A Survey on Cloud Model

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Abstract

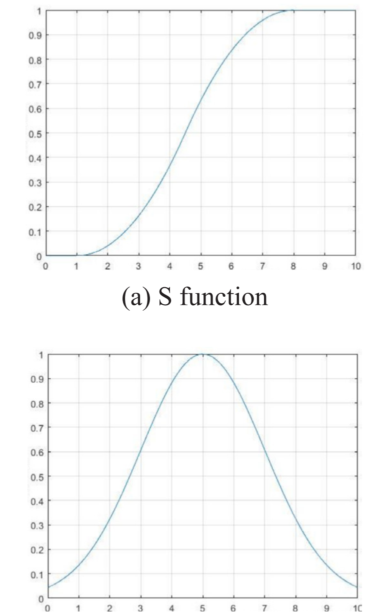
To tackle the uncertainties in life, a model that can efficiently convert qualitative concepts and quantitative values is essential. This model is referred to as a qualitative-quantitative uncertainty model. The conventional membership function provides a fixed membership degree that is incompatible with the fuzziness and randomness of qualitative concepts when a certain element of the theoretical domain is inputted. To address this issue, Academician Li introduced the cloud model, which is a qualitative-quantitative uncertainty model created for converting between qualitative and quantitative values. Unlike the traditional membership function, the cloud model generates a set of random numbers with a stable tendency that better captures the fuzziness and randomness of the qualitative concept when an element of the theoretical domain is inputted. In this paper, the background and fundamental concepts of cloud models are initially presented. Afterwards, we delve into the advancements of cloud models in various fields such as controller, data mining, and reliability. Through these discussions, the paper showcases the significant role that cloud models can play in resolving qualitative and quantitative conversion issues across different domains. The three numerical characteristics of cloud models are then described in detail, as well as cloud generator, virtual cloud and other cloud model related algorithms. Finally, some statistical properties of cloud models are discussed, as well as the current problems and future research directions.

Keywords: Fuzzy sets, Cloud model, Cloud generators, Conditional cloud, Virtual cloud

1 Introduction

In everyday life, individuals encounter numerous abstract concepts, such as “hot weather”, “around 20 years old”, “peak season” and “off-season”. These can all be grouped together as qualitative concepts. These concepts are indefinite and unpredictable, making it challenging to determine if a certain object aligns with the concept, as there is no clear definition of quality and indistinct limits in terms of quantity [1].

To address the common occurrence of fuzzy phenomena, such as predictive knowledge and linguistic rules, L. A. Zadeh introduced the concept of fuzzy sets in 1965 and provided a method to handle fuzzy information [2]. The theory of fuzzy sets emphasizes the crucial idea of “membership degree,” which conveys the extent to which a fuzzy element belongs to a particular set, making it highly effective in describing uncertain information. The concept of membership function is widely used in fuzzy set theory and determines the membership degree of an element with respect to a set through a specific mathematical function. Therefore, the specific function in ordinary set theory, which accepts binary values {0, 1}, is expanded to a function that accepts membership degrees on the interval [0, 1]. Doing so will have a beneficial effect, which can extend the binary logic to a multi-valued logic, and extend the absolute relation to a more flexible gradual relation. Two more typical images of traditional membership functions are shown in Figure 1.



(a) S function

(b) Gaussian function

Figure 1. Images of traditional membership functions

However, the application of the membership function involves making artificial assumptions that convert the fuzzy concept into a definite value for the membership degree, thereby eliminating the uncertainty of the qualitative concept and transforming it from fuzzy mathematics to precise mathematical calculations [3].

In his efforts to preserve the randomness and vagueness of qualitative concepts during their conversion into quantitative

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DOI: 10.53106/160792642023092405014

representations, Professor Li introduced the concept of cloud models in 1995, which he defined as follows.

Consider a quantitative theoretical domain, represented by exact values, denoted as U and its corresponding qualitative concept, represented as C. For any element x that belongs to the domain U, its membership degree $\mu(x)$ to C is a random number with a consistent tendency and falls within the range of [0, 1]. The distribution of x over the domain U is referred to as a cloud model, or simply, a cloud. Each x is referred to as a "cloud drop". [4]. A simple cloud model is shown in Figure 2.

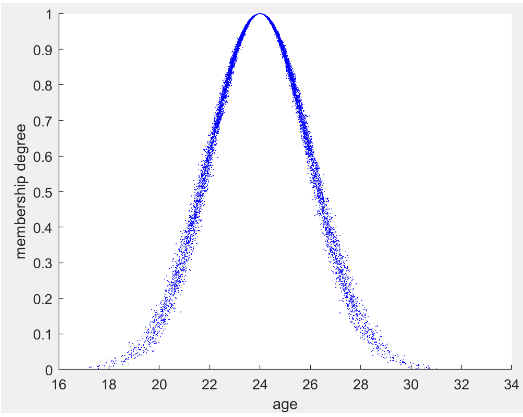


Figure 2. A simple cloud model

By comparing Figure 1 and Figure 2, it is evident that in traditional membership functions, the membership degree of elements in the quantitative domain is a fixed value. In contrast, in cloud models, the membership degree of elements in the quantitative domain is a set of random numbers with a consistent tendency, making it fuzzy and random. This highlights that the cloud model more effectively preserves the vagueness and unpredictability of qualitative concepts when compared to traditional membership functions.

The contributions of this paper are: (a) investigates the current state of research on cloud models in terms of applications such as controllers, data mining, etc. (b) summarizes the existing algorithms for cloud models, such as forward/backward cloud generators, conditional cloud generators, virtual clouds, etc. (c) summarizes the problems and challenges faced by cloud models in terms of two properties of cloud models and consideres the existing problems and future developments of cloud models from a comprehensive perspective.

The next sections of this paper are structured as follows: Section 2 describes the application of cloud models in areas such as controllers and data mining, etc. Section 3 describes the numerical characteristics of cloud models and related algorithms. Section 4 describes two properties of cloud models and analyses the problems and challenges faced by cloud models. Section 5 concludes the full paper.

2 Research Effort

2.1 Controllers

The conventional intelligent control methods usually necessitate the development of a mathematical model for the system under control. However, in certain complex systems, it can be challenging to provide a clear representation of the system, leading to the inability to establish a precise mathematical model. At this point, fuzzy control can be a better solution to this problem. The cloud model can better retain the fuzziness and randomness of the linguistic atoms compared with the traditional fuzzy control methods.

In the literature [5], Chen et al. proposed a specific incentive mechanism for single rule generators and multi-rule generators through which a cloud model representation of one or more qualitative rules could be achieved.

In the literature [6], Li used a multi-rule generator to achieve dynamic balance state maintenance for a one-stage, two-stage and three-stage inverted pendulum controlled by a single motor, and also achieved dynamic switching of two typical dynamic balance modes for a one-stage inverted pendulum system, three typical dynamic balance modes for a two-stage inverted pendulum system and four dynamic balance modes for a three-stage inverted pendulum, and proved that the control system has strong robustness. In the literature [7] Gao et al. designed a new cloud model inverted pendulum controller, which is based on the traditional PID controller design idea and consists of three independent cloud model controllers, namely P-type, I-type and D-type cloud model controllers, where the P-type cloud model controller realizes the proportional control function and takes the deviation value as input. The I-type cloud model controller realizes the integral control function and takes the integral value of the deviation as input, and the type D cloud model controller implements the differential control function and takes the rate of change of the deviation as input.

2.2 Data Mining

Data mining involves the extraction of potentially valuable, unknown information and knowledge from vast, incomplete, indistinct and random data [8]. In the field of data mining, expressions of knowledge described by qualitative concepts are frequently encountered. Here, the application of cloud models can serve as an effective link between quantitative data and qualitative knowledge.

In the literature [9], Du et al. divided the definition domain of data attributes in the database using the cloud model. This method can fuzzify the definition domain of attributes and soften the boundaries of each interval; the association rules generated on this basis are called cloud association rules. Also, new methods of calculated support, trust and relevance have been defined in the literature to measure the significance of association rules. In the literature [10], Jiang et al. applied the cloud model to time series data mining, proposed two types of forecasting knowledge, quasi-periodic change patterns and current trends, and combined these two types of forecasting knowledge to implement a time series forecasting mechanism.

In a study published in [11], Li and colleagues presented a classification algorithm based on the cloud evolution algorithm. This algorithm incorporates attribute significance in its rule template generation, making it more likely for crucial conditional attributes to appear in the rules, leading to shorter classification rules and more effective and more efficient classification.

2.3 Reliability

Reliability refers to the capability of a component, product, or system to carry out a designated function without malfunctioning for a specified duration and under given conditions [12-13]. These conditions, which often take the form of constant, fixed quantitative indicators, reflect the variable and uncertain nature of operating conditions. To better capture this variability and ambiguity, the cloud model can be utilized to transform the qualitative representation of operating conditions into a quantitative description.

In the literature [14], Song et al. proposed how to transform the qualitative description of the operating environment into a quantitative cloud model representation when variable operating conditions are considered, and then proposed a method to evaluate the reliability of electronic products when variable operating conditions are considered. In the literature [15], Song et al. used a multidimensional cloud model to build a cloud model of computer reliability over time when considering two variable operating conditions, namely voltage and temperature, and demonstrated that it is feasible to use the cloud model for reliability evaluation when considering environmental factors, and the results are closer to the actual working conditions.

In their research [16], Luo et al. applied the concept of cloud models to evaluate the dependability of wireless sensor networks. They developed a quantitative cloud reliability evaluation model based on finite Markov chain theory, which is capable of accounting for the uncertain failure patterns in the Markov Model of reliability. In the literature [17], Li et al. constructed a non-normal form, credibility-based reliability metric cloud model based on the conventional stress-strength interference model and borrowed the idea of the three-time normal distribution of the cloud model. This study incorporated conventional reliability and fuzzy reliability methods into a unified theoretical system and expanded the pattern and scope of the cloud model.

In the literature [18], Chen et al. proposed a software reliability metric model based on software reliability metrics, combined with cloud model theory, which gave different weights to different metrics, merged the numerical features corresponding to all metrics into a final reliability merged cloud by a comprehensive cloud algorithm, and finally obtained the final reliability level by comparing the similar cloud algorithm with the benchmark cloud. In the literature [19], Wang et al. proposed a cloud model-based multi-fault diagnosis method, which uses a cloud model to analyze the DGA data of power transformers, and monitors and diagnoses potential faults according to different DGA states of power transformers by setting different association rules. In comparison to conventional techniques, the proposed method considers the indistinctness of power transformer faults, and it is capable of identifying the occurrence of simultaneous potential faults.

In the literature [20], Li et al. proposed a fuzzy comprehensive evaluation method for system reliability based on cloud models, which establishes multiple evaluation matrices for different states of an influencing factor respectively. The numerical characteristics of the cloud model corresponding to the position in these matrices were used as dependent variables, the values of the influence factors corresponding to the different states were fitted as independent variables, and the fitted parameter matrix was multiplied with the weight cloud parameters to obtain the final evaluation result cloud model. The numerical characteristics of the resultant cloud model are functions with independent variables that can represent different cloud models depending on the change in the values of the influencing factors, and can yield a continuous cloud model of the transition state. In the study conducted by Miao et al. [21], a method for assessing the reliability of offshore wind farms using cloud models was introduced. This method incorporates cloud models to consider the uncertain parameters in climatic factors, thereby preserving the uncertainty of the parameters and making use of extended data for further analysis of parameter correlations.

In the literature [22], Xiong et al. presented a risk assessment and identification method for mining work topsides that utilizes cloud models. The approach starts by constructing standard cloud models for each indicator and then creating a composite standard cloud model based on the weight of each indicator. The individual and composite cloud models for the current state of each indicator are then compared with the standard cloud models to determine the final level of risk. In the literature [23], Peng et al. proposed a cloud model-based ship combat readiness assessment method, which uses the weight calculation method of cooperative game and variable weight theory, combined with the integrated fuzzy assessment method of cloud model, to obtain results with higher accuracy than the traditional method.

2.4 Evaluation and Assessment

In a study by Mao et al. [24], a personalized integrated cloud computing method was proposed for heterogeneous multi-attribute group decision making (MAGDM). The heterogeneous MAGDM process allows for the evaluation of different attributes in both qualitative and quantitative forms, such as linguistic terms (LTs), probabilistic linguistic term sets (PLTSs), and linguistic hesitant fuzzy sets (LHFSs). The method calculates the weights of decision makers (DMs) by defining moderation parameters for cloud model entropy and hyper entropy, compares clouds through cloud approximate stochastic dominance relations (CASD) and CASD degrees, and ultimately creates a comprehensive tri-objective programming model to determine attribute weights. This approach has the benefit of greater stability and improved flexibility compared to traditional methods.

In the literature [25], Meng et al. introduced a method for evaluating subjective trust that leverages cloud models. This approach creates a qualitative rule operator that allows for reasoning about the trust between entities that are not directly related by considering the trust relationship between entities that are related. By incorporating the use of a cloud model, the evaluation of subjective trust becomes more adaptable and easier to understand, and can better demonstrate human reasoning habits.

In the literature [26], Deng et al. proposed a cloud model-based road network vulnerability assessment method, which established different standard cloud models for different road congestion patterns, and later used these standard cloud models to construct a state vulnerability identification method, which can better describe the overall operational state and vulnerable sections of the road network. In the literature [27], Xie et al. presented a cloud model-based evaluation system for the comprehensive benefits of energy internet plat- forms, taking into account economic, environmental, social, and energy saving benefits. The results of comprehensive benefit evaluation can be derived and the impact of a particular aspect of benefits on the comprehensive evaluation can also be obtained.

In the literature [28], Cao et al. proposed a cloud model-based index system for evaluating coastal erosion vulnerability in China, in which ten indicators were selected to assess coastal erosion vulnerability from both natural and socio-economic aspects, and obtained evaluation results that were consistent with the current situation.

In the literature [29], Huang et al. proposed a cloud model-based evaluation index system for energy efficiency in earthquake site rescue, which uses analytic hierarchy process (AHP) and a cloud model to calculate the subjective and objective weights of each index, and obtains the final evaluation results by comparing and analyzing the current cloud map with the standard cloud map. In the literature [30], Sudakshina Mandal et al. proposed a cloud model-based multi-metric evaluation scheme for cloud service providers (CSPs), which uses a combined compromised solution (CoCoSo) combined with a cloud model to convert linguistic expressions into a clear weighting matrix to ultimately select a ranking of credible CSPs.

In the literature [31], Zhao et al. presented a system for evaluating the effectiveness of satellite communication against interference, which leverages the cloud model to enhance the hierarchical analysis method. The cloud model adds uncertainty and vagueness to the weight vector of the hierarchical analysis, thus making the evaluation results more impartial and sound. In the literature [32], Gao et al. proposed a cloud model-based variable granularity measurement method for intelligent driving vehicles, which converts qualitative evaluation assessment indexes into interval numbers and then into a cloud model, integrating subjective preferences with objective data, making the evaluation results more scientific.

2.5 Genetic Evolutionary Algorithms

In the literature [33], Zhang et al. proposed a global optimization algorithm based on a cloud model, which is an adaptive high-precision fast stochastic search algorithm. The algorithm uses a cloud model to express an evolutionary model, and the numerical features of the cloud model are given different meanings in the evolutionary model, where *Ex* is the seed individual, which is the individual in a population that best represents the good characteristics of the parent. *En* is the evolutionary entropy, which represents the range of population evolution, and *He* is the evolutionary hyper entropy, which represents the stability of evolution, and the larger the *He* the more unstable the evolution. The algorithm describes heredity and evolution as qualitative knowledge through a cloud model, thus allowing the process of heredity and evolution to be transformed into cloud drops, i.e. the offspring individuals for quantitative representation. Compared with traditional genetic algorithms, the algorithm is better at avoiding the problems of falling into local optimum solutions and premature convergence caused by excessive selection pressure.

2.6 Other

In addition to the research efforts mentioned above, cloud models are also extensively utilized in various areas such as recommendation algorithms, image segmentation, intrusion detection, and user matching.

In the literature [34], Zhang et al. presented a cloud model-based collaborative filtering recommendation algorithm that initially identifies the cloud numerical features of a user based on their historical data. These numerical features are then treated as vectors, with the cosine angle between two feature vectors being used to measure their similarity. Secondly, the set of nearest neighbors of the user is found and recommendations are generated based on the similarity, and the algorithm is able to overcome certain negative effects in the case of extreme sparsity of user rating data.

In the literature [35], Qin et al. proposed a cloud model-based image segmentation method, which decomposes the grayscale function of an image into multiple normal cloud models and regards these clouds as leaf nodes of a concept tree. It then uses a concept leap algorithm to elevate the concepts to several concept levels that can be understood by humans, and sets different grayscale values for each concept level. For each pixel of the image, the degree of membership to the concept is calculated using the forward cloud generator, and the concept with the highest degree of membership is selected as the membership concept, thus achieving image segmentation.

In the literature [36], Zhao et al. proposed an intrusion detection algorithm based on cloud model, which processes the collected system resource usage data, inputs the processed data into a multi-conditional rule generator, and outputs the detection results according to the pre-set rules, and experiments prove that the method has a high detection rate and strong robustness.

In the literature [37], Tong et al. propose a two-stage consensus reaching process (CRP) based on a cloud model, which enables stable matching on large-scale shared platforms. In order to avoid the time-consuming mutual evaluation in traditional matching methods, historical data is chosen as the object of evaluation, in which historical data is processed using a cloud model to unify and integrate star rating data with qualitative characteristics and scoring data with quantitative characteristics, laying the foundation for a two-stage CRP.

3 Numerical Characteristics and Related Algorithms

3.1 Numerical Characteristics

The numerical characteristics of a cloud are represented by three values: expectation (*Ex*), entropy (*En*), and hyper entropy (*He*). These parameters are capable of accurately reflecting the quantitative aspects of a qualitative concept.

Ex, which represents the average of the distribution of cloud drops in the domain space U, acts as the point that best embodies the qualitative concept, or the most representative sample of the quantification of this concept.

En reflects the fuzziness and randomness of the qualitative concept and denotes the range of acceptable values that are subject to fluctuations. It reflects the level of vagueness of the concept, with greater entropy indicating a broader and more general concept.

He quantifies the spread of the cloud droplets and provides a measure of the cloud's thickness. A higher hyper entropy signifies higher fragmentation of the cloud droplets, more randomness in their membership degree, and greater randomness in the concept. He primarily reflects the degree of agreement on the qualitative concept. A smaller hyper entropy indicates higher agreement on the concept, whereas a larger hyper entropy shows greater disagreement [38].

3.2 Forward Cloud Generator

The forward cloud generator can transform the three numerical features of a qualitative concept into a quantitative numerical representation of a cloud model, enabling a qualitative to quantitative transformation, with the following algorithm.

Step 1: Generate a random number, *E'n*, that follows a normal distribution with the expected value of *En* and a standard deviation of *He*.

Step 2: Generate a normally distributed random number *x* with the expected value of *Ex* and a standard deviation of *abs*(*E'n*).

Step 3: *x* is a once specific quantified value of the qualitative concept *A*, called a cloud drop.

Step 4: $y = e^{-\frac{(x-Ex)^2}{2(E_n')^2}}$

Step 5: *y* is the membership degree of *x* to the qualitative concept *A*.

Step 6: $\{x, y\}$ captures the full content of this qualitative to quantitative transformation.

Step 7: Repeat **Step 1-Step 6** until *N* cloud drops are produced, forming a cloud [39].

3.3 Reverse Cloud Generator

A reverse cloud generator can transform a set of quantitative numerical representations of a cloud model into a qualitative concept represented by three numerical features, enabling a quantitative to qualitative transformation with the following traditional algorithm.

Step 1: Using $E\hat{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ as an estimate for *Ex*.

Step 2: Eliminate the cloud drops with $y > 0.999$, leaving *m* drops.

Step 3: Find *En'* from $En' = \frac{|x - E\hat{x}|}{\sqrt{-2\ln y}}$

Step 4: Find $E\hat{n}$ from

$$E\hat{n} = \frac{1}{m}\sum_{i=1}^{m} En_i'$$

Step 5: Find the estimated value $H\hat{e}$ of *He* from $\sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(En_i' - E\hat{n})^2}$ [40]

Since in practice it is rarely possible to obtain a cloud model that contains the degree of membership *y*, but often possible to obtain a set of data values containing only *x*, in 2004 Liu Changyu et al. proposed a reverse cloud generator [41] that only uses the information of cloud drops *x*. The algorithm is as follows.

Step 1: Calculate the sample mean $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$ of this data set based on x_i, and first order sample absolute central moments $\frac{1}{N}\sum_{i=1}^{N}|x_i - \overline{X}|$, and sample variance $S^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{X})^2$

Step 2: Using $E\hat{x} = \overline{X}$ as an estimate of the value of *Ex*.

Step 3: Using $E\hat{n} = \sqrt{\frac{\pi}{2}} \cdot \frac{1}{N}\sum_{i=1}^{N}|x_i - Ex|$ as an estimate of the value of *En*.

Step 4: Using $H\hat{e} = \sqrt{S^2 - En^2}$ as an estimate of the value of *He*.

3.4 Conditional Clouds

3.4.1 X-Conditioned Cloud Generator

In addition to providing the three numerical characteristics of the cloud (*Ex*, *En*, *He*), a cloud generator that generates a cloud drop *drop*(x, μ_i) by providing a specific value *x* in the domain of the argument as a condition. The algorithm is as follows.

Step 1: Generate a random number, *E'n*, that follows a normal distribution with the expected value of *En* and a standard deviation of *He*.

Step 2: Calculate $\mu_i = e^{-\frac{(x-Ex)^2}{2(E_n')^2}}$, generates a cloud drop *drop*(x, μ_i)

3.4.2 Y- Conditioned Cloud Generator

In addition to providing the three numerical characteristics of the cloud (*Ex*, *En*, *He*), a cloud generator with a specific degree of membership μ as a condition to generate a cloud drop *drop*(x, μ_i) is provided with the following algorithm.

Step 1: Generate a random number, *E'n*, that follows a normal distribution with the expected value of *En* and a standard deviation of *He*.

Step 2: Calculate $x_i = Ex \pm En'\sqrt{-2\ln\mu}$, generates a cloud drop *drop*(x, μ_i) [42].

3.5 Virtual Clouds

3.5.1 Integrated Cloud

An integrated cloud can combine two or more qualitative concepts in the same domain into a higher-level, broader qualitative concept. As an example, the algorithm for the synthesis of two qualitative concepts is as follows.

Step 1: Let the numerical characteristics of the two clouds be $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2)$ and the numerical characteristics of the composite cloud be $C_3(Ex_3, En_3, He_3)$.

Step 2: $Ex_3 = \dfrac{Ex_1 \times En_1 + Ex_2 \times En_2}{En_1 + En_2}$

Step 3: $En_3 = En_1 + En_2$

Step 4: $He_3 = \dfrac{He_1 \times En_1 + He_2 \times En_2}{En_1 + En_2}$ [43].

3.5.2 Disintegrated Cloud

Disintegrated clouds are constructed along the opposite lines to comprehensive clouds and play the opposite role. They can be used to decompose a higher-level, broader qualitative concept into two or more lower-level, more detailed qualitative concepts. Because each disintegrated cloud is within the theoretical domain of the base cloud, the entropy of each disintegrated cloud is less than the entropy of the base cloud, and the sum of the entropies of all disintegrated clouds is equal to the entropy of the base cloud [42].

3.5.3 Floating Cloud

A floating cloud can construct a virtual cloud between two neighboring clouds. In some cases, the user defined cloud cannot completely cover the scope of the thesis domain. There will be blank sections between two adjacent clouds in the domain, and these blank sections correspond to a membership degree of 0, which is meaningless for the representation of qualitative concepts. The floating cloud algorithm can be used to construct a virtual floating cloud in the blank part to cover the theoretical domain completely. The algorithm is as follows.

Step 1: Select a point u between two adjacent clouds $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2)$ in the theoretical domain as the locus of the floating cloud $C_3(Ex_3, En_3, He_3)$.

Step 2: Let $Ex_3 = u$

Step 3: Calculate

$$En_3 = \frac{Ex_2 - u}{Ex_2 - Ex_1} \times En_1 + \frac{u - Ex_1}{Ex_2 - Ex_1} \times En_2$$

Step 4: Calculate

$$He_3 = \frac{Ex_2 - u}{Ex_2 - Ex_1} \times He_1 + \frac{u - Ex_1}{Ex_2 - Ex_1} \times He_2 \text{ [44]}$$

3.5.4 Geometric Cloud

Geometric clouds can be fitted by least squares to obtain a complete cloud model when only some of the cloud drops are known, with the following algorithm.

Step 1: Let the known cloud drops be (x_1, μ_1), (x_2, μ_2), ..., (x_n, μ_n)

Step 2: Using the method of least squares, find Ex, En corresponding to the minimum of the following equation

$$\sum_{i=1}^{n} (\mu_i - e^{\frac{-(x_i - Ex)^2}{2En^2}})$$

Step 3: The numerical characteristics of the geometric cloud are (Ex, En, He), where He is specified on a case-by-case basis.

When only two cloud drops (x_1, μ_1), (x_2, μ_2) are known, the following algorithm can be used to find the geometric cloud.

Step 1: $Ex = \dfrac{x_1\sqrt{-2\ln\mu_2} + x_2\sqrt{-2\ln\mu_1}}{\sqrt{-2\ln\mu_1} + \sqrt{-2\ln\mu_2}}$

Step 2: $En = \dfrac{x_2 - x_1}{\sqrt{-2\ln\mu_1} + \sqrt{-2\ln\mu_2}}$ [45]

Step 3: The numerical characteristics of the geometric cloud are (Ex, En, He), where He is specified on a case-by-case basis.

3.6 Similar Cloud

Different clouds often represent different qualitative concepts, but different clouds sometimes represent the same qualitative concept. It is necessary to consider the similarity between these clouds. The similarity between two clouds can be measured by calculating the distance between their cloud drops. If the similarity between two clouds is less than a specified threshold, then these two clouds can be called similar to each other, the algorithm for calculating the similarity is as follows.

Step 1: Let cloud $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2)$, generate n cloud drops *drop*1, *drop*2 respectively using forward cloud generator algorithm.

Step 2: Sort the cloud drops in *drop*1 and *drop*2 from smallest to largest to get *drop'*1 and *drop'*2 respectively.

Step 3: Filter the cloud drops between $[Ex\text{-}3En, Ex\text{+}3En]$ in *drop'*1, *drop'*2 with n_1, n_2 respectively.

Step 4: Let $n_1 \leq n_2$ (and vice versa with the same algorithm), *drop'*2 has $C_{n_2}^{n_1}$ combinations, $drop'2_j$ $(j \in 1, 2, \ldots, C_{n_2}^{n_1})$.

Step 5: Calculate the square of the difference between *drop'*1 and $drop'2_j$ respectively to obtain *distance*(j).

Step 6: Calculate $similar = \dfrac{\sqrt{\sum distance(j) / C_{n_2}^{n_1}}}{n}$ [46].

3.7 Multi-dimensional Cloud

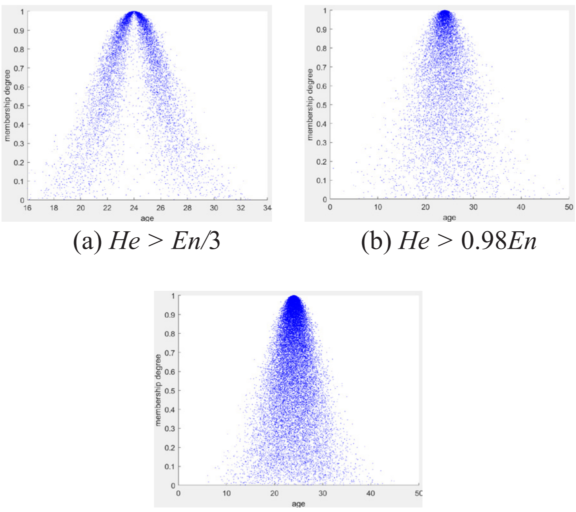
In the real world, there are many concepts that are not elaborated in a single sense, but related to two or even more conditions [47]. For example, whether a road surface will freeze or not depends on both temperature and humidity. It is only possible if the temperature is low and the humidity is high. Furthermore, whether a person is healthy or not can only be concluded through a comprehensive analysis of all body data. Thus, the concept of two-dimensional clouds and even multi-dimensional clouds is introduced on the basis of one-dimensional clouds to describe complex qualitative concepts influenced by two or more conditions. The numerical characteristics of multi-dimensional clouds, like one-dimensional clouds, have multi-dimensional expectations, entropy and hyper entropy, and are able to reflect the more complex quantitative characteristics of multi-dimensional qualitative concepts.

4 Current Problems and Challenges

4.1 Atomization Feature

The hyper entropy He, which represents the dispersion of the cloud, reflects the thickness of the cloud in the three numerical characteristics of the cloud model.When $He = 0$, the cloud model is an ordinary normal distribution curve, and as He increases, the more discrete the cloud droplets deviate from the normal distribution curve. However, as He continues to increase and as $He > En/3$, the cloud pattern moves out of the range of the general normal distribution and becomes sufficiently discreet that the cloud droplets begin to concentrate around Ex, a phenomenon known as cloud atomization. As He continues to increase, the cloud droplets will continue to disperse and as $He > 0.98En$, the density of cloud droplets around Ex will begin to decrease and the density of the fog will begin to fall.

When $He = 0.98En$, the density of cloud droplets around Ex is the highest, and at this point the cloud model can be utilized to symbolize a "qualitative concept that is challenging to attain agreement on." Because Ex is the point that best represents the qualitative concept, when there are large fluctuations in the determinacy of Ex, it means that there is a large disagreement about this qualitative concept, i.e. "difficult to reach a consensus" [48]. The application of this property is not well represented in existing application research, so further research into the application of the cloud model property would be of interest. The image of the cloud model changing with He is shown in Figure 3.



(a) $He > En/3$ (b) $He > 0.98En$

(c) $He = 0.98En$

Figure 3. Atomization feature of cloud model

4.2 Heavy-tailed Property

In the literature [49], Li et al. demonstrated that as He increases, the cloud droplet distribution of the cloud model will transform from a normal distribution to a heavy-tailed distribution. Therefore, the cloud model is a class of distributions between the normal and heavy-tailed distributions, and is a kind of heavy-tailed distribution with expectations.

The normal distribution works well when dealing with natural phenomena without human intervention. However, when dealing with anthropogenic phenomena, the human factor often leads to non-negligible small probability events. So, anthropogenic phenomena can be better represented by a heavy-tailed distribution. The characteristics of both the normal and heavy-tailed distributions are present in the cloud model; how to use this property is a question worth investigating in real-life applications.

4.3 Overall Problems

Cloud models have a unique advantage in the study of qualitative and quantitative conversions, and it is worth further research to expand and develop this advantage and find unique application scenarios for cloud models.

The numerical features of a cloud model play a crucial role in converting qualitative concepts into quantitative ones. However, there is still a need for further exploration in the application process on how to properly establish these numerical features during the qualitative-to-quantitative conversion and how to interpret them in the quantitative-to-qualitative conversion.

The cloud model is a potent tool for investigating conversions between qualitative and quantitative aspects and should be continuously researched and improved in application, therefore, expanding the application areas of cloud model is an effective means of studying cloud model.

As a member of fuzzy set theory, the research on the basic theory of cloud models still needs to be strengthened. Finding out the differences and connections between cloud model and other models in theoretical research is conducive to further exploring the advantages of cloud model and the development of cloud model applications.

5 Conclusion

The cloud model boasts a unique advantage in its ability to retain the fuzziness and randomness of qualitative concepts during qualitative-quantitative conversions. Thus, in many application scenarios, the cloud model achieves quantitative control using language rules, as well as outputting assessment results into qualitative language. There are also a variety of related algorithms in the cloud model that are constantly extending its application.

This paper investigates the application of cloud models in different domains and briefly describes the advantages of cloud models in the application. Then, based on the survey, the existing relevant algorithms for cloud models are summarized and each algorithm is described in detail. Finally, the atomization and heavy-tailed properties of cloud models are described, and on this basis, the current problems and future research challenges of cloud modesl are illustrated.

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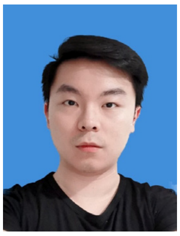

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