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Methods of Measuring Air Pollution in Cities and Correlation of Air Pollutant Concentrations

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Abstract: The monitoring of air quality continues to be one of the most important tasks when ensuring the safety of our environment. This paper aims to look at correlations between different types of pollutants, so that robust air quality measurement systems can be deployed in remote, inaccessible areas, at a reduced cost. The first matter at hand was to design an affordable and portable system capable of measuring different air pollutants. A custom PCB was designed that could support the acquisition of readings of, among others, particulate and CO sensors. Then, correlations between the concentrations of different pollutants were analyzed to identify if measuring the concentration of one type of pollutant can allow the extrapolation of the concentration of another. This particular study focuses on the correlations between the concentrations of particulate matter and CO. Finally, after observing a moderate correlation, it was proposed to measure the concentrations of pollutants that require less expensive sensors, and to extrapolate the concentrations of pollutants that require a more expensive sensor to measure their concentration. The link between particulate pollution and CO concentrations was identified and discussed as the result of this study.

Keywords: air pollution; monitoring; correlation; measurement; wireless data transfer

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1. Introduction

Air pollution continues to play an increasingly significant role in our everyday lives, not only because of its impacts on climate change, but also those on public and individual health due to increasing morbidity and mortality [1]. As countries become more urbanized and as developing economies strive to reach the status of developed economies, the environment is often overlooked [2]. It is estimated that air pollution alone prematurely ends the lives of about 8.8 million people every year, as well as shaving off between 2.3 and 3.5 years of the average life expectancy throughout the world, more than even tobacco smoking [3]. Every nation sets its own laws when it comes to the parameters that describe air quality, and even when the laws are strict and the legislation is tight, rarely is air quality monitored extensively, reliably, and over a large amount of territory. Usually, monitoring is confined to a few locations, even in cities inhabited by millions, and equipment usage tends to be confined to only some key places. The WHO does set its Air Quality Guidelines [4], but the challenge still remains to measure air pollution without the use of expensive and cumbersome equipment. The basis of this study is the measurement of air pollutant levels and the correlation that might emerge between their concentrations. It is important to differentiate between the levels of pollutants, and the general quality of air, since developing an aggregate Air Quality index [5,6] requires data on more pollutants, usually five, such as SO_2, O_3, and VOCs in addition to the pollutants measured in this study.

As the monitoring of air pollution becomes more important throughout the world, many studies and papers have been published that looked into developing cheaper, more accessible air quality measurement systems that can be deployed even in remote or underdeveloped areas. Low-cost solutions are often published [7–10], as many authors try

to develop simpler sensors or techniques to monitor various air quality parameters, such as the concentration of CO, NO_2, and particulate matter. Sometimes these systems are developed for very specific purposes [11], as the world transitions to a fossil-fuel-free future. These systems are necessary to monitor the manner in which alternative and sustainable energy sources affect air quality when deployed. Also relevant is the research which aims to fill the gaps caused by the inevitable malfunction of IoT systems and sensors [12], which results in missing data about air quality parameters and can skew data one way or the other. Such methods are important when reliability and consistency of sensor readings is of utmost importance.

Hence, some authors have taken to evaluating such low-cost solutions and their performance over prolonged periods of time [13]. These experiments have led to suggestions such as using comparisons of timelines of pollutant concentrations, rather than looking simply at raw values. Another important part of reliable data gathering is to ensure that environmental noise and glitches do not affect the end results in a meaningful way. This is why methods were developed [14] to analyze how the noise level of parameters affects prediction inaccuracy and uncertainty.

Emerging technologies that are still expanding can also be of great use when monitoring air quality parameters. Machine learning [15–17] and advanced Learning Edge computing frameworks [18] offer the possibility of predicting future air pollutant concentrations, or simply reduce the amount of data that needs to be transmitted so that air pollutant concentrations can be reliably obtained. Ultimately, what may truly and meaningfully affect air quality monitoring are cheap and available platforms that any average citizen may choose to install at their own location [19]. Such citizen science projects do not only provide valuable resources, but they also have the added benefit of impacting the knowledge and attitudes of those involved [20]. These systems have to be affordable and simple enough to be used by people without a science degree or a background in this field.

The UN has 17 Sustainable Development Goals, one of which targets the atmosphere, specifically the promotion of systematic observation of, among other things, the Earth's atmosphere [21]. This paper aims to develop an affordable solution and demonstrate how its implementation can enable researchers to find correlations between different air pollutants. Later, an estimation could be provided of the concentration of others that may otherwise prove difficult or more expensive to track. As these systems would replace an expensive sensor that is cumbersome to use with a cheaper one, costs can go down and more systems can be deployed around the world.

2. Materials and Methods

Extensive monitoring of air pollution requires a number of sensors, each measuring a different air pollutant. It was deemed necessary to develop a platform that enables all of them to transmit data continuously, as well to utilize a method to transmit data wirelessly to a remote location where it can be analyzed, stored, and used for different purposes, one of which is the very topic of the paper. Hence, a system was designed and developed on a circuit board that has the capability of continuously collecting data from multiple sensors.

The system proposed in this paper consists of a PCB with several components that enable it to work properly. First of all, it utilizes a *Microchip* microcontroller PIC24FJ256GA106 [22], which was mounted on a printed circuit board in a way that offers easy access to all microcontroller pins, and two different voltage levels stabilized at 3.3 V and 5 V. In order to transmit data wirelessly, a *Telit* GE864-GPS [23] modem was added to the board. This modem can communicate over 3 G and GPRS protocols, and it was selected primarily due to its small size, good characteristics, and low price. The microcontroller has a 16-bit infrastructure, possesses 64 pins, 256 kbytes of programming memory, 16 kbytes of SRAM memory, and a 10-bit A/D converter with 16 channels. It was selected primarily because it has 31 remappable pins, which enables users to reconfigure the purpose of the main board without changing the layout. The frequency of its internal oscillator is 8 MHz, but using the PLL it can further be increased to 32 MHz. Overall, it has 53 I/O pins which are divided

into six separate ports. It has 66 mapped interrupts in its interrupt table to choose from. Figure 1 outlines the block diagram of the system, with the designed circuit board at its center, along with the used sensors and the direction of data flow.

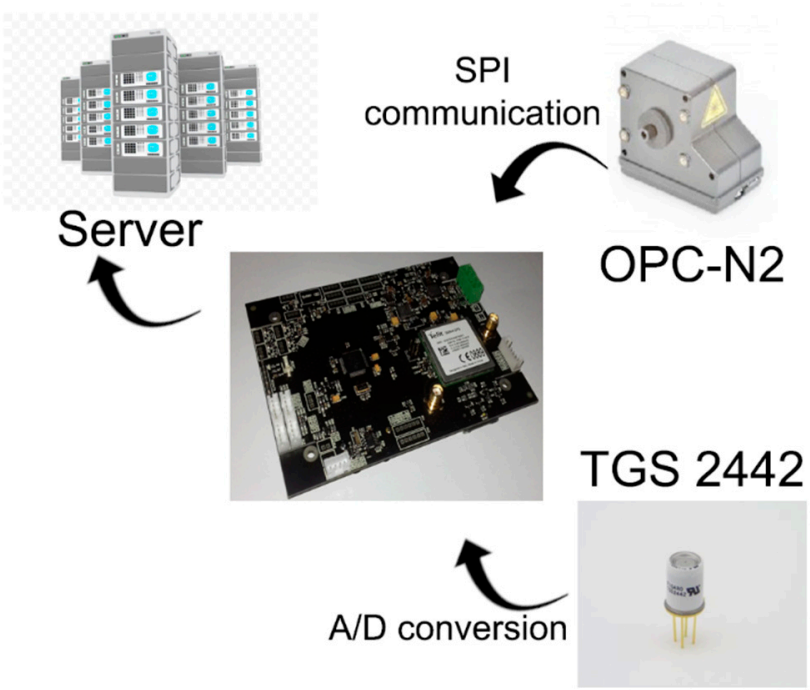

Figure 1. Block diagram of the system, outlining the used sensors and direction of data flow.

Data on particulate matter concentrations were obtained using OPC-N2 [24] sensors, which were connected to the main board via the SPI communications protocol. These sensors are optical particle monitors. They use laser beams to detect particles that can range in size from 0.38 µm to 17 µm. Count measurements are converted into mass concentrations of PM_1, $PM_{2.5}$, and PM_{10}, which have an aerodynamic diameter of up to 1 µm, 2.5 µm, and 10 µm respectively. The conversion is made possible thanks to embedded algorithms. The sensor can count a maximum of 10,000 particles per second, with detection limits for PM_{10} particles set at a minimum of 0.01 $\mu g/m^3$ and a maximum of 1500 $\mu g/m^3$. The sensor can be used in the temperature range of −20 °C to 50 °C, and in environments with a relative humidity of 0 to 95%.

CO levels were monitored using the sensor TGS2442 [25]. This sensor has a glass thermal insulation layer printed between a RuO_2 heater and an alumina substrate, with a pair of Au electrodes formed on a thermal insulator. The gas-sensing layer is formed of SnO_2 and printed on an electrical insulation layer, which covers the heater. The pair of Au electrodes is used to measure sensor resistance, which is done by sampling the sensor output voltage using the microcontroller's A/D convertor. The sensitivity of this sensor (defined by the change ratio of its internal resistance, Rs) is 0.23–0.49. It has a typical detection range of 30–1000 ppm.

The measurements using the sensors that were previously described were conducted over a period of 28 days at the same location in Rumenačka street in Novi Sad, Serbia. The precise geographic coordinates of the station are 45°15′45″ N and 19°49′8″ E [26,27]. The precise location of the station can be seen marked with a green pin on the map of the city of Novi Sad, as displayed in Figure 2.

The sensors were positioned at 1.5 m above ground level. The measurement equipment was situated at a busy intersection, where significant amounts of pollutants were to be expected.

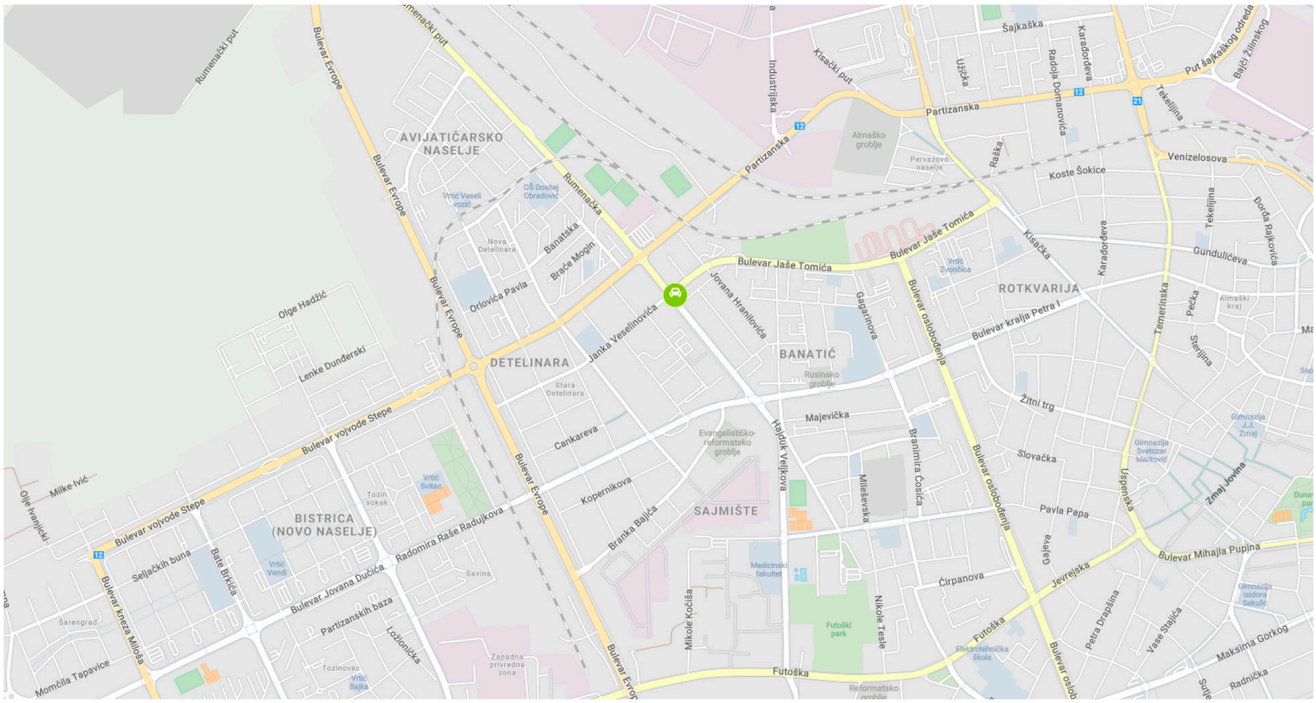

Figure 2. The location of the measuring system in the city of Novi Sad, indicated by the green car icon.

The implemented system resulted in a full four weeks of data, taken between 15 of November and 13 of December 2021, stored as an Excel table, which consists of the concentrations of pollutants on an hourly basis. This raw data had to undergo several mathematical operations so that useful information could be extracted.

First of all, the Least Squares Method (LSM) [28] was used as a standard method for data fitting. The resulting equations yielded the most important parameters that were used in analyzing the correlation of different air pollutants. First, the arithmetic means of each data set, corresponding to every collected air pollutant, were calculated. So, if there were data sets for two different gasses, then the arithmetic means of the concentration of the two gasses would be represented by $\overline{x}$ and $\overline{y}$, respectively.

Then variances were calculated, which represent the mean discrepancy square. Along with variances, co-variances were also calculated, since they represent the measure of strength of correlation among variables.

$$\sigma_x^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{1}$$

$$\sigma_y^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2 \tag{2}$$

$$cov(x,y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}) \tag{3}$$

If the co-variance is 0, it means that there is no linear relation between the variables. A co-variance greater than 0 implies that y changes in accordance with x, and implies a direct linear correlation. On the other hand, if the co-variance is below 0, this means that the correlation exists, but it is negative, or inverse.

The problem with the co-variance is its lack of ability to take into account other degrees of variability and non-linearity, and crucially, it does not take into account measurement units. To express pollutants in a numerically intuitive way, different measurement units and orders of magnitude are used. As an example, concentrations of CO in the outside air can easily climb to over 100 times the concentration of other pollutants, such as nitrous

oxides or sulfur dioxide [29]. It is therefore important to use the correlation coefficient, which gives the same numerical values for the same correlation degree regardless of the order of magnitude or measurement units. This value is defined in the following way:

$$r = \frac{cov(x, y)}{\sigma_x^2 \sigma_y^2} \tag{4}$$

The correlation coefficient r measures the degree of linear dependency between two variables. Its value can lie in a range between -1 and 1, depending on whether the correlation is completely negative or positive, respectively. If it equals zero, there is a lack of linear dependency. Absolute values of r less than 0.3 are not regarded as statistically significant, although they are usually not immediately dismissed. Absolute values of r between 0.3 and 0.7 point to a moderately strong correlation, while values over 0.7 point to a strong correlation between two trend lines. The square of the correlation coefficient (also called the Pearson coefficient) is also included in the table with the results. This coefficient, also called coefficient of determination (R^2), is just the squared Pearson coefficient. This is included as it is easier to explain linear regression in terms of R^2 rather than r. As r ranges from -1 to 1, R^2 ranges from 0 to 1, clearly explaining the relationship, with 0 being not related and 1 being perfectly related.

One thing to note about the correlation coefficient is that it does not recognize non-linear relationships between two trends. The second thing to note is that its significance does not necessarily stem from its absolute value, since the sample size also plays an important role. Hence, the t value for t distribution [30] is calculated as follows:

$$t = r\sqrt{\frac{N-2}{1-r^2}} \tag{5}$$

where N is the number of samples. Using the Student distribution, the value of p is obtained, and a statistically significant correlation emerges whenever p is greater than 0.05.

3. Results

Data were obtained for a number of pollutants, including CO, SO_2, NO, NO_x, and NO_2, which were tracked by separate sensors. The results were saved in a central database and analyzed. Correlations emerged between the concentrations of CO and particulate matter, particularly PM_{10}, $PM_{2.5}$, and PM_1. Proving the assumption that the main source of these gasses is the combustion of fossil fuels in internal combustion engines would enable the approximation of the concentrations of particulate pollution. Another reason for selecting this particular correlation was the fact that phasing out PM sensors in the setup would have the biggest impact on the price reduction of the system. In addition, wind speed was also observed since the system also employs an ultrasonic wind speed meter, as well as air temperature and pressure sensors. These parameters were tracked to ensure that no abnormal weather event would skew the data in a particular direction. Since these parameters did not change in an unexpected way, calculating correlations could proceed.

It should be noted that CO concentration was originally given in mg/m^3, whereas particulate matter concentration was given in $\mu g/m^3$. To ease the visualization of data and provide graphs that can be used to clearly visualize the concentration of both pollutants, CO concentration was multiplied by 100 and is displayed in 10 $\mu g/m^3$. No further changes were made that interfere with the data itself. The Y-axis represents CO and particulate concentrations, with measurement units given for each separate pollutant, while the X-axis denotes the number of samples taken. It is enumerated in hours of time elapsed since samples were taken once every hour.

Figure 3 depicts the change in concentrations of CO vs. PM_1, $PM_{2.5}$, and PM_{10} over time.

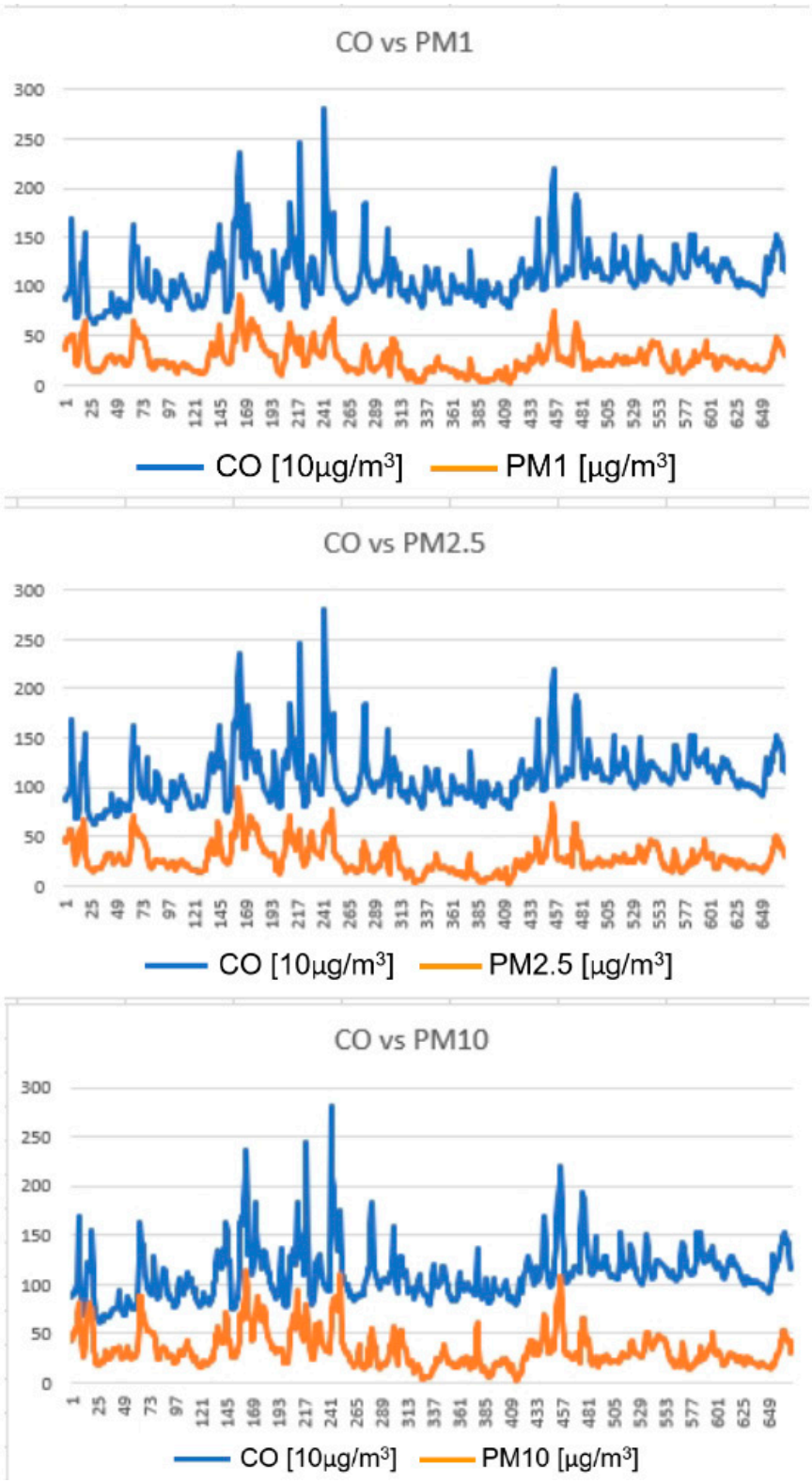

Figure 3. CO vs. PM_1, $PM_{2.5}$, and PM_{10} concentrations in air, over time.

Over the course of 28 days, a total of 697 data points were collected. Twenty-seven of those were discarded so as not to skew the data because of incomplete readings caused by system malfunction, which resulted in one of the parameters (or all of them) not being logged properly. The data that were discarded had at least one sensor give a reading of zero, and if any sensor malfunctioned in such a way, the entire data point was deleted.

Such malfunctions were rare, occurring in only 4% of the samples taken. It should also be noted that these malfunctions were non-consecutive, so there were never more than a couple of hours of coverage missing. Generally, if less than 5% of data points are missing, it is acceptable to ignore them without having a great impact on the reliability of the study. The missing data do not have a pattern of missingness (i.e., the data are missing completely at random, MCAR), so any influence on the results of the study would also be random [31]. This left 671 valid data points for all four tracked air pollutants.

The data show a moderate correlation between CO and particulate concentrations. As seen in Figure 4, the trend holds for all observed particulates, i.e., PM_1, $PM_{2.5}$, and PM_{10}.

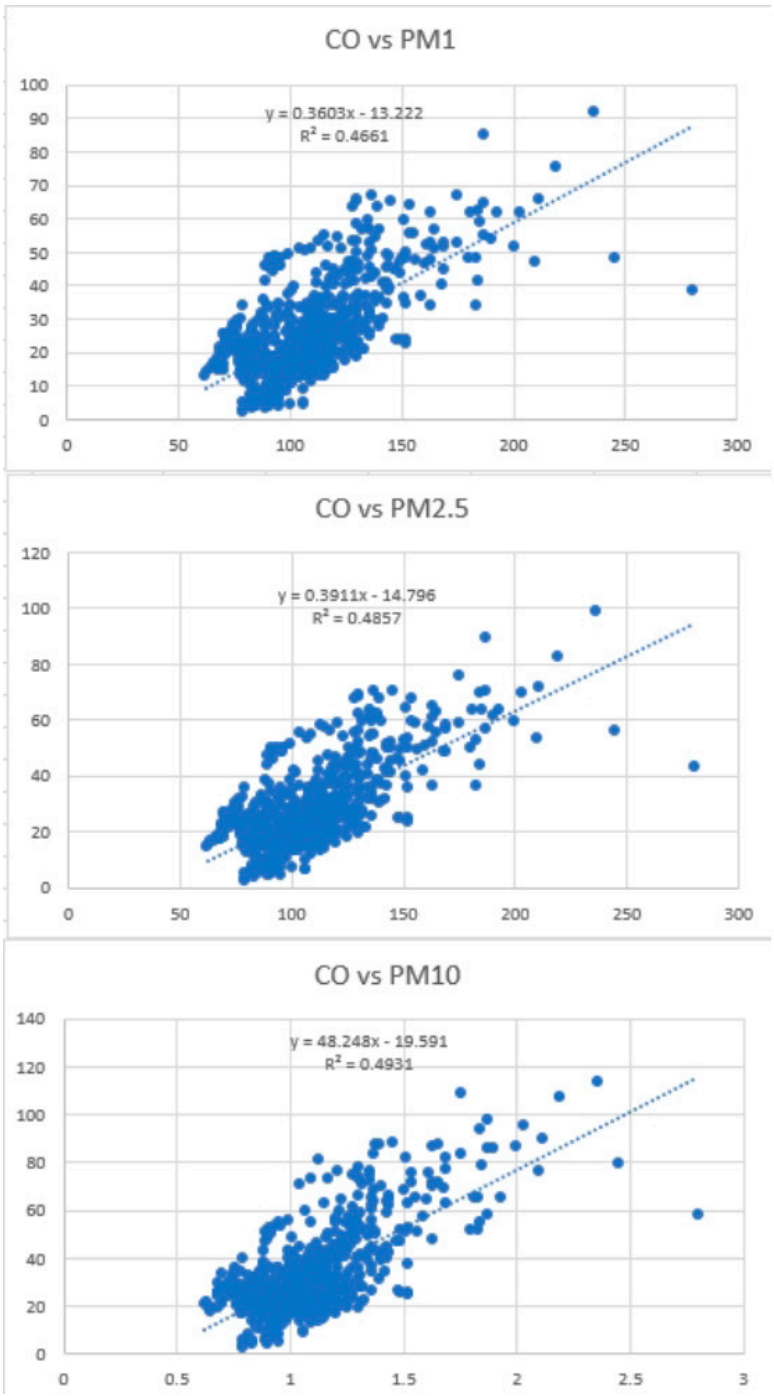

Figure 4. Regression straight line of CO vs. PM_1, $PM_{2.5}$, and PM_{10}.

The Pearson coefficients for each correlation are shown in Table 1. *t*-test values and *p*-values are shown in Table 2. The probability values of the regression coefficient in the significance test are all below 0.05, so the model is feasible.

Table 1. R and R^2 values in correlations between the concentrations of CO and particulates.

Pollutant	R	R^2
PM_1	0.68	0.46
$PM_{2.5}$	0.69	0.48
PM_{10}	0.70	0.49

Table 2. Student's *t*-test and *p*-values and R^2 values in correlations between the concentrations of CO and particulates.

Pollutant	*t*-Test	*p*-Values
PM_1	24.168	0.000
$PM_{2.5}$	25.134	0.000
PM_{10}	25.512	0.000

Table 2 shows the *t*-test values and *p*-values. It should be noted that these values are statistically significant since a large number of samples was obtained. If one takes any lookup table used to convert the *t*-test value into *p*-values, it can be seen that our *t*-test values are very big, which is directly related to the large number of samples taken. For a two-tailed type of *t*-test, and a *p*-value of 0.001, based on our number of samples, the *t*-value would need to be between 3.373 and 3.3. Our *t*-test values were over 24. This is why *p*-values are marked as 0.000, i.e., not even the third digit after the decimal point is above zero.

4. Discussion

The results show a statistically significant relationship between the levels of CO and particulate pollutants in the air. The correlation between CO and $PM_{2.5}$ has been the subject of other studies [32,33]. However, these results were obtained in an indoor environment. A study conducted outdoors on the correlation between CO and $PM_{2.5}$ found the Pearson coefficient to be 0.66 [34], which is similar to the results produced by our measuring station. The study does not, however, mention other particulates such as PM_1 or PM_{10}. Wind speeds are included in the Supplementary Materials. The impact of wind speeds on the concentrations of particulates is not easy to define, as one study [35] shows that lower wind speeds can reduce the concentrations of $PM_{2.5}$ and PM_{10}, but higher wind speeds can increase the concentration of PM_{10} depending on the direction of the wind. This station has no instrument to determine the wind direction, so a more refined version of the station might be able to give a more precise answer. Some authors even found an increase in PM concentrations during low winds in summer, but not in winter [36]. It should be noted that the data used for this study were obtained during parts of November and December, which is a period of low temperatures in Serbia. To ensure that households burning solid fuel for heating did not skew the results, as the primary target was automotive emissions, the measuring station was set up in an urban area of the city, where residential homes and apartments utilize district heating [37]. One study [38] indeed found that vehicles that are high CO emitters also emitted a larger amount of particulate matter. It is, however, noted that there is no consistent quantitative relationship between emissions of these pollutants on an individual vehicle basis.

Another aspect worth discussing is the validity of the acquired data. The system and the sensors used to acquire the results of this study are operated by the Serbian Environmental Protection Agency (SEPA). The CO sensor was calibrated at two CO concentrations, as outlined in the datasheet [25]. It has been shown that this means that the CO sensor can

satisfy strict performance standards such as UL2034 [39] and the CSA 6-96 standard [40]. The OPC-N2 sensor comes pre-calibrated, as is pointed out in the datasheet. The OPC-N2 sensor used in this research was field-tested at the South Coast AQMD Rubidioux fixed ambient monitoring station under ambient weather conditions [41]. In this test, the sensor was compared against professional sensors that cost 50–100 times more than the OPC-N2. While the accuracy of the OPC-N2 varied, the sensor consistently showed high precision and the measurements correlated very strongly (R^2 = 0.99) with the control. Since this study mainly focuses on the change in particulate levels, rather than the absolute value of their concentrations, it is deemed that the OPC-N2 sensors were sufficiently precise. Other studies [42,43] also found that OPC-N2 sensors' readings were highly correlated with the control sensor. The sensors were maintained by professional SEPA personnel during the course of this study. One final remark is that this system also gathered information on the concentration of NO_2. While the correlation between the concentration of CO and NO_2 has already been the topic of another study [44], the Pearson coefficient for this correlation in the data collected during the course of this research indicates 0.65 largely supports the findings of that study ($r \approx 0.7$, depending on the location).

5. Conclusions

Currently, the CO gas sensor used as a part of this study costs less than a tenth of the price of a typical OPC sensor. The price of sensors that detect air pollutants is the main reason why the focus was placed on CO and PM correlation, and other pollutants such as SO_2, NO_x, O_3, and VOCs were excluded. The sensors used to measure their concentration are all significantly cheaper than quality PM sensors. Since OPC sensors used to measure particulate matter in the air are usually much more expensive than CO sensors, based on our analysis, we can potentially enable communities or places without extensive resources for air quality monitoring to assume that particulate levels in the air match the levels of CO, within a reasonable degree of certainty. Our results show that there is a moderate correlation between CO and particulate concentrations in the air. This opens the door to deploying such systems in places where the cost of OPC sensors would be prohibitive, while still being able to give a relatively good estimate of particulate pollution concentrations.

Another reason why the study specifically targeted PM sensors is communication protocols. OPC sensors use the SPI communication protocol. This is more complex than simple AD conversion, which is used to acquire the readings of sensors that monitor other air pollutants. Moreover, AD conversion requires just one wire between the sensor and microcontroller, while SPI communication requires two.

It should be noted that the purpose of the sensor used in this study is limited to indicative measurements only, and that it is not intended to be used to give accurate particulate concentrations based on CO concentrations, but rather to track the change in the concentrations of particulates in correlation with CO concentrations. Another limitation worth mentioning is that the data were collected over 28 days, which is insufficient for far-reaching conclusions. The study would be more precise if the authors could track other confounding factors or sources of variation that may influence the relationship between CO and particulates, such as other meteorological conditions besides wind speed, traffic volume, land use, emission sources, etc. However, because the sensors were placed in an urban part of Novi Sad, where dense traffic accounts for most of the air pollutants emitted, we can conclude with a degree of reasonable certainty that motor vehicles played the most important role in contributing to the air pollutants measured. This part of town utilizes district heating, and measurements were taken at a time of the year when there is little or no agricultural work carried out in the fields. The best addition to this study would be a longer time period during which pollutant concentrations are tracked; however, SEPA only publishes pollutant concentrations for the past 30 days, and yearly concentrations are currently not available to the public.

The system could further be improved if temperature and relative humidity sensors, as well as wind direction sensors, were implemented. This leaves the field open for future research.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/pr11102984/s1, Concentrations of pollutants measured during the course of this study have been archived in an Excel spreadsheet.

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Data Availability Statement: Restrictions apply to the availability of these data. Data was obtained from the Serbian National Network of Automatic Stations for Air Quality Monitoring and are available by contacting the agency at office@sepa.gov.rs Publicly available data are available only for the last 30 days of monitoring.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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