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Comparison between the Application Results of NNM and a GIS-based Decision Support System for Prediction of Ground Level SO_2 Concentration in a Coastal Area

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Abstract

A prototype GIS-based decision support system (DSS) was developed by using a database management system (DBMS), a model management system (MMS), a knowledge-based system (KBS), a graphical user interface (GUI), and a geographical information system (GIS). The method of selecting a dispersion model or a modeling scheme, originally devised by Park and Seok,[1)] was developed using our GIS-based DSS. The performances of candidate models or modeling schemes were evaluated by using a single index(statistical score) derived by applying fuzzy inference to statistical measures between the measured and predicted concentrations. The fumigation dispersion model performed better than the models such as industrial source complex short term model(ISCST) and atmospheric dispersion model system(ADMS) for the prediction of the ground level SO_2 (1 hr) concentration in a coastal area. However, its coincidence level between actual and calculated values was poor. The neural network models were found to improve the accuracy of predicted ground level SO_2 concentration significantly, compared to the fumigation models. The GIS-based DSS may serve as a useful tool for selecting the best prediction model, even for complex terrains.

Keywords: Geographical information system, Decision support system, Model selection, Fumigation model, Modeling performance

1. Introduction

In planning and managing air pollution sources, a number of decisions have to be made, and accurate prediction of the level of environmental pollution is very important for quick and correct decision making. Construction of the GIS-based decision support system (DSS) is essential for fast and accurate modeling for several reasons: (i) a variety of candidate prediction models consisting of many parameters must be examined to select an appropriate model, (ii) the calculations are quite complex, and (iii) there are nonlinear relationships between the independent parameters and the environmental concentration, which is a dependent variable. To reduce the uncertainties associated with conventional modeling, a geographically complex terrain must be considered because this is the basic cause of the intricacy of air pollution formation. Since various statistical measures for predictions have their respective functions and judgment criteria, it is impossible to determine which model performs best using only one statistical measure. Therefore, to select an appropriate prediction model or modeling scheme, the development of a DSS is necessary in the use of multiple candidate models or modeling schemes for the prediction of pollution levels, and the DSS compares the modeling performances in terms of statistical score, that is, a single index integrating various statistical measures for predictions. The DSS also utilizes fuzzy inference to integrate the statistical measures, which are used as premise variables. Fuzzy inferences are necessary because the boundaries of their membership functions are vague. A graphical user interface (GUI) has been built so that users of the prediction models can directly model the dispersion, demonstrate the results, and select an appropriate model using a personal computer. The GUI, related to neural network models, also improves the pollution predictions using the meteorological and environmental data from ubiquitous monitoring stations. The DSS for air pollution source planning (APSP-DSS)(Korean patent No.:10-0661595, 2006) is composed of GUIs, a DBMS, a MMS, a KBS and a GIS. Since there are many industrial complexes in a coastal

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area, and frequent fumigations cause high pollution concentrations at the ground level, it is very important to accurately predict the pollution concentration at the ground level in a coastal area for the planning and managing of air pollution sources.

In this study, some explanations are given on how to apply our model-selection-methodology (Park and Seok[1]) and APSP-DSS for the prediction of ground level SO_2 pollution in a complex area so that users can easily apply the authors' methodology for model selection by using the DSS tool.

2. Method

2.1. Organization of GIS-based DSS

2.1.1. Structure and Function of the DSS

The DSS was constructed as shown in Figure 1. The APSP-DSS was designed: (i) to predict pollution levels in MMS using a variety of prediction models after receiving the data of emission source, meteorology and environment from DBMS, as well as the information on surface altitude, source location and other variables including surface roughness from GIS, (ii) to analyze the modeling results using various graphs and statistical measures in GUI, and (iii) to select an appropriate model according to a comparative evaluation of the model performances. During model-selection, a fuzzy inference program is imported from the KBS and used in the postprocessor of the MMS to generate a single index by integrating the statistical measures. Pollution prediction models, estimation equations of model input parameters, and other informations are stored in the KBS and imported by the MMS during prediction modeling. The rules used for model selection are managed in an external part of the KBS, and retrieved by the MMS via importation into the KBS. The conceptual explanation of MMS, the algorism and module integrated to MMS, and the basic structure of the expert system (KBS) have been explained in detail by Sin.[12] The terrain data for the modeling area is directly imported from the GIS for preprocessing in the MMS's preprocessor. The GIS data on surface-altitude numerical contour maps, surface temperatures and the locations of geographical features are imported via the DBMS, and they are finally used by the MMS during pollution modeling to calculate plume height above ground and to determine appropriate dispersion coefficients. The modeling results (i.e., concentrations) can be displayed in various shapes in GUI window by the postprocessor of MMS, and are then exported to the GIS after checking and treating in the GUI prior to being integrated with the terrain data set.

2.1.2. Information Linkage between Each Subsystem of the DSS

The geographical information of the GIS is transferred to the Excel program of the DBMS, using an export function for importation by the MMS, and it is used in the modeling. Conversely, the concentration data calculated in the MMS is transferred to the DBMS, and then moved to the Arcview program of the GIS, using the GIS import function. The information in the DBMS Excel is linked to the Matlab program of the MMS using the Excel linkage function. The Load command is used to apply the information in the DBMS to the modeling process in the MMS. The calculations in the Matlab worksheet are designed to be transferred to the Excel worksheet in the DBMS, and they are stored in a text file for use by the GIS Arcview.

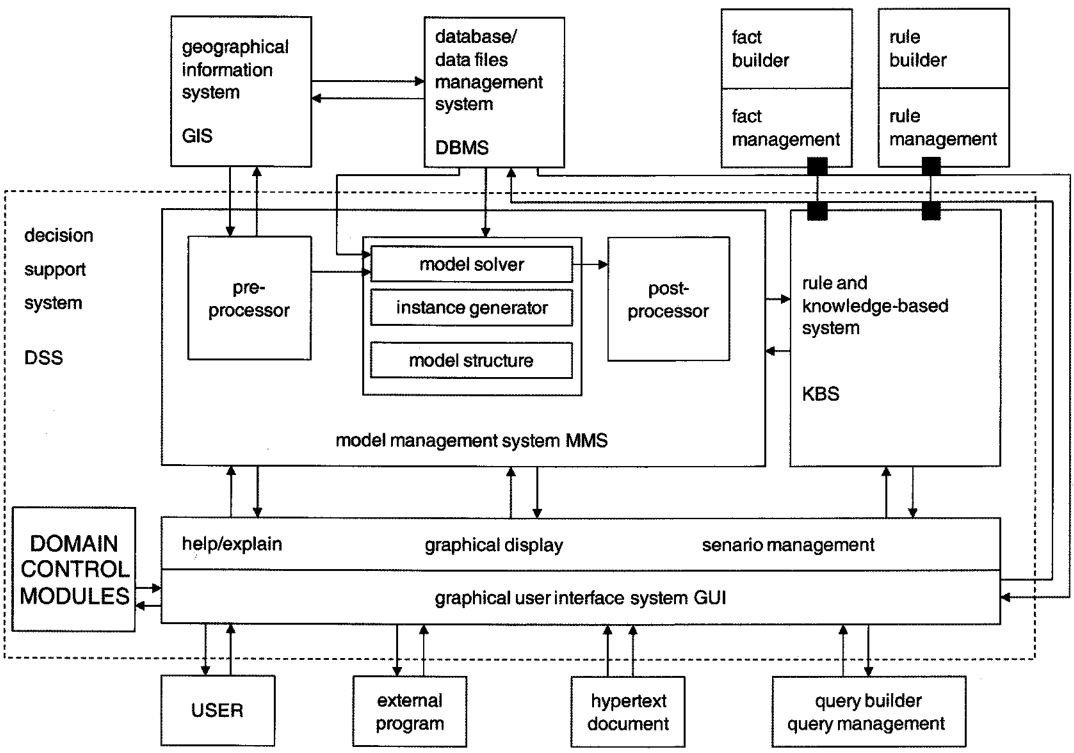


Fig. 1. Structure of the GIS-based DSS.

2.2. Construction of the GUI

The following processes were programmed using the Matlab® 7.0[13] language: (i) calculations of air pollution concentrations using dispersion models, (ii) selection of an appropriate pollution prediction model and (iii) construction of the neural network models (NNMs) based on the meteorological and environmental data from ubiquitous monitoring stations in the past. The GUIs for each process were constructed using the "GUI Development Environment" (GUIDE) toolbox within Matlab.

2.2.1. The GUI for Dispersion Modeling

The GUI for the operation of the MMS was designed to determine the mass flow rate of SO_2 emissions using various source data and to calculate the environmental pollution concentration using dispersion models, which were originally stored in the KBS. Figure 2 shows a view of the GUI associated with the dispersion modeling. Programs for determining variables, such as the plume rise, statistical measures, dispersion parameters, pollution concentrations and fuzzy inference premise membership, are stored in the KBS. The MMS can import these variables for concentration calculations to be conducted on demand by clicking the "Calculation" button in the modeling window of the MMS GUI.

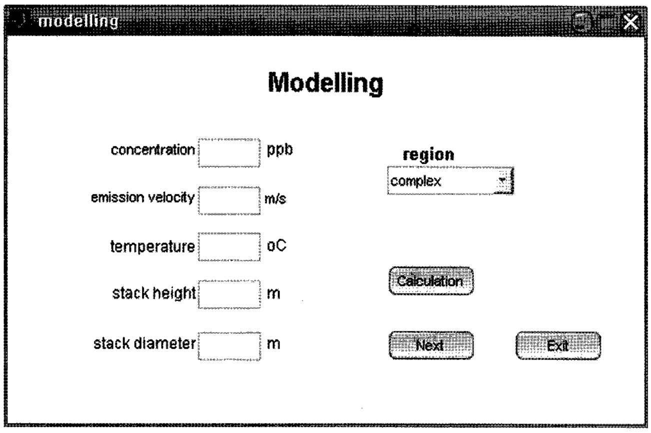


Fig. 2. GUI of the DSS associated with dispersion modeling.

2.2.2. The GUI for Selection of an Appropriate Prediction Model

The GUI system shown in Figure 3 was developed to quickly select a pollution prediction model. Figure 3(a) shows the input window for the model selection factors, which appears when GUI users click the "model selection" button of the MMS GUI. The window shown in Figure 3(b) pops up if the users click the "Next" button after selecting the variables such as source, area, pollutant, terrain and average time. The windows shown in

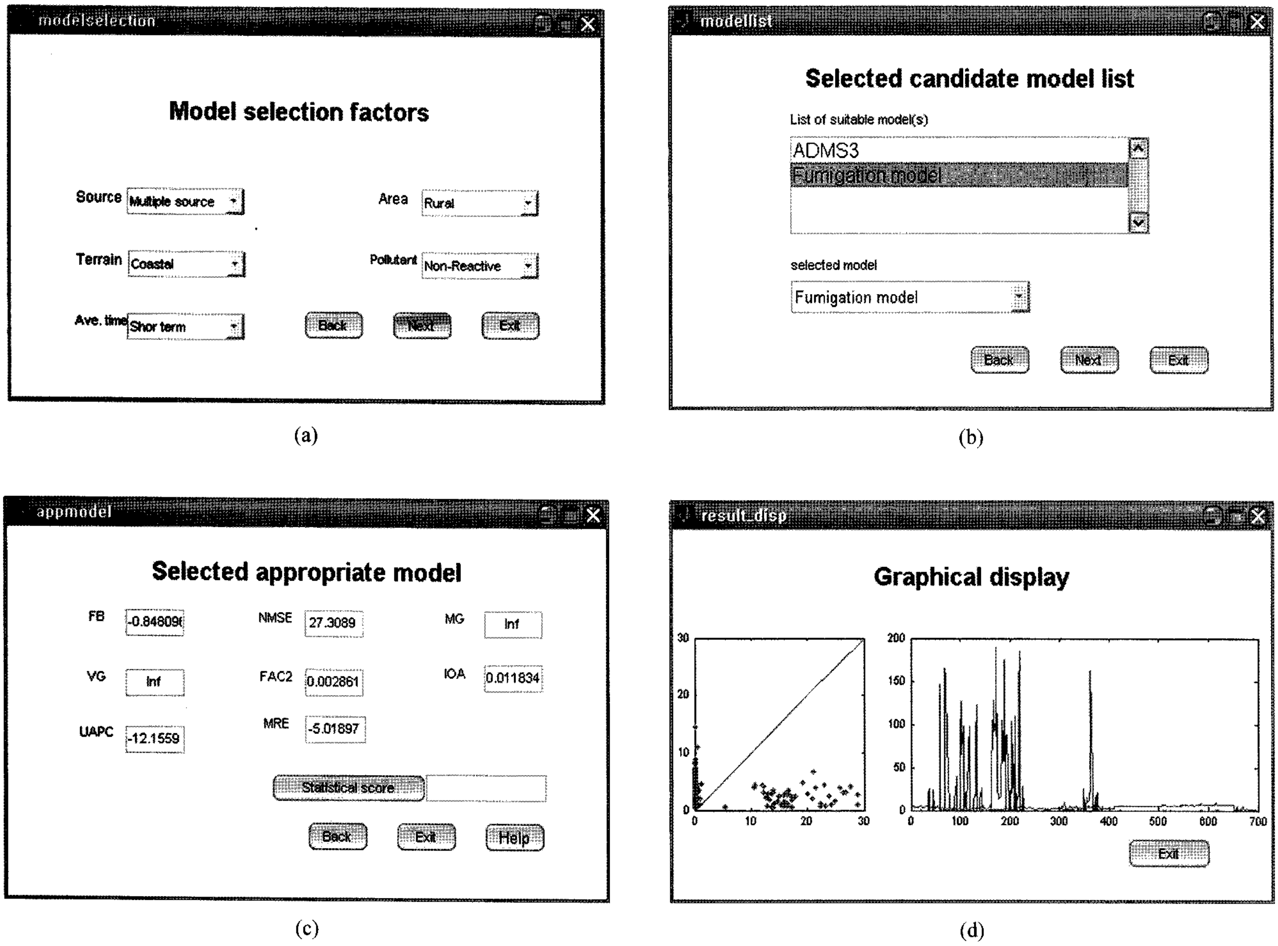


Fig. 3. GUI windows: (a) model selection factors, (b) candidate model list, (c) selected appropriate model and (d) graphical display.

Figures 3(c) and 3(d) pop up when users select ADMS3 and ISCST3, respectively. The rules governing these windows are stored in the KBS.

Another window was provided for the modeling results of competitive modeling schemes to be graphically shown and statistically analysed if "fumigation model" was selected from the candidate model list (Figure 3(b)) and then the "Next" button was clicked. Statistical scores are synthesized for various fumigation modeling schemes by integrating various statistical measures, including fractional bias (FB), normalized mean square error (NMSE), geometric bias mean (MG), geometric bias variance(VG), within a factor of 2 (FAC2), index of agreement (IOA), unpaired accuracy of the peak concentration (UAPC) and mean relative error (URE), and they are displayed in the window if the "statistical score" button is clicked. GUI users can select the modeling scheme with the largest index value in this window. Fuzzy inference programs for determining the index value are stored in the KBS for the following purposes: (i) calculating statistical measures (ii) calculating premise memberships in fuzzy inference, and (iii) selecting an appropriate model or modeling scheme.

2.2.3. The GUI for Neural Network Modeling

In order for quick decisions concerning the planning and control of air pollution sources to be made, it is necessary to use advanced prediction techniques that require little time and cost, and are superior to traditional approaches, such as dispersion and statistical models. In our previous study, neural network models (NNMs) were developed by Sin[12)] as advanced techniques for the prediction of air pollution in complex coastal terrains, with the GUIs constructed for analyzing the NNM results.

Construction of the NNMs

The NNMs were constructed using the neural network toolbox shown in Figure 4, using the following steps: (i) normalized input data were loaded into the GUI by clicking the "Import" button, (ii) the structure of a NNM was established by clicking the "New Network" button in the toolbox, and (iii) logSIG (:SIG means Sigmoid function) was designated as a transfer function in a hidden layer neuron, and five neurons were assigned for the input layer, three for the hidden layer and one for the output layer, as shown in Figure 5. NNM training was initiated by clicking the "Train Network" button in the training process of a neural network model after designating the initial linkage weight and test trials simulating the dependent variable (e.g. 1 hr SO_2 concentration) were performed by applying the test data set to the trained NNM. Five hundred was assigned as the number of iteration to terminate computer training process after checking validation error via some trial. Further descriptions of NNM training and performance test were given in detail in a previous paper written by the authors.[14)]

NNM applications

The graphical analysis GUI shown in Figure 6(a) is displayed

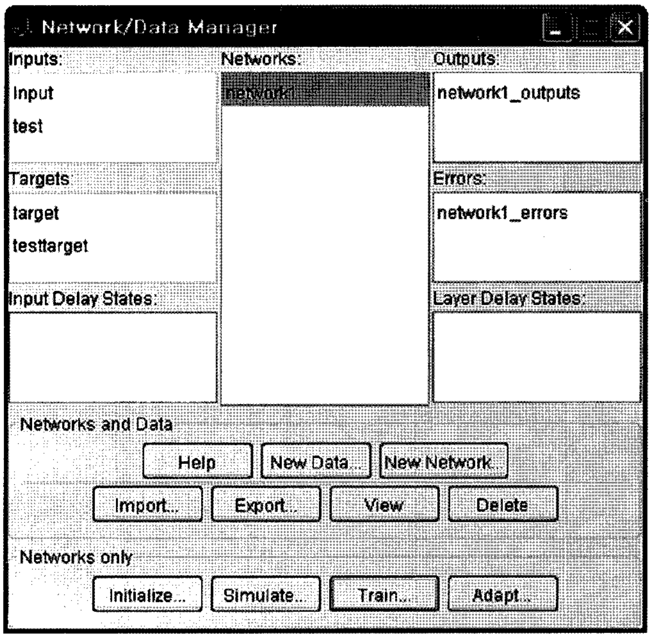


Fig. 4. GUI of the Neural network toolbox.

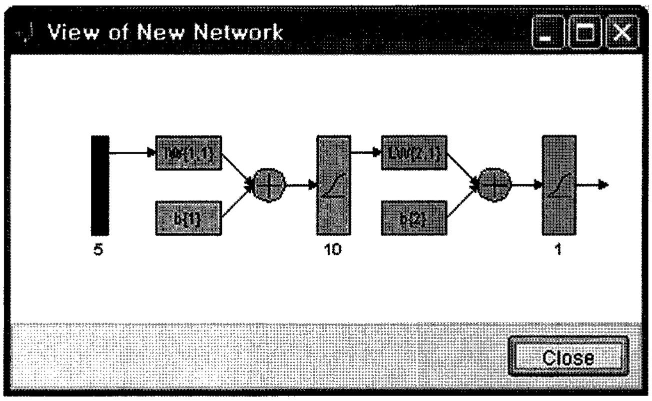


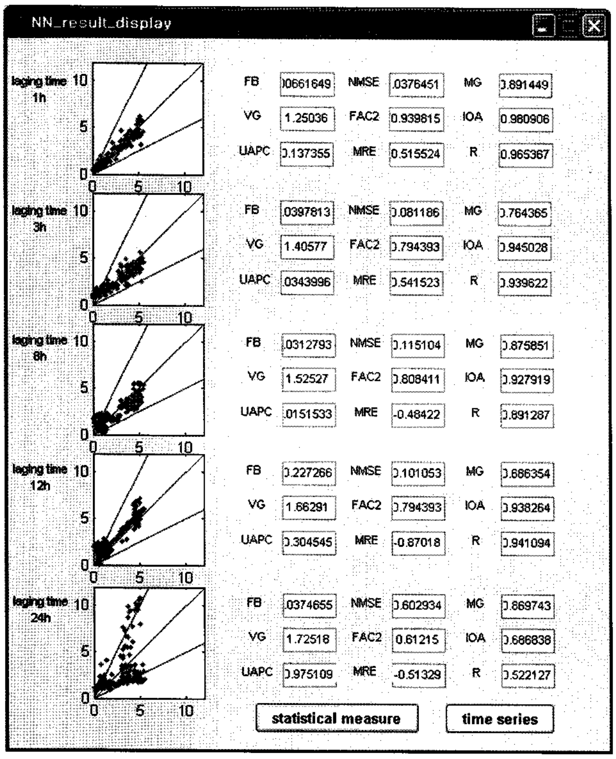
Fig. 5. Structure of a neural network toolbox.

by clicking the "yes" button in the window of the question "do you have a model result?", otherwise clicking "no" transfers the user to the neural network toolbox. GUIs were designed to represent the various statistical measures and time series graphs resulting from the modeling, as shown in Figures 6(a) and 6(b), respectively.

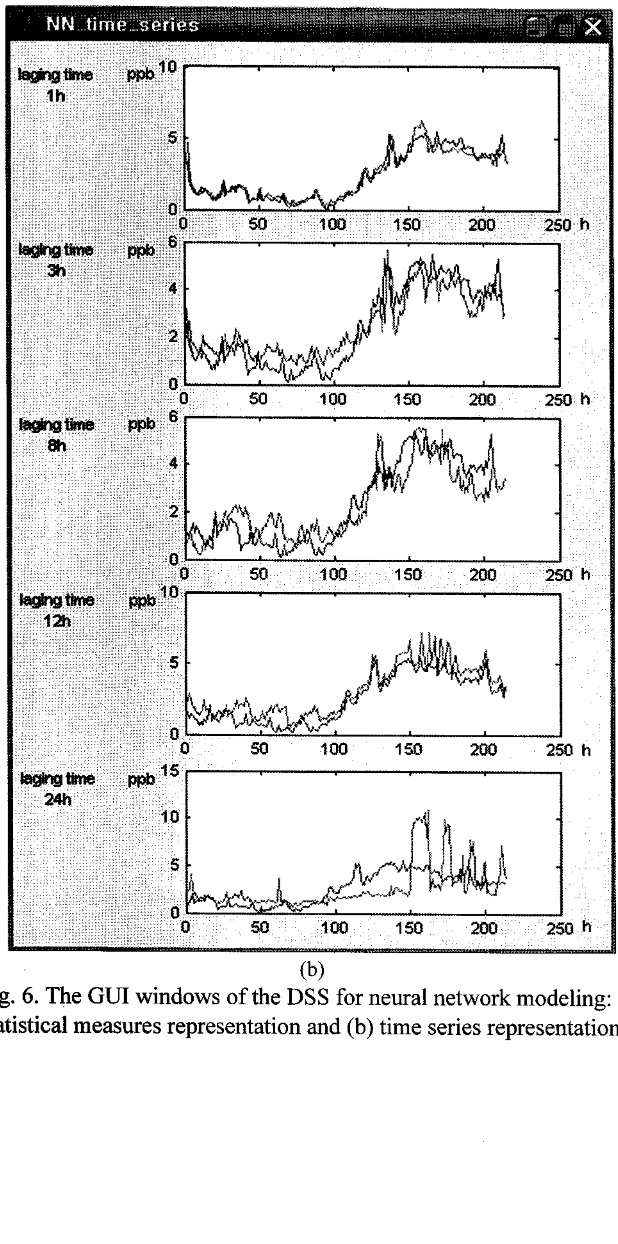
3. Modeling the Ground level SO_2 Concentration in a Coastal Area by Applying GIS-based DSS

3.1. Meteorology, Environment, and Terrain Data of Modeled area

A surface-altitude numerical map (scale: 1/25,000), 1 hr SO_2 concentration data and meteorological data were obtained for a coastal area around the Boryeung Power Plant, South Korea from Jan to Dec 2002. The atmospheric stability was determined on the basis of wind speed, insolation and cloudiness, according to Pasquill's scheme. The wind data were recorded at heights of 10 and 60 m. The terrain grid-file was generated using the triangulate irregular network (TIN), which links altitude points and con-



(a)



(b)

Fig. 6. The GUI windows of the DSS for neural network modeling: (a) statistical measures representation and (b) time series representation.

tour lines using the irregular triangle networks. The terrain data for the grids were used as input data for the dispersion models.

3.2. *Models to Predict Ground Level SO_2 Concentration in a Coastal Area*

The frequency distributions of the 1 hr SO_2 concentration data in 2002, which were forecasted using the ISCST3 and ADMS3 models at the SONGHAK site located 4km SE of the Boryeung Power Plant, underestimated the dispersal of pollutants.

Although dispersion models should be scientifically accurate and their performances good enough for predicting the high concentrations comparable with air quality standards, both of the dispersion models above did not satisfy these requirements. The frequent occurrence of high ground-level concentrations in coastal areas has been attributed to the meteorological characteristics, which cause the fumigation of plumes due to the exchange of sea and land breezes and the formation of a thermal internal boundary layer (TIBL) near the surface of the coastal land after sunrise.[2] Thus, a modeling scheme was constructed based on the single source (;computer program receptor site terrain, (CRSTER)) - shoreline fumigation model (equation (1)) of Lyon and Cole[3], which was formulated on the assumptions that part of the plume is in contact with and penetrated the top of the TIBL and is vertically mixed completely.

$$C_{(x,y)f} = \frac{Q\left[\int_{-\infty}^{p}\left(\frac{1}{\sqrt{2\pi}}\right)\exp(-0.5p^2)dp\right]}{\sqrt{2\pi}\sigma_{yf}\cdot\bar{u}\cdot h_i}\cdot\exp\left(-\frac{y^2}{2\sigma_{yf}^2}\right) \tag{1}$$

In order to estimate σ_{yf}, equation (2) in Turner,[4] was used. The value of σ_y in equation (2) can be estimated using equation (3) in van Dop et al.[5]

$$\sigma_{yf} = \sigma_y + H_e/8 \tag{2}$$

$$\sigma_y^2 = \sigma^2_{ys(x2)} + \sigma^2_{yt(x)} - \sigma^2_{yt(x2)} \tag{3}$$

Park and Seok[1] found that: (i) equation (1) on $C_{(x,y)f}$ was superior to the modified Gaussian fumigation model,[16] (ii) Turner's equation (2) on σ_{yf} was better than the equation of Montgomery et al.[7] and (iii) equation (3) of van Dop et al.[5] on σ_y^2 was better than the equation of Misra.[8] A fumigation modeling scheme for comparison with other general dispersion models was, therefore, organized by combining equations (1), (2) and (3). The dispersion coefficients from a P-G nomogram were corrected using: (i) the terrain factor model (TFM) of Okamoto et al.[9] for terrain rolling, (ii) the equation of Hanna et al.[10] for buoyant plume rising and (iii) the equation of Angell and Pack[11] for the concentration averaging time. In addition, the relationships $\sigma_{y(z2)} = \sigma_{y(z1)}\cdot[\sigma_{\theta(z2)}/\sigma_{\theta(z1)}]$ and $\sigma_{z(z2)} = \sigma_{z(z1)}\cdot[\sigma_{\varphi(z2)}/\sigma_{\varphi(z1)}]$ were used to correct the sigma values for variations in the plume height. NNMs were developed for the modeling area, as explained in detail by Sin,[12] and used as alternatives to dispersion models. The prediction models used in this study were programmed using Matlab 7.0 and stored in the KBS. The DSS was constructed for selection of the best scheme by the users, who directly check the value of a single index (statistical score).

3.3. *Establishment of Fuzzy Inference Integrating Statistical Measures*

The values of the respective statistical measures corresponding to the factors of predictions to measurements, collected from Chang and Hanna,[15] Zawar-Reza et al.[16] and Ziomas et al.,[17] were listed in Table 1, and used to evaluate the performance of the air pollution prediction models. For instance, a factor of two indicates that the predicted concentrations range from 1/2 to 2 times the actual measurements. The membership functions for eight statistical measures were established, as shown in Figure 7, by classifying the statistical measures as "good" for a factor of 2, "fair" for 2~3 and "poor" for 3~4. The statistical measures, which were used as performance indices for each modeling scheme, were taken as the premise of the fuzzy inference for obtaining a statistical score indicating the performance of each modeling scheme by summing all the membership functions. The functions were weighted with 7~10 (avg. 8.5) for "good", 4~7 (avg. 5.5) for "fair", 6 for "fair (overestimation)", 5 for "fair (underestimation)" and 1~4 (avg. 2.5) for "poor" ranges of each premise variable. If the value of a certain statistical measure corresponded to both classes, the mean value of both weights was counted in the process of calculating the statistical score.

3.4. *Comparing the Results of the Dispersion Models and Neural Network Models*

Table 1. Evaluative criteria for various statistical measures

measure			value	Reference
FB	recommended range		-0.3<FB<0.3	
	factor of 3	factor of 3 mean under-prediction	1.0	
		factor of 3 mean over-prediction	-1.0	
	factor of 4	factor of 4 mean under-prediction	1.2	
		factor of 4 mean over-prediction	-1.2	
	factor of 5	factor of 5 mean under-prediction	1.33	
		factor of 5 mean over-prediction	-1.33	
NMSE	recommended range		<4	
	typical error = 3 × mean value		9	
	typical error = 4 × mean value		16	Chang and Hanna (2004)
	typical error = 5 × mean value		25	
MG	recommended range		0.7<MG<1.3	
	factor of 3	factor of 3 mean bias	0.33 or 3.0	
	factor of 4	factor of 4 mean bias	0.25 or 4.0	
	factor of 5	factor of 5 mean bias	0.20 or 5.0	
VG	recommended range		VG<1.6	
	factor of 3	factor of 3 scatter	3.34	
	factor of 4	factor of 4 scatter	6.82	
	factor of 5	factor of 5 scatter	12.0	
FAC2	recommended range		0.5<FAC2	
IOA	recommended range		0.5<IOA	Zawar-Reza et al. (2005)
UAPC	recommended range		-0.2<UAPC<0.2	
	factor of 3	factor of 3 max under-prediction	0.67	
		factor of 3 max over-prediction	-2	
	factor of 4	factor of 4 max under-prediction	0.75	
		factor of 4 max over-prediction	-3	
	factor of 5	factor of 5 max under-prediction	0.8	
		factor of 5 max over-prediction	-4	
MRE	recommended range		-0.15<MRE<0.15	Ziomas et al. (1998)
	factor of 3	factor of 3 under-prediction	0.37	
		factor of 3 over-prediction	-2	
	factor of 4	factor of 4 under-prediction	0.75	
		factor of 4 over-prediction	-3	
	factor of 5	factor of 5 under-prediction	0.8	
		factor of 5 over-prediction	-4	

Table 2 compares the statistical measures between calculated concentrations and the actual measurements at the SONGHAK site near the BORYEUNG Power Plant. The concentrations were calculated using the GIS-based DSS, where the programs of various prediction models were stored in the KBS. The values of VG and MG for the ADMS3 and ISCST3 models were abnormally calculated as very low concentrations were predicted with high frequency; therefore, those values were not recorded in the Table. The VG value for the fumigation model was very large due to the occasional, extremely low predictions, but the accuracy of its predictions was significantly better than those of the ADMS3 and ISCST3 models, which have been used in the coastal area. The NN model for the 1 hr averaging time and 1 hr prediction time in advance was developed using historical pollution and meteorology data, including wind speed, wind direction, temperature and atmospheric stability. The NN model turned out to be more accurate than the fumigation model, as shown in Table 2. The best model for predicting the 1 hr SO_2 concentration at ground level in the morning (10:00~11:00 A.M.), when fumigation can take place over the complex coastal area, app-

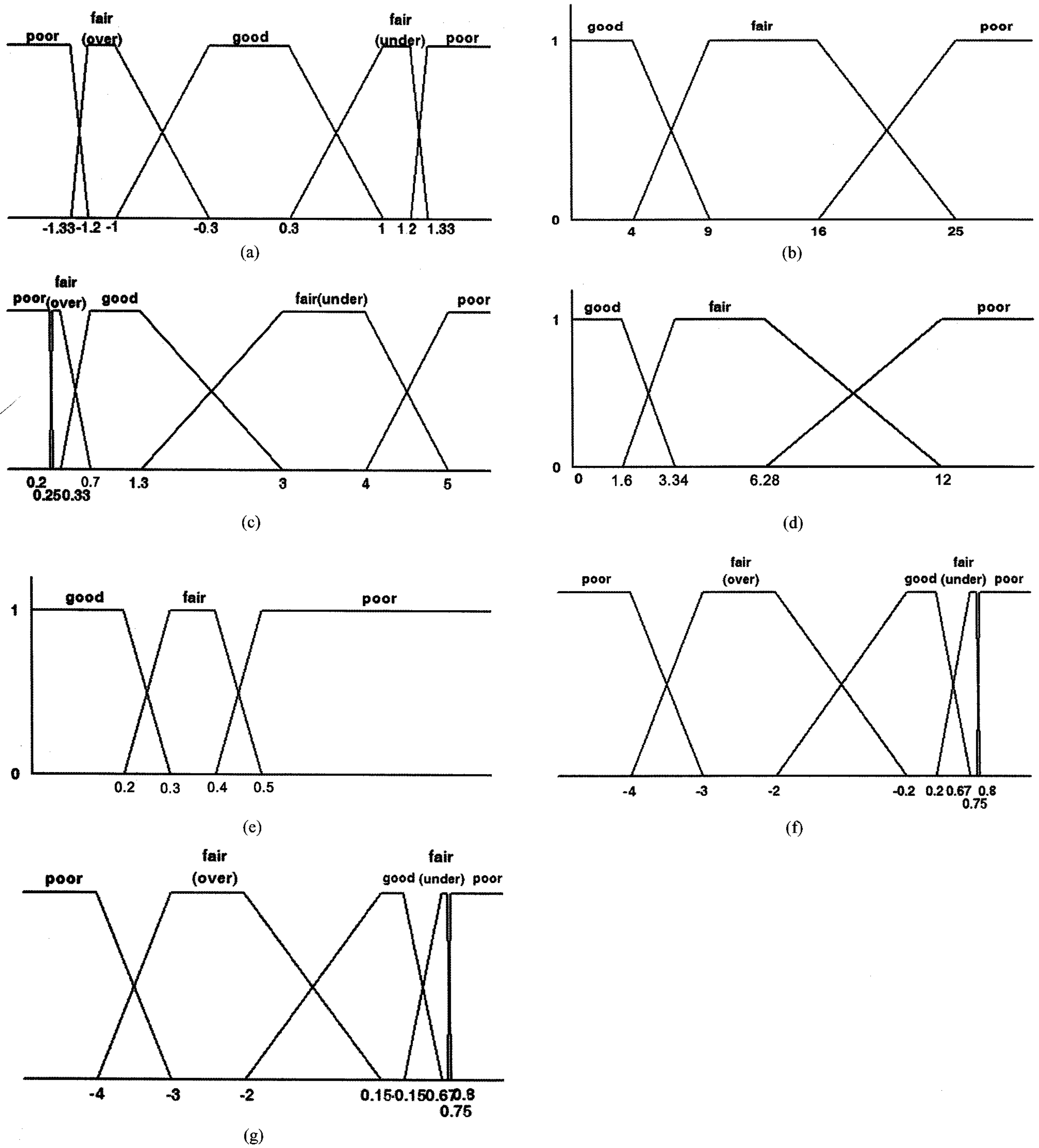


Fig. 7. Typical diagram of the membership function for: (a) FB, (b) NMSE, (c) MG, (d) VG, (e) FAC2 and IOA, (f) UAPC and (g) MRE.

Table 2. The results of statistical measures and statistical scores for the predictions of the morning 1 hr SO_2 concentration over a coastal area using ADMS3 model, ISCST3 model, fumigation model and NN model

Statistical measure	ISCST3 (n=1,820)		ADMS3 (n=700)		Fumigation model (n=230)		NN model (n=216)	
FB	1.74	poor	0.85	good fair (over)	-0.12	good	-0.01	good
MMSE	24.75	fair poor	27.31	poor	1.80	good	0.04	good
MG	-		-		2.19	good fair (under)	1.12	good
VG	-		-		132.51	poor	1.25	good
FAC2	0.003	poor	0.003	poor	0.33	fair	0.94	good
IOA	0.38	fair	0.01	poor	0.26	fair poor	0.98	good
UAPC	-2.45	fair (over)	-12.16	poor	0.07	good	0.12	good
MRE	0.87	poor	-5.02	poor	-1.03	good fair (over)	0.05	good
total count	good : 0 fair : 2 fair (over) : 1 poor : 4		good : 1 fair (over) : 1 poor : 5		good : 5 fair : 2 fair (under) : 1 fair (over) : 1 poor : 2		good : 8	
statistical score	23.0		19.8		51.6		68.0	

eared to be the NN model. The χ^2 test result indicates that: (i) the fumigation model was significantly better than the ISCST3 and ADMS3 models in predicting the 1 hr SO_2 concentration at ground level in the morning over the coastal area and (ii) the NN model was significantly superior even to the fumigation model in predicting the high ground-level SO_2 concentration in the coastal area when the former was built using historical meteorology and environment data. If training data are better organized with more appropriate parameters, the modeling results could be improved further.

4. Conclusion

To facilitate numerous decisions that have to be made quickly, such as selecting plant sites and determining the operating or design conditions for a facility, a prototype GIS-based DSS (patent name : APSP - DSS) was constructed by organizing the GIS, DBMS, MMS and KBS, with a number of GUIs prepared for operation of the DSS. A new methodology was developed for the selection of an appropriate prediction model or modeling scheme by calculating and comparing the statistical scores, which are integrated indices obtained by applying fuzzy inference to statistical measures between measurements and predictions. We wrote the fuzzy inference programs for the selection of an appropriate model or modeling scheme for the prediction of pollution, so that they may be stored in the KBS and operated in the MMS. Although the result of the fumigation model for predicting high SO_2 concentrations at the ground level in the morning over a coastal area was better than those of the ISCST3 and ADMS3 models, the performance of the fumigation model was still not quite satisfactory. The results of the neural network models, based on historical meteorology and environment data, significantly improved the accuracy of the predictions over those obtained by the fumigation model. The GIS-based DSS was found to be a useful tool manifesting the applicability of the methodology of Park and Seok[1] for selecting a dispersion model, even in complex terrains.

Nomenclature

$C_{(x,y)f}$: Ground level concentration at (x,y) during fumigation

h_i : Thickness of TIBL at distance x, estimated by Kouchi et al.'s equation

$p = (h_i - H_e)/\sigma_z$: Difference between H_e (effective stack height in m) and h_i, normalized by σ_z (vertical dispersion coefficient)

$\bar{u}$: Mean wind speed within TIBL

x : Downwind distance

x_2 : Distance from stack to the point where the plume touches the top of the TIBL

y : Lateral departure from the plume's axis to the point of concentration estimation

σ_y : Horizontal lateral dispersion coefficient within the TIBL just before fumigation

σ_{yf} : Horizontal lateral dispersion coefficient at downwind distance, x, during fumigation

σ_{ys} : Horizontal lateral dispersion coefficient in the stable layer

σ_{yt} : Horizontal lateral dispersion coefficient in the turbulent layer

σ_θ : Standard deviation of horizontal wind direction

σ_ψ : Standard deviation of vertical wind direction

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