Power Efficient EV Charging in Smart Grids Using Interval Type-2 Fuzzy Control

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***Abstract*—The growing number of Electric Vehicles (EVs) is putting extra pressure on power grids, mainly because of the uncoordinated way of charging. In this work, we utilize an Interval Type-2 Fuzzy Logic Control (IT2FLC) to manage EV charging and address uncertainty arising from load changes and battery conditions. The method decides charging levels based on the current grid load, expected peak limits, and the vehicle's remaining battery capacity. Furthermore, the Karnik–Mendel type-reduction algorithm is employed to transform the interval type-2 fuzzy output into a type-1 set before centroid defuzzification, improving robustness under uncertainty. This results in a robust and flexible control strategy that not only reduces peak demand and improves energy distribution but also contributes to a more sustainable and resilient smart grid. Simulation results indicate a peak load reduction of about 25%-30%, while optimized load profiles remain below the maximum grid capacity. Charging activities were redistributed, with 40%-50% shifting to off-peak hours and fluctuations being reduced by 35%.**

***Index Terms*—Electric Vehicle, Charging Coordination, Efficient Charging, Fuzzy Logic, Smart Grid stability, Interval Type-2 Fuzzy Logic, Peak Load Reduction, Uncertainty.**

I. Introduction

Optimizing electric energy consumption in EVs is a critical challenge in the development of sustainable transportation [1], [2]. The use of intelligent control systems enables energy management, leading to reduced fuel consumption and lower greenhouse gas emissions [3], [4]. Also, smart control systems enhance vehicle reliability and performance across varying driving conditions by adapting to real-time changes [5], [6]. Furthermore, researchers deal with other significant challenges, such as the uncertainty associated with renewable energy sources [7], [8]. According to the work of Ang et al. [9], the variable nature of renewables imposes complexity in maintaining a stable energy supply. They proposed a fuzzy-cloud theory-based framework for microgrids that effectively reduced uncertainty and optimized energy consumption. Optimizing fuel usage is another prevalent challenge in variable traffic conditions. Jia et al. [10] developed a Model Predictive Control (MPC) strategy integrated with adaptive cruise control, demonstrating significant reductions in fuel consumption for hybrid vehicles. Additionally, driver behavioral variability significantly affects EV energy consumption [11], [12]. Al-Wreikat et al. [13] emphasized that neglecting realistic driving patterns can distort energy models. To address grid-level energy management, Viegas et al [14] proposed a fuzzy logic-based system for EV-integrated smart grids. Their method, which compared metaheuristic optimization with Type-1 fuzzy controllers, demonstrated superior performance in cost minimization and real-time charging/discharging coordination, particularly under dynamic grid conditions. In summary, employing energy consumption approaches in smart vehicles, like predictive algorithms and fuzzy logic frameworks, improves system efficiency and reduces energy usage under uncertainty, which in turn contributes to economic and environmental sustainability [15]–[18]. As a key innovation in this study, we extend the foundational work of Mets et al. [19] and Ahmed et al. [20] by incorporating IT2FLC into a grid-aware coordinated EV charging control strategy to manage uncertainties in base load, SOC, and EV availability. Unlike previous approaches that rely on deterministic or heuristic methods, our framework explicitly handles real-world uncertainties, including variations in EV arrival/departure times, state-of-charge fluctuations, base load variability, and sharp charging peaks, using interval type-2 fuzzy sets.

Briefly, our contributions in this paper are as follows:

- Presenting an efficient Interval Type-2 Fuzzy Inference improves energy distribution and contributes to a more sustainable and resilient smart grid.
- Using IT2FLC with Karnik–Mendel type-reduction algorithm, enabling precise defuzzification and adaptive control to enhance decision accuracy.
- Presenting a robust and flexible control strategy that is grid efficient with reduced peak demand and improved load uniformity.

The paper is further organized into the following sections: Section 2 reviews the related works to the study. Section 3 details the proposed methodology and control framework introduced, Section 4 is about Energy Control Strategies, Section 5 discusses simulation results, and Section 6 provides the conclusion.

II. Related Work

Among the key challenges in sustainable EV development, optimizing electric energy consumption remains critical [21], [22]. This article aims to address newly presented ideas on the

979-8-3315-8138-1

intelligent energy management strategies to enhance both vehicle and grid performance. Chelladurai et al. [23] introduced an IT2FLC in an EV charging system with bidirectional converters, demonstrating superior voltage stabilization and harmonic reduction compared to Type-1 and GA-optimized controllers. Also, Nanibabu et al. [24] applied Frilled Lizard Optimization (FLO) in a DSM-based smart grid model, achieving up to 48.18% peak load reduction; this approach lacked uncertainty management. Bekiroglu et al. [25] proposed a peak shaving strategy using flywheel energy storage systems to balance EV charging loads, resulting in reducing load fluctuations from 230 kW to 123 kW. However, this approach did not include real-time adaptability or uncertainty modeling. Zhang et al. [26] presented a DRL-based integrated thermal and energy management system for connected Plug-in Hybrid Electric Vehicles (PHEVs), achieving 9.6% fuel savings. Zhang et al. [27] developed a two-stage PSO-based charging/discharging strategy incorporating elastic demand response and virtual SOC, achieving 40% to 110% cost savings. However, it lacked adaptability and explicit uncertainty handling. Das et al. [28] proposed a comprehensive multi-objective optimization model for EVs in home microgrids, which reduces costs and grid consumption, yet relied on static models without adaptive control. Sellali et al. [29] developed an EMS algorithm for fuel cell EVs to reduce cost and battery degradation, while Ali et al. [30] introduced an OEC scheme with GA-tuned LPV control for balancing speed and energy use. Rehman et al. [31] explored renewable-based EV charging with 2 MW solar and 1.2 MW wind integration, achieving 45% grid energy reduction and 41% CO2 emission cuts but lacking real-time charging control. Hu et al. [32] used MPC to minimize total cost in hybrid EVs, including degradation effects, yet did not address interactive grid behavior. Xin et al. [33] proposed an MPC-based strategy for EV level coordination and interpretability. While these studies offer important contributions to EV energy optimization, many either focus on onboard performance, assume deterministic conditions, or do not address uncertainty in a structured and interpretable way.

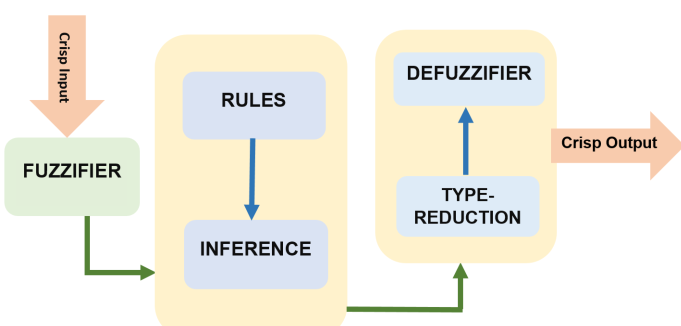

Fig. 1. Interval Type-2 Fuzzy Logic system main stages [34].

III. Proposed Methodology and Control Framework

A. Fuzzy Logic-Based Control Architecture

While Type-1 fuzzy logic systems offer an intuitive and computationally efficient framework for managing imprecision, their reliance on fixed membership functions limits their ability to capture higher-order uncertainties commonly encountered in real-world applications. These limitations have led to the development of a Type-2 fuzzy logic system, which extends the traditional approach by allowing the membership functions themselves to be uncertain. In this section, we propose a novel method for optimizing smart energy control strategies for EV charging by employing IT2FLC. Fig.1 illustrates the main components of the IT2FLC system, which are described as follows [19], [20]:

1) Interval Type-2 Fuzzifier: The inputs $L_b(t)$, $P_{peak}(t)$, and $C_{battery}$ are described with three linguistic terms, including Low, Medium, and High, using the IT2FLC set . Each fuzzy set $\tilde{A}(x)$ can be represented as:

$$\tilde{A}(x) = \langle \underline{\mu}_A(x), \overline{\mu}_A(x) \rangle \tag{1}$$

2) IT2FLC Inference: This inference system generates interval-valued fuzzy outputs based on Mamdani-IT2FLC rule set. Table I lists the 27-rule set, which maps the inputs $L_b(t)$, $P_{peak}(t)$, and $C_{battery}$, which are described by the terms including Low/Medium/High to the charging rate command $u(t)$. The 27-rule set implements a peak-shaving and valley-filling strategy: charging is increased under low-peak situations, regulated at medium demand, and decreased during peak periods. Moreover, u(t) decreases as $C_{battery}$ increases to prioritize low-charge states while limiting grid stress.

3) IT2FLC Type Reduction and Defuzzification: The iterative KM algorithm turns the Type-2 output into a Type-1 output by finding its centroid bounds. The process involves the following steps:

- Compute the left and right endpoints of the type-reduced set as:

$$y_L = \frac{\sum_{i=1}^{N} w_i^{(L)} y_i}{\sum_{i=1}^{N} w_i^{(L)}}, \quad y_R = \frac{\sum_{i=1}^{N} w_i^{(R)} y_i}{\sum_{i=1}^{N} w_i^{(R)}} \tag{2}$$

  where y_i are the rule consequents, and $w_i^{(L)}$, $w_i^{(R)}$ are selected from the lower and upper membership weights based on the current estimate of the centroid.
- Determine the type-reduced set as the interval $[y_L, y_R]$ through the iterative KM procedure.
- Perform defuzzification using the *centroid method*, where the crisp output is:

$$y_{\text{crisp}} = \frac{y_L + y_R}{2} \tag{3}$$

B. Adaptive Control Strategies for EV Charging

The output of the proposed IT2FLC is designed to be smooth and reliable even under dynamic and uncertain operating conditions. The controller generates the optimal charging rate $u(t)$ that is adapted in real time based on the current base

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TABLE I
FUZZY RULE BASE FOR IT2FLC CONTROLLER

$L_b(t)$	$P_{\text{peak}}(t)$	C_{battery}	$u(t)$
Low	Low	Low	High
Low	Low	Medium	High
Low	Low	High	Medium
Low	Medium	Low	Medium
Low	Medium	Medium	Medium
Low	Medium	High	Low
Low	High	Low	Medium
Low	High	Medium	Low
Low	High	High	Low
Medium	Low	Low	High
Medium	Low	Medium	High
Medium	Low	High	Medium
Medium	Medium	Low	Medium
Medium	Medium	Medium	Medium
Medium	Medium	High	Low
Medium	High	Low	Medium
Medium	High	Medium	Low
Medium	High	High	Low
High	Low	Low	Medium
High	Low	Medium	Medium
High	Low	High	Low
High	Medium	Low	Low
High	Medium	Medium	Low
High	Medium	High	Low
High	High	Low	Low
High	High	Medium	Low
High	High	High	Low

load, peak load, and battery capacity. The control problem is defined as:

$$u_{Optimized}(t) = \text{Defuzzify}\left(\text{FLC}\left(L_b(t), P_{peak}(t), C_{battery}\right)\right) \tag{4}$$

In this work, $L_{optimal}(t)$ is defined as a smoothed version of the base load that represents a desirable demand curve with reduced peaks and improved load uniformity. The IT2FLC controller is designed to bring the total load as close as possible to this target. This profile serves as a reference for the total load $\tilde{L}_{Total}(t)$ to follow over time. It is usually obtained by smoothing the original base load $L_b(t)$ using a low-pass filter or moving average function that eliminates sharp peaks while maintaining the total energy consumption. Mathematically, this can be expressed as:

$$L_{optimal}(t) = \frac{1}{\omega} \int_{t-\frac{\omega}{2}}^{t+\frac{\omega}{2}} L_b(\tau)\, d\tau \tag{5}$$

Where ω denotes the length of the time window over which the base load is smoothed. This parameter defines the entire time interval centered at time t used to calculate the optimal (smoothed) load. A larger ω results in a more sharply smoothed load profile considering a wider time period, while a smaller ω provides a profile that responds more accurately to local variations. Accordingly, the following two main objectives are pursued in this work:

1) Grid stability and smooth load: The controller tries to follow $L_{optimal}(t)$. The objective function is formulated as follows:

$$\sum_{t=\alpha_i}^{\beta_i} \left[L_{\text{optimal}}(t) - (L_b(t) + u(t))\right]^2 \tag{6}$$

Where α_i and β_i are the arrival and departure times of vehicle i. The system must satisfy the following constraints:

$$\tilde{L}_{\text{optimized}}(t) \leq L_{\max}(t) \tag{7}$$

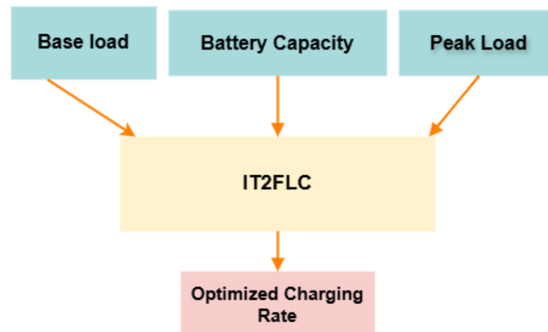

Fig. 2. Interval Type-2 Fuzzy Logic system scenario

$$\sum_{t=\alpha_i}^{\beta_i} u(t) \cdot \Delta t = C_{\text{required\_battery}} \tag{8}$$

where $L_{max}(t)$ is the maximum allowable load.

This adjustment ensures that the total energy demand closely follows the predefined optimal load curve, helping to maintain grid stability by preventing overloads and minimizing abrupt load variations.

2) Efficient energy consumption and peak shaving: The main objective of the proposed control strategy is to improve energy consumption efficiency by reducing peak loads and utilizing off-peak grid capacity. The controller works to lower peak loads and move charging to times when the grid is less busy. The objective is:

$$\min P_{Peak}(t) = min\left(\max_t \left(L_b(t) + u(t)\right)\right) \tag{9}$$

The full-battery constraint ensures that the vehicle is fully charged by the time it needs to depart.

$$\int_{\alpha_i}^{\beta_i} u(t)\, dt = C_{required-battery} \tag{10}$$

C. Local and Global Control Strategies

1) Local Control Strategy: The modified local control objective determines the optimized charging rate based on localized conditions using an IT2FLC. It is expressed as:

$$u_{optimized\_local}(t) = IT2FLC\left(L_b(t), P_{local\_peak}(t), C_{battery}\right) \tag{11}$$

The corresponding optimization problem can be formulated as:

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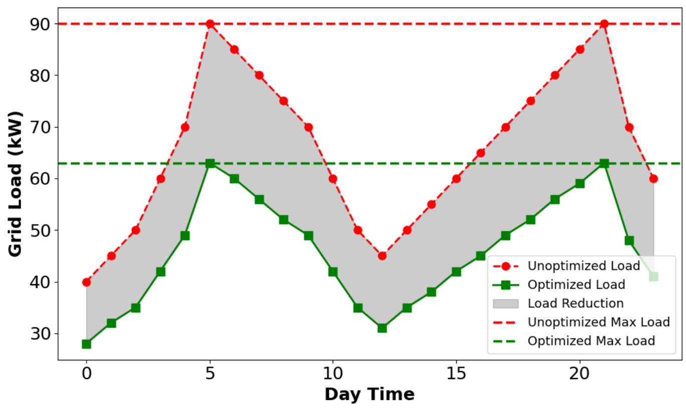

Fig. 3. Maximum load reduction between peak unoptimized and peak optimized loads.

$$\min \sum_{t=\alpha_i}^{\beta_i} \left(L_{optimal\_local}(t) - (L_b(t) + u_{local}(t))\right)^2 \quad (12)$$

The local load must not exceed the maximum allowable load $L_{max}(t)$ at any time:

$$L_b(t) + u_{local}(t) \leq L_{max}(t) \quad (13)$$

2) Global Control Strategy: The global strategy coordinates charging across multiple homes to reduce the overall peak load.

$$u_{optimized-global}(t) = IT2FLC\Big(L_g(t),\ P_{\text{global\_peak}}(t), \sum_i C_{\text{battery},i}\Big) \quad (14)$$

This strategy is easy to implement and works without coordination, but can be suboptimal when many vehicles charge at the same time and fully charged within the available time window. The global control strategy can be expressed as:

$$\min \sum_{t=\alpha_i}^{\beta_i} \left(L_{\text{optimal\_global}}(t) - \sum_{i=1}^{N}(L_b^i(t) + u_{global}^i(t))\right)^2 \quad (15)$$

ensures that the sum of all loads does not exceed the maximum allowable grid capacity. $L_{max\_global}(t)$:

$$\sum_{i=1}^{N}(L_b^i(t) + u_{\text{global}}^i(t)) \leq L_{max\_global}(t) \quad (16)$$

and all vehicles are fully charged:

Hence, it is required that the global strategy works in coordination with a central controller, which better reduces peak loads.

IV. Simulation

In this section, we presented 24-hour simulation results for the EV charging system using the initial parameters listed in Table II. One constraint during the simulation is that the maximum allowable load on the power grid cannot exceed 100 kW across the entire system. The total battery capacity for each EV is set to 20 kWh, with an initial state of charge of 5 kWh. The goal is to optimally balance peak loads while ensuring that each EV reaches a sufficient charge level by the end of the 24-hour cycle. The simulation uses 24-hour synthetic base load profiles with added peaks to mimic typical demand. Each EV can charge at up to 4.6 kW (about 50% of the grid limit), leaving headroom for other household loads, and EV arrival/departure times follow statistical availability data. Figure 3 compares the unoptimized load (red dashed line), which peaks around 90 kW, with the IT2FLC-optimized load (green solid line), where peaks are reduced to about 60-65 kW, corresponding to a 25-30% reduction. The shaded gray area in Fig.3 depicts the load reduction achieved by IT2FLC, showing how the charge is shifted to off-peak hours and the overall profile is flattened, improving the stability and efficiency of the grid.

TABLE II
SIMULATION PARAMETERS

Parameter	Value
Simulation duration	24 hours
Number of EVs	Variable
Battery capacity per EV	20 kWh
Initial SOC per EV	5 kWh
Maximum charging rate per EV	4.6 kW
Maximum total load limit	100 kW
Base load range	20-50 kW
Optimization goal	Peak minimization
Arrival/departure distribution	Random
Optimization method	IT2FLC

Fig.4 shows a sorted comparison between base load and optimized load, highlighting how the IT2FLC redistributes EV charging across the demand range. By sorting the data in ascending order rather than by time, the figure reveals a steady offset, where the optimized load slightly exceeds the base load due to scheduled charging. This illustrates the controller's ability to add EV demand smoothly and avoid sharp spikes, resulting in a stable total load profile that supports grid reliability. The base load ranges from 20 to 50 kW and exhibits a continuous increasing trend across the sorted data. The optimized load consistently remains slightly above the base load due to additional EV charging.

Figure5 illustrates the 24-hour comparison of base load, charging rate u(t), uncontrolled total load, and optimized total load under IT2FLC. The uncontrolled total load shows sharp peaks, expressing uncoordinated EV charging, while the optimized total load is smoother and closely follows the base load, demonstrating reduced grid stress and effective load distribution.

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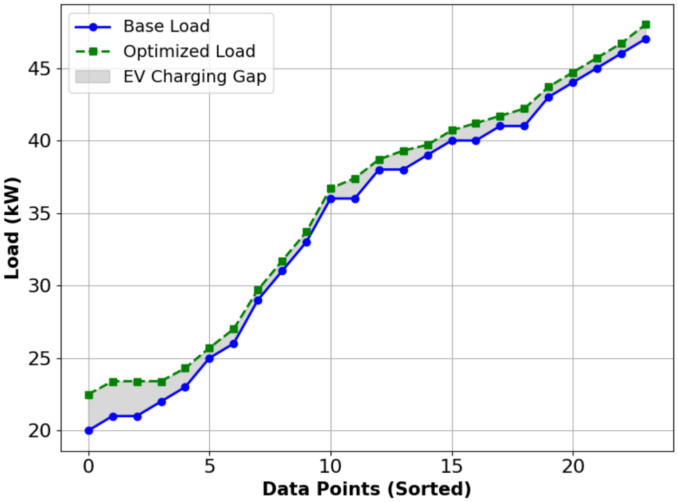

Fig. 4. Comparison of Base Load and Optimized Load with EV Charging on Sorted Data.

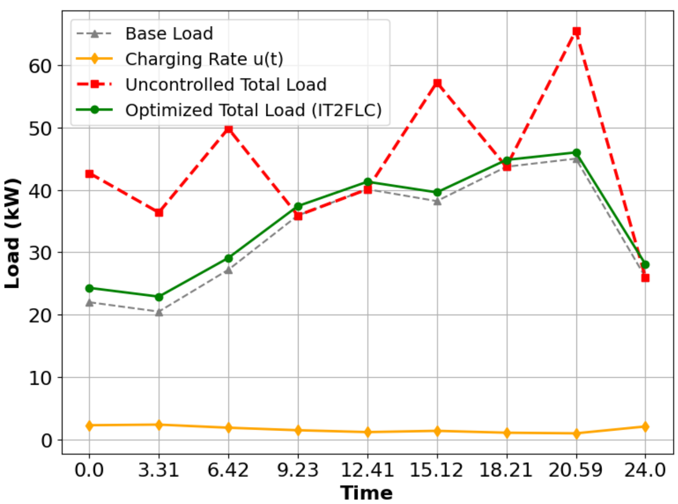

Fig. 5. Flattened total uncontrolled load profile through optimization, with reduced peaks and balanced charging distribution.

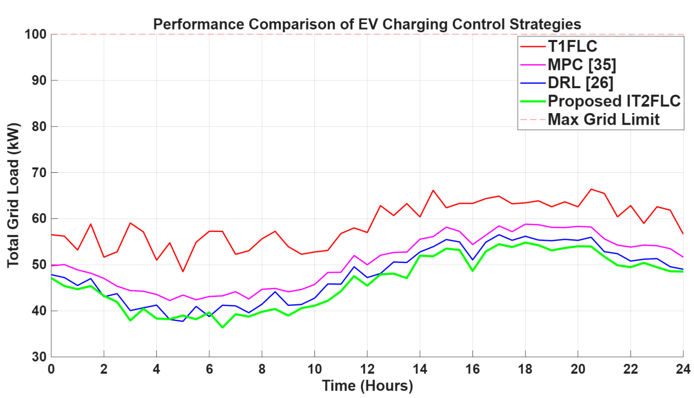

Fig. 6. Flattened total uncontrolled load profile through optimization, with reduced peaks and balanced charging distribution.

Fig.6 provides an analysis of uncertainty handling. We have replaced the simplistic deterministic scenario with a Stochastic Validation Model. We performed a series of simulations where EV arrival times and SOC levels were randomized. Fig.6 shows the overlayed results of these runs for T1FLC, IT2FLC, MPC [35], and DRL [26]. It can be observed that the IT2FLC maintains grid stability despite high input randomness, while traditional methods result in significant peak violations.

The suggested IT2FLC is compared in TableIII to four well-known control strategies, including T1FLC, Model Predictive Control (MPC), Multi-Objective Optimization, and Deep Reinforcement Learning (DRL). All innovative approaches are better than uncoordinated charging, but the IT2FLC can handle a peak power of 60 kW and a load shift of 50% while also being very resilient to uncertainty and requiring less computing power, and in summary, does the best across all of the metrics that were looked at.

TABLE III
COMPARISON OF EV CHARGING CONTROL STRATEGIES UNDER THE SAME SCENARIO.

Metric	T1FLC	**IT2FLC**	MPC [35]	Opt [36]	DRL [26]
Peak Load (kW)	75	**60**	68	65	63
Average Load (kW)	50	**48**	49	49	47
Load Variance	200.5	**140.2**	175.0	160.5	155.2
Charging Delay (hrs)	1.5	**0.5**	1.0	0.8	0.6
Off-Peak Load-Shifting	35%	**50%**	42%	45%	48%
Uncertainty Handling	Low	**High**	Medium	Low	High
Computational Cost	Low	**Medium**	High	High	V. High

V. CONCLUSION

The IT2FLC-based charging strategy noticeably improves grid performance. In 24-hour simulations, it cuts peak load by about 25–30%, reducing the maximum grid demand from roughly 90 kW to 60–65 kW, while shifting 40–50% of EV charging to off-peak hours. The deviation from the target load profile drops by about 35%, giving a smoother, more stable total load, and all EVs still reach their required charge within the allowed time window. The results confirm that the IT2FLC model effectively meets all operational constraints while reducing peak loads and enhancing energy distribution across the grid. These promising outcomes support the potential integration of this approach into real-world smart grid systems.

As future work, one can consider uncertainties in load forecasting and vehicle departure times by incorporating real-time strategies. These strategies should involve intelligent systems with adaptive learning capabilities and short-term energy prediction mechanisms.

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