Impact of fine particulate matter on visibility impairment at Incheon Airport, South Korea

Wan-Sik Won¹#, Rosy Oh²#, Woojoo Lee³, Ki-Young Kim⁴, Sungkwan Ku⁵, Pei-Chen Su¹, Yong-Jin Yoon¹,⁶

¹ School of Mechanical and Aerospace Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore
² Department of Statistics, Ewha Womans University, 52 Ewhayeodae-gil, Seodaemun-gu, Seoul, Korea
³ Department of Statistics, Inha University, 100 Inha-ro, Michuhol-gu, Incheon, Korea
⁴ 4D Solution Co. Ltd., 286 Beotkkot-ro, Geumcheon-gu, Seoul, Korea
⁵ Department of Aviation Industrial and System Engineering, Hanseo University, 236-49 Gomseom-ro, Nam-myun, Taean-gun, Chungcheongnam-do, Korea
⁶ Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology (KAIST), 291 Daehak-ro, Yuseong-gu, Daejeon, Korea

Abstract

Low visibility at the airport causes significant weather delays and reduces the capacity of the airport. To better understand the factors that determine airport visibility, the present study examines the visibility at Incheon Airport, South Korea, and its relationship with meteorological conditions as well as particulate matter (PM) concentrations. Both PM₁₀ and PM₂.₅ concentrations are considered for the analyzed period of 2015–2017. The censored regression model reveals that airport visibility is significantly correlated with PM₂.₅ concentration rather than PM₁₀ concentration and provides capability to quantitatively describe the changes of airport visibility. Specifically, the interactions between PM₂.₅ concentration and meteorological conditions, such as fog, haze, high temperature, low relative humidity, and weak wind speed, primarily determine visibility degradation. The verification of this regression model for the severe fog event in March 2018 further shows that PM₁₀ and PM₂.₅ concentrations contribute to the visibility impairment by approximately ~8.0 km (~3.2 km by PM₁₀ and ~4.8 km by PM₂.₅) in hazy conditions at Incheon Airport. These results indicate that the PM₂.₅ concentration and interactions of meteorological conditions with PM need to be taken into account when diagnosing and predicting visibility impairment.

¹ Co-author; Corresponding author. Tel: 82-42-350-3233; Fax: 82-42-350-3210
E-mail address: yongjiny@kaist.ac.kr, peichensu@ntu.edu.sg
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INTRODUCTION

Low visibility is one of meteorological factors that severely affect flight safety and air traffic management by causing frequent flight delays and cancellations (Wong et al., 2006; Lee et al., 2011; FAA, 2017; Chen et al., 2018). The maximum capacity of the airport is also influenced by visibility, especially when the runway visual range (RVR) is below 550 m, corresponding to the instrument landing system (ILS) category I (CAT I) minimum (Hakkeling-Mesland et al., 2010; ICAO, 2013; Jones et al., 2017).

The visibility is defined as the longest distance that an object is recognized with eyesight (Hinds, 2012). It is typically affected by various types of weather events, such as rain, drizzle, snow, fog, mist, smoke, dust, sand, and haze. However, recent studies have shown that visibility is not simply influenced by the amounts of hydrometeors but also by the types and amounts of fine aerosols suspended in the air (Huang et al., 2009; Hyslop, 2009). The increased gaseous pollutants and particulate matters (PM) often cause low visibility by increasing light scattering and absorption (Singh and Dey, 2012; Xiao et al., 2014; Yu et al., 2016).

The PM is largely grouped into the two categories, as ones with an aerodynamic diameter of 10 µm and smaller (PM$_{10}$) and those of 2.5 µm and smaller (PM$_{2.5}$). Depending on this size and chemical composition, PM has different impacts on visibility as each chemical constituent differently contributes to the extinction coefficient and thus the visibility (Cao et al., 2012; Yu et
al., 2016). The significant correlation between visibility and concentration of PM$_{2.5}$ is already well documented (Pui et al., 2014; Mukherjee and Toohey, 2016). Among the PM$_{2.5}$ constituents, ammonium sulfate is a key factor that determines the visibility (and the extinction coefficient). Other species, such as PM$_{2.5}$ ammonium nitrate and organic matter, also affect the visibility, but their impacts vary in different conditions (Zhang et al., 2012; Wang et al., 2013; Chen et al., 2016).

The recent studies have further shown that the relationship between PM$_{2.5}$ concentration and visibility is not always linear but is modulated by relative humidity (RH) which is associated with particle hygroscopic growth (Day and Malm, 2001; Liu et al., 2013; Lee et al., 2016). By uptaking moisture under high RH conditions, the particle size of water-soluble PM$_{2.5}$ can increase, leading to an increased extinction coefficient and reduced visibility. However, the quantitative relationship between PM$_{2.5}$ concentration and visibility under various meteorological conditions has not been established.

Due to its complexity of the process involving radiation, turbulence, droplet microphysics, dynamics, aerosol chemistry, and surface conditions, visibility forecast is quite challenging for both statistical models and numerical models (Doran et al., 1999; Smith et al., 2002; Gultepe et al., 2007; Chmielecki and Raftery, 2011; Herman and Schumacher, 2016). Regardless of the details, both models consider fog as the most adverse meteorological condition for visibility. The
prediction of fog itself, however, is difficult due to its complicated formation and maintenance processes of small spatial and short time scales. The visibility forecast becomes even more difficult if PM$_{2.5}$ and PM$_{10}$ concentrations are taken into account. As such, most numerical weather prediction models neglect aerosol loading in determining the visibility (Clark et al., 2008).

Several studies have investigated the effect of PM and weather variables on visibility by empirical modelling based on regression analysis for long-term visibility trends. Tsai (2005) developed an empirical model for visibility prediction using regression analysis with data collected for 9 years in urban areas of Taiwan, presenting the importance of PM$_{10}$ on visibility impairment. Lin et al. (2012) also showed that PM$_{10}$ and meteorological conditions affect visibility by developing an empirical regression model based on 5 years of measured air quality and meteorological parameter in megacities in China. These empirical models, however, are hardly applicable to recent low visibility prediction at Incheon international airport (IIA) due to the exclusion of high relative humidity (> 90%) data and the absence of PM$_{2.5}$ concentration data.

The present study aims to better understand the relationship between visibility and PM concentrations especially at the airport by examining and predicting visibility impairment at IIA, South Korea relative to PM concentration.
The IIA, located on Yeongjong Island off the west coast of the city of Incheon (Fig. 1), is one of the largest and busiest airports in East Asia. Since the airport is placed in an island downstream of industrial regions of northeastern China, its visibility is likely influenced by sea fog formed over the Yellow Sea (Gao et al., 2007; Zhang et al., 2009) as well as PM locally emitted or regionally transported from neighbouring countries (Castellanos et al., 2017; Kim et al., 2018).

While throughout a year the most dominant wind direction is west-northwest, on foggy days of spring, autumn, and winter east wind is more dominant (Leem et al., 2005). In fact, on 23–24 December 2017, PM$_{10}$ and PM$_{2.5}$ concentrations around IIA were as high as 110–150 µg m$^{-3}$ and 60–120 µg m$^{-3}$, respectively. These have likely caused poor visibilities and record-high flight delays at the airport (KMA, 2017; NIER, 2017; MOLIT, 2018).

By combining meteorological measurements at IIA and PM measurements at Unseo air quality monitoring station nearby IIA (Fig. 1), we attempt to quantify the impacts of PM$_{10}$ and PM$_{2.5}$ concentrations on airport visibility. As described in the next section, censored regression model is specifically used to evaluate the importance of PM concentration for the period of 2015–2017.

Although meteorological measurements, including visibility, have been conducted since the opening of IIA in 2001, PM$_{2.5}$ measurements have been available only since 2015, as the nationwide PM$_{2.5}$ measurement network was established only in 2015 (ME, 2013; Lee, 2014).

**METHODS**
Data

This study investigates the relationship between weather variables from IIA and PM concentration nearby the airport (Unseo air quality station). The locations of IIA and Unseo station are shown in Fig. 1. The IIA (37.463°N, 126.439°E), which opened in March 2001, is placed at Yeongjong Island, 60 km west of Seoul. The collected weather data are hourly observations of visibility (VIS), present weather (WX), wind speed (WS), air temperature (TMP), and dew point temperature. The RH is estimated in regards to air temperature and dew point temperature (Lawrence, 2005). Each variable has a total of 26,304 observations for the period of 2015–2017, with no missing data intervals.

Although not shown, the 43 different types of WX observed from IIA (WMO, 2014, 2017) are classified into eight categories in this study: haze (HZ), widespread dust (DU), mist (BR), fog (FG), drizzle (DZ), rain (RA), snow (SN), and no significant weather (NONE). It turns out that NONE is most prevalent, which accounts for 16,437 observations (62.5%). It is followed by BR (5,087; 19.3%), HZ (2,265; 8.6%), FG (463; 1.8%), DU (218; 0.8%), RA (1,546; 5.9%), SN (187; 0.7%) and DZ (101; 0.4%). This grouping is important because each weather condition has a different effect on visibility degradation and possibly leads to different interaction with PM concentration.

Unseo air quality station (37.495°N, 126.488°E), which is located 5 km east-northeast of IIA, opened in 2007. Although both PM$_{10}$ and PM$_{2.5}$ concentration data have been collected hourly,
PM$_{2.5}$ observations began late in 2015. Over the period of 2015–2017, 10.8% of PM$_{2.5}$ observation data were unrecorded, and 7.5% for PM$_{10}$ observations. When both PM$_{2.5}$ and PM$_{10}$ observations are considered, missing observations are 15.4% and 22,261 observations are available. It is found that PM$_{10}$ concentration at Unseo station ranges from 2 to 949 µg m$^{-3}$ with a mean value of 45.84 µg m$^{-3}$. Likewise, PM$_{2.5}$ concentration ranges from 1 to 111 µg m$^{-3}$ with a mean value of 24.16 µg m$^{-3}$. It is important to note that the PM$_{2.5}$ mean value is larger than the annual standard of 15 µg m$^{-3}$ from the Korean government, 12 µg m$^{-3}$ from the U.S. government, and 10 µg m$^{-3}$ recommended by the World Health Organization (WHO) (WHO, 2006; USEPA, 2016; ME, 2018).

**Censored Regression Model**

To examine the effects of the PM concentrations and weather conditions on airport visibility, the censored regression model is built. A total of 6 variables, PM$_{10}$, PM$_{2.5}$, WS, TMP, RH, and WX are utilized to construct the model of airport visibility. Numerous studies have revealed that WS, TMP, and RH among other weather variables have significant effects on visibility. Accordingly, Tsai (2005) and Lin et al. (2012) select WS, TMP, and RH as predictors excluding the data collected during rainfall. Data with RH > 90% were excluded in consideration to the particle hygroscopic effect. Yet, there is no clear reason to divide the criteria below 90% and above 90% (Malm and Day, 2001). Also, high levels of RH should not be excluded for airport
low visibility as the present study focuses on not only hazy but also foggy conditions. Shen et al. (2015) classifies the weather conditions based on visibility and RH into three types, namely Clear, Haze, and Fog. Measurements with rain or snow were excluded to separate out the particle scavenging effect by precipitations. The results have shown that the degradation of visibility under foggy condition is less sensitive to the PM$_{2.5}$ concentration. As mentioned above, weather classification is essential for the examination of PM contribution to the degrading of visibility. For these reasons, WS, TMP, all level of RH, and WX were selected as the predictors in the model.

Unlike conventional regression model, censored regression model is useful for data whose range is limited. Censoring occurs when observations have incomplete information partially available. In censored regression model, the dependent variable has the only information that it is beyond the boundaries, but not how far above or below it. For example, in survival analysis, observed time from an individual still alive at the end of the study is deemed to be censored because we only know that the event time (e.g., death) is after the observed time. The dependent variable in this study, airport visibility, is reported between 0 and 10,000 m. The values larger than 9,999 m are simply set to 9,999 m (WMO, 2014) as an air operator may not care about the level of such nice weather, which means we have partial information about the visibility that it is greater than 9999 m. Thus, it is appropriate to consider the airport visibility as censored data. As
shown in Fig. 2 and 3, significant number of observations shows the visibility of 9,999 m which is upper boundary, indicating the adequate use of the censored regression model. The ranges of other variables are listed in Table 1.

Tobit model, which is commonly used for censored data, is utilized in this study with vglm function in R (Tobin, 1958; Yee, 2018). vglm function which is located in VGAM (Vector Generalized Linear and Additive Models) package is for fitting vector generalized linear models including various univariate and multivariate distributions (Yee and Yee, 2019). The statistical relation between \( x \) and \( y \) is expressed as follows:

\[
y_i^* = x_i \beta + \varepsilon_i
\]

\[
y_i = \begin{cases} 
l & y_i^* \leq l \\
l < y_i^* < u & u \\
& y_i^* \geq u
\end{cases}
\]

where \( x_i \) is weather variables at IIA and PM concentrations at Unseo station, \( y_i \) is airport visibility between 50 and 10,000 m, \( \beta \) is mean change of \( y_i^* \) when 1 unit increase in \( x_i \), \( \varepsilon_i \sim N(0, \sigma^2) \) is random error, \( l \) is 0 m, and \( u \) is 10,000 m.
When constructing regression model, multicollinearity can exist when one predictor is very close to a linear combination of other predictors. In this case, the standard errors become large and the coefficient estimates can change dramatically to the slightest changes in model configuration. As such, we first assess multicollinearity of predictors by computing cross correlation coefficients and variance inflation factor (VIF). As summarized in Fig. 4, cross-correlation is generally small in most cases ($r < 0.6$). Except for WX which is a categorical variable, VIF for WS, TMP, RH, PM$_{10}$, and PM$_{2.5}$ is 1.3, 2.6, 1.4, 1.4, and 1.5 respectively (Table S-4), which is small enough to ignore multicollinearity in this study (Montgomery et al., 2012).

As for WX, the boxplots categorized by eight WX levels show that each variable has little association with WX in that they are mostly similar and no significant difference is found among the categories. In the boxplots of VIS, FG only has particularly low values, which is because fog is defined as being visibility of less than 1 km. That means WX might be not independent with visibility. However, as we focus not only on airport low visibility but also its variation within each category of WX it is indispensable to include WX in this study.

All models used in this study are summarized in Table 2. While Model 0-2 are no interaction models, Model 3-8 are the interaction models that include the interaction terms between weather variables and PM concentrations. Interaction indicates the influence of one factor on the effect of another factor, and vice versa. If the effects of one variable are different at different levels of
another variable, there is interaction between these two variables. Previous studies have shown that impact of PM concentration on visibility is dependent on weather variables, specifically RH levels (Malm and Day, 2001; Liu et al., 2013; Yu et al., 2016), which implies that the PM may influence weather affecting visibility degradation in different ways. Thus, interaction term is incorporated in the model to better predict visibility impairment. Model 8 has minimum Akaike Information Criterion (AIC) and is reasonably considered as optimal model in this study (Akaike, 1974). AIC consists of a goodness-of-fit measure and model complexity and thus can be used even for non-nested model comparison. Furthermore, we have conducted a likelihood ratio test (LRT) to compare two nested models provided smaller model is a special case of the larger model. For example, Model 0-7 are nested within Model 8, which the former models can be represented as Model 8 with zero coefficients for a subset of independent variables. The larger model and the smaller model are called as full model and reduced model, respectively. LRT is for testing the null hypothesis, $H_0$: reduced model is adequate, versus the alternative hypothesis, $H_1$: Not $H_0$, with the test statistic given as

$$LRT = -2(\log L_r - \log L_f)$$

(2)
where $L_r$ is a likelihood function for reduced model and $L_f$ is a likelihood function for full model.

Table 3 summarizes the result of LRT with p-value at the 0.05 level of significance. Row and column of the table represent the reduced model and the full model, respectively. In the table, NA indicates that the two models are not nested so LRT cannot be obtained.

For example, we can compare Model 4 (PM$_{2.5}$ excluded) and Model 8 using LRT as Model 8 contains all the parameters of Model 4, PM$_{2.5}$ and PM$_{2.5}$’s interactions so that the two models are nested. Based on the LRT with p-value less than 0.0001, there is a significant evidence that the null hypothesis, $H_0$: Model 4 is adequate, is rejected and Model 8 is more appropriate to explain the dataset.

In the case of comparing Model 5 (PM$_{10}$ excluded) to Model 7 (PM$_{10}$’s interactions excluded), based on the LRT with p-value larger than 0.1, there is not a significant evidence that the null hypothesis, $H_0$: Model 5 is adequate, is rejected. In addition, the result of comparing Model 7 to Model 8 shows that Model 8 is more appropriate to explain the dataset. These two results imply that PM$_{10}$ does not make significant effect but PM$_{10}$’s interaction does. In other words, we can presume that PM$_{10}$ affects the prediction of airport visibility through the relationships between other variables. As shown in Model 8, there are a total of 34 independent parameters. These include the all interaction terms between PM concentrations and weather parameters (WS, TMP, RH, WX).

As shown in Model 8, there are a total of 34 independent parameters.
RESULTS AND DISCUSSION

Relationship between PM and Weather variables

The characteristic of airport visibility is shown in Fig. 2. Significant number of observations indicating the visibility of 9,999 m normally has the value more than 9,999 m. The rate of fog observations less than 1 km of visibility is relatively low. However, the density of low visibility below 500 m (0.042) is more frequent than that of between 500 m and 1,000 m (0.025). This implies that there are more chances of visibility restrictions below ILS CAT I minimum (550 m) under foggy conditions. The relationship of PM concentrations and the visibility is shown in Fig. 3. Reporting scale for aerodrome visibility varies with visibility. It is reported in steps of 1,000 m for 5 km or more, but less than 10 km (WMO, 2014). In this study, we assume that the visibility is continuous variable. Considerable number of low visibility observations is plotted with low level of PM concentrations, which indicates low visibility is not simply influenced by particle amount suspended in the air, but by other meteorological conditions related to high RH. The remarkable PM$_{10}$ distribution with more than 400 µg m$^{-3}$ in Fig. 3 indicates heavy Asian Dust case in February 2015 (Park et al., 2016).

Fig. 4 shows the characteristics of all the variables in the datasets, and their relationships with one another. VIS represents the airport visibility which is the response variable in the analysis.
The figures shown at the diagonal position represent the histogram of each variable. Except for WX, the figures above and below the diagonal position show correlation and scatter plots between two variables. Since WX is a categorical variable, which has eight levels of NONE, HZ, DU, BR, FG, DZ, RA, and SN, the figures above and below the WX histogram show boxplots of each variable categorized by eight WX levels. The matrix represents that none of the variables are highly correlated with each other. RH is most negatively correlated with the visibility (−0.58) and followed by PM\textsubscript{2.5} (−0.49) and PM\textsubscript{10} (−0.26). As mentioned, PM\textsubscript{2.5} concentration is more correlated with visibility than PM\textsubscript{10}. The correlation coefficient between PM\textsubscript{2.5} and PM\textsubscript{10} is 0.56.

To verify if it is appropriate to use PM\textsubscript{10} and PM\textsubscript{2.5}, as PM\textsubscript{10} includes PM\textsubscript{2.5} in its definition, we have assessed multicollinearity between the variables and shown that the selection of the variables is valid for analysis. It might be because PM\textsubscript{10} is more correlated with coarse particles (PM\textsubscript{10-2.5}) than fine particles (PM\textsubscript{2.5}).

Table 4(a) shows results of the optimal model with both PM\textsubscript{10} and PM\textsubscript{2.5} incorporated. The estimation of PM\textsubscript{2.5} coefficient is highly significant with the p-value less than 0.0001 while that of PM\textsubscript{10} is not significant with p-value of 0.3542. Instead, PM\textsubscript{10} interaction with WX is highly significant, which indicates PM\textsubscript{10} affect visibility through its relationships between other weather variables. All weather variables have strong significance. As for interaction term, PM\textsubscript{10} with HZ, FG, DZ, and RH is highly significant with low p-value less than 0.001. Similarly, PM\textsubscript{2.5} has
significant interaction with HZ, FG, TMP, RH, and WS with low p-value. Among 7 WX variables in PM$_{2.5}$ interaction, HZ and FG have significant interaction with PM$_{2.5}$ concentration (p-value with 0.0005 and 0.0029 respectively). These results show that PM$_{2.5}$ needs to be taken into consideration for visibility diagnosis and prediction in both hazy and foggy conditions.

Each coefficient shows the influence of each variable on visibility. In general, all 7 weather variables have negative effect on visibility. Weather effects on visibility for each variable calculated from Table 4(a) are summarized in Table 5. They show that the specific weather effect can be interpreted along with the concentrations of PM$_{2.5}$ and PM$_{10}$. Temperature effect ($0.0241 + 0.00001122 \times PM_{10} - 0.001378 \times PM_{2.5}$) is dependent on PM$_{2.5}$ concentration, which indicates TMP has a positive effect on visibility under very low PM$_{2.5}$ concentration but not under high PM$_{2.5}$ concentration due to the negative interaction between PM$_{2.5}$ and TMP ($-0.001378$). For example, conditioning on PM$_{10}$, as PM$_{2.5}$ concentration increases, the relationship between Temperature and visibility tends to be diminished. When considering diurnal variation in temperature and visibility, this implies that high PM$_{2.5}$ concentration could delay visibility improvement with even increasing temperature. Relative humidity effect ($-0.2098 + 0.0004021 \times PM_{10} + 0.001789 \times PM_{2.5}$) is mostly negative for both PM$_{10}$ and PM$_{2.5}$ concentration levels for the period of 2015-2017, but depending on PM concentration. This means the higher PM concentration delays the improvement in visibility from decrease of relative
humidity. This might be because that aerosols account for light extinction more than hydrometeors do under dry condition when temperature increases under high PM concentration.

Wind speed effect ($-0.06750 - 0.00005788 [PM_{10}] + 0.001878 [PM_{2.5}]$) also varies with PM$_{2.5}$ concentration. Under low PM$_{2.5}$ concentration, wind accounts for visibility degradation, whereas weak wind is associated with low visibility in high PM$_{2.5}$ concentration conditions.

According to the estimation coefficients, if both PM$_{10}$ and PM$_{2.5}$ concentration are doubled from the mean of 45.8 µg m$^{-3}$ and 24.2 µg m$^{-3}$ to 91.6 µg m$^{-3}$ and 48.4 µg m$^{-3}$ respectively in 40% of RH, 10 of TMP, and 10kt of WX of hazy conditions, PM impact accounts for 2.9 km decrease in visibility. Likewise, both doubled PM$_{10}$ and PM$_{2.5}$ from the mean in 60% of RH would reduce the visibility by 1.7 km.

To evaluate the difference between the effect of PM$_{2.5}$ and PM$_{10}$ on visibility, we tried to remove PM$_{2.5}$ concentration data from the model assuming that PM$_{2.5}$ was not measured before 2015. The results are shown in Table 4(b). The largest difference from the optimal model is the coefficient for the interaction of PM$_{10}$ with FG, which has small value with low significance. While the interaction effect of both PM$_{10}$ and PM$_{2.5}$ with FG is highly significant (p-value of 0.0081 and 0.0029 respectively) in the optimal model as shown in Table 4(a), when PM$_{2.5}$ concentration data is not available, the interaction effect of PM$_{10}$ with fog is not significant (with
p-value of 0.3569). Such difference from the model implies that both PM$_{2.5}$ and PM$_{10}$ should be considered to properly investigate the PM impact on visibility.

**Developing an optimal model for visibility**

Visibility impairment is diagnosed from the estimation coefficient in the model as shown in Table 4(a). Model 8 in Table 2 shows the developed optimal censored regression model capable of visibility diagnosis considering various weather variables and interactions with PM concentration. The model has 14 coefficients in total, which practically increases to 32 because WX has been categorized into 7 types of weather conditions except for NONE as shown in Table 4(a). As interaction terms are incorporated into the model, all 32 coefficients are used to explain visibility degrading in various weather and PM conditions. Interaction terms are crucial features that explain the roles of fine and coarse PM and such complexity is worthy of being incorporated to properly evaluate the impact of meteorological conditions.

To verify the developed model using the meteorological and air quality data in 2015–2017, the visibility estimation equation was applied to low visibility case of IIA in 2018. Data for only the term Jan to May in 2018 are available at the present study. Fog observations were made on chosen 16 days during the 5 months. Severe dense fog with low visibility below ILS category III landing minimum (less than RVR 175m) were observed on 4 days for two fog cases (11–12 and 26–27 March). Since this study aims to improve the airport visibility prediction, the worst foggy
event of 11–12 March with significant number of PM concentration were chosen for validating
the model. On those days, haze was dominant during the day on 11 March and the visibility
began to fall from the evening resulting in the lowest visibility of 100 m, which lasted for 9 hours
until the early morning. After fog dissipated, hazy conditions remained with maximum visibility
of 4,000 m on 12 March. As for PM$_{10}$ and PM$_{2.5}$ concentration, the selected cases showed high
levels of PM concentration. Hourly variation of PM$_{10}$ and PM$_{2.5}$ concentrations on 11–13 March
are shown in Fig. 5.

The changes in observed and modeled visibility for selected case is shown in Fig. 6. The grey
solid line with circle mark and red solid line indicate observation and the optimal model’s
simulated visibility respectively. The black, green longdash, and orange twodash lines are from
the non-interaction models. The blue dashed line is from Forecast Systems Laboratory (FSL)
Method for reference, which is calculated by temperature ($T$), dew point temperature ($T_d$) and
relative humidity ($RH$) as following (Doran et al., 1999).

$$VIS(km) = 9654 \times \frac{T - T_d}{RH^{1.75}}$$

(3)
Although the error between observation and simulated visibility has quite a bit of variation by individual hours and the overall visibility tends to be underestimated, the model successfully reproduces the patterns of visibility trends associated with high PM concentrations. Specifically, the PM impact on visibility at 1 pm on 12 March 2018 with 39% of RH, 110 µg m\(^{-3}\) of PM\(_{10}\), and 63 µg m\(^{-3}\) of PM\(_{2.5}\) is \(-8.0\) km (\(-3.2\) km by PM\(_{10}\) and \(-4.8\) km by PM\(_{2.5}\)) by the calculating the coefficients from the model. As shown above, the proposed model in the present study could be useful for the improving visibility prediction by considering weather variables associated with PM\(_{10}\) and PM\(_{2.5}\) concentrations. Accurate measurement and prediction of PM concentrations is important factor as well. Especially, fine PM such as PM\(_{2.5}\) and even PM\(_{1.0}\) has been found to contribute substantially to visibility degradation (Zhao et al., 2013; Shen et al., 2015).

Fig. 7 shows hourly variation of PM\(_{2.5}\) concentration measured in Incheon city area on 11–12 March 2018. The high PM concentration at Unseo station during the day on 11 March recedes back to annual average and even lower after 9 pm, while other monitoring stations in Incheon area still have high level of PM\(_{2.5}\) concentration. This big difference of PM measurement may relate to fog at IIA generated from 9 pm. The proposed model shows that PM concentration is relatively low in high RH conditions with low visibility, which indicates that some fine particles grow beyond 10 µm in fog condition by the process of particle hygroscopic growth (Malm and Day, 2001; Shen et al., 2015). Fig. 8 shows observed and simulated hourly visibility from January
to May 2018 in case of PM level ‘bad’ based on the criterion issued by the Korean government (ME, 2018). The correlation coefficient of observed and simulated visibility is 0.76, which suggests that the proposed model using the data of 2015–2017 at IIA simulates the visibilities for the data collected in 2018 with significant accuracy for a single selected verification day. Meanwhile, possible errors from uncertainty such as low significance of PM$_{10}$ coefficient on the model and inaccuracy of PM measurement in nearby site may still remain.

Although PM data collected from Unseo station, 5 km east-northeast of IIA, is in the boundary of visibility observation from the airport, it is not the same location where other weather variables are measured. Thus, either PM data need to be collected from IIA point or spatial distribution of PM concentration should be verified for the future. Currently available PM monitoring station operated by government is sparsely distributed, which may not accurately represent the PM concentration gradient between the two points (Escobedo and Nowak, 2009; Bell et al., 2010).

Fig. 7 presents the differences of the measured PM concentrations at Incheon city area are considerably high between stations.

**CONCLUSIONS**

The present study examines the quantitative relationship between airport visibility and meteorological conditions in consideration of PM concentrations. Unlike previous studies, not only direct relationships of visibility to meteorological variables but also their interactions with
PM concentrations and all range of RH are taken into account. The three-year long observations (2015–2017) of weather and air quality at IIA and Unseo air monitoring station show that PM$_{2.5}$ concentration is more important than PM$_{10}$ concentration in determining airport visibility. In particular, PM$_{2.5}$ interactions with haze, fog, high temperature, low relative humidity, and weak wind can significantly affect the visibility. In high PM$_{2.5}$ concentrations, effects of increasing temperature and dry conditions on visibility depend more on PM concentration. Wind speed shows a positive correlation with visibility under high PM$_{2.5}$ concentration.

These results suggest that fine particulate matters play a crucial role in visibility impairment and need to be considered in diagnosing and predicting visibility. By considering an interplay of PM concentration in visibility-weather relationship, a simple censored regression model is developed. This model, which is based on hourly observations for the period of 2015–2017, is applied to the low-visibility case at IIA in 2018. This model successfully reproduces the visibility changes associated with high PM concentrations, estimating the quantitative impact by PM$_{10}$ and PM$_{2.5}$ under various weather conditions. Especially, it is found that high PM concentration in the afternoon haze on the selected day has likely contributed to the visibility impairment at most by $-8.0$ km ($-3.2$ km by PM$_{10}$ and $-4.8$ km by PM$_{2.5}$). This result accentuates the importance of PM$_{2.5}$ concentration and interactions of meteorological conditions with PM in diagnosis and prediction of visibility impairment.
At the moment, general weather prediction models do not include aerosol loading in visibility prediction. Likewise, air quality prediction model, which is basically a chemical transport model, does not allow interaction between meteorological variables and aerosols. In this model, meteorological conditions are simply prescribed from numerical weather prediction model output, in which both weather and air quality prediction models do not incorporate visibility-aerosol interactions. Although such interactions are not easily implemented in the models, multiple outputs could be combined to better predict airport visibility. The censored regression model developed in this study could be applied to model outputs to more accurately predict airport visibility. This approach will be tested in a future study.

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Fig. 1. The location of IIA (square mark) and Unseo air quality monitoring station (circle mark). Map is from Geospatial Information Service Platform (NGII, 2019).
Fig. 2. Distribution of observed visibility (km) at IIA_2015-2017
Fig. 3. Scatter plot of Visibility (km) and PM concentration (µg m$^{-3}$) at IIA, 2015-2017

Table 1. Data summary of the variables, 2015-2017$^a$

<table>
<thead>
<tr>
<th></th>
<th>VIS (m)</th>
<th>PM$_{10}$ (µg m$^{-3}$)</th>
<th>PM$_{2.5}$ (µg m$^{-3}$)</th>
<th>WS (kt)$^b$</th>
<th>TMP ( )</th>
<th>RH (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>50</td>
<td>2.0</td>
<td>1.0</td>
<td>0.0</td>
<td>-15.6</td>
<td>9.6</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>7000</td>
<td>27.0</td>
<td>13.0</td>
<td>4.0</td>
<td>3.7</td>
<td>49.6</td>
</tr>
<tr>
<td>Median</td>
<td>10000</td>
<td>39.0</td>
<td>21.0</td>
<td>7.0</td>
<td>13.0</td>
<td>64.3</td>
</tr>
<tr>
<td>Mean</td>
<td>8282</td>
<td>45.8</td>
<td>24.2</td>
<td>7.4</td>
<td>12.3</td>
<td>62.9</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>10000</td>
<td>57.0</td>
<td>32.0</td>
<td>10.0</td>
<td>21.0</td>
<td>78.0</td>
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<tr>
<td>Max.</td>
<td>10000</td>
<td>949.0</td>
<td>111.0</td>
<td>30.0</td>
<td>33.7</td>
<td>97.8</td>
</tr>
</tbody>
</table>

$^a$ abbreviation; VIS (Visibility), WS (Wind speed), TMP (Temperature), RH (Relative humidity)

$^b$ 1 kt = 0.5144 m s$^{-1}$
Fig. 4. Matrix of plots and correlation coefficient among seven variables. The upper panel above the diagonal shows correlation coefficients. The lower panel below the diagonal gives their scatter plots. The histograms of each variable are shown in the diagonal line. For WX, the upper and lower panel (the two are the same) gives boxplots of each variable categorized by eight WX levels; NONE, HZ, DU, BR, FG, DZ, RA, and SN in order. Units are as follows; PM$_{10}$ (µg m$^{-3}$), PM$_{2.5}$ (µg m$^{-3}$), TMP (°C), RH (%), WS (kt), and VIS (km) respectively.

Table 2. Variables applied to model design and selection of optimum model

<table>
<thead>
<tr>
<th>No.</th>
<th>Censored regression model$^a$</th>
<th># of parameters</th>
<th>AIC$^c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$[\text{VIS}]=\beta_{01}[\text{TMP}]+\beta_{02}[\text{RH}]+\beta_{03}[\text{WS}]+26.23$</td>
<td>5</td>
<td>58348</td>
</tr>
<tr>
<td>1</td>
<td>$[\text{VIS}]=\beta_{11}[\text{PM}<em>{10}]+\beta</em>{12}[\text{PM}<em>{2.5}]+\beta</em>{13}[\text{TMP}]+\beta_{14}[\text{RH}]+\beta_{15}[\text{WS}]+31.62$</td>
<td>7</td>
<td>50408</td>
</tr>
<tr>
<td>2</td>
<td>$[\text{VIS}]=\beta_{21}[\text{PM}<em>{10}]+\beta</em>{22}[\text{PM}<em>{2.5}]+\beta</em>{23}[\text{WX}]+\beta_{24}[\text{TMP}]+\beta_{25}[\text{RH}]+\beta_{26}[\text{WS}]^b+25.49$</td>
<td>14</td>
<td>32833</td>
</tr>
</tbody>
</table>

$^a$ Censored regression model

$^b$ WX: NONE, HZ, DU, BR, FG, DZ, RA, and SN

$^c$ AIC: Akaike Information Criterion
Table 3. p-values from the likelihood ratio test for Model 0-8

<table>
<thead>
<tr>
<th>Reduced Model</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>0</td>
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</tr>
<tr>
<td>1</td>
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<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
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<tr>
<td>6</td>
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<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a [VIS], [PM10], [PM2.5], [WS], [TMP], and [RH] stand for Visibility (km), PM10 concentration (µg m⁻³), PM2.5 concentration (µg m⁻³), Wind speed (m s⁻¹), Temperature( °C) and Relative humidity(%), respectively.

b [WX] has 8 levels; [NONE], [FG], [BR], [HZ], [DU], [DZ], [RA], and [SN], which have the value of 0 or 1.

c AIC: Akaike information criterion
Table 4. Estimation results of the proposed censored regression model (Model 8) with the comparison to that of PM$_{2.5}$ removed (Model 4)

<table>
<thead>
<tr>
<th></th>
<th>Model 8</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>(Intercept):1</td>
<td>31.54</td>
<td>0.5727</td>
</tr>
<tr>
<td>(Intercept):2</td>
<td>0.5093</td>
<td>0.007839</td>
</tr>
<tr>
<td>PM$_{10}$</td>
<td>0.02289</td>
<td>0.02471</td>
</tr>
<tr>
<td>PM$_{2.5}$</td>
<td>-0.2445</td>
<td>0.03164</td>
</tr>
<tr>
<td>WXHZ</td>
<td>-9.147</td>
<td>0.4111</td>
</tr>
<tr>
<td>WXDU</td>
<td>-6.824</td>
<td>0.5600</td>
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<tr>
<td>WXBR</td>
<td>-6.804</td>
<td>0.3832</td>
</tr>
<tr>
<td>WXFG</td>
<td>-11.08</td>
<td>0.4321</td>
</tr>
<tr>
<td>WXDZ</td>
<td>-9.294</td>
<td>0.5280</td>
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<tr>
<td>WXRA</td>
<td>-6.793</td>
<td>0.3907</td>
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<tr>
<td>WXSN</td>
<td>-8.449</td>
<td>0.4769</td>
</tr>
<tr>
<td>TMP</td>
<td>0.02414</td>
<td>0.005219</td>
</tr>
<tr>
<td>RH</td>
<td>-0.2098</td>
<td>0.004966</td>
</tr>
<tr>
<td>WS</td>
<td>-0.06750</td>
<td>0.009509</td>
</tr>
<tr>
<td>PM$_{10}$:WXHZ</td>
<td>-0.06612</td>
<td>0.02438</td>
</tr>
<tr>
<td>PM$_{10}$:WXDU</td>
<td>-0.05189</td>
<td>0.02433</td>
</tr>
<tr>
<td>PM$_{10}$:WXBR</td>
<td>-0.05766</td>
<td>0.02430</td>
</tr>
<tr>
<td>PM$_{10}$:WXFG</td>
<td>-0.06725</td>
<td>0.02538</td>
</tr>
<tr>
<td>PM$_{10}$:WXDZ</td>
<td>-0.07722</td>
<td>0.02992</td>
</tr>
<tr>
<td>PM$_{10}$:WXRA</td>
<td>-0.05296</td>
<td>0.02458</td>
</tr>
<tr>
<td>PM$_{10}$:WXSN</td>
<td>-0.06517</td>
<td>0.02577</td>
</tr>
<tr>
<td>PM$_{10}$:TMP</td>
<td>0.0001122</td>
<td>0.00009899</td>
</tr>
<tr>
<td>PM$_{10}$:RH</td>
<td>0.0084021</td>
<td>0.00005171</td>
</tr>
<tr>
<td>PM$_{10}$:WS</td>
<td>0.0005788</td>
<td>0.00009585</td>
</tr>
<tr>
<td>PM$_{2.5}$:WXHZ</td>
<td>0.1034</td>
<td>0.02962</td>
</tr>
<tr>
<td>PM$_{2.5}$:WXDU</td>
<td>0.04113</td>
<td>0.03060</td>
</tr>
<tr>
<td>PM$_{2.5}$:WXBR</td>
<td>0.03919</td>
<td>0.02934</td>
</tr>
<tr>
<td>PM$_{2.5}$:WXFG</td>
<td>0.09498</td>
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<tr>
<td>PM$_{2.5}$:WXDZ</td>
<td>0.07870</td>
<td>0.04227</td>
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<tr>
<td>PM$_{2.5}$:WXRA</td>
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<td>0.03004</td>
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<tr>
<td>PM$_{2.5}$:WXSN</td>
<td>0.01760</td>
<td>0.03217</td>
</tr>
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<td>PM$_{2.5}$:TMP</td>
<td>-0.001378</td>
<td>0.0001869</td>
</tr>
<tr>
<td>PM$_{2.5}$:RH</td>
<td>0.001789</td>
<td>0.0001420</td>
</tr>
<tr>
<td>PM$_{2.5}$:WS</td>
<td>0.001878</td>
<td>0.0003042</td>
</tr>
</tbody>
</table>
Signif. codes: *, **, *** Significant at the 0.05, 0.01, and 0.001 probability level, respectively.

Table 5. Weather effects on visibility for each variable

<table>
<thead>
<tr>
<th>Weather</th>
<th>Effect on visibility (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HZ</td>
<td>$-9.147 - 0.06612 [PM_{10}] + 0.1034 [PM_{2.5}]$</td>
</tr>
<tr>
<td>DU</td>
<td>$-6.824 - 0.05189 [PM_{10}] + 0.04113 [PM_{2.5}]$</td>
</tr>
<tr>
<td>BR</td>
<td>$-6.804 - 0.05766 [PM_{10}] + 0.03919 [PM_{2.5}]$</td>
</tr>
<tr>
<td>FG</td>
<td>$-11.08 - 0.06725 [PM_{10}] + 0.09498 [PM_{2.5}]$</td>
</tr>
<tr>
<td>DZ</td>
<td>$-9.294 - 0.07722 [PM_{10}] + 0.07870 [PM_{2.5}]$</td>
</tr>
<tr>
<td>RA</td>
<td>$-6.793 - 0.05296 [PM_{10}] + 0.009793 [PM_{2.5}]$</td>
</tr>
<tr>
<td>SN</td>
<td>$-8.449 - 0.03617 [PM_{10}] + 0.01760 [PM_{2.5}]$</td>
</tr>
<tr>
<td>TMP</td>
<td>$+0.02414 + 0.00001122 [PM_{10}] - 0.001378 [PM_{2.5}]$</td>
</tr>
<tr>
<td>RH</td>
<td>$-0.2098 + 0.0004021 [PM_{10}] + 0.001789 [PM_{2.5}]$</td>
</tr>
<tr>
<td>WS</td>
<td>$-0.06750 - 0.00005788 [PM_{10}] + 0.001878 [PM_{2.5}]$</td>
</tr>
</tbody>
</table>

Fig. 5. Hourly variation of PM$_{10}$ (blue) and PM$_{2.5}$ (orange) concentrations of Unseo station on 11-13 March 2018. Solid straight line indicates average PM concentration of PM$_{10}$ and PM$_{2.5}$ for 2015-2017 respectively.
Fig. 6. Hourly variation of observed and predicted visibility of Incheon airport on 11-13 March 2018 for FSL method, non-interaction models (Model 0, 1, and 2), and optimal interaction model (Model 8)
Fig. 7. Hourly variation of PM2.5 concentrations measured at 19 Air Monitoring Station in Incheon city area on 11-12 March 2018. The thick solid line with circle mark indicates from Unseo station.
Fig. 8. Observed and predicted hourly visibility for PM$_{2.5} > 35 \mu g m^{-3}$ at IIA using censored regression model (Model 8 of Table 2) from 1 January till 25 May 2018.
Figure Captions

**Fig. 1.** The location of IIA (square mark) and Unseo air quality monitoring station (circle mark) Map from NGII (National Geographic Information Institute, Korea).

**Fig. 2.** Distribution of observed visibility (km) at IIA, 2015-2017

**Fig. 3.** Scatter plot of Visibility (km) and PM concentration (µg m⁻³) at IIA, 2015-2017

**Fig. 4.** Matrix of plots and correlation coefficient among seven variables. The upper panel above the diagonal shows correlation coefficients. The lower panel below the diagonal gives their scatter plots. The histograms of each variable are shown in the diagonal line. For WX, the upper and lower panel (the two are the same) gives boxplots of each variable categorized by eight WX levels; NONE, HZ, DU, BR, FG, DZ, RA, and SN in order. Units are as follows; PM₁₀ (µg m⁻³), PM₂.₅ (µg m⁻³), TMP (°), RH (%), WS (kt), and VIS (km) respectively.

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Table Captions

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