Research on Fuzzy Adaptive Intelligent Decision-making in Complex Environment

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Abstract. Decision-making is an extremely complex proposition. Especially with the development of economy, the progress of science and technology and the acceleration of global integration. All walks of life are facing an increasingly complex and changing environment, and decision-making problems are becoming more and more complex. In complex environments, decision-making is made by multiple stakeholders on the basis of increasingly updated self-confidence and repeated discussions. Enterprise-level decision support system is much more complex than individual decision in decision environment, decision process and decision support technology. Multi-objective intelligent decision making is a difference and multi-objective optimization problem. Based on quantitative mathematical models, intelligent decision-making systems lack corresponding support methods for qualitative, fuzzy and uncertain problems in decision-making. Based on the complex adaptation theory, this paper constructs an adaptive intelligent decision support system. The adaptive decision process is analyzed. It is proved that the decision-making platform based on adaptive intelligent decision theory can help decision makers to provide effective decision-making in complex environments.

1. Introduction
The basic contradiction between limited resources in the real world and unlimited needs of people leads to competition, which makes decision-making necessary. Decision-making is one of the basic activities of human activities [1]. In the process of industrial control, many controlled processes have complex mechanisms, such as high-order nonlinearity, slow time-varying, pure lag, etc. [2]. Under the influence of noise, load disturbance and other environmental conditions, process parameters and even model structure will change [3]. Since ancient times, human beings have been striving for survival and development with their unique decision-making ability. With the emergence and development of computers, people use computer-aided decision-making to develop confidence, system and decision support system [4]. By manipulating the data through the model, decision makers are required not only to have domain knowledge of decision-making problems, but also to have relevant knowledge of data and models [5]. The role of the system in decision support is passive and cannot provide active support based on changes in the decision environment. Traditional decision support systems use a variety of quantitative models to support semi-structured and unstructured decision making issues. Since the intelligent decision-making system requires the participation of decision makers, man-machine dialogue is used to manipulate data through the model. What is actually supported is only the structured and clearly procedural part of the decision-making process. Based on quantitative mathematical models, intelligent decision-making systems lack corresponding support methods for qualitative, fuzzy and uncertain problems in decision-making [6].

Complex system theory is a frontier of system science. Its main purpose is to reveal some of the dynamic behaviors of complex systems that are difficult to interpret with existing scientific methods [7].
The intelligent decision support system utilizes the advantages of artificial intelligence and expert system technology in fixed-point analysis and uncertain reasoning, making full use of human experience and knowledge in problem solving, and provides a new way to solve problems [8]. In the traditional navigation data fusion filter design, the parameters of the filter are often obtained through multiple offline evaluation optimization [9]. Unlike traditional reductionism methods, complex system theory emphasizes the use of a combination of holism and reductionism to analyze systems. The fuzzy controller is generally composed of two parts: control rules and fuzzy inference [10]. Among them, the fuzzy control rules are used to express and memorize the expert's control experience, while the fuzzy reasoning is used to infer the choice [11]. Expert system makes machine intelligence reach or even surpass human expert level in some aspects by establishing domain expert knowledge base and problem solving subsystem [12]. In practical applications, because of different scenarios and inaccurate acquisition of necessary conditions for modeling, the error of state vector solution can not be directly measured and compensated [13].

The application of expert system technology in management often uses static knowledge base and man-machine dialogue system for decision-making problems in specific fields [14]. In the face of different decision-making problems, lack of adaptability. The expert system technology is applied to the decision support system, and the intelligent decision support system is established [15]. It can overcome the limitations of expert system and decision support system, and better support the management decision task [16]. There is no single optimal solution for multi-objective decision-making, but a set of alternative solutions. In a broader sense, these solutions are called non-inferior solutions. That is, in search space, when all targets are taken into account, no other solution can be better than them [17]. Artificial intelligence and expert system technology not only profoundly affect the technology and structure of decision support systems, but also have a profound impact on the concept of decision support systems [18]. Almost all research on decision support systems is based on the application of artificial intelligence technology. The combination of the expert system and the decision support system is directly reflected in the intelligentization of the various components of the decision support system [19]. After finding a non-inferential set of multi-objective decision-making problems through decision-making methods, these solutions do not necessarily meet the requirements of decision makers. The fuzzy controller of this paper gives a reasonable expression and reasoning method of fuzzy control rules. By using the expression of fuzzy control rules, memory ability and the learning ability of a single neuron, a decision algorithm based on fuzzy control rules is given.

2. Materials And Methods

Although the object of research is decision-making, however, whether it is utility decision theory or behavioral decision theory, there is no sign of reconciliation, tolerance and integration, but parallel development. The traditional decision support system selects the corresponding method and model by the user by providing corresponding data and models. The decision-making process is completely controlled by the user, and the system simply completes the auxiliary computing function [20]. The traditional multi-objective decision-making model is not well suited to the multi-objective decision-making problem in reality. In real-world decision-making, the factors that decision makers must consider are complex and involve many aspects. There are quantitative and qualitative ones. Real-time monitoring and adjustment of the internal parameters of the state estimation filter to achieve the purpose of optimizing the filtering. It relies too much on people's psychological and behavioral analysis to deal with decision-making problems, and can not grasp the true connotation of decision-making. It is impossible to deal with complex social decision-making problems by relying too much on the utility theory developed on the basis of precise natural science thinking. It is impossible to reflect the true connotation of decision-making only by quantifying and comparing human values. By introducing intelligent methods such as fuzzy reasoning, expert system and artificial neural network, the working condition of the carrier can be identified and evaluated. Real-time modification of filter internal parameters to correct deviation.
Multicultural integration makes everyone in today's society have the criteria to measure value, resulting in great differences in the judgment of value. Employment needs of enterprises are changing all the time, and a great deal of data are produced. We need to constantly explore and accumulate experience in construction. Figure 1 is the network structure system of talent entrepreneurship consciousness management.

![Talent entrepreneurial awareness management network structure system](image)

The problem of decision-making in reality is hardly a simple problem, but a complex problem, specifically a complex system problem. The intelligent decision support system has the ability to actively support decision-making due to the introduction of domain expert knowledge and partial human intelligence. Traditional multi-objective decision-making models tend to consider quantitative factors much less and consider qualitative factors less or quantify insufficient or inaccurate factors. It is often difficult to quantify qualitative factors. People always make hierarchical and step-by-step decisions when making complex decisions [21]. The processing of more certain information is done at a lower level, and the information needed to process the changes in the environment is carried out at a higher level [22]. From the point of view of knowledge structure and cognitive ability, active decision support system is still static, in fact, it is based on the user's past decision-making experience. In the process of learning, we should not only be able to better explain the known examples by using the learning rules, but also make correct predictions and judgments about future phenomena or unobservable phenomena. Figure 2 is the dynamic evolution of the evaluation system of intelligent decision-making consciousness.
For the sake of simplicity, the traditional multi-objective decision model often simplifies the uncertainty in the real problem to a certain amount. This is useful and necessary for the initial establishment and development of multi-objective decision theory. However, with the maturity of the theory and the deepening of its application, people are increasingly required to fully consider the multi-objective decision-making problem with uncertainty. Establish a risk indicator system for college students' decision-making teams, and use AHP to evaluate risks. Construct a judgment matrix of weights. The relationship between the weight value and the evaluation value data is shown in Figure 3. The relationship between the decision status risk weight value and the evaluation value data is shown in Figure 4.
Fig 4. Relationship between risk weight of decision-making status and evaluation data

The coordination level mainly includes facts and rules. The facts mainly refer to the prior knowledge of the controlled process and the influence of various main parameters such as empirical data and charts on the control performance. The automation of decision-making does not exclude the role of decision makers in the decision-making process, but rather supports a more advanced decision-making process. As long as the initial conditions of the system are known, even if the initial conditions are somewhat inaccurate, as long as the error is small enough, the evolution of the system can be derived. Decisions in complex systems with tens of thousands of interrelated system state variables. Based on complex system theory, information science theory and decision science theory [23]. Research on adaptive intelligent decision support systems in complex environments. Even true human experts play only in decision-making. Decision-making expert system can automatically give decision-making conclusions according to decision-making conditions. Templates are used to express information features extracted from cases, and case-based reasoning technology is used to quickly find similar crises or emergencies and provide corresponding solutions [24]. Expert system is oriented to users in specific fields, and decision support system is used by managers and decision makers. The main function of grading is to select control mode according to environmental change and control process. The initial parameters of adaptive PI control are selected appropriately, and the control rules of FC are modified appropriately.

3. Result Analysis and Discussion

Integrated decision support system (IDSS) is a new generation of decision support system based on adaptive decision support system (ADSS) and decision expert system (DES). The traditional multi-objective decision theory assumes that the decision maker is completely rational in making decisions, that is, he always chooses the optimal solution or the most satisfactory solution. Intelligent electric valve positioner uses high-performance conductive plastic precision rotary potentiometer. The rotation angle of the feedback potentiometer has a linear relationship with the valve opening. By sampling the output voltage of the feedback potentiometer, the valve opening can be obtained indirectly. The control rules of the fuzzy controller are the production rules expressed by the fuzzy sets. Arbitrary deviation and its change rate can be expressed by their respective reference fuzzy sets. So as long as the control rules corresponding to the reference fuzzy set are obtained, the completeness of the control rules can be maintained. Satisfaction is not a reliable criterion for optimality. Reality experience has proven that in some cases, decision makers may be satisfied with a dominant solution. The integrated decision support system does not rely on pre-defined processes and rule-based reasoning, but rather the integration of intelligent activities from beginner to advanced.

A model library system consisting of conceptual models and a flexible and convenient human-computer interaction system can help decision makers make decision-making decisions on decision-making problems in water resources planning. Sensitivity analysis can be performed for each influencing factor of a single project, and the risk management of the project can be performed from the results of
the analysis. The risk assessment sensitivity analysis data is shown in Table 1. The relationship between risk assessment and risk factors is shown in Figure 5.

| Evaluation value | Post-change score |
|------------------|-------------------|
| Production risk  | 0.742             |
| Management risk  | 0.936             |
| Technical risk   | 0.728             |
| Market risk      | 0.619             |

Fig 5. Relationship between risk assessment and risk factors

For the time trajectory of the financial time series, the time series with long-term correlation is:

\[ U_{ij} = \frac{H_{ij}}{\sqrt{\sum_{i=1}^{k} H_{ii}^2}}, i = 1,\ldots,n, j = 1,\ldots,k \]

(1)

Time series have a long-term "memory" effect. The previous observations have long-term effects on the observations of the latter phase, and this effect is measured by the associated scaling function:

\[ I(X;Y) = \sum_{i,j,s,t} \sum p(x,y) \log \left( \frac{p(x,y)}{p(x)p(y)} \right) \]

(2)

Sequences are biased random walks with persistence and long-term memory effects. The statistic for this hypothesis test is \( n \):

\[ n = \sum_{i=1}^{r} PW_{i,j} + b \]

(3)

To describe the impact on the future, an indicator of relevance is introduced:

\[ E_p = \frac{\sum (t-p)^2}{2} \]

(4)

Intelligent decision support system (IDSS) is a knowledge-based system. Because knowledge management is still a rapidly developing field, it is difficult to give a definite induction. Decision makers are often influenced by many complex factors, such as social system, traditional culture, management mode, their own thinking patterns and psychological factors. Real decision-making is often far from the theoretical study of man-made. From the perspective of the development of system intelligence, the relationship between several types is mutually inclusive and complementary. More advanced models
reflect the evolution of system intelligence and do not exclude other types of features. The issue of ecological environment construction and sustainable development has become an important issue for the country to consider in formulating economic development policies. The application of decision support systems in this area is very promising.

Decision makers' intertemporal preferences are based on revenue mix. The model can be expressed in the mathematical form as shown by the special commodity of income:

$$y_j = f \left( \sum w_j x_j - \theta_j \right)$$

(5)

The perpetrator's preference is time-consistent. All discount functions can be expressed as follows:

$$q_i = f \left( \sum T_{ij} - \theta_j \right)$$

(6)

And this expression obviously improves its fit to reality:

$$w_j (k + 1) = w_j (k) + \eta \delta x_j$$

(7)

In general, fuzzy adaptive techniques are used to obtain an optimal estimate of the average rate of return for risk decisions. Subsequently, instead of the usually more complex stochastic dynamic programming method, the optimal strategy is quickly obtained. The unit test results show that each variable is a first-order single-sequence sequence, which conforms to the premise of cointegration test. Test for long-term equilibrium relationships between related variables. The criteria are selected based on the model lag period. The test results are shown in Table 2.

| Eigenvalues | Trace estimate | Threshold |
|-------------|----------------|-----------|
| 1.432       | 56.75          | 25.78     |
| 0.946       | 42.84          | 36.55     |
| 1.275       | 43.56          | 29.47     |
| 0.769       | 25.46          | 48.32     |

In financial markets, the higher the volatility of a financial instrument, the greater the risk. This volatility or risk is measured statistically by the standard deviation. The larger the standard deviation, the higher the corresponding risk. The conditions for combining the model solutions under complete information, define the function:

$$P_s - P_d = \frac{\rho}{2C_q A_q^2} Q^2_i$$

(8)

Call it an indirect utility function. According to the principle of stochastic dynamic programming, we have:

$$Q_i = C_q A_q \sqrt{2 \Delta P_i} / \rho$$

(9)

After appropriate affine transformation, the utility function of the constant absolute risk avoider can be uniformly written as:

$$f(x) = \sum_{j=1}^{n} \alpha_j N(\mu_j, \sigma_j^2)$$

(10)
If the utility function is not a logarithmic type, the calculation of the correlation result is a problem to be solved. According to the analysis, it is almost impossible to obtain an analytical solution. The actual change in the price level of the market factor over the past period is calculated based on the price time series of the market factor in the past period. The above calculation is implemented by language programming, and the calculation results are shown in Table 3.

Table 3. Analysis and related parameter estimation results

|                | Constant term | Coefficient term | Fractal dimension | Correlation scale |
|----------------|---------------|------------------|-------------------|-------------------|
| Daily rate of return | 0.375         | 0.782            | 1.546             | 0.342             |
| Weekly rate of return  | 0.342         | 0.734            | 1.233             | 0.317             |
| Monthly yield       | 0.327         | 0.765            | 1.317             | 0.286             |

The adaptive decision support system uses methods such as inductive reasoning [25]. Has the ability to automatically maintain a knowledge base that can handle incomplete or even conflicting knowledge. So we can think that the decision makers in reality are making decisions based on bounded rationality. Active support is the characteristic of all intelligent decision support systems, and self-adaptability is the basic requirement of integrated decision support systems. The inconsistency of expected return leads to the inconsistency of time discount rate in complex environment. With the time discount rate decreasing, hyperbola is steeper than hyperbola, which means that the degree of inconsistency of time preference is more obvious. As shown in Figure 6.

Fig.6 Time inconsistency curve

Intelligent electrical valve positioners need to be suitable for many different types of control valves, so the characteristic parameters or structure of the controlled object are not fixed. Traditional decision support system components provide quantitative numerical calculation, and knowledge components use knowledge processing technologies such as symbolic reasoning and pattern recognition. The existence of agency problems makes decision makers' time preferences inevitably internalized in decision-making activities in complex environments. The decision status risk comparison data is shown in Table 4. The relationship between the decision status risk weight value and the evaluation value data is shown in Figure 7.
Table 4. Decision status risk comparison data results

| Decision yield | Marginal cost rate |
|----------------|-------------------|
| Decision yield | 1                 |
| Marginal cost rate | 0.76             |

Fig. 7 Relationship between risk value and evaluation value of decision status

By solving ordinary differential equations, the appropriate affine transformation is performed. The utility function of the constant hyperbolic absolute risk avoider can be uniformly written as:

\[ N\left(\mu, \sigma_j^2\right) = \frac{1}{(2\pi)^{1/2} \sigma_j} \exp\left(-\left(\frac{x - \mu}{\sigma_j}\right)^2\right) \]

(11)

By solving ordinary differential equations, the appropriate affine transformation is performed. The utility function of the constant hyperbolic absolute risk avoider can be uniformly written as:

\[ p_n(f) = C \sum_{i=1}^{n} K\left(\frac{f - z_i}{h}\right)^4 \delta\left[b(z_i) - u\right] \]

(12)

In general, fuzzy adaptive techniques are used to obtain an optimal estimate of the average rate of return for risk decisions. Subsequently, instead of the usually more complex stochastic dynamic programming method, the optimal strategy is quickly obtained. The unit test results show that each variable is a first-order single-sequence sequence, which conforms to the premise of cointegration test. Test for long-term equilibrium relationships between related variables. The criteria are selected based on the model lag period. The test results are shown in Table 5.

Table 5. Cointegration test result

| Eigenvalues | Trace estimate | Threshold |
|-------------|----------------|-----------|
| 1.432       | 56.75          | 25.78     |
| 0.946       | 42.84          | 36.55     |
| 1.275       | 43.56          | 29.47     |
| 0.769       | 25.46          | 48.32     |

Research on intelligent decision support systems is showing a trend of integration. Existing systems are generally hybrid systems formed by a combination of methods. The knowledge maintenance of static knowledge systems requires manual intervention, and the behavior of the system has been determined before the solution process begins. Dynamic systems can automatically gain experience from the decision-making process. The knowledge required for the decision-making process is quite complex.
There is both factual knowledge and expert knowledge in the field of reasoning and decision making. Executors did not expect to find information related to decision-making problems in the database to ask, help decision-makers find potential associations between data, find neglected elements, and anticipate future behavior by analyzing existing ways. By adding system components, the system has good scalability and can integrate new decision-making technologies at any time. The knowledge base is automatically maintained and updated to support the decision-making process in complex environments, reflecting higher-level intelligent activities.

4. Conclusion
Decision support system is different from traditional decision support system in the field of decision support, decision method and decision process. The complexity of decision-making problems, the variability of environment and the complexity of decision-making process require that the internal and external data resources be fully utilized in decision-making. The research results of qualitative and quantitative decision-making methods are synthetically used, and the agile and configurable architecture is adopted to support management decision-making. Adaptive decision support system in complex environment should be a man-machine harmonious system. Only by giving full play to the decision-maker's autonomy, the machine's powerful learning and processing ability and the role of previous decision-maker's experience. Due to the complexity and time-varying decision-making of complex problems, the paper establishes a decision support system from the perspective of complex adaptive, in order to achieve a breakthrough. In the decision-making process, there may be no feasible solution to the final decision result for different reasons. This situation may be that there is really no feasible solution, or it may be because the response function's membership function does not reflect the true will of the decision maker. The decision support system supports the decision-making process to the direct decision process and the indirect decision process, and summarizes the decision support points of the existing decision support system. Decision-making is based on the essence of the future. In order to avoid possible damage in the long-term offsetting or even surpassing recent benefits, the decision-making system should be extended to a farther future in the time domain.

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