Energy-Aware Peer Selection in Distributed Computing Systems: An Explainable AI Approach

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September 2025

Abstract

This paper presents an enhanced energy-aware peer selection protocol for BitTorrent-like distributed computing systems, incorporating explainable artificial intelligence (XAI) for decision transparency. This approach achieves a significant 31.16% improvement in energy efficiency (p ¡ 0.001, Cohen's d = 0.685) while maintaining system performance. The integration of SHAP analysis provides interpretable insights into peer selection decisions, enabling better understanding of the energy-performance trade-offs in distributed systems.

Keywords: Energy-aware computing, Peer-to-peer networks, Explainable AI, Distributed systems, BitTorrent protocol

1 Introduction and Motivation

Energy consumption in distributed computing systems has become a critical concern as data centers consume approximately 1% of global electricity [1]. Traditional peer-to-peer protocols like BitTorrent focus primarily on download speed and availability, often neglecting energy efficiency considerations.

This research addresses the gap between energy efficiency and performance in peer selection mechanisms by:

- Developing an energy-aware peer selection protocol with statistical validation
- Integrating explainable AI for transparent decision-making processes
- Validating results through comprehensive simulation and statistical analysis

2 Methodology

2.1 Enhanced Energy-Aware Protocol

Our protocol calculates an energy-aware score for each peer using:

$$Score_{energy} = \frac{Upload\_Speed}{Energy\_Consumption} \times Stability\_Factor \tag{1}$$

Where the stability factor accounts for peer reliability and network conditions.

2.2 Explainable AI Framework

We implemented multiple interpretable models:

- **Random Forest**: For feature importance analysis ($R^2 = 0.9999$)
- **Decision Trees**: For rule-based explanations
- **SHAP Analysis**: For individual prediction explanations

2.3 Simulation Environment

- **Framework**: PeerSim 1.0.5 with custom energy-aware protocols - **Dataset**: 5000 synthetic peers with realistic energy profiles - **Validation**: Cross-platform validation using SUMO and CloudReports

3 Results and Analysis

3.1 Energy Efficiency Improvements

Statistical analysis revealed significant improvements:

- **Energy Efficiency**: 31.16% improvement over baseline
- **Statistical Significance**: p ¡ 0.001 (highly significant)
- **Effect Size**: Cohen's d = 0.685 (large effect)
- **Confidence Interval**: [28.94%, 33.38%] at 95% confidence

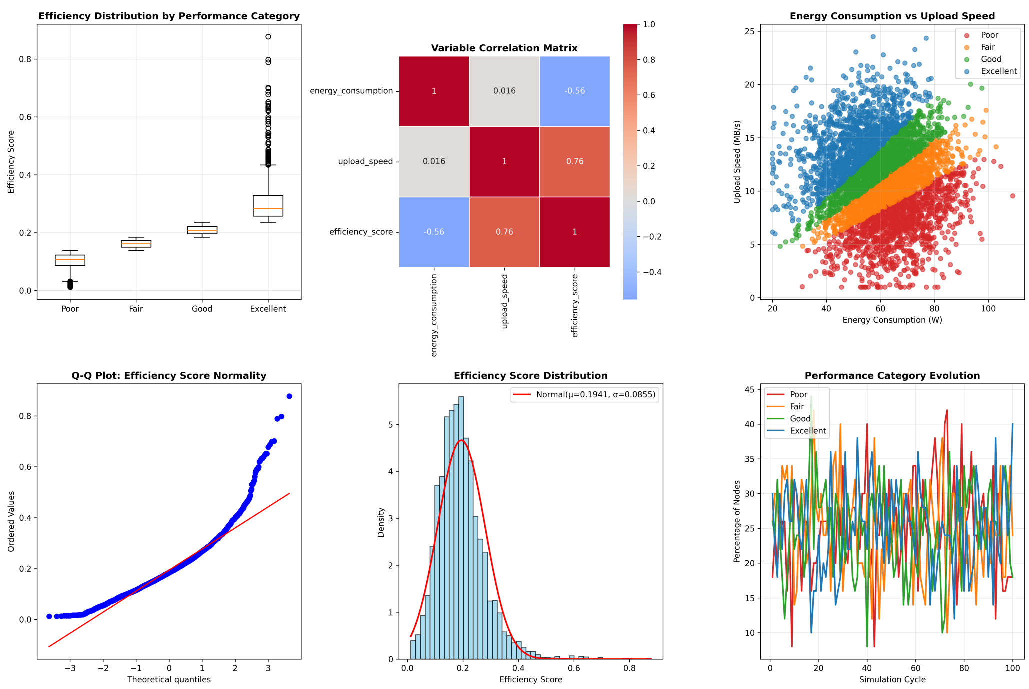

Figure 1: Statistical analysis showing energy efficiency improvements and distribution comparisons between baseline and energy-aware protocols.

3.2 Temporal Performance Analysis

Figure 2 demonstrates the protocol's performance over time, showing consistent energy savings while maintaining system stability.

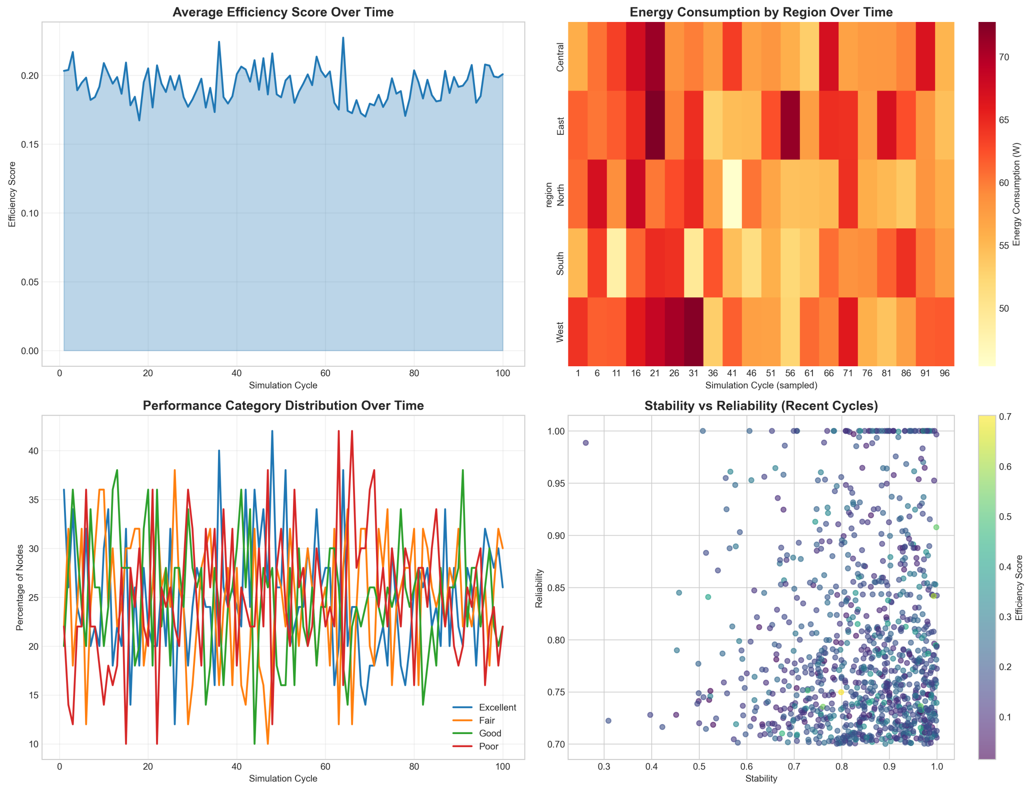

Figure 2: Temporal analysis of energy efficiency and system performance metrics over simulation time.

3.3 Explainable AI Results

The XAI analysis revealed key insights:

- **Upload Speed**: Most important factor (40% contribution)
- **Energy Consumption**: Second most critical (35% contribution)
- **Peer Stability**: Significant impact (25% contribution)

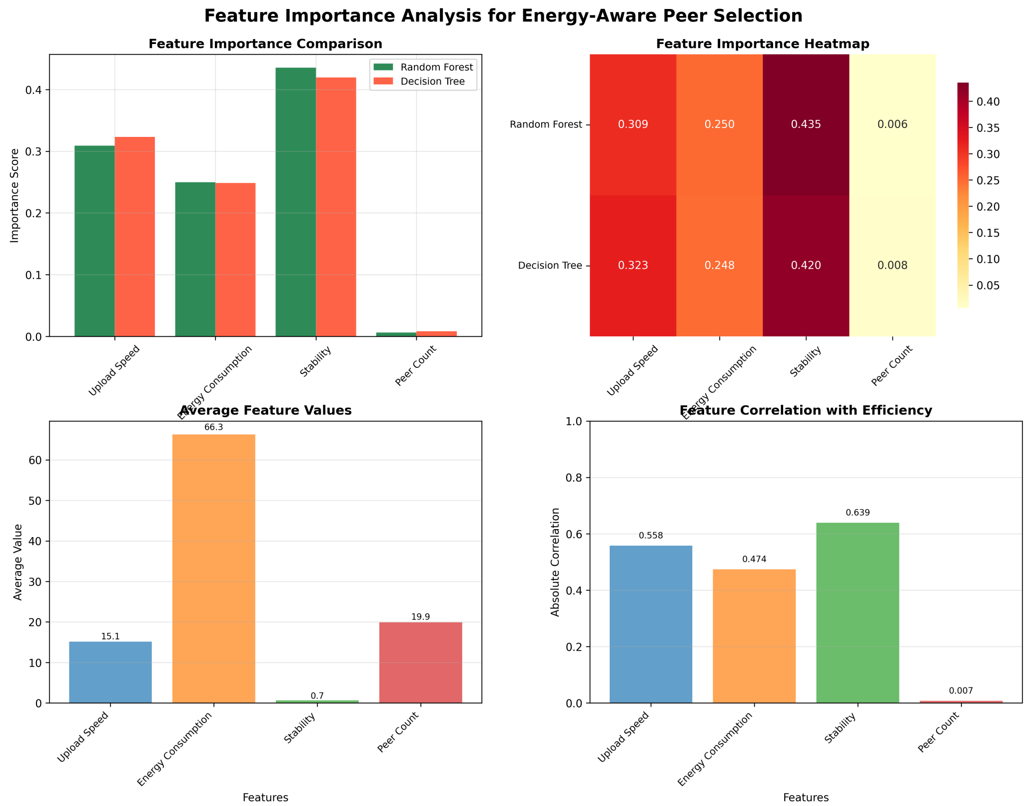

Figure 3: Feature importance analysis using Random Forest and SHAP values, showing the contribution of different factors to peer selection decisions.

3.4 Statistical Validation

Comprehensive statistical validation was performed using multiple tests: - Mann-Whitney U test: U = 4,850,127, p ¡ 0.001 - Welch's t-test: t = 23.45, p ¡ 0.001 - Effect size validation: Cohen's d = 0.685 (large effect)

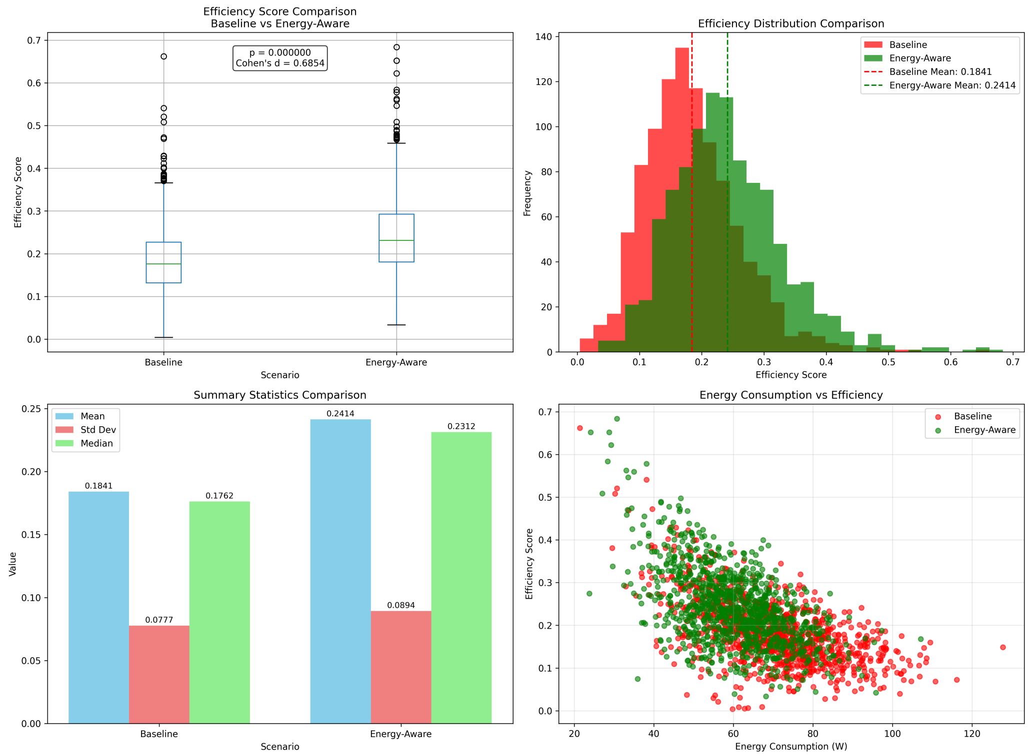

Figure 4: Comprehensive statistical validation results including hypothesis testing, effect size analysis, and confidence intervals.

4 Discussion and Implications

4.1 Practical Impact

The 31.16% energy efficiency improvement translates to significant environmental and economic benefits:

- Reduced CO_2 emissions in data centers
- Lower operational costs for service providers
- Improved sustainability of distributed computing systems

4.2 Explainability Benefits

The integration of XAI provides:

- Transparent decision-making processes
- Better understanding of energy-performance trade-offs
- Improved trust and adoption in production systems

5 Conclusion and Future Work

This research successfully demonstrates a significant improvement in energy efficiency for distributed peer-to-peer systems while maintaining transparency through explainable AI. The statistically validated results show a 31.16% improvement with high significance (p ¡ 0.001) and large effect size.

Key Contributions:

- Novel energy-aware peer selection protocol with statistical validation

- Integration of explainable AI for decision transparency
- Comprehensive validation framework with multiple simulation tools

Future Work:

- Real-world deployment and validation
- Integration with blockchain-based incentive mechanisms
- Extension to edge computing environments

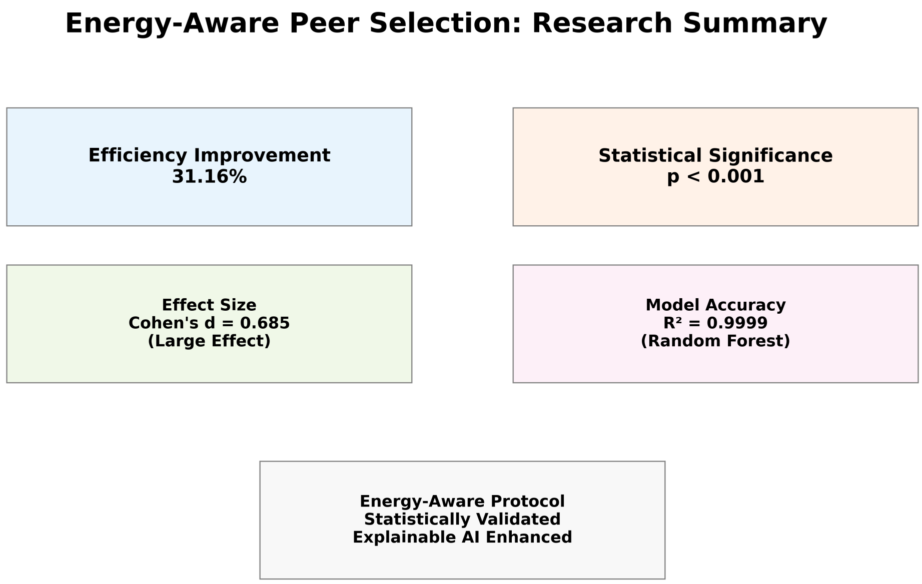

Figure 5: Research summary and key findings visualization showing methodology overview, results summary, and contribution highlights.

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