ARIMA forecasting of $PM_{2.5}$ and PM_{10} trends: effects of continuing social distancing on air quality in a Southeast Asian urban area

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Abstract It has been hypothesized that social distancing as the prevention measures for COVID 19 can affect the air quality including $PM_{2.5}$ and PM_{10} in urban areas. According to this situation, this study aims to compare the $PM_{2.5}$ and PM_{10} before and after the implementation of social distancing. Likewise, this study also forecasts the benefits of social distancing on $PM_{2.5}$ and PM_{10} if social distancing period is continued and extended. To achieve these objectives, an Auto Regressive Integrated Moving Average (ARIMA) model to investigate the daily $PM_{2.5}$ and PM_{10} trends has been developed for social distancing periods (March–May 2020) and after May as well. The model confirms that if social distancing period is extended after May 2020 then the $PM_{2.5}$ and PM_{10} are estimated will be 4% and 9% lower. To confirm that the $PM_{2.5}$ and PM_{10} reductions are only due to social distancing effect, the study has investigated the possible effects of wind speed and rainfall on $PM_{2.5}$ and PM_{10}. Nonetheless, the reductions do not correlate with those factors. To conclude social distancing should be considered as an option to control $PM_{2.5}$ and PM_{10} in urban areas.

Keywords: ARIMA, COVID 19, forecast**,** $PM_{2.5}$, $PM_{10,}$ social distancing

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Presently, particulate matter (PM) is considered as one of the pollutants that can have impacts on urban air quality (Badura 2018). Volcanic dust or desert dust particles and sea spray aerosols are known as the origin of PM in natural settings. Nonetheless, in urban setting the PM is originated from anthropogenic activities. Those activities including transport, agriculture, industrial processes, and household fuel combustions.

The particulate matters which are also known as aerosols are divided into 2 types according to its coarseness. Those suspended particles in the atmosphere include fine particulate matter ($PM_{2.5}$) and coarse particulate matter (PM_{10}). The particle diameters of $PM_{2.5}$ and PM_{10} are <2.5 µm and <10 µm, and both measured as µg/m^3. The $PM_{2.5}$ and PM_{10} have different sources and characteristics and able to interact with solar radiation, affect air quality, visibility, and the climate system including surface temperature and rain fall as well (Cruz and Pandis 1997, Sun and Ariya 2006, Zhang and Cao 2015).

Currently, the presence of fine particulate pollution especially in urban areas in the form of recorded $PM_{2.5}$ and PM_{10} has become a global issue due to its impact on human health, air quality, and the climate system as well. Correspondingly, routine air quality monitoring has been established in many countries for regular measurement of $PM_{2.5}$ and PM_{10}, for epidemiological studies as well as for the management of air quality (Al-Saadi *et al*.

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2005, Gomišcek *et al*. 2004).

Regarding epidemiological studies, the presence of current social distancing as parts of current COVID 19 pandemic prevention has been considered has an effect on the air quality including $PM_{2.5}$ and PM_{10}. A recent study by Xu *et al*. (2020) has provided a very comprehensive coverage regarding the impacts of the COVID 19 event on air quality in central China.

In urban areas mainly in Southeast Asian countries, there are several literatures that have discussed extensively the $PM_{2.5}$ and PM_{10} contents (Mohddin and Aminuddin 2014, Noor *et al*. 2015, Hossen and Hoque 2016). Nonetheless the COVID 19 event prevention in the form of social distancing related air quality studies are still limited. Meanwhile, several urban areas in Southeast Asian countries have experienced significant COVID 19 events. One of the populated urban areas is Jakarta. In here, social distancing was scheduled from mid-March through late May 2020. According that situation, this study aims to compare the $PM_{2.5}$ and PM_{10} before and after the implementation of social distancing. Likewise, an ARIMA model is used to investigate how far social distancing will affect the $PM_{2.5}$ and PM_{10} if social distancing period is extended.

Methodology

$PM_{2.5}$ and PM_{10} monitoring

The $PM_{2.5}$ and PM_{10} were monitored daily from March to May 2020. The March was representing the period before social distancing and April and May were representing the periods after social distancing. The $PM_{2.5}$ and PM_{10} data were obtained from meteorology agency and covered Jakarta, the one of populated urban areas in Southeast Asian. All $PM_{2.5}$ and PM_{10} data were measured as µg/m^3.

Wind and rainfall monitoring

It has been hypothesized that the meteorological parameters including wind speed and rainfall can affect the $PM_{2.5}$ and PM_{10} (Wang and Ogawa 2015, Zhang *et al*. 2017). In this study and to complement the $PM_{2.5}$ and PM_{10} analysis, the daily wind speed (km/h) and rainfall (mm/day) data were also collected from meteorology agency.

ARIMA forecasting

ARIMA is abbreviation for Auto Regressive Integrated Moving Average. This statistical approach is a versatile tool in forecasting an event in many fields (Alsharif *et al*. 2019, Tektas 2010). In ARIMA, autoregressive is stationarized series lags in the forecasting equation and moving average is the forecast error lags. The ARIMA forecasting equation is constructed as follows. First step to construct the equation is denoting the dth difference of Y by y below:

If $d = 0$: $y_t = Y_t$

If $d = 1$: $y_t = Y_t - Y_{t-1}$

If $d = 2$: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$.

Based on y terms, the ARIMA forecasting equation is:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

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The ARIMA model is used to forecast the trends of $PM_{2.5}$ and PM_{10} after the end of May 2020.

Results

A quantile–quantile (QQ) plot of $PM_{2.5}$ and PM_{10} is shown in Figure 1 and 2. The QQ plots were presented as comparisons of before and after social distancing periods. Before social distancing period, there were high frequencies of $PM_{2.5}$ within the ranges of 150-200 ug/m^3. Nonetheless, after social distancing has been implemented, $PM_{2.5}$ within the ranges of 100-150 ug/m^3 were observed frequently. The similar patterns were also observed for PM_{10} for before and after social distancing periods (Figure 2). Even though the $PM_{2.5}$ and PM_{10} showed a fluctuation pattern, there were reductions observed in April and May after social distancing was implemented.

The Figure 3 and 4 shows how the $PM_{2.5}$ and PM_{10} were correlated with the external factors including the wind speed and rainfall. The frequent wind speed ranges were 1-15 km/h while rainfalls within the range of 1-2 mm/day were common. Nonetheless, according to the correlation plots there were no significant effects of wind speed and rainfall on the both $PM_{2.5}$ and PM_{10}.

The ARIMA forecasting confirms that the $PM_{2.5}$ average will be 4% lower and the trend remains stable in a period after social distancing (Figure 5, 6). The lower average value was also observed for forecasted PM_{10}. For the PM_{10}, it is estimated that the average will be 9% lower and it also remains stable.

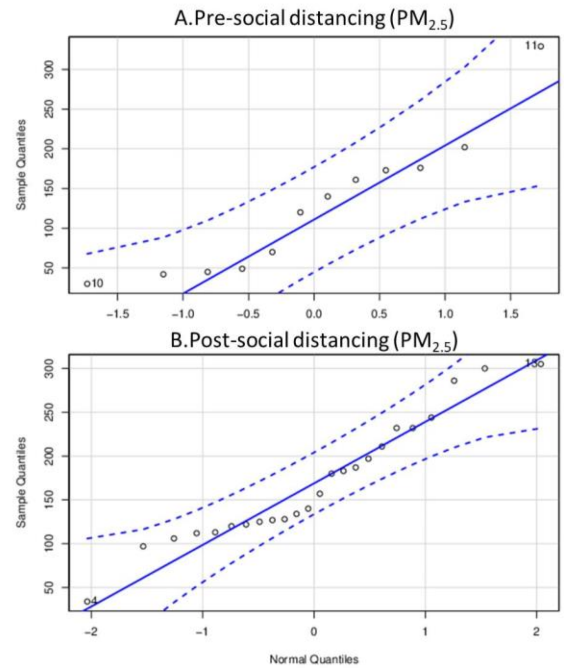

Figure 1. Normal probability plots (QQ-plot) of daily $PM_{2.5}$ before/pre/March (A) and after /post/April-May (B) social distancing.

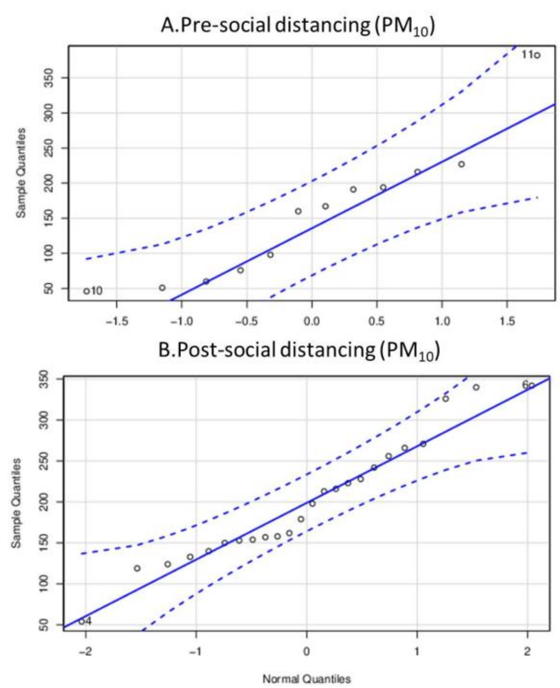

Figure 2. Normal probability plots (QQ-plot) of daily PM_{10} before/pre/March (A) and after /post/April-May (B) social distancing.

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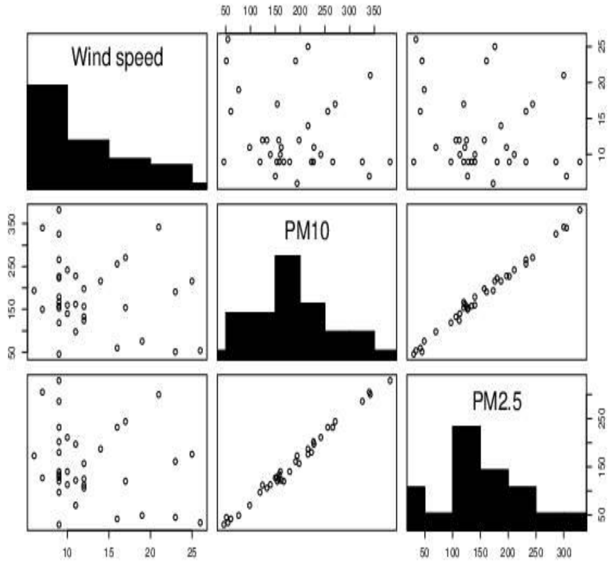

Figure 3. Correlation plots of daily $PM_{2.5}$ and PM_{10} with wind speed (km/h).

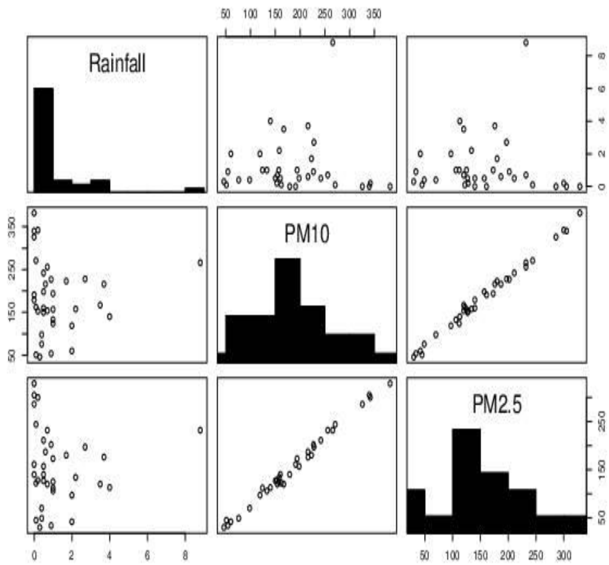

Figure 4. Correlation plots of daily $PM_{2.5}$ and PM_{10} with rainfall (mm/day).

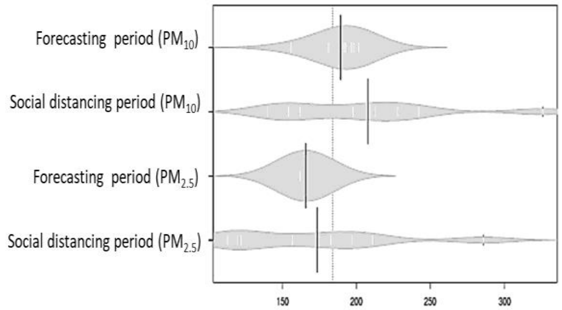

Figure 5. Violin plots of $PM_{2.5}$ and PM_{10} average for social distancing and forecasting periods.

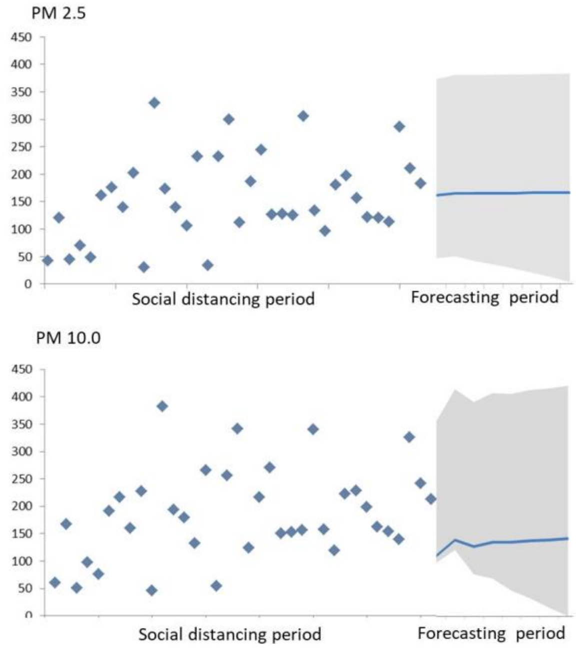

Figure 6. ARIMA model of daily $PM_{2.5}$ and PM_{10} for social distancing and forecasting periods.

Discussion

The $PM_{2.5}$ and PM_{10} measured in this study were also comparable to other urban areas. The data provided by Zhang *et al*. (2017) showed that in an urban industrialized area, the range of $PM_{2.5}$ was 6–209 µg/m^3 and PM_{10} can be higher with the range was 13–422 µg/m^3. Another study in 10 urban areas found the monthly average $PM_{2.5}$ ranges were >150–250 µg/m^3 and >250–300 µg/m^3 for PM_{10} (Li *et al*. 2020). In this study the ranges for $PM_{2.5}$ and PM_{10} are 32–329 µg/m^3 and 46–382 µg/m^3 respectively.

Both the PM_{10} and $PM_{2.5}$ were observed lower after social distancing than before social distancing was implemented. There are several literatures that have reported the impacts of social distancing on PM_{10} and $PM_{2.5}$. A decrease in air pollutant concentration as a consequence

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of social distancing in the form of mobility reduction in São Paulo since March 22, 2020 has been recorded by Freitas *et al.* (2020). The $PM_{2.5}$ values originated from diesel vehicle exhaust, soil resuspension, and biomass burning were on average 3.7 μg/m^3 lower than values without mobility reduction. Similarly, PM_{10} average concentrations were also 4.6 μg/m^3 lower. The similar conditions were also reported in the Asian urban areas. In 3 cities in China after the epidemic prevention and control actions had been taken, the average values of $PM_{2.5}$ and PM_{10} were observed 30% and 40% respectively lower than the values without epidemic prevention (Xu *et al*. 2020).

A comprehensive study of social distancing impacts on air quality in particular Southeast Asian country has been reported by Abdullah *et al*. (2020). In their study, they reported that social distancing in Malaysia or widely known as Movement Control Order (MCO) has been found to reduce $PM_{2.5}$ levels. In several cities in Malaysia, the range variations of $PM_{2.5}$ reductions were 6–23%, 8–16%, 11–13%, 7–11%, 15–23%, and 9–16%.

The above aforementioned situations characterized by $PM_{2.5}$ and PM_{10} reductions are best explained by the anthropogenic activities. Social distancing was fundamental detrimental factors causing the reduction of daily routine activities commonly occurs in the urban, commercial, and industrial areas. Nonetheless, before social distancing was applied, there are significant activities lead to the peak of PM_{10} and $PM_{2.5}$ Noor *et al*. (2015) reported that the PM_{10} peaks in residential areas were frequently observed at 9.00 am when people were leaving their home and reach the maximum peak at 10.00 pm when they were returning from school and work. During some particular times, the numbers of people performing their daily routine increase the motor vehicle numbers along with their emissions. The evening PM_{10} peak starts from 6.00 pm to 11.00 pm. The higher PM_{10} and $PM_{2.5}$ before social distancing period were evidence of the influence of traffic and other anthropogenic activities on PM_{10} and $PM_{2.}$ which is still allowed at that period (Garcia *et al*. 2016).

Beside anthropogenic factors, the PM_{10} and $PM_{2.5}$ are related to other regional external factors. For instance, Noor *et al*. (2015) reported that the PM_{10} variations are influenced by wind, rainfall, and season. The sudden PM_{10} peak can happens due to the wind that contains and delivers particles from other places. Nevertheless, PM_{10} can be so low due to the rainfall (Sansuddin *et al*. 2010). A seasonal variation of rainfall can also affect the PM_{10} seasonal fluctuation (Juneng *et al*. 2009). It requires the increase of rainfall from 20 mm/day to 100 mm/day to reduce the $PM_{2.5}$ ranges from 20-35 μg/m^3 to 5-7 μg/m^3 (Li *et al*. 2017, Wang and Ogawa 2015).

Season was also responsible for the PM_{10} variations (Hamid *et al*. 2018). It was observed that during the Southwest Monsoon the annual average of PM_{10} concentration had exceeded the thresholds while the PM_{10} concentration during the Northeast Monsoon was below the acceptable levels.

Despite the previous studies have found the fundamental correlations of the external factors including seasons, wind, and rainfall, nonetheless those factors are not significant in this study. Regarding the seasons, the location of this study is only having 2 seasons including the rain and dry seasons. This study was conducted during the homogenous rainy seasons with constants and stationary rainfalls. The recorded rainfalls during study period were dominated by the 0-2 mm/day ranges followed by the infrequent 3-8 mm/day ranges. While it takes a 20-100 mm/day rainfall range to cause variation and reduction of the $PM_{2.5}$ (Li *et al*. 2017).

Regarding the wind that assumed hypothetically can increase the PM_{10} and $PM_{2.5}$ due to the particles contained, this situation is not observed in this study. The study site was surrounded by settlement and suburban land uses rather than industrial, commercial, or emission generated land uses. Without the presence of industry in surrounding areas, then the prevailing winds will contain few particles and as consequence it will contribute less to the PM_{10} and $PM_{2.5}$.

Besides delivering the particles, the wind can also remove the particles and reduce the $PM_{2.5}$. Li *et al*. (2017) reported that the reductions of $PM_{2.5}$ from 35 to 15 $\mu g/m^3$ were caused by the increase of wind speed from 5 to 30 km/h. While, in this study, the most frequent wind speed were ranging from 1 to 10 km/h and has less effects on $PM_{2.5}$.

Currently, there are several approaches can be used to forecast PM_{10} and $PM_{2.5}$, they include statistical models, chemical transport, and machine learning (Deters *et al*. 2017). Statistical models emphasized on single variable linear regression have generally shown a negative correlation between PM_{10}, $PM_{2.5}$ and different meteorological parameters (wind, rainfall, and temperature). The recent one is the ARIMA model. Unlike a pure statistical method, ARIMA model only requires the time series prior data to generalize the forecast. Likewise, this model can increase the forecast accuracy while keeping the number of parameters to a minimum. This is the reason why ARIMA model is increasingly used to predict air quality (Abhilash *et al*. 2018, Arafat and Amir 2012, Wang *et al*. 2009).

In this study, a social distancing related ARIMA forecasting of $PM_{2.5}$ and PM_{10} has been proposed. The finding confirms and forecasts that $PM_{2.5}$ and PM_{10} will decrease. A capability of ARIMA model to do the forecasting of $PM_{2.5}$ and PM_{10} has been discussed by Zhang *et al*. (2017). The model can also adopt the environmental factors that may affect the dynamic of $PM_{2.5}$ and PM_{10}. In their study, the forecasted PM_{10} was observed fluctuating according to the seasons. Most recent studies even though have investigated the forecasted $PM_{2.5}$ and PM_{10}, nonetheless none of them have discussed the forecasted $PM_{2.5}$ and PM_{10} resulted

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from conditional factors in the form of policy in this case social distancing. However, as indicated by previous studies that environmental factors may influence the $PM_{2.5}$ and PM_{10} trends, then it is possible that conditional factors like tested in this study can affect the $PM_{2.5}$ and PM_{10} trends. As observed in this study, social distancing period factor if it is continued and extended can lower the $PM_{2.5}$ and PM_{10} in the future. Study by Zhang *et al*. (2018) has confirmed that policy factors can even contribute to reduce the $PM_{2.5}$. In their study, the forecasted $PM_{2.5}$ ranges were reduced from 19–52 $\mu g/m^3$ to 15–30 $\mu g/m^3$. This reduction is assumed related to the local policy on air quality.

Conclusion

Social distancing period has caused reduction of $PM_{2.5}$ and PM_{10} ranges from 150-200 $\mu g/m^3$ to 100-150 $\mu g/m^3$. The wind speed and rainfall were having less contribution in affecting the $PM_{2.5}$ and PM_{10} in before and after social distancing periods. The ARIMA forecasting confirms that by continuing social distancing period, it is estimated that the $PM_{2.5}$ and PM_{10} will be 4% and 9% lower.

Recommendation

Social distancing period is forecasted can lower the $PM_{2.5}$ and PM_{10}. For this reason, social distancing should be opted as a promising solution to control the $PM_{2.5}$ and PM_{10} mainly in the urban areas.

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