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Foreword

The subject of Decision and System Sciences is the analysis of complexity of real systems which has reached such a level, that new frameworks for solving modeling, optimization and information processing problems must be developed. One such framework developed by Japanese scientists is the so-called *Shinayakana Systems Approach*. This approach assumes that mathematical models and formal tools provide only the ***problem solving** support*. Therefore, the essential parts of the problem solving are the issues of man-machine interaction.

This paper presents the basic ideas of the *Shinayakana System Approach* as well as a practical implementation of this concept in the design of a system for environmental monitoring and decision making.

Alexander Kurzhanski
Program Leader
System and Decision Sciences Program

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"SHINAYAKANA" SYSTEMS APPROACH IN DEVELOPING AN URBAN ENVIRONMENT SIMULATOR

Y. Sawaragi and Y. Nakamori

1. Introduction

A collaborative research between the Systems and Decision Science Program of IIASA and Japan Institute of Systems Research started in April, 1987 under the contracted study agreement; the title of the study is *Interactive Modeling and Decision Support Systems.* One of the primary aims of the collaborative research is to exchange ideas and new advances in computer-aided problem solving systems, including modeling methodologies, interactive optimization algorithms and methodologies on group decision making.

The first meeting was held at IIASA in August 1987 to discuss the directions of our collaborative research. Three executives from Japanese enterprises kindly gave lectures at the meeting on the topics of management decision support systems. In April, 1988, we had the second meeting in Kyoto, Japan, with the participation of more than 100 researchers and practitioners. The main topic was the development of decision support systems in the Japanese industry. Participants from IIASA and other European countries gave lectures on their recent ideas and new findings in this field.

We gathered again at IIASA in August, 1988 for the third meeting entitled New Advances in Decision Support Systems. The topics discussed at the meeting were natural resources modeling and management as well as decision support systems in management. This paper is an extended version of the authors' lectures at the meeting. The next section is related to the philosophy of the first author about systems approach. Then we introduce a project, in which the authors are involved, on the development of an urban environment simulator. The final part is a new development in modeling and simulation using ideas in fuzzy sets theory.

2. "Shinayakana" Systems Approach

The role of systems science is to describe the relation between a system structure and its total attribute. It is the principle of the scientific approach to decompose the object into elements and analize them. Systems science is therefore one of the disciplines of modern science. But unlike other analytical approaches, it puts the emphasis on the relationships between elements rather than elements themselves.

Analysis and synthesis for the object with a small number of elements and weak relationships between them have been done in other disciplines as well. The objects of systems science are those which are complex and systemic. But, great difficulties are always encountered in treating complex objects. Any scientific approach is very weak for complexity!.

Sharp criticisms to the traditional operations research or systems analysis are expressed nowadays by not a little number of researchers. Their main argument is the following. The traditional operations research seeks for an objective explanation of an object by the mathematical language to obtain an optimal solution to the problem. The reality, however, is too complex to allow a unique interpretation. It is usually impossible to reduce the complexity to the one which can be modelled. In many cases, the difference between the reality and its model is unavoidable. Any optimal solution is in danger of being born dead.

Checkland (1981 and 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 in the assumption of possibilities that we can recognize or identify the realit 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. Originally, Checkland was interested in the applications of systems engineering to social problems. But he recognized the difficulties mentioned above, and then proposed a soft systems thinking which emphasizes the cycle of modification or learning of the relevant people's perception.

There are other criticisms to the traditional systems approaches and proposals of soft systems approaches. Ackoff (1979a and 1979b) expects that the death of operational research is unavoidable unless it gives up the paradigm of predicting and preparing. Beer (1979, 1981, and 1985) advocates the organizational cybernetics to build viable systems models which can adapt themselves to new environments. In the case of Ulrich (1981 and 1983), it is more severe; he criticizes even those soft systems thinking and organizational cybernetics evade the essence of the problem. He insists that the concept of a system should be used in the context of supporting *what to do* while, so far, it has been used for *how to do*.

It is a matter of common sense that no methodology is applicable to any situation and all methodologies including traditional ones are mutually complementary. Jackson and Key (1984) propose the complementary use of various kinds of systems approaches, classifying them from the points of view of systems and decision makers. After all, we arrive at a common conclusion that soft systems approaches can be used in structuring the problems.

Mathematical systems theory and control theory are of course the members of systems approach. But they seem to be free from the above-mentioned criticism. The main reason is that their objects are engineering systems which have definite objectives and can be modelled. Is this true? Lewandowski and Wierzbicki (1988) observe that although the initial practical motivation underlying any part of mathematical systems theory is responsible for the basic concepts, the theory still remains a branch of applied mathematics, where the fundamental questions are those of syntactical correctness and completeness of mathematical language; questions of semantic importance are considered valid only in the sense of motivation.

It should be emphasized that the theories should not stop at mathematical idealizations because systems or control theory has physical objects in the real world. But we often face the gaps between theory and applications in testing our assumptions and methods on applications. We should recognize that systems theory and control theory are also facing a crisis. The rise of new types of control methods using fuzzy sets theory or intelligent engineering can be recognized as a critical demonstration toward the traditional control theory. Practitioners surely welcome these soft approaches as long as control theory remains at a mathematical idealization.

The root of this difficulty in applying theory lies in our capability to describe the reality. What is most important is the development of theories suitable for the description levels. From this point of view, fuzzy controls and controls by expert systems are typical examples. Can we believe the remarkable activities of control or systems theory in the real world if our capability of description is improved? We doubt it!

Every real problem surrounding us has many factors which are interrelated with each other. The problem solving has been greatly indebted to the experts, so far, and and this will be true in the future, too. However, the rapid development of computers and communication devices brings "light and shade" impacts on problem solving. The increase of information enlarges or complicates the problems, and then makes the problem solving more difficult. This is rather a cynical view. But, in fact, problem solving in the real world is far beyond individual competence. On the other hand, the clever utilization of information processing techniques greatly helps the problem solving. All systems approaches can play an active part in this direction.

The systems analyst provides problem solving tools to the users by analyzing, modeling or optimizing the problem. Here, the most important point is that the systems analyst should be a *coodinator* between tools and users. From this point of view, we would like to emphasize a soft approach which harmonizes the human judgment and the ability of the computer. The main feature of this approach lies in the *intervention* of human beings in every phase of the problem solving.

We name this approach **Shinayakana Systems Approach**. "Shinayakana" is an adjective in Japanese; it does not correspond to any English word. The meaning is something between hard and soft, or it contains the meanings of both hard and soft. The main point is how to use methods or tools developed for well-defined systems when we have to manage ill-defined systems. The Shinayakana Systems Approach is something more than just a mathematical approach. It is an important attitude when we treat real problems. Let us imagine the tree of a willow; better to bend that to break!

Shinayakana Systems Approach never makes light of mathematical methods and models, but limits them to playing the role of problem solving support only. We should always keep it in mind that any precise models of reality will never incorporate all human concerns. Therefore, an essential part of problem solving are the issues of person-computer *interaction*.

Models should be built interactively, involving not only analysts but also domai experts and decision makers. Their perceptions 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 definitely and correctly. The interaction is essential at the decision stage as well, and it should be dynamical. We quote its reason from Lewandowski and Wierzbicki (1988) that human decision makers typically learn when using a decision support system, and we cannot assume that a decision maker comes to the system with fixed preferences. The interaction should be designed carefully only to support the thinking process of decision makers; it should not be a set of leading questions.

In order to make good use of interaction, the support system is required to be *intelligent.* A problem solving support system should have a working area in a knowledge base subsystem. Frameworks of dynamical knowledge utilization should be designed so that we can not only retrieve data or knowledge, but also acquire or modify them interactively. The mechanism of knowledge aquisition has two aspects: one is knowledge recognition from the knowledge base or decision support environment, the second is knowledge association by the communication with knowledge base systems.

At the modelling stage, a model is identified partly and stepwise associated 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' perceptions. At the decision stage, the knowledge base system should suggest the objectives 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.

The third assertion of Shinayakana Systems Approach is that the problem solving should be carried out in an *interdisciplinary* fashion. Here again we can quote the opinion of Lewandowski and Wierzbicki (1988) that the new factor in contemporary systems analysis is the realization that certain methodological principles and mathematical tools can be applied to systems in a multidisciplinary fashion.

In the following section we will introduce a big experiment of developing a support system to predict environmental problems in the early 21st century in Japan and to find effective policy alternatives. This problem is obviously far beyond the capabilities of individual disciplines as well as individual researchers. This project involves more than 100 researchers in the various fields. A small core group is developing a computer system while others are investigating the problems and gathering information and knowledge.

In short, the features of Shinayakana Systems Approach are three "I's", that is, *Interactive*, *Intelligent* and *Interdisciplinary.* These are quite natural manners in solving modern problems. But we hardly fulfill natural things. How can we realize the three "I's" ? Shinayakana Systems Approach has references to the researcher's attitude. They are summarized by three "H's":

- Honesty in modeling the reality.
- Humanity in designing support systems.
- Harmony of the research group.

3. System and Project Summary

Background. The hard period of pollution in Japan was from the last half of the 1950's to the end of the 1960's. The basis of present environmental policies was established during that period. However, as the renovation in socio-economical background and national consciousness, the structure of environmental problems has changed to a great extent. Corresponding to these trends in our society, we are planing to find new environmental policy alternatives which should be different in quality from those established in 1960's.

The key words of the fundamental tide in our society are maturity, urbanization, computerization, internationalization, aging society, etc. These must give various kinds of impacts on our environment. To find new environmental policy alternatives, we have to predict these social changes and their impacts on our environment as precisely as possible. More concretely, our task should include:

- selection of important objects among a wide variety of factors;
- identification of convincing model structures by the limited data; and
- prediction of long-term trends under uncertain circumstances.

Obviously, these are beyond the capabilities of individual researchers, and the traditional analytical methods are not adequate for dealing with these problems.

Our society is developing continuously. We cannot suppose that the future situation will be the same as the past. Therefore, in principle, it is impossible to predict our future based only on the past data. Our main effort should then be concentrated on collecting and utilizing the knowledge or judgement or a variety of domain experts. For this purpose, we are developing a computer system for long-term simulation and policy analysis support based on available information and knowledge of domain experts.

Design Principle. The aim of the computer system that we are developing is the systematic support of a series of tasks form systems analysis to policy analysis by an integrated utilization of knowledge or judgement of domain experts and the available numerical data. The system is planned to be used for:

- identification fo the socio-economical trends of the time span of 10 or 20 years.
- prediction of the impacts of these trends on our environment under the assumed scenarios, and which may influence those scenarios.

Two main mechanisms in our system are:

- the flexible knowledge data management; and
- the interactive functions for person-computer dialogue.

The knowledge base system accumulate and manages knowledge data from various kinds of domain experts systematically, and carries our unification or inference using that knowledge data. The interactive functions are designed so as to reflect the judgement of experts throughout the total process from systems analysis to policy analysis.

System Structure. According to the aim and design principle mentioned above, we have designed an environmental policy analysis support system which consists of the following three parts:

- the knowledge-information system,
- the modeling support system, and

- the long-term simulator.

The knowledge-information system manages both knowledge and numerical data systematically, and retrieves and displays those data immediately as requested in some understandable forms. The modeling support system assists model building by using numerical data and our mental images. The long-term simulator predicts the future environment by using the models and knowledge under some assumptions of scenario variables. Many experts can participate in long-term simulation, looking at the outputs of computers which are displayed on a large screen.

The basis of knowledge-information system was developed at the National Institute for Environmental Studies, the Environment Agency of Japan, as a data base mangement system, and has expanded its functions to manage the knowledge base. The development of other two systems, the modeling support system and the long-term simulator, were originally planned at the same institute as well. The authors have been involved as project members in developing these two systems and in designing the total long-term environment simulator.

The authors main roles are the design and implementation of the modeling support system and the model base system. Therefore, in this paper, we will describe these parts of the total system mainly. The present stage of the system development is the following. We completed the implementation of the knowledge-information system on the Sun work station connected with the VAX 8550; the former is used for the person-computer interaction and the latter is used for the data storage. The other two systems were also developed, but implemented on the microcomputer; the conversion to the Sun station is now carrying on.

Numerical Data Base. The numerical data stored in our data base system on the VAX 8550 are related to socio-economical and environmental domains. The time series data of the last 20 years are 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 by the knowledge-information system. The numerical data base is also accessed by the modeling support system when developing statistical models.

Knowledge Data Base. A knowledge data in the knowledge base consists of a proposition, its inference process, background, evaluation, and information sources. The knowledge-information system can already carry out the inference using those knowledge data and show interconnections between propositions in the form of directed graphs. After implementing out modeling support system, we will be able to access the knowledge base from the modeling support system when thinking about relationships between variables and developing submodel structures.

The knowledge source to our system has been identified with the research results of a big project granted by the Ministry of Education of Japan. The title of the project is Systematic Urban Environmental Planning. The project started in 1987 and possible lasts for six years. More than 100 researchers and experts are involved in this project: they are system engineers, urban engineers, economists, jurists, chemists, biologists, meteorologist, psychologists, sociologists, etc. The research group is divided into the core group and eight subgroups corresponding to each special theme of urban environment.

One of the authors of this paper has been a memberr of the core group and asked to summarize the total research products and put them into the knowledge base on the computer. Therefore, we have a very nice opportunity to use a wide range of up-to-date knowledge and information, which include:

- juridical problems or existing policies and their effectiveness,
- relationships between environmental or sociological factors and the comfortness of urban life,

- relationships between sociological factors and physical or chemical factors,
- resource waste cycle and water resource recycle,
- impacts of the changes in land use on the urban environment,
- impacts of the urban traffic on the air and noise pollution,
- impacts of human activities on the urban ecosystem,
- impacts of high-rise and high-density resident on the human health,
- methods for observation and evaluation of environmental factors, and
- possible changes in our urban life.

Model Base. The models are embedded in the if-then format, i.e., each submodel corresponds to one rule. Three types of models are considered:

- statistical inference type,
- fuzzy inference type, and
- scenario inference type,

depending on the available information and knowledge.

The rule corresponding to a submodel of the statistical inference type is described as follows:

[rule i] if x_1 is A^i_1 and x_2 is A^i_2, ..., and x_m is A^i_m,

$$\text{then } y^i_j = c^i_{jo} + \sum_{k=1}^{m} c^i_{jk} x_k, \quad j = 1,2,...n.$$

Here, x_j 's are input variables. A^i_k 's are fuzzy variables. y^i_j 's are the outputs of the i-th rule. The coefficients of linear models c^i_{jk} 's are estimated by statistical methods. For given inputs x^o_i (i=1, 2,...m), the prediction of the output variable y_j is calculated by

$$y^*_j = \sum_{i=1}^{p} w^i y^i_j \,/\, \sum_{i=1}^{p} w^i, \quad w^i = \prod_{k=1}^{m} A^i_k(x^o_k)$$

where p denotes the number of rules fired, and $A_k^i(x_k^o)$ is the membership grade of x_k^o.

The details of modeling and simulation for this kind of models will be given in the next section. Especially, a new simulation technique for reasonable scenario input and interpretation of the model behaviour will be suggested.

The rule for a second type model, the fuzzy inference type, is expressed as follows:

[rule i] if x_i is A_1^i and x_2 is $A_2^i,\ldots,$

and x_m is A_m^i,

then y_1 is $B_1^i,\ldots,y_n B_n^i$,

where B_j^i 's are also fuzzy variables. For the given inputs $x_1^o, x_2^o,\ldots,x_m^o$, the truth value of the premise of the i-th rule is defined by

$$w^i = \prod_{k=1}^{m} A_k^i(x_k^o),$$

and the combined membership function $B_j^*(y_j)$ for each output variable y_j is defined by

$$B_j^*(y_j) = \sum_{i=1}^{p} w^i B_j^i(y_j) \;/\; \sum_{i=1}^{p} w^i$$

Finally the prediction y_j^* is given by

$$y_j^* = \int y_j x B_j^*(y_j)\,dy_j \;/\; \int B_j^*(y_j)\,dy_j.$$

One can first calculate the center of gravity $\bar{y}_j^i$ in each rule, then compute the estimate of y_j as the weighted sum of $\bar{y}_j^i$'s by w^i .

The essential point in developing this kind of models is the division of data space into fuzzy subspaces. Good divisions are also required in constructing premises for the first type of models. We developed a clustering technique with a new measure of data division, using the graphical information of the clustering process. This technique and the corresponding computer software will be introduced in the following section.

The third type models are described by the usual production rule. Among the knowledge stored in the knowledge base, we choose propositions with high confidence which can be written in the if-then format. This type of model is very important for future prediction because we cannot predict the results of something which did not occur in the past. We therefore greatly expect the success of the research project mentioned before.

The issue of system synthesis, simulation or optimization using the total model are open to argument in our group. This paper treats the modeling and simulation of the first type models only in the next section.

4. Fuzzy Modeling and Simulation

A computer software named IMSS (Interactive Modeling Support System) has been developed for modeling and planning of complex, large-scale systems (Nakamori et al, 1985; Nakamori and Sawaragi, 1987; Nakamori, 1987a). The system integrates structural and statistical modeling methods with advanced graphic techniques that facilitates person-computer communication and interpersonal communication. It has been already successfully applied to the modeling of some concrete problems (Walsum and Nakamori, 1985; Nakamori, 1987b).

The modeling process when using IMSS is divided into three stages:

- determination of a class of models,
- investigation of the model structure, and
- validation of the model.

The initial information required as input is the set of variables with measurements and the casual dependences between variables. The final product of IMSS is a system model in terms of linear equations; but using the facility of data transformation, we can build nonlinear or dynamic system models.

Although IMSS is a powerful tool for system structuring and linear modeling, the success of modeling depends heavily on the capability and experience of the individual modeler. To break through this difficulty, we are studying from two aspects: one is the design of an intelligent environment for the system IMSS (Nakamori et al., 1988), the other is the application of fuzzy set theory in system modeling and simulation. The latter is the topic in this section.

Three facilities have been developed to assist the modeling by IMSS: they are the *visual clustering supporter* (VCS), the *controlled fuzzy simulator* (CFS), and the *knowledge model builder* (KMB). The first one is used for the stepwise least square modeling with a visual clustering technique to obtain nonlinear models consisting of a set of rules. The others are used for the visual simulation with a scenario input controller, and the interpretation of simulation results. The process of total modeling and simulation using these facilities consists of the following five stages:

Stage 1: Model building by IMSS, using all data. If a good model is obtained, then go to Stage 4.

Stage 2: Data division by Visual Clustering Supporter (VCS)

Stage 3: Submodel building by IMSS, using divided data. If good models are not obtained, then return to Stage 2.

Stage 4: Scenario analysis by Controlled Fuzzy Simulator (CFS).

Stage 5: Simulation interpretation by Knowledge Model Builder (KMB).

Fuzzy Modeling.

Fuzzy Modeling (Takagi and Sugeno, 1985; Sugeno and Kang, 1986) has an ability to express nonlinearities of complex systems. It consists of structure and parameter identifications in the premises and consequences, respectively. The identification of the consequences is the same as the usual linear modeling. A fuzzy rule expresses an input-output relation on a fuzzy subspace defined in a premise. The main problem in fuzzy modeling is how to divide the input space into fuzzy subspaces. This paper proposes a visual and stepwise clustering technique to obtain fuzzy subspaces.

The process starts with the calculation of the degrees of data division which will be defined later. Let $x_1, x_{2,\ldots x_m}$ be the input variables, and $S_i{=}x_{i1}, x_{i2,\ldots x_{in}}$ the sequence of standardized data for variable x_i. Identify $\underline{\underline{\alpha}}_j = (x_{1j}, x_{2j,\ldots x_{mj}})$ with a point in the m-dimensional Euclidean space, which corresponds to the j-th data set for all input variables, and let $S = \underline{\underline{\alpha}}_1, \underline{\underline{\alpha}}_2, \ldots, \underline{\underline{\alpha}}_n$.

Divide the set S_i into two subsets A_i^1 and A_i^1 by using the Ward method clustering, and correspondingly divide S into A^1 and A^2 by the following formula:

$$x_{ik} \in A_i^j \longrightarrow \underline{\underline{\alpha}}_k \in A^i, j{=}1,\ 2, k{=}1,\ 2, \ldots, n.$$

Now we can define the ***degree of data division*** with respect to x_i:

$$d(x_i) = \frac{n_1 \bullet n_2}{n_1 + n_2} ||\underline{\underline{m}}_1 - \underline{\underline{m}}_2||^2$$

where n_j is the number of elements in A^j $(j{=}1,2)$, and $\underline{\underline{m}}_j$ is the center of gravity of the elements in A^j $(j{=}1,\ 2)$.

The decision of data division is done by taking account of these degrees of data division and looking at two-dimensional scatter plots which show the divisions of data of other variables. Then, for divided data spaces, two submodels are built by using the system IMSS. It we are satisfied with the submodels, then we calculate the membership functions for each fuzzy subspace, assuming the shape of function as a trapezoid. Otherwise, we repeat the process of clustering and modeling to obtain further divisions of the data space and to build submodels.

It is dangerous to determine data divisions only by a criterian. We carefully look at scatter diagrams to see how the data spaces are divided. By using the system VCS, we can choose a variable with a large degree of data division, which divides the data space well. Moreover, in the clustering process of VCS, we can divide or merge clusters by force.

Fuzzy Simulation.

Since the input variables are not necessarily independent, we should carefully assume scenario values in simulation. First the membership functions of input variables to divided fuzzy subspaces should be identified. For example, choose a trapezoid with height 1 in the range between the first and third quartiles of the data set and 1/2 at the maximum and minimum data points. Denote by $A_j^k(x_j)$ the membership function of x_j to the k-th fuzzy subspace A^k .

Now let us introduce the ***input admissible function*** $w_j(x_j)$ for the input variable $x_j (j=1,2,...,m)$. Its initial setting is defined by

$$w_j(x_j) = \frac{I}{P}\sum_{k=1}^{p} A_j^k(x_j), \quad j=1,2,...m$$

where p is the number of fuzzy subspaces. If we determine scenario values for some input variables x_i 's, then the input admissible functions of other input variables are modified as follows:

$$w_j(x_j) = \sum_{k=1}^{p} w^k A_j^k(x_j) \; / \; \sum_{k=1}^{p} w^k, \quad w^k = \prod_i A_i^k(x_i^o)$$

where x_i^o denotes the fixed scenario value for variable x_i, and the product is taken over the variables whose values are fixed.

Looking at these functions, we set scenario values for some important variables. For the input variables whose scenario values are not determined, the random numbers are generated within their admissible ranges in which the input admissible functions are positive. Thus, a simulation is carried out by fixing scenario values for some input variables and generating random inputs for other variables within their admissible input ranges.

Now let us introduce the level and scatter degree of scenario values. Let m_i and σ_i be the sample mean and standard deviation of the data set for variable x_i. Let L be an integer and s a positive real number, and let $\Delta_i=2s\sigma_i \, / \, L$. Define the ***level of scenario*** $L(x_{ij})$ of the scenario value x_{ij} of the variable x_i by the following formula:

$$m_i - s\sigma_i + (k-1)\Delta_i \leq x_{ij} < m_i - s\sigma_i + k\Delta_i \rightarrow L(x_{ij})=k$$

where k is an integer in the range [1.L.]. Define the *average level* and *scatter degree* of scenario values of input variable x_i in a simulation run as follows:

$$L_i = [\sum_j w_i(x_{ij})L(x_{ij}) \;/\; \sum_j w_i(x_{ij}) + 0.5]$$

$$S_i = [\sum_j w_i(x_{ij})\left\{L(x_{ij}) - L_i\right\}^2 \;/\; \sum_j w_i(x_{ij}) + 0.5]$$

where $[x]$ denotes the greatest integer not exceeding x.

Let y_{ij} be the estimate of variable y_i by the fuzzy model with a set of scenario values $x_{1j}, x_{2j}, \ldots, x_{mj}$, and let $L(y_{ij})$ be the *level of estimate* that is defined in the same way as for $L(x_{ij})$. Let us introduce the *confidence factor* of the estimate y_{ij} as follows:

$$C(y_{ij}) = \prod_{k=1}^{m} w_k(x_{kj}).$$

Define the *average level* and *scatter degree* of estimates of output variable y_i after a simulation run as follows:

$$L_i = [\sum_j C(y_{ij})L(y_{ij}) \;/\; \sum_j C(x_{ij}) + 0.5]$$

$$S_i = [\sum_j C(y_{ij})\left\{L(y_{ij}) - L_i\right\}^2 \;/\; \sum_j C(y_{ij}) + 0.5]$$

After a simulation run, we obtain a knowledge model by KMB, like as

If x_i is level L_i and x_j is level $L_{j,\ldots,}$

then y_p is level L_p and y_q is $L_{q,\ldots,}$

The variables in the premise are those ones whose scenario values are fixed during the simulation run, and the variables in the consequence are those ones whose scatter degrees are less than a designated value. Note that some input variables can be included in the consequence; which corresponds to the use of fuzzy inference using the input admissible functions.

5. Concluding Remarks

We proposed "Shinayakana" Systems Approach in systems analysis. In designing and implementing the systems for modeling and decision support, it requires 3 I's, that is, the support systems should be designed in an interactive, intelligent and interdisciplinary fashion. It also refers to the researcher's attitude summarized by 3 H's: honesty in modeling the reality, humanity in designing support systems, and harmony of the research group.

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