Context- and Situation Prediction for the MyAQI Urban Air Quality Monitoring System

Daniel Schürholz[1], Arkady Zaslavsky[1], and Sylvain Kubler[2]

[1]Deakin University, Melbourne, Australia
daniel.schurholz@deakin.edu.au
arkady.zaslavsky@deakin.edu.au
[2]Université de Lorraine, Nancy, France
s.kubler@univ-lorraine.fr

Abstract. Predicting the time and place where concentrations of pollutants will be the highest is critical for air quality monitoring- and early-warning systems in urban areas. Much of the research effort in this area is focused only on improving air pollution prediction algorithms, disregarding valuable environmental- and user-based context. In this paper we apply context-aware computing concepts in the MyAQI system, to develop an integral air quality monitoring and prediction application, that shifts the focus towards the individual needs of each end-user, without neglecting the benefits of the latest air pollution forecasting algorithms. We design and describe a novel context and situation reasoning model, that considers external environmental context, along with user based attributes, to feed into the prediction model. We demonstrate the adaptability and customizability of the design and the accuracy of the prediction technique in the implementation of the responsive MyAQI web application. We test the implementation with different user profiles and show the results of the system's adaptation. We demonstrate the prediction model's accuracy, when using extended context for 4 air quality monitoring stations in the Melbourne Region in Victoria, Australia.

Keywords: Air Quality · Context-aware Computing · Internet of Things · Visualisation · Environmental Monitoring

1 Introduction

Throughout the last years, even decades, there has been a steady rise of air pollution in major cities around the world. This has brought many health complications to citizens and even increased the mortality rate in urban areas. Already in 2010 for example, a loss of 25 million healthy years and more than 1.2 million premature deaths in China were attributed to outdoor air pollution [22]. A very thorough study [4] done by the Global Burden of Diseases study published in 2017 showed that 4.2 million deaths were attributed to the influence of air pollution in 2015, from which 1.3 million happened in China and 1.2 million in India. As a result of these terrible effects, the need for accurate monitoring and reasoning about environmental phenomena and creating effective measures to mitigate the damage caused by air pollution is clear. A way to improve the understanding of how air pollution behaves throughout time is by applying prediction solutions.

Much of the effort done to predict air quality levels has been aimed at improving the machine learning algorithms used for the forecasts as well as understanding the statistical correlation between the different input parameters [2,20]. However, too little has been done to make the prediction algorithms aware of the context in which the end-user operates (e.g., depending on the end-user's location, identity, activity), which is referred to as context-aware computing in the literature [15]. Some studies have applied context-aware computing on Air Quality (AQ) monitoring and prediction systems, as in [21,3], but there is still room for improvement. First, pollutant sources can be considered as contextual information (e.g., surrounding air pollution incidents such as bushfires, traffic volumes). Second, low-frequency high peaks of airborne pollutant concentration could be predicted, by knowing the source of pollution. Third, provide a customised and adaptive view of the real-time situations, through a accessible web context-aware application.

The objective of this paper is to research and propose an enhanced context-aware AQ prediction model, and evaluate it by a system implementation for the The Melbourne city urban area, in Victoria, Australia, that suffers of poor AQ caused by seasonal bushfires and high traffic levels. Figure 1 gives a glimpse of the structure of this study, to prove the benefits of context-aware computing on AQ prediction. We first review in Section 2, some context-aware computing concepts, along with AQ monitoring definitions and prediction algorithms for outdoor AQ prediction. In Section 3 we present the theoretical and architectural details of the proposed context-aware AQ prediction system, which is called "MyAQI", standing for "My Air Quality Index". Section 4 explain the architecture and implementation of the system. Next, Section 5 presents a real-life scenario in Melbourne (Australia) that both shows (i) how MyAQI can be used for predicting AQ in urban areas; and (ii) how the My Air Quality Index (MyAQI) system's prediction model performs over a historical test dataset. Finally, in Section 6 we discuss the contributions of this study and the possible future work in the AQ prediction area.

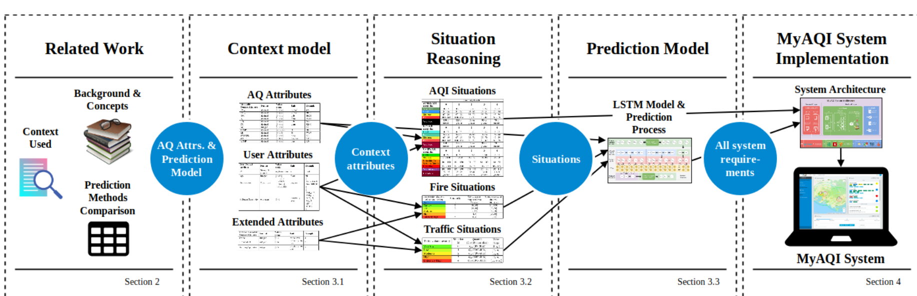

Fig. 1. Research structure for the MyAQI system context and situation prediction model.

2 Background

The core of context awareness is, obviously, the *context*. According to the widely acknowledged definition given in [1], context is "any information that can be used to characterize situation of an entity, where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves." The Context Space Theory (CST) is a method to design contextual models [14]. The approach taken in this method represents the context as a multidimensional space that results in a model that considers context attributes and situations defined to the specific use case.

In the case of this research, the field of application is air quality. The urge to monitor AQ levels is directly linked to the health risks that high levels of airborne pollutants or allergenic agents can have on humans [19]. There is big debate concerning which pollutants are more hazardous and a thorough list of pollutants and their impact on humans is offered in [19]. The selection of these attributes for different outdoor air pollution prediction algorithms and approaches can be seen in Table 1.

Table 1. Use of different air quality characteristics on Deep Learning Neural Network prediction algorithms.

Approach	$PM_{2.5}$	PM_{10}	NO_x	O_3	SO_2	CO	RH	TEMP	WIND	P	VIS	LUM	RP
[3]	✓	✓	✓	-	-	-	-	-	-	-	-	-	-
[20]	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
[2]	-	✓	-	-	-	-	✓	✓	✓	✓	✓	-	-
[16]	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	✓
[24]	✓	-	-	-	-	-	✓	✓	✓	-	-	✓	✓
[23]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-
[21]	✓	-	-	-	-	-	✓	✓	✓	-	-	-	-
[11]	✓	-	-	-	-	-	✓	✓	✓	-	✓	-	-
[13]	✓	-	-	-	-	-	✓	✓	✓	✓	-	✓	-
[8]	✓	-	-	-	-	-	-	-	✓	✓	-	-	-
Total	9	5	4	3	3	3	8	8	9	4	2	2	2

The goal of Table1 is to examine which pollutants are being currently monitored and which ones are considered to be critical for the health of citizens; thus allowing us to select the proper group of variables for the MyAQI system monitoring and prediction features. These values are taken from air quality prediction techniques existing in the literature, which use different artificial intelligence algorithms (incl. machine learning) to estimate the possible levels for pollutants in the future. On this work we focus on methods that use Deep Learning (DL), specifically Deep Learning Neural Networks (DNNs), as their main prediction algorithm.

In recent years the focus of machine learning techniques has hugely shifted towards DNN algorithms, because of their complexity and accuracy for solving previously unattainable problems; and AQ forecasting is not an exception. Applying DL to the AQ problem was arguably started by B. Ong in [13] introducing a novel DL model for AQ prediction and in [24] a composite approach is presented to predict Particle Matter under 2.5 µm of diameter ($PM_{2.5}$) concentrations. Long Short-Term Memory Neural Networks (LSTM) is one of the most widely applied DNNs implementation in AQ problems, as well as in many other use cases, with high performance outcomes. Many approaches with high accuracy are presented for AQ prediction, such as in [20,2,16,11,23,8] where authors improve LSTM algorithms and combine them with input tuning and optimisation techniques. But little has been done to extend the context of the information used as input by the DNNs.

The data structured by a context model is aimed at improving context prediction of future context information, starting from low-level context prediction and ending with situation prediction [18]. Some studies for AQ prediction have applied these algorithms and have been designed considering context awareness. Examples of such a context-aware system, mixed with DNNs are shown in [21,3]. Authors include auxiliary data such as meteorological and aerosol optical depth data and geographic dependency between measuring stations, traffic information, points of interest, social media check-ins, building types in the surroundings, amongst other characteristics, improving the accuracy of the prediction by expanding the applied information.

3 Air Quality Context & Prediction Model

The MyAQI system is meant to be context-aware, thus, the context model used to describe its parts is of critical importance. As mentioned before we use CST to provide a structure to our context model. First we must define the context attributes, which are comprised by AQ attributes, extended extra attributes and user attributes.

3.1 Air quality attributes

As stated in the previous section we consider *Context Attributes* to be of critical importance for the functioning of the MyAQI system. Airborne pollutants play the main role in air quality and must be included. As mentioned before we refer to [19] and our comparison Table 1 to select the most relevant pollutants in relation to human health. These pollutants are $\mathbf{PM_{2.5}}$, **Particle Matter under 10 µm of diameter ($\mathbf{PM_{10}}$)**, **Nitrogen Dioxide ($\mathbf{NO_2}$)**, **Ozone ($\mathbf{O_3}$)**, **Sulphur Dioxide ($\mathbf{SO_2}$)** and **Carbon Monoxide (CO)**. These 6 pollutants are broadly monitored in environmental systems, and are mapped to a human-readable scale using an **Air Quality Index (AQI)**, which are widely implemented by governments worldwide [6,5,19].

Meteorological Variables are crucial for understanding the behaviour of "already emitted" pollutants, as they affect their location, distribution and temporality. We consider **Temperature (TEMP)** as it affects the characteristics of gases, by making more or less airborne [9], **Relative Humidity (RH)** is also relevant as lower humidity enables pollutant particles to become more airborne [17], **Wind Speed (WSPEED)** and **Wind Direction (WDIR)** are clearly related to the dynamics of air pollutants, as they influence the present and future locations of a mass of pollutants.

3.2 Extended external attributes

Air pollutants are measured once they are released into the air and move through the environment. The sources that emit them are usually not considered, although it can supply extra information to the spatio-temporal behaviour of pollutants. One such sources is **Traffic volume**; that is, the amount of motor vehicles driving a certain segment of road or road crossing over a certain period of time. Vehicle emissions are considered one of the primary sources of pollution in cities and contribute largely to high NO_2 and CO levels [5][6]. Other source of pollution, specially in countries such as Australia, where summers can reach high temperatures and low humidity, are **Fire incidents**. They contribute largely to the pollution in urban areas surrounded by dry vegetation areas. Bushfires, specifically, contribute largely to high $PM_{2.5}$ and PM_{10} levels [5][6].

3.3 User attributes

Finally, any context-aware system has to consider relevant user features, that are significant in their interaction with the problem at hand. AQ monitoring is no exception, as air pollutants can affect users differently depending on certain characteristics. We consider the following user attributes: a **User Id** identifies a user to the system and separates information for a customised experience, **Geolocation** determines the spatial reference of a user's location, crucial for outdoor AQ monitoring, **Timestamps** give the specific time and date of interaction with the system to provide updated information and a novel **Pollutant sensitivity** scale, which represents the level of influence that a given pollutant has on the user. Each user has 6 pollutant sensitivity levels assigned, which are derived from answering a small questionnaire [12] at the system's profile section. Each level can take a value between 0 and 4. The values represent the following sensitivities: 0 - "neutral", 1 - "low", 2 - "moderate", 3 - "high" and 4 - "extremely high".

3.4 Situation reasoning

After defining the context attributes, another major building block of a context-aware system is defining the *Situation Space*. For AQ monitoring the following situations and their characteristics were defined. Table 2 shows the situations for AQI levels for different user pollutant sensitivities, traffic volumes for severity levels and fire incidents for severity levels as well, and their corresponding triggering *Context States*. The traffic volumes are dependant of the road and crossing type where the data was collected, so percentages are used for defining the severity of a given measurement. Fire incidents are divided into urban and suburban (and/or countryside) scenarios, because of the size of incidents in each case and the obstacles that could stop the spread of smoke and ashes.

Table 2. Situation spaces definitions for AQ attributes, traffic volumes and fire incidents and their mapped *Context States*.

AQI categories	**User Sensitivity Levels 0**	**1**	**2**	**3**	**4**
Very Good	0 - 33	0 - 33	0 - 33	0 - 33	0 - 23
Good	34 - 66	34 - 66	34 - 66	34 - 54	24 - 44
Moderate	67 - 99	67 - 99	55 - 79	55 - 79	45 - 59
Poor	100 - 149	100 - 124	80 - 99	80 - 89	60 - 69
Very Poor	$\geqslant$ 150	$\geqslant$ 125	$\geqslant$ 100	$\geqslant$ 90	$\geqslant$ 70

Traffic volume	**Situation Id**	**Quantile**	**Value range**
Very low	0	Q_1 (0%-20%)	$[0, q_1]$
Low	1	Q_2 (20%-40%)	$]q_1, q_2]$
Moderate	2	Q_3 (40%-60%)	$]q_2, q_3]$
High	3	Q_4 (60%-80%)	$]q_3, q_4]$
Extremely High	4	Q_5 (80%-100%)	$]q_4, +\infty[$

Fire severity	**Situation Id**	**City range (kms)**	**Suburban range (kms)**
No fire	0	$]20, +\infty[$	$]100, +\infty[$
Very low	1	$[16, 20]$	$[80, 100]$
Low	2	$[12, 16[$	$[60, 80[$
Moderate	3	$[8, 12[$	$[40, 60[$
High	4	$[4, 8[$	$[20, 40[$
Extremely High	5	$[0, 4[$	$[0, 20[$

3.5 Prediction Model

As previously mentioned, the reasoning module implements context-aware prediction for future AQ levels. The selected algorithm for this purpose is an LSTM. LSTMs are being widely used in forecasting solutions throughout different fields and were first introduced in [7]. They improve regular Recurrent Neural Networks (RNN) to keep information for long-term capabilities. In the MyAQI system the algorithm takes the measurements from AQ and meteorological variables for the previous 24 hours as input, as depicted in Figure 2. The notifications then sent to the user will prioritise those pollutants to which the user has more sensitivity towards.

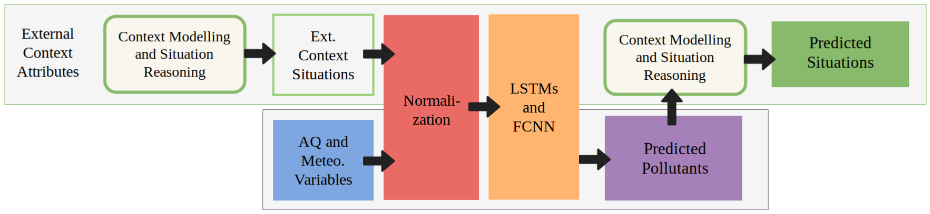

Fig. 2. The MyAQI system prediction algorithm structure, components and data flow.

4 System Architecture & Implementation

4.1 System architecture

The MyAQI system architecture, depicted in Figure 3, is divided into two major layers: *Backend* and *Frontend*. The backend layer comprises two other major layers: the *Data Layer* and the *Logic Layer*. The data layer retrieves the data required to fuel the context model attributes from external Application Programming Interfaces (API) and stored in relational databases, along with user-entered information. The logic layer is comprised by three modules: (i) the context modelling module, that maps the raw data into usable context attributes, (ii) the prediction algorithm module which executes data analysis, such as prediction, on the context attributes, to augment the known information, and (iii) the MyAQI API module which has two interfaces, a Representational State Transfer (RESTful) Hyper Text Transfer Protocol (HTTP) API for regular exchange of information with the frontend modules and a Web Sockets (WS) interface for push notification from the backend server to the user devices. Finally, the frontend layer has only one sub-layer, in charge of the context-aware visualisation of AQ data. The modules of the *Visualisation Layer* are: (i) API consumer, which maps incoming sever information into memory objects, which are then passed to the (ii) *Situation Reasoning* module, where the context states are mapped into real-life events, which are then visualised in the (iii) end-user device views.

4.2 Implementation

Previously the main functionalities, models and goals of the MyAQI system where introduced. In this subsection the implementation of the system is presented. Considering the system architecture presented in section 4.1, the following step is to map each structural element to hardware equipment and it's functioning software.

The backend layer runs in a virtual server in the cloud for better availability. The data modules such as the user and the *PostgGIS* database are installed in this server. PostGIS is used for geographical queries, needed for the distance from users to fires incidents, for example. The logic modules are implemented in the *Python* programming language. Reasoning functionalities, such as prediction, are implemented with the machine learning frameworks *Keras* (with a

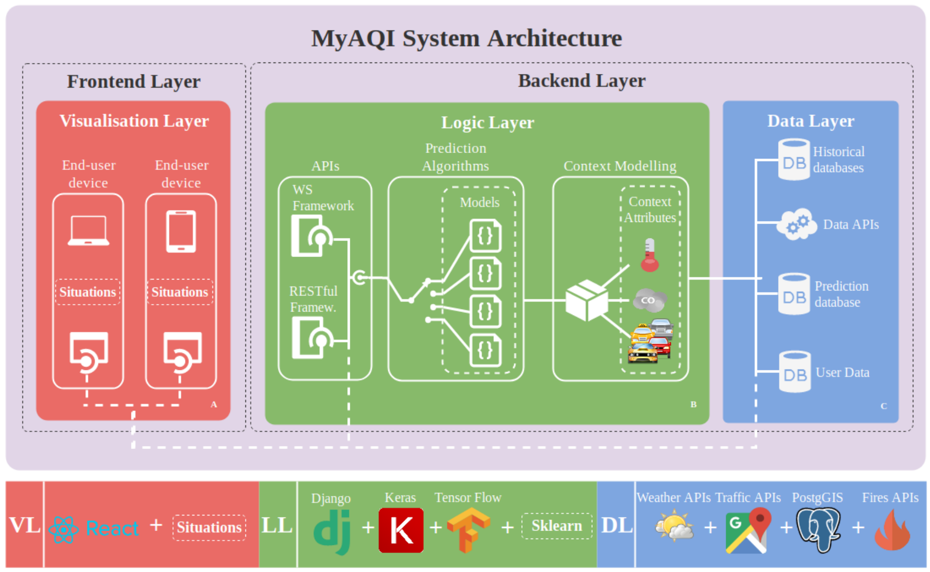

Fig. 3. MyAQI system layers and overall architecture.

TensorFlow backend). Finally, the API modules are implemented using *Django Rest Framework* for the RESTful API and *Django Channels*, plus the in-memory database *Redis*, for the WS interface.

The frontend layer runs in end-user devices, such as mobile phones, tablets and laptops. Thus, the chosen technology for its development is a *JavaScript* responsive web application framework, called *ReactJS*. All the API consumer, situation reasoning and context-aware visualisation logic is developed with this framework and presented via Hyper Text Mark-up Language (HTML) and Cascade Style Sheet (CSS) views. Figure 4 shows different views of the MyAQI web application rendered on different devices, to show the tools responsive nature.

5 Experiments & Results

The previous section introduced the architecture and implementation of the MyAQI system and highlighted its different building blocks. This section presents the experiments that were undertaken to specifically tackle those objectives. First, the experiments' setup and structure is explained, together with the required datasets, and finally, the results of the experimentation are shown.

5.1 Experiments

The AQ attributes required in the context model are presented in section 3. As the data source for the experiments, the Australian Environmental Protection Agency (AU-EPA) in Victoria, Australia, provides a live data API that supplies

Fig. 4. The MyAQI system rendered on different end-user devices, for more accessibility.

both historical and current (updated hourly), and has almost all the needed context variables for many of the sensor stations distributed throughout Victoria, including meteorological data. For traffic information, data from one to four nearby vehicle crossing stations (close to the AQ monitoring stations) where selected to obtain the number of vehicles driving past the site every hour, measured by the *SCATS* system (developed by the government of New South Wales, Australia). Finally, the fire incidents are obtained from a historical dataset, provided by the Victoria government, in which it keeps track of every fire incident in its region since the year 1930. The prediction experiments use data from the previously described data sources, from January 2017 to December 2018.

5.2 Results

In this section the accuracy comparisons of the prediction algorithm are presented, comparing an LSTM that is run considering external context attributes versus one without the extended information. And, finally, the context-aware system views are presented, to complete the user-oriented nature of context-aware computing.

To evaluate AQ predictions we compare them against the ground truth and against the model without the extended environmental context. Table 3 shows the comparison of predictions' MAE, RMSE and precision values for the four stations, once with extended context and once without against the ground truth. The indicators are defined by the following equations:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

$$precision = \frac{|\{true\ AQI\ situations\} \cap \{total\ AQI\ situations\}|}{|\{total\ AQI\ situations\}|} \quad (3)$$

where n is the number of measurements, y_i are the forecasted values and $\hat{y}_i$ are the ground truth values. Precision is a measure used for classification problems, and we apply it see how well the AQI situations corresponding to the ground truth values are kept after the forecast. For all stations except Alphington the improvement in prediction is clear when using the extended environmental context. The case with Alphington can be interpreted as a lack of correlation between extended context variables and the AQ in the area, probably coming from another pollution source. Precision is always improved in the other three stations, specially in Mooroolbark and Traralgon, which are influenced the most by seasonal bushfires.

Table 3. Comparison of MAE, RMSE and precision (Prec) for the prediction results from the LSTM model with and without extended context values, for all four AQ stations.

		Performance Indicators		
Station	**Attributes**	**MAE**	**RMSE**	**Prec**
Traralgon AQ station	*+1hr $PM_{2.5}$ prediction*			
Without Extended Context	$PM_{2.5}$, PM_{10}, NO_2, SO_2, CO	1.678	2.411	0.916
With Extended Context	+ Fires	1.477	2.262	0.943
Mooroolbark AQ station	*+1hr $PM_{2.5}$ prediction*			
Without Extended Context	$PM_{2.5}$, PM_{10}	4.295	6.769	0.872
With Extended Context	+ Traffic, Fires	2.124	8.775	0.909
Alphington AQ station	*+1hr $PM_{2.5}$ prediction*			
Without Extended Context	$PM_{2.5}$, PM_{10}, NO_2, SO_2, CO	1.364	1.922	0.956
With Extended Context	+ Traffic, Fires	1.389	1.949	0.957
Melbourne CBD AQ station	*+1hr $PM_{2.5}$ prediction*			
Without Extended Context	$PM_{2.5}$	2.869	4.115	0.912
With Extended Context	+ Traffic	2.797	3.85	0.93

A snapshot of the prediction algorithm accuracy is presented in Figure 5. The background colours correspond to the AU-EPA AQI categories and show that the prediction stays between the value range of each situations, excepting on some few steps, explaining the overall good precision values.

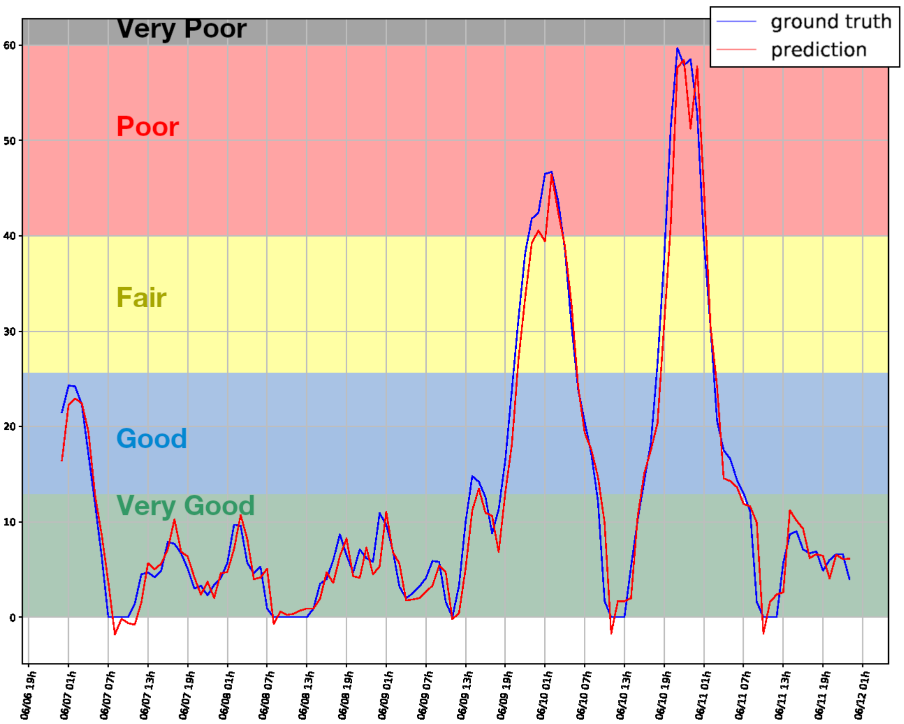

Fig. 5. Alphington AQ measuring station $PM_{2.5}$ levels prediction, considering $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO and nearby traffic volumes. The background colours correspond to the AU-EPA AQI categories, proving that the prediction of AQ situations is accurate.

Another important contribution of the MyAQI system is the personalisation and context-aware views and notifications that the offered to users. Table 4 show three user profiles with different health conditions and corresponding pollutant sensitivities. Using this table's values the MyAQI was run and the notifications received by the user tested. Figure 6 presents the MyAQI web application context-aware air quality monitoring notifications for users with different sensitivity levels to main pollutants, changing the severity according to user health conditions. Finally, the notifications also highlight the source for the pollution (e.g., high traffic volumes) expanding the knowledge of the user over the AQ problem.

Table 4. Context-aware monitoring experiments setup for 3 users with different health conditions and pollutant sensitivities.

User Id	Health Condition	General pollutant sensitivity
alice	Completely healthy	0 - Neutral
bob	Unhealthy diet, casual smoker, no exercise.	2 - Moderate
ana	Has asthma	4 - Extremely High

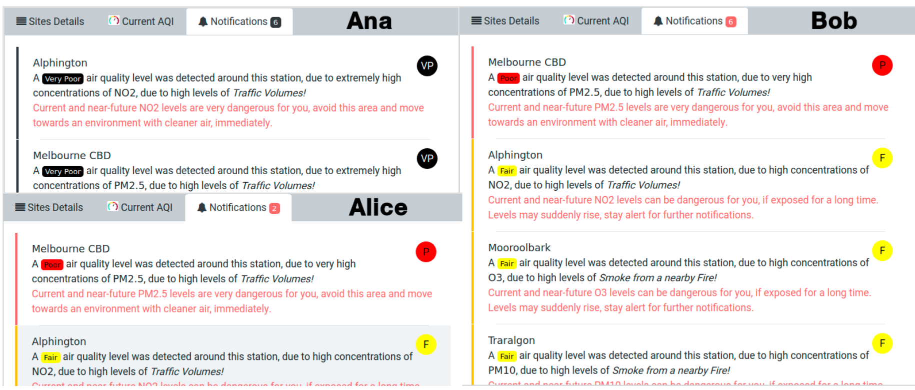

Fig. 6. MyAQI web application context-aware AQ monitoring notifications for users with different health conditions and pollutant sensitivity levels.

6 Conclusion

In this work we research and propose a context-aware model and system architecture for AQ monitoring and prediction systems and we prove its benefits by implementing the MyAQI system. It includes the proposed context- and situation model, the selected prediction algorithm, a thorough architectural design, the implementation, the coupling with selected data sources and the layout of experiments to prove the expected performance of the system. A web application was developed to provide a user-friendly interface to allow user interaction with the monitoring and prediction functionalities. The application is a customisable tool that gives users a highly individualised experience and augments their understanding of the air pollution problem. All the data used in the system was obtained from trusted historical and current data sources and reflect real-life situations obtained from the Victoria EPA in Australia, allowing for an objective assessment of the research results. We prove that the use of extended environmental context sources on the AQ prediction problem improves prediction accuracy, in our specific case, for 3 out of 4 AQ stations.

Finally, the MyAQI system, implemented in this work, provides a proof-of-concept of a context-aware system for the use case of AQ monitoring and prediction in the real-world scenario of the Melbourne area in Victoria, Australia. It showed the benefits that can be drawn from using existing IoT data sources and extracting more information from them by relating them to real-life situations and phenomena.

Acknowledgment

This research was funded by the PERCCOM Erasmus Mundus Joint Masters Program of the European Union [10]. Part of this study has been carried out in the scope of the project bIoTope, which is co-funded by the European Commission under Horizon-2020 program, contract number H2020-ICT- 2015/688203-bIoTope. The research was also supported by Deakin University, Australia. Air pollution data in the city of Melbourne was freely obtained from Victoria EPA API (http://sciwebsvc.epa.-vic.gov.au/aqapi/).

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