CHAPTER 2

LITTERATURE REVIEWS

2.1 Major Air Pollutants

2.1.1 Carbon monoxide

Carbon monoxide (CO) is a colorless, odorless and at high levels, a poisonous gas, formed when carbon in fuel is not burned completely (EPA 1999). It is a component of motor vehicle exhaust, which contributes to about 60 percent of all CO emissions in the US. High concentrations of CO generally occur in areas with heavy traffic congestion. In cities, as much as 95 percent of all CO emissions may come from automobile exhaust. Other sources of CO emissions include industrial processes, non-transportation fuel combustion, and natural sources such as wildfires. Peak CO concentrations typically occur during the colder months of the year when CO automotive emissions are greater and nighttime inversion conditions (where air pollutants are trapped near the ground beneath a layer of warm air) are more frequent.

Carbon monoxide enters the bloodstream through the lungs and reduces oxygen delivery to the body's organs and tissues. The health threat from lower levels of CO is the most serious for those who suffer from cardiovascular disease, such as angina pectoris. At much higher levels of exposure, CO can be poisonous and even healthy individuals may be affected. Visual impairment, reduced work capacity, reduced manual dexterity, poor learning ability, and difficulty in performing complex tasks are all associated with exposure to elevated CO levels.

2.1.2 Nitrogen dioxide

Nitrogen dioxide (NO_2) is a reddish brown, highly reactive gas (EPA 1999) that is formed in the ambient air through the oxidation of nitric oxide (NO). Nitrogen oxides (NO_x), the term used to describe the sum of NO, NO_2 and other oxides of nitrogen, play a major role in the formation of ozone. The major sources of man-made NO_x emissions are high-temperature combustion processes, such as those occurring in automobiles and power plants. Home heaters and gas stoves also produce substantial amounts of NO_2 in indoor settings.

Short-term exposures (e.g., less than 3 hours) to current nitrogen dioxide (NO_2) concentrations may lead to changes in airway responsiveness and lung function in individuals with pre-existing respiratory illnesses and increases in respiratory illnesses in children (5-12 years old). Long-term exposures to NO_2 may lead to increased susceptibility to respiratory infection and may cause alterations in the lung. Atmospheric transformation of NO_x can lead to the formation of ozone and nitrogen-bearing particles (most notably in some western urban areas in the US.) which are both associated with adverse health effects.

Nitrogen oxides also contribute to the formation of acid rain. Nitrogen oxides contribute to a wide range of environmental effects, including potential changes in the

composition and competition of some species of vegetation in wetland and terrestrial systems, visibility impairment, acidification of freshwater bodies, eutrophication (i.e., explosive algae growth leading to a depletion of oxygen in the water) of estuarine and coastal waters (e.g., Chesapeake Bay in the US.), and increases in levels of toxins harmful to fish and other aquatic life.

2.1.3 Ozone

Ground-level ozone (the primary constituent of smog) continues to be a pervasive pollution problem throughout many areas of the United States. Ozone is not emitted directly into the air but is formed by the reaction of VOCs (Volatile organic compounds) and NO_x in the presence of heat and sunlight. Ground-level ozone forms readily in the atmosphere, usually during hot summer weather. VOCs are emitted from a variety of sources, including motor vehicles, chemical plants, refineries, factories, consumer and commercial products, and other industrial sources. Nitrogen oxides are emitted from motor vehicles, power plants, and other sources of combustion. Changing weather patterns contribute to yearly differences in ozone concentrations from city to city. Ozone and the precursor pollutants that cause ozone production also can be transported into an area far from pollution sources. Sometimes, they were found hundreds of miles upwind.

Short-term (1-3 hours) and prolonged (6-8 hours) exposures to ambient ozone have been linked to a number of health effects. For example, increased hospital admissions and emergency room visits for respiratory causes have been associated with ambient ozone exposures. Repeated exposures to ozone can make people more susceptible to respiratory infection, result in lung inflammation, and aggravate pre-existing respiratory diseases such as asthma. Other health effects attributed to ozone exposures include significant decreases in lung function and increased respiratory symptoms such as chest pain and cough. These effects generally occur while individuals are engaged in moderate or heavy exertion. Children active outdoors during the summer when ozone levels are at their highest are the most at risk of experiencing such effects. Other at-risk groups include adults who are active outdoors (e.g., outdoor workers), and individuals with pre-existing respiratory disease such as asthma and chronic obstructive lung disease. In addition, longer-term exposures to moderate levels of ozone present the possibility of irreversible changes in the lungs which could lead to premature aging of the lungs and/or chronic respiratory illnesses.

Ozone also affects vegetation and ecosystems, leading to reductions in agricultural and commercial forest yields, reduces growth and survivability of tree seedlings, and increases plant susceptibility to diseases, pests, and other environmental stresses (e.g., harsh weather). In long-lived species, these effects may become evident only after several years or even decades, thus having the potential for long-term effects on forest ecosystems. Ground-level ozone damage to the foliage of trees and other plants also can decrease the aesthetic value of ornamental species as well as the natural beauty of national parks and recreation areas.

2.1.4 Particulate matter

Particulate matter (PM) is the general term used for a mixture of solid particles and liquid droplets found in the air. Some particles are large or dark enough to be seen

as soot or smoke. Others are so small they can be detected only with an electron microscope. These particles, which come in a wide ranges of sizes ("fine" particles are less than 2.5 micrometers in diameter and coarser-size particles are larger than 2.5 micrometers), originate from many different stationary and mobile sources as well as from natural sources. PM_{10} are particles with diameter of less than 10 microns whereas $PM_{2.5}$ are particles with diameter of less than 5 microns. Fine particles result from fuel combustion of motor vehicles, power generation, and industrial facilities, as well as from residential fireplaces and wood stoves. Coarse particles are generally emitted from various sources, such as vehicles traveling on unpaved roads, materials handling, and crushing and grinding operations, as well as windblown dust. Some particles are emitted directly from their sources, such as smokestacks and cars. In other cases, gases such as sulfur oxide and SO_2, NO_x, and VOC interact with other compounds in the air to form fine particles. Their chemical and physical compositions vary depending on location, time of year, and weather.

Inhalable PM includes both fine and coarse particles. These particles can accumulate in the respiratory system and are associated with numerous health effects. Exposure to coarse particles is primarily associated with the aggravation of respiratory conditions, such as asthma. Fine particles are most closely associated with such health effects as increased hospital admissions and emergency room visits for heart and lung disease, increased respiratory symptoms and disease, decreased lung function, and even premature death. Sensitive groups that appear to be at greatest risk to such effects include the elderly, individuals with cardiopulmonary diseases, such as asthma, and children. In addition to health problems, PM is the major cause of reduced visibility in many parts of the United States. Airborne particles also can cause damage to paints and building materials.

2.1.5 Sulfur dioxide

Sulfur dioxide belongs to the family of sulfur oxide gases (EPA 1999). These gases are formed when fuel containing sulfur (mainly, coal and oil) is burned and during metal smelting and other industrial processes. Most SO_2 monitoring stations are located in urban areas. The highest monitored concentrations of SO_2 are recorded in the vicinity of large industrial facilities.

High concentrations of SO_2 can result in temporary breathing impairment for asthmatic children and adults who are active outdoors. Short-term exposures of asthmatic individuals to elevated SO_2 levels while at moderate exertion may result in reduced lung function that may be accompanied by such symptoms as wheezing, chest tightness, or shortness of breath. Other effects that have been associated with longer-term exposures to high concentrations of SO_2, in conjunction with high levels of PM, include respiratory illness, alterations in the lungs' defenses, and aggravation of existing cardiovascular disease. The subgroups of the population that may be affected under these conditions include individuals with cardiovascular diseases or chronic lung diseases, as well as children and the elderly.

Together, SO_2 and NO_x are the major precursors to acidic deposition (acid rain), which is associated with the acidification of soils, lakes, and streams, accelerated corrosion of buildings and monuments, and reduced visibility. Sulfur

dioxide also is a major precursor to $PM_{2.5}$, which is a significant health concern as well as a main pollutant that impairs visibility.

2.2 National Ambient Air Quality Standards (NAAQS)

Air pollution comes from many different sources. Stationary sources are such as factories, power plants, smelters, and smaller-sized sources such as dry cleaners and degreasing operations. Mobile sources of air pollutants are such as cars, buses, planes, trucks, and trains. And naturally occurring sources are such as windblown dust, and volcanic eruptions. Air quality can be affected in many ways by the pollutants emitted from these sources.

In USA, The Clean Air Act provides the principal framework for national, state, and local efforts to protect air quality (EPA 1999). Under the Clean Air Act, office of air quality planning and standards (OAQPS) is responsible for setting standards for pollutants which are considered harmful to people and the environment. The standard is also known as national ambient air quality standards (NAAQS). OAQPS is also responsible for ensuring that these ambient air quality standards are met, or attained (in cooperation with state, tribal, and local governments) through national strategies to control pollutant emissions from automobiles, factories, and other sources.

The EPA office of Air Quality Planning and Standards (OAQPS) has set national ambient air quality standards for principal pollutants, which are called "criteria" pollutants. They are listed below. Units of measurement for the standards are parts per million (ppm) by volume, milligrams per cubic meter of air (mg/m^3), and micrograms per cubic meter of air at 25°C($\mu g/m^3$).

By the way, Thailand also has its own ambient air quality standards, which are set up by PCD. Thai National ambient air quality standards are considered and adapted so that they are suitable for Thailand situation. NAAQS and TNAAQS are shown in Table 2.1 and Table 2.2, respectively.

Table 2.1 National ambient air quality standard

Pollutant	1-hr avg		8-hrs avg		24-hrs avg	
	mg/m^3	ppm	mg/m^3	ppm	mg/m^3	ppm
CO	40.00	35.00	10.00	9.00	-	-
NO_2	0.10	0.05	-	-	-	-
SO_2	-	-	-	-	0.37	0.14
O_3	0.24	0.12	0.16	0.08	-	-
PM_{10}	-	-	-	-	0.16	-

Table 2.2 Thai national ambient air quality standard

Pollutant	1-hr avg		8-hrs avg		24-hrs avg	
	mg/m^3	ppm	mg/m^3	ppm	mg/m^3	ppm
CO	34.20	30.00	10.26	9.00	-	-
NO_2	0.32	0.17	-	-	-	-
SO_2	0.78	0.30	-	-	-	-
O_3	0.20	0.10	-	-	-	-
PM_{10}	-	-	-	-	0.12	-

2.3 Meteorological Condition in Thailand

There are three seasons in Thailand. Those are summer, rainy, and cold seasons. Summer season is from February to April. Rainy season is from May to October and cold season is from November to January.

In Bangkok during 1997-1998, temperature, relative humidity (RH), and wind were in the ranges of 26 – 33°C, 60 - 80 %RH, and 0.5 – 2 m/s, respectively. However, these values are investigated by monitoring stations in Bangkok, which can not be the representative of whole Kingdom of Thailand.

2.4 Factor Analysis

Factor analysis (FA) is a data reduction technique. It belongs to a family of procedures that can remove redundancy from a set of correlated variables and can represent original variables with a smaller set of " derived " variables, or factors. Alternatively, the factor analysis procedure can be thought of as a way to remove the duplicated information from a set of variables. Factor analysis model can be expressed as:

$$D = CR \tag{2.1}$$

The above relationship is also known as a principal component analysis equation (Henry et al. 1984) which is expressed as the product of factor loading C and factor score R matrix.

The application of factor or principal component analysis can be shown schematically in Fig. 2.1, where nine variables v_1, v_2,..., v_9 are clustered into three separate groupings. Variables v_1, v_4, v_5, and v_8 are clustered together, meaning that they are highly correlated with one another and represent a common underlying variable, or factor as it is called. Similarly, variables v_3 and v_7 define a separate factor. And the variables v_2, v_6, and v_9 contribute to form a third factor. In each case, the subset of variables can be thought of as a manifestation of an abstract underlying

dimension or a factor. So, instead of having to use nine separate variables to represent data, three factors are left for consideration or interpretation. The newly derived three factors contain virtually all the information inherited in the original nine variables.

In practice, the derived factors are never so clear-cut as the ideal case portrayed in Fig. 2.1. There is usually some amount of overlap between factors, since each of the original variables defining a factor usually have some degree of correlation with other variables. It could be, for example, that variables, v_1, v_4, v_5, and v_8, which define the first factor, could be marginally related to the variables constituting the second and third factors. However, it is the task of factor analysis to form factors that are relatively independent of one another. So in Fig. 2.1, we can be confident that the variables defining factor 1 are more intercorrelated than those defining factors 2 and 3.

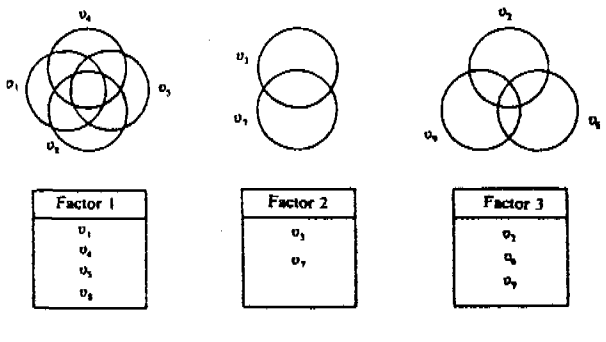

Fig. 2.1 Nine variables reduced to three factors

2.4.1 Identification of underlying factors

One of the most important uses of factor analysis is the identification of factors underlying a large set of variables (Kachigan 1991). By clustering a large number of variables into a smaller number of homogeneous sets and creating a new variable or a factor representing a data set, we have simplified our data and consequently are more likely to gain insight of how to explain the data set.

For example, an airline might study fifty different variables that it conceives to be important to the flier in choosing an airline. Variables are such as courtesy of personnel, degree of on-time performance, convenience of schedules, check-in time, etc. Individually and collectively, the variables would shed little light on the overall consumer dynamics involved in choosing on one airline over another. However, if a factor analysis could reduce these fifty variables into a handful of more general and abstract factors, an airline would gain a better understanding of the fundamental variables underlying a flier's decision process.

Similarly, we could submit social attitudes, mental abilities, personality characteristics, career interests, food preferences, disease histories, or blood characteristics to a factor analysis. In each instance, the large number of possible

variables would be reduced to a smaller, more manageable, and more interpretable number of factors.

2.4.2 Rotation of factors

Factor loading C that is obtained from the extraction processes is not always easy to be interpreted for the meaning. So, factor loading matrix will be transformed by rotation technique to maximize the variance of squared loading. There are many rotation techniques such as varimax, quartimax, equimax, and oblimin rotation. For this study, we used varimax method for factor loading rotation.

The newly formed factors were not easily interpretable since the factor loading matrix still contained many medium size loadings. Factor rotation was then applied to these factors to maximize interpretability and also to maximize the variance of the system of factors.

The essence of the factor rotation concept can be seen in Fig. 2.2. It is a graphical portrait of three of the variables-v_1, v_5, and v_7, from the nine-variable example of the preceding sections. The variables are presented as points on a rectangular coordinate system in which the horizontal and vertical axes represent factors 1 and 2, respectively. The dashed lines in Fig. 2.2 indicate the projections of the points (the variables) onto the axes (the factors), and the point of projection on an axis represents the loading of the variable on that factor. Consider variable v_5, for example, it has a very high loading on factor 1, but only a moderately high loading of factor 2. Variable v_1 has a moderately high loading on both factors 1 and 2. The same is true for v_7.

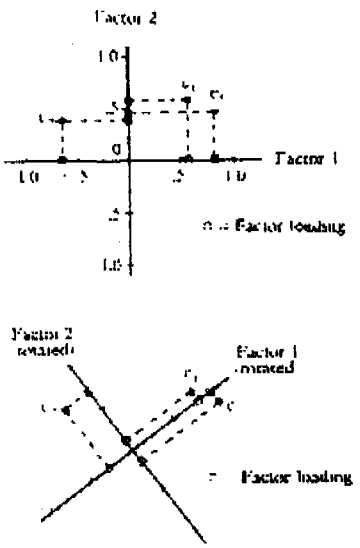

Fig. 2.2 An example of factor rotation and changes in factor loadings

In Fig. 2.2, the factor axes have been rotated approximately 45° counterclockwise. The projections of the variable, i.e., v_1, on the factors indicate

moderate loadings (about 0.5) on both factors 1 and 2. After rotation of the factor axes, v_1 has a fairly high loading on factor 1 and virtually a zero loading on factor 2. This is the primary objective of factor rotation that is to make the rotated factors as distinctive as possible. If a variable loads high on one factor, we do not want it to also load high, or even moderately high, on another factor; otherwise we could not distinguish importance or correlation of certain variables with factors.

In Fig. 2.2, variable v_5 had a high loading on factor 1 and a moderate loading on factor 2 prior to rotation. This is fairly good discrimination, but the rotation accentuates the difference. After rotation, v_5 still has a high loading on factor 1, but now has a near zero loading on factor 2. V_7, which prior to rotation had moderate loadings on both factor, ends up with a fairly high loading on factor 2 and a relatively low loading on factor 1 after the rotation is performed. Again, the result is a more unique definition of the respective factors.

In the preceding example we had not mentioned of factor 3 from our original three-factor solution. In actuality, all three factors would be rotated simultaneously in a three-dimensional space filled with all nine variables. This cannot be adequately portrayed on a two-dimensional paper and the actual rotation is a task for the computer. The computer employs an iterative process of orienting and reorienting the factors until it can no longer improve upon a prespecified criterion of the spread of the loadings on the factors.

2.4.3 Historical research studies

Factor analysis technique has been used for a long time in many different fields because we can use this technique to obtain potential sources with minimal knowledge about source characteristics required.

Blifford and Meeker (1967) reported that FA was used to identify air pollution sources for 30 U.S. cities. In their research, 29 elements and suspended particulate matter (SPM), SO_4^{2-} and NO_3^- in particles were considered as variables. The data consisted of 5 year averages at each of 30 cities to form a correlation matrix. The pollution sources of particles identified were heavy industry, automobiles, fuel burning, and petroleum refining and were classified based on their chemical composition.

Hopke et al. (1976) reported the resulted of FA application in the area around Boston. In their study, the samples were analyzed for eighteen elements utilizing Instrumental Neutron Activation Analysis (INAA). The results showed that the first factor appeared to represent crustal dust being carried into the area. This factor was strongly dependent on concentrations of Al, Fe, Sc, and Th. This factor may also include a significant amount of material from coal combustion. The second factor was strongly dependent on concentrations of Na and Cl and is attributed to the sea-salt aerosol that would be expected in the Boston area. The third factor could be attributed to the combustion of fuel oil. The fourth factor was the only one with a strong dependence of Br. The fifth factor was strongly related to Mn and Se. The sixth factor was strongly related to Zn and Sb. This factor may be associated with refuse incineration.

Morand et al. (1987) developed a modified FA/MR (factor analysis/multiple regression) to apportion suspended particulate matter in New Jersey. They pointed out that previous FA/MR approach was of limited applicability in the airshed area where more than one source type may emit the same tracer. The model indicated that sulfate/secondary aerosol contributed an average of 40% to inhalable particulate matter (IPM) concentrations, followed by 15% of soil resuspension, 13% of paint spraying/paint pigment, 8% of fuel oil burning/spacing, 7% of industrial emissions, and 15% of motor vehicle exhaust. Contributions to ambient Pb concentrations were 36% of motor vehicle exhaust, 24% of soil resuspension, 18% of fuel oil burning/space heating, 17% of industrial emissions, 9% of paint spraying/paint pigment, and 5% of zinc related sources. Contributions to ambient Fe concentrations were 51% of soil resuspension, 33% of paint spraying/paint pigment and 18% of industrial emission. The models were validated by comparing partial source profiles calculated from modeling results with the corresponding published source emissions composition.

Ferrer and Perez (1990) reported the results of the analysis of the aerosol sampled in an industrial area in the neighborhood of the city of Barcelona using FA technique. Varimax procedure was used to transform the abstract vectors by maximizing the total variance of the squared loading. Aerosol samples were collected during a period of 1 year (1986-1987) in Sant Adria de Besos, a little town 10 km north of Barcelona, where serious air pollution had occured. Elements of Zn, Pb, Ni, Mn Fe, V, Ca, Al and ions of Cl^-, NO_3^- and SO_4^{2-} were analyzed by plasma spectroscopy and ion chromatography. In this study, Zn was chosen as a tracer for waste disposal; Pb and Br for traffic; Ni and V for fuel; Ni for steelworks; Mn, Fe, Ca, and Al mainly for soil; NO_3^- and SO_4^{2-} for the gas-particle conversion fraction; and Cl^- for sea spray. The results from varimax rotation showed that the main elements contributing to the first factor are Ca, Al, Mn and Fe which was an indication for soil influence. For the second factor, the most prominent elements were Br, Pb and V. This factor would represent traffic. The third factor had major contribution of SO_4^{2-} and NO_3^-. These may arise from SO_2 and NO_x. The fourth factor had major contributors from V and Ni, which were tracers of fuel-oil burning sources in which Ni was used as the catalyst for burning. The fifth factor was influenced only from Cl^- which was tracer of sea spray. The sixth factor had major contributors of Zn and Pb which were tracer of refuse or waste disposal.

Okamoto et al. (1990) introduced a factor analysis/multiple regression model (FA/MR) for source apportionment of suspended particulate matters in the Tokyo metropolitan area. In the study, aerosol was collected during the period of October to November 1986. Thirty-nine elements and ions were analyzed by instrumental neutron activation analysis (INAA). Cd, Pb, S and Si were analyzed by X-ray fluorescence (XRF): NH_4^+ was analyzed by an indophenol method. SO_4^{2-}, NO_3^- and Cl^- in samples on the quartz filter was analyzed by ion chromatography (IC). By a varimax rotated factor analysis, five sources could be identified; soil, automobile, secondary particles, sea salt and steel mill. Quantitative estimations using the FA/MR model agreed with the calculated contributing concentrations determined by a weighted least-squares chemical mass balance (CMB) model. However, the source type of refuse incineration identified by the FA/MR model was similar to that of biomass burning. The estimated contributions of sea salt and steel mill by FA/MR model contained those of other sources, which had the same temporal variation of

contributing concentrations. This symptom was caused by a multicollinearity problem. Although this result showed the limitation of multivariate receptor model, it was useful information concerning source types. In the Tokyo metropolitan area, the contributions from soil (including road dust), automobile, secondary particles and refuse incineration (biomass burning) were largely correlated with SO_4^{2-} and other secondary particle related elements. A major portion of secondary particles considered was found to be related to fuel oil combustion.

2.5 Time Series Decomposition Technique

A form of time series analysis known as time series decomposition was utilized for this work. This technique assumes that the series are composed of four separate components; trend, seasonality, cycles, and noise (Triola and Franklin 1994).

Trend moves in a consistent direction. It is monotonically unidirectional, either decreasing or increasing. The rate at which it increases may vary over time, even to zero but never falls below zero. Similarly, if it decreases, the rate at which it decreases may vary over time. It may be flat but it would never actually increase. Should the trend line moving in one direction change to the other direction, it may be regarded as a different trend, or perhaps as a long period cycle.

Seasonality reflects the insight that, regardless of any other trend, cycle, or noise influence, certain seasons are inherently different. In time series, seasons are often exactly seasons of the year or cyclical trend with length of one year. For example, regardless of economic conditions and other factors, consumers spend more in late December than at other times of the year in the US.

Cycles are fluctuations in the level of series that have some identifiable repetitive form and structure. Cycles represent the "what goes around, comes around" part of the series. So long as what is going around and coming around can be positively identified, and it repeats itself over some defined period, it forms a cycle. Cycles are not necessarily based on or are thought of as a collection of sine and cosine waves.

Noise represents the residual variation that cannot be explained. It is the effect of those one-time occurrences that happen randomly rather than systematically over time.

2.5.1 Procedures for decomposition technique

Data are conceived to be a combination of four components such as trend, seasonal, cyclic, and irregular component. The basic time-series model expresses the numbers in the series as the multiplicative product of these basic four components.

$$D = T \times S \times C \times I \tag{2.2}$$

where;
D = data

T = long-term trend component
S = seasonal component
C = cyclical component
I = irregular component

The decomposition method isolates each of the components by means of smoothing average. The smoothing average is used to remove the combined seasonal and irregular components $S \times I$ from the original series. Moving average can be the representative of trend and cyclical component, which is expressed as:

$$M = T \times C \tag{2.3}$$

To isolate the seasonal behavior, we start by dividing the original data by the moving average. The result will be the seasonal and irregular components because the moving average itself is a product of trend and cyclic and will cancel out the trend and cyclic components in the data.

$$S \times I = \frac{D}{M} \tag{2.4}$$

To eliminate the irregular component, we average these values for each season. The seasonal component will emerge to indicate seasonal variation whereas the irregular will tend to be averaged away. The end results include a seasonal index for each season of the year and is a factor that indicates how larger or smaller the pollutant concentration in the particular time period compared to an average over a year.

$$Seasonal\ index = Average\ of \left(\frac{D}{M} \right) for\ that\ season \tag{2.5}$$