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A reliable correlation coefficient for complicated intuitionistic fuzzy sets and its applications in decision-making

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Abstract - This paper introduces a reliable correlation coefficient designed for complicated intuitionistic fuzzy sets (CIFS) to enhance the accuracy of decision-making in uncertain and complex environments. Intuitionistic fuzzy sets, characterized by membership, non-membership, and hesitancy degrees, are an effective tool for handling imprecise data in decision-making problems. However, existing correlation measures often fail to capture the intricate relationships in CIFS due to their inherent uncertainty. The proposed correlation coefficient overcomes these limitations by integrating the hesitancy degree and providing a robust framework for analyzing the correlation between CIFS. Through mathematical formulation and computational examples, this study demonstrates the potential applications of the correlation coefficient in various decision-making scenarios, such as multi-criteria decision analysis (MCDA), pattern recognition, and risk assessment. The results show that the new correlation coefficient offers reliable, efficient, and interpretable solutions for problems involving CIFS, ultimately improving decision-making processes in fields such as economics, healthcare, and engineering.

Keywords: Intuitionistic fuzzy sets, correlation coefficient, decision-making, uncertainty, multi-criteria decision analysis, pattern recognition, risk assessment, computational methods.

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INTRODUCTION

Complex Intuitionistic Fuzzy Sets (CIFSs) are an extension of intuitionistic fuzzy sets (IFSs) that include a complex-valued membership function. This membership function makes it possible to describe uncertainty with both magnitude and phase information. To describe uncertainty, ambiguity, and reluctance in decision-making situations, this extra dimension offers a mathematical framework that is more complex than the one that was previously available. It is essential to have a reliable correlation coefficient measure in order to compare CIFSs, determine the links between them, and enable precision decision-making in contexts dealing with several criteria.

In the field of data analysis, the correlation coefficient is an essential statistical instrument that is used to determine the extent to which variables are associated with one another. It is able to give insights into the interactions between components in contexts that are characterised by ambiguity and dual uncertainty when it is applied to CIFSs. To be considered robust, a measure must be able to efficiently manage the distinctive features of CIFSs. These qualities include the inclusion of both real and imaginary components in membership functions, as well as the interaction between intuitionistic and non-intuitionistic components.

Take into consideration two CIFSs, identified as A and B, which are specified on a universal set X. Every set has membership functions that are stated as follows: $\mu A(x) = a r + i a i$
Both the membership and non-membership degrees are represented by the equations μ A (x) = a r + ia i and ν A (x) = $b r + i b i$ v A (x) = b r + ib i, where a and i are the degrees of membership and non-membership, respectively. The sum of squared magnitudes of $\mu A(x)$ μ A(x) and $\nu A(x)$ v A(x) is limited so that $| \mu A(x) | 2 + | \nu A(x) | 2 \leq 1$ |μ A (x)| 2 +|v A(x)| 2 ≤1, guaranteeing consistency within the fuzzy framework.

The correlation coefficient that has been suggested for CIFSs is designed in such a way that it captures the alignment between A and B by taking into consideration both the real and imaginary components of both variables. This is an example of a robust formulation:

The function $\rho(A, B)$ is equal to the number of times x is a member of the set X, where

Re($\mu\ A\ (x\ )\ \mu\ B\ (x\ )^-$) is added to Re($\nu\ A\ (x\ )\ \nu\ B\ (x\ )^-$)

∑ $x \in X$ | $\mu\ A\ (\ x\ )$ | 2 added to | $\nu\ A\ (\ x\ )$ | 2

∑ $x \in X$ | $\mu\ B$ **n** (x) | 2 as well as | $\nu\ B$ | 2

The expression ρ(A,B) is written as follows: ∑ x∈X | |μ A (x)| 2 + |ν A (x)| 2

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∑ x∈X|μ B(x)| 2 +|ν B(x)| 2

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∑ x∈X

The expression "Re(μ A (x) μ B (x))+Re(ν A (x) ν B (x))" is also a mathematical expression.

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According to the equation, the complex conjugates of the membership and non-membership degrees of B are denoted by the symbols $\mu B\ (x)$ and $\nu B\ (x)$ (μ B (x) respectively. While complying to the fuzzy requirements, this formula assures that it is sensitive to both the magnitude and phase variations that exist in the complex-valued memberships.

The robustness of this correlation coefficient is shown by the fact that it addresses the outlier effects and scaling concerns that are often associated with measures. In addition to this, it allows for the interaction between membership and non-membership degrees, so maintaining the dual character of knowledge that is based on intuition. A measure of this kind is quite useful in situations that call for sophisticated comparisons of CIFSs, especially in settings that include decision-making scenarios.

Relevance to the Process of Decision-Making

In decision-making procedures where uncertainty is ubiquitous, the correlation coefficient for CIFSs is shown to be of great use. Take into consideration a situation in which a manufacturing company is faced with the task of selecting suppliers in the face of unpredictable market circumstances and unreliable demand projections. Assessments are supplied in CIFS terms, and each supplier is rated based on a number of parameters, including pricing, dependability, and delivery time, among others.

Using the correlation coefficient, the person in charge of making the choice may determine the degree of congruence that exists between the ideal supplier profile (a benchmark CIFS) and each possible supplier of interest. The provider that has the greatest correlation is chosen, and this ensures that the option is in close alignment with the required characteristics while also taking into consideration the possibility of uncertainty.

An further use is in the field of medical diagnostics, where symptoms and the degree to which they manifest are stated as CIFSs. Through the process of matching the symptom profile of a patient with the archetypal illness profile, medical personnel are able to determine the most probable diagnosis, hence improving the accuracy of decision making in clinical settings that are both complicated and unclear.

The metric makes it easier to reach a consensus in situations involving collective decision-making by quantifying the degree to which experts' judgements, which are represented as CIFSs, are in accord with one another. A robust approach for synthesising a variety of viewpoints and arriving at a conclusion as a group may be obtained by aggregating these correlations.

There are many different domains that may benefit from the adaptability of the suggested correlation coefficient. Some of these domains include project selection, risk assessment, and social network analysis. It does this by using the nuanced capabilities of CIFSs, which allows comprehensive modelling of uncertainty and supports informed decision-making in contexts with many facets.

When it comes to developing the implementation of CIFSs in actual decision-making, the resilience and flexibility of the correlation coefficient measure highlight the significance of its role. The invention of this tool is a major step in the continuous effort to harness the power of fuzzy logic for the purpose of tackling difficulties that are encountered in the real world, where complexity and uncertainty are the greatest factors.

This section introduces the problem of managing inventory when items experience constant deterioration and demand varies with price and time.

The Importance of Understanding the Relationship Between Demand, Price, and Inventory Depletion Phases

Efficient inventory management requires a clear understanding of the interplay between demand, price, and inventory levels across various phases of depletion. The relationship is pivotal in optimizing business operations and profitability. When products deteriorate consistently over time, pricing strategies must adapt dynamically to maintain a balance between stimulating demand and minimizing inventory waste.

Demand often varies across three distinct inventory depletion phases:

1. **Initial Phase**: Abundant inventory and relatively stable demand.
2. **Transition Phase**: Inventory levels begin to decline, requiring adaptive pricing to balance demand and prevent excessive stock loss due to deterioration.
3. **Final Phase**: Approaching stockout, where pricing strategies may focus on clearing remaining inventory or capitalizing on scarcity.

Understanding these phases helps businesses craft tailored strategies to maximize revenue, reduce costs, and align with consumer behavior over time.

When dealing with perishable goods, inventory management becomes even more important to contemporary company operations. In order to maximise operational efficiency and profitability, it is necessary to understand the link between demand, pricing, and inventory depletion stages. The interplay between time and price, which varies over inventory stages, is a major factor in demand. As an example, when inventory is plentiful in the beginning, pricing strategies might focus upon maximising market penetration. In contrast, pricing in the latter stage may focus on selling out inventory or capitalising on scarcity to boost revenue as stock levels near depletion. By keeping track of these stages, companies can better gauge customer behaviour and adjust prices and inventory levels accordingly, striking the perfect balance between stimulating demand and reducing waste (Yao et al., 2016).

In real-world inventory systems, the constant degradation is a major factor, especially for high-tech commodities, medications, seasonal goods, and perishable goods. Fresh fruit and dairy products, among others, are always at danger of spoiling if not sold quickly, which might result in a loss of income. Precise inventory management is essential for preserving both compliance and consumer confidence, especially when it comes to medications, which lose efficacy over time. Seasonal goods, like Christmas decorations or trendy clothing, experience a kind of functional obsolescence similar to degradation when their usefulness decreases after a certain amount of time has passed. It is especially important to manage inventory turnover well when dealing with high-tech items because of how quickly technology may make earlier versions outdated. Constant degradation has many ramifications, such as increased holding costs, the need of precise demand forecasting, and the use of dynamic pricing techniques to maximise turnover while minimising waste (Goyal & Giri, 2001).

Businesses need to take into account the two most important factors influencing demand in today's markets—time and price—when planning their inventory management strategy. Lower prices usually increase demand, while higher prices decrease it; this is known as price-dependent demand, and it represents how customers react to changes in pricing. Pricing plans need to be fine-tuned since this sensitivity differs between product categories and market situations. Promotional sales on perishable commodities, for instance, may increase demand and decrease spoiling costs. In contrast, variables including product life cycles, seasonality, and market trends cause time-dependent demand to vary. Demand may be highest in the beginning of a product's life cycle while it is still relatively new, but it could fall as comparable or better items are introduced by rivals. Wee (1995) argues that firms can better adjust to changing market dynamics and customer preferences when they take price- and time-dependent demand into account together.

Multiple goals may be advanced in decision-making and operational efficiency by analysing inventory throughout the three stages of depletion: initial, transition, and final. The first benefit is a decrease in waste and holding costs caused by optimal inventory levels that are in line with expected demand at each phase. Second, it makes it possible to create adaptive pricing methods, which boost demand during slower times and make the most of high-demand times in terms of income. The third benefit is that it helps with making more informed decisions about promotions, discounting techniques, and when to restock depending on the current inventory phase. Better customer satisfaction and loyalty may be achieved when companies prevent overstocking and make sure products are available when demand is strong. At last, this kind of study lends credence to eco-friendly procedures by reducing trash from expired goods and coordinating stock-taking plans with larger environmental objectives (Bakker et al., 2012).

Ultimately, organisations are better equipped to handle the complexities of contemporary marketplaces when they include continuous degradation and fluctuating demand into inventory management. Maximising profits, improving customer happiness, and reducing waste may be achieved by understanding the interaction between price, time, and inventory depletion stages. Mathematical modelling of such systems and optimisation methodologies for inventory management throughout various stages are covered in the next parts of this chapter.

Mathematical Modeling of the Constant Deterioration Inventory System

This section provides the mathematical foundations for the model, starting with assumptions, notation, and equations.

It is crucial to include mathematical expressions that correctly depict the behaviour of inventory levels over time when modelling inventory systems with continual degradation. Dynamics of inventory depletion, demand that is price and time dependent, and the rate of degradation must all be included in the model. Differential equations, which characterise the time-dependent change in inventory as affected by these variables, provide a good representation of such a system.

Let I(t) represent the inventory level at time ttt. The rate of change in inventory can be expressed as:

$$\frac{dI(t)}{dt} = -D(p,t) - \theta I(t) \quad \text{.....................(1)}$$

In the above equations

1- D(p, t) is the demand function, which depends on price p and time t,

2- θ is the constant deterioration rate (0<θ<1), representing the proportion of inventory that deteriorates per unit time.

Demand Function:

The demand function D(p, t) is assumed to be a combination of price- and time-dependent factors:

$$D(p,t) = (a - b \cdot p) \cdot e^{kt}, \quad \text{................(2)}$$

where:

- a and b are demand coefficients, with aaa representing the maximum potential demand when p=0, and b capturing the sensitivity of demand to price,
- k represents the rate of growth (k>0) or decay (k<0) in demand over time,
- e^{kt} adjusts demand based on time.
- Substituting D(p,t) into the inventory rate equation gives:

$$\frac{dI(t)}{dt} = -(a - b \cdot p) \cdot e^{kt} - \theta I(t).$$

Solution of the Differential Equation:

To determine the inventory level I(t) over time, solve the differential equation using an integrating factor approach. The equation can be rewritten as:

$$\frac{dI(t)}{dt} + \theta I(t) = -(a - b \cdot p) \cdot e^{kt}.$$

The integrating factor is $e^{\theta t}$. Multiplying through by this factor:

$$e^{\theta t}\frac{dI(t)}{dt} + \theta e^{\theta t} I(t) = -(a - b \cdot p) \cdot e^{(\theta + k)t}.$$

Rewriting the left-hand side as a derivative:

$$\frac{d}{dt}\left[I(t) \cdot e^{\theta t}\right] = -(a - b \cdot p) \cdot e^{(\theta + k)t}.$$

Integrating both sides with respect to t:

$$I(t) \cdot e^{\theta t} = \int -(a - b \cdot p) \cdot e^{(\theta + k)t}\, dt + C,$$

where C is the constant of integration determined by the initial condition $I(0)=I_0$

Solving the integral on the right-hand side yields:

$$I(t) \cdot e^{\theta t} = -\frac{(a - b \cdot p)}{\theta + k} \cdot e^{(\theta + k)t} + C.$$

Dividing through by $e^{\theta t}$, the general solution is:

$$I(t) = C \cdot e^{-\theta t} - \frac{(a - b \cdot p)}{\theta + k} \cdot e^{kt}.$$

Using the initial condition $I(0)=I_0$, determine C:

$$I_0 = C - \frac{(a - b \cdot p)}{\theta + k}.$$

Therefore,

$$C = I_0 + \frac{(a - b \cdot p)}{\theta + k}.$$

The final solution for I(t) becomes:

$$I(t) = \left(I_0 + \frac{(a - b \cdot p)}{\theta + k}\right) \cdot e^{-\theta t} - \frac{(a - b \cdot p)}{\theta + k} \cdot e^{kt}.$$

Analytical Insights

1. **Initial Phase** (t≈0): At the beginning, I(t) is close to the initial stock I_0. Demand depends mainly on the price, while the impact of deterioration is minimal.
2. **Transition Phase**: As t increases, the effect of deterioration becomes significant, and $e^{-\theta}$ causes the inventory level to decay exponentially. Demand adjustments due to time (e^{kt}) start to influence inventory levels more prominently.
3. **Final Phase** (t →∞): Inventory levels approach zero. The rate of stock depletion is primarily determined by the interaction of θ, k, and the price-sensitive demand factor (a−b·p) p).

Total Cost Analysis:

The total cost TC over a planning horizon T includes:

- Holding cost H: Proportional to the inventory level.

$$H = \int_0^T h \cdot I(t)\, dt.$$

- Deterioration cost D: Proportional to the deteriorated inventory.

$$D = \theta \cdot \int_0^T c \cdot I(t)\, dt.$$

- Revenue: Dependent on sales and pricing.

Minimizing TC involves optimizing p and T based on the derived I(t). Advanced numerical methods or optimization techniques, such as Lagrange multipliers, can determine the optimal values.

This mathematical approach provides a robust framework for analyzing and managing inventory systems under constant deterioration and demand variability.

Analysis of Demand Variability and Price Sensitivity

In complicated systems, where uncertainty is inherent, understanding price sensitivity and demand fluctuation is critical for decision-making. When dealing with material that is both vague and ambiguous, fuzzy set theory offers a solid foundation. In order to make well-informed judgements, it is crucial to aggregate data from several sources or criteria. In order to examine price sensitivity and demand fluctuation, this part delves into the use of several aggregation operators and novel fuzzy approaches.

Demand Variability and Price Sensitivity in Fuzzy Environments

Demand variability refers to fluctuations in customer demand over time due to factors such as seasonality, economic trends, and pricing strategies. Price sensitivity, on the other hand, reflects how demand responds to changes in price. In a fuzzy environment, these phenomena are not always quantifiable in crisp terms; instead, they are expressed using linguistic variables (e.g., "high demand," "moderate price sensitivity") represented by fuzzy sets.

The demand function in a fuzzy system can be modeled as:

$$\tilde{D}(p) = \mu_D(x) \times f(p),$$

In the above equation

$\tilde{D}(p)$ is the fuzzy demand,

$\mu D(x)$ is the membership function representing the degree of demand,

$f(p)$ is the price-dependent function incorporating sensitivity levels.

The variability of $\tilde{D}(p)$ is captured through fuzzy rules and membership functions that account for uncertainty and linguistic judgments.

Aggregation Operators in Fuzzy Decision-Making

Aggregation operators combine inputs (e.g., demand levels, price indices) to produce a unified output, facilitating decision-making in fuzzy environments. Some commonly used operators include:

Weighted Arithmetic Mean (WAM):

WAM aggregates inputs by assigning weights to criteria based on their relative importance. For fuzzy demand analysis:

$$A = \sum_{i=1}^{n} w_i \cdot \tilde{D}_i,$$

where w_i are weights, and $\tilde{D}_i$ are fuzzy demand values.

OWA (Ordered Weighted Averaging) Operator:

OWA focuses on prioritizing certain criteria by reordering inputs before aggregation. The aggregation is expressed as:

$$OWA = \sum_{i=1}^{n} v_i \cdot \tilde{D}_{(i)},$$

Where v_i are weights based on the decision-maker's preference, and $\tilde{D}_{(i)}$ are the ordered fuzzy demands.

Geometric Mean Aggregation (GMA):

GMA emphasizes multiplicative relationships between criteria, useful for modeling synergies:

$$G = \left(\prod_{i=1}^{n} \tilde{D}_i^{w_i}\right)^{\frac{1}{\sum w_i}}$$

Choquet Integral:

This operator considers the interaction among criteria, making it suitable for analyzing price sensitivity under interdependent factors.

These operators allow for the fusion of fuzzy data into actionable insights, supporting decisions on pricing strategies and inventory levels.

Innovative Fuzzy Methods for Decision-Making

Several advanced fuzzy methods enhance decision-making in scenarios characterized by demand variability and price sensitivity:

Fuzzy Multi-Criteria Decision-Making (F-MCDM):

F-MCDM integrates criteria such as price, demand variability, and cost using fuzzy linguistic terms. Methods like Fuzzy TOPSIS and Fuzzy AHP rank alternatives to identify optimal solutions.

Fuzzy Rule-Based Systems:

These systems use rules to model relationships between variables. For example:

If the price is high and demand variability is low, then reduce inventory levels.

If the price is moderate and demand variability is high, then increase stock cautiously.

Fuzzy Regression Analysis:

Fuzzy regression models estimate demand sensitivity to price under uncertainty. For instance, the fuzzy demand function:

$$\tilde{D}(p) = \tilde{\beta}_0 + \tilde{\beta}_1 p,$$

where $\tilde{\beta}_0$ and $\tilde{\beta}_1$ are fuzzy coefficients, captures variability more comprehensively than traditional regression.

Fuzzy Optimization:

Optimization models under fuzzy constraints help determine optimal pricing and replenishment strategies. For instance, the objective function for minimizing costs can be represented as:

$$\min C = \tilde{H} + \tilde{D} - \tilde{R},$$

where $\tilde{H}$ is holding cost, $\tilde{D}$ is deterioration cost, and $\tilde{R}$ is revenue, all expressed as fuzzy numbers.

Case Example

Consider a business facing uncertain demand for perishable goods. Using fuzzy aggregation operators, the company can evaluate demand under different pricing scenarios:

Assign linguistic terms to demand levels (e.g., "low," "medium," "high") and price sensitivity (e.g., "low," "high").

Use fuzzy rules such as:

If demand is high and price sensitivity is low, maintain high stock levels.

If demand is medium and price sensitivity is high, adopt dynamic pricing.

Apply aggregation operators like OWA to prioritize high-demand scenarios and adjust inventory accordingly.

By leveraging fuzzy methods, the company can make informed decisions that reduce waste, enhance customer satisfaction, and optimize revenue.

Decision Making with Intuitionistic Fuzzy Dombi Aggregation Operators:

Because of a lack of specifics, the presented circumstances in the actual world are imprecise and hard to pin down. The fundamental idea of fuzzy sets in MADM issues was first put up by Bellman and Zadeh in order to appropriately address the intrinsic fuzziness or uncertainty of objects. The decision-makers indicate how unhappy they are with the characteristic and how well the alternative meets the attribute's requirements. Such cases may be appropriately addressed by IFS theory. In order to address the practical issues with MADM, IFSs have expanded their domain.

But there's a major difficulty with aggregating knowledge and preferences when it comes to decision-making. To a certain degree, in the face of complex management situations, decision-makers provide their judgements or certain traits. However, regarding their assessments, they seem somewhat bewildered in almost every instance. A certain amount of hesitation plays a significant role in developing an adequate and satisfactory model for decision-making challenges. When compared to using just numerical numbers, IFSs may provide a more accurate representation of this kind of hesitation. Decisions are therefore most significantly impacted by the accumulation of intuitionistic fuzzy information. In order to combine the intuitionistic fuzzy data, a number of scholars have suggested aggregation operations. In order to address MADM issues, Li expanded the generalised ordered weighted averaging operator to aggregate intuitionistic fuzzy information. Using a generalised order weighted averaging operator, Wang et al. presented a MADM technique. The induced intuitionistic fuzzy order weighted geometric aggregation operator and the interval-valued intuitionistic fuzzy order weighted geometric aggregation operator were developed and used to address MADM issues by Wei. An intuitionistic fuzzy aggregation operator was created by Wang and Liu using Einstein operations.

The procedures that Dombi introduced in 1982, the dombi t-norm and the dombi t-conorm, have a high priority when it comes to variability in parameter operations. In subsequent work, Liu et al. devised decision-making problems involving several attributes and attempted to apply Dombi operations to IFSs. For use in MADM, Chen and Ye developed

Dombi weighted aggregation procedures for use with single-valued neutrosophic data. Typhoon catastrophe assessment was established by him using Dombi hesitant fuzzy information aggregation. Shi and Ye extended Dombi operations to neutrosophic cubic set. For the purpose of solving MADM issues, Lu and Ye developed the Dombi aggregation operator for use with linguistic cubic variables. Wei and Wei introduced a few different ways that prioritised aggregation operators and Dombi operations may work together. Using classical algebra, geometry, and Dombi operations as its foundation, Jana et al. presented a set of bipolar fuzzy Dombi aggregation operators.

When it comes to actual decision-making difficulties, there are a lot of interrelationships between attributes. IFNs are great for expressing the fuzzy information that comes with MADM problems. When it comes to combining intuitionistic fuzzy data, the aggregation operator is crucial. Because of its inherent parameters, the Dombi t-norm and t-conorms provide more flexibility than competing approaches when it comes to developing aggregation operators.

CONCLUSION

Last but not least, a major step forward in uncertain decision-making is provided by the suggested correlation coefficient for complex intuitionistic fuzzy sets (CIFS). This novel method offers a more accurate and dependable way to evaluate CIFS connections by successfully combining the hesitation degree with membership and non-membership values. Its potential to improve decision quality in uncertain and complicated contexts is shown by its wide use in fields such as risk assessment, pattern identification, and multi-criteria decision analysis. In addition to fixing problems with old-fashioned correlation metrics, this study paves the way for fresh investigations into fuzzy set theory and decision-making models. Better, more reliable, and more efficient decision-making in a wide range of domains is possible thanks to the created correlation coefficient, which is a useful tool for dealing with uncertainty.

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