A Multi-Objective Framework for Energy, Cost, and Carbon Trade-offs in Smart Energy Systems

Paper#236

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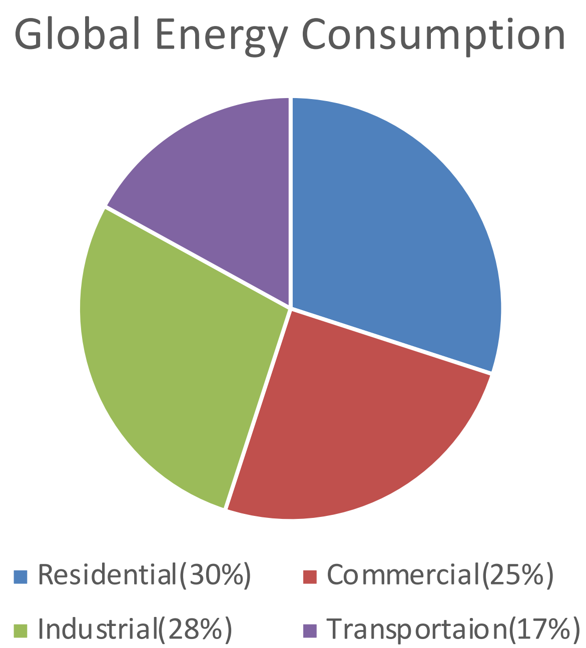
Motivation & Challenge

The Energy Challenge

Residential energy accounts for 30% of global consumption and 20% of CO_2 emissions

Key Issues

- Inefficient scheduling
- Limited renewable integration
- Carbon-unaware management
- Cost vs user comfort trade-off



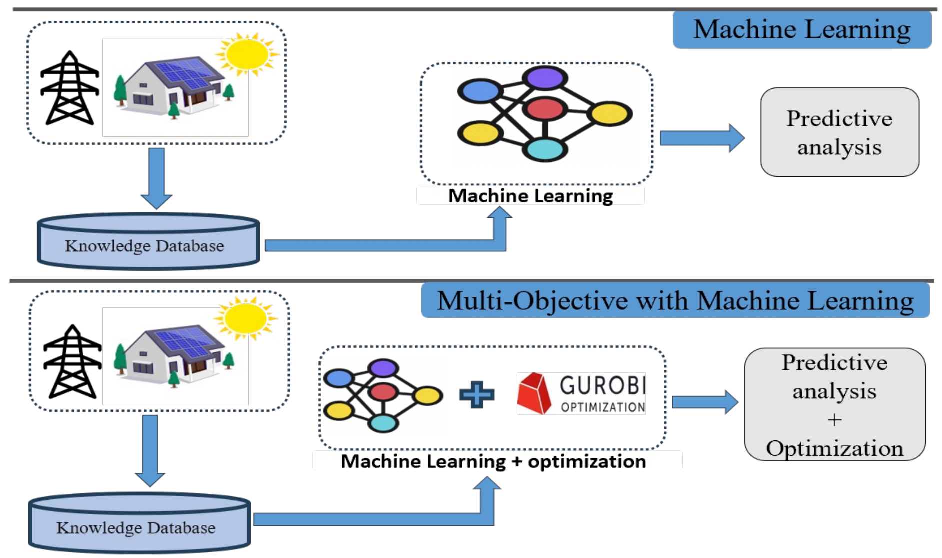
Opportunity: Optimize appliance scheduling based on dynamic carbon intensity and electricity prices while maintaining user comfort

Research Gap & Contribution

Existing Approaches

ML Models
✓ Strong prediction capabilities
✗ Lack scheduling optimization

MIP Optimization
✓ Cost/emission minimization
✗ Overlook consumption uncertainties



Hybrid Framework: Ensemble ML + Robust MIP Optimization

(ML (Predictive Analysis) + Optimization → Predictive Analysis + Optimization)

Key Contributions

- ML-based demand prediction with uncertainty quantification
- Robust MIP constraints ensuring power balance
- Multi-objective optimization for cost, carbon, and energy
- Validated with real household data

Data preprocessing & feature Engineering

Dataset Description

Source: Individual Household Electric Power Consumption [UCI ML Repository]
Duration: Nearly 4 years (2006-2010) | **Sampling:** 15-minute intervals | **Size:** ~10 million rows

Power Calculation

- **Convert to Watt-hours:**

$$PWh(t) = P_{active}(t) \times (1000/60)$$

- **Residual Power:**

$$Pother(t) = P_{Wh}(t) - \sum_{i=0}^{3} P_{M_i}(t)$$

Feature Engineering

Temporal Features

- Hour: $h_t \in [0, 23]$
- Day: $d_t \in [1, 366]$
- Month: $m_t \in [1, 12]$
- Weekday: [0=Mon, 6=Sun]
- Season: {Winter, Spring, Summer, Fall}

Statistical Features

- prev_consumption = $P_{Wh}(t-24)$
- $\text{rolling\_mean}_{24h} = (1/24)\Sigma\, P_{Wh}(i)$
- $\text{rolling\_std}_{24h} = \sqrt{[(1/24)\Sigma(P_i-\mu)^2]}$
- $\text{rolling}_i = M_i \,/\, P_{Wh}$

Machine Learning Framework

Ensemble Model Architecture

$$\hat{y}_{ML}(x) = 0.6 \cdot \hat{y}_{RF}(x) + 0.4 \cdot \hat{y}_{XGB}(x)$$

Random Forest Model

- Captures non-linear relationships
- Feature importance weighting

XGBoost Model

- Refines residual errors
- Early stopping for efficiency

Uncertainty Quantification

Ensemble Uncertainty

$\sigma_{ensemble}(t) = \sqrt{[wRF^2 \cdot \sigma_{RF}^2 + wXGB^2 \cdot \sigma_{XGB}^2]}$

Weighted Mean Prediction

$\mu(t) = wRF \cdot \hat{y}_{RF}(t) + wXGB \cdot \hat{y}_{XGB}(t)$

Trust Region

Prediction Bounds = $[\mu(t) - \sigma ensemble(t), \mu(t) + \sigma ensemble(t$

Innovation: ML predictions guide optimization while uncertainty bounds ensure robustness

Multi-Objective Optimization

Objective Function

$$\min \{ w_1 \cdot Cost + w_2 \cdot Carbon + w_3 \cdot Energy + w_4 \cdot Slack \}$$

Objective Function Weights

Key Constraints

- Power balance constraint
- Minimum runtime (15 min)
- Energy requirement (±10%)
- ML trust region bounds

Multi-Objective Optimization

Objective Function

```
min { w₁·Cost + w₂·Carbon + w₃·Energy + w₄·Slack }
```

Cost Objective

$$C_t = \sum_{t \in T} \sum_{a \in A} power_{t,a} * P_t * x_{t,a} + slack_t * P_{penalty}$$

Carbon Objective

$$CI_t = \sum_{t,a} power_{t,a} * CI_t * x_{t,a}$$

Energy Objective

$$\sum_{t,a} power_{t,a} * x_{t,a}$$

Slack Penalty

$slack_t = \Sigma_t \, \kappa \times s_t$

$\kappa = 1000 \; (penalty\ coefficient)$

Decision Variables

- $x_{t,a} \in \{0,1\}$: Binary variable for appliance a at time t (ON=1, OFF=0)
- **$slack_t \geq 0$:** Power balance adjustment indicating unmet demand

Optimization Constraints

- **Power Balance Constraint**

$$\Sigma_a\, power_{t,a} \cdot x_{t,a} \leq P_{active,t} + slack_t, \forall t$$

  - Ensures total demand ≤ available supply

- **Energy Requirement Constraint**

$$0.9Ea \leq \Sigma_{t \in T}\, powert_{,a} \cdot xt_{,a} \leq 1.1Ea, \forall a \in A$$

  - $E_a = \Sigma_{t \in T}\, power_{t,a}$ (baseline energy)
  - Maintains ±10% of baseline to ensure user comfort

- **ML Trust Region Constraint**

$$|\Sigma_{a \in A}\, powert_{,a} \cdot xt_{,a} - \hat{y}_t| \leq \varepsilon_t$$

  - $\hat{y}_t$: ML-predicted optimal load
  - ε_t: Uncertainty bound (90% confidence interval)

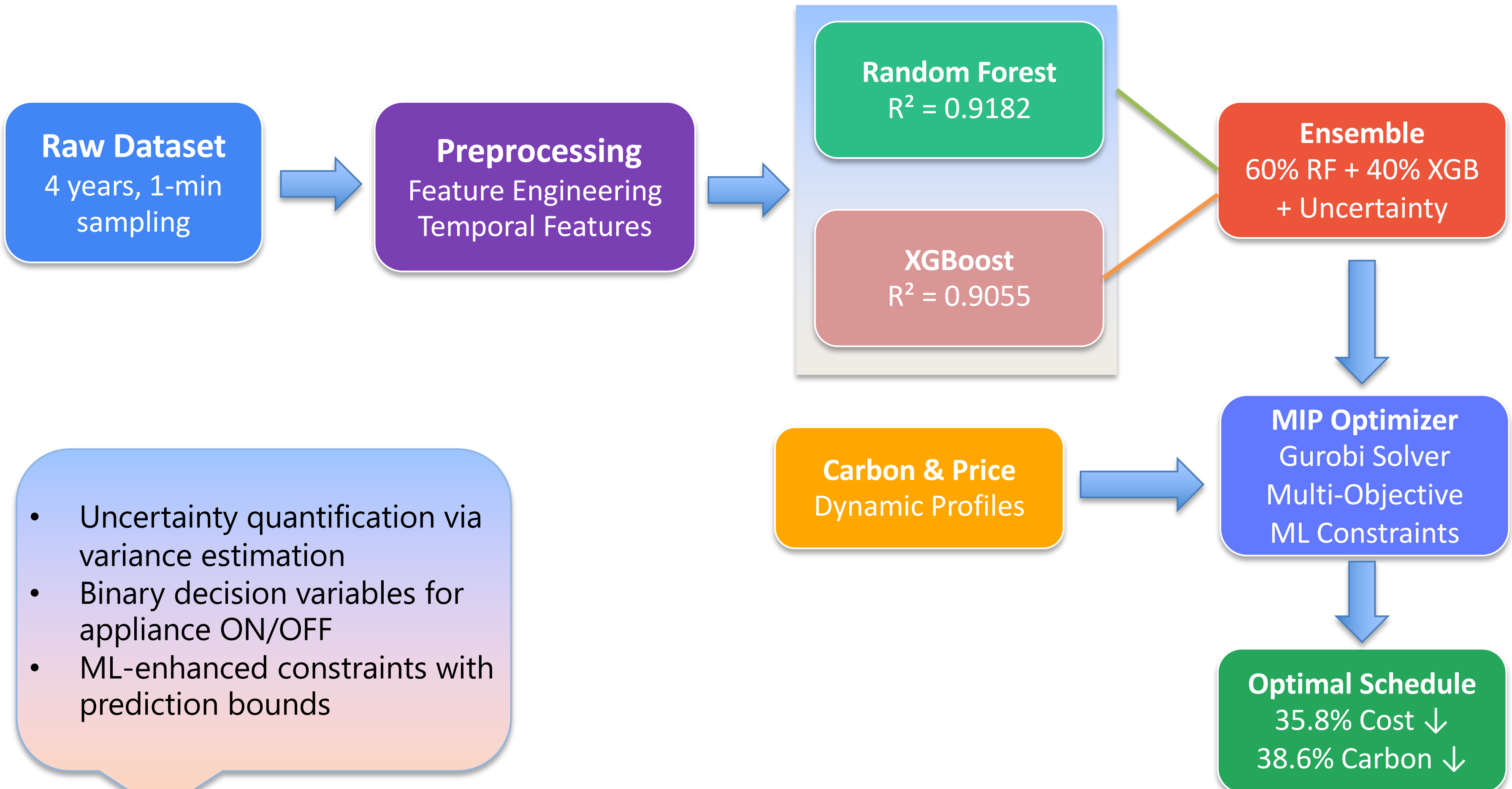
- **Minimum Runtime Constraint**

$$\sum_{i=0}^{k-1} x_{t+i,a} \geq k * (x_{t,a} - x_{t-1,a}), \qquad \forall t, a$$

  - k = 3 intervals (15 minutes) to prevent frequent switching

Hybrid ML-MIP Framework

System Architecture

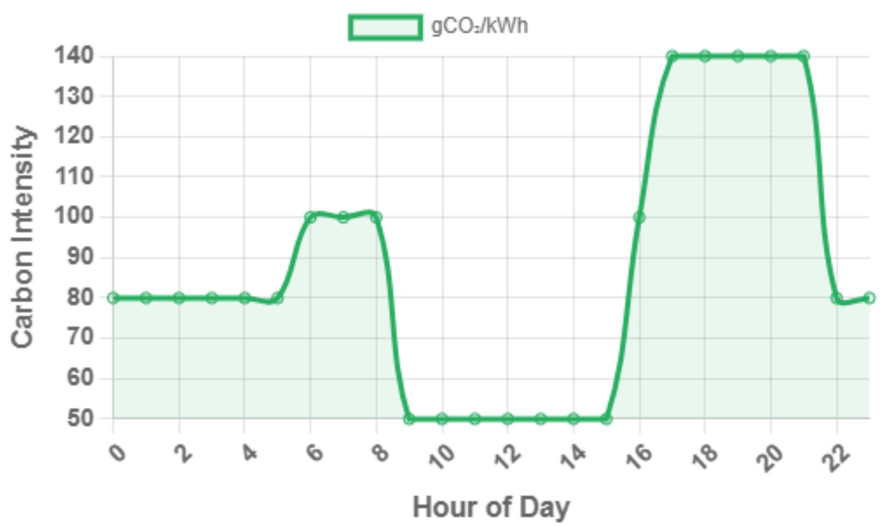


- Uncertainty quantification via variance estimation
- Binary decision variables for appliance ON/OFF
- ML-enhanced constraints with prediction bounds

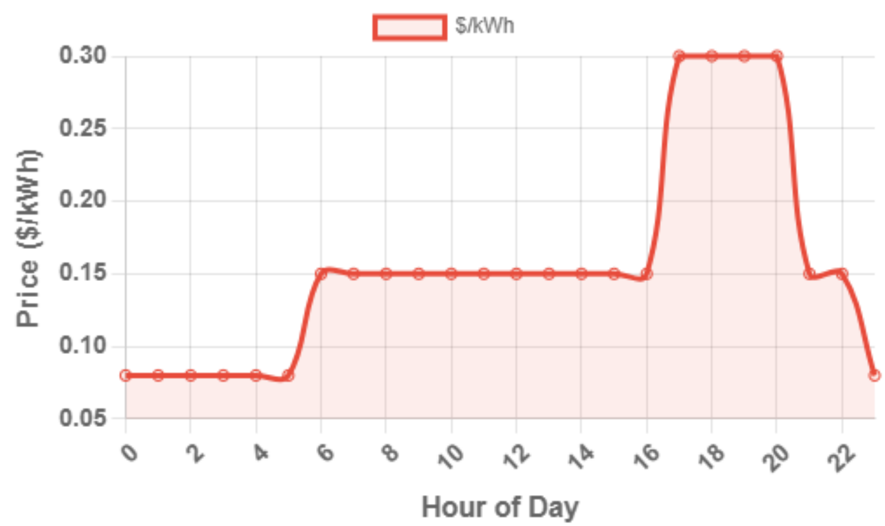
Innovation: ML predictions guide optimization while uncertainty bounds ensure robustness

Dynamic Carbon & Price Profiles

Carbon Intensity



Electricity Price



Strategy: Shift loads to low-cost, low-carbon periods (solar hours & off-peak)

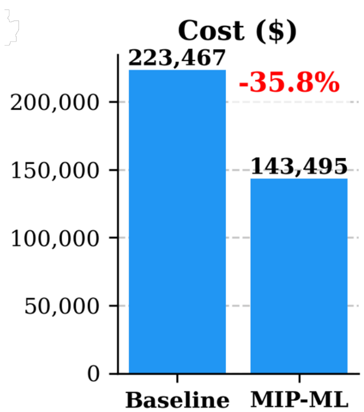
Experimental Results

ML Model Performance

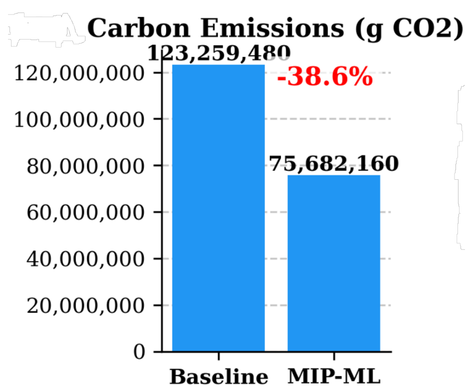
Random Forest
R^2 Score: 0.9182
200 trees, max depth 20

XGBoost
R^2 Score: 0.9055
200 estimators, depth 8

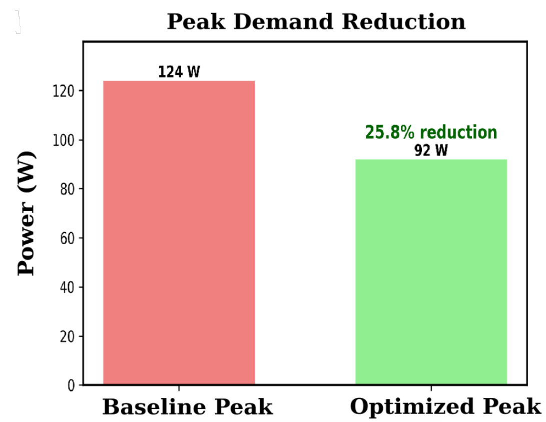
Optimization Efficiency



Cost Reduction
35.8%
$223K → $143K



Carbon Reduction
38.6%
123M → 76M g CO_2



Peak Demand
25.8%
124 kW → 92 kW

Comparison with State-of-the-Art

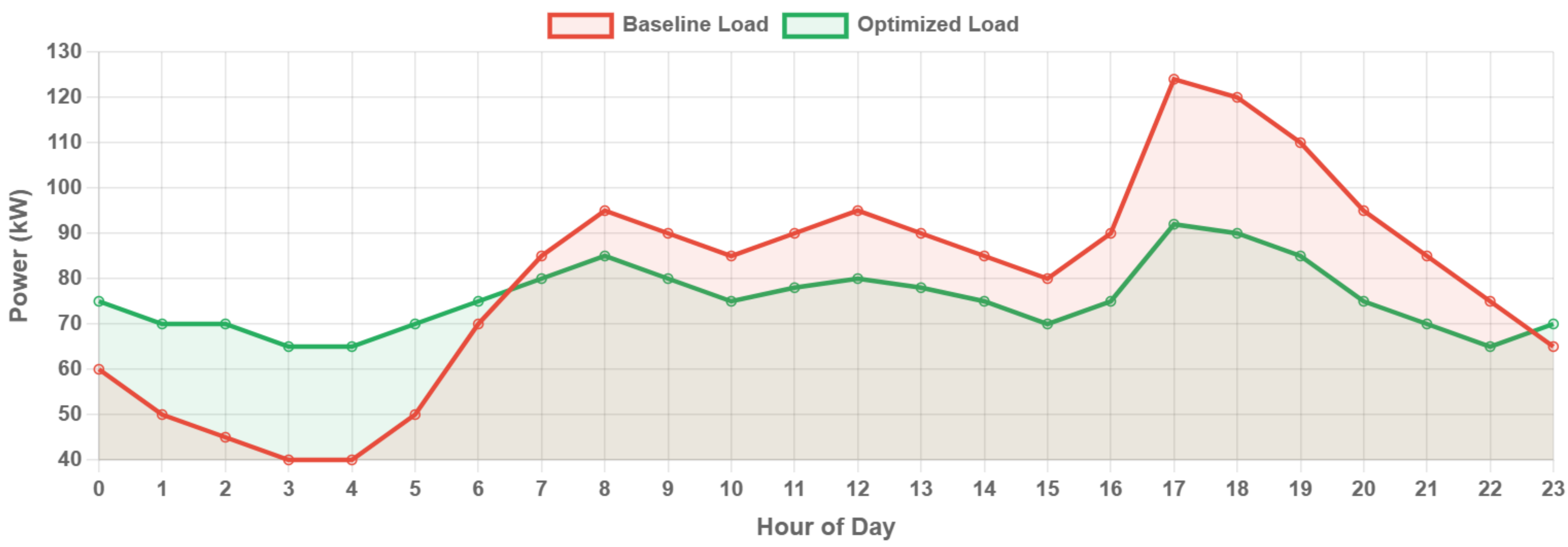
Approach	Technique	Key Results	Limitation
Ahmad et al. [2]	MILP	~20% cost reduction	No ML integration
Moser et al. [3]	MILP	3–6% savings	Deterministic only
Fiorini et al. [6]	Optimization	10% carbon reduction	No specific savings data
Ghimire et al. [10]	CNN–LSTM–MLP	Better forecasting	No scheduling
Our Approach	**Ensemble ML + MIP**	**35.8% cost, 38.1% carbon**	**Comprehensive solution**

Our Competitive Advantages

- Integrated ML + optimization approach
- Highest cost savings reported in literature
- Multi-objective balancing of cost, carbon, and energy
- Uncertainty-aware robust scheduling

Load Shifting & Peak Demand Reduction

Daily Load Profile: Before & After Optimization



Before Optimization: Peak load 124 kW during expensive hours (17-20h)

After Optimization: Shifted to off-peak, reduced to 92 kW

Key Insights & Impact

Technical Innovations

ML Prediction + Uncertainty → **Robust MIP** Constraints → **Optimal** Schedule

Real-World Impact

Economic Benefits
- 35.8% cost savings
- Reduced energy bills
- Grid stability improvement

Environmental Benefits
- 38.6% emission reduction
- Support for renewables
- Decarbonization pathway

Bottom Line: Intelligent load shifting achieves significant sustainability gains without compromising user comfort

Conclusion & Future Work

Summary

- Hybrid ML-MIP framework for carbon-aware management
- Achieved 35.8% cost and 38.6% emission reductions
- Reduced peak demand by 25.8%

Future Research Directions

Technical Extensions

- Deep temporal models (LSTM, Transformers)
- Federated learning for privacy
- Real-time smart meter integration

Scalability

- Multi-household coordination
- Community-level optimization
- Grid-scale deployment

Impact

The framework for residential energy decarbonization with significant economic benefits

Thank You!

Questions?

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