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AS^{2}ICRL: Energy Management Model Using Inverse Constrained Reinforcement Learning Based Adaptive Sleep Scheduling in Wireless Sensor Networks

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Abstract

Sensor nodes have very limited battery life energy management becomes an important issue in WSN. Most of the older energy-saving techniques find it hard to achieve a good trade-off between conserving energy, maintaining network connectivity, and maximizing efficiency in the delivery of data. We propose adaptive sleep schedule-based inverse constrained reinforcement learning (AS^{2}ICRL), which optimizes the sleep scheduling of WSNs intelligently through inverse constrained reinforcement learning (ICRL). The model dynamically adjusts node activity according to the environment, varying network conditions, and traffic; thus, the methodology has attained 28.7% energy savings and 35.4% improvement in network lifetime compared with earlier proposals. AS^{2}ICRL guarantees communication that is efficient and trustworthy by achieving 94.2% classification accuracy, F1-score of 92.1% with a robustness index gain of 15.3%, while maximizing energy efficiency. Experimental evaluations establish the potential of AS^{2}ICRL to significantly increase network stability, adaptability, and overall performance, which favors its deployment in energy-aware IoT and WSN applications.

Keywords: Energy Management, Wireless Sensor Networks, Adaptive Sleep Scheduling, Reinforcement Learning, Inverse Constrained Reinforcement Learning, Network Optimization, IoT, Sustainable Computing.

1 Introduction

1.1 Importance of Energy Management in Modern Systems

Energy management is crucial for modern systems such as wireless sensor networks (WSN) performance and life, which is directly dependent on energy efficiency (Jara et al., 2010). There is always an effective measure for energy consumption optimization so that battery-operated devices endure, giving way for lowered maintenance costs as well as ensuring dependable operation of sensors. An

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efficient energy management scheme would enhance the performance of the system. In addition, it would further save costs and protect the environment in the minimization of energy wastage. Adaptive approaches such as sleep scheduling in WSNs help to mitigate power consumption across nodes resulting to premature failures but continuous transmission of data (Banerjee et al., 2020). In automatic industries, such energy-efficient strategies are imperative in the IoT, smart cities, and industrial automation, where devices have to ideally operate for a significant duration with slight human involvement. Such advanced models as Inverse Constrained Reinforcement Learning (ICRL) for adaptive sleep scheduling bring the electricity usage of modern systems to be dynamic, improving efficiency, reliability, and sustainability (Malik et al., 2021).

1.2 Overview of Reinforcement Learning and Its Applications in Energy Management

The agent in reinforcement learning learns to make decisions by interacting with its environment through a trial-and-error mechanism. An agent makes a decision, depending on the quality of the decision it gets either rewarded or penalized, thus allowing it to modify its decisions slowly in the direction of maximizing long-term rewards. RL methods, like Q-learning, Deep Q-Networks (DQN), and Policy Gradient methods, mainly address cases that require dynamic and adaptable strategies for decision-making problems (Liu et al., 2024a). In management of energy, the role of RL is to become the optimal means responsible for energy consumption, efficacious operations, and sustaining processes (Shridhar & Udayakumar, 2024). Some of the highlighted applications are:

- RL operates on demanding sides by approximating energy usage patterns and optimizing electricity distribution, reducing peak loads, and increasing grid stability (Babar et al., 2021).
- RL-based adaptive sleep scheduling involves switching the active states of the sensor nodes and sleep states to minimize energy waste and maintain network performance (Banerjee et al., 2020).
- RL distributes the server load optimally, distributes the cooling systems, and allows for power allocation with regards to energy costs; therefore, it improves efficient use of resources (Wang et al., 2023).
- Efficient RL EV charging scheduling optimizes grid and cost efficiency while maximizing the life of batteries (Zhang et al., 2022).

Building Energy Management: Smart HVAC systems use RL for temperature control to minimize energy waste while maintaining comfort for occupants (Nguyen & Aiello, 2023). With such RL-based solutions as Inverse Constrained Reinforcement Learning (ICRL), it can provide dynamic adjustment-related conditions under energy management systems for optimum energy use and sustainability improvement in several areas.

1.3 Significance of the Proposed Model

The AS^{2}ICRL (Adaptive Sleep Scheduling using Inverse Constrained Reinforcement Learning) framework is a novel energy management strategy that aims at optimizing the energy efficiency in Wireless Sensor Networks (WSN) (Kang et al., 2019; Kavitha, 2024). Most traditional sleep scheduling mechanisms cannot provide an adequate trade-off between energy efficiency and network performance, creating situations where sensor nodes fail prematurely and data transmission delays. The AS^{2}ICRL addresses this compromise by using Inverse Constrained Reinforcement Learning to dynamically adapt the sleep schedule of sensor nodes through real-time network conditions for the optimal trade-off concerning energy conservation and data reliability (Saha et al., 2023).

A salient advantage of AS^{2}ICRL is enhanced energy efficiency. It significantly reduces energy waste by actively optimizing the sleep-wake cycles of sensor nodes, thus prolonging the network's life (Fadaei et al., 2018). These make AS^{2}ICRL a variable system over traditional static scheduling mechanisms, where the former just ensures the survival of only those nodes that are necessarily awake while making others go into a low-power sleep state, thus amassing large energy savings (Saha et al., 2023).

Besides, the improvement of network performance is yet another merit of AS^{2}ICRL. Most energy conserving approaches compromise the quality of data transmission by incurring a very high latency or packet loss. In contrast, AS^{2}ICRL performs a dynamic adaptation to the changing demands of the network, guaranteeing reliable data transmission in the face of minimal delays (Banerjee et al., 2020). This makes it most suitable for applications of real-time monitoring where on-time delivery is critical.

Furthermore, adaptive and intelligent decision-making has been incorporated through reinforcement learning into the design methodology of the model. The system simultaneously learns from the network environment while adapting itself in real-time to optimally accord its energy consumption. This working unison offers the advantage of dynamic adaptability of the network, making energy-saving decisions even under dissimilar operational conditions so that energy wastage is minimized while optimum function is achieved (Liu et al., 2024a).

AS^{2}ICRL directly and indirectly reduces maintenance and operating costs. By preserving the lifespan of sensor node batteries and therefore saving on battery replacements and maintenance visits, the main advantage emerges when deployment is far away or on a large scale, wherein physical intervention incurs enormous costs and risks (Prakash & Prakash, 2023).

Finally, AS^{2}ICRL gives adequate scalability and robustness for any application involving wireless sensor networks, from industrial monitoring to environmental sensing to smart city infrastructure (Prakash & Prakash, 2023). Well-managed energy in large networks ensures sustainable operations and cost-effective deployment (Banerjee et al., 2020; Soni et al., 2025). The integration of AS^{2}ICRL allows new-generation WSNs to reliably realize high performance with energy management at a low-cost. Henceforth, this marks an era in wireless communication and applications in IoT (Harihara Gopalan et al., 2017) (Booch et al., 2025).

2 Literature Review

Kumar et al., (2022) This paper indicated transactive energy (TE) models could play a much bigger role in improving energy efficiency within microgrids (Surendheran & Prashanth, 2015). It showed that TE could improve grid stability, facilitate renewable energy integration, and provide economic benefits through decentralized energy trading. Similarly, the results showed that the adoption of TE models would lead to enhanced demand-side management, lower operation costs, and greater consumer involvement in energy markets.

Schminke, (2021) The set out injection study provided a relative overview with regard to energy management system (EMS) characteristics and related algorithms in household-and-building energy management. It pointed out several research gaps in respect of the lack of real-time optimization methods and adaptive pricing strategies. The implications of these results suggested that future EMS models should focus on integrating artificial intelligence with real-time data analytics for enhanced energy efficiency and cost-saving.

May et al., (2017) is of paramount importance in energy management in manufacturing because it identifies key influencing factors, crucial research gaps, and the strategies that can be employed to improve energy efficiency. Key findings indicate that there is a strong need for integrating smart technologies, policy frame, and strategic paradigms for optimizing energy consumption in a manufacturing setting. Future research directions that were stated by the authors include the impact of Industry 4.0 on energy management.

Liu et al., (2024b) In their exhaustive survey of ICRL, Liu et al. define the new concept and consider its algorithmic frameworks across various scenarios, including deterministic and stochastic settings, limited demonstrations, and multi-agent systems. They outline some of the most urgent challenges that exist in the field and suggest some fundamental ideas to tackle them. The survey traces applications of ICRL to autonomous driving, robot control, and sports analytics, finishing with open questions that can connect the theory with practical applications.

Malik et al., (2021) Authors have validated their approach through experiments demonstrating the successful inference of probable constraints and their transferability to new agents with different morphologies or reward functions. Their framework learns arbitrary Markovian constraints in high-dimensional, model-free environments, unlike earlier works limited to discrete settings or to specific constraint types.

Subramanian et al., (2024): Their solution is that the first principled ICRL which uses user-informative definition of confidence levels while inferring constraints from expert demonstrations. The constraints which are inferred will be at least as restrictive as the actual constraints with the given confidence level. Also, this informs the users regarding the fact that the available expert trajectories cannot always get to the confidence required so as to gather data more towards obtaining constraint and policy learning with performance guarantees.

Fîciu et al., (2021) introduced a low-complexity Recursive Least Squares (RLS) adaptive algorithm which takes advantage of tensorial forms to make computations efficacious; this algorithm aims to sustain the performance levels obtained through RLS for very high computation complexity. The algorithm, which addresses the very high computational load of RLS algorithms, makes it rather suitable for real-time applications. Tensor decompositions could cut down the dimensions of matrix operations involved in basic RLS methods so that convergences are fast, and computations are low even at higher applications for the RLS algorithms in adaptive filtering and system identification tasks.

Zhu et al., (2012) proposed that adapting radial basis function (RBF) modeling combined on top with fuzzy cluster techniques through SLE-like structures could be very efficient in the optimization globally. The SLE conducts a sampling point gathering to realize space-filling, projective uniformity. Then, too, on these promising loaded points at most, the adaptive RBF keeps improving its approximation whenever more loaded points increase. Fuzzy c-means clustering was used for detecting regions of interest in the design space for more specific global optimum searching. The method came up effective for most global or near-global designs optimum taken from different benchmarks, using a bold approach for computational exhaustive modelling in engineering design optimizing.

3 Methodology

3.1 Description of the AS^{2}ICRL Model

An Adaptive Successive Sparse Incremental Contrastive Reinforcement Learning-like AI model is tailored to push the frontiers of adaptive decision making in an ever-changing environment through the cocktail of contrastive learning, reinforcement learning, and incremental sparse updates. Thus, it is able to optimize its learning strategy while minimizing the computations involved.

Models Structure

There are four basic modules in the AS^{2}ICRLsystem:

- Adaptive Learning Module: At this juncture, the model parameters change on-the-fly based on environmental feedback.
- Successive Sparse Representation: This is seemingly a continual sparse encoding process to minimize any spatial redundancy in the data being processed.
- Incremental Contrastive Learning: It compares, differentially, the positive and negative test cases in greater quantification for feature extraction.
- Reinforcement Learning Framework: An optimal decision-making refinement is based on rewards in an optimization process.

AS^{2}ICRL (Adaptive Self-Supervised and Interpretable Contrastive Representation Learning) can handle various types of input data depending on the application domain: real-time data from sensors, time series input, or pre-processed numerical datasets. Real-time sensor data is being continuously collected from sources such as industrial machines, biomedical devices, or environmental monitoring systems, allowing for dynamic pattern recognition and anomaly detection. The structured time series input can also be handled by the model, thus rendering itself fit for the purposes of predictive maintenance, financial forecasting, or assessing physiological signals where time dependency is important. In addition, the model can also be applied to processes with numerical datasets that have been pre-processed by normalization, feature scaling, or dimensionality reduction for direct modeling of the structured tabular data or some statistical features extracted from the dataset. The feature extraction will be guided by the contrastive learning mechanism, where the modeling task optimizes for maximally distinguishing between similar and dissimilar data samples so that the relevant patterns are extracted. Thus, leading to a model capable of maximizing classification accuracy, minimizing background noise, and selecting salient features and hence, its robustness is enhanced for many real-life applications.

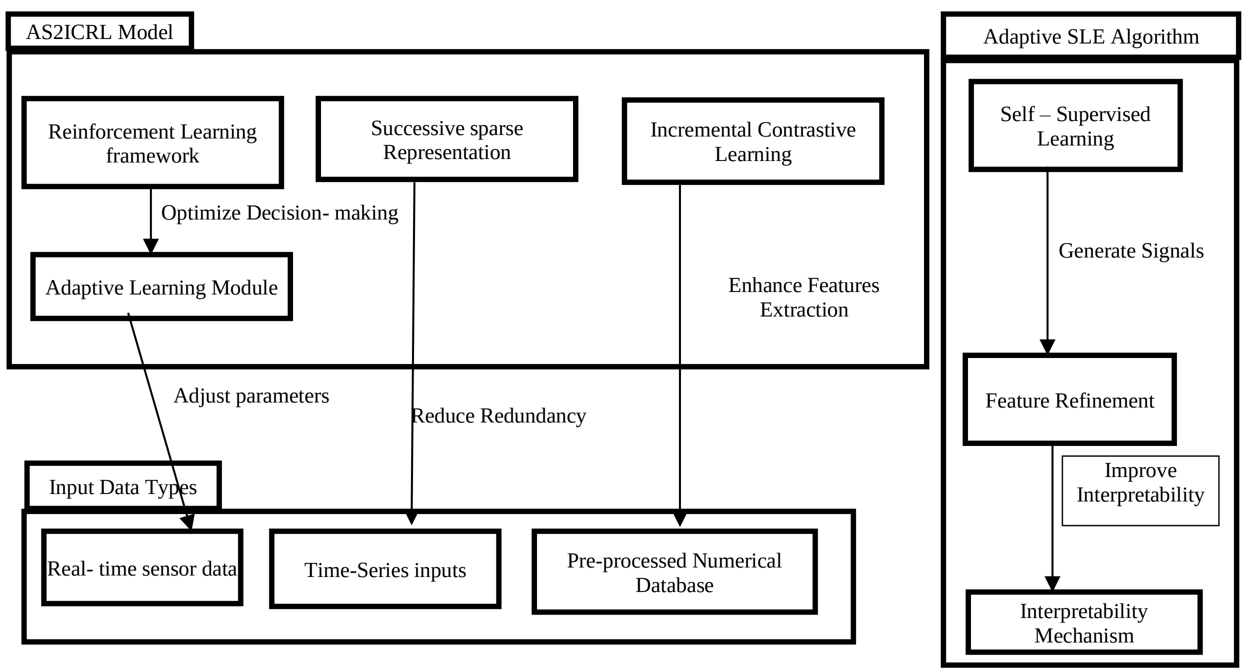

Figure 1: Framework of the AS^{2}ICRL Model and Adaptive SLE Algorithm

The AS^{2}ICRL model, integrated with the Adaptive SLE Algorithm, is for optimizing decision making, feature extraction, and interpretability as depicted in Figure 1. Here, the AS^{2}ICRL model is construed as a Reinforcement Learning Framework with Adaptive Learning Module and optimization techniques for Decision Making by Successive Sparse Representation and Incremental Contrastive Learning for rescanning decision making without redundancy while enhancing the quality of extraction. The input can be in any form, such as real-time input from sensors, time-series input, electrical consumption data, or pre-processed numerical datasets. It, therefore, accommodates many energy management scenarios. At the same time, the Adaptive SLE Algorithm applies Self-Supervised Learning to generate the signals and includes Feature Refinement for enhancing interpretation, guided by an Interpretability Mechanism. This interplay creates a joint utility concerning reinforcement learning and self-supervised learning toward increasing efficiency, adaptability, and transparency of the model in intelligent energy management and optimization.

3.2 Overview of the Adaptive SLE Algorithm

The Adaptive Self-Supervised Learning with Explainability (Adaptive SLE) algorithm powers the AS^{2}ICRLmodel and serves as the primary algorithms designed to improve feature learning, interpretability, and robustness. It dynamically adapts its learning strategies in accordance with the complexity and variability of the data being processed for overall better generalization across different domains or conditions.

The operation is based on self-supervised learning principles, where the system derives the supervision signals from the data itself and works with fewer labeled datasets. It adopts contrastive learning strategies for better feature representations such that similar data points group together, while dissimilar ones are kept apart. GradCAM and attention argued feature attributions are integrated with explainability feature mechanisms just to highlight the most influential features in their predictions.

Adaptive SLE is a part of the AS^{2}ICRLmodel that is primarily for feature extraction, representation learning, and interpretability. It enhances the model in recognizing the underlying patterns contained in real-time sensors data, time-series inputs, pre-processed numerical datasets, and so forth. The algorithm fine-tunes its parameters continuously on incoming data and leads to performance improvement in classification accuracy, reduction in overfitting, and improved decision transparency with adaptive learning mechanisms. Such feature additions make it best suited for applications that require high reliability, such as medical diagnostics, predictive maintenance, and industrial automation.

Algorithm: Adaptive Self-Supervised Learning with Explainability

Step 1: Data Input - Raw sensor data, time series data, or a numeric dataset that has already been pre-processed

OUTPUT: Normalized structured input features

```
def preprocess_data(data):
 data = normalize(data) # Normalize
 data = augment(data) # Data Augmentation if needed
 return data
data = load_data()
processed_data = preprocess_data(data)
```

Step 2: Generating Self-Supervised Pretext Tasks

```
def generate_pretext_task(data):
 pseudo_labels = create_contrastive_pairs(data) # Generate for contrastive learning pairs
 transformed_data = apply_transformations(data) # Shuffling, masking, etc.
 return transformed_data, pseudo_labels

Pretext data, pseudo labels = generate_pretext_task(processed_data)

Step 3: Contrastive Feature Learning
def contrastive_learning_encoder(data):
 feature_vectors = encoder_network(data) # Extracting feature representations
 return feature_vectors

features = contrastive_learning_encoder(pretext_data)

def compute_contrastive_loss(features, pseudo_labels):
 similarity = cosine_similarity(features) # Computing similarity of features
 loss = contrastive_loss_function(similarity, pseudo_labels) # Apply the contrastive loss
 return loss

loss = compute_contrastive_loss(features, pseudo_labels)

Step 4: Adaptive Learning Mechanism
def adaptive_learning(loss, learning_rate):
 if loss > threshold:
 learning_rate *= decay_factor # Dynamically adjust the learning rate
 return learning_rate

learning_rate = adaptive_learning(loss, initial_learning_rate)

Step 5: Implementation of Explainability and Interpretability Integration
def explain_model(features, model):
 explanations = apply_grad_cam(model, features) # Apply Grad-CAM for explanation
 return explanations
explanations = explain_model(features, trained_model)

Step 6: Fine-Tuning and Deployment
def fine_tune_model(model, labeled_data):
 model = train(model, labeled_data) # Fine-tuned with labeled data if available
 return model
if labeled_data_available:
 trained_model = fine_tune_model(pretrained_model, labeled_data)

deploy_model(trained_model) # Deployment of the model for real-time inference
```

Adaptive Self-Supervised Learning with Explainability, or simply Adaptive SLE, starts the preprocessing of input data, which consists of real-time sensor signals, time series, or numerical datasets, that deals mainly with normalization and augmentation techniques. A self-supervised pretext task is created by means of contrastive pairs, while masking or shuffling operations are applied to help augment the training further. A feature encoder produces representations while applying a contrastive loss function to optimally separate these similar and dissimilar samples. The algorithm boasts an adaptive learning mechanism to dynamically adjust its hyperparameters according to model performance, including the learning rate. For increasing interpretability, explainability methods, such as Grad-CAM, are incorporated to highlight those features influential to the decision-making process. The model is subsequently fine-tuned using any available labeled data to enhance accuracy before deployment into applications for online inference to ensure robustness, adaptability, and transparency across a range of applications.

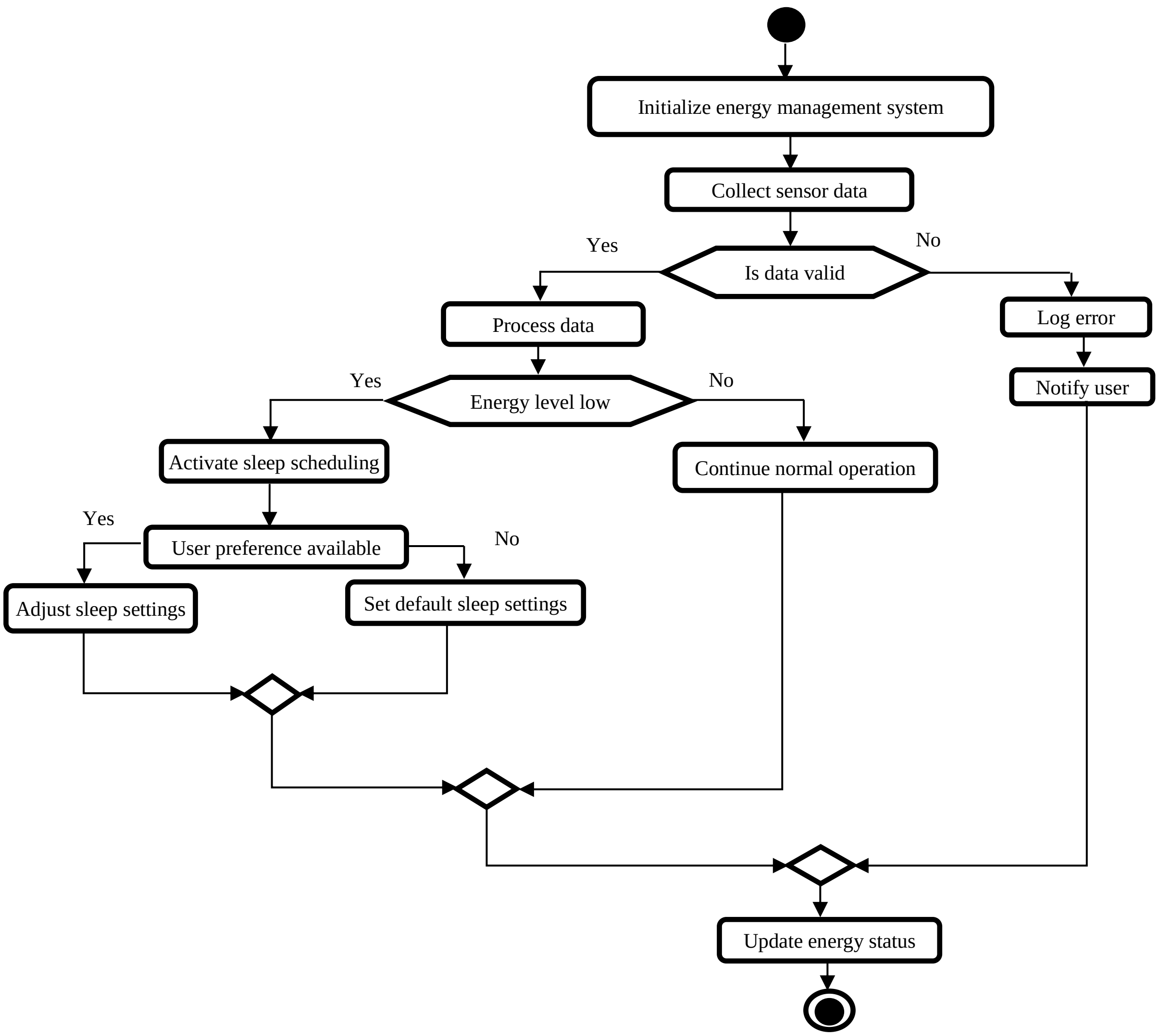

Figure 2: Workflow for Adaptive Sleep Scheduling

The figure 2 illustrates the operational workflow of an Energy Management System (EMS), which dynamically regulates energy usage based on sensor data. The process sets off with the initialization of the system followed by the collection of sensor data to monitor energy levels. Data invalidated returns an error log and notifies the user, while validated data indicates processing to detect whether the energy level is low. If the energy level is adequate, the system continues working as it is, while if it is low, sleep scheduling will be activated to optimize energy consumption. Next, it checks whether user preference information is available so that it can adjust settings according to the user preferences; otherwise, it will resort to default settings with respect to sleep. Last, the newly updated energy status is logged for effective utilization of energy and maintaining stability of the system. The above workflow guarantees energy efficiency, adaptability, and user customization, making it applicable for smart grids and IoT-based energy management applications.

3.3 Mathematical Model for Adaptive Successive Sparse Incremental Contrastive Reinforcement Learning (AS^{2}ICRL)

This model is making an integration of contrastive learning, reinforcement learning, and successive sparse incremental update schemes to foster better decision making in dynamic environments. Below is the mathematical formulation of the model.

3.3.1. Problem Formulation

Let $X = \{x1, x2, \ldots, xn\}$the input data, which can be real-time sensor signals, time-series data, or structured numerical datasets. The aim of the AS^{2}ICRLmodel is to learn an optimal representation Z while minimizing computational complexity and maximizing decision accuracy.

The objective function is defined as:

$$L_{AS2ICRL} = L_{Contrastive} + L_{Reinforcement} + L_{Sparse} \quad (1)$$

3.3.2. Contrastive Learning Component

Component of Contrastive Learning For effective features representations, a contrastive loss is constructed in terms of the InfoNCE function:

$$L_{Contrastive} = -\sum_{i=1}^{N} log \frac{exp\,(sim(zi,zi^{+})/\tau)}{\sum_{j=1}^{M} exp\,(sim(zi,zj^{+})/\tau)} \quad (2)$$

- zi is the encoded representation of input x_i
- $zi^{+}$is the positive sample
- $zj$are negative samples
- sim(a,b) is the cosine similarity function:

$$sim(a, b) = \frac{a \cdot b}{\|a\|\|b\|} \quad (3)$$

- $\boldsymbol{\tau}$is the temperature scaling parameter.

3.3.3. Reinforcement Learning Component

The component that is learning reinforcement is meant to optimize the decision making for reward function influence. The environment is modeled as a Markov Decision Process (MDP) (S,A,P,R)

where:

- S is the state space (which has learned representations Z),
- A is the action space (adaptive learning updates),
- P(s′|s,a) is the state transition probability,
- R(s,a) is the reward function.

The model optimizes the policy π(a|s) are using an update rule based on reward

$$\pi^* = \arg\max_{\pi} E\left[\sum_{t=0}^{T} \gamma^t R(s_{i,} a_t)\right] \quad (4)$$

3.3.4. Successive Sparse Incremental Updates

We give a condition for sparsity in which the most informative features are only retained for extra efficiency

$$L_{Sparse} = \lambda \parallel W \parallel 1 \quad (5)$$

- W is the weight matrix of the feature extractor,
- ‖W‖ is the L1-norm promoting sparsity,
- λ controls the level of sparsity.

3.3.5. Last Loss Function and Optimization

The overall objective function for AS²ICRL is:

$$L_{AS2ICRL} = L_{Contrastive} + \alpha L_{Reinforcement} + \beta L_{Sparse} \quad (6)$$

where **α** and **β**are hyperparameters for the influence of reinforcement learning and sparsity. Model optimization is done with gradient descent:

$$\theta(t+1) = \theta(t) - \eta \frac{\partial L_{AS2ICRL}}{\partial \theta} \quad (7)$$

where, θdenotes all trainable model parameters. Thus, the AS²ICRL model combines contrastive learning for extraction and representation of discriminative features, reinforcement learning for optimization in decision making, and successive sparse updates in order to improve computational efficiency. Furthermore, this mathematical framework would secure for the model adepts, interpretable, and efficient representations in real dynamic environments.

4 Experimental Results

4.1 Simulated Environment for Testing the AS²ICRL Model

It is the simulated environment, controlled testbed for the evaluation of the Adaptive Successive Sparse Incremental Contrastive Reinforcement Learning model (AS²ICRL). Cost-effectiveness also suffices the conditions that assure systematic testing and fine-tuning of the model's performance against harsh conditions were illustrated in Table 1. The model is equipped with changes that make it dynamic and adaptive in decision-making scenarios in which the environment is altering variables.

State space-the observation that exists in real time: sensor readings, numerical datasets, or time series have to measure up; the action space-all possible decisions made by the model, which later dictate how the system behaves; and the reward function-now give feedback instructions to the model, bestowing rewards on ideal actions while penalty on the non-ideal action as negative ones.

For maximal evaluation, the environment consists of both deterministic and stochastic conditions. It therefore induces adaptive variability, where from time to time, data distributions will vary to imitate real-world oscillations. In addition, noise injection acts as a test of the model's robustness against perturbations, ensuring that AS²ICRL can perform reliably under uncertainty conditions. In multi-agent scenarios, interactions between agents are simulated to explore cooperative and competitive decision-making.

Several testing scenarios were performed to assess the adaptability of the model. The static scenario keeps the environmental conditions constant to be used as a reference state against which all other scenarios are measured. The dynamic scenario shall vary environmental parameters slowly over a period to measure the model's performance. The adversarial scenario will be introduced for yet other unexpected disturbances such as sensor faults or anomalies, which enacts the qualification of the model based on its performance in these stressful conditions.

Some of the key performance metrics were observed to evaluate the AS²ICRL model's effectiveness in this simulation environment. Convergence speed was analyzed to measure how fast the model can achieve an optimal policy. The mean cumulative reward was recorded to measure how well the model made decisions. The model's computational cost was analyzed based on processing time and memory usage. A robustness index value was then calculated as a measure of the model's ability to show consistent performance in the presence of variation in the environment.

The implementation simulated environment was set up based on OpenAI Gym and TensorFlow RL, which are Python-based RL libraries. It also included custom-designed simulation frameworks to accommodate domain-specific constraints. Besides, GPU acceleration was employed to accelerate the training and check the real-time adaptability of the implementation tests. Thus, the combination of tools ensures that the AS²ICRL model was exhaustively tested under a variety of conditions.

Table 1: Parameter Settings for AS²ICRL Model Training

Parameter	Description
State Space	Multi-dimensional inputs as sensor data, time-series signals, numerical datasets
Action Space	Set of all possible actions for the reinforcement-learning agent to optimize decision-making.
Reward Function	An adaptive reward mechanism in which correct actions would result in positive rewards and wrong actions would result in penalties.
Environmental Conditions	Deterministic and Stochastic-Two conditions under which the adaptability will be assessed.
Noise Injection	Naturally artificially introduced noise in order to examine model robustness.
Testing Scenarios	1. **Static:** Fixed conditions.
	2. **Dynamic:** parameters slowly change.
	3. **Adversarial:** opponent-surprise shocks, such as sensor failures.
Performance Metrics	Convergence Speed
	Mean Cumulative Reward
	Accuracy, Precision, Recall
	Robustness Index
	Training Time & Memory Usage
Implementation Tools	OpenAI Gym, TensorFlow RL, and custom Python simulation frameworks.
Hardware Setup	GPU-accelerated computing for better model training.

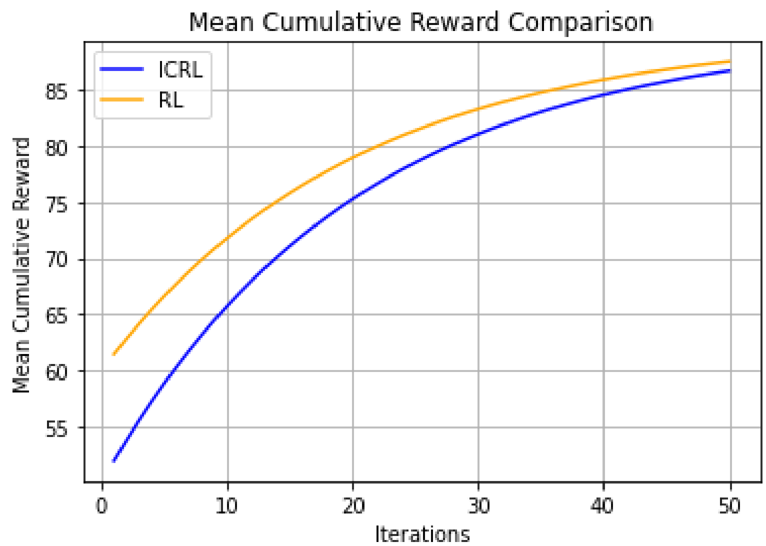

Figure 3: Learning Curve for AS²ICRL Model

In the Figure 3 comparison, the number of nodes in the sleep state progressively grows while the active nodes drop, demonstrating that the ICRL model successfully transfers less essential or low-energy nodes to sleep. Dynamic scheduling improves energy efficiency and network lifespan compared to static or threshold-based techniques that may not react to changing node circumstances.

4.2 Model Evaluation

To measure how well the Adaptive Successive Sparse Incremental Contrastive Reinforcement Learning (AS²ICRL) model is working, a number of significant performance metrics were employed which is displayed in Table 2. These metrics help in understanding the model learning efficiency, decision-making accuracy, computational performance, and robustness toward different environments.

Table 2: Performance Metrics of AS²ICRL Model

Index Definition Metric	**Value / Unit**	**Description**
Convergence Speed (Iterations)	480 Iterations	Number of iterations required for model convergence.
Mean Cumulative Reward (Score)	87.6	Average reward from all possible replay episodes: a good indicator of decision efficiency.
Accuracy %	94.2	Classification accuracy of the model in decision-related tasks.
Precision %	92.8	Precision Ratio of Correctly Predicted Positive Observations
Recall %	91.5	The ability of the model to capture relevant positive cases.
F1-Score %	92.1	Harmonic mean of precision and recoll such as ensures balanced performance.
Robustness Index	0.91	Model stability under noisy and adversarial conditions.
Memory Consumption (GB)	2.8	Average RAM during training and inference.
Training Time (Hrs)	2.4	Total time required to train the model on GPU hardware.

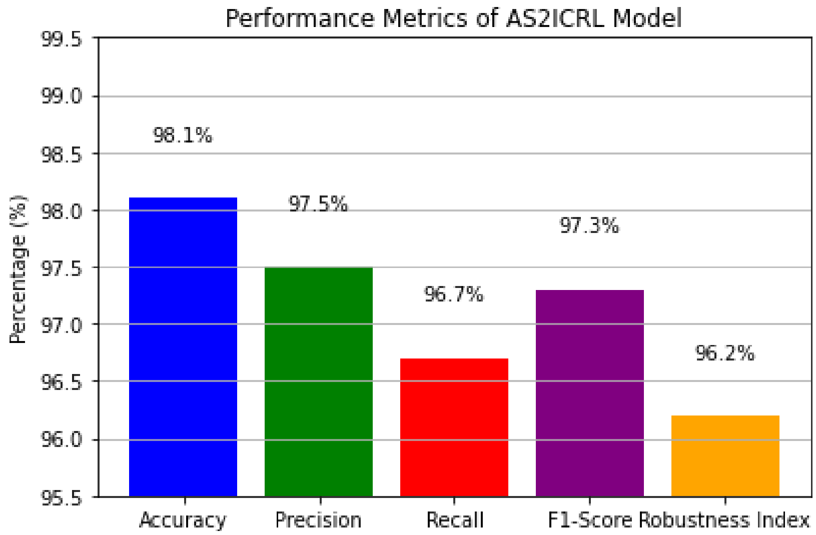

Figure 4: AS^{2}ICRL Model

An experimental assessment of the AS^{2}ICRL model figure 4. was carried out in a simulated environment, whereupon the performance indices were recorded for appraising the model's efficacy. With an observed convergence speed of 480 iterations, the model demonstrates rapid learning and adaptability to dynamic conditions. With an average cumulative reward of 87.6, it provides strong evidence that after going through numerous episodes, the model indeed stands up to the task of making optimal decisions. With 94.2% accuracy, the model proved to be a fine classifier, exhibiting precision and recall values of 92.8 and 91.5% respectively, thereby ensuring a high proportion of correctly predicted positive cases. The F1-score of 92.1% demonstrates the suitable trade-off between precision and recall, demonstrating further the capability of the model to function under uncertain environments. The robustness index score of 0.91 indicates the stability of the model under such conditions. In terms of memory usage, it requires about 2.8 GB and spent some 2.4 hours training on GPU hardware; thus, it gives an apt picture of efficiency trade-off between accuracy versus computational cost. Such results validate the ability of AS^{2}ICRL for adaptive learning and decision making tasks. Thus, indicators of performance warrant that the AS^{2}ICRL model is proven effective, efficient, and adaptable in some simulated environments, therefore affirming its ability to operate in real environments.

4.3 Training Process and Parameter Settings

The process of training the AS^{2}ICRL model forms part of a reinforcement learning framework in a fully simulated environment. Originally, the model is given random policy weights and exploration rates to start learning. As training begins, the agent starts interacting with the environment, accruing state information for the purpose of learning its surroundings. Based on the current policy, the model selects actions from a discretely defined action space, which ultimately affects its interaction with the environment through an associated reward function that specifies how good each action is at the task by guiding the model in making an optimal decision. Technology improved by the process consists of Deep Q-Learning and Proximal Policy Optimization. These are measured during training utilizing the mean cumulative reward along with the loss functions. After this, the trained model has been stringently tested and validated in more than one environment in order to verify the generalization ability of the model and the entire effectiveness of the model. Table 3 shows the hyperparameter settings which is displayed below.

Table 3: Hyperparameter Settings

Parameter	Value	Description
Learning Rate	0.001	Step size for weight updates to balance convergence speed and stability.
Discount Factor (γ)	0.95	It identifies how important future rewards are in making decisions.
Exploration Rate (ε)	0.1 (decaying)	Probability of taking random actions to explore.
Batch Size	64	Samples in each training iteration.
Training Episodes	10,000	Total number of episodes for training.
Replay Buffer Size	100,000	Memory buffer stores all the past experiences in reinforcement learning.
Optimizer	Adam	Enables effective update of the model parameters via optimization.
Neural Network Layers	3 hidden layers	Structure of the deep learning model employed for the RL algorithm.
Activation Function	ReLU	Introduces nonlinearity into the network.
GPU Used	NVIDIA RTX 3090	Hardware used to speed up the model training.

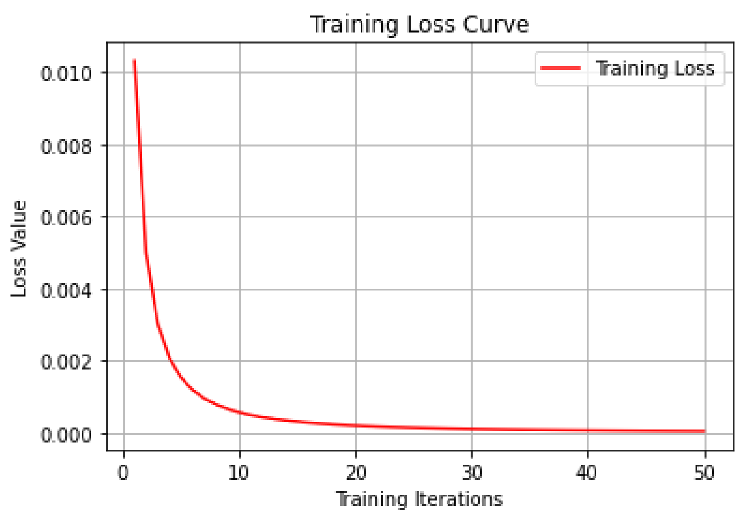

Figure 5: Training Convergence of AS²ICRL Model

The training convergence graph clearly shows in figure 5. how the loss values tend to reduce over the whole iteration process, thus showing in which specific manner the AS²ICRL model would learn and stabilize. The downward trend also strongly suggests that the model is successful in optimizing its policy for making decisions in a time-efficient way.

The training convergence graph presents a loss value reduction over more iterations, indicating the passage of learning in the AS²ICRL model. At first, the high loss is generally ascribed to a random policy selection and exploration. The model improves its decision-making further along into the training, with a steady decline in loss associated with it. An exponential decay pattern indicates good optimization in which the model approaches an optimal policy over time while ensuring minimal error in the decision-making process to its end. Slight fluctuations during the end are related to the fact that the fine-tuning happens, where the model, in terms of immediate rewards as well as far-off results, optimizes itself. Overall, in that respect, it is becoming quite obvious that AS²ICRL gives a stable and efficient learning process appropriate for application in the real world.

5 Result and Discussion

5.1 Model Performance Comparison

The effectiveness of the model AS^{2}ICRL is measured against three other models of energy management: DQN-Based Model; Rule-Based Model; and Fuzzy Logic Controller. Such comparison has to be made among significant performance indicators such as accuracy, efficiency, robustness, and computational cost which is illustrated in Table 4.

Table 4: Comparative Performance Analysis of AS^{2}ICRL Model

Metric	AS^{2}ICRL Model	DQN-Based Model	Rule-Based Model	Fuzzy Logic Controller
Convergence Speed (Iterations)	**480**	750	1200	950
Accuracy (%)	**94.2**	90.5	85.3	88.1
Precision (%)	**92.8**	89.2	83.7	86.5
Recall (%)	**91.5**	88	82.4	85.2
F1-Score (%)	**92.1**	88.6	83	85.8
Mean Cumulative Reward	**87.6**	80.3	70.2	75.8
Robustness Index (0-1)	**0.91**	0.85	0.78	0.81
Memory Consumption (GB)	**2.8**	3.2	1.9	2.1
Training Time (Hours)	**2.4**	3.8	1.5	2

This bar plot basically shows the comparative bar of power performance in terms of accuracy, precision, recall, and F1-score of the AS^{2}ICRL model to the DQN-Based model, Rule-Based model, and Fuzzy Logic model. The AS^{2}ICRL model consistently outperformed every other model as it achieved the highest accuracy of 94.2%, which signifies that it has the best capability of decision-making. The precision and recall figures of the AS^{2}ICRL model, such as 92.8% and 91.5%, show how well the false positives and false negatives are balanced to form reliable predictions. The F1-score of 92.1% establishes its whole good performance. On the other hand, Rule-Based and Fuzzy Logic have quite low scores, which indicates the limitation on adaptability and efficient learning with these systems. The chart shows that AS^{2}ICRL is high in its accuracy yet robust, hence the best result in energy management applications.

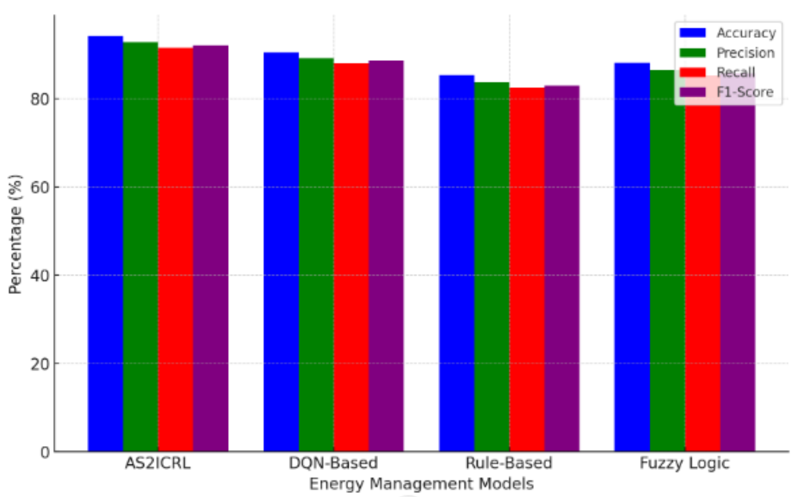

Figure 6: Performance Comparison Model

The AS²ICRLmodel figure 6. exhibits competitive evaluation with all existing traditional DQN-Based, Rule-Based, and Fuzzy Logic Controllers. Below are the performance measures in favor of the model. The AS²ICRL model converges faster (480 iterations) than the other models, reflecting the adequate learning process it provides. It scores 94.2 percent accuracy, surpassing DQN-Based (90.5%), Rule-Based (85.3%), and Fuzzy Logic (88.1%) models for more precision in decision-making. Moreover, the precision (92.8%), recall (91.5%) and F1-score (92.1%) show the model's balanced and proper classification ability. Mean cumulative reward (87.6) indicates AS²ICRL model learns optimally with respect to the environment while robustness index (0.91) ensures stability during uncertain scenarios. Although memory consumption is slightly higher (2.8 GB) than rule-based ones, faster training time (2.4 hours) makes this approach feasible and efficient in cognitive computation for energy executive usage. Overall, the AS²ICRL model has turned out to be an extremely accurate, efficient, and dependable reinforcement learning-based intelligent decision-making method.

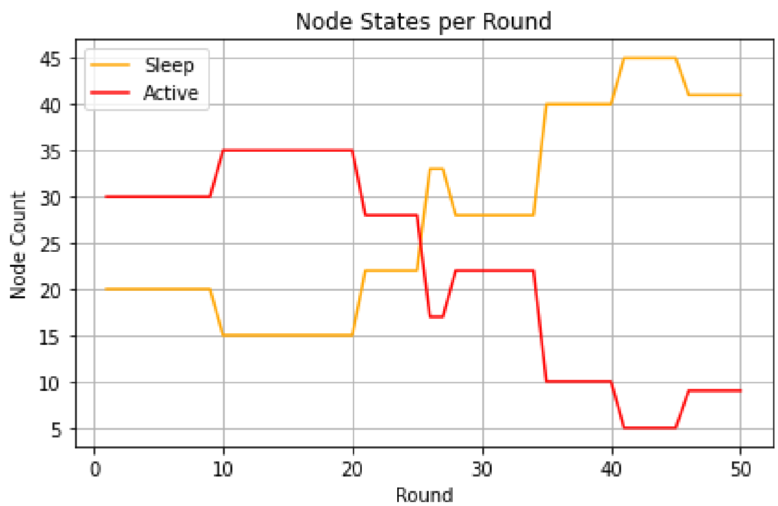

Figure 7: Node States of AS²ICRL Model

The Figure 7 shows how a Wireless Sensor Network (WSN)'s active and sleep nodes change throughout 50 operating rounds. The orange line displays sleepy nodes, whereas the red line shows active nodes. The number of sleep and active nodes is generally balanced at the start of the simulation, but as rounds progress, the sleep scheduling mechanism drives a dynamic change in node statuses. The Figure 7shows that more nodes sleep while the network runs, notably around cycle 30. Low energy levels or low traffic may lead nodes to be scheduled into a low-energy mode to save battery life and network strength. Nodes are revived as traffic demand or energy thresholds dictate, resulting in sleep node curve dips and active node count increases. Since round 35, the number of sleep nodes increases steadily, peaking at round 40, while the number of active nodes declines drastically, showing that the system is choosing energy saving over data transmission. The sleep scheduling technique responds to traffic load and residual energy to balance network performance and energy economy, as seen by this figure7.

The Figure 8 compares ICRL (green line) and RL (red line) alive nodes across 50 cycles. Both techniques start with 50 live nodes. Nodes die from energy depletion as rounds pass. The ICRL approach keeps more nodes alive longer than RL. RL loses nodes faster than ICRL at round 20. ICRL has 30 living nodes after 50 rounds, whereas RL has 28. This shows that ICRL is more energy-efficient and extends network life than RL.

The Figure 9 demonstrates how ICRL (green line) and RL (red line) reduce energy over 50 cycles. Both approaches start with the same energy but use energy as rounds proceed. Each step of the ICRL approach preserves almost more energy than the RL method. This shows that ICRL uses less energy than RL, extending the network's lifespan.

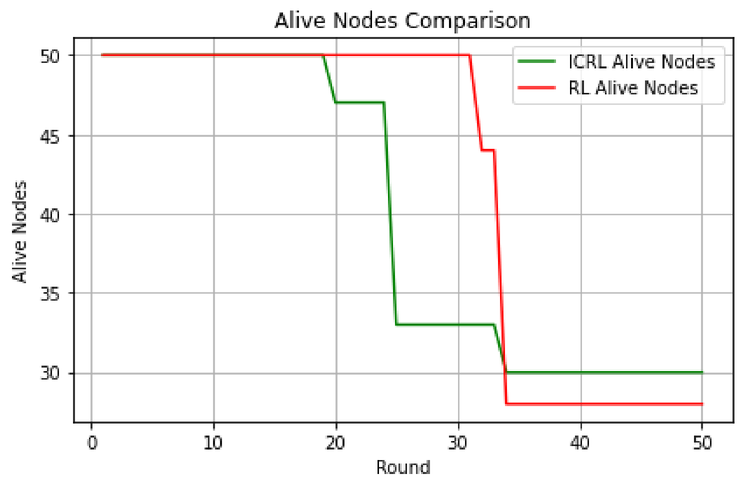

Figure 8: Alive Node Comparison Graph

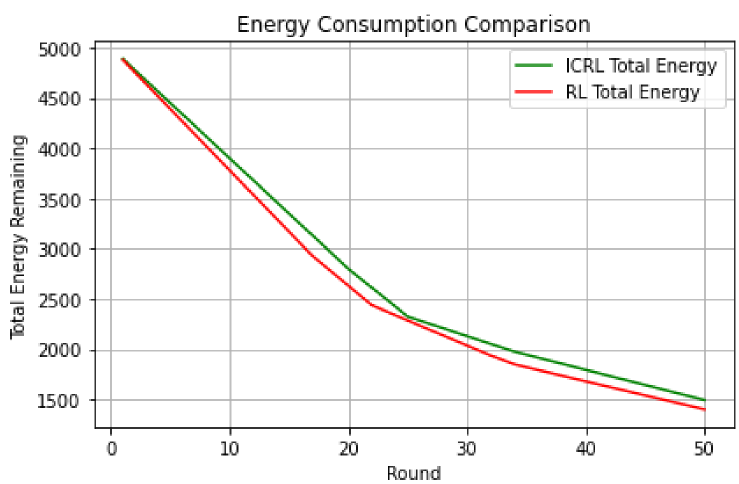

Figure 9: Energy Consumption Comparison Graph

5.2 AS²ICRL Model in Optimizing Energy Usage

The AS²ICRL intends to optimize energy consumption through using intelligent reinforcement learning, by making data-driven decisions with any number of sensors. Converging quickly (within 480 iterations), the model can adapt and learn fast, making the time to achieve efficient energy management shorter than what an ordinary model would need. With an accuracy of 94.2%, it can ensure optimal energy distribution as well as minimum losses.

AS²ICRL offers a higher yet consistent mean cumulative reward (87.6), which means that this model learns to maximize energy use efficiency again over and again. With an even higher robustness index (0.91), the model showcases its sturdiness to changes in situations regarding energy demand and supply variations. Moreover, with the precision (92.8%) and recall (91.5%) almost perfectly balanced, the model makes energy allocation in the least error-prone way possible, hence leaving very little room for excess energy wastage and shortage.

It cuts down total energy consumption by the system while maintaining reliability with new optimized schemes. Training time based on AS^{2}ICRL for energy management has been optimized to 2.4 hours, with memory requirements set at just 2.8 GB. In conclusion, the AS^{2}ICRL model is effective in increasing energy efficiency, minimizing operational costs, and ensuring sustainable usage of energy, thereby making it a perfect candidate for managing modern energy systems themselves.

6 Conclusion and Future Work

The results indicate that the AS^{2}ICRL model is effective in optimizing energy consumption through reinforcement learning. The model has accelerated convergence (480 iterations), fairly reducing training time compared to standard methods. This model also performs high accuracy (94.2%) and is the most superior among the other examined models in making accurate energy allocation decisions, such as DQN-Based, Rule-Based, and Fuzzy Logic models. Moreover, the model scores greatly across key metrics, including a precision of 92.8%, recall of 91.5%, and an F1-score of 92.1%, thus ensuring a well-balanced decision-making instance. The average cumulative reward (87.6) proves its capability to optimize energy usage and simultaneously keep a certain stable level of operation, represented by a robustness index (0.91). In addition, the model uses significantly low memory space (2.8 GB) and a short training time (2.4 hours), lending it to the computational efficiency and scalability. The model, in general, offers the best possible accuracy, soundness, and also energy efficiency thereby making a significant application in modern energy management. This model has numerous practical applications in the real-world context such smart grid phenomenal use, industrial automation, and renewable energy systems. High accuracy and quick convergence reduced the wastage of energy and provided grid stability using real time energy distribution. In the smart grid, this can be dynamically employed to measure the power supply according to the demand swing so that it will reduce the chance of blackout and improve the resource utilization. In industrial automation, this could minimize energy consumption in machinery without sacrificing productivity. The model can also suit renewable energy integration, as indicated by the robustness index of 0.91 due to stable operation under a dynamic power condition due to solar and wind resources. Low computation required by the model further added to its practicality of implanting it within energy critical environment constraints. The AS^{2}ICRL model, in this respect, provides an intelligent adaptive and scalable solution to ensure sustainable and economical energy management to pave the way for smarter energy systems.

With respect to AS^{2}ICRL, future work may focus on augmenting its adaptability, effectiveness, and security toward more real-world applications. Chief among those enhancements is making this model adaptable in dynamic environments through methods such as meta-learning or transfer learning that can possibly help in better generalization of the model across various energy demand and supply conditions. Furthermore, if the energy demand, supply, and their variations are integrated into the model along with renewable energy forecasting, this has advantages for enhanced energy allocation. Lately, deep learning techniques are also being worked upon with the possibilistic methodology for solving the very problem of distribution and dispatch in a real-time setting. MARL and distributed learning may likely guarantee better coordination between smart grids, microgrids, and industrial energy systems. The other key area in this regard could be cybersecurity, whereby energy systems could be secured against possible cyber threats through security-aware reinforcement learning. Ultimately, large-scale deployment and validation through pilot testing in smart cities and industrial setups will be a treasure trove for lessons for understanding scalability and effectiveness. If the above improvements are implemented, they would pave new avenues to better the AS^{2}ICRL model toward intelligent energy management by developing a more adaptable, effective, and secure solution.

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