EMPIRICAL ANALYSIS ON THE RELATIONSHIP BETWEEN AIR POLLUTION AND TRAFFIC FLOW PARAMETERS

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abstract: This paper seeks to initiate a step to what will be a ladder of empirically based, vehicle-attributed, air pollution estimation tool development. It presents the formulation of an empirical model that estimates the ambient concentration of carbon monoxide in a roadside environment. The present form of the model which is expressed in terms of traffic volume, traffic speed and wind speed at a particular direction applies only to mid-block of a straight road section in a flat terrain. The model is also envisioned to include pollution source and receptor locational parameters and may be extented to cover different road layouts in the near future.

1. INTRODUCTION

Increasing motorization trend, aging vehicle fleet, and worsening traffic congestion are among the most significant factors contributing to the severe degradation of air quality in Metro-Manila. With a current population of approximately 8.9 million, the metropolis is expected to become one of the world's megacities by the turn of the century. This phenomenal growth has started to severely strain the existing urban infrastructure and ecology. In particular, the supply and operation of various transport infrastructures cannot cope up with the increasing demand for efficient movement of goods and people, thus resulting to serious traffic congestion which exacerbates the urban air quality problem and causes enormous social welfare and economic losses.

The 1990 Emission Inventory conducted by the Environmental Management Bureau (EMB) showed that motor vehicles contribute about 78% of the total air pollution load in the metropolis. Carbon Monoxide (CO) in particular, the most toxic among the air pollutants, is about 97% attributed to mobile sources. Recent air quality measurements indicated an exceedance of Suspended Particulate Matter (SPM) concentration by 300% of the National Ambient Air Quality Standards. Nitrogen Dioxide (NO_2) standard on the other hand is occasionally exceeded while Carbon Monoxide (CO) concentration is observed to be in an increasing trend.

From 1986 to 1995, vehicle registration record of the Land Transportation Office (LTO) shows an average annual increase of 8.66% without appropriate road and infrastructure provisions. A study conducted by the Asian Development Bank in 1992 forecasted that assuming there is no implementation of additional controls on vehicular emission, pollution load from vehicles in 1990 will at least double by the year 2005.

In this crisis, it is important that transportation planners and air quality analysts should work more closely than ever in providing mobility while improving air quality at the same time (Wayson, 1992). However, the current status of knowledge demonstrates the inability of the existing information to bridge the gap between local transportation and air quality issues. Though several traffic forecasting and estimation tools had long been used in conducting traffic studies, none so far have been used locally in estimating the effect of vehicle traffic on air quality. The circumstances thus bespeaks a need for researches that will provide the transportation community with tools needed to establish the functional relationships which exist between the fields of transportation and environment. Tools that are necessary in the pursuit of sustainable development and the continuation of socially optimal decision-making. In recognition of this need, this study will therefore be an initial step to what will be a ladder of empirically based air pollution investigation and estimation tool development.

2. GENERAL DESCRIPTION

The study is primarily concerned with the development of an empirical model that estimates the ambient concentration of air pollutants particularly carbon monoxide in a road side environment. The model is expressed in terms of traffic flow parameters such as traffic volume and traffic speed and simple meteorological parameters such as wind speed and wind direction.

With the use of a mobile air pollution monitoring system, continuous surveys were conducted to measure the hourly concentration of vehicle-attributed pollutants such as Nitrogen Oxides, Suspended Particulate Matters and Carbon Monoxide as well as the wind speed and direction. A 14-hour classified volume count and spot speed surveys were also undertaken simultaneously with the aid of a traffic monitor mounted on a Mitsubishi Pajero. An actual field layout of the Camp Crame survey is presented in Figure 2.1. Historical data of carbon monoxide concentration, traffic seasonal variation and meteorological measurements were also gathered in order to establish pollution level trends.

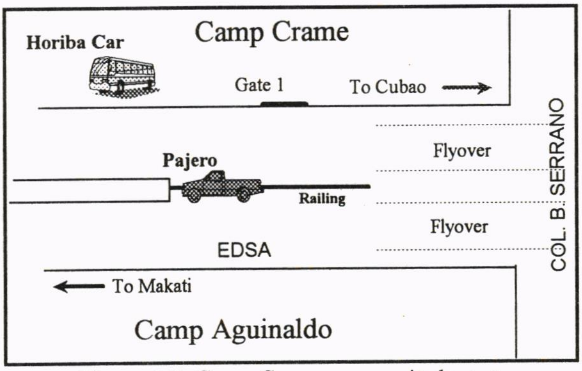


Figure 2.1 Camp Crame survey site layout.

Empirical modeling primarily utilized statistical tools like multiple regression and non-linear parameter estimation techniques available in a statistical software. Residual analysis and fitness tests were likewise performed to further rectify the model. A schematic diagram of the modeling process is presented in Figure 2.2. The effect of wind was considered by classifying the data by wind direction and performing a separate analysis for each group.

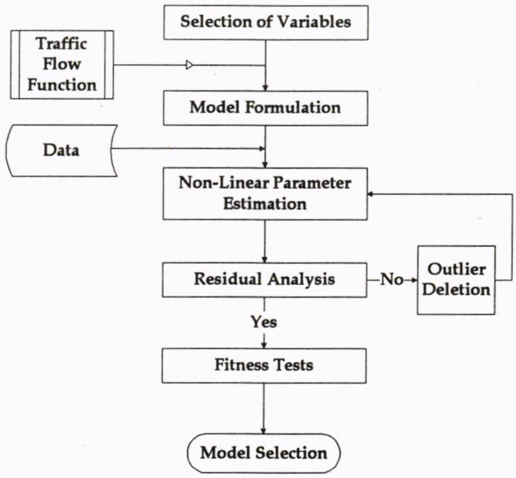


Figure 2.2 Empirical Modelling Process

A sensitivity analysis was also conducted to identify the most significant parameters affecting pollutant concentration. Combinations of traffic level and meteorological conditions that will bring about critical levels of CO were further determined. In addition, the study made an assessment of the ambient air quality of the study area, identified air pollution problems and their causes, and sites workable solutions based on the observed conditions.

Atmospheric stability and boundary layer conditions were not considered in actual modeling. The format of the model however was so designed making it flexible to further developments such as the inclusion of vertical and lateral dispersion coefficients. The chains of chemical reactions occuring in the ambient environment were likewise not included. CO, the main pollutant in focus, is relatively stable as it is difficult to dissolve in water and it does not oxidize without a catalyst. Built-in features of the air pollution monitoring equipment used in the study limits pollutant measurements to a fixed receptor height of 3.5 meters.

3. DATA COLLECTION

In the development of a statistical air pollution model, a basic requirement is the availability of reliable sets of data simultaneously conducted from a particular site. Required data includes hourly measurements of air pollutant concentration, wind speed and direction, classified traffic count and average travel speed. In the absence of secondary sets of data, field surveys were conducted. The following sections present the conduct of some of the major data collection and related activities.

3.1 Survey Site Selection

Generally, the ambient sampler should be located outdoor at a place where the public has free access and where the pollutant concentration is highest (De Nevers, 1995). This requirement, together with other obvious considerations such as accessibility, availability of power, enough space for installation of the instruments, security, and distance from other interferring pollutant sources provided proper guidance in site selection. In an attempt to *control* the conditions involved during monitoring and to ease-up the the modeling process with simplifying assumptions, the following criteria in choosing an ideal survey site, as shown in Figure 3.1 was placed atop the above mentioned general practical requirements.

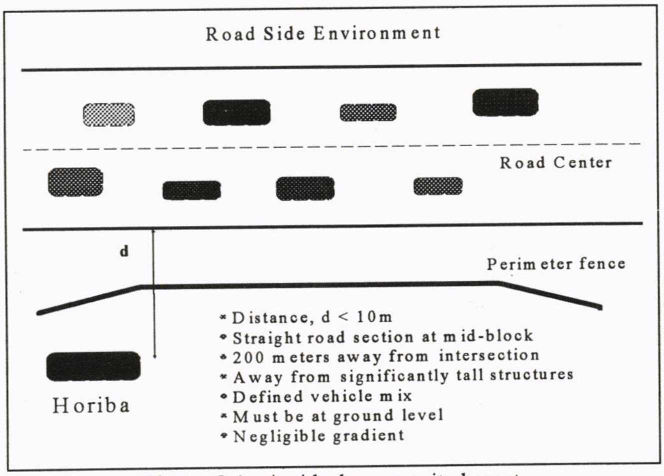


Figure 3.1 An ideal survey site layout.

3.2 Air Pollution Monitoring

The study utilized the state of the art Horiba 350 Series Air Pollution monitoring equipment mounted on a Mitsubishi Rosa. The CO measurement is based on the concept of the absorption of infrared radiation by non-dispersive spectometry. Hourly monitoring was conducted for at least one week per site. Other pollutants monitored during the survey includes oxides of nitrogen which uses the chemiluminescence method and suspended particulate matters which utilizes the beta-ray absorption method.

3.3 Classified Volume Count Survey

A main variable in road side environment air pollution modeling is traffic volume. Defined as the number of vehicles passing a given point during a specified period of time, traffic volume gives an accurate information on the total traffic from each direction contributing to the pollution level in the area (TTC, 1983). Classified volume count likewise presents details regarding traffic composition by vehicle type, and a relative variation of traffic condition for a given span of time.

Five general vehicle classes were used in the survey, namely: cars, utility vehicles, buses, trucks and motorcycles. Car includes all *sedan* while utility vehicles include vans, jeepneys, pick-ups and all other vehicles not belonging to the car category and not bigger than the old *Toyota Tamaraw* model. Vehicles bigger than such model, together with trailers are classified as trucks. Buses include conventional buses and mini-buses. Motorcycle inludes both the motorcycles and the tricycles.

Emission rate for every vehicle varies depending on the size of the engine, the type of fuel used, and the weight of the vehicle including its load. The vehicle classification employed in the survey was primarily based on the above-mentioned factors. Engine size and vehicle weight can be accounted for in vehicle size. The composition of the vehicle fleet by fuel type can be derived by assuming all cars and motorcycles to be using gasoline and all buses and trucks to be using diesel. For utility vehicles, a 45.7% gasoline against 54.3% diesel fleet composition which is based on the 1995 vehicle registration by fuel type was safely assumed.

3.4 Spot Speed Survey

Spot speed survey aims to determine the variation of speed at a given location throughout the day (TTC, 1983). As speed affects the rate of emission of vehicles, it likewise supplements the volume count by accurately describing the traffic condition particularly during congestion. Defined as the instantaneous speed of a vehicle at any specified point, spot speed was determined by taking the time it would take for a vehicle to pass through a trap length of a known distance (TTC, 1983). Hourly traffic speed average for the entire direction was determined by taking spot speed samples from the middle lane with the assumption that it approximately represents the average speed for the entire roadway.

The sampling size, *n* that was used in estimating the hourly mean speed was determined by the equation,

$$n = \left(\frac{k\sigma}{e}\right)^2 \qquad \text{Eq.(3.1)}$$

where k = level of confidence index
σ = standard deviation
e = allowable error in km/h

Using a 95.0% confidence level and an allowable error of +/- 2 km/h, a fixed number of 180 samples per hour per direction was found to safely meet the required minimum number of samples.

Combined speed, *C_Speed* for both directions was calculated by simply taking the average which is expressed as,

$$C\_Speed = \frac{Speed_1 * Vol_1 + Speed_2 * Vol_2}{Vol_1 + Vol_2} \qquad \text{Eq.(3.2)}$$

where $Speed_i$ = average speed for direction *i*
Vol_i = total traffic volume for direction *i*

3.5 Meteorological Monitoring

Meteorological observation only covers the monitoring of simple weather parameters like wind speed and wind direction. Directions with respect to the z-axis were not considered thus simplifying wind into a two-dimentional vector. Wind velocity lower than 0.4 m/s was considered calm. Survey sites were subjected to several locational criteria to simplify topographical considerations.

Measurements were conducted using an anemometer and anemoscope raised to an elevation of 9.0 meters. Hourly measurements of wind speed were expressed in m/s while the most prevalent hourly wind directions were established using the 16 compass points. The power-law function of height commonly used to estimate the mean wind speed at a desired elevation given a set of measurements from a known different altitude was adopted as expressed in the equation,

$$U = U_0 \left(H/H_0\right)^a \qquad \text{Eq.(3.3)}$$

where, U : Assumed wind speed (m/s) at height H (m)
U_0 : Wind speed (m/s) at standard height H_0 (m)
a : Exponential index

The value for the parameter **a** tends to become bigger as surface roughess increases as shown in Table 3.1. For this study, a value of 1/5 was used representing a convertion index for a sub-urban setting for the relatively flat Camp Crame-Camp Aguinaldo areas.

Table 3.1 Wind speed conversion index for different topograghy.

Land Use Condition	Exponential Index (a)
Urban	1/3
Sub-Urban	1/5
Plain Lands without Obstacle	1/7

Wind speed readings were not right away converted to coincide with the 3.5 meter receptor height. Since conversion is done by simply multiplying all wind measurements by a factor $(H / H_0)^a$ which is just equal to a constant 0.827876 for H=3.5 and H_0=9.0, it was expected not to affect the parameter estimate when conducting the modeling. Instead, the coefficient *b* that *absorbs* the correction factor was later corrected.

3.6 Background Air Pollution Estimation

The daytime background concentration of carbon monoxide on the study area was estimated to be within the range of 0.7 ppm to 1.4 ppm. This was based on the results of a survey conducted inside the University of the Philippines, Diliman Campus (Fig.3.2) and the graphical estimation technique (Figure 3.3) that was employed using the wind *Dir D* of the EDSA data. The site in UP Canpus is relatively way from heavily trafficked road while the Wind Dir D in the EDSA data is the case where in wind is blowing The range was used as bases in choosing the reasonable background pollution attributed modeling-generated intercept.

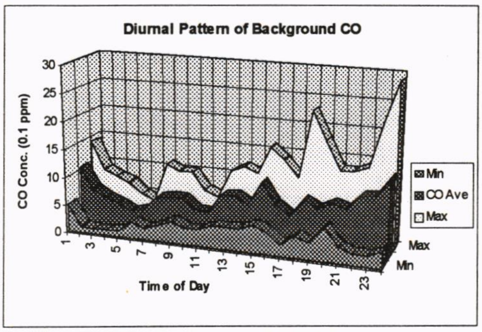


Figure 3.2 Background CO Concentration

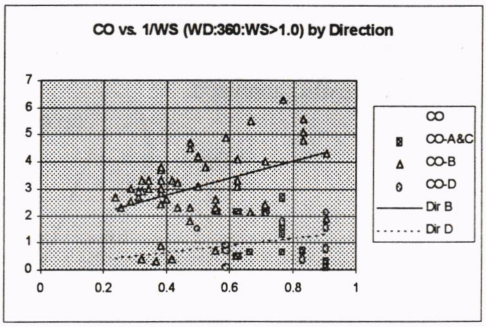


Figure 3.3 Graphical Background CO

4. EMPIRICAL MODEL BUILDING

Air pollution modeling is based on the several generally accepted assumptions. Among them is that pollutant concentration is directly proportional to traffic volume while inversely proportional to wind velocity. Traffic speed, being in general inversely proportional to traffic volume, is likewise assumed to be inversely proportional to the pollutant concentration. Results of previous studies that vehicles traveling in speed lower than 60 km/h tend to emit a more polluted exhaust (Hamilton, 1991) further established the inverse relationship .

Wind direction being a significant factor in the fluctuation of pollutant was accounted for by classifying the data by wind directions. An initial graphical analysis that was conducted showed that relationship between wind speed and CO concentration improved when data are grouped by wind direction. Modeling later focused on the data set where wind blows crossing the road towards the direction of the receptor (Dir B) since it was observed that it gave the most consistent and most significant relationship between the parameters being tested.

Practical modeling considerations included the accuracy, simplicity, applicability and flexibility of the model. Accuracy refered to the model's predictive performance while simplicity was dependent on the amount and availability of the required input. Applicability, on the other hand refered to the vastness of the model's application while flexibility refered to its ability to cater and adopt further modeling developments.

4.1 Model Formulation

Specific format estabishing the relationship between CO and wind speed, was determined by performing a graphical analysis. The analysis was done by generating a scatterplot and drawing a trendline over various sets of data classifications. Data are grouped by wind direction, time of day, and their combinations. A representative format is that having a trendline of higher R^2 and lower intercept.

With EDSA coinciding the NNW-SSE axis, the four groupings by wind direction labeled as Directions A to D are shown in Figure 4.1. In cases where wind direction of a data point coincided with the boundary, the data is accounted for in both adjacent groups. *Directions*

A and *C* were further combined by symmetry, finally reducing the originally 16-point directional classification into three. Various groupings by time of day and combinations thereof were also analyzed.

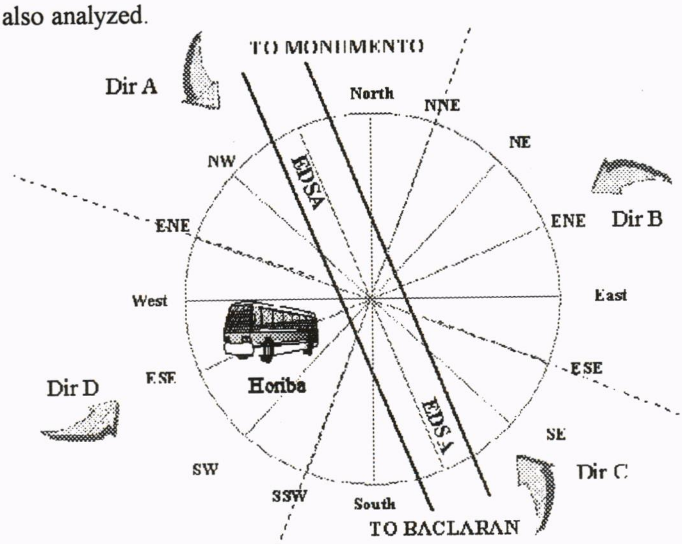


Figure 4.1 Adopted Wind Directional Groupings

The negative exponential and the linear-inverse exhibited a better fit on CO and wind speed relationship. With *a* and *b* as the estimated parameters, the former and the latter take the forms:

$$CO = a * exp(-b * WS) \qquad \text{Eq. (4.1)}$$

and, $$CO = a + b / WS \qquad \text{Eq. (4.2)}$$

Further, scrutiny resulted to a slight preference to the latter since it does not return a zero CO estimate as wind speed approaches the value of infinity. Such behavior is more realistic, for regardless of the extent of dispersion over an area, there is still an initial concentration

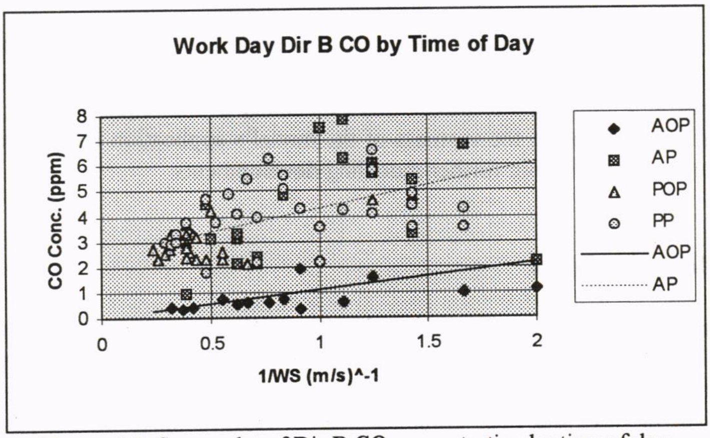


Figure 4.2 Scatterplot of Dir B CO concentration by time of day.

representing the background pollution. This is in addition to the higher R^2 values and the lower intercepts the latter exhibited. The second term of the resulting equation is very similar to the simplified Gaussian dispersion equation used by Colwill, as well as the concentration equation adopted by Manins. Figure 4.2 below shows the linearized curves using the factor (1/WS) for *Dir B* and different time of day groupings.

4.2 Empirical Model Development

Trendline analysis identified wind direction B (Dir B), as the group which exhibits statistically significant CO-wind speed relationship. This set of data was therefore used in model building. Starting from Equation 4.2, intercept a was made to represent the background pollution and the second term as the general dispersion equation used by Manins. This generated a modeling equation in the form,

$$CO = a + k * Q / WS \qquad \text{Eq. (4.3)}$$

where emission rate, Q, is a function of traffic flow parameters while coefficient k is a dimensionless parameter that is a factor of averaging time, location of the source and receptor, and the turbulence in the atmosphere (Manins, 1991). This transforms Equation 4.3 into:

$$CO = a + b * f(TP)_i / WS \qquad \text{Eq. (4.4)}$$

where $f(TP)_i$ can be any traffic flow function and coefficient b a dimensionless parameter empirically derived to approximate the term (k*Q/f(TP)), thus, preserving the equality. Note that by doing so, coefficient b accounted for the factors concerning atmospheric stability.

Several traffic flow functions were evaluated in the model, each of which are depicting a unique blend of simplicity and accuracy. Among the functions are Equations 4.5-a, 4.5-b and 4.5-c. as shown below.

$$F(TP)_1 = \Sigma (Veh_i * E.F._i) * Speed^c \qquad \text{Eq. (4.5-a)}$$

$$f(TP)_2 = Total\ Vol * (\Sigma Speed / n)^c \qquad \text{Eq. (4.5-b)}$$

$$f(TP)_3 = Total\ Vol / (\Sigma Speed / n) = C\_VSR \qquad \text{Eq. (4.5-c)}$$

where, Veh_i = no. of vehicle of type i
E.F.i = emission factor of vehicle i
$Speed^c$ = road section average traffic speed raised to a constant c
Total Vol = total volume

Equation 4.5-a considers vehicle classification by adopting emision rate factors generated by the 1992 ADB Study. Equations 4.5 b & c on the other hand assumes that gasoline and diesel-engined vehicles emit the same amount of carbon monoxide, a simplifying assumption used by Colwill and Hickman on a similar study in 1982 justifying that the lower CO concentration of diesel exhaust is being offset by the larger volume of exhaust produced by large diesel engine. The last function, the simplest, only combines volume and speed into a single traffic flow parameter, *combined volume-speed ratio*.

4.3 Modeling Results

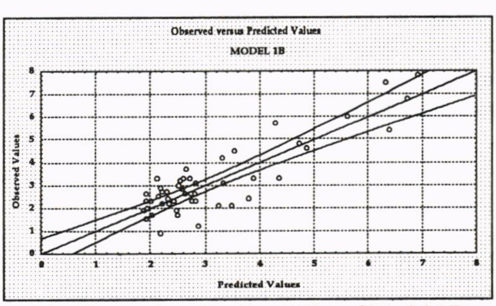
The Non-linear Estimation procedure of STATISTICA, a statistical package by StatSoft, Inc. was used in generating the empirical models. An initial run using all sets of data was conducted followed by a residual analysis. The generated model then was further rectified based on the results of the analysis. Table 4.1 summarizes the statistics of the three modeling equations containing the traffic flow function $f(TP)_i$ plus a fourth equation (Model 1-b) which is basically $f(TP)_1$ with exponent c=-1.

Table 4.1 Summary of the modeling estimates and the fitness tests results.

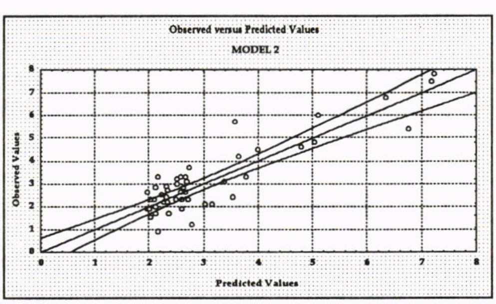
MODELING & FITNESS TESTS RESULTS				
Parameters / Indexes	Model 1	Model 1B	Model 2	Model 3
A	1.60572	1.38811	1.60126	1.37553
Std. Error	0.13738	0.15927	0.13761	0.16050
t(53)	11.68859	8.71568	11.63592	8.57006
p-level	0.00000	0.00000	0.00000	0.00000
B	0.00266	0.00030	0.10689	0.01156
Std. Error	0.00019	0.00002	0.00757	0.00088
t(53)	14.12293	13.14376	14.12248	13.10047
p-level	0.00000	0.00000	0.00000	0.00000
C	-1.64916		-1.66399	
R	0.88886	0.87478	0.88885	0.87410
Fin. Loss	24.94719	27.89751	24.94846	28.03861

The evaluation of model fit involved the examination of the Observed vs. Predicted Values; the Normality Plot of the Residuals and the Plot of the Fitted Functions. Also included were the assessment of statistical indexes such as correlation coefficients, standard error of estimates and percentage of explained variance.

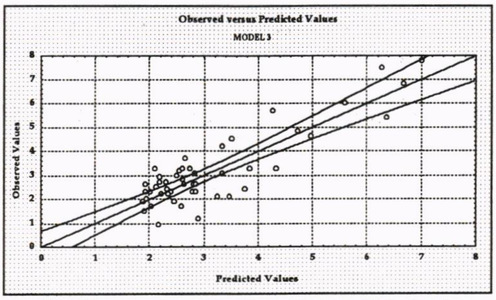
Modeling and fitness tests results as shown in Table 4.1, generally depict set of well fitted models. The The *t-statistics* for instance as indicated by the *p-levels* denoted highly significant parameter estimates. Very low *standard errors* particularly for the coefficients *b* proved the exactness of the estimates to yield the least combined residuals. The *correlation coefficients, R,* with values ranging from 0.874 to 0.889 for a total of 55 samples surpassed the critical values of the Spearman's Rank Correlation Coefficients of 0.478 for $\alpha = 0.005$ for even a smaller sample. The *final loss* values representing the summation of the loss function, which in this case equal to *$(OBS\text{-}PRED)^2$*, posted relatively low values indicating a good set of estimates. The *percentage of explained variance* were simply the equivalent of the coefficient of determination R^2.Figures 4.3 present some of the Observed vs. Predicted plots of the generated models.



(a) Observed vs. Predicted Plot of Model 1B



(b) Observed vs. Predicted Plot of Model 2



(c) Observed vs. Predicted Plot of Model 3

Figure 4.3 Observed vs predicted scatterplots with a 99.0% Confidence band width.

4.4 Endorsement of the Best Model

All four models primarily met the basic statistical guidelines regarding parameter estimates and goodness of fit. An examination of the the models *Observed vs. Predicted (O-P)* plots showed a similar number of points found inside and outside the confidence level band width. Though in general, a very slight difference in the O-P was observed in favor of Model 2 attributed to an extra parameter *c*, the slight edge is leveled off by the presence of few data points that are way off O-P proportionality line. In terms of accuracy, the differences on particularly on the indexes and test values among models were found to be so minimal to merit major consideration in the selection of the best model. Simplicity on the other hand favors Model 3 and its clone Model 2, both requiring only *combined volume-speed ratio (C_VSR)* as input. Models 1 though features a per vehicle type approach. All four models were almost equally adaptable. The inclusion of lateral and vertical diffusion coefficients, σ_x and σ_y, using the same data set for instance will simply replace the coefficient b with $d / (\sigma_x * \sigma_y)$ where d is roughly equal to $(\sigma_x * \sigma_y) * b$ thus preserving the models.

A parameter which differentiates the models over the other is the modeling intercept. Theoretically, models with lower intercepts are better since intercept accounts for the the relative error in the value contributed by the other parameters. Such models likewise has a wider range of guess values as it is capable of generating low estimates due the lower initial cut off. The intercept must likewise fall within the background pollution range established in Section 3.6. Based on above discussions, the study endorses Model 3 as the working equation to be further developed to improve its application on the realms of on-site air pollution estimation and forecasting. A three-dimentional plot of Model 3 is presented in Figure 4.4. It's simplicity, relative accuracy and rational numerical features made it the best model relating a traffic flow function and an air pollutant concentration over the others.

Taking in to account the correction due to the wind measurement altitude as discussed in Section 3.5, a correction factor was introduced to the coefficient *b* yielding the model's final form.

The corrected model, Model 3 in its final format is expressed as follows:

$$CO = 1.37553 + 0.013963 * C\_Volume\ Speed\ Ratio / Wind\ Speed \qquad \text{Eq. (4.6)}$$

where, CO = carbon monoxide ambient concentration in ppm
C_Volume Speed Ratio = the ratio of ombined traffic volume in veh/h and average traffic speed in km/h
Wind Speed = wind speed measurement at 3.5 m altitude in m/s

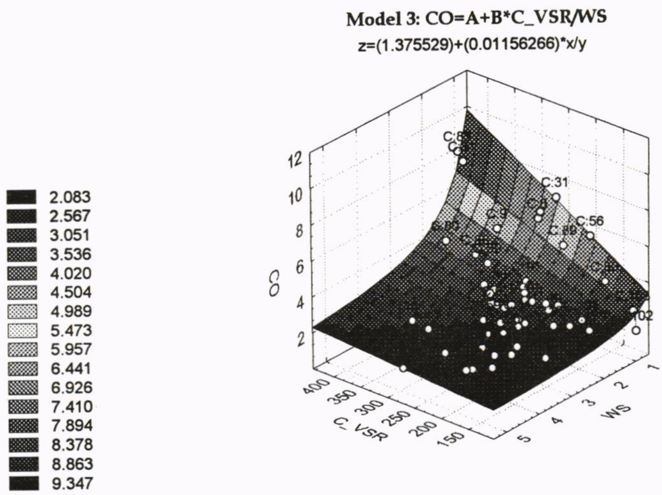


Figure 4.4 Three-dimensional surface plot of Model 3.

5. MODEL PERFORMANCE TEST

Model performance test aimed to evaluate the predictive performance of the model and diagnose the conditions associated with the inaccuracies in the model's prediction (TRB, 1981). In testing the performance of the model, another monitoring activity was conducted to gather the same set of parameters from a different site. The model was utilized to estimate the carbon monoxide levels given a new set of wind and traffic flow measurements. The generated estimates were then compared to the actual measurements through the conduct of fitness tests and residual analysis.

The monitoring activity was conducted along Commonwealth Avenue inside the Asian Institute of Tourism (AIT) compound. Using the same equipment, the mobile air pollution monitor was set up just 6- meters from the side of the road. The survey gathered traffic, air pollution and meteorological parameters using the same data gathering procedures. The orientation of Commonwealth Ave. results to the following groupings namely: (1) Wind Dir A: wind is blowing to Quezon City Memorial Circle (QMC) parallel to the road (NNE to ENE quadrant); (2) Wind Dir B: wind is blowing towards the receptor (E to S quadrant); (3) Wind Dir C: wind is blowing to Fairview parallel to road (SSW to W quadrant); and (4) Wind Dir D: wind blowing away from the receptor (WNW to N quadrant).

5.1 Residual Analysis

Using the calculated CO as the *expected* and the gathered data as the *observed* values, the analysis of the residuals exhibited promising results. Out of the 60 valid data points, only four residuals were found to be lying beyond the +/-2 ppm residual range. Further, almost 80% of the entire data were within the +/-1 ppm and about 50% were within the +/-0.5 ppm expanse. The frequency distribution in Figure 5.1 further shows that most of the residual falls at the left of the bell curve, indicating that with most data points, the model predicted a slightly higher concentration values than that of the observed. It was found out later from the *observed-expected* scatterplot that the distribution of samples and an estimation bias cause the uneven distribution of the residual.

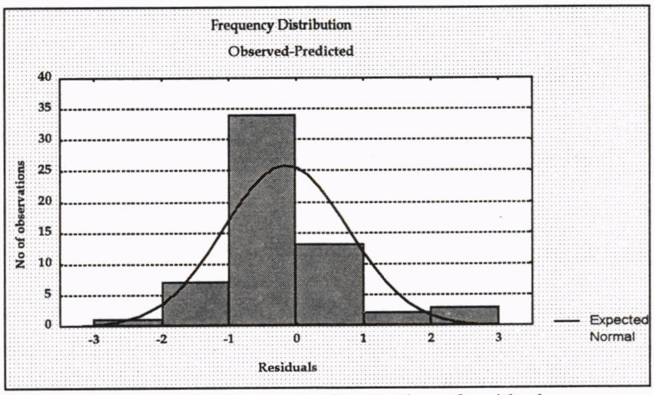


Figure 5.1 Frequency distribution of residuals.

5.2 Fitting Linear Function

The scatterplot as shown in Figure 5.2 was intended to supplement the model performance analysis by residual distribution. Assuming a perfect fit, the data points in the scatterplot will theoretically coincide with the *observed=expected* line. The scattering of the plots with respect to the line was evaluated by fitting a linear regression that would best correlate the *observed* and the *expected* values. The fitted function was then compared to that of the *observed=expected* line. The result of linear regression is presented in Table 5.1.

Table 5.1 Observed Vs. Expected Fitted function.

STAT. REGRESS.	Mult. R = 0.71563 R-Square = 0.51212		Adj. R-Square = 0.50371 Fin. Loss = 47.05158	
N=60	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.96673	0.41336	-2.33875	0.02282
EXPECTED	1.35481	0.17363	7.80275	0.00000

The negative intercept (-0.96673) indicated that the model was inclined to initially overestimate the low-level CO concentration (Fig.5.2). Ideally, an intercept indicating a good fit should be close to zero. The calculated coefficient of 1.35481 (greater than 1.0) indicated that as CO level increases, the observed value gradually outpaces the corresponding increase in the expected value, thus, neutralizing the overestimating effect of the intercept until such level that the model underestimates the observed CO concentration. As a result, good estimates were made between observed CO values of 1.0 ppm and 4.5 ppm. With most AIT measurements falling within this range, a positive result of the previous test was generated. The result can be partly attributed to the measurement ranges of the two data sets. Note that the EDSA data used in the model calibration ranges from 0.9 ppm to 7.8 ppm, encompassing the AIT range of 2.1 ppm to 5.6 ppm.

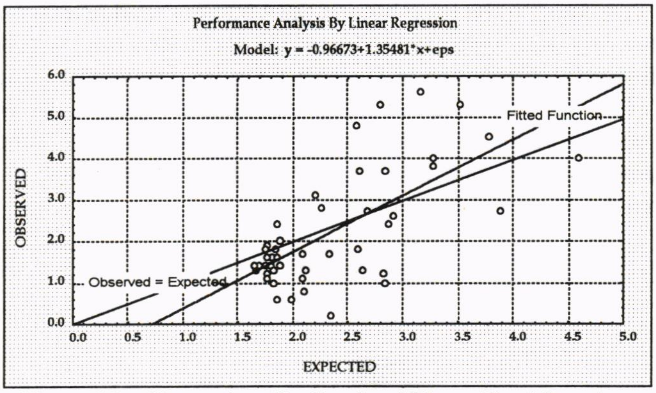


Figure 5.2 Observed vs. Predicted and Linear Fitted Functions

5.3 Diagnostic Analysis

The uneven distribution or the *bias* in the scattering of the observed vs. predicted plot was attributed to certain conditions that are different from each site. This particularly pertained to the factors accounted for by the estimated parameters intercept a, and coefficient b. The negative intercept in Table 5.2 for instance signified that a lower intercept was more suitable in describing the pollution level at AIT. Likewise, the coefficient of 1.35481 indicated that a higher slope would be more appropriate. Since intercept a accounted for the background pollution in the area, and that EDSA was relatively closer to other major roads than that of AIT, then it is just but logical and consistent to conclude that a higher background pollution which exists at EDSA, caused the over estimation of low level CO concentration at AIT.

On the other hand, parameter b mainly accounted for factors represented by the dimensionless parameter K in Eq.(4.3) such as averaging time, location of the source and receptor, and turbulence in the atmosphere. Considering the similarities in averaging time, and atmospheric conditions leaves the location of the source and receptor as the potential factor causing the difference. Source and receptor location is basically a distance parameter. With Horiba at EDSA positioned farther by four (4) meters from the roadside compared to that of AIT, in addition to being a 10-lane two-direction stretch against the 6-lane two-direction Commonwealth Avenue, EDSA differs in distance between the receptor and the road center by at least 11.0 m. The difference in distance is inclined to be even more significant as the wind blowing from the road towards the receptor decreases. Note that assuming equal traffic flow measurements, the decrease in wind speed is characterized by an increase in pollution level. This supposition stands consistent with the identified trend that the difference between *observed* and *expected* was increasing as the CO level increases.

6. SENSITIVITY ANALYSIS

A sensitivity analysis is made by first taking the most likely or best guess value of each inputs and calculating the output value which is taken as a base. Each input value is then altered and the output recalculated, all other inputs remaining at their best guess values. The inputs may be altered to their most plausible high and low bounds or else may be altered by arbitrary amounts simply to see what effects they have. Changes in value is generally expressed as percentage deviations from the most likely values (Jossep,1990).

6.1 Best Guess Values

For the traffic flow parameters, best guess values were based on the frequency distribution and mean of the data gathered. Wind speed on the other hand was based on the historical 40-year measurements gathered from a PAGASA station situated in Science Garden, Quezon City, wherein the wind monitor was installed at an altitude of 43.0 meters. Assuming a suburban surface, the 2.0 m/s normalized wind speed was adjusted to match the receptor height of 3.5 meter using Equation 3.3, generating a wind speed value of 1.2 m/s.

Best guess values for traffic speed, volume and density are as follows:

Average Traffic Speed:	40 km/h
Total Traffic Volume:	10,000 veh/h
Combined Volume-Speed Ratio:	250 veh/per km road section

6.2 Sensitivity Curves

An increment of 5% change was used for the independent variables being tested. Then CO-concentration and its corresponding percent change were computed by manipulating the value of a particular variable while fixing the values of others. Sensitivity curves were then generated by plotting the percent change applied to an independent variable against the resulting percent change in CO concentration. Figure 6.1 below shows the sensitivity curves of the traffic flow parameters assuming that every parameters are independent of the other.

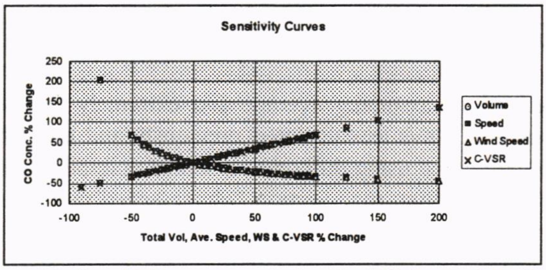


Figure 6.1 Sensitivity curves relatingTotal Volume, Ave. Speed, Wind Speed and C_VSR to CO concentration.

The sensitivity curve in Figure 6.1 shows that the increase in *combined volume-speed ratio* affects the carbon monoxide level greater than the corresponding percent increase in wind speed. On the other hand, a percentage decrease in wind speed is observed to be more influencing to the CO level than the corresponding percent decrease in C_VSR. While wind speed significantly affects CO levels as it decreases from the best guess value, it was observed to become less significant as it reaches a certain percentage increase. Based on the curve, the empirical relationship between CO level and *combined volume-speed ratio* assuming all other parameters are in their best guess values is represented by a 6.79% increase in CO level for every 10% increase in volume-speed ratio. As expected, traffic volume coincides with the C_VSR plot while traffic speed coincides with the wind speed curve.

Further, Figure 6.1 indicates a continuous decrease in CO as traffic speed increases. Though, for this particular study such relationship will most likely hold true, it may not always be particularly in cases wherein there is a wide range of observed traffic speed. It should be noted that with traffic speed as an index of vehicle operation mode, the volume of CO in exhaust gas is least when the vehicle travels between 60 to 80 km/h (Hamilton,1991). This means that as the speed exceeds 80 km/h, the volume of CO in the exhaust starts to increase thus contradicting the continuosly decreasing trend. All average hourly speed measurements in the study are less than 60 km/h.

6.3 Roadside Environment Scenarios

Using the generated sensitivity curves, actual and hypothetical values were affixed to the model to observe the estimated CO level for different combination of roadside conditions. Average and worst case scenarios were depicted by a combination of calm and average wind speed and then average and maximum combined volume speed ratio. The figures below attempt to determine the combination of parameter values that will yield critical CO levels.

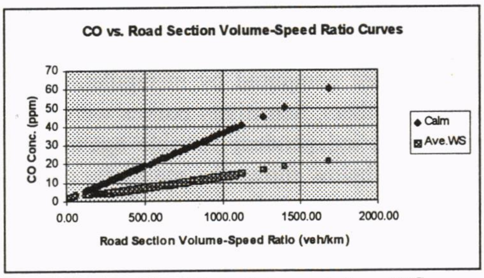


Figure 6.2 CO at Calm and Ave. WS

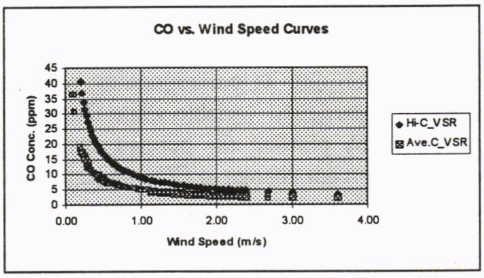


Figure 6.3 CO at High and Ave. C_VSR

Figure 6.2 was generated by assuming average and extremely low wind velocities. The average velocity is set to 1.2 m/s as calculated previously and the calm wind at 0.4 m/s. Then CO values were computed using different combined volume-speed ratios. Figure 10.3 was generated using the maximum road section volume-speed ratio of 560 veh/km and an average ratio of 250 veh/km of road section. CO values were generated using different wind velocities.

Figure 6.2 further shows that at calm winds, a volume-speed ratio of over 800 veh/km will yield a critical hourly CO average. For normal wind velocity, the critical hourly CO level of 30 ppm will be reached with approximately 2000 veh/km of road section volume-speed ratio. The EDSA survey measured a maximum volume-speed ratio of about 560 veh/km of road section. Though calm wind were observed for several hours, most of its occurrences were after midnight coinciding with the period of very low traffic volume.

Figure 6.3 represents two curves relating wind speed and CO level for different C_VSR. With only a maximum of about 560 veh/km volume-speed ratio, the posibility of reaching the 30 ppm CO concentration is very slim. The curves further indicate that for now, CO level in the study site is far beyond the critical level.

7. SUMMARY OF FINDINGS AND RECOMMENDATIONS

7.1 Air Quality Monitoring Results

Results of the air pollution monitoring activity conducted along EDSA identified Suspended Particulate Matters (SPM) as the most critical pollutant in the area exceeding the hourly National Ambient Air Quality Standard value of 250 µg/Ncm by a factor of 1.3. Among the pollutants monitored, SPM was followed by nitrogen dioxide which nearly reached the 0.1 ppm hourly mark and then carbon monoxide which was way below the critical levels.

The hierarchy was basically consistent with other observational studies though actual measurement values were found to be relatively lower. The difference was primarily attributed to the seasonal and locational difference in the conduct of the surveys. This being conducted in the prevalence of the Northeast monsoon with 5.4 m/s maximum wind measurement and at a mid-block where pollution level was mainly contributed by a single road section. Temperature and several other meteorological parameters might also have contributed to the seasonal difference. A 1995 carbon monoxide concentration data collected by the Traffic Engineering Center was analyzed and it showed that the month of February, together with March and April, had one of the lowest CO monthly averages with only 1.2796 ppm. Such figure was twice less than the highest monthly average of 3.7273 ppm which occured in the month of November. The averages were generated using hourly data continuously collected at the TEC Air Pollution Monitoring Station.

7.2 Identified Factors Contributing to the Air Pollution Problem

Traffic speed along EDSA was found to be lower than the fuel-efficient running mode (within 60 kph to 80 kph) resulting to emissions of higher CO volume. The low traffic speed was characterized by intermittent occurrence of congestion and was caused by the increasing traffic volume and the unruly stopping of passenger buses in the area.

Congestion which stalled vehicles in an idling mode was another factor contributing to the high pollutant concentration in the local area. The increasing degree of congestion can be attributed to an increasing number of vehicles outpacing road improvement and other similar projects. The increasing number of vehicles was attributed to the government's vehicle development programs which triggered a sudden increase in vehicle ownership. This was further aggravated by very low vehicle phaseout.

The exceedance of SPM, was attributed to the increasing number of diesel engined vehicles. Increasing diesel registration was found to have some correlation with the difference between gasoline and diesel fuel prices. Historical record showed that an increase in diesel-engine registration consistently coincided with an increase in the difference between gasoline and diesel fuel price.

7.3 Empirical Modeling Results

A simple statistical model designed to estimate the ambient concentration of an air pollutant in a roadside environment was developed. The model was able to particularly estimate carbon monoxide level given basic traffic flow and meteorological parameters. The model was generated using first-hand, hourly day-time data points with wind blowing from the road towards the direction of the receptor. Considerations on coming up with an appropriate format included the adoption of commonly accepted assumptions, some general similarities with other estimation models and the utilization of basic statistical techniques.

At present, the model can handle CO level estimation given traffic speed and volume, or simply the *combined volume speed ratio*, and wind speed blowing from the road towards the point being evaluated. An on site model performance test was conducted yielding positive results and identifying potential areas of improving the model. The generated model is as shown below:

$$CO = 1.37553 + 0.013963 * Comb.Vol\_Spd\ Ratio / Wind\ Speed \qquad \text{Eq.(7.1)}$$

7.4 Model Performance Analysis

The result of the model performance test was encouraging revealing a good correspondence between the expected and the observed values though only for a certain range of CO concentration. Factors contributing to the generation of a good set of estimates were attributed to similarities in general meteorology, the sites' topography and the coinciding CO concentration range of the two study sites. The model however seemed to overestimate CO concentration outside the lower bound of the range and underestimate CO level beyond the upper bound of the range. The biased miscalculations were attributed to the difference in background air pollution, road width and distance between the receptor and the side of the road. Appropriate considerations on the identified parameters together with wind direction are expected to significantly improve the estimating capability of the model.

In general, the results of the test hinted at the possibility of the models applicability to several other sites of different road type and traffic composition. Data points of significant residual values on the other hand echoed a universal truth: that model estimates should not be regarded as numerically accurate description of the actual air quality or prediction of a projected scenarios (Hickman, 1982). Rather, model estimates simply gives a general description of the most likely situation given a particular condition.

7.5 Sensitivity Analysis

Sensitivity analysis was conducted by taking 40 km/h, 10000 veh/h, 250 veh/km, and 1.2 m/s as respective best guess values for traffic speed, volume, volume-speed ratio and wind speed. Based on the results of the analysis, volume-speed ratio was identified as the main factor affecting CO concentration particularly for a wind speed value that was equal or greater than the best guess. For wind speed lower than 1.2 m/s however, wind speed was observed to become more effectual than the volume-speed ratio. Traffic volume and traffic speed assuming independent from each other coincided with the volume-speed ratio and the wind speed curves respectively.

On average condition, that was, assuming all other parameters were in their best guess values, a 10% increase in the volume-speed ratio corresponded to a 6.79% increase in CO level. A CO vs. C_VSR curve also projected that at normal wind velocity, an increase in the current maximum C_VSR by a factor of 3.0 will be required to reach the CO hourly critical level of 30 ppm.

7.6 Recommendations for Further Development

The genetrated model however was far from perfect. Data used were practically limited to a particular relative wind direction, flat terrain, straight road sections, a road side location and a dry-Northeast monsoon season. Numerous simplifying assumptions were likewise adopted in the course of model formulation thus further limiting the applicability of the model to specific conditions. Researches dealing with the effect of a variation in the identified parameters to CO concentration is highly recommended to further the model's applicability. For instance, the inclusion of wind direction as a continuous variable expressed as a function of an angle with respect to the position of the road will make the model applicable to all wind directions.

Model calibration of other pollutants, perhaps, SPM, Hydrocarbons and NO_2, is viewed to be likewise necessary. Though establishing the empirical relationships between the concentration of CO and other pollutants could be possible, an estimation of the concentration of another pollutant based on its relationship to CO can be very unreliable.

The formulation of a simulation program is likewise one of the most immediate steps identified beyond the coverage the study. Simulation program can be very useful in further evaluating and developing the existing models. Being replicable, it will be very useful in conducting evaluation runs with minimal conduct of field surveys. Simulation is likewise a potential start towards a comprehensive software development.

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