

Article

Performance of low-cost sensors for air pollution measurements in urban environments. Accuracy evaluation applying the Air Quality Index (AQI)

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Abstract: Most people living in Europe's cities are still exposed to levels of air pollution deemed harmful by the World Health Organization. In the modern world, air pollution is the foremost concern because of its impact in human health and economy. This strong connection appears gaining a lot of concern, driven by new installed low-cost electrochemical sensors monitoring systems. Highly accuracy, real-time monitoring, daily and yearly statistics, data access from experts or simple users, low-cost equipment and forecasting needs, enforce the market to develop new air quality monitoring systems using advanced technologies and protocols. In this study, a comparison via low-cost electrochemical sensors and of static, fixed site measurement monitoring station, is taking place in Athens, Greece, along with the data quality and Air Quality Index (AQI) including data accuracy and quality of data concerning adverse health effects due to air pollution. The findings presented in this work, relate to different flexible and affordable alternatives adopted during the evaluation and calibration of low-cost gas sensors for the monitoring. The significance of the positive results is particularly useful, especially considering the founding for interference, environmental conditions affections and air quality information including indexes and health recommendations for a specific location.

Keywords: air quality; air pollution measurements; electrochemical sensors; low-cost sensors; AQI (Air Quality Index); Athens

1. Introduction

It is a fact that we live through a critical juncture in terms of the environment. We will face challenges related to human sustainability and the formulation or acceptance of each policy that will be pursued, will be the one that will determine the success of systemic solutions. Now more than ever, the social, economic and environmental dimensions that are developing due to the spread of COVID-19 are identifying serious gaps in citizens' livelihoods. Citizens' expectations are nothing more than being able to live in a healthy environment, where they can be protected, informed and provided immediately and flexibly an adequate "treatment". This might be a specific medication or the implementation of appropriate precautionary or preventive measures, but in any case, society will expect viable solutions. In the forthcoming years, every society is called to act with appropriate answers to the global challenges of climate and environment. The plethora of scientific and non-scientific publications, which we are willing to follow and the global reports of related organizations demonstrate the seriousness and impact of our route so far. Sustainable solutions must now be provided and there must be substantial information on climate

change, biodiversity loss, depletion of natural resources and the environmental risks we are called upon to address.

According to multiple scientific studies, a link between air pollution and human health impacts such as asthma, respiratory disease, chronic bronchitis, heart disease, lung cancer and generally reduced life expectancy and premature mortality has been confirmed [1,2]. Many researchers are also examining the association of meteorology and particulate matter with potential health risks[3]. The World Health Organization [4] has estimated that in developing countries, the increase in urban air pollution has led to more than 2 million deaths per year, as well as to various respiratory illnesses [5,6]. Moreover, technological progress and urbanization in developing and developed countries results to an increase of air pollution [7–9] and due to local soil dust re-suspension from transportation higher dust contribution in observed [10]The appropriate decision-making of strategies and actions, in due course, depends on the recording and analysis of ambient air quality parameters, which create the need for the development of a real-time monitoring network of such parameters. The use of multi-parameter monitoring systems for the quality of the atmospheric environment enables a detailed analysis of the major air pollutants, biometeorological parameters and noise pollution. These integrated monitoring systems are the most important tools, in the so-called "smart cities", for air quality monitoring in urban areas [11], but also for the monitoring of other environmental parameters that determine to a significant extent the quality of life of the city's inhabitants. According to the Directive 2008/50/EC on ambient air quality and cleaner air for Europe, which clearly designate the need of fixed monitoring stations for significant pollutants, the development of a network consists of low-cost electrochemical sensors along with the necessary precision and accuracy of air pollution and meteorological measurements is a solution. Therefore, the use of electrochemical sensors compared to fixed site measurement monitoring stations, is of great interest among other researchers thus adopting similar methodology for this work [12–18], while [19], giving more details for the use of electrochemical sensors to monitor urban air quality, sensor design and laboratory and field performance. Environmental and air quality data obtained by such systems are subject to be less reliable than individual instruments and therefore vital information about the sensitivity, selectivity and stability of sensors is gathered and discussed. Simultaneously, most of web applications and low-cost sensors provide monitor measurements reporting the AQI, the question comes up: Is this safe for our health? Is this information correct?

2. Field Data and Methodology

Recent research on field of air pollution measurements using low-cost sensors is now plentiful worldwide, and in any case, researchers are producing positive results. More specifically, in Gateshead UK [20], CO and NO₂ sensors were monitored and validated successfully, during the development of a protocol where the data had to go through a dual network transmission to reach the destination address.

In New Zealand a team of scientists [21], conducted a study in Auckland where high pollution is produced because of the of the high circulation of diesel cars. Study took place on a busy 2 km road, 4 km away from the center. Researchers used 8 low-cost sensors at distances of 100 to 1000 meters near bus stops. Although the measured daily concentration of NO₂ did not exceed 20 µg/m³ the conclusions they drew highlight the very large deviations for every 100 meters.

[22] during 2016 mapped the NO₂ pollution of the atmosphere of Oslo in Norway, with measurements taken from electrochemical sensors. While the chosen equipment did not conclude in acceptable data accuracy at first, they combined the measurements with data value deriving from forecasting programs and succeed to an accuracy rate of 89%.

Similar methodology appears from researchers in Seoul, South Korea [23], they used low-cost sensors in cells to measure PM_{2.5}. They took a rather small sample of measurements, a total of 169 hours of data and exported it through a free geo-data editable map

(OpenStreetMap). Using algorithms and through machine learning models they optimized the percentages of accuracy and chose the best ones.

In Athens area by using low- cost PM sensors for over 5 months, strongly correlations appeared comparing with reference-grade instrumentation [18]. The result of using this equipment is positive and as the authors conclude low-cost sensors can provide useful data to the research community.

Also, acceptable method used by [24], where they used low-cost sensors connected to an Arduino in order to measure PM_{2.5} indoors and through measurement calibration software succeed to high accuracy.

On the other hand, in Sao Paulo, Brazil [25] researchers collect measurements of CO, CO₂, NO₂ and O₃ as well as temperature, humidity, altitude and velocity. The measurements recorded in 5 different routes with cars equipped with electrochemical sensors and they used geo-data map techniques to capture these measurements. Although the idea was well established, they encountered several problems with the accuracy of the pollutant measurements. It should be noted that using any type of device for air pollution measurements in a car while travelling, has so many limitations and specific features, which is extremely difficult to outcome to a safe result concerning accuracy.

After evaluating different systems of low-cost sensor devices for urban air quality monitoring in the market, the authors in collaboration with Progekta Europe P.C., an Athens (GR)-based company, concluded in the device called "Aether" (Figure 1).



Figure 1. Ather low-cost sensor device for urban air quality monitoring.

The Aether was exclusively designed from the company and authors to be resistant to external conditions, compact and lightweight and thus convenient for users to carry or install in specific urban spots. The Aether supports sensing of a variety gas concentrations using Alphasense Ltd. (UK) electrochemical sensors considered one of the best choices [26], for CO, H₂S, NO, NO₂, O₃, SO₂, photoionisation detection (PID) for VOCs, non-dispersive infra-red (NDIR) for CO₂. In addition, it incorporates the Alphasense optical particle counter (OPC) for PM₁, PM_{2.5} and PM₁₀ particulate matters. Air temperature, relative humidity and atmospheric pressure are also measured.

This study took place in central Athens, in the area of the National Observatory of Athens (NOA) at Thissio (37° 58' N, 23° 43' E), between April 12th to 28th 2018. The specific point is located next to a park (Philopappou Hill) and the distance from mild traffic roads is more than 100m. The access to the spot where field data were collected is limited only to specific personnel, while this point was chosen because lies next to the historic center of Athens and at the same time a certified urban background air pollution monitoring station is already installed there. It belongs to the NOA and its certified analyses comply with the prescribed calibration intervals. More specifically, Horriba AP-360 series and the Thermo 49i automatic analyzers were operated for monitoring of NO_x (NO+NO₂) and O₃ respectively on 1 min resolution, averaged on hourly basis. A beta-radiation attenuation particulate matter measurement system (Eberline Instruments, type FH-62) was operated for the continuous detection of PM₁₀ levels. For the fine fraction of particulates, PM_{2.5} filter samples integrated over 24 hours periods with a Derenda low volume sampler were used.

Finally, meteorological data (ambient temperature and relative humidity) at the sampling site were recorder by NOA's automatic meteorological station at Thissio (1-min resolution). The Ather devise was chosen to measure NO₂, O₃, PM₁₀, air temperature and relative humidity on 2-second intervals.

The methodology followed after the installation of the Ather device at Thissio area consisted of three stages: data collection, processing and evaluation of the results. The first step initially involved setting the time, date and synchronization between the Ather device and NOA monitoring station, along with ensuring data communication from data loggers. Each analyzer and instrument were set to take measurements and record in the minimum interval (1-2sec) having the ability -in the next stage- to define the interval. In the second stage, differences in the mode of operation of the fixed station and the electrochemical sensors were taken into account. If data evaluated in short intervals, e.g. seconds, considerable variations would arise, due to the different response pattern of the analyzers and the Ather device. Hence, it was decided that the interval of the measurements should be in hourly steps.

3. Results

3.1. Data Accuracy Validation

Subsequently, the reliability of the Ather was examined, all the individual measurements were checked and the validity of the data was evaluated by utilizing statistical metrics [27–29] in Table 1. For the evaluation process, the correlation coefficient (R^2) for each data set was calculated, where array-1 was the worksheet range that holds data of NOA station set and array-2 was the worksheet range that holds the Ather device data. The Mean Absolute Error (MAE) was calculated in order to indicate the average magnitude of the errors, without considering their direction (overestimation or underestimation) and last, the Root Mean Square Error (RMSE) was calculated for the two data sets in order to aggregate them into a single measure of predictive power [30]. Final steps concerned the evaluation of the results in relation to their correlation and statistical analysis.

Table 1. Evaluation statistical indices between NOA station and Aether device measurements.

	NO ₂	O ₃	PM ₁₀	PM _{2.5}	T	RH
R²	0.702	0.510	0.637	0.507	0.959	0.936
MAE	8.6 (ppb) 16.0 (μgr/m ³)	18.4 (ppb) 36.0 (μgr/m ³)	15.5 (μgr/m ³)	13.1 (μgr/m ³)	0.6 (°C)	2.4 (%)
RMSE	12.6 (ppb) 24.0 (μgr/m ³)	23.7 (ppb) 47.0 (μgr/m ³)	25.4 (μgr/m ³)	17.61 (μgr/m ³)	0.8 (°C)	3.23 (%)

According to the specific work and methodology described above, one can see the results of the comparison between NOA station and the Aether device (Table 1). Typical time series of average hourly ratios derived from 1-2 sec sampling times are presented. The scatterplot (Figure 2a) and the time series (Figure 2b) reflect the comparison of NO₂ measurements (ppb) with a data completeness of 96.2%. As can be seen, the concentrations are ranging from 0 up to 62ppb (117.0μg/m³) according to NOA station and from 0 up to 89ppb (167.0μg/m³) according to the Aether device. The coefficient of determination is equal to $R^2=0.702$, explaining the 70.2% of the variance of the data, indicating a very good agreement between NOA station and Aether device measurements. Furthermore, low values of MAE and RMSE provide a strong correlation for NO₂ measurements between NOA monitoring stations and Aether device. Finally, it seems that Aether device overestimates the air pollution (MAE>0) in all cases and for all pollutants, in comparison with NOA monitoring station measurements.

In Figure 3, the scatterplot and time series of ozone (O₃) is provided with data completeness of 90.1%. The measurements are ranging from 0 up to 62ppb (122.0μg/m³) according to NOA station and from 0 up to 89ppb (175.0μg/m³) according to the Aether device. The coefficient of determination is equal to $R^2= 0.510$, along with relatively high

values of MAE and RMSE shows that there is a limited tolerable correlation between the measurements of NOAA station and Aether device. According to the above, accurate data of local air quality, concerning O_3 , over long timescales should not be expected.

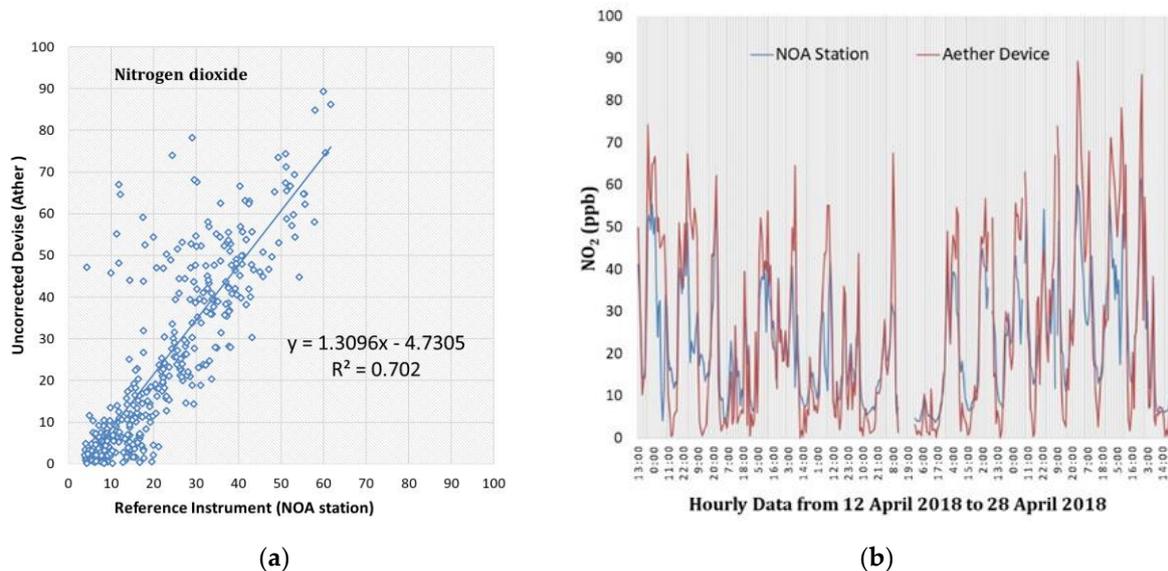


Figure 2. Scatterplot (a) and time series (b) of nitrogen dioxide (NO_2) records.

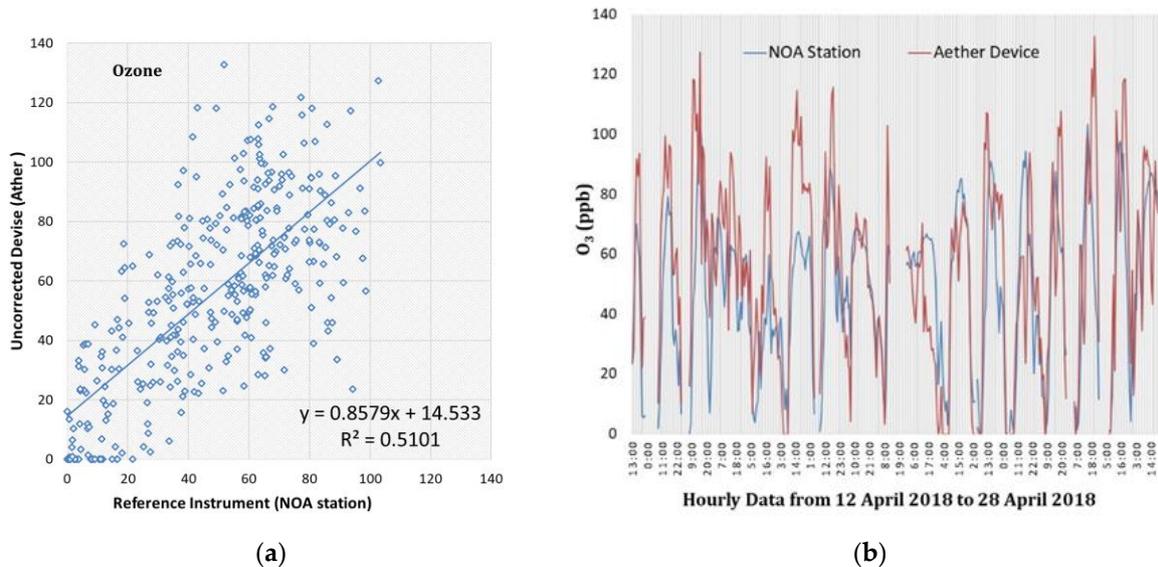


Figure 3. Scatterplot (a) and time series (b) of ozone (O_3) records.

The next data sets concern particulate matters PM_{10} and $PM_{2.5}$. Figure 4 and Figure 5 provide rather moderate correlation results. In this case, data completeness was 95.2% and 81.3% respectively, with values of the coefficient of determination equal to $R^2=0.637$ and $R^2=0.507$ respectively. During the specific period, at least two major Saharan dust events over Athens were occurred (Figure 4b) and in such cases dust can be a significant component of PM [31,32]. In these cases, it is clear that the Aether device could not adapt to these major fluctuations appearing, along with relatively high values of MAE and RMSE revealed. It should be noted, however, that these sensors are also highly affected by humidity phenomena, therefore with the fluctuations that existed low reliability was expected [33].

Finally, the comparison of air temperature and relative humidity measurements (Figure 6) was conducted with data completeness of 100%. The Aether device showed

high correlations with the NOA station with $R^2=0.959$ and $R^2=0.936$ respectively for temperature and humidity, along with low values of MAE and RMSE (Table 1).

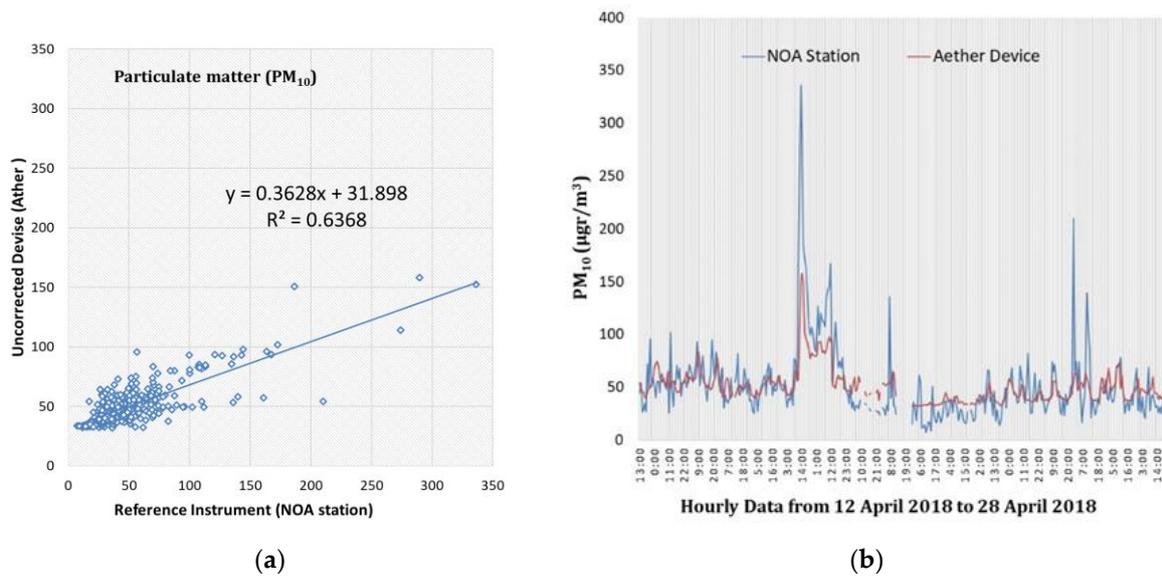


Figure 4. Scatterplot (a) and time series (b) of PM_{10} records.

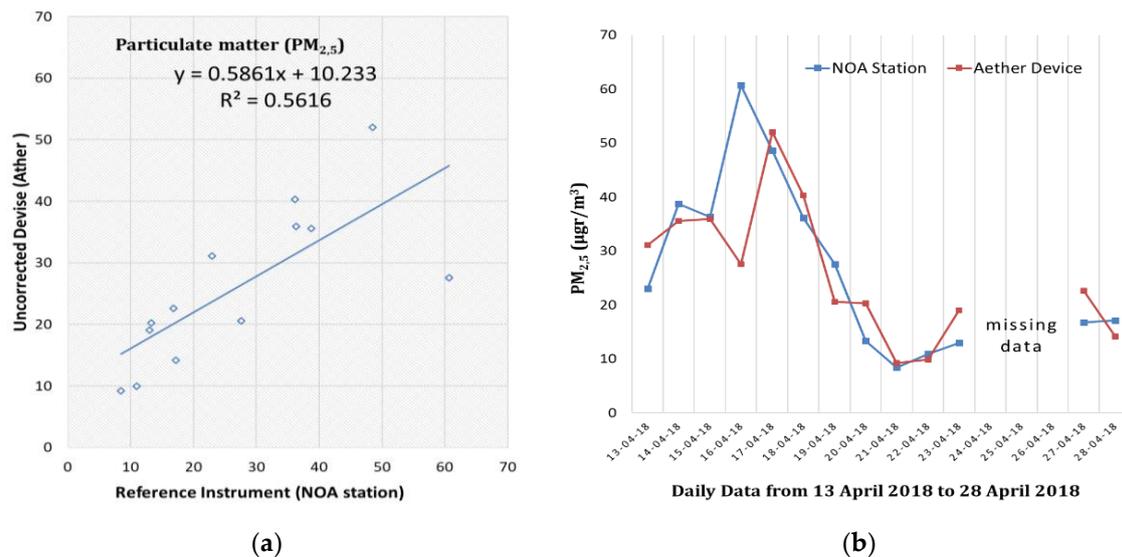


Figure 5. Scatterplot (a) and time series (b) of $PM_{2.5}$ records.

Solutions for improving the reliability of the measurements and their accuracy are specific. You may either correct values directly internally using software calculations on any device with low-cost sensors, or use calibration algorithms using multi-linear regression models, artificial neural network models, etc. to account influences of other factors such as temperature, humidity, solar radiation or for example ozone values when calibrating NO_2 sensors, after obtaining the values. In both cases, correlation coefficients between low-cost devices and reference instruments are improved.

Nevertheless, the need for a better quality and accuracy of sensors measurements concerning their spatial and temporal performance still remains questionable and the important challenge is to manage providing valuable information for human health. Moreover, it is a fact that the multitude of international collaborations and agencies such as companies, universities and organizations that are involved and constantly contribute to the development of quality improvement of low-cost sensors, such as the VAQUUMS project, CEN Technical Committee, EveryAware project, AirSensEUR project, Joint

Research Center and others, improve constantly the reliability and the quality of measurements by low-cost sensors, so that users can have a correct reliable measurements. Therefore, it is emphasized through this paper that the duration of exposure along with the value of concentration of any pollutant, are of major important for human health, which means that except of the value itself of every pollutant, air quality indexes are also important to highlight the effect of human health.

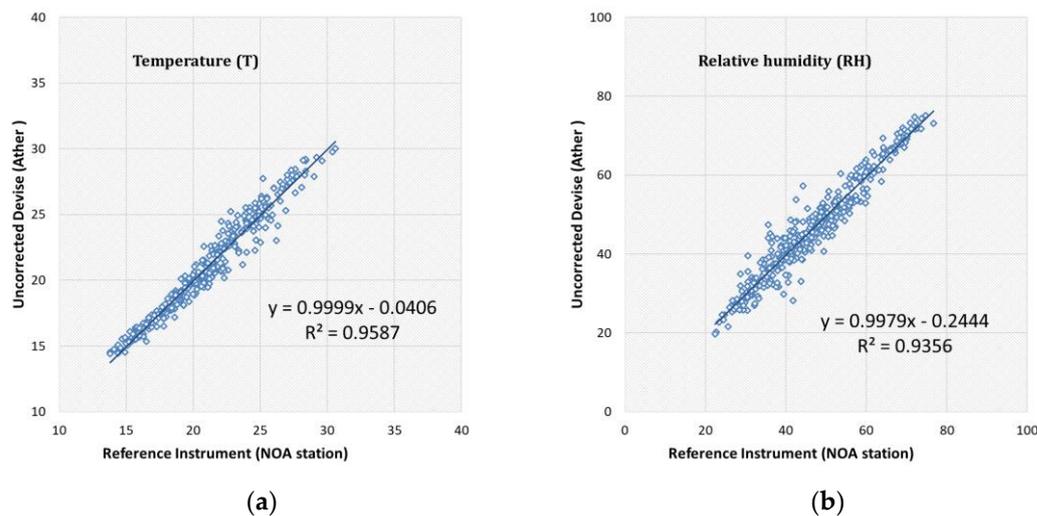


Figure 6. Scatterplot between NOA station and Aether device for air temperature (a) and relative humidity (b) measurements.

3.2. Evaluation of Air Quality Index

In this study, two surveys were conducted for low-cost sensors devices. The first was for the evaluation of air pollution data accuracy and the second for providing valuable data concerning adverse health effects due to air pollution, through the evaluation of the well-known AQI. In both cases, the evaluation based on low-cost sensors devices measurements in comparison with NOA air pollution monitoring station. AQI is reporting daily air quality. AQI shows the association between air quality and public health effects. The U.S.A. Environmental Protection Agency (USEPA) is an independent executive agency of the United States federal government and calculates the AQI for five major air pollutants regulated by the Clean Air Act: ground-level ozone, particle pollution (also known as particulate matter), carbon monoxide, sulfur dioxide, and nitrogen dioxide. For each of these pollutants, USEPA has established national air quality standards to protect public health. Ground-level ozone and particle pollution are the two pollutants that pose the greatest threat to human health in this country [34]. There are a substantial number of different indexes to measure air quality for individual pollutants and even countries that share the same legislation or sometimes areas/cities within the same country have different indices, but in this study, authors focus on most commonly used index AQI.

More specifically, firstly is examined the AQI value obtained from the NOA station in comparison with the Aether device and secondly, whether the AQI value is correctly determined or not by using statistical indices. The main reason that has led researchers to this determination is purely practical. Most of the people are not able to know a given value or an indication which will be given in units such as ppb or $\mu\text{gr}/\text{m}^3$ and even if they are familiar with the units, they will not remember for every pollutant its threshold value in order to understand if the quality of air is good or bad. Therefore, an established categorization of AQI value with intervals of concern (Good (0-50), Moderate (51-100), Unhealthy for Sensitive Groups (101-150), Unhealthy (151-200), Very Unhealthy (201-300), Dangerous (301-500)) and appropriate chromatic scale is definitely more than useful. In order to investigate the ability of the Aether device to determine the accurate value of AQI for every interval of concern, appropriate statistical indices such as the true predicted rate (TPR), the false negative rate (FNR) and the false positive rate (FPR) were used. In this

study, the most important finding is not the exact match or the best possible correlation between the Aether device and the actual concentration value from NOA station, but whether the Aether device was able to correctly predict the right interval of AQI, according to its air pollution measurements.

Table 2 presents the validation statistical indices for different AQI intervals. In Table 2, the number of hours, where for both Aether device and NOA station, for each pollutant AQI value is lying within the same interval (right AQI interval prediction), are denoted as X. The number of hours where AQI calculated via Aether device is lying within the previous AQI interval, based on NOA measurements are denoted as Y, the number of hours where AQI calculated via Aether device is laying within the next AQI interval, based on NOA measurements are denoted as Z, and N is the number of hours where AQI is lying within a specific interval, based on NOA measurements.

Table 2. Statistical indices for the evaluation of the Ather device accuracy for specific AQI intervals.

Pollutant	AQI Interval	X	Y	Z	N	TPR%	FNR%	FPR%
NO ₂	AQI (0-50)	329	0	37	366	89.9	0.0	10.1
	AQI (51-100)	10	1	0	11	90.9	9.1	0.0
O ₃	AQI (0-50)	174	0	57	231	75.3	0.0	24.7
	AQI (51-100)	38	31	39	108	35.2	28.7	36.1
	AQI (101-150)	18	16	8	42	42.9	38.1	19.0
PM ₁₀	AQI (0-50)	241	0	10	251	96.0	0.0	4.0
	AQI (51-100)	106	12	0	118	89.8	10.2	0.0
PM _{2.5}	AQI (0-50)	2	0	0	2	100.0	0.0	0.0
	AQI (51-100)	6	0	0	6	100.0	0.0	0.0
	AQI (101-150)	4	0	0	4	100.0	0.0	0.0
	AQI (151-200)	0	1	0	1	0.0	100.0	0.0

True predicted rate (TPR) represents the percentage (%) of correct cases over total cases with values from 0.0% to 100.0% and a perfect score equal to 100.0%, i.e. when AQI calculated via Aether device is lying within the same AQI interval, based on NOA measurements. False negative rate (FNR) represents the percentage (%) of negative false predictions, i.e. where AQI calculated via Aether device is lying within the previous AQI interval, based on NOA measurements, with values from 0.0% to 100.0% and a perfect score equal to 0.0%. Finally, false positive rate (FPR) represents the percentage (%) of positive false predictions, i.e. where AQI calculated via Aether device is lying within the next AQI interval, based on NOA measurements, with values from 0.0% to 100.0% and a perfect score equal to 0.0%.

According to Table 2, it seems that the Aether device shows a very good overall accuracy in predicting AQI index by using mean hourly concentrations. Specifically, the Aether device with the electrochemical sensors predicts correctly from 35.2 % (O₃ – Moderate level) up to 100 % (PM_{2.5} – Good, Moderate level) of observed exceedances. For every human it is more than important to know, in hourly step, if the AQI index will be correct and much more if the concentration level is above the Good or Moderate level. This is due to the fact that the human body when exposed to high concentrations of air pollution more than 8h during the day is at high unhealthy risk [30]. More specifically, in Figures 7 to 10 is presented in detail for every pollutant, the daily value of AQI index derived from average hourly values along with statistical indices for the evaluation of the Aether device accuracy.

Luckily for the environment and human health during the period of measurements NO₂ emissions were in relatively low levels and ranges below 70ppb (132µg/m³). Therefore, according to AQI calculations only the first 2 categories were explored (Good and

Moderate) and the results are very promising (Figure 7). It is of major interest to understand that even in cases of different categories in AQI calculations considering NO_2 , with FPR 10.1% and 0.0% for Good level and Moderate level respectively, the outcome is not prohibitive. The same conclusions derive as well for FNR (0.0% and 9.1% for Good level and Moderate AQI level respectively).

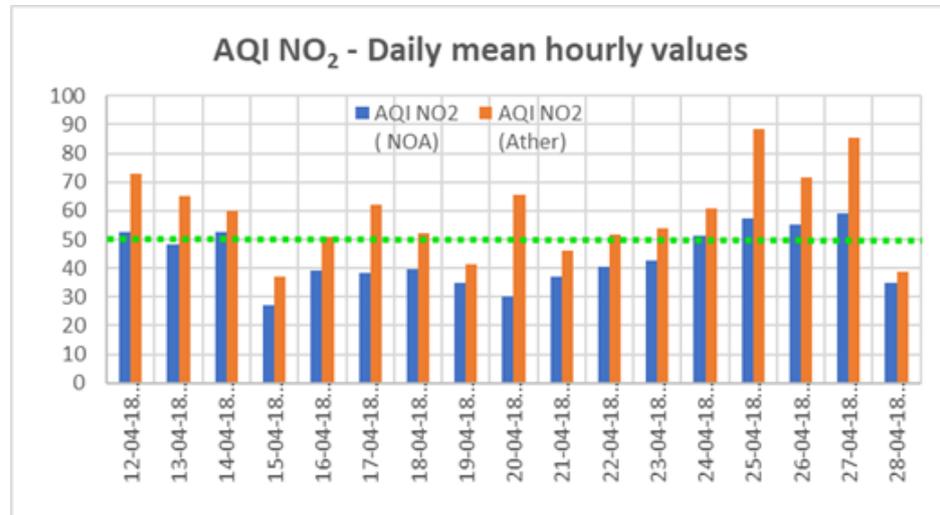


Figure 7. AQI daily values for NO_2 according to NOA monitoring station and Aether device measurements. The green dot line represents the threshold value AQI=50.

Figure 8 depicts the daily AQI concerning O_3 (8 hours moving average concentration) during the examined period. We see that during the examined period, three different AQI levels (health impact) appeared.

It is well known that in Athens and generally in Greece, O_3 is one of the key role pollutants due to high solar irradiation and the huge number of sunny hours during the year. As it can be seen the comparison between the mean daily AQI value derived via Aether device and the respectively NOA monitoring station measurements, may easily be characterized as positive.

Concerning PM_{10} , the comparison between daily AQI values derived via Aether device and the corresponding values derived via NOA monitoring station are almost excellent (Figure 9). For sixteen (16) consecutive days the daily AQI value is lying (for both Aether device and NOA monitoring station) within the same health impact interval (100.0% success).

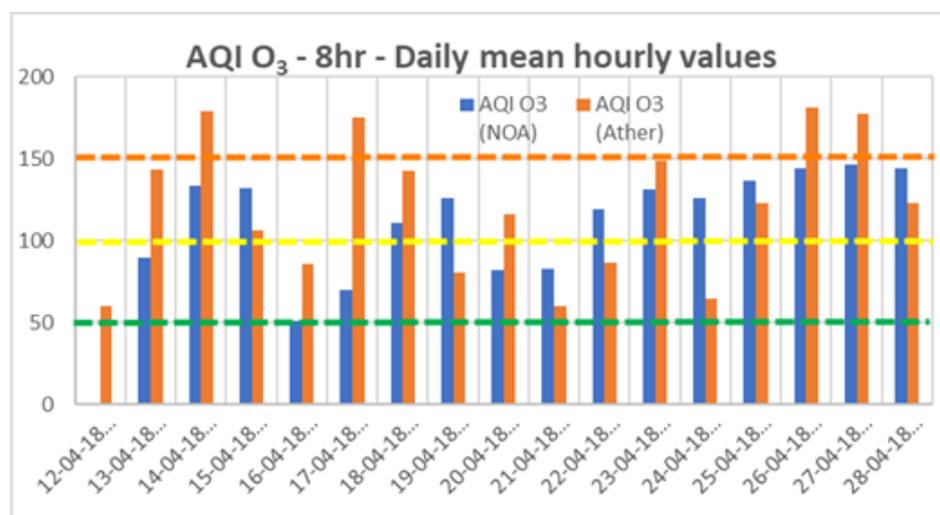


Figure 8. AQI daily values for O₃ (8hrs moving average concentration) according to NOA monitoring station and Aether device measurements. The dots colored lines represent the AQI threshold values between different AQI intervals (health impacts).

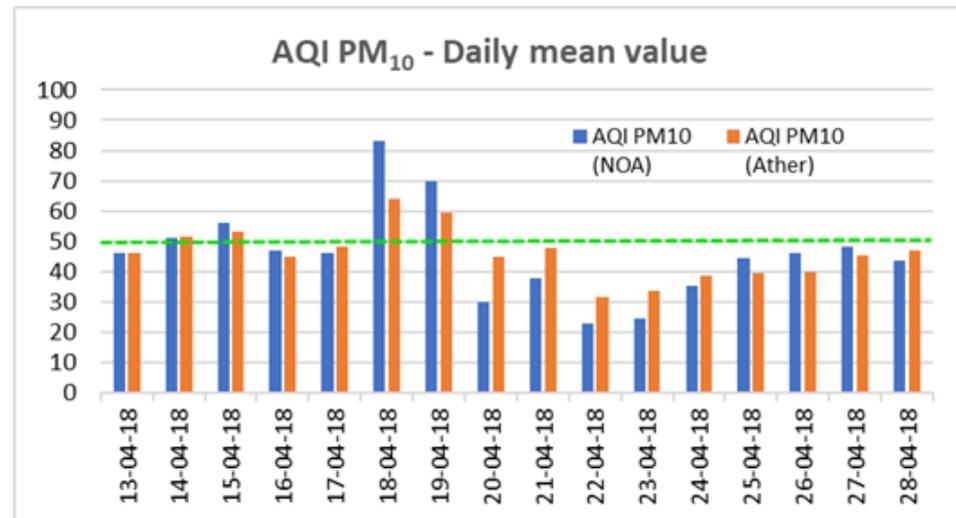


Figure 9. AQI daily values for PM₁₀ according to NOA monitoring station and Aether device measurements. The green dot line represents the threshold value AQI=50.

Exactly the same conclusions were derived for PM_{2.5}. The comparison between daily AQI values derived via Aether device and the corresponding values derived via NOA monitoring station is almost perfect (Figure 10).

For twelve (12) of the thirteen (13) consecutive days, the AQI daily value is lying (for both Aether device and NOA monitoring station) within the same health impact interval (92.3% success). More specifically, only one (1) day the AQI value according to NOA was marginally larger than 150 (Unhealthy) and at the same time according to Aether device was more than 50 and less than 100 (Unhealthy for Sensitive Groups).

4. Discussion and Conclusions

Through the specific work, a low-cost sensor device for urban air quality monitoring which was designed by a private Athens based company and the Authors, is examined in detail. The device supports sensing of a variety gas concentrations using Alphasense Ltd. (UK) electrochemical sensors and optical particle counter (OPC) for PM₁, PM_{2.5} and PM₁₀ particulate matters. Two surveys were conducted for the low-cost sensing device. The first one explored the evaluation of the measured concentrations and the second the worth of providing valuable information concerning human health impact due to air pollution, in other words the evaluation of the info through the application of the well-known air quality index AQI.

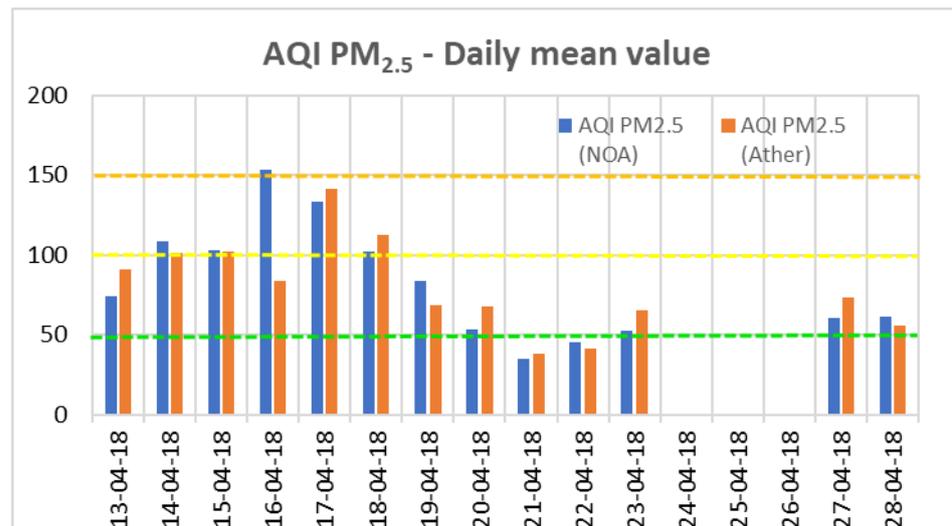


Figure 10. AQI daily values for PM_{2.5} according to NOA monitoring station and Aether device measurements. The dots colored lines represent the AQI threshold values between different AQI intervals (health impacts).

The evaluation of the performance of a device with electrochemical sensors, installed in an urban environment, took part in central Athens, Greece, in the area of the National Observatory of Athens (Thisio). As the results may vary depending on the field conditions and different applications, it was concluded that the main challenges of using such devices with electrochemical sensors lying up to what extent the data quality as well as the respectively information through these data, will be used. Although there are differences in absolute values between the Aether device measurements and the corresponding NOA monitoring station (reference measurements), as well as relatively high values of MAE and RMSE, with poor performance, a positive correspondence exists in the use of the Ather device. Concerning the comparison of Ather device measurements to the NOA fixed site monitoring station corresponding measurements the coefficient of determination is ranging between 0.507 (O₃) and 0.702 (NO₂) which indicates a good enough measuring accuracy at a statistical significant level of $p < 0.005$.

With regard the prediction of different AQI's human health impact intervals, during the examined period, the statistical indices TPR, FNR and FPR examined in detail. With TPR ranging from 35.2% up to 100.0%, FPR ranging from 0.0% up to 36.1% and FNR ranging from 0.0% up to 38.1%, it is clear that a device using electrochemical sensors and optical particle counter, can be the future low-cost solution for measuring and quantifying the air quality. Overall, the vast majority of the false health impact predictions through the use of AQI revealed that the Ather device overestimates and "overreacts". This means that when we are going to use this device, it might provide information for the exactly next worst AQI health impact categorization level than it actually will be. Therefore, if the reason that someone chooses to use such devices is not to measure the absolute concentration values, but to indicate the quality of the atmospheric environment through different health impact levels, then low-cost sensors devices may successfully fit this purpose. Of course, the long-term stability of electrochemical sensors must be further examined using the same method which has been partially described, in order to determine the overall use of such devices compared to big and expensive air quality monitoring stations.

Finally, it should be mentioned that the Authors at this moment have already expand their network with a numerous of similar devices, in different locations within Athens city district and improving their field experience along with the already measured data methodology. Authors believe that the vital question raised through this work concerning the usage of low-cost sensing devices for air pollution measurements in urban environments, is if the information gained concerning adverse health effects due to air pollution is correct, has been answered.

The air pollutants concentration measurements which took place using these devices showed successful predictions of air quality level and the corresponding public health impact. This kind of information is very important for the people (residents and visitors of the city) in order to schedule their daily outdoor activity, as well as for the state in order to take the appropriate measures to avoid short-term and long-term hazardous public health impacts.

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Data Availability Statement: In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Please refer to suggested Data Availability Statements in section “MDPI Research Data Policies” at <https://www.mdpi.com/ethics>. You might choose to exclude this statement if the study did not report any data.

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