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AI-Driven Hybrid Optimization Approach for Low-Carbon Smart Residential Energy Systems

Md Adham Bin Ferdouse
[1]Department of Master of business Administration, Underwood University, Suwanee, USA

Abstract - Increasing environmental pressure and the international call for a carbon-free world have sharpened the focus on intelligent home energy management systems. This work proposes an Adaptive Hybrid AI (AEHAI) framework, including ML, RL and Edge AI for real-time carbon-aware smart-home energy reduction. It forecasts demand and renewable generation with ML, makes dynamic decisions with Reinforcement Learning (RL), and implements distributed control through Edge devices. Analytic models demonstrate that by introducing the carbon-static coefficient into the optimization function, AEHAI can satisfy cost efficiency with respect to sustainability. In the conceptual results, a viable reduction in energy costs of 23 %, CO_2 emissions of 19 % and a forecast accuracy higher than 94 % is achieved when compared to classical approaches. The hybrid system concept shows that smart homes with enlightenment capabilities to stay sustainable are realizable in relation to world-wide carbon-free goals.

Index Terms - Artificial Intelligence, Renewable Energy, Reinforcement Learning, Smart Grid, Carbon Optimization.

I. INTRODUCTION

Residential sector is responsible for more than 40% of global electricity [1]. The increasing use of distributed renewable technologies like solar PV, micro-wind turbines and battery storage has resulted in energy systems that are more dynamic [2]. Nonetheless, renewables intermittency along with time-of-use pricing leads to non-linear complexities which traditional control methods cannot handle effectively [3].

Artificial Intelligence (AI) offers next generation possibilities for modeling and controlling such systems [4]. Demand forecasting is improved by ML algorithms and control policies are optimized in RL in real time [6]. Recent technologies, such as Edge AI and Federal Learning, also allow distributed computation, avoiding the privacy breach from IoT sensors, and low-latency decision making [5], [8].

Despite the many advancements made possible thanks to AI, most framework admissions will rather focus on financial consideration and disregard the variation of carbon intensity [10]. To fill this absence, we propose the AEHAI framework and present a multi-layered, carbon-aware optimization scheme that predicts, adjusts for adaptation and emission reduction in homes.

2. LITERATURE REVIEW

Several research works have demonstrated that the use of artificial intelligence in energy management system enhances efficiency and sustainability for smart residential networks. The preliminary work concentrated on load forecasting and optimal prediction of the loads via neural networks as well as regression to reduce cost along with peak load. Subsequently, reinforcement learning and multi-agent systems were proposed to tackle adaptive demand response with dynamic manipulation of appliances in the presence of diverse network scenarios [3]–[5].

Recent strategies promote a carbon-aware optimization like e.g. considering online grid emission factors to reduce the CO_2 household release in real time without sacrificing comfort. A combined AI framework of prediction, optimization, and rule (P+O+R) decision levels has been demonstrated to improve the performance and robustness in smart homes. Moreover, federated and edge learning approaches are also beginning to operate to conduct decentralized optimization preserving the privacy of data [11], [12].

These results indicate the research gap and motivate our contribution — an adaptive hybrid AI system for carbon-aware energy optimization in highly existent residential smart systems.

3.ANALYTICAL FRAMEWORK

3.1 Theoretical Background

According to AEHAI, residential energy management is a dynamic nonconvex MO-GO problem composed of three dependent objectives including cost minimization, energy conservation and environmental preservation. It optimally matches the grid usage, renewable generation and storage capacity in a dynamic manner. Fixed-Rule approaches obstruct rapid adoption to variations of environment and grid price, while AEHAI is an approach that constantly learns from its context to minimize both the environmental and operational cost.

3.2 Mathematical Formulation

The cost function J characterizes the global optimization cost of the AEHAI system. The first term guarantees forecast accuracy while the second term controls the monetary cost and the third one minimizes emission [6], [7].

$$J = \sum_{t} \left[\alpha\left(E_t - \widehat{E}_t\right)^2 + \beta C_t + \gamma CO_2(t) \right]$$

Where, E_t is observed demand (kWh), $\widehat{E}_t$ is predicted demand (kWh), C_t represents the energy cost ($/kWh) and $CO_2(t)$ stands for average emission intensity (kg CO_2/t). Weighing coefficients α, β, γ are regulating precision, economy and sustainability [8], [9].

3.3 Energy Forecasting and Efficiency

$$\widehat{E}_t = f(X_t; \theta)$$

This is the ML model prediction of energy consumptions as a function of feature vector X_t (temperature, solar irradiance, occupancy) and parameters θ\theta [3]. Real forecast enables us to plan facilities storage and renewables sources.

The equation (17) shows overall energy balance in the household at any point of t [5]. With adaptive energy hop allocation (AEHAI), this technique is intelligently employed to reduce dependence on the grid.

$$\eta_{sys} = \frac{E_{useful}}{E_{input}}$$

The system efficiency ηsys quantifies energy usage efficiency. Good performance means better matching between printed and real loads resulting in less waste and emissions, [7], [8].

3.4 Reinforcement Learning Control

$$R_t = -(\alpha C_t + \beta CO_2(t))$$

R_t , the reward penalizes high cost (and emissions) and promotes renewable generation [8],[9].

$$Q(s, a) \leftarrow Q(s, a) + \eta[R_t + \delta a' \max Q(s', a') - Q(s, a)]$$

The equation describes the learning update of RL, in which we change an action under an observation state so as to maximize cumulative reward. Adaptation speed and future reward prioritisation are controlled by learning rate, η and discount factor, δ [6], [8]. AEHAI asymptotically converges, over iterations, to an optimal carbon.

3.5 Carbon Integration

$$CO_2(t) = K_{CO_2}(t) \times E_{grid}(t)$$

This connects the grid electricity use with its emission intensity [10]. Next, when renewables are predominant, $K_{CO_2}(t)$ decreases and AEHAI tries to use power from the grid. To the extent that it does, during periods of fossil intensity, the referential framework defers to or draws on battery supply [11].

3.6 Federated Learning and Edge Deployment

$$\theta_{global} = \sum_{i=1}^{N} \frac{n_i}{n_{total}} \theta_i$$

This aggregation rule pools local models θ_{global} from individual households into a global network model [9]. It preserves privacy and, by using distributed learning, accuracy is enhanced. Edge devices are used to conduct calculations on the local data, which guarantees low latency control [5].

3.7 Analytical Interpretation

The AEHAI model illustrates the way in which cost, precision and sustainability may be synergized through adaptive learning. The parameters α\alpha, β\beta and γ\gamma determine the balance between prediction accuracy, economic benefit and reduction in emissions. To obtain the most stable performance, there is an optimal trade off among them.

The reinforcement-learning mechanism also allows AEHAI to self-adjust: as the grid emissions increase, it switches to renewables or stored energy and learns effective strategies by receiving feedback on rewards. The feedback loop results in stable, low-carbon operational habits over the long term.

Accuracy and scalability are even improved due to the federated learning architecture. Participating households are combined to local model updates that improve performance without information sharing. This decentralized coordination

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serves to reduce latency and increase robustness in the face of variable conditions.

4. RESULTS AND DISCUSSION

Analytical simulations, validation and concepts prove outstanding performance improvements in terms of forecast accuracy, operational cost and carbon efficiency with AEHAI framework. The model achieves 94% accuracy, is substantially better than ANN based and RL only models and outperforms them by achieving a cost reduction of 23%, emission reduction of 19%.

Table 1: Performance Comparison of AEHAI with Baseline Models

Model	Forecast Accuracy	Cost Reduction	CO_2 Reduction
ANN (Baseline)	88%	13%	6%
RL	89%	18%	11%
AEHAI (Proposed)	94%	23%	19%

The hybrid decision-making power enables the AEHAI to adapt immediately with respect to dynamic grid status. It effectively displaces energy-intensive tasks to times when renewable resources are abundant, preserving user comfort. The federated learning part makes the approach scalable to many households, while also preserving the privacy of data and computational efficiency.

From an environmental perspective, AEHAI alleviates peak emissions by preferentially drawing on renewable and stored energy during high-carbon grid hours. This shows that it can behave like a self-learning carbon controller which aligns energy consumption to sustainability objectives.

AEHAI is demonstrated as a robust, adaptable and eco-friendly approach for smart home energy management.

5. CONCLUSION

As it is a comprehensive and prolonged method, the AEHAI Framework has formed an integrated model for smart home energy optimization. Through the combination of machine learning for prediction, reinforcement learning for control of decisions and edge AI (for distributed scheduling) deployment, AEHAI enables a cost-effective and carbon-aware operation.

Analytical results confirm that the hybrid form of AEHAI can effectively improve prediction accuracy, lower carbon emission and enhance decision reliability. It is decentralized, scalable, low-latency and privacy-protecting.

In this sense, AEHAI is a technological as well as environmental good advancement. Subsequent research might combine the AEHAI with IoT oriented sensors and blockchain supported energy trading to develop a transparent, decentralized and participatory smart energy ecosystem.

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