City Air Management: LCA-Based Decision Support Model to Improve Air Quality

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Abstract Siemens has developed an emission model of cities to understand the root cause and interactions to reduce air emissions. The City Air Management (CyAM) consists of monitoring, forecasting and simulation of measures. CyAM model aims to provide formation on air pollution reduction potential of short-term measures to take the right actions to minimize and avoid pollution peaks before they are likely to happen. The methodology uses a parameterized life cycle assessment model for transport emissions and calculates the local impact on air quality KPIs of individual transport measures at the specific hotspot. The system is able to forecast air quality and by how it is expected to exceed health or regulatory thresholds over the coming 5 days.

In this paper, the LCA model and results from selected cities will be presented: Case studies show how a specific combination of technologies/measures will reduce the transport demand, enhance traffic flow or improve the efficiency of the vehicle fleet in the vicinity of the emission hotspot/monitoring station.

1 Introduction

According to the World Health Organization (WHO), almost 90% of the world's urban population breathe air with pollutant levels that far exceed the recommended thresholds. Approximately seven million people die each year from the effects of air pollution, which, according to the WHO, makes it a greater global health threat than Ebola and HIV [1].

City leaders are under pressure to meet these challenges and define strategies for sustainable, clean and smart growth. However, they often lack sufficient data or

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digital tools necessary to make the best decisions. Additionally, continuous urbanization has resulted in population growth, sprawling land use and changes in mobility behaviour. Despite public transit investments, congestion is worsening globally. The sheer volume of inter- and intra-urban transportation has outpaced improvements in and customer uptake of clean transport technology. As a result, air quality has deteriorated in many cities, large and small, and city leaders are accepting that, at its core, poor air quality is an issue of public health and wellbeing [2].

As trusted global partner for sustainable city development, Siemens has developed a complete, cloud-based software suite to overcome the challenges of poor air quality using artificial neural networks and LCA-based decision support methodology. The City Air Management Tool visualizes air quality data recovered from municipal measuring stations in real time. In addition, it forecasts air pollution levels for the next 3–5 days with up to 90% accuracy and also simulates the impact of short-term measures on air quality. Combining air quality forecasts with the simulation of the effectiveness of planned measures and technologies helps cities in the first instance to activate short-term measures; however, it will also foster long-term air quality improvement measures in the upcoming years, such as the implementation of low emission zones or increased e-mobility.

2 City Air Management: Solution and Methodology

The process of CyAM is depicted in Fig. 1. The system starts with data collection from measuring station at hotspots in cities [3]. Then a simulation predicts the degree of air pollution several days in advance. Based on its analytical capacities, the main drivers for air pollution are identified and monitored continuously in order to improve the prediction capabilities. The software aims to give cities the information needed to minimize and avoid pollution peaks before they are likely to happen.

The main technical specifications of the CyAM are as follows:

Fig. 1 City air management process: monitoring of air quality KPIs, forecast and simulation of applicable measures

- Monitor the citywide, hotspot emissions of all environmental sensors which have been integrated in the tool, focusing primarily on PM_{2.5}, PM₁₀ and NO_x. Data is shown for each sensor on an hourly basis.
- Forecast air quality and inform city leaders through a dashboard about where and by how much air quality is expected to exceed health or regulatory thresholds over the coming 3 days with 90 per cent accuracy and up to 5 days at a level of 75–80%.

Cities/counties/states operate their own air pollution sensor networks in order to prove their compliance with national or international regulations [4, 5]. This data is gathered on central servers and publicly available in most parts of the world. The city would need to provide air quality sensor data, historic and real-time air quality data streams of all available measurement stations from a central database using standard database data interfaces. The CyAM has an API, which allows this data to be pulled from these servers or pushed to the CyAM as soon as the data is available. This is depicted in Figs. 2 and 3.

The dashboard shows the three air quality KPIs, NO₂, PM₁₀ and PM_{2.5}, over a timeline. Potential transportation-related measures to improve the air quality are shown on the right-hand side. The data for the individual measurement stations are visualized, categorized and benchmarked against the legal thresholds in the dashboard. It provides an immediate evaluation of the current situation and information on whether it is necessary to act. The latest history is also available for review, as well as the gliding annual average (Fig. 3).

There are two options to do forecasting for air pollutants, domain models and artificial intelligence [6].

Domain models are models which fully understand the physical and chemical processes of emission source behaviour and the atmospheric processes during transmission of pollutants. Their main disadvantage is that there are a vast variety of emission sources in and around a city. It is very expensive and time consuming to

Fig. 2 Dashboard of measuring stations and potential measures to reduce emissions for KPIs like NO_x and PM_x

Fig. 3 Dashboard of actual air pollution data for NO₂ and PM₁₀

assess them in real time. The modelling of the transmission (distribution plus the physical and chemical processes of the pollutants in the air) is time consuming and requires high computing capacities.

CyAM uses artificial intelligence (AI) to forecast air pollution concentrations at individual air quality measurement stations [7]. It takes few available parameters which are available as forecasts and builds an empiric model based on historic data. CyAM uses air pollution measurement data, weather data/weather forecast data, calendric data and special events. The AI finds correlations and patterns in this data to predict air pollution for individual measurement stations. It doesn't contain any knowledge about the physical and chemical processes, responsible for these concentrations. Based on real-time data and forecasts of weather – and calendric/event data – a 5-day forecast is provided. The Advantage is a model which has a high precision, takes little computing power during operation and requires few data points.

In the air pollution forecasting system, recurrent neural networks are used, which are well suited for this task. They also make it easier to uncover a great deal of previously unobserved, latent information about air pollution-causing factors from traffic, industries, agriculture, etc., in the internal dynamical model of the environment, which is built up during the training of the network. Based on all of the resulting data, as well as seasonal and immediate weather forecasts, the neural network has to learn how to predict the degree of air pollution. During the city-specific training process of the system, which includes hundreds of iterations, the program steadily reduces the difference between its forecasts and the actual levels of pollutants measured in the city's atmosphere by changing the weightings of individual parameters (Fig. 4).

In order to calculate impacts of individual measures, a domain model is inevitable [8]. The key to success is to only model the share of emission and concentrations, which can actually be impacted by interventions. This reduces the data requirements and complexity to a minimum, using forecasting values for different measurement stations, provided by the AI. Depending on their location, they represent certain emission sources, as indicated in Fig. 5. If the measurement station at

Fig. 4 Forecasting of air pollution is realized by domain models or artificial intelligence; CyAM uses the second

Fig. 5 Urban emission concentration profile for PM or NOx

the roadside (referred to as hotspot) and the one representing the local background are located well, they can be used to estimate the local road traffic-based concentration in a street canyon in front of the roadside measurement station. It is a simplified concentration contribution analysis, singling out local traffic-related air pollution concentration.

In parallel, a domain model is used to perform an emission contribution analysis of different vehicles and vehicle categories from the overall local transport emissions. These are based on information such as how many vehicles of which vehicle category and exhaust gas emission class are passing by the measurement station. Temperature, slope and congestion level are represented as well. The combination of the contribution model from roadside emissions and the concentration contribution analysis based on correlating forecasted air quality sensor data provides a full view of which vehicles are responsible for a certain air pollution concentration [9]. This process is executed for any hour of the forecasting period individually. The domain model for traffic emissions also contains a variety of location-specific

scenarios, representing different intervention options. These interventions can be selected short term in order to reduce local emissions and thus local concentrations. There are 17 short-term levers that could be simulated within the CyAM standard model – depending upon the needs of the city. These measures include reducing the price of public transportation and encouraging public transport use, requiring that all buses in that area be electric or encouraging residents to work from home when possible. The selected 17 measures are depicted in Fig. 6.

Triggering any of these interventions results in an emission reduction of one or several modes, what is modelled and translated in concentration reductions at the roadside measurement station via contribution analysis. The result is an hour-by-hour forecast of the saving potential for the modelled interventions within the next 5 days.

To understand the underlying methodology, we use the lever of temporary driving ban for diesel cars. In case of exceeding emission limits, a diesel driving ban is announced and enforced. All diesel cars are restricted to enter the city region. A licence plate recognition system will be installed around city boundaries and near emission hotspots to check the potential driving permission [10].

The LCA model and the mechanism of demand shift are depicted in Fig. 7. After a diesel car ban is in effect, the available additional capacity at peak time will be used by increasing capacity utilization of public transport, shift to bicycle, to carpooling and even absolute reduction of car pkm due to home office, etc.

In the LCA model, passenger kilometre (pkm) of diesel cars is shifted using four different mechanism step-by-step to public transport, to bicycles, to carpooling or ride-hailing and if required to absolute pkm reduction due to home office, work shifting/vacation, etc.

From the 17 levers of our model, the two main impacts of air quality emission reduction are modal shift (from private cars to public transport, taxi and zero emission vehicles) and improved traffic flows by capacity shifting [9].

Fig. 6 Seventeen transportation measures to reduce air pollution at hotspot

Fig. 7 Example for LCA model of urban transportation: diesel car ban reduces the emissions by modal shift and improved traffic flow

Fig. 8 Quantification of reduced NO₂ value at hotspot by applying diesel ban as a measure; temporal behaviour from forecast is also shown

3 Results and Discussion

From Fig. 8, we can understand the decision support function of the CyAM system. The forecast of the emission value for hours and days will be combined with the impact evaluation of the system. By applying different levers, one can see the reduction of certain KPIs for different time scales. The shown example displays a diesel

car traffic ban over certain time and the respective NO₂ reduction at the hotspot. CyAM can support cities to conduct knowledge-driven decisions to avoid exceeding set limits and combine different measures to increase impact analysis and outlook for set mid- and long-term measures. The system can also be used for other applications, i.e. adjust means of private transportation by using dynamic traffic zones or restrict to electric cars, control the production of factories and power plants and monitor the air pollution nearby, plan time and location of sports and social events to ensure a good air quality and monitor air pollution close to hospitals, schools, kindergartens and living communities for early announcements or change of time and location.

In summary, CyAM can be applied to reshape communication about air quality in your city by improved information quality, transparency, measure polling and/or data-based decision support. It also provides possibilities for short-term measures and real-time management of air quality, i.e. by peak shaving or temporal modal shift.

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