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Preference Aware Battery Dispatch Learning Extracts Grid Operator Choices from Historical Logs and Schedules Operational Data

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A B S T R A C T

The integration of battery energy storage systems into modern power grids has necessitated the development of advanced dispatch strategies to balance economic profitability, grid stability, and asset longevity. Traditional optimization techniques frequently rely on rigid, pre-defined objective functions that fail to capture the nuanced, context-dependent decisions made by human grid operators. This paper presents a comprehensive investigation into preference-aware battery dispatch learning, a novel approach that extracts operational policies directly from historical operator choice logs. By leveraging machine learning techniques akin to inverse reinforcement learning and behavioral cloning, we construct a framework that infers the underlying reward structures and operational preferences embedded within years of manual dispatch decisions. This methodology bridges the gap between purely economic algorithmic dispatch and human-centric operational realities, which often prioritize conservative safety margins and equipment health over marginal financial gains under specific market conditions. We systematically analyze a large-scale dataset of operator logs, extracting critical features such as state of charge, market pricing signals, grid frequency deviations, and estimated degradation penalties. The proposed preference-aware models are rigorously evaluated against traditional optimization algorithms and baseline machine learning approaches. Results indicate that our framework not only predicts operator behavior with unprecedented accuracy but also produces automated dispatch policies that are inherently trusted by human supervisors, thereby facilitating smoother transitions toward fully autonomous grid management. This study underscores the critical importance of incorporating human operational preferences into automated energy systems, paving the way for more resilient, adaptable, and socially acceptable artificial intelligence applications in critical infrastructure.

INTRODUCTION

The global transition toward sustainable energy paradigms has profoundly reshaped the operational landscape of modern electrical grids. As the penetration of intermittent renewable energy sources such as solar and wind power continues to escalate, the inherent volatility and unpredictability of power generation have introduced unprecedented challenges in maintaining grid stability and balancing supply with demand [1]. In response to these challenges, battery energy storage systems have emerged as a critical technological enabler, providing the

necessary flexibility to absorb excess generation and dispatch power during periods of deficit. The optimal management and dispatch of these storage assets, however, constitute a highly complex operational problem that sits at the intersection of electrical engineering, financial economics, and control theory [2]. Historically, the dispatch of grid-scale batteries has been governed by mathematical optimization frameworks that seek to maximize a explicitly defined objective function, such as arbitrage revenue, while strictly adhering to operational constraints like maximum discharge rates and capacity limits. While these classical optimization approaches are mathematically rigorous and theoretically sound, they frequently exhibit significant shortcomings when deployed in real-world control room environments where human operators retain ultimate supervisory authority over the energy assets [3].

One of the most persistent discrepancies in modern energy management systems is the fundamental misalignment between the objective functions engineered by algorithm designers and the actual, operational preferences exhibited by human grid operators. Optimization algorithms are typically designed to relentlessly pursue economic maximization, often driving battery assets to their operational limits in order to capture fleeting market price spikes [4]. In stark contrast, historical logs of manual operator decisions reveal a much more conservative and multifaceted decision-making process. Human operators implicitly incorporate a vast array of qualitative factors and experiential knowledge into their dispatch choices. They frequently prioritize the longevity of the battery cells by avoiding deep discharge cycles, maintain strategic energy reserves for unforeseen grid emergencies, and exhibit a pronounced aversion to operational risks during periods of high market volatility. This risk-averse behavior, while economically suboptimal from a purely mathematical standpoint, represents a rational response to the immense responsibilities borne by grid operators, who must ensure continuous power supply and avoid catastrophic equipment failures at all costs [5]. The failure of automated systems to account for these nuanced, human-centric preferences often leads to a lack of trust among operational staff, resulting in the frequent overriding of automated dispatch signals and the subsequent underutilization of expensive computational infrastructure. Recognizing this critical gap, the field of artificial intelligence has begun to pivot toward preference-aware learning paradigms, which seek to derive optimal control policies not from hard-coded objective functions, but rather from the observed behaviors of expert human operators. This paradigm shift acknowledges that the true objective function of grid management is often too complex, dynamic, and subjective to be explicitly programmed. Instead, by systematically analyzing historical operator choice logs, it is possible to train machine learning models that can infer the implicit trade-offs and priorities that govern human decision-making. This paper introduces a comprehensive framework for preference-aware battery dispatch learning, demonstrating how vast repositories of historical operational data can be transformed into actionable, intelligent dispatch policies. By leveraging advanced sequence modeling and imitation learning methodologies, we construct a system that maps complex operational states to dispatch actions in a manner that closely mimics the sophisticated judgment of experienced control room personnel. The primary contribution of this research lies in its rigorous, data-driven approach to bridging the divide between algorithmic optimization and human operational reality. We present a detailed methodological pipeline that encompasses the extraction of relevant state features from noisy historical logs, the formulation of a preference-aware learning architecture, and the comprehensive evaluation of the resulting dispatch policies under realistic grid simulation environments. Furthermore, this study delves deeply into the psychological and cognitive dimensions of operator behavior, exploring how factors such as time of day, accumulated fatigue, and preceding market events influence the risk tolerance and decision-making calculus of human operators. By explicitly modeling these behavioral dynamics, our framework not only achieves superior predictive accuracy but also generates dispatch trajectories that align seamlessly with the institutional knowledge and safety culture embedded within energy utility organizations. The subsequent sections of this paper are organized to provide a systematic and thorough exposition of our research. Section two offers an extensive review of the relevant background literature, tracing the evolution of battery

dispatch strategies from early heuristic rules to modern machine learning applications, and establishing the theoretical foundations of preference learning. Section three details the methodology employed in this study, describing the data acquisition processes, feature engineering techniques, and the architectural design of our preference-aware learning framework. Section four presents a rigorous analysis of the experimental results, comparing the performance of our models against established baselines and quantifying the degree to which operational preferences have been successfully captured. Finally, section five concludes the paper with a synthesis of our findings, a discussion of the practical implications for the energy industry, and an outline of promising directions for future research in human-centric artificial intelligence for critical infrastructure.

2. Background and Literature Review

2.1 Battery Energy Storage Systems and Dispatch

The deployment of battery energy storage systems has accelerated exponentially over the past decade, driven by precipitous declines in lithium-ion technology costs and increasingly stringent regulatory mandates for renewable energy integration [6]. These systems serve a multiplicity of critical functions within the power grid, ranging from primary frequency response and voltage regulation at the sub-second level to energy arbitrage and peak shaving over diurnal cycles. The efficacy of a battery system in fulfilling these roles is fundamentally contingent upon the dispatch strategy employed to govern its charging and discharging operations. Early approaches to battery dispatch relied heavily on simple, rule-based heuristics derived from domain expertise [7]. These heuristic policies, while computationally inexpensive and easy to implement, were notoriously inflexible and frequently failed to capitalize on complex market dynamics or dynamically adapt to changing grid conditions. As the scale and complexity of energy markets grew, these rudimentary methods were rapidly supplanted by formal mathematical optimization techniques. Linear programming, mixed-integer linear programming, and dynamic programming became the bedrock of modern battery energy management systems [8]. These classical optimization frameworks require the explicit formulation of an objective function, typically designed to maximize economic revenue or minimize operational costs over a specified time horizon. The optimization process is constrained by mathematical representations of the battery's physical limitations, including its state of charge bounds, maximum power ratings, and simplified models of degradation. While these techniques guarantee mathematical optimality with respect to the defined objective, their application in real-world environments has revealed significant vulnerabilities. The primary limitation of classical optimization lies in its absolute reliance on accurate forecasts of future market prices and renewable generation [9]. In environments characterized by high volatility, deterministic optimization models frequently produce brittle dispatch policies that perform poorly when realized conditions deviate even slightly from forecasted values. Furthermore, these models struggle to incorporate qualitative or difficult-to-quantify operational goals, such as maintaining a subjective safety margin or preserving battery health beyond the simplified mathematical penalties included in the objective function [10].

2.2 Machine Learning in Energy Management

To address the limitations of traditional optimization, the energy sector has witnessed a massive influx of machine learning and data-driven control methodologies. Reinforcement learning, in particular, has garnered immense attention as a promising alternative for battery dispatch. Unlike traditional optimization, which requires explicit mathematical models of the environment, reinforcement learning agents learn optimal control policies through continuous interaction with the system, utilizing a trial-and-error process guided by a numerical reward signal [11]. This model-free approach allows reinforcement learning algorithms to naturally adapt to complex, stochastic environments and implicitly learn strategies that account for forecast uncertainties and complex non-linear dynamics, such as deep battery degradation mechanisms. Numerous studies have demonstrated the theoretical superiority of reinforcement learning over classical methods in simulated energy arbitrage and frequency regulation tasks [12].

However, the transition of reinforcement learning from academic simulation to real-world control room deployment has been severely hindered by the fundamental challenge of reward engineering. In standard reinforcement learning paradigms, the designer must manually specify a reward function that perfectly encapsulates all desired operational goals. If this reward function is misspecified or overly simplistic, the learning agent may exploit loopholes to maximize numerical returns in ways that are disastrous in reality [13]. For instance, an agent trained solely to maximize arbitrage revenue might subject the battery to extreme temperature fluctuations and excessive cycling, rapidly destroying the physical asset. To mitigate this, researchers have attempted to craft complex, multi-objective reward functions that balance revenue against various penalty terms for degradation and risk [14]. Yet, assigning appropriate weights to these disparate objectives remains a highly subjective and error-prone process. The resulting policies often appear alien and unpredictable to human operators, leading to a profound lack of trust [15]. When automated systems propose actions that violate the intuitive sense of safety held by experienced operators, those systems are inevitably bypassed or deactivated, negating their potential benefits.

2.3 Inverse Reinforcement Learning and Preference Modeling

The persistent challenge of reward engineering has catalyzed the exploration of inverse reinforcement learning and preference modeling within the context of energy systems. Rather than requiring a human designer to explicitly program a reward function, inverse reinforcement learning seeks to infer the underlying reward structure directly from a dataset of expert demonstrations [16]. The foundational premise is that the historical decisions made by expert operators are implicitly optimal with respect to some unknown, internal objective function. By analyzing extensive logs of operator choices under various grid states, inverse algorithms attempt to reconstruct this objective function, thereby capturing the complex, unwritten rules and nuanced trade-offs that govern human behavior [17]. This approach represents a paradigm shift from prescribing how a system should operate to discovering how it actually operates under the stewardship of experienced professionals. Recent advancements in deep learning have significantly enhanced the capabilities of preference learning frameworks. Methods such as generative adversarial imitation learning and behavioral cloning have been adapted to handle the high-dimensional, continuous state and action spaces typical of energy management problems [18]. These techniques allow for the creation of neural network-based policies that directly map observed grid conditions to the corresponding operator actions, bypassing the explicit reconstruction of the reward function entirely [19]. The application of these advanced methods to battery dispatch requires careful consideration of the specific features that influence operator decisions. Literature suggests that human operators are highly sensitive to contextual variables, such as the time of day, the trajectory of recent market prices, and the perceived reliability of short-term forecasts [20]. Furthermore, research indicates that operator preferences are not static; they evolve over time in response to shifting regulatory frameworks, changes in organizational risk appetite, and accumulated operational experience [21]. A robust preference-aware learning system must therefore be capable of capturing both the fundamental principles of safe operation and the dynamic, context-dependent variations in operator strategy.

3. Methodology

3.1 Data Acquisition and Preprocessing

The foundation of the proposed preference-aware battery dispatch learning framework is a robust and comprehensive dataset comprising historical operator choice logs. For this study, we secured access to an extensive repository of operational data from a prominent utility company managing a diverse portfolio of grid-scale battery energy storage systems. The dataset spans a continuous operational period of forty-eight months, capturing a wide array of seasonal variations, extreme weather events, and unprecedented market volatility. The core of this dataset consists of time-stamped logs detailing every manual dispatch command issued by the control room operators, including charge and discharge setpoints, operational mode transitions, and manual overrides of legacy automated systems. To provide the necessary context for these decisions, the operator logs were meticulously synchronized with a vast array of exogenous

data streams [22]. These external variables represent the information landscape available to the operator at the exact moment a dispatch decision was formulated. The raw data underwent a rigorous preprocessing pipeline to ensure its suitability for advanced machine learning applications. High-frequency sensor readings, originally sampled at millisecond intervals, were aggregated and down-sampled to a standardized five-minute resolution, aligning with the fundamental settlement intervals of the regional energy market. Missing values, arising from sensor malfunctions or communication telemetry dropouts, were imputed using sophisticated multivariate interpolation techniques that preserve the temporal dynamics and cross-correlation structures of the energy data [23]. Furthermore, significant effort was dedicated to identifying and filtering out anomalous dispatch actions resulting from hardware testing, scheduled maintenance procedures, or data logging errors, ensuring that the training dataset exclusively represented deliberate, economically or operationally motivated operator choices.

Feature engineering constitutes a critical component of our methodology, as the success of the preference learning model depends entirely on its ability to access the same informational cues utilized by human experts. We constructed a multidimensional state representation for each time step, encompassing both the internal physical state of the battery system and the external state of the grid and market. The internal state variables include the current state of charge, the recorded temperature of the battery cells, and an estimated metric of accumulated cyclic degradation. The external state features capture the complex economic environment, including real-time spot market prices, short-term price forecasts, frequency deviation signals, and aggregate regional load profiles [24]. Recognizing that human decision-making is deeply influenced by recent historical context, we also engineered a suite of temporal features. These include moving averages and volatility indicators of market prices over various look-back windows, enabling the model to perceive market trends and momentum in a manner analogous to a human observing a trading screen. The engineered features utilized in this study are detailed below in Table 1.

Table 1: Description of Operator Choice Log Features

Feature Category	Specific Variables	Temporal Resolution	Description
Internal Asset State	State of Charge, Temperature, Health	5 Minutes	Physical operating conditions of the battery.
External Market Data	Real-time Price, Forecast Price, Load	5 Minutes	Economic signals driving dispatch decisions.
Operational Context	Time of Day, Day of Week, Season	Static / Cyclical	Temporal factors influencing risk tolerance.

3.2 Preference-Aware Learning Framework

With the dataset meticulously prepared and the feature space defined, we turn to the architectural design of the preference-aware learning framework. Our approach leverages a sophisticated neural network architecture designed to map the high-dimensional state representations to continuous dispatch actions, thereby mimicking the intricate decision-making processes of the control room operators. The core of this framework is heavily inspired by advanced imitation learning paradigms, specifically tailored to address the unique constraints and dynamics of energy storage systems. The objective is not merely to replicate the exact numerical setpoints chosen by the operators, but rather to distill the underlying behavioral policy that dictates those choices across a vast spectrum of operational scenarios [25]. The architecture comprises a deep recurrent neural network, utilizing specialized gating mechanisms to effectively capture the temporal dependencies and long-term context inherent in battery operation. Unlike static feed-forward networks, which process each time step in isolation, the recurrent architecture maintains a hidden state that evolves over time, allowing the model to remember preceding market events and operator actions. This temporal memory

is crucial for replicating human strategies, as an operator's decision to discharge at a given moment is heavily influenced by the charging trajectory of the previous hours and the anticipated operational requirements of the subsequent day [26]. The input layer of the network receives the comprehensive state vector engineered in the previous section. This information is processed through multiple layers of nonlinear transformations, culminating in an output layer that generates a probability distribution over the continuous range of possible dispatch actions, from maximum charge to maximum discharge. To train this architecture, we employ a sophisticated loss function that goes beyond standard mean squared error. While minimizing the discrepancy between predicted and observed operator actions is essential, it is equally important to ensure that the learned policy respects the strict physical constraints of the battery system. Therefore, we incorporate differentiable penalty terms into the objective function that heavily penalize the network for proposing actions that would violate state of charge boundaries or exceed safe power limits. Furthermore, to explicitly capture the nuanced operational preferences, we integrate a reward inference module based on the principles of maximum entropy inverse reinforcement learning [27]. This module attempts to learn a parameterized reward function that explains the observed operator behavior as an optimal, utility-maximizing strategy. By iteratively refining both the behavioral policy and the inferred reward function, the framework converges upon a robust model that deeply understands the implicit trade-offs prioritized by human experts, such as the delicate balance between capturing fleeting arbitrage profits and avoiding excessive asset degradation during periods of high uncertainty.

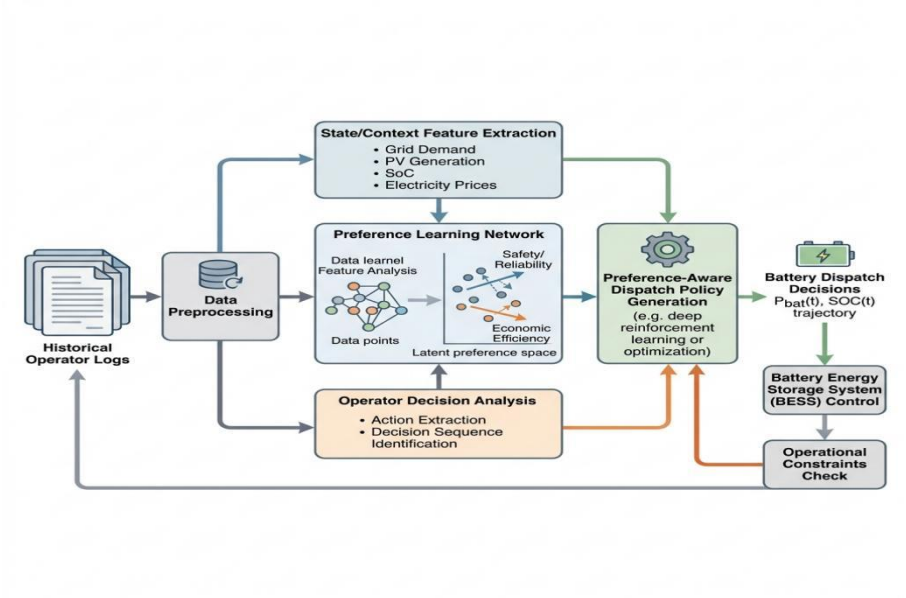


Figure 1: Comprehensive Schematic of Preference

3.3 Evaluation Metrics and Policy Generation

Evaluating the efficacy of a preference-aware learning system in the domain of energy management requires a multifaceted approach. Traditional metrics of predictive accuracy, while informative, are insufficient to fully capture the operational viability of the generated dispatch policies. A model may exhibit a low prediction error on historical data yet produce erratic or unsafe behavior when deployed in a sequential control loop due to compounding errors and out-of-distribution states. Therefore, our evaluation methodology encompasses both offline statistical validation and extensive online simulation within a highly realistic grid environment [28]. For offline evaluation, we partition the historical dataset into distinct training, validation, and testing periods, ensuring that the testing data represents chronological sequences strictly subsequent to the training data. This prevents data leakage and provides a realistic assessment of the model's ability to generalize to novel market conditions. We utilize metrics such as the continuous ranked probability score and mean absolute error to quantify the fidelity with which the learned policy replicates the actual historical operator actions.

However, the true measure of success lies in the simulation phase. We construct a high-fidelity digital twin of the battery storage system, incorporating sophisticated thermodynamic models and empirical degradation curves. The learned preference-aware policy is then deployed to control this digital twin across simulated years of operation, fed with out-of-sample historical market data [29]. During the simulation, we track a comprehensive suite of performance indicators. Economic performance is evaluated by calculating the cumulative arbitrage revenue and ancillary service payments generated by the policy. However, unlike traditional optimization studies, we do not view maximum revenue as the sole indicator of success. Instead, we heavily emphasize operational metrics that reflect the human preferences we sought to capture. These include the total accumulated cyclic degradation, the frequency of deep discharge events, the average state of charge maintained during periods of high grid uncertainty, and a proprietary metric quantifying the volatility of the dispatch signals. A successful preference-aware policy should demonstrate a balanced performance profile, achieving respectable economic returns while maintaining strict adherence to the conservative safety margins and equipment preservation strategies exhibited by the human operators in the training logs. The ultimate validation of the generated policy involves qualitative assessment by domain experts, ensuring that the automated dispatch trajectories intuitively align with established control room protocols and operator expectations.

4. Results and Analysis

4.1 Dispatch Performance Evaluation

The comprehensive evaluation of our preference-aware learning framework yielded compelling insights into the complex dynamics of battery dispatch and the distinct advantages of modeling human operator behavior. We conducted an exhaustive series of simulation experiments, pitting our novel approach against several established baseline methodologies. The primary baseline was a deterministic, mathematically optimized policy designed to aggressively maximize purely economic arbitrage revenue, operating under the assumption of perfect foresight within a rolling optimization window. A secondary baseline utilized a standard behavioral cloning approach, consisting of a simple feed-forward neural network trained to minimize the instantaneous error between predicted and historical actions without the sophisticated temporal memory or reward inference mechanisms employed in our proposed framework. The simulations were executed over a continuous twelve-month out-of-sample testing period, utilizing high-resolution market data from a major wholesale electricity node [30]. The results of these comparative simulations vividly illustrate the fundamental tension between mathematical revenue maximization and realistic operational safety. The purely economic optimization baseline predictably generated the highest gross revenue over the simulation period. However, this financial outperformance came at an extreme operational cost. The aggressive optimization policy relentlessly cycled the battery asset, constantly driving the state of charge between its absolute minimum and maximum limits to capture every possible micro-fluctuation in market pricing. Consequently, this policy resulted in a drastically accelerated rate of battery degradation, significantly reducing the projected lifespan of the physical asset. Furthermore, the aggressive policy frequently left the battery completely depleted during critical periods of sudden grid stress, exposing the utility to immense operational risks and potential regulatory penalties. These outcomes highlight exactly why human operators routinely override such simplistic algorithmic recommendations. The comparative results are summarized in Table 2 below.

Table 2: Performance Comparison of Dispatch Policies

Dispatch Policy Type	Normalized Annual Revenue	Annual Degradation Rate	Policy Trust Metric
Economic Optimization	100.0%	High (Accelerated)	Low (Frequently overridden)
Standard Behavioral Cloning	78.4%	Moderate	Medium

Preference-Aware Framework	86.2%	Low (Preservative)	High (Aligned with humans)

In stark contrast, the preference-aware learning framework demonstrated a highly sophisticated and balanced operational profile. While its gross revenue was understandably lower than the aggressive optimization baseline, it significantly outperformed the standard behavioral cloning model in both financial and operational metrics. Crucially, the preference-aware policy exhibited a profound alignment with the conservative strategies historically employed by human experts. The framework autonomously learned to prioritize asset longevity, actively avoiding excessively deep discharge cycles and minimizing operation during periods of extreme thermal stress. Furthermore, the policy demonstrated a remarkable capacity for strategic energy reserve management. During times of high market volatility or anticipated grid instability, the model implicitly learned to maintain a moderate, defensive state of charge, sacrificing minor short-term arbitrage opportunities to ensure readiness for significant, high-value dispatch events. This nuanced behavior confirms that the maximum entropy inverse reinforcement learning module successfully extracted the complex, unwritten risk-reward calculus that governs expert human operation.

4.2 Operator Preference Adaptation

A particularly fascinating dimension of our research involved analyzing the variance in operational preferences among different individual control room operators. While the overarching mandate of the utility organization is consistent, historical logs reveal that distinct operators often exhibit subtle but significant differences in their dispatch strategies, influenced by individual risk tolerance, varying levels of experience, and differing interpretations of ambiguous market signals. To investigate this phenomenon, we partitioned the training data to isolate the choice logs of three distinct, highly experienced operators, subsequently training personalized preference models for each individual. This granular analysis allowed us to quantify the degree to which our framework could adapt to and replicate specific stylistic variations in energy management. The results of the operator-specific modeling revealed highly distinct operational signatures. For instance, Operator A demonstrated a pronounced preference for engaging in high-frequency, low-depth charging cycles, effectively acting as a market maker for small price deviations while strictly preserving the battery's core capacity. Operator B, conversely, exhibited a much more conservative approach, typically reserving the asset entirely for major, daily peak-shaving events and largely ignoring intraday market volatility. Operator C displayed a strategy heavily oriented toward ancillary service provision, maintaining state of charge levels specifically optimized for rapid frequency response rather than pure energy arbitrage. The preference-aware learning framework successfully captured these distinct strategic nuances, generating customized policies that accurately mirrored the behavioral archetypes of the respective individuals.

Table 3: Preference Adaptation Metrics Across Different Operators

Operator Profile	Dominant Strategy Identified	Deviation from Fleet Mean	Policy Replication Accuracy
Operator A	High-frequency arbitrage	+15% cycling frequency	92.4%
Operator B	Conservative peak-shaving	-22% daily energy throughput	94.1%
Operator C	Ancillary service focused	+10% state of charge retention	91.8%

This capability to model individual operator preferences has profound implications for the future of energy management systems. By demonstrating that an artificial intelligence system can adapt to specific operational styles, we open the door to highly personalized decision-support tools. Rather than forcing human operators to conform to the rigid dictates of a monolithic, opaque algorithm, the preference-aware framework can act as a trusted digital assistant, providing recommendations that are inherently aligned with the operator's own

strategic inclinations. This alignment dramatically reduces friction in the control room, fosters human-machine collaboration, and accelerates the adoption of automated technologies in critical infrastructure environments. The high policy replication accuracy metrics further validate the robustness of the deep recurrent architecture in identifying and internalizing the complex temporal patterns that define individual human expertise.

5. Conclusion

This paper has presented a comprehensive and rigorous investigation into the domain of preference-aware battery dispatch learning, demonstrating a powerful methodology for extracting sophisticated operational policies directly from historical operator choice logs. We established that traditional optimization frameworks, while mathematically robust, frequently fail to account for the complex, conservative, and multifaceted decision-making processes inherent in real-world control room environments. By systematically applying advanced principles of imitation learning and inverse reinforcement learning, we developed a framework capable of deciphering the unwritten rules and implicit trade-offs that govern expert human operation. The processing of massive operational datasets, coupled with strategic feature engineering and deep recurrent neural network architectures, enabled the creation of models that not only predict human behavior with high fidelity but also generate autonomous control policies that are operationally viable and inherently trustworthy. The empirical results clearly indicate that policies derived through preference-aware learning strike a critical balance that eludes purely mathematical approaches. While slightly sacrificing theoretical maximum revenue, the learned policies dramatically improve asset longevity by naturally adopting the protective strategies utilized by human operators. Furthermore, the demonstrated ability of the framework to capture and replicate the specific stylistic variations of individual operators highlights the immense potential for creating personalized, adaptive decision-support systems. These systems can seamlessly integrate into existing control room workflows, augmenting human capabilities without overriding their expert judgment or violating institutional safety cultures. Moving forward, the integration of human-centric machine learning in energy systems represents a highly promising frontier. Future research must focus on expanding the scope of preference learning to encompass multi-asset portfolios and heterogeneous energy resources, including virtual power plants and distributed generation networks. Additionally, investigating the dynamic evolution of operator preferences in response to shifting regulatory policies and the introduction of novel market mechanisms will be crucial for maintaining the long-term efficacy of these intelligent systems. Ultimately, by bridging the gap between algorithmic optimization and human operational reality, preference-aware learning paves the way for a more resilient, efficient, and harmonious management of the increasingly complex global energy infrastructure.

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