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Retraction

Retracted: Analysis of International Competitiveness of Multinational Corporations Based on Rough Sets

Complexity

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Zhao and N. Qi, "Analysis of International Competitiveness of Multinational Corporations Based on Rough Sets," *Complexity*, vol. 2021, Article ID 9922410, 10 pages, 2021.

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Research Article

Analysis of International Competitiveness of Multinational Corporations Based on Rough Sets

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Modern business judgment is mostly faced with complex, unclear nature, and not fully confirmed research objects and needs a lot of relevant data investigation, inherent contradiction retrieval, and the discovery and extraction of potential laws. Formulation of rules and evaluation of system uncertainty: Appropriate decisions can be made based on this. Rough set theory is a new mathematical tool to deal with uncertain knowledge. Therefore, the theory of rough set is helpful for decision-makers to solve the decision problems of complex systems. The simplification of knowledge of information systems and incomplete information systems and the theoretical and methodological study of rule acquisition are the central issues of rough set theory and applied research. A variety of simplified theories and methods have been proposed from a variety of viewpoints. However, there are still many theoretical problems that need to be investigated and solved in these aspects. In addition, the investment environment is a complex organic system that includes economic environment, social environment, resource environment, infrastructure, and other factors. There are a variety of data to measure these factors, which are mutually restrictive and interdependent. At present, domestic and foreign scholars have basically formed a series of assessment methods and models of investment environment assessment, but most of these assessment methods are affected by the differences in the degree of subjective factors of evaluators and the establishment of index weights in the assessment process. In most cases, more reliance is placed on subjective, artificial assignments and scoring loops. Therefore, it is an appropriate and reasonable method to evaluate the investment environment through data to evaluate all the factors affecting the investment environment and reach a comprehensive evaluation conclusion, which can effectively avoid human subjective factors to a certain extent.

1. Introduction

The management of the knowledge economy, which is called the fifth generation of management or knowledge management, is significantly different from the management of the industrial economy because it is not a large-scale repetitive management mainly for material production but an informational and networked management that uses collective wisdom to improve resilience and innovation through the sharing of knowledge within the enterprise. This kind of management is characterized by the decision rules and methods obtained from a large number of cases on the network, completion of correct decision-making behavior, realization of technological and product innovation, and participation in the more complex, changing, and intense social competition in management innovation and technological innovation [1]. Therefore, the focus of knowledge management is not to form a set of inherent management ideas and management models but to adapt to the changes in the social environment and constantly discover new social and economic knowledge and then carry out enterprise management and decision-making accordingly. The expansion of management knowledge includes two aspects: one is the management ideas based on the economy, culture, politics and environment of the society, and the other is the management principles, methods, and means to implement

the management ideas. With the changing social environment, management ideas, principles, methods, and tools are also changing [2]. However, for modern management, it is more important to dig into the laws of operation of the products produced by the enterprise and its customers, to predict the market behavior of the enterprise, to pursue the changing market laws, and to expand the market share of the enterprise. Management ideas, principles, methods, and tools should be closely integrated with the market behavior of the enterprise [3].

In the study by Owen and Lazlo, management is divided into three stages, and different stages have different knowledge of management decisions and different methods of learning decision knowledge. The mechanical stage of management was considered as a complex structured machine due to the stability of industrial production products before the century. It was characterized by the fact that the top management controlled all information resources, rights, and responsibilities from the daily production and operation activities of the enterprise to the formulation of strategic goals, and the management ideology was highly centralized with an emphasis on the operational system and the incentive wage system and the establishment of effective cooperation between labor and management [4]. The knowledge coordinated with the mechanical management stage is the case knowledge in human resources, financial management, organizational resources, and market resources. The means of acquiring management knowledge in this stage was mainly empirical generalization, and the methods of decision-making were mainly empirical decisions. With the development of information technology, enterprises began to pay attention to the importance of information technology diffusion and dissemination within the enterprise, between enterprises, and between enterprises and customers. Systems management, goal management, decision management, and total quality management using information technology came into being [5]. The knowledge types coordinated with this stage are the knowledge of optimization of the enterprise structure, the knowledge of matching the market demand with the production of the enterprise, and the knowledge of rational use of the labor force. These knowledge types were acquired mainly by means of information management, system analysis and optimization calculations, and performance evaluation for the enterprise, as shown in Figure 1. With the advent of the knowledge management era after the century of the knowledge management stage, knowledge discovery and application that can both profoundly reflect the dynamic changes of the current economy and society and gain insight into the interdependence between them become the important content of management in the new era. In order to acquire such knowledge, it is necessary not to fix one's eyes on the enterprise organization structure and the operation mechanism of the enterprise organization or to hope for simple judgments on the future development of things [6]. Due to the complexity of enterprises and markets, the intensity of competition, and the rapid changes in the environment and the nonlinearity of such changes, it is not enough to predict the trends of the evolutionary process itself but to have a deep understanding of the hidden reasons that drive the lasting socio-economic development [7–10]. This era is accompanied not by fixed knowledge, but by the constant discovery of new knowledge and the methods and means of its application [11, 12].

Modern information science and technology have been widely integrated in various application systems closely related to human life and production, such as management information systems, decision support systems, and military command systems, and large-scale complex data have emerged, bringing unprecedented opportunities and challenges for research in data science and other related fields. In recent years, the research on large-scale complex data based on granular computing methods have attracted much attention, especially the research based on the rough set theory method has attracted a large number of scholars to participate and continue to achieve new research results, but the research on some generalized information systems still needs further depth. Therefore, this paper intends to study the dynamic knowledge updating method of time-varying information granular interval-valued sequential information system, the double-quantized decision analysis method in multigranularity information system, the decision analysis method in mixed-valued decision information system value, and the attribute simplification problem based on the rough set theory. The research of large-scale complex data based on rough set theory has an important role in promoting the cross-fertilization of information science with mathematics, cognitive science, and related scientific fields, especially the exploration of data structure and data modeling research based on intelligent human granularity cognitive mechanism, which has an important role in promoting theoretical research and method innovation of large-scale complex data. Therefore, complex data modeling, knowledge discovery, and decision analysis based on rough set theory have important theoretical innovation significance and application value.

2. Related Work

In the early 1980s, Zadeh, a famous American expert in control theory, studied the problem of fuzzy information granulation from the perspective of fuzzy set theory and pointed out that human cognition has three main characteristics, which can be summarized as the decomposition of the whole into parts (Granulation), the integration of parts into the whole (Organization), and the causal association between them (Causation), and the causal connections between them (Causation). In the mid-1980s, some scholars proposed the concept of granularity, and scholars agreed that information granulation is the division of complex information into pieces, classes, and groups of information particles according to their characteristics, and then the deeper understanding and decision analysis of this information [13, 14]. On this basis, Safeer et al. [15] further state that "human cognition of the world has developed a granular view, and human observation, measurement, conceptualization,
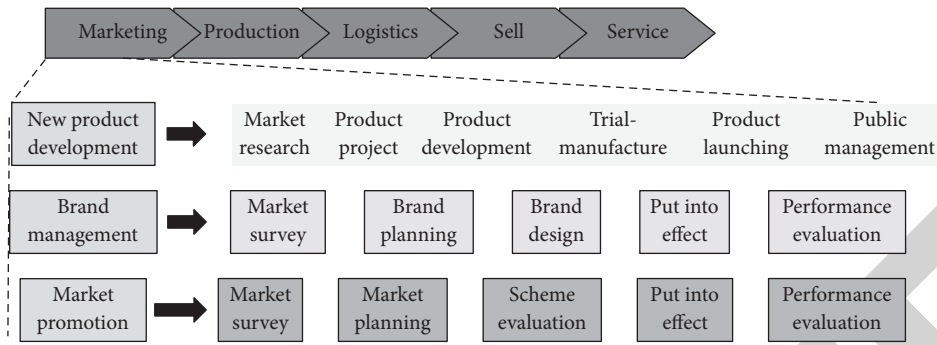
FIGURE 1: International competitiveness analysis of multinational companies.

and even reasoning about the objective world are carried out under a granular view."

Based on these fundamental works on granular computing, scholars have described the importance of granular computing from different perspectives and provided a comprehensive discussion on the theoretical research directions and application prospects of granular computing, which has further stimulated people's interest in the research of granular computing theory and applications [16, 17]. The continuous attention and in-depth research on granular computing by scholars from many different fields around the world have greatly promoted the continuous improvement of granular computing theory, which has gradually become a new direction in artificial intelligence research. Since the concept of granular computing was systematically established, the research on granular computing has been fruitful, with a large number of high-level academic research papers published and international research institutions established for granular computing. A series of international conferences on granular computing are held regularly every year to promote deeper academic exchanges and discussions among scholars in granular computing and related disciplines, such as "IEEE International Conference on Granular Computing". A series of international conferences on granular computing are held regularly every year, such as the IEEE International Conference on Granular Computing. In addition, some international conferences in related fields also have special subforums on granular computing. As one of the three typical granular computing models, the rough set model has made great progress in both theoretical research and practical applications in recent years. Rough set theory was established by Polish mathematician Pawlak in 1982 based on Frege's idea of boundary line region, which is a mathematical tool and method that can be used to describe the representation, learning, and induction of uncertain and incomplete data, and it can effectively analyze and process imprecise, incomplete, and inconsistent information and can extract the implied knowledge from it to further reveal the underlying laws.

Since the establishment of rough set theory, it has gained great attention in the field of artificial intelligence research, especially since the publication of Prof. Pawlak's first monograph on rough set theory in the 1990s; it has attracted the attention of a large number of scholars in many disciplines worldwide. In order to promote the research on rough

set theory, Prof. Pawlak held the first international conference on rough set methods in Poland in 1992, and then there have been international conferences on rough set theory and its applications every year, such as "Rough Sets and Current Trends in Computing," "Rough Sets and Current Trends in Computing," and "Rough Sets and Current Trends in Computing." "Trends in Computing," "Rough Sets, Fuzzy Sets, Data Mining, and Granula-soft Computing," and a series of international conferences are related to rough sets. A series of international conferences related to rough sets were held, which greatly promoted the development and progress of rough set theory [18, 19]. In 2005, the International Rough Set Society was formally established, and the International Journal Transactions on Rough Set Theory was also founded. The creation and improvement of the academic research communication platform has greatly promoted the communication and development of rough set theory in the international academic arena and has played an important role in promoting the further research and wide application of rough set theory in the world. The traditional Pawlak rough set model is based on an indistinguishable binary relationship in a complete information system. In order to apply the indistinguishable relation in a more general context, Peña-Vinces et al. [20] replaced the indistinguishable binary relation with a tolerance relation to build a new extended rough set model, while scholars extended the classical rough set with an asymmetric similarity relation. In order to deal with information systems with biased order, Greco generalized the Pawlak rough set model by using dominance relations.

On the other hand, Mihailova et al. [21] proposed a variable precision rough set extension model for noisy data or inconsistent information systems, which mainly makes the model relatively fault-tolerant through a classification strategy with an error classification rate less than a pregiven threshold, while scholars established a degree rough set model based on modal logic, which is an extension of the classical rough set model in terms of absolute fault-tolerance. In addition, a large number of foreign scholars have been engaged in related researches, and many innovative results have been achieved. In the early 1990s, academician Zhang Cymbal and others in China pointed out that "human intelligence has a recognized characteristic that it can observe and analyze the same problem from very different granularity perspectives and can jump from one granularity world

to another without difficulty in the cognitive process." This ability to deal with different granularity worlds is a powerful manifestation of human problem solving through granularity cognition [22–24]. As one of the important features of human cognitive process, granularity plays a crucial role in modeling and utilizing complex data. Since the establishment of the rough set method, it has rapidly gained the attention of a large number of domestic scholars, who are actively engaged in related theoretical and applied researches and have achieved a large number of internationally advanced research results [25–28]. In recent years, China has successfully held a series of important academic conferences related to granular computing and rough set research, such as the "China Rough Set and Soft Computing Symposium," and the annual symposiums have shown a good growth trend in scale and quality and have been successfully held in Suzhou, Chengdu, Zhoushan, Anshan, Hefei, and other places. In addition, there is also the "Formal Concept Analysis and Soft Computing." In addition, there are "Formal Concept Analysis and Granular Computing" and "Joint Academic Conference on Rough Sets and Soft Computing, Granular Computing, and Three Branch Decision Making" and so on. The successful holding of a series of academic activities has provided a high-quality academic exchange platform for the research on rough set theory and application and greatly promoted the research and application of rough sets and related theories.

3. International Competitiveness Rough Set Method for Multigranularity Information Systems

3.1. Double-Quantized Rough Set Modeling. When using rough set theory to analyze data, we first need to establish a granularity mechanism for information systems from a certain perspective, but for more complex systems, decision makers need to perceive them from different perspectives. When approximating the target concept, several different granularity structures can be considered at the same time, i.e., several different granularity mechanisms are used in one information system, which is also called multigranularity information system. In order to enable the application of decision rough set methods in multigranularity information systems, they further established a multigranularity decision rough set model, and these research results have laid a solid theoretical foundation for the application of decision analysis methods based on rough set theory in multigranularity information systems. On the other hand, the traditional rough set model is defined by the strict inclusion relationship between the basic information grains and the concept set, which leads to certain defects of the rough set model in the application of data with noise, because the strict inclusion relationship is difficult to be satisfied in the practical application.

At the same time, what we pursue in practical production activities often does not require complete inclusion, but only the arrival of specific requirements. In order to apply the rough set model to data with noise, a large number

of scholars have promoted the rough set model from different perspectives, the most common of which are the decision rough set model based on relative information quantification expansion and the degree rough set model based on absolute information quantification expansion. As theoretical research and practical applications continue to progress, it is found that either expansion model is inadequate from the perspective of information quantification, and many problems require consideration of both quantitative information. For this reason, Prof. Xiangyong Zhang et al. fused the relative quantified and absolute quantified expansion rough set models and established a dual quantified rough set model, which establishes a theoretical framework for a rough set decision-making method that satisfies two different quantifiers at the same time. Fruitful research results have been achieved on both multigranularity rough sets as well as double-quantized rough sets; however, the current discussion on double-quantized decision rough sets in the framework of multigranularity information systems is still in depth. For this reason, this chapter will investigate this issue and fuse the decision rough set and degree rough in a multi-grain information system, so as to construct a dual-quantized multi-grain decision rough set, and then discuss the application of the model in practical problems and compare it with the general rough set model.

There are two core variables in the degree rough set model and the decision model, i.e., the potential $|[x]A|$ of the underlying information grain and the potential $|[x]A \cap X|$ of the intersection of the information grain with the concept set. To characterize both relative and absolute quantitative information in a model, we first need to discuss the core metrics in both quantitative extension models, and for ease of presentation, we write $P(X|[x]A) = |[x]A \cap X||[x]A|$ as the metric in the probabilistic rough set model, and $g([x]A, X) = |[x]A| - |[x]A \cap X|$ and $g([x]A, X) = |[x]A \cap X|$ denote the metrics used to inscribe the upper and lower approximation operators of the degree rough set model, respectively. Further, we can obtain the following relationship between these three variables.

$$f\left([x]_A, x\right) = \frac{\left(Q\left(X\big|[x]_A\right)\right)}{\left(1 - Q\left(X\big|[x]_A\right)\right)}. \tag{1}$$

Proof: By the definitions of $g([x]_A, X)$ and $g([x]_A, X)$, $g([x]_A, X)$ $g([x]_A, X) = |[x]_A| - |[x]_A \cap X|\,|[x]_A \cap X|$, and by the definition of $P(X|[x]_A)$, $g([x]_A, X)$ $g([x]_A, X) = 1P(X|[x]_A) - 1$.

Further, we can obtain $g([x]_A, X)$ $g([x]_A, X) = 1 - P(X|[x]_A)$ $P(X|[x]_A)$, i.e., $g([x]_A, X) = P(X|[x]_A)1 - P(X|[x]_A) \times g([x]_A, X)$. It should be noted here that the partition in equation is always meaningful; that is, $1 - P(X|[x]_A) = 0$. If $1 - P(X|[x]_A) = 0$, it follows from $P(X|[x]_A) = |[x]A \cap X||[x]_A|$ that $P(X|[x]_A) = 1$; that is, $[x]_A \subseteq X$, which also implies that $g([x]_A, X) = 0$. At this point, both the probabilistic rough set model and the degree rough set model will degenerate to the classical Pawlak rough set model, and then the upper and lower approximations about the concept set X obtained by two different ways are consistent. At this point, the

significance of considering both relative and absolute information quantification in one model is unclear, and for this reason, the paper will address the more general case $(P(X|[x]A) < 1)$. The formula reflects that the three measures used to define the corresponding approximation operator are interdependent, but not linearly related. At the same time, we can obtain the following relationship between these three variables two by two.

$$f\left([x]_A, x\right) + \widetilde{f}\left([x]_A, x\right) = Q\left([x]_A\right),$$

$$Q\left([x]_A\right) = \frac{\left(Q\left(X|[x]_A|\right)\right)}{\left(1 - Q\left(X|[x]_A|\right)\right)}, \qquad (2)$$

$$Q\left(X|[x]_A|\right) = \frac{1 - Q\left(X|[x]_A|\right)}{[x]_A},$$

where the first equation indicates that the number of elements contained in and not contained in concept set X must be $|[x]_A|$ for any information grain $[x]_A$, while the last two equations show that the metrics in the upper and lower approximation operators of the probability rough set and degree rough set models correspond and are interrelated, which also provides us with the possibility to consider both relative quantified information and absolute quantified information in a unified framework. This also provides the possibility to consider both relative and absolute quantitative information in a unified framework. At present, there are two common ways to integrate two generalized rough set models extended from different perspectives in a unified framework. For example, in an election campaign, a candidate must be elected if the support rate is greater than a certain threshold and the number of votes against him must be less than a certain value. In addition, different logical operations can be considered for the upper and lower approximation operators in the unified model to build a new double-quantized rough set model. Another way to build a double-quantized rough set model is simpler and more direct; instead of fusing the approximation operators of two different quantization methods based on logical operations, the approximation operators of the two models are directly recombined to build a new pair of double-quantized rough set models.

The two different approximation operators are combined in the multigranularity approximation space to build a new multigranularity dual-quantized rough set model. As a special probabilistic rough set model, the decision rough set model obtains the threshold value in the probabilistic rough set model through the minimum risk Bayesian decision, as shown in Figure 2, and the core measure in its approximation operator is still the conditional probability $P(X|[x]_A)$. Combined with the previous analysis, we can fuse the decision rough set and degree rough set models under a unified framework and consider both relative quantitative information and absolute quantitative information in one model. At the same time, in practical applications, we often need to describe a problem from multiple levels and perspectives, such as the story of the blind man touching the elephant,
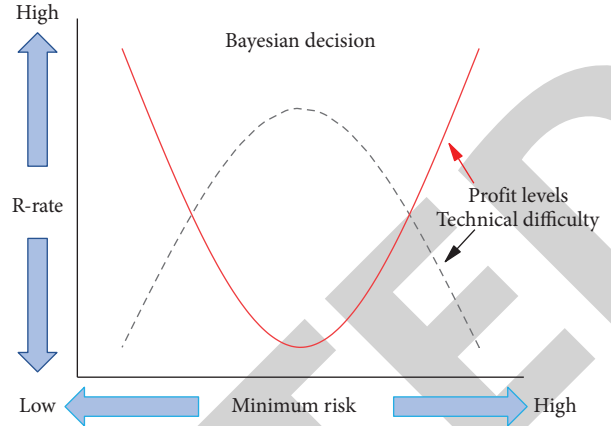

FIGURE 2: Minimum risk Bayesian decision.

where different people have different senses for the same problem, which will lead to different descriptions and different understandings of the problem, and ultimately different conclusions. For a complex system, we need to cognize the problem as comprehensively as possible from different perspectives and at different levels. Scholars introduce the decision rough set method into the multigranularity information system and establish the corresponding multigranularity decision rough set model using three different decision strategies. Since recombining the approximation operators of the decision rough set and the approximation operators of the degree rough set, a new pair of rough set models is generated, i.e., a model consisting of the lower approximation operator of the degree rough set inscribed with absolute quantified information and the upper approximation operator of the decision rough set described by relative information and another model consisting of the upper and lower approximation operators of the exchange correspondence; both of the newly established decision rough set models involve both. Both the new decision rough set models involve both relative and absolute quantitative information. In the following, we will discuss the models in terms of different fusion strategies in a multigranularity information system.   □

3.2. Dual-Quantized Decision Rough Sets for Multigranularity Information Systems. Based on the above analysis, we will recombine the decision rough set approximation operator and the degree rough set approximation operator in the multigranularity information system and build three new pairs of dual-quantized multigranularity decision rough set models, which are the optimistic multigranularity dual-quantized decision rough set based on the "seek-and-exclude" strategy, and the average multigranularity dual-quantitative decision rough set based on a "mean level" strategy, as shown in Figure 3. First, we will give the type I optimistic multigranularity double-quantized decision rough set model; that is, the double-quantized decision rough set model is constructed by combining the degree rough set lower approximation operator and the decision rough set upper approximation operator in the multigranularity information system.
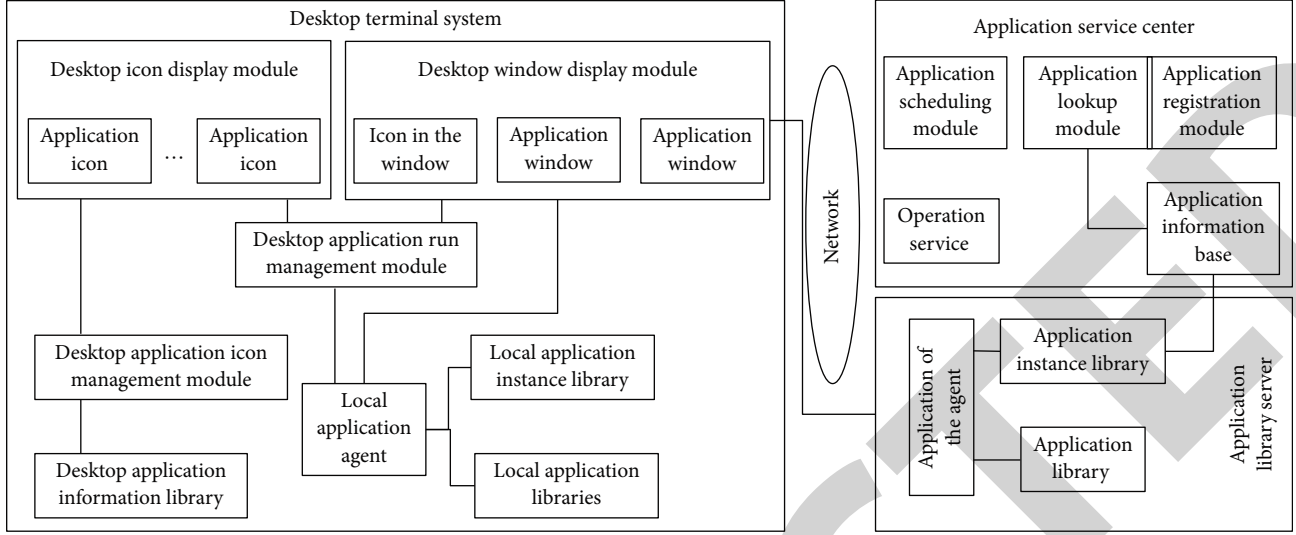
Figure 3: Multigranularity information system.

Definition 1. (Dq-MDTRSOI) Let $S = (U, A_T, V, f)$ be a multigranularity information system in which $A_1, A_2, \ldots, A_m \in A$ are m granularities and for any $x \in P(U), 0 \le b < a \le 1$, $k \in N$ and $k \le |U|$, then the approximation operators of the type I optimistic multigranularity dual-quantized decision rough set are defined as

$$\sum_{i=1}^{m} A_i^O(x) = \left\{ x \in U: \vee\left(\left|[x]A_i\right|\right) - \left(\left|[x]A_i\right|\right) \in k \right\},$$

$$\sum_{i=1}^{m} A_i(x)(a - b) = \left\{ x \in U: \vee\left(\left|[x]A_i\right|\right) \le \beta \right\},$$

$$(3)$$

where the above equation denotes the lower and upper approximation of the type I optimistic multigranularity dual-quantized decision rough set model, respectively, and based on this pair of approximation operators, we can obtain the corresponding rough set regions as follows:

$$\text{pos}_I^O(x) = \left(\left|[x]A_i\right|\right) \cap \sum_{i=1}^{m} A_i(X),$$

$$\text{neg}_I^O(x) = q \cdot \left(\left|[x]A_i\right|\right) \cap \sum_{i=1}^{m} A_i(X),$$

$$(4)$$

denote the positive domain, negative domain, upper boundary domain, and lower boundary domain of the concept set X about the optimistic multigranularity double-quantized decision rough set model of type I, respectively. We know that in the degree rough set model, the inclusion relationship between the lower and upper approximation sets may not hold, so when defining their boundary domains, we usually define their upper and lower boundary domains separately, and then collectively refer to the concatenation of the two boundary domains as the boundary domain of X. Its essence is the symmetric difference between the upper and lower approximation

sets, and here we obtain the boundary domain of the Dq-MDTRSOI model by a similar method, i.e., $bnd_I^O(X) = Ubn_I^O(X) \cup bnd_I^O(X)$, i.e.,

$$bnd_I^O(x) = q \cdot \left(\left|[x]A_i\right|\right) \otimes \sum_{i=1}^{m} A_i(X), \qquad (5)$$

where i and j are uncorrelated and are two mutually independent variables, similar to the Dq-MDTRSOI model; we can obtain the type II optimistic multigranularity double-quantized decision rough set model, which is also based on the lower approximation operator of the decision rough set and the upper approximation operator of the degree rough set, in the multigranularity approximation space from the "seeking common ground" decision perspective for modeling.

3.3. Average Dual-Quantized Multigranularity Decision Rough Set. We will combine the upper and lower approximation operators of the degree rough set and decision rough set models in a multigranularity approximation space to build a new model based on the mean level decision approach, which will also be discussed in two cases. In the classical multigranularity rough set approach, the term "optimistic" implies that we need to satisfy the inclusion condition between the equivalence class and the concept set at least at one granularity structure, while the term "pessimistic" implies that all granularity structures should satisfy the inclusion condition between the equivalence class and the concept set. Using the average level decision method, as shown in Figure 4, we can firstly compare the calculation steps and division. From an invisible model, the measurement of the match identification would be based on the basis reduction. From a practical application point of view, the constraints in these models will inevitably be too weak or too strict. Therefore, we try to
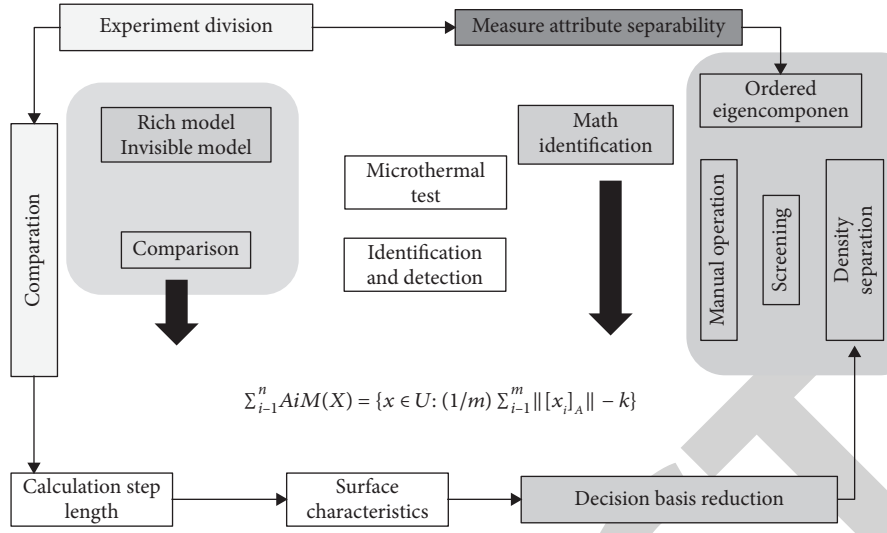
Figure 4: Average level decision method.

build a mean-based average dual-quantized multi-granularity decision rough set model.

Definition 2. (Dq-MDTRSMI) Let $S = (U, A_T, V, f)$ be a multi-grain information system in which $A_1, A_2, \ldots, A_m \in A$ are m grain sizes and for any local divisions $X \in P(U)$, variable terms $0 \le \beta < \alpha \le 1$, $k \in N$ and $k \le |U|$, and maximum size M; then the approximation operators for the type I averaged double-quantized multigranularity decision rough sets are defined as follows, respectively:

$$\sum_{i=1}^{m} A_i^M(x) = \left\{ x \in U: \left(\frac{i}{m}\right) \times \left(|[x]A_i|\right) - \left(|[x]A_i|\right) \in k \right\},$$

$$\sum_{i=1}^{m} A_i^{\alpha - \beta}(x) = \left\{ x \in U: \left(\frac{i}{m}\right) \times \left(|[x]A_i|\right) \le \beta \right\}. \tag{6}$$

From the definition, we know that the upper and lower approximation operators of this model are not the same as those of the classical multigranularity rough set models, which are determined by an overall relationship between the concept set and the knowledge grains at each granularity, i.e., the average value. Therefore, some of its basic properties may change, and we will discuss the model properties and some of its relations with the previous two types of models next.

Proposition 1. *Let $S = (U, A_T, V, f)$ be a multigranularity information system and given $A_1, A_2, \ldots, A_m \in A$ as m granularities of this system, for any $X, Y \in P(U)$, $0 \le \beta < \alpha \le 1$, $k \in N$ and $k \le |U|$, it follows that the Dq- MDTRSMI model has the following properties:*

$$\sum_{i=1}^{m} A_i^Q(x) \in U: \left(\frac{i}{m}\right) \times \left(|[x]A_i|\right),$$

$$\sum_{i=1}^{m} A_i(x) \supseteq |[x]A_i|, \tag{7}$$

$$\sum_{i=1}^{m} A_i(x) \supseteq |[x]A_i(Y)| \times \sum_{i=1}^{n} A_i(y).$$

At the same time, there exists another type of average double-quantized multi-grained decision rough set, which is also based on the decision rough set lower approximation operator. Here, we divided the numbers into three different groups, which referred into lower, medium, and high sets, the degree rough set upper approximation operator, as shown in Figure 5, the average double-quantized multi-grained decision rough set model built in the multi-grained approximation space.

4. Mixed-Value Decision Information System

With the rapid development and wide application of information science and technology, the scale of data available to people is getting larger and more complex, and there are inevitably some uncertainties in the data collection process, and there may be different forms of characterization for different attributes in the same information system, so there is the use of a single value or symbol to characterize the data in traditional information systems. Therefore, the use of a single value or symbol in traditional information systems is inevitably insufficient. In order to portray many different
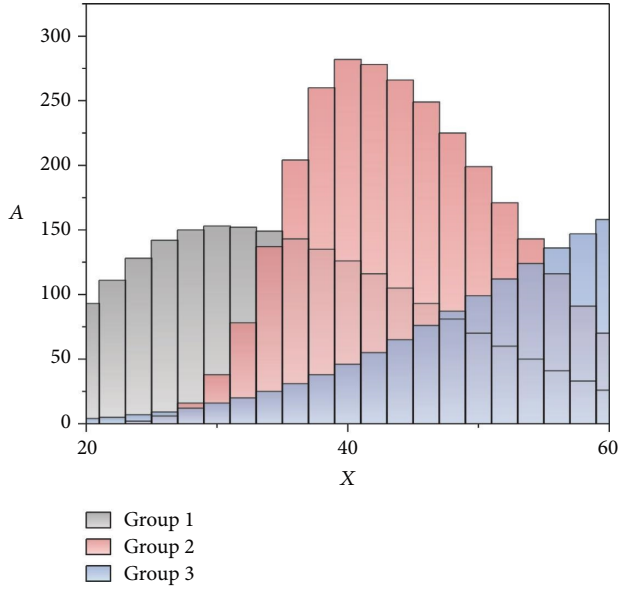
Figure 5: A-values for different X-values.

types of data in one information system, we introduce a mixed-value information system, i.e., the set of attributes of the information system can include Boolean, numeric, interval, set, symbolic, fuzzy, intuitionistic fuzzy, and other unstructured value types at the same time. Since the mixed-value information system has a more complex data structure compared to other information systems with a single type of attribute set, this leads to the fact that the rough set-based decision-making method cannot be directly applied to the mixed-value information system.

In the definition, we give a brief introduction to the general information system, knowing that an information system is inscribed by the quadruple $S = (U, A_T, V, f)$, and in order to describe many different types of attributes in the framework of the same information system, we give the basic concept of a mixed-value information system.

Definition 3. Let the quaternion $S = (U, A_T, V, f)$ be an information system. If the attribute set A_T contains several different types of attributes at the same time, then S is said to be a mixed-value information system, and if the attribute set A_T consists of the conditional attribute set C and the decision attribute set D and $C \cap D = \varnothing$, then $S = (U, C \cup D)$ is said to be a mixed-value decision information system, (V, f) is a mixed-value decision information system. Figure 6 depicts a simple mixed-value decision information system quaternion U and the various decision α. It should be noted that the decision attributes in the mixed-value decision information system we are discussing are all well-defined numeric or symbolic attributes, i.e., the set of decision attributes D can constitute a division of the domain U. From the figure, the set of decision attributes is $D = \{d\}$ and the division of the theoretical domain U induced by $D \pi D = \{D_1, D_2\}$, where $D_1 = \{x_1, x_2, x_5, x_8, x_9\}$ and $D_2 = \{x_3, x_4, x_6, x_7, x_{10}\}$.

Since broad information systems have more complex data forms compared to general information systems, the granulation mechanism established in classical information systems
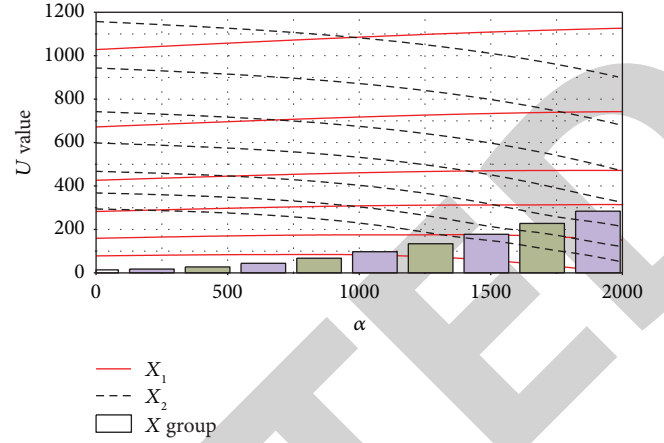

Figure 6: Mixed-value decision information system.

based on indistinguishable relations usually cannot be directly applied to generalized information systems, for which scholars point out that a new granulation mechanism can be established based on the distance between objects, where the neighborhood granulation method constructed based on distance has a wider application in generalized information systems, as shown in Figure 7, in which the horizontal means the values of the test information, and the vertical means the different methods. Given a generalized information system $S = (U, A^T, V, f)$, the neighborhood information granulation constructed for any $x \in U$ and setting maximum q, with respect to the set of attributes $A \subseteq A^T$ is inscribed as

$$\delta_A(x) = \{x \in U: \forall A(\alpha, \beta) \le q\}, \tag{8}$$

where the parameter δ is a threshold controlling the size of the information grain from a defined domain satisfying the precondition, and $\Delta A(x, y) = \|x - y\| p$ is the distance between objects x and y with respect to the set of attributes A, which is usually inscribed using the Minkowski distance.

The approximate simplification, as a subset of the attribute set, induces the same or similar decision rules (HD methods) as those obtained using the whole attribute set or has the same function as the previous attribute set under other constraints. Therefore, when the same decision effect or specified constraints are satisfied, we usually compare the results of the simplification in terms of the length of the simplification, i.e., its base, and consider that the shorter the length of the simplification the better the decision efficiency and the better the result of such a simplification. In the experimental analysis of this chapter, the approximate simplification of the mixed-valued decision information system will be solved based on three different generalized mixed distances using two simplification algorithms, and the lengths of the simplifications obtained by different methods will be compared, and the experimental results are presented in the form of "mean ± standard deviation," and the best results obtained by using the same algorithm in the best results obtained by three different distances in the same algorithm are marked in bold, while the best results among all the approximate simplifications are marked with a "*" sign, and the results are shown in Figure 8. It is not difficult
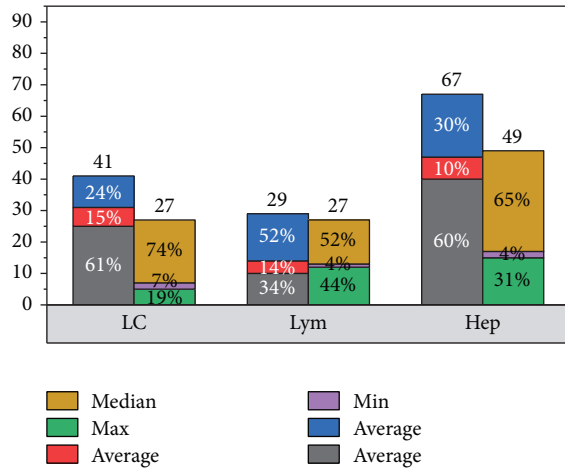
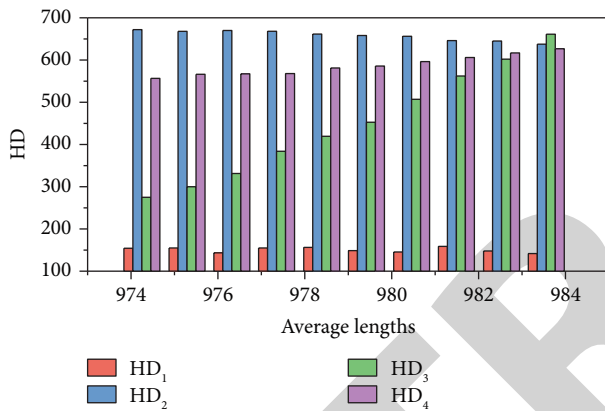FIGURE 7: Distances obtained by the neighborhood granulation method.

FIGURE 8: Comparison of the average lengths of the simplifications.

to find that the shortest approximate length obtained using HD_1, HD_2, and HD_3 in the same algorithm, the longest approximate length corresponding to HD_4, and the approximate length obtained using HD_2 are in between and hold for all data sets in the experiment.

5. Conclusion

This paper discusses decision rough set methods in mixed-valued decision information systems to obtain a decision analysis method based on rough set theory for multiple types of data in a unified framework. Since the general granulation mechanism cannot be directly applied to mixed-valued data, this chapter defines three generalized mixed distances to measure the differences between objects with respect to attributes in the mixed-valued decision information system, and then establishes the corresponding similarity measures and further constructs a neighborhood-based granulation mechanism in conjunction with Gaussian kernel functions. In addition, this chapter also discusses the attribute reduction in mixed-valued decision information systems based on the relative positive domain and the minimum decision cost, designs the corresponding heuristic attribute

reduction algorithms, and then compares and analyzes different granulation mechanisms and reduction methods based on a series of UCI data sets with respect to the reduction length and misclassification cost, respectively. The research results in this chapter address to a certain extent the application of decision analysis methods based on rough set theory to mixed data and enhance the ability of rough set theory to analyze data in complex environments.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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