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Transportation Research Procedia 58 (2021) 591–598

Transportation Research Procedia

www.elsevier.com/locate/procedia

14th Conference on Transport Engineering: 6th – 8th July 2021

Comparison of maritime transport influence of SO_2 levels in Algeciras and Alcornocales Park (Spain)

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Abstract

The main aim of this work was to measure the influence of the volume of shipping over the Sulphur dioxide (SO_2) concentration in the air pollution in two monitoring stations located at Algeciras city and Alcornocales Park developing the same analysis in these two locations. The target is to demonstrate the assumption that Algeciras is more affected by SO_2 than Alcornocales Park which is 30 km far away from Algeciras Port. A multiple regression approach has been applied using wind data: wind direction (degrees) and wind speed (km/h) recorded in two weather stations, together with the volume of the gross tonnage per hour (GT/h) of vessels in the Bay of Algeciras to estimate SO_2 concentration values in the two stations Algeciras and Alcornocales. The database contains records of hourly samples of these variables during the year 2019. Different artificial neural networks (ANNs) models were compared and the results showed that SO_2 in Algeciras station could be better explained than the same pollutant in Alcornocales station. On the other hand, ANNs produced better results than linear models which means that nonlinear models fit best the data. A cross-validation procedure has been applied in order to assure the generalisation capabilities of the tested models. The results showed that in Algeciras a more reliable estimation could be done reaching a correlation estimation between the model and the target (real) values of SO_2. This fact highlights the major influence of maritime transport in the Bay of Algeciras.

Keywords: SO_2 forecasting; Sustainability; Air Pollution; ANNs; Shipping emissions; Port-city.

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2352-1465
10.1016/j.trpro.2021.11.078

1. Introduction

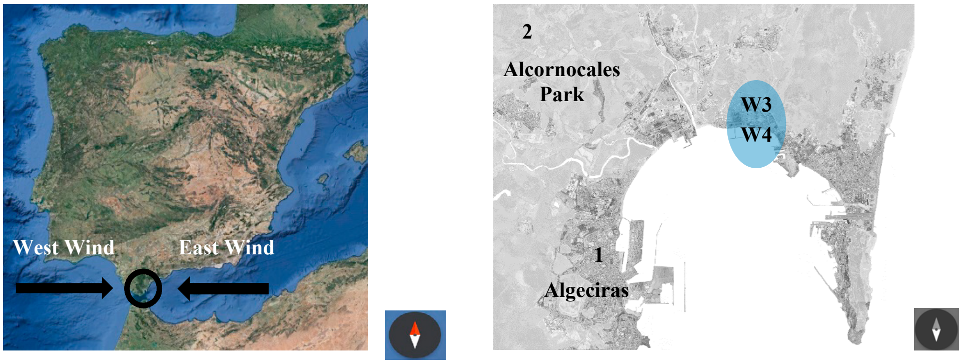
The importance of cities outdoors in pandemic times has increased substantially since people are doing their lives in streets, parks, and common zones. It is now when the air surrounding cities becomes essential to develop secure sports activities and their daily lives. This is what motivates this study, in order to gain knowledge about how ports can affect towns in a pollution scenery. The highly populated Bay of Algeciras is a big exchange site of winds and has a low offer of public transport that makes this zone full of constant private traffic, connected with chemical, steelmaking industries and Gibraltar airport, decreasing the air quality. The Port of Algeciras is one of the most important container freight in Europe, which is a hub of economic activity with road traffic moving goods to the rest of Spain. Maritime traffic has experienced a massive increase in Europe and the whole Globe. Therefore, the appearance of particulate matter is higher in port zones (González et al., 2011, Viana et al., 2014) often motivated by the ineffective maintenance of vessel engines that makes them unnecessarily consume and waste more fuel (Moreno-Gutiérrez et al., 2015). High rates of the total ships' emissions can be dispersed to 400 km inland (González et al., 2011). Worldwide estimations suggest that vessels are responsible for 15% of NO_x and 8% of SO_2 emissions all around the Globe, involving 20-28% of the total emitted gases in the transport sector (Corbett et al., 2007). Besides, other estimations calculated that vessels produce 3% of the total human greenhouse gases, double of aviation (IMO). Not only do navigating ships discharge fumes to the atmosphere but also docked vessels, which can be considerably reduced by switching to lower-sulphur fuel in the ECAs (Emission Control Areas) (Wan et al., 2019). Some pieces of research estimated that 172,000 vessels consumed during voyages about 47 million metric tons of heavy fuel oil and emitted about 2.4 million metric tons of SO_2 (Wang et al., 2007). While berthing only the auxiliary engine (AE) is functioning to generate electricity onboard what produces lower emissions than cruising (Moreno-Gutiérrez et al., 2015). Lee et al., (2020) estimated other emissions from several types of ships (general cargo, cruise, container, and tankers vessels) facing the docking process. Calculations in SO_x emissions in the Strait of Gibraltar went from 8.20 ton/km^2/year in 2007 (Moreno-Gutiérrez et al., 2015) to 11.60 ton/km^2/year in 2017 (Nunes et al., 2020). Several studies present an overview of air quality in Europe and port cities (Wagner 2019). Others, the relationship between transport-related air pollutant concentrations to integrate new models for sustainable mobility of vehicles (Catalano, et al., 2016) and the usage of different methods to predict peaks of pollution in critical meteorological situations, particularly in the Bay of Algeciras (Muñoz et al., 2014). Due to huge vessels with engines running on heavy fuel oil (2,700 times higher than road fuel), the shipping emissions are tackled in many manuscripts (Corbett et al., 2007; Liu, et al., 2014; Puig, et al., 2020); Moreno-Gutiérrez and Durán-Grados (2021)). Sanchez et al., (2020) detailed methods to reduce traffic emissions and to implement policy interventions in cities. In terms of meteorological events that affect pollution, winds seem to be important. Meteorology contribution to pollution events together with forecasting models are faced by Muñoz et al., (2014); Gonzalez-Enrique et al., (2019b); Vellalassery et al., (2021). The evolution of the interaction between ports and cities is shown in Hesse (2013) adapted from Hoyle (1988). In this work, the best estimation model of SO_2 concentrations in Algeciras and Alcornocales Park is achieved using historical data resolving an input-output fitting problem with feedforward ANNs. Linear regression models are applied and compared as a benchmark. The rest of this manuscript is organised as follows. Sect. 2 describes the study case, the database and the methodology. Sect. 3 presents the experimental procedure and the different tested approaches. Sect. 4 discusses the obtained results, and finally, Sect. 5 states the main conclusions.

2. Materials and Methods

The Bay of Algeciras is located in the South of Spain (Fig. 1). The strategic position of the port is due to the specific orographic location of the Bay. The two main directions of wind, East winds (Levante) and West winds (Poniente), are recorded in weather stations (W_{3-4}) (see Table 1). These peculiar ways in which the wind blows are due to the Venturi effect in the Bay. Pollutant monitoring stations where SO_2 concentration data are collected, Algeciras and Alcornocales Park are described in Table 1. Alcornocales Park was chosen because it is a remote unspoilt green area where, theoretically, pollution does affect less.

2.1. Materials

Andalusian Government and Algeciras Bay Port Authority (APBA) have provided to the University of Cádiz the recorded values of SO_2 concentration, wind, and GT (Gross-tonnage) of vessels. The database was recorded hourly for SO_2 concentration (µg/m^3), and weather variables: wind speed (km/h) and wind direction (degrees) (Table 1).



(a) (b)

Fig. 1. (a) Bay of Algeciras location and its frequent winds; (b) Listed monitoring stations (air pollution 1- 2, and meteorological W_{3-4}).

Then, a new data imputation procedure was performed to complete the missing values. Here, missing data values have been included using a data imputation algorithm considering the measured values in other monitoring stations close to each station, following a proceeding previously used in other works by authors (Turias et al., (2006), Turias et al., (2008), Moscoso-López et al., (2016), González-Enrique et al., (2019a), Ruiz-Aguilar et al., (2020)).

Table 1. Variables of the study and stations. SO_2 (µg/m^3) monitoring stations (1-2) and Weather stations (W_{3-4}).

Code	Variables	Measurement	Station /	code	Latitude	Longitude
Output1	SO_2	µg/m^3	Algeciras (EPSA)	1	36º8'11.7" N	5º27'11.44" W
Output2	SO_2	µg/m^3	Alcornocales	2	36º13'35" N	5º31'11.44" W
Input1	Vessels	GT/h	-			
Input2	WS (Wind speed)	Km/h	Cepsa (60 m)	W_3	36º11'37.66" N	5º24'1.24" W
Input3	WS (Wind speed)	Km/h	Cepsa (15 m)	W_4	36º10'54.7" N	5º25'43.42" W
Inpu4	WD (Wind direction)	Degrees	Cepsa (60 m)	W_3	36º11'37.66" N	5º24'1.24" W
Input5	WD (Wind direction)	Degrees	Cepsa (15 m)	W_4	36º10'54.7" N	5º25'43.42" W

Figure 2 shows SO_2 concentration time-series both in Algeciras and Alcornocales Park. Figure 3 shows the wind rose representation of the W_3 station (Cepsa at 60 m high) and the wind rose of the W_4 station (Cepsa at 15 m high). The vessel database provided by APBA contains a register for each vessel in the Bay in 2019 (with corresponding timestamps of arrival and departure). The database was transformed into a GT/h (Gross-tons per hour) computing the number of vessels in an hour and the total of tons of those registered ships.

2.2. Methods

ANNs have been tested in this work together with the use of vessel and wind information in order to predict SO_2 concentrations. ANNs require no prior assumptions about the model in terms of mathematical relationships or data distribution. Feedforward ANNs based on a backpropagation learning rule have been used (Rumelhart et al., (1986)). The output was the hourly SO_2 concentrations, and the inputs were the gross tons of vessels summed each hour in the Bay of Algeciras, and the wind speed and wind direction in a certain timestamp. Furthermore, different models were built, some of them using only the pollutant information and the rest considering exogenous variables (ton-vessel and wind information). The purpose of this modelling approach is to establish a quantitative relationship between a group of predictor variables, X, and a response Y (predicted SO_2 concentration). ANNs have found many applications on air pollution (Nunnari at al., (1998); Gardner et al., (1999); Balaguer, et al., (2002); Perez et al., (2001); Viotti et al., (2002); Kukkonen et al., (2003); Turias et al., (2006); Turias et al., (2008); González-Enrique et al., (2019a)). For feedforward ANNs, a pattern is formed by inputs together with the pollutant concentration to be forecasted, named real or desired output. There is no way to determine the optimum although Hornik et al., (1989) show the capabilities of backpropagation feedforward networks. An experimental procedure has been used to determine the best ANN configuration. A standard Multiple Linear Regression (MLR) model has been used as a benchmark in this study.

3. Experimental procedure

A procedure of resampling simulation was designed to select the model with the best generalization capabilities. First of all, data were selected to create and train the network. Then its performance was evaluated using mean square error and regression analysis. A feedforward ANN with sigmoid hidden neurons and linear output neurons can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. Authors have successfully used similar procedures in other problems (Moscoso-López et al., (2016); Gonzalez-Enrique et al., (2019b); Ruiz-Aguilar et al., (2020)). Besides, in this problem, the best ANN model using 1000 replications was chosen. ANNs were trained with the Levenberg-Marquardt backpropagation algorithm. Finally, the obtained results were statistically analysed and compared in order to select the model with the best generalisation capabilities. ANN models with different hidden units were compared to determine the effect of the addition of non-linear processing capabilities on model performance. The resampling procedure was found to reduce test set prediction error and to mitigate the effects of overfitting. The strategy split randomly the database into three portions (training 70%, validation 15%, and test 15% sets) and the performance results were collected only for the test set in order to estimate the generalization error of each model using unseen data as authors has successfully implemented in other works (Viotti et al., (2002); Turias et al., (2003); Turias et al., (2008); Moscoso-López et al., (2016); González-Enrique et al., (2019a); Ruiz-Aguilar et al., (2020)). In fitting problems, a neural network is needed to map between a data set of numeric inputs and a set of numeric targets. In this manuscript, an input-output fitting problem with feedforward ANN was used to solve the experimental procedure to estimate predictions in Algeciras and Alcornocales stations and to calculate how the effect of wind and vessels affect both stations. Table 2 shows the different tested approaches.

Table 2. List of the tested approaches in the experimental procedure and their models.

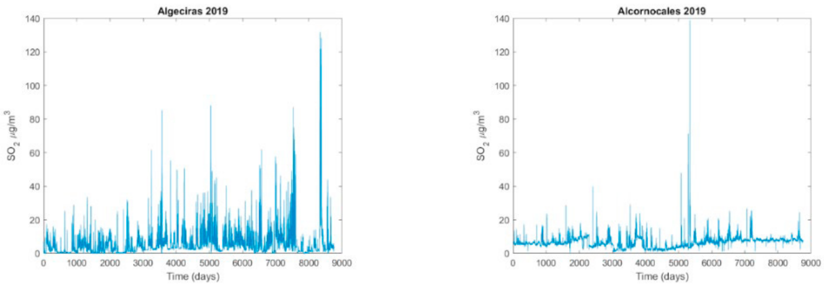
Approach	Input variables	Wind direction	Models
1	Vessels	Levante (East Wind)	$\widehat{SO_2}(t) = f(vessels(t))$
2	Vessels	Poniente (West Wind)	
3	Vessels, WS,WD	Levante (East Wind)	$\widehat{SO_2}(t) = f(vessels(t), wind\ direction(t), wind\ speed(t))$
4	Vessels, WS,WD	Poniente (West Wind)	

The models have been subdivided into two submodels: the first one for wind patterns of “Levante” (East wind) and the second one for wind patterns of “Poniente” (West wind). Fig. 3 shows the wind roses where these two main wind scenarios are highlighted.

4. Results and discussion

The experiment was developed in the two monitoring stations (outputs) (Table 1) and four approaches were conducted (Table 2). The Bay of Algeciras supports a large variability of SO_2 concentrations in Algeciras with higher concentration values than Alcornocales Park (Fig. 2). The simulations were run in MATLAB environment. A complete experiment using shallow ANNs was developed to prove the efficiency and reliability of SO_2 concentration estimation as a function of the total vessel gross-tons per hour (GT/h). Levenberg-Marquardt was used as optimization algorithm and early stopping to avoid overfitting. Figure 2 shows a considerably higher number of concentration peaks of SO_2

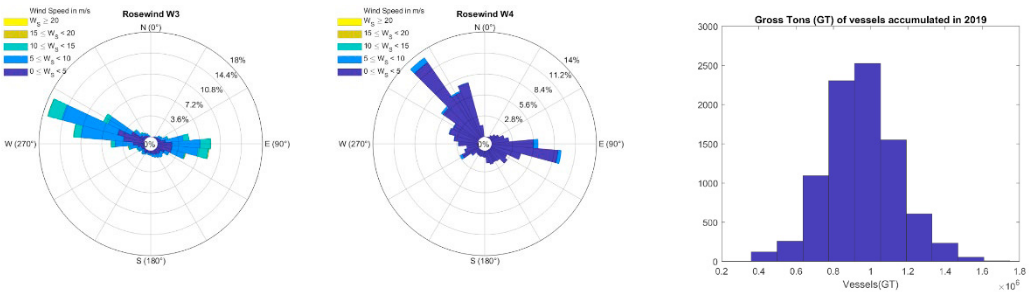
pollutant in Algeciras than in Alcornocales Park monitoring station, also these values in Algeciras station fluctuate considerably more and in Alcornocales Park the values are significantly more stable. Characteristic winds in the Bay of Algeciras are drawn in the wind roses in Fig. 3(a)(b). Both clearly show pure East winds 90º (Levante) and pure West winds 270º (Poniente), although in the Bay the West encompasses an angular range of 270º ± 30º approximately. Most of the winds are normally lower than 54 km/h (15 m/s) and only a few episodes a year are higher than 70 km/h (20 m/s). Figure 3(c) shows the histogram of the 2019 vessel database provided by APBA. This data contains the timestamps of arrival and departure for each vessel in the Bay in 2019. In order to check if this data leverage SO_2 concentrations, the vessel database was transformed into a GT/h (Gross-tons per hour) calculating the number of vessels in an hour and the total of tons of those registered ships.



(a) (b)

Fig. 2. Hourly SO_2 data in 2019 (a) Algeciras (mean,std) = (5.8168, 8.5573); (b) Alcornocales Park (mean,std) = (6.7610, 3.6223).

The most frequent data is about 1E+06 GT/h, producing emissions that can affect a certain area of influence. In Table 3 the results of both models for every approach are exhibited. The highest regression coefficient (r = 0.4499) using the linear model is obtained in Algeciras for approach 4 (vessels + West wind) compared to r = 0.2432 in Alcornocales, which indicates a better explanation of the linear model in Algeciras. Analysing Table 3 it is observed that if we consider only the vessels as input, approaches 1 and 2, the model seems to show more leverage in Alcornocales in the case of East wind conditions. In the case of Algeciras, the linear model produces better results when Poniente conditions are registered. This fact could be explained due to in these specific conditions the SO_2 concentration values show lower values in Algeciras and they are easier to model linearly.



(a) (b) (c)

Fig. 3. (a) Wind roses year 2019 (a) station W_3 at 60 m high; (b) station W_4 at 15 m high; (c) hourly vessel data 2019 in Gross-tons recorded in the port of Algeciras.

Approaches 3 and 4 get better results than approaches 1 and 2, which means a poor linear relation and that input variables affect more strongly if interactions are considered. In the case of Alcornocales, better estimation results were obtained in Levante conditions, and the case of Algeciras, the best estimation model was found in Poniente conditions. The highest result is obtained in Algeciras with 20 hidden neurons (r = 0.7810) compared to the highest coefficient (r

= 0.6356) in Alcornocales with only 1 hidden neuron. ANNs models work better in general when non-linear behaviour exists and this fact is observed in the obtained results. Besides, better results were obtained when wind variables are also used. Furthermore, a differentiation between Poniente and Levante models improves the obtained results as we can see in Table 3.

Table 3. Highest comparison r results in Alcornocales Park and Algeciras station for both methods (MLR and ANNs)

Station	Approach	r (MLR model)	r (ANNs model)				
			1	5	10	20	50
Alcornocales Park (W_3)	1	0.0853	0.3693	**0.3951**	0.3781	0.3744	0.3594
	2	0.1727	0.4183	0.4264	0.4457	**0.4549**	0.4472
	3	**0.2432**	**0.6356**	0.5665	0.6062	0.5608	0.5878
	4	0.0854	0.4835	0.4968	**0.5552**	0.4646	0.5420
Algeciras (W_4)	1	0.1229	0.4272	0.4559	0.4301	0.4607	**0.5012**
	2	0.0583	0.3179	0.3167	0.3021	0.4122	**0.4259**
	3	0.2596	**0.5740**	0.5567	0.5508	0.5623	0.4978
	4	**0.4499**	0.7287	0.7586	0.6965	**0.7810**	0.7055

Figures 4-7 show the training examples in order to analyse how in each case, different conditions appeared. Besides, data after applying normalisation is shown. The training examples of SO_2 are shown in green evidencing Poniente and Levante events in both monitoring stations, Algeciras and Alcornocales Park. In general, West winds (Poniente) produce lower SO_2 situations and the reverse occurs with East winds (Levante). In both stations, Poniente models produce a better fitting in training data for SO_2 (green crosses) than in East wind due to the fluctuating nature of the SO_2 time-series in Levante conditions. Generally, in Poniente conditions, SO_2 data are more stable.

5. Conclusions

The SO_2 database is better suited to ANNs, non-linear models, as we can see from the results in Table 3, going from 0.7810 with 20 hidden neurons to 0.4499 in linear models in Algeciras. Although East winds are supposed to fit better the data in Algeciras, the results show that West winds produce a better fitting training data for SO_2 due to the stability of SO_2 data in Poniente conditions. Once the study is developed, several conclusions can be extracted: i) ANNs models deeply improve results of MLR revealing a strong non-linear behaviour, and ii) The usage of separated models for the two dominant winds (Poniente and Levante events) also enhances the results of an individual model. Future researches will focus on the usage of non-supervised clustering algorithms such as Kohonen's self-organising (SOMs) maps to produce patterns to which separate models can be applied and also deep learning approaches. The analysis presents promising results to be used afterward in SO_2 forecasting models together with historical data of the time-series of SO_2. In this research, the SO_2 data were only used as outputs. Therefore, using a wind separation stage (Levante and Poniente), a robust estimation was developed and the obtained results have allowed us to confirm that this approach can serve as a support decision tool to citizens and/or institutions.

Acknowledgements

This work is part of the research project RTI2018-098160-B-I00 supported by 'MICINN' Programa Estatal de I+D+i Orientada a 'Los Retos de la Sociedad'. Data used in this work have been kindly provided by the Algeciras Port Authority and the Andalusian Regional Government.

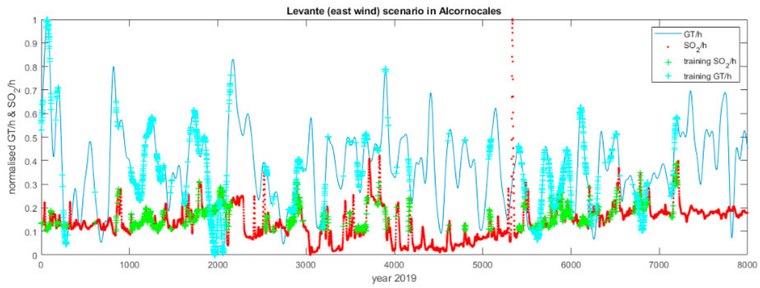


Figure 4 – Levante scenario in Alcornocales Park in the year 2019 (W_3)

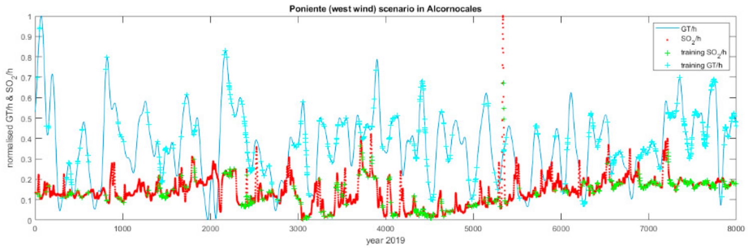


Figure 5 – Poniente scenario in Alcornocales Park in the year 2019 (W_3)

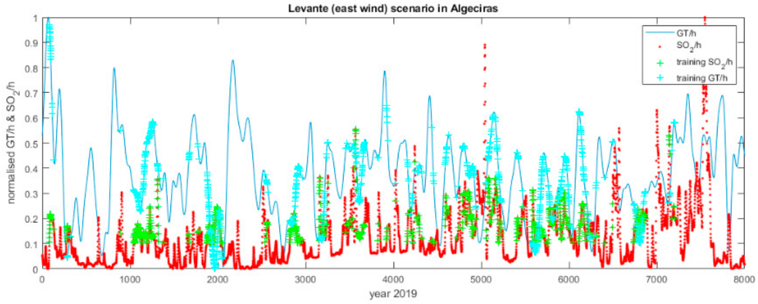


Figure 6 – Levante scenario in Algeciras city in the year 2019 (W_4)

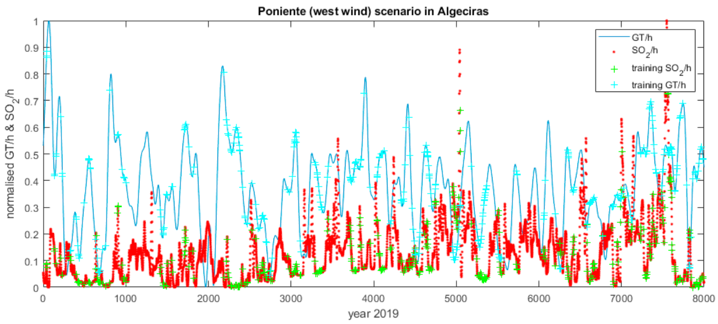


Figure 7 – Poniente scenario in Algeciras city in the year 2019 (W_4)

References

Balaguer Ballester, E., Camps I Valls, G., Carrasco-Rodriguez, J.L., Soria Olivas, E., Del Valle-Tascon, S. (2002). Effective 1-day ahead prediction of hourly surface ozone concentrations in eastern Spain using linear models and neural networks. Ecological Modelling, 156(1), 27-41.

Bishop C.M. (1995). Neural Networks for Pattern Recognition. Oxford University Press, 1995.

Corbett, J.J., Winebrake, J.J., Green, E.H., Kasibhatla, P., Eyring, V., Lauer, A. (2007). Mortality from ship emissions: A global assessment. Environmental Science and Technology, 41(24), 8512-8518.

Catalano, M., Galatioto, F., Bell, M., Namdeo, A., Bergantino, A.S. (2016). Improving the prediction of air pollution peak episodes generated by urban transport networks. Environmental Science and Policy, 60(), 69-83.

Gardner M.W., Dorling S.R. (1999). Neural network modelling and prediction of hourly NOx and NO2 concentrations in urban air in London. Atmospheric Environment, 33, 709-719.

González, Y., Rodríguez, S., Guerra García, J.C., Trujillo, J.L., García, R. (2011). Ultrafine particles pollution in urban coastal air due to ship emissions. Atmospheric Environment, 45(28), 4907-4914.

Gonzalez-Enrique, J., Turias, I.J., Ruiz-Aguilar, J.J., Moscoso-Lopez, J.A., Jerez-Aragones, J., Franco, L. (2019a). Estimation of NO2 concentration values in a monitoring sensor network using a fusion approach. Fresenius Environmental Bulletin, 28(2), 681-686.

Gonzalez-Enrique, J., Turias, I.J., Ruiz-Aguilar, J.J., Moscoso-Lopez, J.A., Franco, L. (2019b). Spatial and meteorological relevance in NO2 estimations: a case study in the Bay of Algeciras (Spain). Stochastic Environmental Research and Risk Assessment, 33(3), 801-815.

Hesse, M. (2013). Cities and flows: Re-asserting a relationship as fundamental as it is delicate. Journal of Transport Geography, 29(), 33-42.

Hornik, K., Stinchcombe, M., White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks, 2(5), 359-366.

Hoyle, B.S. (1988). Transport and Development in Tropical Africa (Case Studies in the Developing World). John Murray, London.

Kukkonen, J., Partanen, L., Karppinen, A., Ruuskanen, J., Junninen, H., Kolehmainen, M., Niska, H., Dorling, S., Chatterton, T., Foxall, R., Cawley, G. (2003). Extensive evaluation of neural networks models for the prediction of NO_2 and PM_{10} concentrations, compared with a deterministic modelling system and measurements in central Helsinki. Atmospheric Environment, 37, 4539-4550.

Liu, T.-K., Sheu, H.-Y., Tsai, J.-Y. (2014). Sulfur dioxide emission estimates from merchant vessels in a Port area and related control strategies. Aerosol and Air Quality Research, 14(1), 413-421.

Moreno-Gutiérrez, J., Calderay, F., Saborido, N., Boile, M., Rodríguez, R., Durán-Grados, V. (2015). Methodologies for estimating shipping emissions and energy consumption: A comparative analysis of current methods. Energy, 86(), 603-616.

Moreno-Gutiérrez, J., Durán-Grados, V. (2021). Calculating ships' real emissions of pollutants and greenhouse gases: Towards zero uncertainties. Science of the Total Environment, 750().

Moscoso-López, J.A., Turias, I.J.T., Jimenez, M.J., Ruiz-Aguilar, J.J., Cerbán, M. (2016). Short-term Forecasting of Intermodal Freight Using ANNs and SVR: Case of the Port of Algeciras Bay. Transportation Research Procedia, 18(), 108-114.

Muñoz, E. and Martín, M.L. and Turias, I.J., Jimenez, M.J., Trujillo, F.J. (2014). Prediction of PM_{10} and SO_2 exceedances to control air pollution in the Bay of Algeciras, Spain. Stochastic Environmental Research and Risk Assessment, 28(6), 1409-1420.

Nunnari, G., Nucifora, A.F.M., Randieri, C., (1998). The application of neural techniques to the modelling of time-series of atmospheric pollution data. Ecological Modelling, 111, 187-205.

Nunes, R.A.O., Alvim-Ferraz, M.C.M., Martins, F.G., Calderay-Cayetano, F., Durán-Grados, V., Moreno-Gutiérrez, J., Jalkanen, J.-P., Hannuniemi, H., Sousa, S.I.V. (2020). Shipping emissions in the Iberian Peninsula and the impacts on air quality. Atmospheric Chemistry and Physics, 20(15), 9473-9489.

Perez, P. (2001). Prediction of sulphur dioxide concentrations at a site near downtown Santiago, Chile. Atmospheric Environment, 35, 4929-4935.

Pizarro, J., Guerrero, E., Galindo, P. (2000). A statistical model selection strategy applied to neural networks. Proceedings of the 9th European Symposium on Artificial Neural Networks, 55-60.

Pizarro J, Guerrero E, Galindo, P. (2002) Multiple comparison procedures applied to model selection. Neurocomputing, (48), 55-173.

Puig, M., Raptis, S., Wooldridge, C., Darbra, R.M. (2020). Performance trends of environmental management in European ports. Marine Pollution Bulletin, 160.

Ruiz-Aguilar, J.J., Turias, I., González-Enrique, J., Urda, D., Elizondo, D. (2020). A permutation entropy-based EMD–ANN forecasting ensemble approach for wind speed prediction. Neural Computing and Applications, 33, 2369-2391.

Rumelhart, D.E., Hinton, G.E., Williams, R.J. (1986). Learning internal representation by error propagation. Parallel distributed processing: explorations in the microstructures of cognition, vol. 1. Cambridge, MA: MIT Press.

Sanchez, K.A., Foster, M., Nieuwenhuijsen, M.J., May, A.D., Ramani, T., Zietsman, J., Khreis, H. (2020). Urban policy interventions to reduce traffic emissions and traffic-related air pollution: Protocol for a systematic evidence map. Environment International, 142.

Turias, I.J., González, F.J., Martín, M.L., Galindo, P.L. (2006). A competitive neural network approach for meteorological situation clustering. Atmospheric Environment, 40(3), 532-541.

Turias, I.J., González, F.J., Martin, M.L., Galindo, P.L. (2008). Prediction models of CO, SPM and SO_2 concentrations in the Campo de Gibraltar Region, Spain: A multiple comparison strategy. Environmental Monitoring and Assessment, 143(1 – 3), 131-146.

Vellalassery, A., Pillai, D., Marshall, J., Gerbig, C., Buchwitz, M., Schneising, O., Ravi, A. (2021). Using TROPOspheric Monitoring Instrument (TROPOMI) measurements and Weather Research and Forecasting (WRF) CO modelling to understand the contribution of meteorology and emissions to an extreme air pollution event in India. Atmospheric Chemistry and Physics, 21(7), 5393-5414.

Viana, M., Hammingh, P., Colette, A., Querol, X., Degraeuwe, B., de Vlieger, I., Van Aardenne, J. (2014). Impact of maritime transport emissions on coastal air quality in Europe. Atmospheric Environment, 90(), 96-105.

Viotti, P., Liuti, G., Di Genova, P. (2002). Atmospheric urban pollution: applications of an artificial neural network (ANN) to the city of Perugia. Ecological modelling, 148, 27-46.

Wagner, N. (2019). Sustainability in port cities - A bibliometric approach. Transportation Research Procedia, 39(), 587-596.

Wan, Z., Zhang, Q., Xu, Z., Chen, J., Wang, Q. (2019). Impact of emission control areas on atmospheric pollutant emissions from major ocean-going ships entering the Shanghai Port, China. Marine Pollution Bulletin, 142, 525-532.

Wang, C., Corbett, J.J., Firestone, J. (2007). Modeling energy use and emissions from North American shipping: Application of the ship traffic, energy, and environment model. Environmental Science and Technology, 41(9), 3226-3232.