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Smart City Air Pollution Monitoring and Prediction: A Case Study of Skopje

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Abstract. One of the key aspects of smart cities is the enhancement of awareness of the key stakeholders as well as the general population regarding air pollution. Citizens often remain unaware of the pollution in their immediate surrounding which usually has strong correlation with the local environment and micro-climate. This paper presents an Internet of Things based system for real-time monitoring and prediction of air pollution. First, a general layered management model for an Internet of Things based holistic framework is given by defining its integral levels and their main tasks as observed in state-of-the-art solutions. The value of data is increased by developing a suitable data processing sub-system. Using deep learning techniques, it provides predictions for future pollution levels as well as times to reaching alarming thresholds. The sub-system is built and tested on data for the city of Skopje. Although the data resolution used in the experiments is low, the results are very promising. The integration of this module with an Internet of Things infrastructure for sensing the air pollution will significantly improve overall performance due to the intrinsic nature of the techniques employed.

Keywords: Internet of Things, Smart City, Air Pollution Monitoring, Air Pollution Prediction

1 Introduction

One of the key problems of major urban areas in developing and industrial countries is air pollution, especially when measures for air quality are not available, or are minimally implemented or enforced [1]. According to the report of the World Health Organization (WHO) [2], around 91% of the world's population lives in places where air quality exceeds the WHO guidelines, and around 4.2 million deaths every year can be directly linked to exposure to outdoor air pollution. Chronic exposure to air pollution increases the risk of cardiovascular and respiratory mortality and morbidity, while acute short-term inhalation of pollutants can induce changes in lung function and the cardiovascular system exacerbating existing conditions such as ischemic heart disease [3][4]. In less developed countries, 98% of children under five are exposed to toxic air. This makes air pollution the main cause of death for children under the age of 15, killing 600,000 every year [5]. The World Bank estimates $5 trillion in welfare losses worldwide due to air pollution premature deaths [6]. Air pollution also contributes to climate changes which increases premature human mortality [7].

Urban outdoor air pollution, especially particulate matter, remains a major environmental health problem in Skopje, the capital of North Macedonia. Long-term exposure to PM2.5 caused an estimated 1199 premature deaths and the the social cost of the predicted premature mortality in 2012 due to air pollution was estimated at between 570 and 1470 million euros according to Martinez et al. in [8]. Additionally, in the same year, there have been 547 hospital admissions from cardiovascular diseases, and 937 admissions for respiratory disease due to air pollution. The study also infers that if PM2.5 was reduced to EU standards (25 μg/m3 at that timepoint), it could have averted an estimated 45% of PM-attributable mortality, but if PM2.5 was reduced to the WHO Air Quality Guidelines (10 μg/m3 at that timepoint), around 77% of PM-attributable mortality could have been averted, which could have provided a substantial health and economic gain for the city. A more recent report on the Air quality in Europe [9], done by the European Environment Agency (EEA), shows that the situation in North Macedonia has deteriorated even further. It shows that the PM2.5 average exposure indicator for the period of 2015-2017 based on measurements in urban and suburban stations is 51 μg/m3, which is substantially over the EU standard of 20 μg/m3.

Many of the world governments deploy and operate stations for air quality monitoring and make the acquired data publicly available. These stations have high quality sensors which allow to sense a wide range of pollutants (like CO, NO2, SO2, O3, PM - particulate matter, etc.). However, the high costs of installing and maintaining them limits their number. In such cases, the low spatial resolution is resolved by using mathematical models that estimate the concentrations of the pollutants over the complete geographical space of interest. Although these models are complex and incorporate various input parameters such as meteorological variables, they can still be inaccurate (due to highly variable meteorological conditions [10]) which can lead to unsubstantiated inferences [11]. The Ministry of environment and physical planning of Republic of North Macedonia has build an infrastructure of 21 stations. 2 of these stations are mobile and the others are distributed throughout the country in 3 major regions: Skopje region (7 stations), Western region (6 stations) and Eastern region (6 stations). These stations apart from the extremely low spatial resolution, have problems reporting data due to sensor malfunctioning for longer periods of time, poor interconnectedness with the central reporting site, and even further not all of them have the appropriate sensors for measuring all relevant pollutants. Therefore, building a proper monitoring infrastructure is the first step towards healthier air.

Once quality data are available it can be used to extract deeper knowledge for pollution. Building air pollution prediction systems allows for the prediction of the air quality index (AQI), the value of each pollutant (i.e. PM2.5, PM10, CO2 and etc.) and high pollution areas. With such systems available, governments can employ smarter solutions for tackling the problem preemptively. To date, there have been many proposed solutions for predicting air pollution, but generally,these models can be classified into two types. The first type generate models that track the generation, dispersion and transmission process of pollutants. The predictive results of these models are given by numerical simulations. On the other hand, the second type of models are statistical learning models or machine learning models. These models attempt to find patterns directly from the input data [12].

The aim of this research is to propose an Internet of Things based system for real-time monitoring and prediction of air pollution. The first objective is to define a general layered management model for an IoT based holistic framework by defining its integral levels and their main tasks as observed in state-of-the-art solutions. Increasing the value of data by developing a suitable data processing sub-system is the second objective. Employing advanced machine learning techniques, especially deep learning, should increase the robustness of the system and provide insight on future trends which is essential for implementing appropriate policies. The final objective is to provide a proof-of-concept for the system considering a case-study for the city of Skopje.

The rest of this paper is organized as follows. State-of-the-art IoT architectures and intelligent data processing in air pollution is covered in the next section. In the third section the proposed IoT based system is presented. The case-study for the city of Skopje is given in the fourth section. Finally, this paper is concluded in the fifth section.

2 Related Work

A cloud-based architecture containing multiple data collection nodes was designed by Sendra et al. in [13]. The nodes are either mobile or static and store the data collected in local databases, but one centralized database is used to integrate the data collected from all the sensors. The integration steps also include the user's opinion left from their mobile device. The main purpose is to have a collaborative decision and alerting system. A network of air sensors connected on Arduino chips is designed in [14]. The pollution measurements from the sensors are sent on a cloud platform and the data is used in a mobile application. The application contains a map where a user chooses two points and the application shows the pollution between the two points. Another approach composed of Arduino chips connected with sensors is proposed in [15]. However, in this approach the sensors are static and are placed on a college campus. The data is stored on a centralized computer and later it can be used for visualizations.

An architecture consisting of multiple static air pollution sensors connected to a Raspberry Pi controller is proposed in [16]. The pollution measurements are collected and sent out to a cloud platform to be stored. The main goal is having a monitoring system which alerts the users when the pollution values are higher than the predefined threshold. Another approach using a Raspberry Pi controller is proposed in [17]. The architecture employs mobile devices to measure the noise pollution using mobile devices. The audio recordings along with GPS coordinates and metadata are sent out and stored in a MongoDB database. The data can then be used for visualisations of the pollution.

A cloud architecture employing the master/slave communication model is proposed by Saha et al. in [18]. Air, water and noise data is collected by sensors and sent out to the cloud for the purpose of monitoring pollution. A noise pollution monitoring network architecture consisting of three tiers is designed in [19]. The bottom tier consists of mobile and static sensors. The middle tier is built of relay nodes which collect the data from the sensors and deliver it to the gateways in the top layer. The gateways deliver the data to the cloud system. A slightly different approach is proposed by Zhang et al. in [20]. They create a knowledge graph which fuses data from social media data, air sensors data, taxi trajectory and traffic condition. The data is firstly converted to abstract entities with semantic data included. The city in the knowledge graph is divided into blocks and external databases block knowledge is collected. The main purpose of the knowledge graph is to detect and predict pollution with semantic explanation of the obtained results. It can also be used to analyse traffic patterns. Ahglren et al. in [21] proposed an architecture containing multiple sensors which use a publish/subscribe protocol and Message Queuing Telemetry Transport (MQTT) to communicate in an open format with the gateways. The gateways send out the data to a cloud architecture to be further preprocessed before it can be requested. The data can be requested as raw or aggregated by predefined time frames (hourly, daily, weekly or monthly averages of the values). A cloud based architecture is also implemented in [22]. The architecture consists of multiple static sensors placed on streetlight poles. The pollution measurements are sent out to a sink node which is their single point of contact. The sink nodes deliver the data to the cloud service to be stored in a database. The cloud can then deliver fine-grained measurements or average values of pollution in a time frame of 7 days.

Apart from many IoT proposed architectures for tackling the problem of monitoring pollution and implementing alerting logic, there are also many approaches tackling the problem of predicting pollution and pollution areas. One such approach is used in [23], where the authors use the CityPulse open dataset. The dataset consists of air data collected by 449 sensors placed besides traffic lights in the city of Brasov - Romania. The main focus of this approach is finding low and high pollution areas by analyzing the density of the ozone using K-means clustering. This approach although simpler than many others, still provides meaningful results.

However, in recent years, deep learning has been the main technique for air pollution prediction. While there have been many different models proposed, they mainly use the same pollution data. In all of the models, pollution measurements at specific time and location are taken into consideration.The pollutants usually measured are the particulate matter (i.e. PM2.5 and PM10) and gaseous species (i.e. NO2, CO, O3 and SO2). The data in the different approaches has different time intervals, but even so the main logic is the same. They also integrate meteorology data such as such as humidity, temperature, wind speed and rainfall. There are some that even consider weather forecast data [24][25]. The preprocessing is mainly the feature extraction part and it consists of principal component analysis, cluster analysis, factor analysis and discriminant analysis. Not much information has been provided on fusing the data from multiple sources, but where it is provided, we can conclude that only simple techniques such as matching by time is used. Most of the approaches execute the preprocessing stage separate from the model [25] [26] [27] [28] [12], but there are some approaches that incorporate this stage into combining the feature analysis and interpolation directly into the model [24], [29]. When talking about the models, they can be mainly separated into two different categories: models predicting pollution level [24], [25], [28], [29], (such as air quality index or air pollution index) and models predicting the level of pollutants (such as PM2.5, PM10, NO2 etc) [26], [27], [12], [30] . For the first types of models the first task is to label the fine-grained data so it can be used as an input to the model. On the other hand, the second type predicts the actual values for the pollutants, so no labeling is needed. The models used in both types are mainly neural networks [24], [30], [29], recurrent neural networks [12] (RNN) and LSTM (long short-term memory) networks as special types of RNN [28]. There are some approaches that use autoencoder model [26], merge neural networks with predictors for example linear predictors [25], Bayesian networks and multilabel classifiers [27]. After the models have been trained, different methods for evaluation are used, but mainly consist of: root mean square error, mean absolute error, mean absolute percentage error, mean prediction error, relative prediction error.

The Weibul-time-to-event Recurrent Neural Network (WTTE-RNN) [31] is a relatively new model for time-to-event prediction, but it has been successfully used in medicine [32], predictive network diagnostics [33], as well as in state-of-the-art video processing and predictive modelling [34].

3 Internet of Things Based System for Air Pollution Monitoring and Prediction

Air quality monitoring and control is an essential part of the concept of smart city which is becoming the standard to which both developing and developed countries aspire, thus the public mindfulness for the process is high. In this section we are going to explain in detail our framework for air pollution monitoring and prediction based on Internet of Things as depicted in Fig. 1 for which the general layered management model is depicted in Figure 1. The main tasks that should be performed at each level are described in the following subsections.

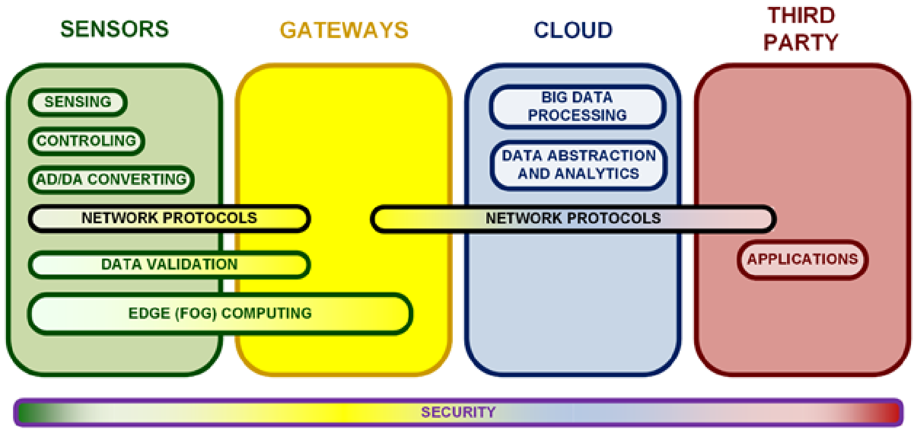

Fig. 1. A general layered management model

3.1 Sensing layer

Sensors are used to sense, actuate, process data and communicate. To successfully sense and actuate, A/D and D/A conversion is needed. The sensors sense and send data periodically, wirelessly or wired, to the gateway. Sensed data can also be sent directly to the cloud, if protocols allow it. Both static and mobile sensors that measure the level of different pollutants need to be considered in order to achieve good spatial data resolution.If possible, sensor should perform basic data processing before sending out the data. Mutual validation of the sensed data can be done by different types of sensors when they spatially overlap (edge computing).

3.2 Communication Gateways Layer

For collecting raw and/or processed data from the sensors, gateways are employed. The gateways forward the data to the cloud. In order to reduce the data flow towards the cloud, whenever possible, the gateways should perform local data processing (fog computing). Edge/fog computing is very important in terms of the robustness of the infrastructure. Lightweight local processing algorithms can reduce the need for transmission,thus saving energy and avoiding latency issues and saturation of the communication channels.

The gateways can also act as a local scheduler, load balancer or regulator, sending out commands to the sensors. Furthermore, because the devices usually cannot communicate with each other, gateways provide interoperability between them. The communication between the sensing layer and the cloud should be effective, robust and operationally consistent so various possibilities should be considered (e.g. mobile network, LoRa, etc.).

3.3 Cloud Processing Layer

The most complex part of our air pollution monitoring and prediction system is the cloud, providing abstraction, data storage and analytics. Because of the high data volume, traditional approaches should be modified to meet the new requirements. New methods and algorithms based on machine learning techniques, time series processing and advanced analytics are to be employed. The data processing sub-system architecture is given in Figure 2.

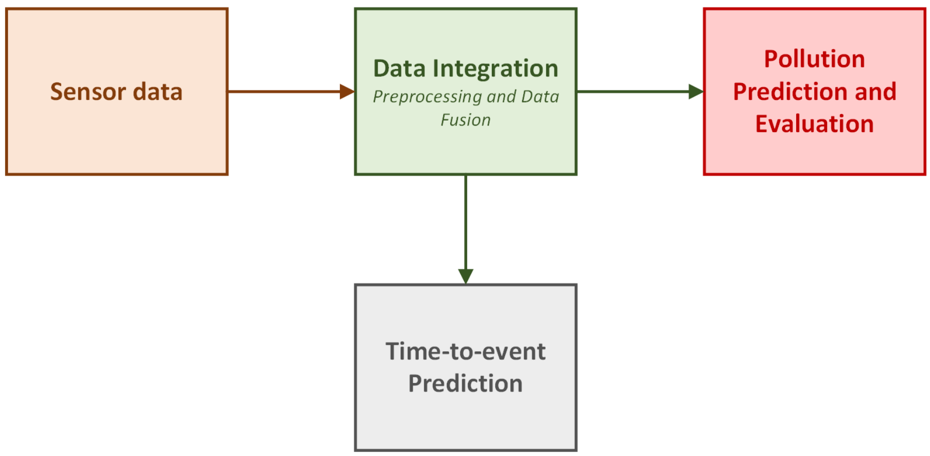

Fig. 2. Data processing sub-system architecture

Data Processing Sub-system. We have developed a more robust approach, taking into consideration the disadvantages of the previous models. The data preprocessing and integration module is the core feeding its results to the other modules for: pollution prediction and time-to-event prediction.

In the first step of data integration and preprocessing, we focus on integrating the data from various sources. Aside from pollution data, meteorological data are also needed, and they can be used from any available web service that provides such data (if our sensing layer does not provide it). The initial preprocessing of the data includes removing outliers and smoothing. Very often sensors encounter problems, data will be missing for the time-frame when a sensor was not working. This problem will be addressed using Deep Belief Networks (DBN) for generating missing data. The next step is to spatially discretize the data into regions using Delaunay triangulation. Finally, additional features from the time-series sensing data are extracted using Principal Component Analysis (PCA).

In the module for pollution prediction different deep learning models are built to predict the pollutant levels and the overall air quality as expressed by the AQI. For each spatial region, a corresponding Convolutional Neural Network

(CNN) and Recurrent Neural Network (RNN) is built. Different architectures for building the neural networks are evaluated as well as the possibilities for their combination to improve overall performance. The evaluation is performed using k-fold cross-validation for the initial building of the model. Once a model is deployed its predictive power is evaluated on the fly. This means that after we conduct a prediction, we would be checking this data with the real data collected to be able to create a back propagation and ensure the parameters of our models are correctly configured. Future developments will evaluate the feasibility of employing reinforcement learning.

Within the last module the system is predicting the hours until the alarming thresholds of pollutants are surpassed. The solution in this module is built using a framework based on survival analysis where a deep learning model, Weibul-time-to-event Recurrent Neural Network (WTTE-RNN), incorporates recurrent events, time varying covariates, temporal patterns, sequences of varying length, learning with censored data and flexible predictions.

3.4 Third-party Applications Layer

Third-party applications use data on a non-real-time basis, which imposes the need to transform the event-based data in the cloud to a format suitable for query-based processing. This is a crucial for enabling third-party applications in a system with real-time IoT networking. The data should be stored persistently and abstracted at multiple levels so that they could be easily combined, recomputed and/or aggregated with previously stored data, with the possibility of some data coming from non-IoT sources. Even more importantly the different levels of abstraction will simplify the application access and usage since data will be presented in a manner required by applications [35].

4 Case-study for the City of Skopje

As a proof-of-concept for the proposed data processing sub-system a case-study for the pollution data for the city of Skopje was considered. There were only 18 monitoring sites throughout the country with only 7 in Skopje, but not all sites measure the concentration of all the pollutants. Even though some sites are couple of hundred kilometers apart, all of them had to be considered when developing the models.

For the pollution prediction model, meteorological data obtained from the DarkSky API[1] are fused with the sensor data. The first step of data preprocessing was outlier analysis using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method, which is an alternative of K-means clustering. The advantage of this method is that it automatically detects the number of clusters while maximizing the similarities between entries in the cluster. Next, data smoothing techniques were employed, which allows for efficient training of

[1] https://darksky.net/dev (last accessed 30.04.2020)

the model, unbiased of the range of the features in the data. Seasonal exponential smoothing was used, because it allows to exponentially assign more weight to recent data points than to older data points, while considering the seasonality of the data. The next step was handling the missing records in the time-series per sensor, which occurs because of sensor malfunction or network errors. For this step, a Deep Belief Network was used consisting of many Restricted Boltzmann Machine (RBM) layers. This step augments the model by generating missing data points of interest, instead of removing them. A very important part of the model is the removal of the spatial relationship between the data, allowing us to view the data as time-series. For this step the Delaunay triangulation was used. While the Delaunay triangulation is a very powerful technique, it generated some regions which did not contain sensor measurements. To tackle this problem, empty regions were merged with the region that had the closest sensor to the empty region. After the data was split per region, the sensor and meteorological data was fused so we could obtain fine-grained data per sensor. Finally, Principal Component Analysis was conducted to further augment the data before training the model. For that purpose, different values for the number of principal components generated were tested. We found that 12 principal components performed best for our data.

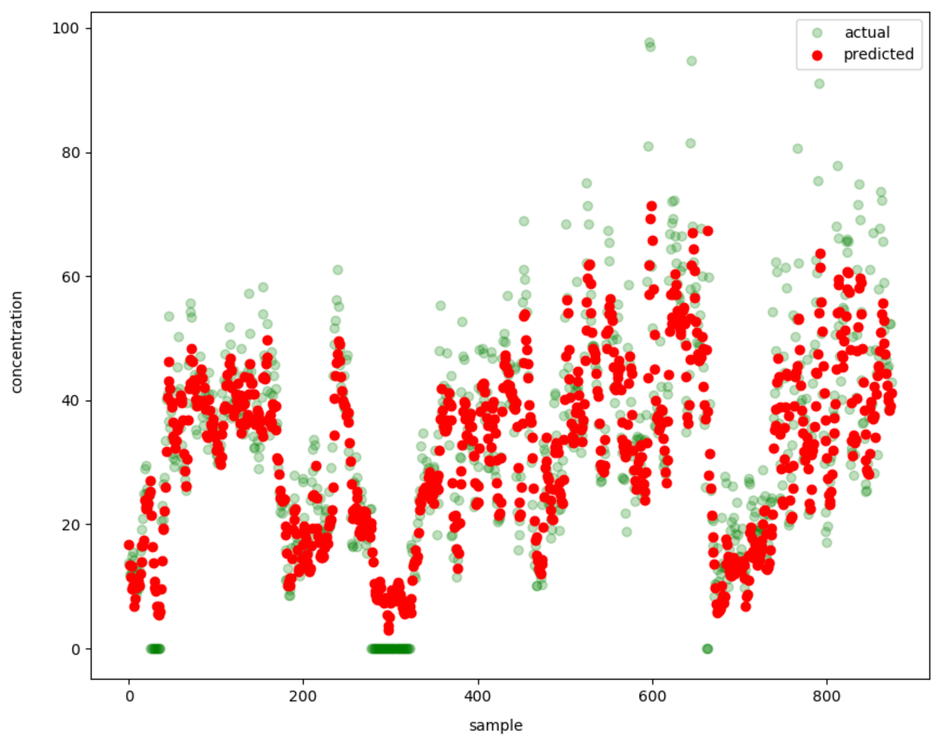

Fig. 3. PM10 pollutant concentration prediction performance for Skopje city center.

The final step of the pollution prediction model was building several Bidirectional Long-Short Term Memory (BiLSTM) models for the PM10 pollutant. The Bidirectional LSTM was used to learn the input sequence both forward and backwards and concatenate both interpretations. The ReLU activation function was used and the backpropagation was done using mean squared error (MSE). After fitting the model, the predicted and actual values were plotted and then the root mean squared error was calculated using the test set for PM10 pollutant for the monitoring site in the Skopje city center as shown in Figure 3.

Regarding time-to-event prediction, the data is modified in a way that complies with the proposed WTTE-RNN objective function and the defined network architecture. A sliding window is used and the following steps are made:

– data for the past several days from the current time is captured, adding empty rows if necessary
– the time until the alarming threshold are surpassed is determined, for every row in the sample and whether that data is censored or not
– the data is split into train and test set and modified accordingly and the GRU model is fitted

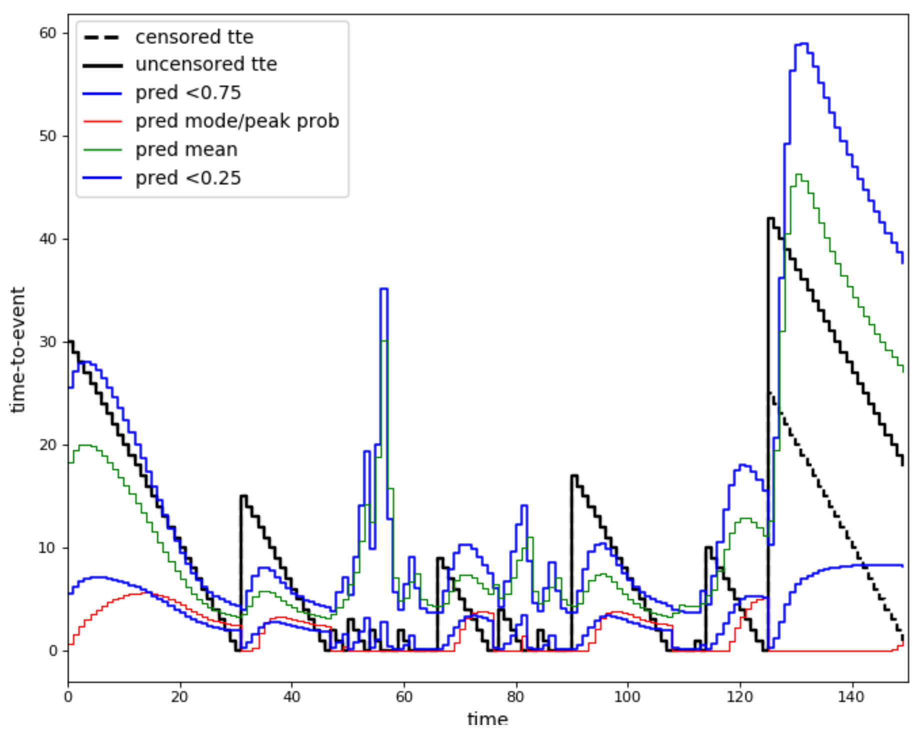

Fig. 4. Time-to-event prediction for PM10 pollutant for Skopje city center

In Figure 4 The Weibull 0.25 and 0.75 quantiles are shown, mode and mean for the α and β parameters learned for PM10 pollutant measured in the Skopje city center. Although, they do not follow the data perfectly, we can observe the matching trends.

The mean squared error for all measurements in the Skopje city center is given in Table 1. The reason why the O3 and PM2.5 pollutants have larger values is because O3 has a lot of missing values that were generated in the augmentation step, while PM2.5 was measured by only three monitoring sites.

Table 1. Mean squared error for different pollutants

Pollutant	CO	NO2	O3	PM10	PM2.5	SO2
MSE	0.21	0.06	26.13	0.22	7.32	0.08

Considering the data resolution this simple prototype system works with, the results are very promising. Once the system is fully developed and the deployed IoT architecture feeds forward the data with significantly improved resolution, we believe that the performance will increase to scale.

5 Conclusion

This paper presents an Internet of Things based system for air pollution monitoring and prediction, composed of four layers cooperating together to enable its functionalities. This integral IoT framework is specific to the air pollution application domain, with the cloud being the central element in the system that serves not only to collect and store data, but also as a core data processing unit and a gateway to third-parties interested in developing applications. The operation of such environment is defined via a model with a set of specific tasks performed at each level to meet the system requirements.

The key element of any air pollution system in the context of smart city is the ability to extract deeper knowledge for the process by building real-time and future predictions. The data processing module proposed in this research has deep learning techniques at its core and provides increased robustness and reliability of the produced results. A case study for the city of Skopje showcases the performance of this module. Although the data resolution used in the experiments is low, the results are very promising. The integration of this module with an Internet of Things infrastructure for sensing the air pollution will significantly improve overall performance due to the intrinsic nature of the techniques employed. Furthermore, the general approach used in the presented system make it applicable in many domains for environment monitoring in smart cities.

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