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EQUIVALENCE OF LOW-COST PM_{10} CONCENTRATION MEASURING DEVICES WITH A REFERENCE METHOD USING VARIOUS CORRECTION FUNCTIONS

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ABSTRACT: The aim of the study was to build a corrective model that can be used in the analysed devices and to assess the impact of such a model on the values of the measured concentrations. The novelty of this study is the test of equivalence with the equivalent reference method for hourly data. The study used hourly data of PM_{10} concentrations measured in a chosen city in Poland. Data was collected from two PM_{10} sensors and a reference device placed in close proximity. In addition, air temperature, humidity and wind speed were also measured. Among the tested models, a linear model was selected that used primary measurements of PM_{10}, temperature, air velocity, and humidity as the most accurate approximation of the actual PM_{10} concentration level. The results of the analysis showed that it is possible to build mathematical models that effectively convert PM_{10} concentration data from tested low-cost electronic measuring devices to concentrations obtained by the reference method.

KEYWORDS: PM_{10}, environmental pollution management, air quality, low-cost devices, measurement equivalence

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Introduction

Classic methods of measuring pollutant concentrations allow the creation of a relatively sparse network of measurement points. The solution to this problem is the use of low-cost electronic measuring devices. They allow measurements of pollutants to be obtained at high spatial and temporal densities at a reasonable cost for their operation. There is a growing demand for low-cost measuring devices, but it is necessary to ensure that the measurements they obtain are the same as the values believed to be correct. This is possible by performing an equivalence test with a reference method.

Monitoring the state of the environment and counteracting the increase in pollution is a growing problem for central and local authorities. Air pollution has an impact on the health and quality of life of society, on the functioning of the region's economy, especially in tourism-related industries, and on real estate prices. Therefore, measures are taken to obtain reliable information not only about the state of pollution but also about the reasons for and causes of its formation. Consequently, it will be possible to manage sources of pollution and gradually reduce pollution.

Particulate matter (PM) plays a very important role among air pollutants. PM is a mixture of solids varying in size, origin, and chemical composition. The most studied fraction is $PM_{10,}$ whose particles have a diameter of less than 10 m. This may result from human activity or natural causes. Their composition and concentration depend on the environment, the presence of emission sources, population density, terrain, and climatic conditions (John et al., 2004; Jędrak et al., 2017; Wielgosiński & Zarzycki, 2018; Zhang et al., 2018; Simon et al., 2020).

An overview of the literature

Poor air quality can affect the health and well-being of residents, causing or exacerbating many diseases, especially in the upper respiratory tract, as well as cardiovascular and nervous systems. Therefore, it is necessary to monitor air quality in places where people are present (Szyszkowicz et al., 2010; Weir, 2012; Dąbrowiecki et al., 2015; Ayres et al., 2006; Jędrak et al., 2017; Zhang et al., 2018).

For this purpose, it is necessary to build a network of measuring devices to monitor PM concentrations. Air monitoring by state institutions (in Poland: GIOŚ – Chief Inspectorate of Environmental Protection, WIOŚ – Provincial Inspectorate of Environmental Protection) is unfortunately insufficient. The devices that they use are very precise, but the measurements are expensive, the measurement network is inadequate, and the results are only obtained once a day. It is, therefore, necessary to supplement that network with devices generating similar results while eliminating the disadvantages of the state network. In that situation, low-cost electronic air quality monitoring devices are the optimum choice.

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Currently, there are many different commercially available devices available that operate based on different methods of measuring pollutant concentrations. The most used ones utilise optical methods based on laser light reflection from pollutant particles, tapered element oscillating microbalance (TEOM), or methods based on the absorption of beta radiation. For each of these devices, it is important to ensure that their indications closely approximate the actual (reference) values of air pollution. It is necessary to carry out a procedure that checks whether the measurements obtained by these devices are close to actual measurements. This procedure is called methods equivalence testing (Buser et al., 2003; Shin et al., 2011; Owczarek & Rogulski, 2018; Rogulski & Badyda, 2018; Sówka et al., 2018; Notardonato et al., 2018; Hodoli et al., 2020).

Measurements obtained from low-cost electronic sensors are not immediately suitable for the assessment of pollutant concentrations. They must first be translated into the language used to assess pollutant concentrations. In most cases, it is also necessary to adjust the results through the appropriate function so that they are comparable with the results obtained by the reference method. This function is called the corrective function (Jaffe et al., 2022; Giordano et al., 2021; Wang-Li et al., 2005; Gębicki & Szymańska, 2012; Owczarek et al., 2018; Considine et al., 2021).

The form of the corrective function, the variables used, and the methods of its creation can be very different. In recent years, a sizeable body of research has emerged regarding the use of offset and gain calibration, temperature and humidity correction, sensor array calibration, multi-hop sensor calibration, and machine learning using random forests, neuro-fuzzy inference systems, and many others (Stavroulas et al., 2020). Most of the studies are based on the data on daily pollutant measurements, and only rarely are they carried out for data with a higher than hourly time density. This is mainly due to the operation of the reference method (gravimetric method) and the sharing of daily data (Maag et al., 2018; Zusman et al., 2020; Badura et al., 2019; Zimmerman et al., 2018; Kureshi et al., 2022; Alhasa et al., 2018; Chu et al., 2020; Lin et al., 2018; Maag et al., 2019; Bisignano et al., 2022).

The aim of this study is to demonstrate the possibility of building a function to correct the concentration measurements from a low-cost PM_{10} sensor to the values compliant with the reference measurements. This function can be implemented by the meter manufacturer in the device. In this study, it has been decided to build models based on multiple regression. Such models, as shown by many empirical studies, have a satisfactory ability to correct measurements. Having a regression model also allows the evaluation of its properties. Once built, the model will be used to correct the results of all devices based on the analysed sensor without the possibility of its continuous calibration at the place of use. For this purpose, reference measurements, which are not available for most locations, would be necessary.

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Tools for assessing the quality of regression models are commonly used to evaluate the resulting function. However, the mathematical compliance of the measurement series does not reflect the purpose of the correction. The aim is to obtain measurements that are largely comparable with the reference measurements. Hence, the methodology of testing the equivalence of PM_{10} measurement methods was used to evaluate the selected models. The methodology is based on the probability of obtaining results close to the reference. The novelty of the study is the use of hourly data for equivalency testing.

The authors have already dealt with the correction of data from the tested device (Owczarek et al., 2020). However, the study used daily data. The models built on their basis improve on the raw PM_{10} measurements satisfactorily enough that the device can pass the test of equivalence with the reference method. However, the basic application of the device is to measure with a much higher observation density. Data density transition into hourly measurements causes many disturbances that do not normally occur in daily data. For this reason, the behaviour of the PM_{10} measurements was also examined at a higher registration density. The results of the corrective models for both types of data are significantly different.

The use of the concepts of 'calibration function' and 'correction function' in concentration measurements in this article requires additional explanation. A calibration function is a tool described in the equivalence test methodology. It is used to transform measurement results, mainly to assess their correctness. It is a basic tool in equivalence testing and has been defined in the Guide to the Demonstration (EC Working Group, 2010). It has a linear form, one independent variable (PM_{10} measurement), its slope coefficient is postulated to be equal to 1, and the constant takes the value 0. This tool is recommended in the literature mainly for equivalence assessment. The second concept is the correction function. Its task is to transform the raw measurements of PM_{10} concentrations to values close to the reference measurements as an internal function of the device. It should take into account specific features of the measurement method and environment and alter the results so that they are correct. It has no restrictions as to its construction, functional form, and factors, as it is an informal creation. Partial correction is applied by manufacturers in the process of translating sensor operation into the language of pollution concentrations.

Research methods

Collecting data

The study used measurements from an electronic measuring device manufactured in Poland. This device is equipped with a laser dust sensor DF Robot Gravity SEN0177, based on the optical method. It can measure the concentrations of PM_{10}, $PM_{2.5}$ and PM_1 with virtually any time density (to hundreds of measurements per second). Additionally, the device is equipped with temperature, humidity, and air pressure sensors, as well as calculation and communication modules. The device is small and mobile. However, in conformity with the procedure described in the "Guide to the Demonstration of Equivalence (…)" created by the European Commission Working Group, two sensors (S1, S2) located a few meters from the reference device were used in the test of equivalence (EC Working Group, 2010). The air intakes of all devices were at the same height.

The measurements were carried out in the city of Nowy Sącz in the south of Poland in the period from 1 February to 30 June 2018. They covered both the cold and warm periods, which allowed for testing the operation of sensors in various weather conditions. The device works mainly in the conditions of urban pollution. In the surroundings, there are low-rise urban buildings, streets, and green areas. In the future, the device will be used in similar conditions of urban pollution. The measurements obtained by the sensor were aggregated and averaged to hourly measurements. In this way, after removing any missing data and erroneous measurements, 3,295 observations were obtained, which were used in the study (Figure 1). The values of PM_{10} concentrations were supplemented with the values of reference concentrations as well as air temperature, pressure, and humidity (Grubbs, 1950; GIOŚ, 2020).

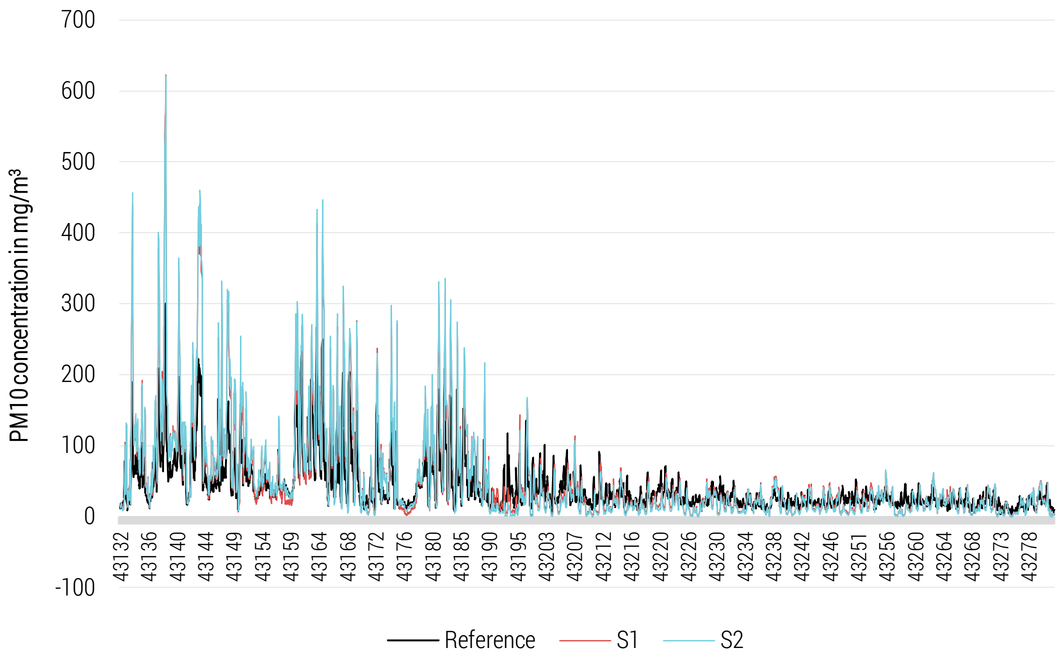

Figure 1. PM_{10} concentrations for the reference device and tested sensors (S1 and S2)

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Mathematical models

To better illustrate the relationship between the reference measurements of PM_{10} concentrations and the results of the operation of both sensors, Figures 2 and 3 show the enlarged fractions of Figure 1 in relation to the winter and summer periods. In the winter period (Figure 2), at low temperatures, high concentrations of PM_{10} and large differences between the measurements of individual devices are visible. In summer (Figure 3), when PM concentrations are low and temperatures are high, the differences are relatively small. This may indicate a significant influence of the PM concentration and, thus, the temperature on the measurement errors.

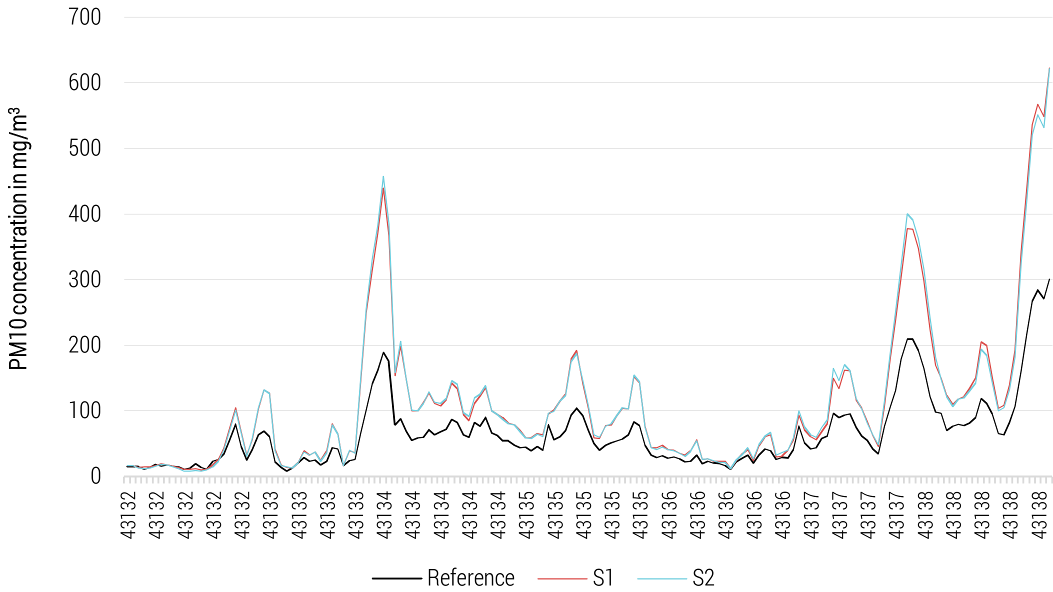

Figure 2. PM_{10} concentrations for the reference device and the tested devices (S1 and S2) in a selected week of the cold period (Feb 1-7, 2018)

The literature also shows a significant influence of air humidity on the correction function (Maag et al., 2018). However, neither of these factors allows for building high-accuracy models. In the study, it was decided to add wind speed to the factors in the models. It appears that particularly rapid air flows can distort the readings. Using this information, multiple regression models were built with different functional forms describing the behaviour of PM_{10} concentrations of the reference device depending on the other variables (GUM, 1999). The best-fit models were selected, and the values of expanded uncertainty were calculated for them.

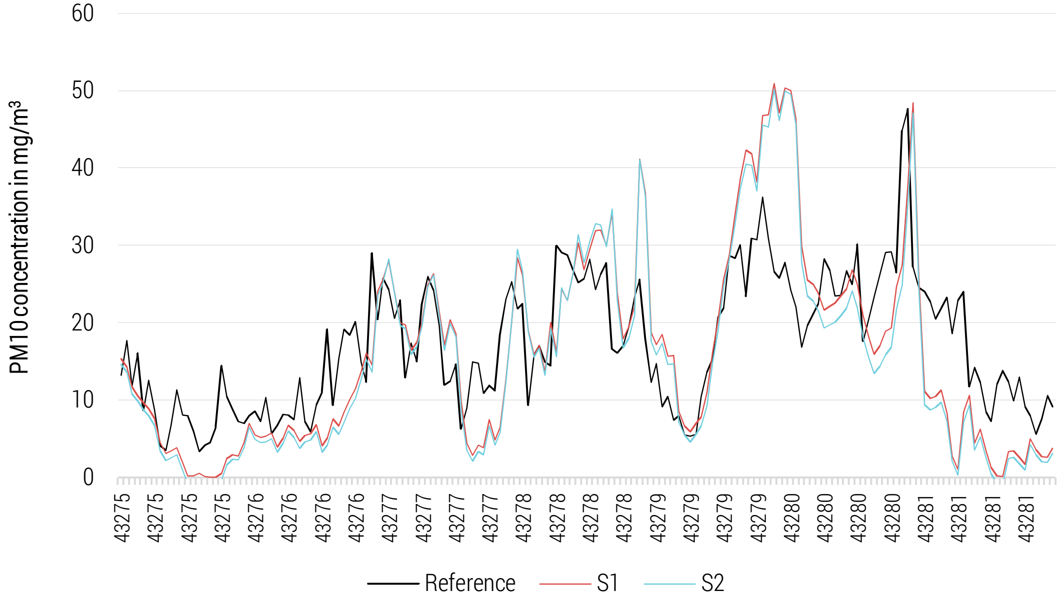

Figure 3. PM_{10} concentrations for the reference device and the tested devices (S1 and S2) in a selected week of the warm period (Jun 24- Jul 1, 2018)

In the further part of the study, only the data from one sensor was used to build the corrective function for the measurements of PM_{10} concentration.

Cross-validation was used to assess the quality of the obtained models. This allows the assessment of the model's ability to describe reality with the use of data that was not used to build this model. All the data we had was randomly divided into two parts: the teaching set, containing about 67% of all observations, and the testing set, containing 33% of all observations. The teaching set was used to build and evaluate the properties of the model. For this purpose, the adjusted coefficient of determination takes values from the range [0; 1]), and the residual deviation (RMSE – Root Mean Square Error) was used. Models with a higher value and less RMSE were better than the others. Then, empirical values were calculated for the resulting models based on the testing set and new RMSE values were calculated. Small differences between the original and the new values indicate the high ability of the model to describe reality and allow its use for practical purposes.

For all the created models, the significance of the structural parameters was tested using the *t*-test. All models with statistically insignificant structural parameters were removed from the analysis. The cumulative significance of parameter estimates of the model was also verified with the Wald *F*-test. Large values of the *F* statistics indicate that the whole model is significant and its structure is correct. In all the tests used, the significance was applied at the level of *a* = 0.05 (Myres, 1990; Czechowski, 2013).

The above-mentioned activities allowed for the identification of several models that had the best statistical properties and were best suited to empirical data. For these selected models, in the further part of the study, an analysis was performed using the procedure of testing the equivalence of PM_{10} measurements, in particular, the measurement uncertainty. This allows for assessing the equivalence of the corrected data with the reference data.

Equivalence testing methodology

The study began by testing the repeatability of the measurements of the analysed devices. It was verified whether two meters (sensors) showed the same PM_{10} concentration values. This was done by calculating Between Sampler Uncertainty using the following equation:

$$u_{BS}^2 = \frac{\sum_{i=1}^{N}\left(y_{i,1}-y_{i,2}\right)^2}{2n}, \tag{1}$$

where:
$y_{i,1}$ and $y_{i,2}$ – are measurements from two tested sensors.

According to the equivalence test guidelines (EC Working Group, 2010), the sampler uncertainty value lower than or equal to 6.25 $(\mu g/m^3)^2$ indicates slight differences between the results obtained by both sensors. This means that both devices measure in the same way, and the results of their measurements are comparable.

The second measure used in testing the equivalence of measurement methods is extended uncertainty (W_{CM}). The extended uncertainty is the product of W_{CM} – the relative combined uncertainty of the candidate method (sensor tested in the study) and the extension coefficient k, which is a critical value in the t-student distribution, for the appropriate number of degrees of freedom and the assumed significance of the study (in studies, the value k = 2 is most often used).

$$W_{CM} = k * w_{CM}. \tag{2}$$

However, the relative combined uncertainty is the sum of all estimates of measurement errors occurring in the equivalence test process divided by the maximum allowable PM_{10} concentration value (LV), i.e., 50 $\mu g/m^3$. The relative total uncertainty can be expressed by the formula:

$$W_{CM} = 2 * \sqrt{\frac{\frac{RSS}{n-2} - u^2(x_i) + [a+(b-1)*x_i]^2}{LV}}, \tag{3}$$

where:
$u^2(x_i)$ – is the measurement uncertainty of the reference method.

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For the gravimetric method, the value 0.67 μg^2/m^3; $[a+(b-1)x_i]^2$ is assumed as the measurement uncertainty arising from the deviation of the calibration function $y = a + bx$ from the identity function (it is assumed that in this function the difference between constant a and 0 is statistically insignificant, while the difference between the slope b and 1 should be considered statistically insignificant); while $\frac{RSS}{n-2}$ is the residual variance for the calibration function.

Large values of the expanded uncertainty of the candidate method indicate its low usefulness for approximating actual PM_{10} concentrations. Values close to 0 mean that the candidate method gives a satisfactory approximation of the reference method. The limit of acceptance of the method is 25% for extended uncertainty (Gębicki & Szymańska, 2012; Working Group, 2010; GUM, 1999; Dorozhovets, 2007; Gębicki & Szymańska, 2011; Green et al., 2009; Owczarek & Rogulski, 2018).

Results of the research

The comparison of the functioning of the two sensors showed that the differences in measurements between them are negligible. The Between Sampler Uncertainty value in the analysed period was . On this basis, it can be concluded that the indications of both devices have the same values. It also allows us to perform the analysis later in the study based on data from one sensor. The S1 sensor was selected for this analysis. In the rest of the article, the tested sensor will be marked as TS.

Correction functions with satisfactory properties were obtained only for the linear form and forms using the quadratic (second-degree) polynomial. The results of the estimation, i.e., the functional forms of the models, the values of the residual variance RMSE and adjusted coefficients of determination for the training set of data and residual variance for the test set, are presented in Table 1 for the linear model and Table 2 for the model with the quadratic polynomial.

In the case of linear models (Table 1), all built models with significant structural parameters were characterised by a high degree of adjustment to the dependent variable. This is confirmed by adjusted determination coefficients from 0.876 to 0.897. Those models also successfully passed Wald's F-test on parameter significance throughout the model. The RMSE values for the training set and the test set are similar. The differences between the RMSE values for training and testing data range from 0.75 to 1.01. The smallest difference was obtained for the LM and LM-TVH models, which were 0.85 for the LM-TVH model and 0.74 for the LM model. The relative difference between the RMSE values is 7.4% and 5.8%, respectively. It can, therefore, be concluded that the difference in the functioning of the model for training and test data is negligible. Thus, it can

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be concluded that the models are constructed reliably and could describe reality outside the training set.

Table 1. Multiple linear regression models for PM_{10} concentrations and the results of model cross-validation

Model description	Estimated form	RMSE for training set	Adjusted	*F* test statistics	RMSE for testing set
LM**	y_W=14.93+0.51*y_T	12.671	0.876	15294.975*	13.412
LM-TVH**	y_W=46.37+0.51*y_T-0.25*T -3.29*V+ -0.31*H	11.552	0.897	4711.376*	12.403
LM-TV	insignificant structural parameters	-	-	-	-
LM-TH	y_W=37.58+0.52*y_T-0.21*T -0.26*H	11.682	0.895	6125.838*	12.570
LM-VH	y_W=37.14+0.53*y_T-2.41*V-0.26*H	11.759	0.893	6037.044*	12.833
LM-T	insignificantstructuralparameters	-	-	-	-
LM-V	y_W=13.86+0.53*y_T+1.86*V	12.618	0.877	7720.975*	13.414
LM-H	y_W=31.81+0.52*y_T-0.22*H	11.830	0.892	8934.002*	12.841

* indicates statistically significant results with ***a***=0,05
** indicates the models selected for further analysis
y_w – reference concentration of PM_{10}, y_T – tested sensor concentration of PM_{10}, T – temperature, V – wind speed, H – relative humidity

The best fit was obtained for the model using PM_{10} concentrations from the tested devices *TS*, temperature *T*, humidity of the air *H*, and wind speed *V* (LM-TVH model). The coefficient of determination for this model had the highest value, equal to 0.897, and RMSE had the lowest value of 11.552. This model was chosen for further analysis. In addition, the simplest of the linear models using only observations from the tested PM_{10} measuring devices (LM model) was further analysed.

It can be concluded that using the reference method and the devices tested, errors in the results grow with increasing concentrations of PM_{10} (Figures 2 and 3). This may suggest a non-linear relationship (Czechowski, 2013; Dorozhovets, 2007). Table 2 presents the results of the estimation of the model using the second-degree polynomial for PM_{10} concentrations and the linear form of the remaining variables.

All obtained models satisfactorily describe the relationship between the dependent variable and the vector of independent variables. They have statistically significant parameters and successfully passed Wald's F-test on parameter significance throughout the model. The adjusted determination coefficients took values from 0.878 to 0.898. RMSE values of the training set ranged from 11.477 to 12.572. Also, the RMSE values for the test set were similar. It can be concluded

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that the resulting models have the correct construction. The exception is the QP-VH model. This model will not be used in further analyses.

Table 2. Multiple regression models for PM_{10} concentrations for the quadratic polynomial and the results of cross-validation of the model

Model description	Estimated form	RMSE for training set	Adjusted	*F* test statistics	RMSE for testing set
QP**	y_w=13.62+0.57*y_T-0.0002*y_T^2	12.572	0.878	7784.455*	14.059
QP-TVH**	y_w=42.40+0.56*y_T-0.0001*y_T^2-0,19*T+ -2.55*V-0.3*H	11.477	0.898	3818.908*	13.037
QP-TV	y_w=8.79+0.61*y_T-0.0002*y_T^2+0.08*T +2.73*V	12.454	0.880	3977.971*	14.730
QP-TH	y_w=34.99+0.58*y_T-0.0002*y_T^2-0.14*T + -0.26*H	11.555	0.897	4708.580*	13.533
QP-VH	y_w=34.77+0.60*y_T-0.0002*y_T^2-1.64*V + -0.26*H	11.579	0.896	4686.681*	110.101
QP-T	y_w=12.45+0.58*y_T-0.0002*y_T^2+0.07*T	12.563	0.878	5199.090*	14.303
QP_V	y_w=10.36+0.59*y_T-0.0002*y_T^2+2.63*V	12.471	0.880	5287.417*	14.384
QP-H	y_w=30.95+0.61*y_T-0.0002*y_T^2-0.24*H	11.610	0.896	6211.692*	14.137

* indicates statistically significant results with ***a***=0.05
** indicates the models selected for further analysis
y_w – reference concentration of PM_{10}, y_T – tested sensor concentration of PM_{10}, T – temperature, V – wind speed, H – relative humidity

For further analysis, models with the highest values were used, i.e., models using temperature *T*, humidity *H*, and wind speed *V*in addition to PM_{10} concentrations from the tested devices *TS* (QP-TVH). The coefficients of determination for this model were 0.898 and RMSE – 11.477. Like the linear function, the simplest form of the square model function (QP) was used for the analysis.

The differences between the RMSE values for training and testing data range from 1.49 to 2.53. For the models selected for further analysis, the difference was: 1.49 for the QP model and 1.56 for the QP-TVH model. The relative difference between the RMSE values is 11.9% and 13.6% respectively. That the difference in the functioning of the model for training and test data is noticeable but not too large. The test and training models behave similarly.

Two models: LF-TVH and QP-TVH have the best features. Of these, the LF-TVH model was chosen arbitrarily to present the results of the correction function. Figures 4 and 5 show sensor 1 data before (TS-before) and after correction (TS-corrected), and reference results. Based on these, it can be concluded that the PM_{10} concentration adjusted for the linear correction function LF-TVH approximates the values of concentrations of PM_{10} obtained using the reference method, and the measurement errors are minor and accidental (no systematic errors).

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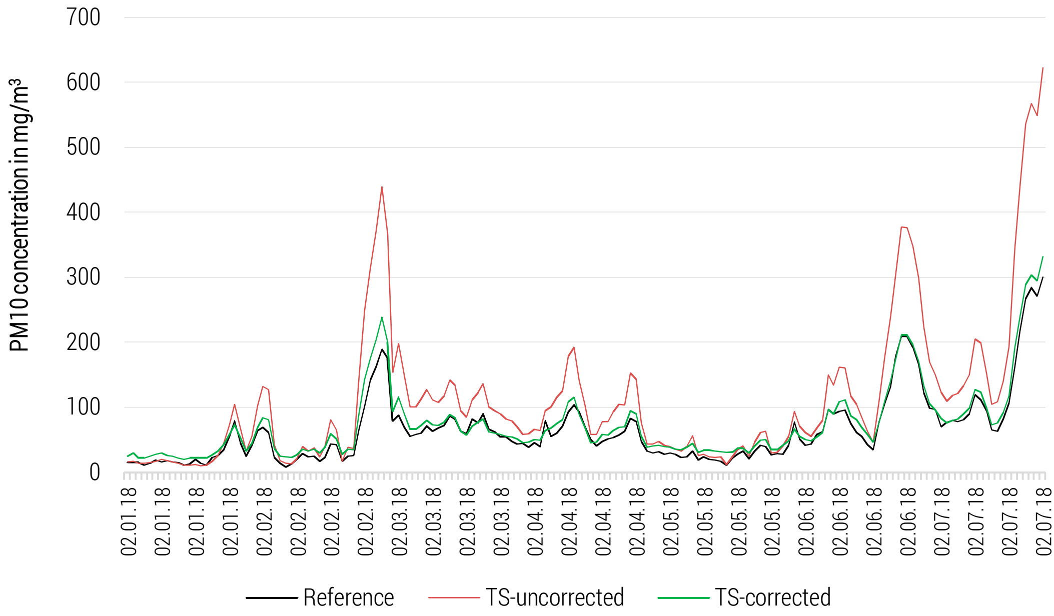

Figure 4. PM_{10} concentrations for the reference device and the tested sensor uncorrected data and after applying the LF-TVH correction function in the selected week of the cold period (Feb 1-7, 2018)

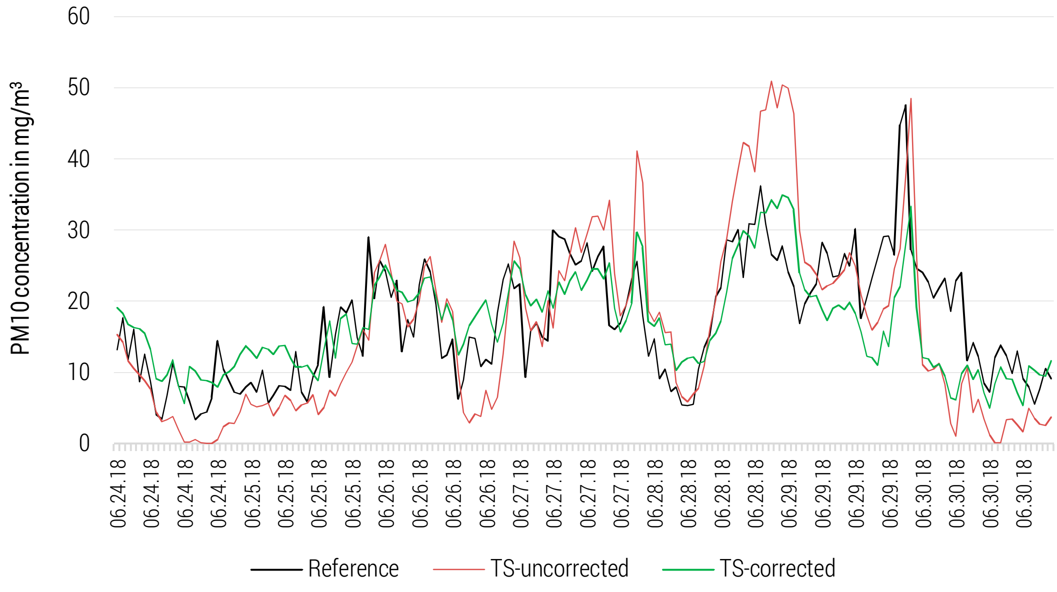

Figure 5. PM_{10} concentrations for the reference device and the tested sensor uncorrected data and after applying the LF-TVH correction function in the selected week of the warm period (24 Jun – 1 Jul 2018)

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It can be assumed that the PM_{10} concentration values from the tested sensor, transformed using each of the chosen models, approximate the concentration values obtained using the reference device. The second part of the analysis was carried out to confirm this assumption and to indicate the model that best corrects the measurement results of PM10 concentrations. It uses a measurement uncertainty testing procedure analogous to that used in the process of testing equipment equivalence (EC Working Group, 2010). In the calculation of the measurement uncertainty, all the collected data were used without division into the training and test sets.

However, the methodology for testing equivalence was created to compare measurements with the gravimetric method. That is the method in which the results are obtained every 24 hours. The equivalence assessment criterion, which is for the value of the candidate method's expanded uncertainty to be below 25%, may not be appropriate due to the higher frequency of measurements and the different nature of the data (the data is subject to at least daily fluctuations). However, no guidance has been developed on the verification of equivalence for hourly data, and therefore, this level has been taken as a critical uncertainty value in the study. Work on the creation of new measurement evaluation criteria, e.g., for hourly data, is currently running (Duvall et al., 2021).

For the selected models, the following were calculated: the residual variance of the model calibrating the method, the combined uncertainty, and the final measure used to assess the equivalence of the methods – expanded uncertainty. The results are presented in Table 3.

Table 3. Measurement uncertainty of PM_{10} concentrations corrected with selected correction models (candidate method)

	No correction function	LM	LM-TVH	QP	QP-THV
Residual variance of the calibration model (in [μg/m^3]^2)	616.49	167.06	140.58	167.50	138.61
Combined uncertainty of the candidate method (in μg/m^3)	30.40	3.23	3.10	5.44	3.30
Extended uncertainty of the candidate method	121.6%	12.9%	12.4%	21.7%	13.2%

The values of residual variances range from nearly 138.61 to 167,5 μg^2/m^3. The uncorrected values have almost four times the value of this measure. The lowest values of residual variance were obtained for the LM-TVH and QP-TVH models.

The values of all three measures indicate similar effectiveness in all tested correction models.

An examination of the combined uncertainty of the candidate method indicates high efficiency for all selected corrective models. The values of expanded uncertainty for these correction models are at a similar level, ranging from 12.4%

to 21.7%, while the value of expanded uncertainty for uncorrected data is over 121%. Values corrected using all the indicated models would meet the requirements for measurement uncertainty set by the Guide of Demonstration. Among the selected models, the LM-TVH linear model should be considered the most effective. It has the best properties of the regression model and the lowest measurement uncertainty. This model takes the following form:

$$y_w = 46.37 + 0.51y_T - 0.25T - 3.29V - 0{,}31H. \tag{4}$$

This model is the best fit for the reference data. For the training data sets, the value of the adjusted coefficient of determination is 0.897, and the RMSE is 11.552. For test data, they have values of 0.915 and 12.403, respectively. It can be assumed that the cross-validation of the model will produce satisfactory results, and the indicated model can be used to correct PM_{10} concentrations. In five similar studies conducted in 2017-2018 on hourly PM_{10} concentrations, coefficients of determination in the range of 0.61-0.84 were obtained (Duvall et al., 2021). Therefore, the results of our model should be considered at least satisfactory.

A similar $PM_{2.5}$ concentration model for Purple Air sensors has been developed by the EPA for the entire US. In this model, air humidity is an important factor, but temperature and wind speed are not used. Differences in the models may, however, result from the assessment of a different fraction of PM. This model has been repeatedly confirmed in field tests (Jaffe et al., 2022).

The estimated model parameters show that the test device overestimates PM10 concentration values. This value depends on other factors. An increase in temperature, relative humidity and wind speed causes the meter to overestimate the obtained values. At low values, the error is small; at high values, the measurement error increases.

An extended uncertainty of 12.4% was obtained in the equivalence study with the reference method. It is sufficient to consider the LM-TVH-corrected data as equivalent to the reference method. The correction model obtained in the study allows for the effective correction of the results provided by the sensors used in the study to a form that allows for demonstrating equivalence with reference values. This, in turn, allows the use of devices equipped with these sensors to properly monitor PM_{10} concentrations.

Discussion/Limitation and future research

The aim of the study was to show that the low-cost electronic device using optical PM_{10} sensors enables measurements consistent with the reference method. For this purpose, it was necessary to construct and test a function to correct the original measurements for additional factors to reference values. Hourly measurement data was used in the study. Due to the additional daily var-

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iability in the daily cycle, the models built on their basis, are more complicated and possibly less effective. In practice, however, such data are more often obtained from low-cost PM_{10} sensors.

In the correction model, as in many other studies, air temperature and humidity were used (Stavroulas et al., 2020; Shin et al., 2011; Owczarek & Rogulski, 2018; Rogulski & Badyda, 2018; Duvall et al., 2021; Giordano et al., 2021; Shahraiyni & Sodoudi, 2016). Many of these works point to different influences of factors, especially relative humidity in different ranges of values (Owczarek & Rogulski, 2018; Giordano et al., 2021). This indicates the non-linear nature of this interaction. However, it was noticed that such a set of factors is insufficient; therefore, it was decided to also include wind speed in the factors. Wind direction and speed were also indicated as important factors by (Shahraiyni & Sodoudi, 2016; Shin et al., 2011; Owczarek & Rogulski., 2018). An additional problem is the use of hourly data. Models using such dense data measurements are relatively rare. Examples could be (Shahraiyni & Sodoudi, 2016; Paschalidou et al., 2011; Fernando et al., 2012; Popescu et al., 2013). The study presents the estimation results of both types of models in which the dependent variables were PM_{10} concentration measured with the tested sensor, air temperature, humidity, and wind speed, while the independent variable was the reference PM_{10} concentration from an electronic device owned by the national measurement network.

It should be stressed that the study was performed for a specific type of PM_{10}-measuring device (although the name of the device was hidden). However, each of the devices available on the market, even if they work on similar principles, has different characteristics. Therefore, this study was intended to demonstrate that this particular device could be considered suitable for measuring PM_{10} concentrations. The results obtained in the study, specifically the parameter estimates of the model, are incomparable to those obtained for other devices. It is only possible to compare the significance of the variables used.

Most of the research in this area is carried out on daily data. This is consistent with the methodology for testing the equivalence of PM_{10} with the reference method developed by the EC Working Group in Guidance for the Demonstration of Equivalence. However, low-cost electronic devices are installed in many cases to ensure higher-density measurements. We want to obtain measurements on an hourly or even, in some cases, a minute basis. Averaging the data from hourly to daily data may change their properties. Some problems with hourly data will disappear after the averages are calculated. In addition to an equivalence test for daily data, an equivalence test for data with higher measurement densities is also necessary. Unfortunately, it is impossible to use the reference data originating from the gravimetric method, as this method functions only for measurements in the daily cycle. The novelty of this study is, therefore, the test of equivalence with the equivalent reference method for hourly data.

Many studies on the performance of low-cost PM_{10} measurement devices use a calibration function in the form of a linear function that transforms the measurements of a candidate method (our sensor) to reference measurements. This function uses these two factors exclusively. However, research shows that the performance of electronic sensors, including low-cost sensors, can be affected by various factors, including atmospheric ones. Primary factors include humidity and temperature, but wind speed and direction, as well as device location, are not to be underestimated. In addition, it is noted that sensors react differently to different levels of PM concentrations, humidity, or temperature. In other words, some sensors show the concentrations well when levels of these concentrations are average but fail to operate properly with high or low levels. The opposite may be the case with other sensors. This is due to the method of pollution detection used. Analogous relations apply to the air humidity factor. At low humidity, the device shows the measurement results correctly, whereas the results become distorted as the humidity increases. The reaction here is non-linear. Therefore, it is difficult to correct it by creating linear transformations. In our research, different forms of functions were used for correction, including non-linear functions (mainly in the form of second-degree polynomials) using a wider package of factors influencing the operation of the sensor. As a result, it was also possible to confirm mathematically the significance of the influence of factors and their type, which is an absolute novelty.

The disadvantage of the model developed is that it is not universal and cannot be used under all conditions. The requirements of the equivalence test indicate that we should calibrate the equipment for each location and each measuring condition. Initial calibration is usually done in the laboratory, but laboratory conditions do not reflect reality. Hence, the devices should be calibrated at the location where they will be used, and the equivalence test should take place under different weather/climate conditions. It should be noted that device calibration does not have to consider external factors. It is only assumed that for instrument calibration, they should be different throughout the data collection process. The data collected for our study are from February to June. So, they contain information about the device operating in different weather conditions, for low temperatures in winter and high temperatures in late spring and summer. Humidity was also different during this period. Our correction function uses these factors if they are deemed important. Our aim in collecting the data was to record observations with as much variation as possible in PM concentration, temperatures, humidity, etc. This allowed us to build an effective model. But, of course, it is effective in the statistical sense, not in the sense of a single measurement. It can therefore be assumed that the correction may not be effective when specific conditions occur that we have not observed before (extremely low temperatures) but it should respond well to different conditions in other seasons and subsequent years, as it has a built-in mechanism to respond to relevant factors (temperature, humidity, and PM_{10} concentration).

Based on the analyses performed, it can be concluded that both linear and quadratic models can be used to effectively correct the measurements of PM_{10}

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concentrations. However, the linear model turns out to be slightly better. It has better statistical properties of the regression model, is better suited to the reference data, and has lower measurement uncertainty. But it also has a simpler design. From a computational point of view, it does not matter much, but simple models are generally considered to be better.

Based on the selected model, it should be stated that the functioning of the tested PM_{10} sensor is statistically influenced to a large extent by temperature, air humidity, and wind speed. Due to the negative values of the relevant model parameters, an increase in the value of these three factors causes a downward correction of the PM_{10} concentration values. The reaction is quite weak for temperature and humidity but quite strong for wind speed.

By applying the indicated correction function, the measurements of PM_{10} concentration obtained with the tested device can be considered equivalent to the measurements obtained with the reference method.

Conclusions

The primary aim of the study was to demonstrate the possibility of mathematical correction of raw measurement data regarding PM_{10} concentrations from the tested low-cost device and to identify factors that significantly affect the operation of this device. An additional difficulty in the study was the use of hourly measurements and an attempt to adapt the model to this type of data. These goals have been achieved.

The results of the analysis showed that it is possible to build mathematical models that effectively transform PM_{10} concentration data from the tested, electronic, low-cost measuring devices to the concentrations obtained using the reference method.

The best correction results were obtained for the linear model using PM_{10} concentrations, wind speed, air temperature, and relative humidity. The statistical significance of the parameters in this model indicates a significant impact of these factors on the measurements of PM concentrations. The adjusted coefficient of determination above 87%, while the value of the expanded uncertainty was relatively low and amounted to 12.4%. This model can be used to correct raw measurements from the tested device effectively. It can be used in the construction of the tested low-cost device.

Further work is needed to design corrective functions. It is necessary to confirm the operation of this function in other terrain and weather conditions and to improve the procedure in terms of new measurement data and possibly other functional forms. Some further attempts planned for the 2020-2021 period failed due to the pandemic and will be carried out shortly.

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The contribution of the authors

Conceptualization, T.O.; literature review, T.O., M.R., P.O.C. and A.B.; methodology, P.O.C. and A.M.; formal analysis, M.R., P.O.C. and A.B.; writing, T.O., M.R., P.O.C., A.B. and E.C.; conclusions and discussion, T.O., M.R., A.B. and E.C.

The authors have read and agreed to the published version of the manuscript.

References

Alhasa, K. M., Mohd Nadzir, M. S., Olalekan, P., Latif, M. T., Yusup, Y., Iqbal Faruque, M. R., Ahamad, F., Abd. Hamid, H. H., Aiyub, K., Md Ali, S. H., Khan, M. F., Abu Samah, A., Yusuff, I., Othman, M., Tengku Hassim, T. M. F., & Ezani, N. E. (2018). Calibration Model of a Low-Cost Air Quality Sensor Using an Adaptive Neuro-Fuzzy Inference System. Sensors, 18(12), 4380. https://doi.org/10.3390/s18124380

Ayres, J., Maynard, E. L., & Richards, R. (2006). *Air Pollution and Health: 1st edition*. London: Imperial College Press.

Badura, M., Batog, P., Drzeniecka-Osiadacz, A., & Modzel, P. (2019). Regression methods in the calibration of low-cost sensors for ambient particulate matter measurements. SN Applied Sciences, 1, 622. https://doi.org/10.1007/s42452-019-0630-1

Bisignano, A., Carotenuto, F., Zaldei, A., & Giovannini, L. (2022). Field calibration of a low-cost sensors network to assess traffic-related air pollution along the Brenner highway. Atmospheric Environment, 275, 119008. https://doi.org/10.1016/j.atmosenv.2022.119008

Buser, M. D., Parnell, C. B. Jr., Shaw, B. W., & Lacey, R. E. (2003). Particulate matter sampler errors due to the interaction of particle size and sampler performance characteristics: PM10 and PM2.5 ambient air samplers. American Society of Agricultural and Biological Engineers, 50(1). https://doi.org/10.13031/2013.22403

Chu, H. J., Ali, M. Z., & He, Y. C. (2020). Spatial calibration and PM2.5 mapping of low-cost air quality sensors. Scientific Reports, 10, 22079. https://doi.org/10.1038/s41598-020-79064-w

Considine, E. M., Reid, C. E., Ogletree, M. R., & Dye, T. (2021). Improving Accuracy of Air Pollution Exposure Measurements: Statistical Correction of a Municipal Low-Cost Airborne Particulate Matter Sensor Network. Environmental Pollution, 268, 115833. https://doi.org/10.1016/j.envpol.2020.115833

Czechowski, P. O. (2013). *New methods and models of data measurement quality in air pollution monitoring networks assessment*. Gdynia: Gdynia Maritime University Press. (in Polish).

Dąbrowiecki, P., Mucha, D., Gayer, A., Adamkiewicz, Ł., & Badyda, A. (2015). Assessment of Air Pollution Effects on the Respiratory System Based on Pulmonary Function Tests Performed During Spirometry Days. Advances in Experimental Medicine and Biology, 873, 43-52. https://doi.org/10.1007/5584_2015_152

Dorozhovets, M. (2007). Proposals for extending the methods for determining the uncertainty of measurement results according to the GUM Guide. Pomiary Automatyka Robotyka, 1, 7-15. (in Polish).

Duvall, R. M., Hagler, G. S. W., Clements, A. L., Benedict, K., Barkjohn, K., Kilaru, V., Hanley, T., Watkins, N., Kaufman, A., Kamal, A., Reece, S., Fransioli, P., Gerboles, M., Gillerman, G., Habre, R., Hannigan, M., Ning, Z., Papapostolou, V., Pope, R., Quintana, P. J. E., & Lam Snyder, J. (2021). Deliberating Performance Targets: Follow-on workshop discussing PM10, NO2, CO, and SO2 air sensor targets. Atmospheric Environment, 246, 118099. https://doi.org/10.1016/j.atmosenv.2020.118099

Fernando, H. J. S., Mammarella, M. C., Grandoni, C., Fedele, P., di Marco, R., Dimitrova, R., & Hyde, P. (2012). Forecasting PM_{10} in metropolitan areas: Efficacy of neural networks. Environmental Pollution, 163, 62-67. https://doi.org/10.1016/j.envpol.2011.12.018

Gębicki, J., & Szymańska, K. (2011). Comparison of Tests for Equivalence of Methods for Measuring PM10 Dust in Ambient Air. Polish Journal of Environmental Studies, 20(6), 1465-1472.

Gębicki, J., & Szymańska, K. (2012). Comparative field test for measurement of PM10 dust in atmospheric air using gravimetric (reference) method and β-absorption method (Eberline FH 62-1). Atmospheric Environment, 54, 18-24. https://doi.org/10.1016/j.atmosenv.2012.02.068

Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V. F., Westervelt, D. M., Beekmann, M., & Subramanian, R. (2021). From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors. Journal of Aerosol Science, 158, 105833. https://doi.org/10.1016/j.jaerosci.2021.105833

Green, D. C., Fuller, G. W., & Baker, T. (2009). Development and validation of the volatile correction model for PM10–An empirical method for adjusting TEOM measurements for their loss of volatile particulate matter. Atmospheric Environment, 43(13), 2132-2141. https://doi.org/10.1016/j.atmosenv.2009.01.024

Grubbs, F. E. (1950). Sample criteria for testing outlying observations. Annals of Mathematical Statistics, 21(1), 27-58. https://doi.org/10.1214/aoms/1177729885

EC Working Group. (2010). *Guide to the demonstration of equivalence of ambient air monitoring methods.* https://www.aces.su.se/reflab/wp-content/uploads/2016/11/Demonstration_of_Equivalence_of_Ambient_Air_Monitoring.pdf

GUM. (1999). *Expressing measurement uncertainty. Guide.* Warsaw: Główny Urząd Miar. (in Polish).

Hodoli, H. C., Coulon, F., & Mead, M. I. (2020). Applicability of factory calibrated optical particle counters for high-density air quality monitoring networks in Ghana. Heliyon, 6(6), E04206. https://doi.org/10.1016/j.heliyon.2020.e04206

Jaffe, D. A., Miller, C., Thompson, K., Finley, B., Nelson, M., Ouimette, J., & Andrews, E. (2022). An evaluation of the U.S. EPA's correction equation for Purple Air Sensor data in smoke, dust and wintertime urban pollution events. Atmospheric Measurement Techniques, 16(5), 1311-1322. https://doi.org/10.5194/amt-16-1311-2023

Jędrak, J., Konduracka, E., Badyda, A., & Dąbrowiecki, P. (2017). *The impact of air pollution on health.* Kraków: Krakowski Alarm Smogowy. (in Polish).

John, A. C., Quass, U., & Kuhlbusch, T. A. J. (2004). Comparison study of the chemical composition of PM10 for days with high mass concentrations in three regions in Germany. Journal of Aerosol Science, 35, 797-808. https://doi.org/10.1016/j.jaerosci.2004.06.011

Kureshi, R. R., Mishra, B. K., Thakker, D., John, R., Walker, A., Simpson, S., Thakkar, N., & Wante, A. K. (2022). Data-Driven Techniques for Low-Cost Sensor Selection and Calibration for the Use Case of Air Quality Monitoring. Sensors, 22, 1093. https://doi.org/10.3390/s22031093

Lin, Y., Dong, W., & Chen, Y. (2018). Calibrating Low-Cost Sensors by a Two-Phase Learning Approach for Urban Air Quality Measurement. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2(1), 1-18. https://doi.org/10.1145/3191750

Maag, B., Zhou, Z., & Thiele, L. (2019). Enhancing Multi-hop Sensor Calibration with Uncertainty Estimates. *Proceedings of 2019 IEEE Smart World, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation,* Leicester, UK, 618-625.

Maag, B., Zhou, Z., & Thiele, T. (2018). A Survey on Sensor Calibration in Air Pollution Monitoring Deployments. IEEE Internet of Things Journal, 5(6), 4857-4870.

GIOŚ. (2020). *Measurement of particulate matter in the air.* http://powietrze.gios.gov.pl/pjp/content/show/1000919 (in Polish).

Myers, R. H. (1990). *Classical and modern regression with applications*. Pacific Grove: Duxbury Thomson Learning.

Notardonato, I., Manigrasso, M., Pierno, L., Settimo, G., Protano, C., Vitali, M., Mattei, V., Martellucci, S., & Fiore, C. D. (2018). The importance of measuring ultrafine particles in urban air quality monitoring in small cities. Geographica Pannonica, 23(4), 347-358. https://doi.org/10.5937/gp23-24447

Paschalidou, A. K., Karakitsios, S., Kleanthous, S., & Kassomenos, P. A. (2011). Forecasting hourly PM_{10} concentrationin Cyprus through artificial neural networks and multiple regression models: Implications to local environmental management. Environmental Science and Pollution Research, 18(2), 316-327. https://doi.org/10.1007/s11356-010-0375-2

Popescu, M., Ilie, C., Panaitescu, L., Lungu, M. L., Ilie, M., & Lungu, D. (2013). Artificial neural networks forecasting of the PM10 quantity in London considering the Harwell and Rochester Stoke PM_{10} measurements. Journal of Environmental Protection and Ecology, 14(4), 1473-1481.

Owczarek, T., & Rogulski, M. (2018). Uncertainty of PM10 concentration measurement on the example of an optical measuring device. SHS Web of Conferences, 57, 02008. https://doi.org/10.1051/shsconf/20185702008

Owczarek, T., Rogulski, M., & Badyda, A. J. (2018). Preliminary comparative assessment and elements of equivalence of air pollution measurement results of portable monitoring stations with using stochastic models. E3S Web of Conferences, 28, 01028. https://doi.org/10.1051/e3sconf/20182801028

Owczarek, T., Rogulski, M., & Czechowski, P. O. (2020). Assessment of the Equivalence of Low-Cost Sensors with the Reference Method in Measuring PM10 Concentration Using Selected Correction Functions. Sustainability, 12(13), 5368. https://doi.org/10.3390/su12135368

Rogulski, M., & Badyda, A. J. (2018). Application of the Correction Function to Improve the Quality of PM Measurements with Low-Cost Devices. SHS Web of Conferences, 57, 02009. https://doi.org/10.1051/shsconf/20185702009

Shahraiyni, H. T., & Sodoudi, S. (2016). Statistical Modeling Approaches for PM10 Prediction in Urban Areas; A Review of 21st-Century Studies. Atmospfere, 7(2), 15. https://doi.org/10.3390/atmos7020015

Shin, S. E., Jung, C. H., & Kim, Y. P. (2011). Analysis of the measurement difference for the PM10 concentrations between beta-ray absorption and gravimetric methods at

Gosan. Aerosol Air Quality Research, 11(7), 846-853. https://doi.org/10.4209/aaqr.2011.04.0041

Simon, E., Molnar, V. E., Tothmeresz, B., & Szabo, S. (2020). Ecological Assessment of Particulate Material (PM5 and PM10) in Urban Habitats. Atmosphere, 11(6), 559. https://doi.org/10.3390/atmos11060559

Stavroulas, I., Grivas, G., Michalopoulos, P., Liakakou, E., Bougiatioti, A., Kalkavouras, P., Fameli, K. M., Hatzianastassiou, N., Mihalopoulos, N., & Gerasopoulos, E. (2020). Field Evaluation of Low-Cost PM Sensors (Purple Air PA-II) Under Variable Urban Air Quality Conditions, in Greece. Atmosphere, 11, 926. https://doi.org/10.3390/atmos11090926

Sówka, I., Chlebowska-Styś, A., Pachurka, P., & Rogula-Kozłowska, W. (2018). Seasonal variations of PM2.5 and PM10 concentrations and inhalation exposure from PM-bound metals (As, Cd, Ni): first studies in Poznań. Archives of Environmental Protection, 44(4), 86-95. https://doi.org/10.24425/aep.2018.122305

Szyszkowicz, M., Willey, J. B., Grafstein, E., Rowe, B. H., & Colman, I. (2010). Air Pollution and Emergency Department Visits for Suicide Attempts in Vancouver, Canada. Environmental Health Insights, 4, 79-86. https://doi.org/10.4137/EHI.S5662

Wang-Li, L., Parnell, C. B., Shaw, B. W., Lacey, R. E., Buser, M. D., Goodrich, L. B., & Capareda, S. C. (2005). Correcting PM10 over-sampling problems for agricultural particulate matter emissions: Preliminary study. American Society of Agricultural and Biological Engineers, 48(2), 749-755. https://doi.org/10.13031/2013.18317

Weir, K. (2012). Smog in our brains. American Psychological Association, 43(7), 32.

Wielogosiński, G., & Zarzycki, R. (2018). *Technologies and processes of air protection.* Warszawa: Wydawnictwo Naukowe PWN. (in Polish).

Zhang, X., Chen, X., & Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. National Academy of Sciences of the United States of America, 115(37), 9193-9197. https://doi.org/10.1073/pnas.1809474115

Zimmerman, N., Presto, A. A., Kumar, S. P. N., Gu, J., Hauryliuk, A., Robinson, E. S., Robinson, A. L., & Subramanian, R. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. Atmospheric Measurement Techniques, 11(1), 291-313. https://doi.org/10.5194/amt-11-291-2018

Zusman, M., Schumacher, C. S., Gassett, A. J., Spalt, E. W., Austin, E., Larson, T. V., Carvlin, G., Seto, E., Kaufman, J. D., & Sheppard, L. (2020). Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. Environment International, 134, 105329. https://doi.org/10.1016/j.envint.2019.105329

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RÓWNOWAŻNOŚĆ NISKOKOSZTOWYCH URZĄDZEŃ DO POMIARU STĘŻENIA PM_{10} Z METODĄ REFERENCYJNĄ WYKORZYSTUJĄCĄ RÓŻNE FUNKCJE KOREKCYJNE

STRESZCZENIE: Celem badań było zbudowanie modelu korekcyjnego, który można zastosować w analizowanych urządzeniach oraz ocena wpływu takiego modelu na wartości mierzonych stężeń. Nowością w pracy jest test równoważności z równoważną metodą referencyjną dla danych godzinowych. W pracy wykorzystano dane godzinowe stężeń pyłu PM_{10} zmierzonych w wybranym mieście w Polsce. Dane były zbierane z dwóch czujników PM_{10} i urządzenia referencyjnego umieszczonych w bliskiej odległości. Dodatkowo mierzono również temperaturę powietrza, wilgotność i prędkość wiatru. Spośród testowanych modeli wybrano model liniowy, który wykorzystując pierwotne pomiary PM_{10}, temperatury, prędkości powietrza i wilgotności, najdokładniej przybliżał rzeczywisty poziom stężenia PM_{10}. Wyniki analizy wykazały, że możliwe jest zbudowanie modeli matematycznych, które skutecznie przeliczają dane o stężeniach PM_{10} z badanych tanich elektronicznych urządzeń pomiarowych na stężenia uzyskane metodą referencyjną.

SŁOWA KLUCZOWE: PM_{10}, zarządzanie zanieczyszczeniem środowiska, jakość powietrza, niskokosztowe urządzenia, równoważność pomiaru

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