# Unsupervised method to classify $PM_{10}$ pollutant concentrations

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***Abstract*—In this paper a method based mainly on Data Fusion and Artificial Neural Networks to classify one of the most important pollutants such as Particulate Matter less than 10 micrometer in diameter ($PM_{10}$) concentrations is proposed. The main objective is to classify in two pollution levels (*Non-Contingency* and *Contingency*) the pollutant concentration. Pollutant concentrations and meteorological variables have been considered in order to build a Representative Vector (*RV*) of pollution. *RV* is used to train an Artificial Neural Network in order to classify pollutant events determined by meteorological variables. In the experiments, real time series gathered from the Automatic Environmental Monitoring Network (*AEMN*) in Salamanca Guanajuato Mexico have been used. The method can help to establish a better air quality monitoring methodology that is essential for assessing the effectiveness of imposed pollution controls, strategies, and facilitate the pollutants reduction.**

## I. Introduction

Air pollution posses significant threats to human health and the environment throughout the developed and developing countries. Air pollution is one of the most important environmental problems that is caused by both natural and man-made sources. Major man-made sources of ambient air pollution include industries, transportation, power generation, unplanned urban areas, etc. Therefore, the issue of air quality is receiving more attention as an increasing fraction of the countries population are now living in urban areas and are in demand of a cleaner environment. Air pollutants, once emerged from a variety of sources, are subject to mixing, dispersion, transport and complex series of chemical interaction and physical transformation processes in urban atmospheres [1].

Meteorological factors such as wind speed, temperature, relative humidity and sunlight intensity are considered as important factors that contributing to air quality [2]. It is extremely important to consider the effect of meteorological conditions on atmospheric pollution, since they clearly influence dispersion capability in the atmosphere. It is well known that severe pollution episodes in the urban environment are not usually attributed to sudden increases in the emission of pollutants, but to certain meteorological conditions which diminish the ability of the atmosphere to disperse pollutants [3], [4]. The frequency distribution of air pollutant concentration is useful in understanding the characteristics of air quality. It can be used to estimate how frequently a critical concentration level is exceeded [5]. However, the air pollutant concentrations usually vary randomly and are correlated with several factors such as types of fuels consumed, geographical and topographical peculiarities, town planning and meteorological factors, etc. [6]. Air quality management and information systems are required to control air pollutants and provide proper actions, controlling strategies and a better and safe environment for future generation [7], [8]. Thus, a thorough understanding of the meteorological field is fundamental to predicting and understanding air pollution in urban areas [9].

Sulphur Dioxide ($SO_2$), and Particular Matter ($PM_{10}$) are the air pollutants with the highest concentration in Salamanca, where three monitoring stations have been installed in order to know the level of air pollution; the measure records of each monitoring station are handled separately. Actually, an environmental contingency alarm is activated when daily average pollutant concentration, in a single monitoring station, exceeds a established threshold [10].

In this paper the suitability of the Artificial Neural Networks (ANNs) specifically the Self Organizing Maps (SOM) for classifying and interpreting the air quality and level of $PM_{10}$ concentrations in Salamanca city was investigated to implement our method to classify in two pollution levels (*Non-Contingency* and *Contingency*) the pollutant concentration. The results were compared to pollution levels for $PM_{10}$ established by Health Authorities.

## II. Study case

Salamanca is a mexican city located in the state of Guanajuato with a population of approximately 234,000 inhabitants [11]. Salamanca is catalogued as one of the most polluted cities in Mexico [12]. In Salamanca, the Program to Improve the Air Quality (ProAire) is composed of measures that affect transportation, industry, service sector, natural resources, health, and education. The ProAire program contemplates the urgent and immediate reduction of pollutant emissions when measurements of these pollutants register levels above those established by Health Authorities. When first ProAire concluded in 2000, environmental authorities undertook a longer, ambitious air quality improvement program ProAire 2002-2010. However, accurate measures were needed to determine how improving air quality would improve health and reduce health expenditures so that the new pollution control strategies could be evaluated [13]–[15].

In our study the established ProAire limits by Health Authorities are taken as references to select the best SOM structure to classify the $PM_{10}$ concentrations correlated with wind fields. Table 1 shows the established ProAire limits for $PM_{10}$.

| Environmental Pre-contingency | | |
|---|---|---|
| Pollutant | Level Activation | Level Annulment |
| $PM_{10}$ | >= $150\mu g/m^3$ and < $255\mu g/m^3$ | < 150 $\mu g/m^3$ |

(a)

| Environmental Contingency Phase I | | |
|---|---|---|
| Pollutant | Level Activation | Level Annulment |
| $PM_{10}$ | >= $255\mu g/m^3$ and < $345\mu g/m^3$ | < 150 $\mu g/m^3$ |

(b)

| Environmental Contingency Phase II | | |
|---|---|---|
| Pollutant | Level Activation | Level Annulment |
| $PM_{10}$ | >= $345\mu g/m^3$ | < 150 $\mu g/m^3$ |

(c)

TABLE I
ESTABLISHED ENVIRONMENTAL CONTINGENCY LEVELS FOR $PM_{10}$ BY ENVIRONMENTAL AUTORITIES IN SALAMANCA, (A) *Pre-contingency* (B) *Phase I* AND (C) *Phase II.*

### *A. Air pollutants and meteorological data*

Currently, in Salamanca an Automatic Environmental Monitoring Network (*AEMN*) is installed in which time series of criteria pollutant and meteorological variables are obtained. The main causes of pollution in Salamanca are due to fixed emission sources such as chemical industry and power generation, $SO_2$ and $PM_{10}$ being the most important pollutants in air [16], [17]. Although in this paper will focus only in $PM_{10}$ concentrations. $PM$ is categorized into particles with aerodynamic diameter less than $2.5\mu m$ ($PM_{2.5}$ or fine $PM$) and those less than 10 $\mu m$ ($PM_{10}$). $PM_{10}$ is usually comprised of smoke and dust from industrial processes, agriculture, construction, road traffic, plant pollen and other natural sources. Particle pollution, especially fine particles are linked to a variety of problems, including: decreased lung function; aggravated asthma; development of chronic bronchitis; irregular heartbeat, etc. [18], [19].

### *B. Proposed method*

AEMN is composed of three monitoring stations (Cruz Roja, DIF, and Nativitas). Unfortunately in each monitoring station the air pollution level is computed without taking into account the meteorological variables. In this paper we propose a method to assess the air pollution levels taking the meteorological variables as a decision factor by means of Data Fusion and ANNs. In the proposal, the air pollutant concentrations are divided in two levels (classes); (1) *Non-Contingency*, pollutant concentrations less than 225 $\mu g/m^3$ for $PM_{10}$; (2) *Contingency*, pollutant concentrations greater than or equal to 225 $\mu g/m^3$ for $PM_{10}$.

Proposed method involves local and global analysis as follows:

1) **Local Air Analysis**
   - Create three-dimensional Feature Vector $3D-FV$ for $PM_{10}$ ($3D-FV_{PM_{10}}$). $3D-FV$ is composed of pollutant concentration and meteorological variables (wind direction and wind speed).
   - Train a Self-organizing Map (SOM) Neural Network with the $3D-FV$ in order to cluster and visualize the involved variables.
   - Analyze and compare the SOM classification with the established air quality regulations.

2) **Global Air analysis**
   - Create three-dimensional Representative Vector for $PM_{10}$ ($3D-RV_{PM_{10}}$). $3D-RV$ is composed of the $3D-FVs$ created in local air analysis.
   - Train a Self-organizing Map (SOM) Neural Network with the $3D-RVs$ in order to cluster and visualize the involved variables.
   - Analyze and compare the SOM classification with the established air quality regulations.

The aim of this method is to combine various data sources to provide an optimal estimate of the spatial distribution of pollutants, taking into account the meteorological variables.

### *C. Data Fusion (DF)*

During the last years, Data Fusion (*DF*) methods have received more and more attention from several communities because of the increasing need to integrate the vast amount of data being collected by systems. *DF* is interpreted widely depending on the applications, technologies and communities of interest [20]. It refers in a broad sense to the processing and distribution of data from two or more sources to obtain a property of an environment or object [21]. In principle, *DF* provides significant advantages over single source data. *DF* applications can broadly be classified into two groups, namely military and non-military applications. Non-military applications cover a wide spectrum, such as air traffic control, robotics, manufacturing, medical diagnosis, environmental sensing, etc. [22], [23]. In this paper, real time series of $PM_{10}$ pollutant concentrations and Wind Direction (WD) and Wind Speed (WS) meteorological variables are applied in order to classify the air pollutant concentrations.

### *D. Self-Organizing Maps (SOM)*

Artificial Neural Networks (ANNs) are biologically inspired networks based on the neuron organization and decision making process in human brain [24]. ANNs are used in a wide variety of data processing applications where real-time data analysis and information extraction are required [25]–[27]. The basic SOM Neural Network consists of the input layer, and the output (Kohonen) layer which is fully connected with the input layer by the adjusted weights (prototype vectors). The number of units in the input layer corresponds to the dimension of the data. The number of units in the output layer is the number of reference vectors in the data space. In SOM, the high-dimensional input vectors are projected in a nonlinear way to a low-dimensional map (usually a two-dimensional space), and SOM can perform this transformation adaptively in a topologically ordered fashion. Therefore, the neurons are placed at the nodes of a two-dimensional lattice. Every neuron of the map is represented by an $n$-dimensional weight vector (prototype vector), $\theta = [\theta_1, ..., \theta_n]$, where $n$ denotes the dimension of the input vectors. The prototype vectors together form a codebook. The units (neurons) of the map are connected to adjacent ones by a neighborhood relation, which indicates the topology of the map. The rectangular topology was used in this study.

In the training (learning) phase, the SOM forms an elastic net that folds onto the "cloud" formed by the input data. Similar input vectors should be mapped close together on the nearby neurons, and group them into clusters. SOM is an unsupervised classification which is used to cluster a data set based on statistics only, and can be trained by an unsupervised learning algorithm in which the network learns to form its own classifications of training data without external help. The SOM is trained iteratively. For major reference of the learning process we can see [28], [29].

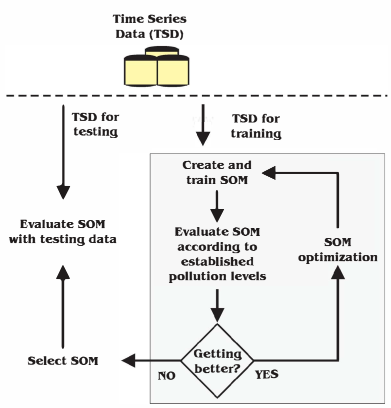


Fig. 1. Clustering process.

In our method, the clustering process is as follows: in the first step, the data are separated into two groups: training and testing. A SOM with four neurons is created and trained using a training dataset. Clustering results are compared with pollution levels established by Health Autorities. Another SOM is created with an additional neuron and trained. The evaluation criterion is compared. The number of neurons in SOM is increased until the evaluation criterion is achieved. The SOM with the best evaluation results is selected and the testing dataset is clustered using the best SOM. We stop the training process when all neurons in SOM structure have a difference of 1 % of each variable in the feature space and will be considered in the error classification. Finally, the evaluation criterion values are reported. Figure 1 illustrates the clustering process.

Each pattern (pollutant concentration and meteorological variables) can be represented as a point in a 3-dimension space and its projection on the 1D lattice using a SOM has been used to detect similar or different behavior among patterns during the analysis period. Patterns with a similar behavior can be expected to be projected onto the same neuron, while patterns with different behavior will tend to be assigned to different neurons in the SOMs. An optimal mapping would be the one that preserves on the 1D lattice, in the most faithful fashion, the existing distances in the 3-dimension space.

## III. Experimental results

According to the proposed method, we first present the local correlation analysis (by monitoring station). In local analysis, a 3-dimensional Feature Vector ($3D - FV$) to $PM_{10}$ is built. Beside pollutant concentration, this $3D - FV$ has associated the meteorological variables by minute.

- Local analysis in Cruz Roja Station

We first find the correlation factor between pollutant and meteorological variables as $R(i, j) = \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}}$, where $C$ is the covariance matrix of the input matrix $X$ and the $(i, j)$ *th* element of the matrix $R$ is related to $C$. Correlations are always between -1 and +1, but can take any value in between. A positive correlation means that the cloud slopes up; as one variable increases, so does the other. A negative correlation means that the cloud slopes down; as one variable increases, the other decreases.

Table II show the matrix of correlation coefficients ($R$) from January to October, 2006 for $PM_{10}$.

TABLE II
Correlation matrix of $PM_{10}$, wind speed and wind direction in Cruz Roja station from January to October, 2006

| $PM_{10}$ | WS | WD |
|---|---|---|
| 1.0000 | -0.1804 | -0.0102 |
| | 1.0000 | -0.1728 |
| | | 1.0000 |

Figure 2 show the SOM Neural Network classification of different $PM_{10}$ pollutant concentrations correlated with the meteorological variables on December 26, 2006.

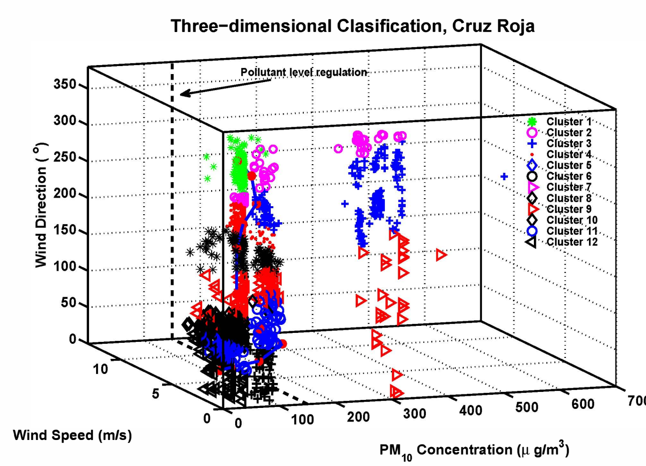


Fig. 2. SOM Neural Network classification of $PM_{10}$ and meteorological variables in the Cruz Roja station for December 26, 2006.

For $PM_{10}$, high concentrations are presented in many directions. This is normal if we consider that $PM_{10}$ is generated by several emission sources [30], [31].
For $PM_{10}$, the SOM parameters in classification process were: train epochs = 5, layer dimension = [5 2 1], topology function = *gridtop*, ordering phase learning rate = 0.9, distance function = *dist*.

- Local analysis in DIF Sation

Table III shows the correlation coefficient matrix in DIF station from January to October, 2006.

TABLE III
CORRELATION MATRIX OF $PM_{10}$, WIND SPEED AND WIND DIRECTION IN DIF STATION FROM JANUARY TO OCTOBER, 2006.

| $PM_{10}$ | WS | WD |
|---|---|---|
| 1.0000 | -0.0702 | 0.2283 |
| | 1.0000 | -0.1074 |
| | | 1.0000 |

Figure 3 shows the SOM classification for $PM_{10}$ pollutant for December 26, 2006.

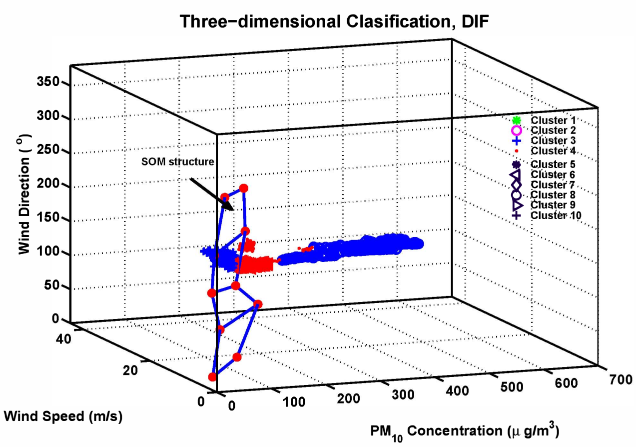


Fig. 3. SOM classification of $3D - FV_{PM_{10}}$ in DIF station for December 26, 2006.

We observe in the figure 3, $PM_{10}$ pollutant concentration presented between 180 to 220 degrees. For $PM_{10}$, the SOM parameters were: train epochs = 5, layer dimension = [2 1 5], topology function = *gridtop*, ordering phase learning rate = 0.9, distance function = *dist*.

- Local analysis in Nativitas Station

Table IV shows the matrix of correlation coefficients for $PM_{10}$ with meteorological variables in Nativitas station from January to October, 2006.
Figure 4 shows the $3D - FV_{PM_{10}}$ classification for December 26, 2006.
We observe in the figure different $PM_{10}$ classification correlated with meteorological variables. For $PM_{10}$, the SOM parameters in classification were: train epochs = 5, layer dimension = [7 1 1], topology function = *gridtop*, ordering phase learning rate = 0.9, distance function = *dist*.

TABLE IV
CORRELATION MATRIX OF $PM_{10}$, WIND SPEED AND WIND DIRECTION IN NATIVITAS STATION FROM JANUARY TO OCTOBER, 2006.

| $PM_{10}$ | WS | WD |
|---|---|---|
| 1.0000 | -0.0525 | 0.0787 |
| | 1.0000 | -0.3027 |
| | | 1.0000 |

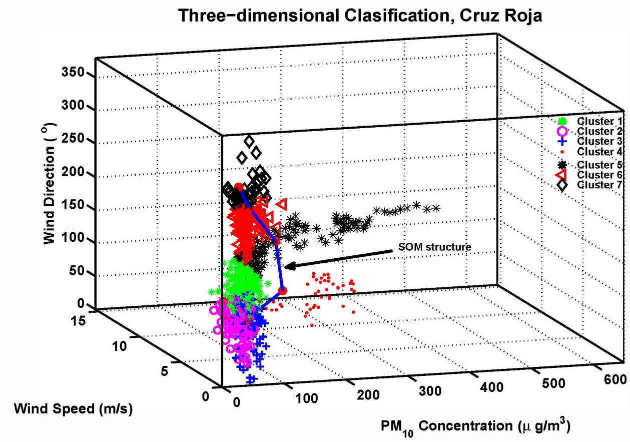


Fig. 4. SOM classification of $PM_{10}$ and meteorological variables in Nativitas station for December 26, 2006.

In all local analysis, training sets were build from January to October, 2006. The testing day was December 26, 2006.
Table V shows the obtained $PM_{10}$ local error with SOM classification for Cruz Roja, DIF and Nativitas stations. Clusters in level 2 belong to pollutant concentrations up to 150 $\mu g/m^3$ for $PM_{10}$.

| $3D - FV_{PM_{10}}$ Local Error (%) | | | |
|---|---|---|---|
| Monitoring station | SOM structure | MAE error | Clusters in level 2 |
| Cruz Roja | [12 1 1] | 5.1 % | 3 (+) y 9 (▹) |
| DIF | [2 1 5] | 2.5 % | 8 (o) |
| Nativitas | [7 1 1] | 2.2 % | 4 (.) y 5(*) |

TABLE V
LOCAL ERROR PERCENT IN CLASSIFICATION FOR $PM_{10}$ USING A SOM NEURAL NETWORK STRUCTURES.

For $PM_{10}$, the minimum error is obtained with [7 1 1] SOM structure for Nativitas station and the maximum with [12 1 1] for Cruz Roja station. Results are obtained for December 26, 2006.

## A. Global analysis

For proposed global analysis, we built a 3-dimensional Representative Vector ($3D - RV$ for $PM_{10}$ ($3D - RV_{PM_{10}}$). The $3D - RV$ is built with the respective $3D - FV$ for pollutant. To build the $3D - RV$, the maximum pollutant concentration among the three $3D - FVs$ with the associated meteorological variables were considered. For this reason, in this analysis we did not correlate pollutant concentrations and meteorological variables. The aim was to combine various data sources to provide an optimal estimation of the spatial distribution of pollutants.

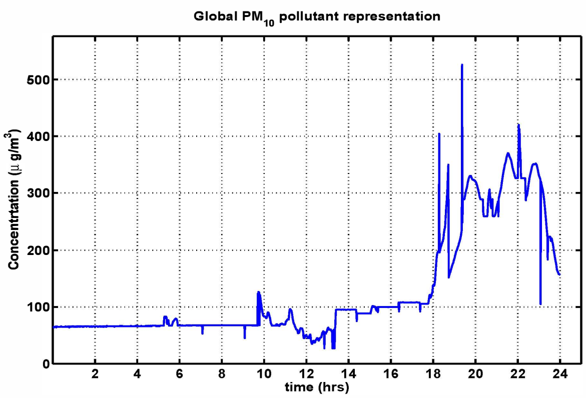


Fig. 5. Global representation of $PM_{10}$.

Figures 6, 7 and 8 show the SOM classification for $PM_{10}$ in Cruz Roja, DIF and Nativitas stations for December 26, 2006 respectively.

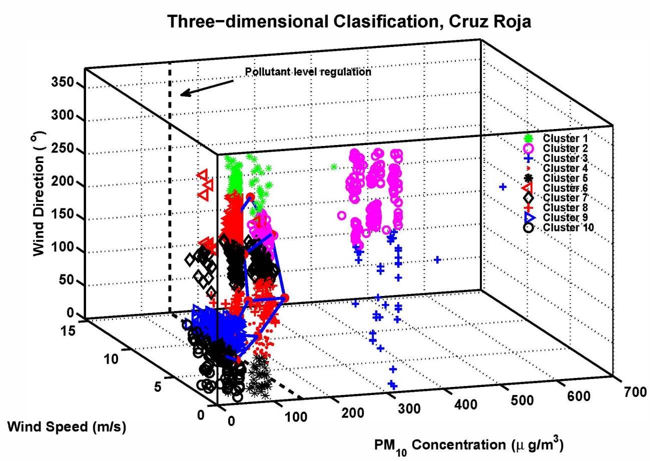


Fig. 6. Classification of $3D-RV_{PM_{10}}$ in global analysis in Cruz Roja.

Classification parameters for $PM_{10}$ were: train epochs = 3, layer dimension [5 2 1], topology function = *gridtop*, ordering phase learning rate= 0.9, distance function = *dist*. In global analysis, training sets were build with maximum pollutant concentrations in the $3D-RV's$. 3-dimensional test was performed on December 26, 2006. Also, several SOM structures were tested to obtain the minimum classification error in the two proposed levels (level 1 as *Non-contingency* and level 2 as *Contingency*). Table VI summarize the minimum classification error obtained with SOM structures and the number of clusters for the proposed level 2 in global analysis. Obtained error is computed by Mean Absolute Error (MAE).

In obtained results, we observe high or low $PM_{10}$ concentrations influenced by wind speed and wind direction.

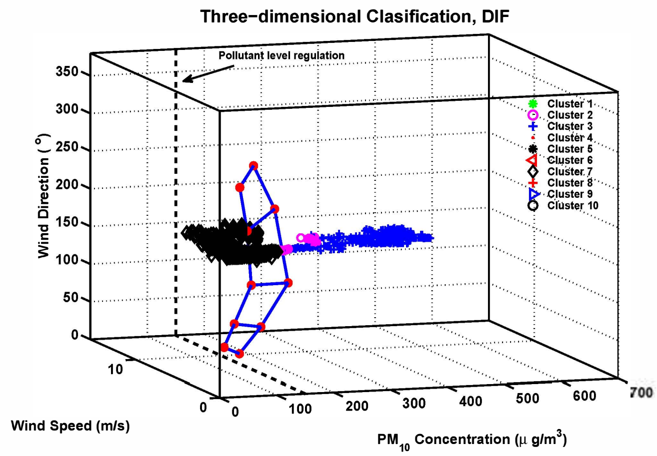


Fig. 7. Classification of $3D-RV_{PM_{10}}$ in global analysis in DIF.

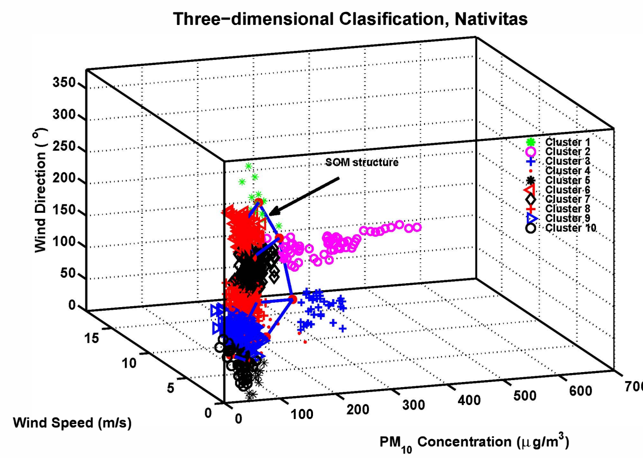


Fig. 8. Classification of $3D-RV_{PM_{10}}$ in global analysis in Nativitas.

| $3D-RV_{PM_{10}}$ Global Error (%) | | | |
|---|---|---|---|
| Monitoring station | SOM structure | MAE error | Clusters in level 2 |
| Cruz Roja | [5 2 1] | 6.9 % | 2 (o) y 3 (+) |
| DIF | | 2.3 % | |
| Nativitas | | 6.6 % | |

TABLE VI
ERROR PERCENT FOR $PM_{10}$ USING A SOM NEURAL NETWORK

Figures 6, 7 and 8 show the SOM structure for $PM_{10}$ concentrations. We observe also in lower wind speed and in many directions high $PM_{10}$ concentrations, this is normal if we consider that $PM_{10}$ have many emission sources [30], [31].

## IV. Conclusion

The aim of this paper was to classify the $PM_{10}$ pollutant concentrations correlated with wind parameters in order to implement a method to identify possible risk health in Salamanca. Meteorological parameters such as *wind direction* and *wind speed* that determine the source and emission rate of the pollutants were taken into account in the proposed method as decision factor in classification process. Experimental results have shown a correlation between pollutant and meteorological variables. Variables help to determine the source and emission rate of the pollutants. Maximum $PM_{10}$ pollutant concentrations are presented in almost all directions. For Data Fusion process, the maximum pollutant concentrations were taken as the main feature to create the $3D-RV$. This vector has associated their correlated meteorological factors (wind speed and wind direction) and built for $PM_{10}$ pollutant. $3D-FVs$ and $3D-RVs$ for local and global analysis were built to train a SOM Neural Network. In SOM classification process, several SOM structures have been trained for local (Cruz Roja, DIF and Nativitas) and global analysis (Salamanca) in order to obtain the minimum error. Obtained results show a good alternative to classify the pollutant concentrations and as an alternative to assess the pollution effects. On the basis of the present study, it can be concluded that wind speed and wind direction are important parameters influencing the $PM_{10}$ behavior in Salamanca. This proposed method will help researchers and policy-makers to select better air pollution control projects and practical insights into how to effectively and efficiently implement environment policies to human health. The resulting data is expected to be useful not only for the future air pollution control applications in other studies, but also for the improvement of monitoring and evaluation systems building air quality management strategies.

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