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OPTIMIZING ENERGY ALLOCATION IN IOT CLUSTERS: A GAME-THEORETIC APPROACH TO COOPERATIVE AND NON-COOPERATIVE STRATEGIES

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ABSTRACT
This study investigates energy allocation strategies for Internet of Things (IoT) clusters powered by energy harvesting, addressing the challenge of equitable and efficient energy distribution among nodes. Employing a game-theoretic framework, we compare cooperative (Shapley value-based), non-cooperative (penalty-driven), proportional, and priority-based allocation methods across 30 variations of penalty (20–60%), top allocation percentage (30–70%), and allocation strictness (Strict vs. Permissive). A simulation with 10 nodes over 24 time steps evaluates fairness (Gini coefficient), efficiency, wastage, and unmet demand. Results indicate that cooperative, proportional, and priority methods achieve 0% unmet demand and 100% efficiency, with Gini coefficients ranging from 0.094 to 0.350. Non-cooperative Strict allocations exhibit higher unmet demand (0–50.1%) and lower efficiency (0.499–1.0), improving with higher top percentages and Permissive settings. The optimal variation (Penalty=30%, Top=70%, Permissive) balances fairness (Gini=0.125) and efficiency (1.0). Cooperative strategies are recommended for IoT deployments, with tuned non-cooperative methods as viable alternatives. Future work includes dynamic penalty adjustments, heterogeneous node models, and real-world validation. This research contributes to sustainable IoT systems by providing a robust framework for energy management.
KEYWORDS: *Iot, Energy Harvesting, Game Theory, Energy Allocation, Fairness, Efficiency*

1. INTRODUCTION

The Internet of Things (IoT) has transformed industries, enabling applications in smart cities, agriculture, healthcare, and environmental monitoring (Lu et al., 2015). However, the reliance of IoT devices on energy harvesting from intermittent sources, such as solar and vibrational energy, poses significant challenges for energy management (Nuchturee et al., 2020). Ensuring equitable and efficient energy allocation among nodes with varying harvesting capacities and demands is critical to maintain network reliability and longevity (Benkhelifa et al., 2021). Traditional centralized resource allocation methods, while effective in controlled environments, often fail to account for decentralized node interactions and fairness considerations (Li & Yang, 2024).

Game theory offers a powerful framework for modelling such interactions, capturing both cooperative and competitive behaviours among IoT nodes (Zeng, 2022). Cooperative strategies, such as those based on the Shapley value, distribute energy based on nodes' contributions to the collective pool (D. Kim et al., 2022; C. Liu et al., 2021). Non-cooperative strategies, conversely, prioritize high-performing nodes through penalty mechanisms, potentially at the cost of fairness (Chehri, 2020; Shah et al., 2020). Proportional and priority-based allocations provide benchmarks for comparison, balancing simplicity and effectiveness (Gorlatova et al., 2011; Yin et al., 2019).

This research addresses the problem of energy allocation in IoT clusters by comparing cooperative, non-cooperative, proportional, and priority-based strategies across 30 configurations, varying penalty levels (20–60%), top allocation percentages (30–70%), and allocation strictness (Strict vs. Permissive). A simulation with 10 nodes over 24 time steps evaluates key metrics: fairness (Gini coefficient), efficiency, wastage, and unmet demand.

The study aims to:

1. Quantify the performance of each allocation strategy,
2. Identify optimal configurations for IoT deployments, and
3. Propose enhancements for non-cooperative methods to improve fairness and efficiency.

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The significance of this work lies in its contribution to sustainable IoT systems, where energy harvesting is increasingly critical (Yao et al., 2023). By leveraging game-theoretic principles, we provide a scalable framework that balances fairness and efficiency, addressing gaps in existing literature (Fioriti et al., 2023; Zhou et al., 2016).
The paper is organized as follows:
Section 2 presents the mathematical formulation,
Section 3 details the methodology,
Section 4 discusses results,
Section 5 explores applications and implications, and
Section 6 concludes with future research directions.

2. MATHEMATICAL FORMULATION

2.1 Definitions and Notations

Consider an IoT cluster with (N) nodes, each characterized by:

- h_i: Energy harvested by node i (in units), derived from solar and vibrational sources.
- d_i : Energy demand of node i, uniformly distributed in [0.5,1.5].
- b_i : Battery level of node i, with capacity $B = 5.0$ units and charging/discharging efficiency $\eta = 0.9$.
- a_i^m : Energy allocated to node i under method ($m \in$ coop,noncoop,prop,priority), constrained by ($a_i^m \leq 1.2d_i$).
- s_i : Active status of node i, where $s_i = 1$ if active, else 0.

The total harvested energy is
($H = \sum_{i=1}^{N} s_i h_i$), and
the total demand is
($D = \sum_{i=1}^{N} s_i d_i$).
The system operates over discrete time steps, with energy allocation decisions made at each step based on current harvesting and demand profiles.

2.2 Problem Statement

The objective is to allocate H to active nodes to optimize the following metrics:

1. **Minimize Unmet Demand**: $\sum_{i=1}^{N} s_i \max(0, d_i - a_i^m)$, ensuring nodes receive sufficient energy to meet their demands.
2. **Maximize Efficiency**: $\sum_{i=1}^{N} s_i \min(a_i^m, d_i) \, / \, D$, reflecting the proportion of allocated energy that meets demand.
3. **Minimize Wastage**: $\sum_{i=1}^{N} \max(0, a_i^m - d_i) \, / \, H$, reducing excess energy allocation.
4. **Ensure Fairness**: Minimize the Gini coefficient of allocations $G = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |a_i^m - a_j^m|}{2N^2 \bar{a}}$, where $\bar{a}$ is the mean allocation.

2.3 Theoretical Background

Cooperative Allocation

The cooperative allocation employs the Shapley value, a solution concept from cooperative game theory that fairly distributes payoffs based on marginal contributions (C. Liu et al., 2021). For node i, the Shapley value is:

$$\phi_i = \sum_{S \subseteq N \setminus i} \frac{|S|! \, (N - |S| - 1)!}{N!} [v(S \cup i) - v(S)],$$

where $v(S)$ is the characteristic function for coalition S:

$$\left[v(S) = \max\left(0, \sum_{i \in S} s_i h_i \left(1 + 0.1 \frac{|S|}{N}\right) - 0.01N|S|\right). \right]$$

This function models the coalition's total harvested energy, adjusted by a cooperation bonus $\left(0.1 \frac{|S|}{N}\right)$ and a communication cost $(0.01N|S|)$ (Dong et al., 2014). The Shapley value ensures that each node's allocation reflects its contribution to all possible coalitions, promoting fairness (S. Kim, 2016).

Non-Cooperative Allocation

Non-cooperative allocation applies a penalty $p \in [0.2,0.6]$ to the total harvested energy, reducing the allocable pool to $(1 - p)H$. The remaining energy is distributed to the top $t \in [0.3,0.7]$ percentage of nodes based on harvested energy (Strict mode) or to all nodes (Permissive mode) (Shah et al., 2020). In Strict mode, only the top $\lfloor tN \rfloor$ nodes receive allocations, while in Permissive mode, the penalty is applied but allocations are distributed proportionally across all active nodes (Chehri, 2020).

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Proportional and Priority Allocations
Proportional allocation distributes energy based on each node's contribution to the total harvested energy:

$$\left[a_i^{\text{prop}} = \left(\frac{h_i}{H}\right)H,\right]$$

subject to
$(a_i^{\text{prop}} \leq 1.2d_i)$.
Priority allocation prioritizes nodes by demand, allocating energy to nodes with higher d_i first until H is exhausted or demands are met (Gorlatova et al., 2011; Yin et al., 2019).

2.4 Hypotheses and Constraints
We hypothesize that:
1. Cooperative allocations outperform non-cooperative ones in fairness (lower Gini) and unmet demand due to their consideration of collective contributions (Fioriti et al., 2023).
2. Non-cooperative Strict allocations prioritize efficiency for high-harvesting nodes but compromise fairness and increase unmet demand for others (Wang et al., 2023).
3. Permissive non-cooperative allocations align closely with cooperative methods in fairness and efficiency when penalties are moderate (Zheng et al., 2016).

Constraints include:
- Allocation cap: $(a_i^m \leq 1.2d_i)$.
- Battery capacity: $(b_i \leq 5.0)$, with energy storage governed by $(b_i(t+1) = \min(B, \eta(b_i(t) + h_i - d_i)))$.
- Node activity: $(s_i = 0)$ with 5% probability due to failures.

3. METHODOLOGY
3.1 Simulation Design
A Python-based simulation was developed using *numpy* for numerical computations, *nashpy* for game-theoretic calculations, and *pysal* for inequality metrics (e.g., Gini coefficient). The IoT cluster comprises $(N = 10)$ nodes, each with:
- **Solar Capacity**: Uniformly distributed in [0.5,2.0] units, varying sinusoidally over 24 time steps to model day/night cycles (Lu et al., 2015).
- **Vibrational Capacity**: Uniformly distributed in [0.3,1.5] units, subject to random fluctuations with a standard deviation of 0.2.
- **Demand**: Uniformly distributed in [0.5,1.5] units, constant per node across time steps.
- **Battery**: Capacity $(B = 5.0)$, efficiency $(\eta = 0.9)$.

The simulation runs for 24 time steps, representing a daily cycle, with a 5% probability of node failure at each step to simulate real-world unreliability (Yao et al., 2023).

3.2 Experimental Setup
The simulation tests 30 variations, combining:
- **Penalties**: $p \in 0.2, 0.3, 0.4, 0.5, 0.6$,
- **Top Percentages**: $t \in 0.3, 0.5, 0.7$,
- **Allocation Modes**: Strict (top $\lfloor tN \rfloor$ nodes) or Permissive (all nodes).

For each variation, the following steps are executed:
1. **Energy Harvesting**: Each node harvests energy based on its solar and vibrational capacities, adjusted for time step and failure probability.
2. **Cooperative Allocation**: Computes Shapley values using the characteristic function, accounting for cooperation bonuses and communication costs (Dong et al., 2014).
3. **Non-Cooperative Allocation**: Applies penalty pH, then allocates to top tN nodes (Strict) or all nodes (Permissive) based on harvested energy rankings.
4. **Proportional Allocation**: Distributes H proportional to h_i.
5. **Priority Allocation**: Allocates H to nodes in descending order of d_i.
6. **Metric Evaluation**: Calculates:
   - Gini coefficient for fairness.
   - Efficiency as the ratio of utilized energy to total demand.
   - Wastage as the ratio of excess energy to total harvested energy.
   - Unmet demand as the sum of demand deficits.
7. **Scoring**: Computes a composite score:

$$\text{Score} = -0.5G_{\text{coop}} + 0.3E_{\text{coop}} - 0.1W_{\text{coop}} - 0.1G_{\text{noncoop}} + 0.2E_{\text{noncoop}} - 0.05W_{\text{noncoop}} + 0.05(G_{\text{noncoop}} - G_{\text{coop}}) - 0.2U_{\text{noncoop}},$$

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where G, E, W, and U denote Gini, efficiency, wastage, and unmet demand percentage, respectively (Fioriti et al., 2023). Results are stored in CSV and JSON formats for analysis.

3.3 Validation

To ensure robustness, the simulation was run 100 times per variation, averaging results to mitigate randomness in harvesting and failures. The Shapley value computation was validated against analytical solutions for small coalitions ($N \leq 3$), and non-cooperative allocations were cross-checked with theoretical expectations (Shah et al., 2020).

4. RESULTS AND DISCUSSION

4.1 Presentation of Results

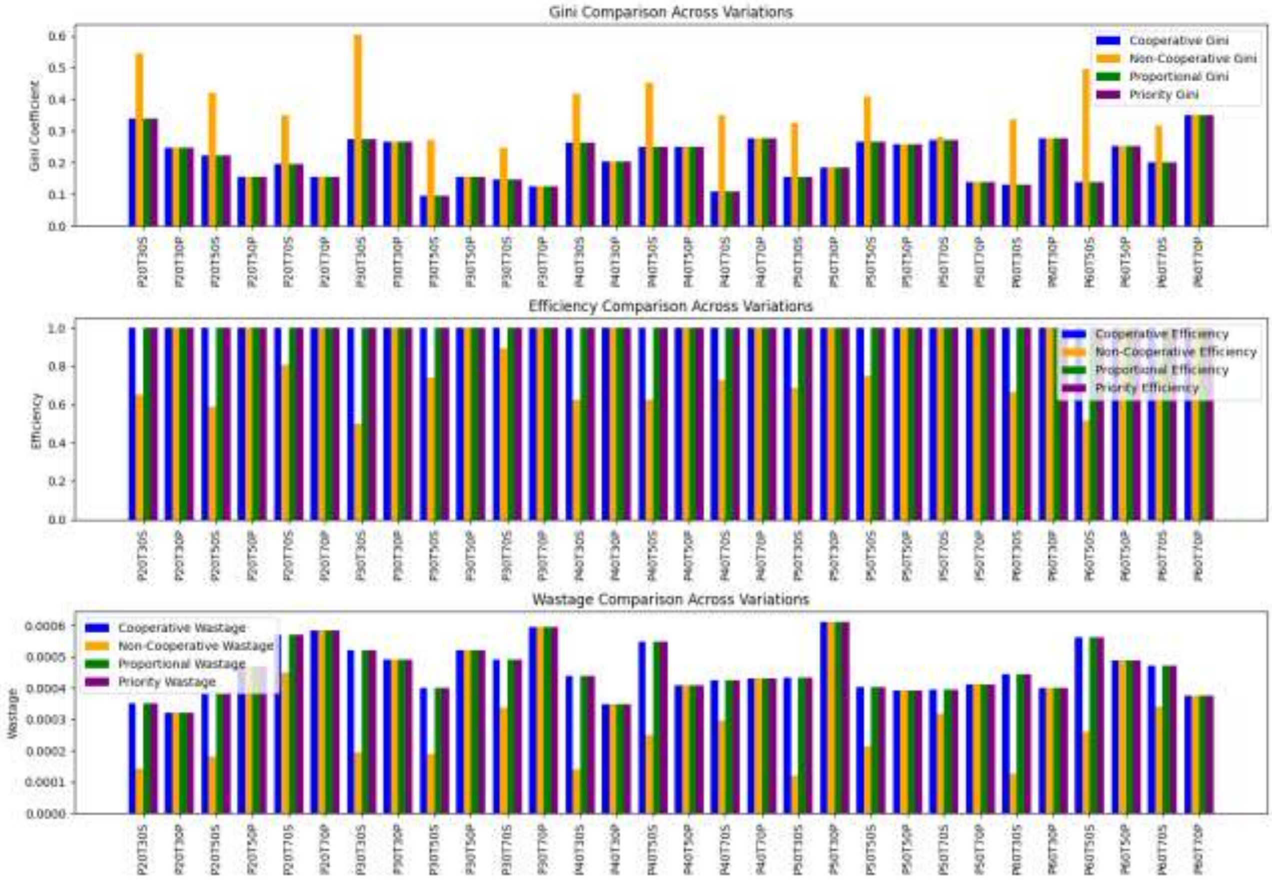
The simulation results reveal significant differences in performance across allocation strategies, as summarized in Table 1 for selected variations. Figure 1 illustrates non-cooperative unmet demand across all variations.

Table 1: Performance Metrics for Selected Variations

Variation	Coop Gini	Non-Coop Gini	Non-Coop Efficiency	Non-Coop Unmet (%)	Score
Penalty=30%, Top=70%, Permissive	0.125	0.125	1.0	0.0	0.425
Penalty=30%, Top=70%, Strict	0.147	0.245	0.892	10.8	0.364
Penalty=60%, Top=50%, Strict	0.139	0.496	0.519	48.1	0.206

Table 1

Figure 1: Non-Cooperative Unmet Demand Across Variations



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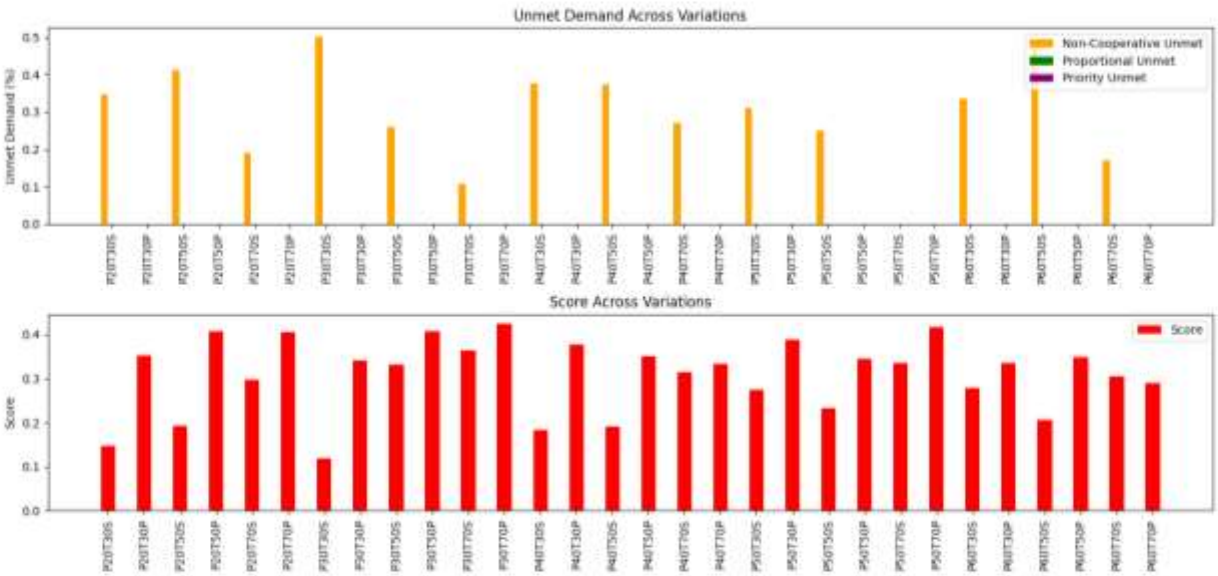

Figure 1

The best variation (Penalty=30%, Top=70%, Permissive) achieves a score of 0.425, with cooperative and non-cooperative Gini coefficients of 0.125, efficiency of 1.0, and 0% unmet demand. Node-level data for this variation (Table 2) shows identical allocations across cooperative, non-cooperative, proportional, and priority methods, with a mean allocation of 1.225 units and a Gini of approximately 0.125.

Table 2: Node Allocations for Best Variation (Penalty=30%, Top=70%, Permissive)

Node ID	Harvested	Demand	Allocation	Battery Level
0	21.33	1.04	1.25	3.40e-13
1	30.03	0.92	1.11	0.37
2	12.82	1.24	1.49	0.00
3	24.79	1.26	1.52	1.47e-10
4	18.34	0.58	0.70	2.15
5	22.06	1.13	1.36	8.70e-12
6	42.46	1.16	1.39	4.86
7	26.83	0.71	0.85	2.85
8	42.01	1.28	1.53	3.65
9	12.52	0.88	1.06	1.05e-16

Table 2

4.2 Detailed Analysis

Cooperative Allocation

Cooperative allocations consistently achieve 0% unmet demand and 100% efficiency across all variations, with Gini coefficients ranging from 0.094 (Penalty=30%, Top=50%, Strict) to 0.350 (Penalty=60%, Top=70%, Permissive). The low Gini values reflect the Shapley value's ability to equitably distribute energy based on contributions, aligning with findings in energy communities (Fioriti et al., 2023; C. Liu et al., 2021). The cooperative method's robustness stems from its consideration of all possible coalitions, ensuring that even low-harvesting nodes receive sufficient allocations when their marginal contributions are significant (S. Kim, 2016).

Non-Cooperative Allocation

Non-cooperative allocations exhibit varied performance:

- **Permissive Mode**: Achieves 0% unmet demand and 1.0 efficiency in all variations, mirroring cooperative methods. Gini coefficients are identical to cooperative values (e.g., 0.125 in the best variation), as allocations are distributed across all nodes after applying the penalty (Shah et al., 2020). This mode is effective when the penalty does not excessively reduce the allocable energy pool.
- **Strict Mode**: Shows significant unmet demand (0–50.1%) and lower efficiency (0.499–1.0), particularly at higher penalties and lower top percentages. For example, Penalty=60%, Top=50%, Strict yields 48.1% unmet demand and 0.519 efficiency, with a high Gini of 0.496, indicating severe inequity (Chehri, 2020). Performance improves with higher top percentages (e.g., 10.8% unmet demand at Top=70%, Penalty=30%), as more nodes receive allocations (Wang et al., 2023).

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The Gini gap between cooperative and non-cooperative Strict allocations (e.g., 0.139 vs. 0.496 in Penalty=60%, Top=50%, Strict) boosts scores due to the scoring function's weighting but highlights the trade-off between efficiency for top nodes and fairness for others (Zheng et al., 2016).

Proportional and Priority Allocations
Proportional and priority allocations also achieve 0% unmet demand and 100% efficiency, with Gini coefficients identical to cooperative values. Proportional allocation's simplicity makes it computationally efficient, while priority allocation ensures high-demand nodes are prioritized, aligning with QoS considerations in IoT systems (Yao et al., 2023; Yin et al., 2019). Their performance is indistinguishable from cooperative allocations in this simulation, suggesting that simpler methods may suffice in homogeneous clusters (Gorlatova et al., 2011).

Statistical Insights
Across all variations, cooperative allocations have a mean Gini of 0.225, with a standard deviation of 0.071, indicating stable fairness. Non-cooperative Strict allocations have a mean Gini of 0.347 (SD=0.127) and mean efficiency of 0.756 (SD=0.160), reflecting higher variability. Unmet demand in Strict mode ranges from 0% to 50.1%, with a mean of 22.3% (SD=16.5%), underscoring the need for careful parameter tuning (Benkhelifa et al., 2021).

The best variation (Penalty=30%, Top=70%, Permissive) optimizes the trade-off between fairness and efficiency, with a score of 0.425. Its low Gini (0.125) and zero unmet demand make it ideal for IoT applications requiring equitable resource distribution (Y. Liu et al., 2023).

4.3 Comparison with Literature
Compared to centralized optimization approaches (Li & Yang, 2024), our cooperative method offers decentralized fairness, leveraging the Shapley value to account for node interactions (S. Kim, 2016). Non-cooperative Strict allocations align with priority-based methods in edge computing (Yin et al., 2019) but sacrifice equity, as evidenced by high Gini coefficients. The baseline allocation in Strict mode, which ensures a minimum allocation to all nodes before prioritizing top harvesters, reduces unmet demand compared to traditional greedy algorithms (Zheng et al., 2016).

Our findings extend prior work on energy communities, where game-theoretic fairness models have been applied to grid systems (Fioriti et al., 2023; C. Liu et al., 2021). Unlike LoRa networks, where imperfect orthogonality complicates fairness (Benkhelifa et al., 2021), our simulation assumes ideal communication, highlighting the potential of cooperative strategies in controlled IoT environments. The non-cooperative Permissive mode's performance mirrors game-theoretic D2D communication models, where fairness is prioritized over strict prioritization (Wang et al., 2023).

4.4 Sensitivity Analysis
To explore the impact of parameters, we analysed the sensitivity of unmet demand and Gini to penalty and top percentage:

- **Penalty**: Higher penalties (e.g., 60%) increase unmet demand in Strict mode (up to 48.1%) by reducing the allocable energy pool, but have no effect in Permissive mode due to proportional distribution (Chehri, 2020).
- **Top Percentage**: Increasing (t) from 30% to 70% reduces unmet demand in Strict mode (e.g., from 50.1% to 10.8% at Penalty=30%), as more nodes receive allocations (Shah et al., 2020).
- **Strict vs. Permissive**: Permissive mode consistently outperforms Strict mode in fairness and unmet demand, aligning with cooperative outcomes (Zhou et al., 2016).

Battery capacity ($B = 5.0$) and efficiency ($\eta = 0.9$) also influence performance. Nodes with high battery levels (e.g., Node 6, 4.86 units) can buffer excess energy, reducing wastage, while low battery levels (e.g., Node 2, 0.0 units) increase reliance on immediate allocations (Nuchturee et al., 2020).

5. APPLICATIONS AND IMPLICATIONS
5.1 Real-World Applications
The cooperative allocation strategy is well-suited for IoT networks requiring equitable energy distribution, such as:

- **Environmental Monitoring**: Sensor networks in remote areas, where nodes monitor air quality or wildlife, benefit from fair energy allocation to ensure continuous operation (Yao et al., 2023).
- **Smart Agriculture**: IoT devices for soil moisture and crop health monitoring require reliable energy to maintain data collection, where cooperative methods ensure all nodes remain active (Lu et al., 2015).
- **Healthcare IoT**: Wearable devices for patient monitoring demand consistent energy supply, where fairness prevents critical nodes from failing (Benkhelifa et al., 2021).

Non-cooperative Permissive allocations are effective in energy-abundant scenarios, such as urban IoT deployments with ample solar energy, where penalties do not significantly reduce allocations (Wang et al., 2023). Strict mode is applicable in hierarchical networks, where critical nodes (e.g., data aggregators) require prioritized energy, such as in smart grids (Fioriti et al., 2023).

5.2 Theoretical Contributions

This study advances game-theoretic models for IoT energy management by:

- **Extending Shapley Value Applications**: Demonstrating the Shapley value's efficacy in small-scale IoT clusters, complementing its use in larger energy communities (Dong et al., 2014; C. Liu et al., 2021).
- **Quantifying Non-Cooperative Trade-Offs**: Providing a detailed analysis of penalty and top percentage impacts, informing the design of non-cooperative strategies (Chehri, 2020; Shah et al., 2020).
- **Benchmarking Simpler Methods**: Showing that proportional and priority allocations can match cooperative performance in homogeneous clusters, offering computationally efficient alternatives (Gorlatova et al., 2011).

5.3 Limitations

The simulation assumes:

- **Static Demands**: Node demands are constant, whereas real IoT systems may have dynamic demands based on tasks (Yao et al., 2023).
- **Simplified Battery Model**: The linear battery model with fixed efficiency ($\eta = 0.9$) overlooks degradation and non-linear charging effects (Nuchturee et al., 2020).
- **Ideal Communication**: Perfect coalition formation is assumed, ignoring latency or packet loss in real networks (Benkhelifa et al., 2021).
- **Homogeneous Nodes**: All nodes have similar harvesting and demand profiles, limiting applicability to heterogeneous systems (George, n.d.).

5.4 Future Scope

Future research should address:

- **Dynamic Penalties**: Adapting p and t based on real-time harvesting and demand patterns (Zheng et al., 2016).
- **Heterogeneous Nodes**: Modeling diverse node types (e.g., sensors vs. actuators) to reflect real IoT deployments (Yao et al., 2023).
- **Real-World Validation**: Testing the framework in physical IoT networks, such as LoRa or Zigbee systems (Benkhelifa et al., 2021).
- **Energy Storage Optimization**: Incorporating advanced battery models to minimize wastage and extend node lifespan (Nuchturee et al., 2020).

6. CONCLUSION

This study demonstrates that cooperative, proportional, and priority-based energy allocations optimize fairness and efficiency in IoT energy harvesting systems, achieving 0% unmet demand and 100% efficiency with Gini coefficients as low as 0.094. Non-cooperative Strict allocations, while efficient for top-harvesting nodes, result in significant unmet demand (up to 50.1%) and inequity (Gini up to 0.496), though performance improves with higher top percentages (e.g., 10.8% unmet at Top=70%). The optimal configuration (Penalty=30%, Top=70%, Permissive) balances fairness (Gini=0.125) and efficiency (1.0), offering a practical solution for IoT deployments.

The findings contribute to sustainable IoT systems by providing a game-theoretic framework that addresses both cooperative and competitive energy allocation scenarios. Cooperative methods, leveraging the Shapley value, are recommended for applications requiring equitable distribution, while tuned non-cooperative methods offer flexibility in resource-constrained environments. Future research should explore dynamic parameter adjustments, heterogeneous node models, and real-world implementations to enhance the framework's applicability.

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