APPLICATION OF ECHO STATE NETWORK FOR THE FORECAST OF AIR QUALITY

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ABSTRACT

A study on the application of Echo State Network (ESN) for the forecast of air quality in Hanoi for a period of seven days, which is based on the nonlinear relationships between the concentrations of an air pollutant to be forecasted and meteorological parameters, was conducted. Three air pollutants being SO_2, NO_2 and PM_{10} were selected for this study. Training data and testing data were extracted from the database of Lang air quality monitoring station, Hanoi, from 2003 to 2009. Values forecasted by ESN are compared with those by MLP (Multilayer Perception). Results shown that, in almost experiments, the performance of ESN is better than that of MLP in terms of the values and the correlation of concentration trends. The average of RMSE of ESN and MLP for SO_2 are 5.9 ppb and 6.9 ppb, respectively. For PM_{10}, the accuracy of ESN is 83.8 % with MAE of 53.5 μg/m^3, while the accuracy of MLP is only 77.6 % with MAE of 68.2 μg/m^3. For NO_2, the performance of ESN and MLP is similar; the accuracy of both models is in the range of 60 % to 72.7 %. These suggest that, ESN is a novel and feasible approach to build the air forecasting model.

Keywords: forecast, air quality, ESN, MLP, ANN, Hanoi, Vietnam.

1. INTRODUCTION

In recent years, forecasting models have been being an efficient tool in air quality management. They provide with more comprehensive information on the status and trend of air quality. With such information, authorities are capable of timely warning to help people prevent the negative effects of air pollution. Models that have been used for the forecast of air quality in Vietnam are mainly numerical ones. The advantage of these models is that they can provide with the status of air quality in detail, not only for the local but also for the regional and global scale. However, the development and operation of these models are costly and complicated. Whereas, statistical forecasting models are simpler and inexpensive [1].

There are various tools that have been used to develop the statistical forecasting models of air quality. Among them, the artificial neural networks (ANNs) are the most widely used. Many successful applications of ANN for the forecast of air quality have been published including the forecasting of PM_{10} [2, 3], ambient ozone [4 - 8] and other pollutants such as SO_2, NO_x, VOC… [9 – 15]. A new type of ANNs is echo state network (ESN), proposed by Jaeger in 2001 [16]. It is a recurrent neural network (RNN). ESN is based on the use of a large RNN, which is called a “reservoir”, to supply dynamical signals that are applied in the training mechanism of network [16]. ESN has been successfully applied in the many fields such as wireless communication [17], process and robot control [18, 19], economic forecast [20], etc. However, to the best of our knowlegde, no studies on the application of ESN in the forecast of air quality are available in the open literature. This study is, therefore, aimed at the application of ESN for the forecast of air quality focusing on the concentrations of SO_2, NO_2 and PM_{10} in Hanoi city.

2. METHODOLOGY

2.1. Echo state network

Echo state network was introduced by Jaeger in 2001 [16] to deal with nonlinear problems and to predict chaotic time series. ESN has a number of advantages in the comparison with traditional neural networks (ANNs). Firstly, the identification of optimal structure (such as the number of hidden layers, the number of neurons in the hidden layer) and learning parameters of ANNs is difficult and this impacts significantly on the reliability of forecasting results. Whereas, the hidden layer of the ESN is a RNN used to store dynamic linking signals between neurons, and only output signals can be changed agreeing with the most recent experiences, therefore, the neuron structure of the ESN influences almost nothing on the output results. Secondly, in the training process, the ESN always has the mechanism of memory decay with the time because it is interested in recent experiences only, thus, quantity of calculations is significantly reduced in the comparison with traditional ANNs. In addition, this mechanism also provides with more memory spaces to identify and store historical intervals – that is one of the issues noted in traditional ANN to reduce the system memory. Thirdly, the training process of ESN is simpler, requires a shorter training time and parameters obtained are more optimal than those of ANNs [20]. Fourthly, the forecasting results of ESN are much better than those of ANN in terms of statistical indicators and the correlation trends [18, 20].

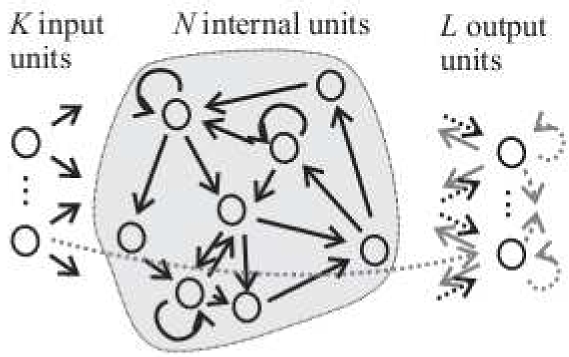


Figure 1. The architecture of ESN [16].

The structure of a standard ESN consists of three layers: K input units (neurons) in the input layer, N internal units in the reservoir (hidden layer) and L output units in the output layer (Figure 1). The neurons in the reservoir can connect with each other and themselves in the internal reservoir and directly connect with the neurons in the input and output layers. In addition, according to Jaeger [16], the connections of neurons directly from the input units to the output ones and the connections of neurons within the output units are allowed, meaning that, the connections W of neuron in the reservoir can be a direct link from input units to output units passing through the reservoir [16].

The activation and update of the internal units $x(n+1)$ are conducted as follows:

$$x(n+1) = f\left(W^{in}u(n+1) + Wx(n) + W^{back}y(n)\right) \tag{1}$$

where, $x(n)$ and $x(n+1)$ are the internal states of the reservoir at the time n and $n+1$, respectively; $f(.)=(f_1, f_2, \ldots, f_n)^T$ are the activation function; $u(n+1)$ is the input vector at the time $n+1$; $y(n)$ is the output at the time n; W^{in}, W and W^{back} are weights for input connections, of the reservoir and feedback connections, respectively.

The output of ESN is determined as follows:

$$y(n+1) = f^{out}\left(W^{out}\left(u(n+1), x(n+1), y(n)\right)\right) \tag{2}$$

where, $u(n+1)$ and $x(n+1)$ are the input vectors and the states of reservoir at the time $n+1$, respectively; $y(n)$ is the output vector at the time n; W^{out} denotes the weight matrix of output connections and f^{out} is the activation function of the output units.

2.2. Procedure of the study

The study was done on Matlab©2010. The procedure of this study includes the following steps: data preparation, the architecture of ESN, the training of models and the estimate of the reliability of the models.

2.2.1. Data preparation

Data used for this study are extracted from the database of Lang air quality monitoring station, Hanoi, from 2003 to 2010, including the concentrations of air pollutants (SO_2, NO, NO_2, O_3, NMHC, PM_{10} and TSP) and meteorological parameters (wind speed – WS, wind direction, relative humidity – RH, temperature – T, ultraviolet radiation – UV, rainfall – RAIN and etc.). Three air pollutants being SO_2, NO_2 and PM_{10} were selected to evaluate the feasibility of ESN in the development of a statistical forecasting model for air quality in Hanoi, as they are closely related to each other. The part of the data set from 2003 to 2008 is used for training and the remaining part, from 2009 to 2010, are used for testing. Input vectors of the models include the maximum values of the hourly concentrations of the pollutants (SO_2, NO_2 and PM_{10}) of the day and daily meteorological parameters (WS, RH, T and RAIN). Data are set as follows:

$$(\text{DATA}) = (SO_2, NO_2, PM_{10}, \text{WS}, \text{RH}, \text{RAIN}, \text{T}). \tag{3}$$

2.2.2. Architectures of ESN

According to [16, 20], at present, the optimum number of neurons in the reservoir is mainly determined by the preliminary tests of researchers and often in the range of 50 to 1000. Preliminary tests of this study indicated that the number of neurons in the reservoir of models to be developed in the range of 50 to 60 is the best. When the number of neurons in the internal layer is higher than the optimum value (being 50 in this case), the accuracy of forecasting results is reduced like the change of neuron number in the traditional ANN. However, the change of reliability of ESN is very small compared with that of ANN (based on the verificatory MLP). In order to reach to the echo states of neurons in the reservoir, the magnitude of the largest eigenvalue of the internal connection weight matrix must satisfy $|\lambda_{max}| < 1$ [16, 20]. Testes showed that, $|\lambda_{max}| = 0.1$ is the most suitable for the structure of selected ESN.

The architecture of the selected ESN to build the forecasting model in this study consists of one input layer with five neurons, one output layer with one neuron (the concentration of the pollutant being predicted) and reservoir with 50 neurons.

2.2.3. Training of the models

The model to be studied was built based on the network structure defined in the previous step. It is based on the structure of a standard ESN that consists of 50 neurons in the internal layer with spectral radius of weight matrix $|\lambda_{max}|$ being 0.1; the input weights W^{in} are set randomly between [-0.5, 0.5]; the reservoir weights W are set randomly between [-1, 1]; and the feedback connection weights W^{back} are set randomly between [-0.5, 0.5], thus ensuring the requirements of ESN according to [16]. For the verificatory MLP model, tests showed that the structure of MLP giving the best results in this study includes three layers with the number of neurons in each layer being 5 (input layer), 10 (hidden layer) and 01 (output layer). Both the models were trained by the information on the relationship of the pollutant to be predicted and meteorological parameters that are existed in the training data set. The training process of ESN model is described by equation (1).

2.2.4. Estimate of the reliability of the models

The performance of the ESN and verificatory MLP is evaluated based on statistical indicators including mean absolute error (MAE), mean absolute percentage accuracy (MAPA), root mean square error (RMSE) and normalized root mean square error (nRMSE) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_i^{pred} - C_i^{observ}\right)^2} \; ; \quad nRMSE = \frac{RMSE}{\frac{1}{N}\sum_{i=1}^{N} C_i^{observ}}.100\% \; ;$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|C_i^{pred} - C_i^{observ}\right| \; ; \quad MAPA = \left(1 - \frac{MAE}{\frac{1}{N}\sum_{i=1}^{N} C_i^{observ}}\right) * 100\%$$

where, N is time steps of the forecast, C_i^{pred} is the predicted concentration and C_i^{observ} is the observed concentration.

3. RESULTS AND DISCUSSIONS

A number of preliminary tests were conducted to select the suitable period of forecast. Main criteria for the selection are that the period of prediction is long enough (so that concerning authorities/people would have enough time to cope with the negative change of air quality) and the accuracy of prediction is acceptable. Obtained results shown that, the performance of both models are unstable when the time steps of forecast are increased. For example, for SO_2, in the first step (day), the MAE is 2 ppb (and the MAPA is about 86 %); in the third step, the MAE is increased to 5.7 ppb; and in the 5th and 7th steps, the MAE is relatively stable with the values of 5.8 ppb and 5.3 ppb, respectively. However, if the number of time steps is continued to increase, the error of the forecasting results is high and unstable (in the 10th step, the MAE is 11.6 ppb). In addition, the MAE of the models being studied can be increased up to 30 ppb and their accuracy can be lower than 50 % in the cases of the high variation of the pollutant concentrations. Therefore, the period of seven days for the forecast was selected for this study.

3.1. SO_2 forecasting

The concentration of SO_2 is the first parameter selected to evaluate both ESN and MLP models with the experimental stage of 90 days (the first quarter of 2009) and the forecasting period of seven days. The variation of SO_2 concentration of 90 days in the first quarter of 2009 is shown in Figure 2.

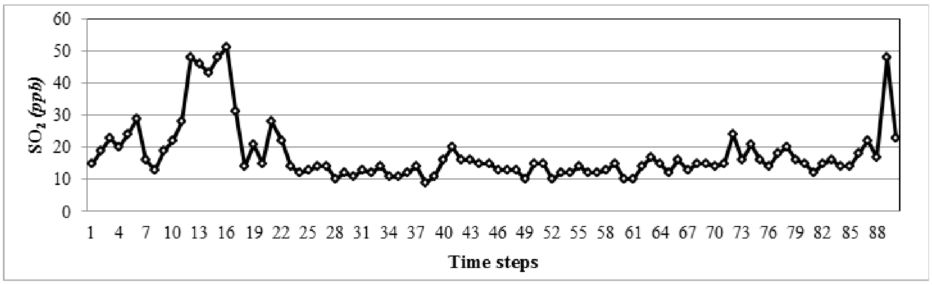


Figure 2. The variation of SO_2 concentrations measured in the first quarter of 2009.

It can be seen from Figure 2 that, there are two high peaks of SO_2 concentrations, from 8th day to 18th day and from 88th day to 90th day. In the remaining time, the concentrations of SO_2 are relatively stable. The forecasting results of ESN and MLP models are presented in Table 1.

Table 1. Comparison of forecasting results between ESN and MLP.

Forecasting intervals	**Model**	**RMSE,** (ppb)	**nRMSE,** (%)	**MAE,** (ppb)	**MAPA,** (%)
(*) Jan. 02 - 08, 2009	MLP ESN	6.5 **4.8**	31.7 **23.4**	4.8 **3.9**	80.7 **81.1**
(*) Feb. 15 - 21, 2009	MLP ESN	7.3 **4.9**	57.6 **38.3**	6.9 **4.4**	45.5 **65.7**
(*) Mar. 01- 07, 2009	MLP ESN	5.2 **4.7**	35.5 **32.7**	4.3 **4.1**	70.5 **71.8**
(**) Jan. 08 - 21, 2009	MLP ESN	**8.5** 9.0	**27.8** 29.3	**7.1** 7.7	**76.5** 74.7

Note: (*) no high fluctuation of concentrations; (**) high fluctuation of concentrations.

The results shown that, in most experiments, the MAPA of ESN with the range of 65.7 % to 81.1 % is better and more stable than that of MLP. These results are also in the same range with those of other studies [12, 13]. For example, in the stage of Feb. 15 to 21, 2009, although there was no high fluctuation of SO_2 concentrations, the MAPA of the MLP was down to below 50 %. The nRMSE and MAE of MLP model in this stage were 57.6 % and 6.9 ppb respectively while these values of the ESN were 38.3 % and 4.4 ppb, respectively.

According to [1], the traditional ANNs are not well adapted in the cases of high fluctuations of the pollutant concentrations. Therefore, the stage of Jan. 08 to 21, 2009 (14 days) with the high fluctuation of SO_2 concentrations was selected for testing. The comparison between the forecasted concentrations of SO_2 done by both models and measured ones is presented on Figure 3. Obviously, the forecasting performance of both ESN and MLP models is improved positively in this case and can be considered to be the same. The MAPA of MLP (76.5 %) is slightly higher than that of ESN (74.7 %). However, the maximum deviation of ESN is 17.2 ppb, smaller than that of MLP (20.4 ppb) in the 11th day of that stage. The trends of both models are quite consistent with the reality.

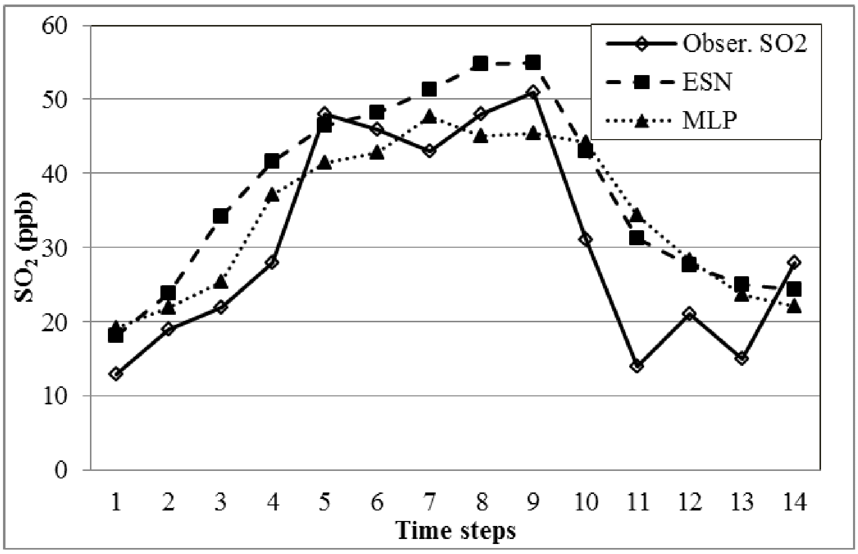


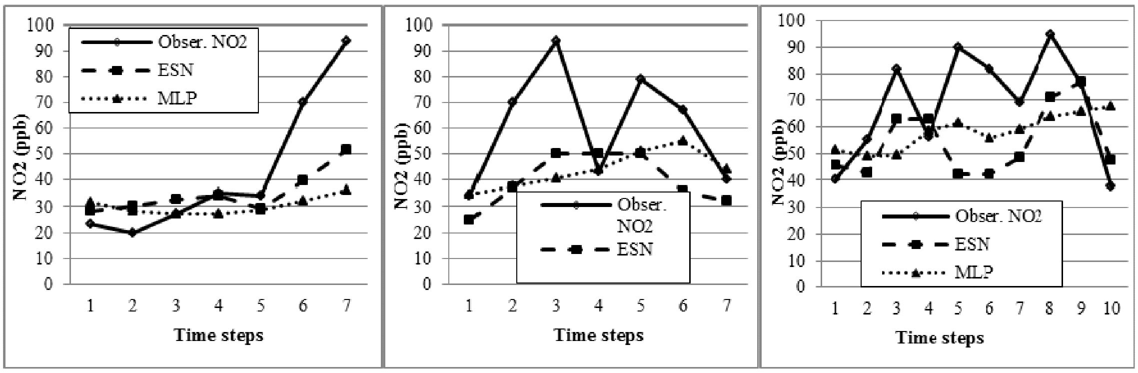
Figure 3. Comparison of forecasted and measured concentrations of SO_2 in the case of the high fluctuation (Jan. 08 to 21, 2009).

It can be seen from the above results that, in general, the predicting performance of ESN for SO_2 is better than that of MLP, but not much. In addition, the results of a long period (14 days, from Jan. 06 to Jan. 19, 2009) confirm that the stability of forecasting results is highly dependent on the number of time steps. To evaluate this point in a more comprehensive manner, the performances of both models were tested for NO_2 and PM_{10} in this study.

3.2. NO_2 forecasting

Due to some technical problems, from the middle of January, 2008 to the end of 2010, NO_2 was not measured at the Lang station. It means that, in the data set of this study, data of NO_2 concentrations in this stage are missing (not available). Therefore, for this pollutant, data set from 2003 to 2006 is used for training and data set from 2007 to the end of January, 2008 is used for testing. Figure 4 represents the comparison between the forecasted concentrations of NO_2 done by ESN and MLP models and the measured ones for different stages in the study.

Where, (a) is a stage with the stable fluctuation of NO_2 concentrations; (b) and (c) are stages with highly fluctuation of NO_2 concentrations. The performance of ESN model in all three experiments is better than that of MLP model. Namely, in the stage with the stable concentrations of NO_2 (Figure 4a), the MAE is 14.3 ppb for ESN model, while being 18.0 ppb for MLP model. For the cases with the high fluctuation (Figure 4b and 4c), in the stage from Jan. 6 to 12, 2007, the MAPA of the MLP is 69.1 %, slightly higher than that of ESN model (62.2 %). However, it can be seen from Figure 4b that, the trend of forecasted concentrations of the ESN is more consistent with the measured data than that of MPL. In the period of 10 days (from Jan. 24 to Feb. 02, 2007) with the complex changes of NO_2 concentrations (Figure 4c), the accuracies of ESN and MLP in terms of statistical indicators are the same; the MAE of ESN model and MLP model are 18.6 ppb and 18.8 ppb, respectively. And, similarly to the stage of Figure 4b, ESN model forecasts the trend of concentrations better than MLP model do. In addition, these experiments one again confirms that, the accuracy of forecasting results depends on the length of time steps. The reliability is decreased when the number of time steps is increased, and the best reliability is obtained in the period of the first day to third day. However, in the prediction period of seven days, the accuracy of all studied experiments is over 60 %, which is acceptable and in the same range with studies [13 - 15] but slightly lower than that of Stanislaw Osowski and Konrad Garanty (the average MAE is 8.5 ppb) [12].



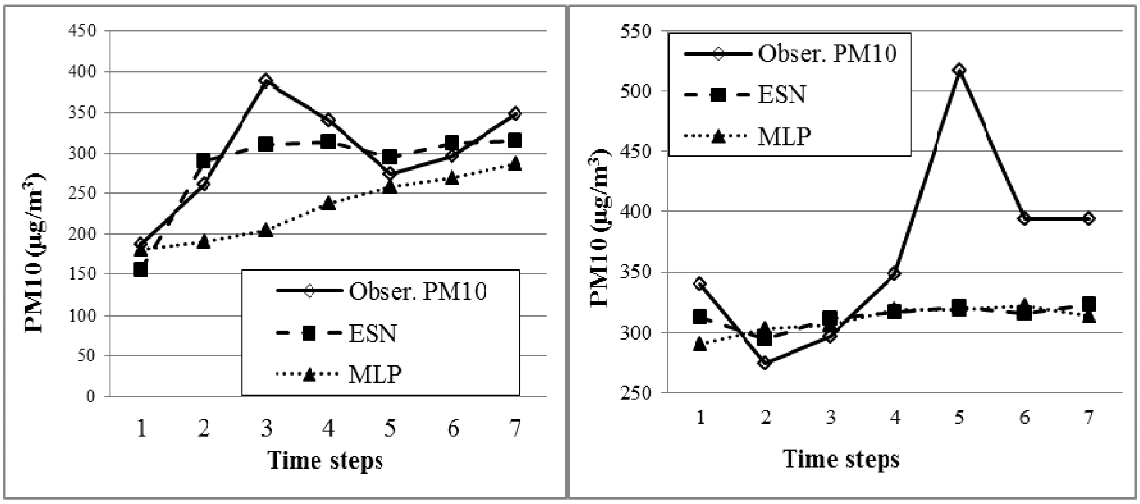
(a) (b) (c)

Figure 4. Comparison of NO_2 concentrations predicted by both models with measured data [(a) Jan. 02 – 08, 2007; (b) Jan. 06 -12, 2007; (c) Jan. 24 – Feb. 02, 2007].

It can be seen that, the prediction of both models for NO_2 is lower than that for SO_2; the maximum average accuracy is only 72.7 % for ESN and 72.5 % for MLP. This may be explained that, the change of NO_2 concentrations in the air is extremely complex [21], therefore, meteorological parameters only may not be enough input information for the prediction of NO_2.

3.3. PM_{10} forecasting

PM_{10} is a typical air pollutant and closely related to SO_2 and NO_2. Like SO_2, there was a high fluctuation of PM_{10} concentrations in the stage of 09 to 21 January, 2009. However, the experimental results of all studied stage shown that the total performance of ESN is much better than that of MLP. The average accuracy is 83.8 % for ESN and 77.6 % for MLP. Their maximum accuracy is 88.9 % and 80.5 %, respectively, which is slightly higher than that of the study [12] (the average error is in the range of 13.11 % to 21.53 %). Figure 5 also indicates that the ability of ESN is better than MLP in terms of trend forecasting. Even for the period in which the accuracy of MLP is the best (Figure 5), the trend of PM_{10} concentrations predicted by ESN has better correlation with measured data than MLP.



(a) (b)

Figure 5. Comparison of PM_{10} concentrations predicted by both models with measured data

(a) – Stage in which the accuracy of ESN is the highest (88.9 %);

(b) – Stage in which the accuracy of MLP is the highest (80.5 %).

4. CONCLUSIONS

ESN model proves to produce the good results of prediction in terms of the trends and values. In almost experiments of this study, the average accuracy of ESN with the forecasting period of seven days is over 70 % which is in the same range of many other studies in the world. ESN has more advantages than MLP including simpler structure and less free parameter than MLP, smaller quantity of calculation and shorter time of calculation, better adaptation in the cases of highly change of pollutant concentrations, better forecasting of the trends of pollutant concentrations. Therefore, ESN is a promising and feasible tool to build statistical forecasting models for air quality, not only for Hanoi in particular but also for Vietnam in general. In addition, ESN model can be used to fill in the missing monitoring data of air quality. This is very important in the standardization and use of air quality data for environmental protection.

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TÓM TẮT

NGHIÊN CỨU ỨNG DỤNG MẠNG TRẠNG THÁI PHẢN HỒI
ĐỂ DỰ BÁO CHẤT LƯỢNG KHÔNG KHÍ

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Mạng trạng thái phản hồi (Echo State Network -ESN) đã được nghiên cứu ứng dụng để xây dựng mô hình dự báo chất lượng không khí tại thành phố Hà Nội với chu kỳ 07 ngày, dựa trên mối quan hệ phi tuyến giữa nồng độ của chất ô nhiễm cần dự báo và các yếu tố khí tượng. Ba (03) chất ô nhiễm gồm SO_2, NO_2 và bụi PM_{10} đã được lựa chọn. Dữ liệu đào tạo và dữ liệu kiểm tra được trích xuất từ bộ dữ liệu chất lượng không khí của trạm Láng, Hà Nội, từ 2003 đến 2009. Việc dự báo bằng mô hình ESN được so sánh với mô hình MLP (Multilayer Perception). Kết quả cho thấy, trong hầu hết các thực nghiệm, khả năng dự báo của mô hình ESN đều tốt hơn mô hình MLP về mặt giá trị cũng như tính tương quan của xu thế diễn biến nồng độ. Giá trị RMSE trung bình khi dự báo SO_2 của ESN và MLP tương ứng là 5,9 ppb và 6,9 ppb. Đối với PM_{10}, độ chính xác trung bình của ESN đạt 83,8 % với MAE là 53,5 $\mu g/m^3$, trong khi đó MLP chỉ đạt 77,6 % với MAE là 68,2 $\mu g/m^3$. Với thông số NO_2, độ tin cậy của ESN và MLP là tương đương nhau, độ chính xác của cả hai mô hình đều nằm trong khoảng từ 60 % đến 72,7 %. Điều này cho thấy, công cụ ESN là một hướng đi mới, triển vọng để xây dựng mô hình dự báo thống kê chất lượng không khí.

Từ khóa: dự báo, chất lượng không khí, ESN, MLP, ANN, Hà Nội, Việt Nam.