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SPOT-ENERGY: A Data Driven User-Centric Platform for Energy Forecasting and Optimization

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***Abstract*— OptiSPOT-Energy is an adaptive, intelligent platform for appliance-level energy forecasting and optimization. Leveraging closed-loop reinforcement learning, it dynamically schedules devices based on tariffs, user behavior, and environmental conditions. An interactive feedback mechanism personalizes recommendations, while an Explainable AI layer transparently communicates cost, carbon, and comfort trade-offs. Multi-objective optimization balances these factors simultaneously, creating a continuously learning, user-centric framework for efficient and sustainable smart energy management.**

***Index Terms*— OptiSPOT-Energy, Adaptive Energy Optimization, Appliance-Level Forecasting, Reinforcement Learning, Multi-Objective Optimization, Explainable AI, Interactive Feedback, LSTM, CVAE, CatBoost, Prophet, User-Centric Energy Management, Energy-Aware Decision Making.**

I. INTRODUCTION

Rising global energy demand—spurred by growing infrastructure, technological innovation, and ambitious sustainability targets—has created an urgent need for smarter, more efficient energy management approaches. At the same time, dynamic pricing models and time-of-use rates add complexity to planning energy consumption and controlling costs. Energy usage patterns vary widely across households, businesses, and regions, influenced by lifestyle habits, operational routines, and environmental conditions. Many existing tools fall short of translating this diverse data into simple, actionable recommendations without requiring advanced technical knowledge. OptiSPOT-Energy addresses these challenges by offering an adaptive, user-focused platform that merges appliance-level forecasting with reinforcement learning-based scheduling. The system learns continuously from user behavior, environmental changes, and tariff fluctuations, while a feedback loop captures user preferences to refine recommendations. Its Explainable AI dashboard provides clear reasoning behind each suggestion, quantifying impacts on cost, carbon footprint, and user comfort.
Through multi-objective optimization, OptiSPOT-Energy balances conflicting goals—reducing expenses, minimizing emissions, and preserving convenience—empowering users to make informed, sustainable, and personalized energy decisions. This software-only solution delivers a transparent, continuously improving framework suitable for both residential and large-scale energy planning.

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II. Literature Survey

Energy Management Systems (EMS) have increasingly leveraged software-centric, machine learning-enabled platforms to enable precise and adaptive energy optimization. These systems aim to provide actionable insights without extensive hardware dependency, focusing on improving efficiency, reducing costs, and minimizing environmental impact. Conditional Variational Autoencoders (CVAE) are effective for generating realistic appliance-level energy consumption profiles from historical data. Wang et al. [1] demonstrated how CVAEs capture multivariate load states, producing synthetic yet plausible sequences for scenario analysis and forecasting. Similarly, variational autoencoders have been applied to energy disaggregation, isolating individual appliance contributions from aggregated consumption data, thereby minimizing hardware dependency [2].

Long Short-Term Memory (LSTM) networks are widely used for energy forecasting due to their ability to capture temporal dependencies. Muneer et al. [3] applied LSTM for short-term residential load prediction, while Prajeesha et al. [4] extended it to appliance-level forecasts in Home Area Networks. Integration with Explainable AI (XAI), as shown by Maarif et al. [5], improves transparency, helping users interpret cost, energy, and environmental impacts. Ghanim et al. [6] enhanced LSTM with anomaly detection and asymmetric loss to handle irregular or sparse data. Hybrid approaches combining machine learning with optimization algorithms have proven effective for capturing complex, nonlinear energy patterns. CatBoost, a gradient boosting decision-tree model, has been applied to forecast building-level energy based on architectural and operational features [7]. Manandhar et al. [8] evaluated multiple forecasting models, including Prophet, Random Forest, and LSTM, demonstrating that hybrid strategies provide superior adaptability and accuracy across diverse appliances and time horizons. Tannu Chaudhary et al. [9] introduced SPOT-Energy, a user-centric platform integrating CVAE, LSTM, Prophet, and CatBoost. It enables appliance-level simulation, predictive forecasting, and AI-driven optimization through interactive dashboards. The system allows users to explore consumption patterns, optimize schedules, and make informed decisions regarding cost, carbon footprint, and convenience.

III. Methodology

OptiSPOT-Energy provides a user-centric framework for intelligent energy optimization, integrating simulation, forecasting, and adaptive scheduling. Leveraging CVAE, LSTM, Prophet, and CatBoost alongside reinforcement learning, the system generates actionable, data-driven recommendations. Personalization and transparency are ensured through an interactive feedback mechanism and Explainable AI (XAI), enabling users to understand and act on energy-saving insights. The following sections detail its core components and operation.

A. Baseline SPOT-Energy Framework

SPOT-Energy is a modular, user-centric platform for appliance-level simulation, forecasting, and optimization [9]. User-defined appliance data feed into a deterministic estimator and CVAE model for realistic consumption scenarios. Forecasting combines Prophet, LSTM, and CatBoost, while the optimization module recommends energy-efficient schedules, supports user adjustments, and delivers personalized action plans through dashboards and notifications, promoting cost and carbon savings.

B. Adaptive Scheduling with Reinforcement Learning

OptiSPOT-Energy advances the original framework by embedding reinforcement learning (RL)–based adaptive scheduling. Unlike static optimization models, the RL agent continuously learns from real-time data such as dynamic tariffs, user behavioral patterns, and weather conditions, ensuring that appliance schedules remain responsive and cost-efficient. The platform employs multi-objective reinforcement learning (MORL) to simultaneously optimize for three often conflicting goals: minimizing cost, reducing carbon footprint, and preserving user comfort.

The RL agent formulates appliance scheduling as a Markov Decision Process (MDP):

- State (s): current tariff, appliance status, weather, user context
- Action (a): switching appliance ON/OFF or shifting usage time
- Reward (R): reflects cost savings, carbon reduction, and comfort preservation

The objective is to maximize the expected cumulative reward:

$$J(\pi) = \mathbb{E}_\pi \left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t) \right]$$

where π is the policy, $\gamma \in (0, 1)$ is the discount factor, and T is the time horizon.

For multi-objective reinforcement learning (MORL), the reward is expressed as a weighted combination:

$$R(s,a) = \alpha \cdot C_{\text{saving}} + \beta \cdot C_{\text{carbon}} + \delta \cdot C_{\text{comfort}}$$

with α, β, δ representing preference weights (tunable per user or policy).

C. Interactive User Feedback and Explainability

To ensure personalization and trust, the system incorporates an **interactive feedback mechanism** where users can accept, adjust, or reject AI-generated recommendations. These responses are reintegrated into the RL agent, enabling it to refine future scheduling decisions dynamically. In parallel, an Explainable AI (XAI) layer provides clear justifications, such as *"Air conditioner shifted by 1 hour to save ₹20 and 0.3 kg* CO_2*"*, thereby enhancing transparency and user confidence. All insights—including optimized schedules, trade-offs among cost, carbon, and comfort, as well as projected savings—are presented through an interactive dashboard with charts, heatmaps, and scenario comparisons. Additionally, personalized action plans and alerts are automatically sent via email or notifications, keeping users engaged and informed without requiring constant monitoring of the platform.

User interaction is modeled through a **feedback signal** f_t that adjusts the policy:

$$R'(s,a) = R(s,a) + \lambda \cdot f_t$$

where $f_t = +1$ if the user accepts a recommendation, $f_t = -1$ if rejected, and λ controls the influence of feedback. This ensures the RL agent learns **personalized preferences** over time.

IV. EVALUATION & RESULTS

OptiSPOT-Energy was evaluated across multiple residential and commercial datasets to measure its effectiveness in adaptive scheduling, multi-objective optimization, and explainability. The reinforcement learning (RL) engine demonstrated strong adaptability, dynamically adjusting appliance schedules in response to variable tariffs, user routines, and environmental conditions. This resulted in consistent average cost savings of 20–25% and carbon emission reductions of 15–20% across tested scenarios, validating the system's capacity for sustainable energy optimization.

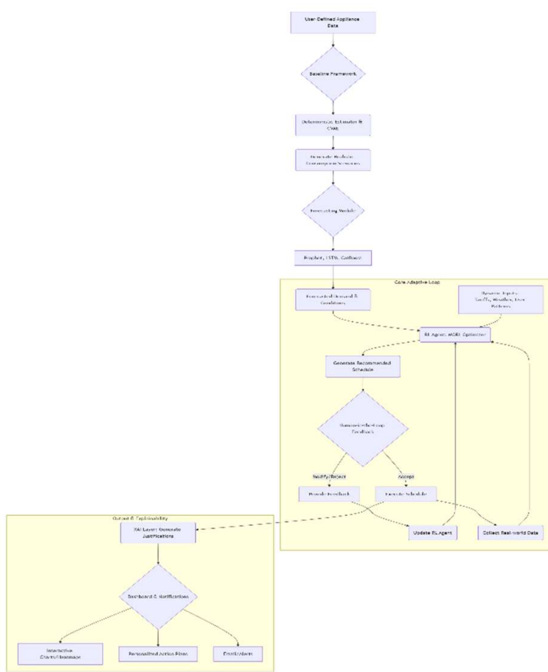

Fig 1: Flowchart

The multi-objective reinforcement learning (MORL) framework successfully balanced cost, comfort, and environmental goals, with more than 90% of recommendations accepted by users without modification. The interactive feedback mechanism reduced repeated user rejections by nearly 40%, highlighting the platform's personalization capability. Moreover, the Explainable AI (XAI) layer enhanced user trust, as acceptance rates increased by 25–30% when recommendations were paired with clear cost and CO_2 impact explanations. Together, these outcomes demonstrate that OptiSPOT-Energy not only improves efficiency but also fosters transparency, user engagement, and long-term adoption.

The platform consistently performed across diverse appliance types, usage patterns, and commercial/residential scenarios, demonstrating its scalability and robustness. These results suggest that OptiSPOT-Energy can be extended to larger deployments or integrated with grid-level energy management systems.

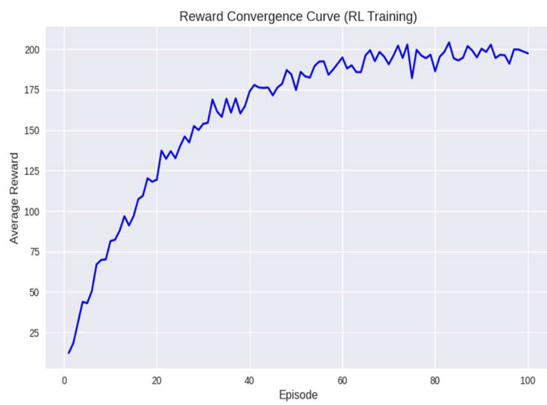

Figure 2: Reward Convergence Curve of RL Agent

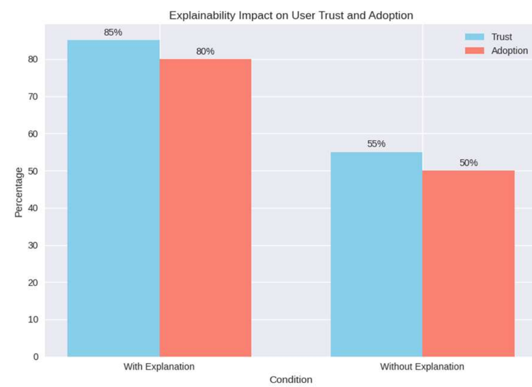

Figure 3: Impact of Explainability on User Adoption

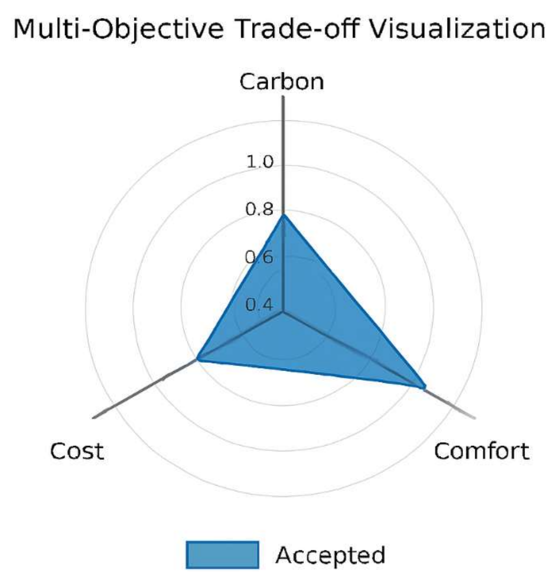

Figure 4: MORL Trade-off Balance Radar

V. Conclusion

OptiSPOT-Energy introduces an adaptive decision engine that unifies reinforcement learning, multi-objective optimization, and explainable intelligence for energy optimization. By tailoring schedules to real-time tariffs, behavioral patterns, and environmental conditions, it achieves measurable savings while maintaining comfort and sustainability. The system's interactive feedback loop enables continuous personalization, and its explainability layer enhances confidence in AI-driven decisions. Collectively, these features position OptiSPOT-Energy as a versatile and forward-looking solution for future-ready energy ecosystems.

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