20.7628	27.7547	29.8077	35.3774
RMSE	28.3007	36.0526	39.3739	48.9395
MAPE	0.2727	0.3841	0.4337	0.4182
R	0.8783	0.8490	0.8089	0.6968
R^2	0.9213	0.9125	0.8811	0.8388

Also, comparison between predicted and actual values for the FFBPNN and MLR models by using the training and testing are graphically illustrated in the Figs. 4 and Figs. 5, respectively. The linear least square fit line, its equation, and the R^2 values were shown in these regression figures Fig. 4 (b and d) and Fig. 5 (b and d) for the training and testing data. It can be obviously seen from the Fig. 4 (a and c) as well as Fig. 5 (a and c) that the FFBPNN-yielded *WNID* predicted values are in closer agreement with the corresponding actual values for training and testing samples than those for MLR model, especially peak points. The underestimation of the peak values and overestimation of the low values are much more for the MLR than the FFBPNN models. The MLR model seems to be insufficient for the forecasting *WNID*, especially the peak values.

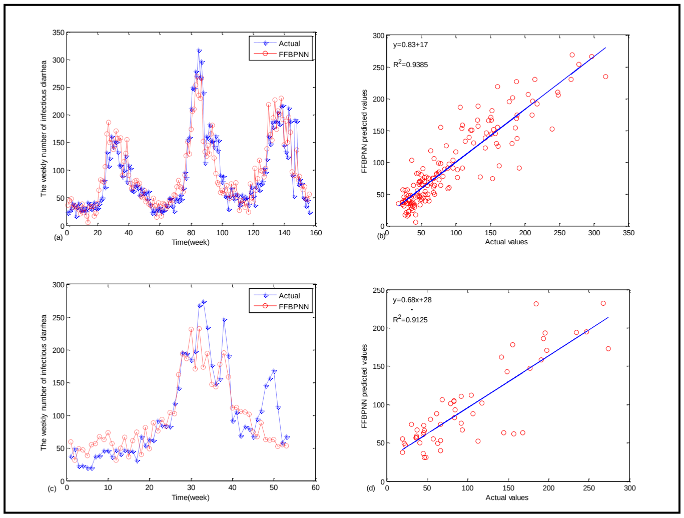

Figure 4. Comparison between actual and FFBPNN predicted result in training ans testing dataset. (a) Comparison curves plot of actual vs. predicted trends for training dataset, (b) Scatter plot of actual vs. predicted values for training dataset, (c) Comparison plot of actual vs. predicted trends for testing dataset, (d) Scatter plot of actual vs. predicted values for testing dataset

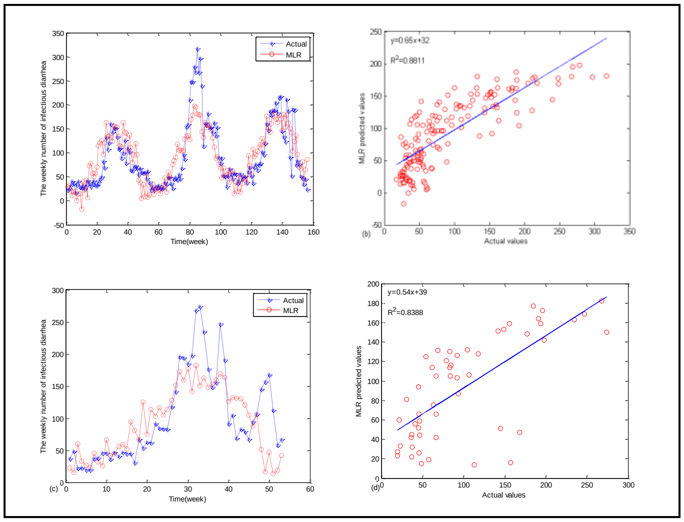

Figure 5. Comparison between actual and MLR predicted result in training and testing dataset. (a) Comparison curves plot of actual vs. predicted trends for training dataset, (b) Scatter plot of actual vs. predicted values for training dataset, (c) Comparison plot of actual vs. predicted trends for testing dataset, (d) Scatter plot of actual vs. predicted values for testing dataset.

The reason of better performances of the FFBPNN model over MLR model may be attributed to the complex nonlinear relationship between infectious diseases and meteorological factors. This implies the nonlinearity of the investigated phenomenon. The MLR method was chosen only as a representative statistical model in this study. It is based on the polynomial fitting approach. In many other studies [17, 18] multiple liner regression method was also selected as a benchmark model to compare and also found to be unacceptable against the FFBPNN in different application fields for forecasting.

For the FFBPNN models, it is very difficult to know which network structure and network parameters will be the accurate for a given problem (*WNID*). It will depend on many parameters, including the complexity of the problem, hidden neurons, the number of data points in the training set, the number of weights and biases in the network, the error goal, momentum and learning rate. For instance, for the FFBPNN models (As shown in Fig. 2) trained with 3 to 27 hidden neurons produce inconsistent RMSE values, although both models were trained with the same other network parameter. In addition, an appropriately learning rate chosen is significant. The learning rate chosen too large appeared an unstable learning condition, and the too small value caused a slow learning condition [19]. So, the model must be trained through multiple iterations.

VII. Sensitivity Analyses

Although the *WNID* can be estimated based on the meteorological factors by using the FFBPNN model, it is difficult to obtain explicit knowledge solely based ANN models, as it is an implicit or a black-box structure. A sensitivity analysis can be used to identify the significance of each input parameter on the objective (output) parameter in the modeling. Identifying sensitive inputs can be helpful for the model designers to carefully treat with such influential parameters in the designing models process. The Cosine Amplitude Method (CAM) is one of the sensitivity analysis methods that used to determine the effect of each individual input on the output [20]. So, in this study, CAM was adopted to determine the effect of each individual input on the output.

In this method, the degree of sensitivity of each meteorological factor is assigned by establishing the strength of the relationship (r_{ij}) between the *WNID* and meteorological factors under consideration. The larger the value of CAM becomes, the greater is the effect on the *WNID*. To use this method, all of the data pairs were expressed in common X-space. The data pairs used to construct a data array X defined as: $X=\{X_1, X_2, ..., Xm\}$. Each of the elements X_i, in the data array X is a vector of lengths, that is: $X_i=\{x_{i1}, x_{i2}, ..., x_{im}\}$. Thus, each of the data pairs can be thought of as a point in m-dimensional space, where each point requires m-coordinates for a full description. Each element of a relation, r_{ij} results in a pairwise comparison of two data pairs. Therefore, the strength of the relation between the data pairs, x_i and x_j, is given by using (4):

$$r_{ij} = \sum_{k=1}^{m} x_{ik} x_{jk} \Big/ \sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2} \qquad (4)$$

Here, the strengths of relations (r_{ij} values) between the infectious diarrhea (output) and input parameters using the CAM method are shown in Fig. 6. As can be seen, the most effective parameter on the *WNID* is the weekly average temperature, whereas the weekly average rainfall is the least effective parameter on the infectious diarrhea.

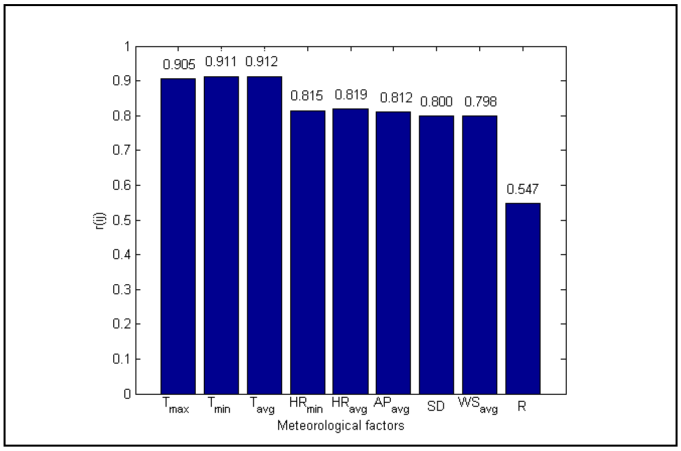

Figure 6. The effect of meteorological factors on *WNID*

VIII. CONCLUSIONS

In this study, ANNs model (FFBPNN) was developed to predict the weekly number of infectious diarrhea of the Shanghai in China. For achieving this goal, an investigation was carried out to prove the potential of using meteorological factors dataset for producing higher accuracy of prediction. Nine meteorological factors in the Shanghai were considered. In order to obtain true and effective evaluation of the performance of FFBPNN model, the same dataset were also trained and tested by multiple linear regression models. The results presented in this paper suggested that a feed-forward back-propagation neural network (FFBPNN) model with architecture 9-4-1 has the best accurate prediction results in prediction of the weekly number of infectious diarrhea. The experiments results indicate that FFBPNN model shows a good prediction performance as compared to the traditional MLR model. Moreover, sensitivity analysis revealed that most effective meteorological factor on the infectious diarrhea is weekly average temperature, whereas weekly average rainfall is the least effective parameter on the infectious diarrhea in this study. Considering the above results, it can be concluded that the ANNs model has good capability in predicting *WNID*. Therefore, this technique can be used to predict infectious diarrhea. The results of this study may be used as a baseline against which to compare other prediction techniques in the future.

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