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An intelligent decision support system for fuzzy comprehensive evaluation of urban development

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Abstract

More applications that integrate knowledge-based decision support systems, artificial neural networks, and fuzzy systems are starting to appear, and interest in such integrated systems is growing rapidly. This paper presents an integrated system in which a knowledge-based decision support system is integrated with a multilayer artificial neural network for urban development. By integrating decision support systems, knowledge-based systems, artificial neural networks, and fuzzy systems, the system achieves improvements in the implementation of each, as well as increases in the scope of the application. The paper discusses the structure of the integrated system, as well as providing an example of decision support systems application. © 1999 Elsevier Science Ltd. All rights reserved

1. Introduction

Hybrid architectures for intelligent systems is a new field of artificial intelligence research concerned with the development of the next generation intelligent systems (Liebowitz, 1996; Yip et al., 1997). Currently a synergism is rapidly developing in the fields of expert systems and neural networks, and an understanding is starting to develop about the theoretical basis and methodology for integrating these two technologies. The research interests in the fields focus on integrating the computational paradigms of expert systems and neural networks, both conventional and fuzzy, and exploring the underlying structures of these two methods of knowledge manipulation, as well as on various applications in which intelligent hybrid systems may and can play an important role.

Neural networks can analyze large quantities of data to establish patterns and characteristics in situations where rules are not known and can in many cases make sense of incomplete or noisy data. These capabilities have thus far proven difficult for the traditional symbolic/logic approach. The complementarity of neural networks and expert systems make hybrid systems a very promising area for research and development. Recently more applications that integrate knowledge-based decision support systems and artificial neural networks (ANN) are starting to appear, and interest in such hybrid systems is growing rapidly (Medsker & Turban, 1994). In this paper, we present a knowledge-based decision support system that integrates with a multilayer ANN for urban development.

In the last decade, as a result of economic reform, China has experienced significant structural changes in the national economy. The policy-makers in the Chinese public sector are eager to trace the pace as well as the trends of such changes. Since large cities are one of the focuses of structural changes, the policy-makers pay close attention to the comprehensive evaluation of the development of large cities. Such comprehensive evaluation processes are often highly complex and require voluminous input data to be mapped through a substantial number of logical and quantitative interactions; and it is expected that the evaluation will provide insights into the cause–effect relationship between a variety of factors such as natural, financial resources, policy, and the level of development. The resultant evaluation is expected to provide useful decision support to the policy-makers. As mentioned earlier, the integration of expert systems and ANNs is an ideal step in developing intelligent systems since the two methods complement each other such that expert systems allow hard constraints, while ANNs accommodate soft constraints. Specifically, expert systems involve formal logic and rule interpretation, while ANNs perform nonlinear functions and pattern recognition capabilities. In this study, we explore their complementary strengths to create a hybrid system for urban development.

First, the comprehensive evaluation of urban development is conducted by a group of experts from various fields and a number of approaches are used to aggregate individual

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opinions into a group consensus (Warfield, 1994). Based on the idea of decision support system (DSS)/knowledge-based system (KBS) integration, a knowledge-based decision support system for comprehensive evaluation of urban development (*KB-CEDSS*) is constructed as a front-end to the ANN (El-Najsawi & Stylianou, 1993). The main function of the *KB-CEDSS* is to elicit and organize expert opinions, to display analytical results and to demonstrate policy alternatives. For each city being evaluated, the *KB-CEDSS* generates a set of observation pairs [*x*, *f(x)*], i.e., factor index and evaluation result indicator.

Secondly, the [*x*, *f(x)*] pairs generated by the *KB-CEDSS* are used as training samples as well as a validation set to train the multilayer ANN, such that we complement the knowledge-based evaluation conducted by the *KB-CEDSS* with black box models of ANN. It is expected that a well-trained ANN can rapidly process input vectors to produce associated facts and results for the evaluation task. After supervised training processes, the ANN abstracts and generalizes the information provided by [*x*, *f(x)*] pairs, and produces an output vector.

Thirdly, current maintenance of the knowledge base of a KBS is mostly done manually. In complex decision environments, expert knowledge is limited from time to time and the knowledge base needs to be refined continuously. ANNs can be used as a knowledge refinement paradigm. The ANNs, as a result of their pattern recognition characteristics, support the implementation of automated knowledge refinement. In this study, we use the output from the ANN to facilitate the automation of knowledge based maintenance. The recursive process is: the *KB-CEDSS* knowledge-based comprehensive evaluation supervises the training of the ANN, and the output of the ANN automatically refines the knowledge of the *KB-CEDSS* (the refinement of those imprecise and incomplete rules which were obtained initially).

Fourthly the integrated system is based on a knowledge-based DSS that incorporates techniques from approximate reasoning to neural networks (Yip et al., 1997). It is expected that the integration of DSS, KBS and ANN will have the potential to provide solutions that no single system alone can deliver.

The paper is organized as follows: Section 2 provides a description of the *KB-CEDSS*, Section 3 presents a description of the approximate reasoning models in the DSS. Section 4 provides an application example of fuzzy comprehensive evaluation to demonstrate the usefulness of the system, while Section 5 presents the conclusions and discusses future research.

2. Knowledge-based decision support systems (*KB-CEDSS*)

2.1. System architecture

The *KB-CEDSS* is a complex system consisting of a number of individual subsystems. The framework of *KB-CEDSS*

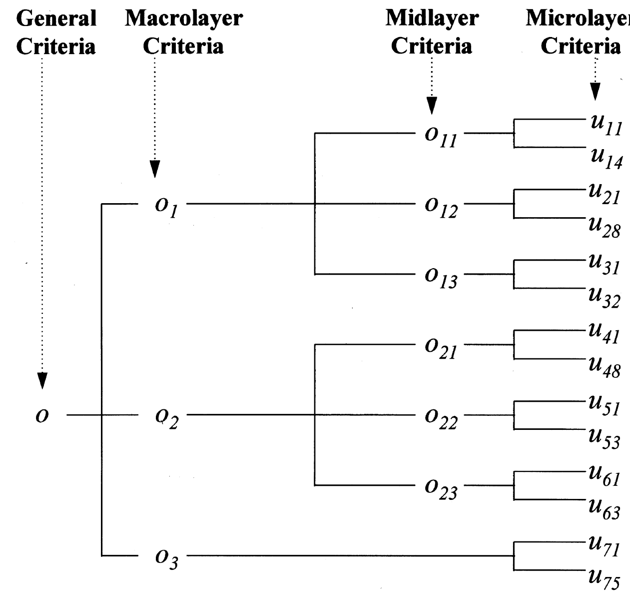

Fig. 1. The four-layer comprehensive evaluation index system.

can be represented as: $S_{KB\text{-}CEDSS} = (I_{KB\text{-}CEDSS}, D, D^*, M, M^*, A, A^*, R, G)$, $I_{KB\text{-}CEDSS} = (I, KB)$, $KB = (OBJECT\text{-}KB, ANALYSIS\text{-}KB, TOOLS\text{-}KB)$, $D = (DBO, DBI)$, where $S_{KB\text{-}CEDSS}$ denotes the system *KB-CEDSS*, in which the $I_{KB\text{-}CEDSS}$ represents the dialogue management subsystem of the *KB-CEDSS* and includes two components: the interface (*I*); and the knowledge base (*KB*). *KB* is subdivided into three components: *OBJECT-KB* provides knowledge on ‘what’ kind of evaluation index system should be used when different objects are evaluated (a comprehensive evaluation index system is shown in Fig. 1); *ANALYSIS-KB* provides knowledge on ‘how’ to make evaluation on the objects given; and *TOOLS-KB* provides knowledge on ‘how’ to use the tools in the system. *D* represents the database and includes two subsystems: the Database for Objects (*DBO*) stores the attributes of the original indexes of the objects to be evaluated; and the Database for Indexes (*DBI*) stores the structured index attributes according to the index formed and the relevant membership functions. *D** represents the database management system (DBMS); *M* represents the set of mathematical models that can be used to evaluate urban development; *M** represents the model management system; *A* represents the set of programs; *A** represents the program management system; *R* represents various types of report generators; and *G* represents visual display capabilities.

2.2. Fuzzy systems

Human elements have played a crucial role in the evaluation process. In addition, the evaluation of the overall development of large cities consists of a multi-participant setting. The participants include individuals, small groups as well as large organizations. When such a variety of parties are involved, their preferences and value systems are often diverse since an area of expertise can be viewed diversely by different experts. Therefore, issues related to vagueness, imprecision and ambiguity in human judgments should find a proper place in the formal evaluation process.

Traditional study of such issues is conducted using probabilistic tools and techniques. However, it is not difficult to see that aspects related to imprecision or vagueness clearly have a non-probabilistic character since they are related to imprecision of meanings. Thus, a proper tool for their analysis seems to be the fuzzy set theory and its related possibility theory that makes it possible to formally represent imprecise concepts. Therefore, an important issue in the development of automated decision aids for urban development is handling fuzziness, since the evaluations involve human expertise and knowledge, which are invariably imprecise or incomplete. This would enable the system to better emulate human evaluation processes. Several experiments in KBSs address the problem of developing approximate reasoning methods for dealing with imprecise data (Pal, 1991; Xu, 1995). In our approach, we use a fuzzy logic framework that provides an appropriate language for both acquiring and representing the fuzzy components underlying experts' knowledge (for details see Sections 3 and 4). In the *KB-CEDSS*, conventional mathematical tools and fuzzy mathematical tools are organized in parallel within *TOOLS-KB*. Linguistic terms involving indexes, weights, the antecedent and consequent parts of rules are encoded as fuzzy sets. The system is able to represent experts' knowledge using membership functions and fuzzy production rules.

2.3. M^3CEP

The comprehensive evaluation on large cities made by experts can be formalized as a multiparticipant, multilayer, multicriteria evaluation problem M^3CEP and represented as follows, M^3CEP $= (C,IS,EM,EO,ER,E)$. For M^3CEP, the evaluative object set, i.e. cities $C = (C_1, C_2,..., C_k,..., C_m)$, $1 < k < m$; IS represents the index system of hierarchical architecture (see Fig. 1), where r^t_{kuh} represents expert t's evaluation of the *uth* index in the *kth* layer of the *hth* object in the set C, and $r^t_{kuh} = r^t_{ku1}, r^t_{ku2},..., r^t_{kuk},..., r^t_{kum}$; *EM* represents the time–area–event indicator, for example, the time as year 1997, the area as 9 large cities, and the event as annual regular evaluation; *EO* represents the current evaluation goal, e.g. the spacial structure of investment decisions; *ER* represents aggregation, e.g. *GER1* represents an aggregation of individual expert's C^3CEP final results, and *GES2* indicates that an index-specific aggregation is completed and reduced to the overall measure; and E represents human experts' set $E = (E_1, E_2,..., E_t)$.

Given C, IS, EM, and EO, a matrix $B = (b_1,b_2,...,b_m)$ is generated by E according to ER. For each city being evaluated, a mapping $x_1 \rightarrow b_1$ is validated and called the observation-result pair or $[x, f(x)] = b$ pair. Fuzzy techniques are applied in the process to solve M^3CEP in such a way that allows fuzzy measures to be presented in both subjective judgment and object description. Those fuzzy operations and rules are packed into an independent module as a component of *TOOLS-KB* (Feng, 1993).

2.4. Structuring knowledge bases

The knowledge base $KB =$ *(OBJECT-KB*, *ANALYSIS-KB*, *TOOLS-KB)* is of large scale. For example, *OBJECT-KB* has four layers that are consistent with the layer objectives. Structuring is essential in order to manage such a knowledge base. Since the desired knowledge support depends on changing evaluation environments, i.e. the changing *EM*, a structured, modular knowledge base is always defined with respect to a current evaluation focus. Such structuring has ameliorated the problems in efforts to make a knowledge base comprehensible and maintainable.

There are two kinds of module connections. An *AND*-connection implies that modules on the top layer can input and do not contain competing knowledge, but rather contain information on different topics of the related domain; in other words, all of this knowledge may be used at the same time. The second, *OR*-connection implies that the modules on the lower layer contain competing knowledge; in this case, only one of these modules may be used at a given time. The combination of modules is implemented in such a way that lower layer modules' results can be the input of a corresponding upper layer.

2.5. Artificial neural networks

One of the primary attractions of the ANN approach is that knowledge is ascertained directly from accumulated case data through the use of a learning algorithm that may be either supervised or unsupervised. The advantages of ANN include the ability to classify patterns that vary in an unknown manner, recognize patterns within noise, and recall patterns even if some processing units fail (Jain et al., 1996). However, ANNs fall short where KBSs excel; such as handling logic, heuristics, and domain knowledge. Therefore, expert systems and ANNs present complementary approaches to knowledge representation: the logical, cognitive, and mechanical nature of the expert systems versus the numeric, associative, and self-organizing nature of the neural network. Compared to conventional methods, the ANN approach shows particular promise in domains where features of different types collectively contribute to the solution of a problem such as a multi-participant, multi-criteria decision making problem. A typical example of such a problem is the comprehensive evaluation of urban development. By combining the powers of expert systems and neural networks in an hybrid system, one that allows for imprecise information and/or uncertain environments, we would have a system more powerful than either one of its components standing alone. In order to benefit from the capabilities of each method, this study uses a hybrid architecture that integrates KBSs and ANNs to generate solutions for urban development. ANNs are useful because they can be considered as a way of learning knowledge without prior specification of a representation scheme. Utilizing the ANN characteristics, we use the [*x*, *f(x)*] pairs generated by *B* as the sample sets to train the multilayer ANN. We initialize the structure of the ANN as a 4-layer neural network for evaluating urban development. For the comprehensive evaluation of the development level of a group of cities, *n* input and *m* output units are chosen to match the [*x*, *f(x)*] pairs specified by the evaluation goal. The number of units in the first and second hidden layer is determined by the on-going learning procedure. The self-configuration algorithm is adopted. In implementing the BP algorithm for the multilayer feed-forward ANN, for each input–output pair [*x*, *f(x)*], a forward pass starting at the input units computes the activity level y_i of all the units in the network. Then a backward pass starting at the output units computes $\partial E/\partial y_i$ for each unit *j* of hidden layer *J*.

3. Approximate reasoning models in the DSS

As discussed in Section 2.3., fuzzy techniques are applied in the process to solve M^3CEP. In the *KB-CEDSS*, fuzzy mathematical models are organized within *TOOLS-KB*. The following is one of the fuzzy mathematical models used in the integrated DSS.

It is known that there exists an economic relationship among the growth pattern of national economy, urbanization and the distribution of the sizes of cities. Statistical data show that, for a particular country, there is a positive correlation between the gross national product and the degree of urbanization. Since 1983, the Chinese government has approved 14 medium to large size cities as independent economic entities and granted them the status of partial economic autonomy. Although these cities are still governed by the provinces where they are located, their economic development plans as well as social development plans no longer need to be approved by the respective provincial government but directly by Chinese central government. These independently-planned cities are mostly regional business and financial centers that significantly impact on the regional economic growth. It is important to trace the trend of urban development in these cities both quantitatively and qualitatively.

It is known that the urban system is one of the most complicated systems. Such a complex system is characterized by complex mechanism, ill-defined systems boundary and layers, multiple variables and fuzziness (Nijkamp, 1986). Generally speaking, it is a difficult task to provide a comprehensive evaluation on the overall development of urban systems. The main reasons include the fuzziness and the tremendous amount of factors involved as well as the multiple layers involved with even a single factor. In order to provide a comprehensive evaluation on complex urban systems and contribute to the solution of a multi-participant, multi-criteria problem, it is necessary to develop appropriate index systems and models. Current literature suggests that while more and more fuzzy multicriteria models were developed in recent years, little was done to develop such models for evaluating urban development (Ng, 1992; Liou & Wang, 1994).

3.1. Multilayer comprehensive evaluation index system

A city can be evaluated from a single aspect such as industry development, environmental quality, and so on. Such a single-aspect evaluation simply does not reflect the overall urban development. In order to provide an effective evaluation on the overall urban development, it is necessary to establish a systematic, comprehensive index system. The objectives for developing the comprehensive index system are as follows:

1. The index system must be able to reflect every aspect of the urban development.
2. The data for the indexes must be able to be collected from the reliable sources and be consistent.
3. The index system must be able to accommodate the relationship between the evaluation indexes and the evaluation criteria, especially to generate corresponding evaluation indexes based on evaluators' criteria.

According to these objectives, a four-layer comprehensive evaluation index system is proposed (see Fig. 1). This index system considers the overall urban development (O) determined by three major indexes: the combined index for social development (O_1), the combined index for economic development (O_2), and the combined index for environmental protection (O_3), i.e. $O = f(O_1, O_2, O_3)$.

O_1 is further determined by the urban population status (O_{11}), the quality of urban life (O_{12}), and the urban administration (O_{13}). O_{11} is measured by the natural growth rate of population (u_{11}), population density (u_{12}), the enrollment of colleges and universities (u_{13}), and the number of scientists/engineers per ten thousand employees (u_{14}). O_{12} is measured by the per capita income of urban residents (u_{21}), the average salary of urban employees (u_{22}), the per capita annual saving of urban residents (u_{23}), the per capita living space of urban residents (u_{24}), the per capita water consumption of urban residents (u_{25}), the number of automobiles per ten thousand urban residents (u_{26}), the number of telephones per hundred urban residents (u_{27}), and the number of medical doctors per ten thousand urban residents (u_{28}). O_{13} is measured by the number of traffic accidents per hundred thousand urban residents (u_{31}), and the number of fires per hundred thousand urban residents (u_{32}).

O_2 is further determined by the regional economic activities (O_{21}), the regional combined economic benefits (O_{22}) and the regional international investment (O_{23}). O_{21} can be measured by the regional gross domestic production (u_{41}), the regional per capital income (u_{42}), the regional gross industry and agriculture output (u_{43}), the regional total fixed investment (u_{44}), the regional total retail value of commodities (u_{45}), the regional government revenue (u_{46}), the income generated by tourist industry (u_{47}), and the regional gross export (u_{48}). O_{22} can be measured by the per capital national income (u_{51}), the per capital domestic production (u_{52}), and the per capital industry and agriculture output (u_{53}). O_{23} can be measured by the number of the new business ventures involving international investment (u_{61}), the amount of international capital on the ventures (u_{62}), and the amount of international capital actually used (u_{63}).

O_3 is further measured by the coverage of trees and flowers within urban areas (u_{71}), the per capita coverage of trees and flowers within urban areas (u_{72}), the processing rate of industrial water disposal (u_{73}), the processing rate of industrial gas disposal (u_{74}), and the processing rate of industrial solid disposal (u_{75}).

3.2. Fuzzy multicriteria multilayer evaluation model

As Fig. 1 shows, those major factors affecting urban development were classified into a number of subsystems according to their contribution to the criteria. Assuming the set of cities under evaluation $C = \{C_1, C_2,..., C_m\}$, the set of evaluation criteria is $O = \{O_1, O_2,..., O_q\}$. Since O_i ($i \in \{1, 2,..., q\}$) is composed of q_i sub-criteria, then. The evaluation index set U is composed of all evaluation indexes; U is divided into n indivisible subsets, i.e. $U = \{U_1, U_2,..., U_n\}$ which satisfy the following:

$$\bigcup_{i=1}^{n} U_i = U,\ U_i \cap U_j = \Phi,\ i \neq j,\ i,j \in \{1,2,...,n\}$$

Assuming that the *ith* subset U_i has n_i evaluation indexes, for C_j in C, vector $\boldsymbol{i}^{\vec{x}_j}$ can be used to represent the eigenvalue of the n_i evaluation index:

$$i^{\vec{x}_j} = (i^{x_{1j}}, i^{x_{2j}}, ..., i^{x_{n,j}})^T \tag{1}$$

For the *ith* criterion that corresponds to U_i, the eigenvalue of the m urban evaluation indexes can be represented by the following matrix:

$$i^X = \begin{bmatrix} i^{x_{11}} & i^{x_{12}} & \dots & i^{x_{1m}} \\ i^{x_{21}} & i^{x_{22}} & \dots & i^{x_{2m}} \\ \dots & \dots & \dots & \dots \\ i^{x_{n_i 1}} & i^{x_{n_i 2}} & \dots & i^{x_{n_i m}} \end{bmatrix} = \left[i^{x_{kj}} \right]_{n_i\ x\ m} \tag{2}$$

The eigenvalue matrix (2) can then be transformed to the following membership grade matrix (evaluation matrix) using membership functions:

$$i^{\underset{\sim}{R}} = \begin{bmatrix} i^{r_{11}} & i^{r_{12}} & \dots & i^{r_{1m}} \\ i^{r_{21}} & i^{r_{22}} & \dots & i^{r_{2m}} \\ \dots & \dots & \dots & \dots \\ i^{r_{n_i 1}} & i^{r_{n_i 2}} & \dots & i^{r_{n_i m}} \end{bmatrix} = \left[i^{r_{kj}} \right]_{n_i\ x\ m} \tag{3}$$

Where $i^{r_{kj}}$ represents the degree of membership of the *kth* index of the *ith* criterion for city C_j, and. Let $i^{\vec{r}_k}, i^{\vec{r}_j}$ represent the *kth* single index evaluation of the U_i that corresponds to the m cities being evaluated and the single-city evaluation of C_j that corresponds to n_i evaluation index:

$$i^{\vec{r}_k} = (i^{r_{k1}}, i^{r_{k2}}, ..., i^{r_{km}}) \tag{4}$$

$$i^{\vec{r}_j} = (i^{r_{1j}}, i^{r_{2j}}, ..., i^{r_{n_i j}})^T \tag{5}$$

Assuming the weighting coefficient set of the n_i evaluation indexes of the subset U_i as:

$$i^{\underset{\sim}{A}} = (i^{a_1}, i^{a_2}, ..., i^{a_{n_i}}) \tag{6}$$

where ($k = 1,2,...,n_i$) is the weighting coefficient of the *kth* evaluation index, and $i^{a_k} \geq 0$, $\Sigma_h i^{a_k} = 1$. The fuzzy comprehensive evaluation set of the U_i is:

$$i^{\underset{\sim}{B}} = i^{\underset{\sim}{A}} \circ i^{\underset{\sim}{R}} = (i^{b_1}, i^{b_2}, ..., i^{b_m}) \tag{7}$$

where i^{b_j} is the result of fuzzy comprehensive evaluation of the city C_j on U_i. It is calculated as follows:

$$i^{b_j} = \mu_{\underset{\sim}{A}_{i=i^{\vec{r}_j}}} = \underset{\vee}{*}(\mu_{i^{\underset{\sim}{A}}}(U_i) \underset{\wedge}{*} \mu_{i^{\vec{r}_j}}(U_i, C)) \tag{8}$$

$$= \underset{\vee\, k=1}{\overset{n_i}{*}} (i^{a_k} \underset{\wedge}{*} i^{r_{kj}}),\ (k = 1,2,...n_i;\ j = 1,2,...,m)$$

In Eq. (8) $\underset{\vee}{*}$ and $\underset{\wedge}{*}$ are the generalized fuzzy operators. They are the extensions of the compound operation $\vee$ (max) and $\wedge$ (min) of the fuzzy matrix.

The higher level set of fuzzy comprehensive evaluation can be obtained by employing Eq. (8) and using this as the row of the higher level evaluation matrix. Finally, the result set of comprehensive evaluation is as follows:

$$\underset{\sim}{B} = \underset{\sim}{A} \circ \underset{\sim}{R} = (b_1, b_2, ..., b_m) \tag{9}$$

Since in most cases a variety of criteria are used by the decision makers to evaluate urban systems, we further extend the techniques of combining fuzzy operators. The model is able to provide a fuzzy comprehensive evaluation under the following rules (for U_i, the following models will determine the i^{b_j} in Eq. (8)):

Rule 1: Considers every single factor overall. This rule requires the inclusion of all factors that are based on the weighting coefficients. It is suitable to the evaluation in which all indexes must be accommodated. The model is:

$$i^{b_j} = \sum_{k=1}^{n_i} (i^{a_k} \cdot i^{r_{kj}}) \tag{10}$$

Rule 2: Considers only those important factors. According to this rule, only those factors with the largest indexes determine the evaluation result. Meanwhile, the evaluation result will not be affected by the variations of the remaining factors within a certain range. It is suitable to the evaluation in which single items are emphasized. The model is:

$$i^{b_j} = \max_k\{\min_k\{i^{a_k},\ i^{r_{kj}}\}\},\ (k = 1,2,...,n_i) \tag{11}$$

Rule 3: Emphasizes important factors. This rule is similar to Rule 2; however, its evaluation result is finer than that of Rule 2 since some non-major indexes are included in evaluation. This rule is suitable to for evaluation in which the result obtained from Rule 2 is indistinguishable and needs to be fine-tuned. The model is:

$$i^{b_j} = \max_k\{i^{a_k}\cdot i^{r_{kj}}\} \tag{12}$$

$$i^{b_j} = \sum_{k=1}^{n_i} \min\{i^{a_k}, i^{r_{kj}}\} \tag{13}$$

Rule 4: Considers overall as well as emphasizes important factors. This rule requires to consider all factors overall as well as to emphasize important factors. The model is a weighted combination of the models under Rule 1 and Rule 3.

$$i^{b_j} = \lambda \sum_{k=1}^{n_i} (i^{a_k}\cdot i^{r_{kj}}) + (1-\lambda)\max_k\{i^{a_k}\cdot i^{r_{kj}}\}$$
$$(k = 1, 2, \ldots, n_i;\ 0 < \lambda < 1) \tag{14}$$

3.3. Determining weighting coefficients of the multicriteria evaluation model

In complex urban systems, decisions are usually semi-structured or unstructured. The multicriteria weighting coefficients assigned to such decision structures always reflect decision makers' preference and knowledge. To some extent, such coefficients determine the degree of combining multicriteria. The determination of weighting coefficients includes the following steps: (i) determination of the initial value of the weighting coefficient; (ii) consistency test; (iii) normalization; and (iv) adjustment.

In order to allow the decision makers to assign weighting coefficients to the criteria subset or index subset with various characteristics, the following techniques are used to determine in Eq. (6): the Direct Determination Method (DDM); the Comparative Matrix Method (CMM); the Analytical Hierarchy Process (AHP); the Circular Comparison Method (CCM); the Fuzzy Interval Method (FIM); and the Importance Ordering Method (IOM) (Saaty, 1990; Pereira & Duckstein, 1993). The process for determining weighting coefficients is shown in Fig. 2.

Considering that the different criteria (index) sets usually have different properties and characteristics, and different decision makers may choose different methods to assign weighting coefficients, our strategy is to create different methods of determining weighting coefficients available to decision makers. The advantages are: (i) the decision makers are able to choose the preferred method conveniently based on their understanding of the decision issues as well as the decision environments they are in; and (ii) the decision makers are not required to know the technical details of each different method. Fig. 3 shows the process of selecting weighting methods.

3.4. Quantifying the eigenvalues of the evaluation indexes

The two major characteristics of multicriteria decision issues are the conflicts among the criteria and the difficulty of measuring them. Because of the difficulties of measuring the criteria, it is not easy to analyze and compare such criteria if the eigenvalues in the eigenvalue matrix of the original evaluation indexes are directly used. Therefore, the eigenvalues of the evaluation indexes must be converted to the range of [0,1] before comprehensive evaluation can be conducted. However, because of the different types of the

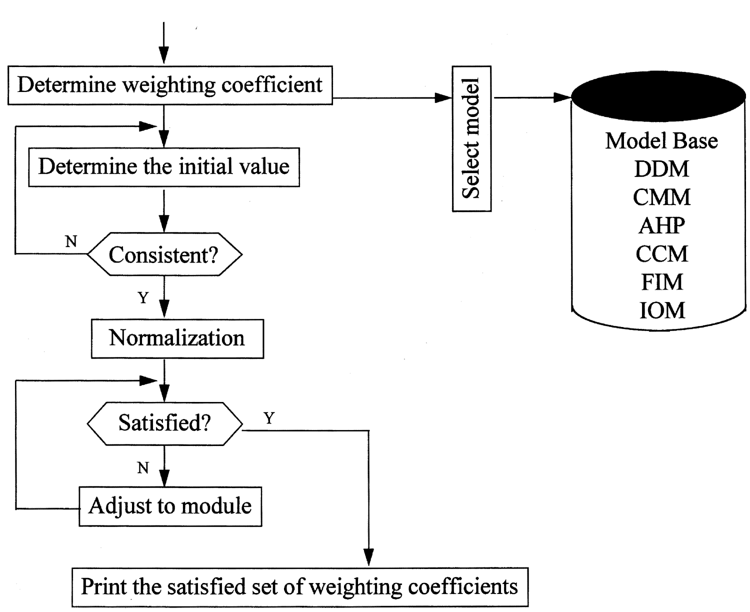

Fig. 2. The process of determining weighting coefficients.

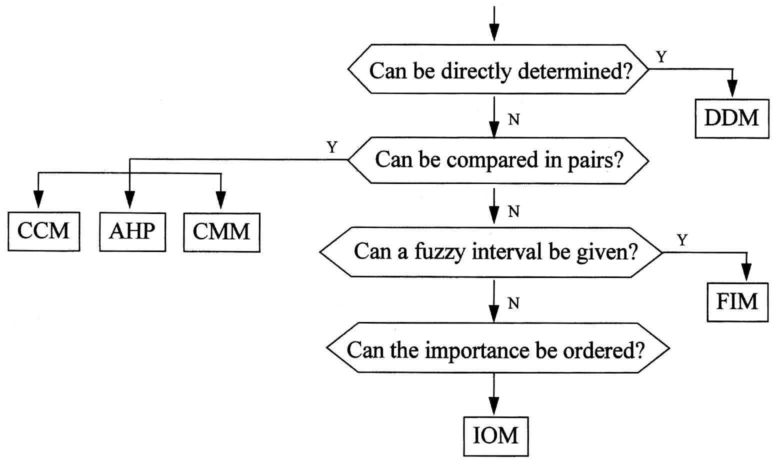

Fig. 3. The process of selecting weighting methods.

evaluation indexes, the methods used to quantify eigenvalues must be different too.

The indexes of the urban system generally fall into the following categories: the cost type (the better the smaller); the benefit type (the better the larger); the in-between type (not too large not too small); and the interval type (it is expected that the eigenvalues fall into a certain interval). The n_i indexes in the subset U_i can be divided into four subsets:

$$U_i = \{u_{i1}, u_{i2}, ..., u_{in_i}\}$$

$$= \{u_{i1}, u_{i2}, ..., u_{il}\} \cup \{u_{il+1}, u_{il+2}, ..., u_{im}\} \cup \{u_{im+1}, u_{im+2}, ..., u_{ir}\} \cup \{u_{ir+1}, u_{ir+2}, ..., u_{in_i}\}$$

$$= U_{i1} \cup U_{i2} \cup U_{i3} \cup U_{i4}$$

Where U_{i1} is the cost type index subset, U_{i2} is the benefit type index subset, U_{i3} is the in-between type index subset and U_{i4} is the interval type index subset.

For the convenience of calculation and extension, the following four types of membership functions are used to calculate the degree of membership in Eq. (3):

(1) Cost-type membership function ($k = 1, 2, ..., l$):

$$i^{r_{kj}} = \frac{\max_j\{i^{x_{kj}}\} - i^{x_{kj}}}{\max_j\{i^{x_{kj}}\} - \min_j\{i^{x_{kj}}\}} \tag{15}$$

(2) Benefit-type membership function ($k = l + 1, l + 2, ..., m$):

$$i^{r_{kj}} = \frac{i^{x_{kj}} - \min_j\{i^{x_{kj}}\}}{\max_j\{i^{x_{kj}}\} - \min_j\{i^{x_{kj}}\}} \tag{16}$$

(3) In-between-type membership function ($k = m + 1, m + 2, ..., r$):

$$i^{r_{kj}} = \frac{2(i^{x_{kj}} - \min_j\{i^{x_{kj}}\})}{\max_j\{i^{x_{kj}}\} - \min_j\{i^{x_{kj}}\}},\ i^{x_{kj}} < \frac{\max_j\{i^{x_{kj}}\} + \min_j\{i^{x_{kj}}\}}{2} \tag{17}$$

$$i^{r_{kj}} = \frac{2(\max_j\{i^{x_{kj}}\} - i^{x_{kj}})}{\max_j\{i^{x_{kj}}\} - \min_j\{i^{x_{kj}}\}},\ i^{x_{kj}} \geq \frac{\max_j\{i^{x_{kj}}\} + \min_j\{i^{x_{kj}}\}}{2} \tag{18}$$

(4) Interval-type membership function ($k = r + 1, r + 2, ..., n_i$):

$$i^{r_{kj}} = 1 - \frac{V_0 l_1 - i^{x_{kj}}}{\max\{V_0 l_1 - \min_j\{i^{x_{kj}}\},\ \max_j\{i^{x_{kj}}\} - V_0 l_2\}},\quad i^{x_{kj}} < V_0 l_1 \tag{19}$$

$$i^{r_{kj}} = 1,\ i^{x_{kj}} \in [V_0 l_1, V_0 l_2] \tag{20}$$

$$i^{r_{kj}} = 1 - \frac{i^{x_{kj}} - V_0 l_2}{\max\{V_0 l_1 - \min_j\{i^{x_{kj}}\},\ \max_j\{i^{x_{kj}}\} - V_0 l_2\}},\quad i^{x_{kj}} > V_0 l_2 \tag{21}$$

where the $[V_0 l_1, V_0 l_2]$ is the optimal stable interval of the indexes.

In addition, the decision makers are able to set the maximal and minimal thresholds interactively according to the characteristics of the indexes as well as their own preferences. For those indexes which can be measured qualitatively rather than quantitatively, the techniques of determining fuzzy membership functions are used to convert qualitative measurement to quantitative measurement.

4. An application example

The model discussed earlier is one of the fuzzy models in the DSS. This model was implemented by Chinese government for the city of Wuhan in central China. Wuhan is one of the largest cities in China with a population of six million. The model was used to provide decision support for planning urban development in Wuhan. The project had a major impact. The areas it affected include the insight and consensus on the strategic choices in urban development, the quality of urban planning, and the quality of urban planning information. During the implementation of the model, we found that we could supply information that was necessary to direct the planning process.

The success of the project has encouraged the Chinese government to introduce the model to other urban areas, and the study team is now extending the project to other provinces. The study has therefore demonstrated that fuzzy mathematical methods can have a profound impact at a high level of urban development policy making.

For illustration purposes, the following is an example of application. In this application, the index system and evaluation methods discussed earlier were used to evaluate the overall development of fourteen independently-planned Chinese cities. The eigenvalues of the major indexes are shown in Table 1 (Chinese State Statistical Bureau, 1991). In Table 1, $C_1 =$ Wuhan, $C_2 =$ Shenyang, $C_3 =$ Guangzhou, $C_4 =$ Harbin, $C_5 =$ Chongqing, $C_6 =$ Nanjing, $C_7 =$ Xian, $C_8 =$ Dalian, $C_9 =$ Chengdu, $C_{10} =$ Changchun, $C_{11} =$ Qingdao, $C_{12} =$ Ningbo, $C_{13} =$ Xiamen, $C_{14} =$ Shenzhen.

The following are the detailed evaluation procedures and the results:

Step 1: Enter the evaluation year as 1989, the fourteen cities to be evaluated and the 33 indexes to be used; and specify that the fuzzy model to be used corresponds to Rule 1.

Step 2: Evaluate the fourteen cities in terms of the index layers that correspond to O_i $(i = 1, 2, 3)$. For example, for O_1:

(1) choose a membership grade calculation method. The evaluation matrix for U_1 using Eqs. (15) and (16) is as follows:

Table 1
The eigenvalues of major indexes

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
u_1	u_{11}	9.40	7.70	10.40	9.30	5.40	11.10	14.80	9.50	6.90	17.00	9.90	8.10	11.00	11.00
	u_{12}	2307	1288	2454	1709	1929	2607	2462	981	2009	1854	1846	1039	1063	1104
	u_{13}	99254	57176	67969	50228	45344	70181	83173	35475	56674	51410	15183	4871	13239	4419
	u_{14}	899	1050	396	844	631	1118	315	786	1292	1044	1077	418	458	345
u_2	u_{21}	1324	1453	2351	1146	1335	1373	1343	1484	1565	1175	1455	1742	2024	3434
	u_{22}	1943	2144	3377	1938	2010	2188	1926	2334	2070	1914	2251	2208	2878	3900
	u_{23}	1162	1517	2868	1445	804	1354	1568	1938	1211	1442	1365	1303	1649	7454
	u_{24}	5.92	5.43	4.489	5.50	4.87	6.99	6.09	5.96	7.31	5.71	6.39	7.15	7.33	10.91
	u_{25}	119.50	77.00	161.90	51.20	47.00	82.80	41.70	35.30	75.70	53.20	27.30	82.30	67.30	166.30
	u_{26}	5.19	2.88	4.07	3.67	4.42	4.57	3.01	4.98	3.08	3.33	3.83	1.70	2.69	10391
	u_{27}	3.60	3.70	7.40	0.00	2.50	5.10	5.10	3.80	4.10	4.30	3.80	5.60	5.90	28.40
	u_{28}	34	34	36	38	17	31	31	22	24	21	20	15	22	47
u_3	u_{31}	41.65	50.16	43.36	26.47	47.69	25.82	56.59	36.91	36.57	20.95	14.25	31.28	57.47	96.49
	u_{32}	0.87	0.69	1.48	0.54	1.60	0.33	1.23	0.17	0.36	1.57	2.42	4.21	1.08	1.75
u_4	u_{41}	110.21	121.31	156.86	69.55	119.27	100.00	71.22	110.49	105.18	61.84	106.20	93.33	27.64	56.79
	u_{42}	96.42	104.40	117.89	52.30	106.21	81.82	56.34	96.89	78.28	52.47	92.16	85.83	23.68	48.05
	u_{43}	238.65	259.19	292.56	138.86	246.00	210.88	147.26	219.67	195.94	135.06	270.46	242.52	59.55	122.03
	u_{44}	257904	445364	829811	249962	345957	403111	242453	311363	259227	135322	269587	183645	108354	483919
	u_{45}	974337	1051072	11519460	784301	1073083	750318	680497	808259	883014	578116	703175	601314	252035	561347
	u_{46}	311663	339178	465117	162352	281934	200068	130120	254585	195905	121174	221183	153	81086	187696
	u_{47}	3665	4870	94762	1882	4548	12181	14125	10913	5308	790	9459	1545	11352	47658
	u_{48}	163266	114436	446900	87660	155431	103069	39088	218547	56818	59342	257641	177661	196519	71761
u_5	u_{51}	2251	2865	3530	1979	1154	2345	1342	2748	1360	1273	2026	2468	3393	11550
	u_{52}	2606	3401	4953	2670	1343	2854	1657	3244	1704	1481	2380	2702	4054	15655
	u_{53}	5227	6668	7712	4898	2516	6008	3177	6278	3186	2999	5597	6003	7226	22893
u_6	u_{61}	54	63	297	32	38	42	8	173	9	790	9459	1545	11352	47658
	u_{62}	10507	6268	52887	3561	3887	9589	108	37233	490	1387	13097	10290	82313	48904
	u_{63}	7893	5723	29842	3801	22479	5192	4161	19363	490	360	10815	3493	23822	45809
u_7	u_{71}	0.25	0.19	0.19	0.21	0.16	0.34	0.25	0.29	0.19	0.36	0.20	0.09	0.23	0.37
	u_{72}	7.11	5.59	6.04	8.05	0.91	8.80	5.80	5.65	1.76	6.17	2.81	1.00	8.38	35.24
	u_{73}	0.23	0.12	0.41	0.10	0.24	0.28	0.12	0.39	0.32	0.29	0.41	0.18	0.23	0.34
	u_{74}	0.85	0.64	0.72	0.64	0.42	0.50	0.63	0.67	0.41	0.69	0.57	0.48	0.74	0.52
	u_{75}	0.19	0.10	0.38	0.04	0.04	0.10	0.07	0.10	0.18	0.02	0.03	0.02	0.43	0.50

$$1^{\underset{\sim}{R}} = \begin{bmatrix} .655 & .802 & .569 & .664 & 1.000 & .509 & .190 & .647 & .871 & .000 & .612 & .767 & .517 & .517 \\ .185 & .811 & .094 & .552 & .417 & .000 & .089 & 1.000 & .368 & .463 & .468 & .964 & .950 & .924 \\ 1.000 & .554 & .669 & .481 & .429 & .692 & .830 & .324 & .549 & .493 & .109 & .000 & .089 & .000 \\ .589 & .752 & .083 & .541 & .323 & .822 & .000 & .482 & 1.000 & .746 & .780 & .105 & .146.031 & \end{bmatrix}$$

(2) choose a weighting method and then calculate the weights for the index subsets. Using CMM, the weights for U_1 are as follows:

$$1^{\underset{\sim}{A}} = (.262, .226, .256, .256)$$

(3) determine whether the weights are satisfactory; then adjust the weights if they are not satisfactory and continue if they are satisfactory.

(4) use the fuzzy model that corresponds to the appropriate evaluation rule to do the calculation. The following are the results using Eq. (10):

$$1^{\underset{\sim}{B}} = 1^{\underset{\sim}{A}} \circ 1^{\underset{\sim}{R}} = (.662, .728, .363, .560, .549, .521, .282, .602, .708, .422, .494, .446, .410, .352)$$

(5) let the comprehensive evaluation values of this layer as the row vector ($k = 1,2,3$) of the upper layer evaluation matrix, $\underset{\sim}{R}_1$ *for* U_1,

$$\vec{r}_1 = 1^{\underset{\sim}{B}} = (.662, .728, .363, .560, .549, .521, .282, .602, .708, .422, .494, .446, .410, .352)$$

(6) repeat steps (1) to (5) until all of the evaluations for the index subsets U_1, U_2 and U_3 for the level corresponding to O_1 are finished. The results obtained are:

$$\vec{r}_2 = 2^{\underset{\sim}{B}} = (.370, .317, .678, .230, .123, .512, .339, .378, .519, .211, .376, .508, .703, 1.000)$$

$$\vec{r}_3 = 3^{\underset{\sim}{B}} = (.580, .503, .487, .794, .423, .827, .364, .718, .699, .736, .713, .303, .500, .292)$$

The evaluation matrix of the upper layer, i.e. the middle layer, is as follows:

$$\underset{\sim}{R}_1 = \begin{bmatrix} \vec{r}_1 \\ \vec{r}_2 \\ \vec{r}_3 \end{bmatrix} = \begin{bmatrix} .622 & .728 & .363 & .560 & .549 & .521 & .282 & .602 & .708 & .422 & .494 & .446 & .410 & .352 \\ .370 & .317 & .678 & .230 & .123 & .512 & .339 & .378 & .519 & .211 & .376 & .508 & .703 & 1.000 \\ .580 & .503 & .487 & .794 & .423 & .827 & .364 & .718 & .669 & .736 & .713 & .303 & .500 & .292 \end{bmatrix}$$

(7) calculate the weighting coefficient set of the middle layer, and conduct a comprehensive evaluation, the result is:

$$\underset{\sim}{B}_1 = \underset{\sim}{A}_1 \circ \underset{\sim}{R}_1$$

$$= (.331, .379, .289) \circ \underset{\sim}{R}_1$$

$$= (.514, .507, .518, .503, .351, .606, .327, .551, .634, .433, .512, .428, .547, .581)$$

(8) let the comprehensive evaluation set of this layer as the row vector of the evaluation matrix of the macro-layer, then:

$$\vec{R}_1 = \underset{\sim}{B}_1 = (.514, .507, .518, .503, .351, .606, .327, .551, .634, .433, .512, .428, .547, .581)$$

Step 3: Calculate the weighting coefficient set of the macro-layer and conduct a comprehensive evaluation. Here the weighting coefficient set $\underset{\sim}{A}$ is obtained using CCM:

$$\underset{\sim}{A} = (.333, .333, .333)$$

Finally, the comprehensive evaluation result, i.e. the combined index values which reflect the overall development of individual cities, are obtained:

$$\underset{\sim}{B} = \underset{\sim}{A} \circ \underset{\sim}{R} = (.414, .344, .535, .284, .270, .378, .233, .452, .328, .307, .356, .204, .433, .703)$$

Step 4: Reorder the combined index values obtained from Step 3:

$$Q(\underset{\sim}{B}) = (.703, .535, .452, .433, .414, .378, .356, .344, .328, .307, .284, .270, .233, .204)$$

The order of the combined index values for the overall development for individual cities is as follows:$Q(C) =$ (Shenzhen, Guangzhou, Dalian, Xiamen, Wuhan, Nanjing, Qingdao, Shenyang, Chengdu, Changchun, Harbin, Chongqing, Xian, Ningbo)

Policy makers may use other evaluation criteria as well as their own subjective judgment to determine the weights for each index subset. If Eq. (14) which corresponds to Rule 4 is used, the combined index values for the overall development of urban areas becomes:

$$\underset{\sim}{B} = (.159, .185, .233, .103, .117, .134, .103, .178, .114, .141, .135, .060, .189, .278)$$

Then the order of the combined index values for the overall development for individual cities is as follows:$Q(C) =$ (Shenzhen, Guangzhou, Xiamen, Shenyang, Dalian, Wuhan, Changchun, Qingdao, Nanjing, Chengdu, Harbin, Xian, Ningbo)

Under Rule 1, the cities with higher *Q(C)* than the average combined index value 0.374 include Shenzhen, Guangzhou, Dalian, Xiamen, Wuhan and Nanjing. The cities with *Q(C)* that fall in the range of 0.374 and 0.3 include Qingdao, Shenyang, Chengdu and Changchun. The cities with *Q(C)* below 0.3 include Harbin, Chongqing, Xian and Ningbo. Under Rule 4, the cities with *Q(C)* higher than the average combined index value, 0.152, include Shenzhen, Guangzhou, Xiamen, Shenyang, Dalian and Wuhan. The cities with *Q(C)* that fall in the range of 0.152 and 0.130 include Changchun, Qingdao and Nanjing. The cities with *Q(C)* below 0.120 include Chongqing, Chengdu, Harbin, Xian and Ningbo. After comparing the combined indexes of individual cities under the two different rules, it is obvious that the overall development level of Shenzhen, Guangzhou, Dalian, Xiamen and Wuhan is the highest, that of Shenyang, Nanjing, Qingdao, Changchun and Chengdu is in the middle, and that of Harbin, Chongqing, Xian and Ningbo is lower.

Data show that the five cities with highest *Q(C)* in this study are actually listed as the first eight in terms of comprehensive evaluation index values for social development, the first six in terms of comprehensive evaluation index values for economic development, and the first five in terms of comprehensive evaluation index values for environmental considerations. The four cities with lower *Q(C)* have lower scores for the comprehensive evaluation index values for social development, economic development as well as environmental protection. It is worth mentioning that cities such as Shenzhen and Xiamen are small in terms of size (the population of each city excluding farmers is below four hundred thousand), but they are strong in social development, economic development, international capital utilization as well as environmental protection.

5. Conclusion

This paper describes and illustrates an integrated intelligent decision support system that combines a knowledge-based DSS and an ANN, with the inclusion of approximate reasoning. We have found the system to be effective in evaluating urban development. One can apply the general approach utilized in the integrated system to a diverse set of problems in many areas of automated decision making.

In this study, we have merged three technologies, ie. DSS, KBS and ANN in the same complex application. The study confirms the complimentary nature of these three technologies. By integrating these three technologies one can achieve improvements in the implementation of each as well as increase the scope of application; therefore, this approach is rewarding in its synergism of three technologies to solve complex problems. The major advantages of the hybrid approach include: (i) KBSs are good for closed-system applications for which inputs are precise, leading to logical outputs; for applications with well-defined rules, KBSs can provide good performance. ANNs can analyze large quantities of data to establish patterns and characteristics in situations where rules are not known. The hybrid system is able to complement the evaluation provided by the *KB-CEDSS* using rules with pattern recognition capability of ANNs; (ii) by integrating ANN with KBS we can automate knowledge refinement. The ability to learn in unknown environments is an essential component of any intelligent system and is particularly crucial to its performance. This ability can be enhanced by incorporating neural network learning mechanisms into KBSs. ANN techniques enable the KBS to modify and/or enrich its knowledge structures autonomously. Rules and facts may be frequently modified, and knowledge in rules may be evolutionary, dependent on human experience in the domain. The integrated system offers the means to overcome some of the major drawbacks of conventional KBSs, such as their reliance on consultation with human experts for knowledge refinement, and their inability to synthesize new knowledge. The ANN in the integrated system analyzes the data sets originally derived from experts to identify underlying patterns and relationships that subsequently refine the knowledge of the KBS and produces specific knowledge relevant to the evaluation of urban development. The KBS can then perform further analysis. For complex applications, it is obvious that hybrid approaches that combine methods of traditional DSS, KBS and ANNs are more appropriate.

The use of fuzzy modeling techniques as a method of evaluation for urban development is innovative (Nijkamp, 1986; Saxena et al., 1990). The model we developed has made a contribution to academic knowledge in relation to its

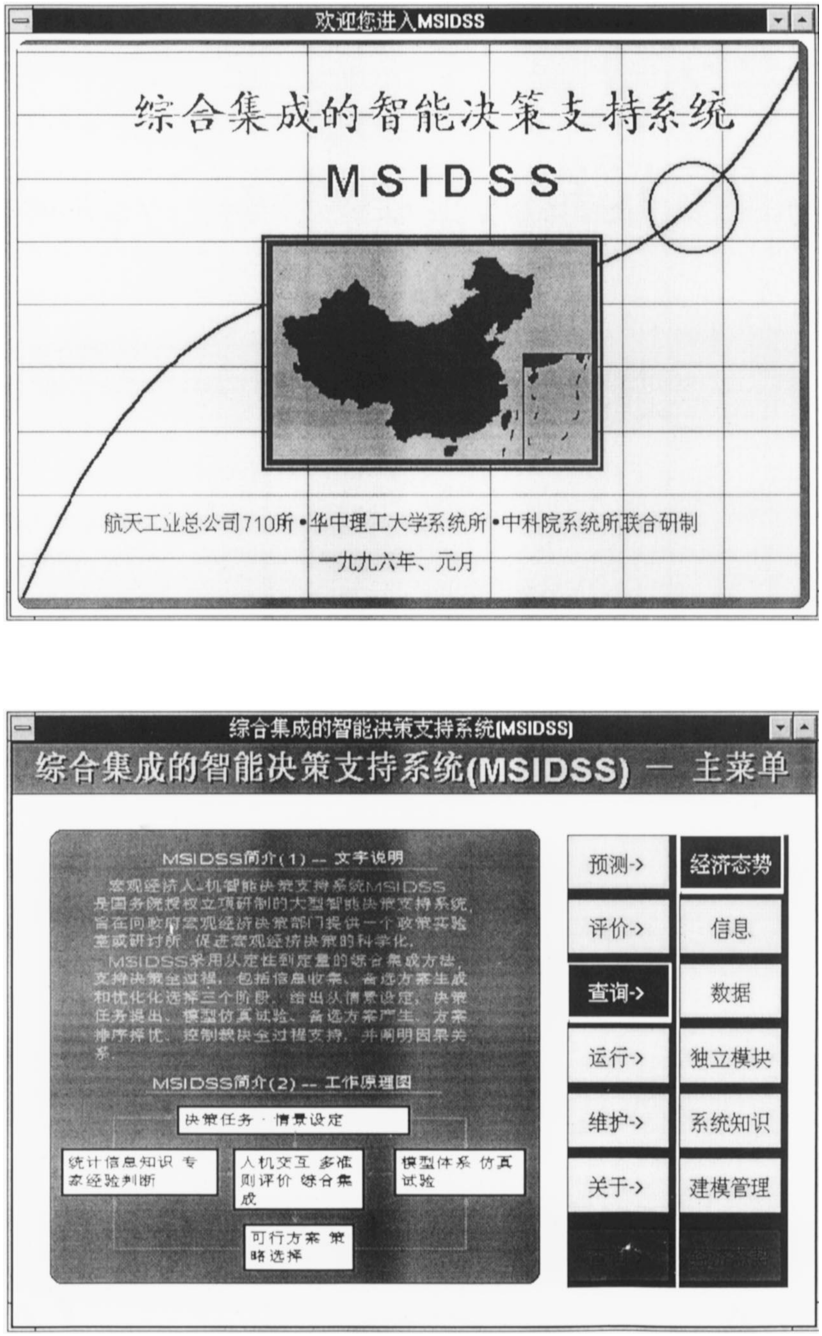

Fig. 4. A sample main menu of MSIDSS.

fuzzy mathematical evaluation in urban development. The model was implemented by Chinese government in central China. The implementation results show that it is useful to classify those factors affecting urban development into multiple layers and multiple subsets, and later to evaluate them from a lower layer up to a higher layer. One of the main advantages of this technique is that those factors affecting urban development can be directly represented through different layers and stages and thereby ensure both the objectivity and effectiveness of the comprehensive evaluation. The DSS in the integrated system has contributed to the acceptance of fuzzy mathematics in public decision making, particularly among urban development policy making. For example, much of the decisions on the urban planning of Wuhan are based on the achievements of the model. Probably the greatest long-term impact of the model will be in the general improvement of the nation's urban planning.

Currently, the system is being improved from a number of viewpoints. Firstly, it is known that the three technologies complement each other to achieve better coverage of perspectives involved in complex decision making. More research is required to answer an important question; that is, how to achieve best coverage of perspectives through combining and refining three technologies as well as to avoid their disadvantages by enhancing the desirable properties of each other. Secondly, currently the model is integrated with a number of existing decision support systems including a large scale integrated intelligent decision support system called MSIDSS which was developed recently (Wang & Feng, 1992, 1995; Feng, 1993; Tian & Feng, 1996; Feng & Xu, 1996). *KB-CEDSS* can be accessed through MSIDSS now. Fig. 4 shows a sample page of the main menu of MSIDSS.

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