Air pollution in European countries and life expectancy—modelling with the use of neural network

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Abstract

The present paper discusses a novel methodology based on neural network to determine air pollutants' correlation with life expectancy in European countries. The models were developed using historical data from the period 1992–2016, for a set of 20 European countries. The subject of the analysis included the input variables of the following air pollutants: sulphur oxides, nitrogen oxides, carbon monoxide, particulate matters, polycyclic aromatic hydrocarbons and non-methane volatile organic compounds. Our main findings indicate that all the variables significantly affect life expectancy. Sensitivity of constructed neural networks to pollutants proved to be particularly important in the case of changes in the value of particulate matters, sulphur oxides and non-methane volatile organic compounds. The most frequent association was found for fine particle. Modelled courses of changes in the variable under study coincide with the actual data, which confirms that the proposed models generalize acquired knowledge well.

Keywords Air pollution · Life expectancy · Public health · Artificial neural network · Modelling · Multi-layer perceptron

Introduction

Air pollution is a very important environmental factor. In order to take effective actions aimed at reducing the impact of air pollution on people, ecosystems and climate, it is necessary to understand the causes of its formation, transportation and transformation in the atmosphere ([European Environment Agency](#)). Pollutants such as particulate matters (PM₁₀, PM_{2.5}), sulphur dioxide (SO₂), volatile organic compound (VOC), carbon monoxide (CO) and nitrogen oxides (NO_x) are mainly released from gasoline used in diesel-run vehicles, industrial plants and heating processes due to anthropogenic activities (Ashraf et al. 2019). For individual people, the possibility to avoid exposure to air pollutants is very limited; therefore, actions must be taken by the national, regional and

international public authorities. To reduce the impact of air pollution on human health, it is necessary to develop long-term policies involving multiple sectors, such as transport, housing, energy production and industry ([World Health Organization WHO](#)). Air pollution is responsible for many diseases affecting the heart, skin, eyes and other organs, and exposure to smog is the cause of various inflammatory responses. Therefore, it is of vital importance to use ambient air quality measurements in order to get an insight into the air quality of a given region (Cacciotolo et al. 2017).

Even short-term exposure to air pollution affects health. In studies carried out in Europe and worldwide, a link has been documented between the level of air pollution with particulates and gases and the state of health, measured in the form of deaths and/or hospitalizations (Alessandrini et al. 2016; Fann et al. 2019; Li et al. 2016; Samoli et al. 2013; [World Health Organization](#)).

Emissions of many air pollutants in Europe have decreased significantly over the last decades, which has contributed to the improvement of air quality ([European Economic Area EEA](#)). Much progress has been made in tackling air pollutants such as SO₂, CO, lead (Pb), and benzene (C₆H₆). On the other hand, road transport, industry, power plants, households and agricultural activities continue to emit significant amounts of air pollutants (Guerreiro et al. 2014). Consequently, concentrations of air pollutants are still too high and problems with air quality

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persist. A significant part of the European population lives in areas where air-quality standards are constantly exceeded (Fig. 1).

Although targeted policies and technological advancement have brought about positive changes in European air quality over the last decade, between 2014 and 2016, the concentration of certain air pollutants in many European cities was still above EU limit or target values. In relation to the WHO guidelines established for the protection of human health, the numbers of people exposed were even higher (Fig. 1, EEA).

Air pollution continues to have a significant impact on the health of the European population, particularly in urban areas. Several sectors failed to limit emissions significantly enough to meet air-quality standards (European Environment Agency EEA). Emission levels of certain pollutants have even increased. For example, the levels of NO_x emissions from road transport in many urban areas still exceed air-quality standards. Coal and biomass combustion in households and from commercial and institutional building is still the main culprit of PM and benzo(a)pyrene (BaP) emissions in the EU, and attempts at their reduction have brought no success (EEA). Concentrations of PM continued to exceed the EU limit and target values in large parts of Europe in 2014 (EEA). Several economies with particularly high levels of atmospheric emissions stand out among European countries (Fig. 2).

To fully meet EU air-quality standards set for the protection of human health and natural environment, it is necessary to undertake efforts aimed at limiting emissions of air pollutants. All countries should follow European Community guidelines concerning air pollution emissions. EU countries differ in many respects (population, area of the country, topographic diversity, degree of industrialization, degree of conventional energy sources usage, condition of roads, condition of vehicle fleet, etc.). This diversity accounts for differences in the sources and quantities of emitted pollutants.

An estimated 4.5 billion people are currently exposed to PM levels at least twice the concentration that the WHO considers safe (Ebenstein et al. 2017). Among the many health

problems which can be caused by air pollution are respiratory and cardiovascular diseases, lung cancer and even premature death (Park and Kwan 2017).

The impact of air pollution on LE is being increasingly addressed in scientific research. However, despite the well-documented literature on the association between air pollution and health problems, studies regarding the effects on LE are still globally scarce (Aboubacar et al. 2018; De Keijzer et al. 2017; Wang et al. 2013; Jonker et al. 2014). Fann et al. 2017 estimated that the US population will experience an increase in LE due to reductions in annual mean $\text{PM}_{2.5}$ concentrations from 1980 to 2010. De Keijzer et al. (2017) presented that air pollution concentrations were associated with important reductions in LE. Studies conducted by Dziubanek et al. (2017) confirmed the presence of significant correlations between the size of the chronic exposure of the inhabitants of the cities of the Silesia Province in Poland to PM_{10} and BaP and their LE, excluding external causes of death. Air quality might have contributed substantially to the LE in China (Wang et al. 2013). LE increased from 2003 to 2009, but slightly decreased in 2010, which was related to the increased PM_{10} level in 2010. Approaches of Aboubacar et al. (2018) provide similar results indicating that household $\text{PM}_{2.5}$ is significantly and negatively associated with higher aggregate LE in the long-run, and to a greater degree for female's. Also, among the control variables, $\text{PM}_{2.5}$ from the transport sector has a greater influence on male's LE. Etchie et al. (2018) estimated the share of the deaths, DALYs (disability adjusted-life years), economic cost and loss in LE attributable to population exposure to ambient $\text{PM}_{2.5}$ pollution at the local, sub-national level in Nigeria in 2000 and 2015. Hill et al. (2019) estimated models with interaction terms to formally assess whether the association between fine particulate matter and LE varies by level of state income inequality.

Air pollution models represent an important tool in environmental and epidemiological science (Liu et al. 2019; Mehdipour et al. 2018). Little attention is given to applying the modelling technique to investigate not only share of PM

Fig. 1 Urban population in percentage exposed to air pollutant concentrations above selected limit and target values according to **a** UE air-quality standards; **b** WHO air quality guideline. ¹Percentage of population exposed to annual $\text{PM}_{2.5}$ concentrations above $25 \mu\text{g}/\text{m}^3$; percentage of population exposed to daily PM_{10} concentrations exceeding 50

$\mu\text{g}/\text{m}^3$ for more than 35 days a year; percentage of population exposed to maximum daily 8-h mean O_3 concentrations exceeding $120 \mu\text{g}/\text{m}^3$ for more than 25 days a year; percentage of population exposed to annual NO_2 concentrations above $40 \mu\text{g}/\text{m}^3$

Fig. 2 Air pollution in European countries in 2015

but also other air pollutants in the impact on LE. The goal of this study was to develop a new approach to modelling of life expectancy (LE) depending on air pollutants (sulphur oxides SO_x , NO_x , CO, $\text{PM}_{2.5}$ and PM_{10} , polycyclic aromatic hydrocarbons PAHs and non-methane volatile organic compounds NMVOCs) using artificial neural networks (ANN) (multi-layer perceptron MLP). Research has been undertaken to determine which air pollutants are statistically highly significant and correlated with the output variable (LE) in particular countries. Evaluating the potential impact of air quality improvement on public health and LE is very important for providing continued support to mitigate air pollution in many European countries. The presented ANN model can be used not only for LE forecasting but also for simulating various scenarios of LE by changing the values of the input variables.

Methods and materials

Methodology

The present paper discusses a novel methodology based on neural network to determine air pollutants' correlation with LE at the

national level in European countries. The models were developed using historical data from the period 1992–2016. The dataset for this analysis is based on several sources (Eurostat, OECD, European Union emission inventory report 1990–2016) for a set of 20 European countries. Study area is presented in Fig. 3.

The impact of air pollution on LE is often modelled with the use of regression analysis (Dziubanek et al. 2017; Pope et al. 2009; Pope et al. 2015; de Keijzer et al. 2017). However, the regression approach can face serious difficulties when the independent variables are correlated with each other. Multicollinearity, or high correlation between the independent variables in a regression equation, can make it difficult to correctly identify the most important contributors to a physical process (Abdul-Wahab et al. 2005). Moreover, as shown in Fig. 4, not all independent variables show purely linear correlations with the dependent variable. For these reasons, it was decided to carry out tests based on ANN.

Figure 5 presents a two-dimensional scatterplot showing the dependence of LE on individual pollutants. Some independent variables show a simple linear relationship with LE, while others, despite high Pearson correlation coefficient, are better presented in the form of logarithmic functions. The graphs indicate negative correlations.

Data source for neural network training was a set of 70% of data from the period of 25 years. LE modelling was performed using an MLP and Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm of learning. The parameters of the network, i.e. weight values and threshold values of neurons, were selected

Fig. 3 Countries included in the study

Fig. 4 MLP neural network architecture

in a manner allowing for the minimisation of error function of the network. To achieve this, a special learning algorithm was applied, which enabled automatic modification of the mentioned value, based on input data and respective appropriate solutions. The training of created network model was performed by the backpropagation method, which is the most commonly used and one of the most effective learning algorithms for multilayer neural network. Its essence is based on minimising the sum of squares of network learning errors. Errors occurring at the output of the network are propagated in the opposite direction than that of signals passing through the network, i.e. from the output layer to the input layer. An automatic ANN designer simultaneously searches for multiple types of networks. Each of the analysed countries is divided into three subsets: 70% train, 15% validate, 15% test. A series of tests of the network types were carried out using the Automatic Network Designer. Sensitivity of the neural network to particular pollutants was determined in relation to LE by sensitivity analysis (SA). The Statistica Neural Networks module implemented in Statistica 12.5 was used to generate neural models.

Multi-layer perceptron

The structure of basic MLP model is composed of three layers: the input layer where the input data are received, the hidden layer where the objects are processed and the output layer where the forecasted results are presented.

In order to choose the most precise structure of MLP model, the method of trial and error is applied. The model's final architecture depends on the hidden layer and the values of neuron. The inputs to the i th layer (x_1 to x_j) multiplied by their weights (w_{i1} to w_{ij}) are summed up. The net input value (Net_i) is determined by adding the threshold (b_i) to the input. The received net input value is always greater than zero.

$$\text{Net}_i = b_i + \sum_{j=1}^n w_{ij}x_j \quad (1)$$

Weights, which represent how strong a neuron connection is, are adjusted in the process of learning. In the next step, inputs and outputs received by the member function are transferred to the next layer. In order to introduce nonlinearity in the model, sigmoid functions can be applied.

$$f(\text{Net}_i) = \frac{1}{1 + e^{-\text{Net}_i}} \quad (2)$$

The ANN architecture used in this study is presented in Fig. 4.

Several dozens of network neurons with different numbers of neurons in the hidden layer were tested for each country. The selection criterion was the minimum error of mean square error (MSE) value for the data from the validation set.

BFGS algorithm of learning

For the purpose of the study, the BFGS algorithm of learning was chosen. Consider the following problem:

$$\min_{x \in R^n} f(x) \quad (3)$$

where $f: R^n \rightarrow R$ is twice continuously differentiable function.

The methods which are most often applied in order to solve the problem of unconstrained minimisation are the quasi-Newton methods (Broyden 1965). They are based on the iterative formula

$$x_{k+1} = x_k + \lambda_k p_k \quad (4)$$

where $\lambda_k > 0$ is the step length that is updated by line search and backtracking procedure and $p_k = -B_k^{-1} \nabla f(x_k)$ is the quasi-

Fig. 5 Scatterplot for individual pollutions and LE for analysed countries summary: **a** CO; **b** PM_{2.5}; **c** NO_x; **d** NMVOCs; **e** SO_x; **f** PM₁₀; **g** PAHs

Newton search direction, where $\nabla f(x)$ is the gradient mapping of $f(x)$. In this class of methods B_k , which is an approximation of the Hessian $\nabla^2 f(x_k)$, is updated at every iteration with a low-rank matrix. BFGS is a widely used example of a formula which can be applied in order to perform the updates and it is given by

$$B_{k+1} = B_k - \frac{B_k s_k s_k^T B_k}{s_k^T B_k s_k} + \frac{y_k y_k^T}{y_k^T s_k} \quad (5)$$

where $s_k = x_{k+1} - x_k$ and $y_k = \nabla f(x_{k+1}) - \nabla f(x_k)$. BFGS update formula possesses good properties that are very useful for establishing convergence results (Krejić et al. 2009; Kolasa-Więcek 2018).

Materials

The subject of the analysis included the input (explanatory) variables of the following air pollutants: sulphur oxides (SO_x), NO_x , CO, PM_{2.5} and PM₁₀, polycyclic aromatic hydrocarbons (PAHs) and non-methane volatile organic compounds (NMVOCs). Emission data were retrieved from the European database (Eurostat, European Union emission inventory report 1990–2016). The dependent variable (output) in the form of LE was obtained from OECD databases (OECD). Due to lack of data for the analysed period of 25 years, the modelling was finally performed for only 20 European countries. In some cases (e.g. in case of data for PAHs), the missing data was supplemented with averaged data from two neighbouring years. The modelling was performed for the averaged data of all 20 European countries and, due to the different levels of pollution in individual countries, separately for each of them. The descriptive statistics of the data set for all European countries is presented in Table 1.

Results and discussions

Our findings suggested that air quality plays an important role in LE of the residents of European countries. An interesting

aspect of this research is that it is a simple, direct, and transparent exploration of the association between air pollution and LE. Air pollution control should be reinforced in the future, especially for fine particles that constitute a great influence on LE (Table 4).

The values presented in Table 2 show a summary of the Pearson correlation coefficients between LE and analysed pollutants for European countries. All variables are statistically significant (for $p < 0.05$). Obtained values of Pearson coefficients indicate a strong relationship between LE and individual pollutants. With an increase in the amount of pollutants, LE decreases.

Table 3 presents the best generated MLP networks for individual countries obtained as a result of modelling. In the first of the analysed cases (20 European countries jointly), a tree-layer MLP network with 7 neurons in the first layer, 11 neurons in the hidden layer, and 1 output layer achieved greatest prediction efficiency. A single neuron at the output of the network reflects the LE. As a result of the tests, the correlation between real and descriptive values expressed in Pearson coefficients was obtained. Received network quality parameters (learning, testing, validation) are very high—over 99% in all cases. Validation and test prediction errors are parameters that testify to the quality of the network, and their similar values indicate that the network generalizes acquired knowledge well. The quasi-Newton BFGS algorithm, which uses the inverse of the matrix of the second derivatives of the error function counted against successive weights, proved to be the most useful learning algorithm.

The basic measure of network sensitivity is the error quotient obtained on launching the network for a set of variables without one variable and the error obtained with a full set of variables. The bigger the error after rejecting the variable in relation to the original error, the more sensitive the network is to the lack of that variable. If the error quotient is smaller than 1, then deleting the variable does not affect network sensitivity; it even improves it. The global SA for the inputs indicates that each of the variables obtained the values above 1, or rounded 1, which suggests a significant impact of each of them on the output variable.

Table 4 presents the summary of the value of global SA for all countries under study and for studied pollutants.

Table 1 Statistical description of the data

Variable	Mean	Standard deviation	Min	Max	Median
NMVOCs ¹	493.116	145.629	300.771	773.065	457.774
NO_x	575.447	133.121	353.819	804.594	568.67
PM _{2.5}	71.216	12.345	50.616	91.215	67.836
PM ₁₀	108.494	17.347	79.779	136.205	103.921
SO_x	456.611	300.094	126.646	1143.401	356.932
CO	1703.372	582.502	973.104	2850.794	1523.435
PAHs	0.216	0.135	0.073	0.518	0.151
LE ²	77.380	1.924	74.485	80.69	77.23

¹ All air pollutions in thous. tonnes. ² In years

Table 2 Pearson correlation coefficients matrix

Variable	NMVOCs	NO _x	PM2.5	PM10	SO _x	CO	PAHs	LE
NMVOCs	1.000							
NO _x	0.985	1.000						
PM2.5	0.986	0.982	1.000					
PM10	0.986	0.987	0.999	1.000				
SO _x	0.983	0.955	0.950	0.949	1.000			
CO	0.997	0.976	0.981	0.980	0.991	1.000		
POHs	0.973	0.939	0.946	0.943	0.989	0.983	1.000	
LE	0.977	− 0.992	− 0.984	− 0.988	− 0.932	− 0.965	− 0.923	1.000

For the summarily analysed 20 countries, PM2.5 is the pollutant which, based on MLP neural network, showed the most significant impact on LE. The dominant emissions in Europe are mainly released by several countries: Germany, France, Poland, Italy, UK and Spain (Fig. 2a). SA of the MLP 7-11-1 network showed the highest sensitivity to changes in PM emissions in relation to LE in the case of large European economies—Germany, Spain, Italy, and Poland (where PM pollutants are located on the second and third positions). The sensitivity of the designed neural network to PM pollution (both PM2.5 and PM10) in these countries is as follows: Germany PM2.5 (3082.86), Spain PM2.5 (18.31), Italy PM10 (463.74) and PM2.5 (273.82), Poland PM10 (1.95) and PM2.5 (1.48). During coal combustion millions of tons of coal fly ash

(CFA) and coal dust were emitted annually to contribute to the formation of PM, and, therefore, underlying risks to LE (Chen et al. 2004; Miller et al. 2007; Munawer 2018).

Out of the 20 countries under study, the SA for 6 countries (MLP 7-10-1, MLP 7-7-1, MLP 7-5-1, MLP 7-8-1, MLP 7-11-1) showed the greatest sensitivity to SO_x pollution changes. These are the following countries: Hungary (90.78), Ireland (5.50), Luxembourg (9.55), Poland (33.96), Slovenia (129.99), Sweden (19.65). Coal is a heavily polluting fuel in terms of black carbon (BC), sulphates and other gaseous compounds, especially when incompletely and inefficiently combusted. Numerous studies indicate several diseases resulting from human exposure to SO_x compounds. For example, inhaling SO_x pollutants can be a cause of heart attacks as it destabilizes the

Table 3 Summary of active MLP networks for individual countries

Country	Type of network	Quality			Error			Algorithm of learning
		learn.	test.	valid. ¹	learn.	test.	valid.	
European countries summary	MLP 7-11-1	0.998	0.999	0.999	0.004	0.001	0.005	BFGS 41
Austria	MLP 7-12-1	0.995	0.990	0.999	0.017	0.015	0.175	BFGS 10
Belgium	MLP 7-9-1	0.996	0.993	0.999	0.008	0.012	0.098	BFGS 48
Czechia	MLP 7-4-1	0.998	0.992	0.999	0.005	0.018	0.073	BFGS 32
Denmark	MLP 7-6-1	0.996	0.993	0.999	0.011	0.011	0.087	BFGS 29
Estonia	MLP 7-11-1	0.992	0.994	0.998	0.076	0.046	0.031	BFGS 25
Finland	MLP 7-8-1	0.997	0.999	0.999	0.006	0.001	0.031	BFGS 33
France	MLP 7-10-1	0.992	0.999	0.999	0.025	0.015	0.088	BFGS 24
Germany	MLP 7-9-1	0.999	0.999	0.999	0.002	0.002	0.027	BFGS 43
Hungary	MLP 7-10-1	0.994	0.998	0.999	0.022	0.013	0.022	BFGS 27
Ireland	MLP 7-7-1	0.993	0.998	0.997	0.032	0.004	0.081	BFGS 10
Italy	MLP 7-4-1	0.996	0.999	0.999	0.011	0.010	0.048	BFGS 29
Luxembourg	MLP 7-5-1	0.976	0.997	0.999	0.096	0.035	0.091	BFGS 37
Netherlands	MLP 7-11-1	0.998	0.999	0.999	0.002	0.004	0.001	BFGS 59
Poland	MLP 7-8-1	0.986	0.985	0.999	0.067	0.059	0.069	BFGS 12
Portugal	MLP 7-9-1	0.995	0.999	0.999	0.023	0.012	0.017	BFGS 22
Slovakia	MLP 7-7-1	0.993	0.996	0.999	0.015	0.013	0.045	BFGS 36
Slovenia	MLP 7-9-1	0.996	0.999	0.998	0.022	0.011	0.018	BFGS 22
Sweden	MLP 7-11-1	0.987	0.994	0.999	0.021	0.010	0.081	BFGS 14
UK	MLP 7-7-1	0.996	0.994	0.999	0.010	0.011	0.026	BFGS 13

¹ Learning, testing, validation

Table 4 Results of SA

Country	Variable						
European countries	PM2.5	PAHs	SO _x	NMVOCs	CO	PM10	NO _x
	102.67	47.97	47.45	35.97	31.37	24.94	16.08
Austria	PM10	PM2.5	CO	SO _x	NO _x	PAHs	NMVOCs
	21.38	20.98	4.955	1.65	1.11	1.03	1.00
Belgium	CO	NMVOCs	PM10	NO _x	PM2.5	PAHs	SO _x
	30.89	23.02	18.58	7.81	7.18	3.58	2.99
Czechia	PM2.5	PAHs	PM10	NMVOCs	NO _x	CO	SO _x
	107.88	81.39	23.94	21.85	15.55	14.97	4.71
Denmark	NMVOCs	NO _x	CO	PAHs	PM10	PM2.5	SO _x
	29.86	10.85	4.63	2.28	1.88	1.18	1.14
Estonia	NMVOCs	SO _x	PAHs	CO	NO _x	PM10	PM2.5
	59.88	40.59	35.62	7.78	7.19	7.04	3.46
Finland	CO	NMVOCs	PAHs	PM10	PM2.5	NO _x	SO _x
	66.43	57.23	14.51	8.93	4.14	1.63	1.22
France	NMVOCs	SO _x	NO _x	CO	PAHs	PM2.5	PM10
	10.85	3.38	2.79	2.14	1.69	1.35	1.17
Germany	PM2.5	NO _x	PM10	NMVOCs	CO	SO _x	PAHs
	3082.86	286.67	120.98	45.65	15.78	5.08	4.04
Hungary	SO _x	PM10	CO	PM2.5	NO _x	NMVOCs	PAHs
	90.78	36.09	14.37	8.25	4.26	3.00	1.63
Ireland	SO _x	NO _x	CO	PAHs	NMVOCs	PM10	PM2.5
	5.50	1.75	1.72	1.21	1.20	1.00	0.98
Italy	PM10	PM2.5	NO _x	CO	SO _x	PAHs	NMVOCs
	463.74	273.82	35.29	13.28	8.27	2.42	2.30
Luxembourg	SO _x	NMVOCs	CO	PM2.5	PM10	PAHs	NO _x
	9.55	7.61	6.37	5.81	5.52	2.72	1.46
Netherland	NO _x	PM2.5	PM10	NMVOCs	CO	PAHs	SO _x
	1117.15	473.28	356.10	112.41	53.21	28.18	16.68
Poland	SO _x	PM10	PM2.5	NO _x	CO	NMVOCs	PAHs
	33.96	1.95	1.48	1.23	1.13	1.10	0.99
Portugal	NO _x	SO _x	PAHs	CO	PM10	PM2.5	NMVOCs
	47.57	43.35	41.43	15.61	7.23	4.93	1.30
Slovenia	SO _x	NMVOCs	CO	PAHs	NO _x	PM2.5	PM10
	129.99	44.21	18.00	11.68	8.16	6.21	1.58
Spain	PM2.5	PAHs	PM10	NMVOCs	SO _x	CO	NO _x
	18.31	12.69	2.46	2.33	1.97	1.67	1.45
Sweden	SO _x	CO	PM10	NMVOCs	NO _x	PM2.5	PAHs
	19.65	8.52	4.26	2.14	1.99	1.85	1.72
UK	CO	NO _x	PM2.5	SO _x	NMVOCs	PM10	PAHs
	163.69	53.21	28.17	14.82	9.27	5.02	1.03

rhythm of heart beats (Peters et al. 1999). Populations inhabiting areas in the proximity of power plants frequently suffered from suffocation, wheezing and coughing, and their lung function was reduced due to high exposure to SO₂ (Bascom 1996). Among the effects of SO₂ pollution are also bronchial reactions, premature death and numerous diseases, such as lung and colon cancers (Hussain et al. 2016; Pourgholami et al. 2005).

Sensitivity of the neural network to CO pollution was obtained in four European countries: Belgium (30.89), Finland (10.85), Portugal (47.57) and UK (163.69). During coal combustion, as a result of oxidation, CO₂ and CO gases are emitted. They lead to harmful environmental effects in the form of global warming and GHG emissions and are also correlated directly and indirectly with many health problems, including

Fig. 6 Observed and modelled value of LE

malaria, cardiovascular diseases and asthma (Munawer 2018). At a cellular level, the CO combines with blood haemoglobin reducing its efficiency and lowering its capacity to transform O₂ (Badman and Jaffé 1996).

In Denmark (29.86), Estonia (59.88) and France (10.85), the highest sensitivity of the neural network to changes in NMVOC pollution was obtained. NMVOCs have been shown to be responsible for several health problems. Among them respiratory and cardiovascular system diseases can be noted, which are related to an increased concentration of tropospheric ozone and secondary organic aerosols due to NMVOC pollution (Laurent and Hauschild 2014). Some toxic NMVOCs, e.g. benzene and formaldehyde, can have a more direct impact on human health. They can be a direct cause of acute and chronic diseases and be carcinogenic or mutagenic (Weichenthal et al. 2012).

The data obtained as a result of modelling were compared with the actual data. Forecasted courses of changes in the variable under study coincide with the actual data, which confirms that the proposed models generalize acquired knowledge well (Fig. 6).

The models (sensitivity of constructed neural networks to pollutants) proved to be particularly important (depending on the country) in the case of changes in the value of PM (PM_{2.5} and PM₁₀), SO_x and NMVOC. The methods under study allow for quantification of the deterministic relationship between emissions and LE, including the consequences of past and upcoming scenarios, and the determination of the effectiveness of air pollution management strategies. This makes the models indispensable in several research applications. The SA of inputs has proven to be a useful technique for understanding the mechanism of the modelled function, giving more insight into the internal mechanism of the ANN model. It also helps to understand the relative contribution of input parameters that can be used to eliminate irrelevant inputs to make the model more robust. The obtained values of Pearson coefficients indicate a high negative relationship between LE and individual pollutants, which means that with an increase of the emissions, LE decreases. The proposed approach can be used to illustrate how the neural network modelling technique can be used to identify the key air pollution variables required to adequately capture the variability in LE for a specific scenario. The presented models can be used not only for LE forecasting but also for simulating various scenarios by changing the values of the input variables.

Conclusions

The study suggests an association between long-term air pollution exposure and the reduction of LE. The air pollutants PM₁₀, PM_{2.5}, NO_x, NMVOC, SO_x, PAHs and CO were

identified as correlated with LE. The most frequent association was found for fine particle.

Constructed models, thanks to the network's ability to generalize data, can be used in the prediction of the LE value, based on the analysed air pollutants. Proposed models can be used to simulate LE scenarios and can be used by regulatory authorities to support policy creation and implementation process, and for the development of strategies for improving air quality at regional and national levels. The results of the study can also support the development and effective implementation of long-term policies that reduce the risk of impact of individual air pollutants on human health and life.

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References

- Abdul-Wahab SA, Bakheit CS, Al-Alawi SM (2005) Principal component and multiple regression analysis in modelling of ground-level ozone and factors affecting its concentrations. *Environ Modell Softw* 20(10):1263–1271. <https://doi.org/10.1016/j.envsoft.2004.09.001>
- Aboubacar B, Deyi X, Razak MYA, Leyla BH (2018) The Effect of PM_{2.5} from household combustion on life expectancy in Sub-Saharan Africa. *Int J Environ Res Public Health* 15(4):748. <https://doi.org/10.3390/ijerph15040748>
- Alessandrini ER, Stafoggia M, Faustini A (2016) Association between short-term exposure to PM_{2.5} and PM₁₀ and mortality in susceptible subgroups: a multisite case-crossover analysis of individual effect modifiers. *Am J Epidemiol* 184(10):744–754. <https://doi.org/10.1093/aje/kww078>
- Ashraf A, Butt A, Khalid I, Alam RU, Ahmad SR (2019) Smog analysis and its effect on reported ocular surface diseases: a case study of 2016 smog event of Lahore. *Atmos Environ* 198:257–264. <https://doi.org/https://doi.org/10.1016/j.atmosenv.2018.10.029>
- Badman DG, Jaffé ER (1996) Blood and air pollution; state of knowledge and research needs. *Otolaryn head neck* 114(2):205–208. <https://doi.org/10.1016/S0194-59989670166-3>
- Broyden CG (1965) A class of methods for solving nonlinear simultaneous equations. *Math Comput* 19:577–559
- Cacciotolo M, Wang X, Driscoll I et al (2017) Particulate air pollutants, APOE alleles and their contribution to cognitive impairment in older women and in amyloidogenesis in experimental model. *Transl Psychiatr* 7(1):e1022. <https://doi.org/10.1038/tp.2016.280>
- Chen Y, Shah N, Huggins FE (2004) Investigation of primary fine particulate matter from coal combustion by computer-controlled scanning electron microscopy. *Fuel Process Technol* 85(6):743–761. <https://doi.org/10.1016/j.fuproc.2003.11.017>
- de Keijzer C, Agis D, Ambrós A, Arévalo G, Baldasano JM, Bande S, Barrera-Gómez J, Benach J, Cirach M, Dadvand P, Ghigo S, Martínez-Solanas E, Nieuwenhuijsen M, Cadum E, Basagaña X (2017) The association of air pollution and greenness with mortality and life expectancy in Spain: a small-area study. *Environ Int* 99:170–176. <https://doi.org/10.1016/j.envint.2016.11.009>

- Dziubanek G, Spychała A, Marchwińska-Wyrwał E, Rusi M, Hajok I, Ćwieląg-Drabek M, Piekut A (2017) Long-term exposure to urban air pollution and the relationship with life expectancy in cohort of 3.5 million people in Silesia. *Sci Total Environ*. 580:1–8. <https://doi.org/10.1016/j.scitotenv.2016.11.217>
- Ebenstein A, Fan M, Greenstone M, He G, Zhouh M (2017) New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proc Natl Acad Sci USA* 114(39):10384–10389. <https://doi.org/10.1073/pnas.1616784114>
- Etchie TO, Etchie AT, Adewuyi GO, Pillarisetti A, Arora NK (2018) The gains in life expectancy by ambient PM_{2.5} pollution reductions in localities in Nigeria. *Environ Pollut* 236:146–157. <https://doi.org/10.1016/j.envpol.2018.01.034>
- European Economic Area, EEA <https://www.eea.europa.eu/data-and-maps/indicators/exceedance-of-air-quality-limit-3/assessment-4>, (accessed on 12.12.2018)
- European Environment Agency, Air quality in Europe — 2016 report, EEA Report No 28/2016. <https://doi.org/10.2800/80982> (accessed on 21.12.2018)
- European Union emission inventory report 1990–2016 under the UNECE Convention on Long-range Transboundary Air Pollution (LRTAP). EEA Report No 6/2018 (accessed on 5.12.2018)
- Eurostat. <https://ec.europa.eu/eurostat/data/statistics-a-z/def> (accessed on 1.11.2018)
- Fann N, Kim S-Y, Olives C, Sheppard L (2017) Estimated changes in life expectancy and adult mortality resulting from declining PM_{2.5} exposures in the contiguous United States: 1980–2010. *Environ Health Perspect* 125(9):097003. <https://doi.org/10.1289/EHP507>
- Fann N, Coffman E, Hajat A, Kim S-Y (2019) Change in fine particle-related premature deaths among US population subgroups between 1980 and 2010. *Air Qual Atmos Health* 12:1–10. <https://doi.org/10.1007/s11869-019-00686-9>
- Guerreiro CBB, Foltescu V, Leeuw F (2014) Air quality status and trends in Europe. *Atmos Environ* 98:376–384. <https://doi.org/10.1016/j.atmosenv.2014.09.017>
- Hill TD, Jorgenson AK, Ore P, Balistreri KS, Clark B (2019) Air quality and life expectancy in the United States: An analysis of the moderating effect of income inequality. In: Air quality and life expectancy in the United States: an analysis of the moderating effect of income inequality. *SSM - Population Health*. 7, Article 100346. <https://doi.org/10.1016/j.ssmph.2018.100346>
- Hussain MRM, Din N, Hassan M, Razaq A, Iqbal Z (2016) Physiological significance of Fuc and sialic acid containing glycans in the body. *Arab J Chem* 9(1):S9–S20. <https://doi.org/10.1016/j.arabjc.2011.06.028>
- Jonker MF, van Lenthe FJ, Donkers B, Mackenbach JP, Burdorf A (2014) The effect of urban green on small-area (healthy) life expectancy. *J Epidemiol Community Health*. 2014 Oct; 68(10):999–1002. <https://doi.org/10.1136/jech-2014-203847>. 999.
- Kolasa-Więcek A (2018) Neural modeling of greenhouse gas emission from agricultural sector in European Union member countries. *Water Air Soil Poll* 229(6):205. <https://doi.org/10.1007/s11270-018-3861-7>
- Krejić N, Lužanin Z, Stojkowska I (2009) Gauss–Newtonbased BFGS method with filter for unconstrained minimization. *App Math Comput* 211(2):354–362. <https://doi.org/10.1016/j.amc.2009.01.041>
- Laurent A, Hauschild MZ (2014) Impacts of NMVOC emissions on human health in European countries for 2000–2010: use of sector-specific substance profiles. *Atmos Environ* 85:247–255. <https://doi.org/10.1016/j.atmosenv.2013.11.060>
- Li Y, Henze DK, Darby KJPL (2016) The influence of air quality model resolution on health impact assessment for fine particulate matter and its components. *Air Qual Atmos Health* 9(1):51–68. <https://doi.org/10.1007/s11869-015-0321-z>
- Liu H, Duan Z, Chen C (2019) A hybrid framework for forecasting PM_{2.5} concentrations using multi-step deterministic and probabilistic strategy. *Air Qual Atmos Health* 12:1–11. <https://doi.org/10.1007/s11869-019-00695-8>
- Mehdipour V, Stevenson DS, Memarianfard M, Sihag P (2018) Comparing different methods for statistical modeling of particulate matter in Tehran, Iran. *Air Qual Atmos Health* 11(10):1155–1165. <https://doi.org/10.1007/s11869-018-0615-z>
- Miller KA, Siscovick DS, Sheppard L, Shepherd K, Sullivan JH, Anderson GL, Kaufman JD (2007) Long-term exposure to air pollution and incidence of cardiovascular events in women. *New Eng J Med* 356(5):447–458. <https://doi.org/10.1056/NEJMoa054409>
- Munawer ME (2018) Human health and environmental impacts of coal combustion and post-combustion wastes. *J Sustain Min* 17(2):87–96. <https://doi.org/10.1016/j.jsm.2017.12.007>
- OECD, <https://data.oecd.org/healthstat/life-expectancy-at-birth.htm> (accessed on 28.11.2018)
- Park YM, Kwan MP (2017) Individual exposure estimates may be erroneous when spatiotemporal variability of air pollution and human mobility are ignored. *Health Place* 43:85–94. <https://doi.org/10.1016/j.healthplace.2016.10.002>
- Peters A, Perz S, Döring A (1999) Increases in heart rate during an air pollution episode. *Am J Epidemiol* 150(10):1094–1098. <https://doi.org/10.1093/oxfordjournals.aje.a009934>
- Pope CA III, Ezzati M, Dockery DW (2009) Fine-particulate air pollution and life expectancy in the United States. *New England J Med* 360(4):376–386. <https://doi.org/10.1056/NEJMsa0805646>
- Pope CA III, Ezzati M, Dockery DW (2015) Tradeoffs between income, air pollution and life expectancy: brief report on the US experience, 1980–2000. *Environ Res* 142:591–593. <https://doi.org/10.1016/j.envres.2015.08.014>
- Pourgholami MH, Akhter J, Wang L, Lu Y, Morris DL (2005) Antitumor activity of albendazole against the human colorectal cancer cell line HT-29: in vitro and in a xenograft model of peritoneal carcinomatosis. *Cancer Chemother Pharmacol* 55(5):425–432. <https://doi.org/10.1007/s00280-004-0927-6>
- Samoli E, Stafoggia M, Rodopoulou S, Ostro B, Declercq C, Alessandrini E, Díaz J, Karanasiou A, Kelessis AG, le Tertre A, Pandolfi P, Randi G, Scarinzi C, Zauli-Sajani S, Katsouyanni K, Forastiere F, the MED-PARTICLES Study group. (2013) Associations between fine and coarse particles and mortality in Mediterranean cities: results from the MED-PARTICLES project. *Environ Health Perspect* 121:932–938. <https://doi.org/10.1289/ehp.1206124>
- Wang C, Zhou X, Chen R, Duan X, Kuang X, Kan H (2013) Estimation of the effects of ambient air pollution on life expectancy of urban residents in China. *Atmos Environ* 80:347–351. <https://doi.org/10.1016/j.atmosenv.2013.08.018>
- Weichenthal S, Kulka R, Bélisle P, Joseph L, Dubeau A, Martin C, Wang D, Dales R (2012) Personal exposure to specific volatile organic compounds and acute changes in lung function and heart rate variability among urban cyclists. *Environ Res* 118:118–123. <https://doi.org/10.1016/j.envres.2012.06.005>
- World Health Organization, Review of evidence on health aspects of air pollution – REVIHAAP Project Technical Report, WHO Regional Office for Europe 2013 http://www.euro.who.int/_data/assets/pdf_file/0004/193108/REVIHAAP-Final-technical-report-final-version.pdf?ua=1 (accessed on 15.10.2018)