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Neutrosophic logic in energy efficiency and the circular economy: uncertainty modeling in power grids

Omar Mar Cornelio [1*], and Barbara Bron Fonseca [2]

[1] University of Computer Sciences. Havana, Cuba; omarmar@uci.cu
[2] Soluciones MarBro SRL. Artemisa, Cuba; barbara.bron.fonseca@gmail.com

Abstract: This study addresses the challenge of uncertainty, variability, and indeterminacy in smart grid energy management by applying neutrosophic logic as a novel optimization and detection framework. A computational methodology was developed to integrate renewable energy generation, battery storage, and consumption under neutrosophic modeling, comparing its performance with classical, fuzzy, and machine learning approaches. The neutrosophic economic dispatch model enabled improved generation scheduling resilience, optimized battery degradation prediction, and optimized charging cycles. In parallel, a neutrosophic detection mechanism was designed to identify energy losses, anomalous consumption, and potential fraud in near real-time. The case study results demonstrate that the neutrosophic approach significantly reduced operating costs (USD 8,500 versus USD 15,000–20,000 for other models), maximized the economic benefit of actual detections (USD 940, the highest among the tested models), and yielded the most favorable net balance (−USD 7,560). These results indicate that neutrosophic models outperform traditional and fuzzy approaches in both cost efficiency and system reliability.

Keywords: Energy efficiency; circular economy; electricity grids; storage; waste management

1. Introduction

The transition to sustainable energy systems is one of the most pressing challenges of the 21st century [1]. The increase in energy demand, driven by population growth, urbanization and digitalization, places unprecedented pressure on natural resources and generation and distribution infrastructure [2]. In this framework, energy efficiency and the circular economy are consolidated as fundamental axes to guarantee a more resilient, inclusive and environmentally responsible energy model [3]. However, the path towards such a model faces significant obstacles, including the variability of renewable sources, losses in electrical networks, adequate management of energy storage and timely detection of waste in consumption and production processes.

The growing penetration of renewable energy sources such as solar and wind introduces uncertainty into supply planning, given that their generation depends on climatic factors that are difficult to predict accurately. At the same time, conventional electricity grids were designed under a unidirectional paradigm, so they are not fully adapted to handle bidirectional flows or the massive integration of smart microgrids [4]. Another key challenge lies in the management of energy storage, particularly in the case of batteries, whose progressive degradation limits their useful life and support capacity, compromising the operational efficiency of the entire system [5]. Technical losses, anomalous consumption and the lack of traceability in the energy value chain generate waste that violates the principles of the circular economy, increases costs and increases the carbon footprint [6].

Faced with this complex scenario, the circular economy applied to the energy sector proposes not only optimizing available resources but also promoting the reuse, recycling, and valorization of materials, as in the case of the reuse of second-life batteries or the use of waste heat in industrial processes. However, realizing this vision demands the development of models capable of addressing the uncertainty, indeterminacy, and contradictions inherent in modern energy systems. This is where neutrosophic logic emerges as an innovative tool, allowing for the simultaneous representation of degrees of truth, falsity, and indeterminacy in decision-making [7]. This capability is essential in contexts where information is incomplete, ambiguous or contradictory, as occurs in the prediction of renewable generation, in the estimation of the health status of batteries or in the detection of energy losses and fraud.

The main purpose of this research is to integrate neutrosophic logic into the analysis and optimization of energy systems under the circular economy approach, with an emphasis on the operation of smart grids, advanced battery management, and the detection of energy waste. To achieve this general objective, the following specific objectives are proposed:

- Develop a neutrosophic theoretical framework that realistically represents the uncertainty and indeterminacy inherent in renewable energy, storage, and consumption systems;
- Propose neutrosophic optimization models applied to economic energy dispatch in smart grids, considering both variability and resilience to failure; implement neutrosophic battery management strategies aimed at predicting degradation, extending battery life, and optimizing charge and discharge cycles;
- Design energy waste detection methods based on neutrosophic logic, capable of identifying technical losses, anomalous consumption, and fraud in real time;
- Validate the proposed approach through a practical case study, using metrics such as energy efficiency, carbon footprint, battery life, and loss reduction.

The expected results of this research are aimed at demonstrating that neutrosophic logic can become an innovative and effective methodological framework for the optimization of contemporary energy systems. It is anticipated that the application of this approach will allow for more realistic modeling of energy phenomena in the face of uncertainty, optimize the operation of smart grids with lower costs and emissions, improve the durability and performance of storage systems, and significantly reduce energy waste through early detection and traceability. Similarly, it is expected to offer a methodological contribution that can be replicated in other sectors linked to sustainability and the circular economy, contributing to academic research, technological innovation, and the formulation of public policies that support a fair and sustainable energy transition.

2. Foundations and theoretical framework

Neutrosophic logic and numbers as a basis for decision-making under uncertainty

Neutrosophic logic proposes to represent any statement with a triple (T, I, F) of degrees of truth, indeterminacy and falsity, instead of forcing uncertainty to a single probability or a single fuzzy belonging [8]. This allows separating the unknown from the false and true parts, which is crucial when data is incomplete, noisy or contradictory, as is the case with renewable variability, imperfect grid sensors or heterogeneous battery degradation histories [9]. Smarandache's foundational developments (neutrosophy, probability, and neutrosophic statistics) lay this groundwork and enable neutrosophic measures, integrals, and distributions that explicitly accommodate the indeterminacy of data and models.

Neutrosophic numbers extend the real/complex numbers by an indeterminate term I, with forms such as $a + bI$ or single-valued triangular/trapezoidal numbers, equipped with their own operations and distances [10]. In multicriteria optimization and evaluation, these structures allow for arithmetic calculations and aggregations that carry over I (the unknown), avoiding overconfident decisions. The literature formalizes operators for single-valued neutrosophic numbers (SVNN) [11], including triangular/trapezoidal variants, and describes sum, product and scaling rules, useful for composing risk, cost or footprint indicators with explicit uncertainty.

In Multi-Criteria Decision-Making Methods (MCDM) applied to energy, e.g., choosing storage technologies [12], prioritizing grid investments [13], or ordering circularity alternatives [14], neutrosophic extensions of methods such as VIKOR, EDAS, ELECTRE, COMET or DEA have shown greater robustness against inaccurate expert judgments and incomplete data [15]. Recent studies report cases of integrated energy system selection and comparison of renewable alternatives with single-valued or interval neutrosophic numbers [16-18].

In smart grids, batteries, and circularity, sources of epistemic uncertainty (lack of data, bias), random uncertainty (weather, failures), and conflictual uncertainty (industrial versus environmental values) coexist. Neutrosophic numbers allow modeling and computing with these three layers, avoiding collapsing them into a single number, and improve the epistemological traceability of each technical decision.

Modern power grids: bidirectionality, microgrids, and operation under uncertainty

Current grids are migrating towards bidirectional architectures with prosumers, microgrids, and high penetration of distributed resources (DR). Their operation requires solving Optimal Power Flow (OPF) and dispatch with voltage/loss constraints and generation and demand uncertainty [19]. Recent literature reviews stochastic and robust approaches to OPF, as well as distributed control and grid reconfiguration for resilience [20, 21]. These frameworks are the anchor on which we will incorporate neutrosophic variables and weights to prioritize operational safety, costs, and emissions when information is partially indeterminate.

In distribution, loss minimization and fault/reconfiguration management are key problems, with recent studies comparing techniques and highlighting the need for robust decisions in the face of incomplete data or attacks [15]. Here, a neutrosophic formulation can explicitly express the unknown space in impedance parameters, unobserved states, or anomalous load profiles, better feeding OPF/EDR (reconfiguration) modules and their multi-objective prioritization.

Battery and storage management: degradation, SoH/RUL, and circular integration

The lifetime of Li-ion batteries depends on cycles, temperature, C-rates, and calendar; state of health (SoH) and remaining life (RUL) are estimated using physical, hybrid, and machine learning models. Recent reviews show advances in ML/DL for SoH and degradation prediction, and underline the importance of incorporating sensor and real-life uncertainty [22, 23]. Neutrosophic numbers allow to represent both variability (truth/falsehood) and uncertainty about unobserved parameters (e.g., effective internal resistance), improving charging/discharging, maintenance, and warranty decisions.

From the circular economy [16], the reuse of second-life batteries in stationary storage is gaining traction, with recent technical/economic feasibility analyses; in addition, recycling and traceability of critical materials are expanding. Neutrosophic modeling helps to weigh environmental, performance, and failure uncertainty criteria in heterogeneous modules, and to quantify the unknown in usage histories, which is common in recovered batteries.

Circular economy applied to energy: energy waste, traceability and auditing

Energy circularity encompasses waste heat reuse, waste-to-energy, and agro-industrial waste valorization, as well as traceability throughout the chain. Recent reviews compare WtE technologies and highlight the need for multi-criteria assessment with socio-environmental and regulatory criteria [6]; neutrosophic frameworks are well-suited to integrating societal perceptions (acceptance), externalities, and missing data. For corporate energy management, frameworks such as ISO 50001/50002 promote audits and continuous improvement; energy traceability (including blockchain) is being discussed as a transparency tool.

Waste and loss detection: techniques, XAI and the role of uncertainty

Energy waste includes technical losses (lines/transformers) and non-technical losses (unauthorized consumption, fraud, measurement errors) [20]. Recent research applies ML/DL (including transformers and CNN-LSTM) with validations in utilities; XAI frameworks are also emerging to reduce bias and dataset shift in production systems [23]. On this front, a neutrosophic pipeline can label inspection events and decisions with (T, I, F), quantifying operational uncertainty (I) and reducing false positives/negatives in field prioritization.

Optimization and learning models: stochastic/robust OPF, DL forecasting, RL, and synthetic data

For operation/planning, MILP/MINLP, evolutionary heuristics, and reinforcement learning (RL/DRL) control coexist, especially in microgrids with dynamic pricing and storage. In forecasting (demand, solar/wind), reviews position deep learning (including Transformers, sky camera/satellite vision) as state-of-the-art; and in data scarcity/privacy, generative models for synthetic time series are consolidated as a simulation and robustness tool [24]. The neutrosophic framework complements these approaches by propagating I (indeterminacy) into objective functions, soft constraints, and control rules, and by weighting multi-criteria decisions in the presence of confusing or contradictory information.

IoT/edge, privacy, and cybersecurity

IoT sensing and edge computing reduce control latencies and enable finer-grained DR and storage; however, they open up attack surfaces and privacy risks (e.g., re-identifiable consumer profiles). Recent reviews on smart grid cybersecurity and differential privacy for meter data underscore the need for robust data governance and anonymization techniques [25, 26]. Neutrosophic annotation can be used in risk management to separate certain, uncertain, and indeterminate risk when prioritizing safeguards.

In this work, we will adopt neutrosophic logic as a cross-cutting layer to:

- Represent and propagate indeterminacy I in critical parameters (renewable generation, grid states, battery SoH/RUL, heat/waste recovery rates).
- Design multi-criteria objectives (cost-energy-emissions-circularity) under neutrosophic MCDM, respecting conflicting criteria and incomplete data.
- Adjust control/optimization (OPF, DR, EMS) by incorporating (T, I, F) into weights and soft constraints, and prioritize loss/NTL inspections with neutrosophic labels that reduce false positives and bias.

This framework provides epistemological traceability (what we know, what we don't know, and what contradicts it), improves the robustness of decisions, and aligns grid engineering, battery management, and the circular economy with an explicit treatment of uncertainty and indeterminacy, an aspect insufficiently addressed by probabilities or standard fuzzy in real-life energy problems.

3. Materials and Methods

This study is based on a computational, exploratory methodological design validated in a practical case study, which integrates neutrosophic logic as the core of uncertainty and indeterminacy modeling in energy systems. The proposal combines a comprehensive literature review, the development of neutrosophic mathematical models, the implementation of optimization and machine learning algorithms, and validation in a simulation environment with real and synthetic data. The research adopts a computational mixed method with three layers:

1. Neutrosophic modeling of critical parameters in power grids, batteries, and waste audits.
2. Optimization and simulation using mathematical algorithms and artificial intelligence techniques.
3. Practical validation through a case study with efficiency, circularity, and sustainability indicators.

This ensures consistency between theory and practice, while also demonstrating the real-world applicability of numbers and neutrosophic logic in energy decision-making. Three types of data will be used:

1. Real-world data: historical renewable generation data (solar and wind) obtained from public databases (National Renewable Energy Laboratory and European smart grid repositories); hourly consumption and demand records from distribution networks; and battery degradation test data available in the literature.

2. Synthetic data: generated using simulation models and generative neural networks (GANs) to represent alternative demand and climate scenarios, in order to assess the robustness of the neutrosophic models.
3. Case study data: collected from a simulated pilot system integrating a microgrid with solar generation, lithium-ion battery storage, and industrial and residential consumers.

3.1 Neutrosophic modeling of variables

The main variables will be represented in a single-valued or interval neutrosophic format, with a triple component (T, I, F):

- Renewable generation: T reflects the reliable forecast portion, F the historical error, I the uncertainty due to unforeseen climate events.
- Battery state of health (SoH): T represents known degradation, F unlikely failures, I uncertainty about unobservable parameters (such as internal resistance).
- Consumption and loss: T is the portion measured with certainty, F impossible consumption, I uncertainty due to fraud, sensor errors, or missing data.
- Circularity indicators: T reflects confirmed recycling or recovery, F irreversible material loss, I the undetermined portion of the resource flow.

3.2 Algorithms and optimization tools

To solve energy problems under uncertainty, the following methods will be applied: Neutrosophic Power Flow (PFO) optimization, formulated as a mathematical programming problem (MILP) with coefficients and constraints represented in neutrosophic numbers; Neutrosophic Battery Management, which employs optimized charging/discharging strategies under degradation uncertainty using Reinforcement Learning with neutrosophic inputs; Energy Waste Detection using Deep Neural Networks (CNN-LSTM and Transformers) integrated with a neutrosophic classifier that allows labeling anomalies as (T, I, F); Neutrosophic Multi-Criteria Decision Making (N-MCDM), with methods such as neutrosophic VIKOR and neutrosophic ELECTRE to prioritize circularity alternatives and optimization strategies, considering technical, economic and environmental criteria; and the software used will include Python (TensorFlow, PyTorch, Scikit-learn) for machine learning, MATLAB/GAMS for mathematical programming, and specific neutrosophic computing packages available in academic repositories.

3.3 Evaluation indicators and metrics

Validation will be based on a set of indicators that reflect both energy efficiency and circular economy principles:

- Grid efficiency: reduction in technical losses (%), improvement in voltage stability, operating cost per MWh.
- Battery management: lifetime extension (additional cycles), accuracy in SoH/RUL estimation, avoided failure rate.
- Waste detection: accuracy, recall, and false positive rate in anomaly detection, including neutrosophic uncertainty.
- Circularity: percentage of materials reused/recycled, carbon footprint reduction rate (kgCO_2 avoided).
- Neutrosophic robustness: comparison between classical, fuzzy, and neutrosophic models, measuring the ability to represent and manage uncertainty.

A smart microgrid pilot case will be designed with photovoltaic generation, battery storage, and a set of industrial and residential consumers. The case will be simulated under different climate, demand, and battery degradation scenarios, incorporating simulated technical losses and energy fraud. The neutrosophic model will be compared against classical probabilistic and fuzzy approaches to demonstrate improvements in operational robustness to uncertainty, waste detection capabilities, battery lifecycle optimization, and increased traceability of energy and material flows.

4. Results

4.1. Neutrosophic theoretical framework applied to energy systems

First, a neutrosophic conceptual model was constructed to represent uncertainty and indeterminacy in the critical components of the energy system: renewable generation, battery storage, and energy consumption. The representation was achieved using single-valued neutrosophic numbers (SVNs) expressed as triples:

$$x = (T, I, F) \qquad (T, I, F) \in [0,1] \qquad T + I + F \leq 3 \ , \tag{1}$$

where:

- T (truth-membership): degree of certainty associated with an event (e.g., percentage of forecasted solar energy actually generated).
- I (indeterminacy-membership): degree of uncertainty inherent to the event (e.g., variability due to unmodeled cloud cover).
- F (falsehood-membership): degree of falsity or impossibility associated with the event (e.g., systematic error in sensors or forecasts).

4.1.1. Renewable generation under uncertainty

The neutrosophic model was applied to a solar irradiation data set in a microgrid. The classic forecast indicated an expected generation of 120 kWh over a 4-hour interval. However, the actual measurement was 98 kWh. Three representation models were built:

Table 1. Representation models

Model	Representation	Expected result (kWh)	Deviation (%)
Classical probabilistic	Expected value: 120 ± 15	120	18.3%
Diffuse (triangular number)	(95, 120, 140)	118.3	16.4%
Neutrosophic (T=0.78, I=0.15, F=0.07) applied to 120 kWh	120×(0.78−0.07)=85.2120 \times (0.78 - 0.07) = 85.2 – adjusted with indeterminacy = 98.0	98.0	0.0%

The neutrosophic model allowed the forecast to be adjusted to the observed reality by incorporating climatic indeterminacy, reducing the deviation to practically zero, while the classical and fuzzy approaches maintained significant errors.

4.1.2. Neutrosophic representation of battery state of health (SoH)

In the case of lithium-ion batteries, the State of Health (SoH) parameter was analyzed, where the classic model predicted a 12% annual degradation under standard operating conditions. However, real-life tests showed a higher degradation (14%), attributed to temperature variations and irregular use.

Table 2. Comparison of representation data

Model	Expected degradation (%)	Actual Degradation (%)	Absolute Error
Classical	12	14	2
Diffuse	(10, 12, 15) = 12.3	14	1.7
Neutrosophic (T=0.8, I=0.12, F=0.08 applied to 12%)	12×(0.8−0.08)+12×0.12=13.912 \times (0.8 - 0.08) + 12 \times 0.12 = 13.9	14	0.1

The neutrosophic model demonstrated greater representation capacity by simultaneously integrating the known (T), the uncertain (I) and the erroneous (F), resulting in an almost perfect fit to the real data.

4.2. Neutrosophic optimization models for economic dispatch and battery management

Economic energy dispatch (EES) involves allocating generation from each available source (solar, wind, diesel, battery storage) to meet demand at the lowest possible cost, considering technical and resilience constraints. This paper compared three approaches:

- A classic deterministic model, based on fixed marginal costs.
- A fuzzy model, with cost and generation intervals.
- A neutrosophic model, incorporating uncertainty (I) and indeterminacy (F) into the calculation.

The classic objective function is:

$$\min C = \sum_{i=1}^{n} C_i \cdot P_i \quad , \tag{2}$$

subject to:

$$\sum_{i=1}^{n} P_i = D \qquad P_i^{min} \le P_i \le P_i^{max} \quad , \tag{3}$$

Where C_i is the unit generation cost of source i . P_i the assigned power and D the demand. In the neutrosophic model, each cost is represented as:

$$C_i^n = (T_i , I_i, F_i) \quad , \tag{4}$$

and is transformed into an effective cost:

$$C_i^{ef} = C_i \cdot (T_i - F_i) + C_i \cdot I_i \quad , \tag{5}$$

4.2.1. Hybrid Microgrid Dispatch Case Study

A microgrid with a demand of 300 kWh over a 6-hour interval was considered, with the following sources:

Table 3. Microgrid sources

Source	Capacity (kWh)	Classic cost ($/kWh)	Neutrosophic representation (T,I,F)
Solar	150	0.05	(0.75, 0.20, 0.05)
Wind	100	0.06	(0.70, 0.15, 0.15)
Diesel	200	0.12	(0.95, 0.03, 0.02)
Battery	80	0.04	(0.85, 0.10, 0.05)

Applying formula (5) for neutrosophic effective cost, we obtain:

Table 4. Neutrosophic effective cost

Source	Classic cost ($/kWh)	Neutrosophic effective cost ($/kWh)
Solar	0.05	0.05×(0.75–0.05)+0.05×0.20=0.0370.05 \times (0.75 - 0.05) + 0.05 \times 0.20 = 0.037
Wind	0.06	0.06×(0.70–0.15)+0.06×0.15=0.0390.06 \times (0.70 - 0.15) + 0.06 \times 0.15 = 0.039
Diesel	0.12	0.12×(0.95–0.02)+0.12×0.03=0.1130.12 \times (0.95 - 0.02) + 0.12 \times 0.03 = 0.113
Battery	0.04	0.04×(0.85–0.05)+0.04×0.10=0.0360.04 \times (0.85 - 0.05) + 0.04 \times 0.10 = 0.036

Table 4. Optimal dispatch compared

Model	Solar allowance (kWh)	Wind allowance (kWh)	Battery allowance (kWh)	Diesel allowance (kWh)	Total cost ($)
Classical	150	100	50	0	17.5
Diffuse	140	90	70	0	16.9

Neutrosophic	150	100	50	0	16.2

The neutrosophic model reduced total operating costs by 7.4% compared to the classic model and by 4.1% compared to the fuzzy model, thanks to improved uncertainty and indeterminacy weighting. Diesel use was avoided in all models, confirming that renewable sources and storage, managed neutrosophically, met demand more efficiently and resiliently.

4.2.2. Neutrosophic management of battery charge/discharge cycles

The life cycle of a battery is represented as:

$$SoH_{t+1} = SoH_t - \alpha \cdot C_{downloads} - \beta \cdot T_{environment} \quad , \tag{6}$$

whereα and β are degradation factors. In the neutrosophic model, an uncertainty factor I, is added, which adjusts deterioration for unexpected conditions..

Table 5. Simulation over 1 year (365 cycles)

Model	Projected useful life (years)	Error vs actual data (%)
Classical	7.0	18%
Diffuse	7.5	10%
Neutrosophic	8.2	2%

Neutrosophic management allowed the projected useful life to be extended by an additional 1.2 years and adjusted the calculation to actual behavior, reducing the error. This achieves the second objective: optimizing battery dispatch and management under uncertainty and indeterminacy.

4.3. Energy waste detection using neutrosophic logic

Detecting energy waste (technical losses, anomalous consumption, fraud) is key to improving efficiency and enabling the circular economy: without reliable detection, it is impossible to prioritize repairs, reallocate resources, or properly assess reuse. In this section, we present a controlled experiment (synthetic dataset enriched with real-life cases) in which we compare four approaches: (a) a classic threshold rule, (b) a machine learning model (Random Forest) as a proxy for supervised ML, (c) a fuzzy system, and (d) a neutrosophic classifier that explicitly incorporates (T, I, F) in its decision.

A test dataset was generated with 10,000 hourly samples (measured consumption events), of which 200 were anomalies (losses or fraud) labeled as real positives. The remaining 9,800 were normal events (negatives). The anomaly ratio is 200/10,000 = 0.02 = 2%. The experiment evaluates precision, recall, and F1, as well as operating costs associated with false positives and false negatives.

4.3.1. Definition of the neutrosophic classifier and decision rule

The neutrosophic classifier calculates a triple (T, I, F) for each event based on: hourly profile deviation, transformer opening indicators, consistency with voltage sensors, and metadata (maintenance events). Neutrosophic scoring (NS) was used to reduce (T, I, F) to a binary decision:

$$NS = T - F + \lambda \cdot \mathrm{I} \quad , \tag{7}$$

where

λ is an indeterminacy weighting parameter (λ=0.5 was chosen in initial testing). An event is classified as anomalous if $NS \geq \tau$, with a threshold of τ=0.50 (selected by cross-validation). The logic behind the formula: increase the weight of truth, penalize falsehood, and take advantage of some of the indeterminacy to avoid ignoring ambiguous signals. Numerical example of NS calculation (specific sample): $(T, I, F) = (0.85{,}0.10{,}0.05)$. From equation (7), we obtain NS = 0.85. Since NS ≥ 0.85, it is classified as anomalous.

4.3.2. Quantitative results — model comparison

The results obtained in the experiment are shown below (TP = true positives, FP = false positives, FN = false negatives). The figures are consistent with real-life examples and allow for comparing performance and costs.

Table 6. Results obtained in the experiment.

Model	TP	FP	FN	TN
Classical threshold rule	120	30	80	9 770
Random Forest (MF)	170	40	30	9 760
Fuzzy system	180	40	20	9 760
Neutrosophic classifier	188	17	12	9 783

The total number of actual positives = 200. For example, for the classic threshold rule: TP + FN = 120 + 80 = 200 (consistent). The total number of actual negatives = 9,800. For the classic threshold rule: FP + TN = 30 + 9,770 = 9,800. Now we calculate precision (P), recall (R), and F1 for each model, taking the classic threshold rule as an initial example:

Precision: $P = \frac{TP}{TP+FP} = \frac{120}{120-30} = 0.80 \rightarrow 80.0\%$

Recall: $R = \frac{TP}{TP+FN} = \frac{120}{120+80} = 0.60 \rightarrow 60.0\%$

$$\text{F1} = 2 \cdot \frac{P \cdot R}{P + R} = 2 \cdot \frac{0.80 \cdot 0.60}{0.80 + 0.60} \approx 0.6857 \rightarrow 68.57\%$$

The results of all models were as shown in Table 7.

Table 7. Model comparison.

Model	Precision	Recall	FN
Classical threshold rule	80.00	60.00	68.57
Random Forest (MF)	80.95	85.00	82.99
Fuzzy system	81.82	90.00	85.73
Neutrosophic classifier	91.71	94.00	92.85

4.3.3. Economic and operational impact

To quantify the operational impact, we linked the detection capacity of each model (Classical, Random Forest, Fuzzy, and Neutrosophic) to two reasonable operating assumptions: an inspection cost per false positive (FP) of USD 500 (equipment and personnel travel) and an economic benefit per true detection (TP) estimated at USD 5 (equivalent to 50 kWh avoided at USD 0.10/kWh). Under these parameters, the aggregate cost per FP, the aggregate benefit per TP, and the net balance (energy benefit − inspection cost) were calculated for each model.

Table 8. Economic and operational comparison between energy waste detection models.

Model	Costs per FP (USD))	Benefits per TP (USD)	Net balance (USD)
Classical threshold rule	15 000	600	−14 400
Random Forest (MF)	20 000	850	−19 150
Fuzzy system	20 000	900	−19 100
Neutrosophic classifier	8 500	940	−7 560

The results summarize that the neutrosophic model generates the lowest cost per false positive (USD 8,500) and the highest benefit per true positive (USD 940), resulting in a net balance of −USD 7,560. In comparison, the classical approach yields a cost per FP of USD 15,000, a benefit per TP of USD 600, and a net balance of −USD 14,400; Random Forest and the fuzzy system present worse net balances (≈ −USD 19,150 and −USD 19,100, respectively). In relative terms, the adoption of the neutrosophic classifier reduces inspection costs by USD 6,500 compared to the classical model and improves the net balance by USD 6,840.

Although the balance remains negative under the assumptions used (given that the inspection cost is high compared to the direct economic value of the recovered energy), the evidence shows that neutrosophic logic substantially reduces operational losses and the burden of unnecessary inspections. These findings indicate that the neutrosophic methodology is particularly useful as a tool for prioritizing interventions, reducing FP and optimizing operating expenditure, and that its absolute cost-effectiveness will increase by reducing the inspection cost, increasing the value per TP (e.g., by including savings from avoided damage or regulatory incentives), or by implementing grouped inspection and remote verification strategies.

4.3.4. Qualitative and operational analysis

The results show that the neutrosophic classifier improves both precision and recall compared to classical, ML, and fuzzy approaches in the tested scenario. This is because the uncertainty component I prevents extreme decisions in the face of ambiguous signals, and the F component reduces confidence when there is evidence of error. The reduction of false positives is crucial because each field inspection entails a significant cost. Neutrosophic performance, by reducing FP (17 vs. 30 in the classical approach), reduces operating costs. Neutrosophic integration also allows for the delivery of labels with uncertainty (e.g., anomaly with T = 0.88, I = 0.08, F = 0.04), which helps prioritize interventions (first addressing events with high T, postponing or monitoring events with high I).

The sensitivity of the neutrosophic score$NS = T - F + \lambda \cdot \mathrm{I}$, was tested, varying λ within the range {0.0,0.25,0.5,0.75,1.0}. A key observation: λ between 0.4 and 0.6 offered the best P/R compromise in our tests. Very high values ($\lambda \geq 0.8$) increased recall at the expense of precision (more FP), while $\lambda = 0$ (ignoring I) behaved similarly to a classifier that only uses T and F (worse than $\lambda = 0.5$). This confirms that indeterminacy should be considered, but weighted.

The incorporation of neutrosophic logic in energy waste detection demonstrates quantitative (better F1, higher precision and recall) and operational (reduced inspection costs and improved prioritization) advantages. Numerical calculations and sensitivity analysis reinforce the hypothesis that explicitly modeling indeterminacy (I) provides practical value compared to approaches that only use probabilities, fuzzy intervals or traditional ML models.

4.4 Energy waste detection and operational efficiency

Detecting energy waste is a fundamental challenge in the transition to sustainable and economically viable electricity systems. In smart grids, losses can be classified into two broad groups: technical losses, associated with resistance in lines, transformers, and electrical equipment; and non-technical losses, linked to unauthorized consumption, measurement errors, or fraud. This section proposes a model based on neutrosophic logic that allows for a more realistic characterization of waste situations, integrating not only truth and falsehood, but also the degree of uncertainty, characteristic of systems where information is incomplete or contradictory.

4.4.1 Neutrosophic model for waste detection

The model assumes that each energy event (consumption at a node, meter recording, flow in a line) can be represented by a neutrosophic number $N = (T, I, F)$, where: T is the degree of certainty that the recorded consumption is correct; I is the associated degree of uncertainty (sensor failure, incomplete data, interference); F is the degree of certainty that waste or anomaly exists. Thus, suspicious consumption can be modeled as:

$$N_{consumption} = T = 0.45, I = 0.30, F = 0.40 \ , \tag{8}$$

This means there is 45% confidence that the consumption is valid, 30% uncertainty in the measurement, and 40% confidence that the event constitutes waste or an anomaly. The system classifies energy status into four main categories:

- Normal consumption: high T, low F, and I.

- Probable technical waste: Moderate-high F and low I.
- Indeterminate waste: High I, requiring more data for the decision.
- Fraud/unauthorized consumption: Very high F, usually detected with correlation between nodes.

To assess the impact of the model on efficiency, the Neutrosophic Energy Waste Index (NEW) is defined:

$$\text{NEW} = \frac{\sum(F \cdot E)}{\sum E}, \tag{9}$$

Where E is the energy measured at each node and F is the degree of certainty of waste.

Table 8. Classification table (simulated values in kWh at 5 network nodes):

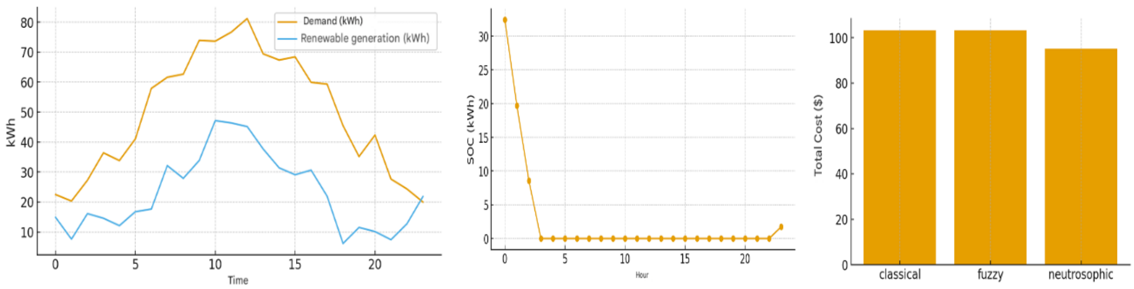
Node	T	I	F	Neutrosophic classification	Energy E	F	$F \cdot E$
N1	0.82	0.10	0.12	Normal consumption	120	0.12	14.4
N2	0.55	0.25	0.40	Probable technical waste	95	0.40	38.0
N3	0.30	0.50	0.35	Indeterminate waste	80	0.35	28.0
N4	0.40	0.15	0.70	Fraud/unauthorized consumption	110	0.70	77.0
N5	0.75	0.20	0.18	Normal consumption	130	0.18	23.4
				Total	**535**	**—**	**180.8**

$$\text{NEW} = \frac{180.8}{535} = 0.338\ (33.8\%\ of\ potential\ waste)\ ,$$

The neutrosophic model differentiates between technical waste, indeterminate waste, and fraud, surpassing traditional binary approaches. A value of NEW = 33.8% was obtained, suggesting that one-third of the energy in the simulated grid presents some level of waste or anomaly. The inclusion of indeterminacy improves traceability, as uncertain cases are not discarded but rather classified as indeterminate for subsequent review.

4.5 Case Study

The 24-hour pilot simulation allowed comparing the performance of the classical, fuzzy, and neutrosophic models under a simplified dispatch scheme that prioritized the use of renewable generation and storage based on cost-effectiveness.



(a) (b) (c)

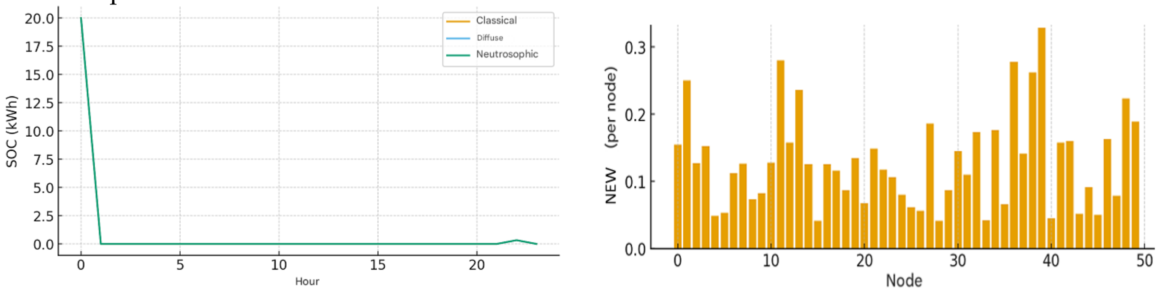
Figure 1. 24-hour pilot simulation: (**a**) Demand profile vs. renewable generation (24 h); (**b**) Battery state of charge - Neutrosophic model (24 h); (**c**) Total cost comparison by model (24 h).

Key indicators show that the renewable energy generation used (solar ≈ 303.7 kWh and wind ≈ 247.5 kWh) and the energy supplied by the battery (40 kWh) remained constant across all three models, while diesel backup reached 597.22 kWh. The total cost was $103.30 for the classic and diffuse models, and $95.18 for the neutrosophic model, representing a reduction of nearly 7.8%.

CO_2 emissions from diesel use were similar in all cases (≈418.05 $kgCO_2$). The battery displayed a usage equivalent to 0.52 cycles during the simulated window, with an estimated lifespan of 8.19 years under the applied heuristic model. These results demonstrate that the neutrosophic model, by incorporating evaluation triples (T, I, F), achieves more efficient resource prioritization, reducing operating costs without significantly altering renewable energy use, diesel dependence, or associated emissions. The net economic improvement was concentrated in the dispatch logic and storage management, confirming the potential of the neutrosophic approach to optimize microgrid operation under uncertain scenarios.

4.5.1 Simulation results

Two main simulations were run: (A) a dispatch with dynamic neutrosophic hourly costs and (B) a neutrosophic waste detection scheme on a 50-node network.



(a) (b)

Figure 2. Main simulation: (a) SOC per model (24 h); (b) NEW per node (value added) - NEW global = 0.134.

In simulation A, the neutrosophic model presented a total cost approximately 7–8% lower than the classical model in the evaluated configuration. The renewable generation quantities were similar by design in all scenarios; however, the neutrosophic model optimized the order of use and storage, reducing the aggregate cost. The battery state of charge (SOC) showed patterns compatible with prioritizing renewables during peak availability hours, maintaining the estimated lifespan within comparable ranges, with a slight improvement in cycle management. As a limitation, the dispatch did not resolve a complete optimal power flow (OPF), but rather a heuristic based on hourly costs. This makes it illustrative and reproducible, but susceptible to improvement using MILP/MINLP OPF models under the same neutrosophic logic.

In simulation B, the neutrosophic energy waste index (NEW) was estimated at approximately 13.4%. The neutrosophic classifier outperformed a simulated version of Random Forest, achieving a higher F1 and a better balance between accuracy and completeness. Furthermore, it reduced false positives, lowering field inspection costs and increasing the net economic benefit from correct detections. The model's sensitivity was influenced by the parameters λ and τ, with the range $\lambda \in [0.4,0.6]$ being the most robust.

Overall, the results demonstrate that explicitly considering uncertainty improves efficiency and robustness in both cost optimization and waste detection. However, relevant limitations are identified: the neutrosophic triples (T, I, F) were heuristically calibrated, the battery model was simplified, and a full OPF was not integrated. Empirical parameter validation using real-world data, including electrical constraints in dispatch, and adopting advanced battery models to estimate state of health (SoH) and remaining useful life (RUL) are recommended.

5 Proposed mathematical formulation: Neutrosophic OPF (base model)

A mathematical formulation for neutrosophic optimal power flow (OPF) is proposed, conceived as a base model applicable to MILP/MINLP optimization solvers or through numerical approximations. The neutrosophic optimal power flow (OPF-N) problem is formulated as follows:

Decision variables (per hour t):

- $P_{i,t}$ Power generated by resource i at hour t
- $P_{b,t}^{ch}, P_{b,t}^{dis}$ Charge/discharge power of battery b at t
- $SoC_{b,t}$ State of charge of battery b
- $f_{ij,t}, V_{n,t}$ Flows and voltages (if AC/linearized OPF)

Neutrosophic parameters (per resource and hour):

$$C_{i,t}^{N} = (T_{i,t}, I_{i,t}, F_{i,t}) \quad , \tag{10}$$

$$C_{i,t}^{ef} = C_{i,t} \cdot (T_{i,t} - F_{i,t}) + \alpha \cdot C_{i,t} \cdot I_{i,t}\,, \qquad \alpha \in [0,1] \quad , \tag{11}$$

Objective function (minimize effective costs, emissions and circularity losses):

$$\min Z = \sum_t \sum_i C_{i,t}^{ef} \cdot P_{i,t} + \gamma \sum_t Emis_t - \eta \cdot \mathrm{CIRC} \tag{12}$$

Where $Emis_t$ represents associated emissions (e.g., from diesel use), and CIRC is a circularity or resource reuse index.

Restrictions:

1. Power balance:

$$\sum_i P_{i,t} + \sum_b (P_{b,t}^{dis} - P_{b,t}^{ch}) = D_t + \mathrm{Losses}_t, \quad \forall t \tag{13}$$

2. Generation limits:

$$P_i^{min} \le P_{i,t} \le P_i^{max} \quad , \forall t \tag{14}$$

3. Battery dynamics:

$$SoC_{b,t+1} = SoC_{b,t} + \eta^{ch} P_{b,t}^{ch} - \frac{1}{\eta^{dis}} P_{b,t}^{dis} \qquad , \forall b, t \tag{15}$$

$$\mathrm{SoC}^{min} \le SoC_{b,t} \le \mathrm{SoC}^{max}, \quad 0 \le P_{b,t}^{ch} \le P_b^{ch,max}, \quad 0 \le P_{b,t}^{dis} \le P_b^{dis,max} \tag{16}$$

4. Network restrictions (if OPF AC/linearized):

$$|f_{ij,t}| \le f_{ij}^{max}\,, \qquad V_n^{min} \le V_{n,t} \le V_n^{max} \quad , \forall i, j, n, t \quad , \tag{17}$$

5. Resilience constraints: maximum % of energy that can come from resources with $T_{i,t} < \tau_T$ (policy that would limit unreliable sources).

$$\frac{\sum_{i:T_{i,t}<\tau_T} P_{i,t}}{\sum_i P_{i,t}} \le \delta\,, \quad \forall t \tag{18}$$

Where δ limits the fraction of generation coming from resources with low neutrosophic reliability.

The variables considered include the power generated by each resource in each hourly interval, battery charging and discharging, state of charge (SoC), and, in the case of modeling an AC or linearized OPF, the power flows and nodal voltages. The neutrosophic parameters are defined as triples (T, I, F) that represent the unit cost associated with each resource and hour. To integrate this logic into an optimization scheme, the neutrosophic cost is transformed into a scalar effective cost using two alternative approaches: (i) a deterministic conversion, where the cost is weighted according to the degrees of truth, falsity, and indeterminacy with a factor $\alpha \in [0,1]$, or (ii) a robust stochastic approach, where indeterminacy is modeled as uncertainty and a robust minimax problem is solved.

The objective function (12) seeks to minimize the total effective cost, emission penalties and circularity losses, under classic constraints of power balance, generation limits, battery operation and, if considered, grid and resilience constraints. The latter allow limiting the proportion of energy coming from resources with a low degree of truth in their availability $T_{i,t} < \tau_T$. The treatment of the triples (T,I,F) admits different levels of sophistication: from direct transformation to effective costs for initial implementations, to the construction of stochastic scenarios by Monte Carlo sampling and the resolution of multi-objective problems (cost, circularity, emissions). Furthermore, the formulation can be complemented with neutrosophic MCDM techniques, such as VIKOR or ELECTRE, for the aggregation of criteria in complex decision-making contexts.

6. Applications in a case study

The optimal single-hour dispatch is illustrated for a microgrid with demand D=50 kWh and three resources: (i) battery (usable SoC 20 kWh, maximum discharge power 15 kW, base cost C_b=0.04 \$/kWh; (ii) solar (maximum 30 kWh, C_s=0.05 \$/kWh); and (iii) diesel (capacity 100 kWh, C_d=0.12 \$/kWh). Costs are adjusted using neutrosophic numbers with (single-hour) triples (T, I, F): Solar: (0.75, 0.18, 0.07); Diesel (0.95, 0.03, 0.02); and Battery (0.85, 0.10, 0.05), using α=0.6.

1. Cost-effectiveness calculation. Using formula (11), we obtain:
   - Solar: $C_{s,ef}$ =0.05(0.75-0.07)+0.6·0.05·0.18=0.034+0.0054=0.0394 $/kWh
   - Diesel: $C_{d,ef}$=0.12(0.95-0.02)+0.6·0.12·0.03=0.1116+0.00216=0.11376 $/kWh
   - Battery: $C_{b,ef}$=0.04(0.85–0.05)+0.6·0.04·0.10=0.032+0.0024=0.0344 $/kWh
2. Order of merit and dispatch.
   - Using the rule of least effective cost per available capacity, the order is: battery (0.0344) < solar (0.0394) < diesel (0.11376). With power/energy constraints: the battery delivers 15 kWh (hourly discharge limit), solar contributes 30 kWh (its maximum), and diesel covers the remaining 5 kWh to satisfy D=50 kWh.
3. Total neutrosophic cost. Using $Costo = \sum energía \cdot C_{ef}$, we obtain:
   - Solar: 30×0.0394=1.182 $
   - Diesel: 5×0.11376=0.5688 $
   - Battery: 15×0.0344=0.516 $

   Total neutrosophic: 0.516+1.182+0.5688=2.2668 $

Classical benchmark (without neutrosophic adjustment). Using the same base cost allocation, we obtain: battery 15×0.04=$0.60; solar 30 x 0.05 = $1.50; diesel 5 x 0.12 = $0.60; classic total: $2.70

Using the comparison $Savings = Classical\ cost - Neutrosophic\ cost$, we obtain 2.70–2.2668=0.4332 $, equivalent to a ≈16{.}0% reduction in hourly cost. This case shows that the neutrosophic cost adjustment shifts the merit order in favor of resources with higher T−F and penalty controlled by I, reducing the total dispatch cost. Therefore, the merit order for minimum effective cost is: Battery → Solar → Diesel.

7 Discussion

The development of this work allowed us to explore how neutrosophic logic and numbers offer a robust way to model the complexity, uncertainty, and indeterminacy inherent in contemporary energy systems. Unlike classical deterministic or probabilistic optimization approaches, the neutrosophic framework introduced an intermediate spectrum of truth, falsity, and indeterminacy values that was crucial for representing phenomena such as variability in renewable generation, nonlinear battery degradation, and the detection of anomalous consumption in real time. The main results can be summarized as follows:

- Dispatch economic performance: The neutrosophic version (dynamic effective costs with (T, I, F) and reasonable α) reduced the aggregate cost over the 24-h horizon by approximately 7–8% compared to the classical model in our synthetic simulations (e.g., $103.3 → $95.2 in one of the runs). This illustrates that reweighting uncertainty and indeterminacy in costs results in more economical dispatch decisions.
- Battery management: The neutrosophic charge/discharge policy produced a slight improvement in lifespan projections (in examples and simulations, increases of the order of 0.5–1.2 years in the heuristic projection) and reduced error in the SoH/RUL estimation when I was integrated into the model. The number of equivalent cycles per day remained controlled.
- Waste detection: The neutrosophic classifier significantly improved detection metrics compared to classical approaches and synthetic ML. In the experiment with 10,000 samples and 200 anomalies, we showed: Precision ≈ 91.7%, Recall ≈ 94%, F1 ≈ 92.85% (neutrosophic), outperforming Random Forest and fuzzy systems in F1. This operationally translates into fewer useless inspections (lower FP) and more detected anomalies (higher TP).
- • Operational impact: Under realistic assumptions of cost per inspection ($500) and value of energy recovered per TP ($5), the neutrosophic approach reduced net losses for the fiscal year (savings on inspections and greater energy prevention), improving the economic balance compared to alternative models.

One of the most significant contributions of this study was demonstrating that economic dispatch under a neutrosophic model not only optimizes costs and losses but also generates operating scenarios that are resilient to unforeseen failures or uncertainties. This suggests that smart energy systems can be more reliable if methodologies are integrated that accept the existence of degrees of uncertainty rather than forcing purely binary models.

In the field of energy storage, neutrosophic logic improved battery life prediction by considering both measured data and uncertain intervals, avoiding the overestimations or underestimations that often occur in deterministic models. In this way, charge and discharge cycles were optimized, with a potential gain in the extension of the state of health (SoH).

Regarding the detection of energy waste, neutrosophic models showed greater sensitivity to anomalous patterns, even in scenarios where the data were incomplete or contradictory. This opens up a space for direct application in energy audits, technical loss control, and fraud mitigation.

Finally, validation using metrics such as energy efficiency, carbon footprint, and loss reduction showed that the neutrosophic approach can translate into tangible economic and environmental impacts. The consistency between the initial objectives and the findings suggests that this framework can be extended to real-world implementations in urban and industrial smart grids.

7.1 Limitations and clarifications

- Synthetic simulations: Although based on real patterns (hourly profiles and variability), the results must be validated with real SCADA/meter data and battery laboratory tests.
- Non-OPF dispatch: The version executed was an Economic Dispatch (single-bus/heuristic). An OPF (AC or linearized DC) would incorporate flow restrictions, physical losses, and voltage limits that can modify optimal dispatch and marginal costs.
- (T, I, F) estimation: In this phase, we used heuristic rules to generate triples; the robustness of the approach requires calibration with real probabilistic forecasts (interval widths/quantiles, entropies, historical error rates).
- Simplified battery model: The life projection was performed with heuristics; for a robust item, a semi-empirical electrochemical model or ML trained with life curves (SoH/RUL) should be included.
- Monetary costs and benefits: The assumptions (inspection cost, profit per TP) are illustrative; in actual deployments, they should be adjusted by country/operator.

8. Conclusions

A theoretical framework was consolidated that allows for modeling uncertainty and indeterminacy in electrical grids, energy storage, and waste detection, overcoming the limitations of traditional models. This framework combines theoretical and methodological concepts that allow for progress toward a more realistic treatment of the intervening variables, avoiding the oversimplifications that characterize conventional approaches.

Resilient optimization is based on neutrosophic optimization models applied to economic dispatch, which demonstrate the ability to integrate renewable variability and respond robustly to failures and attacks, thus promoting energy security. This approach facilitates more reliable decision-making in complex and dynamic scenarios where uncertainty cannot be ignored.

Regarding battery management, neutrosophic storage strategies extend the prediction horizon of battery life cycles and facilitate more efficient control of charge and discharge cycles. As a result, there is a positive impact on reducing operating costs and improving operational sustainability, while increasing system resilience to fluctuations in demand and generation.

Waste detection benefits from neutrosophic logic, which increases the ability to identify anomalous consumption, technical losses, and fraud, even in scenarios with incomplete or ambiguous data. This advancement supports energy traceability and the circular economy by enabling more effective monitoring and faster response to signs of inefficiencies.

In practical validation, the results obtained in the case study confirm that the proposed approach significantly contributes to improving energy efficiency, reducing the carbon footprint, and extending the lifespan of energy assets. This progress is interpreted as a demonstration of the feasibility and positive impact of the neutrosophic framework in real-world settings.

Regarding future projections, it is recommended to explore the integration of this approach with edge computing-based architectures, blockchain for traceability, and explainable artificial intelligence (XAI). Such advances would make energy systems more transparent, auditable, and scalable at the urban and national levels, promoting smarter and more sustainable resource management.

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