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ARIMA

ARIMA

Collet &)

(Oluyemi,

Finzi)

(Tebaldi, Ziomas et al., , &

(Comrie,)
(ANN)

()

SO₂ ANN

()

SO₂

(MLP)

MLP

ANN

ANN

MLP

ANN

Input

Output

Artificial Neural Network (ANN)

Boznar. M

Multilayer Perceptron (MLP)

Gardner. M.W

Dorling. S.R

Mok. K.M

Tam. S.C

Gaussian

(Hooyberghs et al.,)

CO

MLP

MLP

NO₂ NO_x

(LM)

ANN

(MLR)

ANN

CO

(RBF)

/ ()

MLP

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()
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() /
()

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Levenberg- Marquart (LM)

Shi. J.P

Harison. R.M

Multiple Linear Regression (MLR)

Postolache. O

Radial Basic Function (RBF)

Hooyberghs. J

Back Propagation

Overtraining

Validation

Test

...

(Pastor- Barsenas,) .

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:

$$X_{norm} = \left(\frac{X - X_{min}}{X_{max} - X_{min}} \right) * (r_{max} - r_{min}) + r_{min}$$

$$\frac{X_{min} \quad X_{max} \quad X}{r_{min} \quad r_{max}}$$

(Cheleni,)

Kolehmanin,) MLP

(Pastor- barsenas, & Gardner,

MLP

(Haykin,)

MLP

$$X = \left(\frac{X_{norm} - r_{min}}{r_{max}} \right) * (X_{max} - X_{min}) + X_{min}$$

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N MLP

L

S

excel

:

MLP

$$y_k^o = f_k^o(n_k^o)$$

for $k = 1, \dots, l$

Neuralpower 2.5

MATLAB 7

$$Out = f_k^o \left(b_k^o + \sum_i^s w_{ik}^o f_i^h(n_i^h) \right)$$

Time series prediction

Transfer function

Haykin. S

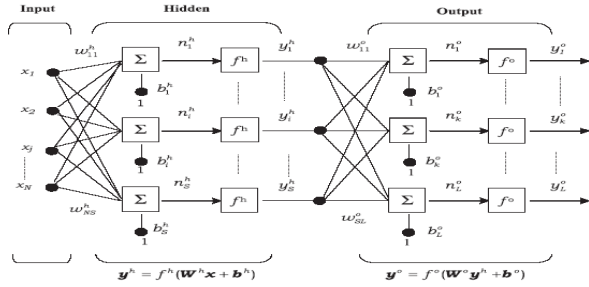
Pattern recognition

System identification

k y_k^o k t_k

$$n_k^o = b_i^o + \sum_{i=1}^s w_{ik}^o y_i^h$$

$$n_i^h = b_i^h + \sum_{j=1}^n w_{ji}^h x_j$$



MLP

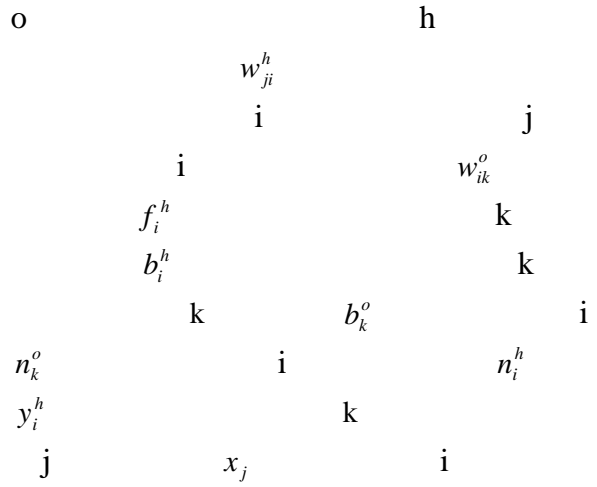
ANN

ANN

Quick prop

MLP -

()



(Agirre- basurko,)

$$\tan sig(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$\log sig(x) = \frac{1}{1 + e^{-x}}$$

E

$$E = \frac{1}{L} \sum_{k=1}^L (t_k - y_k^o)^2$$

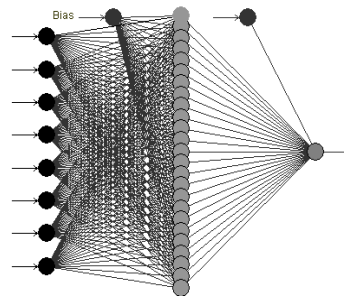
Epoch

Sigmoid (Logsig)

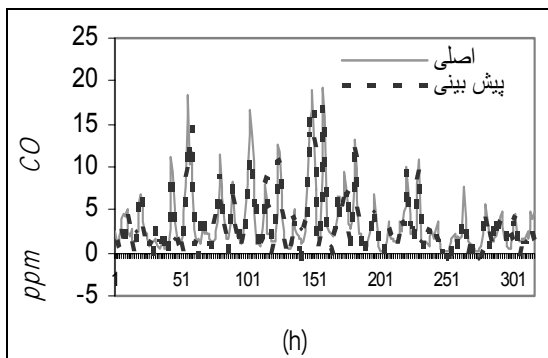
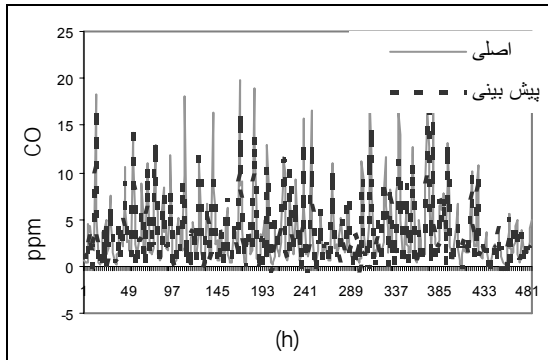
Hyperbolic tangent (Tansig)

...

$$R^2 = \frac{\sum_{i=1}^n [p_i - \bar{O}]^2}{\sum_{i=1}^n [O_i - \bar{O}]^2}$$



CO ANN
CO

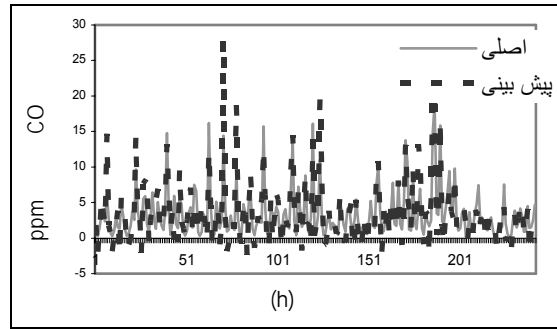
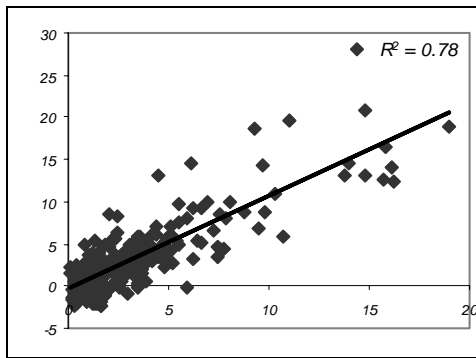


$$RMSE = \left(\frac{1}{N} \sum_{i=1}^N (p_i - O_i)^2 \right)^{1/2}$$

p_i O_i N
RMSE

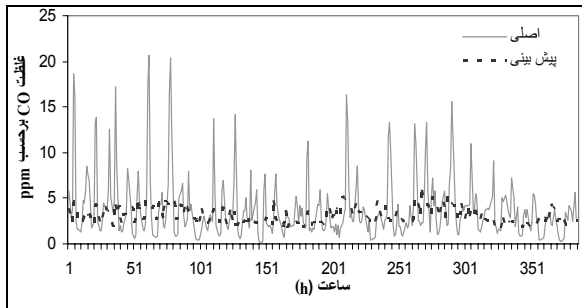
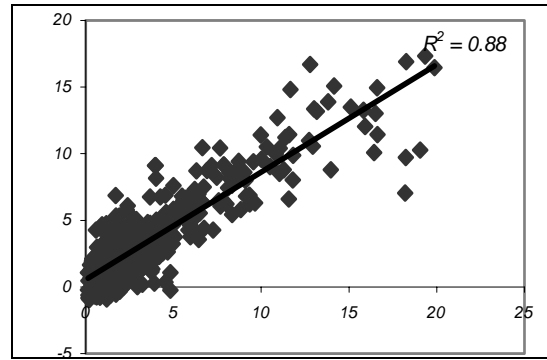
Correlation coefficient (R^2)

Learning rate
Momentum
Root mean square error (RMSE)



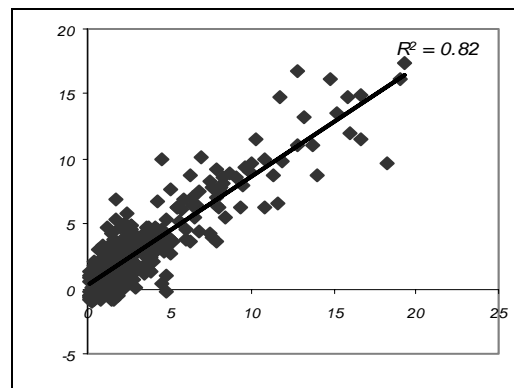
CO

ANN
 ARIMA
 ARIMA RMSE
 R^2
 / /

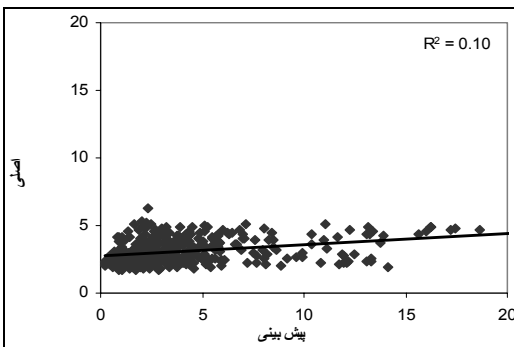


CO

ARIMA



CO



ARIMA CO

Auto-regressive integrated moving average (ARIMA)

MLP

CO

ANN

ARIMA

CO
ANN

CO

CO

CO

MLP

ARIMA

ANN

CO

$$I_j = \frac{\sum_{m=1}^{N^h} \left(\frac{|W_{jm}^{ih}|}{\sum_{k=1}^{m=N^h} |W_{km}^{jh}|} * |W_{mn}^{ho}| \right)}{\sum_{k=1}^{k=N^i} \left\{ \sum_{m=1}^{m=n^h} \left(\frac{|W_{jm}^{ih}|}{\sum_{k=1}^{m=N^h} |W_{km}^{jh}|} \right) * |W_{mn}^{ho}| \right\}}$$

N^i

N^h

W_{mn}

ih

& Olden)

N

(Jackson,

Garson,

and

ANN

CO

CO

	/	/	/	/	
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The application of artificial neural networks in prediction of CO concentration: A case study of Tabriz

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Abstract

Air pollution is one of the main problems in metropolitan areas. Therefore, the prediction of air pollution can be regarded as one of the important issues of air quality research in urban areas. There are many methods for the prediction of air pollutant concentration. In recent years, there has been considerable progress in the development of neural network models for air quality prediction. In this paper, artificial neural network has been used for the prediction of CO concentration in Tabriz. Hourly correlation between the concentration of CO and metrological variables was calculated by multilayer perceptron for the months of December and January 2003. Multilayer perceptron performance was compared with traditional methods such as auto-regressive integrated moving average (ARIMA). The results indicated that there was a high non-linear correlation between CO concentration and metrological variables such as: speed and direction of wind; and relative humidity. The location of large industries in the west and southwest of Tabriz were found to be the most effective elements in air pollution. Blowing of winds from west and southwest directions, on the months of December and January have caused pollution are transferred to the inner parts of Tabriz.

Keywords: Artificial Neural Networks, Multilayer perceptron, ARIMA, Air pollution, CO concentration.