Computational intelligence for evaluating the air quality in the center of Madrid, Spain

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Abstract. This article presents the application of data analysis and computational intelligence techniques for evaluating the air quality in the center of Madrid, Spain. Polynomial regression and deep learning methods to analyze the time series of nitrogen dioxide concentration, in order to evaluate the effectiveness of Madrid Central, a set of road traffic limitation measures applied in downtown Madrid. According to the reported results, Madrid Central was able to significantly reduce the nitrogen dioxide concentration, thus effectively improving air quality.

Keywords: smart cities; air pollution; computational intelligence.

1 Introduction

Mobility is a crucial issue in nowadays cities, having direct implication on the quality of life of citizens. Sustainable mobility contributes to reduce environmental pollution, which has serious negative effects on health. Sustainable mobility is a relevant subject of study under the novel paradigm of smart cities [1].

Most of modern cities have been designed without considering air quality concerns. In fact 91% of the world population lives in places where the air quality levels specified by World Health Organization (WHO) are not met [24]. Many cities have prioritized the use of motorized vehicles, causing a significant negative impact on health and quality of life, especially for children and the elderly.

One of the major concerns arising from the rapid development of car-oriented cities is the high generation of air pollutants and their impact on the health of citizens [20]. WHO estimates that 4.2 million deaths per year are due to air pollution worldwide [24]. International authorities have taken actions by enacting environmental policies oriented to reducing pollutants (e.g., the Clean Air Policy Package adopted by the European Union (EU) to control harmful emissions).

This article analyzes the Madrid Central initiative, which has been implemented in Madrid (Spain) in order to diminished air pollutants and thus comply with the requirement demanded by the EU. Madrid Central, defined as a low emissions zone, extends a series of traffic restrictions aimed at reducing the high levels of air pollution in the city. As a result, most pollutants vehicles cannot access to the central downtown area.

The proposed methodology for air quality evaluation applies data analysis and computational intelligence methods (polynomial regression and deep learning) to approximate the time series of nitrogen dioxide (NO_2) concentration, which is a direct indicator of environmental pollution. The main results indicate that the deep learning approach is able to correctly approximate the time series of NO_2 concentration, according to standard metrics for evaluation. Results allow concluding that Madrid Central was able to significantly reduce the nitrogen dioxide concentration, thus effectively improving air quality.

The main contributions of this work are: *i)* the analysis of the air quality, regarding NO_2 concentration, in Madrid downtown and *ii)* the application of computational intelligence to assess the environmental impact of car restriction measures in Madrid Central. The proposed approach is generic and can be applied to analyze other policies to deal with different challenges in smart cities.

The article is organized as follows. Next section describes the case study and reviews related works. Section 3 introduces the proposed approach. The evaluation of air quality via data analysis and computational intelligence is presented in Section 4. Finally, Section 5 presents the conclusions and the main lines of future work.

2 Case study and related works

This section presents the case study and reviews relevant related works.

2.1 Reducing traffic: residential priority areas and Madrid Central

In the EU air pollution it is considered the biggest environmental risk, causing more than 400,000 premature deaths, years of life lost as well as several health derived problems (i.e. heart disease, strokes, asthma, lung diseases and lung cancer). Besides, it has an impact over natural ecosystems, biodiversity loss, and climate change [6, 16]. Less known is that it can harms deeply the built environment and so, the cultural heritage [6]. Finally, it produces an economic cost in terms of increasing expenses associated to health issues and in terms of diminished production (e.g. agricultural lost and lost of working days).

Those factors have lead the EU to take action by enacting stronger air policies and a bigger control among their Member States. The Clean Air Policy Package refers to the `Directive 2008/50/EC` [5] and to the `2004/107/EC` [4] and it sets different objectives for 2020 and 2030. This EU clean air policy relies on three main pillars mandatory to every member state: *i)* ambient air quality standards and air quality plans accordingly; *ii)* national emission commitments enacted on the National Emissions Ceiling Directive; and *iii)* emissions and energy standards for key sources of pollution.

One of these key sources of pollution are vehicles. In fact, the biggest contribution of NO_2 emissions and big part of particulate matter emissions are caused by the transport sector. The maximum levels established by the EU have been exceeded in some EU countries, Spain among them. Under the risk of huge economic fines, the EU required the reduction of the referred pollutants. As an attempt avoid the economic sanction, the city of Madrid (one of the largest contributors to air pollution) implement a low emission zone in the downtown area: Madrid Central. This zone is established by the *Ordenanza de Movilidad Sostenible* (October 5th, 2018) starting the traffic restriction on November 30, 2018 and fining for noncompliance in March 16, 2019. The designed area covers the *Centro* District (4.72 km^2). A series of car restrictions are applied, except to residents and authorized cars (e.g., people with reduced mobility, public transport, security and emergency services, vehicle-sharing) are progressively applied to eliminate transit traffic. For the rest, a environmental sticker system is followed: depending on how contaminant is a car it will be labelled with an environmental sticker, marking so if you can access and park in the area, access but not park or neither one nor the other. The idea behind those measures are not just improving air quality in the short term, but change mobility behaviour. As a first victory, this measure succeeds in paralysing EU disciplinary measures.

2.2 Related works

A number of researches have studied the efficacy of car restriction policies in different cities. Several of them have included some type of analysis of air pollution. A brief review of the related literature is presented next.

Several articles studied the rapid growth of car ownership in Beijing, China and its impact on transportation, energy efficiency, and environmental pollution [13,14]. In general, authors acknowledged that implementing and evaluating car restriction policies is somehow difficult. First measures on Beijing were taken in 2010, with the main goal of mitigating the effects of traffic congestion and reduce air pollution. Liguang et al. [13] analyzed data from Beijing Municipal Committee of Transport to evaluate the implementation of car use restriction measures. Results reported confirmed that fairly good effects on improving urban transportation and air quality were achieved. No computational intelligence methods were applied for the analysis, but just a comparison of average and sampled values and qualitative indicator. Liu et al. [14] proposed an indirect approach to evaluate the impact of car restrictions and air quality, by applying a generalized additive model to explore the association of driving restrictions and daily hospital admissions for respiratory diseases. Several interest facts were obtained from the analysis, including higher daily hospital admissions for respiratory disease for some days, and the stronger effect on cold season. Female and people older than 65 years benefited more from the applied environmental policy. Overall, authors found positive effects on the improvement of public health.

Wang et al. [23] applied a data analysis approach to address traffic congestion and air pollution in Beijing, regarding driving restriction policies. Using data from Beijing Household Travel Survey, the authors analyzed short-term effects of driving restriction policies on individual mode choice and the impact in pollution. The main results showed an impact on public transit transportation and a large number of drivers (about 50%) breaking the rules, i.e., driving illegally when not allowed to. Evidence of reductions in congestion and mobile source pollution were also confirmed. As a result, driving restrictions have shown effective in curbing air pollution and traffic congestion. Using data from multiple monitoring stations, Viard anf Fu [22] confirmed that air pollution fell up to 21% when one-day-per-week restrictions were implemented, with the consequent benefits on improved health conditions. Recently, Li et al. [12] performed a similar study for Shanghai, but focusing on the impact of restrictions for non-local vehicle on air quality. CO concentration and Air Quality Index were studied applying regression discontinuity statistical analysis. The main results confirmed that non-local vehicle restriction policy was a key factor to improve the air quality and commuters health in Shanghai. Other cities have implemented temporary measures, e.g., Paris prohibited circulation of more than half of the cars registered in the suburban region in the summer of 2019, due to a notorious worsening of the air pollution [19].

In Latin America, the efficacy of car restriction policies and their impacts on pollution and health have been seldom studied. Indeed, some researchers have argued that car restrictions policies have not yielded a positive impact on air pollution yet (e.g., in the Colombian city of Medellín [8]). Other researches have claimed that restricting the car utilization by license plate numbers is a misguided urban transport policy that does not help to significantly improve the quality of life of citizens [3, 25]. In any case, researchers must take into account that the effects of vehicle restriction policies are often neutralized by the continuous growth of vehicle ownership and utilization in modern cities.

Several researches have applied data analysis to study the relationship between transportation and health of citizens (e.g., [21]). Some other articles have applied neural networks approaches to evaluate urban policies and air pollution (e.g., [18]), especially to deal with complex urban systems, but no studies relating car restriction policies and air pollution were found in the bibliographic review. This article contributes in this line of research by applying a learning approach for pollution prediction and evaluation of car restriction policies in the center of Madrid, Spain,

3 Methodology for air quality evaluation

This section presents the applied methodology for air quality evaluation and assessing the impact of the Madrid Central initiative.

3.1 Data analysis approach

Data analysis methods have been applied in several related articles for studying air quality in modern cities [10, 17, 25]. It is a also a common methodology for public services analysis and evaluation in smart cities [2, 7, 15, 26].

In order to determine the objective effects of the car restriction policies implemented by Madrid Central, the NO_2 concentration is evaluated as a relevant indicator of the environmental pollution. The main goal of the study is to determine whether the implementation of Madrid Central caused a statistically significant decrease in NO_2 pollution or not. In order to meet that goal, computational intelligence methods are applied to learn from the time series of NO_2 concentration and to predict the pollutant emissions in case Madrid Central were not implemented in December 2018. After that, the real measurements are compared to the predictions in order to determine if significant deviations from the learned model have occurred or not.

The analysis extends and complements a previous study of environmental pollution in the center of Madrid [11]. That work applied a linear regression method and considered a lower resolution on the observed data, thus non-conclusive results were obtained for the O_3 pollution, mainly because the simple linear regression method was not able to capture the complexity of several interacting effects in the analyzed urban zone.

3.2 Data description

The source of data studied in the analysis is provided by the Open Data Portal (ODP) offered by the Madrid City Council (`https://datos.madrid.es/`), an online platform that promotes access to data about municipal public management. The data gathered by the sensor located in Madrid Central (*Plaza del Carmen*) is analyzed to evaluate the impact of the car restriction policies.

The analysis is performed considering a temporal frame of nine years, from January 2011 to September 2019. Two relevant periods are distinguished: *pre-Madrid Central*, i.e., the period before implementing the initiative (from January 2011 to November 2018), and *post-Madrid Central*, i.e., the period after implementing the initiative (from December 2018 to September 2019). Every dataset considers hourly values of NO_2 concentration.

Regarding the computational intelligence methods, the following datasets were considered:

- *Training dataset*: 90% of the data from pre-Madrid Central is used for training. Data from January 1^{st}, 2011 to November, 30^{th}, 2017 is used, accounting for a total number of 60168 observations.
- *Validation dataset*: the remaining 10% is used for validation. Data from December 1^{st}, 2017 to September, 30^{th}, 2018 is used, accounting for a total number of 7248 observations.
- *Comparison dataset*: Finally, the comparison is performed over 7248 observations, taken from December 1^{st}, 2018 to September, 30^{th}, 2019.

3.3 Computational intelligence methods applied in the study

Polynomial regression and Recurrent Neural Networks (RNN) are applied to predict the general future trend in NO_2 concentration after the implementation of the road traffic restrictions in Madrid Central.

Polynomial regression. Polynomial regression is one of the simplest methods for analysis and estimation of time series , yet it is one that is frequently used in the related literature [11, 12, 14]. In this article, three polynomial regression methods are studied: linear, quadratic, and polynomial (grade 10). These methods provide a set of baseline results to compare the prediction accuracy of more sophisticated learning methods.

Recurrent Neural Network. RNNs are artificial neural networks whose connections form a directed graph along a temporal sequence, allowing to capture temporal dynamic behavior of studied phenomena [9]. RNNs are more useful to analyze time series than standard feed forward neural networks.

In this article, instead of applying a traditional fully connected RNN, a Long Short Term Memory (LSTM) RNN is used. The main reason for applying LSTM is that they allow modeling the sequential dependence of input data. In this case, LSTM are (a priory) a better method for capturing the daily pattern of NO_2 concentration, (described in Fig. 2).

Regarding the RNN architecture, it contains two hidden layers and 50 neurons per layer. Lookback observations are set to 24 (corresponding to 24 hours), in order to capture the daily patterns of NO_2 concentration. A standard linear activation function is applied. The RNN was trained using backpropagation, applying Stochastic Gradient Descent optimization.

3.4 Metrics and statistical tests

Three metrics are considered in the analysis. The Mean Squared Error (MSE) is used for training the proposed computational intelligent methods and to analyze their prediction quality over validation data. MSE is the mean of the squares of the differences between the observed (x_m) and the predicted value ($\widetilde{x_m}$) for each observation m in the comparison data set M (Eq. 1). For the comparison of time series in order to determine the effect of the car restriction policies implemented by Madrid Central, MSE and Mean Absolute Error (MAE) are applied. MAE is similar to MSE but it takes into account the absolute difference instead of the squared one (Eq. 2). The aforementioned absolute metric is also considered to account for the real difference between NO_2 concentration.

$$MSE = \frac{1}{|M|}\sum_{m\in M}(x_m - \widetilde{x_m})^2 \quad (1) \qquad MAE = \frac{1}{|M|}\sum_{m\in M}|(x_m - \widetilde{x_m})| \quad (2)$$

Finally, the percentage of predictions that are over the real value ($\uparrow$*real*) is reported. This metric is applied to determine if the difference is over (thus, the method overestimates) or below (the method underestimates) the real value.

Regarding the methodology to determine statistical significance of the obtained results, the following procedure was applied:

1. Shapiro-Wilks statistical test was applied to check if the results follow a normal distribution or not. The test was applied considering a statistical significance of 99% (i.e., p-value<0.01).

2. Analysis of Variance (ANOVA) statistical models are applied to analyze the differences between the predicted and the observed NO_2 values, after the Shapiro-Wilks results confirmed that MSE values do not follow a normal distribution, with a statistical significance of 99% (i.e., p-value<0.01).
3. Wilcoxon statistical test was applied to analyze MSE and MAE results, considering a statistical significance of 99% (i.e., p-value<0.01).

4 Experimental evaluation

This section describes the experimental evaluation of the proposed approach.

4.1 Development and execution platform

The proposed computational intelligence methods were developed using python (version 3.7) and the pytorch (version 1.0) open source machine learning library.

The experimental evaluation was performed in a Intel Core i7-8700K @3.70 GHz with 64 GB RAM, 6 cores and using hyper threading (12 execution threads). The RNN training phase was performed using a NVIDIA GeForce GTX 1080 GPU with memory of 16GB.

4.2 Experimental results

This subsection reports the experimental results of the proposed computational intelligence methods.

Analysis of NO_2 concentration data. The first step of the study involved analyzing NO_2 concentration data. Weekly, daily, and hourly analysis were performed to detect patterns and periodicity in the time series. Fig. 1 reports the box plots corresponding to NO_2 concentration for each day of the week. Fig. 2 shows the average values corresponding to the hourly NO_2 concentration for each day of the week.

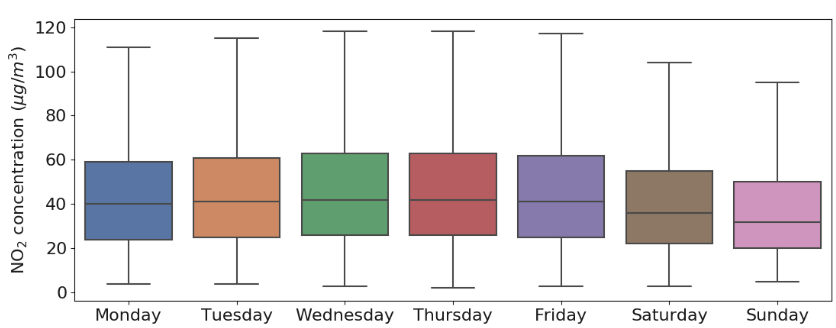

Fig. 1: NO_2 concentration distribution along weekdays.

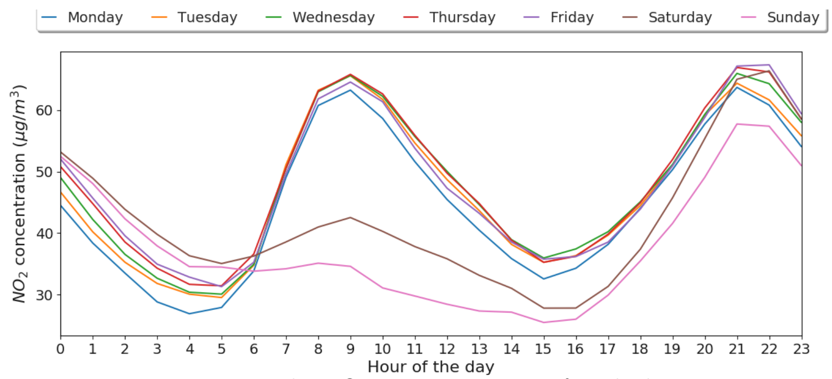

Fig. 2: Hourly NO_2 concentration of each day.

Results reported in Fig. 1 indicate that there are two clear clusters: working days and weekends. Absolute differences on the median NO_2 concentration values are significant: $MAE = 8\mu\text{g/m}^3$ (19% of the average value for a working day) for Saturday and $MAE = 11\mu\text{g/m}^3$ (26% of the average value for a working day) for Sunday. These values account for a significant reduction of vehicles circulating in the studied area as reported by several media. Furthermore, the analysis of the time series of hourly values in Fig. 2 clearly shows that the morning peak of NO_2 concentration in working days reduces to almost the half on Saturdays and to lower than the half on Sundays. On the other hand, the afternoon peak is still present on weekends.

Table 1 reports the computed values for NO_2 concentration before and after installing the Madrid Central initiative. Minimum (*min)*, median, inter-quartile range (IQR), and maximum (*max*) values are reported, since the results do not follow a normal distribution, according to the shapiro-Wilks statistical test (confidence level = 0.99). The Δ column reports the average difference between post-Madrid Central and pre-Madrid Central values. ANOVA values indicate that the differences are statistically significant. The box plots in Fig. 3 present the comparison of the NO_2 concentration per day, between pre-Madrid Central values and post-Madrid Central values.

Table 1: Summary of the NO_2 concentration (in $\mu g/m^3$) sensed in the center of Madrid. Negative values of Δ indicate a reduction of NO_2 concentration

weekday	*Pre-Madrid Central*				*Post-Madrid Central*				Δ	*ANOVA*	
	min	*median*	*IQR*	*max*	*min*	*median*	*IQR*	*max*		F-value	p-value
Monday	9.0	41.0	27.0	149.0	2.0	35.0	35.0	147.0	-2.96	8.5	4×10^{-3}
Tuesday	10.0	44.0	31.0	134.0	2.0	33.0	33.0	128.0	-8.49	70.8	$<10^{-3}$
Wednesday	12.0	43.0	32.0	185.0	2.0	31.0	34.0	123.0	-9.45	87.5	$<10^{-3}$
Thursday	10.0	43.0	32.0	138.0	1.0	31.0	34.0	131.0	-9.24	72.9	$<10^{-3}$
Friday	9.0	46.0	32.0	125.0	1.0	33.0	34.0	139.0	-9.68	95.6	$<10^{-3}$
Saturday	9.0	36.5	23.0	132.0	1.0	30.0	32.0	122.0	-4.99	34.4	$<10^{-3}$
Sunday	10.0	34.0	21.0	120.0	1.0	23.0	26.0	117.0	-6.63	50.9	$<10^{-3}$

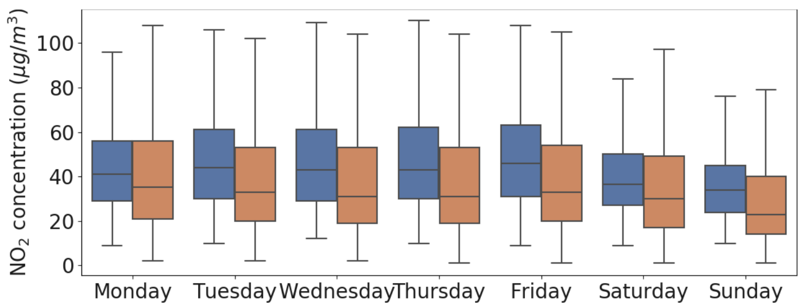

Fig. 3: NO_2 concentration for each day of the week: ■ pre-Madrid Central, ■ post-Madrid Central.

Differences between pre- and post-Madrid Central NO_2 concentration values seem to be significant, but the simple analysis of median values does not account for other effects that can be considered to model NO_2 pollution. Thus, the proposed approach applies computational intelligence methods to learn and predict the corresponding time series. The main results are reported next.

Polynomial regression results. Fig. 4 graphically presents the training data (red dots) and the polynomial used for approximation. The graphics shows that the quadratic model provides a better approximation than linear and the degree 10 polynomial for pre-Madrid Central observations. In turn, the degree 10 polynomial is the best method to predict values for the post-Madrid Central period. Results are confirmed by the MSE and MAE values reported in Table 2. For the pre-Madrid Central period, the quadratic polynomial improves 2.6% over the linear regression method, and 2.6% over the degree 10 polynomial, regarding the MSE metric. For the post-Madrid Central period, the degree 10 polynomial improves 20.9% over the linear regression method, and 1,8% over the quadratic polynomial, regarding the MSE metric.

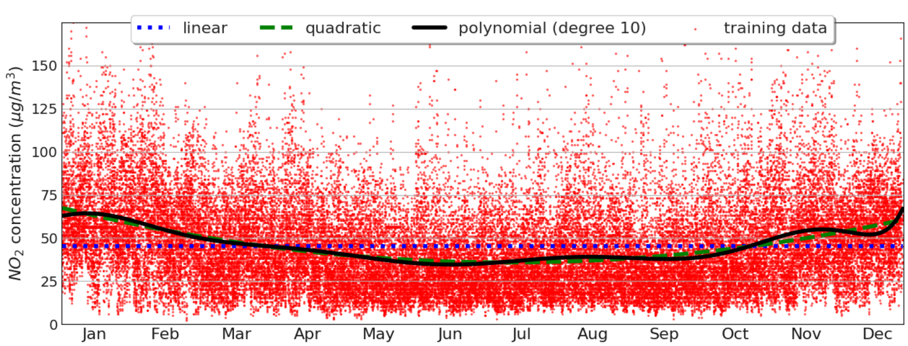

Fig. 4: Polynomial regression fitting

Table 2: Polynomial regression fitting results

fitting method	*pre-Madrid Central*			*post-Madrid Central*		
	MSE	MAE	↑*real*	*MSE*	MAE	↑ *real*
linear	426.07	16.74	0.58	633.75	21.43	0.68
quadratic	414.77	16.06	0.55	510.42	18.83	0.69
polynomial (degree 10)	423.76	16.21	0.54	501.40	18.63	0.68

RNN results. Table 3 reports the main results of the RNN accuracy analysis, regarding the two studied metrics (MSE and MAE). Minimum (*min*), median, IQR, and maximum (*max*) values of both metrics are reported, since the Shaphiro-Wilks confirmed that results do not follow a normal distribution. Results indicate that the proposed LSTM RNN is able to accurate approximate the time series of NO_2 concentration. Relative values of MAE were lower than 0.2 (in median) and lower than 0.06 (in maximum). MSE values were significantly lower than those computed with polynomial regression. Vales of ↑real indicate that for post-Madrid Central period, the RNN predicted values over the real measurement in 62% of the observations, accounting for a real reduction on NO_2 concentration in that period. Results are statistically significant, according to the reported p-values of the Wilcoxon test (p-values $<10^{-7}$).

Table 3: Results of the RNN accuracy analysis

metric	*Pre-Madrid Central*				*Post-Madrid Central*				*Wilcoxon*
	min	*median*	*IQR*	*max*	*min*	*median*	*IQR*	*max*	p-value
MSE	153.56	160.33	4.40	169.69	153.91	161.79	5.10	169.62	$<10^{-4}$
MAE	9.64	9.89	0.19	10.28	9.59	9.91	0.26	10.20	2×10^{-2}
↑*real*	0.55	0.56	0.01	0.57	0.60	0.62	0.01	0.64	$<10^{-4}$

Global discussion. As expected, the RNN provided more accurate predictions than the ones using polynomial regression, accounting for lower MSE and MAE metrics. RNN allows capturing the complex relationships and periodicity on the time series data. For the post-Madrid Central period, MSE and MAE values reduced up to 0.25 of those of linear regression and up to 0.31 of those of quadratic and degree 10 polynomials. Furthermore, all methods predicted a majority of observations *over* the real values, and the difference was statistically significant. Thus, results reported in the previous subsection allows concluding that the Madrid Central initiative has certainly reduced concentrations of the NO_2 pollutant in the city,

5 Conclusions and future work

This article presented an approach applying data analysis and computational intelligence techniques for evaluating the air quality in the center on Madrid, Spain. Air quality and pollution are relevant problems in the context of smart cities, and a reliable diagnosis is key to address such challenges.

Polynomial regression and deep learning methods were applied to analyze the time series of NO_2 concentration, in order to evaluate the effectiveness of car restriction policies instrumented in the Madrid Central initiative. Real data was processed, obtained from a sensor installed in the studied area. The accuracy of the proposed method was evaluated applying standard metrics for prediction. Results indicated that RNN accounted for accurate predictions for both pre-Madrid Central and post-Madrid Central scenarios. MSE and MAE values were significantly better that polynomial regression.

According to the reported results, Madrid Central was able to significantly reduce NO_2 concentration, thus effectively improving air quality. This a very positive result, with direct implications on the health of citizens, which is confirmed by the learning approach presented in this article.

The main lines for future work include extending the analysis to nearby zones in the city, performing a multivariate analysis by taking into account related data (e.g., wind speed, temperature, etc.); and evaluating the impact on other relevant indicators (e.g., economical impact, mobility behaviour, citizens' health, etc.) The proposed approach can be applied to other scenarios too.

Acknowledgements I. Lebrusán has been partially funded by RCC Harvard program. J. Toutouh has been partially funded by EU Horizon 2020 research and innovation programme (Marie Skłodowska-Curie grant agreement No 799078) and by the Spanish MINECO and FEDER projects TIN2017-88213-R and UMA18-FEDERJA-003. The work of S. Nesmachnow is partly funded by ANII and PEDECIBA, Uruguay. Authors acknowledge Spanish Ministerio de Economía, Industria y Competitividad and ERDF for the support provided under contract RTI2018-100754-B-I00 (iSUN project).

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