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MODELING PLANT-BASED ELECTRICITY GENERATION UNDER ENVIRONMENTAL UNCERTAINTY USING NEUTROSOPHIC LOGIC

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ABSTRACT

Plant microbial fuel cells (PMFCs), bio-photovoltaic arrays, and hybrid electrochemical platforms are all examples of new types of renewable energy systems that use living plants to generate a small but steady amount of electricity. These systems depend on the metabolic interactions between roots, soil microorganisms, and materials that can conduct electricity. But their performance is always uncertain because changes in the environment, biological variability, and limits on measurements make things less clear than classical deterministic models can show. Fuzzy logic as it is used now can show different levels of truth, but it combines ignorance and vagueness into one value, making it harder to understand in complicated natural systems. This study presents a conceptual and mathematical model based on neutrosophic logic that aims to define and measure uncertainty in plant-based electricity generation. Neutrosophic triplets (T, I, F) show key environmental and biological factors like solar radiation, soil moisture, temperature suitability, and plant vitality. This lets truth, indeterminacy, and falsity be shown separately. A rule-based inference mechanism puts these triplets together to make an interval-based guess about how much electricity will be produced. The work lays out the theoretical framework for this method and makes it clear how it can be used to model environmental energy. In general, the framework shows how neutrosophic reasoning gives us a better way to understand the uncertainty that comes with living green energy systems.

1. INTRODUCTION

Electricity generation from living plants (PBEG) has gained attention as a long-term, sustainable strategy for renewable power production. These systems exploit the natural interactions among plant physiological processes, microbial metabolism, and electrochemical reactions to yield continuous, low-level energy. In PMFC designs, plants release organic compounds into the rhizosphere, which electrogenic microorganisms convert into electrons that flow through an external circuit [1–5]. Over the past several decades, researchers have expanded the scientific foundation of these systems. Early studies such as those of Strik et al. and Timmers et al. demonstrated that PMFCs using species like Spartina anglica can operate reliably over long periods, confirming their potential as sustainable bioelectrical platforms [1,2]. Subsequent work by Cui et al. [3] emphasized the suitability of PMFCs for ultra-low-power sensing applications in environmental monitoring, while complementary reviews detailed developments in microbial community engineering, electrode materials, and system optimization [4,5]. More recent studies have diversified PMFC configurations and applications. Horizontal, vertical, and tubular designs have been proposed to improve electron capture and to link energy production with wastewater treatment [6]. PMFCs have been framed as elements of integrated ecological infrastructure [7], and have been evaluated for their role in emerging bioelectricity technologies and associated challenges [8–10]. Despite their ecological advantages, PBEG systems are highly sensitive to environmental conditions such as irradiance, soil moisture, nutrient availability, and temperature [11]. These factors vary irregularly and interact with microbial and plant processes in nonlinear ways.

Traditional deterministic and probabilistic approaches often fail to capture such complex uncertainty, either by ignoring epistemic indeterminacy or requiring precise probability distributions that are rarely available for living systems. Neutrosophic logic, originally proposed by Smarandache [12] and extended to single-valued neutrosophic sets by Wang et al. [13], offers a promising foundation for modeling such uncertainty. Unlike fuzzy logic which merges uncertainty and vagueness into a single membership value neutrosophic logic distinguishes between truth (T), indeterminacy (I), and falsity (F). This triadic separation enables the explicit representation of incomplete information, conflicting sensor readings, and environmental variability. Recent work using neutrosophic multi-criteria decision-making in renewable energy planning illustrates the value of this approach under conditions of incomplete and imprecise data [14]. In the context of plant microbial systems, neutrosophic reasoning enables hybrid models that reflect biological complexity, environmental noise, and sensor imperfections. Bibliometric analyses of PMFC research reveal a rapidly expanding field, including efforts to integrate bio-photovoltaic systems and to develop data-driven environmental monitoring tools [15]. The scientific and technological maturity of plant-based electricity generation systems is further supported by recent literature. Chong et al.'s thorough review [16] summarizes developments in the biological, electrochemical, and material aspects of plant microbial fuel cells (PMFCs), emphasizing advancements in long-term stability, electrode–root interfaces, and rhizodeposition mechanisms. Their analysis highlights how environmental variability and dynamic biological states have a significant impact on PMFC performance, underscoring the need for modeling frameworks that can handle incomplete and changing data. In support of this viewpoint, Brugellis et al. [17] assessed a novel PMFC prototype that integrated low-noise power management circuits and optimized electrode geometries, showing enhanced energy harvesting in practical settings while also recording significant output fluctuations brought on by biological and environmental factors. Attah et al.'s experimental studies [18] offer more empirical proof that the bioelectric output in PMFCs is context-dependent and nonlinear. Even in controlled laboratory settings, their findings show a high sensitivity to soil moisture gradients, plant developmental stages, and microbial community composition, resulting in sporadic and partially indeterminate power profiles. In terms of technology, PMFCs are positioned within the growing field of microbial fuel cell technologies by Dakal et al. [19], who highlight new hybrid systems, ecological integration, and the ongoing problem of uncertainty resulting from coupled biological–electrochemical processes. Together, these studies show that uncertainty is still an inherent characteristic rather than a secondary disturbance, even as PMFC architectures and materials continue to progress. Simultaneously, research on renewable energy has embraced methodological advancements in uncertainty modeling. Neutrosophic logic provides a strong analytical framework for renewable energy systems with sparse data, contradictory measurements, and epistemic ambiguity, as shown by Salam et al. [20]. Their results demonstrate that in situations where sensor imperfection and environmental variability coexist, neutrosophic approaches perform better than classical fuzzy and probabilistic methods. Neutrosophic representations allow for the explicit modeling of ambiguous environmental signals, contradicting sensor observations, and partially known biological states in PMFC-based PBEG systems. A solid conceptual basis for creating next-generation hybrid models that are both computationally reliable and biologically realistic is provided by this alignment between the inherent uncertainty of plant–microbial bioelectrical systems and the expressive potential of neutrosophic logic.

The present study introduces a neutrosophic modeling framework tailored to plant based electricity generation, with two main aims: (1) to explicitly represent environmental and biological uncertainty, and (2) to link neutrosophic logic with ecological energy modeling. By combining logical formalism with living-system dynamics, the work contributes both theoretical insight and practical tools for designing intelligent, uncertainty-aware renewable-energy systems.

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2. BACKGROUND AND MOTIVATION

2.1. Living-Plant Electricity Generation

Plant microbial fuel cells (PMFCs) produce electricity by using organic compounds that plants release from their roots. These compounds are then oxidized by electroactive microorganisms on the anode surface. This mechanism depends on the close interaction of three main subsystems: (i) the plant's photosynthesis-driven production and exudation of rhizodeposits, (ii) microbial metabolic pathways that allow extracellular electron transfer, and (iii) electrochemical reactions that happen within the electrode assembly [2,4]. Every part is very sensitive to changes in the environment. Intense light increases photosynthetic productivity but may also elevate respiration and water loss through transpiration. Soil moisture regulates both microbial electron transfer efficiency and plant root physiology, while temperature control microbial reaction rates according to Arrhenius-type kinetics. These dynamic factors create an interdependent, nonlinear system in which feedback loops continually reshape energy generation potential.

The instantaneous electrical output, $I(t)$, of a PMFC can be conceptually expressed as a function of multiple environmental and biological drivers:

$I(t) = f(S(t), M(t), T_{env(t)}, H(t)) + \varepsilon(t)$, where S represents irradiance, M soil-water status, T_{env} thermal suitability, H plant physiological condition, and $\varepsilon(t)$ unmodeled variability. Since the functional relationship $f(\cdot)$ is often unknown or only partially observable, PMFC studies increasingly rely on rule-based or data-driven frameworks.

2.2. Sources of Uncertainty in PBEG

There is uncertainty in plant-based electricity generation because of the interaction of a number of factors:

a) Environmental variability: random changes in sunlight, rain, and temperature cause aleatory uncertainty.

b) Measurement uncertainty: sensor drift, noise, errors in discretization, and missing readings all add to epistemic uncertainty.

c) Biological and structural uncertainty: Plant physiology and microbial activity change over time, which makes it hard for deterministic equations to describe their behavior.

These types of uncertainty work together in a way that makes them stronger, not weaker. Even when individual variables seem stable, their combined effect can create system states where it's impossible to say for sure if conditions are "favorable" or "unfavorable."

2.3. Existing Modeling Approaches

Traditional physical models represent PMFC processes through coupled differential equations such as: $\frac{dC}{dt} = \varphi(S, M, H) - \psi(C)$, where C denotes substrate concentration, φ production rate, and ψ consumption rate. While mechanistically informative, such models require extensive parametrization and fail when critical data are missing. Fuzzy modeling provides a more flexible alternative through linguistic rules (e.g., "if light is high and moisture is optimal, then output increases"). However, fuzzy sets employ a single membership degree $\mu \in [0,1]$, merging vagueness and incomplete knowledge into one measure. This limits their capacity to distinguish between conflicting observations and genuine ignorance. Neutrosophic logic overcomes this limitation by introducing the explicit triplet (T, I, F), enabling separate treatment of truth, uncertainty, and falsity. This capability makes it particularly suitable for environmental systems in which data uncertainty and ambiguity are intrinsic features rather than exceptions.

3. METHODOLOGICAL OVERVIEW

This section presents the neutrosophic modeling strategy, integrating rule-based logic with environmental-system representation.

Conceptual representation:

Each environmental input $X \in \{S, M, H, T_{env}\}$ is represented as a neutrosophic triplet:

$$X = (T_X, I_X, F_X)$$

where T_X quantifies support for the condition being favorable, F_X, captures evidence against it, and I_X represents the degree of indeterminacy associated with limited, noisy, or contradictory information. These components are mathematically independent and satisfy:

$$0 \leq T_X, I_X, F_X \leq 1,$$

$$0 \leq T_X + I_X + F_X \leq 3.$$

This independence allows modeling of contradictory conditions—for example, when sensors simultaneously report signals suggesting both high and low values.

From measurement to neutrosophic state:

Given a normalized measurement $x \in [0, 1]$ and an uncertainty parameter σ_X, the neutrosophic components are computed as:

$$T_X = \mu_{X(x)},$$

$$I_X = \alpha\, \sigma_{X(x)},$$

$$F_X = 1 - T_X - \beta\, I_X,$$

where $\mu_{X(x)}$is a fuzzy membership function describing favorability, and α, β are adjustment

parameters governing uncertainty propagation. This formulation connects fuzzy membership with neutrosophic indeterminacy. Logical inference Let R denote a set of rules $R_{\,k}$ of the form:

$R_{\,k}$: If (S is $L_{\{S,k\}}$) ∧ (M is $L_{\{\mathrm{M,k}\}}$) ∧ (H is $L_{\{\mathrm{H,k}\}}$) then E is $L_{\{\mathrm{E,k}\},}$

where $L_{\{X,k\}}$ are linguistic labels (e.g., “high,” “moderate,” “low”). The neutrosophic conjunction and disjunction operators are defined as:

$$A \wedge B = (min(T_A, T_B), max(I_A, I_B), max(F_A, F_B)),$$

$$A \vee B = (max(T_A, T_B), min(I_A,\ I_B), min(F_A, F_B)).$$

Each rule produces a neutrosophic triplet $(T_{E^{(k)}}, I_{E^{(k)}}, F_{E^{(k)}})$ reflecting its inferred outcome.

Aggregation and output estimation:

After evaluating all rules, the aggregated neutrosophic output yields an uncertainty-aware power estimate:

$$P_{low} = (T_E - I_E)\, P_{max},$$

$$P_{high} = (T_E + I_E)\, P_{max},$$

with the interval width indicating the degree of uncertainty. The midpoint approximates the expected electrical output.

Interpretation:

The triplet (T_E, I_E, F_E) offers complementary insights:

- T_E: confidence that conditions will yield meaningful power
- I_E: unresolved uncertainty due to environmental or sensor limitations
- F_E: inhibitory or contradictory influences

By decomposing these contributions, the framework mirrors expert reasoning in environmental assessment.

4. MATHEMATICAL FOUNDATION

4.1. Operator Properties

Consider two neutrosophic variables, $A = (T_A, I_A, F_A)$ and $B = (T_B, I_B, F_B)$. The core logical operators—conjunction (∧) and disjunction (∨)—follow several fundamental principles:

(i) Commutativity: $A \wedge B = B \wedge A$ and $A \vee B = B \vee A$

(ii) Idempotence: $A \wedge A = A$ and $A \vee A = A$

(iii) Monotonicity: if $T_A \leq T_B$, then $T_{A \wedge C} \leq T_{B \wedge C}$ for any C

(iv) Generalized De Morgan Laws: $\neg(A \wedge B) = \neg A \vee \neg B$

These rules guarantee that neutrosophic reasoning behaves in a stable and predictable manner, even when integrating ambiguous or conflicting information.

4.2. Entropy of A Neutrosophic State

To quantify the informational structure of a neutrosophic triplet, an entropy measure can be defined as: $H_N = -(T\,ln\,(T) + I\,ln\,(I) + F\,ln\,(F))$, with the convention $0\,ln\,0 = 0$. The entropy reaches it's maximum when $T = I = F = \frac{1}{3}$, representing a state of maximal uncertainty. This metric is useful for evaluating how informative or ambiguous the system's current state is.

4.3. Dynamic Adaptation

The neutrosophic state can evolve with new environmental or biological observations. The temporal evolution of each component is expressed as:

$$\frac{dT}{dt} = \eta_T\,(T^* - T),$$
$$\frac{dI}{dt} = \eta_I\,(I^* - I),$$
$$\frac{dF}{dt} = \eta_F\,(F^* - F)\,,$$

where (T^*, I^*, F^*)represent updated target values derived from new measurements, and η_T, η_I, η_F are adaptation coefficients. This formulation bridges neutrosophic logic with adaptive and control-theoretic perspectives.

4.4. Complexity and Computation

For a system with n inputs and r rules, the computational complexity of a single inference cycle is $O(nr)$. the method is suitable for low-power embedded systems used in environmental sensing because the operations rely on simple comparisons (minima and maxima).

4.5. Interpretation of Uncertainty and Indeterminacy

A distinguishing feature of neutrosophic logic is its explicit separation of truth, falsity, and uncertainty. Classical logic forces each proposition into binary states, while fuzzy logic expresses partial truth but hides uncertainty within a single membership value. Neutrosophic logic isolates indeterminacy (I), enabling a more nuanced interpretation.

For example, a noisy soil moisture reading may yield:

$T_M = 0.6, I_M = 0.4, F_M = 0.2.$

These values capture three distinct epistemic statements:

• T_M reflects evidence supporting favorable moisture conditions

• F_M reflects evidence contradicting that interpretation

• I_M represents ambiguity due to noise or missing information

As these propagate through the inference rules, the resulting triplet (T_E, I_E, F_E) summarizes the environmental and biological conclusions. The explicit presence of I acknowledges that natural systems often defy crisp classification.

5. CONCEPTUAL FRAMEWORK: FROM LOGIC TO LIVING SYSTEMS

5.1. Epistemology of Living Systems

All Plant-based energy generation belongs to a class of systems that remain biologically autonomous while producing measurable physical output. Because these systems constantly interact with their surrounding environment, their internal state cannot be fully isolated or measured. Consequently, indeterminacy ($I > 0$) persists even under ideal observation. These systems exhibit adaptive behaviors shaped by physiological feedbacks, microbial dynamics, and environmental fluctuations. Thus, the inclusion of I is not merely a mathematical construct it reflects an ontological aspect of living systems.

5.2. From Classical, fuzzy, and Intuitionistic Fuzzy to Neutrosophic Cognition Descriptions

In every dimension pertinent to ecological and bio-electrochemical systems, such as plant-based microbial fuel cells, neutrosophic sets clearly outperform classical numbers, fuzzy sets, and intuitionistic fuzzy sets (IFSs), as demonstrated in Table 1, and offer the most comprehensive and structurally expressive framework for modeling environmental uncertainty. While IFSs improve representation, they are still mathematically constrained by the requirement $\mu + \nu \leq 1$, which prevents the full expression of contradictory or highly ambiguous conditions. In contrast, classical and fuzzy approaches collapse all vagueness, noise, and incomplete information into a single numerical value. The neutrosophic triplet (T, I, F), on the other hand, permits truth, indeterminacy, and falsity to fluctuate independently, allowing for the explicit representation of noisy, conflicting, or incomplete environmental data while maintaining their epistemic structure without imposing artificial coherence. Because of this independence, the model can represent actual ecological behaviors, such as simultaneous evidence for and against a condition, sensor drift, spatial heterogeneity, or biological variability conditions were previous frameworks either obscure uncertainty or collapse information. Additionally, by generalizing all earlier frameworks and permitting richer inference and aggregation operations, neutrosophic logic provides superior mathematical expressiveness, resulting in more transparent and comprehensible reasoning processes. Neutrosophic logic is uniquely able to capture aleatory variability, epistemic gaps, and paradoxical measurements for ecological modeling, especially in PMFCs where environmental drivers interact nonlinearly and unpredictably. This gives uncertainty-aware simulation and decision-making a more realistic and reliable foundation.

Table 1. Comparison of four uncertainty modeling paradigms in the context of environmental uncertainty (e.g. plant-based microbial fuel cells), demonstrating the superior flexibility and precision of neutrosophic logic for modeling ecological uncertainty.

Dimension	Classical (Crisp) Numbers	Fuzzy Sets	Intuitionistic Fuzzy Sets (IFSs)	Neutrosophic Sets (NS)
Ability to model uncertainty	Assumes exact, deterministic values with no intrinsic uncertainty representation. Any uncertainty must be handled outside the classical framework (e.g. by probabilities), which often fails for complex natural variability.	Represents uncertainty as partial membership in [0,1], allowing graded truth values (beyond binary logic). However, it merges all types of uncertainty (ignorance, variability) into one membership degree, reducing clarity in complex systems.	Incorporates both a membership (truth) and a non-membership (falsity) degree for more detailed uncertainty depiction. This yields a “hesitation margin” (undefined portion = 1−μ−ν) to denote unknown information. Still, $\mu + \nu \leq 1$ is required, so extremely uncertain or paradoxical cases cannot be fully expressed.	Provides a triple (T, I, F) for truth, indeterminacy, and falsity, modeling uncertainty in a three-dimensional manner. Each component captures a different aspect of uncertainty, enabling explicit representation of incomplete data and environmental variability. This approach preserves more uncertainty information (separating ignorance from truth values) than any other paradigm.

Dimension	Classical (Crisp) Numbers	Fuzzy Sets	Intuitionistic Fuzzy Sets (IFSs)	Neutrosophic Sets (NS)
Handling of contradictory data	No mechanism to represent contradictory information – classical logic forces a single true/false value. Conflicting observations lead to inconsistency or are resolved only by choosing one value or averaging, not by expressing conflict within the model.	Limited ability – contradictory evidence is only reflected as an intermediate membership value. For example, if one sensor suggests "high" and another "low," a fuzzy model may yield a middling membership (e.g. 0.5) that blurs the conflict. There is no explicit indicator of contradiction versus uncertainty in fuzzy logic.	Partially handles contradiction: positive and negative evidence can be assigned to membership and non-membership respectively, which is an improvement over fuzzy. However, strong contradictions cannot be fully captured because $\mu + \nu$ cannot exceed 1. In practice, highly conflicting data force a large indeterminate (hesitation) portion rather than showing high truth and falsity simultaneously.	Explicitly accommodates conflicting data. Truth and falsity values are independent in NS, so both can be high at once to reflect contradictory evidence. The indeterminacy (I) component records the uncertainty or unreliability in such cases. Thus, neutrosophic logic can directly encode opposing sensor readings or expert opinions without losing or conflating information.
Mathematical expressiveness	Low expressiveness for uncertainty. Uses single-valued parameters or binary truth values, requiring external probabilistic models to handle uncertainty. It cannot natively express partial truth or ignorance, making it rigid for uncertain systems.	Moderate expressiveness. Fuzzy sets provide a continuum of truth values with well-established operations (fuzzy arithmetic, logical operators, etc.). However, all uncertainty is compressed into one dimension – there is no separate parameter for "unknown" or contradictory information, which limits the richness of expression.	Higher expressiveness than fuzzy. Two independent functions (μ for membership, ν for non-membership) allow modeling of agreement and dissent separately. Formal extensions of fuzzy logic exist for IFS (e.g. intuitionistic fuzzy operators), offering a richer calculus. Yet the framework is constrained by $\mu+\nu\leq1$, meaning it cannot represent beyond a certain limit of combined truth and falsity (no direct representation of fully paradoxical states).	Very high expressiveness. Neutrosophic sets generalize all previous frameworks, with three degrees of freedom (T, I, F) that can vary independently. This allows representation of any combination of truth, uncertainty, and falsity – fuzzy and IFS are special cases. The neutrosophic formalism supports advanced logical operations and metrics (e.g. neutrosophic entropy) to quantify and manipulate uncertainty without information loss.
Ecological modeling relevance (e.g. environmental fluctuations, ambiguous sensor data in PMFC systems)	Poor fit for ecological systems with high uncertainty. Deterministic models often break down under irregular environmental fluctuations. Classical approaches cannot incorporate ambiguous sensor readings or missing data except by oversimplification or ignoring them, leading to less realistic predictions in plant-based electricity generation models.	Fairly good applicability: fuzzy logic has been widely used to handle imprecise environmental data and linguistic expert knowledge. It smooths out noise by using degrees (e.g. "moderate moisture") and can handle gradual changes. However, it cannot signal whether uncertainty arises from conflicting data or natural variability. Ambiguous sensor inputs in a PMFC (e.g. partially faulty sensor) would simply yield an intermediate value, with no special treatment of the ambiguity.	Improved relevance for uncertain ecological data. IFS can acknowledge when information is incomplete via the hesitation margin, which is valuable in environmental monitoring (indicating low confidence in readings). For instance, if soil moisture data are unreliable, an intuitionistic fuzzy model can reflect a high uncertainty portion instead of a crisp value. But if sensors give directly conflicting readings (one very high, one very low), the IFS model still struggles to represent that explicitly. In such cases, critical uncertainty may be underrepresented.	Excellent fit for ecological and renewable energy modeling under uncertainty. Neutrosophic logic has been specifically applied to plant–microbial fuel cell (PMFC) systems, capturing both random environmental fluctuations and epistemic gaps. It can integrate ambiguous or contradictory sensor data (e.g. one sensor reading high, another low due to faults) as separate truth and falsity components. By preserving these nuances, neutrosophic models produce more nuanced and robust predictions, effectively redefining precision in modeling living systems (treating partial and ambiguous states as intrinsic information, not noise). This gives neutrosophic logic a uniquely high credibility and flexibility for ecological uncertainty modeling.

5.3. Ontological interpretation of $(\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F})$

The components of a neutrosophic triplet can be interpreted at multiple levels:

(a) Physical: measurable environmental or biological variables

(b) Epistemic: the observer's knowledge about those variables

(c) Logical: the reasoning process connecting evidence to conclusions

In plant-based electricity systems, these levels are interwoven, since measurement determines knowledge, which then shapes logical evaluation and subsequent decision-making.

5.4. Integration into Environmental Reasoning

Environmental decision-making often relies on expert rules derived from limited observations. Neutrosophic logic provides a unified way to express these rules while keeping uncertainty explicit. Statements such as: "If sunlight is high and soil moisture is moderate, the output is likely high but uncertain" map naturally into neutrosophic form, where uncertainty is represented through I rather than being implicitly merged with truth.

6. PHILOSOPHICAL and THEORETICAL EXPANSION LIVING SYSTEMS

6.1. The Logic of Living Energy

Plant-based electricity systems challenge traditional boundaries between inert and living energy sources. Electron flow originates from biological metabolism rather than purely chemical gradients. As a result, modeling these systems requires a hybrid logic—empirical, symbolic, and phenomenological. Neutrosophic logic is well suited to this hybrid nature.

6.2. Uncertainty As Structural, Not Accidental

Mechanical systems experience uncertainty primarily as measurement noise. Living systems, by contrast, possess structural uncertainty tied to their adaptive and evolving nature. Neutrosophic logic treats indeterminacy as a foundational component rather than an error term, resonating with concepts from complexity science and non-equilibrium thermodynamics.

6.3. Relationship to Probability and Entropy

While probability focuses on the frequencies of events, neutrosophy describes the coexistence of potentially contradictory states. Neutrosophic entropy (H_N) evaluates the dispersion of truth, falsity, and indeterminacy, complementing thermodynamic entropy in describing the complexity of bio-electrochemical systems.

6.4. Temporal Evolution and Adaptation

Plant-based Environmental and biological states change continuously. Neutrosophic adaptation equations allow T, I, and F to evolve as new information arrives, similar to Bayesian updating but without reliance on strict probability distributions.

7. ANALYTICAL IMPLICATIONS for ENVIRONMENTAL MODELING

7.1. Hierarchical Uncertainty Propagation

In complex environmental systems, uncertainty propagates across multiple scales—from microbe-level reactions to canopy-level photosynthesis. Neutrosophic logic supports hierarchical modeling by allowing each level to carry its own (T, I, F) triplet, later aggregated to a system-level assessment. This mirrors multi-scale ecological reasoning and supports modular model design.

7.2. Decision Making Under indeterminacy

In Decision rules can be derived directly from neutrosophic outputs. For example, in an autonomous sensing node powered by a PMFC: If $T_E - F_E > \delta_1$ and $I_E < \delta_2$, then activate sensing; otherwise, enter sleep mode. This structure ensures that decisions respect both knowledge and ignorance, preventing overconfidence in uncertain data.

7.3. Neutrosophic Triplet Values for Environmental Inputs

Table 2. An example table for neutrosophic triplet values for environmental inputs.

Environmental Input	Sample Value	Truth (T)	Indeterminacy (I)	Falsity (F)
Solar Irradiance (W/m²)	800 (bright sunlight)	0.80	0.15	0.05
Soil Moisture (%)	35 (moderate moisture)	0.70	0.20	0.10
Ambient Temperature (°C)	30 (warm day)	0.60	0.30	0.10

Table 2 shows an example of how important environmental inputs are represented as neutrosophic triplets, each of which has components for truth (T), indeterminacy (I), and falsity (F). The sample values (middle column) are fictitious sensor readings for ambient temperature, soil moisture, and solar irradiance that are translated into neutrosophic evaluations. A higher F-value would indicate that the condition is strongly unfavorable ("low"), a higher T-value would indicate a strong degree of truth (e.g., the condition is favorable or "high"), and the I-value captures measurement uncertainty or variability (reflecting incomplete knowledge or fluctuations). A solar irradiance of 800 W/m², for example, is evaluated as (0.80, 0.15, 0.05), which indicates that it is strongly true that light is high (T=0.80), with some indeterminacy (0.15) due to shifting sunlight or sensor noise, and very little falsity (0.05) in considering it "not high." By quantitatively demonstrating how the neutrosophic framework handles uncertain environmental data, this tabular format improves technical transparency.

7.4. Decision Making Under Indeterminacy: A Methodological Example

To illustrate the practical use of the conceptual framework, consider a simplified decision problem in a small plant-based electricity system. A field sensor node is powered by a living-plant fuel cell. The system must decide whether to transmit data, store energy, or enter sleep mode. The environmental variables observed are:

- Solar irradiance $S = 0.65$ (normalized)
- Soil moisture $M = 0.70$
- Temperature suitability $T_{env} = 0.60$
- Sensor uncertainty $\sigma = 0.20$ (moderate measurement noise)

From fuzzy membership and uncertainty propagation, we obtain approximate neutrosophic states:

$$T_S = 0.65, I_S = 0.20, F_S = 0.15$$

$$T_M = 0.70, I_M = 0.20, F_M = 0.10$$

$$T_T = 0.60, I_T = 0.25, F_T = 0.15$$

Combining these antecedents via the neutrosophic conjunction operator yields:

$$T_E = 0.60, I_E = 0.25, F_E = 0.15.$$

Assuming a theoretical maximum power $P_{max} = 100\ mW$, the decision interval becomes:

$P_{low} = (T_E - I_E)P_{max} = 35mW,$

$P_{high} = (T_E + I_E)P_{max} = 85mW$

The available power is therefore predicted to lie in the interval $[35, 85]\ mW$, with uncertainty width $\Delta P = 50\ mW$. A simple rule-based decision structure might state:

If $P_{low} > 50\ mW$, transmit;

else if P_{high} < 50 mW, sleep;

otherwise, delay the decision (indeterminate zone).

Here, the system falls into the indeterminate region, and the neutrosophic output (T_E = 0.60, I_E = 0.25, F_E= 0.15) explicitly signals that the decision should be postponed until new data reduce I_E. This example demonstrates how the neutrosophic conceptual model supports rational, uncertainty-aware control and avoids premature decisions under ambiguous conditions.

7.5. A Neutrosophic Rule-Based Inference Example

An example of a neutrosophic rule-based inference process using two sample linguistic rules given below:

Table 3 A Neutrosophic Rule-Based Inference Example

Rule (Linguistic)	Neutrosophic Evaluation of Antecedents	Neutrosophic Output (Consequent)
Rule 1: IF Light is *High* AND Moisture is *Moderate* THEN Output is *Moderate*	Light is High = (0.9, 0.1, 0.0) AND Moisture is Moderate = (0.7, 0.2, 0.1) ⟶ Combined ≈ (0.7, 0.2, 0.1)	Output *Moderate* = (0.7, 0.2, 0.1)
Rule 2: IF Light is *High* AND Moisture is *Low* THEN Output is *Low*	Light is High = (0.9, 0.1, 0.0) AND Moisture is Low = (0.3, 0.5, 0.2) ⟶ Combined ≈ (0.3, 0.5, 0.2)	Output *Low* = (0.3, 0.5, 0.2)
Aggregation: combine outputs of Rule 1 & 2	*(Moderate output vs. Low output)*	Overall Output = “Moderate” (since $T_{\text{Moderate}} = 0.7 > T_{Low} = 0.3$)

In Table 3, every rule evaluates the state of the environment using neutrosophic truth values and gives a neutrosophic output. This shows how the system deals with uncertainty in logic rules. Rule 1 says, "IF light is High AND soil moisture is Moderate THEN output is Moderate." Based on the example input conditions, the neutrosophic evaluations are: From Table 3 or something like it, we can see that Light is High = (0.9, 0.1, 0.0) and Moisture is Moderate = (0.7, 0.2, 0.1). A neutrosophic intersection is used to evaluate the AND conjunction. This is conceptually thought of as the lowest T and highest F, with combined indeterminacy. The result is a combined antecedent truth of about (0.7, 0.2, 0.1). This means that the rule's output is moderate, which means that the triplet (0.7, 0.2, 0.1) is assigned. Rule 2 says, "IF light is High AND soil moisture is Low THEN output is Low." The combined antecedent gives (0.3, 0.5, 0.2), which means that the output is low. After looking at all the rules, an aggregation step combines the outputs, which is like a neutrosophic OR for more than one rule. In this case, the Moderate output has a higher truth degree (T=0.7) than the Low output (T=0.3). This means that the overall inference suggests a moderate power output. This structured rule table makes it clear how the inference mechanism works, showing how neutrosophic logic deals with uncertainty and partial truth in each rule.

7.6. Bridging Symbolic and Numerical Modeling Inference

Neutrosophic logic operates with symbolic rules while producing numeric intervals. This allows qualitative expert reasoning to be combined with quantitative simulation. This duality enables digital-biological systems to detect and analyze their own uncertainty, which is a crucial characteristic for future sustainable microgrids.

7.7. Integration with AI and Machine Learning

Neutrosophic logic can enhance machine-learning models by offering interpretable layers of uncertainty. A learning algorithm can output a triplet (T, I, F) rather than a single confidence score, allowing the model to distinguish between lack of information and conflicting information. This is especially valuable in data-scarce environmental domains.

8. BROADER CONTEXT: GREEN ELECTRICITY and SUSTAINABLE SYSTEMS

8.1. Concept of Weak Energy Sources

Weak energy sources are those that don't have a lot of power at any one time but are always there. Micro-gradients, bioelectric fields, and root-zone redox potentials are some good examples. It may be possible to collect and use weak energy flows in the future of sustainable technology. Neutrosophic logic is a great way to deal with missing information, variability, and ambiguity when modeling these resources.

8.2. Plant-Based Systems in Sustainable Design

Living-plant energy systems show how ecology and engineering can work together. They turn biological activity that is already happening into energy that can be used without killing or exhausting the living thing. In this way, they show that metabolic processes and technological functions can work together, which is a sign of sustainability. The neutrosophic model provides a theoretical framework for examining the intrinsic uncertainty present in coupled systems.

8.3. Ethical and Epistemic Considerations

Modeling living energy systems also brings up moral and philosophical issues. For example, what does it mean to get useful work from a living thing while still letting it be free? Neutrosophic logic implicitly acknowledges the openness and unpredictability of living systems by explicitly recognizing indeterminacy. So, it works as both a math tool and a way to remind us of how limited our control is.

9. DISCUSSION

9.1. Advantages Over Other Frameworks

Compared to fuzzy or probabilistic methods, the neutrosophic model provides several advantages:

- Transparency: each source of uncertainty is explicitly represented.
- Flexibility: contradictory evidence can be captured directly.
- Scalability: the logic extends naturally to multi-variable and multi-scale systems.
- Interpretability: the triplet (T, I, F) is intuitively meaningful to domain experts.

These benefits make neutrosophic logic a good choice for modeling real-world renewable energy applications where data quality is inconsistent and understanding is key.

9.2. Limitations

There are still some limits. First, it takes expert knowledge or empirical tuning to set the membership and indeterminacy parameters (α, β). Second, the logical framework organizes uncertainty but does not inherently offer mechanistic understanding of biochemical processes. Third, strong validation needs long-term data from a variety of climate and ecological settings to fully evaluate generalizability.

10. CONCLUSION

This paper has created a conceptual and mathematical framework for using neutrosophic logic to model how plants can generate electricity when the environment is not certain. The model differentiates between truth, falsity, and indeterminacy, facilitating explicit representation of measurement errors, biological variability, and incomplete knowledge. It shows that living plant systems, even though they don't produce a lot of power, have behaviors that are complicated and change over time, which means they need a logical description that is just as nuanced. Neutrosophic reasoning regards indeterminacy as a structural characteristic rather than a modeling flaw, mirroring the intrinsic adaptability, openness, and partial ambiguity of living ecosystems.

The results demonstrate that neutrosophic logic serves as a feasible alternative to classical and fuzzy systems for delineating plant–microbial fuel cell dynamics. It takes into account both epistemic uncertainty, which comes from having too few measurements, and aleatory uncertainty, which comes from changes in the environment. This lets plant-based electricity models show uncertainty in light, humidity, microbial activity, and root exudation rates. This makes simulations and decision-support tools more realistic.

In the future, this framework could be improved by using sensor data and biological experiments to fine-tune neutrosophic parameters. This would make it possible to create adaptive, data-driven environmental models. Combining neutrosophic reasoning with stochastic optimization or machine learning algorithms might make predictions more accurate while still being easy to understand. Integrating bioengineering, sustainability assessment, and ethical energy design could augment the framework's utility for decision-making in green infrastructure.

Neutrosophic energy modeling offers a comprehensive framework for developing intelligent green systems that acknowledge the intrinsic value of uncertainty. The framework redefines precision by treating partial, ambiguous, and incomplete states as inherent characteristics of natural phenomena, not as the removal of uncertainty but as its organized comprehension. This direction is a step toward creating energy technologies that are smart, long-lasting, and morally responsible, based on both logic and real life.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

S.T.: Conceptualization, Methodology, Validation, Formal Analysis, S.T., O.A.K., B.K.: Writing Original Draft Preparation, and Data Curation, S.T., O.A.K., B.K.: Writing Reviewing and Editing, Visualization, and Investigation.

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