Prognosis of Urban Air Pollution by using a Fuzzy Clustering System In Northwest England

Abstract. In this contribution, a system that allows a prediction of urban airborne pollution has been modeled. A case study is carried out for the city of Liverpool in north-west England for one of the most dangerous particles to human health such as PM10.

Previous research include models that mostly use neural networks to tackle the prediction issues.

However a model based on a combination of neural networks and fuzzy logic is proposed for this work. This approach shows a closer estimation for the non-linear behavior of the airborne pollution model in comparison with previous works using neural networks. Also, the model proposed shows lower error and lower computational cost, making it convenient to use.

The specific neuro-fuzzy model is generated, outlining the features and membership functions of each model and by designing a better model in terms of error and computational cost the model is validated.

Keywords: Fuzzy Clustering, ANFIS, Airbone Pollution, Particulate matter, Pollution Prognosis.

1 Introduction

In recent times, urban air pollution has been a growing problem especially for urban communities. There are different kinds of air pollutants. For instance, some compounds like sulphur dioxide, nitrogen, carbon monoxide, and particulate matter (PM) are considered as typical indicators of air quality. This situation appears to be more relevant in urban areas where particular atmospheric and geographic conditions may cause an accumulation of the pollutants in the atmosphere [1].

The size of particles in the atmosphere varies over four orders of magnitude, from a few nanometers to tens of micrometers. Size, shape and chemical properties govern the lifetime of particles in the atmosphere and the site of deposition within the respiratory tract. Health effects of ultrafine particles (UFP, diameter <100 nm) are likely very different from those caused by coarse particles

($< 2.5\mu m$) whilst PM10 includes all particles with diameters less or equal to $10\mu m$. In this contribution, PM10 airborne particles are considered due to their effect on human health. For example: this is the fraction of particles that is most likely to be deposited in the lung [2], being the children and the elderly more vulnerable to both PM10 and PM2.5[3]

According to studies presented on the composition of PM10, Particulate matter from combustion generally comprises carbon, low volatile organic compounds, sulphates, metals and some other inorganic material, in various amounts from different combustion sources and fuels. Thus, making it difficult to model the behavior.[4],[5].

There are many monitoring methods available to measure PM10 concentrations. In past contributions, It has been shown that a mobile Self-Contained Unit (SCU) made possible an accurate, cost-effective and robust method to measure PM10 concentration [6],[7],[8],[9],[10] using a technique called chromatic modulation and cross-correlating the results with a TEOM (Tapered Element Oscillating Microbalance) apparatus via a calibration curve [6].

In this contribution, the validated immediate PM10 particle concentration from the SCU, humidity and mean temperature for specific dates are used in a computing system developed to predict the following PM10 concentration

2 ANFIS Architecture

In a conventional Fuzzy Inference Fystem (FIS), the number of rules is decided by an expert who is familiar with the system to be modelled. In this particular case study the number of membership functions assigned to each input is chosen empirically. This is carried out by examining the desired input-output data and/or by trial and error. In this section ANFIS topology and the learning method used for this neuro-fuzzy network are presented. Both neural network and fuzzy logic algorithms are model-free estimators and share the common ability to deal with the uncertainties and noise. It is possible to convert fuzzy logic architecture to a neural network and vice versa [10]. Consequently, this makes feasible to combine the advantages of neural network and fuzzy logic together [11][12], as shown on Figure 1.

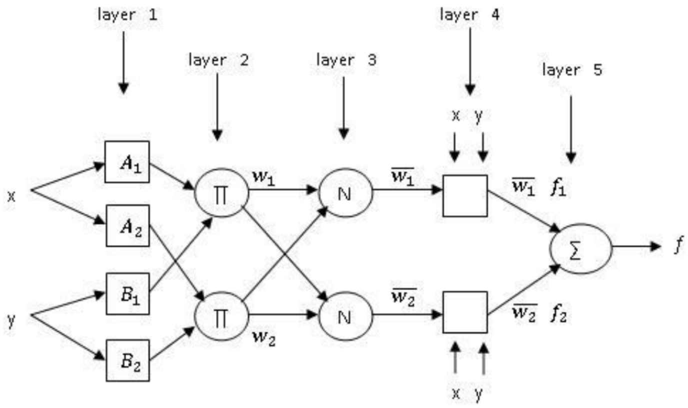

Figure 1: ANFIS structure

Layer 1: Every node in i in this layer is a square node with a node function

$$O_i^1 = \mu A_i(x) \tag{1}$$

Where x is the input node i, and A_i is the linguistic label(small, large, etc.) associated with this node function. In other words O_i^1, is the membership function of A_i and it specifies the degree in which the given x satisfies the quantifier A_i.

Usually, $\mu A_i(x)$ is chosen to be Gaussian function with maximum equal to 1 and minimum equal to 0, such as:

$$\mu A_i(x) = \frac{1}{1 + \left[\left(\frac{x-c_1}{a_i}\right)^2\right]^{bi}} \tag{2}$$

where a_i, b_i, c_i are the set parameter. As the values of these parameters change, the best Gaussian functions are chosen, thus showing various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions may be used for node functions in this layer. Parameters in this layer are referred to as *premise parameters.*

Layer 2: Every node in this layer is a circle node labelled π which multiplies the incoming signals and outputs the product. This is shown on equation 3

$$w_i = \mu A_i(x) * \mu A_i(y), i = 1, 2 \tag{3}$$

Each node output represents the firing strength of a rule (In fact, other T-norm operators that perform generalized AND can be used as the node function in this layer).

Layer 3: Every node in this layer is a circle node labelled *N*. The *ith* node calculates the ratio of the *ith* rules firing strength to the sum of all rules firing strengths:

$$\overline{w_i} = \frac{w_i}{w_1 + w - 2}, i = 1, 2 \tag{4}$$

For convenience, outputs of this layer are called *normalized firing strengths.*

Layer 4: Every node in this layer is a square node with a node function

$$O_i^4 = \overline{w_i} f = \overline{w} \left(p_i x + q_i y + r_i \right) \tag{5}$$

Where $\overline{w_i}$ is the output of layer 3, and p_i, q_i, r_i are the set parameter. Parameters in this layer will be referred to as *consequent parameters.*

Layer 5: The single node in this layer is a circle node labelled Σ that calculates the overall output as the summation of all incoming signals, ie.

$$O_1^5 = overalloutput \sum_i \overline{w_i} f = \frac{\sum_i w_i f}{\sum_i w_i} \tag{6}$$

An adaptive network, which is functionally equivalent to a fuzzy inference system, has been constructed[11],[12]. The hybrid algorithm is applied to this architecture. This means that, as the process moves along in hybrid learning algorithm, functional signals are calculated in the fourth layer and output parameters are identified using the least-square estimation. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent [11].

3 Related Work

Neural Networks and fuzzy systems have recently become an alternative method to conventional deterministic and stochastic methods[13][14].Several studies demonstrate that neural based models could be used for developing air pollution distribution models (e.g.[11][15])Viotti et al 2002 uses a MLP to forecast short and middle long-term concentrations levels for O_3, NO_x, NO_2,Also Hooyberghs [15]describes the development of MLP neural network to forecast the daily average PM10 concentrations in Belgian urban areas one day ahead. Zhang and San ([16]) uses a wavelet neural network to model hourly NOx and NO2 concentrations of emission source. However, the authors acknowledge no related work using a hybrid neuro-fuzzy system to predict PM10 harmful particles.

4 Data analysis and pre-processing

System Description:

The parameters to be taken into account are: Humidity and Temperature, these datasets are provided by the UK National Air Quality Archive. A total of 13 sites were used with similar characteristics: they used a TEOM monitoring method (microanalyzer that uses a microbalance to weigh the amount of particle concentration) and the geographical location (northwest England). The list of sites is shown on Table 1 and the Figure 2.

Blackpool	*Bolton*	*Bradford*
Bury	*Leeds*	*Liverpool*
Manchester	*Preston*	*Salford*
Sheffield	*Stockport*	*Wigan*
Wirral		

Table 1: List of sites where TEOMs are located.

Figure 2: TEOMs location map

This paper consists of modelling the behaviour of particle concentration in northwest England (Liverpool city) different years, The location of this site is shown in Figure 3:

Figure 3: Location of Liverpool in United Kingdmon map

The relationship between PM10 Concentration and the Humidity and average temperature has a non-direct relationship as shown on Figures 4 and 5.

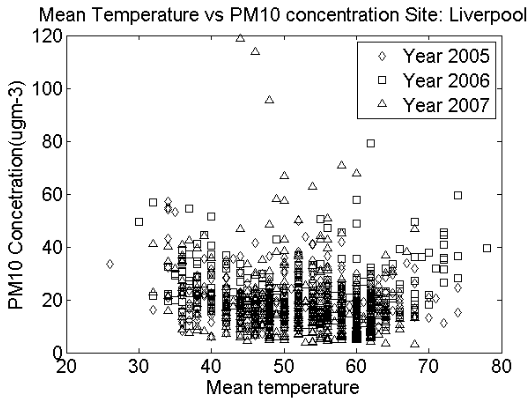

Figure 4: Mean temperature vs. PM10 Concentration ithe city of Liverpool in the years between 2005 to 2007

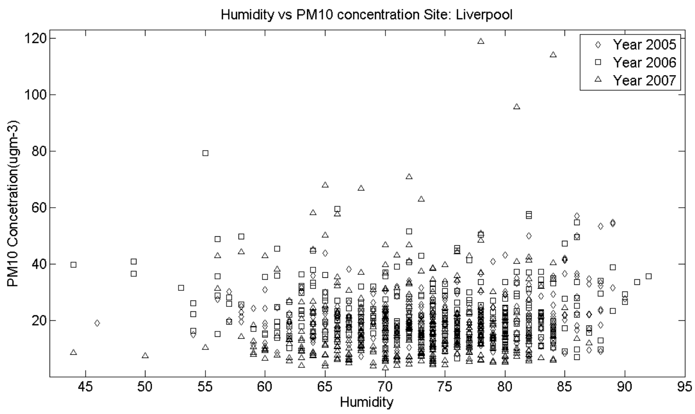

Figure 5: Humidity vs. PM10 Concentration ithe city of Liverpool in the years between 2005 to 2007

This city has a diverse behaviour in terms of particle concentration, humidity and temperature. Figure 6 shows the average PM10 concentration for all years by day, Figure 7 shows the mean Temperature, and Figure 8 shows the Humidity.

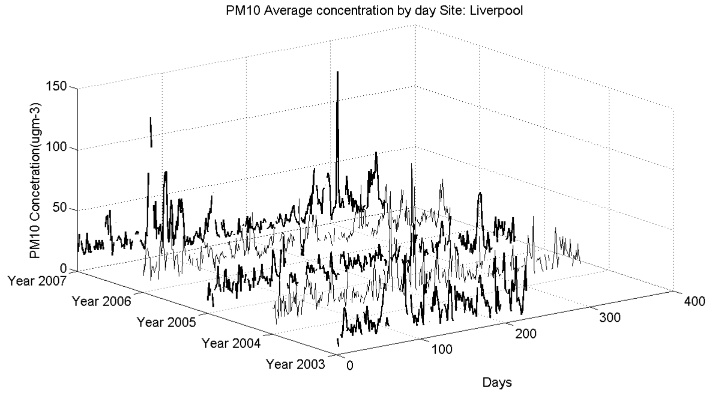

Figure 6: Average Humidity in Liverpool and Manchester in the year: 2006

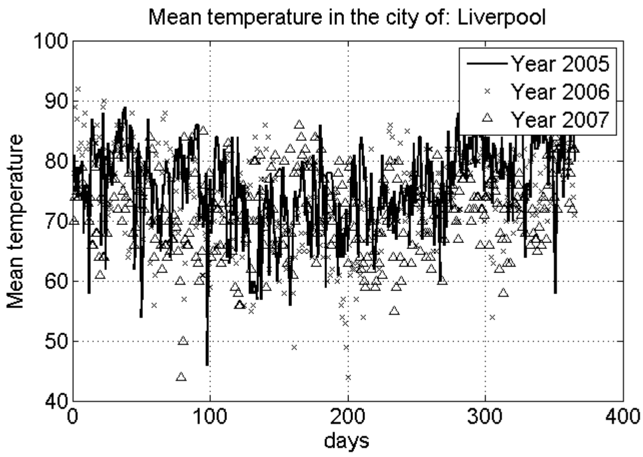

Figure 7: Average Temperature in Liverpool and Manchester in the year: 2006

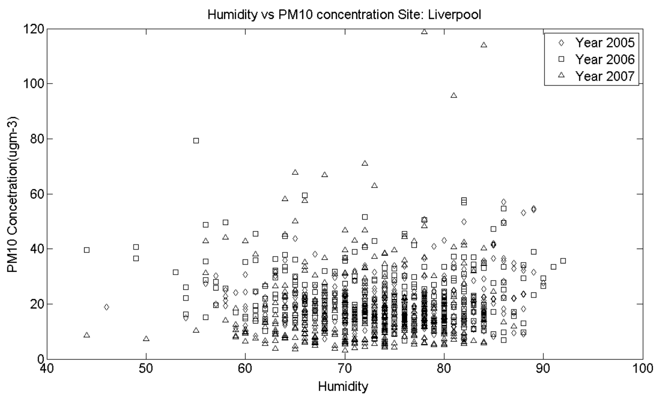

Figure 8: Average PM10 Concentration, Sites: Liverpool and Manchester, Years:2005-2007.

5 Discussion of Results

Airborne particulate monitoring in the city of Liverpool in the Northwest England for different years has been carried out using a Fuzzy Inference System structure (FIS)by getting the most important membership functions and rules of two different algortitms the Fuzzy C-means Clustering algorithm (FCM) is a method that is frequently used in pattern recognition. It has the advantage of giving good modeling results in many cases, although, it is not capable of specifying the number of clusters by itself, and the Substractive Clustering wich method assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points.

This model was designed with the data set of the city of Liverpool during the year 2006 and and tested for each case of study. A general FIS model has been generated for every case with a lower computational cost; this is because the specific models vary between 12 and 18 membership functions and rules, as shown in Table 2. The general model has only 4 membership functions and rules, as shown on Table 3. The system shows reliable results for one hour ahead of PM10 concentration prevision, with a low least-mean square error doing the proposed forecaster a powerful tool for health warning systems.

$Site$	$Variables$	$Membership\,Functions$	$Rules$
$Liverpool\,2005$	5	18	18
$Liverpool\,2006$	5	12	12
$Liverpool\,2007$	5	14	14

Table 2: Characteristics of each specific model.

$Variables$	$Membership\,Functions$	$Rules$
5	4	4

Table 3: Characteristics of FIS proposed model in Liverpool abetween the years 2005 to 2007.

The Efficiency of this FIS model was optimized impacting on a closer results between the PM10 raw and this model of each site and year, making a comparasion between the each raw data and the system FIS model, This is shown in the Figures 9, 10 and 11.

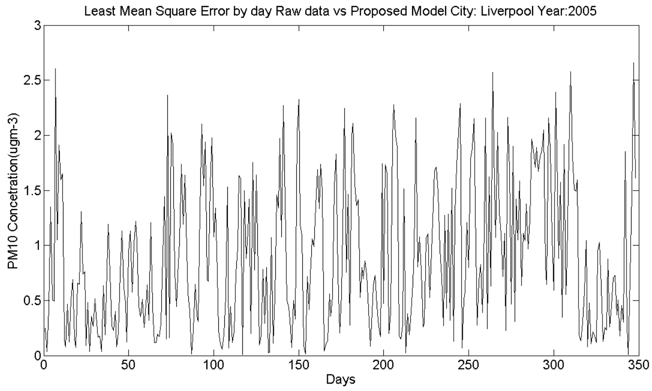

Figure 9: Least Mean Square Error between PM10 Raw Data vs.FIS model city: Liverpool year: 2005

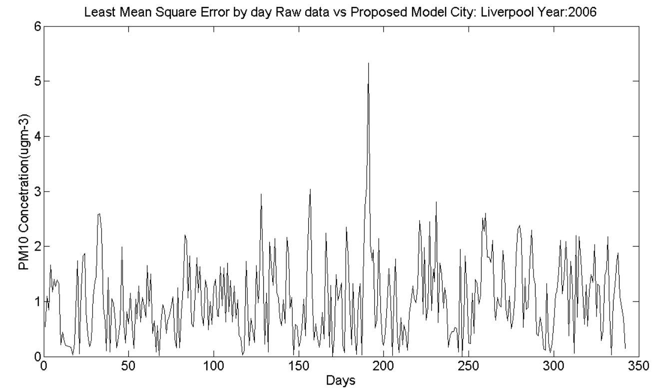

Figure 10: Least Mean Square Error between PM10 Raw Data vs.FIS model city: Liverpool year: 2006

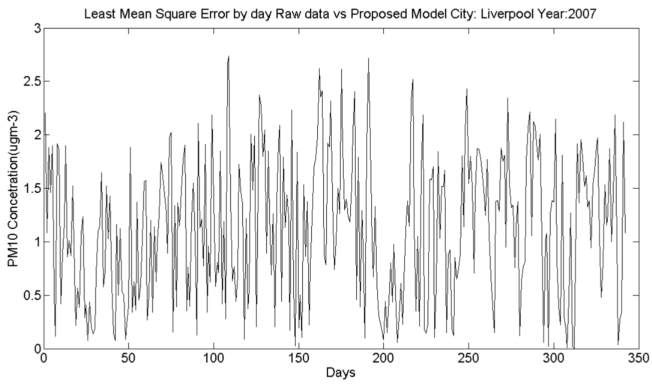

Figure 11: Least Mean Square Error between PM10 Raw Data vs.FIS model city: Liverpool year: 2007

This model was also tested tested using Manchester city in the year 2006 proving its performance as shown in Table 6, and the Figure 12

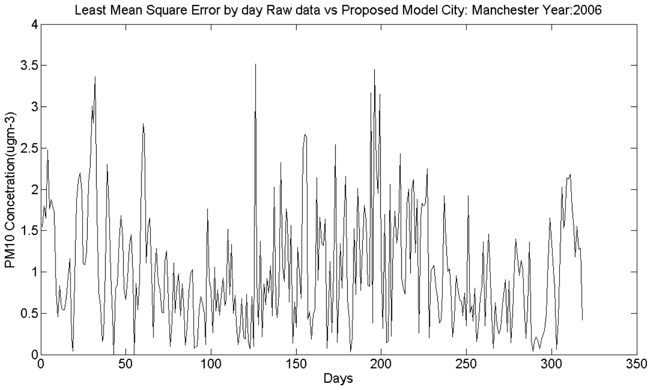

Figure 12: Least Mean Square Error between PM10 Raw Data vs.FIS model city: Manchester year: 2006

6 Conclusion and Future Work

In this paper an optimized Fuzzy Inference System has been developed. An unique model for every year and site were developed to reduce the computational cost and lower the number of membership functions in comparison with the original FIS model of each case of study, thus enhancing the capability of the Fuzzy Inference System(FIS). However, a generalized model could be obtained and tested over other datasets proving the correctness of results.
The model proved robustnes in predicting harmful airborne particles with moderate accuracy.
Several hybrid FIS models could be optimized to provide real-time prognosis for PM10. This optimized model may be embedded on a device (e.g. FPGA) to provide real-time prediction of airborne particulates. Also, more tests may be carried out using other particles (e.g. SOx, NOx) to determine whether this model can be applied to other harmful particles.

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