LUT University
School of Engineering Science
Erasmus Mundus Master's Program in Pervasive Computing & COMmunications for sustainable development (PERCCOM)

Master's Thesis in
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Daniel Schürholz

CONTEXT- AND SITUATION-PREDICTION FOR OUTDOOR AIR QUALITY MONITORING

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ABSTRACT

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Context- and Situation-Prediction for Outdoor Air Quality Monitoring

Master's Thesis

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Examiners: *Prof. Eric Rondeau* (Université de Lorraine)
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The staggering increase in deaths caused by the rise of air pollution in urban areas is a growing global concern, hence predicting the time and place where concentrations of pollutants will be the highest is critical for air quality monitoring systems. We provide a thorough review of the latest air quality prediction algorithms and show that they are usually focused mainly on improving the forecasting algorithms themselves, leaving valuable contextual information aside. Thus, we introduce a context-aware computing model for outdoor air quality monitoring and prediction systems. We design and describe a novel context and situation reasoning model, that considers external environmental context, specifically traffic volumes and fire incidents, along with user based context attributes, to feed into a state-of-the-art machine learning prediction model. We demonstrate the adaptability and customisability of the proposed design in the implementation of our responsive My Air Quality Index (MyAQI) web 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 test the implementation with different user profiles and show the results of the system's adaptation. We also demonstrate the prediction model accuracy, when considering user and extended environmental context, for 4 air quality monitoring stations in the Melbourne Region in Victoria, Australia.

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For all that I'm thankful!

Daniel Schürholz
June 2019
Melbourne, Australia

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbols

AQI	Air Quality Index
ATMP	Atmospheric Pressure
CO_2	Carbon Dioxide
CO	Carbon Monoxide
GB	Giga-bytes
GHz	Giga-hertz
LUM	Luminosity
$\mu g/m^3$	micro grams per cubic meter
NO_2	Nitrogen Dioxide
NO	Nitrogen Monoxide
O_2	Oxygen
O_3	Ozone
PM_{10}	Particle Matter under 10 μm of diameter
$PM_{2.5}$	Particle Matter under 2.5 μm of diameter
ppb	parts per billion
ppm	parts per million
PREC	Precipitation
RH	Relative Humidity
SO_2	Sulphur Dioxide
TEMP	Temperature
VIS	Visibility
WDIR	Wind Direction
WSPEED	Wind Speed

Abbreviations

AE	Auto-Encoders
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Application Programming Interface
AQ	Air Quality
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average

ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
AU-EPA	Australian Environmental Protection Agency
BDS	Brocke-Decherte-Scheinkman
BIC	Bayesian Information Criterion
BN	Bayesian Network
BP	Back-Propagation Algorithm
BPNN	Back-Propagation Neural Network
CEEMD	Complementary Ensemble Empirical Mode Decomposition
C-LSTME	Extended Convolutional Long-short Term Memory Neural Network
CNN	Deep Convolutional Networks
CSA	Cuckoo's Search Algorithm
CSS	Cascade Style Sheet
CST	Context Spaces Theory
CSVM	Critical Support Vector Machines
DBM	Deep Belief Networks
DBN	Dynamic Bayesian Net
DL	Deep Learning
DLS-SVM	Dynamic Least Square Support Vector Machines
DM-LSTM	Deep learning-based Multi-output LSTM Neural Network
DNN	Deep Learning Neural Network
DSRM	Design Science Research Methodology
DT	Decision Tree
EEA	European Environmental Agency
EGARCH	Exponential Generalized ARCH
EM	Expectation-Maximization
FF	Feed Forward Algorithm
GA	Genetic Algorithm
GCN	Graph Convolutional Network
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
HMM	Hidden Markov Models
HTML	Hyper Text Mark-up Language
ICT	Information and Communication Technology
IID	Independent and Identically Distributed
IMF	Intrinsic Mode Functions
IoT	Internet of Things
KNN	K-nearest Neighbours
LM	Levenberge-Marquardt

LS-SVM	Least Square Support Vector Machines
LSTM	Long Short-Term Memory Neural Network
MA	Moving Average
HSMM	Hidden Semi Markov Models
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron
MP5	Multivariate Regression Tree
MPR	Multivariate Polynomial Regression
NAR	Non-linear Autoregressive
NMA	Non-linear Moving Average
ORM	Object-relational Mapping
OWA	Ordered Weighted Averaging
PCA	Principal Component Analysis
PDF	Probability Distribution Function
PERCCOM	Erasmus Mundus Joint Master's Degree for Pervasive Computing and Communications for Sustainable Development
PLSR	Partial Least Squares Regression
PNN	Probabilistic Neural Network
RAM	Random Access Memory
RBFNN	Radial-Basis Function Neural Network
RBM	Restricted Boltzmann Machine
RF	Random Forest
RLS-SVM	Recurrent Least Square Support Vector Machines
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SA	Simulated Annealing Algorithm
SANN	Seasonal Artificial Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SVM	Support Vector Machines
SVR	Support Vector Regressor
TAR	Threshold Autoregressive
TCP	Transmission Control Protocol
TLNN	Time Lagged Neural Networks
TPR	True Prediction Rate
US-EPA	United States Environmental Protection Agency
WD	Wavelet Decomposition

1 INTRODUCTION

The application of technologies for monitoring the environment and the way humans affect has never been so critical. In this research work, we concentrate on one of the environmental issues exacerbated by people, namely air pollution. By applying state-of-the-art technologies and proposing new models we supply a new approach to understand the issue and present it in an understandable way to citizens. The following subsections of this chapter present the air pollution problem in more depth, provides the research motivation and objectives, the expected contribution and finally, the structure of the rest of the document.

1.1 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 (Yin et al., 2017). A very thorough study (Cohen et al., 2017) 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 mechanisms.

Monitoring and predicting the environment, specifically air pollution levels, is mostly done using extensive sensor networks, which are part of a greater paradigm of cyber-physical systems implemented nowadays, the Internet of Things (IoT). This term was coined by Kevin Ashton (Ashton, 2009) in a presentation in 1998 and it encompasses the notion that most of all objects surrounding our daily activities are going to be connected to the Internet at some point, if not already. This means that the amount of raw data and analysed data that we can collect from the “real world” will multiply extensively. Needless is to state that our information systems and application should be prepared to take the most possible advantage out this surplus. In order to do that, many advances are being done in different areas that comprise the IoT such as networking, end-user-device technologies, sensors, machine intelligence and reasoning, etc Guillemin and Friess (2009). Many of these parts are still in their early stages and there is a lack of standards for many of them. But other areas have been thoroughly studied over the last years and can be a used to improve the effectiveness of the usage we give to data gathered by IoT systems.

One of such fields is context-aware computing systems. The study of context awareness in information systems started long ago, specifically in 1990, and has shifted from regular desktop applications at its early stages, towards IoT in the last years. Research work on context-aware computing expanded when the term “ubiquitous computing” was introduced by Mark Weiser (Weiser, 1999) in his paper The Computer for the 21st Century in 1991 and started the transition to IoT, which happened seamlessly given the structured approach that context-awareness brings to systems that use large amount of data coming from different sensor sources.

To tackle the Air Quality (AQ) monitoring and prediction a combination of IoT networks, context-aware concepts and machine learning techniques can be applied. In this work we combine these areas to prove that improvement can be achieved over other conventional approaches.

1.2 Research Motivation

For a long time, researchers have been improving AQ prediction techniques in order to give citizens and governments more accurate information that helps them make decisions that impact their own health and the overall well-being of their communities. Much of the effort has been aimed at improving the machine learning algorithms used for forecasting AQ levels as well as understanding the statistical correlation between the input parameters to these methods. But, as previously stated in section 1.1, context-aware computing offers a new aid in improving these forecasts. By extending our knowledge of the environment surrounding air pollution incidents and the influence of other external context factors, the accuracy of AQ predictions can be improved.

Motivational use case: the city of Melbourne, Victoria in Australia has been keeping track of its AQ levels throughout the past 10 years, with many sensors scattered across many districts of the megalopolis. The usual information consists of meteorological factors (such as temperature, humidity, wind speed and direction, amongst others) and air pollutants (such as Particle Matter under 2.5 µm of diameter ($PM_{2.5}$), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), etc). These historical datasets can be used to predict future AQ levels to a certain degree of accuracy, but they can not handle high sudden peaks of pollution occurring due to abnormal phenomena, like sudden high vehicle traffic peaks in highways, or a sudden bushfire outbreak. The Australian government issues notices about controlled bushfires or accidental bushfire outbreaks, which can be used to improve our prediction of AQ levels close to a user's position.

As an example, let's take a usual path that Frank, a student in an Australian University in Melbourne, takes usually towards his home on the outskirts of the city. The region is surrounded by native bushland that in summer is prone to experience high temperatures and as a result a bushfire is very imminent. The government of Victoria has planned a controlled fire, to reduce the chances of it happening naturally and without any previous warning, which could put the inhabitants of the region in peril. Frank uses the MyAQI application for knowing the air quality levels on the paths he bikes through. Given that he has asthma, he is very prone to suffer health complications when the air is filled with certain air pollutants. This time he checks the app before returning home and he clearly sees that given that the bushfire is planned for that day in the afternoon, the air quality is gone be hazardous, and he decides to get a train home instead, avoiding the dangerous region. A regular prediction method would not have detected this peak of air pollution, given that from historical data it is impossible to know that it would happen exactly at that time and place. Other context information can be similarly added to the system, like abnormal traffic peaks given to city events, unusual meteorological phenomena, construction sites, factories' locations, etc.

1.3 Research Objectives

The aim of this work is to propose a new model that applies context-aware computing and machine learning techniques to predict future dangerous air pollution levels and present the results in a personalised manner to the end-user. This section focuses on the main objectives that are to be reached in order to achieve such aim.

1. **Make a state-of-the-art review of context-based prediction methods for outdoor air quality applications.**
    - Understand the efforts done so far by other researches to tackle the problem of predicting outdoor air quality, as well as identify other work that uses context-aware computing in this specific scenario.
2. **Identify and/or define set of air quality attributes and extended context based on context discovery, validation, reasoning about, provisioning and sharing.**

   - Identify the most important AQ describing variables that influence the prediction outcomes.

   - Identify the extra context variables to improve the prediction outcomes accuracy.

3. **Identify and/or define the prediction method to use.**

   - Choose two prediction techniques, based on the state-of-the-art review, that can be used as benchmarks and whose prediction outcome can be improved by the extended context.

4. **Design and develop an approach for context- and situation prediction system and compare results with other important reviewed approaches.**

   - Implement a context-aware solution that can be used to compare the selected prediction techniques and that can be used to show relevant information about air pollution levels to the user.

1.4 Contribution

The previous section states the research objectives stated at the beginning of the thesis project, their fulfilment has led to the following contributions:

1. A thorough state-of-the-art review of existing outdoor air prediction techniques has been done, in order to select the most suitable ones for proving the benefit of extending their context information.

2. A context-aware system was developed to benchmark the chosen outdoor air prediction methods against their context extended versions.

3. The results gathered from the system's tests and executions suggests that involving context-aware approaches indeed improve the prediction accuracy. Furthermore, we prove that the combination of more techniques under certain scenarios combined with an extended knowledge of the context attributes needed can further increase such accuracy.

4. The outcomes of this research work include two accepted papers in conferences relevant to the topic of this work:

- Schürholz D. and Nurgazy M. et al., MyAQI: Context-aware Outdoor Air Pollution Monitoring System, *Accepted for publication in ACM SigCHI IoT Conference*, Bilbao Spain, 2019.
- Schürholz D. et al., Context- and Situation Prediction for the MyAQI System, *Accepted for publication in RuSMART Conference*, Saint Petersburg, 2019.

1.5 Research Methodology

This thesis follows the Design Science Research Methodology (DSRM) for Information Systems Research introduced by K. Peffers et al. in (Peffers et al., 2007). This methodology breaks the research work down into 6 steps Identify Problem & Motivate, Define the Objectives of a Solution, Design & Development, Demonstration, Evaluation and finally Communication. These steps are defined as follows:

1. Identify Problem & Motivate: identify the need for better outdoor AQ prediction outcomes, learn the efforts done by other researchers on this field and find gaps in those efforts.
2. Define the Objectives of a Solution: define the specific aims that this thesis will accomplish in order to fill the previously identified gaps.
3. Design & Development: design and develop a framework that will allow to test the new proposed improvements over the current outdoor AQ prediction techniques.
4. Demonstration: demonstrate the implemented system with accurately selected AQ datasets that will provide a fair benchmark for the techniques involved.
5. Evaluation: evaluate the implemented system using the datasets obtained on the previous stage and draw the results in an understandable manner. Find aspects that can be improved about the this or the previous stages and recourse to stages 2 or 3 if needed. Measure the prediction accuracy of the chosen and developed outdoor air prediction techniques using standardized performance evaluators.
6. Communicate: communicate the results and findings in a publication.

The previously defined steps applied to this specific work can be understood in Figure 1.1.

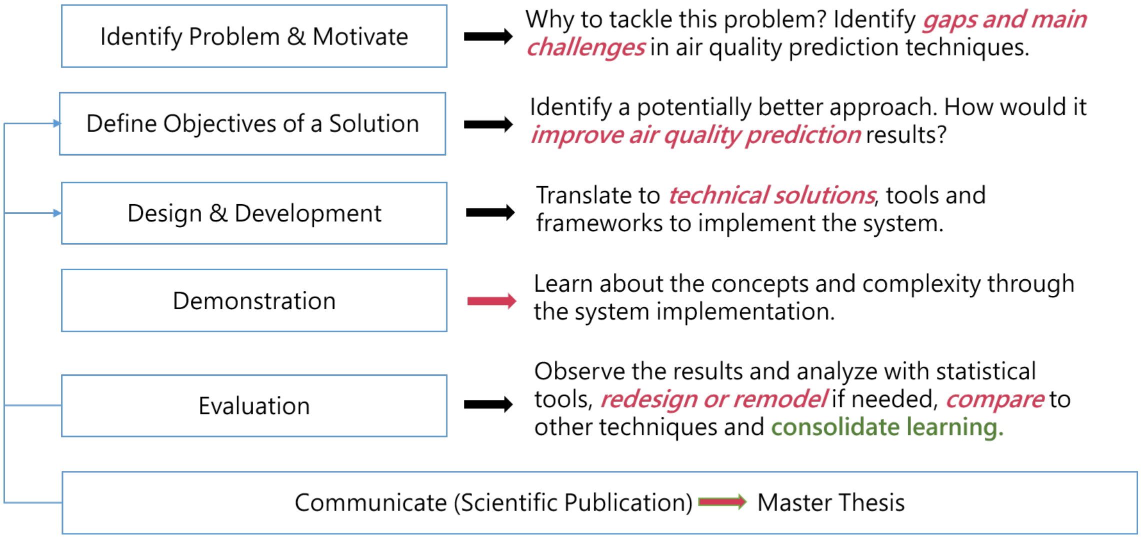

Identify Problem & Motivate
Why to tackle this problem? Identify gaps and main challenges in air quality prediction techniques.
Define Objectives of a Solution
Identify a potentially better approach. How would it improve air quality prediction results?
Design & Development
Translate to technical solutions, tools and frameworks to implement the system.
Demonstration
Learn about the concepts and complexity through the system implementation.
Evaluation
Observe the results and analyze with statistical tools, redesign or remodel if needed, compare to other techniques and consolidate learning.
Communicate (Scientific Publication)
Master Thesis

Figure 1.1: Design Science Research Methodology for Information Systems Research adapted to this thesis.

1.6 Thesis Structure

This section briefly introduces the following chapters of the thesis.

Chapter 2 provides literature review of other works in the field of Context-Aware computing and AQ Prediction techniques in order to reveal current challenges that the work in the following chapters will address.

Chapter 3 presents the context- and situation model for AQ monitoring and prediction, to be used throughout the context-aware system as well as the selected forecasting algorithm.

Chapter 4 gives a detailed description of the MyAQI system architecture and implementation to accomplish the research objectives.

Chapter 5 presents the setup and design of experiments and out-coming results and analyses the advantages that context-aware computing brings to air pollution prediction.

Chapter 6 concludes the thesis contribution and results, bringing forward a discussion about possible future work that can be done to improve the current approach.

2 BACKGROUND

The previous chapter introduced the high-level context and problem on which this work is built. Now we provide a more in-depth theoretical frame, where key definitions are introduced and related work explored, to build the necessary knowledge to build a proposal for a new model that will improve on previous research. First we discuss theoretical key-points that enable context-aware computing and context prediction, then we discuss AQ monitoring approaches, followed by AQ prediction techniques in the related work and finally, some few works done for context prediction for AQ monitoring.

2.1 Context awareness

As mentioned in the previous chapter, context-aware computing aims at using the available contextual information of the environment of a system's functioning to adapt the output to users' needs. The key point in this methodology is context awareness and how to formalise all the different aspects that define a contextual model. In this first subsection of the background we define key knowledge that enables the building of a context-aware model.

2.1.1 Definitions

The core of context awareness is, obviously, the context. Even though we take its concept for granted, there needs to be a clear understanding and definition for its correct use. So, according to the widely acknowledged definition given in (Abowd et al., 1999), 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." Countless attributes can be part of that information, thus usually some of them are selected and grouped to describe the context, creating an application space. A context only accounts to the values or states such attributes can hold, but they can also describe a current more abstract occurrence, called a situation. Linking contextual attributes to descriptive names, a situation is defined as an external semantic interpretation of raw data. Using these definitions of context and situation, applications can benefit from translating real-world raw data to meaningful information to users or other services, expanding their knowledge by making them context and situation aware.

A system is context aware if it considers the importance of users' tasks for providing relevant information or services to them. Pervasive systems are by default context-aware to some extend, because of the characteristics of IoT applications and given the temporal nature of people's location and environment, time is almost always considered together with other dimensions like location, identity and activity. Considering this, the awareness of abstracted context (situation awareness) in pervasive computing and IoT is the highest level of context generalization. Situation awareness formalises and infers real-life situations from measured context data that is interesting to applications, thus enabling a set of predefined actions as response to the situation.

Further work has been done to extend the use of context in pervasive computing. The need to formalize the representation of the context attributes leads to the introduction of a context model or representation, that introduces the important characteristics of the context, retrievable data from sensors, applications and users (Henricksen, 2003). Many ways to model context exist. The techniques to do so are classified as key-value, mark-up schemes, graphical, object, logic and ontology-based modelling (Perera et al., 2014). Each approach provides different benefits or disadvantages in terms of their accuracy, their applicability of context representation and their complexity.

Once the context information is gathered and modelled, we can analyse it and make decision with it. Here is where context reasoning, or context inference, comes into place. Context reasoning relates to deducing new knowledge from available context data (Bikakis et al., 2008). The foundation for context reasoning are context models that are application independent. Context reasoning has three phase: (i) pre-processing, the data is sanitised of inaccurate and missing values; (ii) combination of data from multiple sensors to remove redundancy and provide higher level context; and (iii) context inference in which low-level context data is used to infer context information of a higher level (Nurmi and Floréen, 2004)(Perera et al., 2014).

2.1.2 Context Spaces Theory (CST)

Context spaces theory is a method to design contextual models Padovitz et al. (2010). The approach taken in this method represents the context as a multidimensional space. All concepts described in the previous section are used to define a context space. The context attributes, for instance, define its dimensionality (axes); those attributes can be humidity, temperature, location of the subject, current CO levels, etc. The sum of these attributes give shape to the application space, where the context will be recognized at a given point in time, given the values of the attributes.

Situation spaces are also contained in the application space, each one of them covering a multidimensional area or point, where if the context happens to occur, we can eventually infer a given situation. Each situation space represents a situation in the real world. So, if the context state happens to be in one of those spaces, we can assume that the real-world scenario is currently in the setting of such a situation.

Thus, the context space theory provides a tool for mapping the behaviour of the context of a system inside a modelled world. Even more so, future events can be forecasted, by calculating the possible trajectories through which the context will evolve inside the application space. The whole concept of the context space theory can be understood easily from the following figure (Figure 2.1).

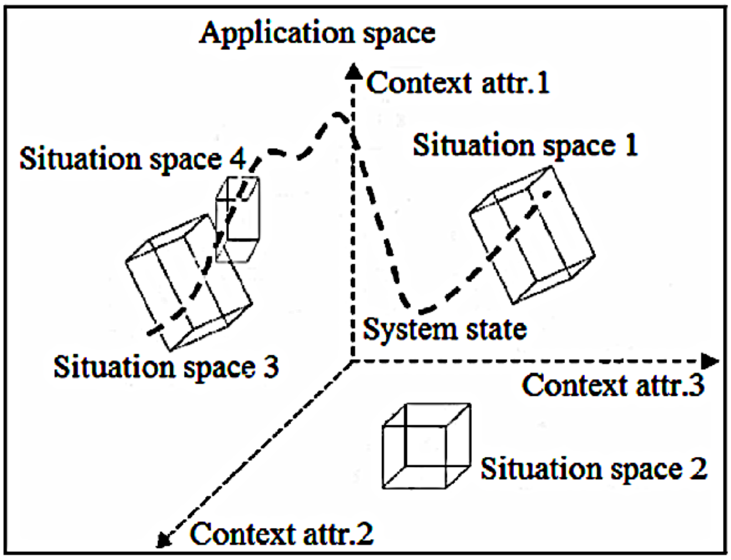


Figure 2.1: A graphic representation of the Context Spaces Theory.

In this thesis the context space theory was selected for modelling the world around the application space, since it provides all necessary means to model the outdoor AQ variables and states, and to map them from sensor readings towards real world scenarios. But, since the main goal is to forecast accurately future situations of AQ settings using context prediction, this will be further explained in the next section.

2.1.3 Context Prediction

Predicting future context information is the goal of context prediction and it can be applied on any stage of context processing all the way up to situation prediction. It infers future context information by acknowledging the behaviour of a time series of such context (Sigg et al., 2012), where historical and current context data can be used to forecast upcoming contexts (Sigg, 2008). Prediction of future context beforehand enables pro-activity of future tasks (for example, applications could prepare services in advance and offer them as required by the user) (Anagnostopoulos et al., 2005). Any pervasive system that tries to predict some event based on a context model must consider certain characteristics of real world events and data derived from sensors. For instance, ubiquitous systems execute their tasks in real time, they usually have the requirement of forecasting human actions, they work in discrete time, data is highly heterogeneous, sometimes hardware capabilities are limited, connectivity problems are a possibility, learning steps should not be extensive, sensors contain a certain amount of uncertainties in their measurements and configurations and automated decision making is often required.

Thus, to implement an accurate forecasting algorithm, some questions must be addressed, so that the best option is used for the specific use case Zaslavsky et al. (2016).

- Can it be pre-trained? It is important to know if the method can use previous knowledge as a starting point, thus making the prediction more accurate from the beginning.
- Can it be updated in run time? Real-world systems are always updated constantly, requiring them the algorithms that forecast their behaviour to be able to support such rapid amount of new data.
- Is the method black-box or white-box? Some methods do not make it possible to know what the underlying process represents, regarding the real-world phenomenon, while others do. White-box methods (Markov Chain Models, for instance), give more insights as to what the model exactly represents, while black-box methods only return the forecast (Neural-Networks, for example). So, it is important to consider how much about the process we want to know while running a prediction.
- Can the method incorporate prediction reliability? It is important to know if we will need more information from the algorithm than only the forecasted value (confidence level, for example, amongst other statistical variables).
- Can it determine outlier sensitivity? It is important to know if the method lets us know

the amount of influence of outliers (data that is statistically far from the average) have on the predicted values.

- What type of data can it support? The exact amount, structure and format of the data supported by the algorithm should be considered, given that the context data sources can differ from one source to another.
- Is there information loss in the process? When the input data to the prediction algorithm needs preprocessing operations, it is relevant to consider whether it conveys information loss and if this loss impacts on the accuracy or truthfulness of the algorithm's outcome.

In subsection 2.3.1 we will discuss in deeper detail some existing methods for AQ prediction using context, and trying to understand how these models comply with the criteria explained in this section.

2.1.4 Context aware system architecture

All the previous definitions of context awareness and prediction can be seen in an architectural setting in Figure 2.2. Sensors and user input are combined in the data fusion layer, are validated and then passed as understandable preprocessed (if required) information to the context awareness layer, where such information is mapped into a context state inside the application space. In this layer the state can be directly sent to the adaptation block and/or passed towards the situation awareness part, in which it is checked against real-world situations, and if it belongs to any of them, that information is sent to the adaptation block. The pervasive computing system responds to the provided input and such reaction is defined in the adaptation block, also defining and providing commanding the actuators. These actuators execute tasks or actions for the applications, services or systems and are usually physical devices, but can also be APIs that send notifications to users subscribed to some service to receive such feeds. Actuators can be, for example: a smart-light that turns on or off depending on the presence of the user in a certain room, a mobile service that alerts users if air pollution levels are high in the areas surrounding their current location, or a flood prevention system that closes some barrier-gates on a stream if the level of the water rises abruptly. The most important layer, though, for the purpose of this thesis is the context-prediction block. Both, the context and situation awareness blocks, send data to the context prediction layer and this, in turn, tries to forecast possible future scenarios to enrich the available information on the adaptation layer for precise decision making. Thus, the prediction layer can augment the information making the actuator actions more relevant and helpful.

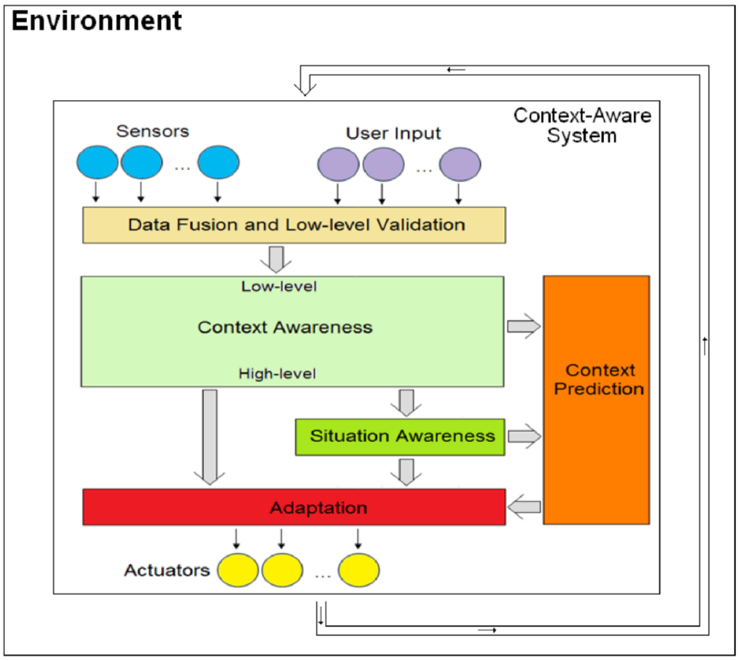


Figure 2.2: Context aware system architecture.

In the use case of AQ prediction, the information can be used to forecast hazardous levels of some pollutants that could affect the health or well-being of people in some area. Furthermore, by combining it with the user's personal health characteristics, a customized response can be supplied, considering the use cases of planning aid and early coordination of individuals, defined in (Zaslavsky et al., 2016) as applicable for using context prediction approaches. To understand how to apply context reasoning to outdoor quality monitoring, first we need to understand what is being done in this field and what possible techniques are being researched and which others have been already applied in real-world use cases. In the next section, we explore those approaches and try to link them to context space theory and prediction.

2.2 Context Prediction Methods

Context prediction is a process undertaken in context reasoning and is characteristic of proactive context-aware systems. Proactivity is usually referred to the ability of an agent to take initiative in adapting its behaviour to fulfil a desired goal. In pervasive computing in contrast, goals are defined by the user of the system and applications should aid the user in pursuing them. It should be noted that, in this work, the term proactivity explicitly describes the use of prediction techniques to refer to future contexts, inferring them from past (observed) context. A comprehensive summary of prediction techniques applicable to context-aware systems is presented in (Mayrhofer, 2004). In this work algorithms are separated into two categories. First, methods that include continuous time series prediction are presented, which try to predict the future development of the degrees of membership of each context state to all situations. Afterwards, categorical time series prediction techniques are explained, whose goal is to give an integral view by considering only the “best matching” context, i.e. the highest ranked context class at each time and analysing the trajectory of context classes to predict future best matching contexts. Next, we will do a short recap of these algorithms and extend the list with newer machine learning approaches.

2.2.1 Continuous time-series prediction

Statistical tests The main idea behind statistical tests is to understand the general structure underlying and generating the variability in time series data. A series of testing techniques are available to determine that the variables included in the system are Independent and Identically Distributed (IID) allowing us to extract information only via the mean and standard deviation of the time series. These tests are the sample autocorrelation function, the portmanteau tests, the turning point test, the difference-sign test, the rank test and others, which are explained extensively in (Brockwell and Davis, 2002). If these tests fail on a time series, it means that it does not comply with being IID and thus, another model must be applied to the data.

Trend, seasonal, analysis In a classical decomposition of continuous, time series, data is represented by one of the two models (Adhikari and Agrawal, 2013):

Multiplicative Model (dependent components):

$$Y(t) = T(t) \times S(t) \times C(t) \times I(t)$$

Additive Model (independent components):

$$Y(t) = T(t) + S(t) + C(t) + I(t)$$

Where $T(t)$ is the trending component of the time series, $S(t)$ is the seasonal component with a known period of d, $C(t)$ is a cyclic component and $I(t)$ is the residual or irregular component, which is assumed to be stational and can be modelled by known prediction techniques such as ARMA, which we explain later. Considering the previous models, the trend can be estimated with a number of techniques like smoothing with finite moving average filter, exponential smoothing, smoothing by elimination of high-frequency components or polynomial fitting or it can be eliminated by differencing repeatedly (Brockwell and Davis, 2002). The seasonal component's function can be estimated by linear combinations, and it is possible to eliminate the seasonality by differencing with a lag of d. Nonetheless, the entire time series data must be used to accurately estimate the seasonality and thus this analysis is characteristic of batch training algorithms.

ARMA, ARIMA and other linear stochastic models as extensively shown in (Brockwell and Davis, 2002), (Adhikari and Agrawal, 2013) and (Montgomery et al., 2008) there are a number of methods founded on the basis of the Autoregressive (AR) and Moving Average (MA) concepts. The combination of the two created the Autoregressive Moving Average (ARMA) model and the Autoregressive Integrated Moving Average (ARIMA), used for non-stationary data. In an AR model future measurements of variables are considered as combinations of n past observations and random errors together with constant terms. Afterwards, an MA model considers historical errors as the variables for explanation, similar to how AR models regress against the series' historical data. ARIMA uses this model and adapts it to non-stationary time series and the SARIMA model adapts to non-seasonal data and in this fashion, other derivations of ARMA adapts to different datasets. Finally, the question of which model to use to produce accurate forecasts in each use case becomes relevant. A practical approach (the Box-Jenkins model) to build an ARIMA model that best fits to a given time series and satisfies the parsimony principle was presented by G. Box and G. Jenkins.

From ARMA and ARIMA many other expansions where created like the Autoregressive Fractionally Integrated Moving Average (ARFIMA), the Autoregressive Conditional Heteroskedasticity (ARCH), the Seasonal Autoregressive Integrated Moving Average (SARIMA), Threshold Autoregressive (TAR), Exponential Generalized ARCH (EGARCH), the Non-linear Autoregressive (NAR) model, the Non-linear Moving Average (NMA) model, etc. each one tackling some limitations of their predecessors in specific use cases.

Artificial Neural Networks (ANN) are a group of Artificial Intelligence (AI) techniques that mimic the functions of the human brain, by combining simple neurons into a network structure that executes a desired behaviour. The most known ANN type is the Multi-Layer Perceptron (MLP) with a strict Feed Forward Algorithm (FF) structure, composed of three layers: (i) the input layer that takes the form of the input parameters as a vector and does not handle any other function, (ii) the hidden layer is fully connected to the input layer and usually uses the sigmoid function as output function, and (iii) the output layer with a number of neurons corresponding to the dimensionality of the output vectors is again fully connected to the hidden layer and applies a linear output function. MLPs are regarded as universal function approximation, meaning that they can be applied on different arbitral and multi-dimensional functions. The Back-Propagation Algorithm (BP) is then applied to adapt the weights in the hidden and output layers to approximate the statistical distribution of the data, which usually needs to be defined a priori. For a thorough introduction of MLPs and the back-propagation learning algorithm see (Zell, 1994). In an extensive comparison with 16 time series of different complexity, it has been shown that MLPs can outperform ARMA models for time series prediction in many cases.

Many extensions have been developed on MLPs for tackling specific data-driven problems. Some examples of such extensions are Seasonal Artificial Neural Network (SANN), (TLNN)Time Lagged Neural Networks (TLNN), Radial-Basis Function Neural Network (RBFNN), Probabilistic Neural Network (PNN), Generalized Regression Neural Network (GRNN), Recurrent Neural Network (RNN), etc. For an extensive survey on ANN and their applications refer to (Oludare et al., 2018). ANNs are amazingly simple though powerful techniques for time series forecasting.

Support Vector Machines (SVM) are a newer technique for machine learning and are suitable for both pattern recognition and regression estimation, applicable to time series prediction. SVMs' basic concept is that data that is non-separable in its original space can be mapped to another space where it is separable by a linear hyperplane. The hyperplane so that the space between the classes that should be separated is maximized. SVMs overcome problems generally attributed to ANNs like local minima and overfitting, thus outperforming them in certain cases; but it is important to notice that nowadays techniques to make ANNs more resilient towards these problems exist. SVMs' main goal is to provide a well generalizable decision rule when selecting a subgroup from the support vectors (training data). SVMs also have another important characteristic, which is that they provide a solution that is always globally optimal and unique, given that they solve a linearly constrained quadratic problem as a training. Nonetheless, SVM has a big disadvantage with large training set, because the required computational resources increase the solution's time complexity (Adhikari and Agrawal, 2013). Based on SVMs other extensions have been developed to further increase their accuracy. Some of these extensions are: the Least Square Support Vector Machines (LS-SVM) algorithm and its variants, i.e. the Recurrent Least Square Support Vector Machines (RLS-SVM), the Dynamic Least Square Support Vector Machines (DLS-SVM), the Critical Support

Vector Machines (CSVM) algorithm, etc. In all these representatives of SVMs the proper choice of parameters such as the kernel parameter ρ, the regularization constant γ, the Support Vector Regressor (SVR) constant ϵ, etc. is of utter importance and an improper selection may result in totally ridiculous forecasts.

Deep Learning Neural Network (DNN) where developed by taking deep hierarchical structures of human speech perception as a reference. In the late 20th century Deep Learning (DL) algorithms were introduced and originated from the concepts immersed in ANNs and the search for global optimums from SVMs and K-nearest Neighbours (KNN). It comprises many different methods but started with the basic notion of a layer-wise-greedy-learning algorithm, which explains that before the subsequent layer-by-layer training the unsupervised learning for network pre-training should be performed. A great overlook on the principles and examples of DNNs is presented in (Liu et al., 2017). Four techniques are thoroughly explained, (i) Restricted Boltzmann Machine (RBM) used to create stochastic models of ANNs having the ability to learn the PDF with respect to their inputs, (ii) Deep Belief Networks (DBM), which are built from multiple layers of variables and are a special variation of Bayesian probabilistic generative models or layers of RBM networks, (iii) Auto-Encoders (AE), which is a learning algorithm that is unsupervised and applied to encode the dataset to reduce dimensionalities, and finally, (iv) Deep Convolutional Networks (CNN), a subtype of the have shown satisfactory performance when working with 2D information like images and videos.

DL techniques largely enhance the analysis and forecasting power of previous approaches, but are still computationally very demanding. In context-driven use cases, where usually the computation must be executed in mobile devices, this becomes a drawback. With further advances in mobile hardware though, it could become possible to adapt such methods for this environment.

2.2.2 Categorical time-series prediction

In these group of time-series prediction we focus only on forecasting the trajectory of the best matching context classes.

Central tendency predictor The most simple prediction method is to predict the central tendency, like the average or median, value considering a window of the n last values of the time series. Usually, the geometric or arithmetic mean is selected as this predictor. But of course it can not handle periodicity or sequentiality in time-series data. In context-driven systems they can be used to detect most often value seen over a time window for simple datasets. First order Markov model for each context we calculate the frequency of each successor (called the transition probability) and the successor with the highest probability is selected. The drawback for these models are that only the next step can be predicted. For time-series forecasting where any $t + d$, where $d = 1, 2, 3, ...$ need to be calculated this method is not applicable.

Higher order Markov Model To overcome the stated issue with first order Markov models, High order Markov models were introduced. They are capable of exploiting relationships between temporally distant states. Despite their simplicity, Markov models have been successfully implemented on complex systems, such as on crude search engines, to predict the importance of a web-page using its link connections (Barber, 2012).

Hidden Markov Models (HMM) HMMs have been applied throughout the last decades on a variety of time series classification and prediction projects. In context-aware applications they have played an important role as well, like recognizing location based on audio and video, task prediction or action recognition. The need for HMMs comes from some limitations of regular Markov Models when the simple mapping of problems to states is not sufficient. To overcome the issue, a hidden layer is introduced, hence the name. The value of an output is determined by the previous observation and, as an improvement, from the value of the related hidden variable. A detailed explanation of the mechanisms of HMMs and the associated training procedures, we refer to the standard tutorial (Rabiner, 1989). The strength of HMMs comes from the maturity of the methods for parameter estimation and simulation in existing studies. Some drawbacks are the rigidity of the model to changes, once it has been defined and trained. But nowadays much has been developed in this regard and new implementations of HMMs such as Factorial HMMs, Coupled HMMs, HMMs with different Probability Distribution Function (PDF) and HMMs with Bayesian Information Criterion (BIC) have been introduced, leveraging many of their initial disadvantages.

Bayesian Network (BN) is a subset of HMMs, Kalman Filters and other probabilistic models. A BN or causal model, is just a graphical representation using a directed graph for describing conditional independencies between a set of random variables. Furthermore, they are data-driven models that have the characteristic of inferring, from observations, the joint probability distribution of the set of related variables. As evidence is input into a BN inference is performed to obtain new posterior probability distributions for the other nodes in the network. A big part of the training of a BN is the construction of the networks and it consists of two elements both of which may be inferred from observational data. First the graph structure must be created and then the corresponding conditional probability tables for this structure must be learnt. everal different techniques for creating the structure of the BN exist: Hill Climbing Algorithm, Genetic

Algorithms, Force Naïve Bayes, Simulated Annealing, K2 Algorithm, Tabu Search, etc. When the structure is built, there is a need for probabilities between the variables to be defined. Many methods for doing this estimation exist: Multi-Nominal Bayes Model Averaging, Bayes Model Averaging, Simple Probability Estimation, etc. (Russel and Norvig, 2009) Dynamic Bayesian Net (DBN) introduce time dependencies into the model and can be used to analyse time series. Also, by discretising the state variables of a DBN, one obtains an HMM model with the standard properties. For the problem of context prediction, the more general class of DBNs does not offer any immediate benefit over its special case of HMMs.

Fuzzy logic as a final mention, consists of a probabilistic model that distributes the domain of a variables values in to fuzzy sets (Sheik Safeer, 2008). The training data forms clusters, to which each point contribute with a certain probability and a centre is determined which represents the highest probability of membership. Fuzzy systems identification is focused on the solution to creating IF-THEN rules from data coming from raw inputs and outputs. So, when a set of this data is clustered, every group centre can be assumed to be a fuzzy rule which describes the system's characteristic behaviour. These rules consider approximations of truth values, separating, thus, itself from traditional logic, which only accepts values of 0 and 1. For context prediction and reasoning this is a great advantage since some variable are not only binary but can take a range of numeric values; e.g., notions such as big, small, bright, untrustworthy and reliability can be assigned, something quite relevant to context information processing (Román et al., 2002).

All the aforementioned techniques can be applied to context prediction problems and have been applied by existing works in the literature. In the next two subsections we go over the AQ monitoring and prediction definitions and over the existing prediction applications of these methods.

2.3 Outdoor Air Quality Monitoring

In recent years there has been a rise in the amount of research and applications dedicated to monitoring and predicting AQ. This is in part, because of the rising airborne pollution levels in cities (outdoors), which is the focus of this thesis, and buildings (indoors). Also, as the world-wide population increases and most of it moves to large cities, the amount of people affected by pollution increases accordingly. Countries with the highest air pollution problems are desperately reaching towards technology for help. This is reflected in the fact that China, the most populated country in the world and holder of 4 of the Top 20 most populated cities in the world (United Nations, 2018), is the country that is submitting the highest amount of research works regarding outdoor AQ monitoring and prediction.

The urge to monitor AQ is directly linked to the health risks that high levels of airborne pollutants or allergenic agents can have on humans, as described in 1. There is big debate concerning which pollutants are more hazardous, but most researchers attribute these health hazards to the $PM_{2.5}$, PM_{10} (Particle Matter under 10 µm of diameter) and NO_x (NO_2 and NO(Nitrogen Monoxide) pollutants. These molecules and particles are all part of what is called chemical air characteristics, in which CO, CO_2 (Carbon Dioxide), SO_2 (Sulphur Dioxide) and O_3 (Ozone) belong as well. Other outdoor AQ attributes relate to physical phenomena or meteorological data. Some of these attributes are Relative Humidity (RH), Temperature (TEMP), Wind Speed (WSPEED) and Wind Direction (WDIR), Luminosity (LUM), Atmospheric Pressure (ATMP), Visibility (VIS), Precipitation (PREC), amongst others (USEPA, 2013). The use of these attributes for different outdoor air pollution algorithms and approaches can be seen in Table 2.1.

The pollutant that is monitored more extensively, especially in the most recent research documents, is by far $PM_{2.5}$, given the serious health risks that it can convey; followed closely by NO. Usually all other attributes are used as influencing parameters on the prediction of these two pollutants' levels. To determine which attributes influence levels of $PM_{2.5}$ the most, and which combination gives the best result for prediction purposes is indeed an issue, that many researches try to tackle.

There are other attributes that influence outdoor AQ but are not necessarily as hazardous as the ones mentioned before. Such elements can be allergenic agents such as pollen and dust, breathing and visibility obstacles like smoke or just comfortability influencers, such as bad smells. Also, in countries where unrefined fossil fuels are used in transportation, the concentration of lead in the air is a major concern. But harder regulations on the composition and expected purity of diesel and petrol, have lessened its impact on humans. These attributes can also be considered when determining the quality of air in a certain area, but, as with the previous ones, it strongly depends with the health conditions of each individual person.

As stated by the European Environmental Agency (EEA): age and health conditions, especially cardiovascular and respiratory, really influence vulnerability towards airborne pollutants (EEA, 2017). Thus, the context of the user's health conditions must be considered as part of the definition of a good AQ level. Some details about hazards for people with certain health conditions can be found in Table 2.2 delivered by the United States Environmental Protection Agency (US-EPA) in (USEPA, 2013).

Table 2.1: Use of different air quality characteristics on prediction algorithms.

Approach	**$PM_{2.5}$**	**PM_{10}**	**NO_x**	**O_3**	**SO_2**	**CO**	**RH**	**TEMP**	**WIND**	**PREC**	**VIS**	**LUM**	**ATMP**
(Shaban et al., 2016)	-	-	✓	✓	✓	-	-	-	-	-	-	-	-
(Zhao et al., 2010)	-	✓	✓	-	✓	-	✓	✓	✓	✓	✓	✓	✓
(Bai et al., 2016)	-	✓	✓	-	✓	-	✓	✓	✓	✓	✓	✓	✓
(Huang and Cheng, 2008)	-	-	-	✓	-	-	-	-	-	-	-	-	-
(Singh et al., 2012)	✓	✓	✓	-	✓	-	-	-	-	-	-	-	-
(Chen et al., 2016)	✓	✓	✓	-	-	-	-	-	-	-	-	-	-
(Donnelly et al., 2015)	-	-	✓	-	-	-	✓	-	✓	-	-	✓	✓
(Biancofiore et al., 2017)	✓	✓	-	-	-	✓	✓	✓	✓	✓	✓	✓	✓
(Feng et al., 2015)	✓	-	-	-	-	-	✓	✓	✓	✓	-	-	✓
(Sun et al., 2013)	✓	-	✓	-	✓	✓	✓	✓	✓	-	-	-	-
(Dong et al., 2010)	✓	-	-	-	-	-	✓	✓	✓	✓	✓	✓	✓
(Domańska and Wojtylak, 2012)	✓	✓	✓	-	✓	✓	✓	✓	✓	-	✓	-	✓
(Sun and Sun, 2017)	✓	✓	✓	✓	✓	✓	-	✓	-	-	-	-	-
(Perez and Gramsch, 2016)	✓	✓	-	-	-	-	✓	✓	✓	-	-	-	-
(Catalano and Galatioto, 2017)	-	-	✓	-	-	✓	-	-	-	-	-	-	-
(Wang and Song, 2018)	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
(Athira et al., 2018)	-	✓	-	-	-	-	✓	✓	✓	✓	✓	-	-
(Qi et al., 2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	✓
(Zhu et al., 2018)	✓	-	-	-	-	-	✓	✓	✓	-	-	✓	✓
(Zhou et al., 2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-
(Wen et al., 2019)	✓	-	-	-	-	-	✓	✓	✓*	-	-	-	-
(Li et al., 2017)	✓	-	-	-	-	-	✓	✓	✓	-	✓	-	-
(Ong et al., 2016)	✓	-	-	-	-	-	✓	✓	✓	✓	-	✓	-
(Huang and Kuo, 2018)	✓	-	-	-	-	-	-	-	✓	✓	-	-	-
(Kurt and Oktay, 2010)	-	✓	-	-	✓	✓	✓	✓	✓	-	-	-	✓
TOTAL (out of 25)	17	12	13	6	11	9	18	18	19	9	7	7	10

As seen, government agencies around the world have tried to make air pollution more understandable for citizens, and have thus created their own Air Quality Index (AQI). The most notorious and widely used ones have been developed by the US-EPA (USEPA, 2013) and by the EEA in (Fraser et al., 2016) and modified in (EEA, 2019). Also, for the purpose of this thesis' use case we are considering the AQI introduced by the Australian Environmental Protection Agency (AU-EPA) and applied by the government of Victoria; the AQI is explained in Table 2.5.

The AQI referenced in Table 2.3 is also defined in the same document by the US-EPA. It gives a general idea of how hazardous or inoffensive the levels of a certain pollutant are and

Table 2.2: Description of the hazards posed by different airborne pollutants towards humans.

When this pollutant has an AQI above 100...	Report these Sensitive Groups
Ozone	People with lung disease, children, older adults, people who are active outdoors (including outdoor workers), people with certain genetic variants, and people with diets limited in certain nutrients are the groups most at risk.
$PM_{2.5}$	People with heart or lung disease, older adults, children, and people of lower socio-economic status are the groups most at risk.
PM_{10}	People with heart or lung disease, older adults, children, and people of lower socio-economic status are the groups most at risk.
CO	People with heart disease is the group most at risk.
NO_2	People with asthma, children, and older adults are the groups most at risk.
SO_2	People with asthma, children, and older adults are the groups most at risk.

maps it to a general index that can be used to define the AQ in a certain area. It's european counter-part can be seen in Table 2.4, defined by the EEA.

The way the index level is calculated is given by the Equation 2.1.

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}(C_p - BP_{Lo}) + I_{Lo} \tag{2.1}$$

Where I_p is the index for pollutant p; C_p is the truncated concentration of pollutant p; BP_{Hi} is the concentration breakpoint that is greater than or equal to C_p; BP_{Lo} is the concentration breakpoint that is less than or equal to C_p; I_{Hi} is the AQI value corresponding to BP_{Hi} and I_{Lo} is the AQI value corresponding to BP_{Lo}.

With this index we can obtain an objective level of AQ regarding human health conditions.

Table 2.3: Mapping pollutants concentrations to the US-EPA AQI values and categories.

This category...	...equals this AQI	... and these Breakpoints						
	AQI	O_3 (ppm) 8-hour	O_3 (ppm) 1-hour	$PM_{2.5}$ ($\mu g/m^3$) 24-hour	PM_{10} ($\mu g/m^3$) 8-hour	CO (ppm) 8-hour	SO_2 (ppb) 1-hour	NO_2 (ppb) 1-hour
Good	0 - 50	0.000 - 0.054	-	0.0 - 12.0	0 - 54	0.0 - 4.4	0 - 35	0 - 53
Moderate	51 - 100	0.055 - 0.070	-	12.1 - 35.4	55 - 154	4.5 - 9.4	36 - 75	54 - 100
Unhealthy for Sensitive Groups	101 - 150	0.071 - 0.085	0.125 - 0.164	35.5 - 55.4	155 - 254	9.5 - 12.4	76 - 185	101 - 360
Unhealthy	151 - 200	0.086 - 0.105	0.165 - 0.204	55.5 - 150.4	255 - 354	12.5 - 15.4	186 - 304	361 - 649
Very unhealthy	201 - 300	0.106 - 0.200	0.205 - 0.404	150.5 - 250.4	355 - 424	15.5 - 30.4	305 - 604	650 - 1249
Hazardous	301 - 400	-	0.405 - 0.504	250.5 - 350.4	425 - 504	30.5 - 40.4	605 - 804	1250 - 1649
Hazardous	401 - 500	-	0.505 - 0.604	350.5 - 500.4	505 - 604	40.5 - 50.4	805 - 1004	1650 - 2049

Table 2.4: Mapping pollutants concentrations to the EEA AQI categories.

Band Descriptor	**O_3**	**NO_2**	**PM_{10}**	**$PM_{2.5}$**	**SO_2**
	1-hour $\mu g/m^3$	1-hour $\mu g/m^3$	Running 24-hour $\mu g/m^3$	Running 24-hour $\mu g/m^3$	1-hour $\mu g/m^3$
Good	0 - 80	0 - 40	0 - 20	0 - 10	0 - 100
Fair	81 - 120	41 - 100	21 - 35	11 - 20	101 - 200
Moderate	121 - 180	101 - 200	36 - 50	21 - 25	201 - 350
Poor	181 - 240	201 - 400	51 - 100	26 - 50	351 - 500
Very Poor	> 240	> 400	> 100	> 50	> 500

Table 2.5: Mapping pollutants concentrations to the AU-EPA AQI categories.

Pollutant	**$PM_{2.5}$ (24-hour)**	**$PM_{2.5}$ (1-hour)**	**PM_{10} (1-hour)**	**CO (1-hour)**	**SO_2 (1-hour)**	**NO_2 (1-hour)**	**O_3 (1-hour)**	**VIS (1-hour)**
Units	**$\mu g/m^3$**	**$\mu g/m^3$**	**$\mu g/m^3$**	**ppm**	**ppb**	**ppb**	**ppb**	
Very Good	0 - 8.2	0 - 13.1	0 - 26.3	0 - 2.9	0 - 65	0 - 39	0 - 33	0 - 0.77
Good	8.3 - 16.4	13.2 - 26.3	26.4 - 52.7	3.0 - 5.8	66 - 131	40 - 78	34 - 66	0.78 - 1.56
Moderate	16.5 - 24.9	26.4 - 39.9	52.8 - 79.9	5.9 - 8.9	132 - 199	79 - 119	67 - 99	1.57 - 2.34
Poor	25.0 - 37.4	40 - 59.9	80 - 119.9	9.0 - 13.4	200 - 299	120 - 179	100 - 149	2.35 - 3.52
Very Poor	37.5 or greater	60 or greater	120 or greater	13.5 or greater	300 or greater	180 or greater	150 or greater	3.53 or greater

Other criteria used can be the Humidex index (Canadian Government, 2019), which is linked to human comfortability in a given indoor environment; and as mentioned before: allergenic agents levels (such as pollen or dust) or breathability (presence of smoke or other gases).

2.3.1 Outdoor air quality prediction

There are many existing outdoor AQ prediction techniques that use different machine learning and artificial intelligence algorithms to estimate the possible levels for pollutants in the future. In this section we will present some of these techniques and highlight their advantages and weak points. The first set of techniques use Artificial Neural Networks (ANNs) as main artificial intelligence methods for the prediction of pollutant levels.

In (Shaban et al., 2016) the authors compare three techniques to predict air pollution levels, specifically for O_3, SO_2 and NO_2. They state that since data is generally non-linear in the case of AQ and therefore, approaches based on linear modelling may not be suitable for such data. They check non-linearity with the Brocke-Decherte-Scheinkman (BDS) method. The three implemented approaches are as follows: a regular SVM, a Simple Perceptron ANN and a Multivariate Regression Tree (MP5), in which the regression models at the leaves are linear multivariate regression equations that can be solved to find the predicted value. The MP5 approach is more accurate, but also more complex. Based on all experiments done on 3 pollutants (O_3, NO_2 and SO_2), the ANN achieved the worst outcomes for all horizons. The SVM outperformed ANN because it is less resistant to training data dimensionality and size, so it can efficiently handle data with high dimensionality and small size. Finally, the MP5 tree outperformed both the SVM and ANN due to its tree structure and high generalization ability.

The authors of (Zhao et al., 2010) propose an ANN in their approach, which is a RBFNN as the non-linear regression tool, and a Genetic Algorithm (GA) that is used to find the best set of inputs to predict a given AQ feature (pollutant in this case). Each individual for the GA is a 9bit string, one bit for each AQ attribute considered (see table with pollutants used per paper), where each bit turns off or on any input. Then a whole ANN is created for each individual and the fitness function is the output value of that ANN, which runs a set of training steps every time. Fit individuals will keep their ANNs through the whole algorithm, so not to lose their training. every time. Fit individuals will keep their ANNs through the whole algorithm, so not to lose their training. The added value in this approach, is adapting the inputs to those that influence the most on the prediction efficiency of a pollutant.

Similarly as in the previous work, in (Bai et al., 2016) a Back-Propagation Neural Network (BPNN) is presented as the main prediction technique, but with a Wavelet Decomposition (WD) method for parameter tuning. The non-linear capabilities of BPNNs and the multi-resolution characteristics of the wavelet transformation are integrated to improve the forecasting accuracy: (i) multiple single features are decomposed from mixed features by applying Stationary Wavelet Transform (SWT) to enhance the characterization air pollutants concentrations; (ii) correlation analysis is used to identify the relation of pollutants and weather information; (iii) they employ a BPNN model to create the wavelet coefficient for the next-day pollutants levels in each SWT scale to simulate the changes of the pollutant concentrations, and afterwards they use the inverse SWT to reconstruct results from the outputs of all the scales.

In (Singh et al., 2012) Because of the complexity and non-linear nature of AQ data, the authors use Partial Least Squares Regression (PLSR) and Multivariate Polynomial Regression (MPR), which are low-level non-linear regression techniques to predict the behaviour of future data. They also implement a MLP, a RBFNN and a GRNN, to compare their proposal to the accuracy of the first two approaches. They conclude that the neural networks are much better when considering AQ prediction domains, because of the non-linearity nature of the data.

Another research work that uses ANNs is presented in (Biancofiore et al., 2017). The authors compare the prediction capabilities of $PM_{2.5}$ concentrations, with one to three days of time lag, of the RNN, the non-recursive BPNN and of the MPR, were compared. For the RNN the middle layer contains the information for the meteorological and chemical model E that uses a back-propagation algorithm with the steepest descent gradient, and, at each training step the error function E is calculated. They show that, in the forecast of $PM_{2.5}$ one day ahead, the ANN with recursion outperforms the MPR model; the same happens also for 2 or 3 days forecasting. It is important to note that the percentage of correct forecasts lowers to 57% when they consider only days with exceedance. Furthermore, false positives represent a percentage of 30%. According to the authors, their results pinpoint the limitations of the ANN model in simulating low-frequency high peaks of pollution. Another good conclusion is that they show that $PM_{2.5}$ levels can be predicted by using only PM_{10} and CO levels, and that CO concentration improve the forecasting accuracy.

In (Perez and Gramsch, 2016) the authors state that the selection of the algorithm for prediction is not as important as the input parameters and their correlation. So, they do not put too much effort into explaining the MLP that they apply but discuss extensively the relation between and the reason for the selected inputs. They also say that their added value is that their algorithm can predict values of $PM_{2.5}$ within hours range, not only on per-day basis. Putting emphasis into explaining complex meteorological happenings they state that their prediction gain accuracy. Specifically, in Santiago de Chile the thermal inversions and the reasons behind it, add strong descriptive power of the forecasted $PM_{2.5}$ concentrations in the air. They conclude that their method is good for the specific scenario of Chile's capital air pollution prediction problem and that it can be applied in other cities with similar environmental issues.

The last work that uses neural networks as the prediction technique is presented in (Feng et al., 2015), where the authors compare three approaches to predict $PM_{2.5}$ concentrations on the Ji Jin Jing area in China, by measuring different variables on 4 stations. The first approach is a plain ANN, specifically a MLP with a logical sigmoid function and the Levenberge-Marquardt (LM) algorithm for training and stopping earlier to avoid overfitting. For the second approach they capture both atmospheric and geo-spatial information by considering the trajectory based geographic model. Adding this information improves the accuracy of the prediction and extends the context of the AQ data. For the last approach, besides the geographical data, they also decompose the original time series with high variability into sub-parts with fewer variability, employing the modelled ANN to each sub-series and then adding up the individual results. They use a five-level WD on the original signal of measurements of $PM_{2.5}$, further increasing the accuracy of the model. They conclude that the mixed approach is the most optimal and that, to some extent, it solves the problem of the under-prediction of days with high $PM_{2.5}$ peaks. This last problem is worth noticing, since they state that, the higher the number of peaks (variability), the harder it is to predict with regular ANNs.

Another group of techniques use fuzzy logic as their main prediction technique. In (Huang and Cheng, 2008) the authors show that AQIs can be represented as time series, that mostly change during different annual seasons. Therefore, they use Ordered Weighted Averaging (OWA). OWA operators can aggregate multiple lag periods into single aggregated values by situational weight. They compare their results to a simple MA approach and against the ARMA, with better outcomes in several statistical measurements.

A second research focused on applying fuzzy time series for air pollutant levels prediction is described in (Domańska and Wojtylak, 2012). The authors' focus on forecasting different pollutant concentrations, specifically: SO_2, $PM_{2.5}$, PM_{10}, O_3, NO and CO, and they state that their model outperforms most of other models, given its ability to predict the concentration of a selected pollutant considering the time step between the data for a given number of hours in advance. They achieve this by using Fuzzy Sets and Numbers; the steps of their air pollution forecasting model are: at the beginning weather predictions are clustered, afterwards selected weather situations are translated into fuzzy sets and then into numbers. Consequently, using fuzzy grouping, they get a set of pollutant concentrations. Finally, using standardization methods they obtain forecasted aero-sanitary situations. The model performs better when the time in advance that is predicted is smaller, i.e. +12 hours.

Amongst other approaches we find methods like the LS-SVM with Principal Component Analysis (PCA) and Cuckoo's Search Algorithm (CSA) presented in (Sun and Sun, 2017). The LS-SVM is a modified form for SVM with improved operation speed and convergence accuracy, and that reduces the convergence speed to a linear one. But one of the biggest problems in SVMs is the selection of good parameters and for that the authors apply the CSA algorithm. The PCA is used to reduce the dimensionality of the pollution parameters into just two, which represent the component with the highest variability and the rest. They state that the highest correlation is between all pollutants, except for O_3. For meteorological parameters they only use highest and lowest temperatures. Finally, they compare their results with other regular SVMs and GRNNs, and they conclude that the CSA-LS-SVM outperforms other models in terms of Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), since the they detect duplicates with the PCA, they avoid randomness of parameters' setting in the LS-SVM model using the CSA optimization part.

Mixing parametric and non-parametric modelling techniques into a new model that provides hourly predictions of NO_2 levels is introduced in (Donnelly et al., 2015). The authors state that a high variation of pollutant concentrations at both rural and urban locations can be explained by non-linear connections between wind direction, wind speed and pollutant concentrations. A non-parametric technique, introduced in another work by the same authors, is used to produce seasonal and diurnal factors using wind speed and direction measurements. Then their model uses a multiple regression analysis driven by the previous factors together with other meteorological parameters. The results present a good agreement between ground truth and forecasted data for predictions up to 48 hours in advance. The model presents low computational resources use as a major advantage, as well as the easy availability of input data and the minimization of assumption-based errors.

Next, we find a group of approaches that use HMM as their main method. First, we have an approach with Hidden Semi Markov Models (HSMM) with Gaussian distributions (Dong et al., 2010). The authors use a HSMM to overcome the problem that the state duration of an HMM is represented by an exponential distribution. They mention that a regular HMM does not provide a helpful description of the time-dependant structure for accurate forecasting purposes. They propose a Forward-Backward Algorithm with a simple multi-dimensional normal distribution that is employed for the state process model. Two HSMMs are constructed, one for the low concentrations $(<= 40\mu g/m^3)$ and one for the high levels $(> 40\mu g/m^3)$ of $PM_{2.5}$. After training the HSMMs, the following step is, given these models, to obtain the likelihood of the observation sequence. Afterwards sequences are classified following the value of highest log-likelihood and the conclusion is that a high accuracy of $PM_{2.5}$ concentrations for the next 24 hours predictions can be attained by using HSMM models.

Another, more extensive approach is presented in (Sun et al., 2013), in which a technique that applies HMM with non-Gaussian distributions and WD is described. The authors compare their approach to a HMM with regular Gaussian-distribution. The non-Gaussian distributions are specifically the following: a log-normal distribution, a gamma distribution and a G.E.V. distribution (the Gumbel, Fréchet and Weibull families). The HMM uses the Expectation-Maximization (EM) algorithm to converge the HMMs and they are trained separately, depending if they belong to exceedance days or non-exceedance days. The objective of the training step is to obtain HMM parameters that maximise the likelihood for a given observation sequence. But, to avoid terminating at a local maximum, Simulated Annealing Algorithm (SA) is used in this work. At the beginning of the process the observation sequences are decomposed into 12 wavelet coefficients for each variable, and used as the observation sequence for training the HMM. This is done to reduce the complexity and amount of data on each 96 hours intervals and are used as the emission distribution of the HMM. They conclude, that the HMMs with these three non-Gaussian distributions can improve the True Prediction Rate (TPR) and reduce false alarms significantly, specially compared to a conventional HMM.

As explained in 2.1.3, in recent years the focus of machine learning techniques has hugely shifted towards DNN algorithms. Their complexity and accuracy have improved the solutions for existing problems and helped tackle the one's that were unattainable with previous methods. AQ forecasting is not the exception. Applying DL to the AQ problem was arguably started by B. Ong in (Ong et al., 2016). It introduces a novel pre-training method called Dynamic pre-training (DynPT), which is especially designed for time series prediction. This method might be the first applied research on $PM_{2.5}$ concentrations levels forecasting that uses the predictive power of DNNs, whilst also using only “real-life data”, and that considers spacial information in selected sensors. The authors present an empirical way to mitigate computational costs by only selecting sensors that do significantly contribute to better forecasts. They mention that the use of DNNs allows to extract useful information from the data while being robust enough to handle the noise and errors. They compare their method against a well-established method used by the Japanese government, VENUS, and outperform it with allegedly much less computing power and information.

In (Wang and Song, 2018), the authors propose a novel ensemble technique based on DL to forecast AQ levels in Beijing, using historical and meteorological data. They consider how meteorological characteristics alter the AQ levels and utilize an ensemble model to work with various weather situations. They adopt Granger causality, thus learning the spatial-temporal properties of AQ, to model the spatial dependencies between two stations and then select relative stations and enclosing areas to retrieve the spatial correlation. Finally, they categorise the temporal properties of AQ into two groups: short-term and long-term dependencies and apply a Long Short-Term Memory Neural Network (LSTM) to learn both. Their results show that the LSTM model increases the accuracy of predictions over more traditional regression methods and machine learning techniques.

The authors in (Athira et al., 2018) use 3 state-of-the-art DL techniques to prove their suitability on AQ forecasting. They state that the time changeability of AQ prediction is longer than the one of climate estimates, which changes regularly in four or five days, the one for AQ being 10 or more days. They also mention that extra persuasive variables must be considered in AQ prediction, for example, the progression of air-borne pollutants and the connection with meteorological conditions. Given this conditionals, they propose the three DL methods RNN, LSTM and Gated Recurrent Unit (GRU); stating that they can model the intricate relations of AQ changeability and meteorological factors that affect it. They show the results demonstrating the capacity of these algorithms, by accurately predicting values from their AirNet dataset and concluding that the GRU model is best fitted one for this problem.

In (Qi et al., 2019) the authors' objective is to address the limitations of other existing prediction models and propose a hybrid model to improve the forecast of $PM_{2.5}$ concentration levels. They extract spatial dependencies between different stations by applying Graph Convolutional Network (GCN) and then use an LSTM to capture temporal dependencies among observations at different times. The Graph part of the approach covers the spatial relationship between stations, having an influence factor relative to the distance from one another up to 200km. In contrast, the LSTM maps the temporal relationship between the air pollutants and meteorological data from the historical dataset. They define the input of LSTM as the original signals concatenated to the graph convolutional features. Finally, the outcome of LSTM is employed in the input of a densely connected layer and the output that layer is the prediction of $PM_{2.5}$ levels at a selected time. They state that their method outperforms a MPR technique, a MLP and a naïve LSTM for the given dataset.

Next, in (Zhu et al., 2018), a complex system is presented to predict $PM_{2.5}$ concentrations. The outcome of this process is then passed to the Complementary Ensemble Empirical Mode Decomposition (CEEMD) to reduce the input signal in to simpler Intrinsic Mode Functions (IMF) and a residual, which represent the input data. The decomposed signal is then input into a combination of the Particle Swarm Optimization and Gravitational Search algorithms, which apply formulas related to gravitational theories and output a relational velocity and positional vector to the input signals. Finally, the SVR is used to model the relationship between the IMFs, the $PM_{2.5}$ signal and the residual signal and to predict the new values for each signal. The method ends with Gray Correlation Analysis, to extract the relation between the IMFs and select only the suitable ones to pass to the GRNN prediction method. This last one is less explained in the paper, but they state that its use is to predict the $PM_{2.5}$ levels with the IMFs and residual signal and aggregate it to the SVR predictions. They state that their algorithm is better than any other combination of all these methods, but they do not compare it with other techniques outside of their scope.

The authors in (Zhou et al., 2019) developed a Deep learning-based Multi-output LSTM Neural Network (DM-LSTM) model, that makes predictions by regions at different time-in-advance lags in multiple outputs at the same time. The model they introduce has 2 hidden layers and used three combined DL algorithms for training as well as for extracting patterns that have spatio-temporal characteristics, and that are complex in nature, together with meteorological factors, AQ inputs and multiple AQ outputs at different AQ monitoring stations. The reliability and accuracy achieved are clearly improved in comparison with other versions of the LSTM network, which they used to compare there method against.

In (Wen et al., 2019) the authors presents a novel LSTM model in which neighbouring distribution of each station were taken into consideration, which means that the k-nearest neighbouring stations for each station were selected considering the highest correlation. Also, the spatio-temporal characteristic of air pollutant concentration data was considered and processed by the model, which consists of an Extended Convolutional Long-short Term Memory Neural Network (C-LSTME). The model added some contextual data as well, including weather data and aerosol optical depth data. Context data can improve prediction accuracy to a certain extent, and simultaneously, aid the model obtain better predictions for the sudden changes in AQ. The authors state that the proposed method can efficiently extract better spatio-temporal correlation features and achieve high accuracy and stability for AQ prediction of different spatio-temporal scales. This was shown by the fact that they outperformed many other DNN approaches on the used dataset.

The work in (Li et al., 2017) presents an extended LSTM that captures the long-term spatio-temporal dependency of air pollutant concentrations, to forecast the air pollutant concentration over the next 24 hours. Their proposed method extracts effectively spatio-temporal correlations within air pollutant concentration information. Contextual data is integrated into a traditional LSTM model, in the form of weather and stationary time-related data (i.e. month and hour of day). Authors conclude that the model performs better than other deep learning and statistical approaches.

The authors of (Huang and Kuo, 2018) propose a combination of a CNN and a LSTM to predict levels of $PM_{2.5}$ in a Smart City. The context used for their approach is cumulative rain volume, cumulative wind speed, and cumulative $PM_{2.5}$ concentrations. In order to predict the next hour concentration of $PM_{2.5}$, the aforementioned 24 hours cumulative values are fed into a trained CNN and LSTM networks. According to their results their approach outperforms a simple CNN, LSTM, besides more simpler techniques like SVR, Random Forest (RF), Decision Tree (DT) and a MLP.

As we can observe from these state-of-the-art urban AQ prediction algorithms, the correct selection of parameters is considered a major factor that authors consider when improving their proposals. From GA to PCA are applied to understand which elements are more correlated. ANNs are widely used as the main forecasting algorithm, because of its simplicity, but they are a black-box approach, not explaining the underlying process. HMMs on the other hand, though more complex, can give more insight on the statistics obtained, and can handle better the high peak concentration of pollutants. We can also notice that $PM_{2.5}$ and NO_2 are the most forecasted pollutants, given their hazardous characteristics for human health. The research works presented try to estimate if one of those pollutants will surpass the national limit of health standard for the pollutant, respectively. Finally, there must be a trade-off between complexity and accuracy/performance in the approaches, since the forecasting occurs in real-time and data is updated in small time intervals.

In the next section we will describe prediction methods that approach the problem of forecasting AQ levels, not only with the level of pollutants and meteorological factors, but considering a wider context, i.e. considering motor-vehicles traffic levels or nearby factories.

2.3.2 Context Aware Outdoor Air Quality Monitoring and Prediction

As presented in the previous section, many algorithms for the forecasting of air pollutants levels have been developed. Some existing systems have applied these algorithms and have been designed considering context awareness. In this section of the document, those systems, that were developed for the urban AQ monitoring and prediction using context awareness, are presented and compared to each other.

In (Dutta et al., 2009) the authors describe a personal and portable AQ monitoring system, that tells the users the air conditions around them in real time using the same AQI (US-EPA) presented in previous sections of this document. A test with 16 participants was undertaken and each person carried a sensor that measured CO, O_3 and NO_2 levels, and other meteorological factors, such as temperature, atmospheric pressure and relative humidity, during their daily commutes. They concluded that the visualization of the data and the information presented was helpful for the users. Nevertheless, this system can be further improved by adding prediction algorithms, depending on where a user will commute next, besides letting the person add their health conditions, to make the AQI output even more accurate.

In (Kurt and Oktay, 2010), the authors propose an air pollution forecasting solution that includes an ANN and geographic relationship models for the sensor stations. They state that only using the time series data for each individual station's pollutant prediction is not enough and that considering the geographical distribution of the sites can increase the accuracy of the predictions. Given that there are many stations in a certain area, they select the most influential ones towards the predicting station, by using their statistical influence on each other's data and by assigning weights to the relation according to the distance between each of them. They conclude that their results improve the prediction over other simpler models that do not take geographical elements, which count as an extended context, into account.

The authors in (Catalano and Galatioto, 2017) state that pollution cases should be treated as individual cases that depend on the location and context they are studied in. Their idea was to develop a self-managing model framework, or meta-model, able to select, for different emission and dispersion factors of airborne pollutants, the passing prediction model from a group of alternative AQ models, which are set to consider a wide spectrum of contexts and situations. This means that if a model from a city A suits the one for a city B under certain circumstances, like rare high peaks of NO_2, then it should be used when needed. They applied their model on two sites in the United Kingdom (UK) and compared it with the meta-model that decided from each of the two models when needed. The meta-model takes the decisions based on a simple Euclidean distance between the attribute points in the attribute space. They also compared it to a cross-site model, where they trained a MLP with data from both sites. In the first case, the meta-model showed improvement as high as 11% when predicting low frequency pollution exceeding peaks. In the next case, it showed a maximum gain of up to an impressive 113% in the site with very high NO_2 hourly concentrations. They consider the context of each site for the forecasting algorithm to be applied, which is a good approach to get more accurate outputs. This approach can be even further improved by using other prediction techniques presented in the previous section of this document and by adding the user's context as well.

Finally, in (Chen et al., 2016), a prediction approach is presented, which expands the usual context used in all the other algorithms (mainly pollutants and meteorological variables). First, they divide the region under monitoring in a grid of equally sized squares, and consider a set of different attributes in each one of them. The characteristics considered are: i) traffic related features: a) vehicle speed and b) variance of vehicle speed over the last n hours, ii) road-network related features: a) road density and b) road types, iii) Point of Interest (POI) related features: a) location types, i.e. stadiums, parks, factories, etc., iv) check-in features: a) human mobility in the region, v) nearby monitoring-related features: a) the AQ from neighbouring grid areas is considered as it influences the current region directly. On the data collected for these variables a semi-supervised ensemble pruning technique is applied. This method, in contrast to all the previous uses only external context to predict AQ. The results are encouraging for context driven approaches, even though they are not nearly as good as the ones obtained with DNNs, they can be used to improve the data driven techniques that have problems recognizing sudden changes in a pollutant's level. It also allows to give users a more thorough explanation of what the sources of the a given pollutant's level are, expanding the contextual understanding.

With this final thought in mind we conclude the background section and start the introduction to our proposed system. In it we have combined the strengths of the aforementioned techniques to overcome the known issues with AQ prediction.

3 Context Modelling

This chapter introduces the details of a novel context- and situation monitoring and prediction model for AQ monitoring, which is further used in the implementation of the MyAQI system.

3.1 Introduction

The previous chapter introduces context theories, outdoor Air Quality monitoring, it's effects on human health, different ways to measure it and the different prediction techniques that have been applied to solving the problem of urban AQ forecasting. The purpose of the rest of this research is to develop a system that can help monitoring and predicting AQ levels considering all the possible context, that provides a user-personalized service to aid people to understand the hazards of air pollution presented directly to each individual, in real-time and in advance.

First, and to achieve the objective of developing the aforementioned system, it is required to describe the *Context Attributes* that will be involved in the whole of the system's operation. This description will guide the data retrieval stage, by explaining the data requirements for the system. Figure 3.1 presents how all the *Context Attributes*, *Situations Reasoning* and *Prediction Model* fall into place in an overview of the system's data flow. First the AQ attributes are used to obtain a prediction or real-time value of the AQI value. Then, combined with the extended context attributes, the prediction is refined and contextualized and last, the user's context is used to define the situation in which the user is found. In the following sub-sections the different context groups and characteristics are going to be explained, as well as their roles in the system. At the end, we also mention the relationship amongst all of the *Context Attributes'* groups and their connections with the *Situation Space* and *Prediction Model*.

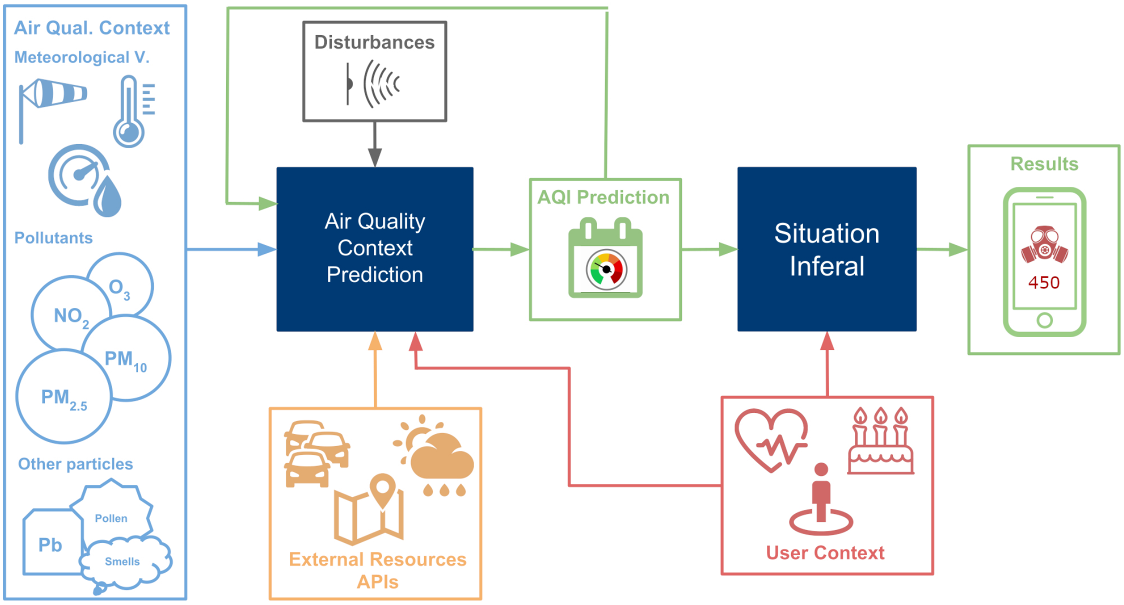


Figure 3.1: MyAQI system data flow and contextual function overview.

3.2 Context Modelling

As this system is meant to be context-aware, the context model used to describe its parts is of critical importance. This section describes how the model will be defined, which groups it encompasses, how it will processed and what role it will play in the end-system.

In the previous chapter, specifically in section 2.1.2, the Context Spaces Theory was introduced. Now we apply it to our model, as it provides a general scheme to build a context model for any context-aware system. The core of the approach is to model the context as a multidimensional Euclidean space with several dimensions, that represent features of the required data that will feed the prediction algorithm and the monitoring functionalities. Each feature has a defined set of values, that are either a set of discrete values or continuous values inside a number range. The benefits of such and approach is the simplicity of the information mapping from source to model, as many of the existing data formats are already represented in an Euclidean form or ready to be transformed into one.

Next, we briefly formally define the features of the CST that will be used during the rest of this research.

- **Context Space** is a N-dimensional Euclidean space, denoted as $C = (a_1, a_2, ..., a_N)$, which is defined over collection of N *Context Attributes* (dimensions).
- **Context Attribute** each specific feature, denoted as a_i, is a characteristic of the system's environment, where it is critical for fulfilling its functions. Each attribute consists of an ID, a value type and a set of values that it can take within the *Context Space*, in which it represents a dimension.
- **Context State** every *Context Attribute* takes a value inside the *Context Space* during the functioning of the system. The set of all the attributes' values assigned at a given point in time is called a *Context State* and is represented by $C^V = (a_1^V, a_2^V, ..., a_N^V)$, where a_i^V is the specific value for a_i in a certain point in time.
- **Situation Space** a situation represents a happening in the real world. In CST situations can be derived as the result of mapping *Context States* to the *Situation Space*, which is a sub-space of a *Context Space* and is denoted by $S = (a_1^V, a_2^V, ..., a_N^V)$, in which case each a_i^V must be either be exactly a required value or fall in the range of values defined for that attribute in the *Situation Space*.

To illustrate the CST in action, consider the following example. In the scenario of users' geo-location, latitude (represented by "lat") and longitude (represented by "lon") are used as *Context Attributes*, in the *Context Space* comprised by all the values that these 2 variables can be assigned, which are floating numbers in the range of $[-90, 90]$ for latitude and $]-180, 180]$ for longitude. The *Situation Spaces* selected could be "in Southern Hemisphere", "in Northern Hemisphere" and "on the Equator". The *Context State* required to deduce that the first situation is happening would be a one-dimensional line where $lat \in [-90, 0[$ and the for the second one it would be $lat \in]0, 90]$ and $lat = 0$ for the last one. Note that not all attributes from the *Context Space* have to be involved in a *Situation Space*.

These definitions are crucial for the definition of the model used in this research. Given that our focus is outdoor AQ monitoring and prediction and a personalized output for each user, we consider AQ Attributes, User Attributes and Extended External Attributes to be key factors in the pursue of developing the system.

3.2.1 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. Given that its principal goal is to monitor and predict AQ in outdoor environments, it is obvious that the elements that comprise AQ have to be taken into account. As shown in section 2.3 of chapter 2, AQ measurement is usually represented by airborne pollutants, the AQI, used to help users understand the status of AQ, and the meteorological variables representing weather factors affecting the air pollutants concentrations.

Pollutants are usually airborne chemical particles that pose a threat to living creatures, including humans, and the whole of the environment. Common sources of pollution are explained in section 3.2.2. For the purpose of the MyAQI system context model we consider the following pollutants to be the most relevant.

- **Particle Matter under 2.5 μm of diameter ($PM_{2.5}$)**, this pollutant is the usual focus of researchers when tackling AQ issues. The reason is that it is largely related to deaths caused by air pollution. These particles are so small that they can reach deeper into the lungs than others. The health issues that $PM_{2.5}$ can cause are decreased lung function, increased respiratory symptoms, exacerbation of cardiac conditions and respiratory conditions (e.g. asthma), premature mortality and lung cancer (EPA Victoria, 2013). They are also directly related to levels of the other pollutants in this group, so that by sampling $PM_{2.5}$, the levels for the others can be derived.
- **Particle Matter under 10 μm of diameter (PM_{10})** is directly related to $PM_{2.5}$, but not as hazardous. Some older AQ measuring stations consider PM_{10} instead of $PM_{2.5}$ and thus, it has to be considered into the monitoring. Besides, long exposures to this pollutant can become very hazardous to sensitive people.
- **Nitrogen Dioxide (NO_2)** is a gas that is produced by the burning of fuels such as natural gas, petrol or diesel. NO_2 is extensively measured in Smart Cities, as it is directly linked to motor vehicle emissions. The health hazards of this chemical are increased respiratory symptoms, exacerbation of asthma and other respiratory diseases. Next to $PM_{2.5}$ it is the most broadly used pollutant in AQ monitoring applications and prediction algorithms.
- **Ozone (O_3)** is similar to Oxygen (O_2), but with an extra atom making it very reactive. O_3 is not directly emitted into the air, instead it forms when other air pollutants combine together on warm summer days. Ozone is harmful to the lungs, especially for the elderly and patients with asthma.
- **Sulphur Dioxide (SO_2)** this chemical gas can irritate the lungs, and is particularly harmful for people with asthma. Most of the SO_2 in our air comes from coal-fired power stations and metal smelting operations. This gas is not usually measured as its sources are usually further away from urban areas those of other pollutants.

- **Carbon Monoxide (CO)** this odourless gas, is mainly emitted from petrol exhaust and can get into the bloodstream where it displaces oxygen. It can cause heart problems, especially in the elderly and a decreased exercise capacity. It is also closely related to levels of $PM_{2.5}$ and, thus, used in some of the AQ prediction algorithms as a feature.

These 6 pollutants are considered in our context model, because they have been extensively used in the literature and because the relevant AQIs use them to calculate their indexes. But, in a future other airborne particles and gases can be used to extend the context. Elements such as formaldehyde, pollen, dust, lead, amongst others. The main reason for not considering in this research is the lack of quality data sources or streams for them.

Air Quality Index (AQI) is a representation of the state of AQ at a certain point in time. It is a context derived attribute, because it does not come directly from sensor equipment, but is calculated from the pollutants' atomic measurements. The three AQIs formats considered in this research are the ones presented in 2.3, each one having different pollutants limits mapped to their categories. The most strict one is presented by the AU-EPA, followed by the EEA and US-EPA, in that order. They also differ in the units for pollutant measurement, making it important to consider transformations between them. But the 3 scales agree that the final AQI value is taken from the highest pollutant level at a certain point in time, disregarding the other pollutants.

Meteorological Variables are crucial for understanding the behaviour of "already in the environment" pollutants, as they affect their location, distribution and temporality. We consider the following meteorological variables to be relevant in the context of our system.

- **Temperature (TEMP)** is important as it affects the characteristics of gases, by making more or less airborne (Kalisa et al., 2018). It also contributes to the creation of thermal inversions, which occur when masses of hot air are dragged close to the ground trapping pollutants in areas that are more hazardous for people.

- **Relative Humidity (RH)** is the most vastly used meteorological factor used in AQ prediction. It is also directly related to the effects of certain pollutants to human health, usually being that in lower humidity the effects become more acute because particles become more airborne (Qiu et al., 2013).

- **Wind Speed (WSPEED)** is clearly related to the location of air pollutants, as it moves masses of air from one area to another.

- **Wind Direction (WDIR)** is of major importance as WSPEED is, given that it will explain the present and future locations of a mass of pollutants.

- **Atmospheric Pressure (ATMP)** takes part in some meteorological episodes such as thermal inversions and exchanges of air masses. It also affects the speed of volatility of gases and is, thus, and important factor to consider.

There are other meteorological factors involved in AQ monitoring, but given the data sets that are going to be considered in 5.1.2 we consider that the presented ones are enough to get an accurate model of their impact on the air pollutants. Other factors are Precipitation, Visibility, Luminosity, aerosol depth and planetary boundary height (when measured from satellites).

3.2.2 Extended External Attributes

Given that it is an obvious approach to consider the previously presented attributes as they are directly connected to AQ and thoroughly used in AQ prediction and monitoring, other factors are seldom taking into account, but their relation to AQ is equally important. These external factors are the sources of pollutant emissions and rare meteorological events, such as the previously mentioned thermal inversions. We consider the following external attributes for the MyAQI system.

Traffic volume is the amount of motor vehicles driving a certain segment of road or road crossing. Vehicle emissions are considered one of the primary sources of pollution in cities and contribute largely to high NO_2 and CO levels (EEA, 2017)(EPA Victoria, 2013).

Fire incidents are a major factor of pollution in urban areas surrounded by dry vegetation areas in countries such as Australia (where this research's experiments will be undertaken). Bushfires, specifically, contribute largely to high $PM_{2.5}$ and PM_{10} levels (EEA, 2017)(EPA Victoria, 2013).

Buildings' pollution is the emission of pollutants by industrial, commercial or private buildings, such as exhausts from factories, chemicals from retail stores or smoke from wooden heaters in households. Many pollutants are emitted from different factories, but is the only source producing high SO_2 levels. The data available for this pollution source makes it unusable for prediction algorithms, but it can be used to give the user an understanding of why certain pollutant levels are higher in certain region.

Besides giving a customized experience to the user about AQ, the MyAQI system's goal is also to improve existing prediction techniques by applying more context into its reasoning. Specifically by tackling one of the most notorious problems in the existing literature, the low-frequency peaks of high pollutant concentrations. By adding pollutants sources, we try to predict with higher accuracy these episodes.

3.2.3 User Attributes

Finally, we consider some user attributes, to be able to customize the experience for each individual end-user of the system. Given that air pollutants can affect users differently depending on certain characteristics.

User ID identifies a user to the system. Necessary to separate the configurations for each individual user. This ID is entered by the user at registration.

Geo-location determines the spatial reference of a user's location. We consider the geographic coordinate system, consisting of latitude and longitude, to be applicable to our system, because we are dealing with outdoor AQ, in which case the environment takes place at some point on Earth's surface. The geo-location is obtained from the user's device when accessing the MyAQI system.

Timestamp gives the specific time and date of interaction with the system, so that the latest information can be retrieved or some historical data should be retrieved instead.

Pollutant sensitivity represents the level of influence a given pollutant has on the user. Each user has 6 pollutant sensitivity levels assigned, which are derived from answering a small questionnaire at the system's profile section (Nurgazy et al., 2019). 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”.

All the previously introduced *Context Attributes* must be formatted in a way that fits the data sources and the algorithms and system requirements. Thus, a type of variable„ a range of fields and a unit of measurement (if needed) must be assigned to each of them. Table 3.1 maps each attribute to this information.

Table 3.1: Mapping of *Context Attributes* required for the MyAQI system to their format, value ranges and units of measurement.

Air quality Context Attribute	**Format**	**Values range**	**Unit**	**Example**
$PM_{2.5}$	decimal	$[0, +\infty[$	$\mu g/m^3$	4.5
PM_{10}	decimal	$[0, +\infty[$	$\mu g/m^3$	30.25
NO_2	decimal	$[0, +\infty[$	ppb	40.74
O_3	decimal	$[0, +\infty[$	ppm	55.11
SO_2	decimal	$[0, +\infty[$	ppb	24.9
CO	decimal	$[0, +\infty[$	ppm	328.0
AQI	integer	$[0, +\infty[$	-	62
TEMP	decimal	$[-\infty, +\infty[$	°C	18.0
RH	decimal	$[0, 100]$	%	77.87
WSPEED	decimal	$[0, +\infty[$	m/s	2.3
WDIR	decimal	$[0, 360]$	degrees	235.5
ATMP	decimal	$[0, +\infty[$	bars	1.0
External Extended Context Attribute	**Format**	**Values range**	**Unit**	**Example**
Traffic	integer	$[0, 4]$	traffic level	4
Fire incident	integer	$[0, 5]$	proximity to user	2
Buildings’ pollution	integer	$[0, 5]$	proximity to user	1
User Context Attribute	**Format**	**Values range**	**Unit**	**Example**
ID	String<32 chars>	Alphanumeric	-	frank
Age	integer	$[0, 200]$	Years	66

Geo-location	2 decimals	$lat \in [-90, 90]$,
		$lon \in [-180, 180]$
			degrees	{
				lat: -34.421,
				lon: 140.64
				}

Pollutant Sensitivity	6 integers	$[0, 4]$	Sensitivity level	{
				$PM_{2.5}$: 2,
				PM_{10}: 2,
				NO_2: 1,
				O_3: 0,
				SO_2: 1,
				CO: 2
				}

3.3 Situation Reasoning

Defining the *Context Attributes* is only the first part of the creation process for a context-aware system. The next step is to define the *Situation Spaces* that will be deduced from the *Context States*. Situations suit the case of AQ perfectly, as the AQIs define different categories that depend on the values of other air features. Each situation will depend on the user's pollutant sensitivity, the preferred or relevant AQI scale and the current AQI value. Table 3.2 represents the situations and their aforementioned details.

Table 3.2: Mapping of AQI levels to their triggering *Context States*.

	Sensitivity Levels				
AU-EPA AQI categories	**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	150 or greater	125 or greater	100 or greater	90 or greater	70 or greater
EEA AQI categories	**0**	**1**	**2**	**3**	**4**
Good	0 - 33	0 - 33	0 - 33	0 - 33	0 - 23
Fair	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	150 or greater	125 or greater	100 or greater	90 or greater	70 or greater
US-EPA AQI categories	**0**	**1**	**2**	**3**	**4**
Good	0 - 50	0 - 50	0 - 50	0 - 50	0 - 33
Moderate	51 - 100	51 - 100	51 - 100	51 - 80	34 - 60
Unhealthy for Sensitive Groups	101 - 150	101 - 150	101 - 130	81 - 100	61 - 85
Unhealthy	151 - 200	151 - 190	131 - 150	101 - 115	86 - 105
Very unhealthy	201 - 300	191 - 230	151 - 165	116 - 130	106 - 115
Hazardous	301 or greater	231 or greater	166 or greater	131 or greater	116 or greater

The MyAQI system lets the user choose which AQI scale to use or will choose it depending on the user's geographical location; i.e. if a user is in Australian territory, the AU-EPA AQI will be used. In summarized views, the final AQI value will be the one relative to the highest pollutant concentration level.

Other situations in a different *Situation Space* are those related to the traffic volume and fire incidents context attributes. The traffic volume values are mapped to a severity of vehicular congestion, described in Table 3.3. The values are calculated from the 5 quantiles for each traffic station's traffic volume's data. Quantiles are the Q groups obtained from dividing the range of a probability distribution into (nearly) equal sized parts, divided by $Q-1$ values of the form: $0 < q_i \leq Q-1$. We consider five quantiles as representing a fair amount of different traffic situations, from "very low" to "Extremely high". The reason for using quantiles is that each traffic measuring station represents a vehicular crossing and different amounts of vehicles represent different situations in each of them, thus an adaptive approach is needed. This approach could be exchanged by a more in depth mapping for each station, by directly relating it to each pollutant measurement over time.

Table 3.3: Traffic volume context data mapped to different traffic volume severity situations, by the division of the data into 5 quantiles.

Traffic volume severity	Situation Id	Quantile (Distribution slice)	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%)	$]q_4, +\infty[$

Similarly, the fire incidents are categorized according to distance to the AQ measuring stations; obviously, the closer the incident to the station the higher the the severity. The relevant distances are described by 5 different radii sizes of circles centred in each AQ measuring station. We considered that the furthest distance for a fire to be effective over a station is relative to the location of the station. For example, if a station lies in the outskirts of a city, with less obstacles for fire and smoke to spread, the higher has to be the considered distance; conversely, inside a city, specially a big city with skyscrapers, the distance is to be smaller. For stations in cities we considered a distance of $20kms$ to be relevant and for those in the outskirts of the urban area or countryside, a distance of $100kms$; then the other distances are 5 equals fraction of this distances, as seen in Table 3.4. The representation can be improved by studying the exact impact of distance from fire sources to the stations and taking wind speed and directions, as well as thermal inversions into account, but this is out of scope for this thesis.

Table 3.4: Fire incidents' context data mapped to different fire severity situations, by the creation of 5 circles of different radii around AQ monitoring stations.

Fire severity relative to AQ station location	Situation Id	City distances range (in kms)	Countryside range (in 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	$[0, 4[$	$[0, 20[$

The outcome of *Context States* and deducted situations are used in the monitoring views of the MyAQI system, as well as in its prediction model. In the following section the selected forecasting model and its interaction with context and situation variables is explained.

3.4 Prediction Model

The previous subsection introduced the necessary context attributes and situations for the MyAQI system's operation. Another critical building block of the system is the inclusion of a prediction model, that consumes the environmental context information and forecasts values for future time steps. The task to select a relevant prediction technique, that fits the data at hand, arises. For this work we rely on the research explained in section 2 about existing machine learning and AI data analysis methods. On of these trending and highly accurate approaches is Deep Learning, specifically Deep Learning Neural Networks. Because the nature of the AQ related data follows a time-series format, these networks have been already applied to the AQ monitoring and forecast use case, presenting extremely promising results and outperforming almost all of other older data based regression models. For these reasons the MyAQI system uses a LSTM DNN for its prediction feature. In this subsection we introduce some of the concepts relevant for a LSTM's functioning.

3.4.1 Long Short-Term Memory Neural Network

A LSTM DNN is a type of gated RNN first introduced in (Hochreiter and Schmidhuber, 1997), that keeps information for long time dependencies, which were neglected by former ANN models. It consists of an input layer, that takes the incoming features, followed by one or more recurrently interconnected hidden layers, also know as memory blocks, and an output layer, that produces the final result for the regression. The main improvement of LSTMs takes place in the memory blocks. Each block is composed by various memory cells (which in turn can be connected to itself) and by multiplicative gates. The gates are for input, output and forgetting tasks. These tasks can be mapped to read, write and reset operations, respectively. The input gate controls if the cell's internal state is to be affected by incoming signals and the output gate controls if the result of the cell's processing will affect other cells. But the novel concept in a LSTM neuron structure is the forget gate, which resets the cells state once the information held by it is outdated thus preventing the saturation of the squashing function, that occurs with the out-of-bounds growth of a cell's state. The state itself is maintained by the activation of a self-connected linear unit-constant error carousel (CEC), which is part of the cells memory and can stop any stimulus coming from the outside, thus retaining the same state over certain periods of time. This feature allows LSTMs to solve the vanishing gradient problem, that is accentuated with the increase of layers with different activation functions making the gradient of the loss function approach zero, affecting the networks ability to train. Figure 3.2 describes a single cell memory block for an LSTM network.

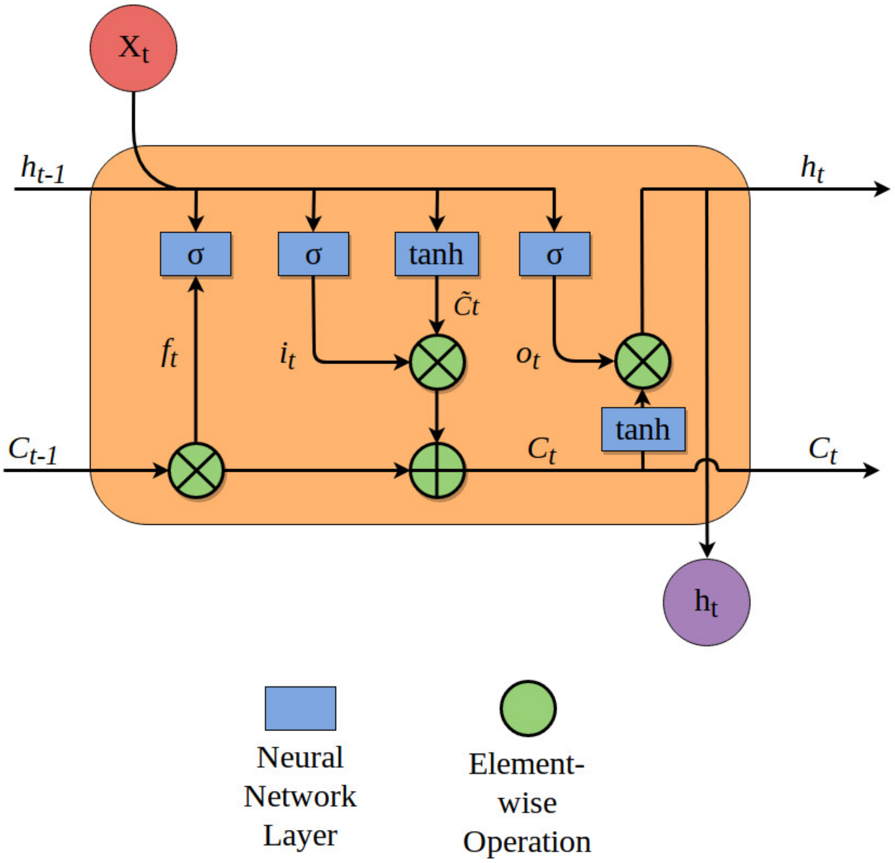


Figure 3.2: A LSTM memory block with one memory cell.

The input of the block is represented by X_t where $X = (X_1, X_2 \dots , X_N)$ and $X_i \in R^T$; N is the number of dimensions in the input, T the time lag and $Y = (Y_1, Y_2 \dots , Y_N)$ the output values. For the MyAQI system's AQ prediction use case, X vectors take the values of the AQ, meteorological and extended context attributes; the Y vector takes the values of the desired to-be-predicted pollutant's predicted concentrations. The functions denoted in Figure 3.2 by the free floating letters are characterised by the following equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \tag{3.1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \tag{3.2}$$

$$C_t = f_t * C_{t-1} + i_t * tanh(W_C \cdot [h_{t-1}, X_t] + b_C) \tag{3.3}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \tag{3.4}$$

$$h_t = o_t * tanh(C_t) \tag{3.5}$$

where f_t denotes the forget gate, i_t the input gate and o_t the output gate. $\sigma(\cdot)$ stands for the sigmoid function and $tanh(\cdot)$ the tanh function, defined in function 3.6 and 3.7, respectively. C_t and h_t are the activation vector for each cell and memory block, respectively. W represents the weight matrix and b the bias vector.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3.6}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3.7}$$

Considering the LSTM's structure and theory, its application to the MyAQI was to be done. Figure 3.3 presents the structure for the LSTM model adapted to the MyAQI system's features. The inputs are given by the time series for AQ, meteorological and extended context variables. The latter group are first transformed through the *Situation Reasoning* model to the values relevant to each situation. Then, all the variables are normalized to values between 0 and 1, to immediately after be fed into the LSTMs layer. The DNN depends on some hyper-parameters (such as batch size, hidden layers numbers, neurons numbers per layer, training epochs, etc.) that have to be twitched and tested to achieve an heuristically best outcome. In section 5 some work done to obtain the best possible values for these hyper-parameters for the MyAQI AQ prediction is presented. With these parameters the LSTM's training epochs are executed, the error loss calculated and a validation set used for assuring the model fitness. The outcome of the LSTM layer is forwarded to a fully-connected ANN (FCNN) and the result of its execution are the predicted values for the desired pollutant (specified at the input, i.e. $P_{1(t+1)} \dots\ P_{1(t+24)}$) for different time lags, if required. Lastly, the pollutant predictions are used to reason the AQ situation at the given time point.

Finally, with the prediction model, the MyAQI system's prediction and monitoring functioning flow presented in Figure 3.1 has been completed. But obtaining the outcoming values from the prediction are not enough, they have to be presented in a comprehensive and context-aware

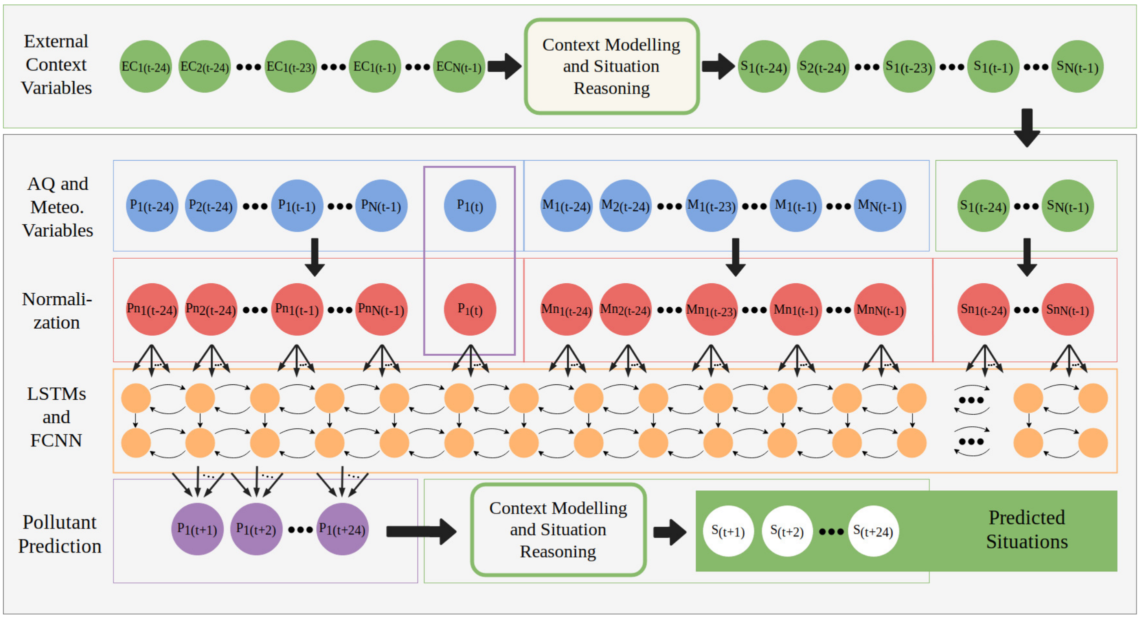


Figure 3.3: The MyAQI system LSTM's structure and general prediction work-flow.

manner to the end-users. The outcome of the forecasts and the current data is presented through the MyAQI web-application visualization tools. These tools along with other key building blocks of the system's implementation and design are presented in the next section of this thesis.

3.5 Summary

This chapter of the thesis described the most relevant aspects of the context model used in the MyAQI system. It defines some important theory to enable the modelling, then proposed the list of *Context Attributes* together with their format, value range, unit of measurement and example, and finally presented the situations in the *Situation Space* and their triggering factors. The following step in this research will handle the implementation of the system, together with the explanation of the prediction algorithm chosen and the role of context-awareness in this process.

4 MyAQI Architecture and Implementation

In this chapter the details of the MyAQI system's, architecture and implementation are presented, considering the theory and models presented in the previous sections.

4.1 System Architecture

In the previous chapter the main aspects of the critical functionalities of the MyAQI system where explained. Context and situation modelling, as well as the prediction method to apply where introduced. Considering these characteristics, we now present an architecture that will suit the requirements of this system.

First, it is necessary to remind that these system, even though an IoT based system, is not concerned with the creation and layering out of physical sensors. Given that the focus of the thesis is to improve prediction accuracy by applying context-aware concepts into the process, we utilize existing data streams from already functioning sensor networks, which are going to be presented in section 5.1.2. Bearing this in mind, the architecture of the system starts with the recognition of incoming AQ and context data streams and databases. This happens in the *Data Layer*, which is encapsulated by the Backend or *Server Layer*. The formatted data streams are passed to the *Logic Layer*, which prepares the context model, applies the prediction algorithms and acts as an Application Programming Interface (API) to the *Frontend Layer*, which in turn is responsible for Situation Reasoning and for presenting the data to the user, through the *Visualization Layer*. Next we go over each layer and explain thoroughly their parts and functionalities. Figure 4.1 gives an overview of the architecture and the technologies that are used to implement each part.

4.1.1 Backend Layer

The backend layer encapsulates the *Data Layer* and the *Logic Layer*. It resides in the server side and is tasked with preparing the context information for the *Frontend Layer* to be able to reason the situations and present customize data to the user.

Data Layer it is responsible for storing, processing and formatting incoming streams of data coming from different sources, such as third party APIs, historical data sets or live sensor

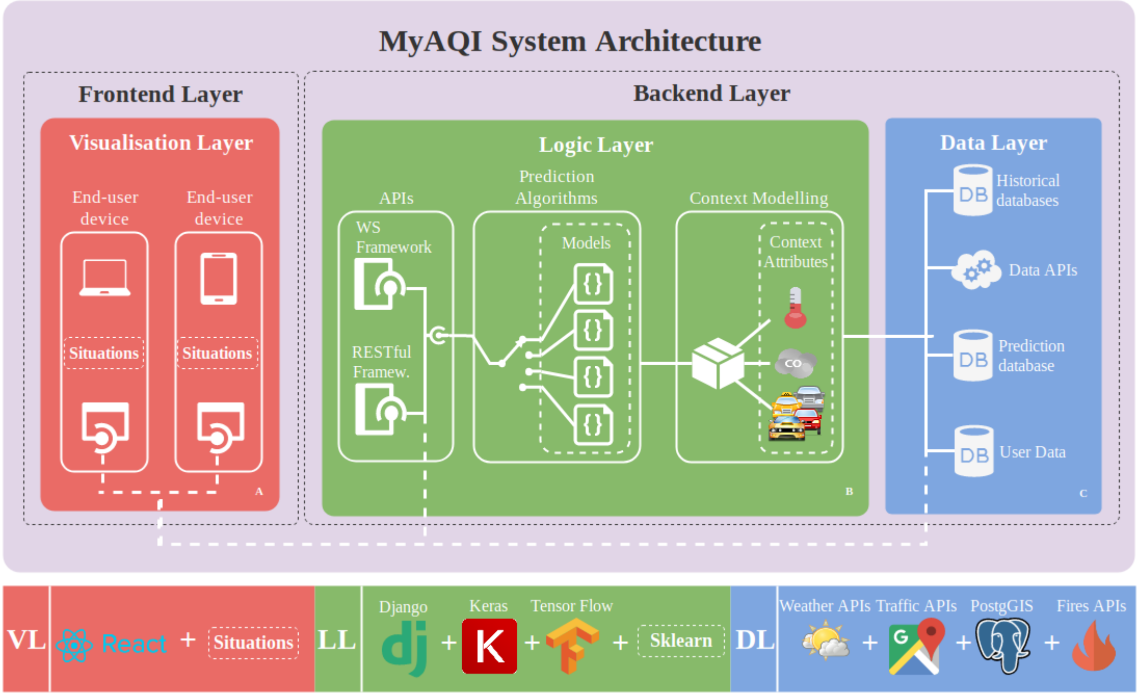


Figure 4.1: MyAQI system architecture and technologies for each layer's implementation.

nodes' data. The most relevant data is:

- **User profiles** store the information regarding the system's user, such as user id, email, password, age, preferred AQI scale, last geo-position, the user's questionnaire answers and pollutant sensitivity levels.

- **Air Quality data** can come from different sources. For AQ characteristics in the state of Victoria in Australia, for example, we use a data stream offered by the Victoria government and save the some relevant information into our database, such as the AQ sensor sites, the time basis for measurements updates, the available pollutants per sensor site, amongst others. The individual measurements' data (live and historical) is retrieved every time from the API itself. The data is presented in such a way that the *Frontend Layer* is agnostic of the source of the data and whichever format it had. AQI scales' information is also stored in this database, each which their own categories, limits and health messages.

- **External context data** is also stored in this layer. Traffic APIs and historical datasets provide the required information to extend the understanding of the user and aid the AQ prediction process. Live bushfire feeds also expand the user's understanding of the AQ sources and historical databases help improve the accuracy of forecasting techniques.

This data, independent of source, is formatted in a way that the frontend can be unaware of the data source, because the presentation is kept constant.

- **Prediction data** is saved to allow the prediction algorithm to work with data of previously ran forecasting processes. After a prediction sequence is run, the data is then stored in a format that the same algorithm can use as an input in oncoming loops.

The final goal of the data layer is to make the adding of APIs and datasets general, in a way in which user's can add their own. For example, if users own an AQ personal sensor they could add plug and play it to the system and obtain information that the device provides in the MyAQI frontend. Next, the data streams made available by the data layer is consumed by the logic layer which will format it into the context model and apply the prediction algorithms on it.

Logic Layer contains the business logic for the MyAQI system. It receives the information from the data layer and process it in such a way that the functionalities required by the user are covered, and sends the resulting information to the *Frontend Layer*. It is divided into three modules.

- **Context modelling** handles the transformation of the raw data received from the data layer to a format that fits into the context model described in section 3. It maps each API or database data into the required *Context Attributes* allowing the next module to apply the prediction algorithms on top of it.
- **Prediction algorithm selector** is a meta model selector, which means that it can apply different algorithms depending on the system's configuration. The algorithms expect the data to be formatted so that it can be directly applied in their logic. A more in-depth explanation about the algorithm selection and data flow will be presented in the implementation subsection 4.2.
- **API** administers the frontend calls from the user devices to get the required data. Requests for information may trigger certain functions in the *Backend Layer* or they may just interact directly with the *Data Layer* to retrieve simple static information. The API module should be independent of framework technology and should adapt to the end-user device's requirements and the required functionality. For demonstration purposes, a Hyper Text Transfer Protocol (HTTP) Representational State Transfer (RESTful) API, for frontend triggered requests, and a Web Sockets (WS) API, for notification purposes, are implemented.

The *Backend Layer* will prepare all data necessary for frontend clients to retrieve and use.

4.1.2 Frontend Layer

Having a backend system in place, as explained in the previous sub-section, we need a client that can consume the prepared information and present it to the user in a customized and context-aware form; such is the task of the *Frontend Layer*. It consists of only one module, the **Visualization Layer** which in turn is made of three main parts, each of which will be run on an end-user device.

- **API consumer** handles the interaction and calls to and fro the backend interfaces. It also prepares the data for the situation reasoner and visualization interface, given that some data formats vary depending on the source (i.e. Web Sockets vs. RESTful API).
- **Situation reasoner** contains all the logic for the *Situations Space* define in chapter 3. It will compare the data obtained from the APIs against the rules defined for each situation and give the resulting output to the visualization interface, to be rendered to the user.
- **Visualization interface** consists mainly of display technologies that lets the user interact with the system. It shows the outcomes from the whole AQ monitoring and prediction process to the end-user. It also lets users actuate over the system, in that it gives the option to customize details of the user profile and visualization settings.

The whole system architecture is designed in a way that prioritizes the customizability and context-awareness execution. But it is also simple to notice that the main concept behind the architecture is that of a server/client Web System, following the Model-View-Controller (MVC) framework. The model being the *Data Layer* which is mapped with a Object-relational Mapping (ORM) to the *Logic Layer*, which is the controller and where the data is transformed and worked upon, and finally, the view which in the frontend acts as the interface towards the outside world.

4.2 Implementation

In the previous chapters the main functionalities, models and goals of the MyAQI system where introduced. In this section 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.

4.2.1 Hardware

Given that the system is divided in two mayor layers, they both need to run on devices that match their requirements. The backend layer is a server node that requires high availability, reliability and bandwidth, to be able to interact with many clients at the same time. And the frontend devices should be any devices that user's have regular access to, i.e. laptops, mobile phones and tablets.

The server characteristics chosen for the purpose of the experiments in this system is a Linux 18.04 Server with 500GB of storage, 16B of RAM and a 4-cores 2.60GHz processor. The server is hosted in the Deakin University's Intranet and available through *http://schurholz.it.deakin.edu.au/*. The storage size and other characteristics of the server are due to the fact the prediction algorithms can be quite expensive in resources and the server must still be able to function as a web server on the mean time.

The end-user devices can be any modern laptop, mobile phone or tablet, given that the purpose of the system is to be available to any user. The only condition is that the devices can render a modern version of any web-browser and display it to the user. For the purpose of the experiments of this research a Lenovo X1 Carbon laptop, a Huawei P8 mobile phone and a 2017 iPad tablet were used, as shown in Figure 4.2.

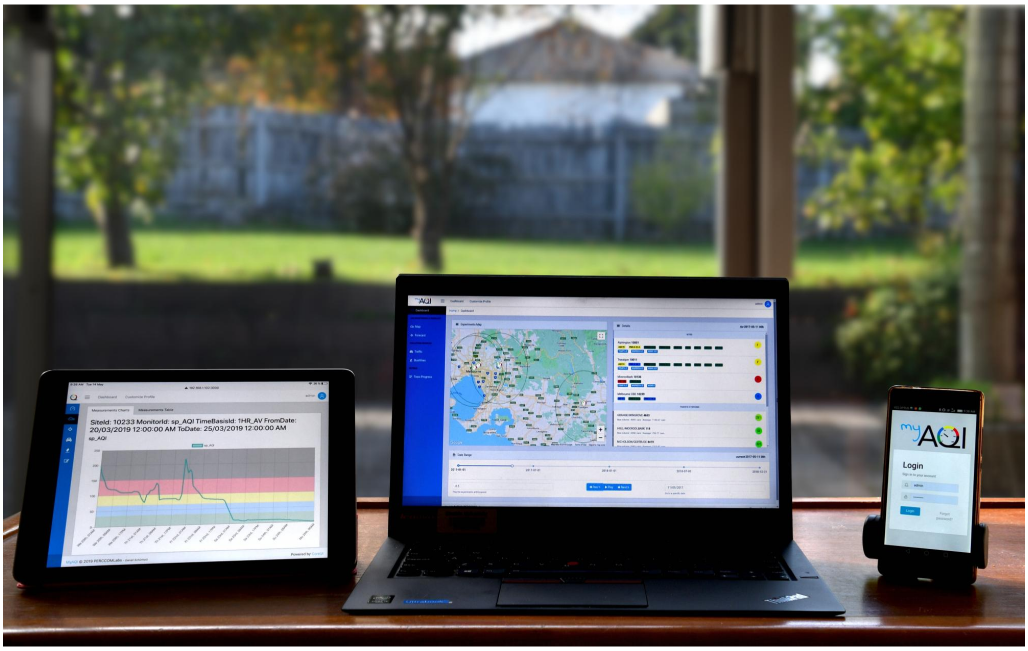

SiteId: 10233 MonitorId: sp_AQI TimeBasisId: 1HR_AV FromDate: 20/03/2019 12:00:00 AM ToDate: 25/03/2019 12:00:00 AM
sp_AQI
myAQI
Login

Figure 4.2: The MyAQI system rendered on different end-user devices, for more accessibility.

The goal of the MyAQI system is to be able to be accessible to as many users as possible and given the ubiquity and cross-platform characteristics of web browsers, the best approach is to develop a web-system with a responsive frontend web site for the prototype.

4.2.2 Software

For each previously mentioned layer different software tools have been used to accomplish their goals. Figure 4.1 shows the main frameworks used for each module, but there are more libraries involved in the process. As a rule for all the technologies chosen, we expect the technologies to be open-source, free and with a sufficient amount of documentation, community and research involvement to be able to qualify for this research. Next, the reasons for why each tool was chosen are explained.

The *Data Layer* requires a database engine that is capable of handling large sets of data in an organized way. The tool chosen is **PostgreSQL**, given the large acceptance in the development community. It also carries the benefit of having the **PostGIS** plug-in, that allows the database to run geographical queries, i.e. geo-locations that fall inside a given polygon area of land. This is specially useful for querying the traffic and bushfire datasets for the extended context. Besides the interaction with databases, the *Data Layer* also handles requests from external third party APIs. The tool handling this communications is the **Requests** python library. Given that the *Logic Layer* is going to be programmed in the **Python** programming language, the choice of the aforementioned frameworks makes more sense; the ORM to map database records to memory objects is the **Psycopg2** python library.

As previously explained the *Logic Layer* will be mostly programmed using Python. The context modelling, bundling and interaction will be handled by the **Django** web framework. It is a well established tool, with a vast on-line community and used amongst a large set of web systems. The seamless interaction with the PostgreSQL database records is also of great benefit. For the development of the prediction algorithms the python libraries **Tensor Flow** and **Keras** were applied. They are largely accepted in the research community as tools to implement robust algorithms for data analysis using ANNs and DL. [TO-DO, explain more about the prediction tools]. At the very front of the *Backend Layer* and acting as a RESTful API, the python library **Django Rest Framework (DRF)** is used. It is a third party tool developed to fit into the Django framework and is used in a large number of projects. The requests to the API are handled by an NGINX HTTP server, which is together with Apache HTTP, one of the most widely used ones. The other interface, besides HTTP, is a Web Sockets system, which is developed using the **Django Channels** python library and **Redis** as a memory data structure framework for faster socket connection handling.

The *Frontend Layer* requires a framework that will easily produce an interactive visualization application, that is responsive and compatible with different devices. For that purpose, we selected the ReactJS framework, because it is widely used, is constantly maintained and has a vast support community. It is a cross-platform technology as it uses mainly a modified version of JavaScript (called JSX), Hyper Text Mark-up Language (HTML) and Cascade Style Sheet (CSS), and can be rendered in any modern browser. React also offers a large number of plug-ins designed to aid with different common tasks in web applications. The main plug-in used in the MyAQI system is the Redux tool, that helps keep the state of the application updated during its execution, triggers API requests, updates views and re-renders components of the web site. Other important plug-in is the GoogleMapsAPI, which aids in visualizing geographical relevant data, such as AQ information, traffic and bushfire data. Other minor libraries and tools are used to simplify the development of the application. For exact versions and links for tools and plug-ins see APPENDIX 1.

As part of the Frontend layer we designed an end-user interface considering that the interface of any context-aware system has to convey a sense of individualization to the user. It has to allow them to customize many characteristics, like colours, tool-placing, element sizes, etc. It also has to be simple to understand and easy to use. The design concept adopted for the MyAQI is that of a Dashboard, which is widely used in monitoring oriented applications. All the views are be easily accessible and the user is allowed to customize certain aspects of the application's behaviour, besides the context model. A map of the navigation of the web app can be observed in Figure 4.3.

The navigation of a user session in the web application starts in the *Authentication* module. One of the requirements from the MyAQI Context Model is that user have a related ID. For these purpose, the system lets new users register in the *Registration* view. For already signed-up users, the access to the web application is through the *Login* page, where only user-name (User ID) and password are asked for. Once authenticated the user is redirected to the *Dashboard*. From this view, users can navigate to any information panel they require. First, there is the *AQI Monitoring* module, which contains the *AQI Historical Map* and the *AQI Forecast Map* pages. On these sites users can interact with data coming from different sources that reveal the AQI and pollutants' levels from past, current and future time intervals and from different locations. Another panel accessible to the user is the *Pollution Sources* module, which contains two views. First, there is the *Traffic Map* view, where users can understand the traffic related issues and traffic flows that could be causing air pollution problems. Similarly,

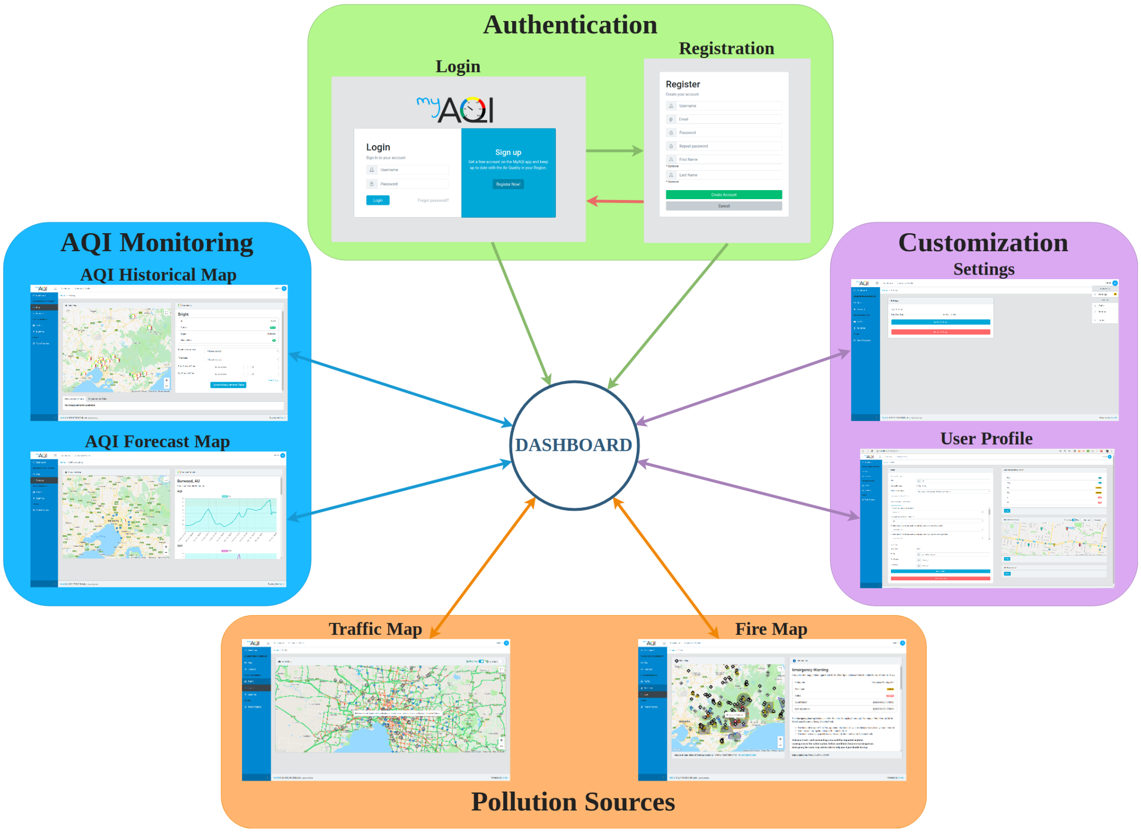
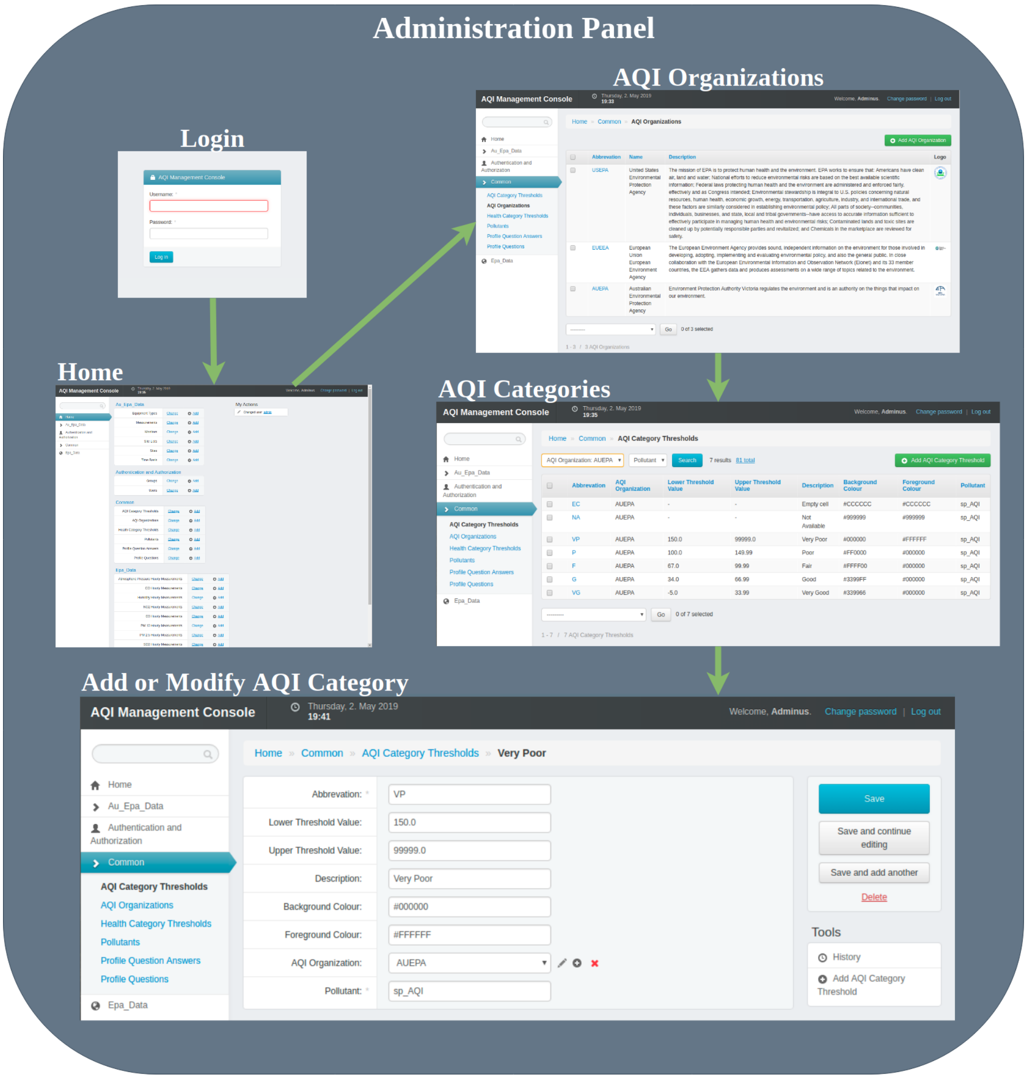


Figure 4.3: The MyAQI web application's views and navigation.

the second view, the *Fire Map*, shows fire related issues on a map, from which users can grasp the effect of bushfires or household fires that could be causing a rise in Air Pollutants around a region. Finally, the logged-in user can customize the experience given by the MyAQI in the *Customization* module, which contains the *User Profile* and *Settings* panels. The first one, gives the ability to modify personal information, answer the pollutant sensitivity questionnaire, select the preferred AQI scale and preview the pollutant sensitivity levels, the AQI maps overlays and colours and view the selected AQI scale information.

Another requisite for context-aware systems is the ability to configure the overall systems settings on run-time. For this purpose an **Administration Dashboard** was developed. From this dashboard, a user with higher level permissions can create, update or delete the information that the web application will use. In 4.4 for example, administrators can modify the colours, limit, descriptions, abbreviations, etc. of the AQI scales. Other scales can be seamlessly added and the web application's users will notice the change in real time.

The end-user interfaces allow users to interact with the system and also validate the context-aware research goals of this thesis.



AQI Management Console

Username: *

Password: *

Log in

AQI Management Console — Thursday, 2. May 2019 19:33 — Welcome, Adminus. Change password | Log out

Home » Common » AQI Organizations

Add AQI Organization

	Abbrevation	Name	Description	Logo
□	USEPA	United States Environmental Protection Agency	The mission of EPA is to protect human health and the environment. EPA works to ensure that: Americans have clean air, land and water; National efforts to reduce environmental risks are based on the best available scientific information; Federal laws protecting human health and the environment are administered and enforced fairly, effectively and as Congress intended; Environmental stewardship is integral to U.S. policies concerning natural resources, human health, economic growth, energy, transportation, agriculture, industry, and international trade, and these factors are similarly considered in establishing environmental policy; All parts of society--communities, individuals, businesses, and state, local and tribal governments--have access to accurate information sufficient to effectively participate in managing human health and environmental risks; Contaminated lands and toxic sites are cleaned up by potentially responsible parties and revitalized; and Chemicals in the marketplace are reviewed for safety.	
□	EUEEA	European Union European Environment Agency	The European Environment Agency provides sound, independent information on the environment for those involved in developing, adopting, implementing and evaluating environmental policy, and also the general public. In close collaboration with the European Environmental Information and Observation Network (Eionet) and its 33 member countries, the EEA gathers data and produces assessments on a wide range of topics related to the environment.	
□	AUEPA	Australian Environmental Protection Agency	Environment Protection Authority Victoria regulates the environment and is an authority on the things that impact on our environment.	

0 of 3 selected

1 - 3 / 3 AQI Organizations

AQI Management Console — Thursday, 2. May 2019 19:35 — Welcome, Adminus. Change password | Log out

Home » Common » AQI Category Thresholds

AQI Organization: AUEPA — Pollutant — Search — 7 results 81 total — Add AQI Category Threshold

	Abbrevation	AQI Organization	Lower Threshold Value	Upper Threshold Value	Description	Background Colour	Foreground Colour	Pollutant
□	EC	AUEPA	-	-	Empty cell	#CCCCCC	#CCCCCC	sp_AQI
□	NA	AUEPA	-	-	Not Available	#999999	#999999	sp_AQI
□	VP	AUEPA	150.0	99999.0	Very Poor	#000000	#FFFFFF	sp_AQI
□	P	AUEPA	100.0	149.99	Poor	#FF0000	#000000	sp_AQI
□	F	AUEPA	67.0	99.99	Fair	#FFFF00	#000000	sp_AQI
□	G	AUEPA	34.0	66.99	Good	#3399FF	#000000	sp_AQI
□	VG	AUEPA	-5.0	33.99	Very Good	#339966	#000000	sp_AQI

0 of 7 selected

1 - 7 / 7 AQI Category Thresholds

AQI Management Console — Thursday, 2. May 2019 19:41 — Welcome, Adminus. Change password | Log out

Home » Common » AQI Category Thresholds » Very Poor

Abbrevation: *	VP
Lower Threshold Value:	150.0
Upper Threshold Value:	99999.0
Description:	Very Poor
Background Colour:	#000000
Foreground Colour:	#FFFFFF
AQI Organization:	AUEPA
Pollutant: *	sp_AQI

Save — Save and continue editing — Save and add another — Delete

Tools: History — Add AQI Category Threshold

Figure 4.4: The MyAQI web application's administration dashboard and AQI categories example.

More information about the specific structure of the code both in the backend and frontend is described in the appendix section APPENDIX 2.. Each of the layers is a separate system or sub-system. So, a mean for communication must be considered.

4.2.3 Communication

As briefly mentioned in the previous sections the communication in the MyAQI system is twofold. The first set of interactions happen between the system and the data sources required for each function. And secondly, the *Frontend Layer* requests information from the

Backend through HTTP and in both directions through WS, which is handled directly through the Transmission Control Protocol (TCP). A diagram of some example communications can be observed in Figure 4.5.

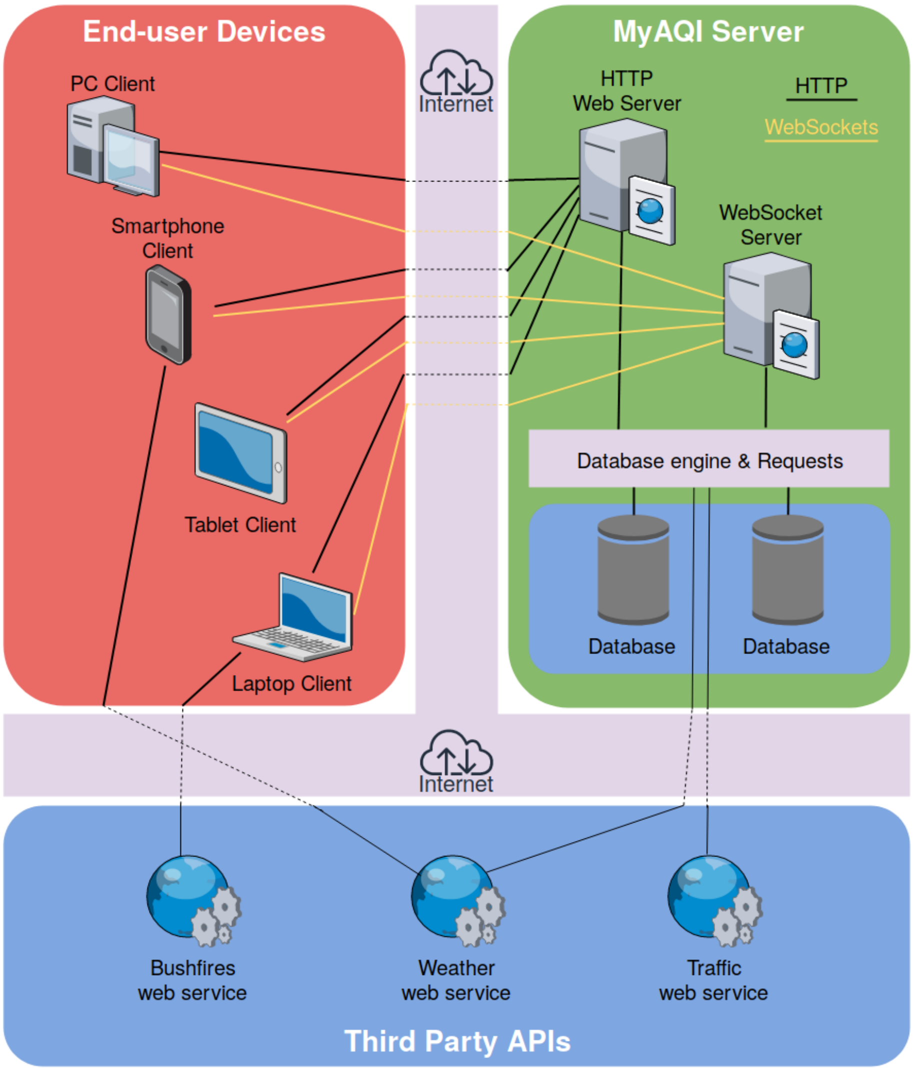


Figure 4.5: The MyAQI system's flow of information and communication protocols.

Note that frontend devices can communicate with third party APIs to consume data directly, if it is for visualization purposes only. But any data that has to be processed by the context model for AQ monitoring or prediction purposes has to be queried via the MyAQI server. The WS server tuns in a different server and is in charge of handling notifications with urgent information to users, i.e. when a pollutant concentration peak was measured in the recent past.

4.3 Summary

This chapter described the process of developing the whole MyAQI system. From the architecture that guided the technology selection, passing through the necessary equipment and devices for its functioning, through the software choices to achieve the desired outcomes, the networking requirements that make possible the communication between layers, the interface design to allow the user interaction with the system, to the very development process gone through to be able to create the application. The completion of the system is only a starting point for the goal of this research, which is to experiment and obtain results that can answer the research objectives. Considering this, the experiment setup and the results are presented in the following chapter.

5 EXPERIMENTS AND RESULTS

This chapter lays out the details of the MyAQI system's, experiments and their results, as well as the sustainability analysis performed on the proposed model and implemented prototype.

5.1 Experiments

The previous section introduced the architecture and implementation of the MyAQI system and highlighted its different building blocks. The goal of the system is to prove the advantages of context prediction, as well as proving its usability in a real-case scenario. This section presents the experiments that were undertaken to specifically tackle those objectives. First experiments' location, setup and structure is explained, and later the datasets used to "fuel" the system and create the necessary context are described.

5.1.1 Experiment Setup

Considering that the use case example presented in section 1 occurs in Melbourne, Australia, and the propensity of the region to suffer under large bushfires on the late summer and early autumn months, the experiments will take place in the Victoria state in Australia, specifically in the greater Melbourne area. The goal of the experiments is to prove that the inclusion of *Context Aware* concepts in AQ prediction and monitoring can improve the prediction accuracy and user-experience.

For the prediction accuracy measurements a selection of the data for the input layer of the prediction model (described in section 3.4) has to be done. Given the large amount of data that can be collected for each context attribute, a smaller subset of the whole available datasets (explained in section 5.1.2) has been used. Only data between the first of January 2017 and the first of January 2019 is considered, due to the datasets availability. Then, only four weather and pollutant measuring stations are considered. The criteria for their selection is the impact of the extended context variables on them. Usually the urban locations that suffer most from large wildfire are the outskirts of cities, while those who suffer most from traffic pollution are located close to the city centre. Thus, two stations for the each case where selected, the *Alphington* and *Melbourne CDB* stations are situated in Melbourne's centre area with huge vehicle crossings around them; the Mooroolbark station lies in the eastern city suburbs, close to forest and grassland covered area, prone to summer fires; and lastly, the Traralgon station is located in a separate town to the east of Melbourne called Traralgon as well, which sits near vast areas of forests susceptible to large bushfires.

For each measuring station, one to four nearby vehicle crossing stations where selected to obtain the number of vehicles driving past the site every hour. The only station that this does not apply to is *Traralgon*, since there is no crossing being measured nearby the AQ monitoring site and the traffic volume in the town is not relevant. For this station, and for *Mooroolbark*, the fires that affect the nearby areas have to be considered for the context and prediction models. A radius of 100 km is considered to encompass the fires that could affect the pollutant concentration levels at the measuring sites. As shown in section 3.3, depending on the distance from the fire, the effect on the measurements are larger or lower.

The complete experimental setup can be navigated and understood in through “Experiments” view in the MyAQI web application, as seen in Figure 5.1. The data can be queried on specific dates or played at different speeds to see its evolution throughout time and how each attribute affects the others. Figure 5.2 shows a zoomed in view of the *Melbourne CBD* station surrounded by the traffic volume measuring stations, the coloured streets (according to the traffic situations); and on the right panel the actual values for the measured pollutants and AQI, as well as the values for the traffic volumes and the existing fires in the influence area of the site.

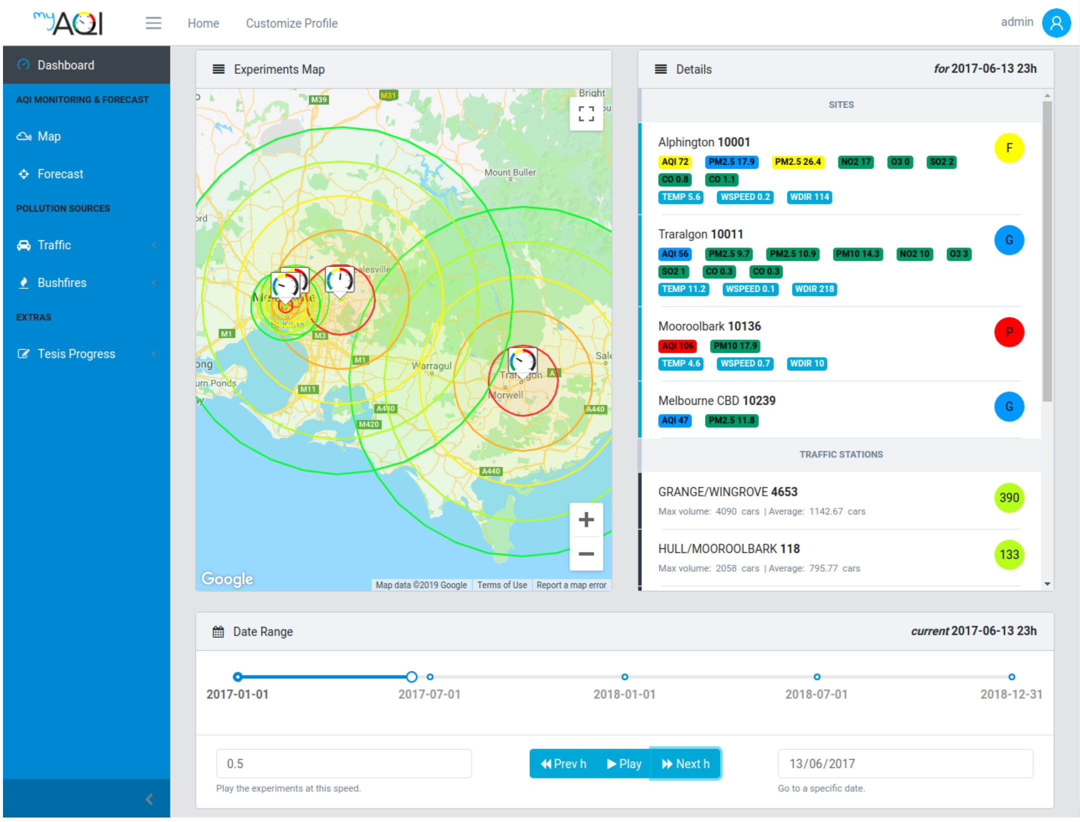
The experiments as explained in the previous paragraphs, requires existing data sources that feed each of the variables. The data shown on the panel and used in the experiments were taken from different such sources and are defined in the following subsection.

5.1.2 Dataset Description

In section 3 the context and situations models were described. Each of those require data sources to create a usable system and to test the proof-of-concept. Consecutively, the different datasets used for the AQ, meteorological, traffic and fires attributes are presented.

5.1.3 AQ dataset

The AQ attributes required in the context model are the AQI and the $PM_{2.5}$, PM_{10}, O_3 ,NO_2, SO_2 and CO pollutants. As explained in the previous section (section 5.1.1), the experiments



Details *for* 2017-06-13 23h

SITES

Alphington **10001** F
AQI 72 PM2.5 17.9 PM2.5 26.4 NO2 17 O3 0 SO2 2 CO 0.8 CO 1.1
TEMP 5.6 WSPEED 0.2 WDIR 114

Traralgon **10011** G
AQI 56 PM2.5 9.7 PM2.5 10.9 PM10 14.3 NO2 10 O3 3 SO2 1 CO 0.3 CO 0.3
TEMP 11.2 WSPEED 0.1 WDIR 218

Mooroolbark **10136** P
AQI 106 PM10 17.9
TEMP 4.6 WSPEED 0.7 WDIR 10

Melbourne CBD **10239** G
AQI 47 PM2.5 11.8

TRAFFIC STATIONS

GRANGE/WINGROVE **4653** 390
Max volume: 4090 cars | Average: 1142.67 cars

HULL/MOOROOLBARK **118** 133
Max volume: 2058 cars | Average: 795.77 cars

current 2017-06-13 23h

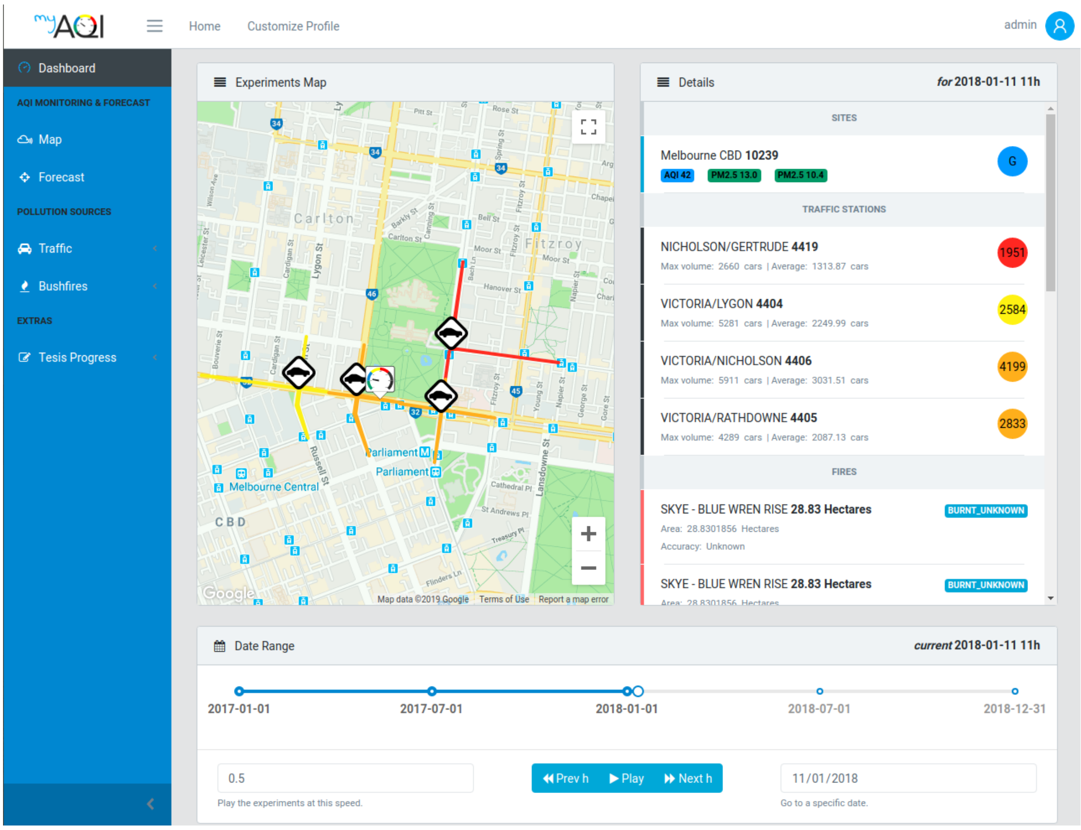
0.5
Play the experiments at this speed.

13/06/2017
Go to a specific date.

Figure 5.1: MyAQI general experimental setup view on the “Experiments” view of the web application.

and system are located in the Victoria region, thus a dataset found to be quite useful is the AirWatch live API maintained by Victoria’s AU-EPA branch. The data provided is both historical and current (updated hourly), and has almost all context variables for many of the sensor stations distributed throughout Victoria, including meteorological data, such as Wavelet Decomposition, Web Sockets and Temperature. For stations that do not measure all the pollutants, only the relevant pollutants for the pollution sources in the area of the sensor will be used. Figure 5.3 presents a panel in the MyAQI application, where users can retrieve historical and current information on the measurements for each of the AQ stations and sensors available in the dataset; and visualize the information as a chart or table.

For comparison purposes the MyAQI web-app also presents a view for AQ forecasts provided by the WeatherBit API. It is a third party provider for external models such as the European Centre for Medium-Range Weather Forecasts (ECMWF) weather and air quality datasets. These models are run by Bureaus of Meteorology and other big organizations and use modern ensemble techniques for prediction and satellite atmospheric composition measurements. These models rely solely on a time-series based analysis and forecast, they do not take ex-



Details *for* **2018-01-11 11h**

SITES

Melbourne CBD **10239** — AQI 42 — PM2.5 13.0 — PM2.5 10.4 — G

TRAFFIC STATIONS

NICHOLSON/GERTRUDE **4419** — 1951
Max volume: 2660 cars | Average: 1313.87 cars

VICTORIA/LYGON **4404** — 2584
Max volume: 5281 cars | Average: 2249.99 cars

VICTORIA/NICHOLSON **4406** — 4199
Max volume: 5911 cars | Average: 3031.51 cars

VICTORIA/RATHDOWNE **4405** — 2833
Max volume: 4289 cars | Average: 2087.13 cars

FIRES

SKYE - BLUE WREN RISE **28.83 Hectares** — BURNT_UNKNOWN
Area: 28.8301856 Hectares
Accuracy: Unknown

SKYE - BLUE WREN RISE **28.83 Hectares** — BURNT_UNKNOWN
Area: 28.8301856 Hectares

Date Range *current* **2018-01-11 11h**

0.5
Play the experiments at this speed.

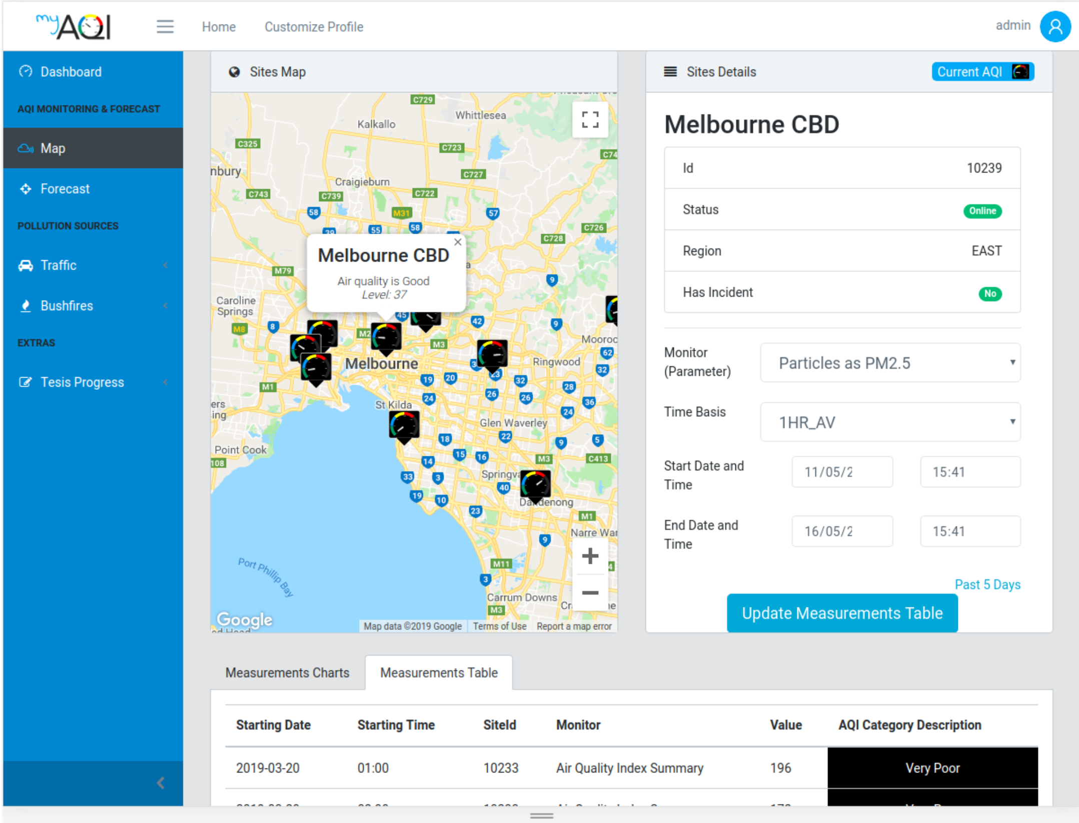
11/01/2018
Go to a specific date.

Figure 5.2: MyAQI specific experimental setup view for the *Melbourne CBD* AQ station on the "Experiments" view of the web application.

ternal context, such as pollution sources, as inputs.

5.1.4 Traffic volume datasets

One of the relevant pollution sources considered in the MyAQI model is the level of traffic close to the desired prediction location. In Victoria, as in almost every major city in Australia, the traffic lights system has the *SCATS* system (developed by the government of New South Wales, Australia) integrated into their public roads network. This system has the function of counting the amount of cars for every 15 minutes time span on each major crossing in the city and adapting the traffic light operation according to it. The government of Victoria releases the vehicle loads at the end of each month. This dataset was used for the prediction algorithm, as input for traffic levels close to the prediction location. The information of traffic volume for every 15 minutes where summed by the end of each hour, to correlate to the way the air quality datasets are structured.



Melbourne CBD

Id	10239
Status	Online
Region	EAST
Has Incident	No

Monitor (Parameter): Particles as PM2.5

Time Basis: 1HR_AV

Start Date and Time: 11/05/2 15:41

End Date and Time: 16/05/2 15:41

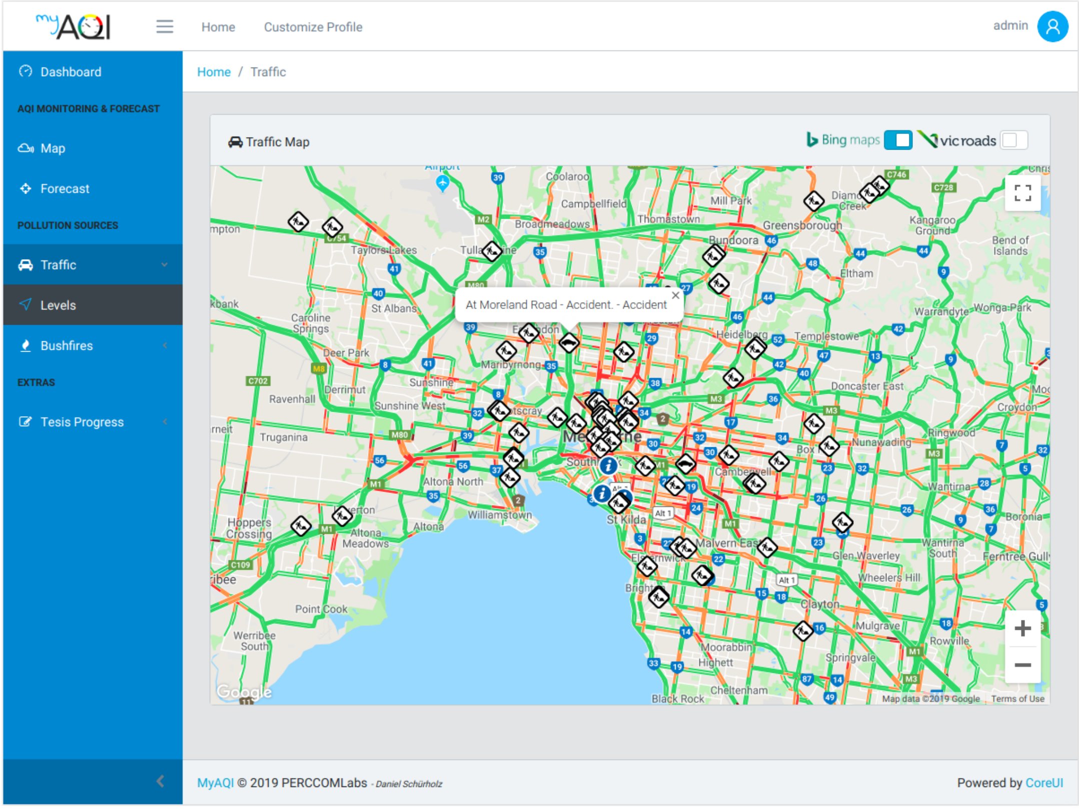
Starting Date	Starting Time	SiteId	Monitor	Value	AQI Category Description
2019-03-20	01:00	10233	Air Quality Index Summary	196	Very Poor

Figure 5.3: AQ sensor network used in the MyAQI system, provided by the local government's AU-EPA branch, in Victoria, Australia.

Other datasets used for monitoring in the MyAQI system are the *VicRoads* and the *Bing Maps* live traffic incidents feeds, as well as the *Google Maps* traffic map layer. Even though the information retrieved from the previous three sets were not used in the prediction algorithm as inputs, they are used to aid the system's end-users understanding of the current Air Quality in their location. Figure 5.4 shows the traffic view on the MyAQI web application.

5.1.5 Fire incidents datasets

Another context attribute required for the context model explained in section 3 is information about fire incidents (such as household fires or bushfires) close to the prediction location. Again, the Victoria government offers such a dataset, as it keeps track of every fire in its region since the 1930's. For the purpose of this work only the information for season's 2017 and 2018 where imported into the system. Every fire incident in the Victoria region present in the dataset has a severity attribute, a geographical polygon describing its covering area,



At Moreland Road - Accident. - Accident

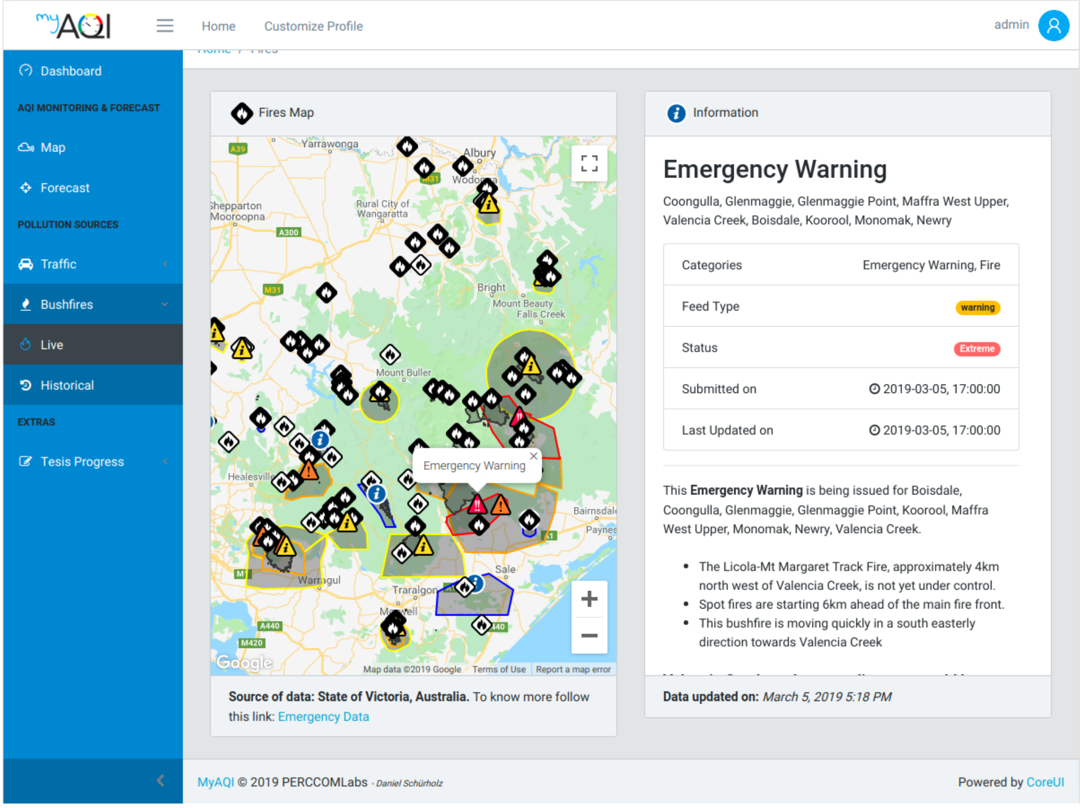
Figure 5.4: Traffic incidents' information used in the MyAQI system, provided by Victoria's local government through the *VicRoads* platform; other sources are *Bing Maps* and *Google Maps*.

a starting date and a referential identification field. The fire instances do not have an ending date assigned, but it can be approximated depending on the severity of the fire, as shown in Table 5.1; if a fire has a severity of BURNT_4, which is the worst case, the duration will be of 10 days and the ending date can be calculated from this value.

Table 5.1: Fire incidents, taken from the Victoria government's fire incidents historical dataset, depending on their severity.

Fire Severity	Duration (in days)
BURNT_1	3
BURNT_2	5
BURNT_3	10
BURNT_4	15

Similar to the traffic information, there are other data streams available for fire incidents, that can aid in the general understanding of current AQ levels by the users. The MyAQI system consumes the data from the *Victoria Emergency* live feed. This information is updated every minute and contains many types of urgent incidents in the region, including fire incidents. Figure 5.5 shows the view on the MyAQI web-application that presents this information.



Source of data: State of Victoria, Australia. To know more follow this link: Emergency Data

Emergency Warning

Coongulla, Glenmaggie, Glenmaggie Point, Maffra West Upper, Valencia Creek, Boisdale, Koorool, Monomak, Newry

Categories	Emergency Warning, Fire
Feed Type	warning
Status	Extreme
Submitted on	2019-03-05, 17:00:00
Last Updated on	2019-03-05, 17:00:00

This **Emergency Warning** is being issued for Boisdale, Coongulla, Glenmaggie, Glenmaggie Point, Koorool, Maffra West Upper, Monomak, Newry, Valencia Creek.

- The Licola-Mt Margaret Track Fire, approximately 4km north west of Valencia Creek, is not yet under control.
- Spot fires are starting 6km ahead of the main fire front.
- This bushfire is moving quickly in a south easterly direction towards Valencia Creek

Data updated on: *March 5, 2019 5:18 PM*

MyAQI © 2019 PERCCOMLabs - *Daniel Schürholz*

Powered by CoreUI

Figure 5.5: Fire incidents' information view in the MyAQI system; data provided by the Victoria's local emergency platform *Victoria Emergency*.

The resulting graphics and analysis are presented in the following section of this thesis.

5.2 Results

The previous subsection described the experimental setup and datasets laid out to obtain measurements of the accuracy of the approach presented in this thesis. In this subsection we present these results and explain their significance. First, data analysis work done on the available input information, such as variable correlations and data histograms are described. Then, the accuracy comparisons of the prediction algorithm are presented, comparing an LSTM 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 implementation of the MyAQI system.

5.2.1 Data Analysis

The information found in the datasets introduced in subsection 5.1.2 allow the application of different analysis tools to understand the data that goes into the prediction algorithm and monitoring systems, as well as explaining the relationship amongst different phenomena. Figure 5.6 describes the attributes for all the AQ stations for a short period of time. This allows to understand the behaviour of the variables and see their relation at specific points in time. For the two stations located in the outskirts of the Melbourne urban area, Mooroolbark and Traralgon, the fire activity is significant during the months of February through to May and impact in some high peaks in $PM_{2.5}$ and PM_{10} levels, rising the AQI as well. For the city-located stations, Melbourne CBD and Alphington, the traffic levels influence in the fluctuation of pollutants suck as $PM_{2.5}$ and O_3.

Another explicative analysis is obtained through correlation heat-maps. Figure 5.7 presents for the four stations. We can conclude again, that in the city Fire has no incidence over AQI levels, but traffic does, and the other way around on the countryside.

The previous figures show that there exists a correlation between the extended context variables and some of the pollutants. This helps to select the specific input variables for executing the prediction of each pollutant.

5.2.2 Prediction Accuracy

Previously, the data analysis of the variables for each AQ measuring station was done. With this information the prediction model was trained and tested. To proof the accuracy of the model and the selection of variables, a comparison against the ground truth (the real values) was made, as seen in Figures 5.8 and 5.9. The former presents the values for a one-hour-ahead prediction of $PM_{2.5}$ levels made on the Melbourne station, using only values for the previous 24 hours on $PM_{2.5}$ concentrations and the traffic volume information for four of the traffic measuring stations, presenting a good performance. The latter figure shows the values for a one-hour-ahead prediction of $PM_{2.5}$ concentrations using NO_2, SO_2, PM_{10} and CO, besides the traffic volume information for the closest traffic station to the AQ measuring station; the outcome of this prediction is much more accurate given the higher availability of data.

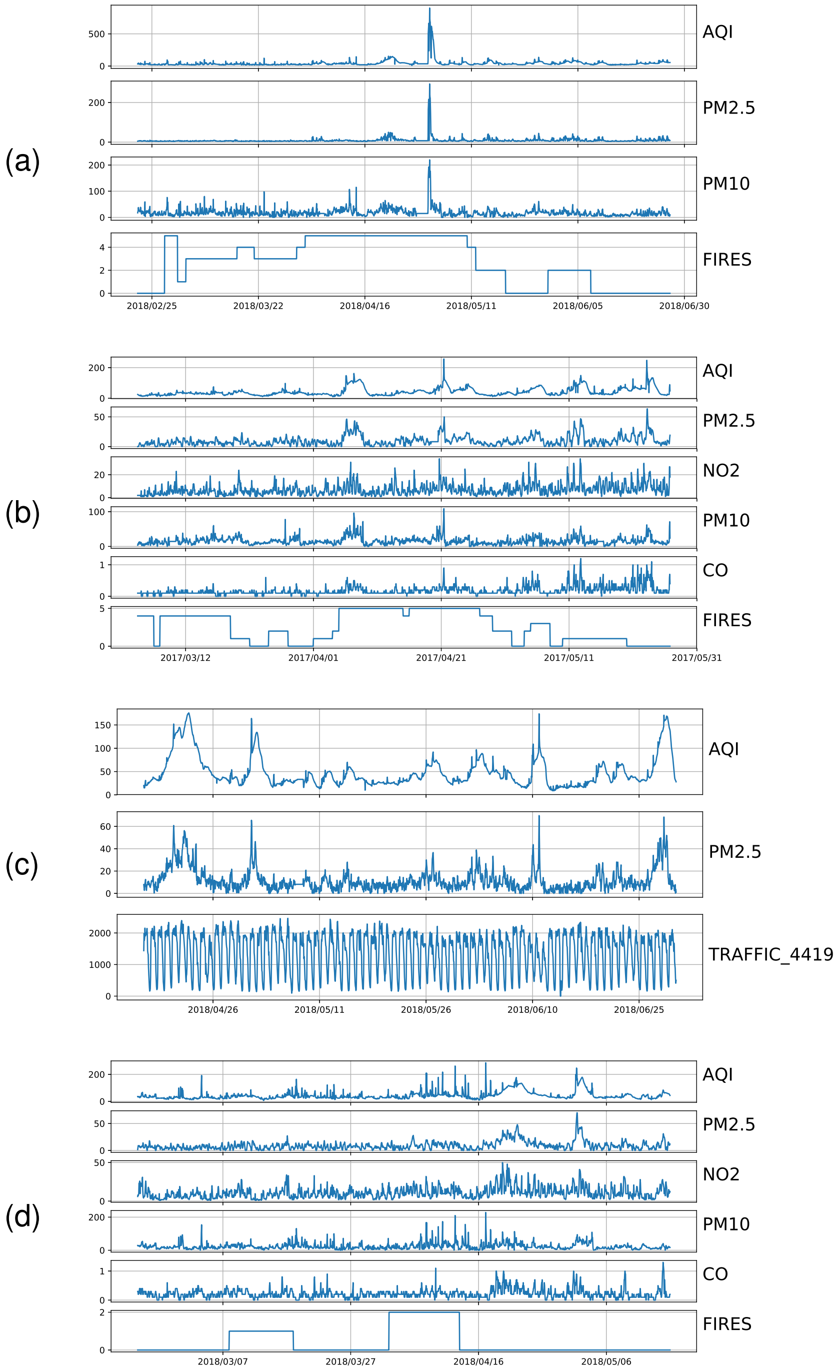
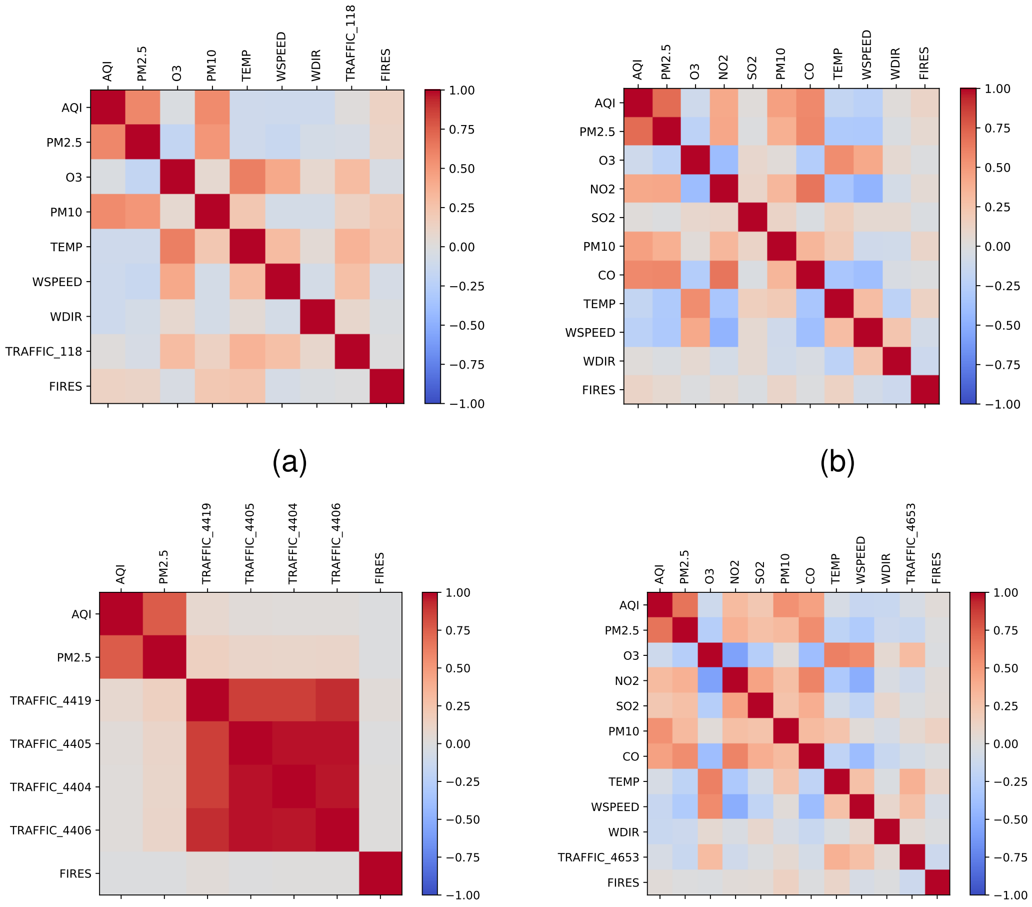


Figure 5.6: Measurements for the most relevant context variables all AQ measuring stations. (a) Mooroolbark measurements during the 2018 bushfire season, (b) Traralgon AQ measuring station measurements during a 2017 bushfire period, (c) Melbourne CBD on a regular period of time and (d) Alphington context attributes measurements during a regular period of time.



(a)

(b)

(c)

(d)

Figure 5.7: Correlation map for all context variables for the countryside Mooroolbark (a) and Traralgon (b) AQ measuring stations; and city Melbourne CBD (c) and Alphington (d) AQ measuring stations.

The previous two results show the benefits of using traffic information for predicting $PM_{2.5}$ values. And for the rest of the AQ stations, which are located in a more rural area, the prediction is augmented by the use of fire incidents informations. Figures 5.10 and 5.11 present the $PM_{2.5}$ predictions on the Mooroolbark and Traralgon stations respectively. The first one uses

Furthermore, Table 5.2 shows the comparison of predictions' MAE, RMSE, precision and correlation (R) values for the four stations, once with extended context and once without against the ground truth. 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, which measures the accuracy of the classifi-

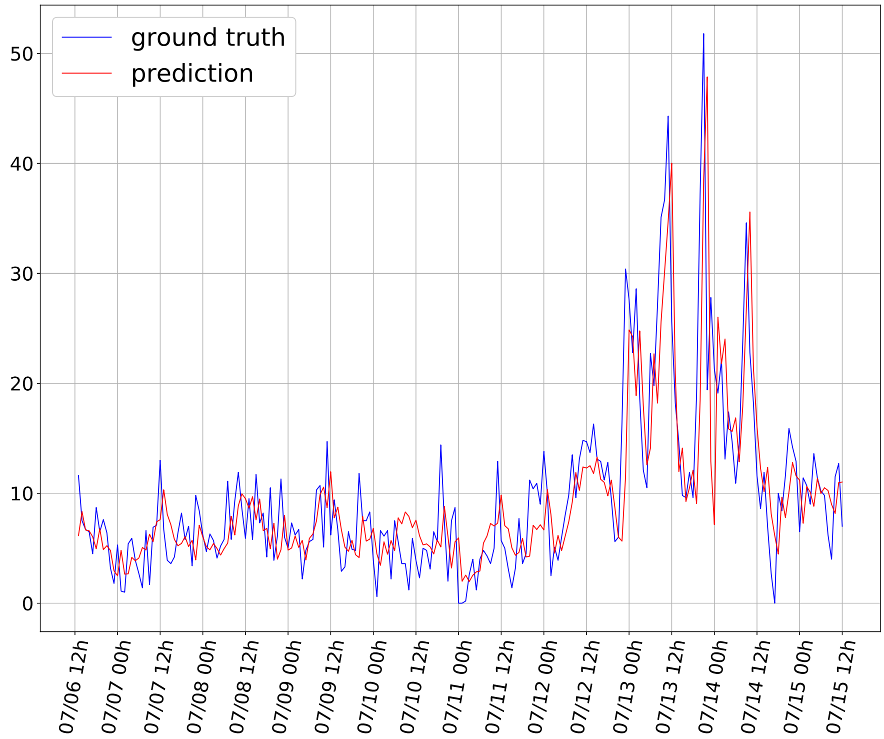


Figure 5.8: Melbourne CBD AQ measuring station $PM_{2.5}$ levels prediction, considering four adjacent traffic stations.

cation of situations after the forecast, is always improved in the other three stations, specially in Mooroolbark and Traralgon, which are influenced the most by bushfires.

5.2.3 Context-Aware Views

The previous subsection explains the performance benefits of the MyAQI extended context prediction. In this section we introduce another contribution related to the user experience of the web application itself. Given the context aware nature of the system, its reconfigurability is essential to allow it to adapt to the user requirements. Thus, the application contains a view of the user profile, where users can customise their needs and see the changes reflected throughout the system. Figure 5.12 shows the configuration panel. End-users can change their personal information, as well as answer health related issues, select their preferred AQI scale and review their pollutant sensitivity levels.

Another important impact of context-awareness is the creation of personalized notifications

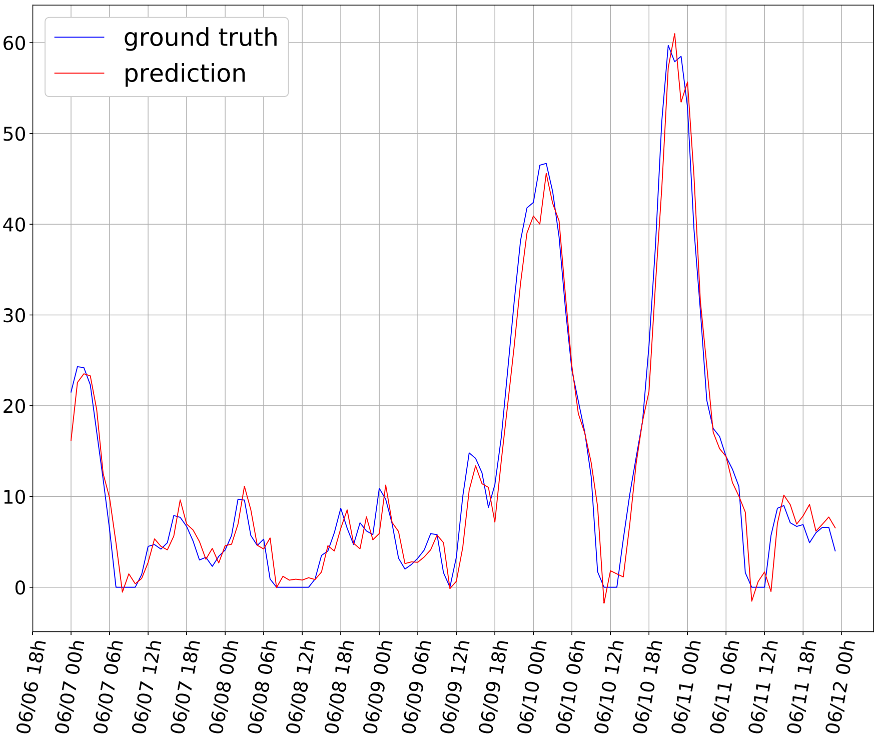


Figure 5.9: Alphington AQ measuring station $PM_{2.5}$ levels prediction, considering NO_2, SO_2, PM_{10}, CO and one traffic station levels.

about situations that could affect the users' activity. Figure 5.13 presents the My Air Quality Index (MyAQI) web application context-aware air quality monitoring notifications for users with different sensitivity levels to main pollutants. It shows that Ana, who is has the most delicate health condition, because of her asthma, receives more severe alerts for the same pollutant levels. Bob is second and given his moderately unhealthy condition he receives more warning for pollutant levels in some locations. Finally, Alice, who does not present any bad health conditions, receives only alerts for those locations that have very high pollutant concentrations, hence being unhealthy for everyone.

Finally, given the general lack of understanding of the AQI scale numbering and indexing from the general public, it was critical to incorporate a visualisation tool that allows users to understand the air quality measuring system in an easy way. Thus, a gauge allows the viewer to know the current status while understanding the whole range of the indexes was created. Figure 5.14 shows the visualisation tool in the web application with EEA AQI as preferred AQI scale (the tool accepts all three AQI scales).

The results reflect a system's capability for context-aware AQ monitoring and prediction. It

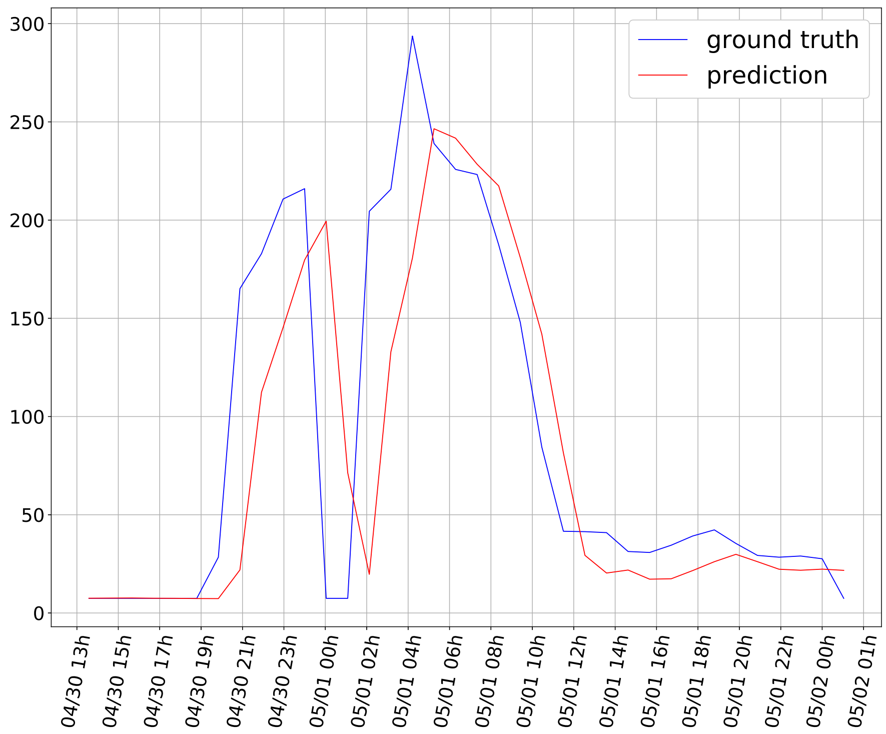


Figure 5.10: Mooroolbark AQ measuring station $PM_{2.5}$ levels prediction, considering $PM_{2.5}$, PM_{10}, one traffic station and fire incidents.

incorporates a robust prediction mechanism and allows the end-user to follow a customizable experience of air pollution monitoring.

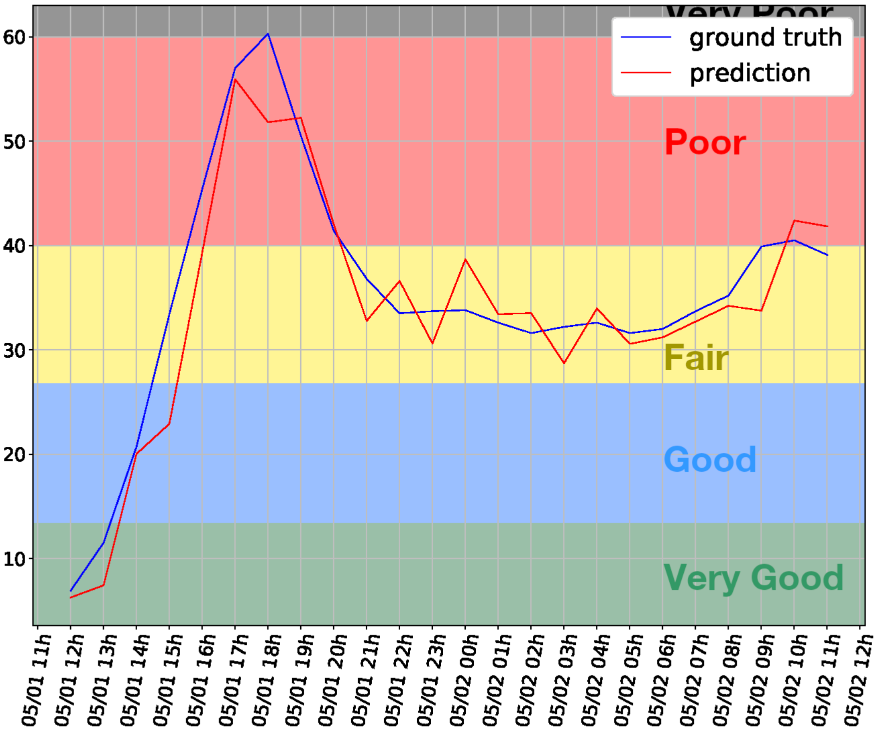
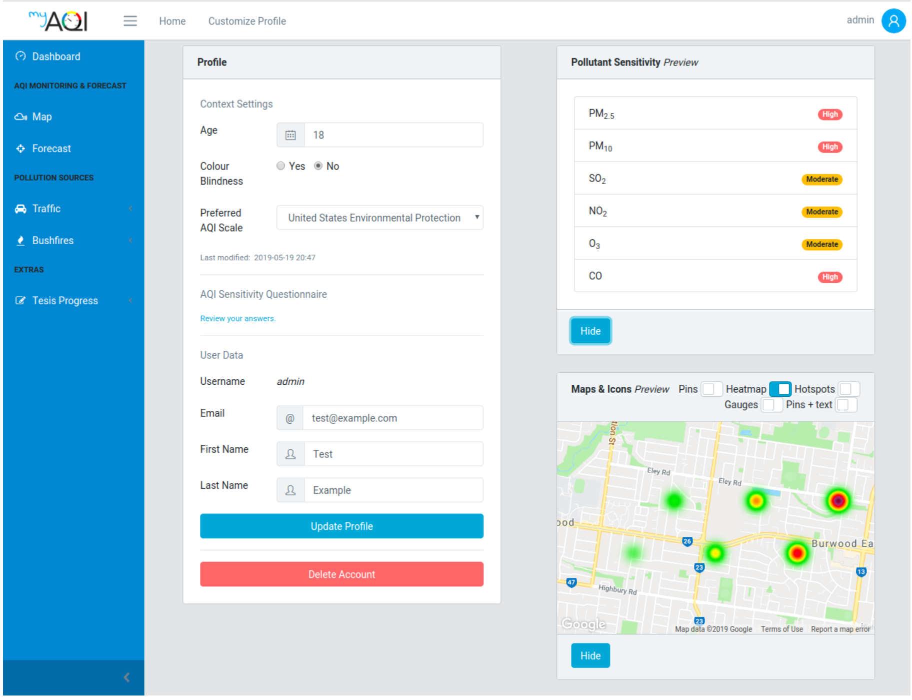


Figure 5.11: Traralgon AQ measuring station $PM_{2.5}$ levels prediction, considering NO_2, SO_2, CO, temperature, wind direction, wind speed and fire incidents. The background colours correspond to the AU-EPA AQI categories, proving that the prediction of AQ situations is accurate.

Table 5.2: Comparison of MAE, RMSE, precision and R values 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**	**Precision**	**R**
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	0.776
With Extended Context	+ Fires	1.477	2.262	0.943	0.772
Mooroolbark AQ station	*+1hr $PM_{2.5}$ prediction*				
Without Extended Context	$PM_{2.5}$, PM_{10}	4.295	6.769	0.872	0.583
With Extended Context	+ Traffic, Fires	2.124	8.775	0.909	0.629
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	0.788
With Extended Context	+ Traffic, Fires	1.389	1.949	0.957	0.791
Melbourne CBD AQ station	*+1hr $PM_{2.5}$ prediction*				
Without Extended Context	$PM_{2.5}$	2.869	4.115	0.912	0.233
With Extended Context	+ Traffic	2.797	3.85	0.93	0.353



Profile

Context Settings

Age: 18

Colour Blindness: ○ Yes ● No

Preferred AQI Scale: United States Environmental Protection ▾

Last modified: 2019-05-19 20:47

AQI Sensitivity Questionnaire

Review your answers.

User Data

Username: *admin*

Email: @ test@example.com

First Name: Test

Last Name: Example

Update Profile

Delete Account

Pollutant Sensitivity *Preview*

$PM_{2.5}$	High
PM_{10}	High
SO_2	Moderate
NO_2	Moderate
O_3	Moderate
CO	High

Hide

Maps & Icons *Preview* Pins □ Heatmap ☑ Hotspots □ Gauges □ Pins + text □

Hide

Figure 5.12: The MyAQI web application user profile editing view, for a more personalized experience of air quality monitoring.

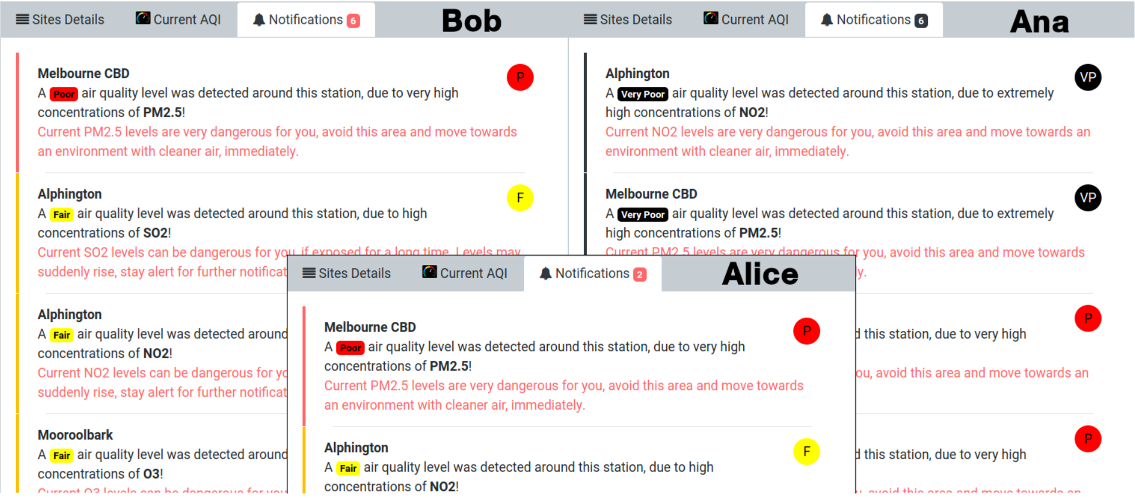
Table 5.3: Context-aware monitoring experiments setup. a) Three users with different health conditions and pollutant sensitivities. b) Pollutant AQI levels snapshot for 4 AQ monitoring stations in the Melbourne urban area.

(a)

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

(b)

AQ Station	Pollutant AQI value					
	$PM_{2.5}$	PM_{10}	NO_2	SO_2	O_3	CO
Alphington	22	15	113	98	21	45
Melbourne CBD	164	-	-	-	-	-
Mooroolbark	21	39	-	-	87	-
Traralgon	61	79	-	0	23	86



Bob:

Melbourne CBD
A Poor air quality level was detected around this station, due to very high concentrations of **PM2.5**!
Current PM2.5 levels are very dangerous for you, avoid this area and move towards an environment with cleaner air, immediately.

Alphington
A Fair air quality level was detected around this station, due to high concentrations of **SO2**!
Current SO2 levels can be dangerous for you, if exposed for a long time. Levels may suddenly rise, stay alert for further notificat

Alphington
A Fair air quality level was detected around concentrations of **NO2**!
Current NO2 levels can be dangerous for yo suddenly rise, stay alert for further notificat

Mooroolbark
A Fair air quality level was detected around concentrations of **O3**!

Ana:

Alphington
A Very Poor air quality level was detected around this station, due to extremely high concentrations of **NO2**!
Current NO2 levels are very dangerous for you, avoid this area and move towards an environment with cleaner air, immediately.

Melbourne CBD
A Very Poor air quality level was detected around this station, due to extremely high concentrations of **PM2.5**!
Current PM2.5 levels are very dangerous for you, avoid this area and move towards y.

d this station, due to very high
ou, avoid this area and move towards an

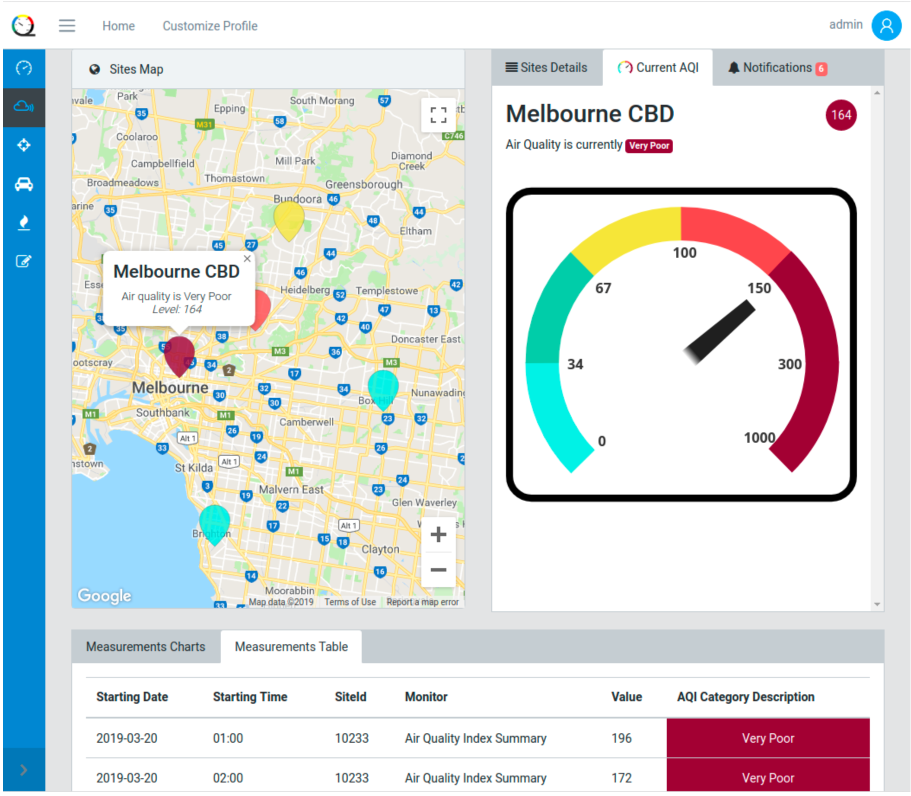
d this station, due to very high

Alice:

Melbourne CBD
A Poor air quality level was detected around this station, due to very high concentrations of **PM2.5**!
Current PM2.5 levels are very dangerous for you, avoid this area and move towards an environment with cleaner air, immediately.

Alphington
A Fair air quality level was detected around this station, due to high concentrations of **NO2**!

Figure 5.13: Web application personalized notifications for dangerous AQI values predicted by the MyAQI prediction tool.



Melbourne CBD

Air quality is Very Poor
Level: 164

Melbourne CBD 164

Air Quality is currently Very Poor

Starting Date	Starting Time	SiteId	Monitor	Value	AQI Category Description
2019-03-20	01:00	10233	Air Quality Index Summary	196	Very Poor
2019-03-20	02:00	10233	Air Quality Index Summary	172	Very Poor

Figure 5.14: MyAQI web application view using the context-aware visualisation tool for better AQI understanding.

5.3 Sustainability Analysis

The research work and results presented in the previous sections of this thesis have been developed as part of the Erasmus Mundus Joint Master's Degree for Pervasive Computing and Communications for Sustainable Development (PERCCOM) program (Kor et al., 2019). This program makes an emphasis on the sustainability aspects of Information and Communication Technology (ICT) projects, hence it is very important to state the sustainability analysis of this work. But first, it is important to define sustainability and its connection to the ICT environment.

A widely accepted definition of sustainable development was first mentioned in the Brundtland Report (Brundtland et al., 1987). The definition reads, that something can be considered sustainable if "it meets the needs of the present without compromising the ability of future generations to meet their own needs". Today's way of doing business is going the opposite direction. We, as a society, are vastly prioritizing short-term economic growth for the enrichment of a few people and are neglecting the dangerous consequences towards the environment that these can bring. It is the same in the ICT area, where projects and companies prioritize their economic performance over their impact on the environment. Therefore, a thorough screening must be done at the conception of every ICT project in order to minimize the impact of the out-coming product on the health of the environment and people depending on such health.

To understand this impact of this project we utilize a tool described in (Duboc et al., 2019). It consists of a five-pillar scheme, in which each pillar represents a field of our societal mesh on which the project can have an impact. Each field can be affected by three different levels of effects, a structural effect, an enabling effect and an immediate effect. The pillars and their effects on this outdoor air prediction project are the following:

1. Economic: A structural effect on the economic area is that by making air pollution levels public, the mitigation of their emissions will take more importance over economic growth during important decisions, due to transparency and consciousness of the community (seen as a chain effect from the social pillar). The availability of forecasted AQ levels can enable companies to make decisions to mitigate their impact and avoid fines, having an enabling effect on from the project and laying the foundations for more transparency. Finally, as an immediate effect, citizens will be able to avoid polluted areas in cities leading to less health complications and their expenses on medicines and medical attention will drop, having a positive economic impact for them. This last effect is triggered by the individual immediate effect of users avoiding polluted areas.
2. Technical: Context-aware systems allow new data sources and prediction algorithms to

be seamlessly added to the platform, depending on everyone's needs, enabling more customizable content for citizens, co-enabling better decisions for businesses for sustainable objectives and an overall awareness of the environment (as presented by the structural effect in the environment pillar). As an immediate effect, we take the availability of a developed system that extends the context for AQ levels predictions.

3. Environmental: a clear structural effect on the environment is that individuals, organizations and governments are more aware of the impact that each has on the AQ and can, thus, make more informed eco-friendly decisions.

4. Individual: users can be prevented from going to hazardous areas, with high air pollution levels, by receiving constant and personalized updates on AQ. But not everything has a positive effect for end-users, because they could develop a dependability on the system that can reduce their ability to decide and listen to their own intuition. Constant paranoia can arise from the dependence of users; so the application should be able to show confidence levels on the predicted and monitored values, to leave space for people's common sense. Finally, as a more structural effect, individuals can demand better policies and regulations from authorities, given that they have access to the same transparent information, enabled by the social effect of communities knowing the sources of pollution.

5. Social: communities will know the pollution levels and performance on their living areas, they can share the effects on how these levels affect each of them and demand better managing of AQ from their communal authorities. This pillar is tied closely to the previous one and enabled by transparency from governments and businesses.

The whole impact of this work on the afore mentioned pillars can be clearly seen in Figure 5.15.

5.4 Summary

In this chapter, the setup for the experiments that prove the theoretical work of previous sections is described, as well as the required datasets and information used in their execution. Then, the obtained results and outcomes of the system are presented, which showed promising values and improvements for context-aware systems. Lastly, the performed sustainability analysis proved that the proposed approach can provide benefits to important sectors of today's society if applied correctly. In the next section, conclusions are drafted for all the work

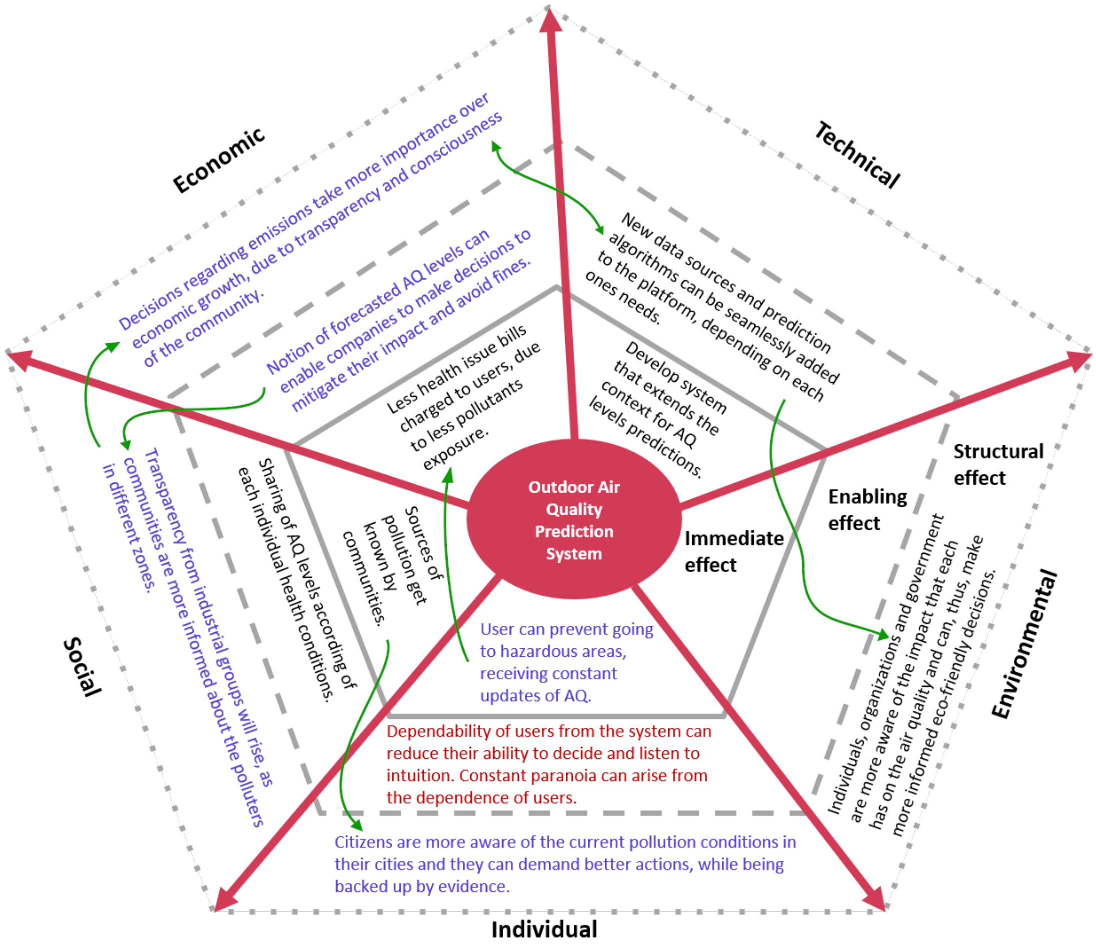

Economic
Technical
Environmental
Individual
Social
Outdoor Air Quality Prediction System
Immediate effect
Enabling effect
Structural effect
Decisions regarding emissions take more importance over economic growth, due to transparency and consciousness of the community.
Notion of forecasted AQ levels can enable companies to make decisions to mitigate their impact and avoid fines.
Less health issue bills charged to users, due to less pollutants exposure.
New data sources and prediction algorithms can be seamlessly added to the platform, depending on each ones needs.
Develop system that extends the context for AQ levels predictions.
Individuals, organizations and government are more aware of the impact that each has on the air quality and can, thus, make more informed eco-friendly decisions.
User can prevent going to hazardous areas, receiving constant updates of AQ.
Dependability of users from the system can reduce their ability to decide and listen to intuition. Constant paranoia can arise from the dependence of users.
Citizens are more aware of the current pollution conditions in their cities and they can demand better actions, while being backed up by evidence.
Sources of pollution get known by communities.
Sharing of AQ levels according of each individual health conditions.
Transparency from industrial groups will rise, as communities are more informed about the polluters in different zones.

Figure 5.15: Sustainability analysis in the economic, technical, environmental, individual and social pillars of this work.

presented in this thesis, some limitations encountered in the planning and execution process are mentioned and potential future work in this topic is discussed.

6 CONCLUSIONS AND FUTURE WORK

This chapter contains the conclusions for the overall work in this thesis, with emphasis on the contribution, some limitations encountered during the process, and possible future work in the topic's area.

6.1 Conclusions

The main goal of the research done in this thesis was to research and propose a context- and situation model for AQ monitoring and prediction systems that could prove the advantages of context-aware computing when applied in air quality monitoring field. Context-aware systems require a high level of personalisation and augmented information to allow users to interact with it in a friendly and helpful manner. Also, the system was required to predict future concentrations of pollutants with high accuracy and using extended context information in the process.

The contribution of this work is the proposed context-aware model and system architecture for AQ monitoring and prediction and we prove it 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.

Another contribution of the MyAQI system is the use of extended environmental context sources on the AQ prediction problem, by adding data directly linked to the pollution sources. As the results section (5) of this thesis shows, by adding these sources the prediction accuracy was improved for 3 out of 4 AQ station. By applying pollution sources as input to the prediction model, the unavailability of AQ attributes (e.g., airborne pollutants measurements) can be covered and hence the prediction improved. Complying with the context-awareness of the system, predictions also offer augmented and customised information to the end-users, by relating forecasts to possible pollution sources and showing the AQI level according to the users' health conditions.

In this research we do not focus on optimising the prediction algorithm or on developing a novel prediction algorithm due to the limited scope of this thesis. The background and literature review information of Chapter 2 was intended to select the best model to be used in this system. The usage of real-life data sources allows for a good assessment of the system's operation, but it also introduces some limitations, as there only exists information for certain locations and some data might have disturbances, due to malfunctioning of the measuring devices. This reflects on having to use existing measuring stations to simulate the locations of users; ideally each user would carry an air pollution device constantly with them and the network of these devices would yield a more dynamic range and wider covering result.

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.

6.2 Future Work

Considering the contributions and foundations laid out in this research, further research can be done. The pollution sources used in the MyAQI system traffic and fire incidents, for instance, are only two members of a large group, which includes factories, commercial businesses, household artefacts, air planes, gas pipeline leaks, etc. Extreme natural phenomena can also be taken into account, such as thermal inversions, volcanic eruptions, as they exacerbate, diminish or contribute directly to air pollution. As mentioned in the previous section the prediction algorithm could be improved and optimised as well. Furthermore, different prediction models could be selected for different situations and locations, depending on their suitability. An ensemble model can provide the best outcomes of different approaches for a specific scenario.

Lastly, the larger goal of a context-aware system is to be data source and use case independent. The MyAQI system covers the specific AQ monitoring and prediction use case and acts as a prototype for it, but it could be potentially extended to allow the coupling of other datasets and context-situation logic to cover other real-life issues.

APPENDICES

APPENDIX 1. Development Tools

Section 4 explains the implementation process for the MyAQI system and mentions software tools and frameworks used for this process. Here we provide a list of names and links to each mentioned tool's resources.

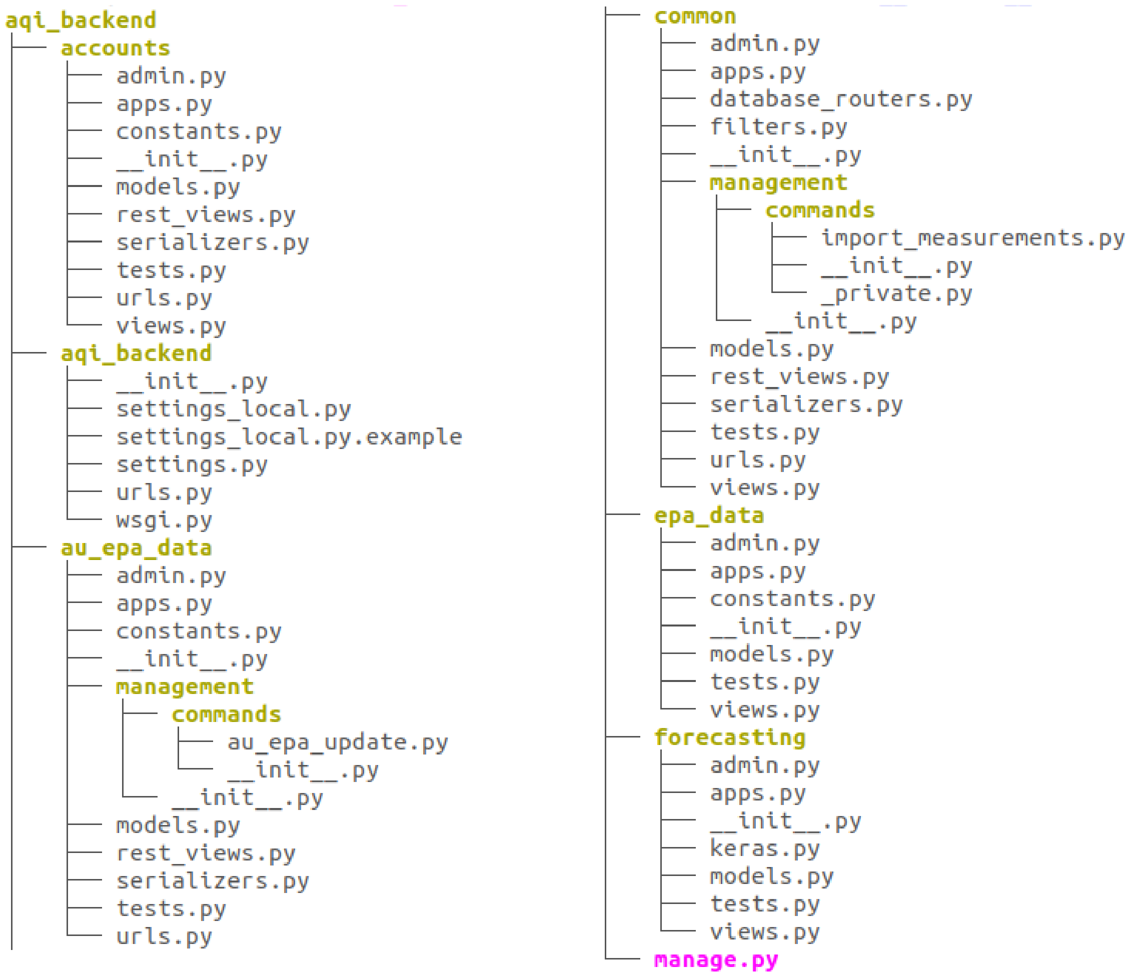
- Bing Maps API: *http://dev.virtualearth.net/REST/v1/Traffic/Incidents/*
- Core-UI: *https://coreui.io/*
- Django Channels: *https://github.com/django/channels*
- Django Rest Framework: *https://www.django-rest-framework.org/*
- Django: *https://www.djangoproject.com/*
- Google Maps JavaScript API: *https://developers.google.com/maps/documentation/javascript/tutorial*
- Keras: *https://keras.io/*
- Matplot Lib: *https://matplotlib.org/*
- Pandas: *https://pandas.pydata.org/*
- PostGIS: *https://postgis.net/*
- PostgreSQL: *https://www.postgresql.org/*
- ReactJS: *https://reactjs.org/*
- Sklearn: *https://scikit-learn.org/stable/*
- Tensor Flow: *https://www.tensorflow.org/*
- Victoria Emergency API: *http://emergency.vic.gov.au/public/osom-geojson.json*
- Victoria EPA AirWatch API: *http://sciwebsvc.epa.vic.gov.au/aqapi/*
- Victoria Roads API: *https://traffic.vicroads.vic.gov.au/maps.js*
- Weather Bit API: *https://api.weatherbit.io/v2.0/forecast/airquality*

APPENDIX 2. Source Code Most Important Features

Section 4 explains the development process for the MyAQI system and describes the project structure for the two frontend and backend sub-systems. The two main layers (*Backend* and *Frontend*) were implemented on different source codes, given that they are written in different programming languages and are heavily decoupled programs. Each project has its own structure and lives in a separate GitHub repository. This appendix shows explains the sublayers development process in more detail, presents the project structures and explains three of the implemented core functions to enable the context- and situation model presented in Section 3. Figure APPENDIX 2..1 and APPENDIX 2..2 show the structure for the Backend and Frontend projects, respectively.

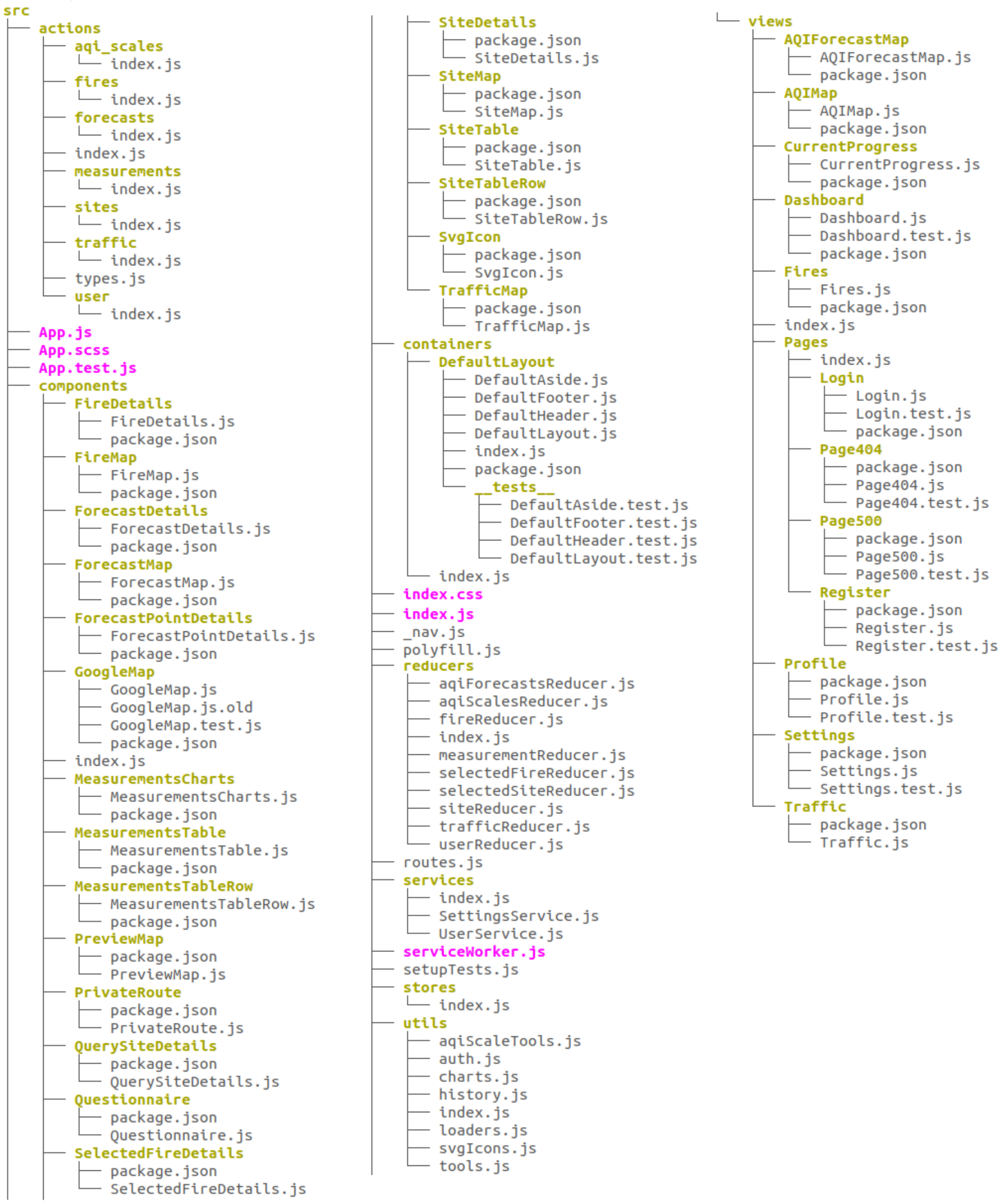
The **MyAQI Frontend Project** is structured as a React project. The actions module handles the calls to the APIs and the structure of the received data. In the components module, major blocks of HTML elements that share a common functionality are bundled together for reuse. The container directory contains theme-related files, like the layout of components in the web site's dashboard. The reducers module contains the Redux functionality that keeps every component up to date, after changes in the data flow happened or the user interacted with components. Finally, the views folder contains the frames for the major views, shown in Figure 4.3, where components are used to create the site's layout. The source code can be found in the *https://www.github.com/dschurholz/myaqi-frontend.git* repository. More in depth information about the purpose of certain files can be found in APPENDIX 2..

The **MyAQI Backend Project** is structured similarly to a Django project. Each major functionality and its resources are bundled together in a "project app". Each one has a set of ORM models, which map database records to in-memory objects, RESTful views, which control the API calls, a set of Uniform Resource Locator (URL) where the API calls will be handled and serializers, which control the the formatting of incoming and outgoing data. Other files which have more specialized functions are located in the *Common* app. The source code can be found in the *https://github.com/dschurholz/myaqi-backend.git* repository. Some of the most important features are described in APPENDIX 2., as well as the project's file structure. One critical part of the backend project is the forecasting app. It contains all the files necessary for the creation of prediction-ready data files, that consist of the cured data for each context attribute to be used as input for the forecasting algorithm; the files for training and testing the LSTM model with that data; and files to create the data with the forecasting output to be consumed by the system developed in the *Frontend Project*, which is exactly the next step in the development face.



```
aqi_backend
├── accounts
│   ├── admin.py
│   ├── apps.py
│   ├── constants.py
│   ├── __init__.py
│   ├── models.py
│   ├── rest_views.py
│   ├── serializers.py
│   ├── tests.py
│   ├── urls.py
│   └── views.py
├── aqi_backend
│   ├── __init__.py
│   ├── settings_local.py
│   ├── settings_local.py.example
│   ├── settings.py
│   ├── urls.py
│   └── wsgi.py
├── au_epa_data
│   ├── admin.py
│   ├── apps.py
│   ├── constants.py
│   ├── __init__.py
│   ├── management
│   │   ├── commands
│   │   │   ├── au_epa_update.py
│   │   │   └── __init__.py
│   │   └── __init__.py
│   ├── models.py
│   ├── rest_views.py
│   ├── serializers.py
│   ├── tests.py
│   └── urls.py
├── common
│   ├── admin.py
│   ├── apps.py
│   ├── database_routers.py
│   ├── filters.py
│   ├── __init__.py
│   ├── management
│   │   ├── commands
│   │   │   ├── import_measurements.py
│   │   │   ├── __init__.py
│   │   │   └── _private.py
│   │   └── __init__.py
│   ├── models.py
│   ├── rest_views.py
│   ├── serializers.py
│   ├── tests.py
│   ├── urls.py
│   └── views.py
├── epa_data
│   ├── admin.py
│   ├── apps.py
│   ├── constants.py
│   ├── __init__.py
│   ├── models.py
│   ├── tests.py
│   └── views.py
├── forecasting
│   ├── admin.py
│   ├── apps.py
│   ├── __init__.py
│   ├── keras.py
│   ├── models.py
│   ├── tests.py
│   └── views.py
└── manage.py
```

Figure APPENDIX 2..1: The MyAQI Backend project structure.



```
src
├── actions
│   ├── aqi_scales
│   │   └── index.js
│   ├── fires
│   │   └── index.js
│   ├── forecasts
│   │   └── index.js
│   ├── index.js
│   ├── measurements
│   │   └── index.js
│   ├── sites
│   │   └── index.js
│   ├── traffic
│   │   └── index.js
│   ├── types.js
│   └── user
│       └── index.js
├── App.js
├── App.scss
├── App.test.js
├── components
│   ├── FireDetails
│   │   ├── FireDetails.js
│   │   └── package.json
│   ├── FireMap
│   │   ├── FireMap.js
│   │   └── package.json
│   ├── ForecastDetails
│   │   ├── ForecastDetails.js
│   │   └── package.json
│   ├── ForecastMap
│   │   ├── ForecastMap.js
│   │   └── package.json
│   ├── ForecastPointDetails
│   │   ├── ForecastPointDetails.js
│   │   └── package.json
│   ├── GoogleMap
│   │   ├── GoogleMap.js
│   │   ├── GoogleMap.js.old
│   │   ├── GoogleMap.test.js
│   │   └── package.json
│   ├── index.js
│   ├── MeasurementsCharts
│   │   ├── MeasurementsCharts.js
│   │   └── package.json
│   ├── MeasurementsTable
│   │   ├── MeasurementsTable.js
│   │   └── package.json
│   ├── MeasurementsTableRow
│   │   ├── MeasurementsTableRow.js
│   │   └── package.json
│   ├── PreviewMap
│   │   ├── package.json
│   │   └── PreviewMap.js
│   ├── PrivateRoute
│   │   ├── package.json
│   │   └── PrivateRoute.js
│   ├── QuerySiteDetails
│   │   ├── package.json
│   │   └── QuerySiteDetails.js
│   ├── Questionnaire
│   │   ├── package.json
│   │   └── Questionnaire.js
│   ├── SelectedFireDetails
│   │   ├── package.json
│   │   └── SelectedFireDetails.js
│   ├── SiteDetails
│   │   ├── package.json
│   │   └── SiteDetails.js
│   ├── SiteMap
│   │   ├── package.json
│   │   └── SiteMap.js
│   ├── SiteTable
│   │   ├── package.json
│   │   └── SiteTable.js
│   ├── SiteTableRow
│   │   ├── package.json
│   │   └── SiteTableRow.js
│   ├── SvgIcon
│   │   ├── package.json
│   │   └── SvgIcon.js
│   └── TrafficMap
│       ├── package.json
│       └── TrafficMap.js
├── containers
│   ├── DefaultLayout
│   │   ├── DefaultAside.js
│   │   ├── DefaultFooter.js
│   │   ├── DefaultHeader.js
│   │   ├── DefaultLayout.js
│   │   ├── index.js
│   │   ├── package.json
│   │   └── __tests__
│   │       ├── DefaultAside.test.js
│   │       ├── DefaultFooter.test.js
│   │       ├── DefaultHeader.test.js
│   │       └── DefaultLayout.test.js
│   └── index.js
├── index.css
├── index.js
├── _nav.js
├── polyfill.js
├── reducers
│   ├── aqiForecastsReducer.js
│   ├── aqiScalesReducer.js
│   ├── fireReducer.js
│   ├── index.js
│   ├── measurementReducer.js
│   ├── selectedFireReducer.js
│   ├── selectedSiteReducer.js
│   ├── siteReducer.js
│   ├── trafficReducer.js
│   └── userReducer.js
├── routes.js
├── services
│   ├── index.js
│   ├── SettingsService.js
│   └── UserService.js
├── serviceWorker.js
├── setupTests.js
├── stores
│   └── index.js
├── utils
│   ├── aqiScaleTools.js
│   ├── auth.js
│   ├── charts.js
│   ├── history.js
│   ├── index.js
│   ├── loaders.js
│   ├── svgIcons.js
│   └── tools.js
└── views
    ├── AQIForecastMap
    │   ├── AQIForecastMap.js
    │   └── package.json
    ├── AQIMap
    │   ├── AQIMap.js
    │   └── package.json
    ├── CurrentProgress
    │   ├── CurrentProgress.js
    │   └── package.json
    ├── Dashboard
    │   ├── Dashboard.js
    │   ├── Dashboard.test.js
    │   └── package.json
    ├── Fires
    │   ├── Fires.js
    │   └── package.json
    ├── index.js
    ├── Pages
    │   ├── index.js
    │   ├── Login
    │   │   ├── Login.js
    │   │   ├── Login.test.js
    │   │   └── package.json
    │   ├── Page404
    │   │   ├── package.json
    │   │   ├── Page404.js
    │   │   └── Page404.test.js
    │   ├── Page500
    │   │   ├── package.json
    │   │   ├── Page500.js
    │   │   └── Page500.test.js
    │   └── Register
    │       ├── package.json
    │       ├── Register.js
    │       └── Register.test.js
    ├── Profile
    │   ├── package.json
    │   ├── Profile.js
    │   └── Profile.test.js
    ├── Settings
    │   ├── package.json
    │   ├── Settings.js
    │   └── Settings.test.js
    └── Traffic
        ├── package.json
        └── Traffic.js
```

Figure APPENDIX 2..2: The MyAQI Frontend project structure.

The following function is used to determine the AQI category given a certain pollutant and a list of its concentration levels for the AU-EPA AQI.

```
def get_categories(self, values, pollutant):
    if self.abbreviation == 'AUEPA':
        aqi_cats = self.aqi_category_thresholds.filter(
            pollutant=pollutant,
            lower_threshold_value__isnull=False).order_by(
                'lower_threshold_value')

        def get_cat(val):
            for cat in aqi_cats:
                if val < cat.upper_threshold_value:
                    return cat.abbreviation

        return map(get_cat, values)
    return None
```

The next function determines calculates the quantiles for the traffic flows for a traffic station, in order to get the situation spaces.

```
@property
def quantiles(self):
    data = TrafficFlow.objects.filter(
        nb_scats_site=self.station_id).values_list(
            'traffic_volume', flat=True)
    df = pd.DataFrame(data=data, columns=['traffic_volume'])
    return df.traffic_volume.quantile([0.2, 0.4, 0.6, 0.8])
```

The last function retrieves the fire incidents that happened in an area that are relevant to a current location, which could represent an AQ monitoring station or the user's position.

```
@classmethod
def get_fire_intersects_situation(
        cls, areas, start_date=None, end_date=None, seasons=[]):
    fires = cls.objects.all()
    queries = [Q(geom__intersects=area) for area in areas]
    query = queries.pop()
    for item in queries:
        query |= item
    if start_date is not None:
        fires = fires.filter(start_date__gte=start_date)
    if end_date is not None:
```

```
    fires = fires.filter(start_date__lte=end_date)
if len(seasons) >  0:
    fires = fires.filter(season__in=seasons)
fires = fires.filter(query)
return fires
```

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