International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 5
ISSN: 2088-5334

Prediction of Particulate Matter (PM) Concentration of Wooden Houses in the Highlands by Two Statistical Modelling Methods

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Abstract*—Wooden houses can potentially contain high levels of Particulate Matter (PM), which can cause lung disease in residents. Wooden houses have advantages in terms of maintaining the sustainability of building materials. Building design needs to pay attention to PM predictions in residential homes to avoid sick building syndrome. This study aimed to investigate and find predictive models for PM 10, PM2.5, and PM1.0 in wooden houses based on PM content in outdoor spaces. The study used quantitative methods by measuring PM10, PM2.5, and PM1.0 indoors and outdoors in wooden houses in Wonosobo Regency. The number of samples is 100 wooden houses. Measurements were carried out for one full day for each residential house. Data recording is done every 15 minutes—prediction model development using linear regression test and structural equation modeling (SEM). The results obtained three equations based on PM10, PM2.5, and PM1.0. $PM10_{indoor} = 53.202 + 0.406\ PM10_{outdoor}$; $PM2.5_{indoor} = 36.865 + 0.373\ PM2.5_{outdoor}$; $PM1.0_{indoor} = 34.143 + 0.194\ PM1.0_{outdoor}$. The difference with the results from SEM is $PM10_{indoor} = 52.89 + 0.41\ PM10_{outdoor}$, $PM2.5_{indoor} = 38.31 + 0.37\ PM2.5_{outdoor}$, $PM1.0_{indoor} = 26.58 + 0.19.PM1.0_{outdoor}$. There is no significant difference in the prediction results, so it can be concluded that the Prediction Model is valid. The implications of this research can provide input for improving the standard of PM content in wooden houses. The study results become input for the government in monitoring PM content in simple houses.

***Keywords*—Wooden house; highland; particulate matter (PM); prediction model.**

Manuscript received 17 Oct. 2022; revised 27 Nov. 2022; accepted 13 May 2023. Date of publication 31 Oct. 2023.

I. INTRODUCTION

Energy saving and health are the main issues in realizing Indoor Air Quality (IAQ) [1]. Energy use in buildings is at an alarming stage. The use of clean technology in buildings is expected to be one solution to reducing energy wastage. Using clean technology will create security, a clean environment, and economic benefits [2]. Energy savings in buildings are related to the thermal discomfort factor of building occupants [3]. Architectural elements have a role in thermal dispersion in buildings [4].

Thermal is one of the factors that cause energy wastage. Heat distribution can be a factor that is detrimental or beneficial for humans. To create good thermal performance, heat distribution in buildings needs to be considered. Building planning must be supported by predictions of human comfort in an area [5]. Thermal spread in urban areas makes the user community uncomfortable. The spread of heat in urban areas is increasing, giving rise to Urban Heat Islands [6]. Increasing Urban Heat Islands affects indoor air conditions. Indoor Air Quality (IAQ) will get worse.

Indoor Air Quality (IAQ) is critical to the health and success of indoor activities. PM10 content is one of the factors that affect IAQ. PM10 prediction will help realize IAQ [7]. In addition to PM10, PM2.5 content is also a factor that affects IAQ. PM2.5 is a smaller particle than PM10. Highland areas can potentially have high PM2.5 content [8]. The relationship between PM2.5 with local environmental factors and viruses is very close. The greater the concentration of PM2.5, the greater the possibility of spreading the virus [9]. Environmental factors around the building are one of the factors that increase the PM2.5 content in the room. Areas with many industrial areas will increase the PM content in the room [10].

PM10, PM2.5, and PM1.0 are the three particles significantly affecting the IAQ. The content of the three particles needs to be seen in the outdoor and indoor spaces of the building [11]. Prediction models are needed to estimate the success of planning conditions in buildings and land use [12]. Proper building planning will produce good building characteristics. Building characteristics can be disclosed in architecture with a narrative [13]. The characteristics of the building will affect the acceptance of the occupants of the thermal and air quality in the room [14]. Prediction of the relationship between surface temperature and air temperature in the architectural realm is still relevant using regression analysis [15]. There is a close relationship between indoor air quality variables.

The relationship between PM10 and PM2.5 in outdoor and indoor spaces was also strong in a Krakow residential study. Indoor IAQ is cleaner than outdoor IAQ [16]. The PM2.5 concentration in the indoor room is more influenced by the PM2.5 concentration outside the room [17]. Indoor activity can also cause particulate matter to form. The PM2.5 content in the classroom can be affected by the use of chalk to write on the blackboard [18]. Indoor pollutants were caused by activities in Hair care [19]. Activities in the house, especially cooking, cause an increase in the concentration of PM2.5 and PM1.0. The characteristics and types of cooking technology differ in the concentration of PM in the chamber [20].

The air exchange rate is essential in reducing the room's PM content. The results showed good ventilation could reduce PM content [21]. Windows are one of the architectural elements or tools that can be developed to reduce pollutant concentrations [22]. Filtration can also be a window companion tool to prevent the entry of pollutants into space [23]. Ventilation is challenging in soundproof buildings, so PM concentrations are high. Furniture in the room causes the addition of PM content [24].

Poor indoor IAQ occurs in residential homes. A study in China of 117 residential houses showed that only 2% of residential houses had PM2.5 content below 75 μg/m3 [25]. Residential houses in Portugal showed that 75% had PM10 concentrations above the threshold, and 41% had PM2.5 concentrations above the required threshold [26]. Air containing high PM concentrations is not only in urban and rural areas [27]. High PM in the air makes indoor air quality worse in all areas.

The composition of PM2.5 consists of various substances, including heavy metal compounds. Research results in Malaysian state kindergartens show that PM2.5 content worries children's health [28]. Research on PM content in residential homes will add information on the health of children and babies who still spend much time in their homes. Information will help increase IAQ in space [29].

The fulfilment of clean indoor air quality (IAQ) is carried out in various ways. Sensors to monitor particles can be placed in residential homes to monitor indoor air quality (Wang et al., 2020). Data-based sensors can also predict indoor pollutant concentrations [30]. Data-based sensors can also predict indoor pollutant concentrations [31]. How to build a model to predict pollutant concentrations can be done using machine learning [32]. Some models are added with pollutant purification equipment as a tool used to create a good IAQ [33].

Many people in Indonesia still belong to the lower class and live in wooden houses. Health factors often go unnoticed. IAQ in wooden houses is feared to have effective PM content. The community cannot afford to provide equipment to monitor PM concentrations. Research on PM content in wooden houses is still rarely done. A healthy home needs to pay attention to the maximum levels of PM10, PM2.5, and PM1.0. The residential design needs PM10, PM.2.5, and PM.1.0 predictions. This study aims to investigate and find predictive models for PM 10, PM2.5, and PM1.0 in wooden houses based on PM content in outdoor spaces.

II. Materials and Method

Climatic conditions in an area will also affect the concentration of pollutants in a particular area [34]. Highlands are areas with a certain height, so they have different climatic characteristics from the lowlands. Characteristics of the object of research affect the amount of a pollutant in the air [35]. PM content prediction research can be done by using linear regression statistical tests. Statistical tests are widely used to process data in indoor air quality (IAQ) research [36]. Linear regression analysis is relevant to be used as an analysis in making predictive models in indoor air quality research [37]. His study uses linear regression statistical test analysis using SPSS software.

A. Characteristics of the Area and Research Object

The research was conducted in Wonosobo Regency, Central Java, Indonesia. Wonosobo is an area with an altitude of 275-2250 meters above sea level. The location of Wonosobo Regency is shown in Figure 1. The air temperature in Wonosobo Regency is around 18-28ºC, and the average humidity is 81%. Wonosobo Regency is located in a mountainous area. Some of the mountains in the Wonosobo area are Mount Sindoro, Mount Sumbing, Mount Pakuwojo, Mount Bismo, and several others. Wonosobo also has the Dieng plateau, which is famous for its temples. The average air temperature in the Dieng Plateau is relatively low at 6-20 ºC. Humidity is quite high at 80-100%. Wonosobo Regency has several industries engaged in the timber sector, which are significant. The Wonosobo area still has a reasonably large forest. Wonosobo City also has public spaces like squares and city parks. Currently, housing and homestays are developing due to the increasing number of immigrants who stay for long or short periods to travel. Building developments can make air conditions worse.

The research object is a wooden house with a tin roof. The house has various floors. Some of the houses have concrete floors. Some houses have tiled floors, and some have earth floors. The house has a size that is not too wide. All residential houses use natural ventilation. Some houses rarely open their windows because the climatic conditions in Wonosobo Regency tend to be cold, so residents rarely open windows. The house has a ceiling height of approximately 3 meters. The front view of the wooden dwelling house can be seen in Figure 1a. Most houses have traditional fire stoves that use wood fuel to produce smoke when the stove is used for cooking. Furnaces are also sometimes used to warm the bodies of house residents. The traditional furnace can be seen in Figure 1b.

The research object that was studied was 100 houses. The number of samples in statistical research is at least 30 data.

Some experts say that statistical tests will get good results with a more significant number of research objects. Research with the number of research objects of 100 houses has met the statistical requirements.

Fig. 1 Characteristic of the object (a)Front view of a wooden house, (b)Traditional fire stove

B. Data Collection

PM10, PM2.5, and PM1.0 measurements were carried out in 100 residential houses for one day from 6 am to 9 pm every 15 minutes. Measurements were carried out outside and inside the room using a measuring device with the Krisbow brand. The tool is placed using a tripod (Figure 2). The data that has been obtained is graphed to show the fluctuations of the existing data.

Fig. 2 Measurement method

C. Data Analysis and Validation

Data analysis was using the statistical linear regression test with the PM as the variable. Three models are tested, namely PM10 outside and PM10 inside, PM2.5 outside and PM2.5 inside, and PM1.0 outside and PM1.0 inside. Linear regression requires data validity, data reliability, and classical assumption tests. Equation model was based on a regression test (Equation 1,2,3). Another analysis was carried out using structural equation modelling (SEM). Analysis with SEM as a form of Validation of regression analysis using SPSS. SEM analysis using AMOS software.

$$\text{PM10 indoor} = a + b.\text{PM10 outdoor} \quad (1)$$

$$\text{PM2.5 indoor} = a + b.\text{PM2.5 outdoor} \quad (2)$$

$$\text{PM1.0 indoor} = a + b.\text{PM1.0 outdoor} \quad (3)$$

III. Result and Discussion

A. Description and Test Data

The data obtained from one house are 61 data sets, so the data from 100 houses are 6100 data sets for one variable. The total data obtained from 6 variables (PM10 indoor, PM2.5 indoor, PM1.0 indoor, PM10 outdoor, PM2.5 outdoor, PM1.0 outdoor) is 18,300. The description of the data can be seen in Table 1. The minimum value is obtained from the indoor PM1.0 data and the maximum from the outdoor PM2.5. The average maximum value is obtained from the indoor PM10 data.

TABLE I
DESCRIPTIVE STATISTICS

	N	Range	Min	Max	Mean		Std. Deviation
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**
Particulate Matter 10 Indoor	6100	430.00	4.00	434.00	83.8807	.87046	67,98536
Particulate Matter 2.5 Indoor	6100	425.00	1.00	426.00	62.1143	.74268	58,00490
Particulate Matter 1.0 Indoor	6100	345.00	.00	345.00	44.6987	.52780	41,22247
Particulate Matter 10 Outdoor	6100	483.00	3.00	486.00	75.6557	.93132	72,73807
Particulate Matter 2.5 Outdoor	6100	498.00	5.00	503.00	67.6430	.79262	61,90595
Particulate Matter 1.0 Outdoor	6100	460.00	4.00	464.00	54.4467	.66020	51,56327
Valid N (listwise)	6100						

Test the validity of the data using Bivariate Pearson. The results of the data validity test show that the data validity test has a significance value of 0.000 (Table 2). The required significance value should not be more than 0.05 so that the data results include valid data. The data reliability test uses Cronbach's alpha value. The existing data has a Cronbach's alpha value of 0.876. The interpretation of Cronbach's alpha value is that if the alpha value is more than 0.90, then the reliability of the data is perfect. The reliability is high if the alpha value is 0.70 to 0.90. If the alpha value is less than 0.50, the reliability is low. The results of the alpha value of the existing data are high, so it includes reliable data.

TABLE II
DATA VALIDITY TEST

		PM10 Indoor	PM2.5 Indoor	PM1.0 Indoor	PM10 Outdoor	PM2.5 Outdoor	PM1.0 Outdoor
PM 10 Indoor	Pearson Correlation	1	.936**	.868**	.434**	.402**	.253**
	Sig.		.000	.000	.000	.000	.000
	N	6100	6100	6100	6100	6100	6100
PM 2.5 Indoor	Pearson Correlation	.936**	1	.873**	.395**	.398**	.246**
	Sig.	.000		.000	.000	.000	.000
	N	6100	6100	6100	6100	6100	6100
PM 1.0 Indoor	Pearson Correlation	.868**	.873**	1	.380**	.363**	.243**
	Sig.	.000	.000		.000	.000	.000
	N	6100	6100	6100	6100	6100	6100
PM 10 Outdoor	Pearson Correlation	.434**	.395**	.380**	1	.917**	.732**
	Sig.	.000	.000	.000		.000	.000
	N	6100	6100	6100	6100	6100	6100
PM 2.5 Outdoor	Pearson Correlation	.402**	.398**	.363**	.917**	1	.859**
	Sig.	.000	.000	.000	.000		.000
	N	6100	6100	6100	6100	6100	6100
PM 1.0 Outdoor	Pearson Correlation	.253**	.246**	.243**	.732**	.859**	1
	Sig.	.000	.000	.000	.000	.000	
	N	6100	6100	6100	6100	6100	6100

**. Correlation is significant at the 0.01 level (2-tailed).

B. *Outdoor PM Regression Test against indoor PM*

A regression test can be done if the variables to be tested are successfully tested with classical assumptions consisting of normality, heteroscedasticity, autocorrelation, and multicollinearity tests. Normality tests can use normality histograms. Standard data can be seen from the perfect bell-shaped histogram. The histogram results from the existing data show a perfect bell shape, so the existing data is classified as standard (Figure 3a, 3b, 3c).

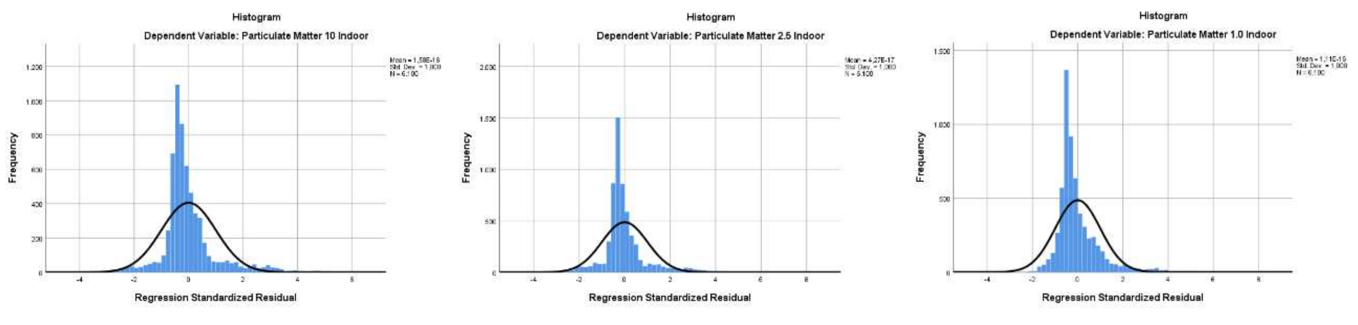

Fig. 3 Normality histogram, (a)outdoor PM10 to indoor PM10, (b)outdoor PM2.5 to indoor PM2.5, (c)outdoor PM1.0 to indoor PM1.0

Heteroscedasticity test using scatterplot diagram. Scatterplot data can be read by looking at the spread of data points. If the data points are spread out and do not make a clear pattern, it can be concluded that the data does not have heteroscedasticity symptoms. From the scatterplot results, it can be seen that the data points do not have a specific pattern, so it can be concluded that the existing data do not have heteroscedasticity symptoms (Figure 4a, 4b, 4c). The data includes the effect of outdoor PM on indoor PM, both PM10, PM2.5, and PM1.0.

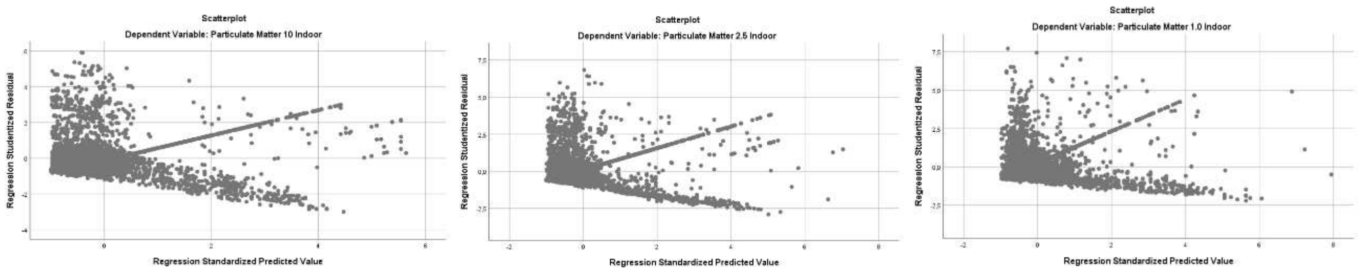

Fig. 4 Scatterplot, (a)outdoor PM10 against indoor PM10, (b)outdoor PM2.5 against indoor PM2.5, (c)outdoor PM1.0 against indoor PM1.0

The autocorrelation test was carried out by looking at the Durbin-Watson value and the multicollinearity test using the Tolerance and VIF values. The Durbin-Watson values are compared with the table values, and the significance values indicate the results in SPSS. The results of calculating the DW values are all significant, so there is no autocorrelation between the variables tested. The multicollinearity test has a Tolerance value greater than 0.1 or a VIF value of less than 10. The resulting Tolerance and VIF values are all the same, which is 1.00. The Tolerance value of 1.00 is higher than 0.1, and the VIF value of 1.00 is less than ten, so there is no multicollinearity of the independent variables. This result is consistent with the assumption that multicollinearity will likely occur when the independent variable is more than one. The equation used and tested uses only one independent variable.

TABLE III
AUTOCORRELATION AND MULTICOLLINEARITY TEST

Equation	D-W Value	Significant level	Tolerance	VIF
PM10_Ind = a + b.PM10_Out	0.751	0.000	1.00	1.00
PM2.5_Ind = a + b.PM2.5_Out	0.705	0.000	1.00	1.00
PM1.0_Ind = a + b.PM1.0_Out	0.828	0.000	1.00	1.00

The regression coefficient was obtained from the unstandardized coefficient B value from the linear regression test. The results of the regression coefficients become the values used to predict the tested variables. The results of the significance of the regression test get a value of 0.000. The value obtained is smaller than 0.05, so the regression results indicate that the resulting value is significant, explaining the strong influence between the independent variables on the dependent variable. The value of R^2 is also obtained from the linear regression test (Table 4).

TABLE IV
REGRESSION TEST

Equation	R^2 value	a value	b value	Significant level
PM10 Indoor = a + b.PM10 Outdoor	0.434	53.202	0.406	0.000
PM2.5 Indoor = a + b.PM2.5 Outdoor	0.398	36.865	0.373	0.000
PM1.0 Indoor = a + b.PM1.0 Outdoor	0.243	34.143	0.194	0.000

The regression coefficients' results can be written as an equation (Equation 4,5,6).

$$\text{PM10 indoor} = 53.202 + 0.406\ \text{PM10 outdoor} \tag{4}$$

$$\text{PM2.5 indoor} = 36.865 + 0.373\ \text{PM2.5 outdoor} \tag{5}$$

$$\text{PM1.0 indoor} = 34.143 + 0.194\ \text{PM1.0 outdoor} \tag{6}$$

C. Structural Equation Modeling (SEM)

Model development using SEM as a form of Validation of the linear regression test using SPSS. SEM has been used to create a predictive indoor air quality model and shows valid results as a decision support system [38]. The model development results using SEM are not much different from the prediction model made by regression analysis using SPSS software (Figure 5).

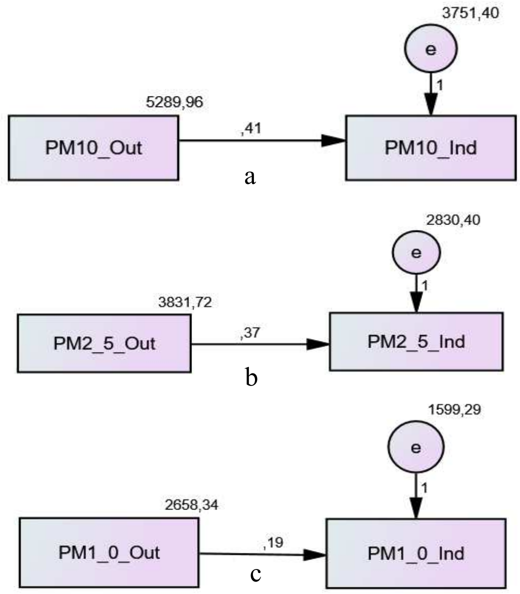

Fig. 5 Amos model, (a)outdoor PM10 against indoor PM10, (b) outdoor PM2.5 against indoor PM2.5, (c) outdoor PM1.0 against indoor PM1.0

$$\text{PM10 indoor} = 52.89 + 0.41\ \text{PM10 outdoor} \tag{7}$$

$$\text{PM2.5 indoor} = 38.31 + 0.37\ \text{PM2.5 outdoor} \tag{8}$$

$$\text{PM1.0 indoor} = 26.58 + 0.19.\text{PM1.0 outdoor} \tag{9}$$

The resulting mathematical equations are three according to the PM10, PM2.5, and PM1.0. The influence of outdoor PM on indoor PM is not absolute. This result is because factors within the room cause the amount of PM, such as smoke from cooking or smoking activities [39]. Residential houses in rural areas have a higher PM value than the required threshold, even though rural areas are believed to have less air pollution. Residential houses in the Qiqihar area have a high PM value that endangers elderly residents [40].

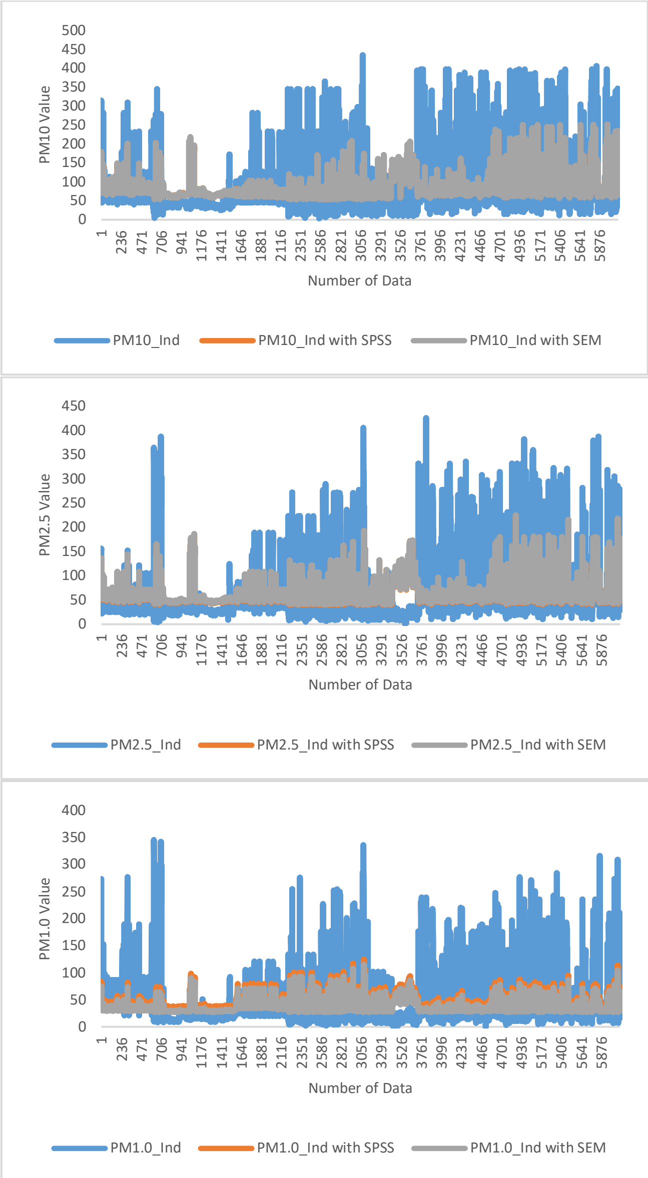

Fig. 6 Differences in the results of field data (PM2.5 Ind), the results of calculations using the SPSS model and the results of calculations using the SEM model, (a) outdoor PM10 against indoor PM10, (b) outdoor PM2.5 against indoor PM2.5, (c) outdoor PM1.0 against indoor PM1.0

Seasons also affect PM concentrations. Different seasons will create different PM concentrations. PM concentrations are more significant in summer than spring or winter [41]. The PM concentration does not affect the air conditioning in the room that uses air conditioning equipment. PM10 has a 4% impact, while PM2.5 has a 19% impact on poor indoor air quality. The impact caused by PM is considered insignificant in indoor air quality [42]. Research in China states that indoor PM concentrations can mediate the spread of the COVID-19 virus [43]. The concentration of PM in the room is still necessary to pay attention so that it does not exceed the required threshold. In addition, the construction of residential houses needs to pay attention to materials that can cause a large concentration of PM in the room. Human activities that cause PM must also be reduced and anticipated with healthy equipment. The accuracy of a predictive model needs to be compared with data from the field. Not all models can predict accurately according to the data in the field. A valid model can be similar to the data in the field [44].

Comparing the results obtained from calculations using the SPSS and SEM models is not much different. The prediction calculations for PM10 and PM2.5 are almost indistinguishable. Judging from the value of PM1.0, the calculation result using SPSS is slightly higher than the calculation from the SPSS model. The two predictions obtained by the SPSS model and the SEM model are quite different from the data from the field. The difference in data between SEM and SPSS predictions in the field is seen in the PM value above 200. The PM value above 200 from the field data includes anomaly values due to house factors. The PM prediction inside the room is calculated based on PM data from outside.

IV. Conclusion

Prediction of indoor PM concentration can be formed using linear regression test. Model validation is done by using a structural equation modeling model. The results of the two models built from SPSS or SEM show similar results. Slightly different results are seen in the formulation of the PM1.0 model. The calculation of data using SEM and SPSS has differences from field data. The data reference is a PM from outside the room. Factors causing the high PM concentration also come from inside the house, with activities that cause smoke. The model made to predict the PM concentration needs to be added to the factors causing the high PM from inside the room.

Acknowledgements

Ministry of Higher Education through PDKN 2022 (158/E5/PG.02.00.PT/2022), LLDIKTI 6 (No.021/LL6/PB/AK.04/2022), and LP3M UNSIQ (No.A.2.01/PDKN/LP3M-UNSIQ/2022) funded this research.

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