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New Strategy for a good Management and Control of Pollution Caused by urban Traffic

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ABSTRACT: Pollution control is based on correctly measuring pollutant concentrations but, at the moment, the principal European cities only monitor pollution levels by means of a few fixed stations co-located in selected points of the urban layout far from hotspots and/or by means of meteorological prediction models of future pollution. Few cities integrate the information from both sources. The implementation of wireless sensor network provides an alternative solution by deploying a larger number of disposable sensor nodes and it is the key that enable more flexible real-time environmental monitoring. This paper presents a new system for sustainable traffic management by using models that predict pollution levels, which are fed with data, gathered by the air quality sensors network and may help to take early action. This new system has been implemented in Salamanca (Spain), thus allowing, to test in real urban environments the collection and processing of data from 35 motes located in experimental roads during a year-round period. Monitoring results allow building a database with the temporal evolution of the different environmental indicators registered. In general the prediction model has an average error around 20% for predictions at one hour and 30% at three hours. The results highlight the very good performance of the prediction model. The strategic approach proposed is highly innovative and embodies great scientific and technological advances. The use and integration of measured and modeled data thus becomes a key element in the future management of atmospheric pollution.

Key words: Pollution control, Sensors network, Sustainable traffic management

INTRODUCTION

Tons of polluting agents are discharged into the air of principal cities every day. Furthermore, it has been confirmed that emissions from motor vehicles are the main cause of air degradation, especially now that industrial emissions have been reduced thanks to the progressive displacement of industrial facilities outside urban areas (Jacquemin, 2007). Loss of environmental quality is one of the biggest threats of our century to health and human well-being, together with environmental impacts. Several analyses have proven a relationship between air pollution and the emergence and/or aggravation of respiratory diseases (Molitor *et al.,* 2006) (Gehring *et al.,* 2010), as well as other related illnesses, such as cardiovascular diseases or cancer (Vineis & Husgafvel, 2005) (Wild, 2009). Furthermore, its relationship to the increase in allergies and, thus, the decline in many people´s quality of life, appears to be very clear (Gehring *et al.,* 2010). On the other hand, polluting agents affect historical buildings causing severe deterioration and the correspondingly high maintenance costs of the city's architectural heritage. In general, air quality in an area depends on the geographical distribution of emission sources, the amount of pollutants emitted, the physical-chemical processes taking place in the atmosphere and the climatology and topography that very much determine the dispersion and transport processes (OSE, 2007). Vehicular traffic is increasing around the world, especially in urban areas. This increase results in a huge traffic congestion, which has dramatic consequences on economy, human health and environment (Amine & Challal, 2012). The highest percentage of air pollution comes directly from road traffic and not anymore from large industries, currently placed outside metropolitan and urban areas. Road traffic is considered to be responsible for 22.4% of all emissions in Spain (CNE, 2013).

European concern regarding this matter has resulted in the creation of new legislation, aimed at adding new chemical compounds to the list of pollutants to be controlled and promoting the

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reduction of threshold emission levels, in order to reduce atmospheric pollution (Greening, 2004 ; Twigg, 2007). In 2008, the EU Directive (2008/50/EC) on ambient air quality and cleaner air for Europe was adopted. This Directive aimed to show the European Union's strong commitment to improving air quality in the EU. In response to this, substantial policy measures have taken to reduce air pollution. Europe-wide polices include emission standards for motor vehicles and definition of national emission ceilings. In addition, local polices have been implemented to reduce air pollution concentrations at busy urban roads (Boogaard *et al.*, 2012). Environment monitoring has become an important field of control and protection, providing real time system and control communications with the physical world. An intelligent and smart Wireless Sensor Network system can gather and process a large amount of data from the beginning of the monitoring and manage air quality, the conditions of traffic, to weather situations.

From the studies, it has been proved to be an alternative way to replace the conventional method (Fauzi & Khairunnisa, 2012).

Wireless Sensor Networks (WSN) is an emergent technology with an effective potential and have a great added value to intelligent transportation systems (ITS) (Amine & Challal, 2012). It is clear that ITS´s goal is enabling smart cities and in this respect, pollution prevention is becoming a sensible field and needs more and more attention (Amine & Challal, 2013). The implementation of wireless sensor network provides an alternative solution by deploying a larger number of disposable sensor nodes. Wireless sensor a network is an emerging technology that transforming the way we measure and actively participates in creating a smart environment (Oliveira & Rodrigues, 2011) (El-Bendary *et al.*, 2013). This air-quality sensor network together with prediction models will help to define a new Urban Traffic Management and Control Strategy based on the prevention of high pollution episodes caused by urban traffic. The use and integration of measured and modelled data thus becomes a key element in the future management of atmospheric pollution.

Therefore, taking into account this fact, the aim of the present work has been to test in real urban environments the quality of the information supplied by 35 motes located in experimental roads of city of Salamanca (Spain) during a year-round period, as a new tool for traffic pollution control.

MATERIALS & METHODS

Pollution control is based on correctly measuring pollutant concentrations but, at the moment, the principal European cities only monitor pollution levels by means of a few fixed stations co-located in selected points of the urban layout far from hot-spots and/or by means of meteorological prediction models of future pollution. Few cities integrate the information from both sources (Berkowicz *et al.*, 2006) (Zito *et al.*, 2008), aimed at attaining the permanent control of traffic flows, as these can cause emergency episodes related to pollution levels surpassing the legal thresholds. The main handicaps to date have been the lack of reliability of the prediction models used, as well as the difficulty of making precise online measurements of urban "hot-spots" available. On the other hand, traditional traffic management systems are usually based on mobility models, their main purpose being to solve traffic volume demands on urban roads, although not taking into consideration environmental points of view.

It is evident that departments in charge of urban mobility cannot integrate in their traffic management models predictions that are difficult to compare with real time data, as their decisions are based on instant mobility data in particular. An innovative strategy consists of achieving the sustainable management of traffic in cities by using two key elements: a pervasive air-quality network of sensors and prediction models. Such a development will help to define a new Urban Traffic Management and Control Strategy based on the prevention of the usually high pollution episodes caused by urban traffic. Air quality control is currently restricted to the collection of meteorological and pollutant concentration data at several fixed stations around the city. On rare occasions, such a control incorporates real density or traffic flow data from those spots, and it therefore becomes unfeasible to deduce any empirical causal relationship between the data gathered and traffic in the "hot-spots". On the other hand, many cities have developed air quality prediction models based on real or estimated data referring to traffic and car emissions, as well as to weather forecasts, producing mid-term predictions (meso-models for 24 to 72 hours) which are difficult to contrast empirically against live measures from fixed measurement stations. The relevance of such models is scarce in practice, since they are not used to take traffic management control measures in most cases, but as a forward indicator of high pollution episodes. Traditional environmental prediction models allow for coverage of a broad area but they are very time-demanding and difficult to implement. These models need to be provided with very precise and extensive data to obtain acceptable results. This is why, for many cities, the cost associated with modeling activities is not justified. On the other hand, most of the existing air quality models were originally developed to predict emissions and concentrations of pollutants discharged by fixed sources. However, air quality problems today in urban areas are mainly caused by vehicles, which is the reason for the better modeling of traffic emissions. Emissions are higher when vehicles speed up, slow down or are left in neutral, specifically under congested traffic conditions, and not many air quality models can work out these situations. Moreover, few models can take into consideration pollutant dispersion within the complex topography of a city, including the well-known "canyon effect" in street sectors flanked by high buildings, which cause the accumulation of traffic-related pollutants, due to limited air exchange caused by the isolation of the air stock. Furthermore, for modeling road traffic emissions with more complex models, the lack of dynamic data will limit the models´ ability to predict pollution levels in the vicinity of streets (i.e. sidewalks). Consequently, predictions of air pollutant concentrations in urban areas are often too imprecise to allow for re-distributing traffic flows.

The availability of more precise and shorter-term prediction models based on live traffic and car emission data referred to the real vehicle traffic conditions, as well as the recent appearance on the market of a wide range of measurement tools for the different contaminating agents which are far less expensive than those used in fixed stations, together with today's communication systems technology, means that a large amount of online pollution measurements corresponding to the "hot-spots" within the city are now available. When comparing these measures with the predictions from a shorter than usual term model (3 to 5 hours), it is possible to predict some hours in advance, and with a high degree of reliability, the high pollution occurrences for different places of all urban areas, as well as to draw up alternative scenarios based on simulated traffic flow deviations or restrictions, across those or nearby areas which influence them. In this way, the current urban traffic management and control system would have at its disposal another absolutely reliable decision element, complementary to the traditional mobility and accessibility decision algorithms, which would help to develop a more rational and environmentally friendly management of traffic flows. The application of the current legislation regarding air quality conditions in cities, which compels them to draw up Air Quality Plans for several forthcoming years, will therefore provide another management tool that will undoubtedly contribute to improving the air breathed by citizens and act upon the most important urban contaminating agent (i.e. traffic) by organizing traffic flows following the "ecological capacity" of the city corresponding to each weather condition, thus allowing only sustainable flows through the "hot-spots". The practical implementation of this strategy includes three components: monitoring, modeling and information feedback. Monitoring refers to the measurement of parameters (pollutant concentrations, traffic flows, meteorological conditions, etc.) by means of an innovative and extensive low-cost network of sensors deployed in the area under study. The information gathered will be a dynamic input to the modeling phase in order to generate pollution predictions in real time and to calculate the effects of a variety of hypotheses (scenarios) of traffic regulation. The impact of the selected pollution scenarios at "hot-spots" will be contrasted with the new data collected by the same measuring instruments. Finally, by introducing a feedback into the regulation system, a fine-tuning among pollution results and traffic control measures taken in real time will be achieved.

Fig.1. One of the streets under study with some motes identified in circle

35 motes have been installed on two different roads of Salamanca with high traffic density (Fig.1), which has allowed to test in real urban environments the collection and process of data during a year-round period.

Motes information is essential for traffic monitoring and control, since urban data diagnosis is the basis of the mobility plan. Information refers to the following parameters collected from pollution “hot-spots”: carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), particulates (PM), noise, humidity, and temperature. Other variables can be measured according to local circumstances. Design and manufacture of the motes is based on a commercial model (Libelium Waspmote).

Each mote is composed of seven sensors: CO (Figaro TGS 2422), NO_2 (e2V MICS-2710), O_3 (e2V MICS-2610), particles (Sharp GP2Y1010AU0F), noise (Panasonic WM-61B), temperature (Microchip MCP9700A) and humidity (Sencera 808H5V5).

The sensor node sends the collected data to the router. The router (Meshlium, Libelium) includes Wi-Fi technology that allows (2.4 GHz, 5GHz), 502.15·4/ ZigBee, GPRS, Bluetooth and GPS in the same equipment. Multi-sensors networks can be used in a two-fold approach to city pollution abatement: pollution characterization and traffic monitoring and control. During the testing period (one year), more than two millions data were collected and processed in the project data center.

Air pollution monitoring is considered as a very complex task. Traditionally data loggers were used to collect data periodically and this was very time consuming and quite expensive. The use of wireless sensor networks can make less complex air pollution monitoring and a reading can be obtained instantly. The motes are integrated into a power system and protective enclosure and which in turn are coupled to a post similar to parking meters. In this way, the mote is protected of possible acts of vandalism and also facilitates the placement of the power system as well as to know the real concentration of a pollutant that is inhaling a passer. The data transmission system used is Waspmote XBee-802.15.4, consisting of three elements: microcontroller (ATmega 1281), antenna (XBee-802.15.4) and gases board (port adapted for microsensors). This system allows the data transmission through radio signals that are being transmitted from a mote to another until the signal arrives at the sites where the motes information is collected and transmitted to the data processing system. Each of the roads under study has a router that is connected to a single database. The routers store data temporarily and later send the information via GPRS or Ethernet to the database located in the traffic management center.

Once the motes were installed, to check the communications and validate the information that the sensors collect, they begin to collect continuous information of each pollutant concentration level achieved. These data will be used by the prediction models to achieve the sustainable traffic management. Previously, the sensors were calibrated in laboratory and verified in situ in the streets under study. The new system for sustainable traffic management is based on the use of models that predict pollution levels, which are fed with data, gathered by the air quality sensors network and may help to take early action. For this, the modelization of the motes data are based on advanced statistical techniques. Monitoring results allow building a database with the temporal evolution of the different environmental indicators registered. This allows be studied from the perspective of the Bayesian process that maximizes the use of the large amount of information available at all times.

The result is a prediction model to estimate the short term evolution of the different pollutants and implement traffic control strategies to mitigate the negative impacts expected. In the air quality literature, time-series analysis is generally carried out to understand the cause and effect relationships, which in turn helps in forecasting the future concentrations. In this direction, a class of techniques including autoregressive integrated moving average (ARIMA) or Box-Jenkins models and structural models have been applied to analyse air pollutant concentrations. These approaches are widely applied in the air-quality literature due to the lack of data on emissions of air pollutants (Chelani & Devotta, 2006). ARIMA is a statistical model that uses variations and statistical regressions data in order to find patterns for predicting the future. These methods are applied in cases where the data show evidence of being non-seasonal, where an initial step of differentiation of the series can be applied to remove the non-seasonal series. The ARIMA model needs to identify the coefficients and number of regressions which will be used. This model is very sensitive to the accuracy with which the coefficients are determined. As the application of these models is very common, further details to estimate the parameters and order of the model are given in Box & Jenkins, (1970). ARIMA model has four main components that need to be defined: tendency component, cycle, seasonal variation and remainder or erratic compound.

The prediction model allows to the Authorities to know the prediction of high pollution episodes, at one hour and three hours, for one or several motes and sensors, to show the expert/manager predictions and the traffic pollution alarms screen. As any other model, it was carried out an adjustment and optimization of the ARIMA model iteratively through a process in which we can distinguish four stages: identification, estimation, validation and prediction. In the identification stage, more than one candidate model that can describe the series has been identified, using data in chronological order. A data treatment has been performed calculating the moving average and applying a filtrate to obtain manageable values to determine the values of the ARIMA model parameters. As a result of calculating the model parameters and as the final phase of the estimation process, the estimation at one and three hours of model behaviour is performed.

In the estimation stage, considering the appropriate model for the time series has been performed inference on the parameters. In the validation stage, diagnostic contrast to validate if the selected model is fitted to the data predicted with a reliability level higher than 95% has been performed. ARIMA model adjustments have been modified for each pollutant until achieve the desired level of reliability in the prediction. In the prediction stage, once the ARIMA model has been adjusted and optimized, it has been also checked its validity by comparing the predictions made in terms of probability of future values with measures “in situ” of the pollution at the time of predicted time.

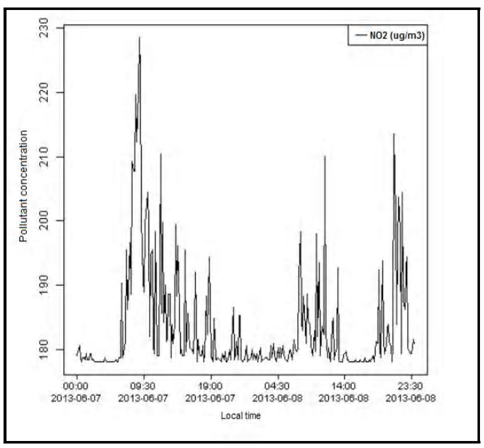

Fig.2. Collected data by the NO_2 sensor

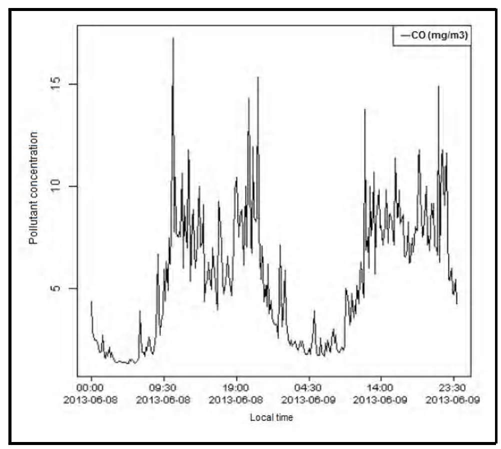

Fig. 3. Collected data by the CO sensor

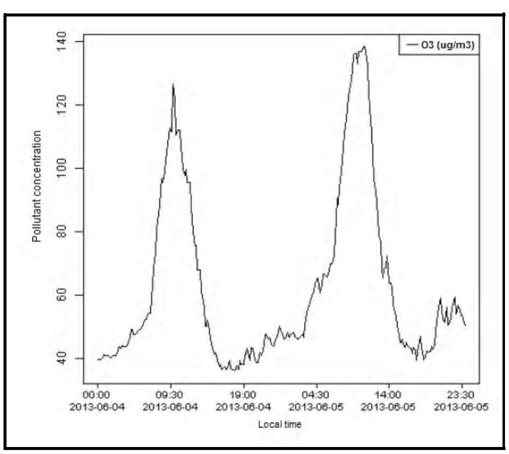

Fig.4. Collected data by the O_3 sensor

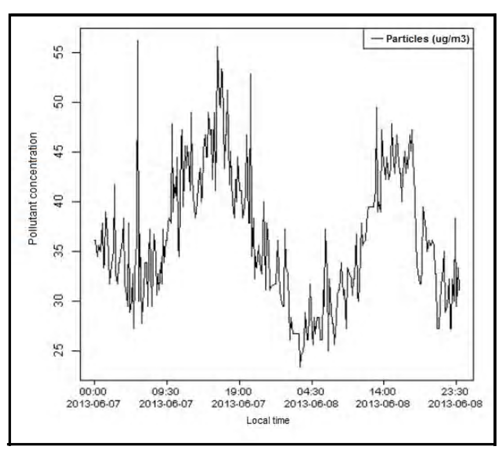

Fig.5. Collected data by the particles sensor

The result of this process has been an alternative model of traffic management adjusted and optimized.

RESULTS & DISCUSSION

Figs from 2 to 5 show recorded data for some motes and sensors, in particular NO_2 (Fig.2), CO (Fig.3), O_3 (Fig.4) and particles (Fig.5), collected for two days.

Figures shows that the maximum concentrations are given in traffic rush hours (early morning, midday and late afternoon) as expected, the concentration being minimal at night. In the case of the ozone (Fig.4), the highest values were obtained from the morning to midday, mainly. It is due to a maximum solar radiation (summer) and high traffic. Emissions from traffic in the presence of sunlight are formed high ozone concentrations. A software tool has been created to display the results of the prediction model. Maximum values for each pollutant were established in the software prediction model. These maximum values are taking into account a margin above the maximum allowed by law. In this way, when the system predicts that a value greater than the allowed by law will be reached; an alarm is generated in the software tool for the corresponding mote. It allows that a traffic manager to assess the need to carry out an action that prevents the prediction is fulfilled. Following some of the prediction results for some motes and some specific pollutants are gathered (Fig.6 and Fig.7). The prediction of the carbon monoxide is showed in the Fig. 6. The point (•) indicates the prediction to one hour and the square (■) point to three hours. The cross (**x**) point indicates the last prediction where the accuracy of the prediction model can be observed.

The prediction of the nitrogen dioxide is showed in the Fig. 7. The symbol of the marks indicates the same as in Fig. 6.

The prediction results for ozone and particles have not been collected because the measures are not good, so the prediction results either. In the case of the ozone, probably due to the specific characteristics of the pollutant, as it is a secondary pollutant. The predicted concentrations values were compared with the measured concentrations values for 24 hours, for predictions at one hour and three hours. In order to determine the accuracy of the predictions and to evaluate the performance of the proposed model, the following parameters were calculated:

Prediction error (PE):

$$\text{PE} = \text{measured value} - \text{predicted value} \qquad (1)$$

Statistic error (SE):

$$\text{SE} = \frac{\text{PE}}{\text{measured value}} \times 100 \qquad (2)$$

Mean absolute error (MAE):

$$\text{MAE} = \frac{1}{\text{N}} \left(\sum_{i=1}^{N} |\text{PE}|\right) \qquad (3)$$

Mean absolute porcentaje error (MAE %): MAE

$$\% = \frac{1}{\text{N}} \left(\sum_{i=1}^{N} |\text{SE}|\right) \qquad (4)$$

Where: N = 24 (in the case of predictions at one hour) and N = 8 (in the case of predictions at three hours).

It is considered that the measured value is the value of concentration in hour i, where $i = 1, 2, 3, \ldots, 24$ and the predicted value is the value of concentration for the same hour. The results obtained when applying these equations, Eqs. (3-4) are presented in Table 1.

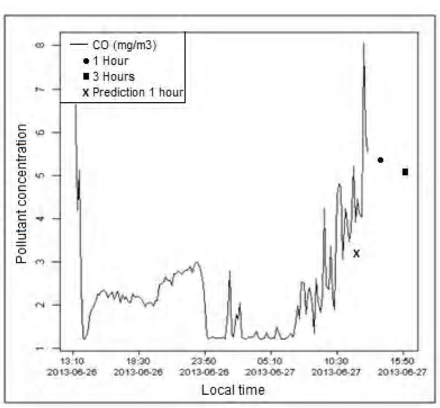

Fig.6. Prediction of the carbon monoxide

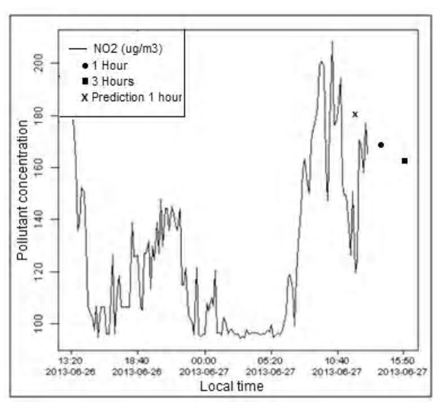

Fig.7. Prediction of the nitrogen dioxide

Table1. Results of the values of the predictions accuracy for 24 hours.

Air pollutant	Parameters	Predictions at one hour	Predictions at three hours
NO_2	MAE ($\mu g/m^3$)	9.41	12.22
	MAE (%)	4.67	5.96
CO	MAE (mg/m^3)	1.95	3.11
	MAE (%)	36.57	44.73

Taking into account the results presented in the table 1, it is obvious that predictions at one hour are more accurate than predictions at three hours. With respect to the mean absolute percentage error (MAE %) the best performance is for the NO2, with a value of 4.67% for the predictions at one hour. Obviously, an error in the sensor measurement may lead to a prediction error. For this reason, it is very important that the sensors are calibrated correctly and in perfect condition. Prediction method demonstrates the more realistic problems in the field. The results highlight the very good performance of the model. As discussed above, the prediction of emission variables are dependent on past history of the data. It is expected that availability of more emission data can improve the performance of prediction model.

CONCLUSION

The strategic approach proposed is highly innovative and embodies great scientific and technological advances. The availability of more accurate predictive and shorter-term models, based on traffic data and atmospheric emissions in real traffic conditions and the use of low cost instruments for measuring pollutant concentrations, together with advanced communication systems existing today, make it possible to have a large number of measures related to pollution “hot-spots” in the city through a wireless sensors network. When comparing these measurements with the predictions of a short-term model (1-3 hours), it is possible to anticipate, with high reliability, high pollution episodes in different points of all urban area, and develop alternative scenarios based on the simulation of deviations or restrictions of traffic flows through or near their areas of influence. It is very difficult by using traditional means to predict emission levels for a specific pollutant, at a given time and location, due to the large amount of factors that are constantly changing and, thus, affecting the actual pollution. This is certainly what this new strategy of traffic pollution control intends: to create an information platform aimed at understanding, assessing and evaluating the impact derived from actions carried out in order to improve accessibility, to tackle the congestion problem, to improve air quality or to implement a Traffic Information System. The proposal to integrate mobility management needs and air quality into a single urban traffic management model is not only necessary to achieve the goal of reducing pollution levels below the limits imposed by the European Directives, but it is also absolutely essential to organize the city traffic in a rational manner: i. e., without causing excessive trouble to the mobility needs of citizens and achieving sustainable traffic levels in a systematical and unequivocal way at any one time. The ultimate objective is to provide Local Authorities with an efficient and sustainable urban traffic management system in accordance with the existing environmental policies and legislation. In this way, Management Systems and Urban Traffic Control may have another decision element absolutely reliable, complementary to traditional decision algorithms mobility and accessibility, which helps develop a management, more rational and respectful with the environment of the traffic flows, being based on active surveillance.

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