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Fuzzy Rule Generation from the EMEP Ozone Model to Examine Source-Receptor Relations

Mina Ryoke

WP-96-130
November 1996

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Foreword

This paper summarizes the results of the research conducted during the IIASA's 1996 Young Scientists Summer Program (YSSP) in the Methodology of Decision Analysis (MDA) project in collaboration with the Transboundary Air Pollution (TAP) project. The TAP project develops models for assessing results of various policy options aimed at reducing troposheric ozone concentrations. Such reductions can be achieved by reducing emissions of two precursors: nitrogen oxides (NO_x) and volatile organic compounds (VOCs). One of the main objectives of developing and examining ozone models is to identify cost-effective strategies that lower ozone concentrations below acceptable levels at various locations (grids).

A detailed model developed by the Cooperative Programme for the Monitoring and Evaluation of the Long-Range Air Pollutants in Europe (EMEP) is available for simulating the effects of emission reductions on the ozone concentrations at all European grids. However, the EMEP ozone model cannot be used to determine cost-effective strategies. For this purpose a simplified model must be used.

The objective of the research in the report is to examine if the fuzzy rule generation approach can be successfully used to develop simplified ozone models for selected grids in Europe. The results of the study are promising. In particular, it was found that fuzzy models provide good predictions of ozone concentrations; the predictions are better than those derived from traditional regression models.

Due to the complexity of the problem and limited time of the YSSP, the author was not able to develop fuzzy models for all European grids. However, the results in this paper illustrate that the applicability of the applied methodology for development of simplified ozone models.

Abstract

The objective of this paper is to describe research on the development of a simplified version of the European ozone model using fuzzy rule generation methodology. The ozone model is used to predict tropospheric (at the ground level) ozone concentration. The simplified ozone model illustrates source-receptor relationships between ozone precursor emissions (NO_x and VOCs) and ozone concentration in the troposphere, taking into account meteorological conditions. This ozone model was developed by the Cooperative Programme for Monitoring and Evaluation of Long-Range Air Pollutants in Europe (EMEP). The EMEP model provides a detailed prediction of ozone concentration at every grid in Europe by taking into account physical and chemical mechanisms. However, the model is too complicated for nonspecialists, such as policymakers trying to set emission reduction levels that result in ozone concentrations below given limits. Therefore, there is a need for a simplified ozone model that can be verified by the EMEP model and that can be used for analyzing policy options.

One approach is to use the fuzzy rule generation methodology. In this approach, the simplified model consists of a number of fuzzy rules. Fuzzy rules have a fuzzy proposition in the conditional statement and a linear regression model in the conclusion. The rules describe a complete nonlinear system by using several linear models and membership functions. The development of such fuzzy rules is called fuzzy modeling. The membership functions of conditional variables are determined by the subset of data which is obtained by a clustering method. The degree of confidence of a rule is determined by the grade of the membership functions for input values. The role of fuzzy logic is to integrate fuzzy rules smoothly.

In this paper, a basic scenario, which predicts no reduction of ozone precursor emissions, is used to determine fuzzy rules, subsequent scenarios are derived from the basic scenario, which includes information on source-receptor relationships. Simplified models of three grids have been developed to show the effectiveness of this approach. This methodology can be used to develop models of all grids.

Keywords : ozone concentration, the EMEP ozone model, fuzzy rules.

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Fuzzy Rule Generation from the EMEP Ozone Model to Examine Source-Receptor Relations

Mina Ryoke[*]

1 Introduction

Recently, interest in transboundary air pollution has been intensified by the increase of empirical evidence. The environmental impacts of tropospheric ozone have been analyzed in Heyes *et al.*, (1995). Ozone in the troposphere has a harmful influence on crops, forests, raw materials, and human health. To protect agricultural crops and forests, critical levels have been established for long-term exposure to accumulated excess ozone (Heyes *et al.*, 1995). Recently the amount of 40 parts perbillion (ppb) has been established as a threshold concentration for both crops and trees (Fuhrer and Achermann, 1994). The exposure index is referred to as AOT40, the accumulated exposure over a threshold of 40 ppb. In many grids in Europe ozone concentrations are above this index, therefore, an important research activity is to develop a tool, to examine policy options that would reduce the concentration of tropospheric ozone below the critical level.

A detailed European ozone model has been developed by the EMEP. The EMEP ozone model is a single-layer Lagrangian trajectory model that takes into account physical and chemical mechanisms of ozone production and meteorological conditions. It can predict ozone concentrations in Europe over six-month period. Simulations are carried out by using a number of practical scenarios. Many precursor emission reduction scenarios have been examined by using this EMEP ozone model.

The optimization problem to minimize costs for reducing precursor emissions below critical levels in each grid is developed by Zawicki and Makowski (1995). Their approach is based on the simplified ozone model documented in Heyes and Schöpp (1995), which was developed and verified using the EMEP ozone model. The resulting optimization problem is a large-scale nonlinear programming problem.

The EMEP ozone model requires various emission scenarios to simulate possible ozone concentrations; however, the result from the model are too complicated for policymakers to understand. The fuzzy models developed in this paper can be used to summarize and simplify important scenarios for decision makers. The objective is to express the theoretical, powerful, and complex model of the basic scenario by a fuzzy model that consists of a number of rules, and to carry out the sensitivity analysis by using this simplified model to obtain possible future scenarios. The problem is to build a number of fuzzy rules about the source-receptor relationships between ozone precursor emissions (NO_x and VOCs) and ozone concentrations in the troposphere. The set of fuzzy rules (if developed for all grids) can be used as an alternative simplified model for the optimization problem.

The problem is introduced in detail in Section 2. The EMEP ozone model, 1990 input-output data, and various scenarios of this model are also introduced. In Section 3, the fuzzy model (Takagi and Sugeno, 1985) consisting of a number of fuzzy rules are introduced; after an introduction of the problems in model identification, a method of fuzzy modeling is described simply (Nakamori and Ryoke, 1994; Ryoke *et al.*, 1996). In Section 4, several fuzzy models

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based on the basic scenario are developed to predict ozone concentrations at three grids. One in southern United Kingdom, one in Stuttgart, one in upper Austria.

2 Preparation

2.1 Problem and approach

Concern about transboundary air-pollution issues, including the ozone problem, is increasing. To estimate ozone concentrations in Europe, an international effort must be taken to identify the physical and chemical mechanisms.

The EMEP ozone model (Simpson, 1992, 1993, forthcoming) is based on the Norwegian photochemical trajectory model developed at the Meteorological Synthesizing Centre-West in Oslo (Eliassen *et al.*, 1982).

The EMEP ozone model is a single-layer Lagrangian trajectory model, and can predict ozone concentrations at defined grids every six hours, by using annual data of precursor emissions reported by each country in Europe and meteorological data taken every two hours. To determine effective emission reduction scenarios, the EMEP ozone model must examine many scenarios of precursor emissions. The EMEP ozone model is a very powerful tool for estimating ozone concentrations and provides many complicated scenarios. To help policymakers use the model results effectively, the important scenarios must be simplified. One way to simplify the EMEP model results is with a fuzzy model consisting of a number of fuzzy rules specific to the conditions in each area (or grid) under investigation. In this paper, we apply the fuzzy model to three areas: southern United Kingdom, Stuttgart, and upper Austria.

The fuzzy model simulates input-output relationships of the EMEP ozone model. The fuzzy rules include physical and chemical information on ozone production. The fuzzy model is a nonlinear model consisting of a number of fuzzy rules. A fuzzy rule has a fuzzy proposition statement, and a regression model in the conclusion. A country's ozone concentration is predicted by fuzzy rules that take into account meteorological conditions inside the country and deposition from other countries. The fuzzy rules obtained are evaluated by their ability to predict possible scenarios.

2.2 Definition of data set

Heyes and Schöpp (1995) provide an explanation of data set:

> The EMEP ozone model (Simpson, 1992, 1993, forthcoming) is a single-layer Lagrangian trajectory model with a variable depth that extends from the ground to the top of the atmospheric boundary layer, and calculates the concentrations of photochemical oxidants every six hours for a set of up to 740 arrival points (on a 150km$\times$150km grid) covering the whole of Europe and taking into account chemical mechanism reactions. The air column in the atmospheric boundary layer is followed along specified 96-hour trajectories that pick up emissions of NO_x, VOC, CO, and SO_2 from the underlying grid. The height of the air column (the mixing height) containing the bulk of the polluted air is reset at 12 GMT each day using radiosonde data. Along each trajectory the mass conservation equations are integrated, taking into account the emission inputs, photolysis and chemical reactions, dry and wet removal rates, and the influence of meteorological parameters. These equations are solved numerically using the quasi-steady-state approximation method with a fixed time step of 15 minutes.
>
> The six-hourly meteorological data required by the EMEP ozone model are taken from the output of the Norwegian Numerical Weather Prediction model. Wind velocity data permit calculation of 96-hour back-trajectories to any point in the EMEP grid. The ozone model simulates the exchange of boundary layer air with

free tropospheric air as a result of convective clouds. Photolysis rates are adjusted for cloud cover, and temperature data are used to calculate appropriate chemical reaction rates and to estimate both natural VOC emissions and emissions of NO_x from soils. Other meteorological data are used in estimating deposition velocities, which are calculated as a function of atmospheric stability, latitude, time of year and time of day.

In this paper fuzzy models are applied to data gathered from April to September; this period was selected because the sun has its strongest influence on ozone production during this time. Photolysis rate of NO_2 is also considered in the model because it is an importance element in ozone production. The ozone concentration is estimated with the EMEP ozone model every six hours, but in this paper the daily maximum concentration is considered more important measure because we are trying to study the relationship between precursor emissions and ozone concentrations.

The EMEP ozone model simulates the exchange of boundary-layer air with free tropospheric air that results from convective clouds. The EMEP ozone model uses a chemical mechanism in which each important VOC class is represented by one or two members whose chemical degradation is addressed in (Heyes and Schöpp, 1995). The EMEP ozone model requires the following inputs:

- Annual emissions of NO_x, VOC, and SO_2 from anthropogenic source (these data are taken from official national statistics) and national emissions of VOC and NO_x.
- The meteorological data calculated by using the Norwegian Numerical Weather Prediction model. Data are recorded every six hours and wind velocity data permit calculation of 96-hour back-trajectories at any point in the EMEP grid.
- The variables related to meteorological conditions used in the fuzzy model include photolysis rate of NO_2 and the influence of emissions from each country depending on meteorological conditions. The countries and regions contributing data of annual emissions of NO_x and VOC are shown in Table 1.

Table 1: Countries and regions contributing annual data.

1	Albania	2	Austria	3	Belgium
4	Bulgaria	6	Denmark	6	Denmark
7	Finland	8	France	10	United Germany
11	Greece	12	Hungary	13	Iceland
14	Ireland	15	Italy	16	Luxembourg
17	Netherlands	18	Norway	19	Poland
20	Portugal	21	Rumania	22	Spain
23	Sweden	24	Switzerland	25	Turkey
27	United Kingdom	29	Other areas	30	Baltic Sea
31	North Sea	32	Remaining Atlantic	33	Mediterranean
35	Nat ocean emissions	36	Kola/Karelia	37	St. Peter/Novgo Pskov
38	Kaliningrad	39	Belarus	40	Ukraine
41	Moldova	42	Russian Federation	43	Etonia
44	Poland	45	Lithuania	46	Czech Republic
47	Slovakia	48	Slovenia	49	Croatia
50	Bosnia Herzegovina	51	Serbia, Montenegro	52	Macedonia

Using national data, the EMEP ozone model can calculate total emissions in every EMEP grid in an air trajectory over a four-day period. These emissions are called effective emissions (Heyes and Schöpp,1995):

> In the EMEP ozone model, emissions and meteorological input data are revised at two-hour intervals, so that there are 49 time steps during the four-day trajectory. Two processes are included in the model which lead to mixing of the boundary layer air parcels with free tropospheric air: the venting effect of cumulus clouds and day-to-day increases in mixing height. The exchange mechanisms operate at two-hour intervals, with chemical reactions calculated within each two-hour time step.
>
> If the emissions of an ozone precursor during time step i are denoted by E_i, and the exchange processes result in a dilution of the boundary layer air by a factor f_i $(0 < f_i \leq 1)$, the contribution from time step i to the trajectory-integrated value of the precursor emissions, E, at time step $(i+1)$ is given simply by:
>
> $$E_i \times f_i. \tag{1}$$
>
> Subsequent mixing events further reduce the contribution of E_i, so that the contribution of time step i to the final trajectory-integrated value is:
>
> $$E_i \times (f_i \times f_{i+1} \times f_{i+2} \times \cdots \times f_{49}). \tag{2}$$

Therefore, the integrated contribution from all 49 time steps, denoted by $< E >$, are given by

$$< E > = \sum_{i=1}^{i=48} E_i \times \prod_{j=i+1}^{j=49} f_i + E_{49}. \tag{3}$$

Such quantities are calculated for both NO_x and VOC emissions along each trajectory and investigated as predictor variables in regression models of the fuzzy model. The variables considered are shown in Table 2.

Table 2: Variables considered in the development fuzzy models.

The influence of the precursor emissions of NO_x from each country presented by effective NO_x emissions [10^{10} molecules cm^{-2}sec^{-1}]
Effective NO_x emissions in one grid [10^{10} molecules cm^{-2}sec^{-1}]
Effective VOC emissions in one grid [10^{10} molecules cm^{-2}sec^{-1}]
Photolysis rate of NO_2 [10^{-3}sec^{-1}]
Square of effective NO_x emissions in one grid
Square of effective VOC emissions in one grid
Product of the effective NO_x and effective VOC in one grid
Ozone concentration [ppb]

2.3 Definition of scenarios

Scenarios are required for the period from April to September. The EMEP ozone model can use new data on the emissions of pollutants, such as anthropogenic and natural sources, chemical reaction rates, deposition velocities, and background concentrations. However, the rules that determine a country's contributions to ozone concentrations in a particular area must be applied in the reduction problem. The EMEP ozone model is designed to simulate ozone formation over long periods of time and over all Europe, so that the effects of emission control measures on long-term ozone concentrations can be estimated.

The scenario has two patterns. One pattern is concerned with total emissions in all of Europe; the values in Table 3 show the total rate for NO_x and VOC emissions. The other pattern provides more detailed results. The various scenarios in the Table 4 are derived from the information in the basic scenario, Although there are many possible combinations for reducing precursor emissions, we have limited out study to the scenarios summarized in Table 5.

Table 3: Rate of each emission for all countries in Europe.

	NO_x	VOC
Basic Scenario1	1.0	1.0
Basic Scenario2	0.3	0.3

Table 4: Rate of each emission for each country in Europe.

	NO_x	VOC
Reduction Pattern1	1.0	0.6
Reduction Pattern2	0.8	1.0
Reduction Pattern3	0.6	1.0
Reduction Pattern4	0.3	0.7
Reduction Pattern5	0.5	0.3
Reduction Pattern6	0.7	0.3

Table 5: Outline of scenarios.

	All Countries	Country1	Country2	$\cdots$
Basic Scenario1	No Reduction	—	—	$\cdots$
Basic Scenario2	All Reduction	—	—	$\cdots$
Scenario1	—	Reduction Pattern1	No Reduction	$\cdots$
Scenario2	—	Reduction Pattern2	$\vdots$	$\cdots$
Scenario3	—	Reduction Pattern3	$\vdots$	$\cdots$
Scenario4	—	Reduction Pattern4	$\vdots$	$\cdots$
Scenario5	—	Reduction Pattern5	$\vdots$	$\cdots$
Scenario6	—	Reduction Pattern6	$\vdots$	$\cdots$
Scenario7	—	No Reduction	Reduction Pattern1	$\cdots$
Scenario8	—	$\vdots$	Reduction Pattern2	$\cdots$
$\vdots$	—	$\vdots$	$\vdots$	$\vdots$

3 An Approach to Fuzzy Rule Generation

3.1 Fuzzy models and identification problems

The fuzzy prediction model is a nonlinear model consisting of several rules. The original form is presented in Takagi and Sugeno (1985). In this paper the following rule is applied:

$$\text{Rule } \mathrm{R}_i: \quad \text{if } \boldsymbol{z} \text{ is } F_i, \quad \text{then } \boldsymbol{y} = \boldsymbol{g}_i(\boldsymbol{x}) = \boldsymbol{a}_{i0} + \boldsymbol{x} A_i, \tag{4}$$

where $\boldsymbol{x} = (x_1, x_2, \cdots, x_s)$ is the vector of consequence variables, $\boldsymbol{z}=(z_1, z_2, \cdots, z_t)$ is the vector of premise variables, and $\boldsymbol{y} = (y_1, y_2, \cdots, y_r)$ is the vector of response variables. Often, there is an intersection between two variable sets $\{x_1, x_2, \cdots, x_s\}$ and $\{z_1, z_2, \cdots, z_t\}$. The variables F_i denotes a fuzzy subset with the membership function $f_i(\boldsymbol{z})$ with premise parameters. The regression parameters $\Omega = \{\boldsymbol{a}_{i0} \in R^r,\ A_i \in R^{s\times r};\ i = 1, 2, \cdots, c\}$ are called consequence parameters. The prediction of $\boldsymbol{y}$ is given by

$$\hat{\boldsymbol{y}} = \frac{\sum_{i=1}^{c} f_i(\boldsymbol{z}^*) \cdot \boldsymbol{g}_i(\boldsymbol{x}^*)}{\sum_{i=1}^{c} f_i(\boldsymbol{z}^*)}, \tag{5}$$

where $\boldsymbol{x}^*$ and $\boldsymbol{z}^*$ denote actual inputs and c is the number of rules.

The fuzzy modeling involves the following interdependent problems:

1. Fuzzy partition of the given data set,
2. Selection of consequence variables and identification of consequence parameters in the linear models.
3. Selection of premise variables and identification of premise parameters in the membership functions.

If the variables in the model are determined by the system under study, the first and second problems may be solved simultaneously. This paper modifies the method in Hathaway and Bezdek (1992) for simultaneous analysis of classification and regression and applies it to fuzzy modeling, based on Dave (1990) where the shapes of clusters are changed adaptively in the clustering process.

For the third problem, there is a possibility of relaxing the constraint that the membership grades of a data vector across clusters must equal one (Krishnapuram and Keller, 1993). In our experience, however, the relaxation sometimes produces a poor partition of the data set, especially when the data distribution is complex. In such a situation, the relaxation method recognizes many data points as noise, and all membership grades of a data point converge at the same value. It is inconvenient to build a prediction model by applying this approach directly. Given this fact, the membership values resulting from the fuzzy clustering are not used in the study. Instead, the membership functions are identified by using the results from clustering.

3.2 Fuzzy clustering and regression

Let $\{(\boldsymbol{x}_1, \boldsymbol{y}_1, \boldsymbol{z}_1), \cdots, (\boldsymbol{x}_n, \boldsymbol{y}_n, \boldsymbol{z}_n)\}$, $\boldsymbol{x}_k \in R^s$, $\boldsymbol{y}_k \in R^r$, $\boldsymbol{z}_k \in R^t$ be the set of standardized data corresponding to consequence, response, and premise variables, respectively. The clustering is done in the space defined by the union of all variables. However, because the premise and consequence variables often interset, the dimension of the clustering space is usually less than $s + r + t$. Let $\{\boldsymbol{w}_1, \cdots, \boldsymbol{w}_n\}$, $\boldsymbol{w}_k \in R^v$ $(v \leq s + r + t)$ be the union of standardized data.

Consider the well-known fuzzy partition matrix U with u_{ik} for the (i, k)-entry, satisfying

$$0 \leq u_{ik} \leq 1, \quad i = 1, 2, \cdots, c;\ k = 1, 2, \cdots, n \tag{6}$$

$$0 < \sum_{k=1}^{n} u_{ik} < n, \quad i = 1, 2, \cdots, c, \tag{7}$$

$$\sum_{i=1}^{c} u_{ik} = 1, \quad k = 1, 2, \cdots, n. \tag{8}$$

Define the degree of fitness of the k-th data to the i-th model by

$$E_{ik}(\Omega) = \|\boldsymbol{y}_k - \boldsymbol{g}_i(\boldsymbol{x}_k; \Omega)\|^2. \tag{9}$$

The objective function of the fuzzy clustering is then defined by

$$J(U,\Omega) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m E_{ik}(\Omega), \tag{10}$$

where $m(>1)$ is the smoothing parameter indicating the degree of fuzziness. This formulation is given in Hathaway and Bezdek (1993) , and the method is called the fuzzy c-regression models (FCRM).

This approach provides a fuzzy partition of the given data set and a set of regression models corresponding to the data partition. However, since this method does not take into account data distribution, it is not necessarily appropriate for fuzzy modeling.

3.3 Adaptive fuzzy clustering and regression

In this section, the FCRM is modified based on Dave (1990). The modified version can be called the adaptive fuzzy c-regression models (AFCR). Denote the set of centers of clusters in the space of premise variables by $V = \{\bar{\boldsymbol{z}}_1, \cdots, \bar{\boldsymbol{z}}_c\}$; these variables are also parameters to be determined in the clustering

$$\bar{\boldsymbol{z}}_i = \frac{\sum_{k=1}^{n} (u_{ik})^m \ \boldsymbol{z}_k}{\sum_{k=1}^{n} (u_{ik})^m}. \tag{11}$$

Introduce an objective function that takes into account a balance between the minimization of regression errors and the minimization of variances within clusters:

$$J(U,\Omega,V,\alpha_1,\cdots,\alpha_c,\eta) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m L_{ik}(\Omega,V,\alpha_i,\eta). \tag{12}$$

Here, the function $L_{ik}(\Omega,V,\alpha_i,\eta)$ is defined by

$$L_{ik}(\Omega,V,\alpha_i,\eta) = (1-\alpha_i)\ \eta\ D_{ik}(V) + \alpha_i\ E_{ik}(\Omega), \tag{13}$$

and $D_{ik}(V)$ is the square distance between $\bar{\boldsymbol{z}}_i$ and the k-th data point $\boldsymbol{z}_k$ in the space of premise variables

$$D_{ik}(V) = \|\boldsymbol{z}_k - \bar{\boldsymbol{z}}_i\|^2. \tag{14}$$

The parameters $\alpha_i \ \ (0 \le \alpha_i \le 1)$ are changed in the clustering process adaptively as in Dave (1990). Let $\lambda_{i1}, \lambda_{i2}, \cdots$ be the eigenvalues of the fuzzy scatter matrix S_i calculated by using all data in the space of all variables:

$$S_i = \sum_{k=1}^{n} (u_{ik})^m \ (\boldsymbol{w}_k - \bar{\boldsymbol{w}}_i)^\top (\boldsymbol{w}_k - \bar{\boldsymbol{w}}_i), \qquad \bar{\boldsymbol{w}}_i = \frac{\sum_{k=1}^{n} (u_{ik})^m \ \boldsymbol{w}_k}{\sum_{k=1}^{n} (u_{ik})^m}. \tag{15}$$

Then, define

$$\alpha_i = 1 - \frac{\min_j\{\lambda_{ij}\}}{\max_j\{\lambda_{ij}\}}, \qquad i = 1,2,\cdots,c. \tag{16}$$

The parameter η balances between the absolute values of the first and second terms in the objective function. Unlike the adaptive fuzzy c-elliptotypes clustering algorithm in Dave (1990). in this paper D_{ik} and E_{ik} are distance measures defined over different spaces, hence this parameter is needed. The appropriate value of η depends on a given data set. One possibility is that it is determined by the ratio of the data spread over two spaces.

The clustering algorithm is given below; in this algorithm the solutions to the minimization problems can be obtained by the necessary conditions of optimality.

Step 1: Let $l = 0$. Set values of the smoothing parameter m and the threshold parameter $\varepsilon(> 0)$ in the stopping rule. Assume an initial fuzzy partition matrix $U^{(l)}$.

Step 2: Compute $\Omega^{(l)}$ that minimizes

$$J_1(\Omega) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}^{(l)})^m \; E_{ik}(\Omega). \tag{17}$$

Step 3: Compute $V^{(l)}$ that minimizes

$$J_2(V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}^{(l)})^m \; D_{ik}(V). \tag{18}$$

Step 4: Compute the trade-off parameters $\alpha_i^{(l)}$ $(i = 1, 2, \cdots, c)$ by using the eigenvalues of the fuzzy scatter matrices.

Step 5: Update the partition matrix form $U^{(l)}$ to $U^{(l+1)}$ which minimizes

$$J_3(U) = J(U, \Omega^{(l)}, V^{(l)}). \tag{19}$$

Step 6: If the condition

$$\max_{i,k} \{|u_{ik}^{(l+1)} - u_{ik}^{(l)}|\} < \varepsilon, \tag{20}$$

holds, then stop. Otherwise, let $l = l + 1$ and go to **Step 2**.

3.4 Premise modeling

In this section, we propose a method of identifying membership functions of premise variables. First the data set of premise variables is partitioned crisply by introducing an α-cut to the fuzzy partition obtained in the clustering algorithm.

Let ζ_{ij} be the local coordinate of input vector $\boldsymbol{z}$:

$$\zeta_{ij} = (\boldsymbol{z} - \boldsymbol{c}_i)\, \boldsymbol{e}_{ij}^{\top}, \tag{21}$$

where $\boldsymbol{c}_i$ is the center of cluster i and $\boldsymbol{e}_{ij}$ is the j-the principal component with $\|\boldsymbol{e}_{ij}\| = 1$. When $\boldsymbol{e}_{ij}$ is a unit vector, the membership function is defined on the original axis. Denote the first, second and third quartiles on the j-th principal axis of the cluster i by ρ_{ij1}, ρ_{ij2}, and ρ_{ij3}, respectively. The second quartile corresponds to the median of data distribution on the principal axis. The first and third quartiles are defined so that the first is smaller than the third. If they are equal, one quartile must fluctuate to maintain $\rho_{ij1} < \rho_{ij2} < \rho_{ij3}$.

Define membership functions on the principal axes of the cluster i as follows:

$$\begin{cases} \mu_{ij}(\zeta_{ij};\ \rho_{ij1}, \rho_{ij2}, \rho_{ij3}, t_{ij1}, t_{ij2}) = \exp\Big\{-\frac{(\zeta_{ij}-\rho_{ij2})^2}{2(t_{ij1})^2(\rho_{ij1}-\rho_{ij2})^2}\Big\}, & \zeta_{ij} \le \rho_{ij2}, \\ \mu_{ij}(\zeta_{ij};\ \rho_{ij1}, \rho_{ij2}, \rho_{ij3}, t_{ij1}, t_{ij2}) = \exp\Big\{-\frac{(\zeta_{ij}-\rho_{ij2})^2}{2(t_{ij2})^2(\rho_{ij3}-\rho_{ij2})^2}\Big\}, & \zeta_{ij} \ge \rho_{ij2}, \end{cases} \tag{22}$$

where t_{ij1}, t_{ij2} (> 0) are tuning parameters with the unit default. They are optimized by the nonlinear optimization algorithm (see Box *et al.*, 1969). Now, define the membership function corresponding to rule i:

$$f_i(\boldsymbol{z}) = \prod_{j=1}^{t} \mu_{ij}(\zeta_{ij};\ \rho_{ij1}, \rho_{ij2}, \rho_{ij3};\ t_{ij1}, t_{ij2}). \tag{23}$$

There are several reasons for using such a membership function. Because the premise variables are usually correlated to each other, we recommend using multi dimensional membership functions. These are derived from the product of one-dimensional membership functions which are defined on the principal axes. The reasons for using quartiles are that they are robust statistics, are not easily influenced by extraordinary data units, and are suitable to represent nonsymmetrical cluster spread. The function defined in equation(22) is an asymmetrical curve with two inflection points that are internally or externally dividing points between the median and the first (or the third) quartile in the ratio $t_{ij1} : 1-t_{ij1}$ (or the ratio $t_{ij2} : 1-t_{ij2}$). That is, the parameters t_{ij1}, t_{ij2} appear to be related to a cluster spread and are optimized to minimize the sum of square errors of predictions defined in equation (9).

It should be noted that good linear regression models are not always obtained for some data sets. For such data sets one can examine nonlinear regression or try to build ordinary fuzzy proposition models(see Kainuma *et al.*, 1990).

4 Fuzzy Rule Generation for Selected EMEP Grids

4.1 Review of each grid

Fuzzy models of grids in southern UK, Stuttgart, and upper Austria, are provided in this section.

The EMEP ozone model can simulate the influences on each grid from all the countries in Europe. The results from the simulations for NO_x emissions are shown in Table 6; the numbers correspond to countries defined in Table 1. Each fuzzy model considers influences from sources outside, and possibly inside the countries. The large influence on each grid is represented by the five main sources (countries). Total effective NO_x emissions from foreign sources and the effective NO_x from domestic sources are used for building the fuzzy model.

Table 6: Influences on each grid of effective NO_x emissions; numbers correspond to countries listed in Table 1.

Southern UK	27	10	17	8	3	14	6	19	15	39	42	46
Stuttgart	10	8	27	46	17	3	19	15	24	2	16	23
Upper Austria	10	2	15	46	8	27	19	24	17	3	47	6

Effective VOC emissions from all countries in Europe are also used in the fuzzy model. The response variable is ozone concentration and the explanatory variables are effective NO_x and effective VOC emissions. These effective emissions are calculated by the EMEP ozone model along the simulated trajectory under meteorological conditions over a 96-hour period. The variable representing the photolysis rate of NO_2 is also considered. Photolysis rate of NO_x acts as a catalyst for ozone generation (Heyse and Schöpp, 1995).

The effective emissions of NO_x and VOC are highly correlated. This situation causes the collinearity problem, so explanatory variables should be selected. The reason why they have such a high correlation is that sources of these emissions are very similar; for instance, they often come from the same plants, and large-scale sources contribute to both. To analyze the reduction of precursor emissions using the fuzzy model, the variables related to NO_x and VOC are used in fuzzy rules.

Figure 1, Figure 2 and Figure 3 show the levels of NO_x emissions in the selected grids. The horizontal axis shows the number of days and the vertical axis provides the amount of effective NO_x emissions. The white diamonds denote effective NO_x emissions from sources in all countries in Europe, the white squares denote effective NO_x emissions from sources in the four main countries, and the black diamonds denote effective NO_x emissions from domestic sources.

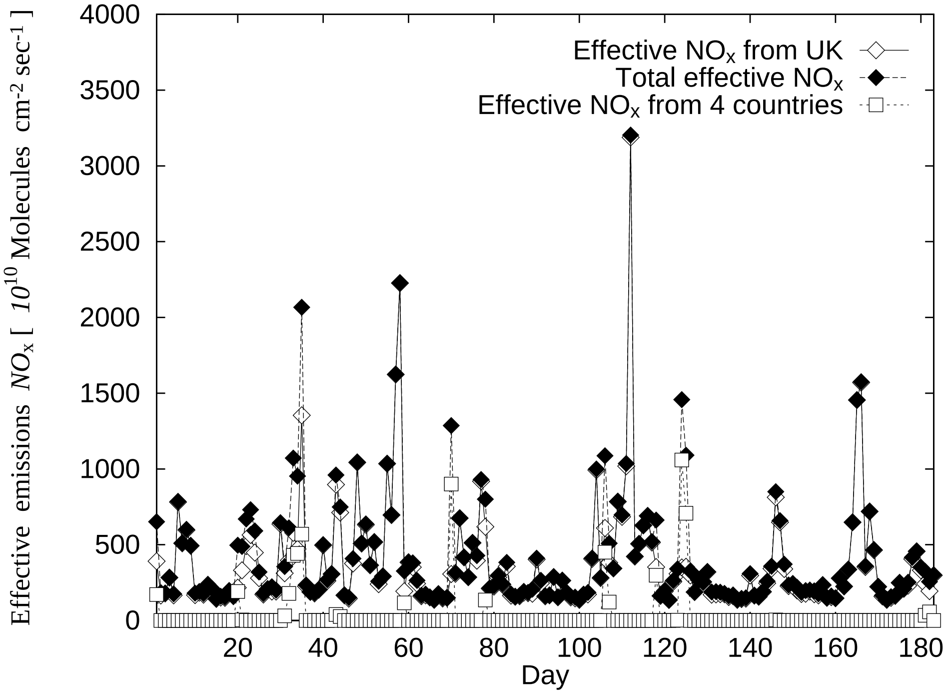

Figure 1: Effective NO_x emissions in the grid of southern UK.

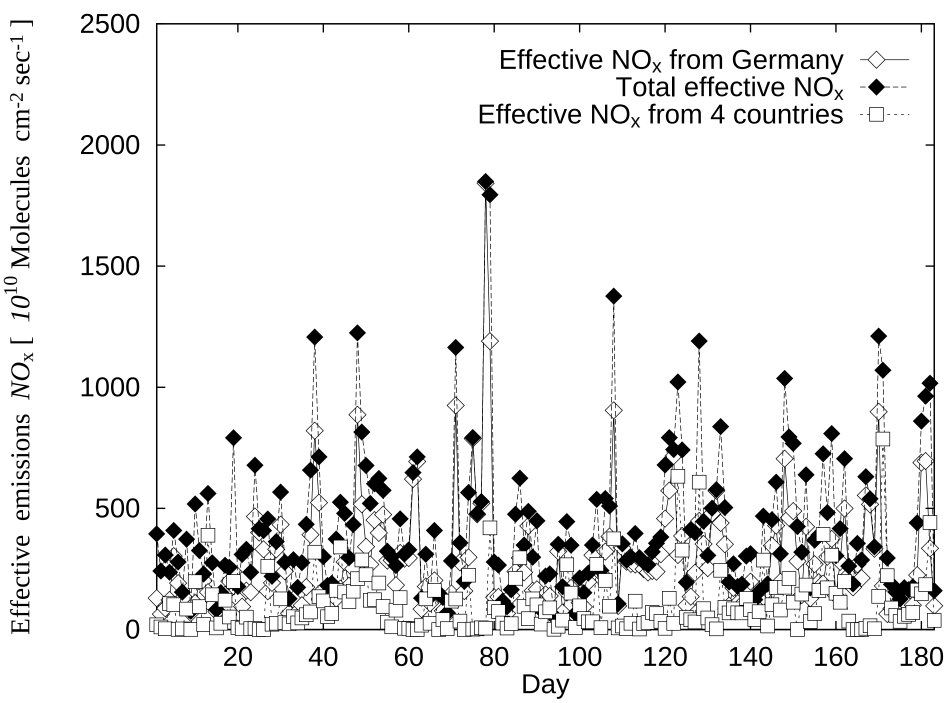

Figure 2: Effective NO_x emissions in the grid of Stuttgart.

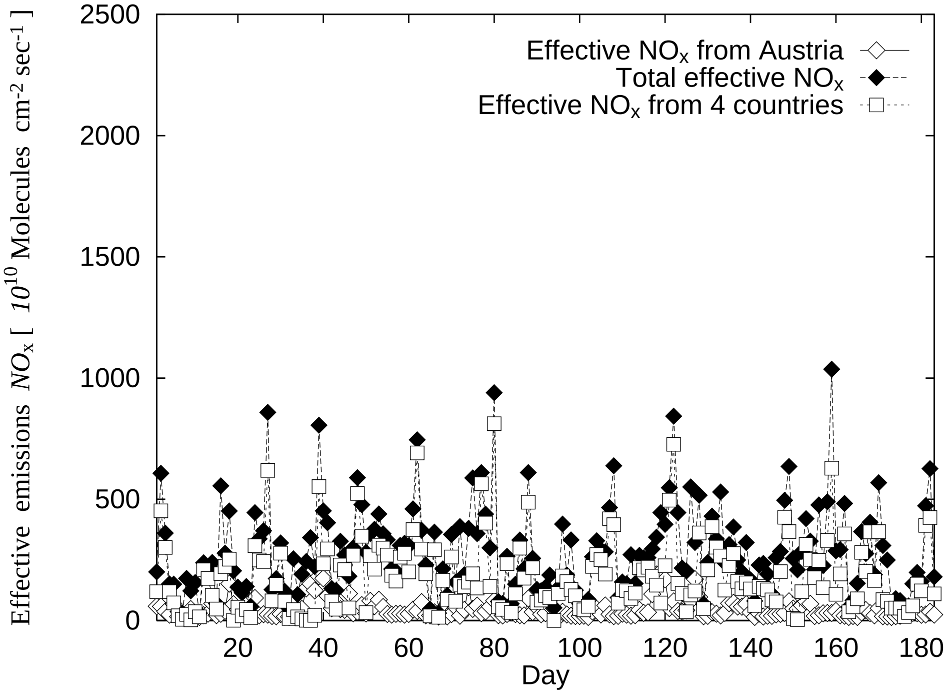

Figure 3: Effective NO_x emissions in the grid of upper Austria.

Figure 1 shows that southern England receives a small amount of NO_x from countries. Effective NO_x emissions from UK sources have a strong influence on the grid. A fuzzy model of this grid may be developed without considering other countries.

Figure 2 shows that in Stuttgart, Germany, total effective NO_x emissions are almost equal to the amount contributed by other countries. The emissions from sources in Germany are the main influence on this grid.

Figure 3 shows that in upper Austria receives more effective NO_x emissions from sources in other countries than from sources in Austria. Germany contributes the largest amount of effective NO_x emissions to this grid.

4.2 Fuzzy models of the grid of southern United Kingdom

The grid of southern UK (Figure 1) shows that only a small amount of effective NO_x emissions comes from other countries. Table 7 presents a regression model and its prediction power. The explanatory variables are also shown in Table 7; these variables are used in the simplified model (Heyse and Schöpp, 1995).

Table 8 shows that the correlation coefficients between explanatory variables are very high. This situation causes the general collinearity problem. However, as mentioned earlier, the level of effective emissions in the grid must be used for fuzzy rules even though the correlation coefficients between explanatory variables are high.

The grid of southern England shows that the amount of effective NO_x emissions from foreign sources is very small. This variable is not suitable as a premise variable, but it is necessary for policy making. Therefore, two fuzzy models are developed for this grid: one includes the level of effective NO_x emissions from foreign sources and the other does not.

Model I: A fuzzy model using effective NO_x emissions from foreign sources countries.

Table 7: A regression model developed from data of the grid of southern UK.

Explanatory Variables				
Const.	E.NO_x	E.VOC	E.$NO_x{}^2$	E.$NO_x \times$E.VOC
36.549	-0.016165	0.010392	-5.0058e-5	2.20768e-5

The correlation coefficient of predictions between the EMEP model and the regression model is 0.5633.

Table 8: Correlation coefficients between explanatory variables of the grid of southern England.

	Ozone	E.NO_x	E.VOC	E.$NO_x{}^2$	E.$NO_x \times$E.VOC
Ozone	1.0	0.4227	0.4812	0.3726	0.4044
E.NO_x		1.0	0.9821	0.9076	0.9158
E.VOC			1.0	0.8790	0.9003
E.$NO_x{}^2$				1.0	0.9968
E.$NO_x \times$E.VOC					1.0

In this model, the premise variables are effective NO_x emissions from sources in the United Kingdom, the effective NO_x emissions from sources in Germany, the Netherlands, France, and Belgium, and the photolysis rate of NO_2. The model has four rules. The estimation results of Model I are shown in Figure 4.

The correlation coefficient of predictions between the EMEP model and Model I is 0.6270. The selected premise variables are effective NO_x emissions from UK sources, the photolysis rate of NO_2, and effective NO_x emissions from the four countries.

The identified membership functions of premise variables are shown in Figure 5, Figure 6, and Figure 7. In these figures, the vertical and horizontal axes correspond to the grade of the membership function and the premise variable, respectively. The membership function of effective NO_x emissions from sources in the four countries is not partitioned in this model. The premise and consequence of the fuzzy model are summarized in Table 9 through Table 13.

Model II: A fuzzy model without effective NO_x emissions from the four countries.

A fuzzy model that does not consider effective NO_x emissions from sources in Germany, the Netherlands, France, and Belgium is described in this section. The model has three fuzzy rules. The estimation results of Model II are shown in Figure 8.

The correlation coefficient of predictions between the EMEP model and Model II is 0.7707. The selected premise variables are effective NO_x emissions from the UK and the photolysis rate of NO_2. The identified membership functions of premise variables are shown in Figure 9 and Figure 10. The premise and consequence of the fuzzy model are shown Table 14 through Table 17.

4.3 Fuzzy models of the grid of Stuttgart site in Germany

In this section, two fuzzy models of the grid of Stuttgart are introduced. This grid receives some effective NO_x emissions from other countries (see Table 6). As shown in Figure 2, this grid is strongly influenced by precursor emission NO_x from Germany. A regression model based on all data from the grid of Stuttgart site is shown in Table 18. Correlation coefficients between explanatory variables in the grid of Stuttgart are summarized in Table 19.

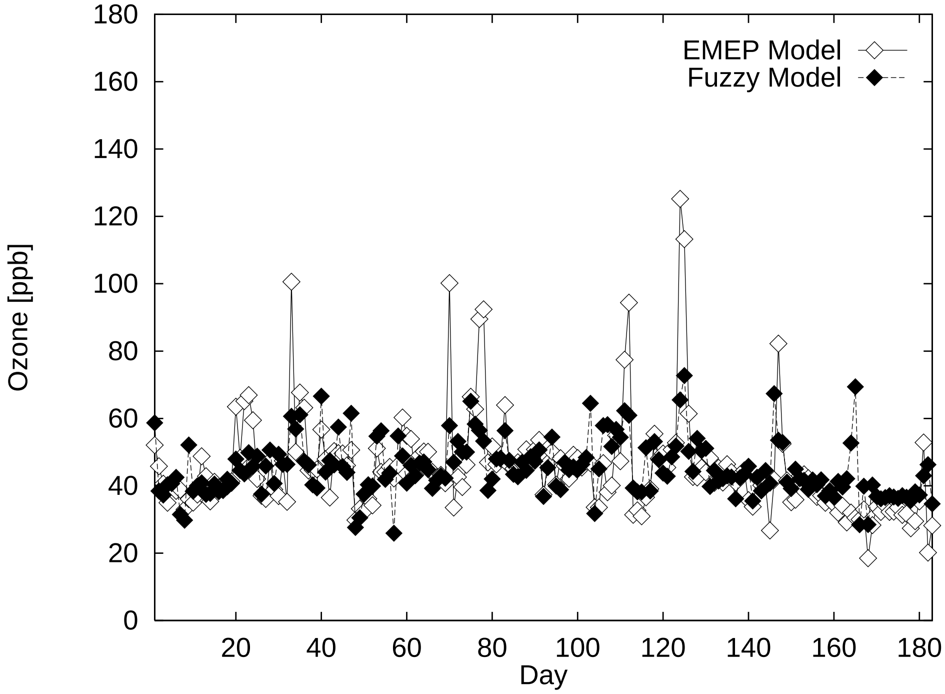

Figure 4: Estimation results from Model I of the grid of southern UK.

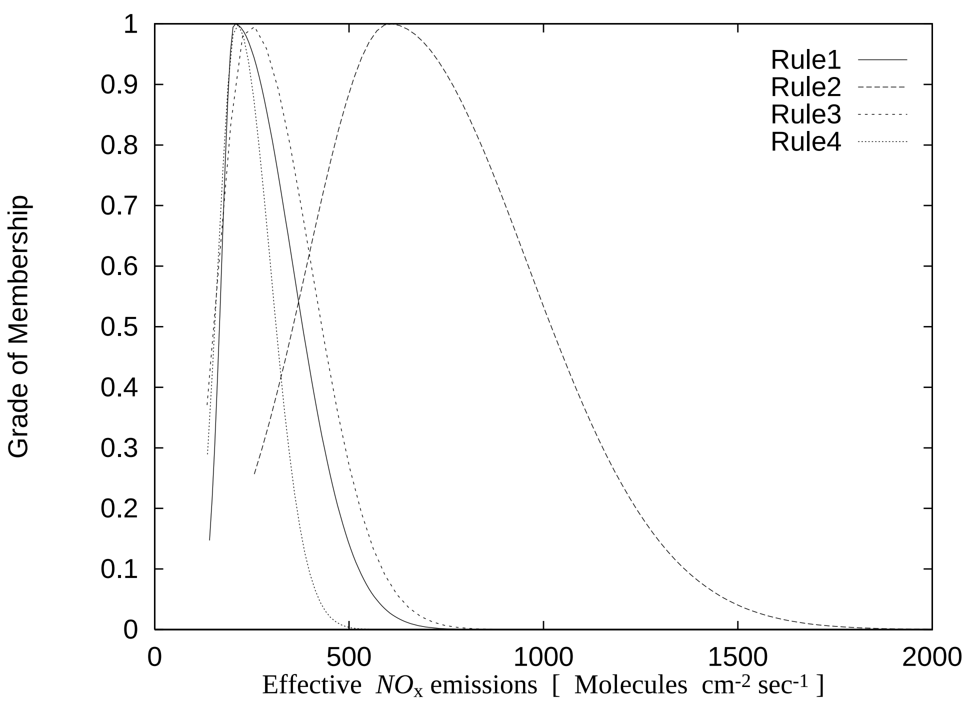

Figure 5: Effective NO_x emission in the grid of southern UK from sources in the United Kingdom.

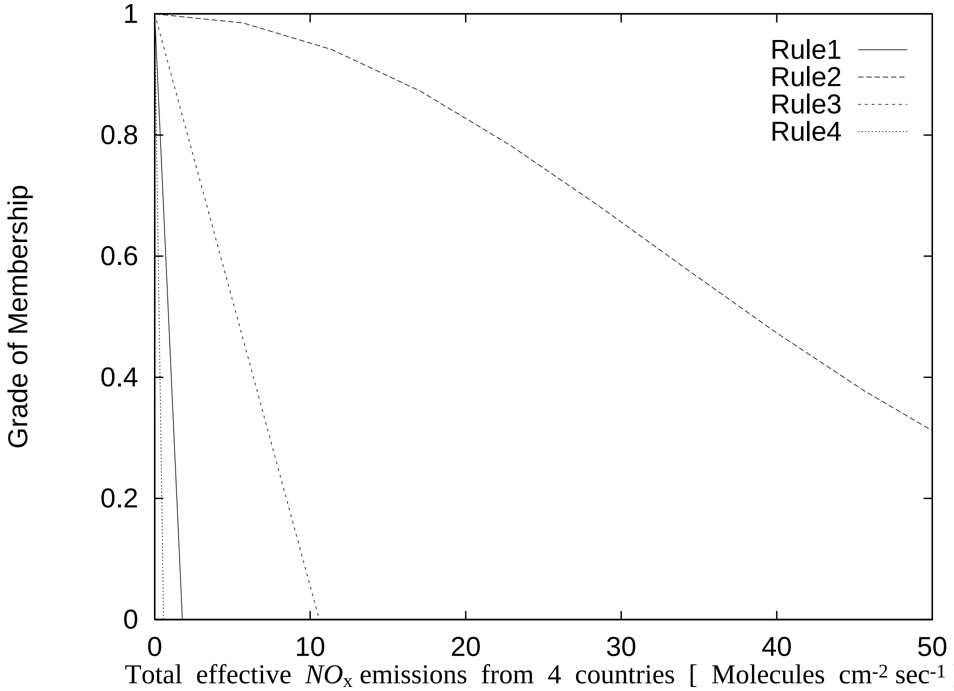

Figure 6: Effective NO_x emissions in the grid of southern UK from sources in Germany, the Netherlands, France, and Belgium

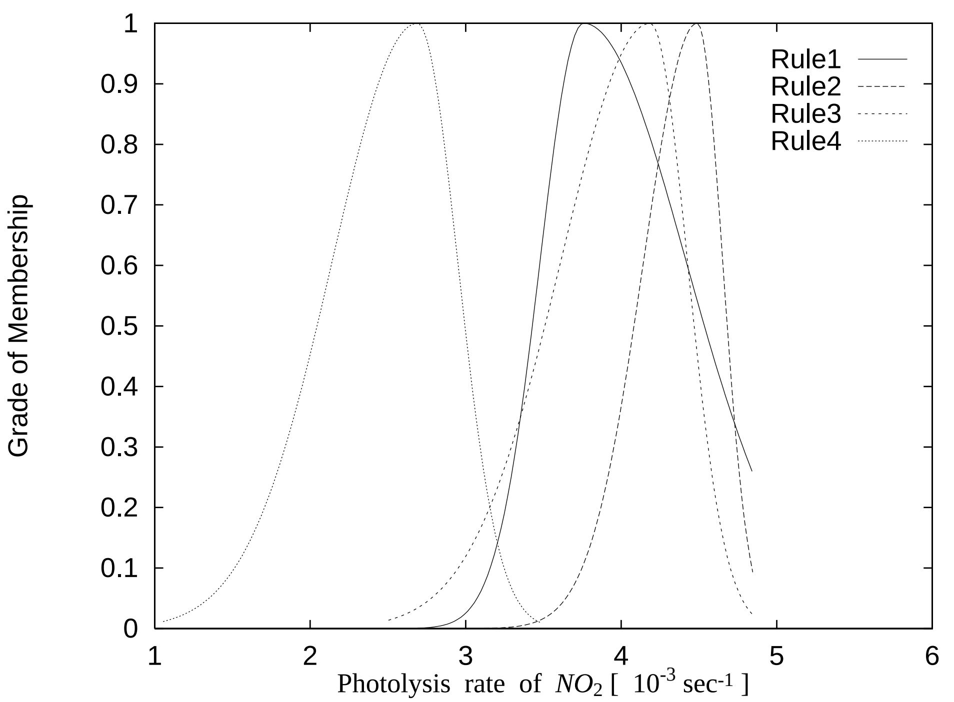

Figure 7: Photolysis rate of NO_2 in the grid of southern UK

Premise of Model I of the grid of southern UK

Table 9: Minimum, quartiles, maximum, and tuning parameters in rule 1.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from UK	141.13	172.38	205.00	354.10	813.43	2.1	3.8
Photolysis rate of NO_2	2.6894	3.4781	3.7578	4.4180	4.8417	3.5	3.6
E.NO_x from 4 countries	0.0000	0.0000	0.0000	0.0000	178.48	3.9	4.1

Table 10: Minimum, quartiles, maximum, and tuning parameters in rule 2.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.No_x from UK	256.33	393.00	603.59	957.39	2226.3	2.2	2.7
Photolysis rate of NO_2	3.0645	4.1436	4.4889	4.6528	4.8461	2.4	4.0
E.NO_x from 4 countries	0.0000	0.0000	0.0000	32.700	570.00	3.5	4.9

Table 11: Minimum, quartiles, maximum, and tuning parameters in rule 3.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.No_x from UK	134.85	165.76	241.38	401.35	3187.5	2.7	2.1
Photolysis rate of NO_2	2.5032	3.6112	4.1865	4.4265	4.8489	0.9	1.5
E.NO_x from 4 countries	0.0000	0.0000	0.0000	1.5375	1058.8	3.2	4.2

Table 12: Minimum, quartiles, maximum, and tuning parameters in rule 4.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.No_x from UK	135.80	163.09	210.54	297.01	1454.5	3.4	3.1
Photolysis rate of NO_2	1.0540	2.1413	2.6888	2.9491	3.4782	2.0	4.1
E.NO_x from 4 countries	0.0000	0.0000	0.0000	0.0000	57.100	1.2	3.6

Consequence of Model I of the grid of southern UK

Table 13: Regression models of Model I of the grid of southern UK.

Rule	Const.	Effective NO_x	Effective VOC
Rule 1	39.215	-0.084880	0.030136
Rule 2	37.919	-0.081425	0.037291
Rule 3	28.084	-0.21351	0.10015
Rule 4	36.566	0.010581	-0.0056247

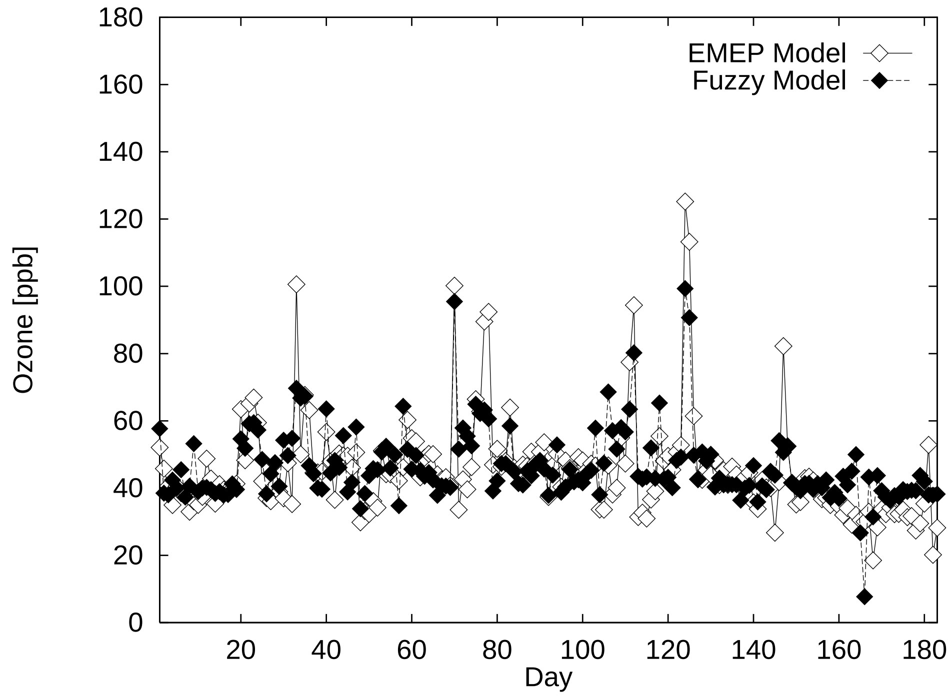

Figure 8: Estimation results from Model II of the grid of southern England.

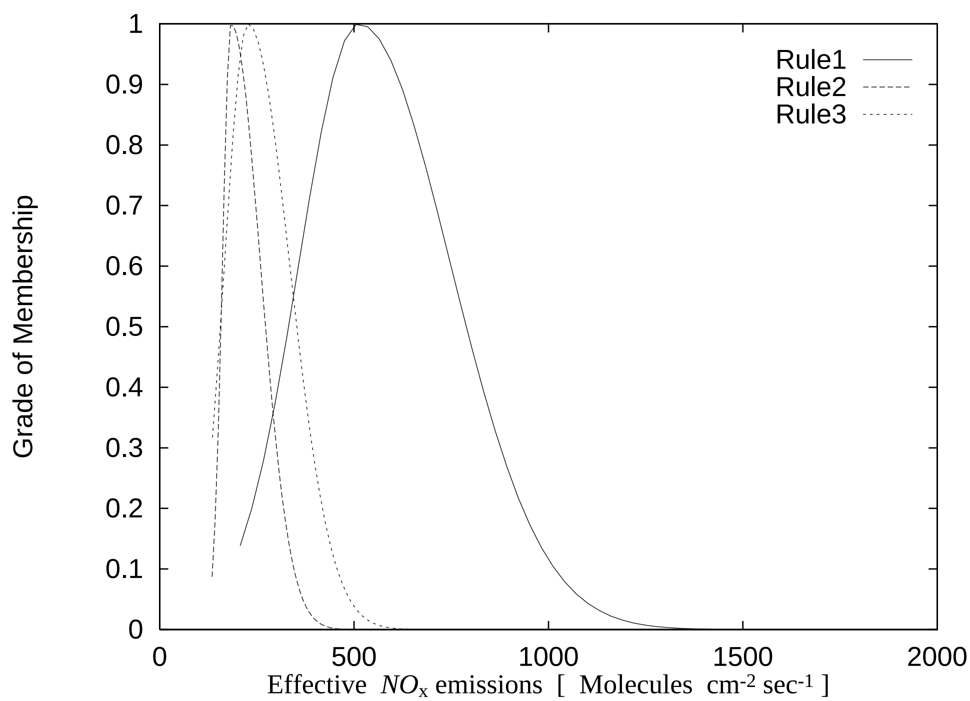

Figure 9: Effective NO_x emissions in the grid of southern UK from UK sources.

Premise of Model II of the grid of southern UK

Table 14: Minimum, quartiles, maximum, and tuning parameters in rule 1.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from UK	207.13	358.60	511.81	746.98	3187.5	0.8	3.2
Photolysis rate of NO_2	2.9910	4.0880	4.4522	4.6102	4.8417	0.6	1.7

Table 15: Minimum, quartiles, maximum, and tuning parameters in rule 2.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from UK	134.85	161.50	183.54	258.93	918.00	2.5	4.4
Photolysis rate of NO_2	1.8333	3.3500	3.7674	4.3236	4.8489	3.4	3.9

Table 16: Minimum, quartiles, maximum, and tuning parameters in rule 3.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from UK	135.80	166.90	227.18	333.93	1454.5	1.7	4.9
Photolysis rate of NO_2	1.0540	2.1413	2.6888	2.9653	3.6126	4.2	2.4

Consequence of Model II of the grid of southern UK

Table 17: Regression models of Model II of the grid of southern UK.

Rule	Const.	Effective NO_x	Effective VOC
Rule 1	24.706	-0.056971	0.031271
Rule 2	30.577	0.0019158	0.021854
Rule 3	33.671	-0.046039	0.013568

Table 18: A regression model developed from data of the grid of Stuttgart.

Explanatory Variables				
Const.	$E.NO_x$	E.VOC	$E.NO_x{}^2$	$E.NO_x \times E.VOC$
40.339	-0.0028820	0.020350	-6.2404e-5	1.60638e-5

The correlation coefficient of predictions between the EMEP model and the regression model is 0.7794.

Table 19: Correlation coefficients between explanatory variables of the grid of Stuttgart.

	Ozone	$E.NO_x$	E.VOC	$E.NO_x{}^2$	$E.NO_x \times E.VOC$
Ozone	1.0	0.5356	0.7097	0.4832	0.2656
$E.NO_x$		1.0	0.9196	0.9357	0.9059
E.VOC			1.0	0.8666	0.9122
$E.NO_x{}^2$				1.0	0.9781
$E.NO_x \times E.VOC$					1.0

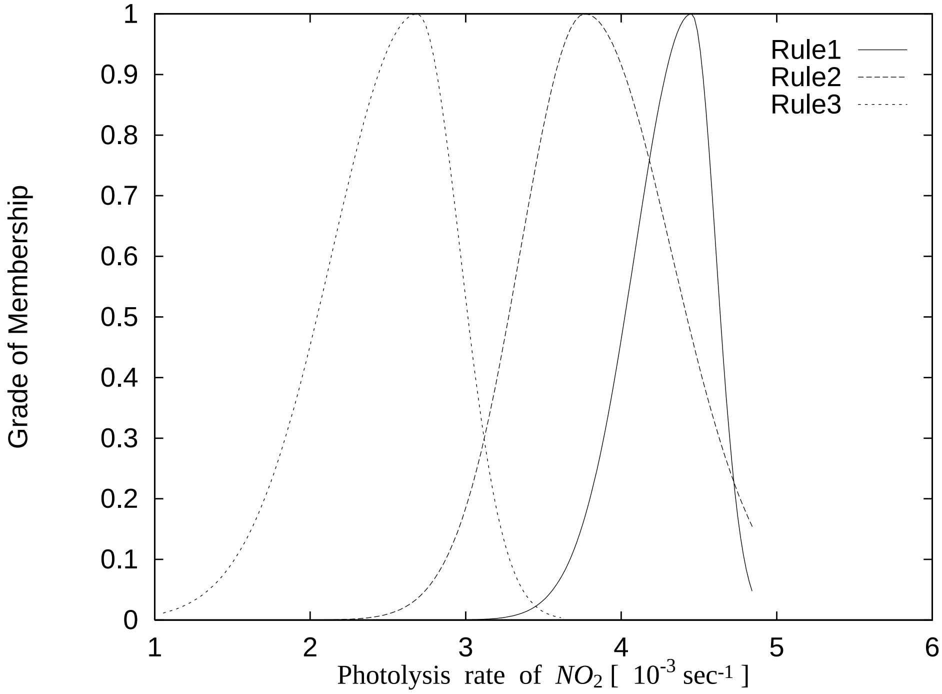

Figure 10: Photolysis rate of NO_2 in the grid of southern UK.

For this grid, two fuzzy models have been developed. One has a higher correlation coefficient between predictions by the EMEP ozone model and predictions by the fuzzy model than the other. It is quite difficult to judge which fuzzy model is better because the rules of the fuzzy model with better prediction are not clearly separated.

Model III: A fuzzy model with two fuzzy rules

The premise variables selected in this fuzzy model are the photolysis rate of NO_2, effective NO_x emission from sources in Germany, and effective NO_x emissions from sources in France, the UK, the Czech Republic, and Belgium. The selected consequence variables are effective NO_x emissions and effective VOC emissions. The predictive power of the model is shown in Figure 11.

The correlation coefficient of predictions between the EMEP model and Model III is 0.9296. The identified membership functions of premise variables are shown in Figure 12, Figure 13, and Figure 14.

As mentioned before, the membership functions of the photolysis rate of NO_2 are not well partitioned, although the correlation coefficient between the simulated values of the EMEP ozone model and the predictions of this fuzzy model is high. The model is summarized in Table 20 through Table 22.

Model IV: A fuzzy model with three fuzzy rules

The variables in this model are the same as those in the Model III, but the model has three fuzzy rules. The predictive power of Model IV is shown in Figure 15.

The correlation coefficient of predictions between the EMEP model and Model IV is 0.8970. The premise variables are effective NO_x emissions from Germany, the photolysis rate of NO_2, and effective NO_x emissions from four countries. The identified membership functions of the premise variables are shown in Figure 16, Figure 17, and Figure 18.

The model is summarized in Table 23 through Table 26.

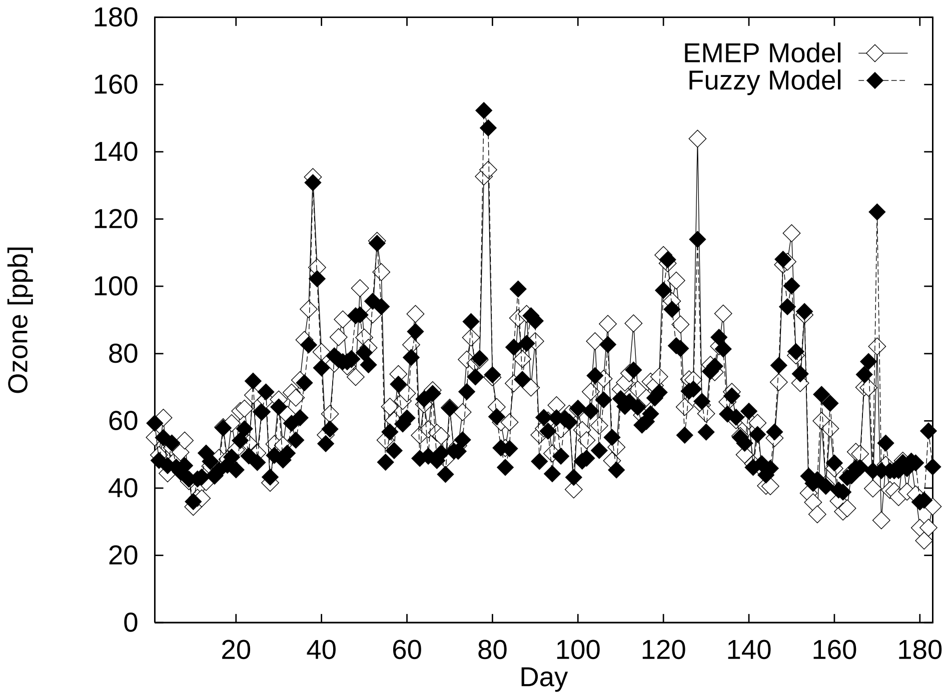

Figure 11: Estimation results from Model III of the grid of Stuttgart.

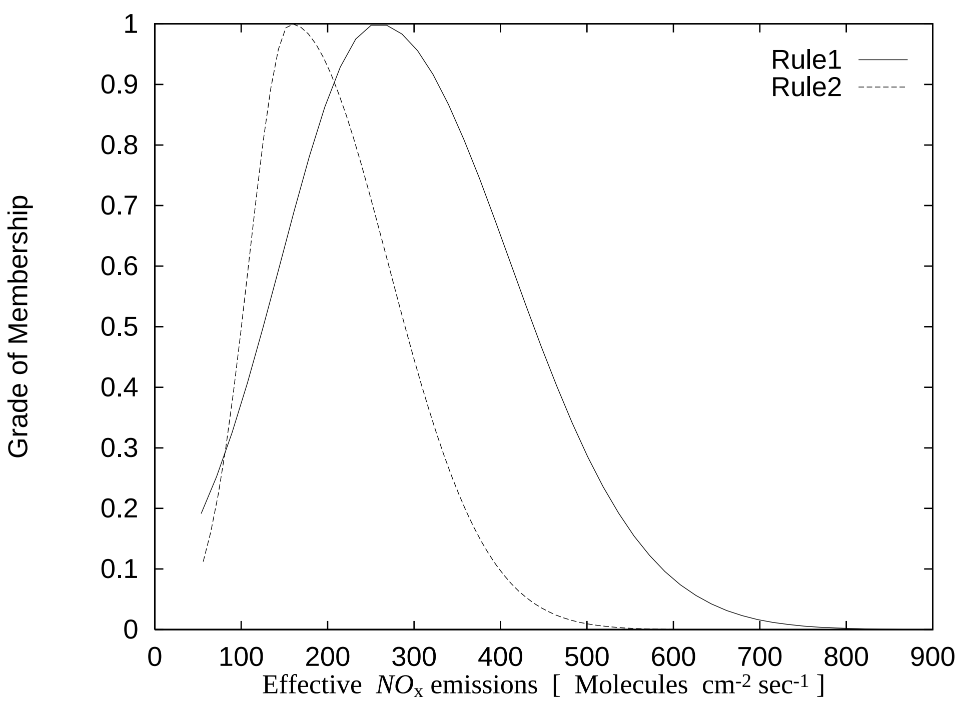

Figure 12: Effective NO_x emissions in the grid of Stuttgart from sources in Germany.

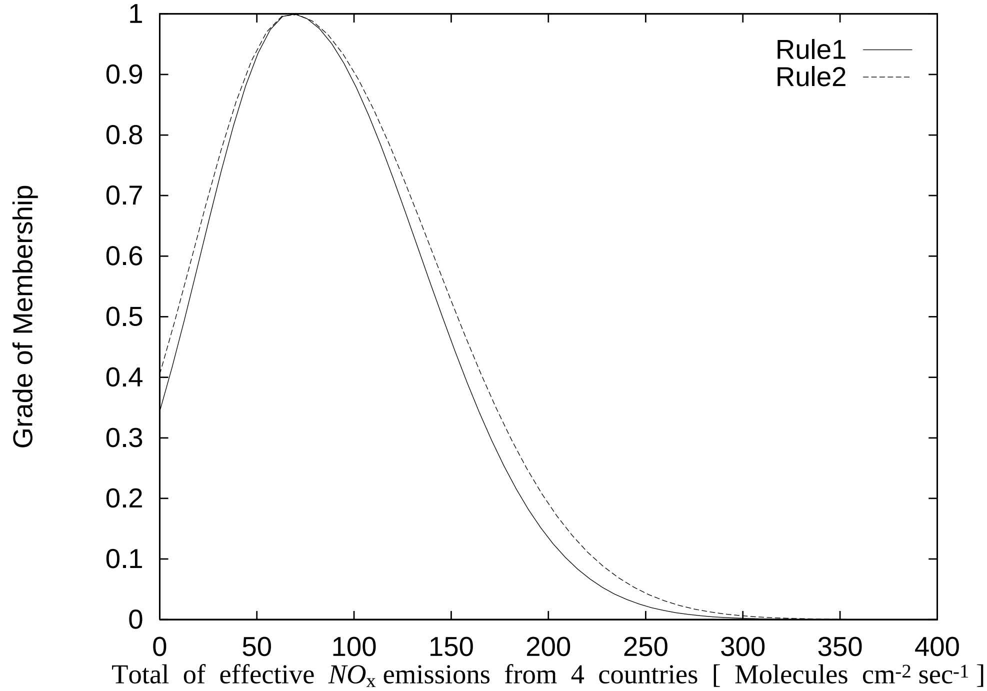

Figure 13: Effective NO_x emissions in the grid of Stuttgart from sources in France, the UK, the Czech Republic, and the Netherlands.

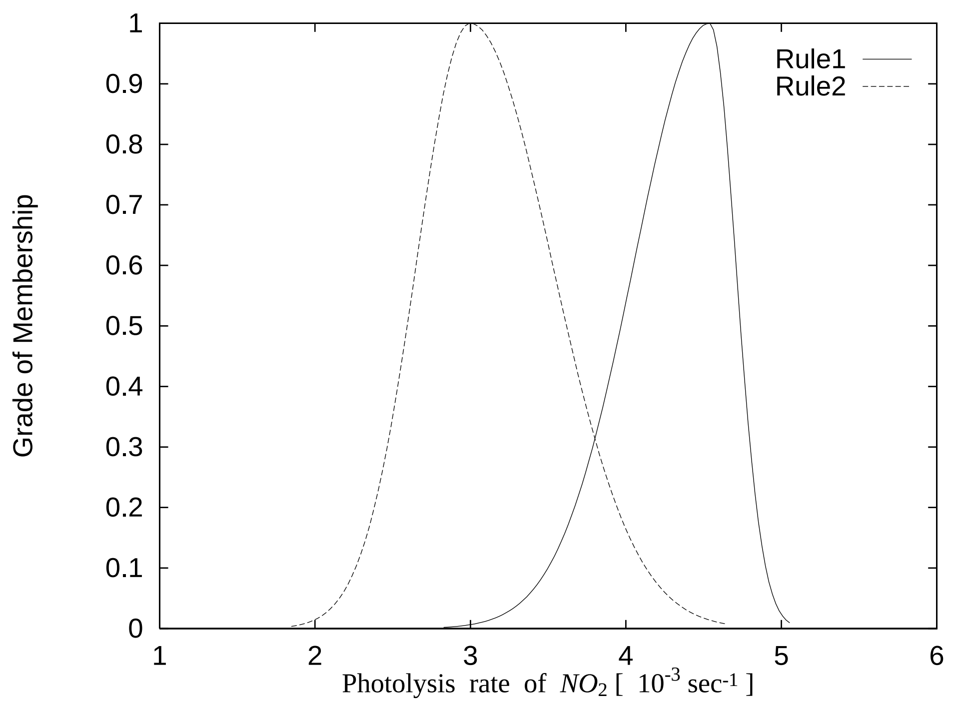

Figure 14: Photolysis rate of NO_2 in the grid of Stuttgart, Germany.

Premise of Model III of the grid of Stuttgart, Germany.

Table 20: Minimum, quartiles, maximum and tuning parameters in rule 1.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from Germany	53.650	145.50	257.78	411.28	1842.3	2.0	4.1
Photolysis rate of NO_2	2.8271	4.0540	4.5387	4.7073	5.0535	1.0	1.0
E.NO_x from 4 countries	0.0000	21.325	67.475	133.66	632.38	2.7	4.6

Table 21: Minimum, quartiles, maximum and tuning parameters in rule 2.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from Germany	56.125	108.90	157.25	269.59	925.20	3.5	3.6
Photolysis rate of NO_2	1.848	2.6537	2.9969	3.5247	4.6394	1.0	1.0
E.NO_x from 4 countries	0.0000	17.275	67.350	140.28	786.50	2.3	3.6

Consequence of Model III of the grid of Stuttgart, Germany.

Table 22: Regression models of Model III of the grid of Stuttgart, Germany.

Rule	Const.	Effective NO_x	Effective VOC
Rule 1	49.9128	-0.010790	0.019682
Rule 2	41.6517	-0.055144	0.022326

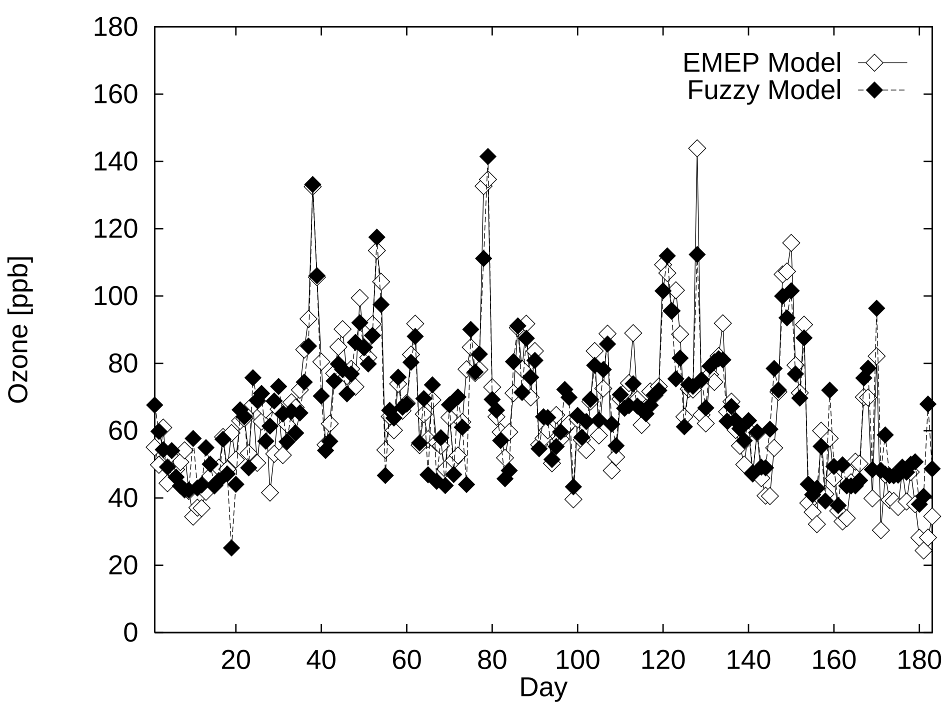

Figure 15: Estimation results from Model IV of the grid of Stuttgart, Germany.

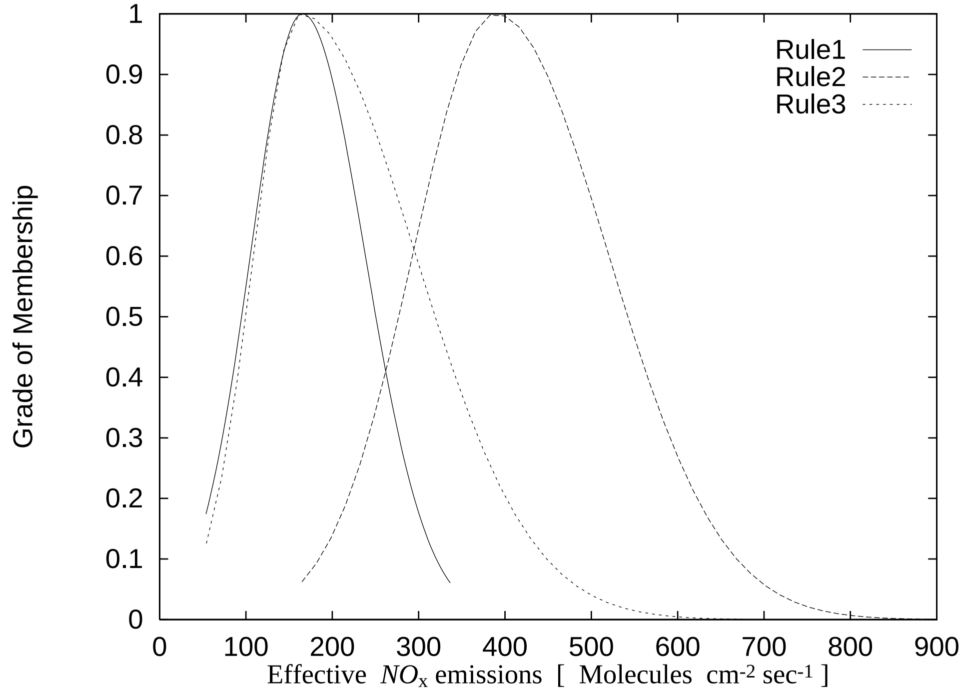

Figure 16: Effective NO_x emissions in the grid of Stuttgart from sources in Germany.

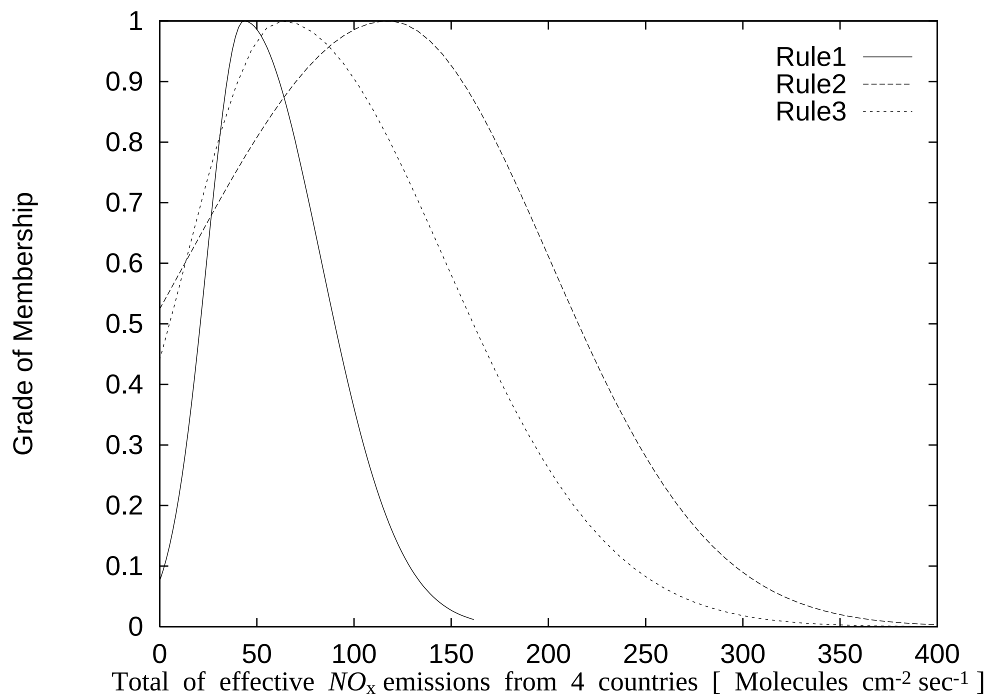

Figure 17: Effective NO_x emissions in the grid of Stuttgart from sources in France, the UK, the Czech Republic, and the Netherlands.

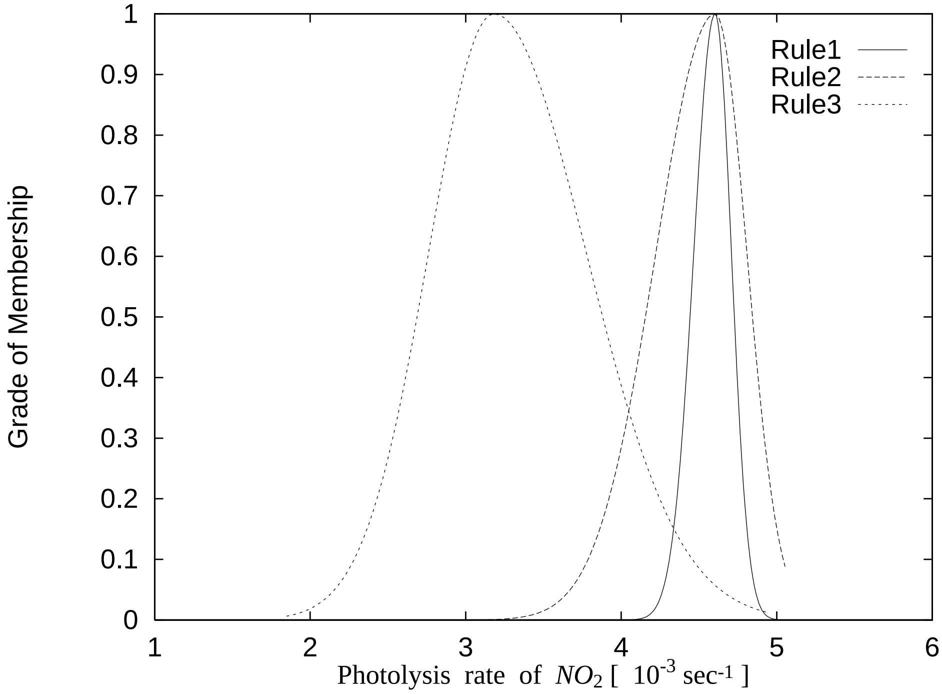

Figure 18: Photolysis rate of NO_2 in the grid of Stuttgart, Germany.

4.4 Fuzzy model of the grid of upper Austria

A comparison of Figures 1, 2, and 3 shows that the grid for upper Austria (Figure 3) influenced more by NO_x emissions from specific countries, especially from Germany, than by emissions from Austria or by emissions from all countries in Europe. A regression model developed using data from the grid and its prediction power are shown in Table 27. Because of the collinearity problem in this model, the coefficients are not stable as shown in Table 28.

The four foreign that have the most influence on this grid are Germany, Italy, the Czech Republic, and France. The estimation results from the fuzzy model are shown in Figure 19.

The correlation coefficient of predictions between the EMEP model and this fuzzy model is 0.9251. The premise variables selected are effective NO_x emissions in the grid of upper Austria from sources in Austria, the photolysis rate of NO_2, and effective NO_x emissions from sources in Germany, Italy, the Czech Republic, and France. The membership functions of premise variables are shown in Figure 20, Figure 21 and Figure 22.

The premise and consequence of the fuzzy model are summarized in Table 29 through Table 32.

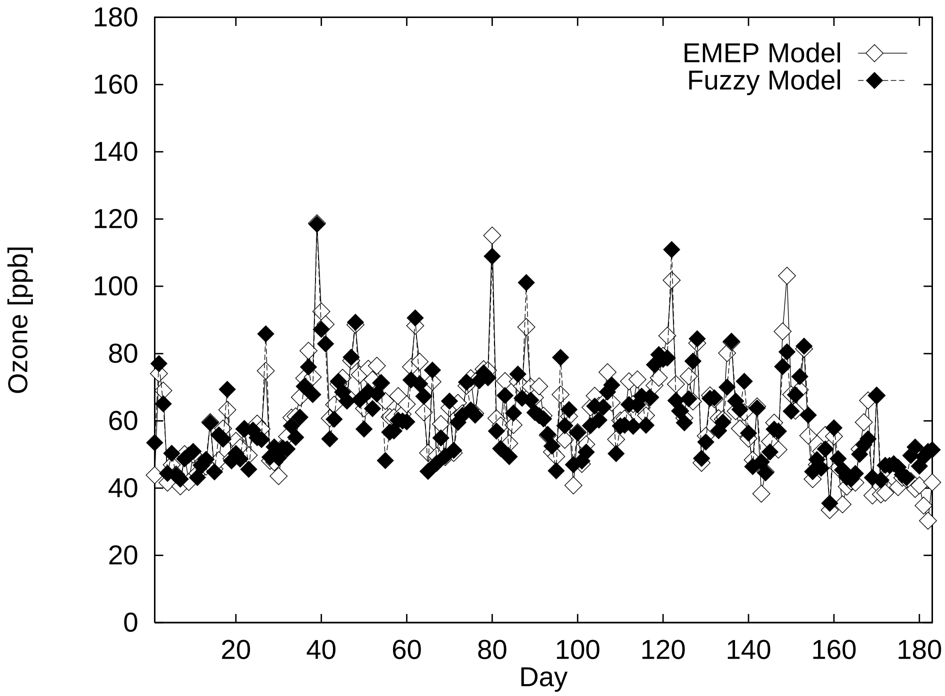

Figure 19: Estimation results of the grid of upper Austria.

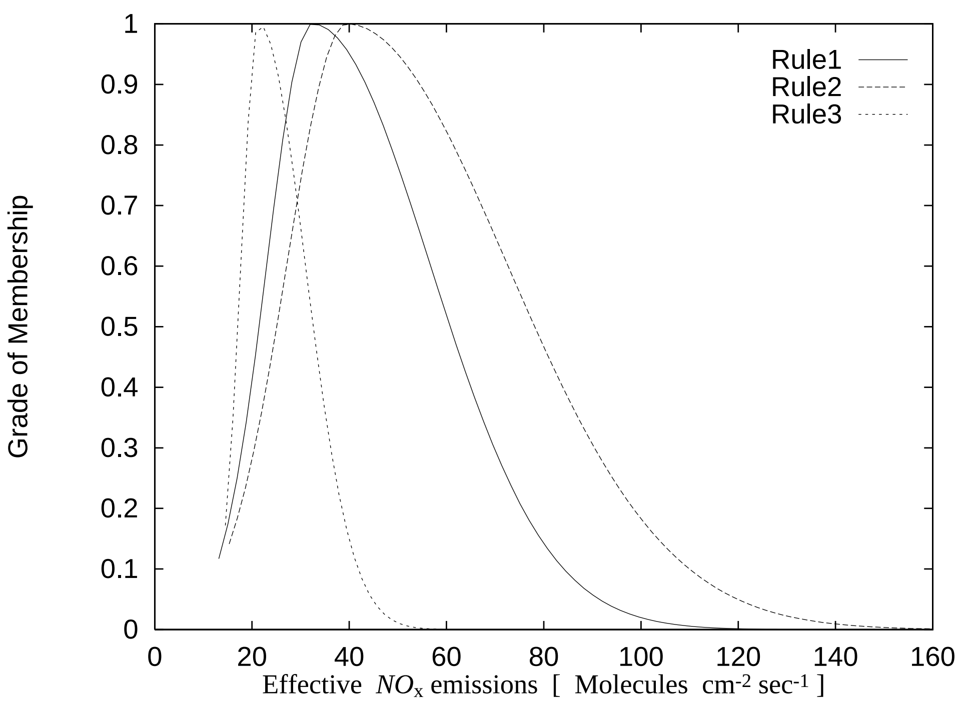

Figure 20: Effective NO_x emissions in the grid of upper Austria from sources in Austria.

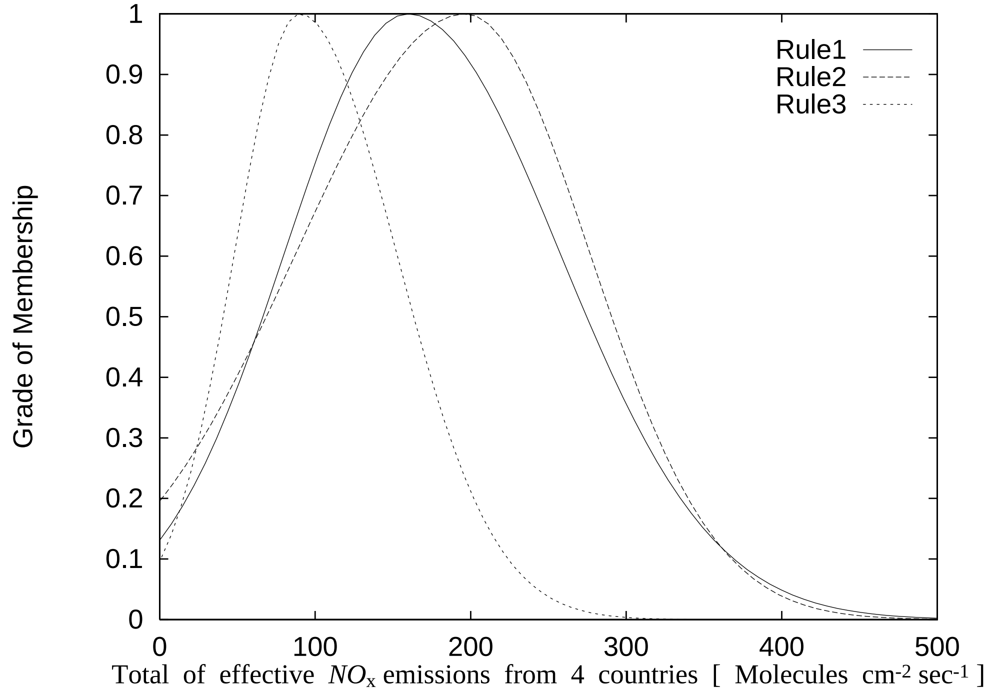

Figure 21: Effective NO_x emissions in the grid of upper Austria from sources in Germany, Italy, the Czech Republic, and France

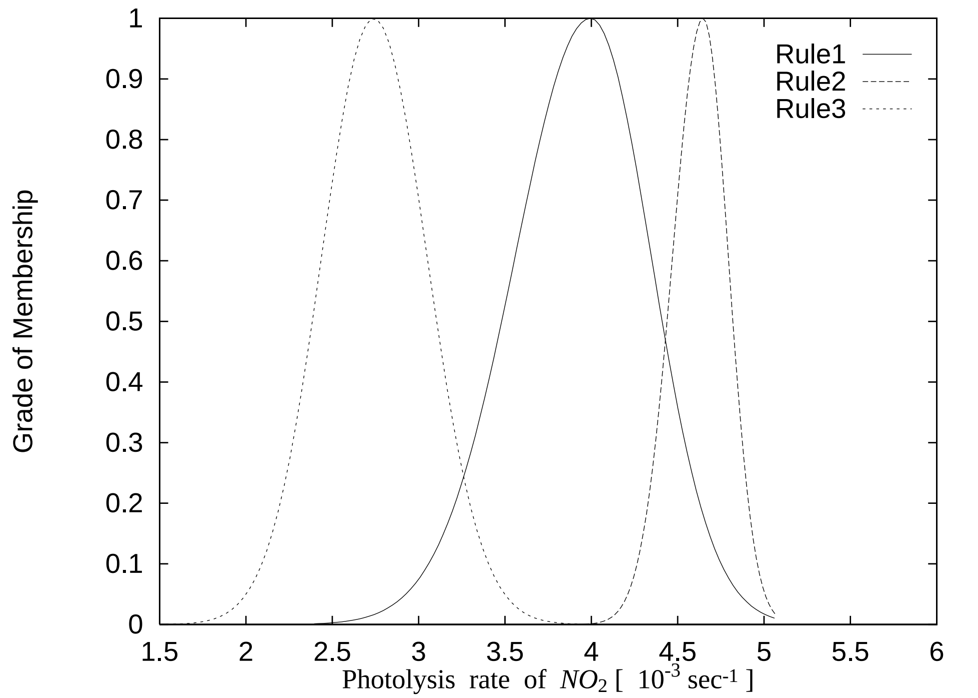

Figure 22: Photolysis rate of NO_2 in the grid of upper Austria.

Premise of Model IV of the grid of Stuttgart, Germany

Table 23: Minimum, quartiles, maximum and tuning parameters in rule 1.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from Germany	53.650	105.60	165.34	237.64	336.60	1.9	2.6
Photolysis rate of NO_2	3.9937	4.4668	4.6039	4.7090	5.0091	2.8	1.8
$E.NO_x$ from 4 countries	0.22500	24.275	43.338	83.025	161.60	4.5	3.1

Table 24: Minimum, quartiles, maximum and tuning parameters in rule 2.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from Germany	164.75	293.85	388.96	519.15	1842.3	0.2	1.9
Photolysis rate of NO_2	2.8271	4.2233	4.6042	4.8081	5.0535	2.7	1.3
$E.NO_x$ from 4 countries	0.0000	14.113	117.58	200.64	632.38	4.3	4.5

Table 25: Minimum, quartiles, maximum and tuning parameters in rule 3.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
$E.NO_x$ from Germany	54.125	109.25	162.45	295.65	1842.3	3.4	3.9
Photolysis rate of NO_2	1.8479	2.7615	3.1794	3.7749	4.9486	4.4	0.6
$E.NO_x$ from 4 countries	0.0000	13.725	62.550	146.45	786.50	0.5	2.4

Consequence of Model IV of the grid of Stuttgart, Germany.

Table 26: Regression models of Model IV of the grid of Stuttgart, Germany.

	Const.	Effective NO_x	Effective VOC
Rule 1	49.248	0.038496	0.0062520
Rule 2	56.634	-0.034042	0.024643
Rule 3	40.9011	-0.087600	0.036111

Table 27: A regression model developed from data of the grid of upper Austria.

Explanatory Variables				
Const.	$E.NO_x$	E.VOC	$E.NO_x{}^2$	$E.NO_x \times E.VOC$
42.639	0.0049415	0.018019	-9.0036e-5	2.29272e-5

The correlation coefficient of predictions between the EMEP model and the regression model is 0.7971.

Table 28: Correlation coefficients between explanatory variables of the grid of upper Austria.

	Ozone	$E.NO_x$	E.VOC	$E.NO_x{}^2$	$E.NO_x \times E.VOC$
Ozone	1.0	0.5748	0.7489	0.4878	0.6333
$E.NO_x$		1.0	0.9047	0.9396	0.9171
E.VOC			1.0	0.8301	0.9234
$E.NO_x{}^2$				1.0	0.9556
$E.NO_x \times E.VOC$					1.0

Premise of the Model of the grid of upper Austria

Table 29: Minimum, quartiles, maximum and tuning parameters in rule 1.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from Austria	13.175	23.100	32.363	56.488	200.95	2.6	3.6
Photolysis rate of NO_2	2.3953	3.5583	3.9952	4.3477	5.0609	2.9	2.7
E.NO_x from 4 countries	0.2500	80.388	159.48	257.24	726.60	2.2	1.8

Table 30: Minimum, quartiles, maximum and tuning parameters in rule 2.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from Austria	15.300	27.250	39.463	72.313	182.48	1.9	2.1
Photolysis rate of NO_2	3.2453	4.4697	4.6479	4.7939	5.0647	2.1	3.4
E.NO_x from 4 countries	0.5000	87.913	196.78	276.46	811.95	3.8	4.4

Table 31: Minimum, quartiles, maximum and tuning parameters in rule 3.

Premise Variables	min	q1	q2	q3	max	t_1	t_2
E.NO_x from Austria	14.525	17.725	21.375	30.913	170.50	3.5	2.9
Photolysis rate of NO_2	1.0049	2.4377	2.7393	3.0494	4.3831	4.0	2.0
E.NO_x from 4 countries	1.2500	48.200	89.650	152.26	628.08	3.9	3.9

Consequence of the Model of the grid of upper Austria

Table 32: Regression models of the grid of upper Austria.

	Const.	Effective NO_x	Effective VOC
Rule 1	45.594	-0.047080	0.027122
Rule 2	51.209	-0.010746	0.020866
Rule 3	40.143	-0.076712	0.028836

5 Conclusion

This paper documents fuzzy models of relationships between precursor NO_x and VOC emissions, and ozone concentrations. A detailed, theoretical model and basic scenarios of emissions have been used in the development of these fuzzy models.

Time limitation have restricted the study to fuzzy models three grids; these grids represent different source-receptor relations. The grids are located in southern England, Stuttgart, and upper Austria. Results from the EMEP model have been used to verify the fuzzy models obtained. Research shows that fuzzy models provide better predictions of the ozone concentrations than traditional regression models based on data from each grid.

The results in this paper illustrate how one can use a detailed, theoretical model to develop simple fuzzy models. Detailed models (such as the EMEP model) are very powerful tools, but these type of models are quite difficult to understand or use in policy analysis aimed at finding cost-effective scenarios. Simple fuzzy models can be developed and verified by using a detailed model; the results of the fuzzy models can then be used to analyze various policy options.

This study supports the development of fuzzy models for all grids. It is an open question if it will be possible to identify a relatively small number of clusters of grids and to develop for each cluster a model which can be applied to all grids belonging to this cluster.

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