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Use of Bayesian inference method to model vehicular air pollution in local urban areas

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ABSTRACT

Traffic Related Air Pollution (*TRAP*) studies are usually investigated using different categories such as air pollution exposure for health impacts, urban transportation network design to mitigate pollution, environmental impacts of pollution, etc. All of these subfields often rely on a robust air pollution model, which also necessitates an accurate prediction of future pollutants. As is widely accepted by the heath authorities, *TRAP* is considered to be the major health issue in urban areas, and it is difficult to keep pollution at harmless levels if the time sequenced dynamic pollution and traffic parameters are not identified and modelled efficiently. In our work here, artificial intelligence techniques, such as Bayesian Networks with an optimized configuration, are used to deliver a probabilistic traffic data analysis and predictive modelling for air pollution (SO_2, NO_2 and CO) at very local scale of an urban region with up to 85% accuracy. The main challenge for traditional data analysis is a lack of capability to reveal the hidden links between distant data attributes (e.g. pollution sources, dynamic traffic parameters, etc.), whereas some subtle effects of these parameters or events may play an important role in pollution on a long-term basis. This study focuses on the optimisation of Bayesian Networks to unveil hidden links and to increase the prediction accuracy of *TRAP* considering its further association with a predictive GIS system.

1. Introduction

The term air pollution is linked to harmful substances in the air such as gases, solid particles or liquid droplets. The more specifically, traffic related air pollutants may be categorised as primary and secondary pollutants where the first category incudes carbon monoxide, sulphur dioxide, nitrogen oxides (Alvarez-Vazquez et al., 2017) and also Hydrocarbons, particulate matter, mobile-source air toxics such as lead, benzene, and formaldehyde (Health Effects Institute, 2010) whereas the second category covers ozone and the other minor pollutants. The pollutant emission measures are usually described as the weight of pollutant divided by a unit weight, volume, distance or duration of the pollution activity (US Environmental Pollution Agency, 1995). The air pollution is automatically measured by Air quality stations located at the critical points of urban areas where population or traffic flow is at certain density.

Nowadays with the increasing population of different vehicle types and by inadequate traditional transport or traffic system designs, air pollution has become one of the key issues to be solved urgently for urban areas. Traffic related air pollution (*TRAP*), which contains harmful chemicals, is a major threat for cities. In dense urban areas, vehicle emissions may be responsible for 90–95% of carbon monoxide and 60–70% of nitrogen oxides within the atmosphere (Schwela, 2000). Recent epidemiological studies suggest

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that at present air pollution results in an average 7-month reduction in life expectancy and costs UK society up to £20 billion per year (HCEA Committee, 2011).

The immediate solution is not easy if the time sequenced dynamic pollution and traffic system parameters are not properly identified and modelled. Particularly multidisciplinary areas such as artificial intelligence (AI) methods (e.g. data mining, inference methods, etc.), state-of-art instrumentation, supercomputing facilities, distributed sensors, etc. would be expected to bring the most promising solutions to the problem. In our work here an artificial intelligence technique, Bayesian Networks, are used for a probabilistic data analysis whose performance has already been proven by our previous works (Orun and Aydin, 2010; Orun, 2004). One of the traditional common issues of manual data analysis is the lack of visibility of the hidden links between distant and the least correlated data attributes (e.g. pollution sources, dynamic traffic parameters, geographic location characteristics, etc.); whereas some subtle effects of these parameters or specific combinations of them may play an important role in traffic related air pollution on a long-term basis. The proposed work here targets an optimised Bayesian model to unveil such hidden links between the *TRAP* factors and parameters.

Many works have previously investigated air pollution. The most similar methodology was used with Bayesian classifier by Corani and Scanagatta (2016), but only for the prediction of $PM_{2.5}$ (Atmospheric aerosol particles) pollutant and O_3 (Ozone gas). In another work Karatzas and Kaltsatos introduce a computational intelligence method (Karatzas and Kaltsatos, 2007) for air pollution modelling by which the environmental system is simulated. Their work was also at a large geographic scale for a city area. Zhu et al. (2015) investigate traffic-related air pollution in a street canyon by utilising a genetic algorithm-back propagation artificial neural network but even though it introduces an AI-based approach, it is only based on a single pollutant parameter, nitrogen dioxide (NO_2), rather than focusing on a multi parameter solution. In (Passow et al. 2012) authors also used NO_2 used as a tracer for pollution but included additional factors derived from meteorological data, traffic data and earth observation data to create framework for near-real time traffic management and air quality control. In contrast, the method introduced in this paper is dedicated to long-term forecast to support design and re-assessment of air quality models in local urban areas. The method proposed here will also include several diverse types of parameters (pollutant, environmental, etc.), processed in an interactive form, to identify subtle connection between them.

On the other hand, geographic information systems (GIS) (Orun, 1993) are one of the major tools that could also potentially be used for the transport planning (Niemeier and Beard, 1993). One of the earlier works (Thonga and Wongb, 1997) introduced a specific database design for use by GIS for urban transport planning. In the work, even though some "predictive" techniques (called what-if) were suggested, their implementation was not considered within the proposed system. Another statistical predictive model based on a "distance decay regression" approach was introduced by Jason et al. (2009). Even though the method effectively used statistical algorithms with high prediction accuracy, it was limited with NO_x gases and no GIS utility was used or evaluated for a pollution map formation. The majority of past studies Jason et al. (2009), Matthias et al. (2006), Zhu et al. (2015), and Shekarrizfard et al. (2017) were limited to NO_x pollutants, whereas in our work the additional SO_2 and CO based pollutions were also studied.

Only a few earlier works combined the prediction methods with GIS for a pollution analysis. A direct estimation of traffic related air pollution was made by a GIS based component-oriented integrated system which was developed by Rebolj and Sturm (1999). In the paper, the generic outline of proposed system was introduced. However, the presentation did not exhibit the numerical test results in details other than a single output. The current statistical traffic-related air pollution models (Gulliver and Briggs, 2005) used for traffic design may cause several problems such as, Available data may not provide accurate pollution information for the future if processed by inappropriate linear predictive models. Such inappropriate modelling may later cause bulky re-construction and development for road network amendments.

Within this work we overcome the above issues by deploying a predictive modelling based GIS system in which AI technique, Learning Bayesian Networks, is used for a new target layer generation.

This paper is organised as follow; The method and materials used here are introduced in Section 2, with a presentation of a limited data sample set. In the subsections Bayesian Networks and predictive Bayesian model are also introduced by the presentation of a flow chart and pseudo code of the proposed method. The results of model accuracy are finally represented in Section 3 as results and discussion followed by the conclusion section.

2. Methods and materials

2.1. Data set specifications

The restricted data set consists of weekly recordings of traffic flows (at local data collection stations), air pollution values (e.g. SO_2, NO_2, CO), local temperature readings, wind records, air pressure, rainfall and global radiation values within Leicester City local urban areas for the year 2012. The local regions selected in this work are Newark and Aunsite. The whole data set was utilised for Bayesian Network (BN) construction as seen in Fig. 3, where the abbreviations "st" refers to traffic data collection stations in the Leicester city area. The traffic flow data were collected over the 56 station locations with additional 9 parameters including pollution types, temperature, global radiation, air pressure, rainfall, wind speed and wind direction.

Parameter units in Table 1: (NO_2, SO_2) = parts per billion, CO = parts per million, Temperature = °C, Global Radiation = W/m^2, Air pressure = mbar, Wind direction = Degree.M, Wind speed = m/s, Rainfall = mm/h, traffic flow (st_i) = number of vehicles/h.

The collected raw data need additional processing in which different fractions of data segments with different data types were re-arranged so they can be integrated within this work. This inevitably caused a limitation of data volume and relatively limited training of the BN system at low efficiency.

Table 1
Display of a sample for the traffic data set. The whole set contains total number of 56 stations (only station "st1" is shown below). Station values correspond to traffic flow at the specific city locations.

Date	NO2_aunsite	CO_Newarke	SO2_Newarke	Temperature	Global_radiation	Air_pressure	Wind_direction	Wind_speed	Rainfall	St1
120103	6.78031	0.0569999	0	5.778	0	989	186.1	6.841	1.23	12
120103	3.66683	0.109333	0	6.522	0	985	187.4	6.729	0.615	7
120103	2.50571	0.113833	0	7.43999	0	984	200	5.921	0	14
120103	3.38851	0.171	0	9.10999	0	982	204.8	5.586	0.205	31
120103	2.85849	0.169167	0	10.12	0	981	205.2	5.931	0	79
120103	3.67437	0.160333	2.11295	10.28	0	980	204.2	5.23399	0	227
120103	5.51909	0.162667	3.07007	10.52	0	979	207.9	6.03899	0	307
120103	7.56551	0.152167	4.73001	11	0	982	280	6.864	2.46	237
120103	6.88575	0.0196667	0.873518	8.15999	0	982	281.6	4.866	0	279

2.2. Data analysis with use of Bayesian Networks

In general terms, Bayesian Networks (*BN*) or Casual Probabilistic Networks are very useful techniques which can achieve efficient knowledge representation and reasoning. They are also capable of generating very accurate classification results under uncertainty where the data set may include many uncertain conditions (Koski and Noble, 2009). Bayesian Networks graphically encode and represent the conditional independence (CI) relationships among a set of data (Orun, 2004). In this work, a learning Bayesian Network software tool (PowerConstructor™) (Cheng et al., 2002) is used for the analysis of air pollution, traffic and environmental data and the Bayesian inference to construct the network (Fig. 3). The algorithm examines information flow between two highly related variables (attributes) from a data set and decides if these variables (e.g. traffic parameters) are independent or linked and it also investigates into how close the relationship between those variables is. This process continues for all variables in turn in the data set. This information flowed between the two variables is called conditional mutual information of two variables X_i, X_j which may be denoted as:

$$I(X_i,X_j|C) = \sum_{xi,xj,c} P(x_i,x_j,c)\log\frac{P(x_i,x_j|c)}{P(x_i|c)P(x_j|c)} \tag{1}$$

In Eq. (1), C is a set of nodes and c is a vector (one instance of variables in C). If $I(X_i,X_j|C)$ is smaller than a certain threshold t, then we can say X_i and X_j are conditionally independent. In the equations $P(x_i, x_j|c)$ may be extracted from the conditional probability tables, where i, j are indices for the different cases of two variables whose link is investigated.

One early example in which a Bayesian approach for an analysis of air pollution data was introduced by Suggs and Curran (1983). In their work air pollution data and air quality standards were compared and a combination of pollution history with instrumental precision in a Bayesian probabilistic model was comprehensively discussed. Some of our previous works also focused on the different application fields of Bayesian inference method and classification process separately, which provide a useful guidance for this work (Orun, 2004; Orun and Aydin, 2010). In those works two different experiments were done by use of a Bayesian Network tools such as PowerPredictor™ (Cheng et al., 2002) for the analysis of data produced by the real-time lab experiments. The other Bayesian package used here is PowerConstructor (Cheng et al., 2002) which is a different tool than Bayesian classifier as it only exhibits the links between the attributes in a semantic graphical domain. But both utilities use the Markov condition to obtain a collection of conditional independence statements from the networks (Pearl, 1988). One of the advantages of Bayesian Networks over the other AI systems (e.g. neural networks or fuzzy logic) is that, it identifies direct and indirect links between the attributes which can be easily interpreted. In both utilities, the algorithms establish the links between the attribute nodes and show them graphically. The nodes that are not connected are not necessarily excluded from the process, but it means that their contribution would not improve the classification results further (Cheng et al., 2002).

The inference characteristics of BN is concerned with the interpretation of data flow between the network attributes and establishing the links between those whose data flow exceed the certain threshold then they are automatically assigned as relevant. The BN prediction process is achieved by two steps (a) training stage (learning) and (b) test stage (cross-validation) where in first stage the network is trained by the data to establish rule-based model with the selected network parameters (e.g. data flow threshold, discretisation method, etc.) and in the second stage the network processes the test data to achieve a classification. At BN training stage, the cases (rows) in training data set are expected to be independent from each other to avoid any overfitting problem which means, BN system works well with available data but outperformed with another data set. Overfitting problem is most common issue of the classifiers but Bayesian networks have a distinctive advantage over the other classifiers such as Neural networks (Iruansi et al., 2012)

2.3. Bayesian predictive model

Geographic information systems (GIS) are very popular multi-layer spatial data storage, analysing and presentation tools. By the optimised integration of GIS (shown in Fig. 2) and Bayesian Networks for an intelligent query via the system layers (e.g. temperature, pollutions, topography, etc.), the development of a predictive model is possible. Within this work a predictive model is created in

```
Do {for each pixel of Target Layer}
        Select BN parameter options ;
                Train BN with data set :
                        Classify Target Pixel :
                Assign CO value to Target Pixel ;
                Go to next pixel ;
        If (Target Layer generated)
                then exit ;
        else target
                then Return ;
Go to {next pixel}
```

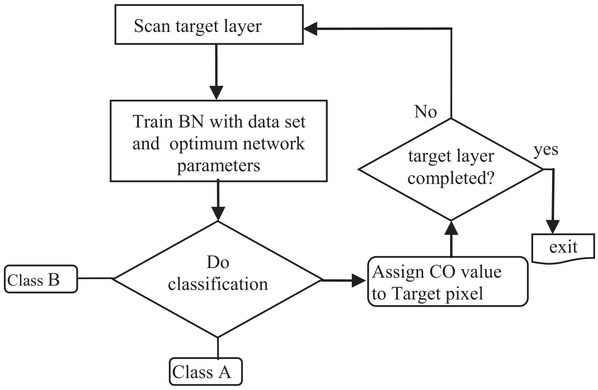

Fig. 1. The pseudo code of a new GIS target layer generation loop by Bayesian classifier based predictive model (on the left) and its flow chart representation (on the right). In the pseudo code a process loop is defined by *Do-Return* commands whereas *exit* command indicates the completion of whole process.

which some critical target parameters (e.g. CO, SO_2, NO_2 pollutions) would be predicted in advance on a specific (city) location. Such models could be invaluable at the planning stage for urban transportation networks designers as the outcomes from the model can assist long-term planning to avoid later high-cost amendments, bulky re-construction of road or infrastructural network, or to avoid hazardous situation (e.g. breaching the levels of air quality gas concentrations). The predictive model process uses an iterative prediction loop to classify each point of the target layer (see Fig. 1) whose parametric data are provided to form a complete layer, but its accuracy would depend on density of data collection stations distribution. In case of low distribution, the necessary interpolations between the stations must be done. This iterative process can be described by the pseudo code and the flowchart shown in Fig. 1. The Bayesian classifier used in the iterative process is fundamentally based on the Bayesian theorem that is described by the formula:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2}$$

where P(A) and P(B) are probability of observation of A and B, respectively. P(A|B) probability of observing A given that B is true. P (B|A) is the probability of observing B given that A is true. This principal is related to the Bayesian classifier cited in Fig. 1.

3. Results and discussion

As is seen in the Bayesian Network (Fig. 3) which was built after Bayesian inference based data processing by use of the package

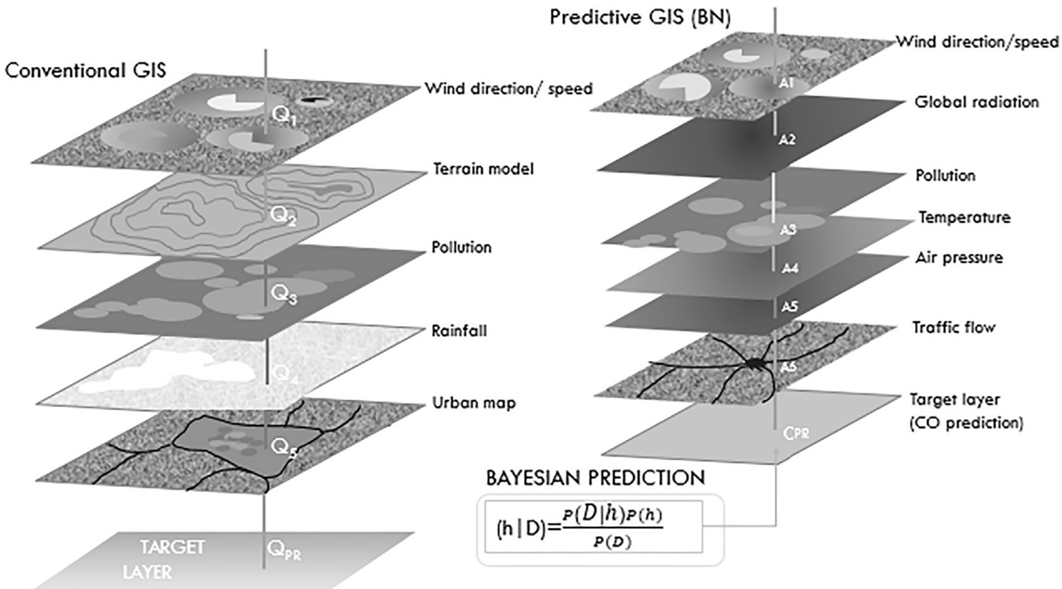

Fig. 2. Traditional query based GIS system (on the left) and predictive model based GIS (on the right) in which a prediction of each sample layer (CO) point is calculated. In our experiments, the sample prediction has been made with 81% accuracy with the limited data set by use of Bayesian classifier.

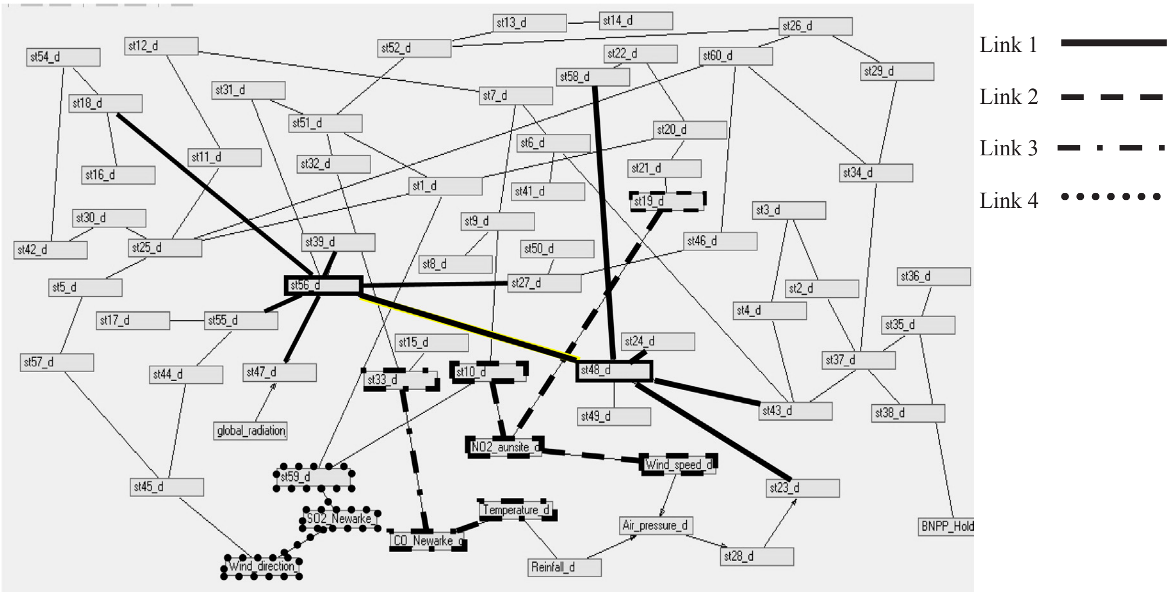

Fig. 3. Established Bayesian Network (BN) configuration created with the use of inference tool, PowerConstructor™ to connect links between the data attributes. The network connection threshold was kept at min level (t = 0.1) to maximize the number of links between the nodes. As is seen in the figure, different cause-effect relations of the attributes are represented by different link characteristics (links 1–4).

PowerConstructor™, the following conclusions would be drawn to interpret the links between the attributes in the network.

- Traffic data collection Station56 (shown as St56) has a vital role as it has 7 connections with other stations (for vehicle flow data). This means that any structural change on Station56 would have substantial effect on the other stations. (*Link 1*)
- Air pollution attributes have natural links with some parameters like: temperature, rainfall, CO_Newarke, air pressure, wind speed, NO_2. This will lead to a natural modelling to be associated with the main traffic air pollution model (*Link2, Link 3*)
- CO in Newarke area has a link with traffic Station33, NO_2 Aunsite area has link with Station10, SO_2 Newarke area has link with Station59, it has also link with wind direction whose cause-effect relationships would need an efficient interpretation before a modelling (*Link 4*)
- The stations (Sti) for vehicle flow data collection have links with each other's, which may give an idea about the interactions between the high-density vehicle flow regions in the city. (*Link 1*)
- One of examples for a hidden interaction would be between temperature and CO pollution. Which may help in traffic planning to bring some restriction on CO emission (e.g. by speed reduction in warm days of the year) (*Link 3*)

The attributes' cause-effect connections can be further exhibited as demonstrated in Figs. 2–5 by the separate local links. Note that the direction of arcs in Figs. 1–5 should to be ignored as the formation of arrows are due to software utility characteristics and have no specific function other than link.

3.1. Discovering cause-effect connections

The effectiveness of artificial intelligence techniques which support data interpretation is the most essential and challenging

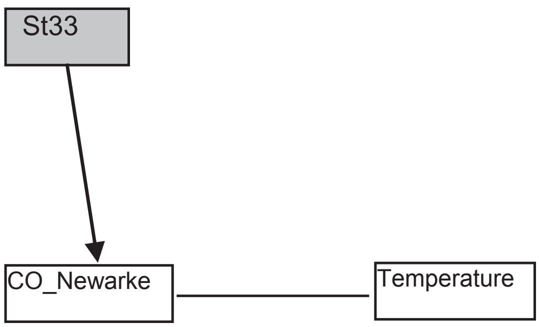

Fig. 4. Traffic flow effect of Station33 on CO pollution in Newark area with an influence of temperature variations.

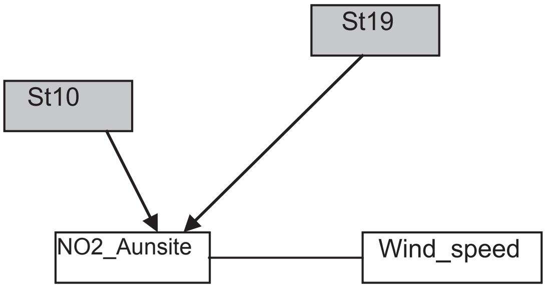

Fig. 5. Traffic flow effects of stations St19 and St10 on NO_2 pollution in Aunsite area with the influence of wind speed variations.

factor for the data analysis which would otherwise not be possible to achieve manually. In our work, local link analyses have been made as shown in Figs. 4–7 where each was derived from the global Bayesian Network configuration (grey boxes indicate the traffic data collection stations).

In our work, the BN attribute connection threshold "t" is set to 0.1 for establishing the maximum number of links. The discretization method for data set values was selected as equal frequency. The examples of local cause-effect connections (in Figs. 4–7) may provide useful initial information for design strategy of the air pollution predictive model. In the example, an interpretation of configuration can be made as shown in Fig. 4 where the CO pollution in Newarke area is caused by Station 33 as the temperature variation also seems to be an impact factor. If there would be a direct link between the temperature and Station33, then the possible conclusion would be made that the temperature variation might be caused by high density of traffic flow or traffic jam. But in this circumstance temperature is possibly the function of CO gas emission. In Fig. 5, traffic flow effects of stations St19 and St10 on NO_2 pollution in the Aunsite area with the influence of wind speed variations, which is concerned with topographic characteristics of the location. Similarly, in Fig. 4, the pollution caused by Station59 (labelled as st59) is under the influence of wind direction where it has to be taken into account during the traffic network design phase in regards to geographic location. In Fig. 7 an interaction between the stations provide a beneficial information for easing the traffic load on any of those station junctions by transferring its traffic flow to the other. In Fig. 6, SO_2 Newarke area has link with Station59, it has also link with wind direction whose cause-effect relationships requires an interpretation of the wind effect.

3.2. Bayesian predictive model

The predictive GIS layer generation for a single point is shown in Fig. 1. The same procedure (for each desired location) can be repeated by assigning each layer point (e.g. traffic flow, other gas pollutions) as a class node in turn in the predictive Bayesian model (Fig. 1). It needs to be highlighted that the calculation of each predicted pollution value on the generated GIS layer will depend on the availability data collection stations at sufficient frequency so that a feasible interpolation between the stations can be done to calculate a map grid. Table 2 shows that NO_2 and CO pollutions are only linked to traffic flow data where for the SO_2 the environmental parameters are additionally involved. The likely reason would be that in the formed BN the environmental attributes have very indirect effects on such pollutions, and their additional links in BN would not improve the prediction accuracy further. The prediction of pollution/air quality linked to the traffic flows (at the data collection station areas) would give us the numerical results (e.g. pollution below or above the hazardous threshold) which means that we can predict the pollution phenomenon such as, if traffic flow at Station14 exceeds a specified threshold value (e.g. specified at network design stage) in association with certain wind speed/direction, then SO_2 pollution would become > 0.18 ppb (parts per billion) which is specified as high pollution. Similarly, if traffic flows exceed the specific values at stations 1, 33, 59 simultaneously, then NO_2 air pollution would be > 8.41 ppb that is beyond the specified pollution level (please note that the pollution thresholds are selected according to our limited data set symbolically to enable class attribute values to include both (high/low) classes for proper BN training whereas at the system design stage those thresholds will be selected more properly specific to the residential issues whether for school, hospital or less sensitive urban areas. In

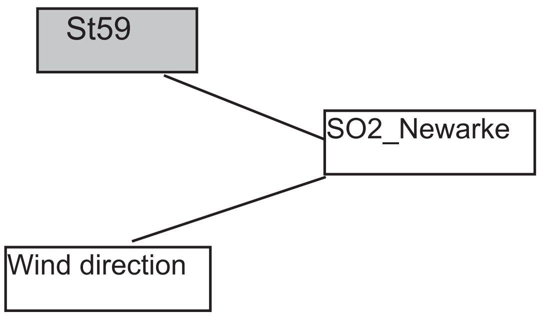

Fig. 6. Traffic flow effects of stations St59 on SO_2 pollution in Newarke area with the influence of wind direction parameters.

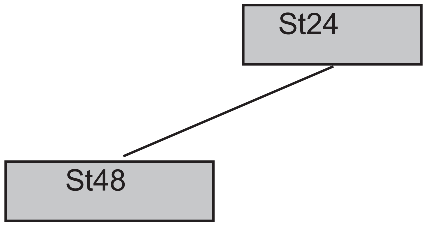

Fig. 7. Traffic flow interaction between the stations St24 and St48 which may be taken into account for easing the traffic load of each one at traffic network design stage.

Table 2
Prediction accuracies of the predicted pollution values of a new GIS layer calculated by BN classifier with the PowerPredictor system options, and automatically selected attributes that primarily influence the prediction process.

Gas pollutant	Prediction accuracy (in GIS layer)	Influencing attributes	Bayesian network options
SO_2	85%	Wind direction, wind speed, traffic flow at Station14	t = 0.1, equal frequency discretization
NO_2	78%	Traffic flow at Stations 1, 33, 59	t = 0.1, equal frequency discretization
CO	81%	Traffic flow at Station 42	t = 0.1, equal freq. discretization

the prediction results (Table 2) calculated by use of Bayesian classifier (PowerPredictor™) (Cheng et al., 2002), SO_2 values are calculated with 85% accuracy of low/high gas emission level prediction, based on: wind direction, wind speed, station 14 traffic flow attributes. Meanwhile NO_2 values are calculated with 78% accuracy of low/high gas emission level prediction, based on: station1, 33, 59 traffic flow attributes and CO values with 81% accuracy of low/high gas emission level prediction, based on: station 42 traffic flow attributes. This means that new pollution layers (maps) in GIS can be predicted as (low = harmless, high = harmful) with 78–85% accuracy at the design stage of a road network, residential areas, hospitals, etc. before their construction stage to avoid harmful effects of air pollution (see Table 3).

4. Conclusion

The method proposed in this article aims on establishing relation between traffic and traffic-induced air pollutants, (SO_2, NOx, CO) whose considerable impact on public health and environment had already been highlighted, e.g. by Health Effects Institute (2010) and Alvarez-Vazquez et al. (2017). Meanwhile the distinguished role of GIS systems that associate with the pollution models have also been emphasized by several authors (Gulliver and Briggs, 2005; Hochadel et al., 2006). In our work we consider the above factors to develop a Bayesian predictive model by inclusion of the major pollutants. To achieve this by the experiments, the sample layers (SO_2, NO_2 and CO pollutions assigned as class nodes in turn) are constructed using a Bayesian Classifier (PowerPredictor™) utility with 85%, 78% and 81% classification accuracies respectively by an optimised network parameters selection (Table 2), but based on limited and partially missing data set due to local stations sensors' data capturing discontinuity. By the experiments it has been proven that the proposed method would lead to development of predictive layers to be integrated with a GIS system with prediction capability. As stated in the past literature, the learning classification systems like Bayesian Networks used in this application have several advantages over the other traditional data analysis systems in terms of flexibility of adaptation against the potential changes (e.g. additional data inclusion without any structural change of system). These advantages are still in question even though the earlier non-learning systems presented in the introduction section above provide higher prediction accuracy but with a potential of overfitting problem. In the literature, it is indicated that Bayesian method guards against overfitting (Kass and Raftery, 1995) and it also exhibits better performance than other classifiers like Neural Nets or Maximum likelihood (Denzer et al., 1995).

Table 3
Bayesian statistical results about SO_2 pollution with 85% accuracy, 90% sensitivity and 80% specificity. Sensitivity value is linked to high pollution detection with 90% accuracy which is more important than the detection of non-pollution that refers to specificity (with 80% accuracy). The lift index indicates the ratio between the results predicted using the classification model and the results using no model (predicted randomly). The ROC area under curve (AUC) measure of the accuracy values.

Predicted	High pollution (SO_2)	Low pollution (SO_2)	Lift index
Confusion matrix (for SO_2 pollution)			
High pollution (SO_2)	0.000017	0.000002	0.72
Low pollution (SO_2)	0.000004	0.000016	0.71
ROC indices			
High pollution (SO_2)	0.00	0.90	
Low pollution (SO_2)	0.90	0.00	
Accuracy = 85%, Sensitivity = 90%, Specificity = 80%			

An accurate and reliable modelling is always a big challenge for high parameter-interactive time-sequenced domains, like air pollution measures of a traffic area. Such a modelling issue would only be solved by state-of-art techniques such as artificial intelligence assisted prediction in association with efficiently distributed low-cost sensor networks, etc. Our ultimate target within this framework was an optimised method for a predictive traffic air pollution modelling at very local scale of urban areas by which maximum desired reliability and accuracy would be obtained by use of feasible instrumentation and labour work at moderate cost (that is affordable by local governments). The method would be particularly useful at traffic network design stages where subtle parametric impacts would be more effective than expected on the environment and economy on the long-term basis.

The proposed predictive model introduced here would be further extended to be used in areas with critical importance (e.g. nuclear plants, airports, hospitals, schools or other strategic and public constructions) with aim to support planners and potentially avoid irreversible fatal mistakes or significant economic implications. For each application, a specific data layers and prediction layers that are expected to be in interaction in a reasonable time domain should be designed and developed with efficient data collection. The accuracy result obtained would be further improved by availability of data (e.g. for longer period and more efficient data types integration). As an overall conclusion, the proposed work will enable conventional GIS systems to be upgraded to an intelligent level in assistance with AI methods.

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