On the Use of Air Quality Microsensors for Supporting Decision Makers

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In this poster we present how a network of Internet-of-things (IoT) devices facilitated through machine learning can improve decision making. Our application domain is air quality in the municipality of Trondheim. Ambient air pollution poses a major threat to both health and climate with millions of premature deaths occurring every year. To enable solutions to this problem, accurate measurements of the phenomenon are required and tools for decision makers need to be in place to quickly understand situations as well as suggest actions that lead to the best possible outcome.

CCS Concepts: • **Computing methodologies** → **Artificial intelligence**; **Machine learning**; • **Human-centered computing** → **Visualization**; • **Information systems** → *Data management systems.*

Additional Key Words and Phrases: decision making, visualisation, machine learning, iot, microsensor, air quality

ACM Reference Format:
Kerstin Bach, Sigmund Akselsen, Tiago Veiga, and Ilias Kalamaras. 2020. On the Use of Air Quality Microsensors for Supporting Decision Makers. In *10th International Conference on the Internet of Things Companion (IoT '20 Companion), October 6–9, 2020, Malmö, Sweden.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3423423.3423463

1 INTRODUCTION

Air pollution is a widespread problem due to its impact on both humans and the environment. Urban cities usually have the worst air pollution due to human activities [5]. Clear links between pollution and health effects have been revealed, which includes both short- and long-term consequences [2].

Providing decision makers with AI-based solutions requires to monitor the ambient AQ accurately, as AI models highly depend on the underlying data used to justify the predictions. Unfortunately, the hyper-locality of AQ, varying from street to street, makes this difficult to monitor using high-end sensors, as the cost of the amount of sensors needed for such local measurements is too high.

2 DECISION MAKING

The desired goal is the reduction of pollution and the actions towards this goal may include traffic route modifications, municipal restrictions in the use of fuels, street cleaning actions, etc. In classical, non-automatic, decision making, the decision about which actions to take is taken by the decision maker, an expert who assesses the situation and decides on the most appropriate action. In automatic decision making, the decision can be taken by the system itself, after estimating the potential impact of alternative scenarios.

IoT '20 Companion, October 6–9, 2020, Malmö, Sweden

ACM ISBN 978-1-4503-8820-7/20/10.
https://doi.org/10.1145/3423423.3423463

Fig. 1. AQ Sensors deployed in Trondheim.

2.1 Facilitated Decision Making

A *Decision Support System (DSS)* is a system that facilitates a decision maker in taking a decision, by presenting them with the collected data, detected trends, predictions for future events, potential risks, etc., and suggesting possible actions that can have a significant impact. In the context of air pollution DSSs usually present the decision maker with several views of the data (interactive maps, tables, timelines, etc.), presenting the raw data along with the results of data analysis, e.g. meteorological model predictions [3, 6]. In this study we create a microsensor network using low-cost sensors (see Figure 1) that are distributed in several places within a city to measure AQ.

Data analysis. The collected data are in the form of time-series, so time-series models will be employed in order to extract useful information. Prediction models, based on traditional machine learning techniques as well as deep learning techniques and trained neural networks, are being developed with the goal to provide important information to the decision maker. Predicting future states of air pollution or other related quantities (e.g. traffic) allows decision makers to better plan their actions and take preventive measures. Part of the data analysis methods we use employs computation of correlations among the collected variables (e.g. between weather conditions and pollutant concentrations, or between measurements from different geographical areas), which is also important and may provide hints to the decision maker about the causes of specific pollution patterns. We make use of matrix factorization techniques, in order to discover significant events that can explain much of the pollution behaviour within a time window. We are also examining the use of probabilistic models of pollution and traffic, which will allow the quantification of the uncertainty in our predictions and consequently the risk of certain decisions. Probabilistic modeling will also allow the simulation of alternative scenarios and the measurement of their potential outcomes, in order for decision makers to examine the impact and risks of potential decisions. This tool set of data analysis and decision support methods aims to provide high-level information to the decision maker, allowing them to see the patterns behind the noise, which is crucial for taking better decisions.

Data visualization. Visualizing the available data in a comprehensive manner allows the decision maker to have a better insight in the situation, in order to take better decisions. In the context of the air quality pilot, we have been developing the VisualBox [1] and the VFlow [4] systems for interactive dashboard design. VisualBox facilitates the connection to data sources through the concept of *integrations*, and allows the user to create customized dashboards, by dropping ready-to-use visualization components (maps, timelines, bar charts, etc.) on a canvas and connecting them to data sources. VFlow is a web library for dashboard design in which different types of visualization and data analysis are considered as components supporting specific functionalities, and the

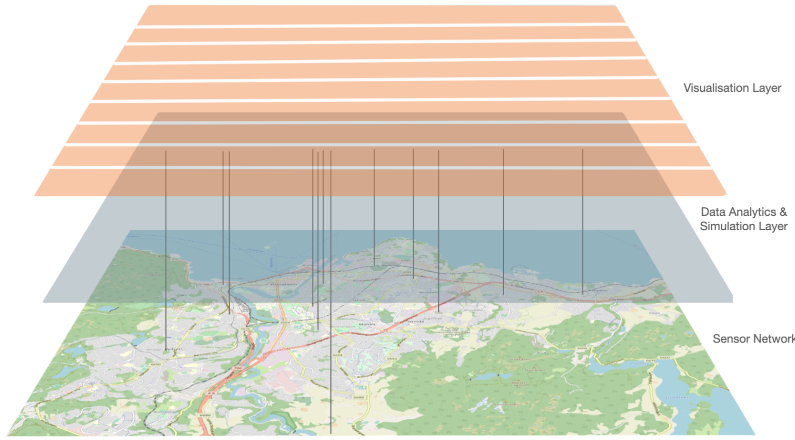


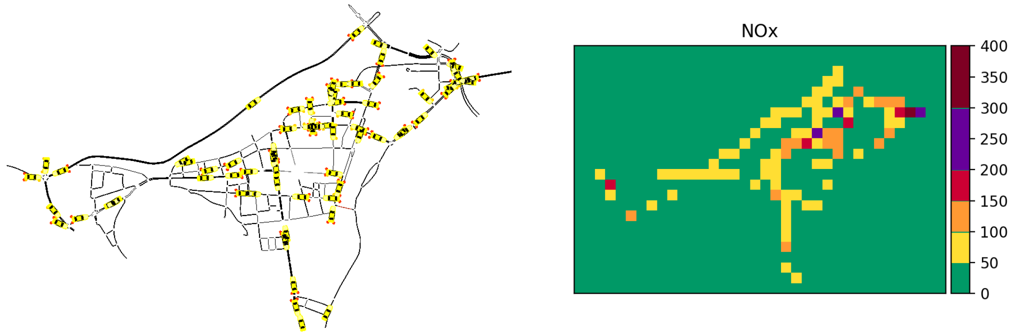
Fig. 2. Data, analysis and visualisation layers based on the sensor deployment used for facilitated and automated decision making.

connections between components determine the dashboard logic and the user interaction. An important challenge regarding visualizations, which is one of our major goals, is how to use visualizations not only for displaying raw data, but also as a means to better explain the results of AI models trained on the data. Explainability of the AI models is important so that the decision makers know why e.g. a specific prediction was computed, which will let them be better informed about the decisions they take. Our effort regarding the above developed systems is to also include means of visually explaining the results of our AI models.

2.2 Automated Decision Making

In a world increasingly connected and robotized, automated decision making may provide a tool to, simultaneously, improve the readings and/or calibration of mobile sensors and actuate in the environment to prevent high pollution peaks. For instance, mobile sensors may be mounted on-board public buses which provide a good coverage of an urban scenario but run on fixed routes while other types of vehicles might have a more flexible route scheduling (e.g. street cleaning vehicles). Automated agents can facilitate solutions to prevent pollution peaks: For instance, taking into account the traffic and weather patterns to reroute traffic to prevent pollution accumulating at a particular region.

Traffic simulation. First, we are building a simulated scenario in which we can test our models and show the utility of the proposed solutions. This is based on the Simulation of Urban Mobility (SUMO) traffic simulator [7]. SUMO is a traffic simulator that is able to generate traffic routes from input data. Traffic data readings from public roads in Norway are publicly available with traffic data aggregated per time for each detector, with the minimum shortest time interval of one hour. We are now at the stage of analyzing the output of the simulator with the aggregated real data as input and understanding whether the outputted traffic patterns are realistic or if some work on top of that is needed. This software also implements pollutant emission models for the passing traffic, which will allow us to map pollution measures to traffic patterns. With this tool we are able to model and test automated decision making in the scenario.



(a) Traffic screenshot (b) Pollution screenshot

Fig. 3. Screenshots of visualizations for the traffic simulator outputs: traffic and pollution levels. Pollution is aggregated in a grid with cells of 100×100 metres.

3 CONCLUSION AND FUTURE WORK

This ongoing work shows the utilization of AI and visualisation methods on sensor data capturing the air quality in order to implement guided or automated decision making. Main challenges arise on securing data quality from the microsensors, transferability of machine learning models from different sensors and incorporating explainability (to guarantee that an explanation is given to users) and verifiability (to guarantee that safety of the city is ensured). We will investigate together with policy makers, decision makers and researchers how to utilize IoT devices to increase the health and safety of the population. In the future we will develop tools that allow municipalities to implement their own AQ framework based on AI methods and tools that will run on the AI4EU platform[1].

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[1]**Acknowledgement:** The work has been partially funded by an ERCIM "Alain Bensoussan" Fellowship and conducted as part of the AI4EU project, which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 825619. https://www.ai4eu.eu