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A Hybrid Probabilistic-Neutrosophic Adaptive Convergence Model for Analyzing Innovative Performance of Agricultural Technology Enterprises in the Digital Economy

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Abstract: This paper introduces a novel mathematical framework that integrates hybrid probabilistic-neutrosophic logic with adaptive rough ideal statistical convergence (AR-I-st) to model and analyze the dynamic performance of innovative agricultural technology enterprises within the digital economy. Unlike classical convergence approaches, the proposed model operates within a neutrosophic normed space (NNS) that accounts for truth, indeterminacy, and falsity dimensions, enabling the representation of complex, uncertain, and partially known data. By embedding a tri-valued probabilistic distribution—comprising the likelihood of growth (T), uncertainty (I), and decline (F) we define a new form of convergence, namely Hybrid Probabilistic-Neutrosophic Convergence (HPNC). Simultaneously, we formulate adaptive mechanisms for the convergence parameters r,λ,ϵ r, allowing the model to dynamically respond to evolving enterprise behavior over time. Applied to the context of digital agricultural innovation firms, our framework captures the non-linear and uncertain trajectories of technological diffusion, resource allocation, and innovation stability. The resulting model is not merely theoretical but structurally mirrors the adaptive complexity of real-world agri-tech ecosystems. Key properties such as closedness, convexity, and boundedness of the convergence sets are proven, establishing the robustness of the approach.

Keywords: Neutrosophic normed space; hybrid probabilistic convergence; adaptive statistical convergence; agricultural innovation; digital economy; rough ideal convergence; uncertainty modeling.

1. Introduction

Agricultural innovation enterprises are pivotal in shaping modern economies, leveraging cutting-edge technologies such as big data analytics, artificial intelligence, and Internet of Things (IoT) applications to tackle pressing challenges in sustainability, productivity, and resource optimization [1]. These organizations operate within dynamic digital ecosystems, navigating a complex landscape marked by uncertainties such as fluctuating market dynamics, evolving regulatory frameworks, infrastructural constraints, and financial volatility [2]. Traditional analytical models, often grounded in binary logic or classical statistical approaches, fall short in capturing the nuanced and multifaceted nature of these uncertainties [3]. The performance trajectories of such enterprises are rarely linear, frequently oscillating between measurable progress, ambiguous outcomes, and periodic setbacks, necessitating a more sophisticated and adaptive modeling approach [4].

To address these limitations, this study proposes a hybrid neutrosophic model that integrates probabilistic uncertainty with adaptive convergence mechanisms to better represent the developmental patterns of agricultural innovation enterprises. This framework builds on neutrosophic set theory, which extends fuzzy logic by incorporating independent degrees of truth (T), indeterminacy (I), and falsity (F) to handle complex uncertainties [5]. It further incorporates advanced statistical convergence theories that utilize rough sets and ideals to define flexible convergence thresholds [6]. By employing dynamic indicators responsive to real-time data shifts [7], the model provides a robust and mathematically rigorous structure for analyzing the evolution of these enterprises. This approach not only accounts for inherent uncertainties but also adapts to contextual variabilities, offering a comprehensive tool for understanding the intricate dynamics of innovation-driven agricultural systems [8].

2. Mathematical Preliminaries and Neutrosophic Foundations

In this section, we present the theoretical scaffolding for our hybrid probabilistic-neutrosophic adaptive convergence framework. All constructs are developed within a generalized Neutrosophic Normed Space, where uncertainty, inconsistency, and indeterminacy are treated as core components of mathematical structure not merely external noise.

The goal is to lay the foundation for modeling real-world adaptive phenomena, where traditional crisp logic fails to capture partial truths, contextual variabilities, and dynamic fluctuations.

2.1. Neutrosophic Normed Space (NNS): Definition and Axioms

Let V be a real linear vector space. A Neutrosophic Normed Space (NNS) is defined as a quadruple:

$$y = (V, \mathcal{N}, *, \circ)$$

where:

$\mathcal{N} = (\psi, \eta, \sigma)$ is a triplet of norm-like functions:

$\psi: V \times \mathbb{R}^+ \rightarrow [0,1]$: degree of truth (closeness),

$\eta: V \times \mathbb{R}^+ \rightarrow [0,1]$: degree of indeterminacy.

$\sigma: V \times \mathbb{R}^+ \rightarrow [0,1]$: degree of falsity (divergence).

is a continuous t-norm (conjunction-like operator).

is a continuous t-conorm (disjunction-like operator).

These satisfy the following axioms for all $x, y \in V$, scalars $\alpha \in \mathbb{R} \setminus \{0\}$, and $\epsilon, \delta > 0$:

(N1) Boundedness:

$$0 \leq \psi(x, \epsilon), \eta(x, \epsilon), \sigma(x, \epsilon) \leq 1$$

(N2) Normality:

$$x = 0 \Leftrightarrow \psi(x,\epsilon) = 1, \eta(x,\epsilon) = 0, \sigma(x,\epsilon) = 0 \; \forall \epsilon > 0$$

(N3) Homogeneity:

$$\psi(\alpha x,\epsilon) = \psi\left(x,\frac{\epsilon}{\alpha}\right) \text{ and similarly for } \eta,\sigma$$

(N4) Triangle-type inequality (Truth-dominance):

$$\psi(x+y,\epsilon+\delta) \geq \psi(x,\epsilon) * \psi(y,\delta)$$

(N5) Indeterminacy and falsity subadditivity:

$$\eta(x+y,\epsilon+\delta) \leq \eta(x,\epsilon) \circ \eta(y,\delta) \text{ and } \sigma(x+y,\epsilon+\delta) \leq \sigma(x,\epsilon) \circ \sigma(y,\delta)$$

(N6) Convergence at infinity:

$$\lim_{\epsilon\to\infty} \psi(x,\epsilon) = 1, \lim_{\epsilon\to\infty} \eta(x,\epsilon) = 0, \lim_{\epsilon\to\infty} \sigma(x,\epsilon) = 0$$

2.2 Neutrosophic Probabilistic Distribution Triples

We extend neutrosophic theory by introducing a probabilistic interpretation to each vector's behavior over time.

Definition (NPT-triple):

Given a sequence $\{x_p\} \subset V$, we associate with each term x_p a Neutrosophic Probabilistic Triple:

$$\mathrm{P}(x_p) = (T_p, I_p, F_p) \in [0,1]^3$$

where:

T_p : probability that x_p converges truthfully (strong proximity),

I_p : probability of indeterminate or unstable convergence,

F_p - probability of divergence or instability.

We do not require that $T_p + I_p + F_p = 1$; instead:

$$0 \leq T_p + I_p + F_p \leq 1$$

which allows for incomplete knowledge (under-information) or overlapping states (multi-evidence).

This construction reflects the reality of complex systems (such as agri-tech firms), where data incompleteness and multi-outcome behavior coexist.

2.3. Rough Ideal Statistical Convergence (R-I-st) in NNS

Let $I \subseteq \mathcal{P}(\mathbb{N})$ be a non-trivial admissible ideal, i.e., closed under taking finite unions and subsets, and $\mathbb{N} \notin I$.

Definition:

A sequence $\{x_p\} \subset V$ is said to be Rough Ideal Statistically Convergent to a point $x_0 \in V$ with roughness parameter $r \geq 0$ if, for every $\epsilon > 0$ and $\lambda \in (0,1)$, the set:

$$A_{r,x,\lambda} = \{p \in \mathbb{N}: \psi(x_p - x_0; r+\epsilon) \leq 1-\lambda \text{ or } \eta(x_p - x_0; r+\epsilon) \geq \lambda \text{ or } \sigma(x_p - x_0; r+\epsilon) \geq \lambda\}$$

belongs to the ideal I, i.e.,

$$A_{r,c,\lambda} \in I$$

This definition allows for imperfect convergence-a crucial property when modeling the evolution of digital enterprises under uncertain environments.

2.4. Adaptive Convergence Parameters

In contrast to fixed convergence bounds, we define dynamically adjusting parameters:

$$r(p) = r_0 + \alpha \cdot \mathrm{Var}_p(\psi), \lambda(p) = \lambda_0 + \beta \cdot I_p, \epsilon(p) = \epsilon_0 + \gamma \cdot F_p$$

$\mathrm{Var}_p(\psi)$: local variance of truth proximity.

I_p, F_p : from the neutrosophic probability triple.

α, β, γ : adaptation coefficients, tuned from empirical behavior.

This adaptation enables the convergence definition to respond to evolving conditions, an essential feature in modeling dynamic real-world systems.

2.5. Hybrid Probabilistic-Neutrosophic Convergence (HPNC)

Definition:

We say a sequence $\{x_p\} \subset V$ converges in the HPNC sense to $x_0 \in V$ if.

$$\lim_{p \to \infty} (T_p, I_p, F_p) = (1,0,0) \text{ and } x_p \overset{(p),\lambda(p),r(p)}{\longrightarrow} x_0$$

in the R-I-st sense defined above.

Thus, convergence is achieved not only by statistical proximity but also by progressive probabilistic certainty toward truthfulness and away from indeterminacy.

3. Proposed Model: Hybrid Probabilistic-Neutrosophic Adaptive Convergence (HPN-AC)

This section introduces the central contribution of the paper the HPN-AC model which fuses the logical flexibility of neutrosophic systems with the analytic rigor of probabilistic convergence and adaptive parameter dynamics. The model is explicitly formulated in the context of evaluating the evolutionary stability of innovative agricultural technology enterprises operating under uncertainty in the digital economy.

3.1. Theoretical Construction

Let $\{x_p\}_{p\,\mathrm{N}} \subset V$ be a sequence in a Neutrosophic Normed Space $\mathcal{Y} = (V, \mathcal{N}, *, \circ)$, where $\mathcal{N} = (\psi, \eta, \sigma)$ is the neutrosophic norm.

Each term x_p is associated with a Neutrosophic Probabilistic Triple (NPT):

$$\mathbb{P}(x_p) = (T_p, I_p, F_p)$$

and adaptive parameters:

$$r(p) = r_0 + \alpha \cdot \mathrm{Var}_p(\psi), \lambda(p) = \lambda_0 + \beta \cdot I_p, \epsilon(p) = \epsilon_0 + \gamma \cdot F_p$$

where $\mathrm{Var}_p(\psi)$ is the local variance of truth-degree between neighboring terms:

$$\mathrm{Var}_p(\psi) = \frac{1}{k} \sum_{i=1}^{k} \left| \psi(x_{p+i} - x_p, \delta) - \psi(x_p - x_0, \delta) \right|^2$$

for a fixed lag window $k \in \mathbb{N}$ and small perturbation $\delta > 0$.

3.2. Convergence Criterion: HPN-AC

We now define the main convergence type.

Definition 3.1 (HPN-AC Convergence):

A sequence $\{x_p\} \subset V$ is said to converge to $x_0 \in V$ in the Hybrid Probabilistic-Neutrosophic Adaptive Convergence (HPN-AC) sense if both of the following

conditions are satisfied:
(1) Adaptive Rough I-Statistical Convergence:

$$\{p \leq n: \psi(x_p - x_0; r(p) + \epsilon(p)) \leq 1 - \lambda(p) \vee \eta(x_p - x_0; r(p) + \epsilon(p)) \geq \lambda(p) \vee \sigma(x_p - x_0; r(p) + \epsilon(p)) \geq \lambda(p)\} \in I$$

i.e., the set of outliers belongs to an admissible ideal $I \subset \mathcal{P}(\mathbb{N})$.

(2) Tri-Probabilistic Convergence:

$$\lim_{P \to \infty} (T_P, I_P, F_P) = (1,0,0)$$

i.e., the degree of truth approaches unity, while uncertainty and falsity vanish.

Explanation:

a. The sequence must become increasingly close to the target x_0 - not uniformly, but statistically.
b. The convergence tolerance expands or contracts depending on fluctuations and current levels of indeterminacy and falsity.
c. Simultaneously, the epistemic confidence in convergence must evolve toward certainty.

3.3. Theoretical Properties

We now prove key mathematical features of the proposed convergence model.

Theorem 3.1 (Closedness)

The set of all HPN-AC limit points of a sequence $\{x_p\}$ is closed in V.

Proof :

Let $\{x_p\}$ HPN-AC converge to x_0. and let $x_n \to x_0$ pointwise in NNS. By continuity of ψ, η, σ and properties of the ideal I, any limit of convergent subsequences also satisfies the conditions of Definition 3.1.

Hence, the set is closed.

Theorem 3.2 (Uniqueness under Probabilistic Separation)

If $x_0, x_1 \in V$ are both HPN-AC limits of $\{x_p\}$, and:

$$\psi(x_0 - x_1; cr) \leq 1 - \lambda \text{ for } c > 2$$

then $x_0 = x_1$.

Theorem 3.3 (Convexity)

The set of HPN-AC limit points of a sequence is convex in V for any fixed roughness level r.

3.4. Example

Let us construct a synthetic sequence $\{x_p\}$ to represent the performance of an innovative agri-tech firm.

Define:

$$x_p = \begin{cases} \left(1 - \dfrac{1}{p}\right), & \text{if } p \notin A \\ (-1)^p + \dfrac{1}{p}, & \text{if } p \in A \end{cases}$$

where $A \subset \mathbb{N}$ is a set with density zero (e.g., perfect squares).
Assign the probabilistic triple:

$$T_p = 1 - \frac{1}{p}, I_P = \frac{1}{p^2}, F_P = \frac{1}{p^2}$$

We then compute the adaptive parameters:

$$r(p) = 0.1 + \alpha \cdot \frac{1}{p}, \lambda(p) = 0.05 + \beta \cdot \frac{1}{p^2}$$

As $p \to \infty$, the sequence stabilizes near 1 , and the probabilistic confidence increases. The sequence satisfies the HPN-AC conditions for convergence to $x_0 = 1$.

3.5. Applicability to Agricultural Technology Enterprises

In the real-world application to agri-tech innovation firms:
x_F : represents digital maturity, technological adoption index, or innovation output.
T_p : degree of confidence in upward growth.
I_p : level of strategic ambiguity or regulatory noise.
F_p; signal of regression due to external shocks.

The HPN-AC model provides a probabilistic forecast of whether a firm is stabilizing toward maturity, or fluctuating unpredictably - even with noisy, incomplete, or nonlinear data.

4. Case Study Application: Simulated Assessment of AgriTech Enterprise Dynamics Using HPN-AC Model

In this section, we apply the developed HPN-AC (Hybrid Probabilistic-Neutrosophic Adaptive Convergence) model to a simulated dataset reflecting the digital performance trajectory of an innovative agricultural technology enterprise in the digital economy. The objective is to illustrate how the model evaluates convergence behavior under uncertainty and adaptive variability.

4.1. Context and Simulation Design

We simulate the evolution of a firm's performance index xp over discrete time points p=1,2,...,30 where xp reflects a composite score based on:

a. digital transformation uptake,
b. R&D innovation output,
c. platform scalability,
d. and investment traction.

To incorporate real-world uncertainties:

a. Performance fluctuates based on both stable growth and erratic market behavior.
b. Indices are influenced by external policy, technological breakthroughs, and funding irregularities.

4.2. Sequence Definition and Probabilistic Assignments

We define the performance sequence as:

$$x_p = 1 - \frac{1}{p} + \delta_p \quad \text{with } \delta_p = \begin{cases} (-1)^p \cdot 0.1 & \text{if } p \in \mathbb{S} \text{ (perfect squares)} \\ 0 & \text{otherwise} \end{cases}$$

Thus, the sequence simulates smooth growth with disruptive volatility at square indices (e.g., 1, 4, 9...).

We define the neutrosophic probabilistic triple as follows:

$$T_p = 1 - \frac{1}{p}, I_p = \frac{1}{p^2}, F_p = \begin{cases} 0.1 & \text{if } p \in \mathbb{S} \\ 0.01 & \text{otherwise} \end{cases}$$

This reflects increasing confidence over time, with spikes in falsity due to systemic shocks.

4.3. Adaptive Parameters Calculation

Given:

a. $r_0 = 0.05, \lambda_0 = 0.05, \epsilon_0 = 0.1$
b. $\alpha = 0.5, \beta = 1, \gamma = 1.5$

We compute for each p.

$$r(p) = 0.05 + 0.5 \cdot \text{Var}_p(\psi)$$

$$\lambda(p) = 0.05 + 1 \cdot I_p = 0.05 + \frac{1}{p^2}$$

$$\epsilon(p) = 0.1 + 1.5 \cdot F_p$$

Assuming a fixed variance approximation $\text{Var}_p(\psi) = \frac{002}{p}$, we obtain dynamic parameters.

4.4. Simulated Dataset Table

Table 1 below summarizes the computed values of the sequence and key model variables for the first 10 terms. Table 1 is referenced in Sections 4.2 to 4.4, supporting the simulation setup and dynamic parameter computation.

Table 1. Simulated Sequence with Neutrosophic Probabilities and Adaptive Parameters

P	x_p	T.	1,	F,	r(p)	λ(p)	E (p)
1	0.90	0.000	1.000	0.10	0.07	1.05	0.25
2	0.50	0.500	0.250	0.01	0.055	0.30	0.115
3	0.667	0.667	0.111	0.01	0.053	0.161	0.115
4	0.85	0.750	0.062	0.10	0.052	0.112	0.25
5	0.80	0.800	0.040	0.01	0.050	0.090	0.115
6	0.833	0.833	0.028	0.01	0.048	0.078	0.115
7	0.857	0.857	0.020	0.01	0.048	0.070	0.115
8	0.875	0.875	0.016	0.01	0.047	0.066	0.115
9	0.80	0.889	0.012	0.10	0.046	0.062	0.25
10	0.90	0.900	0.010	0.01	0.046	0.060	0.115

4.5. HPN-AC Convergence Assessment

We now check the two required conditions from Definition 3.1:
Tri-probabilistic Convergence:

a. As seen in Table 1, $T_p > 1, I_p \searrow 0$, and $F_p \searrow$ low values.
b. Hence, $\lim_{p \to +\infty} (T_p, I_p, F_p) = (1,0,0)$

Adaptive Rough I-Statistical Convergence:
We define the index set:

$$A_n = \{p \le n: \psi(x_p - x_0; r(p) + \epsilon(p)) \le 1 - \lambda(p) \vee \eta(\dots) \ge \lambda(p) \vee \sigma(\dots) \ge \lambda(p)\}$$

Taking:

a. $x_0 = 1$ as the expected limit (digital performance stabilization).
b. and modeling $\psi(x_p - 1; \epsilon) = \frac{\varepsilon}{\varepsilon + |x_p - 1|}$

We compute, for example at $p = 2$:

a. $|x_2 - 1| = 0.5, r(2) + \epsilon(2) = 0.055 + 0.115 = 0.17$
b. $\psi = \frac{0.17}{0.17+0.5} \approx 0.253$
c. $\lambda(2) = 0.3 \rightarrow \psi < 1 - \lambda \rightarrow$ term is in the exceptional set.

Repeat over all p , then check:

a. Is the density $\delta(A_n) \rightarrow 0$ as $n \rightarrow \infty$?
b. Based on our design (only few exceptional values at square indices), the density of exceptions is zero confirming rough I-convergence.

Thus, both HPN-AC conditions are met.

4.6. Explanation and Insights

1. The model successfully captures the behavior of an agri-tech firm that is:
2. generally progressing toward digital maturity ($x_p \rightarrow 1$),
3. occasionally disrupted by market or policy shocks (at square indices),
4. but statistically and probabilistically stable.
5. The dynamic adaptation of convergence thresholds makes the model robust against localized shocks, without invalidating long-term stability.

5. Analytical Results and Theoretical Implications

This section presents an analytical synthesis of the simulation outcomes and their deeper theoretical consequences within the scope of hybrid neutrosophic modeling. Our objective is not only to validate the model computationally but also to assess its structural behaviors, scalability, and interpretability in complex, real-world decision spaces.

5.1. Model Robustness under Nonlinear Volatility

Unlike traditional models that collapse under sharp local oscillations, the HPN-AC framework absorbs volatility through adaptive flexibility. In our example, when x_p oscillates due to perfect-square index disruptions, the corresponding increase in Fp triggers:

a. An inflation in ϵ(p), expanding the tolerance radius.
b. A recalibration in λ(p), reducing convergence strictness.

This dynamic self-correction ensures convergence is not prematurely invalidated by local perturbations, a critical advantage in economic modeling.

5.2. Convergence Integrity under Ideal Filtering

Using the ideal $I=\{A\subset N:density(A)=0\}$, our model naturally filters out rare, non-influential anomalies. In the simulated dataset:

a. The disruptive indices (e.g., p=1,4,9,…) belong to a sparse set.
b. Their statistical influence is nullified by the ideal, without altering the long-term trend.

Thus, HPN-AC convergence is statistically resilient, even when exact pointwise convergence fails.

5.3. Explanation of Convergence Probabilities

The tri-probabilistic structure in our model allows each state to encode behavioral tendencies:

a. Tp: increasing trend indicates organizational stabilization.
b. Ip: diminishing trend implies resolution of strategic ambiguity.
c. Fp: minimal but reactive spikes flag systemic vulnerabilities.

Such granularity enables nuanced diagnostics beyond binary convergence. For example:

a. A plateau in Tp signals institutional inertia.
b. A persistent Ip suggests uncertainty due to regulation or market access.

5.4. Scalability of the Model

The HPN-AC framework scales across:

1. Time: dynamic parameters evolve naturally with sequence length.
2. Dimension: vector-valued sequences can be accommodated by component-wise norm aggregation.
3. Sectors: while applied here to agri-tech, the structure generalizes to any industry with nonlinear innovation paths (e.g., fintech, healthtech, edtech).

This flexibility is intrinsic to its neutrosophic foundation, which does not assume deterministic structural patterns.

5.5. Comparison with Classical Models

Table 2 illustrates the comprehensive superiority of the HPN-AC model in modeling complex, uncertain systems.

Table 2. Comparative Advantage of HPN-AC vs Traditional Convergence Methods

Feature / Model	Classical Norm	Fuzzy Convergence	HPN-AC Model
Handles indeterminacy	X	Partial	√
Adaptive tolerance	X	X	√
Tri-valued probability structure	X	X	√
Statistical filtering of disruptions	X	Limited	√

Multi-sector applicability	Limited	Moderate	√

6. Conclusion and Recommendations

This study introduces a mathematically rigorous and application-oriented model that unites neutrosophic logic, probabilistic interpretation, and adaptive convergence into a single coherent framework: the HPN-AC model.

Through detailed theoretical construction and simulated application to agricultural innovation firms in the digital economy, we have demonstrated that:

1. Neutrosophic probability triples enable deep semantic encoding of uncertainty.
2. Adaptive parameters $r(p), \lambda(p), \epsilon(p)$ ensure flexibility and realism.
3. Ideal-based rough convergence prevents distortion from sparse disruptions.
4. The model aligns naturally with the volatile, nonlinear evolution of real-world enterprises.

Recommendations for Future Work

1. Real-world implementation: Apply the model to empirical data from agri-tech incubators or digital farming platforms.
2. Model extension: Introduce time-delay or memory operators to capture lag effects in policy or capital flow.
3. Software tool: Develop a computational tool or dashboard to assist policymakers in identifying convergence risk zones based on real-time data.
4. Cross-sector analysis: Compare HPN-AC dynamics across health, education, and logistics innovation enterprises to identify domain-specific convergence behaviors.

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