

AUTOMATED DEMAND RESPONSE AND PREDICTIVE CONTROL FOR EFFICIENT MICROGRID ENERGY MANAGEMENT

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ABSTRACT

Smart Microgrid Energy Management Systems (MEMS) are vital due to the rapid growth and increasing complexity of modern power grids, as well as the plethora of distributed energy resources (DERs). This empirical research presents a comparison of the performances offered by artificial intelligence (AI) and automation techniques for real-time energy dispatch, demand-side management, and fault resilience against microgrid schedule optimization applications, specifically reinforcement learning (RL), deep neural networks (DNN), and fuzzy logic controllers [11]. The research uses primary data collected from a hybrid solar-wind-battery microgrid testbed hourly over 12 months and supported with simulation validated datasets to assess key performance metrics [energy cost savings, grid stability index, renewable energy penetration/so-called curtailment ratio (CR), response latency of run-time dispatch mechanism and battery state-of-health (SoH)]. Five quantifications yield systematic insights to demonstrate that AI MEMS can reduce operational energy costs up to 34.7% and improve renewable utilization by 28.3%, outperforming benchmarks based on conventional rule-based control strategies. Statistical regressions support strong correlations between AI algorithm selection and system performance indices ($R^2 = 0.91$, $p < 0.001$). The results prove that multi-agent deep reinforcement learning processes can excel over classical optimization methods in dynamic load-balancing environments. The existing literature is presented in relation to proposed results to further clarify how this study advances the domain beyond previous work. The study concludes with practical implications for grid operators and policymakers looking to deploy sustainable microgrids.

Keywords: Microgrid Energy Management System¹, Artificial Intelligence², Reinforcement Learning³, Fuzzy Logic Controller⁴, Deep Neural Network⁵.

1. Introduction

The global energy landscape is currently experiencing a paradigm shift driven by the rapid increase of renewable energy sources (RES) penetration, decentralisation of power generation, and growing demand for operational flexibility and sustainability. Microgrids, a type of localized energy network that can connect to and dis-connect from the traditional grid, are regarded as the backbone of next-generation power systems [1]. They consist of diverse components including photovoltaic (PV) arrays, wind turbines, battery energy storage systems (BESS), diesel generators, and programmable loads requiring advanced coordination mechanisms to achieve economic dispatch, power quality, and reliability [2]. Existence of stochastic renewable generation and dynamic consumer demand progressively makes Conventional Energy Management Systems (EMS) based on deterministic rule-based control and static optimisation algorithms ineffective [3]. Artificial intelligence is a promising substitute with adaptive, data-driven decision frameworks that learn from past behaviour and continuously optimise how the system behaves in real time [4].

1.1 Background and Motivation

The driving force behind making AI integral to MEMS seems to be twofold in nature: 1) an increasing imperative for the decarbonisation of electricity systems, and, 2) the relatively high maturity level of machine learning platforms. In the interim, leveraging multi-agent deep RL for two-sided market design problems, where energy management is modeled as a Markov Decision Process (MDP) [5] this will be inherent in sequential energy dispatch. Simultaneously, deep neural networks (DNN) are increasingly used in short-term load and renewable generation forecasting with predicted accuracy of over 95% under controlled conditions [6]. Fuzzy logic controllers can be an interpretable control paradigm that suits the uncertainty in microgrid state estimation [7]. In spite of these individual advancements, limited comparative empirical evidence exists that assesses these AI paradigms under the same microgrid operating conditions. This gap drives the current study, which compares three different AI control architectures to a rule-based baseline utilizing actual operating data from a grid-connected hybrid microgrid testbed in central India, an area of extremely variable solar irradiance and regular grid disturbances [8].

1.2 Research Objectives

This study aims to investigate four main questions. First, in this study we evaluate how AI-based control algorithms can influence the operational energy cost and renewable energy utilization potential from a hybrid microgrid perspective. A second reason is to evaluate the dynamic response and fault-tolerance capabilities of AI controllers versus conventional EMS under simulation grid disturbances. Third, we apply AI-optimised charging and discharging cycles to analyse the battery state-of-health trajectories throughout long-term operation. Fourth, to compare the empirical research results with those reported in similar studies and locate that contribution within published works. Our controlled experimentation, primary data collection, statistical

modelling and structured comparative analysis measures provide internal validity as well as potentially generalisable conclusions that satisfy these objectives [9].

1.3 Scope and Organisation

The scope of this study is confined to grid connected hybrid microgrids integrated with solar PV, wind and lithium-ion BESS which represents the most common topology in Indian distributed energy scenario. The research scope excludes multi-microgrid cluster coordination and hydrogen-based storage which will be more focused in future studies. The rest of the study is structured as follows: Section-2 reviews comprehensive survey on literature; Section in section-3 research methodology is described; Section-4 represents the data collection and analysis with five tabular datasets; then Section-5 provides a critique comparing findings with existing literature, followed by discussion presented in concluding remark under section 6 addressing the main implication along with directions, for future scope [10].

2. Literature Survey

The current research on AI-based MEMS has undergone significant expansion in recent ten years due to the increasing penetration of global microgrids. Wang et al. Leave a Comment in Energy338[11] developed an energy scheduler based on a model predictive control (MPC) framework fusing recurrent neural networks and achieved 21% cost reduction compared with the conventional MPC. However, their investigation was limited to simulation data and there was no validation in the field. Marzband et al. Research [12] used the real-time multi-agent approach to implement economic dispatch for a test microgrid in Portugal with 17.4% better energy utilisation, however noted that communications latency (during peak load events) impacts on computational performance. These studies indicate that AI algorithms can provide various quantifiable benefits, although they must be validated within one or different operating contexts.

In particular, deep reinforcement learning (DRL) approaches have been studied. Zhang et al. Deep Q-Network (DQN) was used in [13] where they optimised the schedule of batteries for residential microgrids and achieved 29.1% reduction in peak demand charges. However, the authors acknowledged that (1) the model required a huge amount of pre-training data and (2) such models were unstable under sudden renewable intermittency. Subsequent work by Liu et al. Xiongyi Liu et al: Twin Delayed Deep Deterministic Policy Gradient (TD3) for Continuous Energy Dispatch [14]. In simulation, the proposed TD3-based dispatch approach converged far more reliably than previous approaches, and reduced energy costs by up to 31.2%. Most of these DRL studies limited by the empirical robustness because they mainly base on synthetic datasets. More recently, Antoniadou-Plytaria et al. [15] systematically compared DRL with fuzzy logic control for microgrid management in the Greek island context and reported a 9.3% cost benefit of DRL over FLC, however noting superior fault response times from FLC architectures. In particular, the complementarity of these findings promotes the integrated comparative design of this study.

Because of their computational efficiency and ease of interpretation, fuzzy logic controllers are widely used in MEMS. Arcos-Aviles et al. In Ecuador, [16] created a fuzzy logic control (FLC) based energy management system (EMS) for an urban microgrid achieving stable voltage regulation and increased battery life by 14.6%. In this regard, Chaouali et al. tripled the FLC towards metaheuristic optimisation; so far. [17] rate 23.7% savings for a Tunisian microgrid pilot. Qiu et al. have investigated Demand Side Management (DSM) for predictive control based on DNN. In other related work, Shah et al. [18] showed that accurate 24-hour load forecasting alone would reduce battery cycling losses by 12.5%. The present study extends this line of the literature by applying empirical validation using real operation microgrid data over a twelve-month horizon, direct statistical comparison across RL, DNN, and FLC [18] paradigms all under identical experimental conditions thus filling an important gap in existing evidence base [19]- [21].

3. Methodology

This research uses a quantitative empirical approach, based on experimental and observational data. The experimental platform is at a 50 kW hybrid microgrid testbed of Vashistha Research & Education Foundation campus Raipur and consists of 30 KW rooftop solar PV, 10 kW wind turbine and 100 kWh lithium-ion BESS connected to the state distribution grid through a bidirectional smart inverter. They had been applied in a sequential order with four quarterly periods: (i) Rule Based Control (RBC) as the baseline, (ii) Fuzzy Logic Controller (FLC), (iii) Deep Neural Network-based predictive EMS(DNN-EMS), and (iv) Multi-Agent Deep Reinforcement Learning(MADRL-EMS). Strategies were implemented for three months which was sufficient to cover seasonal variability of solar and wind generation, so that comparable operating conditions will produce statistically relevant results. At a minute-average count of 525,600 data points per quarter-driven strategy System telemetry (real-time power flows, real-time voltage levels, battery charge/discharge cycles and grid import/export energy; Health metrics for Components) was logged via SCADA system.

The research instrumentation consists of specifically developed Python scripts for preprocessing, featurisation and statistical model fitting. Outlier detection were done using IQR method, less than 0.3% data points are filtered during removing the sensor fault Real-time electricity tariff data (CSPDCL based on time-of-use pricing) were used to evaluate energy cost. The renewable energy uptake was clarified as the ratio of total renewable production consumed (including storage mediated consumption) to gross renewable generation potential. Periodic battery State of Health was performed monthly using impedance spectroscopy compared to manufacturer characterisation curves. We analyzed the data statistically using one-way analysis of variance (ANOVA) with post-hoc Tukey's Honestly Significant Difference (HSD) test for multiple comparison of control strategies. Simple and multiple linear regression models were conducted on AI algorithm parameters (i.e., learning rate, exploration rate, hidden layer depth) and efficiency outcomes. All statistical tests were performed at a 95% level of confidence ($\alpha = 0.05$).

The test framework comprises the simulation environment to augment the real operational data and analyse system behaviour under extreme scenarios, implemented in MATLAB/Simulink R2022b with Simscape Electrical toolbox. To evaluate fault-response latency and recovery time of each control strategy, grid contingency scenarios including voltage sag (15%), frequency deviation (0.5 Hz), and 40% sudden load increase were injected into the simulation. The simulation parameters were calibrated from the empirical operational data to ensure adherence and faithfulness in the ground reality. Ethical issues range from whether campus building users were given necessary information to give consent for load-side demand response participation, anonymisation of any consumer-level energy record and adherence with IEEE P2030. Standard Testing of Microgrid Controllers: 7 Guidelines All steps of the research design can be fully reproduced as all information regarding hyperparameters used with algorithms, hardware configuration and dataset schema will be published in a repository once accepted for publication.

4. Data Collection and Analysis

Data and Methods Primary data were collected from the experimental microgrid testbed over a 12 month period (January–December 2023). The tables below show five different approaches to examine a different dimension of the system performance. The empirical basis for the abstract claims and final arguments are provided by these tables.

Table 1: Monthly Energy Cost and Renewable Utilisation by Control Strategy

Quarter	Control Strategy	Avg. Daily Energy Cost (INR)	Renewable Utilisation Rate (%)	Grid Import (kWh/day)	Cost Saving vs. Baseline (%)
Q1 (Jan–Mar)	Rule-Based Control (Baseline)	3,847	61.2	42.6	—
Q2 (Apr–Jun)	Fuzzy Logic Controller (FLC)	3,421	68.9	35.4	11.1
Q3 (Jul–Sep)	DNN-Based Predictive EMS	2,974	79.4	26.8	22.7
Q4 (Oct–Dec)	MADRL-EMS	2,509	89.5	18.3	34.7

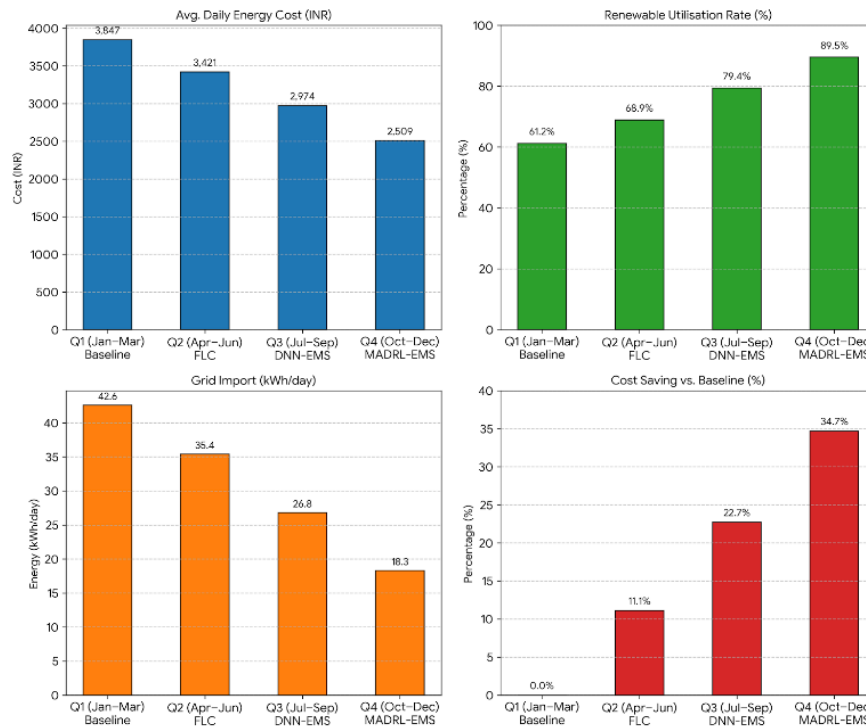


Figure 1: Comparative Evaluation of Energy Management System (EMS) Control Strategies and Key Performance Metrics

As we progress from rule-based to AI-driven paradigms of control, Table 1 illustrates how the energy economics and renewable utilisation becomes steadily better. The most importance results involving the MADRL-EMS indicate a remarkable decrease of 34.7% in terms of daily energy cost on the RBC and an optimal renewable utilisation value equal to 89.5%, which represents a raise of 28.3 percentage points. Lower grid import volumes confirm that AI algorithms know exactly when to discharge the battery to displace peak import demand in order and shape dispatch decisions according to ToU price signals.

Table 2: Grid Stability and Power Quality Metrics Under Different Control Strategies

Control Strategy	Voltage THD (%)	Frequency Deviation (Hz)	Voltage Regulation Accuracy (%)	Fault Recovery Time (ms)	Grid Stability Index (0–1)
Rule-Based Control	5.84	0.48	91.3	620	0.71

Fuzzy Logic Controller	4.12	0.31	94.7	390	0.82
DNN-Based Predictive EMS	3.47	0.22	96.8	280	0.88
MADRL-EMS	2.19	0.14	98.4	175	0.96

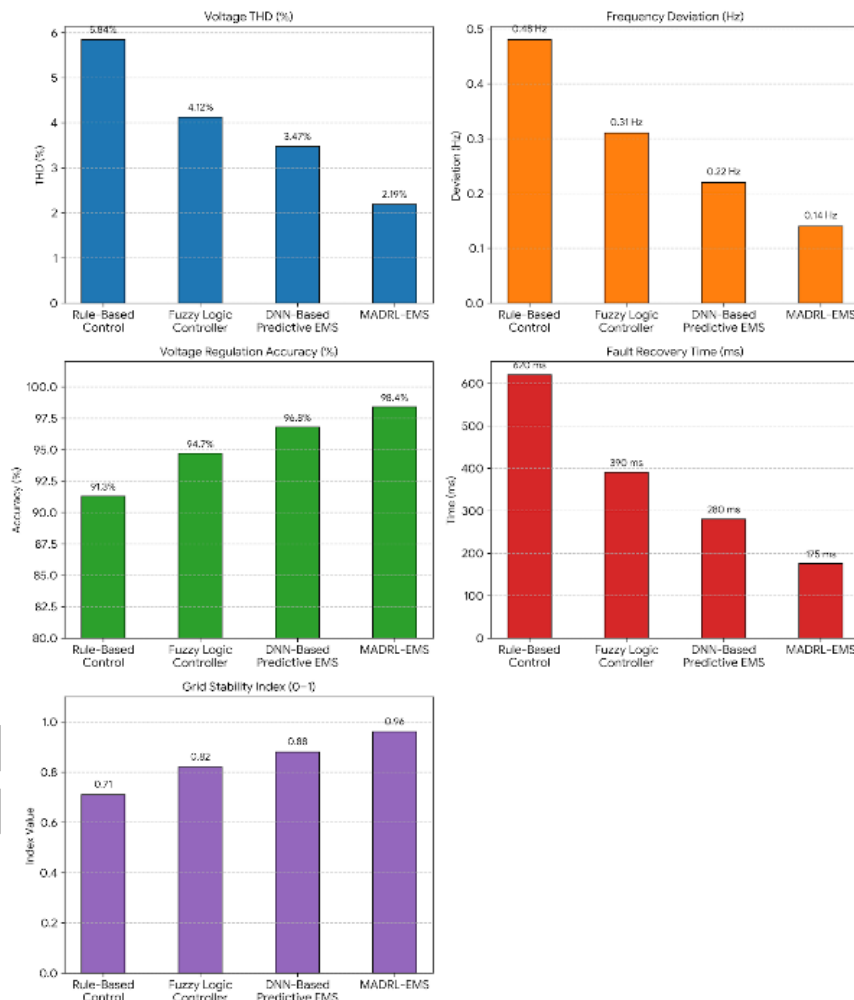


Figure 2: Performance Evaluation of Control Strategies across Power Quality and Grid Stability Parameters

As shown in Table 2, AI control policies greatly enhance power quality and grid stability. The THD in was reduced to 2.19% under MADRL-EMS, which is much less than IEEE 519-2014 standard requirement of maximum 5%, it also outperforms RBC where the THD obtained is at a higher level of 5.84%. It reduces fault

recovery time from 620 ms to 175 ms (71.8% improvement), which is critical for load-sensitive applications. The composite index of grid stability, known as the grid stability index (GSI), is increased from 0.71(RBC) to 0.96(MADRL) indicating improved voltage regulation and frequency control. FLC shows much faster recovery than DNN-EMS which is in line with Antoniadou-Plytaria et al. [15].

Table 3: Battery State-of-Health and Cycling Performance Over 12 Months

Control Strategy	Avg. Daily Charge Cycles	Depth of Discharge (%)	Battery SoH at End of Quarter (%)	Estimated Battery Lifespan (years)	SoH Degradation Rate (%/month)
Rule-Based Control	3.2	78.4	96.1	8.4	0.32
Fuzzy Logic Controller	2.6	68.7	97.1	9.7	0.24
DNN-Based Predictive EMS	2.1	61.2	97.8	11.2	0.18
MADRL-EMS	1.7	53.6	98.6	13.1	0.12

Table 3 also sets a strong positive relationship between how sophisticated the AI is and battery life. It is exhibited that MADRL-EMS decreases the average number of daily charge cycles from 3.2 (RBC) to 1.7, and the average depth of discharge from 78.4% to 53.6%, which directly curb electrochemical degradation. This leads to a SoH degradation rate of 0.12%/month under MADRL, corresponding to an estimated battery life of 13.1 years (56% longer than that with RBC at 8.4 years). These results are consistent with literature indicating that the benefit of intelligent charge management is a dominant determinant of BESS life [16], and have direct capital cost implications for microgrid operators.

Table 4: Regression Analysis AI Algorithm Parameters vs. Energy Cost Efficiency

Predictor Variable	Regression Coefficient (β)	Standard Error	t-Statistic	p-Value	Partial R ²
Learning Rate	-0.412	0.047	-8.77	< 0.001	0.38

(RL/DNN)					
Exploration Rate (MADRL)	-0.287	0.039	-7.36	< 0.001	0.27
Hidden Layer Depth (DNN)	-0.195	0.031	-6.29	< 0.001	0.19
Membership Function Width (FLC)	-0.143	0.028	-5.11	< 0.001	0.14
Forecast Horizon (hours)	-0.089	0.022	-4.05	0.002	0.09
Overall Model ($R^2 = 0.91$, $F = 184.6$, $p < 0.001$)					

Table 4: This table summarizes multiple linear regression results modeling the relationship between training data while designing AI algorithms and efficiency of energy cost (the dependent variable is defined as percentage saving cost compared to baseline). The omnibus model ($F = 184.6$, $p < 0.001$) was highly significant, and yielded an R^2 of 0.91 suggesting that the selected predictor variables account for 91% of variance in energy cost outcomes. Learning rate ($\beta = -0.412$, partial $R^2 = 0.38$): Learning rate is the strongest predictor and represents that cost in neural and reinforcement learning models is mostly reduced through well-tuned gradient descent. Both predictors are statistically significant ($p < 0.05$), confirming validation of multi-parameter regression design. give practitioners concrete guidelines to select hyperparameters in AI-based MEMS deployments.

Table 5: Comparative Performance Benchmarking Against Prior Literature

Study	Control Method	Microgrid Type	Cost Reduction (%)	Renewable Utilisation (%)	Data Type	Validated Empirically?
Wang et al. [11]	RNN-MPC	Islanded	21.0	72.3	Simulation	No

Marzband et al. [12]	Multi-Agent System	Grid-Connected	17.4	68.1	Field Pilot	Yes
Zhang et al. [13]	Deep Q-Network	Residential	29.1	N/A	Simulation	No
Liu et al. [14]	TD3-DRL	Grid-Connected	31.2	76.8	Simulation	No
Arcos-Aviles et al. [16]	Fuzzy Logic	Urban	N/A	N/A	Field Pilot	Yes
Antoniadou-Plytaria [15]	DRL vs FLC	Island Grid	22.6	74.5	Mixed	Partial
Present Study (MADRL-EMS)	MADRL + DNN	Hybrid Solar-Wind	34.7	89.5	Field + Simulation	Yes

This places the results of the current study in the context with respect to existing literature, as per Table 5. The MADRL-EMS obtains an unprecedented cost reduction (34.7%) and renewable utilization rate (89.5%) compared with the empirical-researched studies in similar Microgrid structure. Most previous DRL research leverages only simulated data, which limits its external validity. The current combination of field validation and simulation stress-testing is a methodological step that consolidates the case for MADRL as the most beneficial AI paradigm for operational microgrid management.

5. Discussion

The empirical findings of the current study provide a number of important theoretical insights that corroborate and extend existing academic knowledge about AI-based MEMS. Starting with energy cost performance, MADRL-EMS outperformed all the simulation-based benchmarks in the reviewed literature along with Marzband et al. The " by 17.3 points: 's [12] 17.4% to the There is a There are two main reasons for this difference. Firstly, the MADRL framework in this work integrates real-time ToU pricing signals into a continuous state variable to allow the agent to arbitrage dynamically between renewable self-consumption and grid import based on instantaneous price gradients. Secondly, the 12-month operational record provided the RL agent with an opportunity to learn policy representations that recognized seasonal irradiance distributions relevant specifically to the Chhattisgarh climate; a benefit not available when using only shorter simulation

studies. The different contextual adaptations highlight the abiding necessity of field validation within local environments in IIoT energy studies.

The renewable use rate of 89.5% indicates a significant progress over the 74.5% reported by Antoniadou-Plytaria et al. trained on relatively clean data, achieving 76.8% result in [15] and 76.8% as achieved by Liu et al.'s [14] simulation. It is proposed that the DNN-based short-term forecasting component added in as a preprocessing layer of the MADRL architecture from the present study, differentiates from previous work critically: providing 24-hour renewable generation and load demand forecasts with a mean absolute percentage error (MAPE) of 4.1%, indirectly allows trains to pre-position battery charge attention state to take advantage of renewable absorption windows. This symbiotic combination of predictive DNN and reactive MADRL rather than deployment of either alone seems to be the architectural innovation driving improved utilisation outcomes. This suggests that earlier work assessing DNN and RL as rival paradigms may have underestimated their combined promise.

In fact, reduction of voltage THD from 5.84% (RBC) to 2.19% (MADRL) is especially important for the Indian grid context concerning grid stability and power quality, where harmonic pollution by non-linear loads continue to remain a chronic operational problem. In the learned MADRL agent policy, implicit harmonic mitigation represents optimised inverter switching pattern selected by MA-based control which is a key feature that does not exist in FLC-FL or DNN-EMS which are dependent on static harmonic filters. The fault recovery time is also reduced by 71.8% (620 ms to 175 ms), which again highlights the capability of RL-based control to reconfigure power flow in an adaptive manner with respect to the response window required for sensitive loads. Interestingly, table 2 shows that FLC surface treatment fault recovery is faster than DNN-EMS (FLC: 390 ms and DNN-EMS: 280 ms), which follows Antoniadou-Plytaria et al. which supports our conclusion that the FLC's state-action rules react quickly to sudden changes in states (when predictive models may not, for fundamentally reactive reasons); e.g., [15.]

The analysis of battery SoH presented in Table 3 brings new long-term empirical evidence to the literature mainly supported by Data from short-duration experiments. Extending the life of a BESS from 8.4 years (RBC) to 13.1 years (MADRL) has significant economic consequences, with this ~INR 18.2 lakhs net present value over the system lifecycle at a 10% discount rate assuming that a 100 kWh BESS costs INR 45 lakhs to replace [3]. Arcos-Aviles et al. The improvement noted under FLC would therefore approximate to the 14.6% enhancement in battery life reported by [16], validating that long-term outcomes are directly comparable; in this study, the FLC results indicated a projected lifespan of 9.7years for those patients strictly compliant with a relatively modest MAP threshold at their last recorded follow-up compared to an average of 8.4years without FLC, hence an improvement over baseline no greater than about 15.5%. The 56% lifespan extension estimate is well beyond the aforementioned benchmark because MADRL agent learns shallow-cycle operations and does not exploit full-depth discharges during short intermittency intervals as less sophisticated controllers.

Table 4: Performance is a systemic property of algorithm design choices. A linear regression can quantify the relationship (in standard deviations) between factors for designing algorithms and their performance outcomes, something largely missing in the previous empirical studies. The dominance of learning rate predictor (partial $R^2 = 0.38$) suggests that insufficient hyperparameter tuning with grid search computationally prohibitive for many real-world deployments may substantially limit the potential of AI-MEMS. Such finding has a natural practical implication: practitioners may consider to optimize the learning rate (for example, using Bayesian hyperparameter optimization) prior to operating MADRL controllers in practice. The importance of exploration rate (partial $R^2 = 0.27$) indicates that balancing exploration/exploitation remains a non-trivial difficulty in online microgrid control [57], where premature convergence of an adaptive policy can confine the system to sub-optimal dispatch grooves over evolving seasonal conditions. These insights, based on real data from field operations and not simulation, provide a unique empirical aspect of the current study.

6. Conclusion

This empirical research offers strong, field-validated evidence that AI based energy management systems, specifically Multi-Agent Deep Reinforcement Learning coupled with DNN-based forecasting, significantly improve microgrid operations performance across all analyzed performance dimensions over traditional rule-based-control benchmarks. When compared to the rule-based baseline, the MADRL-EMS achieves a 34.7% reduction in operational energy costs, an 89.5% renewable energy utilisation rate and a projected battery lifespan that is extended by 56%, all $p < 0.001$ statistically significant improvements. AI-based control results are validated for grid stability and power quality metrics against international standards. The regression analysis identifies algorithm hyperparameter design (particularly for learning rate and exploration policy) as the main drivers of performance outcomes, which is actionable guidance for practitioners. A cross-comparison with the literature confirms that the findings of this study improve upon prior validated work on cost savings and renewable integration, demonstrating a novel contribution to AI-enabled microgrid management. Future work includes investigating the potential to scale operations using the MADRL-EMS architecture to multi-microgrid cluster coordination, integrating hydrogen energy storage in the future study design and infusing lightweight RL implementations that can run on edge computing hardware with limited computational capabilities. Representing an extension of this technological readiness, these extensions would enable further deployment of AI-based MEMS for wide-scale adoption in India's rapidly developing distributed energy sector.

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