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Application of Neural Net Model to Estimate the Cardiovascular and Respiratory Diseases by Air Pollution Data in Urban Area

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1. Introduction

One of the major environmental problems is air pollution that has important effects on human health. According to the World Health Organization (WHO), air pollution is the eighth cause of death and is the main environmental risk factor in Europe.
Air pollution depends by number and diversity of emission sources and concomitant risk factors that took into account meteorology that plays an inferential action on adverse effects of pollution in term of space-time.
Such situations are very important especially for the Mediterranean coastal countries (like Italy) and for urban sites that are affected by the microclimatic conditions that could lead to atmospheric stagnation events.
In recent years, a broad number of scientific studies have shown that the linkage between urban settlements with high population density and large industrial centers resulted worsening of air pollution due to the impact resulting from intensive traffic, from domestic heating and from industrial and energy plants. Severe cases of pollution, which have had important impacts on the population, have occurred in urban or industrial areas and this in conjunction with unfavorable atmospheric dispersion and dilution of air pollutants. Air pollution is a set of pollutants, many of which are correlated to each other. In this work, we will focus only on the particulate matter (PM10) and ground-level ozone (O3) [Gariazzo et al., 2007],that in general have been identified as two of the most important air pollutants for Europe [Jol and Kielland, 1997]; [Brunekreef and Holgate, 2002].
Particulate Matters (PM) are tiny particles of solid or liquid suspended. They range in size from 0.1 nanometers to 100 micrometers in diameter. PM10 can be either primary or secondary, in nature. In general, primary particles are emitted directly into the atmosphere by natural and anthropogenic sources, whereas secondary particles are formed in the atmosphere from chemical and physical reactions of SO2, NOx, NH3 and VOC. The PM10 composition depends on the source of emission. The PM10, being rich in biologically active substances, contains inside carcinogens substances (polycyclic aromatic hydrocarbons, volatile organic compounds), elemental carbon, heavy metals, mineral dust, fragments of soil, sulfates and nitrates that can have an irritating action, ammonium. In the atmosphere, particulate concentrations depend on both natural sources (soil erosion, marine aerosol,

production of biogenic aerosols plant fragments, pollen, spores , volcanic emissions –fire- and long distance transport sand) and anthropogenic sources (motors, heating, industry, power plants, etc.).In urban areas, the most important anthropogenic factors, leading to increase in PM10, are linked to road traffic and heating, as well as those related to possible industrial plants (refineries, cement plants, power plants, incinerators, etc...).
The territorial distribution of the emission sources of PM10 is an important aspect in order to have a complete analysis of the PM pollutant. They are analyzed through the inventory of emissions at local scale (province).The Table 1 shows in the short period the disaggregation of emissions as regards sectors of Transport, Industry and Domestic. In particular, the table shows the percentage of each sector of the total actual emissions. These percentages represent quantitatively the potential for absorption of the respective sectors.

	Tons	%
Transport	3263.20	48%
Industry	887.73	13%
Domestic sectors and Commercial	14151.91	17%
Agriculture and forests	16.07	0,23%
Energy	1004.10	15%
Other	541.94	8%
Total	**6864.95**	**100%**

Table 1. Emission sources of PM10 (tons) in Rome (2000) - (Source: www.**sinanet**.**apat**.it)

In Rome the traffic's contribution is around 48%. The portion of the PM10 produced by civil heating represents a share ranging from 20% to 30% of the total. The item "Other" were collected PM10 emissions are not considered in the inventory. These emissions, produced by raw materials handling, construction activities, smoke and fireworks, together represent approximately 10% of total emissions of PM10.
Ozone is a well known secondary air pollutant, results from complex chemical reactions such as nitrogen oxides (NOx) and volatile organic compounds (VOCs) and is a very reactive gas and presents concentration levels which are strongly dependent both from the micro-meteorological conditions and the seasonal effects.
Its presence as a layer in stratosphere serves as a screen (called ozone shield) to block harmful ultraviolet radiation from reaching the earth's surface. At ground level it is formed by the combination of hydrocarbons and nitrogen oxides (NOx) at the presence of sunlight and is the main ingredient of smog.
In the air, the persistence time of ozone is a few hours in the presence of other pollutants, whereas clean air could remain to several months.This means that the highest concentrations levels of ozone are often in rural areas near cities or industrial areas.
In addition, the Ozone:

- is absent in the cold months and short (no sunshine duration)
- smell is noticeable at a concentration 0.008 and 0.02 parts per million (ppm)
- is an irritant at a concentration of 0.10 to 0.15 ppm
- is harmful mainly for people with respiratory and cardiac diseases.

The relationship between the various factors and daily occurrence of pathologies related to cardio-respiratory apparatus is a task not easy and immediate to solve. In recent years, a great number of environmental and epidemiological publications [World Health Organisation, 2006, 2003, 2001] have confirmed that the linkage between urban sites with high population density and great industrial centers resulted in the deterioration of air pollution due to the impact resulting by auto-vehicular traffic, the domestic heating and by the industrial and energy plants. High levels of air pollution concentrations have had major impacts on the population. They have occurred in urban or industrial areas and this in conjunction with not favorable situations of atmospheric dispersion and of dilution of pollutants. It is to underline that the impact of the fine and total particulate matter on health are related to the air quality by means of pollutants across during the time of work. In particular, PM10 and O3 have been associated with pulmonary function decrements in exposed populations. Inhalation of fine, airborne particulate matter has serious chronic human health effects and is a major cause of premature death, whereas high levels of ozone concern their effects on human health related with respiratory problems, above all for children during the peak episodes [World Health Organisation, 2003]. These symptoms can last for a few hours after exposure to ozone and may even become painful. Furthermore, these effects could cease once the person is no longer exposed to elevated levels of pollutant.
This paper is a contribution in the field of air pollution due to particulate matter and ozone concentrations. In particular, the objective of this pilot study was to determine a way of assessing exposure to outdoor pollution. In the short term (the data used covered a period of two years: 2005 and 2006) their impact assessment on population (especially on children, the patients, pregnant women and elderly and on people who suffer from chronic cardio-respiratory diseases) in terms of morbidity and mortality by cardio-pulmonary diseases [Murray & Mittleman, 2007] in the urban area of Rome.
Our aim is to analyze the annual trend of morbidity and mortality in hospital for cardio-respiratory diseases due to PM10 and ozone by using neural net (NN) techniques [Bishop, 1995], which are important tools to forecast because it can work as universal approximators of non-linear functions. The NN capacity to learn non-linear functions is an important issue in our problem. Moreover, neural network does not require assumptions about the input variable distribution or absence of correlations between such variables. Consequently, NN can be used in evaluating cardio-respiratory diseases due to environmental systems [Rojas, 1996] and can capture without many of the usual limiting assumptions of other traditional advanced statistical methods, which make not particularly appropriate.
Thus it will be possible to increase the knowledge of levels of concentration of pollution in urban areas and inform the public about environmental risks on human health.
By applying NN to the field of environmental epidemiology [World Health Organisation, 2004] we want to:

- examine the most injurious pollutants to human health and their mechanisms of dispersion
- identify the factors and mechanisms of epidemic diffusion
- model the cardiovascular and respiratory diseases by means the use of air pollution data coming from urban monitoring station
- formulate a methodological suggestion to apply to Neural Net to predict the human health impact due to the different pollutants

2. Material and methods

2.1 Data collection

In short-term, data of the hospital discharge records Hospital Discharge Records (HDR) were analyzed for the calendar years 2005 and 2006 in Rome, to measure the effects on population health due to exposure to physical, chemical and biological agents outside the human body. In public health, the HDRs are the tool of information gathering for every patient discharged from public and private hospitals throughout the territory. They provide relevant information about the diagnosis. This information is collected in a special database (EPICS) by Agency of Public Health (ASP) of Lazio, that contain list the variables to be reported, their descriptions and reporting format, and other information associated with data submission.
The minimum data set for each reported discharge include the following data elements:

- Patient's Address: City, State and Zip Code
- Patient's age (0-14; 15-64, over 65; the class's distribution allows you to observe with greater precision the effects of pollution on cardio-respiratory)
- Patient's Sex
- Admission and dismissal date: admissions were examined from 01 January 2005 to17 December 31, 2005
- Type of care: acute hospital admissions in ordinary regime (until 60 days), i.e. taking 19 into account the rules for implementing the treatment
- Admission type: at home, death, dismissal protection, voluntary dismissal, transfer to another inpatient, transfer
- Days in hospital
- Source of admission
- Patient's Status
- Principal Diagnosis Codes (ICD9CM -390-459: Circulatory system diseases ;460-519: Respiratory Diseases) Local Health Units of Residence: were analyzed only hospitalized residents in Rome
- Mode of arrival at hospital: general practitioners, first aid physicians, specialist doctor, transferred from another hospital, transferred from the first aid of the same hospital (including voluntary presentation of the patient), transferred from another regime of inpatient of the same hospital, transferred from first aid of another hospital. The mode of arrival at hospital determines which part of the cardio-pulmonary disease is attributable to the characteristics of patients - and which part is attributable to the quality of care.

Instead, the data used on primary pollutants and meteorological variables cover the 2005 and 2006 period and coming from monitoring stations of the ARPAL (Environmental Protection Agency of Lazio Region) positioned in Rome, which have had for each year at least 50% valid data (taking count of EoI – Exchange of Information).
In Table 2, it is described the network of the main monitoring stations of the pollutants of Rome. The urban monitoring stations are used to measure the concentration level of pollution influenced mainly by emissions from traffic. They are located in high risk areas such as roads with high traffic exhibition (Decision 2001/752/EC).
The background station is located within Villa ADA's park , in other words, in an area not directly affected by urban emission sources. It is used to monitor the natural level of pollution in urban areas. Villa Ada monitoring station is particularly important to measure

the concentration levels of ozone. In the same monitoring station, we have available a set of meteorological variables such as solar radiation, temperature and humidity, and the main primary pollutant variables (NO, NO2, CO).

Monitoring Station	Activation Date	Type Station	Type Area
Corso Francia	01/01/1993	Traffic	Urban Area
Cinecittà	13/01/1998	Traffic	Urbana Area
Largo Arenula	01/01/1993	Traffic	Urban Area
Largo Magna Grecia	01/01/1993	Traffic	Urban Area
Villa Ada	01/04/1994	Background	Urban Area

Table 2. Air quality monitoring station of Lazio (Source: BRACE's database - http://www.brace.sinanet.apat.it/)

As can be seen from Table 2, five monitoring stations have been taken into consideration: four traffic stations and one station of background. In this case, we considered at hourly time steps concentrations of primary pollutants and meteorological variables coming from monitoring stations. This study utilises a significant number of pollutants (ozone and main relevant primary and secondary pollutants) and main meteorological variables in order to maintain parsimony [Occam's razor] and keep the resulting models simple enough for meaningful comparison.

Our environmental dataset examines about 90,000 hourly pattern data, coming from 5 monitoring stations, and is composed by pollutants variables and conventional meteorological variables:

- observed pollutants variables:
  - Carbon monoxide (mg/m^3)- CO-
  - Nitrogen Oxide (μg/m3) –NO-
  - Nitrogen Dioxide (μg/m3) -NO2-
  - Mono-Nitrogen Oxides (μg/m^3) -NOx-
  - Ozone (μg/m3) - O3 -
  - Pm10 (μg/m3) - PM10
- meteorological variables:
  - Temperature (C°) – T;
  - Global Solar Radiation (W\m^2) – GSR;
  - Relative Humidity - RH (%)
  - Pressure (mbar)–P-
  - Rain (mm).

It was decided that this study would use a conservative number of pollutant (concentrations of ozone, PM10 and other relevant pollutants) and meteorological variables, according to parsimony principle, and keep the NN models simple enough for meaningful comparison. We observed that global radiation were analysed to investigate the ozone correlation with photochemical reactions.

Moreover, we observe that our environmental time series contain information at different scales, some of which are periodic, such as day and hour that represent seasonality and

diurnal variation. These variables were treated in term of cosine and sine. In this way, it is possible to take into account the effects of seasonality and diurnal variation.
Before conducting any analysis, previously all data were standardised (pollutants and meteorological conditions).

2.2 Pre-processing

Table 3 and Table 4 show the general statistics calculated by the pollutants and meteorological parameter analysed in this study for 2005 and 2006. The descriptive statistics are a necessary passage to establish some properties of the distribution of our dataset. We examine the following statistical characteristics of the distribution of hourly data: mean, standard deviation, skewness (SK) that shows the direction and measures the asymmetry of the distribution of our variables, kurtosis, that refers to the peak of a frequency curve, maximum, minimum and variation filed values calculated on the chemical and meteorological parameters.
O3's concentrations present a significant variability between 2005 and 2006 (0.98 and 0.97 respectively). The concentration values of NO2 are within a range (0 to 250.19 mg/m^3).
As regard to acute events exceeding the recommended limits for NO2 and O3 concentrations, which was fixed at 180 μg/m^3 for ozone (hourly information threshold for human health protection) and 200 μg/m^3 1-hour mean for NO2 [DM25/11/1994]. A first indication of their occurrence can be deducted from the maximum value for each time series. In particular, it is noted that NO2 and O3 concentrations exceeding the level of attention.

- The CO has kurtosis's values greater than the critical value, 3, and its distribution is highly asymmetrical, with a value of sk near to 3
- The NO2 has kurtosis's values below the critical value, 3, and with a value of sk near to zero
- Kurtosis's ozone does not exceed the critical value for 2005 and 2006, while there is a positive asymmetry (sk is equal to 1 for two years)
- The NO and NOx kurtosis values are higher than the critical value, 3, and their distributions are highly asymmetrical, with a value of sk near to 3
- The kurtosis of PM10 exceeds the critical value in two years, whereas there is a discrete positive asymmetric (sk is approximately 1) for 2005. For 2006 it is noted that the kurtosis value is less than the critical value, while there is a slight positive asymmetry.

The analysis of meteorological data provides support interpretive information of descriptive statistics calculated on data from pollution, because air pollution is also strongly influenced by meteorological factors [Seinfeld and Pandis, 1998].
On a local scale, air pollution depends by meteorological variables such as temperature, humidity, solar radiation, cloudiness and rain. This means that the distribution of pollutants is not only dependent on the spread of its emissions, but is also affected by various meteorological drivers [Giorgi and Meleux, 2007].
As known, global radiation was analyzed to investigate the ozone correlation between and photochemical reactions. In fact, when solar radiation is high, Table 3 and Table 4 temperature becomes a key variable between the meteorological data. Remarkably, NO2 and atmospheric pressure show low values. Finally, relative humidity appears as input of minor relevance; this does not mean that they do not influence the pollutant values.
Finally, the analysis of epidemiological data shows that for cardio-respiratory admission, kurtosis does not exceed the critical value for 2005 and 2006, moreover the skewness is approximately zero.

At the end, in our environmental time series, we observed that missing values depend on different working periods of the monitoring stations or occasional malfunctions of the instruments. In this analysis, missing values were not taken into account.

2005		**Mean**	**Sd**	**Skewness**	**Kurtosis**	**N**	**Missing**	**Min**	**Max**	**CV (%)**
CO	(mg/m³)	1.06	0.82	2.99	16.70	40795	3005	0.00	12.16	0.77
NO2	(μg/m³)	63.42	31.85	0.53	0.26	40773	3027	0.45	249.84	0.50
NO	(μg/m³)	47.85	67.62	2.95	13.11	40784	3016	0.00	860.07	1.41
Nox	(μg/m³)	136.76	126.82	2.40	9.41	40806	2994	0.50	1365.47	0.93
O3	(μg/m³)	35.99	35.30	1.12	0.75	24300	19500	0.00	220.54	0.98
PM10	(μg/m³)	36.33	17.15	1.52	5.06	23478	20322	0.00	202.49	0.47
Rain	(mm)	0.09	0.64	14.19	290.46	8494	35306	0.00	20.00	6.88
Press	(mbar)	1016.14	6.80	-0.42	0.95	17396	26404	986.47	1035.81	0.01
GSR	(W/m2)	133.56	230.59	1.88	2.44	34394	9406	0.00	1031.11	1.73
Temp	(C°)	14.37	8.12	0.10	-0.70	43145	655	-5.90	41.61	0.57
RH	(%)	70.21	19.49	-0.32	-0.83	43143	657	0.05	99.14	0.28
Cardiac Admission		172.48	50.30	-0.60	-.29	365	0	3	286	29.16
Respiratory Admission		78.74	25.51	0.07	-0.14	365	0	1	149	32.40

Table 3. General statistics (2005)

2006		Mean	Sd	Skewness	Kurtosis	N	Missing	Min	Max	CV (%)
CO	(mg/m³)	0.99	0.75	2.68	12.46	36322	7478	0.00	11.34	0.75
NO2	(μg/m³)	69.80	35.47	0.49	0.15	40385	3415	0.00	250.19	0.51
NO	(μg/m³)	50.50	71.78	2.85	12.95	40392	3408	0.00	1228.35	1.42
Nox	(μg/m³)	147.18	134.82	2.25	8.17	40400	3400	0.00	1734.78	0.92
O3	(μg/m³)	36.63	35.41	1.04	0.63	15248	28552	0.00	227.59	0.97
PM10	(μg/m³)	39.83	17.35	0.80	0.35	33102	10698	0.18	104.90	0.44
Rain	(mm)	0.60	5.53	18.11	435.33	8697	35103	0.00	182.00	9.17
Press	(mbar)	1017.51	6.06	-0.07	0.45	17401	26399	996.00	1040.00	0.01
GSR	(W/m2)	138.38	230.18	1.78	2.08	34853	8947	0.00	1005.00	1.66
Temp	(C°)	15.64	7.79	0.26	-0.56	42813	987	0.00	44.00	0.50
RH	(%)	70.25	19.92	-0.37	-0.79	34794	9006	1.00	99.00	0.28
Cardiac Admission		167.78	48.21	-0.60	-0.31	364	1	7	259	28.73
Respiratory Admission		72.89	21.09	-0.08	-0.04	364	1	6	134	28.93

Table 4. General statistics (2006)

The size of the archive data that you have allows for an analysis of correlation between the variables available with the aim of identifying those most related. The correlation matrix of Pearson calculated over the entire set of hourly data is shown in Table 5 that describe:

- CO is both very marked positive correlations with NOx and NO2

- NO2 is anti-correlated with O3
- O3 presents positive correlation values with temperature and solar radiation, negative values, with relative humidity and cardio-respiratory admissions
- PM10 presents positive correlation values with air pollutants, excepted O3, HR and low positive values with cardio-respiratory admissions. Negative values with meteorological variables.

	PM10	*CO*	*NO2*	*NOX*	*O3*	*Rain*	*T*	*UR*	*GSR*	Cardiac	Respiratory
PM10	1										
CO	0.76	1									
NO2	0.67	0.79	1								
NOX	0.72	0.93	0.78	1							
O3	-0.42	-0.71	-0.57	-0.76	1						
Rain	-0.14	-0.05	0.00	-0.03	-0.06	1					
T	-0.21	-0.45	-0.33	-0.49	0.64	-0.08	1				
RH	0.14	0.40	0.13	0.34	-0.59	0.25	-0.39	1			
GSR	-0.30	-0.56	-0.40	-0.60	0.79	-0.20	0.74	-0.61	1		
Cardiac	0.05	0.28	0.34	0.21	-0.16	-0.01	-0.16	0.05	-0.04	1	
Respiratory	0.19	0.41	0.36	0.33	-0.32	0.00	-0.46	0.16	-0.29	0.73	1

Table 5. Correlation Matrix

The analysis of stratified data by day allow you to see what shape it takes the distribution of different variables at each day and verify the existence of particular trends in the time series associated with these layers of time (see Fig.1 and Fig.3). In particular, in Fig.1 and Fig.3, it is possible to observe a not linear relation between averages of CO's daily distributions and their skewness (Sk), of the CO's daily distributions and averages of O3's daily distributions and their skewness (Sk). These relations allow explaining in a good manner the latent factors that are not manifest variables. For this reason, we included these indices as input for NN, because the greatest advantage of a neural network is its ability to model a complex non-linear relationship between independent and dependent variables [Gardner, 1999], [Gardner, 2000], [Abdul-Wahab, 2002].
In particular for CO, it can observed the following:

- CO is less than 1 mg/m3 the Sk's values are very higher up to 10
- CO is greater than 2 mg/m3 the Sk's values are low (from 2 to 0),therefore daily distributions are symmetric
- CO is greater than 2 mg/m3 the Sk's values are approximately zero.

Fig. 1 explains very well the significant positive asymmetry of CO distribution.
For this study, we calculated the daily distributions (PDF) of each pollutant (760 PDFs for each variable), for confirming the hypothesis of a concentration trends related to changes in the day. In Table 6 and Fig.2 we synthesized these PDFs through their mean, standard deviation and skewness that are able to capture environmental performance. If a daily distribution presents a negative asymmetry, it means that its values will be below of alert values for the exposure of population.

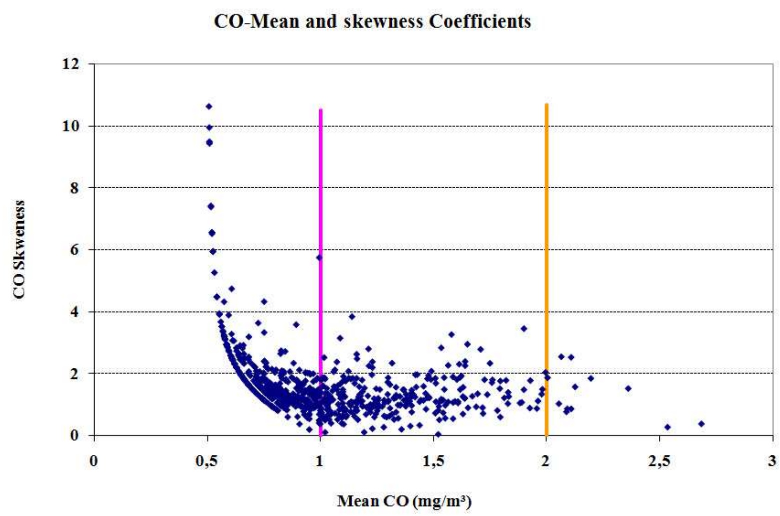

Fig. 1. Relation between Mean(CO) and Skenewss(CO)

Table 6 and Fig.2 show that when the daily average value of the PDF of CO is between 0.5 and 1.0 mg /mc, the skewness is 1.95 and contains 58.2% of data, whereas in the second class the skewness is 1.26 and contain 40.2% of overall data and the third class only 1.6%. In particular, Fig.2 shows that CO presents a decreasing skewness, but not too much variable.

CO Range	Mean	Standard Deviation	Skewness
CO(0.5.-1.0)	0.77	0.48	1.95
CO(1.0-2.0)	1.31	0.92	1.26
CO(2.0-3.0)	2.20	1.55	1.34

Table 6. General statistics of daily distributions of CO

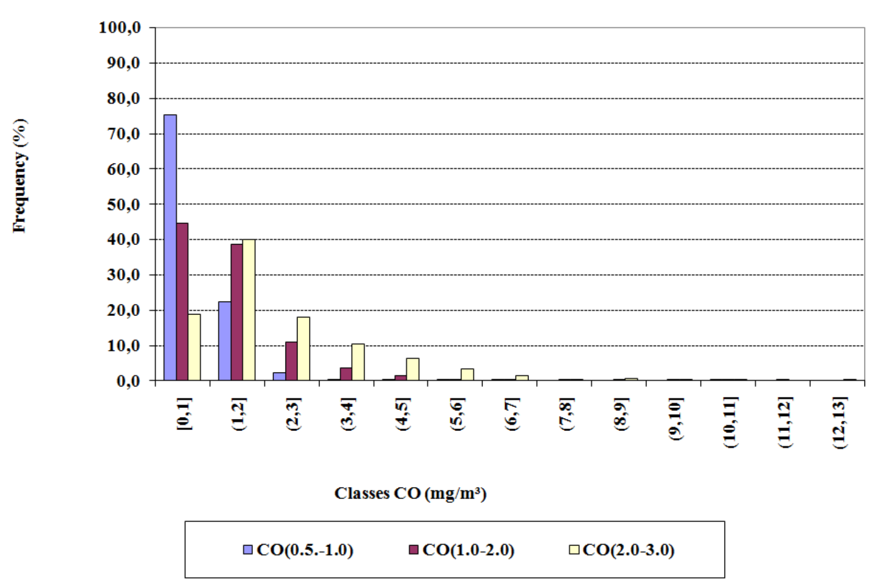

Fig. 2. Distribution of CO for different classes

For ozone (see Fig.3), you can see the following:

- O3 is less than 30 µg/m3, the Sk's values are very higher up to 8
- O3 is greater than 30 µg/m3 and less than 60 µg/m3 the Sk decreases.
- O3 is greater than 60 µg/m3, the Sk's values are decreases further (from 2 to -2).

Fig.3 shows that first function of SK is inefficient and then it is very efficient. This trend resembles the potential of the neural network.

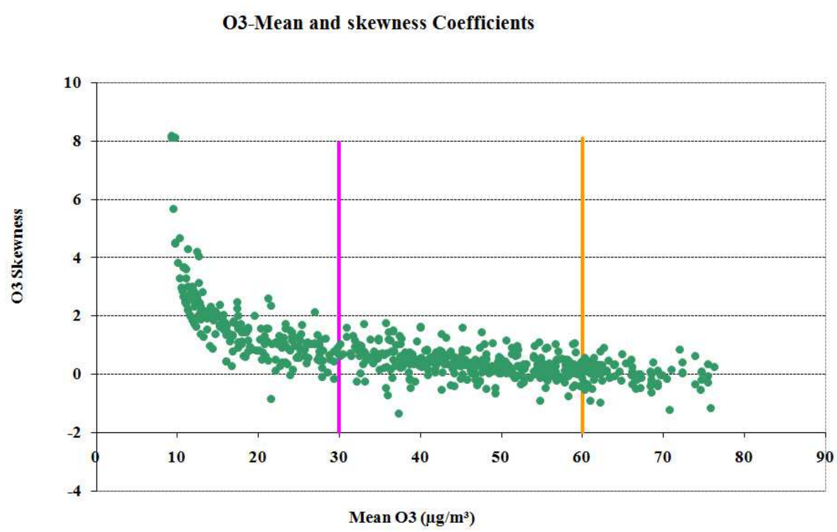

Fig. 3. Relation between Mean(O3) and Skenewss(O3)

In Table 7 and Fig.4, the values of the third class of ozone are those associated with exposure, whereas the values of the first class, with 1.88 skewnees, have no great relevance to the exposure.

O3 Range	Mean	Standard Deviation	Skewness
O3(0.0-30.0)	17.65	1.40	1.88
O3(30.0-60.0)	47.42	0.45	0.36
O3(60.0-120.0)	72.25	0.39	-0.03

Table 7. General statistics of daily distributions of O3

By modulating the time-series of daily values of CO, O3, NO, NO2, NOx and PM10 based on the profile average weekly (or typical week) , calculated as the average concentrations for each day of the week. The Fig.5 and Fig.6 show the weekly evolution of the concentrations of CO, O3, NO, NO2, NOx and PM10 that are characterized by "critical" days, typically Thursday and Friday, by minimum values at the weekend, excepted for ozone, due to the physiological decrease in traffic volumes and the reduction of industrial activity and by an increase in the levels of pollutant concentration by the resumption of work activities during the week.
For the weekly cycle of ozone we observe an increasing of O3 levels over the weekend, whereas the situation is reversed on working days. This effect known as "weekend" [European Environment Agency, 1989] can be explained by the low level of NOx and volatile organic compounds during the Saturday and Sunday(Fig.5 and Fig.6), taking into

account the meteorological conditions. During weekend, elevated ozone levels are caused by NOx emissions. Under stagnant meteorological conditions, week-day morning's become NOx saturated due to the morning rush hour.

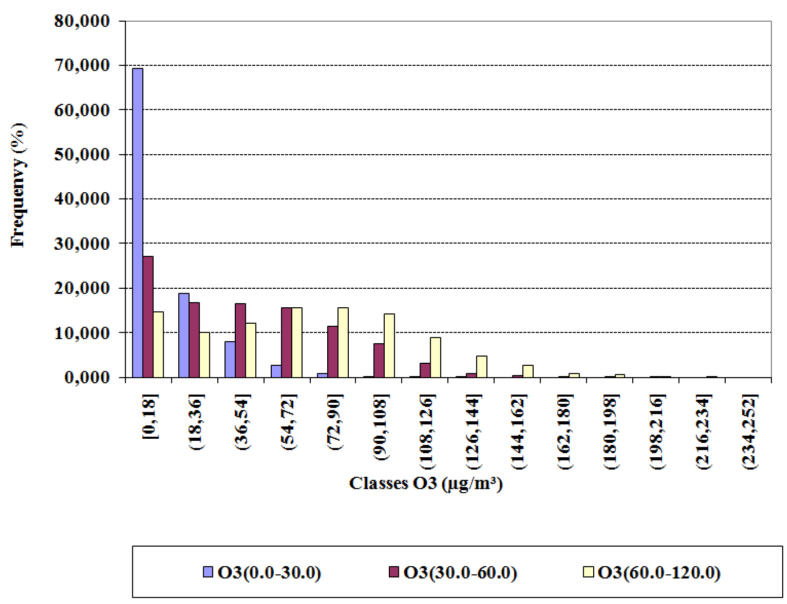

Fig. 4. Distribution of O3 for different classes

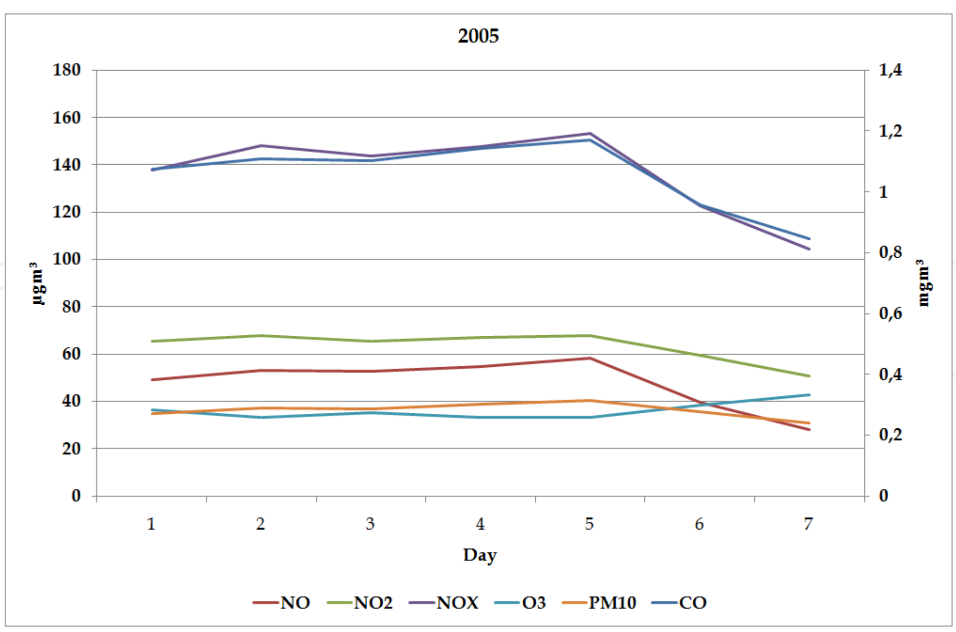

Fig. 5. Weekly cycles for CO, O3, NO, NO2, NOx and PM10 concentrations (2005)

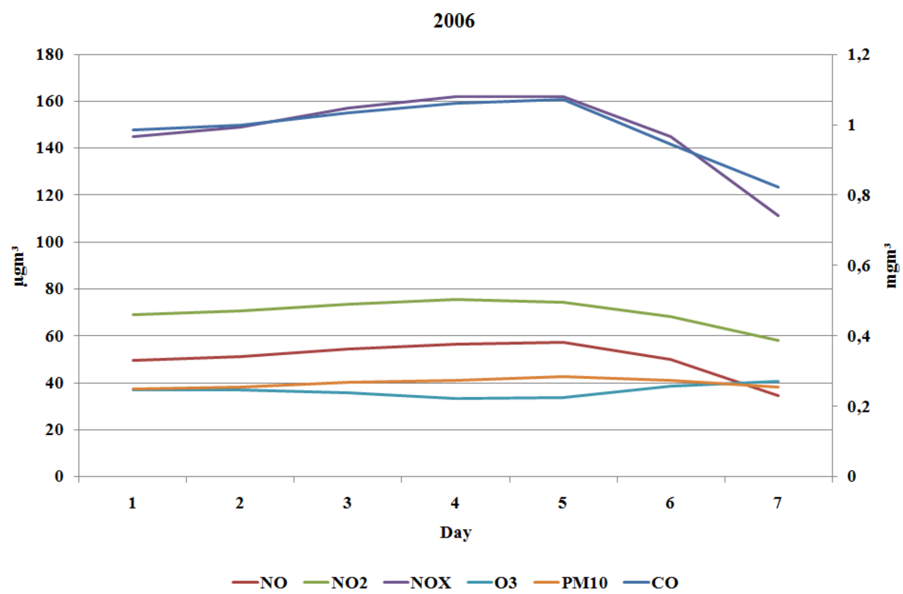

Fig. 6. Weekly cycles for CO, O3, NO, NO2, NOx and PM10 concentrations (2006)

In terms of weekly cycle, for respiratory disease we observed a decrease approximately 40% of admissions at the weekend and equal to nearly 50%for cardiovascular admissions. This reduction is probably due to the fact that in general the hospitalizations, except in urgent cases, are scheduled on weekdays (Fig. 7-8).
For deaths from respiratory disease, there were no significant differences, whereas for cardiac deaths there is a moderate decrease in the weekend, which is almost completely irrelevant when considering only deaths sent from the hospital emergency room.

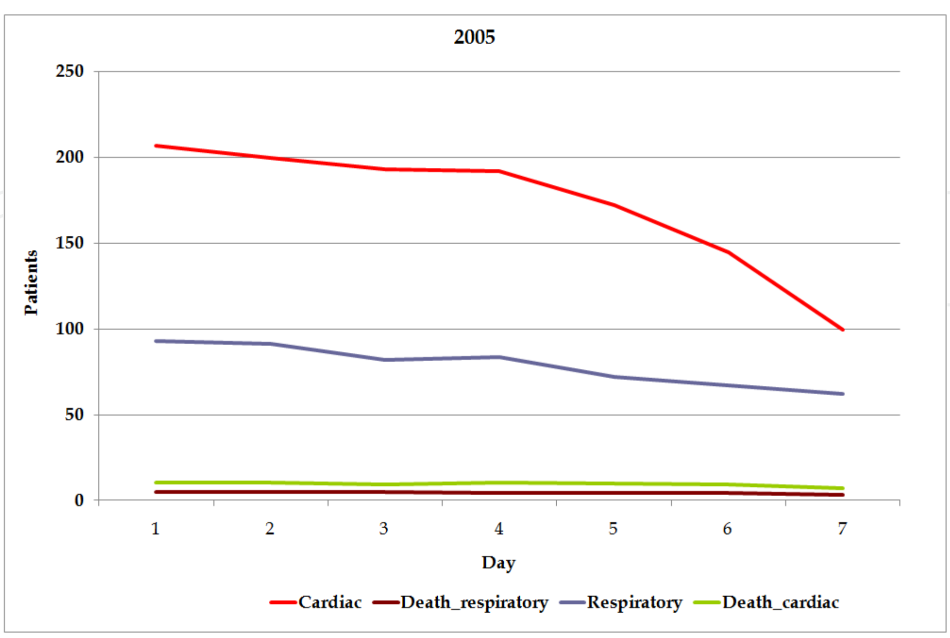

Fig. 7. Weekly cycles for cardio-respiratory admissions (2005)

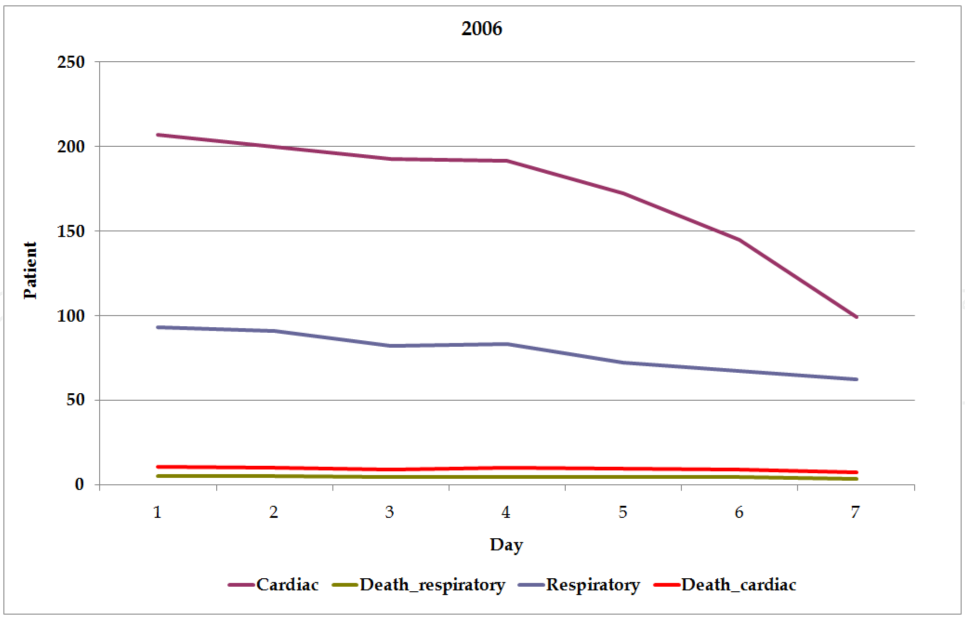

Fig. 8. Weekly cycles for cardio-respiratory admissions (2006)

3. Methodologies

Some preliminary retrospectives analysis were carried out on hourly environmental time series [Battaglia, 2007] (pollutants and meteorological variables) and on daily time series related to admissions for cardio-respiratory disease, identifying and examining graphically their trends. Such time series constitute a summary of the "history" of the phenomenon under study. Thus we proceeded first to examine the fundamental characteristics of the series.
Then by a spectral analysis we proceeded to detect the most relevant periodic components for the explanation of the variability of the series. The Fourier analysis is based on the decomposition of the original time series in a sum of periodic functions at different frequency:

$$Y_t = \sum_{k=0}^{n/2} (a_k \cos w_k t + b_k \sin w_k t) \quad \text{con t} = 1,2...n \tag{1}$$

where Y_t is the observation at t time and w_k, a_k e b_k are respectively the frequencies and the Fourier coefficients.
The spectral analysis consents to highlight what are the frequencies (and hence the periodicity) more important. The periodogram, in fact, measures the intensity of k-frequency within the range of values and hence the importance that assume each period p_k.
Based on the results coming from the preliminary analysis of these series, was designed and developed a simulation model of interpretation implemented by neural network. The greatest advantage of a neural network is its ability to model a complex non-linear relationship [Gardner & Dorling, 1999, 2000]; [Abdul-Wahab & Al-Alawi, 2002], such as those in the environmental systems, without a priori assumptions on its nature [BuHamra et al, 2003], by means of an accurate choice of the variables of the system and of the meaningful patterns, and data distribution.
For transfer function, the most suitable architectures are considered to be the Multi Layer Perceptron (MLP) [Abdi, 1994], [MacQueen, 1967], [Fausett, 1994]; [Bishop, 1995], [Ripley

1996] with an error-back-propagation supervised learning rule [Rojas, 1996]. This net architecture is able to reproduce non linear models, without any a priori assumptions, by means of an accurate choice of the variables of the system and of the meaningful patterns. A learning algorithm is an adaptive method by which a network of computing units self-organises to reproduce the desired model. This is done with learning algorithms that present some examples of the desired input-output mapping to the network. A correction step (the error-backpropagation rule) is performed iteratively until the network learns to produce the desired response.

"Backpropagation nets" can be interpreted in statistical terms as variations of maximum likelihood estimation and is a feed-forward neural network type and generally uses back-propagation algorithm to develop a model to illustrate relationships between inputs and desired output for training data (see Fig.9)

Multi Layer Perceptron (MLP) is also the most popular architecture for NNs and is used to identify models for the prediction of cardio-respiratory diseases.

The selection of appropriate network architecture depends on the number of parameters, the network weights, the selection of an appropriate training algorithm and the type of transfer functions used.

As architecture we used a 3-layer perceptron model with a single hidden layer, 10 hidden neurons and with sigmoid activation function (see equation 2) that approximates nonlinearities.

$$F(P) = \frac{1}{1+e^{-(p-s)}} \tag{2}$$

where P is the activation potential and S is the activation threshold.

The model optimisation mechanism takes place through the automatic update of the weights. The update of weights among neurons is guided by the following function (see equation 2 and 3):

$$\Delta w_{ij} = -\eta \ \frac{\partial E}{\partial \mathrm{w}_{\mathrm{ij}}} \tag{3}$$

where η is the learning rate (a characteristic parameter for updating) and the network output error is defined as:

$$E = \frac{1}{2}\sum_{j=1,npatt}(y_j - \overline{y_j}) \quad (4)$$

where E provides a quantification of the overall difference over all the examples and for all the reproduced variables.

The first input layer contains the input variables of the net, pollutants and meteorological variables. The second layer consists of the neurons of the hidden layer. The third layer is the output layer, which consists of the target of the forecasting model.

The number of neurons of the hidden layer is one of the parameters to be chosen in the NN model architecture, the well known multi-layer perceptron. We tested different numbers of neurons in the hidden layer (8, 10 and 12 hidden neurons), but the best performance of perceptron network was obtained by 10 neurons. The choice of 10 hidden neurons is based

on two considerations: maximizing the hidden neurons to increment the NN parameters and simultaneously minimizing this number in relation with the main situations linked to the input patterns. Moreover, we utilise different methods to optimize the weight values of hidden layers, in the manner that the errors of the network's output could be minimized.
During the training phase, one of the most important parameters of selection is the choice of the function of correction related to each weight between the different layers of NN. In fact, the inner weights to the NN have to be determined by minimizing a well defined function (namely Error Function -EF) that usually coincides with the sum of error square. The best solution for the weights derives from the search of the minimum of EF in the space of total weights. This work is very complex and is the target of the NN training. There is no way to find absolute minimum for the NN's weights and the performances of NN are highly dependent by the way to find this "local" minimum. We try three different way to find the best solution.
In according with Table 8, we utilized different methods: Conjugate gradient (CG), the Quasi-Newton or Broyden-Fletcher-Goldfarb-Shanno (BFGS) and the popular Gradient Descent (GD) [StatSoft, Inc. , 2006]
While the first two are based on the second order approximations for search of the minimum of EF, the last method is a first order of approximations and can be used to find a local minimum in very fast way.
In particular, Conjugate Descent is a training algorithm that proceeds by a series of line searches through error space. After search directions are selected to be conjugates (non-interfering). It is a good generic algorithm with generally fast convergence.
The Quasi-Newton method is a powerful second order training algorithm with very fast convergence but require a high computational complexity due to memorize the Hessian matrix.
The comparison of different performances of these three methods is out of aim of the work and results will be not shown here. For ours data set, we selected the CG as better method of work respect to the BFGS or GD ones.
As second important choice to be considered is the activation function. We tested mainly the two main functions that are usually used: the logistic (LOGISTIC) and Hyperbolic tangent (TANH).
As schematized in figure 9, each layer uses a linear combination activation function. The inputs are fully connected to the first hidden layer, each hidden layer is fully connected to the next, and the last hidden layer is fully connected to the outputs.
In our study, we observed that the input and the hidden layer contain multiple units whereas the output layer only has a single unit.
The nature of the functional relationship between inputs and outputs is learnt during a supervised training process directly from the data. In our case, Neural Net model takes into account the influence of the pollutant and meteorological variables and latent variables such as source emission factors, turbulence conditions, local topology, reactions rate.
A great advantage of Neural Networks is that it can be trained to generalize accurately when it is presented a new data.
As above, by testing the best choice of NN parameters, we found that the Multi Layer Perceptron (MLP) model with a single hidden layer that was able to explain about the total 90% of the variance of the phenomena investigated, with 10 hidden neurons and with conventional sigmoid activation function (logistic) for the hidden units.

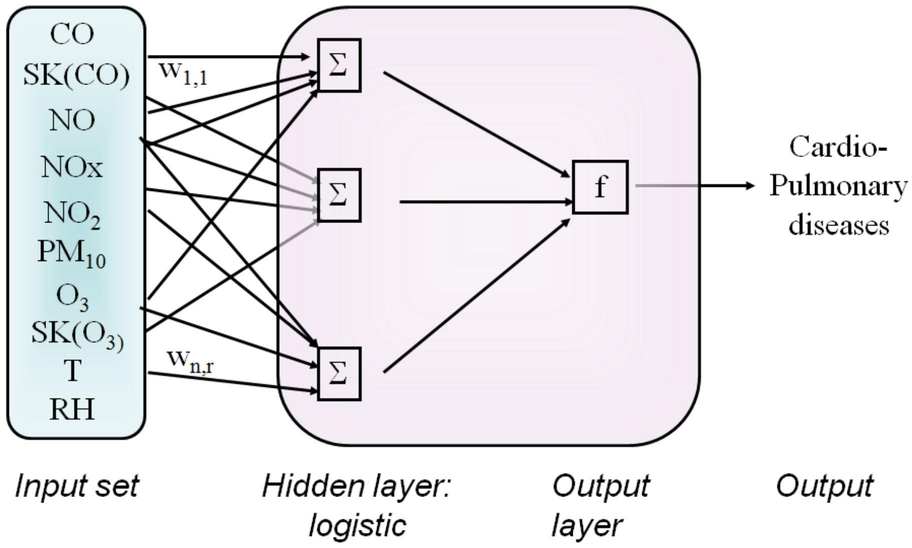

Fig. 9. MLP architecture

NEURAL NETWORK MODEL	MLP 6-10-1
Hidden neurons	8-10-12
ALGORITHM	CG-BFGS-GD
EPOCH	3000
ERROR FUNCTION	Sum of Square
HIDDEN ACTIVATION FUNCTION	LOGISTIC-TANH
OUTPUT ACTIVATION FUNCTION	IDENTITY
NETWORK RANDOMIZED	NORMAL

Table 8. Neural Networks architecture

The nature of the functional relationship between inputs and outputs is learnt during a supervised training process directly from the data. Neural Networks can be trained to accurately generalize when presented with new, unseen data. Often, especially in the atmospheric sciences, successfully modeling the average behavior of a system is not the main goal. It is important sometimes that the model can also interpret infrequent outliers, which are often of great importance, as for the health related with exposure.

In this work, we face also the question of the best variables of input to be used and the optimum selection of patterns for having results that represent the health response to the different pollutants and to meteorological factors.

At the end, to compare NN result we analysed the results coming from autoregressive model that assess the linear nature of the relationship between the dependent and independent datasets. The main disadvantages consist in transformation of non-linear relations are into linearity and the existence of multicollinearity.

4. Results and discussion

4.1 Pollutants and meteorological trends

Based on the analysis of the time series of PM10 concentration levels coming from the monitoring stations of the city of Rome, is observed that in 2005, there were about 20% of

exceedances of the daily maximum value (50µg/m³) of PM10 (approximately 72 days). The maximum annual value was equal to 39.4 µg/m³ just below the limit value for the protection of human health (40µg/m³).
Elevated levels of PM10 concentrations have occurred during the winter and late autumn, especially in December and January, where we can observe frequent thermal inversion conditions (in the evening and in the night), high traffic volumes, intensive use domestic heating systems, whereas during the summer season there is a low concentration of the pollutant due to favourable meteorological conditions that allow a major dispersion in the atmosphere (see Fig.10). On average, in January and March, there have been no less than 16 days of exceedances over the threshold. The concentrations over 50µg/m³ during the summer season, however, depend on factors other than those that led to the overcoming of this limit during the winter season.
Moreover, we observe that the number of days with PM10's values greater than 75µg/m³ (equal to the value limit for the protection of human health plus 25µg/m³) was equal to 10 days where the most of exceedances is found in the winter season. The distribution of values between 50 and 75µg/m³ notice a predominance of winter season with a dozen of exceedances.

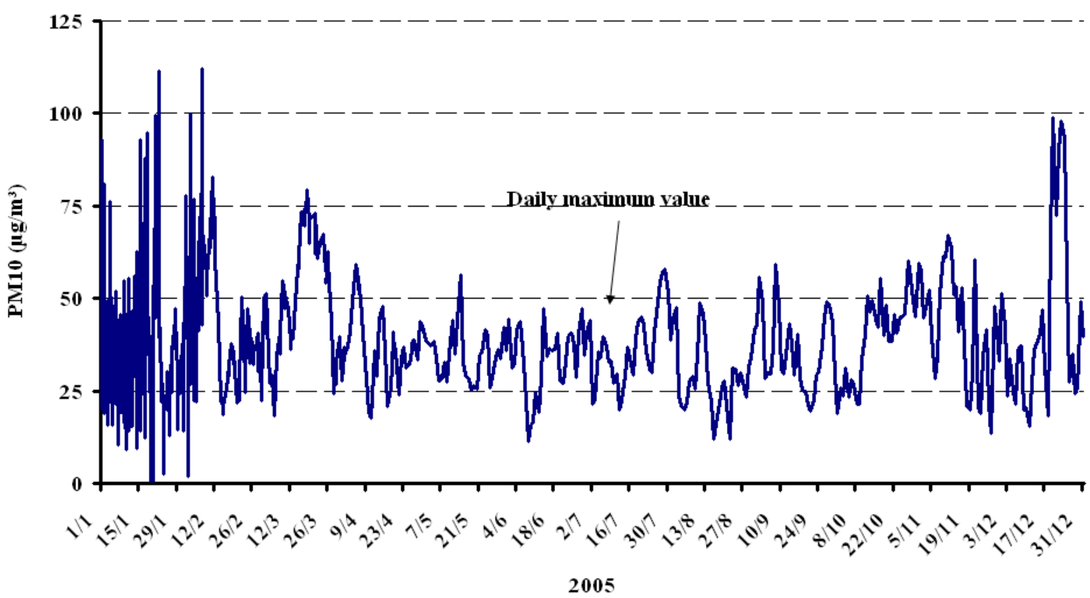

Fig. 10. PM10 trend (2005)

For 2006, PM10 exceeds about 23% of exceedances of the daily maximum value (50µg/m³) of PM10 (approximately 83 days). The maximum annual value was equal to 39.64 µg/m³ just below the limit value for the protection of human health (40µg/m³).
Elevated levels of PM10 concentrations have occurred during the winter and late autumn, especially in December, January and February, whereas during the summer season there is a low concentration of the pollutant (see Fig.11). The concentrations over 50µg/m³ during the summer season, however, depend on factors other than those that led to the overcoming of this limit during the winter season.
Moreover, we observe that the number of days with PM10's values greater than 75µg/m³ (equal to the value limit for the protection of human health plus 25µg/ m³) was equal to 12 days. The distribution of values between 50 and 75µg/m³ notice a predominance of winter season with 71 days of exceedances.

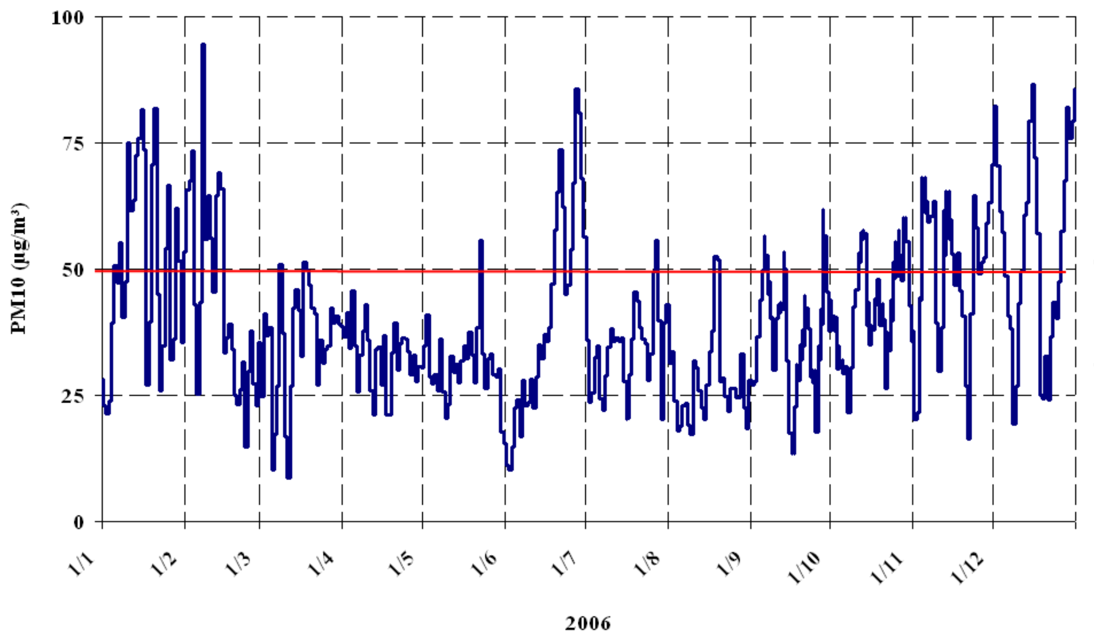

Fig. 11. PM10 trend (2006)

For 2005, O3 shows the peak maximum equivalent to 221µg/m³, exceeding the limit value of 200µg/m³, especially in summer (June-September) is characterized by a greater number of Days, where it is most noticeable the action of solar radiation and the increase of temperature. In addition, for 2005 we can observe that the number of days exceeding the information threshold (180µg/m³) is 11 (Fig.12).

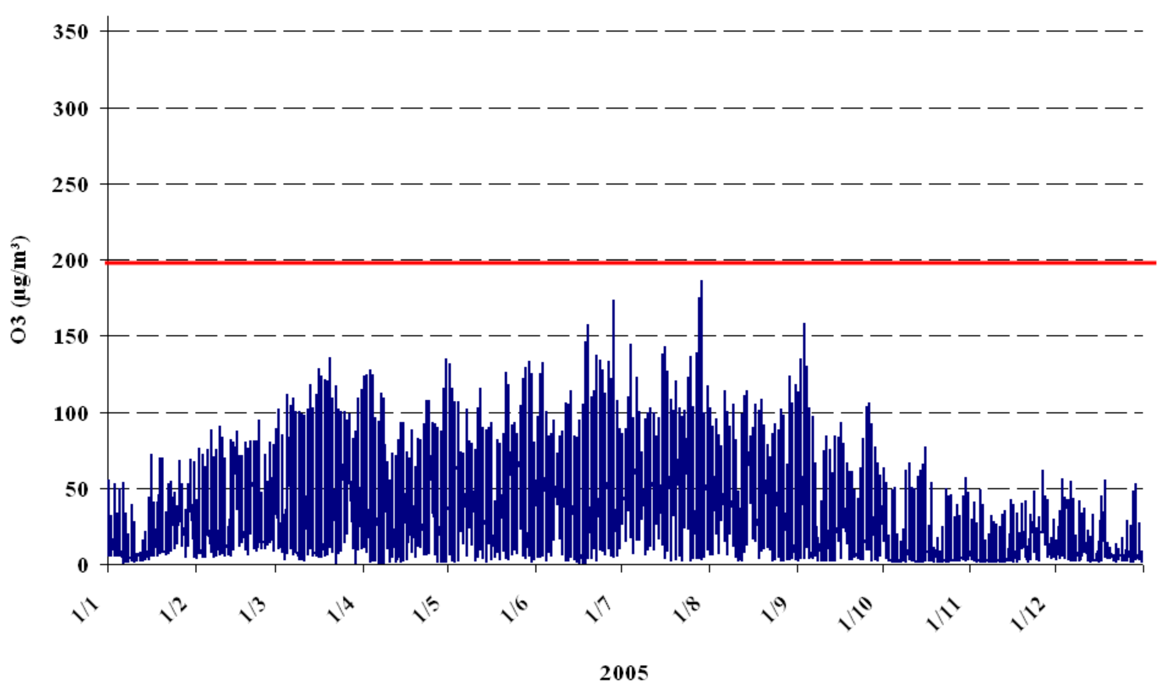

Fig. 12. O3 trend (2005)

For 2006, O3 shows the peak maximum equivalent to 228μg/m³, exceeding the limit value of 200μg/m³, especially in summer (June-September) is characterized by a greater number of days where it is most noticeable the action of solar radiation and the increase of temperature. As known, O3 levels have the highest peak concentrations in summer, on the contrary NO and NO2, have characterized by a summer minimum and a maximum in winter (Fig.13).

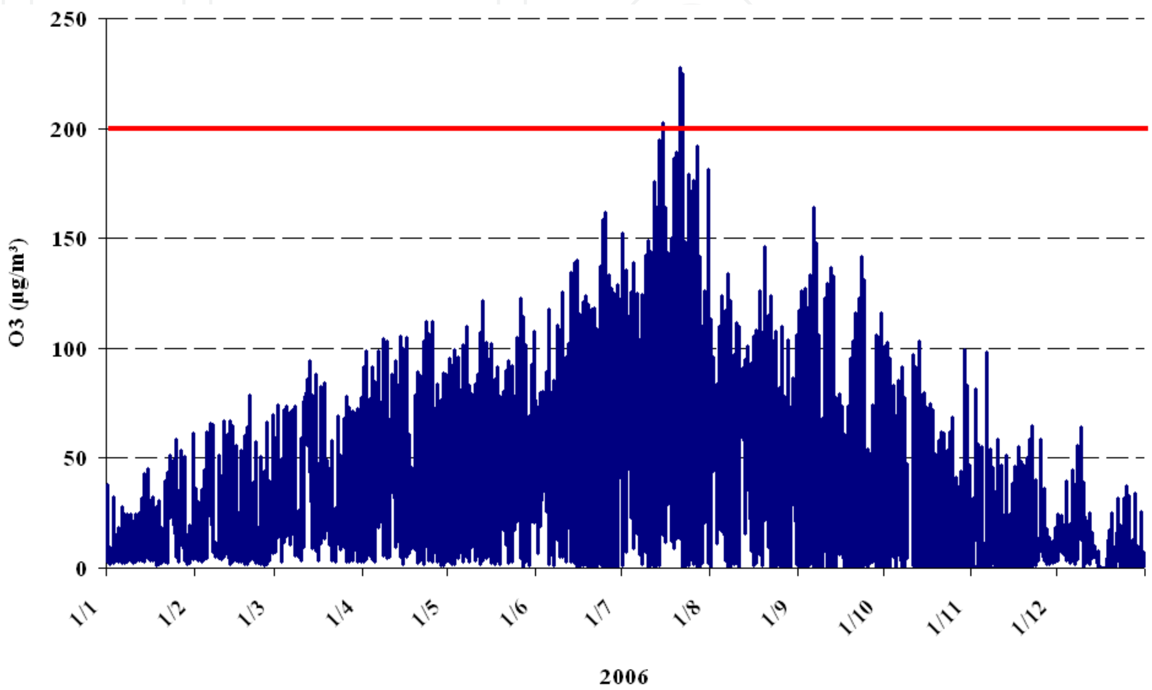

Fig. 13. O3 trend (2006)

Finally, the Fourier analysis has identified a periodicity of PM10 on 2 and 6 days for 2005 and 2 and 12 days for 2006 (see Fig.14 and 15).

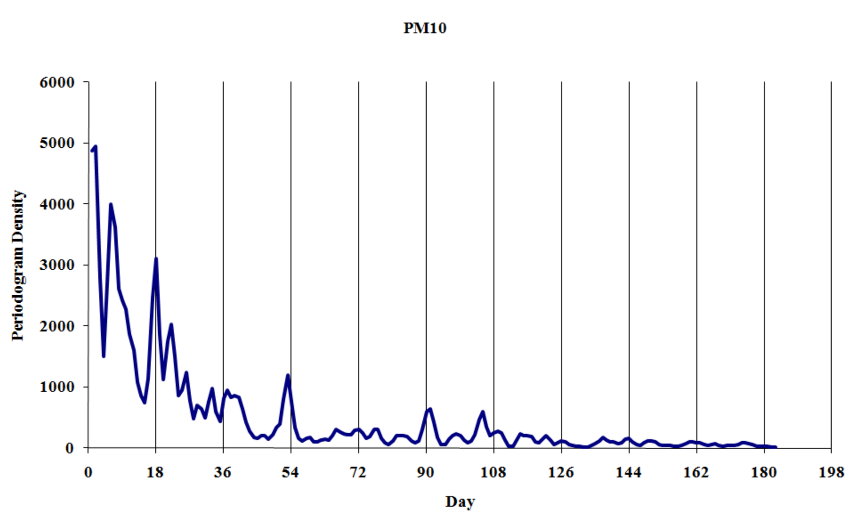

Fig. 14. Fourier analysis for PM10 (2005)

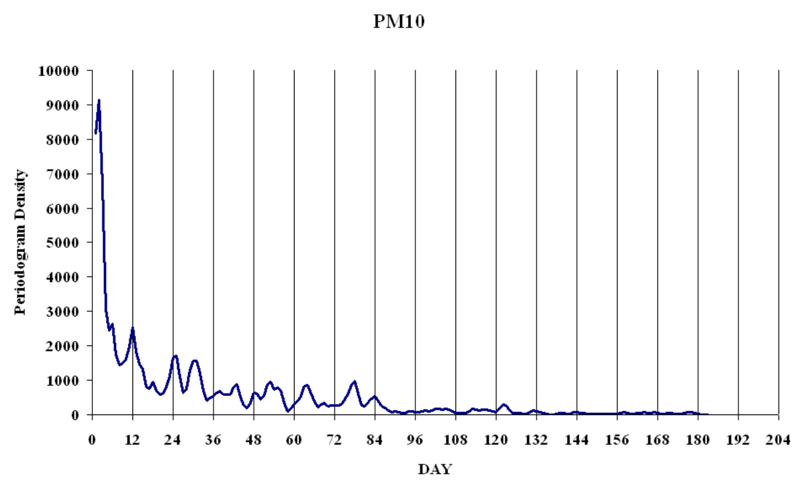

Fig. 15. Fourier analysis for PM10 (2006)

For 2005 and 2006 the spectral analysis of ozone (see Fig.16 and 17), carried out by periodogram, shows a peak at 3 hours and 684 hours (approximately 28 days).

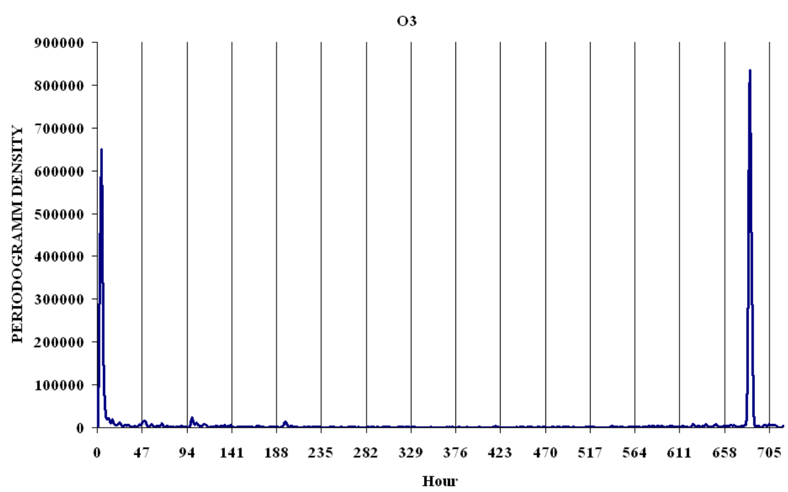

Fig. 16. Fourier analysis for O3 (2005)

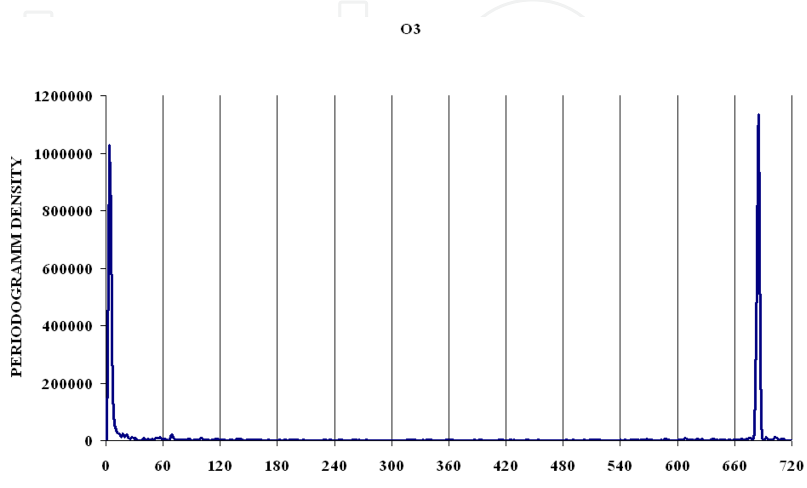

Fig. 17. Fourier analysis for O3 (2006)

4.2 Epidemiological analisys

It is to be noted that epidemiological data refer cases to hospital admissions rather than sick or dead the whole city of Rome, so there is an under-estimation of the morbidity and mortality.

For 2005, the analysis of hospitalizations related to cardio-respiratory disease, shows a peak at the end of March. A meaningful number of hospitalizations are found in the first four months of the year and later a decrease for those related to respiratory disease until the summer season, with a recovery by the cold season (autumn-winter).

The admissions for cardiac disease are the trends in absolute terms, ranging from 100-250 patients for almost all of 2005. Patients with respiratory disease are also the trends in absolute terms, ranging from 0-150 patients (Fig.18).

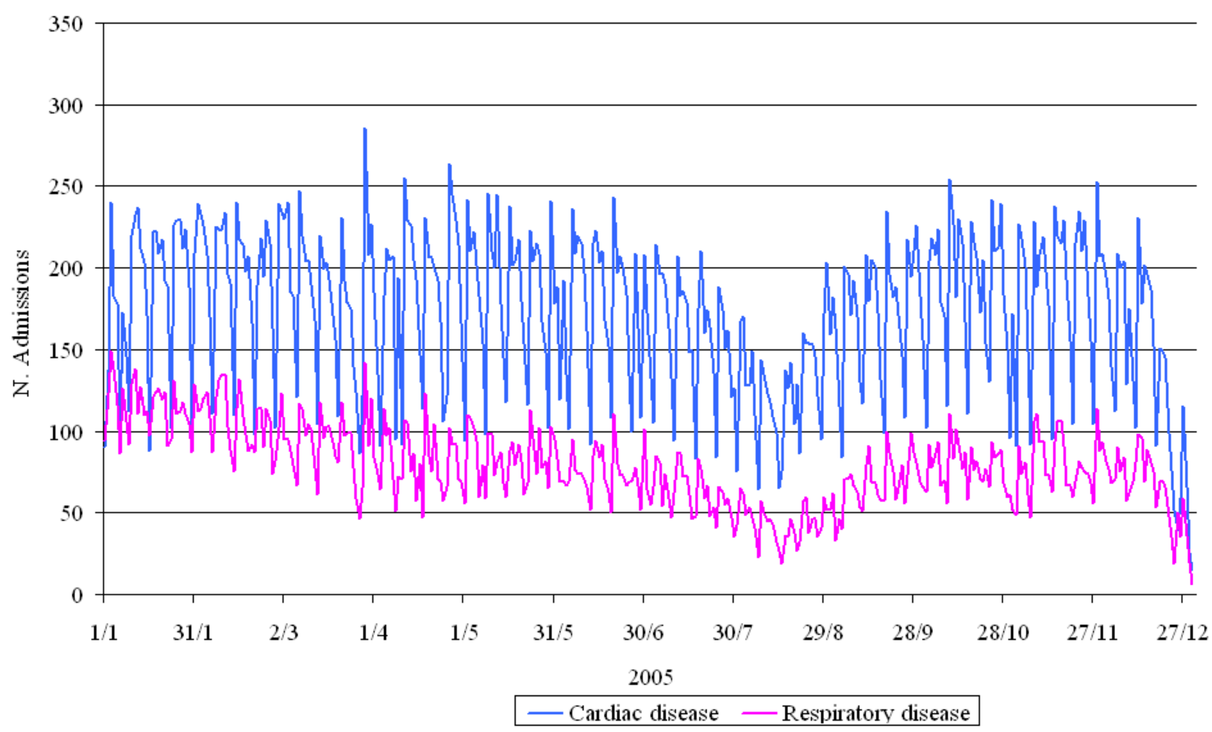

Fig. 18. Cardio-respiratory disease trend – 2005- (Source: Elaboration on EPICS Database of Public Health Agency of Lazio)

For 2006, the analysis of hospitalizations related to cardio-respiratory disease, shows a peak at the end of April. A meaningful number of hospitalizations are found in the first four months of the year and later a decrease until the summer season, with a recovery by the cold season (autumn-winter) (Fig. 19).

The admissions for cardiac disease are the trends in absolute terms, ranging from 100-250 patients for almost all of 2006. Patients with respiratory disease are also the trends in absolute terms, ranging from 0-150 patients (Fig.18).

For 2005 and 2006, deaths for cardio-respiratory disease, which constitute a very small percentage of total admissions (about 5.5%), are higher in colder months. The deaths from respiratory disease do not exceed 15 units (see Fig.20 and 21).

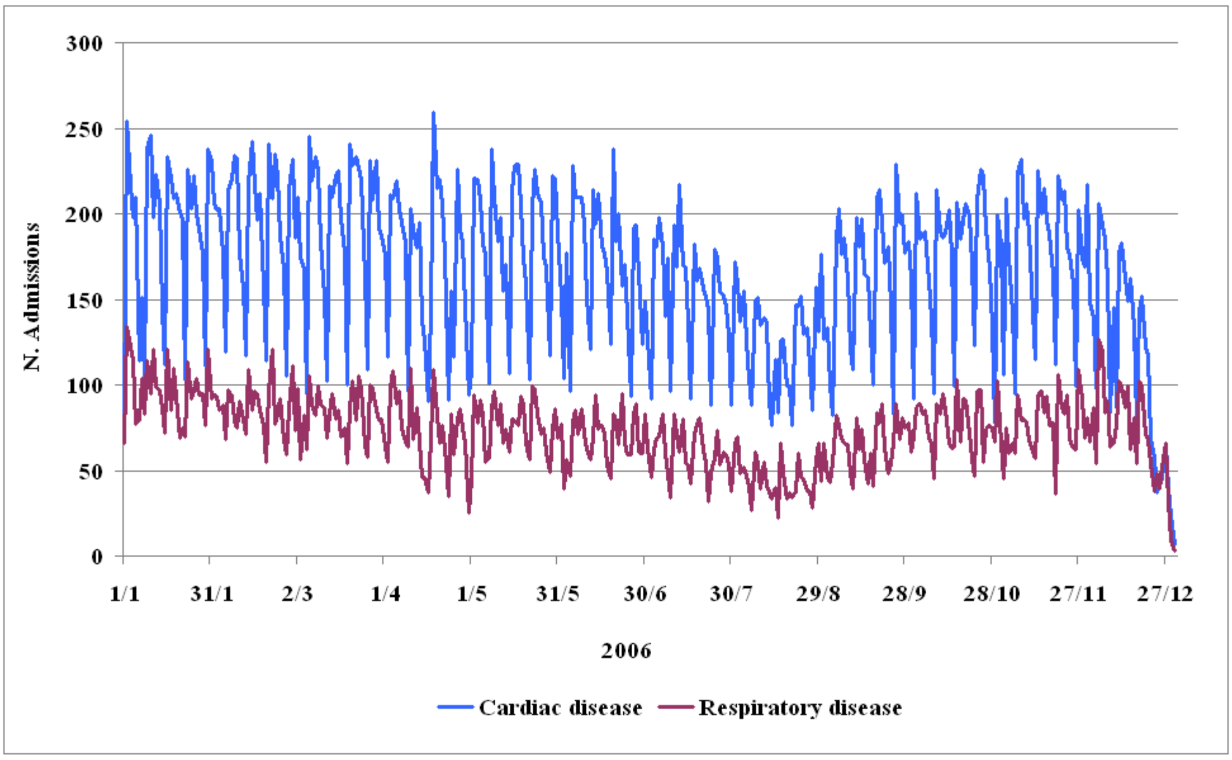

Fig. 19. Cardio-respiratory disease trend – 2006- (Source: Elaboration on EPICS Database of Public Health Agency of Lazio)

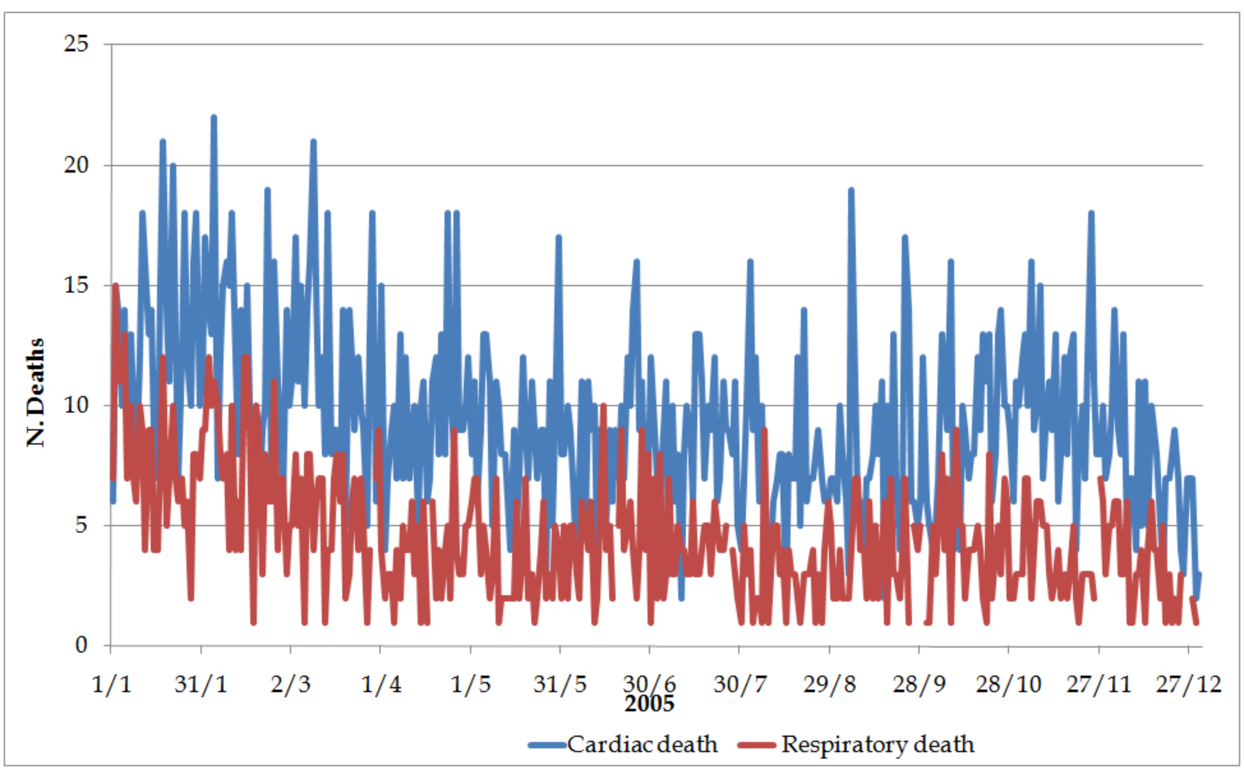

Fig. 20. Cardio-respiratory death trend – 2005- (Source: Elaboration on EPICS Database of Public Health Agency of Lazio)

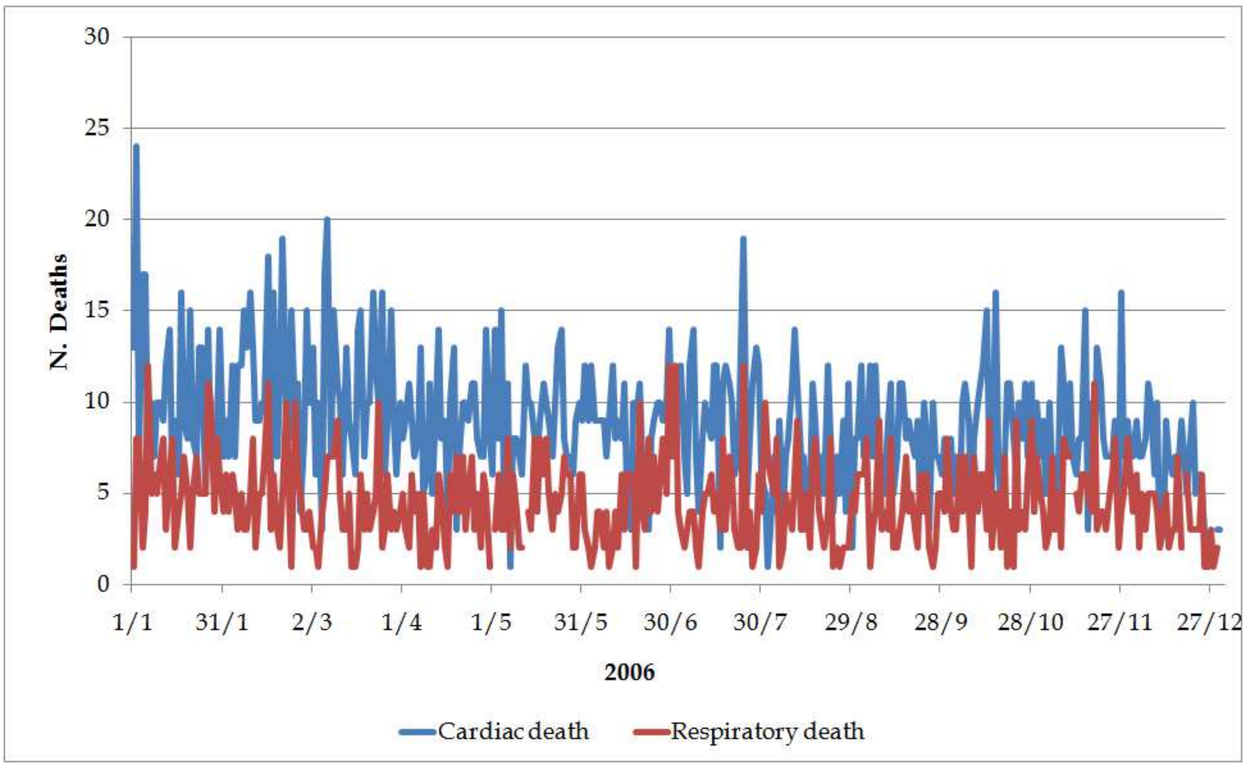

Fig. 21. Cardio-respiratory death trend – 2006- (Source: Elaboration on EPICS Database of Public Health Agency of Lazio)

For 2005 and 2006 the spectral analysis carried out by periodogram, shows a peak at two days for respiratory diseases and cardiac disease for 3 days (see Fig.22-25).

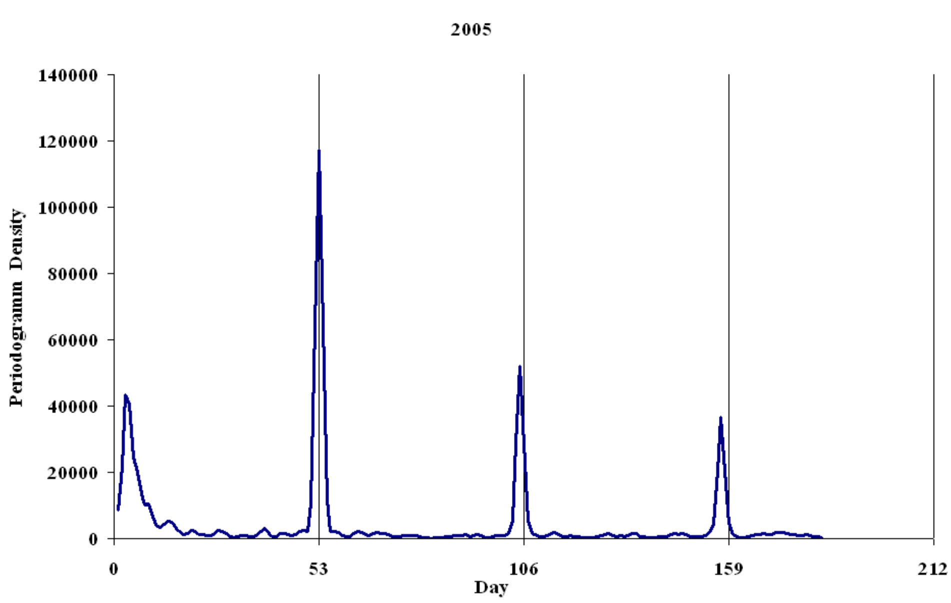

Fig. 22. Fourier analysis for cardiac disease (2005)

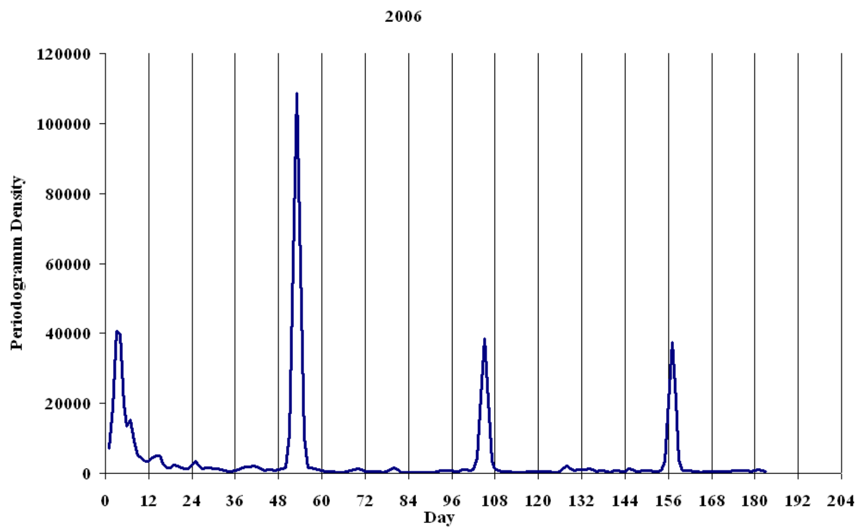

Fig. 23. Fourier analysis for cardiac disease (2006)

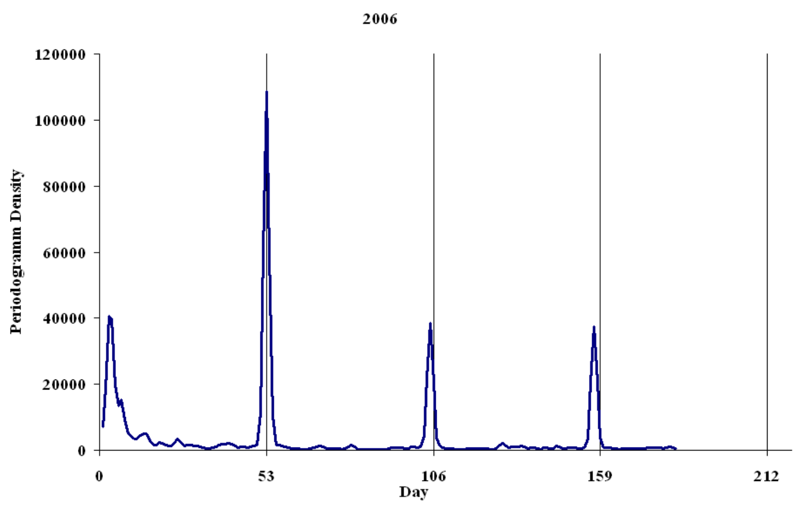

Fig. 24. Fourier analysis for respiratory disease (2005)

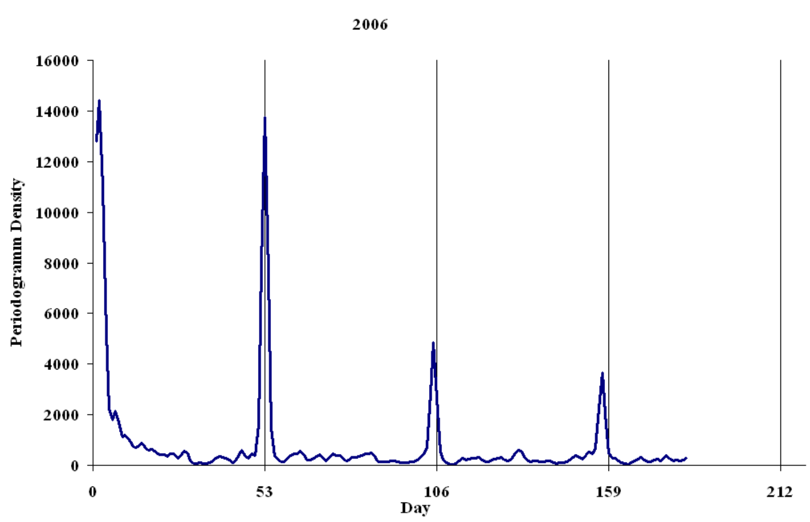

Fig. 25. Fourier analysis for respiratory disease (2006)

For 2005 and 2006 the spectral analysis carried out by periodogram, shows a peak at two days for respiratory deaths and cardiac death for 4 days (see Fig.26-29). Moreover, we observed that harmonic secondary for respiratory deaths is related to 68 days and for cardiac death is related to 53 days.

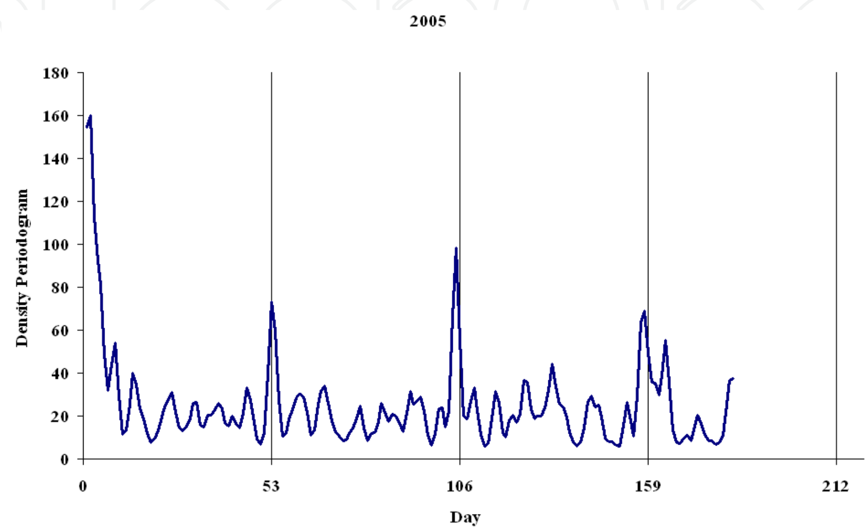

Fig. 26. Fourier analysis for cardiac death (2005)

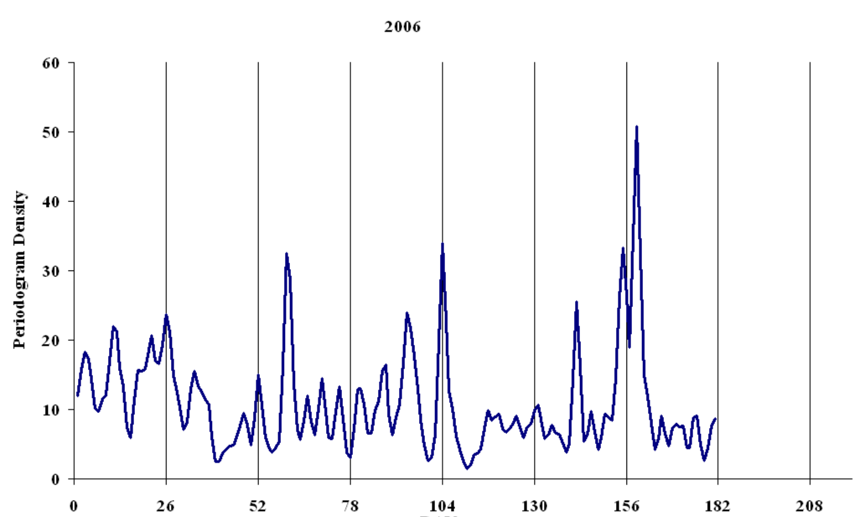

Fig. 27. Fourier analysis for cardiac death (2006)

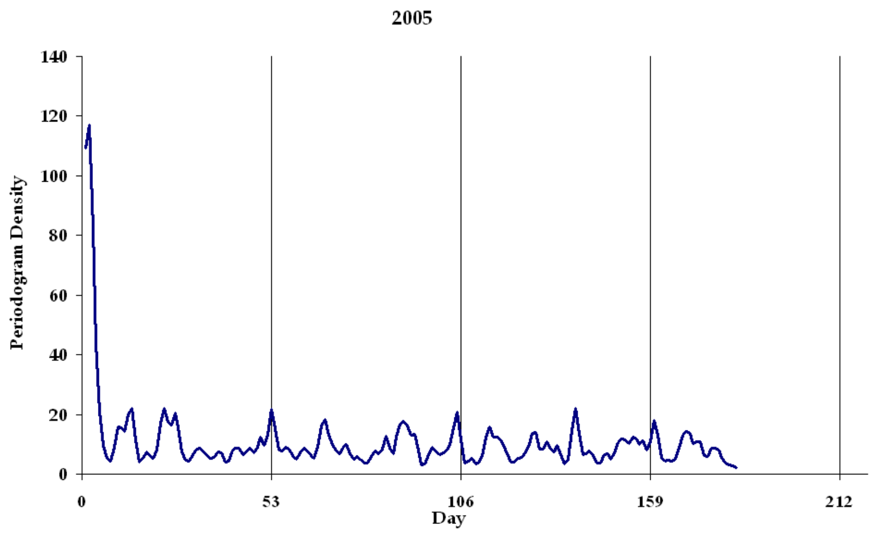

Fig. 28. Fourier analysis for respiratory death (2005)

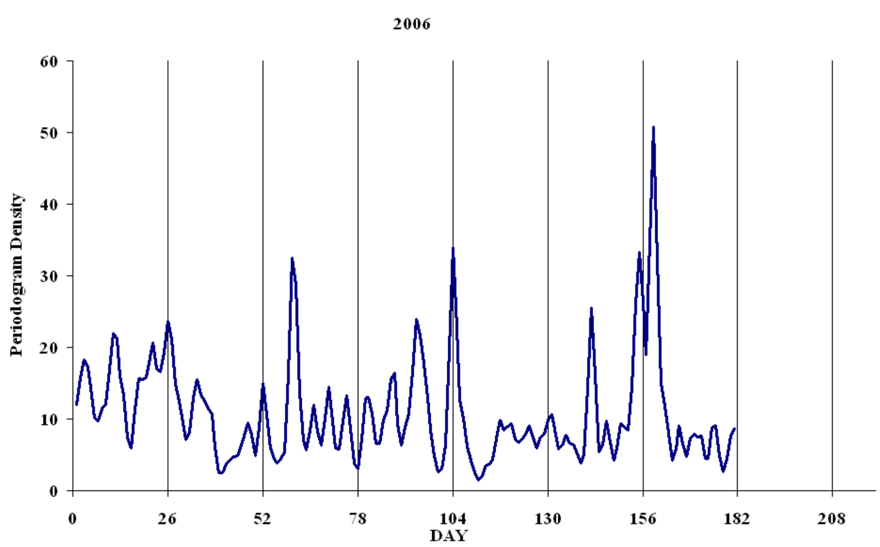

Fig. 29. Fourier analysis for respiratory death (2006)

4.3 Environmental and epidemiological analisys

The effects of PM10 and ozone linked to short-term exposure on cardio-respiratory diseases have been documented by the joint study of time series that examines changes of health outcomes related to changes in concentration levels of pollutants. To this end, the distributions daily of O3 and PM10 and hospital admissions were examined in terms of morbidity and mortality. Thus, it was possible to verify the existence of dynamic relationships between time series of pollutants and the time series of hospitalizations for cardiopulmonary disease.

In terms of morbidity, it was observed a possible causal link between the respiratory and cardiovascular diseases.

For ozone, the results show a meaningful increase in daily hospital admissions for cardio-respiratory system due to high concentration levels of this pollutant.

In terms of mortality for respiratory disease, it was observed that at high of concentration levels of PM10 increase the number of deaths. The relationship, however, is less evident than for cardiovascular disease, as there is found a lower proportion of deaths. Results for ozone show significant increases in deaths related to exposure to high levels of concentration.

4.3.1 NN results

Besides carrying out the analysis of trends of pollutant concentration levels and hospital admissions, we proceeded with the description of the main results obtained with the neural network model. The daily PM10 and O3 data and the aggregated data for cardio-respiratory disease (ICD9CM 390-519) that relate to hospital were taken into consideration.
From our results, we can observe that the neural network is able to reproduce a good approximation the causal link between the concentration levels of PM10 and of O3 and admissions [World Health Organisation, 2006].
Epidemiological data are used to investigate the relationship between PM10 and O3 and morbidity and mortality, suggests that most of the differences in mortality can be attributed to a worsening of pre-existing conditions rather than the oneset, due to air pollution, of new diseases.
As suggested by above considerations, the performances of the NN or the ability to reproduce the target variables (in our case the hospitalisation for cardiovascular and respiratory diseases) are strictly linked to the variables and patterns selections. As usually, we use 65% of random patterns during the training and the remaining 35% as test, never seen by NN during the learning phase.
Our aim is that we attempt to reproduce the average five days in advance of hospitalisation for the two considered pathologies given as input data the following variables (see Table 9):

NN Input Variables		
Julian Day	Sin (Jd)	Cos (JD)
Week Day	Sen (Week)	Cos (Week)
Pollutants	PM10	
	NO2	
	CO	SK (CO)
	O3	Sk (O3)
Meteorological	T	HR

Table 9. NN input variable

As evident, we collect the input data: general information (Julian day and week Day), air quality data (pollutants) and meteorological data.
During the search of the optimal architecture of neural net, we tested different input variables and we found that data related to general information are essential to reproduce the hospitalisation in best way. This sensitivity analysis will be not shown. In this chapter only we showed only the best architecture.
In order to facilitate the comparison of NN modelling, we show results related to the cardio-respiratory hospitalisations separately.

4.3.2 Results of simulations related to cardiac hospitalisation

As hidden neurons the best choice is 10 neurons for the MLP architecture. In the figure 30, we provided the results of NN's forecasting for all data (training and test sets) for the Rome area during the calendar years 2005-2006.

As evident, the NN predicted well the hospitalisations during all the days of period. The determination coefficient is very high (R^2=0.93) and we underestimate the extremes values of admissions both in term of the lower than upper limits. It is to note, that NN is able to forecast also the fall of the cardiac hospitalisation due to the Christmas holydays and this can be simulated mainly by the information related to Julian day and the week.

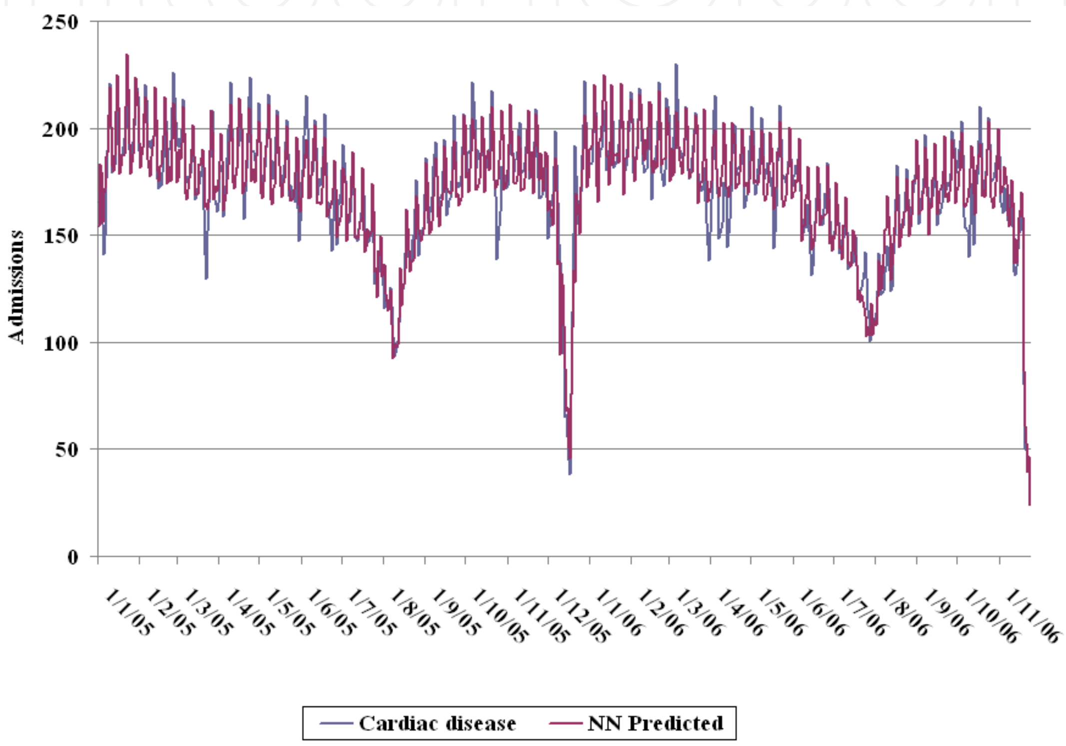

Fig. 30. Cardiac admissions for Rome (2005-2006)

When we compared the forecasting for cardiac diseases, it was more convenience to admit a band of error within to accept the results. We decided to take as reference levels the 10% of real value as confidence range for the acceptability of NN forecasting. Doing so, we find following results described in Table 10:

Cardiac hospitalisation by NN	
Percent of wrong simulation	**9.5**
Percent of right simulation	90.5

Table 10. NN performances for the forecasting within 10% of real data

In the short period, the NN is able to reproduce hospitalisation for cardiac disease for the 90.5% of the total hospitalisation. It is to underline that these excellent results meant that NN is able to understand the “global answer of the Rome city" respect to seasonal effects and the observed pollutants' levels.

4.3.3 Results of simulations related to respiratory hospitalisation

For this data, the number of the hidden neurons selected is related to 8.
The results for simulations of the respiratory hospitalisations are showed in fig 31. The determination coefficient is a little worse respect to previous simulation (R^2=0.92), even if levels are very significant.
If we account of compare the confidence limits of 10%, we find that the NN predicts only 82.1% of the respiratory admissions. Also for the confidence limits, the performances of NN for the respiratory are slightly lower respect to that of cardiac hospitalisation. By the Fig.31, it seems that NN makes some difficulty to simulate the minima during the winter season.
These results can suggest that, for the simulation of the respiratory admissions by NN, further analysis could be used (for example, it is be necessary to select the right patterns during the training phase in such a way to consider the real answer of the city of Rome to the pollution episodes).

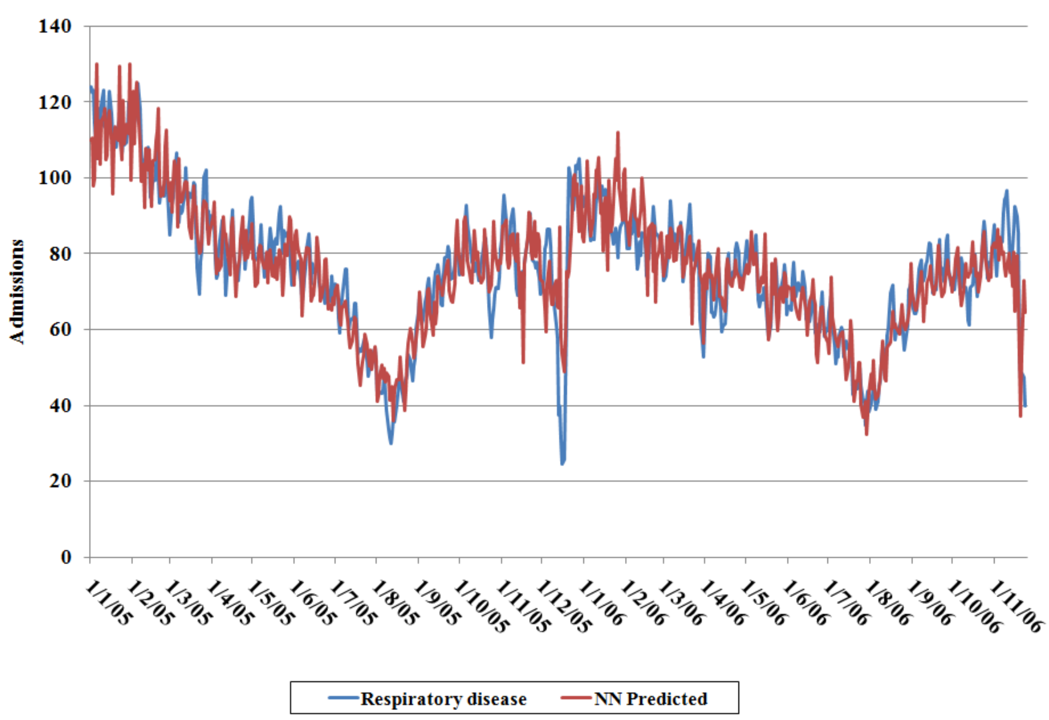

Fig. 31. Respiratory admissions for Rome (2005-2006)

Respiratory hospitalisation by NN	
Percent of wrong simulation	17.9
Percent of right simulation	82.1

Table 11. NN performances for the forecasting within 10% of real data

4.3.4 Autoregressive results

At the end, we compared the conventional autoregressive model with neural networks to forecast cardio-respiratory diseases under different meteorological and pollution variable.

Table 12 shows the resulting model coefficients for both cardio-respiratory admissions. All the variables introduced in the model are associated to a coefficient that is statistically significant.

Cardiac Admissions		**Respiratory Admissions**	
Coefficient	**Variable**	**Coefficient**	**Variable**
0.2324	Sin(Jd)	0.3627	Sin(Jd)
-0.1589	Cos(JD)	0.2128	Cos(JD)
0.1694	Sin (Week)	0.0629	Sin (Week)
0.2997	Cos (Week)	0.2567	Cos (Week)
-0.1402	PM10	-0.0717	PM10
0.2613	CO	0.385	CO
-0.0953	SK(CO)	-0.1299	SK(CO)
0.0055	NO2	-0.143	NO2
-0.0272	O3	0.099	O3
-0.0518	Sk(O3)	0.0137	Sk(O3)
-0.1176	T	-0.2198	T
0.0378	HR	-0.0565	HR
0.0485	constant	0.0203	constant

Table 12. Autoregressive model coefficients

Autoregressive model performances are evaluated using appropriate scalar measures and skill scores [Wilks, 1995], namely: explained variance in% (R^2), correlation coefficient (R), mean absolute error (MAE), root mean square error (RMSE) , relative absolute error and root relative squared error (see Table13).

Training phase		
	Cardiac Admissions	Respiratory Admissions
R^2	0,44	0,78
Correlation coefficient	0.67	0.88
Mean absolute error	0.25	0.27
Root mean squared error	0.43	0.32
Relative absolute error	62.32 %	53.28%
Root relative squared error	74.60 %	46.79 %
Total Number of patterns	451	451
Test phase		
	Cardiac Admissions	Respiratory Admissions
R^2	0,31	0,765
Correlation coefficient	0.557	0.875
Mean absolute error	0.271	0.261
Root mean squared error	0.449	0.317
Relative absolute error	73.14 %	54.13%
Root relative squared error	83.34%	48.43%
Total Number of patterns	242	242

Table 13. Validation of the autoregressive model related to cardio-respiratory admissions

The autoregressive models perform less satisfactory than NN models perform, especially for cardiac admissions, with an R^2 of 31% and 76% for respiratory admission.
As note in Fig.32, the results achieved with all the developed models show that in general, autoregressive model underestimate cardiac hospitalisation.
In general for cardio-respiratory admissions this model explains more of the observed variance in term of seasonal difference and less in term of transition seasons.

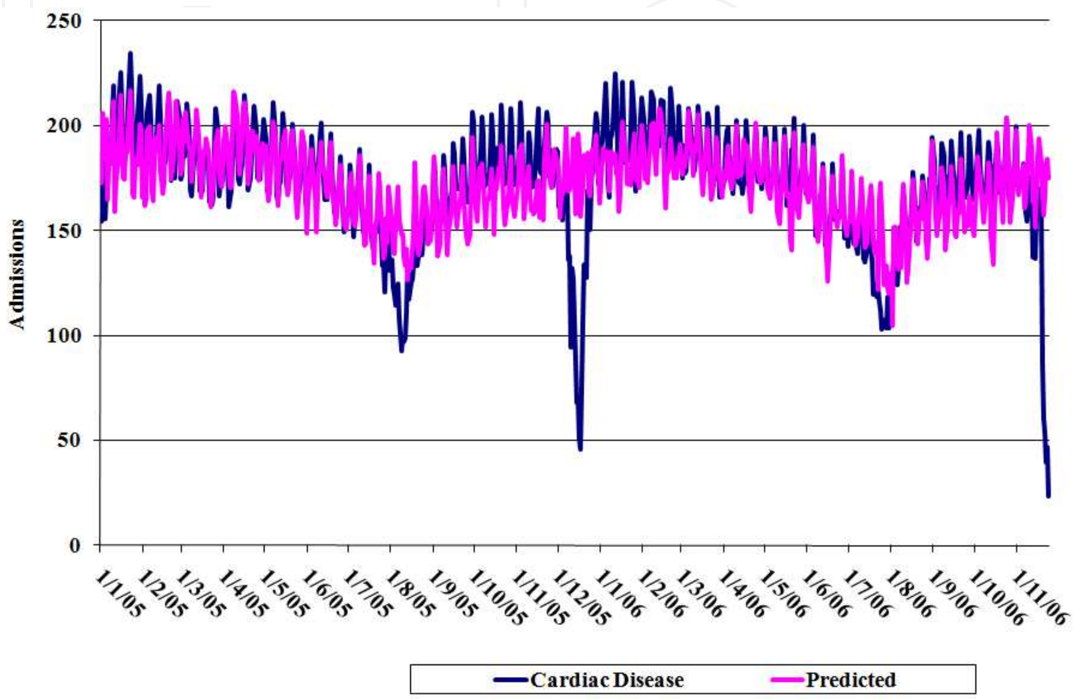

Fig. 32. Cardiac admissions for Rome (2005-2006)

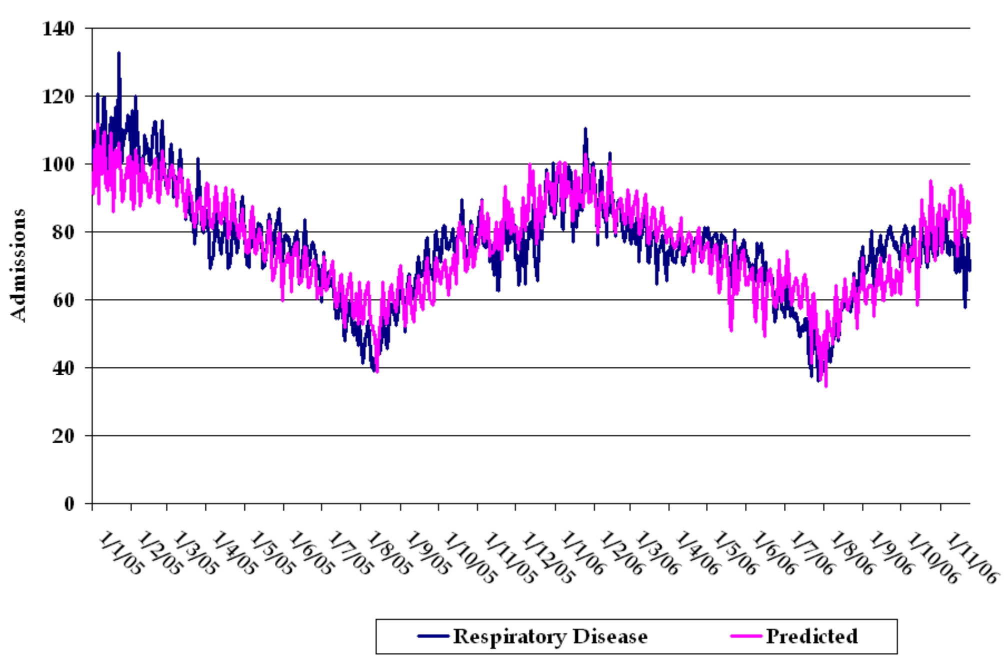

Fig. 33. Respiratory admissions for Rome (2005-2006)

5. Conclusion

In Rome and in general all the Italian cities, high concentration levels of air pollution, are one of the key risk factors of public health. Our data show that in Rome the concentration of PM10 and ozone have exceeded the danger levels suggested by the European Guidelines (DIR2008/50/CE).

One more interesting aim of for the health and environmental question are the connections between the air quality data and the relative effects on the human health, i.e. the hospitalisation. In general, while is well know that air quality impacts on the health, the quantification of this the effect is hard to simulate. This happen because the relation between the main variables (such as meteorological and pollutants ones) and health effects cannot be determined directly by deterministic models or by simplified statistical models. In fact, we can suppose that this relation could be non linear type and that the role of the important variables is hidden by the complexity of the phenomena.

In this context, we use one of the most advanced non linear models, such as the Neural Network, to attempt to model the relations between the environment and meteorological data and health effects on the populations. To this regards, we investigate the cardio-respiratory hospitalisations for total population of the Rome city, during the 2005 and 2006.

To that regards, we found that the conventional statistical descriptors, such as the daily average of pollutants, often cannot be link to the exposure levels, if they are taken standalone. By the pre-processing analysis, we demonstrated that the skewness coefficients for the pollutants can be given a more accurate connection with the real human exposure.

In our work, we applied an intelligent models constituted by a Neural network model (using the Mulilayer Perceptron architecture) to connect the environmental data with the hospitalisations for the two considered diseases.

The results obtained by NN model are very encouraging and suggest a way to modelling this complex relation. In fact, we obtained a very meaningful correlations (higher than 0.90) for both simulations. While the cardiac pathology is better reproduced by NN, the respiratory ones have needed more analysis in deep. However, both simulations exhibit that, to optimize the training phase, the choice of the input variables and the choice of patterns are the main factors to be considered for successful of intelligent methodology.

In our study, it is evident that the performances obtained is link to the right choice of input factors and that the NN performance is good only if some heavy pre-processing evaluation are given on input data.

These first results showed the importance of the environmental-epidemiological problem and the major areas in order to forecast with some accuracy the short-term effects on human health of the environmental component.

By using neural networks, it was possible to determine numerically the association statistically meaningful between the cases of death or hospitalization and pollutants (PM10 and/or O3).

The results coming from this work have used neural networks to investigate short-term the relationship between air pollution, mortality and hospital admissions, identifying and evaluating the sources of pollution in order to define and adopt effective mitigation measures for air quality improvement of Rome and the promotion of strategies for the prevention and treatment of cardio-respiratory diseases.

As last consideration, we underline that the results obtained seem encouraging to simulate the effects of air quality on the health through NN model, but at the same time indicate that further study are necessary in future as to extend the NN's prediction to more years and to consider also the spatial distribution of pollutant in relation with the local hospitalisation.

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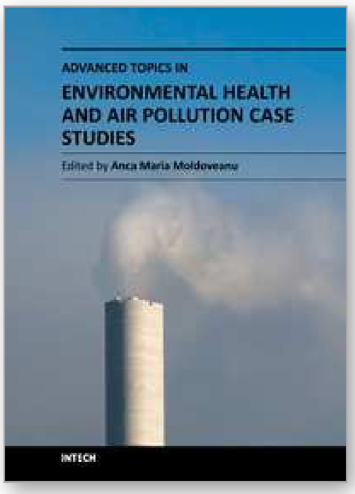

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The book describes the effects of air pollutants, from the indoor and outdoor spaces, on the human physiology. Air pollutants can influence inflammation biomarkers, can influence the pathogenesis of chronic cough, can influence reactive oxygen species (ROS) and can induce autonomic nervous system interactions that modulate cardiac oxidative stress and cardiac electrophysiological changes, can participate in the onset and exacerbation of upper respiratory and cardio-vascular diseases, can lead to the exacerbation of asthma and allergic diseases. The book also presents how the urban environment can influence and modify the impact of various pollutants on human health.