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Development of an Intelligent Decision Support System for Environmental Modeling and Planning

環境のモデリングと計画のための知的意志決定支援システムの開発

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PREFACE

The mechanism of human decision-making is very difficult to analyze, to formulate in mathematical form and, therefore, to implement into computers. Looking back the history of the study of human decision-making, we found that several normative theories, such as optimization theory, theory of games, theory of preference structure, utility theory and multiple objective decision theory, have made only partial success in describing the attributes of human decision-making. This simply due to the fact that the way of human thinking is not at all normative nor rational but very conditional in a sense that a human uses in his decision-making his whole accumulation of experiences acquired during his entire life.

It seems to be very attractive, therefore, to decompose the human decision-making precess into elementary precesses and to accumulate as many the elementary processes as possible so that one can reconstruct decision-making under given specified conditions by traversing over the set of the elementary processes. The human decision-making representation of this type, which was once only a dream, came to reality when computer capability in hardware and in software became able to realize the scheme in expert systems. Expert systems have drawn much interest of people in the decision sciences. This is one breakthrough in the mechanization of human decision-making.

Another breakthrough came from the notion of fuzzy reasoning based on the fuzzy set theory introduced by Zadeh. Fuzzy reasoning has a very strong affinity with expert systems, since it offers a very good means for converting qualitative into quantitative reasoning. The combination of the fuzzy modeling and expert systems provides an effective way to implement so-called intelligent decision support systems into computers.

Environmental problems are by their nature social problems since if there is no human society, there is no environmental problem. We must develop proper means to handle human decision-making within environmental problem solving. Even in the analysis of environmental phenomena, which is often thought to be done purely scientifically, human decision-making plays a very important role, since environmental phenomena are so complex that *no single nor multiple combination of normative scientific ways of* analysis may be able to analyze the entire scheme of the phenomena, and *therefore the use of human decision-making is indispensable.*

This report intends to make a further step in the progress of the study of human decision-making. *We would be very happy if this report becomes* of any help for people who are struggling with complex environmental phenomena.

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ABSTRACT

Social phenomena related to environmental processes are governed by complicated factors such as urbanization, aging population and international trade. Future environmental conditions are becoming difficult to predict by individual discipline or research. Estimation should be made by systematically combining the skills of experts with the available numerical data. We have developed a computer system for supporting these operations. Two new trends in systems approach are: 1) incorporating human judgment and experience in the system, and 2) greater interactive use of computers in a conversational manner. This system is based on artificial intelligence techniques as well as usual normative ones and is used recursively to build models for predicting future environmental conditions.

First, a computer system for supporting interactive modeling is presented. This system utilizes graphical information effectively to facilitate not only human-computer communication but also interpersonal communication. As an application, we present the process of identifying an environmental prediction model. It is emphasized that this computer system greatly reduces the burden of trial and error necessary in developing such a model, and helps us think about the problem systematically and intensively.

Second, fuzzy modeling and simulation techniques are presented. The fuzzy modeling technique is used for modeling nonlinear systems with the aid of the division of the data space and the identification of membership functions. The fuzzy simulation technique is used for reasonable scenario inputs and interpretation of the model behavior. The proposed techniques are applied to an urban environmental problem.

Third, a method is presented for predicting phenomena consisting of many complicated factors by modeling the process of human thinking and judgment. Input-output relations of the system are described in the form of if-then rules. Then, using fuzzy reasoning, the behavior of the system will be predicted. This method is applied to the prediction of Oxidant concentration in the Osaka district, Japan. It is shown that this method is appropriate for predicting phenomena with limited input-output data.

Finally, an intelligent decision support system is presented. This computer system aims at the systematic support of a series of tasks from systems analysis to policy analysis by the aid of the above mentioned techniques and by integrated utilization of the knowledge and judgment of experts from relevant fields. The application presented deals with the processes involved in analyzing environmental problems and the formulation of a fuzzy model to estimate environmental impact of possible development programs in Tokyo Bay, Japan.

Chapter 1

Introduction

1.1 Introduction and Historical Remarks

The computer system that we have developed aims at the systematic support of a series of tasks from systems analysis to policy analysis by integrated utilization of the knowledge and judgment of experts together with the available numerical data. The system is planned to be used for: identifying socio-economic trends over the time span of a couple of decades, predicting the impact of those trends on our environment under the assumed scenarios, and selecting the important policy alternatives which may influence those scenarios.

We should keep in mind that any precise models of reality will never incorporate all human concerns. Therefore, the models should be built interactively, involving not only the analysts but also the domain experts and the decision makers. Their perception of the problem, the relevant data and the model validity should be taken into account in model building so that the model can express their goals and preferences within a defined reliability. The interaction is essential at the planning stage as well, and it should be dynamic because the decision makers typically learn when using a decision support system with fixed preferences.

In order to make good use of interaction, the support system must be intelligent. The system should have a working area in the knowledge base system. Frameworks of dynamic knowledge utilization should be designed so that we are able not only to retrieve data or knowledge but also to acquire or modify this interactively. At the modeling stage, the model is identified in parts and associated stepwise with mental models for the object and the knowledge in the support system. The registered knowledge for modeling support can be improved both in quality and quantity by the results of data analysis or by the users' perception. At the planning stage, the knowledge base system should suggest the objective of optimization or the order of priority in constraints. New knowledge can be obtained by considering the gaps between the target and actual plan, or the feasibility and effects of the plan (Nishioka, Morita, Kainuma and Harasawa, 1987).

It is difficult to formulate a practical model for a large complex system that includes human elements, for example, the environmental, traffic, economic or other socio-technical systems. Hence, it is essential to combine the mathematical approach with the heuristic approach (Nakamori and Sawaragi, 1987).

Nakamori (1989) has developed a computer system that assists in model building with recursive interaction between a man and computer. The system consists of a combined modeling technique of algebraic and graph-theoretic approaches, and related man-machine interfaces (Nakamori, Ryobu, Fukawa and Sawaragi, 1985). Although a simulation model must be comprehensible, flexible and simple, it needs to be appropriately complex for the purpose of decision-making.

Recently, ill-defined systems are being modeled, in which emphasis lies on structure characterization instead of parameter estimation. In fact, Linstone, Lendaris, Rogers, Wakeland and Williams (1979) identify about 100 structural modeling techniques, and develop guidelines in the choice and proper use of seven famous tools. They define a structural model as "any model that represents a complex system as a set of elements with relations – nearly always in pairs – linking some or all of them; and places the emphasis on the geometry or structure rather than on quantitative aspects of the relations." Because decision-makers are generally not mathematicians or scientists, a structural model is far more appropriate for learning experience. The structure of a system is fundamental to the understanding of what is happening. It gives new insights into the system to decision-makers and the modelers as well.

Structural modeling is useful for dealing with complex social and environmental phenomena. Structural models demonstrate the interactions of the separate elements of a system and their combined effects. Norberg and

Johnson (1979) state that structural modeling is a technique that holds promise as a means for examining the makeup of complex systems and also giving insight about long-term effects of change.

Lendaris (1980) emphasizes the importance of *qualitative (geometric*, topological, etc.) aspects rather than exact numerical or statistical properties of the systems being modeled. Structural modeling holds the promise of converting a completely intuitive process of model building into a more systematic approach, and *enhancing communication within* a *heterogeneous* group.

Lendaris (1979) also points out that the human aspects play an important role in structural modeling. The two aspects which must not be overlooked are the three human roles and the group *procedures. These roles* are 1) the method technician, 2) the facilitator, and 3) the participant. The group procedures assist modelers in defining the elements of the system to be modeled.

From among the many tools of structural modeling we extract the concept, for our purpose, from the Interpretive Structural Modeling (ISM) proposed by Warfield (1974). Combining various methodologies, we have developed Interactive Modeling Supporter (IMS). The system consists of several modern modeling techniques with highly interactive human-computer interfaces. As an application of using IMS, we present the process of identifying an environmental prediction model (Nakamori, Nishioka and Kainuma, 1988).

Fuzzy set theory also plays an important role in model building. The concept of fuzzy set theory was introduced by Zadeh (1973), to serve as a means of approximate characterization of phenomena that are too complex or too ill-defined to be described in precise terms.

In model building of environmental systems, we often encounter difficulty in obtaining linear models. Fuzzy modeling is a key to express nonlinear relations (Takagi and Sugeno, 1985). Sugeno and Kang (1988) have developed a fuzzy modeling technique. They discuss the problems of structure identification of a fuzzy model and formulate its processes.

In fuzzy modeling the data space is divided into several fuzzy subspaces and in each fuzzy subspace a linear relation is built. It is usually difficult to divide the data space so that we can find a suitable model. We have developed a support system, Visual Clustering Supporter (VCS), for this purpose. We have also developed Controlled Fuzzy Simulator (CFS) for controlling the input ranges. With VCS and CFS we can obtain a suitable fuzzy model for environmental planning (Nakamori and Kainuma, 1989).

It often happens that although we cannot obtain sufficient numerical data to build up statistical models, we have to analyze environmental systems. This makes essential to use experts' knowledge and judgment for analyzing environmental systems. Approximate calculus of linguistic variables has been developed which could be of use in a wide variety of practical applications (Zadeh, 1975).

A fuzzy controller is one example. The basic idea behind this approach is to incorporate the "experience" of an expert into the model building. From a set of linguistic rules that describe the operator's control strategy, a control algorithm is constructed where the words are defined as fuzzy sets (Kickert and Mamdani, 1978). The controller's heuristics take the form of a set of linguistic decision rules that are expressed quantitatively and manipulated by using fuzzy set theory (Procyk and Mamdani, 1979).

Wenstop (1976) explored the idea that loosely defined simulation models of organizational behavior can sometimes yield more significant information than conventional precisely defined ones. He presented a simulation study that shows that verbal models indeed may yield significant information based on rather general premises. This indicates that they may, under certain circumstances, be superior to corresponding conventional simulation models.

Kickert (1979a) also developed linguistic modeling. This method makes use of linguistic variables and linguistic causal relationships instead of the numerical variables and relations that are useful in systems modeling.

We have developed Linguistic Fuzzy Simulator (LFS) that assists in predicting future environmental conditions with fuzzy reasoning. LFS can predict the changes of environmental conditions by the use of the linguistic modeling. This type of model is very important, because it is very difficult to predict the results of policies which have not been implemented in the past by the numerical modeling approach.

We propose a method to predict phenomena composed of many complicated factors by modeling the process of human thinking and judgment.

Input-output relations of the system are described in the form of if-then rules. Then using fuzzy reasoning, the behavior of the system will be predicted. We apply fuzzy modeling to the prediction of Oxidant concentrations in the Osaka district, Japan, and show that it is appropriate for the prediction of phenomena with limited input-output data (Kainuma and Nakamori, 1989).

It is necessary to make estimates by systematically combining the skills of experts with the available numerical data for modeling urban environmental problems. To elicit experts' knowledge, Gordon and Helmer (1964) proposed the Delphi method. This method has been widely used to get expert's intuition systematically.

Recently, imprecision in decision analysis has been modeled by using fuzzy set theory. Kaufmann and Gupta (1988) proposed a variation of the Delphi method under triangular fuzzy numbers. They state that a long range forecasting problem must be considered as an uncertain but not a random problem. The direct use of the probabilistic methods is not suitable. The use of fuzzy numbers and fuzzy methods seems to be more compatible and well suited.

Watson, Weiss and Donnell (1979) modeled imprecision in decision analysis by using fuzzy set theory. Fuzziness on the probabilities and utilities used in a decision analysis implies fuzziness on the outputs. They proposed a method for calculating imprecise, though informative, statements about the attractiveness of the different options in a decision tree, which depends on the imprecision of the inputs.

Hipel (1982) suggested multicriteria modeling in order to select the more promising alternative solutions. The various alternatives can be characterized according to both nonquantitative and quantitative factors or criteria, and the *fuzzy* aspects of the given information can be incorporated into the analyses.

Though the Delphi method is useful for obtaining experts' knowledge systematically, it also has shortcomings. There are two main shortcomings. One is that experts may assume different premises and answer a questionnaire from different points of view. The other is that aggregated opinion may be less reliable if opinions of different specialists are counted equally. Using fuzzy set theory, we improved the Delphi method and collected certain knowledge about future scenarios (Morita and Kainuma, 1989 and Morita, Kainuma, Harasawa and Nakasugi, 1990). This knowledge is translated into knowledge data and put into the Knowledge Base (Kainuma, Morita and Nakamori, 1988 and 1989).

Elicited knowledge or ideas are combined to develop a group product of *higher quality* than otherwise usually available. A number of tools have been developed to assist in building and analyzing structural models (Harary, Norman and Cartwright, 1965 and Harary, 1969). Automatic graph drawing and readability of diagrams are important factors for understanding environmental structures.

Crossing theory of multilevel digraphs has been discussed by Warfield (1977). Lempel and Cederbaum (1966) suggested a method to determine a minimum set of arcs of an arbitrarily directed graph. Sugiyama, Tagawa and Toda (1981) have proposed methods for generating a visually understandable drawing of a hierarchy automatically by computer. Tamassia, Battista and Batini (1988) surveyed the methods of automatic graph drawing from the point of readability.

We extract the idea from the methods proposed by Sugiyama, Tagawa and Toda (1981) for drawing graphs automatically. This is because their methods are easy to implement and the results are readable. We have modified the methods and developed Visual Structuring Supporter (VSS).

Stanciulescu (1986) presented principles of modeling and simulation of large-scale and complex systems. He suggested mathematical-heuristic modeling, which can be used both in simulation and control. The model consists of two parts: 1) a standard simulation model, composed of a set of non-linear differential equation and 2) a heuristic model, composed of a set of logical-linguistic rules, derived from the actual process. As an application, he studied the case of the ecological system.

We sometimes find fuzzy subspaces in which we can barely obtain linear models because of the nature of the data. To deal with these cases, we propose a heuristic fuzzy modeling that develops a pattern or linear model for each explained variable in each subspace. This model differs from that of Stanciulescu in that a heuristic rule of Stanciulescu's model concerns parameters of differential equations, whereas our rule concerns possibility distribution of data. In model building of environmental problems, it is dif-

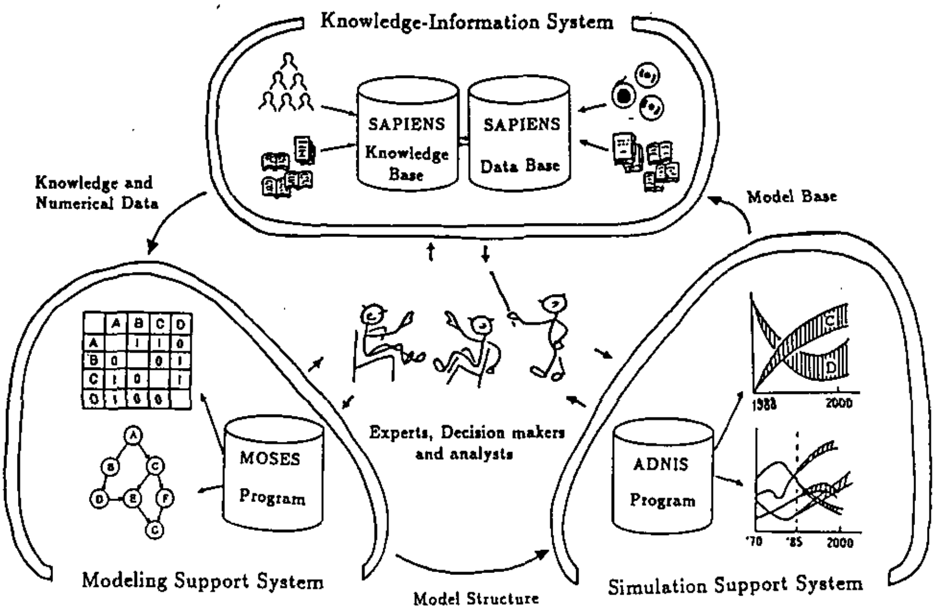


Fig. 1.1 Overview of the intelligent decision support system

ficult to formulate a mathematical model by differential equations, whereas it is easier to obtain possibility distribution of concerned variables.

With the developed system we have analyzed environmental problems in Japan in the early stage of the 21st century. We obtain a fuzzy model for predicting NO_2 concentration based on several future scenarios (Kainuma, Nakamori and Morita, 1989 and 1990).

1.2 Structure of the Support System

An interdisciplinary approach is needed to identify the structure of environmental problems, because it is complicated by socio-economic factors such as urbanization, aging population and international trade. We have tried to identify environmental structures by utilizing experts' knowledge and judgment systematically. When numerical data are available, we can build computer simulation models and analyze environmental systems quantitatively. We have built a computer system for supporting these processes. Figure 1.1 illustrates how experts, decision makers and analysts partici-

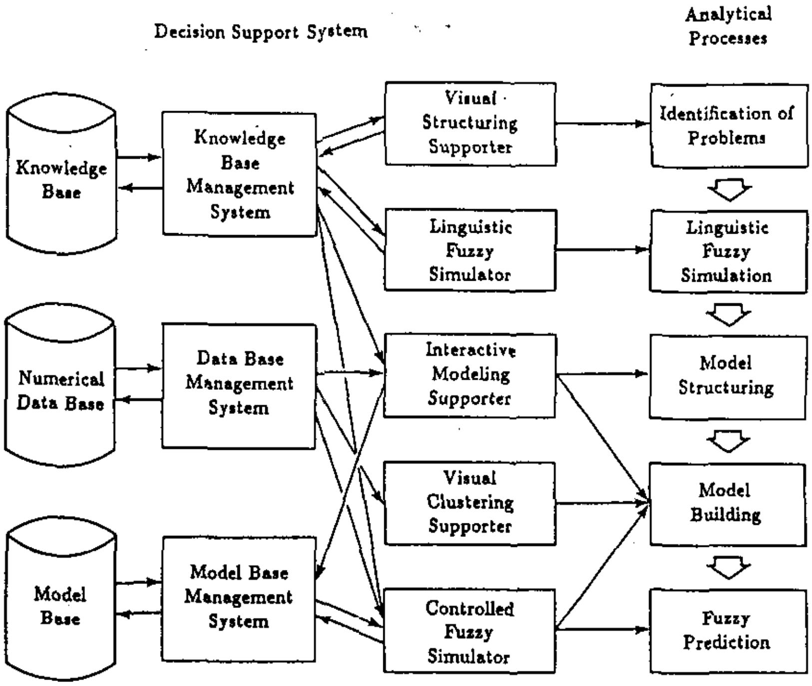


Fig. 1.2 Structure of the intelligent decision support system

pate in model building with Intelligent Decision Support System (IDSS). Figure 1.2 illustrates its subsystems.

Knowledge Base Management System (KBMS), Visual Structuring Supporter (VSS) and Linguistic Fuzzy Simulator (LFS) have been developed for identifying environmental problems. KBMS stores knowledge data that contain cause and effect relations of environmental problems, and retrieves and displays these data immediately on request in an understandable form. VSS is designed to obtain effective representations of system structures by linking knowledge data together. LFS performs fuzzy reasoning by querying a user about interaction among important factors such as leisure time, quality of life and traffic nuisance.

Data Base Management System (DBMS) has also been developed for understanding future environmental trends. The numerical data stored in DBMS are related to socio-economic and environmental domains. Software and the related database used in SAPIENS(Systems Analysis and Planning on Intelligent ENvironmental information System) are explained by Nishioka and Naito (1984). The time series data of the last 20 years is classified into about 200 series of international data and more than 800 series of national data. The latter is further classified into 570 series of prefectural data and 250 series of municipal data. This data can be easily retrieved and displayed in the form of graphs such as maps or scatter diagrams. The numerical data base is also accessed when developing statistical models.

Interactive Modeling Supporter (IMS), Visual Clustering Supporter (VCS) and Controlled Fuzzy Simulator (CFS) have been developed for assisting in model building by using numerical data. IMS assists in statistical model building by using such functions as graphic representations of the obtained model structure and selection of explanatory variables. We sometimes encounter a case where it is very difficult to obtain a global linear model for a nonlinear system such as an environmental system. If so, we divide the data space into several fuzzy subspaces and in each fuzzy subspace we find a set of local input-output relations describing a complex system. VCS is designed to divide the data space with stepwise clustering. CFS is designed to set values of explanatory variables and to represent the model behavior.

To manage different types of models together, Model Base Management System (MBMS) has been developed. We can add up-to-date submodels to the system whenever we develop them. Combining submodels with future scenarios, we can predict future environmental conditions with prescribed confidence.

The system runs on Sun 3/160c under UNIX. Most of the programs are written in C language. The programs for statistical analyses are written in Fortran. Many experts can participate in long-term simulation, looking at the computer outputs displayed on a large screen.

1.3 Outline

Chapter 2 presents a highly user-friendly software for developing mathematical models. The system consists of several modern modeling techniques with highly interactive human-computer interfaces. Section 2.2 gives the functions of IMS. Section 2.3 describes an application to the prediction of NO_2 concentration. Section 2.4 gives the purpose of developing IMS and its advantages. The system assists in model building and reduces the burden of trial and error necessary for developing a computer simulation model.

Chapter 3 presents a fuzzy modeling technique with a visual and stepwise clustering method, and a fuzzy simulation technique for reasonable scenario input and interpretation of the model behavior. Section 3.2 describes stepwise modeling by the use of visual clustering technique. Section 3.3 describes a simulation technique. An input admissible function is defined for reasonable scenario inputs. Confidence factors and degrees of scatter are defined to see to which degree the obtained model is suited for simulation. Section 3.4 shows an application of the simulation techniques to the prediction of NO_2 concentration. Several fuzzy rules are constructed with the developed system.

In Chapter 4 linguistic fuzzy modeling is presented. Input-output relations of the system are described in the form of if-then rules. Then using fuzzy reasoning, the behavior of the system will be predicted. Section 4.2 describes a check sheet for the prediction of Oxidant concentration. Its result is compared with that of fuzzy reasoning. Section 4.3 explains the method of fuzzy reasoning. Section 4.4 describes its application to the prediction of Oxidant concentration. In Section 4.5 some problems that arise in building fuzzy rules are presented and their modifications are suggested.

Chapter 5 presents the identification of environmental problems by using IDSS. Section 5.2 describes the identification process that consists of collecting knowledge as well as numerical data, identifying the structure of the problem and analyzing environmental conditions through linguistic fuzzy simulation. Section 5.3 describes the modeling process that consists of building computer simulation models by combining expert's judgment and numerical data. Section 5.4 describes the simulation process that is useful for predicting future environmental conditions by assuming some policy scenarios. An example is considered in Section 5.5, showing how simulation models are built with the aid of the developed system.

Chapter 2

Interactive Modeling

2.1 Introduction

It is a hard task to identify environmental systems, because many factors are interrelated and the future condition of each factor is somewhat uncertain. A heuristic approach that utilizes the expert's judgment and the ability of the computer is needed when we have to build up a model of ill-defined systems. This approach is helpful for resolving actual and complex problems and for bridging the gap between the real system and the modeling theory.

Checkland (1981,1983) points out the common paradigm between traditional operations research, systems engineering and systems analysis, and calls them *hard systems approaches*. According to him, the common paradigm is the assumption that we can recognize or identify the reality by observation and analyze it by the methods in natural science. Under this assumption, he continues, the subjectivity or perception of the observer cannot be treated, and there are limitations in treating the complexity. He then proposed the *soft systems thinking*, emphasizing the cycle of modification or learning of the relevant people's perception.

In this chapter presented is Interactive Modeling Supporter (IMS), which is a highly user-friendly software to develop mathematical models

A part of this chapter was published in Trans. of the Institute of Systems, Control and Information Engineers (vol. 1, no. 5, pp.160-168, 1988) by Y. Nakamori, S. Nishioka and M. Kainuma.

in system analytic research. Interactive Modeling Support System (IMSS) was developed by Nakamori (1989). IMSS utilizes graphic information effectively to facilitate not only human-computer communication but also interpersonal communication (Nakamori and Sawaragi, 1987). This has been improved and integrated to Intelligent Decision Support System (IDSS), which is useful for scenario analysis and sensitivity analysis as well as for developing statistical models.

As an application, the process of identifying an environmental prediction model is presented. It is emphasized that IMS greatly reduces the burden of trial and error necessary in developing such a model, and helps us think about the problem systematically and intensively.

2.2 Functions of Interactive Modeling Supporter

The purpose of IMS is to build up a mathematical model of a complex system through recursive communication between experts and computer. The system consists of several modern modeling techniques with highly interactive human-computer interfaces. Its original version was developed on the personal computer by Nakamori (1989) and now it is implemented on the work station as an important part of our support system.

As shown in Fig. 2.1, the inputs to the system are a set of variables, measurement data and a binary relation, and the outputs are structural and statistical models. The data analysis part gives understandable graphical expressions of measurement data so that one can think of model structures before statistical modeling. We are continuously elaborating this part, referring to the exploratory data analysis (Tukey, 1977).

The system includes facilities for:

- data transformation,
- structural analysis,
- *statistical modeling*, and
- model verification and validation.

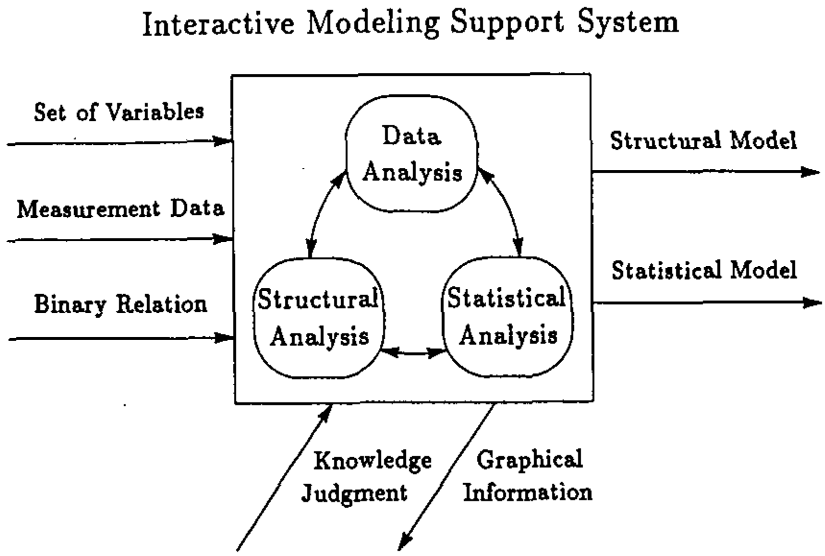


Fig. 2.1 Input-output relation of the interactive modeling support system

The modeling process using the system consists of three different but interdependent stages of dialogues as shown in Fig. 2.2. Of the facilities mentioned above, structural analysis is used in all three stages, and is the most emphasized feature of the system.

The *first stage dialogue* is required for preparation of modeling. It includes input of measurement data and the initial version of the cause-effect relation on the set of variables. Transformation of variables, data screening, and refinement of the cause-effect relation are also executed at this stage.

The *second stage dialogue* is devoted to finding a trade-off between the measurement data and the modeler's knowledge about dependencies between variables. Based on the measurement data and the initial version of the cause-effect relation, the computer continues to find a model until the stage when further repetition would not improve the model. An analyst can choose any of the regression methods for selecting explanatory variables. The options include:

- forward selection procedure,
- backward elimination procedure,

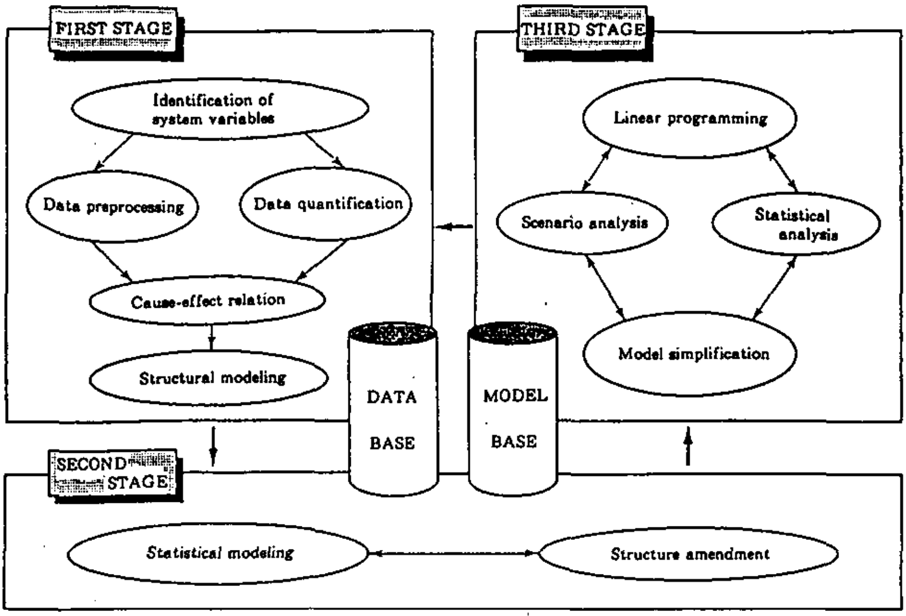


Fig. 2.2 Structure of the interactive modeling support system

- all possible selection procedure, and
- group method of data handling.

Then the corresponding digraph models are drawn to facilitate understanding and elaboration of the obtained model. If the structure of the model is modified, the affected parts of the model are again tested with regression methods. The analyst modifies the new relation referring to these computer models and his knowledge. The process continues repeatedly until no change occurs or the analyst is satisfied with the modified relation.

The *third stage dialogue* is related to model simplification and elaboration. Model simplification is based on using the equivalence relation. Model elaboration is an application of regression analysis including the hypothesis testing on estimated coefficients, and examinations of the explanatory and predictive powers of the model.

2.2.1 Structural Consideration

At the first stage, a mental image of a system is obtained by referring to information displayed on a computer. The input to the system is denoted by

$$D = (S, X, R), \tag{2.1}$$

where

$S = \{x_1, x_2, \cdots, x_m\}$: set of variables considered as elements of the model,

$X = \{\alpha_1, \alpha_2, \cdots, \alpha_n\}$: set of all data points in R^m,

$\alpha_j = (x_{1j}, x_{2j}, \cdots, x_{mj})$: jth data point in $R^m, j = 1, 2, \cdots, n$, and

$R = (r_{ij})$: initial version of the cause-effect (binary) relation on $S \times S$.

Note that the set S includes all input, state and output variables, and the relation R indicates their interconnections.

The structural consideration of the model is important for verifying whether the model behaves in the overall fashion we intend it to. By the structure of the model is meant the cause-effect relation between variables. To introduce the cause-effect relation, the adjacency matrix $R = (r_{ij})$, $i, j = 1, 2, \cdots, m$, is prepared; the entries are defined by

$$r_{ij} = \begin{cases} 0 & \text{if } x_i \text{ never affects } x_j \\ 1 & \text{if } x_i \text{ possibly affects } x_j \\ 2 & \text{if } x_i \text{ certainly affects } x_j \\ 3 & \text{if } x_i \text{ is identical with } x_j \end{cases} \tag{2.2}$$

To fill in entries of this matrix is sometimes quite difficult because the state variables (including the intermediate ones) often influence each other in such a manner that it is difficult to separate causes and effects. Hence, the work requires a deep insight into the real system under study. The burden of entering the adjacency matrix is reduced, however, by initially assuming the validity of transitive inference (Warfield, 1974 and 1976). It is then possible to subsequently check the resulting adjacency matrix by drawing a digraph corresponding to it and modifying it if necessary.

2.2.2 Finding Trade-off Structures

The purpose of this step, which is the main objective of the *second stage dialogue*, is to find a trade-off structure between the computer model and the mental model. First an environmental model is obtained by the methods of stepwise or all-subset regression. (See for instance Mosteiler and Tukey, 1977). Then the corresponding digraphs are drawn to facilitate the understanding and elaboration of the obtained model. If the structure of the model is modified, the affected parts of the model are again tested by the regression methods. A series of reciprocal considerations and calculations by the analysts and the computer are repeated until the structure of the model becomes satisfactory with respect to the current problem. This process is summarized below.

Let us define two subsets S_i^c and S_i^0 of S for each x_i :

$$S_i^c = \{x_j : r_{ji} = 2\},$$
$$S_i^0 = \{x_j : r_{ji} = 1\}.$$

Following the terminology in statistics, we call S_i^c the *core* variable set and S_i^0 the *optional* variable set for x_i. The elements of S_i^c are always chosen as the explanatory variables for x_i and those of S_i^0 are *candidates*. When $r_{ji} = 3$, x_j does not appear as an explanatory variable for x_i and x_j is expressed only with x_i.

For each x_i, if $S_i^c \cup S_i^0 \neq \phi$, then the coefficients of the equation:

$$x_i = c_{i0} + \sum_{x_j \in S_i^c \cup S_i^0} c_{ij} x_j \tag{2.3}$$

are identified using the measurement data and a regression method. The criterion of goodness of fit used here is the *controlled determination coefficient*, i.e., the square of the modified coefficient of multiple correlation:

$$R^2 = 1 - \frac{\sum_k (x_{ik} - \hat{x}_{ik})^2/(n-p-1)}{\sum_k (x_{ik} - \bar{x}_i)^2/(n-1)}, \tag{2.4}$$

where $\hat{x}_{ik}$ is estimates of the kth data x_{ik} of the variable x_i, $\bar{x}_i$ the sample mean of x_i, n the number of data points and p the number of selected explanatory variables ($x_j's$). The set of selected variables (which in any case includes all the *core* variables) includes the combination of *candidate* variables that yields the value of R^2 nearest to unity.

The separate interpretation of the coefficients is quite difficult or impossible. Therefore, at this step, the suitability of the structure of the model for the purpose of scenario analysis is checked by the digraph.

2.2.3 Model Validation

In this step the explanatory and predictive powers of the model are examined by the following statistics:

- standard errors of estimated coefficients,
- t-ratios of estimated coefficients,
- standard deviation of residuals,
- F-ratio against a null hypothesis,
- controlled determination coefficients,
- correlation coefficients, and
- residuals and predictions.

An analyst can elaborate the computer model by adding or removing some explanatory variables referring to these statistics. If the analyst wants the data preprocessing, he can call the subroutines in the first stage:

- transformation of variables, and
- data screening.

It is desirable to choose proxy variables for model simplification and elaboration if there is a chance that the variables in an equivalence class can be connected by a linear relation. The variables are eliminated as long as the reduction does not destroy the cause-effect relation structure necessary for the intended use of the model.

Table 2.1 List of variables used in the modeling

	Variable	Symbol
1	NO_x concentrations (annual average)	NO_x
2	population	pop. tota
3	population density	pop. dens
4	rate of population incresase	pop. chan
5	members of households	pop. hous
6	farmland area/km^2	farmlan%
7	building area/km^2	buildin%
8	traffic area/km^2	traffic%
9	total industrial outputs	ind. tota
10	total industrial outputs of process type	ind. proc
11	total industrial outputs of non-process type	ind. npro
12	commercial sales volume*	trade
13	annual average temperature	temprat
14	annual average wind velocity	wind. vel
15	distance from sea	dic. sea
16	distance from mountain	dic. moun
17	altitude	altitude
18	number of cities within 20 km	cities 20
19	number of cities within 40 km	cities 40
20	traffic of passenger cars**	traf. car
21	traffic of buses**	traf. bus
22	traffic of small trucks**	traf. str
23	traffic of big trucks**	traf. btr

* : per 1 km^2 ** : translated into emission

2.3 Interactive Systems Approach for Heuristic Modeling

With the system, an environmental prediction model has been identified. The list of variables used in the modeling is shown in Table 2.1. The main object here is to build up a model that predicts NO_x concentration by other variables listed in Table 2.1. Though it is very difficult to obtain data without missing values, annually averaged data in 22 cities are collected during three years, that is, 1977, 1980 and 1983. The cities are listed in Table 2.2. Sixty-six lots of annually averaged data for each variable

Table 2.2 List of cities

Prefecture	City
Ibaraki	Mito Hitachi
Tochigi	Utsunomiya
Gunma	Maebashi Takasaki
Saitama	Kawagoe Kawaguchi Urawa Ohmiya Tokorozawa Koshigaya
Chiba	Ichikawa Funabashi Matsudo Kashiwa Ichihara
Tokyo	Hachioji Machida
Kanagawa	Yokosuka Hiratsuka Fujisawa Sagamihara

are used in the analysis, that is, 22 cities $\times$ 3 years. Interdependence of variables is analyzed through processes of building regression models. Relations between city activities and environmental pollution have been studied by Moriguchi and Nishioka (1985). These results are referred to at each modeling stage.

First, the input data are divided into training and checking data. The data measured in the cities from 1 to 20 in Table 2.2 are used as the training data. The other data are used as the checking data. The training data are used for model building and the checking data are used for model validation. Then, referring to basic statistics and histograms of the training data, 5 outliers are identified and removed from the set of data points. Two dimensional scatter plots are drawn for each pair of variables and relations are discussed among analysts.

Initial input of the cause-effect relation is obtained by the transitive imbedding method (Warfield, 1976). Figure 2.3 shows an opening screen for obtaining the cause-effect relation. Entries of a matrix shown in Fig. 2.3 are filled in by the number 0 or 1. The number representing a relation is restricted to 0 or 1 at this scene, though there are four kinds of relations in the entries of an adjacency matrix as shown in Equation 2.2. This is because it is very difficult to clarify such a relation. At the next stage, the relation is obtained, referring to other information such as statistics or scatter diagrams. When an intermediate variable is pointed to, *ind.proc* for example, relations between an intermediate variable and other variables are asked by the computer and the corresponding entries of the matrix are filled

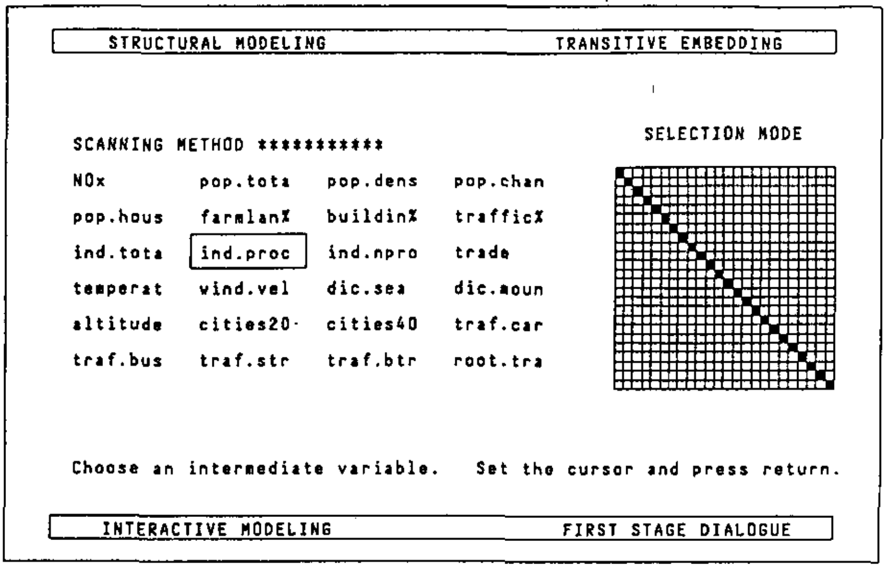


Fig. 2.3 The opening of the introduction of a relation

in. By repeating this process, a reachability matrix is obtained. Figure 2.4 shows a reachability matrix at the first stage. Then a skeleton matrix is calculated and a digraph model is obtained (Fig. 2.5).

Here it should be noted that the introduced relation is obtained through the effort of trial and error and intensive discussion to modify the model structure by using the digraph maps and visual displays of data.

At the second stage, variables are selected by using the forward selection method and information obtained at the first stage. At the third stage, the obtained prediction model is examined by several statistics. The resultant model is fairly satisfactory from the point of t-ratios and other statistics, but the result of simulation is not satisfactory. Then we return to the second stage, and input-output relations are reexamined. Here, the forward selection method is adopted again. Figure 2.6 shows a system model consisting of a set of linear equations. Figure 2.7 is the corresponding graphic expression of the model structure.

At the third stage, some statistics such as t-ratio, correlation, controlled determination coefficient and F-ratio are calculated. Table 2.3 shows the result of a linear relation and some relevant statistics. Table 2.4 shows the standard deviation of residuals and the mean square error. With these

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1																							
2	1	1	1		1		1					1						1	1	1	1	1		1
3	1	1	1		1		1					1						1	1	1	1	1		1
4				1																				
5	1	1	1		1		1					1						1	1	1	1	1		1
6	1	1	1		1	1	1		1		1	1						1	1	1	1	1		1
7	1	1	1		1		1					1						1	1	1	1	1		1
8	1							1																
9	1								1		1													
10			1							1					1	1							1	
11	1								1		1													
12	1											1								1	1	1		
13													1				1							
14	1													1										
15			1					1							1	1							1	
16			1					1							1	1							1	
17													1											
18	1	1	1		1		1					1						1	1	1	1	1		1
19	1	1	1		1		1					1						1	1	1	1	1		1
20	1																			1	1	1		
21	1																			1	1	1		
22	1																					1		
23																							1	
24	1	1	1		1		1					1						1	1	1	1	1		1

Fig. 2.4 A reachability matrix at the first stage

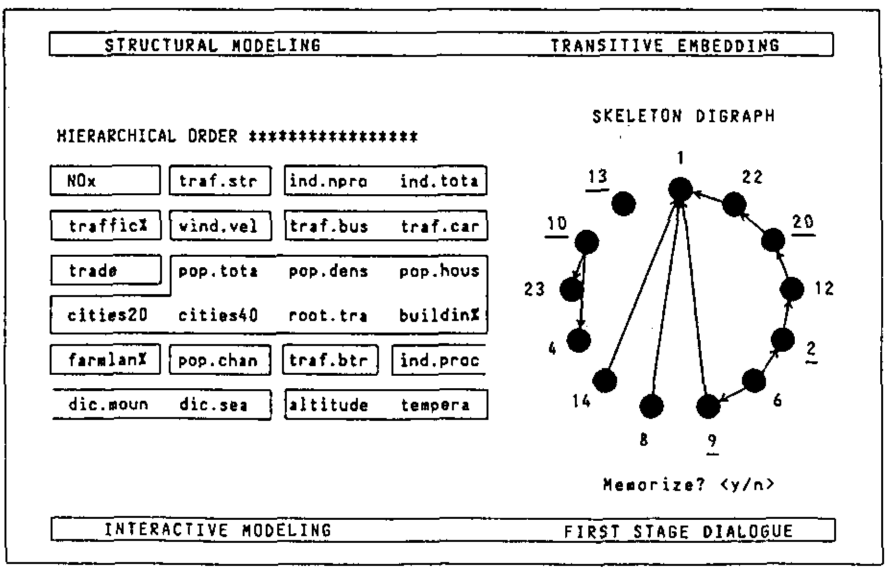


Fig. 2.5 A digraph model corresponding to the introduced relation

```
NOx      = 2.5067e+01 -3.3672e-01 buildin% -1.2098e-07 ind.tota
                      +3.2710e-05 ind.npro +2.3460e-01 cities40
                      +2.0829e-03 traf.car +2.8620e-04 traf.btr

pop.hous = 3.3246e+00 -5.1593e-07 pop.tota -5.5840e-05 pop.dens
                      +7.0042e-03 buildin%

buildin% = 2.3243e+01 -3.9689e-05 pop.tota +5.4968e-03 pop.dens

ind.npro = 2.0992e+04 +2.4290e-03 ind.tota

trade    = 4.1107e+04 +6.1321e-03 pop.tota -1.3588e+00 pop.dens
                      -1.3967e+04 pop.hous +9.2540e+01 farmlan%
                      +2.3669e+02 buildin%

cities40 = 6.7757e-01 +3.2292e-03 pop.dens +1.8973e+00 cities20

traf.bus = 5.5582e+03 +1.2763e-03 pop.tota -1.6272e+03 pop.hous
                      +6.4841e+00 buildin% -1.3082e+01 cities20
                      +1.2884e-01 traf.car

traf.str =-1.1000e+03 +3.9610e-01 pop.dens +1.4023e+01 buildin%
                      +2.4809e+01 cities40 +1.0873e+00 traf.car

traf.btr = 4.1327e+03 +1.6459e+00 pop.dens -1.5634e+02 buildin%
                      -1.4051e+02 traffic% +2.2359e-02 ind.proc
                      +6.5000e-03 ind.npro +7.9807e-01 traf.str
```

Fig. 2.6 A system model consisting of a set of linear equations

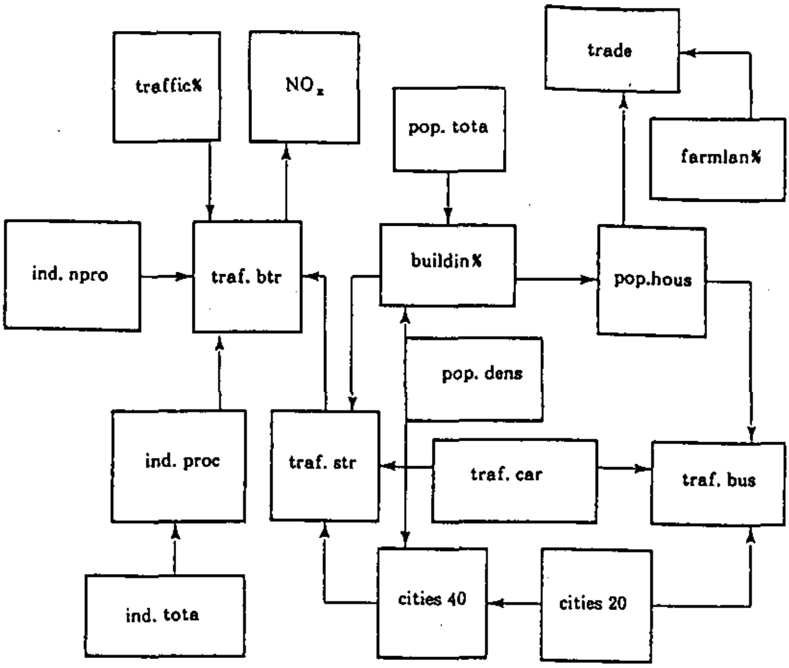


Fig. 2.7 A graphical expression of the model structure

Table 2.3 A result of the linear regression

=== Current Linear Model === NOx ===		Regressand ==> NOx		
variable	coefficient	standard error	t-ratio	correlation
buildin%	-.3367D+00	0.1671D+00	-.2015D+01	0.4992
ind.tota	-.1210D-06	0.4213D-07	-.2871D+01	-.2123
ind.npro	0.3271D-04	0.6250D-05	0.5233D+01	0.3582
cities40	0.2346D+00	0.5243D-01	0.4475D+01	0.5486
traf.car	0.2083D-02	0.6006D-03	0.3468D+01	0.2854
traf.btr	0.2862D-03	0.2583D-03	0.1108D+01	0.3867
constant	0.2507D+02			
Degrees of Freedom = 48			Adjusted R-Square = 0.5914	
S.D. of Residual = 0.6686D+01			F-Ratio = 0.1403D+02	
T(48 , 0.05) = 2.0106			F(6 , 48 , 0.05) = 2.2946	

Table 2.4 An examination of the predictive power of the model

RESULT 6	Regressand ==> Variable X21		Ranking 1
Case Number	Measurement	Prediction	Standard Error
No. 61	0.1367D+04	0.1636D+04	0.2801D+03
No. 62	0.1207D+04	0.1293D+04	0.2758D+03
No. 63	0.1217D+04	0.1370D+04	0.2754D+03
No. 64	0.1459D+04	0.1567D+04	0.2892D+03
No. 65	0.1122D+04	0.1277D+04	0.2897D+03
No. 66	0.1251D+04	0.1425D+04	0.2919D+03
The Number of Cases = 6		Correlation (meas,pre) = 0.8956	
Mean Square Error = 0.2821D+05		Mean Absolute Error = 0.3232D+00	

figures, the predictive power of the derived model is examined. Note that much effort is needed again at this stage. The result shown in Fig. 2.6 is actually the one that is obtained after several repetitions of these steps and intensive discussion.

At the simulation mode, we input values of scenario variables and select variables to be predicted. Then simulation results and the model structure are displayed on the computer. Figure 2.8 shows these simulation results. Simulation results of up to six variables can be displayed. Trends of variables such as NO_x, $traf.bus$, and $traffic\%$ displayed in Fig. 2.8 are examined for model validity. Figure 2.9 shows an example of the sensitivity analysis by linear programming. The coefficients of the objective function shown in Fig. 2.9 are denoted by α and β. The α is given by the reciprocal of the standard deviation of NO_x, and the β is given by that of $trade$. The upper limit of each variable is given by $\bar{x}_i + \sigma_i$ and the lower limit is given by $\bar{x}_i - \sigma_i$, where $\bar{x}_i$ denotes the mean and σ_i the standard deviation of each variable. The result of linear programming is given in Table 2.5. The model validity is examined from a different point of view from that mentioned above at the third stage.

As time series of environmental data are limited, we use data from different cities. The main purpose of this modeling is to analyze the effects of city structure on environmental conditions such as NO_x concentration and traffic volumes. To check the obtained model, we examine whether the model behaves reasonably with the checking data. Table 2.4 shows the prediction results for the checking data. In Table 2.4, the variable $traf.bus$

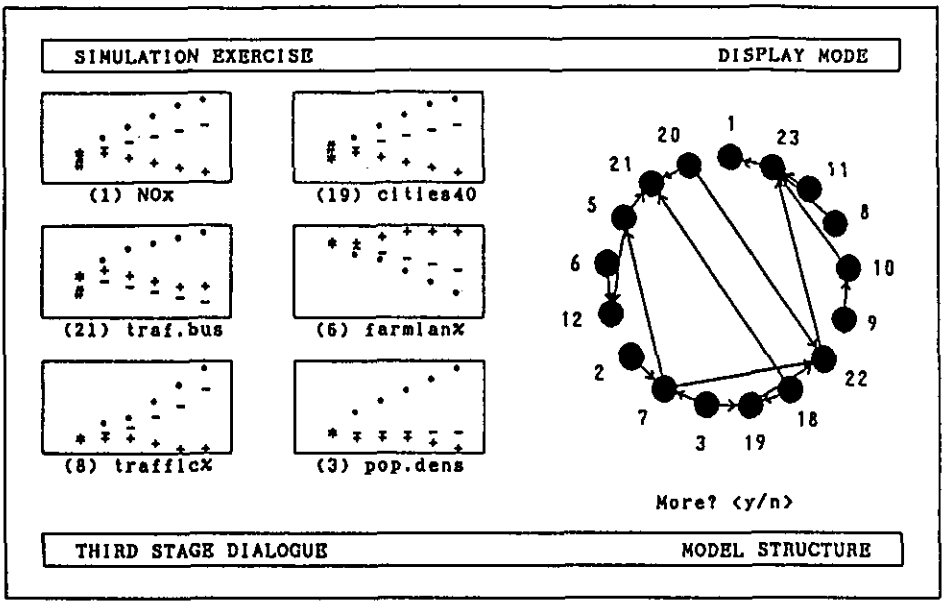


Fig. 2.8 The scenario analysis in the third stage

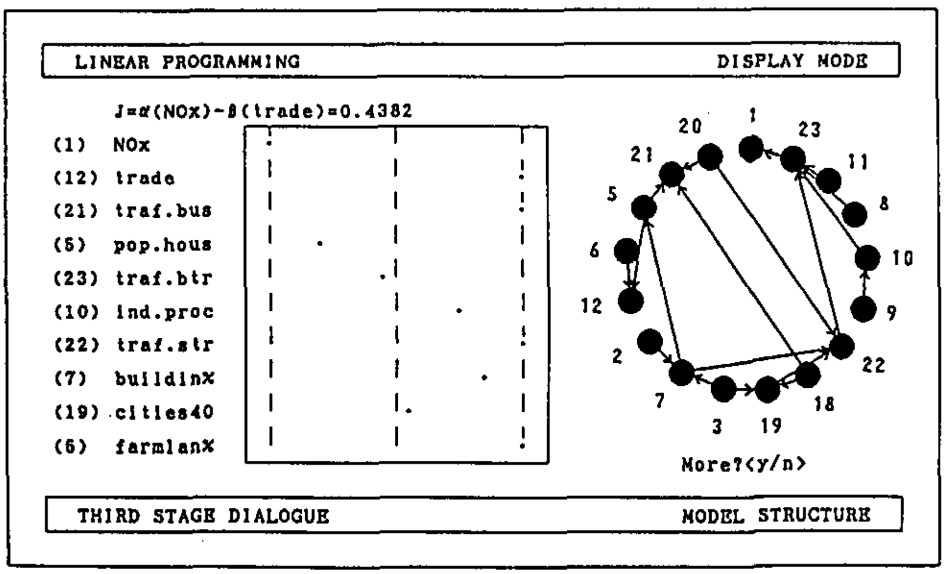


Fig. 2.9 The sensitivity analysis by linear programming

Table 2.5 *A result of linear programming*

variable	lower limit	LP-solution	mean value	upper limit
(1) NOx	0.3071×10^2	0.3071×10^2	0.4107×10^2	0.5143×10^2
(12) trade	0.1076×10^4	0.5168×10^4	0.3122×10^4	0.5168×10^4
(21) traf.bus	0.8099×10^3	0.1760×10^4	0.1285×10^4	0.1760×10^4
(5) pop.hous	0.2957×10^1	0.3107×10^1	0.3191×10^1	0.3249×10^1
(23) traf.btr	0.4715×10^4	0.8363×10^4	0.8804×10^4	0.1290×10^6
(10) ind.proc	0.0000×10^6	0.2135×10^6	0.1361×10^6	0.2813×10^6
(22) traf.str	0.3836×10^4	0.8596×10^4	0.6216×10^4	0.8596×10^4
(7) buildin%	0.2082×10^2	0.3646×10^2	0.3000×10^2	0.3918×10^2
(19) cities40	0.1581×10^2	0.4259×10^2	0.4015×10^2	0.6449×10^2
(6) farmlan%	0.1158×10^2	0.3724×10^2	0.2441×10^2	0.3724×10^2
(8) traffic%	0.1534×10^2	0.7632×10^2	0.4583×10^2	0.7632×10^2
(11) ind.npro	0.1039×10^6	0.1039×10^6	0.3416×10^6	0.5793×10^6
(9) ind.tota	0.1551×10^6	0.7927×10^6	0.4739×10^6	0.7927×10^6
(20) traf.car	0.2586×10^4	0.5629×10^4	0.4191×10^4	0.5796×10^4
(2) pop.tota	0.2161×10^6	0.3691×10^6	0.2990×10^6	0.3819×10^6
(3) pop.dens	0.1646×10^4	0.5069×10^4	0.3388×10^4	0.5130×10^4
(18) cities20	0.4640×10^1	0.1346×10^2	0.1504×10^2	0.2544×10^2

is predicted for the cities whose data are not used for model building. Table 2.4 shows that the correlation between the measured data and the predicted ones is fairly satisfactory though predicted values are somewhat greater than that of the measured ones. As the prediction model simulates the average behavior in general, this systematic error is inevitable. To reduce prediction errors, the data must be divided into several subgroups and a simulation model derived for each subgroup. As it is usually difficult to find the criteria for dividing the data, a heuristic approach is also necessary for this purpose. This problem will be explained again in Chapter 3.

2.4 Advantages of Interactive Modeling

Usually, prediction models are built through recursive interactions between man and computer or man and man. The purpose of IMS is to support this process so as to reduce the burden of trial and error necessary in developing such a model. The system also helps us think about the problem systematically and intensively. Let us briefly mention why this supporter is required. It is very difficult to formulate a practical model for a large complex system such as an environmental system. Even for an analyst who has devoted much time to environmental problems, it is not easy to build a suitable prediction model. This is because there are various kinds of information and discrepancies in their interpretation. The relation between analysts can be crucial to the success of systems analysis. Analysts may approach problems from different aspects, so it is helpful if they sit at a round table to fully discuss the problem with the aid of the supporter. The system is also useful for analyzing information and understanding model structures.

For decision makers, the system is useful for understanding what is known up to date and what is not known. A simple model for understanding the behavior of the environmental system can be obtained by using the developed system. The process of modeling enables the extraction of information that is not known before analyzing the system.

The purpose of the system is to assist in systematic thinking and to deepen mutual understanding. The advantages of the system are summarized as follows:

- The system displays relevant data in graphic forms such as scatter diagrams and maps. It is useful for finding outliers or collinearity between variables.

- The system assists in structural modeling. It is useful for understanding the structure of real systems.

- The system assists in evaluating the validity or the predictive power of the model. It is useful for improving the prediction models.

- The modeling process necessitates concentrating on the problem. It helps analysts to understand a real phenomena or problem.

- The system reduces the burden of trial and error necessary in model development. Once the model is built up, planners will seldom reexamine it because of the difficulty in running the model. However, with the aid of the system, it will become easier to examine the model and to modify it if necessary.

2.5 Concluding Remarks

Interactive Modeling Support System (IMSS) is introduced and its application to structuring of environmental systems is presented. The system has been applied to various fields such as simplification of a comprehensive model (Walsum and Nakamori, 1985) and gaming simulation for group decision making (Nakamori, 1987). The system has been improved so that anyone can participate in model building and sensitivity analysis. The system is a part of IDSS, which will be presented in Chapter 5. There are other subsystems in IDSS such as Knowledge and Model Base Management Systems. These subsystems are used for model building in various fields. It is expected that an effective model can be built by referring to a mathematical model as well as a knowledge model and by filling up gaps between them.

Chapter 3

Fuzzy Modeling and Simulation

3.1 Introduction

In model building for the urban environment, we often encounter the difficulty of structure identification and the lack of homogeneity in data. These problems are interrelated. The difficulty of structure identification is aggravated by the lack of homogeneity and vice versa, so that the problem is complex. To deal with this type of problem, we have developed a modeling support system to use objective information and subjective knowledge effectively.

In this chapter we propose a fuzzy modeling technique with a visual and stepwise clustering method, and a fuzzy simulation technique for reasonable scenario input and interpretation of model behavior. The processes are summarized as follows:

(1) In the process of fuzzy modeling, we introduce a *degree of data division*. An input space is divided into several fuzzy subspaces according to this criteria and with the aid of the computer display of a clustering process.

A part of this chapter was published in Trans. of the Institute of Systems, Control and Information Engineers (vol. 2, no. 5, pp.166-174, 1989) by Y. Nakamori and M. Kainuma.

(2) An *input admissible function* that expresses an effective range of an input of a developed model is proposed to simulate future environmental conditions.

(3) For evaluating linear models, a *confidence factor* is introduced. The confidence factor is calculated by using a membership function and expresses the frequency of past occurrences of the combination of input values.

(4) A *degree of scatter* is introduced to express the model validation. From the simulation result with fuzzy inference and statistical inference, the future environmental condition is analyzed. The fuzzy relation is expressed in a linguistic formula to aid understanding of the obtained results. Through these processes, fuzzy simulation supports the understanding of the model and the actual system.

In modeling and simulation processes, four subsystems are utilized. Interactive Modeling Supporter (IMS), a part of which is explained in Chapter 2, assists in building linear models with structural modeling and statistical modeling. We have developed Visual Clustering Supporter (VCS) and Controlled Fuzzy Simulator (CFS) to assist in fuzzy modeling. These support systems assist in modeling and simulation of a large-scale system. Model Base Management System (MBMS) is also developed to analyze a mathematical model and a knowledge model and to add an up-to-date model to the system.

We present an application of the proposed techniques to an urban environmental problem. The relations between urban activities and an environmental condition are analyzed and fuzzy models have been constructed by the use of the developed system. The results of a mathematical model are interpreted and then expressed in linguistic formula to assist in understanding.

3.2 Piece-wise Linear Modeling

Fuzzy modeling enables nonlinearity of a complex system to be expressed and numerical data to be converted to knowledge data systematically. By the use of fuzzy set theory, we can express human thinking in linguistic formula. It helps to encourage experts to participate in model building.

In this section we introduce stepwise modeling by the use of visual clustering technique.

3.2.1 Fuzzy Modeling

According to its original definition (Takagi and Sugeno, 1985), a fuzzy model is described as follows. Consider a system with multiple inputs, say $x_1, x_2, \cdots, x_r$, and multiple outputs, say $y_1, y_2, \cdots, y_q$. A fuzzy model consists of several fuzzy rules such as

$$
\begin{aligned}
&\textit{Rule } L^i: && \textit{if } x_1 \textit{ is } A_1^i,\ x_2 \textit{ is } A_2^i, \ldots, x_r \textit{ is } A_r^i, \\
&\textit{then} && y_1^i = c_{10}^i + c_{11}^i x_1 + c_{12}^i x_2 + \cdots + c_{1r}^i x_r, \\
& && \cdots\cdots\cdots \\
& && y_q^i = c_{q0}^i + c_{q1}^i x_1 + c_{q2}^i x_2 + \cdots + c_{qr}^i x_r,
\end{aligned} \tag{3.1}
$$

where A_j^i's are fuzzy sets, y_k^i's the outputs of Rule L^i, and c_{kj}^i's are coefficients of the linear model.

Given input values x_{1*}, x_{2*}, ..., x_{r*}, the prediction of output y_{k*} is calculated by

$$y_{k*} = \frac{\sum_{i=1}^{p} w^i y_{k*}^i}{\sum_{i=1}^{p} w^i}, \qquad w^i = \prod_{j=1}^{r} A_j^i(x_{j*}), \quad k = 1, 2, \cdots q, \tag{3.2}$$

where p denotes the number of rules, $A_j^i(x_{j*})$ the membership grade of x_{j*} to the fuzzy set A_j^i, and y_{k*}^i the prediction by Rule L^i.

The identification of a fuzzy model using input-output data is divided into two parts: structure identification and parameters identification. The structure identification consists of premise structure identification and consequent structure identification. The parameters identification also consists of premise parameters identification and consequent parameters identification. The consequent parameters are the coefficients of linear equations (Sugeno and Kang, 1988).

The most important feature of a fuzzy model is that it behaves as a nonlinear model though it consists of a set of linear equations. The main tasks in the fuzzy modeling are:

- division of the data space into fuzzy subspaces,
- identification of membership functions, and
- statistical modeling with selection of explanatory variables.

We have developed VCS for supporting such operations by the use of visual clustering and stepwise modeling. The above tasks are mutually dependent, and very difficult if we follow the traditional analytical approach. One can introduce some criteria in carrying out those tasks, but the final result depends heavily on the capability and experience of the individual modeler. This is the reason why we have developed an interactive and intelligent environment in model building.

3.2.2 Degrees of Data Division

The most important practice in fuzzy modeling is to divide the data space into fuzzy subspaces. For this purpose we introduce degrees of data division.

To describe stepwise fuzzy modeling, we need the following

Notations.

- $I = \{x_1, x_2, \cdots, x_r\}$: set of explanatory (input or past state) variables.
- $O = \{x_{r+1}, x_{r+2}, \cdots, x_m\}$: set of explained (state or output) variables.
- $X_i = \{x_{i1}, x_{i2}, \cdots, x_{in}\}$: sequence of measurement data for x_i, $i = 1, 2, \cdots, m$.
- m_i, σ_i: sample mean and standard deviation of the data set X_i, $i = 1, 2, \cdots, m$.
- $\alpha_j = (x_{1j}, x_{2j}, \cdots, x_{mj})$: jth data point in R^m, $j = 1, 2, \cdots, n$.

- $X = \{ \alpha_1, \alpha_2, \cdots, \alpha_n \}$: set of all data points in $\boldsymbol{R}^m$.
- $S_i = \{s_{i1}, s_{i2}, \cdots, s_{in} \}$: sequence of standardized data for x_i, $i = 1, 2, \cdots, m$.
- $\beta_j = (s_{1j}, s_{2j}, \cdots, s_{mj})$: jth standardized data point in $\boldsymbol{R}^m$, $j = 1, 2, \cdots, n$.
- $S = \{ \beta_1, \beta_2, \cdots, \beta_n \}$: set of all standardized data points in $\boldsymbol{R}^m$.

First we introduce the range in which we build a fuzzy model by

Definition 3.1: (support set).

Let B_i be the range of variable x_i ($i = 1, 2, \cdots, m$) determined by its nature, and defined as wide as possible. Define the support set A_i of the variable x_i by

$$A_i = [m_i - t\sigma_i, m_i + t\sigma_i] \bigcap B_i, \quad i = 1, 2, \cdots, m, \tag{3.3}$$

where t is a real number to be designated and m_i is the sample mean of the data set. The support set A of all variables in $\boldsymbol{R}^m$ is defined by

$$A = A_1 \times A_2 \times \cdots \times A_m. \tag{3.4}$$

We call the support set A the *data space*.

Next we introduce a criterion in dividing the data space by

Definition 3.2: (degrees of data division).

Divide the set S_i ($i = 1, 2, \cdots, r$), where x_i is an explanatory variable, into two subsets S_i^1, S_i^2 by some clustering method, the *Ward method* for instance (Oosumi and Yanazawa, 1977), and correspondingly divide S into S^1 and S^2 by the following formula:

$$\textit{if} \;\; s_{ij} \in S_i^k \;\; \textit{then} \;\; \beta_j \in S^k, \;\; k = 1, 2; \; j = 1, 2, \cdots, n. \tag{3.5}$$

The *degree of data division* with respect to an explanatory variable x_i is defined by

$$d_i = \frac{n_1 \cdot n_2}{n_1 + n_2} \; \|\mathbf{c}_1 - \mathbf{c}_2\|^2_{\boldsymbol{R}^m}, \quad i = 1, 2, \cdots, r, \tag{3.6}$$

where n_k is the number of elements in S^k ($k = 1, 2$), and c_k the center of gravity of the elements in S^k ($k = 1, 2$).

The degree of data division, d_i, indicates how separated the two clusters are with respect to an explanatory variable x_i. For each input variable, the degree of data division is calculated by Equation 3.6. The larger the degree of data division is, the more separated the two clusters are.

3.2.3 Stepwise Modeling

It is dangerous to make a decision by the above criterion only, because d_i tells how separated the two clusters are, but not how the data are scattered in each cluster. We are now developing a criterion taking account of linearity in data in each cluster. But, for the present, we decide the division using the above criterion and looking at two-dimensional scatter plots to see how data are divided and scattered.

The developed system VCS has a facility to display such two dimensional scatter plots. By displaying various pairs of scatter plots, and referring to the degree of data division, the input space is divided into two fuzzy subspaces.

Figure 3.1 shows an example of computer display of scatter plots with VCS. In this figure two dimensional data space (*pop.dens* and $traffic\%$) is divided by the variable $traffic\%$. This figure shows not only how the data are divided with the variables *pop.dens* and $traffic\%$, but also how other data are scattered and divided.

With the system VCS, two dimensional scatter plots can be easily obtained and the data space can be divided. We divide the data space into two fuzzy subspaces. One input variable is considered at a time for fuzzy modeling or construction of a knowledge model. With the system VCS the data space can be divided into two to five clusters. Each cluster is displayed with the same mark, which indicates that data are contained in the same cluster. Looking at such a display it is possible to find outliers that will be removed from the data set. It is also possible to move a data point from one cluster to another.

If we make a decision that the data space should be divided with respect to an explanatory variable x_i, then we construct fuzzy subspaces by

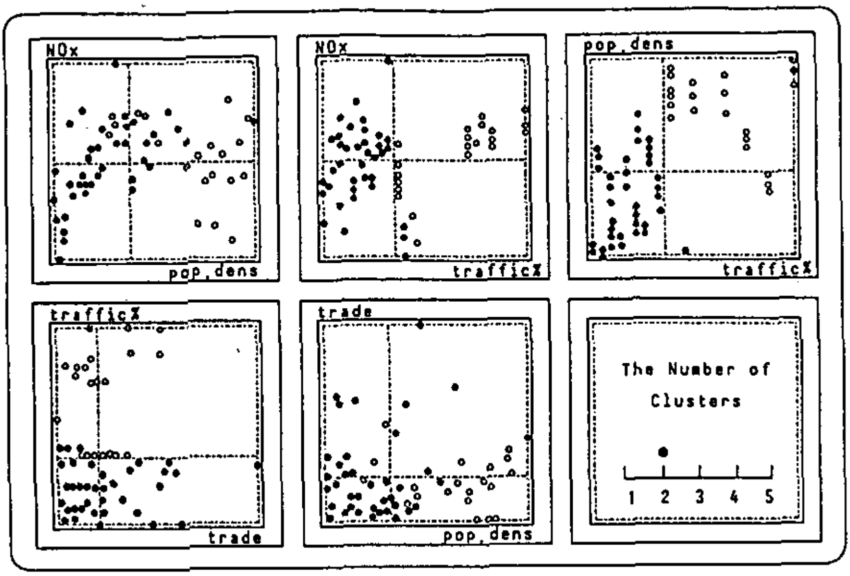


Fig. 3.1 Data division by the visual clustering supporter

Definition 3.3: (fuzzy subspaces).

Divide X into X^1 and X^2 corresponding to the division of S:

$$\textit{if } \beta_j \in S^k \textit{ then } \alpha_j \in X^k, \quad k = 1, 2; \; j = 1, 2, \cdots, n. \tag{3.7}$$

Define two *fuzzy subspaces* corresponding to X^k by

$$A^k = A_1 \times \cdots \times A_i^k \times \cdots \times A_m, \quad k = 1, 2, \tag{3.8}$$

where A_i^1 and A_i^2 are the fuzzy sets with the support set A_i.

From this we obtain premises of two rules:

- L^1 : *if* x_i *is* A_i^1, and
- L^2 : *if* x_i *is* A_i^2.

Corresponding to these premises, we develop two linear models with the aid of IMS. The obtained submodel corresponds to a consequent part of a rule. Then back to the process of clustering, the input space is divided into three clusters. One part of the subspace is again divided into two subspaces. At this time, degrees of data division and scatter plots are also referred to. It may be that the same variable is used to divide the data space as in the previous stage. Again submodels are constructed with the aid of IMS. This process is repeated until sufficient model accuracy is obtained. Model accuracy is judged by several elements such as model structure, statistics and simulation result.

3.3 Fuzzy Simulation and Knowledge Model Construction

At the simulation stage it may sometimes occur that input values cannot be decided independently. We have developed a system to control input values, called the Controlled Fuzzy Simulator (CFS).

3.3.1 Membership Functions

With the aid of the system VCS, the data space is divided into several fuzzy subspaces. In each subspace a membership value is determined for each variable.

We identify the membership function with a kind of possibility distribution function referring to several lots of information, including distribution of the data and model validation. In the following, we adopted such a trapezoidal function: 1 for the data from the first quartile to the third quartile, 0.5 at the minimum and maximum data points. We cannot say that this is the best membership function, since there are possibly several other membership functions. We take another definition of membership functions in Chapter 5. We decide its shape heuristically. We denote the membership function of a variable x_j in the kth fuzzy subspace A^k by $A_j^k(x_j)$.

3.3.2 Input Admissible Functions

Suppose that we obtain a submodel consisting of p rules with the set of explanatory variables $I = \{x_1, x_2, \cdots, x_r\}$ and the set of explained variables

$O = \{x_{r+1}, x_{r+2}, \cdots, x_m\}$.

We define how the submodel produces estimates of the variables in O when all values of variables in I are given, by

Definition 3.4: (nonfuzzy estimates).

Given values of inputs $x_{1*}, x_{2*}, \cdots, x_{r*}$, satisfying

$$\sum_{k=1}^{p} A_i^k(x_{i*}) \; > \; 0, \quad i = 1, 2, \cdots, r, \tag{3.9}$$

the estimates of variables in O, denoted by x_{j*}^k $(j = r+1, r+2, \cdots, m)$, based on Rule L^k are given by the simple data fitting.

Define the relative degrees of belief of Rule L^k by

$$\bar{w}^k = \frac{\prod_{i=1}^{r} \; A_i^k(x_{i*})}{\sum_{h=1}^{p} \{\prod_{i=1}^{r} \; A_i^h(x_{i*})\}} \qquad k = 1, 2, \cdots, p. \tag{3.10}$$

Then the final estimate is given by

$$x_{j*} = \sum_{k=1}^{p} \; \bar{w}^k \; x_{j*}^k, \quad j = r+1, r+2, \cdots, m. \tag{3.11}$$

Usually, the variables in I are not strictly independent of each other in the environmental system. We have developed a stepwise procedure to fix values of some important explanatory variables taking account of correlations between variables. We introduce

Definition 3.5: (input admissible function).

We say that an explanatory variable x_i $(i = 1, 2, \cdots, r)$ is *active* if it has received a real number, say x_{i*}, such that

$$\sum_{k=1}^{p} A_i^k(x_{i*}) \; > \; 0. \tag{3.12}$$

Let I_a denote the set of active variables, and let $I_{\bar{a}} = I - I_a$. One can define the set I_a arbitrarily. When $I_a = \phi$ (i.e., $I_{\bar{a}} = I$), we define the *input admissible function* for $x_j \in I_{\bar{a}}$ by

$$w_j(x_j) = \frac{1}{p}\sum_{k=1}^{p} A_j^k(x_j), \quad j = 1, 2, \cdots, r. \tag{3.13}$$

When $I_a \neq \phi$ and $I_{\bar{a}} \neq \phi$, we define the *input admissible function* for $x_j \in I_{\bar{a}}$ by

$$w_j(x_j) = \frac{\sum_{k=1}^{p} w^k \ A_j^k(x_j)}{\sum_{k=1}^{p} w^k}, \quad w^k = \prod_{x_i \in I_a} A_i^k(x_{i*}). \tag{3.14}$$

where x_{i*} is the fixed input for $x_i \in I_a$. We call the set $\{ x_j \mid w_j(x_j) > 0 \}$ the *input admissible range* for $x_j \in I_{\bar{a}}$, and $w_j(x_{j*})$ the *input admissibility* at $x_j = x_{j*}$. Note that $w_j(x_j)$ does not depend on the order in which we determine the values of $x_i \in I_a$.

Looking at these functions, we can fix values of some important explanatory variables one after the other. For the variables in $I_{\bar{a}}$, the random numbers are generated within their admissible ranges. Thus a simulation is carried out by fixing scenario values for some explanatory variables and generating random inputs for the rest.

An example of the scene by our simulator is shown in Fig. 3.2. The explanatory variables are placed on the left with the input admissible functions drawn in a discrete form. The circles above the functions indicate that the scenario values are fixed for those variables throughout the simulation. The input admissible functions for other variables are calculated by Equation 3.14.

It may sometimes occur that the maximum value of the input admissible function does not reach 1 at the initial stage. This happens when the data of the variable is well divided into several fuzzy subspaces. As for the variable $traffic\%$, the data are neatly divided into two clusters. The maximum value of the input admissible function of the variable $traffic\%$ is not 1, as is shown in Fig. 3.2. Figure 3.2 is explained in more detail in Section 3.3.4.

Referring to the input admissible function, the scenario variables are fixed one after the other, where the scenario values are chosen so that Equation 3.12 is satisfied. The closer the value of $w_j(x_j)$ is to 1, the more

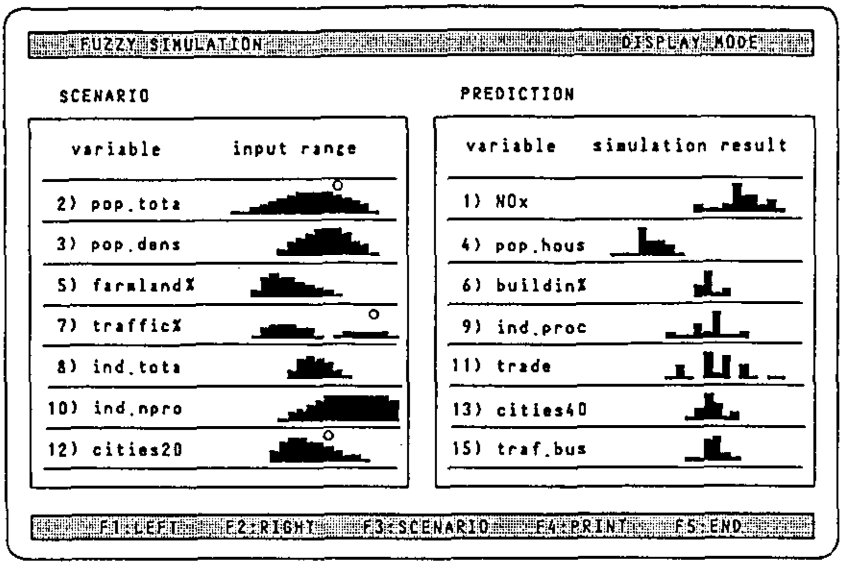


Fig. 3.2 Scenario analysis by the controlled fuzzy simulator

often the variable x_j actually occurred in the past. Note that the value $w_j(x_j)$ does not depend on the order specified. If the variable x_i is highly correlated with the variable x_j, and if the value of the variable x_i is fixed, the input admissible function $w_j(x_j)$ is modified so that the input range becomes very narrow. On the other hand, if the variable x_i is independent of the variable x_j, the input admissible function $w_j(x_j)$ is not influenced by the value of x_i.

3.3.3 Confidence Factors and Degrees of Scatter

To evaluate linear models, we introduce the confidence factors and degrees of scatter of the estimates as follows:

Definition 3.6: (confidence factor).

Denote by x_{i*} the fixed value for $x_i \in I_a$, and by x_{il} ($l = 1, 2, \cdots, N$) the generated random inputs for $x_i \in I_{\bar{a}}$. For $x_i \in I_a$, put $x_{il} = x_{i*}$ ($l = 1, 2, \cdots, N$). Let x_{jl} be the nonfuzzy estimate of the variable $x_j \in O$ ($j =$

$r+1, r+2, \cdots, m$), using the procedure in Definition 3.4, based on the set of input values $\{ x_{1l}, x_{2l}, \cdots, x_{rl} \}$. The confidence factor of the estimate x_{jl} ($j = r+1, r+2, \cdots, m$) is defined by

$$c_l = \frac{\prod_{i=1}^{r} w_i(x_{il})}{\max_l \{\prod_{i=1}^{r} w_i(x_{il})\}}, \quad l = 1, 2, \cdots, N. \tag{3.15}$$

The $w_i(x_i)$ is defined by Equation 3.13 or Equation 3.14. In Equation 3.15, every input admissible function is considered. There are two main reasons. One is that even if the variable is not selected as an explanatory variable of x_j, it may influence on it. The other is that the model is composed of simultaneous linear equations with $(m-r)$ unknowns. Each variable is interrelated, and it is very difficult to distinguish direct and indirect effects. For a set of input variables, a confidence factor is assigned, that is, a confidence factor does not depend upon the explained variable x_j. A confidence factor indicates how often a set of input variables has occurred in the past. It does not indicate the predictive power of the model. The predictive power can be better explained by the degree of scatter.

Definition 3.7: (degree of scatter).

Define the weighted average $\bar{x}_j$ and degree of scatter s_j of the estimates x_{jl} ($l = 1, 2, \cdots, N$) over the total simulation run as follows:

$$\bar{x}_j = \frac{\sum_{l=1}^{N} c_l \ x_{jl}}{\sum_{l=1}^{N} c_l}, \quad j = r+1, r+2, \cdots, m, \tag{3.16}$$

$$s_j = \frac{\sum_{l=1}^{N} c_l \ \{x_{jl} - \bar{x}_j\}^2}{\sum_{l=1}^{N} c_l}, \quad j = r+1, r+2, \cdots, m. \tag{3.17}$$

Note that the derivation of confidence factor is a similar idea to obtain a membership function of an output of a fuzzy system with multiple inputs by using the max-prod composition.

3.3.4 Construction of Knowledge Models

The simulation result is shown on the right in Fig. 3.2. The estimated values and confidence factors (x_{jl}, c_l) are drawn with 21×7 levels. Here, the range of each variable is divided into 21 levels such that the levels 1, 11 and 21 correspond to $m - 3\sigma$, m and $m + 3\sigma$, respectively. The range is controlled by assigning the number t introduced in Definition 3.1.

With the system, the simulation result is interpreted as follows:

if x_i is in Level L_i and x_j is in Level L_j, $\cdots$,

then x_p is in Level L_p and x_q is in Level L_q, $\cdots$.

Here, premise variables consist of those whose values are fixed. Consequent variables consist of those whose degree of scatter is below a specified value.

3.4 Application to Environmental Prediction

In Chapter 2 the IMS is introduced and applied to model building of environmental systems. Variables such as shown in Table 2.1 are used and their relations are analyzed. The variables are measured in the cities listed in Table 2.2. The 17 variables listed in Table 2.1 are classified into input, intermediate and output variables and simultaneous linear equations are obtained and solved to predict future environmental conditions. At the modeling stage, it is very difficult to identify cause and effect. The objective of the model was specified and the structure of the model was identified. There were some variables in the input variables whose behavior was very difficult to control. Here we call input variables scenario variables, that is, we input scenario values and predict future trends of other variables.

3.4.1 Construction of Fuzzy Rules

We have developed three models and compared them.

(1) Model 1

We have built a model for NO_x, using data listed in Table 2.1 and named it as Model 1 and a corresponding rule as Rule L^0. The explanatory variables of Model 1 are listed in the row of Rule L^0 in Table 3.1. The models for other variables developed in Chapter 2 are not explained here. These models are obtained with the structural modeling and the forward selection method.

Table 3.1 Fuzzy rules and submodels for NO_x

Model	Rule	Explanatory variables		Correlation
1	L^0	ind.proc	ind.npro	0.5816
		cities40	traf.car	
2	L^1	buildin%	ind.tota	0.7655
		ind.proc	cities20	
		cities40	traf.btr	
	L^2	buildin%	ind.tota	0.6414
		ind.proc	cities20	
		traf.str	traf.btr	
3	L^1	buildin%	ind.tota	0.7655
		ind.proc	cities20	
		cities40	traf.btr	
	L^3	traffic%	ind.proc	0.7582
		ind.npro	cities20	
		traf.str		
	L^4	pop.tota	pop.dens	0.6333
		traffic%	ind.tota	
		traf.str	traf.btr	

Table 3.2 Degree of data division

Scenario variables	Degree of data division	
	Step 1	Step 2
Population	61.49	39.88
Population density	59.02	45.88
Land use for farmland	59.58	40.38
Land use for traffic	71.05	31.98
Total industrial shipment density	53.15	61.55
Urban industrial shipment density	53.20	32.93
Number of cities within 20 km	52.83	73.62
Traffic of passenger cars	58.94	37.14

We used the data in 22 cities whose names are listed in Table 2.2. In dealing with such different cities, we face the following dilemma. To evaluate effects of city structure, data in different types of cities should be taken into account at the same time. However, it is very difficult to clarify this type of difference in a single linear model. This is why we have developed a fuzzy modeling technique. With the developed system, a data space is divided into several fuzzy subspaces and a fuzzy model is obtained for simulation.

(2) Model 2

Eight scenario variables are selected out of 17 variables. These variables are listed in Table 3.2. We have to decide which variable is taken as a key variable to subdivide the data space. The decision is made based on the degrees of data division defined by Equation 3.6 and the degrees of scatter defined by Equation 3.17. First, the degrees of data division are obtained for scenario variables that are listed in the column of Step 1 in Table 3.2. Data averaged over three years are used in clustering so that data in the same city belongs to the same cluster. In identification of membership functions and model building, annually averaged data are used.

The largest degree of the data division is 71.05, which is shown in Table 3.2. It is the degree of the variable, *land use for traffic*. The data space is divided into two subspaces, $A1$ and $A2$, by *land use for traffic*. There are six cities in $A1$, that is, Kawaguchi, Ichikawa, Yokosuka, Hiratsuka, Fujisawa and Sagamihara. The other 16 cities belong to $A2$. Though the numbers of the cities does not balance, clustering results by VCS show fairly good results. We use $traffic\%$ as the first premise variable. The premises of the fuzzy rules are as follows:

L^1: $traffic\%$ is big, and

L^2: $traffic\%$ is small.

The model composed of Rule L^1 and Rule L^2 is called Model 2. With IMS, consequent models are identified. The rows with L^1 and L^2 in Table 3.1 show the explanatory variables for Model 2. The correlations are 0.7655 and 0.6414, which are better than those of Model 1.

(3) Model 3

We subdivided the data space in group $A2$. The data averaged in three years are also used to obtain the degrees of data division. The results are listed at the column of Step 2 in Table 3.2. The largest one is that of *number of cities within 20 km*, the next one is that of *total industrial shipment density*, and the third is that of *population density*. With the system VCS the results of clustering are displayed. We find that if we divide the data by *number of cities within 20 km*, one group lies in a corner and the other group is scattered widely. If we divide the data by *total industrial shipment density*, one data point with a very large value belongs to one cluster and all other data belong to another cluster.

The third largest degree of data division is that of *pop.dens*. The clustered result of cities based on $traffic\%$ and *pop.dens* is shown in Fig. 3.3. This is fairly satisfactory. The number in Fig. 3.3 shows the city number in Table 2.2. We use *population density* as the second precedent variable to obtain three fuzzy rules as follows:

L^1: $traffic\%$ is big,

L^3: $traffic\%$ is small and *pop.dens* is small, and

L^4: $traffic\%$ is small and *pop.dens* is big.

This model is called Model 3. Group $A2$ is divided into groups $A3$ and $A4$. For each group a model is identified. The rows with L^1, L^3 and L^4 in Table 3.1 show the explanatory variables for Model 3. In Model 3, group $A2$ is subdivided. Seven cities belong to group $A3$, that is, Mito, Hitachi, Utsunomiya, Maebashi, Takasaki, Kawagoe and Hachioji. Nine cities belong to group $A4$, that is, Urawa, Ohmiya, Tokorozawa, Koshigaya,

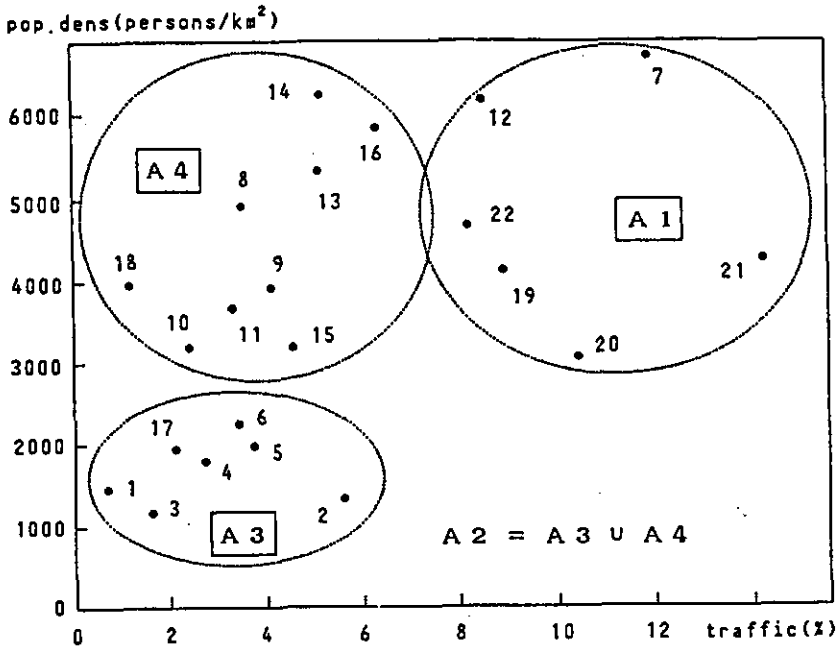


Fig. 3.3 Clustering of cities based on *traffic%* and *pop.dens*

Funabashi, Matsudo, Kashiwa, Ichihara and Machida. We cannot further subdivide the data space because of the number of data. We proceed to the simulation stage with these models.

3.4.2 Fuzzy Simulation

The premise of the rule is identified as a trapezoidal membership function as follows.

$$A_i(x_i) = \begin{cases} \frac{1}{2(x_{i2}-x_{i1})}x_i + \frac{x_{i2}-2x_{i1}}{2(x_{i2}-x_{i1})} & \text{if } 2x_{i1} - x_{i2} \leq x_i < x_{i2} \\ 1 & \text{if } x_{i2} \leq x_i < x_{i3} \\ -\frac{1}{2(x_{i4}-x_{i3})}x_i + \frac{2x_{i4}-x_{i3}}{2(x_{i4}-x_{i3})} & \text{if } x_{i3} \leq x_i < 2x_{i4} - x_{i3} \\ 0 & \text{if } x_i < 2x_{i1} - x_{i2} \text{ or } 2x_{i4} - x_{i3} \leq x_i, \end{cases} \tag{3.18}$$

where, x_{i1}, x_{i2}, x_{i3} and x_{i4} are the minimum, the first quartile, the third quartile and the maximum of the data set of the variable x_i. Membership functions for *traffic%* and *pop.dens* are illustrated in Fig. 3.4. The result

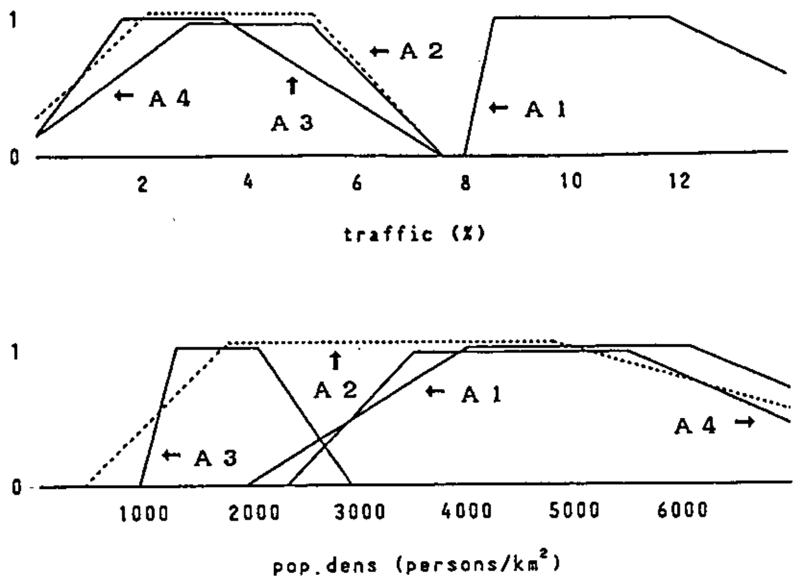


Fig. 3.4 Membership functions for *traffic%* and *pop.dens*

of fuzzy simulation by Model 3 is shown in Table 3.3. The level in Table 3.3 indicates an averaged level. The range is between $m_i - 3\sigma_i$ and $m_i + 3\sigma_i$. The maximum level is 21.

At each result, the variable whose degree of scatter is 0 indicates that the value is fixed at that level. For other variables, the value is set by generating random numbers 100 times.

The variables whose degree of scatter is below six are used as consequent variables. Through these processes, we get knowledge models as shown in Table 3.4. Some scenario variables are included in consequent variables.

3.5 Concluding Remarks

In this chapter we present the methods to divide the data space, to control input ranges in the process of simulation, and to interpret the simulation results. In dividing data spaces, we introduce *degrees of data division* and stepwise visual clustering with the aid of VCS. There still remains the

Table 3.3 Fuzzy simulation by Model 3

Variable		Result 1		Result 2		Result 3	
		Level	Degrees of Scatter	Level	Degrees of Scatter	Level	Degrees of Scatter
Scenario Variable	pop.tota	15.0	0.0	11.1	6.3	13.6	13.8
	pop.dens	14.1	5.4	7.0	0.0	17.0	0.0
	farmlan%	9.2	3.3	11.3	11.3	12.1	8.8
	traffic%	19.0	0.0	7.0	0.0	8.0	0.0
	ind.tota	12.5	2.0	10.9	1.5	13.6	13.1
	ind.npro	15.8	8.1	11.5	3.3	10.2	3.3
	cities20	14.0	0.0	10.2	4.9	11.0	0.0
	traf.car	14.8	10.3	10.1	5.3	11.8	12.7
Explained Variable	NOx	15.3	5.8	7.2	13.8	4.8	2.8
	pop.hous	5.4	2.9	10.3	0.3	8.3	6.8
	buildin%	12.1	0.6	4.7	1.2	7.2	11.8
	ind.proc	12.4	4.1	10.5	1.3	13.2	7.5
	trade	13.2	6.7	10.4	2.4	9.7	10.5
	cities40	12.7	1.5	9.8	7.5	11.0	0.0
	traf.bus	12.6	0.9	10.7	13.9	11.7	10.0
	traf.str	14.6	7.9	8.5	1.9	11.1	7.3
	traf.btr	5.4	16.5	7.0	0.7	10.5	5.0

Table 3.4 Translation of simulation results

Result	Variables in if-close	Variables in then-close [Level]	
	Scenario variable	Scenario variable	Explained variable
1	pop.tota [15] traffic% [19] cities20 [14]	pop.dens [14] farmlan% [9] ind.tota [13]	NOx [15] pop.hous [5] buildin% [12] ind.proc [12] cities40 [13] traf.bus [13]
2	pop.dens [7] traffic% [7]	ind.tota [11] ind.npro [12] cities20 [10] traf.car [10]	pop.hous [10] buildin% [5] ind.proc [11] trade [10] traf.str [9] traf.btr [7]
3	pop.dens [7] traffic% [8] cities20 [11]	ind.npro [10]	NOx [5] cities40 [11] traf.btr [11]

problem of defining membership functions. For the present, we define them case by case, examining the distribution of data. In building submodels, there is also a problem of handling data that belongs to several clusters.

In a simulation process, *input admissible function* is introduced. With this function, effective input ranges are taken into account and input values can be controlled. We have to further study the calculation method of the input admissible function. Since it takes much time to recalculate the input admissible function, we do not change it in case of random inputs. The simulation result is given with the confidence factor, which is effective for model validation.

The translation from the simulation result to knowledge data is considered. The input admissible function, the confidence factor and the degrees of scatter give useful information for their transformation.

In model building, it is important that analysts discuss the problem with each other. The developed computer system assists discussion by giving information and showing simulation results.

Chapter 4

Linguistic Fuzzy Modeling

4.1 Introduction

There are many complicated factors such as social activities, meteorological factors and topography, which make it difficult to predict future environmental conditions. Statistical prediction models have been studied by many researchers. However, there are some cases where statistical models alone do not lead to satisfactory results when we have to predict future environmental conditions with limited data.

In model building of environmental systems, we have to predict a high concentration more correctly than a low one for planning countermeasures. Linear regression models may be appropriate for predicting values around a median, but they are inappropriate for predicting peak values. Also, the prediction formula must be explained reasonably, which is sometimes difficult with regression models because of collinearity.

Recently, the concept of fuzzy set theory was introduced by Zadeh (1973). An approximate calculus of variables has been developed and used in a wide variety of practical applications (Zadeh, 1975 and Holmblad and Ostergaard, 1982). The linguistic modeling approach based on fuzzy set theory has received much attention; several applications are found in the social sciences (Kickert, 1979b and Wenstop, 1979).

A part of this chapter was published in Trans. of the Institute of Systems, Control and Information Engineers (vol. 2, no. 7, pp.231-240, 1989) by M. Kainuma and Y. Nakamori.

In this chapter, we propose a method to predict phenomena composed of many complicated factors by modeling the process of human thinking and judgment. Describing input-output relations of the system in the form of if-then rules, the behavior of the system is predicted using fuzzy reasoning. To improve the model, we adjust the parameters of the membership functions by the use of the nonlinear optimization technique.

We apply linguistic modeling to the prediction of Oxidant concentration in the Osaka district, Japan. The data measured in the Osaka district for the period from June to August from 1975 to 1977 are used and an Oxidant prediction model has been developed using meteorological data. It is shown that linguistic modeling is appropriate for the prediction of phenomena with limited input-output data, and the obtained model is particularly useful for predicting peak values.

4.2 Criteria for the Prediction of Oxidant Concentration

Let us briefly introduce a practical method to predict Oxidant concentration at a high level (Mizoguchi, Ochiai, Naito and Uchida, 1979). Levels of Oxidant concentration are classified into three groups: Level 0 for concentration less than 10 pphm, Level 1 for between 10 pphm and 15 pphm, and Level 2 for 15 pphm or higher. A check sheet is normally used to predict into which level Oxidant concentration falls. The data for the period from June to August for three years, 276 days in total, are used. The data of Oxidant concentration were measured at 19 measuring points in the Osaka district. The level of the day is decided by the highest Oxidant concentration for the period from 6:00 A. M. to 8:00 P. M.. As the values of Oxidant concentration are missing for 3 days out of 276 days, we use data of 273 days. Meteorological data, such as duration of sunshine, weather and wind velocity, are also used to predict the levels of Oxidant concentration.

Because of the mechanism of Oxidant generation, Oxidant level is very low during bad weather. The relation between the hours of sunshine and the level of Oxidant concentration is shown in Table 4.1. As hours of sunshine increase, days of Level 2 also increase. However, even on sunny days, there

Table 4.1 Cross table between the duration of sunshine and the level of Oxidant concentration

Level \ Shining Hours	0 h	0.1-0.5 h	0.6-2.0 h	2.1-5.0 h	5.1- h	Total
0	30	10	17	22	73	152
1	0	2	5	11	59	77
2	0	0	0	6	38	44

Table 4.2 Cross table between the weather (from 6:00 A. M. to 6:00 P. M.) and the level of Oxidant concentration

Level \ Weather	Raining Almost All Day	Raining, but Not All Day	Rainless	Total
0	22	64	66	152
1	1	17	59	77
2	0	12	32	44

are some days which fall into Level 0. We cannot say that a level depends only on hours of sunshine. When the duration of sunshine is less than 0.5 hours, 40 out of 42 days fall into Level 0, which is shown in Table 4.1.

The relation between the weather and the level of Oxidant concentration is shown in Table 4.2. When it rains almost all day, 22 out of 23 days fall into Level 0. We can say generally that when it rains almost all day, the day falls into Level 0.

As we have seen above, when the duration of sunshine is less than 0.5 hours or it rains most of the day, the day is classified into Level 0. Following these criteria, 45 out of 273 days are classified into Level 0.

Next, we consider the relation between the atmospheric pressure gradient and wind velocity of the upper layer. The pressure gradient in the

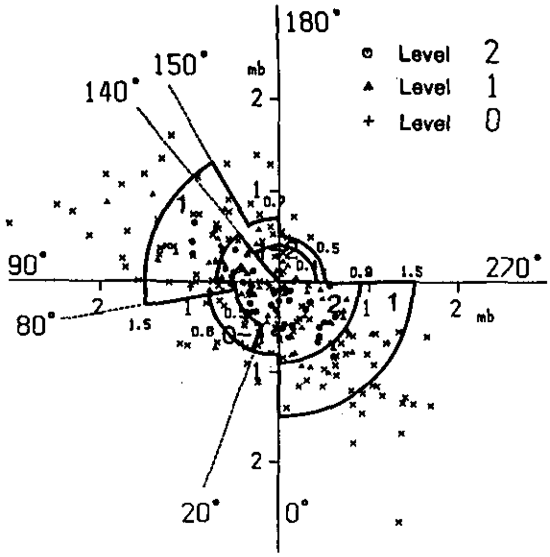


Fig. 4.1 Relation between the pressure gradient and the level of Oxidant concentration

Osaka district is calculated with data at five points, that is, Osaka, Maizuru, Shionomisaki, Nagoya and Kohchi. The pressure gradient is closely related with wind velocity and its direction. Figure 4.1 shows the relation between the pressure gradient and the level of Oxidant concentration. Scatter plots of pressure gradients are distributed in an oval shape, from the north-west quadrant to the south-east quadrant. Points in Level 0 are distributed mainly in the area where pressure gradients are greater than 1.5 mb in the north-west and south-east quadrants, and 0.8 mb in the south-west quadrant. Keeping these factors in mind, we can classify the pressure gradient into five levels: Level 0, Level 0-1, Level 1, Level 1-2 and Level 2. These are illustrated in Fig. 4.1.

The relation between the maximum wind velocity of the upper layer and the level of Oxidant concentration is shown in Table 4.3. As wind velocity increases, the level of Oxidant concentration decreases. When the wind velocity of the upper layer is greater than 10 m/s, 47 out of 57 days fall into Level 0, as illustrated in Table 4.3.

Figure 4.2 is the check sheet for the prediction of Oxidant concentration based on the above criteria. Table 4.4 shows criteria associated with Fig. 4.2. Comparison between the measured values and the predicted

Table 4.3 Cross table between the maximum wind velocity of the upper layer and the level of Oxidant concentration

Wind Velocity / Level	m/s 0-4.9	m/s 5.0-9.9	m/s 10.0-	Missing Values	Total
0	21	54	47	30	152
1	28	37	8	4	77
2	22	20	2	0	44

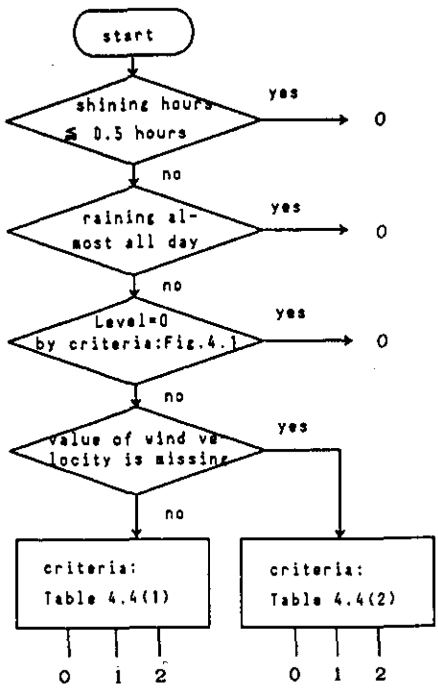


Fig. 4.2 Check sheet for the prediction of Oxidant concentration

Table 4.4 Decision tables for the prediction of Oxidant concentration

(1) When wind velocities of upper layer are obserbed.

Level of Atmospheric Pressure Gradient	Level of Wind Velocity 0	1	2
0-1	0	(*) 0 − 1	1
1	(*) 0 − 1	1	(*) 1 − 2
1-2	1	(*) 1 − 2	2
2	1	2	2

(*) Use the following criteria:

① high when highest temperature ≧ 35℃,and

② low when highest temperature < 35℃.

(2) When wind velocities of upper layer are missing.

Level of Atmospheric Pressure Gradient	① + ② + ③(*) -2	-1	0	1
0-1	0	0	0	1
1	0	0	1	2
1-2	0	1	1	2
2	0	1	2	2

(*) Add the corresponding number when the following conditions are satisfied:

① -1 when shining hours ≦ 2 hours,

② -1 when highest temperature ≦25℃, and

③ 1 when highest temperature ≧ 35℃.

Table 4.5 Results of Oxidant predictions

(a) Check sheet.

Measured \ Predicted	0	1	2	Total
0	95 (0.63)	40 (0.26)	17 (0.11)	152
1	10 (0.13)	31 (0.40)	36 (0.47)	77
2	0 (0)	6 (0.14)	38 (0.86)	44

(b) Multi-regression model.

Measured \ Predicted	0	1	2	Total
0	76 (0.63)	45 (0.37)	0 (0)	121
1	17 (0.23)	56 (0.77)	0 (0)	73
2	0 (0)	44 (1)	0 (0)	44

(c) Fuzzy model.

Measured \ Predicted	0	1	2	Total
0	107 (0.70)	35 (0.23)	10 (0.07)	152
1	15 (0.19)	45 (0.58)	17 (0.22)	77
2	2 (0.05)	20 (0.45)	22 (0.50)	44

ones with this check sheet is shown in Table 4.5 (a). The goodness of fit is defined by

$$p_{ij} = \frac{n_{i\to j}}{n_i}, \quad i, j = 1, 2, 3, \tag{4.1}$$

where n_i denotes the number of data in level i, and $n_{i\to j}$ the number of times when the data in level i is predicted as that in level j. The goodness of fit is shown in parentheses in Table 4.5. Although data such as duration of sunshine, weather and highest temperature have to be predicted in advance, such data can be predicted more precisely by using physical and/or statistical models.

Regression analysis is also applied to the prediction of Oxidant concentration. On 35 days, the data of wind velocity of the upper layer were

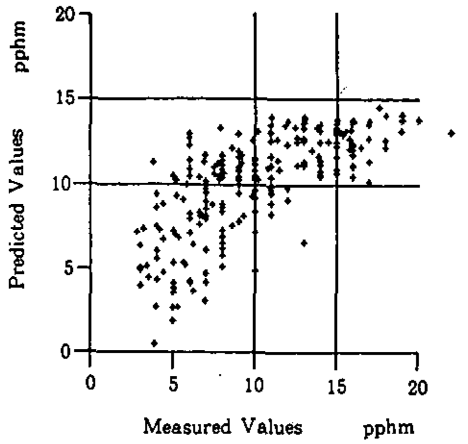


Fig. 4.3 Measured Oxidant concentration versus predicted ones by the multi-regression model

missing. The obtained linear prediction model is as follows:

$$Y = 76. + 0.33\,X_1 - 2.2\,X_2 + 21.\,X_3 - 1.3\,X_4 \\ +0.025\,X_5 - 0.76\,X_6, \tag{4.2}$$

where Y denotes Oxidant concentration, X_1 duration of sunshine, X_2 level of weather (0: rainless, 1: raining, but not all day, and 2: raining almost all day), X_3 level of atmospheric pressure gradient classified with Fig. 4.1, X_4 wind velocity of the upper layer observed with a pilot balloon, X_5 temperature, and X_6 wind velocity at the ground. Figure 4.3 shows scatter plots with measured Oxidant concentration and predicted ones by Equation 4.2. Comparison between the measured values and the predicted ones with the linear model is shown in Table 4.5 (b). The controlled determination coefficient is 0.49, which is fairly satisfactory for an environmental prediction model, but Equation 4.2 cannot predict the values at high concentration.

4.3 Linguistic Modeling for Oxidant Prediction

Fuzzy controllers have been introduced by Mamdani (1974) and Mamdani and Assilian (1975) for the control of complex processes, such as industrial plants, especially when no precise model of the process exists and most of a priori information is available only in qualitative form.

The intuitive control strategies used by trained operators may be viewed as the fuzzy algorithm (Zadeh, 1973), which provides a possible method for handling qualitative information in a rigorous way. Input-output relations of the system are described in the form of if-then rules. Then, using fuzzy reasoning, the behavior of the system will be predicted. An example of such a fuzzy rule is as follows:

$$\begin{aligned} &\textit{if } x_1 \textit{ is very small, and } x_2 \textit{ is large,} \\ &\quad\textit{then } z \textit{ is a little high.} \end{aligned} \tag{4.3}$$

where such words as "*very small*", "*large*" and "*a little high*" are fuzzy sets.

These rules are of the form:

$$\begin{aligned} \textit{Rule } L^j : \quad &\textit{if } x_1 \textit{ is } A_{1j},\ x_2 \textit{ is } A_{2j}, \ldots, x_m \textit{ is } A_{mj}, \\ &\textit{then } z \textit{ is } C_j, \end{aligned} \tag{4.4}$$

where x_i $(i = 1, 2, \cdots, m)$ are input variables, and z is an output variable. A_{ij}, C_j $(i = 1, 2, \cdots, m;\ j = 1, 2, \cdots, n)$ are fuzzy sets, m is the number of input variables, and n is the number of rules. Given input values x_{i*}, the prediction of output z_* is calculated by a set of n rules.

First, the truth value of the premise of the jth rule is calculated as follows:

$$w_j = A_{1j}(x_{1*}) \otimes A_{2j}(x_{2*}) \otimes \cdots \otimes A_{mj}(x_{m*}), \qquad j = 1, 2, \cdots, n, \tag{4.5}$$

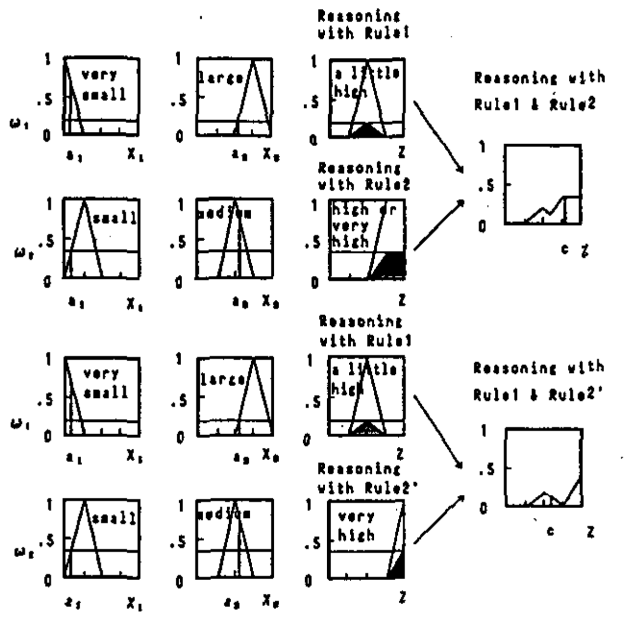
where $\otimes$ denotes a mini operator or product according to cases. $A_{ij}(x_i)$ $(i = 1, 2, \cdots, m;\ j = 1, 2, \cdots, n)$ are membership functions of the fuzzy set A_{ij}. $A_{ij}(x_{i*})$ is the truth value of a given input x_{i*}.

The result of fuzzy reasoning with the jth rule is given by

$$\hat{C}_j(z) = w_j \times C_j(z), \qquad j = 1, 2, \cdots, n. \tag{4.6}$$

The combined membership function C^* is defined by

$$C^*(z) = \max_j \hat{C}_j(z). \tag{4.7}$$



Rule1 :If X_1 is very small, and X_2 is large then Z is a little high.
Rule2 :If X_1 is small, and X_2 is medium then Z is high or very high.
Rule2':If X_1 is small, and X_2 is medium then Z is very high.
a_1:Value of X_1. a_2:Value of X_2. c:Predicted value of Z.
ω_1:Confidence factor of the premise of rule 1.
ω_2:Confidence factor of the premise of rule 2.

Fig. 4.4 Fuzzy reasoning

Finally, the prediction z_* is given by the center of gravity of the membership function $C^*(z)$, namely,

$$z_* = \frac{\int z \times C^*(z)d(z)}{\int C^*(z)d(z)}. \tag{4.8}$$

Figure 4.4 illustrates fuzzy reasoning. The membership function derived from the jth rule $\hat{C}_j(z)$ is shown in Fig. 4.4 with slanted lines. The combined membership function $C^*(z)$ is shown on the right in Fig. 4.4. Resultant prediction z_* is shown as the center of gravity of the combined membership function with a bold line.

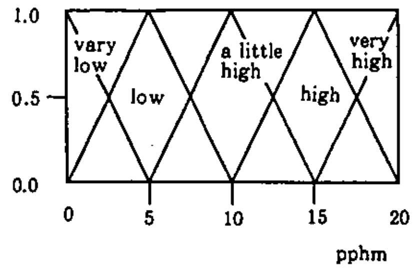


Fig. 4.5 Fuzzy sets of Oxidant concentration

4.4 Application to the Prediction of Oxidant Concentration

It is sometimes difficult to predict environmental conditions at high values with a regression model. A check sheet has been practically used for environmental prediction. Since a check sheet can be viewed as a collection of if-then rules, fuzzy set theory can be applied to improve the check sheet. We express rules in the form of if-then rules and predict Oxidant concentration with fuzzy reasoning.

Examples of rules are:

Rule 1 : *If the duration of sunshine is short,*
then Oxidant concentration is low or very low.

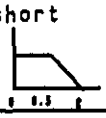
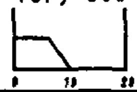
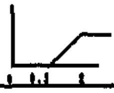
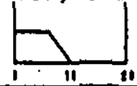
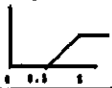
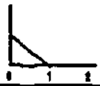
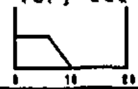
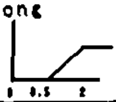
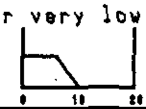
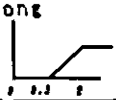
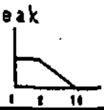
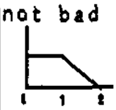
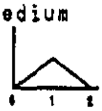
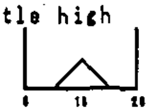
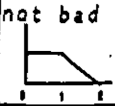
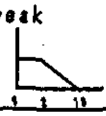
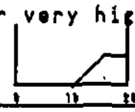
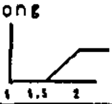
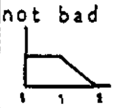
Rule 2 : *If the duration of sunshine is long and the weather is bad,*
then Oxidant concentration is low or very low.

Rule 8 : *If the duration of sunshine is long, the weather is not bad,*
the level of pressure gradient is large,
and the wind velocity of the upper layer is strong,
then Oxidant concentration is a little high.

(4.9)

Table 4.6 lists eight initial rules for predicting Oxidant concentration. Membership functions are also shown in Table 4.6. Figure 4.5 illustrates fuzzy sets of Oxidant concentration. For representing Oxidant levels, five fuzzy sets are used, that is, "*very low*", "*low*", "*a little high*", "*high*", and "*very high*". A membership function that expresses a combination of two

Table 4.6 Rules for the prediction of Oxidant concentration

Rule No.	If-close				Then-close
	Shining Hours	Weather	Level of Atom_Pres_Gra*	Wind velocity of UL** (m/s)	Oxidant concentrations (pphm)
1	short 				low or very low 
2	Long 	bad 			low or very low 
3	long 	not bad 	small 		low or very low 
4	long 	not bad 	medium or large 	missing values 	low or very low 
5	long 	not bad 	medium 	weak 	high 
6	long 	not bad 	medium 	strong 	a little high 
7	long 	not bad 	large 	weak 	high or very high 
8	long 	not bad 	large 	strong 	a little high 

* Atmospheric Pressure Gradient
** Upper Layer

fuzzy sets, for example "*high or very high*", is defined by

$$A_{ij}(x_i) \cup A_{ik}(x_i) = \min\{A_{ij}(x_i) + A_{ik}(x_i),\ 1\}. \tag{4.10}$$

The predicted result by using these rules is shown in Table 4.5 (c). The linguistic model is better than the check sheet for Level 0, but for the points in Level 2, the check sheet is better. Also the linguistic model is better than the regression model for Level 2.

4.5 Modification of Prediction Models

The result of linguistic modeling in Table 4.5 (c) is not so satisfactory, because there are two days when the linguistic model mistakes the data in Level 2 for that in Level 0. We modify fuzzy rules from three points of view. They are the subdivision of rules, modification of fuzzy sets in consequence, and the parameter optimization of the membership functions.

4.5.1 Subdivision of Rules

There are some points where the data in Level 2 are not correctly predicted with the linguistic model as shown in Table 4.5. Table 4.7 shows times and weight of failure for each rule. The value at the upper row indicates the sum of the truth value of the premise. The value at the lower row in parentheses indicates the times to be applied. Rule 8 is mainly applied to the case when the linguistic model mistakes the data in Level 2 for that in Level 0. Rule 7 and Rule 8 are mainly applied to the case when the linguistic model mistakes the data in Level 0 for that in Level 2. Rule 8 is subdivided as follows.

Table 4.7 Times and weight of failure for each rule

Measured → Predicted \ Rule No.	1	2	3	4	5	6	7	8
Level 0 → Level 1					13.21 (28)	14.58 (26)	2.8 (7)	3.77 (7)
Level 0 → Level 2							8.77 (11)	2.27 (10)
Level 1 → Level 0	5.39 (6)		3 (3)	1.54 (4)		3 (3)		2 (2)
Level 1 → Level 2					1.5 (3)	13.96 (18)		
Level 2 → Level 0								2 (2)
Level 2 → Level 1					1.27 (4)	2.27 (4)	6.31 (16)	7.81 (16)

Rule 8 − 1 : *If the duration of sunshine is a little long, the weather is not bad, the level of pressure gradient is large, and the wind velocity of the upper layer is strong, then Oxidant concentration is a little high.*

Rule 8 − 2 : *If the duration of sunshine is long, the weather is not bad, the level of pressure gradient is large, and the wind velocity of the upper layer is strong, then Oxidant concentration is high.*

(4.11)

These rules are illustrated in Table 4.8; the predicted result with these nine rules is shown in Table. 4.9 (a). Although the goodness of fit lowers from 0.70 to 0.67 for the data in Level 0, it increases from 0.50 to 0.77 for the data in Level 2.

Figure 4.6 illustrates scatter plots between measured values of Oxidant concentration and predicted ones with the subdivided linguistic model. This model is better than the linear model, because it can predict the data in Level 2 more correctly.

Table 4.8 Parts of subdivided rules for the prediction of Oxidant concentration

Rule No.	If-close				Then-close
	Shining Hours	Weather	Level of Atmo_Pres_Gra*	Wind Velocity of UL** (m/s)	Oxidant Concentrations (pphm)
8 − 1	a little long	not bad	large	strong	a litte high
8 − 2	long	not bad	large	strong	high

* Atmospheric Pressure Gradient
** Upper Layer

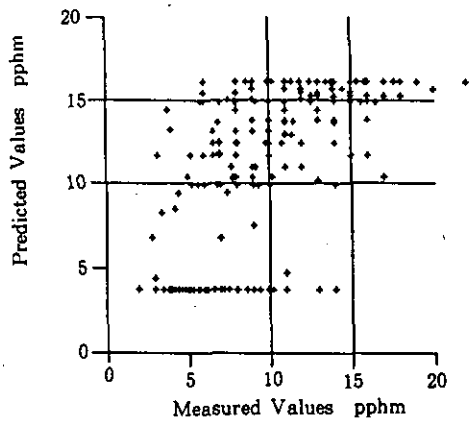


Fig. 4.6 Measured Oxidant concentration versus predicted ones by the fuzzy model with subdivided rules

Table 4.9 Results of Oxidant predictions with three modified linguistic models

(a) Fuzzy model(with subdivided rules).

Predicted / Measured	0	1	2	Total
0	102(0.67)	38 (0.25)	12 (0.08)	152
1	13 (0.17)	33 (0.43)	31 (0.40)	77
2	0 (0)	10(0.23)	34 (0.77)	44

(b) Fuzzy model(with modified fuzzy sets, using normalized fuzzy reasoning).

Predicted / Measured	0	1	2	Total
0	101 (0.66)	32 (0.21)	19 (0.13)	152
1	13 (0.17)	30 (0.39)	34 (0.44)	77
2	0 (0)	4 (0.09)	40 (0.91)	44

(c) Fuzzy model(with modified membership functions).

Predicted / Measured	0	1	2	Total
0	101(0.66)	32 (0.21)	19 (0.13)	152
1	13 (0.17)	31 (0.40)	33 (0.43)	77
2	0 (0)	4 (0.09)	40 (0.91)	44

Table 4.10 Parts of modified rules for the prediction of Oxidant concentration

(a) Modification of rules(before normalization)

Rule No.	If-close				Then-close
	Shining Hours	Weather	Level of Atm_Pres_Gra*	Wind velocity of UL** (m/s)	Oxidant concentrations (pphm)
7 − 1	a little long	not bad	large	weak	very high
7 − 2	long	not bad	large	weak	high or very high

(b) Modification of rules(after normalization)

Rule No.	If-close				Then-close
	Shining Hours	Weather	Level of Atm_Pres_Gra*	Wind velocity of UL** (m/s)	Oxidant concentrations (pphm)
7 − 1	a little long	not bad	large	weak	high or very high
7 − 2	long	not bad	large	weak	very high

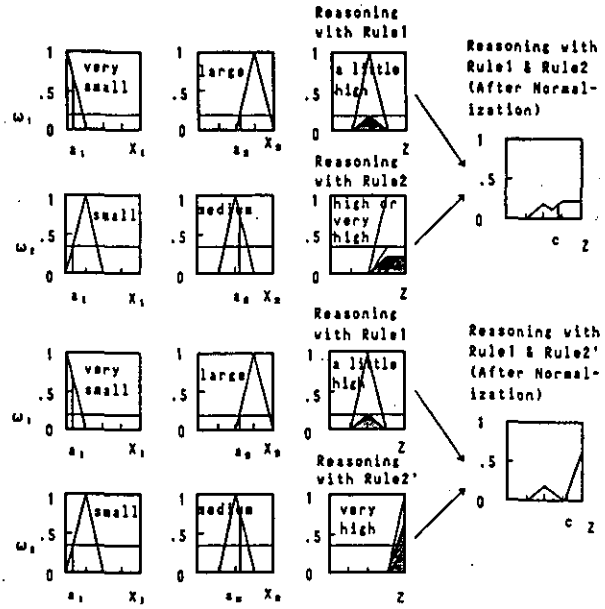
* Atmospheric Pressure Gradient
** Upper Layer

4.5.2 Modification of Fuzzy Sets in Consequence

We have thus far made rules intuitively, referring to the check sheet. In this section, we modify fuzzy sets by using the measuring data. There are many combinations of the five fuzzy sets. We leave the rules from 1 to 4 unchanged, as these rules are obvious (see Table 4.6). For the remaining four rules, we subdivide the rule with duration of sunshine and get eight rules. We define the total goodness of fit as follows:

$$p = p_{11} + p_{22} + p_{33}. \tag{4.12}$$

A part of the rules is illustrated in Table 4.10 (a) as the rules before normalization. When the duration of sunshine is long and other conditions



Rule1 :If X_1 is very small, and X_2 is large then Z is a little high.
Rule2 :If X_1 is small, and X_2 is medium then Z is high or very high.
Rule2':If X_1 is small, and X_2 is medium then Z is very high.
a_1:Value of X_1. a_2:Value of X_2. c:Predicted value of Z.
ω_1:Confidence factor of the premise of rule 1.
ω_2:Confidence factor of the premise of rule 2.

Fig. 4.7 Modification of fuzzy reasoning

are the same, the value of Oxidant concentration is usually higher than that when the duration of sunshine is short. The result of Table 4.10 (a) contradicts this observed phenomenon. This is because by the reasoning with Equations 4.5-4.8, the result is sensitive to the following value.

$$\int C_j(z)\, d(z). \tag{4.13}$$

The result of fuzzy reasoning with the jth rule is now modified. Instead of Equation 4.6, the following normalized equation is used.

$$\hat{C}_j(z) = \frac{w_j\, C_j(z)}{\int C_j(z)\, d(z)}. \tag{4.14}$$

Modified fuzzy reasoning is shown in Fig. 4.7. Now we explain briefly this modified fuzzy reasoning. Suppose

$$\int C_1(z)\, d(z) = 1, \tag{4.15}$$

for the integrated value of a fuzzy set "*a little high*". Then the integrated value of a fuzzy set "*high or very high*" is

$$\int C_2(z)\, d(z) = 1.5. \tag{4.16}$$

And the integrated value of a fuzzy set "*very high*" is

$$\int C_{2'}(z)\, d(z) = 0.5. \tag{4.17}$$

As shown in Fig. 4.4, the result of fuzzy reasoning with Rule 1 and Rule 2 is greater than that with Rule 1 and Rule 2', which contradicts the observed phenomena. A fuzzy set of "*high or very high*" is more sensitive than that of "*very high*" in the calculation of center of gravity with Equation 4.8. As shown in Fig. 4.7, the result of modified fuzzy reasoning with Rule 1 and Rule 2 is less than that with Rule 1 and Rule 2'. Table 4.10 (b) shows a part of the modified rules after normalization. Fuzzy sets in the consequence are coincident with the observed phenomena. The result is shown in Table 4.9 (b). The total goodness of fit with modified fuzzy sets is 1.96, which is better than that of the linguistic model, 1.86.

4.5.3 Parameter Modification of Membership Functions

Parameters in premises in Tables 4.6, 4.8 and 4.10 were given by experts, looking at the distribution of data. For example, the fuzzy set "*duration of sunshine is short*" is given by the following function:

$$short\,(x) = \begin{cases} 1 & if \quad 0 \le x < 0.5 \\ -\frac{2}{3}\,x + \frac{4}{3} & if \;\; 0.5 \le x < 2 \\ 0 & if \quad 2 \le x \;. \end{cases} \tag{4.18}$$

Now we optimize parameters that characterize membership functions. Figure 4.8 shows fuzzy sets on duration of sunshine. The duration of sunshine is expressed with three fuzzy sets, that is, "*short*", "*a little long*" and "*long*". Parameters q_1, q_2, and q_3 shown in Fig.4.8 are determined with the nonlinear optimization technique. We set

$$0 \le q_1 \le q_2 \le q_3 \tag{4.19}$$

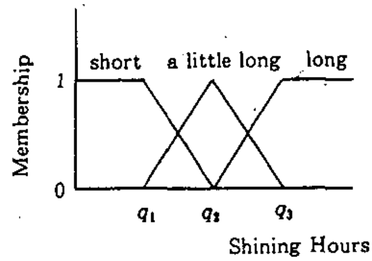


Fig. 4.8 Trapezoidal fuzzy sets

and maximize the total goodness of fit defined by Equation 4.12.

The Simplex method for unconstrained minimization was devised by Spendley, Hext and Himsworth (1962). Box has modified this method to find constrained minima, and termed his constrained Simplex method the "Complex" method (Box, Davies and Swann, 1969).

In the Complex method, $k \geq 4$ (the number of variables + 1) points are used to form a configuration. The objective function is evaluated at each of these points and the vertex of smallest function value determined. This worst point is replaced to increase the value of the objective function iteratively. It can be expected that there is a point on the produced line joining the rejected point and this centroid, where its value of the objective function is greater than that of the rejected point. Q_{0r} is expressed as

$$Q_{0r} = (1 + \alpha)\, Q_0 - \alpha\, Q_r, \tag{4.20}$$

where Q_r denotes the worst point, Q_0 the centroid of the remaining vertices, and Q_{0r} a new point. α is an empirical parameter.

Various cases, calling for different treatments, arise as follows (Box, Davies and Swann, 1969):

(i) If this trial point satisfies all the constraints and is not the worst point in the new configuration, the whole process is repeated.

(ii) The trial point happens to be the worst point in the new configuration, in which case a move halfway towards the centroid is made instead of the basic iteration of over-reflection, where by over-reflection is meant the point on the produced line joining the rejected point and this centroid, but α times as far from the centroid as the reflection of the rejected point.

(iii) If the trial point moved halfway towards the centroid happens to be the worst point again, the point is laid aside.

(iv) If the trial point does not satisfy some constraint, that variable is reset just inside the appropriate boundary (by an amount of, for instance, 0.0000001) to give a further trial point.

(v) If no trial point improves the objective function, we stop the iteration.

Suitable empirically determined values for α and k are said to be $\alpha = 1.3$ and $k = 2\times$ (the number of variables). k ($>$ (the number of variables) $+ 1$) points have been found necessary to prevent the configuration from collapsing prematurely into a sub-space. The use of the over-reflection factor $\alpha > 1$ enables the Complex to expand whenever possible, while the moves towards the centroid allow the Complex to contract when necessary.

Accordingly, we set $\alpha = 1.3$ and $k = 20$. As initial points, 20 sets of three variables were obtained randomly. The worst point is removed from the vertex of configuration and a new point is added to increase the total goodness of fit.

Modification of the Complex method

Any iterative minimization may converge to a local minimum instead of the required global minimum. In this case, points are converged where the goodness of fit is $p = 1.5$. The goodness of fit is worse than that of the fuzzy model with modified fuzzy sets where $p = 1.96$. This is because a small change of a parameter does not usually change the goodness of fit when fuzzy reasoning is used. Then we add another criteria for iteration

(vi) If the number of the remaining points becomes less than (the number of variables) $+ 2$, the removed points will be included again to give further trial points.

The obtained parameters are as follows:

$$q_1 = 0.4, \quad q_2 = 1.8, \quad q_3 = 10.0, \quad and \quad p = 1.98. \qquad (4.21)$$

The estimation result using these parameters is shown in Table 4.9 (c). There does not exist great difference between this result and that of the fuzzy model with modified fuzzy sets. This shows that we can obtain the fuzzy model by experts as well as by the optimization technique.

4.6 Concluding Remarks

A proper model can be built with regression analysis if we can obtain sufficient data. However, it is very difficult to obtain satisfactory results with a regression model if the number of data is limited. We tried to make a prediction by modeling and incorporating the process of human thinking and judgment. The data in Level 2 can be predicted correctly with a linguistic model, but not with a linear model. As a linguistic model is expressed in terms of fuzzy sets, a model can be obtained even if we have no numerical data. It is practically applicable to any case, as long as suitable knowledge is obtained. We have also studied the method to modify a membership function and showed that parameter optimization is applicable to this case.

In order to improve the total goodness of fit, it is very important to extract human knowledge and to construct effective rules. It is expected that computer graphics will help this task, which will be presented in the following chapter.

Chapter 5

Intelligent Decision Support System for Environmental Planning

5.1 Introduction

It is obviously far beyond the capabilities of individual disciplines as well as individual researchers to predict environmental problems in the early part of the 21st century. To cope with such a problem, we have developed a computer system, the main feature of which is integrated utilization of the knowledge and judgment of experts in relevant fields.

Coupled with progress in systems science and methodology, advances in digital computer technology have produced great progress in the field of decision support systems (Sage, 1981, Gruver Ford and Gardiner, 1984 and Wang and Courtney, 1984). Artificial intelligence technology has also had a great influence in this field (Zadeh, 1973 and Sage and White, 1984). User-friendly man-machine interfaces and heuristic modeling techniques are useful tools for modeling large-scale and complex systems (Nakamori, 1989).

Tools to elicit (experience-based) intuitive or inner, personal knowledge or ideas are surveyed by Lendaris (1979). Elicited knowledge or ideas are combined to develop a group product of "higher quality" than otherwise usually available. A number of tools have been developed to assist in building and analyzing structural models (Warfield, 1974 and Lendaris, 1980).

*A part of this chapter was published in IEEE Trans. Sys., Man and Cybern. (vol. 20, no. 4, pp.777-790, 1990) by M. Kainuma, Y. Nakamori and T. Morita.

Techniques applicable to machine construction of digraph maps are given by Warfield (1977) and Sugiyama, Tagawa and Toda (1981).

The purpose of developing Intelligent Decision Support System (IDSS) is to combine such methodologies systematically with experts' knowledge and to clarify current and future environmental problems. The system is used recursively to build environmental models for predicting future environmental conditions.

In this chapter we present the processes to use the intelligent decision support system: the identification process, the modeling process and the simulation process. The identification process consists of collecting knowledge as well as numerical data, identifying the structure of the problem and analyzing environmental conditions through linguistic fuzzy simulation. The modeling process consists of building computer simulation models by combining experts' judgments and numerical data. The simulation process consists of predicting future environmental conditions by assuming some policy scenarios.

As an example, we analyzed environmental problems and obtained a fuzzy model for predicting NO_2 concentration based on several future scenarios about Tokyo Bay development programs in Japan.

5.2 Identification of Environmental Problems

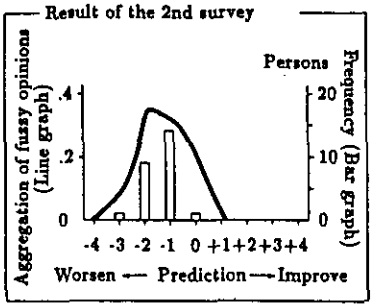
The purpose of this section is to explain identification processes for environmental problems in Japan in the early part of the 21st century. Using the Delphi method, scenarios of future environmental trends were collected and stored in the system. Then relations between socio-economic activities and environmental problems were identified in the form of graphs by using such knowledge and Visual Structuring Supporter (VSS). To further investigate the structure, we have simulated interaction among important factors by Linguistic Fuzzy Simulator (LFS).

5.2.1 How to Collect Experts' Knowledge

There are many complicated relations between socio-economic trends and environmental problems. There are socio-economic trends such as coming

Table 5.1 A scenario of traffic nuisance

Traffic Nuisance

<table>
<tr><th>Result of Survey</th><th>Approved Scenario</th></tr>
<tr><td>Trend 1: Increase in Income

</td><td><u>Pessimistic Scenario; 96%</u>
With the increase in income per capita, people will demand a much greater variety of goods. It will become important for the transportation industry to transport small quantities of goods quickly and punctually, rather than transporting large amounts of goods at low cost. Because of such a situation, traffic volume will increase throughout the whole country. Traffic for leisure will also increase with the increase in income. Although people will have much greater concern for the living environment and traffic nuisance, it will become very difficult for authorities to take effective countermeasures. Consequently, with the increase in income, traffic nuisance will become worse.</td></tr>
</table>

of information-intensive society, aging population, international trade and Tokyo Bay development. There are many environmental problems such as traffic nuisance, water pollution, solid waste problem and city amenities. We expressed such complicated relations by an 80- to 200-word scenario, as shown in Table 5.1. More than two hundred such scenarios were prepared. To check the validity of the scenarios, we used the Delphi method, which has been widely used in various fields to elicit experts' knowledge (Gordon and Helmer, 1964).

We asked experts to check whether each scenario was reasonable or not and to add a new scenario, if necessary. We asked them again, showing the previous result. Nearly one hundred scenarios were approved and translated into knowledge data.

5.2.2 What Are Knowledge Data ?

Figure 5.1 illustrates knowledge data. To explain knowledge data, we will take the scenario that describes how the increase in personal income per capita will affect traffic nuisance. We call the essence of the scenario the 'proposition'. An example of a proposition is as follows: 'As income per

Knowledge Base

FIELD: Traffic Nuisance CODE: 891103

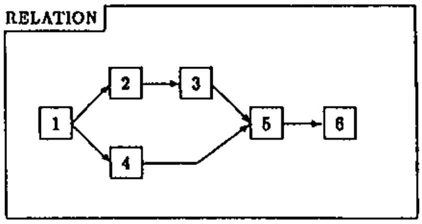
AUTHOR: S. Nishioka DATE: 01/31/89

MODIFIER: T. Morita DATE: 03/23/89

PROPOSITION

As personal income per capita increases, traffic nuisance will become worse.

RELATION



EVENT 1

CAPTION	CONTENT	REFERENCE	DATA BASE
Increase in Income	Personal income per capita will be much higher in the early part of the 21st century.	Bank of Long-Term Fund: Income and saving in Japan: Monthly Report, Apr.,1985 (in Japanese).	M0801 M0802 M0803

INDICATOR			SAME	SIMILAR	CAUSE-EFFECT	KEY WORD
Income	TREND	Increase	891113-1	891109-1		INCOME
	VALUE	Medium	INVERSE			LIVING
	CERTAINTY	High				

EVENT 2

CAPTION	CONTENT	REFERENCE	DATA BASE
Variety of Goods	Consumers will demand a variety of goods in both time and in place.	K. Iwata: Economic Incentives for Automobile Pollution Control; Environmental Research Quarterly, No.71, 61/70, 1988.	M0301 M0303

INDICATOR			SAME	SIMILAR	CAUSE-EFFECT	KEY WORD
Items of Merchandise	TREND	Increase		891108-1		CONSUMER
	VALUE	Medium	INVERSE			GOODS
	CERTAINTY	High				

EVENT 3

CAPTION	CONTENT	REFERENCE	DATA BASE
Traffic Service	Transport services change from low-cost to high quality (high speed and punctuality).	Ministry of Transportation: A long-range plan for transportation; Government of Japan, 1987 (in Japanese).	M0501 M0511

Fig. 5.1 An example of knowledge data

capita increases, traffic nuisance will become worse.' Then we analyzed the scenario and extracted several events and their relations as follows: 'Increase in income', → 'Needs for a variety of goods', → 'Change of traffic service', → 'Increase in traffic volume', → 'Worsening of traffic nuisance.' Besides such relations, other items of information such as information sources and related data base numbers are stored as knowledge data.

Knowledge Base Management System (KBMS) can find interesting knowledge data with key words and display this data immediately on request.

5.2.3 How to Identify System Structures

Several events and their relations are written in knowledge data. There are some other relations between events stored in different knowledge data. These events are linked together by VSS. The supporter can display these relations in the form of digraphs where vertices correspond to events and edges correspond to relations among these events. It is recognized empirically that drawings of the digraphs are useful as a visual aid to understand overall images of the structures of the complex systems. Sugiyama has developed methods for generating a visually understandable drawing of a hierarchy automatically by computer (Sugiyama, Tagawa and Toda 1981). We adopted these methods and modified them so as to express "similar" and "inverse" relations.

Figure 5.2 illustrates such an example. This graph is obtained by linking the event 'Worsening of traffic nuisance (Traffic Worsened)' to other related events. We find that 'Information Industry', 'Land Price Increase' and 'Production of many kinds of goods (Multi-Production)' affect traffic nuisance in addition to the event, 'Increase in Income'.

VSS has several other functions besides drawing such a structure. We can open an 'event' subwindow to find a detailed explanation of an event. Cause and effect of an event can be examined by the functions of the 'upper' and 'lower' search. The 'layout' function draws the structure in a more compact form to look at the whole structure in one frame.

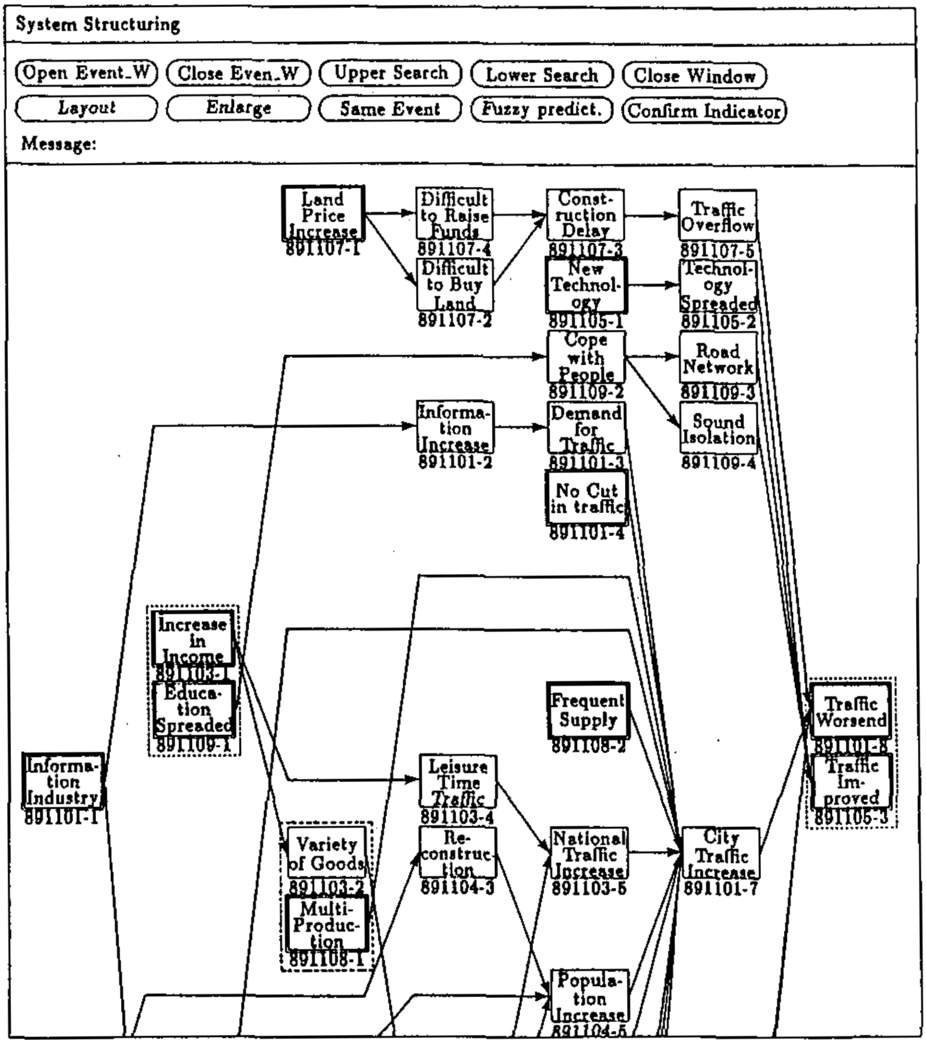


Fig. 5.2　An example of the environmental system structure

5.2.4 Analysis of System Structures

Though the process of simulating interaction between events is important in understanding the system structure, it is usually difficult to obtain sufficient numerical data to build statistical models. LFS has been developed to assist in building prediction models using experts' knowledge and the method of fuzzy reasoning.

The concept of fuzzy set theory was introduced by Zadeh (1973). A linguistic model consists of several fuzzy rules such as

$$\textit{rule } L^k \;:\; \textit{if } x_1 \textit{ is } A_1^k,\; x_2 \textit{ is } A_2^k, \cdots,\;\; x_r \textit{ is } A_r^k,$$

$$\textit{then } x_j \textit{ is } A_j^k, \quad j = r+1, r+2, \cdots, m, \tag{5.1}$$

where $x_i\,(i = 1, 2, \cdots, r)$ and $x_j\,(j = r+1, r+2, \cdots, m)$ are input and output variables, respectively. A_i^k $(i = 1, 2, \cdots, m;\ k = 1, 2, \cdots, p)$ are fuzzy sets such as *low*, *medium* and *high*. The integer p is the number of rules. LFS performs fuzzy reasoning by referring to knowledge data or querying a user about fuzzy relations.

Figure 5.3 shows an example of a linguistic fuzzy simulation. We can choose several important events from among those displayed in Fig. 5.2. Such items of information as indicators, initial values and relations are assumed initially to be those stored in the knowledge base. These data are displayed in the 'setting' subwindow. We can add, modify, or delete these data interactively. We can assign a control function to each variable. We prepared four functions, a step, unit, linear and logarithmic function for control functions. When we point to a panel of each function, a subwindow is opened for setting parameters. We can also change relations interactively with the aid of the 'relation' subwindow. The result of fuzzy reasoning is shown in the 'prediction' subwindow.

As an example, we simulated interaction among indicators such as information industry, fuel price and traffic nuisance. When fuel price rises steeply, traffic nuisance is improved slightly. As time goes on, it gets worse again with urbanization and an increase in service industries. We can analyze the environmental problems by illustrating such interaction with LFS.

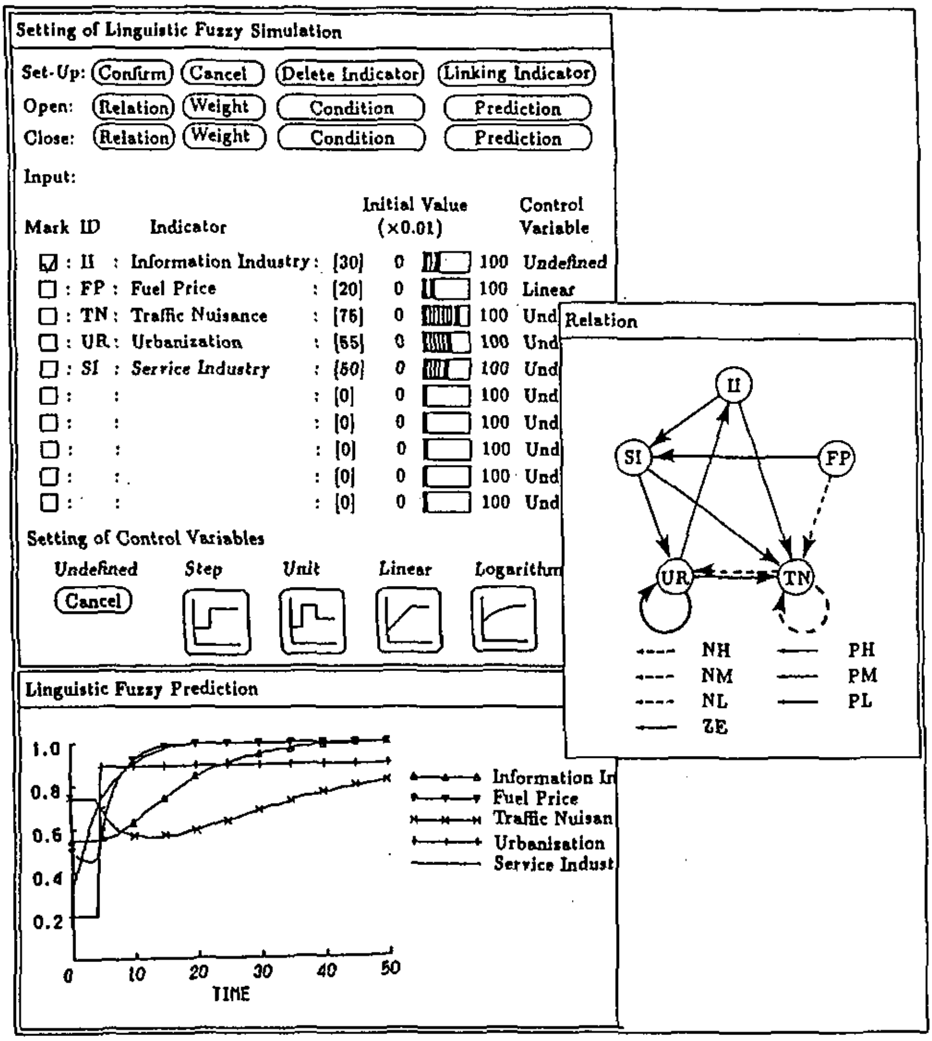


Fig. 5.3 A result of linguistic fuzzy simulation

5.3 Modeling of Environmental Systems

In Section 5.2 we analyzed environmental problems only with experts' knowledge and judgment. In this section we explain the processes of building computer simulation models by combining experts' judgments and numerical data. Three subsystems have been developed for assisting in model building, namely, Interactive Modeling Supporter (IMS), Visual Clustering Supporter (VCS) and Controlled Fuzzy Simulator (CFS).

5.3.1 Heuristic Fuzzy Modeling

In model building of environmental systems, we often encounter difficulty in obtaining linear models. To cope with such a case, we divide the data space into several fuzzy subspaces and in each fuzzy subspace we find a set of local input-output relations describing a complex system (Sugeno and Kang, 1988). The most important feature of a fuzzy model is that it can express nonlinear relations by combining fuzzy rules developed in each fuzzy subspace.

We use the same notations defined in Chapter 3. Suppose we have a set of explanatory variables $I = \{x_1, x_2, \cdots, x_r\}$ and a set of explained variables $O = \{x_{r+1}, x_{r+2}, \cdots, x_m\}$.

It is desirable to extract a linear relation in each subspace. It is, however, very difficult to do so, because we have to build $(m - r)$ equations to explain behavior of variables in the set O, and some of the elements in O are explained by not only variables in the set I but also those in O. Moreover, some of the state variables in O become explanatory variables at the next time step. Because of such a complex situation, it is very difficult to divide the data space so that we can find linear models.

In the following we adopt a stepwise process explained in Chapter 3. We divide the data space into two fuzzy subspaces with the aid of VCS.

Suppose we obtain premises of two rules:

- L^1 : *if* x_i *is* A_i^1, and
- L^2 : *if* x_i *is* A_i^2.

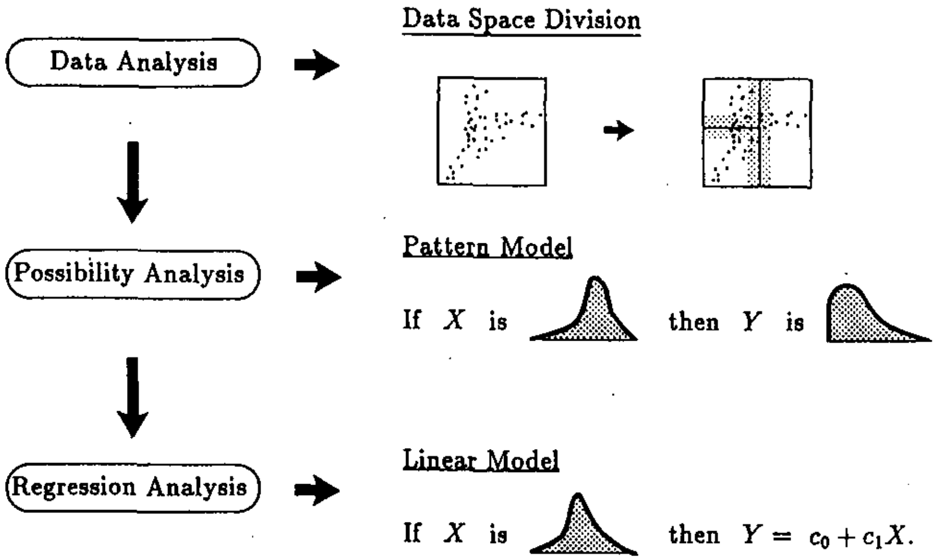


Fig. 5.4 The process of fuzzy modeling

Corresponding to these premises, we develop two pattern models by defining membership functions and two linear models with the aid of IMS. Figure 5.4 shows these processes schematically. Now we give

Definition 5.1: (membership functions).

Let us define the characteristic functions:

$$\chi_i(x_i) = \begin{cases} 1, & x_i \in A_i \\ 0, & x_i \notin A_i \end{cases} \qquad i = 1, 2, \cdots, m. \tag{5.2}$$

Let us put

$$T_i^k = \{x_{ij} \in X_i \mid \alpha_j \in X^k, j \in \{1, 2, \cdots, n\}\}, \quad i = 1, 2, \cdots, m; \ k = 1, 2, \tag{5.3}$$

and let q_{i1}^k, q_{i2}^k and q_{i3}^k be the first, second and third quartiles of the data set T_i^k. We define the membership function $A_i^k(x_i)$ of the variable x_i to the fuzzy subspace A^k as follows:

$$A_i^k(x_i) = \begin{cases} inf\{\ exp(-\frac{(x_i-q_{i2}^k)^2}{2t_1^2(q_{i1}^k-q_{i2}^k)^2}),\ \chi_i(x_i)\ \}, & x_i \leq q_{i2}^k, \\ \\ inf\{\ exp(-\frac{(x_i-q_{i2}^k)^2}{2t_2^2(q_{i3}^k-q_{i2}^k)^2}),\ \chi_i(x_i)\ \}, & x_i > q_{i2}^k, \end{cases} \tag{5.4}$$

where t_1 and t_2 are tuning parameters.

We identify the membership function with a kind of possibility distribution function and define the pattern model by

- *Pattern Model.* L^k: *if* x_i *is* A_i^k, *then*

$$x_j \textit{ is } A_j^k \quad [\textit{the membership function is } A_j^k(x_j)], \quad j = r+1, r+2, \cdots, m. \tag{5.5}$$

On the other hand, we develop a linear model in each fuzzy subspace, i.e.,

- *Linear Model.* L^k: *if* x_i *is* A_i^k, *then*

$$x_j = c_{j0}^k + \sum_{l \neq j}^{m} c_{jl}^k\ x_l, \quad j = r+1, r+2, \cdots, m. \tag{5.6}$$

IMS offers several statistics to check goodness of linear models, such as standard errors and t-ratios of estimated coefficients, and the standard deviation of residuals.

However, as it is dangerous to check goodness of linear models only by statistics, we have developed CFS to evaluate them by examining how estimates are distributed. Let us introduce

Definition 5.2: (confidence factor of estimates).

Let us generate many, say N, random numbers x_{il} such that $A_i^k(x_{il}) > 0$ $(l = 1, 2, \cdots, N)$ as input values for x_i $(i = 1, 2, \cdots, r)$. Let x_{jl}^k be the estimate of variable x_j $(j = r+1, r+2, \cdots, m)$ by the linear model of the rule L^k with the set of generated values $\{\ x_{1l},\ x_{2l}, \cdots, x_{rl}\ \}$. Let us define the *confidence factor* of the estimate x_{jl}^k by

$$c_l^k = \frac{\prod_{i=1}^r A_i^k(x_{il})}{\max_l\{\prod_{i=1}^r A_i^k(x_{il})\}}, \quad l = 1, 2, \cdots, N. \tag{5.7}$$

Note that all estimates x_{jl}^k have the same confidence factor for the l-th set of random inputs. The confidence factor indicates how the combination of input values occurred in the past. It is different from that defined in Equation 4.15 which is used when checking the model behavior with several rules. This factor is used when checking a rule.

We examine goodness of linear models by plotting (x_{jl}^k, c_l^k), $l = 1, 2, \cdots, N$, and comparing them with pattern models using computer graphics, and then decide which model we should adopt in each rule. We can fix values of some important explanatory variables throughout the simulation to reveal any special cases that may occur in the future.

Now, we summarize the algorithm of the first stage of heuristic fuzzy modeling. In principle, we divide the data space into two fuzzy subspaces and develop a pattern or linear model in each subspace. Then we repeat this process in each fuzzy subspace as long as we can obtain good models; of course the word *good* is used here somewhat subjectively.

Algorithm 1: (heuristic fuzzy modeling: stage 1).

Step 1. Develop a linear model with IMS, using all data. If a good model is obtained, then stop.

Step 2. Define the data space (support set) in $\boldsymbol{R}^m$.

Step 3. Divide the data space into two fuzzy subspaces, referring to degrees of data division and looking at scatter plots.

Step 4. Develop a pattern model in each subspace by defining membership functions.

Step 5. Develop a linear model in each subspace with IMS and carry out simulation to evaluate it.

Step 6. Determine the final model in each rule between pattern and linear models. If a good model is obtained in each subspace, then stop.

Otherwise, repeat the process from Step 3, treating each subspace as the whole data space.

5.3.2 Modification of Fuzzy Models

Suppose we obtain a submodel consisting of p rules. We explain how the submodel produces estimates of the variables in heuristic fuzzy modeling. Now we give

Definition 5.3: (estimates of heuristic fuzzy models).

Given values of inputs $x_{1*}, x_{2*}, \cdots, x_{r*}$, satisfying

$$\sum_{k=1}^{p} A_i^k(x_{i*}) > 0, \quad i = 1, 2, \cdots, r, \tag{5.8}$$

the estimates of variables in O, denoted by x_{j*}^k $(j = r+1, r+2, \cdots, m)$, based on the rule L^k are given by the simple data fitting in the case of a linear model, and by

$$x_{j*}^k = \frac{\int_R x_j \; A_j^k(x_j) \; dx_j}{\int_R \; A_j^k(x_j) \; dx_j}, \quad k = 1, 2, \cdots, p \tag{5.9}$$

in the case of a pattern model. Define the relative degrees of belief of the rule L^k by

$$\bar{w}^k = \frac{\prod_{i=1}^{r} \; A_i^k(x_{i*})}{\sum_{h=1}^{p} \; \{\prod_{i=1}^{r} \; A_i^h(x_{i*})\}} \quad k = 1, 2, \cdots, p. \tag{5.10}$$

Then the final estimate is given by

$$x_{j*} = \sum_{k=1}^{p} \; \bar{w}^k \; x_{j*}^k, \quad j = r+1, r+2, \cdots, m. \tag{5.11}$$

Now we summarize the algorithm of the second stage of heuristic fuzzy modeling, which uses several criteria defined in Chapter 3.

Algorithm 2: (heuristic fuzzy modeling: stage 2).

Step 1. Fix the values of input variables one after the other referring to the input admissible functions. If the set of active variables I_a becomes the whole set I, then set $N = 1$ and goto Step 4.

Step 2. For the variable $x_i \in I_a$, put

$$x_{il} = x_{i*}, \quad l = 1, 2, \cdots, N. \tag{5.12}$$

Step 3. For the variable $x_i \in I_{\bar{a}}$, generate N random numbers $x_{i1}, x_{i2}, \cdots, x_{iN}$ from the distribution:

$$p_i(x_i) = \frac{w_i(x_i)}{\int_R w_i(x_i)\, dx_i}. \tag{5.13}$$

Step 4. Calculate the estimates and their averages over the rules:

- estimates: x_{jl}^k, $j = r+1, r+2, \cdots, m$; $l = 1, 2, \cdots, N$; $k = 1, 2, \cdots, p$,
- averages: x_{jl}, $j = r+1, r+2, \cdots, m$; $l = 1, 2, \cdots, N$,

according to the procedure in Definition 5.3.

Step 5. Calculate the confidence factors c_l $(l = 1, 2, \cdots, N)$, the weighted averages $\bar{x}_j$ over random numbers, and the degrees of scatter s_j $(j = r+1, r+2, \cdots, m)$ according to Definitions 3.6 and 3.7.

Step 6. Plot the points

- (x_{jl}, c_l), $j = r+1, r+2, \cdots, m$; $l = 1, 2, \cdots, N$,
- $(\bar{x}_j, s_j)$, $j = r+1, r+2, \cdots, m$,

in order to evaluate the model behavior.

Step 7. Repeat the process from Step 1 to 6 several times and if necessary, modify the parameters in membership functions or build heuristic rules consisting of pattern or linear models.

5.4 Simulation of Environmental Systems

In Section 5.3 we explained the processes involved in building computer simulation models. In simulation processes we have to take different models together and set the values of explanatory variables by referring to possible policy options or constraints in carrying out the plans. The model base management system stores up-to-date submodels and combines such models with future scenarios for predicting future environmental conditions.

Note that explanatory variables are not independent in the usual case. Therefore we carefully choose explanatory variables which should be included in I_a, the set of active variables. Moreover, as mentioned in Section 5.3.1, the same variable can be included in both the sets I and O, representing its states at subsequent time steps.

To make the discussion clear, we introduce some notations. Let $I(t)$ and $O(t)$ be the set of explanatory and explained variables at time t. They are decomposed as follows:

$$I(t) = C(t) \bigcup S(t-1), \quad C(t) \bigcap S(t-1) = \phi, \tag{5.14}$$

$$O(t) = S(t) \bigcup Y(t), \quad S(t) \bigcap Y(t) = \phi, \tag{5.15}$$

where $C(t), S(t)$ and $Y(t)$ are the control, state and output variables, respectively.

Some of the variables in $I(t)$ can take fixed values at time t and others can take random values within their input ranges which will be defined later. Let $I_a(t)$ be the set of active variables: this means that their values are fixed by the feedback control or manual control in the case of control variables, and by the result of simulation in the case of state variables. Note that even control variables can take their values randomly in the defined ranges.

We introduce the input distributions at each time step for the variables in $I_{\bar{a}}(t)$ $(= I(t) - I_a(t))$, taking account of the states at one-step before and the input admissibility that is related to the confidence of the model. Now we introduce

Definition 5.4: (input distribution).

Consider the discrete time sequence $t = 0, 1, 2, \cdots$, and at each time step t, define the data set $T_i(t)$ for $x_i \in I_a(t)$ by

$$T_i(t) = \begin{cases} X_i, & t = 0 \;\; or \; x_i \in C(t), \\ \{x_{i1}^*, x_{i2}^*, \cdots, x_{iN}^*\}, & t > 0 \; and \; x_i \in S(t), \end{cases} \tag{5.16}$$

where X_i is the measurement data set for x_i, and x_{il}^* is the l-th estimate for x_i at $t-1$. Let q_{i1}, q_{i2} and q_{i3} be the first, second and third quartiles of the set $T_i(t)$, respectively. We define the *input distribution* of a variable $x_i \in I_a(t)$ by

$$f_i(x_i) = \begin{cases} inf\{exp(-\frac{(x_i - q_{i2})^2}{2(q_{i1}-q_{i2})^2}), \;\; w_i(x_i)\}, & x_i \le q_{i2}, \\ inf\{exp(-\frac{(x_i - q_{i2})^2}{2(q_{i3}-q_{i2})^2}), \;\; w_i(x_i)\}, & x_i \ge q_{i2}, \end{cases} \tag{5.17}$$

where $w_i(x_i)$ is the input admissible function introduced in Definition 3.5, which are changed by the values of variables in $I_a(t)$. If $q_{i1} = q_{i2}$ or $q_{i3} = q_{i2}$, then we put $q_{i1} = q_{i1} - \epsilon$ or $q_{i3} = q_{i3} + \epsilon$, where ϵ is a positive small number. We call the set $\{\ x_i \mid f_i(x_i) > 0\ \}$ the *input range* for $x_i \in I_a$.

The algorithm for dynamic fuzzy simulation is given as follows:

Algorithm : (dynamic fuzzy simulation).

Step 1. Set $t = 0$. Fix the values of explanatory variables as x_{i*} one after the other in their input ranges for some important variables in $I(t)$.

Step 2. Calculate the input distributions of variables in $I_a(t)$ by the procedure in Definition 5.4.

Step 3. For the variable $x_i \in I_a(t)$, put

$$x_{il} = x_{i*}, \quad l = 1, 2, \cdots, N. \tag{5.18}$$

Step 4. For the variable $x_i \in I_a(t)$, generate N random numbers $x_{i1}, x_{i2}, \cdots, x_{iN}$ from the distribution:

$$p_i(x_i) = \frac{f_i(x_i)}{\int_R f_i(x_i)dx_i}. \tag{5.19}$$

Step 5. Calculate the estimate

$$x_{jl}^k, \quad j = r+1, r+2, \cdots, m; \quad l = 1, 2, \cdots, N; \quad k = 1, 2, \cdots, p,$$

according to the procedure in Definition 5.3.

Step 6. Calculate the average values x_{jl} of x_{jl}^k $(k = 1, 2, \cdots, p)$ over the rules by

$$x_{jl} = \frac{\sum_{k=1}^{p} w_l^k x_{jl}^k}{\sum_{k=1}^{p} w_l^k}, \quad w_l^k = \prod_{i=1}^{r} A_i^k(x_{il}), \quad l = 1, 2, \cdots, N. \tag{5.20}$$

Step 7. Let $t = t+1$. Modify the sets $T_i(t)$ and $I_a(t)$. Repeat the process from Step 2 until the specified terminal time step.

5.5 Case Study on Tokyo Bay Development

Tokyo and its surroundings form one of the biggest metropolitan areas in the world and its population is expected to increase by about three million in ten years. Industrial activities will also grow rapidly in this area. There are many Tokyo Bay development programs to supply offices and houses for promoting such progress. The purpose of this section is to estimate the environmental impacts of Tokyo Bay development programs by modeling air pollution concentration.

Table 5.2 List of variables in Submodel 1

Notation	Meaning
NO2	NO2 concentration (ppb) [yearly mean in the area]
bay_dist	Distance from Tokyo Bay (km) [to the center of the area]
pop_day	Population density in the daytime (persons / km^2) [*in the area & neighbors*]
ind_proc	Industrial shipment density (10^4 yen / km^2) [in the area & neighbors]
ind_city	Urban industrial shipment density (10^4 yen / km^2) [in the area & neighbors]
trade	Density of the wholesale and retail sales (10^4 yen / km^2) [in the area & neighbors]
traf_den	Weighted traffic density ($10^4/km^2$ h) [*in the area & neighbors*]
ind_squ	Land use for industry (%) [in the area & neighbors]
traf_squ	Land use for traffic (%) [in the area & neighbors]

5.5.1 Model Structuring

Referring to system structures analyzed in Section 5.2, model structures were discussed among experts, decision makers and analysts. The developed model consists of two submodels. Submodel 1 estimates the average concentration of nitrogen dioxide (NO_2), the weighted traffic density ($traf\_den$), etc. in an administrative area based on the changes in population density in the daytime (pop_day) in the area and neighboring regions. Submodel 2 estimates the changes in population density in the daytime in the area based on the scenarios about the increase in offices and houses along the coast of Tokyo Bay.

The selected variables to develop Submodels 1 and 2 are summarized in Table 5.2 and 5.3, respectively. Figure 5.5 shows the hierarchical model structure assumed at the beginning. Note that any variable with incoming arcs should be explained by some of the lower level variables in terms of a pattern or linear model. There are five and seven explained variables in Submodels 1 and 2, respectively.

Table 5.3 List of variables in Submodel 2

Notation	Meaning
pop_dens	Population density (persons / km^2) [in the area]
pop_inc	Rate of population increase (% / year) [in the area]
pop_day	Population density in the daytime (persons / km^2) [in the area]
pop_dinc	Rate of population increase in the daytime (% / year) [in the area]
hous_rat	Land use for housing (%) [in the area]
hous_inc	Rate of increase of housing area (% / year) [in the area]
off_inc	Rate of increase of offices (% / year) [in the area]
cent_dis	Distance from the center of Tokyo (km) [to the center of the area]
pop_prop	Population density (persons / km^2) [in the neighbors affecting the area]
pop_inc*	Rate of population increase (% / year) [the year before] [in the area]
pop_pro*	Rate of population increase (% / year) [the year before] [in the neighbors affecting the area]
off_pro*	Rate of increase of offices (% / year) [the year before] [in the neighbors affecting the area]

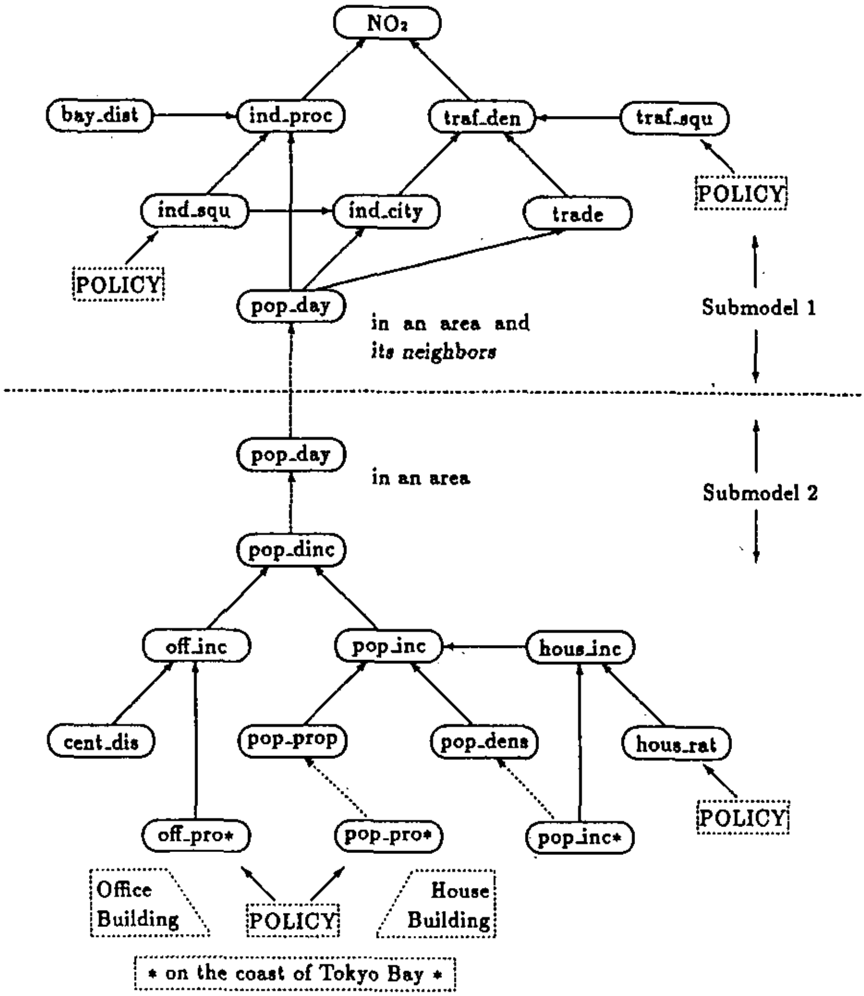


Fig. 5.5 The hierarchical model structure assumed at the beginning

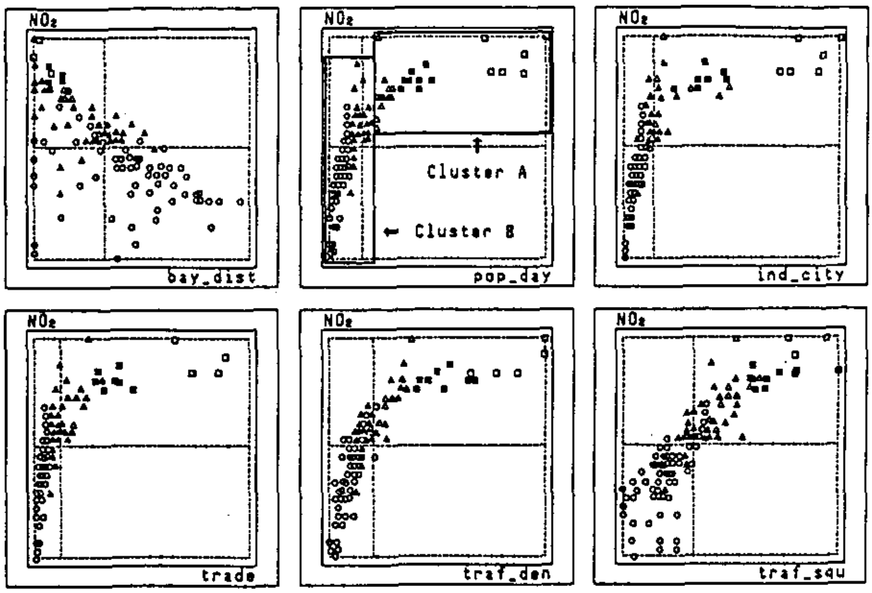


Fig. 5.6 Scatter plots of NO_2 versus the main explanatory variables

5.5.2 Fuzzy Model Building

The main purpose of this section is to build models to estimate the influence of building new offices and houses along the coast of Tokyo Bay. For developing Submodel 1, we divide the data space by the variable *pop_day* by looking at scatter plots like Fig. 5.6 in which the same marks indicate that the corresponding data are contained in the same cluster. In practice they are distinguished by different colors on the computer. We build Rules 1_1 (*pop_day* is large) and 1_2 (*pop_day* is small) independently, using the divided data sets that correspond to clusters A and B, respectively, in Fig. 5.6.

We examine goodness of linear models by the proposed simulation technique. Figure 5.7 illustrates random simulation with Rule 1_1. The explanatory variables are placed on the left with the membership functions drawn in a discrete form. The simulation result is shown on the right in Fig. 5.7. The estimated values and their confidence factors (x_{jl}^1, c_l^1) are drawn with 21×7 levels. Figure 5.7 shows that all explained variables are well estimated by linear models. We first set the tuning parameters t_1 and

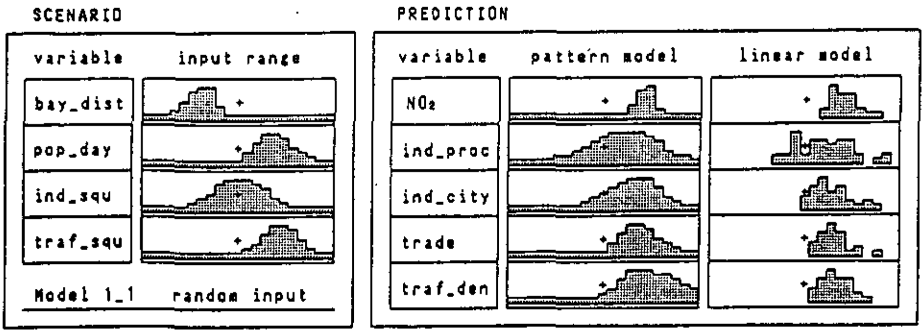


Fig. 5.7 Random simulation with Rule 1_1

t_2 in membership functions as 1 for all variables. We also adopted linear models for Rule 1_2.

Figure 5.8 shows a result of fuzzy simulation using Rules 1_1 and 1_2. The simulation is carried out by fixing the values of *bay_dist* at the levels 7, 10 and 13, and changing the values of *pop_day* from level 8 to 17.

From Fig. 5.8 we can see that as population density (*pop_day*) becomes higher, NO2 concentration (NO_2) becomes lower when *bay_dist* is large, which contradicts the observed phenomena. It is necessary to adjust parameters in membership functions and to build another rule for the case where both *pop_day* and *bay_dist* are large. However, we have few data for such a case. Figure 5.9 shows random simulation when both *pop_day* and *bay_dist* are large. Here, we use the linear models developed in Rule 1_1 (*pop_day* is large). The estimates of the linear models for NO_2 and *ind_proc* are smaller than those of the pattern models. We develop Rule 1_3, in which NO_2 and *ind_proc* are explained by pattern models and others are explained by linear models. Moreover, we change the tuning parameters as follows: $t_1 = 2.0$ for *bay_dist* in Rule 1_1, $t_1 = t_2 = 2.0$ for *pop_day* in Rule 1_2, and $t_1 = 0.5$ for *bay_dist* in Rule 1_3. Figure 5.10 shows the simulation result after the above modification, which is fairly satisfactory.

For Submodel 2, we develop Rules 2_1 and 2_2 corresponding to two premises: *pop_inc** is large and *pop_inc** is small. In Rule 2_1 we use linear models for all explained variables, but in Rule 2_2 we have to use pattern models for *pop_dens*, *pop_prop* and *off_inc*. We omit here any further

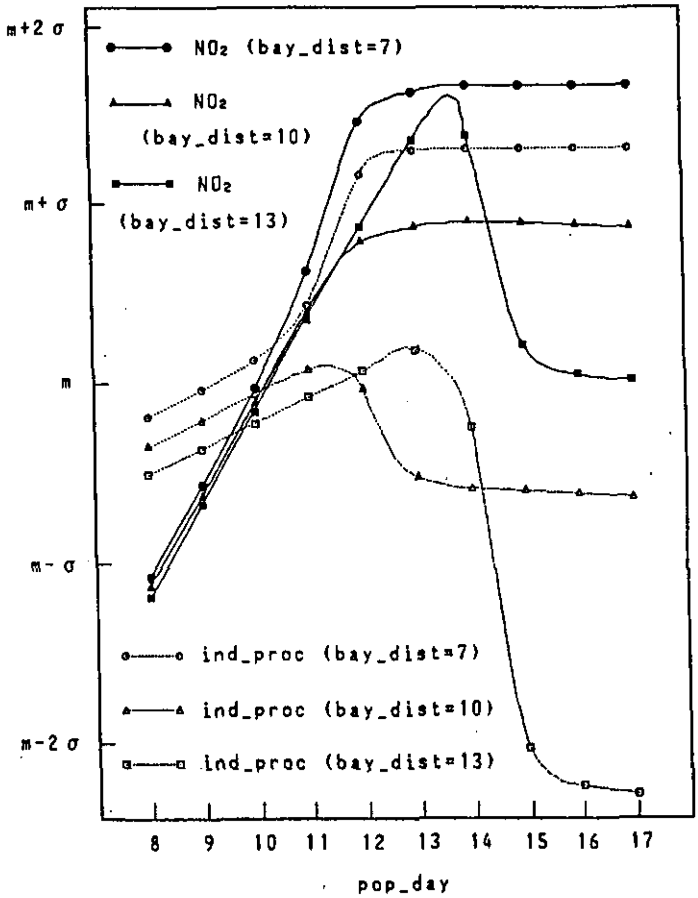


Fig. 5.8 Fuzzy simulation with Rules 1_1 and 1_2

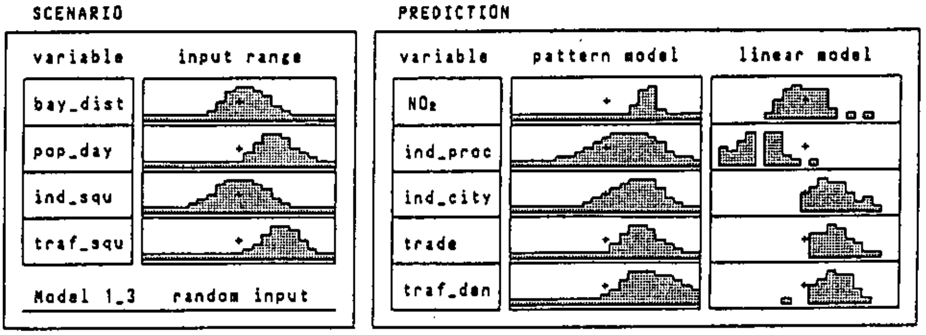


Fig. 5.9 Random simulation with Rule 1_3

explanation about Submodel 2.

Figure 5.11 is an example of the scene in simulation. Using the developed Submodels 1 and 2, we can simulate future states of explained variables by assuming some scenarios regarding Tokyo Bay development. We are continuously developing other rules concerning our future environment.

5.6 Concluding Remarks

In order to predict the future environment, we have developed a computer system, the main feature of which is integrated utilization of the knowledge and judgment of experts in relevant fields. There are many cases when we cannot obtain sufficient numerical data to build up statistical models. This computer system is designed to cope with such a situation and to analyze the environmental problems.

With this system, we identify the environmental problems and can obtain a fuzzy model for estimating the environmental impact of Tokyo Bay development programs. The system is useful as a decision support tool for clarifying current and future issues concerning the environment, for planning an effective management program and for promoting communication among researchers.

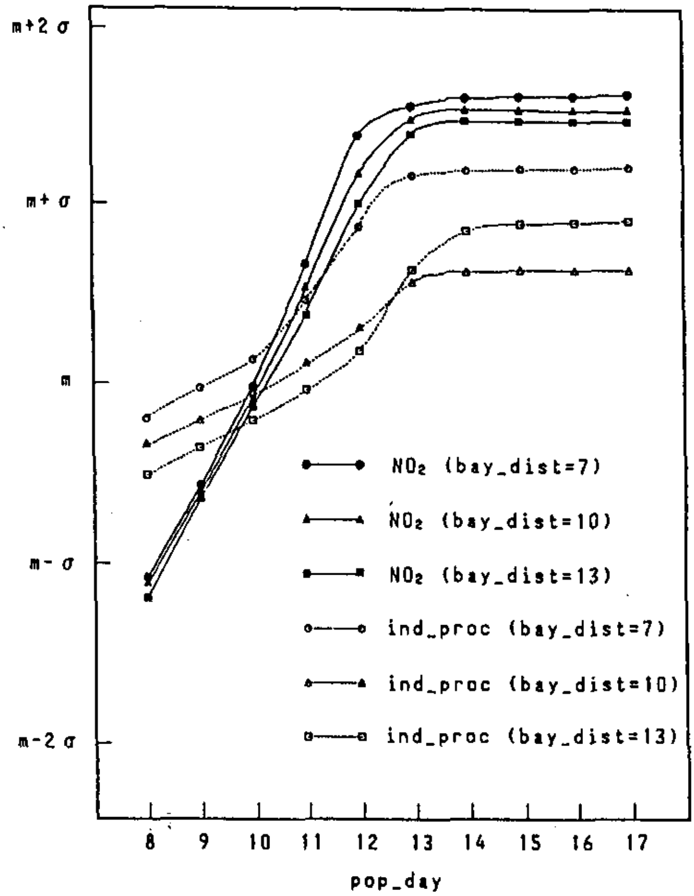


Fig. 5.10 Fuzzy simulation with Rules 1_1, 1_2 and 1_3

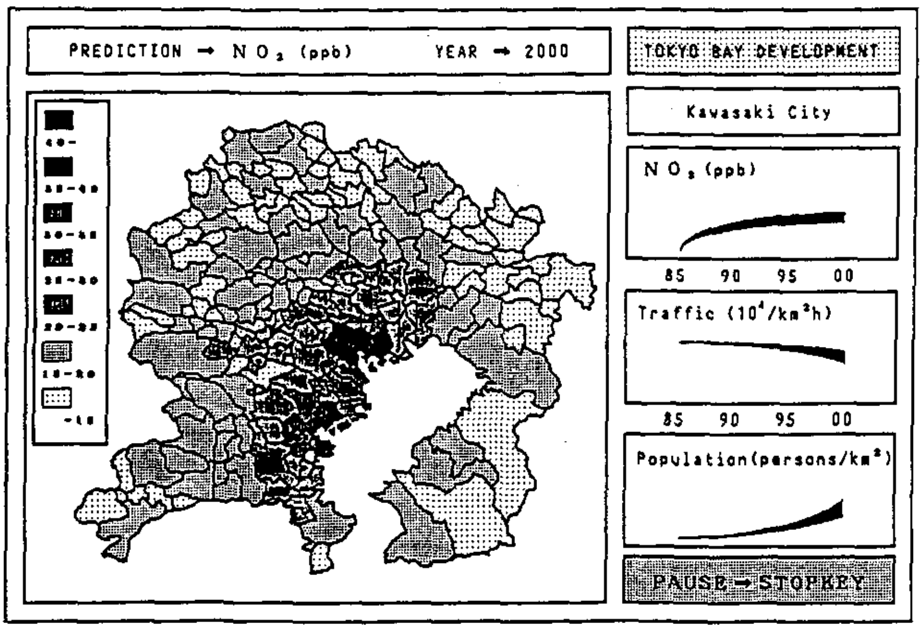


Fig. 5.11 Dynamic fuzzy simulation with the Tokyo Bay model

Chapter 6

Concluding Remarks

6.1 Summary

An intelligent decision support system for use in environmental planning has been developed. It consists of eight subsystems; three subsystems are used for managing relevant data and models, two subsystems are used for identifying environmental problems and three subsystems are used for their modeling and simulation.

It is difficult to obtain sufficient numerical data to build up statistical models for the prediction of environmental problems. The purpose of developing this computer system is to assist in identifying environmental problems as well as in building statistical models that use experts' knowledge and judgment from the relevant fields.

To use experts' knowledge effectively, we have developed a highly user-friendly software. This system assists in model building and reduces the burden of trial and error necessary for developing a computer simulation model.

Fuzzy modeling techniques have also been developed for modeling non-linear systems. Confidence factors and degrees of scatter are defined to see to which degree the obtained model is suited for simulation. The developed computer system assists in understanding model behavior.

Linguistic fuzzy modeling is also an effective tool where we cannot obtain a satisfactory model by statistical modeling. The developed system is helpful for building linguistic fuzzy models.

With this system, we have analyzed urban environmental problems. The relations between urban activities and environmental conditions are identified and future environmental conditions have been simulated.

The system is useful as a decision support tool because it can clarify current and future issues concerning the environment, as well as assist in the planning of effective management programs. It also promotes communication between researchers in different scientific fields who are studying complicated environmental problems.

6.2 Future Directions

There are a number of avenues available for the improvement and/or extension of Intelligent Decision Support System. One that is currently being researched is a method of classifying knowledge data. There are various kinds of knowledge data and it is very difficult to find relations among them. We are developing methods to classify these data interactively and to draw graphs which represent their relations.

We are also studying a method to modify graphs drawn on a computer. It is recognized empirically that graphs are useful as a visual aid to understand overall images of structures of complex systems. We have implemented the method to draw graphs automatically. However, there are some cases when we want to modify the results. For this purpose we are implementing the method to change the relations and corresponding graphs interactively. This method is also useful for classifying knowledge data.

Another area for future research that is being examined is improvement of algorithms. To use the system interactively, it is essential that the response time is short. Since execution of dynamic fuzzy simulation requires much time, we are improving some algorithms. It requires much time to calculate input admissible ranges and confidence factors and to simulate future environmental conditions.

For utilizing the knowledge base more effectively, we have to store as much knowledge data as possible. One bottleneck is the conversion from a scenario to knowledge data. It is important to develop methods of automatically interpreting scenarios and translating them into knowledge data. For this purpose natural language expression should be studied.

We sometimes find conflicts between knowledge data. It is necessary to clarify these conflicts and to treat them so that users do not misunderstand their relations. Methods to detect conflicts and to interpret them should be studied.

A problem also lies in understanding the simulation results and translating them into knowledge data. We suggested a method in Chapter 3, where input admissible functions, confidence factors and degrees of scatter give useful information for their translation. It is necessary to develop a method to translate the simulation results into the form of if-then rules for storing the simulation results and making use of them.

It is also useful to further study methods of fuzzy reasoning for analyzing environmental structures. There are many cases when we cannot obtain sufficient numerical data to build up statistical models. Knowledge and judgment of experts are important factors to clarify current and future environmental problems. Methods to represent and utilize knowledge data should be extended.

These methods, if implemented, would make the system more useful and would encourage users to prepare more detailed and more accurate models. This system would become more effective for clarifying the long-term changes of environment, and reflecting it in environmental planning processes.

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環境のモデリングと計画のための知的意思決定支援システムの開発

甲斐沼美紀子・中森義輝・森田恒幸

環境システムに代表される，多くの変数が複雑に絡み合った非線形システムの制御を総合的に行うことは非常に困難である。本報告はこの種の問題に対して，客観的データに加え主観的知識を有効に活用するための方法論及び支援システムの開発に関する研究をまとめたものである。

第1章では，環境システムのモデリングの課題，及び，従来のモデリング手法の問題点を述べたのち，専門家の知識の利用の重要性を指摘し，それを支援するシステムの概要を説明するとともに，本研究の目的について述べた。

第2章では，計算機との対話によるモデリング手法に関する研究成果を述べた。まず，環境システムのモデリングで生じる問題点を指摘したのち，人間と計算機との対話によるモデリングの重要性を述べた。大気汚染濃度の予測を取り上げ対話型支援システムの有効性を述べた。

第3章では，非線形現象に対するモデル構造を決定するためのファジィシミュレーションに関する研究成果をまとめた。客観的情報に加え主観的知識を有効に利用する方法を提案した。複雑なシステムの非線形現象を表現するために，視覚的クラスタリングを用いた段階的モデリングについて述べた。ファジィシミュレーションの際，入力を制御する方法及びシミュレーション結果から知識モデルを構築する方法について述べた。大気汚染濃度の予測を例としてファジィモデリングの有効性を示した。

第4章では，専門家の経験的な知識をモデリングに取り込む方法について述べた。ファジィ理論を適用して専門家の知見を数式表現し，大気汚染濃度の予測に活用する手法を提案した。

第5章では，各種のモデリング手法を統合的に使用するための予測支援システムについて述べた。環境問題を同定する際の問題点を指摘し，予測支援システムの役割を述べた。環境システムのモデリングのために，発見的なファジィモデリングを提案し，そのアルゴリズム及びシミュレーション手法について述べた。東京湾開発による環境影響予測を取り上げ，支援システムの有効性を検討した。

国立公害研究所特別研究成果報告
第１号　陸水域の富栄養化に関する総合研究－－霞ヶ浦を対象域として－－昭和51年度.(1977)
第２号　陸上植物による大気汚染環境の評価と改善に関する基礎的研究－－昭和51/52年度 研究報告.(1978)

(改称)
国立公害研究所研究報告
※第３号　A comparative study of adults and immature stages of nine Japanese species of the genus Chironomus (Diptera, Chironomidae).(1978)
(日本産ユスリカ科 Chironomus 属9種の成虫，サナギ，幼虫の形態の比較)
第４号　スモッグチャンバーによる炭化水素-窒素酸化物系光化学反応の研究－－昭和52年度 中間報告.(1978)
第５号　芳香族炭化水素-窒素酸化物系の光酸化反応機構と光酸化二次生成物の培養細胞に及ぼす影響に関する研究－－昭和51，52年度 研究報告.(1978)
第６号　陸水域の富栄養化に関する総合研究（Ⅱ）－－霞ヶ浦を中心として－－昭和53年度.(1979)
※第７号　A morphological study of adults and immature stages of 20 Japanese species of the family Chironomidae(Diptera).(1979)
(日本産ユスリカ科20種の成虫，サナギ，幼虫の形態学的研究)
※第８号　大気汚染物質の単一および複合汚染の生体に対する影響に関する実験的研究－－昭和52，53年度 研究報告.（1979)
第９号　スモッグチャンバーによる炭化水素-窒素酸化物系光化学反応の研究－－昭和53年度 中間報告.(1979)
第10号　陸上植物による大気汚染環境の評価と改善に関する基礎的研究－－昭和51～53年度 特別研究報告.(1979)
※第11号　Studies on the effects of air pollutants on plants and mechanisms of phytotoxicity.(1980)
(大気汚染物質の植物影響およびその植物毒性の機構に関する研究)
第12号　Multielement analysis studies by flame and inductively coupled plasma spectroscopy utilizing computer-controlled instrumentation.(1980)
(コンピュータ制御装置を利用したフレームおよび誘導結合プラズマ分光法による多元素同時分析)
※第13号　Studies on chironomid midges of the Tama River.(1980)
Part 1. The distribution of chironomid species in a tributary in relation to the degree of pollution with sewage water.
Part 2. Description of 20 species of Chironominae recovered from a tributary.
(多摩川に発生するユスリカの研究
－－第１報　その一支流に見出されたユスリカ各種の分布と下水による汚染度との関係
－－第２報　その一支流に見出された Chironominae亜科の20種について)
※第14号　有機廃棄物，合成有機化合物，重金属等の土壌生態系に及ぼす影響と浄化に関する研究－－昭和53，54年度 特別研究報告.(1980)
※第15号　大気汚染物質の単一および複合汚染の生体に対する影響に関する実験的研究－－昭和54年度 特別研究報告.(1980)
第16号　計測車レーザーレーダーによる大気汚染遠隔計測.(1980)
※第17号　流体の運動および輸送過程に及ぼす浮力効果－－臨海地域の気象特性と大気拡散現象の研究－－昭和53，54年度 特別研究報告.(1980)
※第18号　Preparation, analysis and certification of PEPPERBUSH standard reference material.(1980)
(環境標準試料「リョウブ」の調整，分析および保証値)
※第19号　陸水域の富栄養化に関する総合研究(Ⅲ)－－霞ヶ浦(西浦)の湖流－－昭和53，54年度.(1981)
※第20号　陸水域の富栄養化に関する総合研究(Ⅳ)－－霞ヶ浦流域の地形，気象水文特性およびその湖水環境に及ぼす影響－－昭和53，54年度.(1981)
※第21号　陸水域の富栄養化に関する総合研究(Ⅴ)－－霞ヶ浦流入河川の流出負荷量変化とその評価－－昭和53，54年度.(1981)
第22号　陸水域の富栄養化に関する総合研究(Ⅵ)－－霞ヶ浦の生態系の構造と生物現存量－－昭和53，54年度.（1981)
第23号　陸水域の富栄養化に関する総合研究(Ⅶ)－－湖沼の富栄養化状態指標に関する基礎的研究－－昭和53，54年度.(1981)
第24号　陸水域の富栄養化に関する総合研究(Ⅷ)－－富栄養化が湖利用に及ぼす影響の定量化に関する研究－－昭和53，54年度.(1981)
第25号　陸水域の富栄養化に関する総合研究(Ⅸ)－－Microcyctis（藍藻類)の増殖特性－－昭和53，54年度.(1981)

※第26号　陸水域の富栄養化に関する総合研究(X)－－藻類培養試験法によるAGPの測定－－昭和53，54年度.(1981)
第27号　陸水域の富栄養化に関する総合研究(XI)－－研究総括－－昭和53，54年度.(1981)
第28号　複合大気汚染の植物影響に関する研究－－昭和54，55年度 特別研究報告.(1981)
※第29号　Studies on chironomid midges of the Tama River.(1981)
Part 3. Species of the subfamily Orthocladiinae recorded at the summer survey and their distribution in relation to the pollution with sewage waters.
Part 4. Chironomidae recorded at a winter survey.
(多摩川に発生するユスリカ類の研究
－－第３報　夏期の調査で見出されたエリユスリカ亜科Orthocladiinae 各種の記載と，その分布の下水汚染度との関係について
－－第４報　南浅川の冬期の調査で見出された各種の分布と記載)
※第30号　海域における富栄養化と赤潮の発生機構に関する基礎的研究－－昭和54，55年度 特別研究報告.(1982)
※第31号　大気汚染物質の単一および複合汚染の生体に対する影響に関する実験的研究－－昭和55年度 特別研究報告.(1981)
第32号　スモッグチャンバーによる炭化水素-窒素酸化物系光化学反応の研究－－環境大気中における光化学二次汚染物質生成機構の研究（フィールド研究１）－－昭和54年度 特別研究中間報告.(1982)
※第33号　臨海地域の気象特性と大気拡散現象の研究－－大気運動と大気拡散過程のシミュレーション－－昭和55年度 特別研究報告.(1982)
※第34号　環境汚染の遠隔計測･評価手法の開発に関する研究--昭和55年度 特別研究報告.(1982)
第35号　環境面よりみた地域交通体系の評価に関する総合解析研究.(1982)
※第36号　環境試料による汚染の長期モニタリング手法に関する研究－－昭和55，56年度 特別研究報告.(1982)
※第37号　環境施策のシステム分析支援技術の開発に関する研究.(1982)
第38号　Preparation, analysis and certification of POND SEDIMENT certified reference material.(1982)
(環境標準試料｢池底質｣の調整，分析及び保証値)
※第39号　環境汚染の遠隔計測･評価手法の開発に関する研究－－昭和56年度 特別研究報告.(1982)
※第40号　大気汚染物質の単一及び複合汚染の生体に対する影響に関する実験的研究－－昭和56年度 特別研究報告.(1983)
※第41号　土壌環境の計測と評価に関する統計学的研究.(1983)
※第42号　底泥の物性及び流送特性に関する実験的研究.(1983)
※第43号　Studies on chironomid midges of the Tama River.(1983)
Part 5. An observation on the distribution of Chironominae along the main stream in June with description of 15 new species.
Part 6. Description of species of the subfamily Orthocladiinae recovered from the main stream in the June survey.
Part 7. Additional species collected in winter from the main stream.
(多摩川に発生するユスリカ類の研究
－－第５報　本流に発生するユスリカ類の分布に関する６月の調査成績とユスリカ亜科に属する15新種等の記録
－－第６報　多摩本流より６月に採集されたエリユスリカ亜科の各種について
－－第７報　多摩本流より３月に採集されたユスリカ科の各種について)
第44号　スモッグチャンバーによる炭化水素-窒素酸化物系光化学反応の研究－－環境大気中における光化学二次汚染物質生成機構の研究（フィールド研究２）－－昭和54年度 特別研究中間報告.(1983)
※第45号　有機廃棄物，合成有機化合物，重金属等の土壌生態系に及ぼす影響と浄化に関する研究－－昭和53～55年度 特別研究総合報告.(1983)
※第46号　有機廃棄物，合成有機化合物，重金属等の土壌生態系に及ぼす影響と浄化に関する研究－－昭和54，55年度 特別研究報告 第１分冊.(1983)
※第47号　有機廃棄物，合成有機化合物，重金属等の土壌生態系に及ぼす影響と浄化に関する研究－－昭和54，55年度 特別研究報告 第２分冊.(1983)
※第48号　水質観測点の適正配置に関するシステム解析.(1983)
第49号　環境汚染の遠隔計測･評価手法の開発に関する研究－－昭和57年度 特別研究報告.(1984)
※第50号　陸水域の富栄養化防止に関する総合研究(Ｉ)－－霞ヶ浦の流入負荷量の算定と評価－－昭和55～57年度 特別研究報告.(1984)

※第51号 陸水域の富栄養化防止に関する総合研究(II)－－霞ヶ浦の物質循環とそれを支配する因子－－昭和55～57年度 特別研究報告.(1984)

※第52号 陸水域の富栄養化防止に関する総合研究(III)－－霞ヶ浦高浜入における隔離水界を利用した富栄養化防止手法の研究－－昭和55～57年度 特別研究報告.(1984)

第53号 陸水域の富栄養化防止に関する総合研究(IV)－－霞ヶ浦の魚類及び甲かく類現存量の季節変化と富栄養化－－昭和55～57年度 特別研究報告.(1984)

※第54号 陸水域の富栄養化防止に関する総合研究(V)－－霞ヶ浦の富栄養化現象のモデル化－－昭和55～57年度 特別研究報告.(1984)

第55号 陸水域の富栄養化防止に関する総合研究(VI)－－富栄養化防止対策－－昭和55～57年度 特別研究報告.(1984)

第56号 陸水域の富栄養化防止に関する総合研究(VII)－－湯ノ湖における富栄養化とその防止対策－－昭和55～57年度 特別研究報告.(1984)

※第57号 陸水域の富栄養化防止に関する総合研究(VIII)－－総括報告－－昭和55～57年度 特別研究報告.(1984)

※第58号 環境試料による汚染の長期的モニタリング手法に関する研究－－昭和55～57年度 特別研究総合報告.(1984)

第59号 炭化水素-窒素酸化物-硫黄酸化物系光化学反応の研究－－光化学スモッグチャンバーによるオゾン生成機構の研究－－大気中における有機化合物の光酸化反応機構の研究－－昭和55～57年度 特別研究報告(第1分冊).(1984)

第60号 炭化水素-窒素酸化物-硫黄酸化物系光化学反応の研究－－光化学エアロゾル生成機構の研究－－昭和55～57年度 特別研究報告(第2分冊).(1984)

第61号 炭化水素-窒素酸化物-硫黄酸化物系光化学反応の研究－－環境大気中における光化学二次汚染物質生成機構の研究（フィールド研究1）－－昭和55～57年度 特別研究報告(第3分冊).(1984)

※第62号 有害汚染物質による水界生態系のかく乱と回復過程に関する研究－－昭和56～58年度 特別研究中間報告.(1984)

※第63号 海域における富栄養化と赤潮の発生機構に関する基礎的研究－－昭和56年度 特別研究報告.(1984)

※第64号 複合大気汚染の植物影響に関する研究－－昭和54～56年度 特別研究総合報告.(1984)

※第65号 Studies on effects of air pollutant mixtures on plants－－Part 1.(1984)
(複合大気汚染の植物に及ぼす影響－－第1分冊)

※第66号 Studies on effects of air pollutant mixtures on plants－－Part 2.(1984)
(複合大気汚染の植物に及ぼす影響－－第2分冊)

※第67号 環境中の有害物質による人の慢性影響に関する基礎的研究－－昭和54～56年度 特別研究総合報告.(1984)

※第68号 汚泥の土壌還元とその環境影響に関する研究－－昭和56～57年度 特別研究報告.(1984)

※第69号 中禅寺湖の富栄養化現象に関する基礎的研究.(1984)

※第70号 Studies on chironomid midges in lakes of the Nikko National Park.(1984)
Part I. Ecological studies on chironomids in lakes of the Nikko National Park.
Part II. Taxonomical and morphological studies on the chironomid species collected from lakes in the Nikko National Park.
(日光国立公園の湖沼のユスリカに関する研究
－－第1部 日光国立公園の湖のユスリカの生態学的研究
－－第2部 日光国立公園の湖沼に生息するユスリカ類の分類学的，生態学的研究)

※第71号 リモートセンシングによる残雪及び雪田植生の分布解析.(1984)

第72号 炭化水素-窒素酸化物-硫黄酸化物系光化学反応の研究－－環境大気中における光化学二次汚染物質生成機構の研究(フィールド研究2)－－昭和55～57年度 特別研究報告(第4分冊).(1985)

※第73号 炭化水素-窒素酸化物-硫黄酸化物系光化学反応の研究－－昭和55～57年度 特別研究総合報告.(1985)

※第74号 都市域及びその周辺の自然環境に係る環境指標の開発に関する研究. 環境指標－その考え方と作成方法－昭和59年度 特別研究報告.(1984)

第75号 Limnological and environmental studies of elements in the sediment of Lake Biwa.(1985)
(琵琶湖底泥中の元素に関する陸水学及び環境化学的研究)

第76号 A study on the behavior of monoterpens in the atmosphere.(1985)
(大気中モノテルペンの挙動に関する研究)

※第77号 環境汚染の遠隔計測·評価手法の開発に関する研究－－昭和58年度 特別研究報告.(1985)

第78号 生活環境保全に果たす生活者の役割の解明.(1985)

第79号 Studies on the method for long term environmental monitoring－－Research report in 1980-1982.(1985)
(環境試料による汚染の長期的モニタリング手法に関する研究)

※第80号 海域における赤潮発生のモデル化に関する研究－－昭和57/58年度 特別研究報告.(1985)

※第81号　環境影響評価制度の政策効果に関する研究－－地方公共団体の制度運用を中心として.(1985)
※第82号　植物の大気環境浄化機能に関する研究－－昭和57～58年度 特別研究報告.(1985)
第83号　Studies on chironomid midges of some lakes in Japan.(1985)
(日本の湖沼のユスリカの研究)
※第84号　重金属環境汚染による健康影響評価手法の開発に関する研究－－昭和57～59年度 特別研究総合報告.(1985)
第85号　Studies on the rate constants of free radical reactions and related spectroscopic and thermochemical parameters.(1985)
(フリーラジカルの反応速度と分光学的及び熱力学的パラメーターに関する研究)
第86号　ＧＣ／ＭＳスペクトルの検索システムに関する研究.(1986)
第87号　光化学二次汚染物質の分析とその細胞毒性に関する研究－－昭和53～58年度 総合報告.(1986)
※第88号　都市域及びその周辺の自然環境等に係る環境指標の開発に関する研究Ⅱ. 環境指標－応用例とシステム－－昭和59年度 特別研究報告.(1986)
第89号　Measuring the water quality of Lake Kasumigaura by LANDSAT remote sensing.(1986)
(ＬＡＮＤＳＡＴリモートセンシングによる霞ヶ浦の水質計測)
※第90号　ナショナルトラスト運動にみる自然保護にむけての住民意識と行動－－知床国立公園内100平方メートル運動と天神崎市民地主運動への参加者の分析を中心として.(1986)
第91号　Economic analysis of man's utilization of environmental resources in aquatic environments and national park regions.(1986)
(人間による環境資源利用の経済分析－水環境と国立公園地域を対象にして)
第92号　アオコの増殖及び分解に関する研究.(1986)
※第93号　汚泥の土壌還元とその環境影響に関する研究(Ⅰ)－－昭和58～59年度 特別研究総合報告第１分冊.(1986)
※第94号　汚泥の土壌還元とその環境影響に関する研究(Ⅱ)－－昭和58～59年度 特別研究総合報告第２分冊.(1986)
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