International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Load Scheduling and PredictionUsing AI for Optimal Operation

[1] Chaitanya Singh Chandra, [2] Ajay Chandravanshi, [3] Mrityunjay

[1 2 3]Computer Science & Engineering Shri Shankaracharya Technical Campus Junwani, Bhilai

ABSTRACT:

The increasing complexity and volatility of modern electricity markets necessitate innovative approaches for optimizing power procurement strategies. This paper proposes an AI-driven framework for optimal load scheduling by determining the ideal procurement mix across the Day-Ahead Market (DAM), Term Ahead Market (TAM), and Real-Time Market (RTM). Leveraging advanced machine learning techniques— namely Long Short-Term Memory (LSTM) networks, Deep Q-Networks (DQN), and Proximal Policy Optimization (PPO)—the system aims to minimize total procurement costs, reduce deviation penalties, and maintain a reliable electricity supply. The study highlights the effectiveness of hybrid AI models in adapting to market fluctuations, enhancing procurement efficiency, and supporting grid stability in a dynamic energy landscape.[5]

1. Introduction: -

As electricity markets become increasingly deregulated and interconnected, utility providers face the complex challenge of optimizing procurement strategies to balance cost, reliability, and operational efficiency. Traditional methods—often based on static schedules or heuristics—struggle with the volatile nature of modern power markets. This research proposes an AIdriven framework that integrates demand forecasting, cost optimization, and real-time adaptability to support smarter procurement decisions. The framework aims to minimize procurement costs, avoid deviation penalties, and ensure a reliable power supply. It identifies the optimal electricity mix by strategically procuring from the Day-Ahead Market (DAM), Term Ahead Market (TAM), and Real-Time Market (RTM). [1, 5]

1.1Problem Statement: -

Electricity procurement across multiple markets necessitates careful management of trade-offs among cost, risk, and grid stability. The inherent volatility in electricity pricing within the Day-Ahead Market (DAM), Term Ahead Market (TAM), and Real-Time Market (RTM), coupled with fluctuating demand and supply conditions, poses significant challenges to formulating an optimal procurement strategy. This research seeks to develop an intelligent load scheduling system that leverages predicted market prices, real-time conditions, and grid parameters to optimize procurement decisions. The proposed system aims to minimize overall costs and deviation penalties while maintaining system reliability and operational efficiency.

1.2Objective

The primary objective of this research is to develop an AI-based system that determines the optimal electricity procurement mix across the Day-Ahead Market (DAM), Term Ahead Market (TAM), and Real-Time Market (RTM). The system is designed to minimize overall procurement costs, mitigate penalties arising from demand-supply deviations, and ensure a stable and reliable electricity supply. By leveraging advanced machine learning techniques, the proposed framework forecasts market conditions, optimizes procurement strategies, and dynamically adapts to real-time fluctuations in demand and pricing.

2.Literature Review

Previous research has investigated various methodologies for optimizing electricity procurement, including heuristic algorithms, traditional optimization models, and machine learning-based techniques. While these methods have shown promise, many face limitations in adapting to the dynamic and uncertain nature of real-time electricity markets. Recent advancements in deep learning and reinforcement learning have demonstrated significant potential in improving prediction accuracy and supporting more adaptive decision-making in energy systems. Building upon these developments, this study proposes a hybrid model that integrates Long Short-Term Memory (LSTM) networks, Deep Q-Networks (DQN), and Proximal Policy Optimization (PPO) to enhance load scheduling and procurement optimization.

3.Methodology

The proposed system consists of three key modules: LSTM-based prediction, PPO for DAM and TAM procurement, and a DQN + PPO model for RTM adjustment. Each module is designed to address a specific aspect of the procurement process, from forecasting to real-time adjustment. [1, 4, 5]

3.1 LSTM Model for DAM Forecasting

The Long Short-Term Memory (LSTM) model is employed to forecast the optimal procurement percentage from the Day-Ahead Market (DAM) using historical data. Key input features include temporal information, Market Clearing Price (MCP), Market Clearing Volume (MCV), and relevant weather parameters. Owing to its capability to capture longterm dependencies and patterns in time-series data, the LSTM model is particularly well-suited for predicting fluctuations in DAM prices and volumes, thereby enabling more informed and accurate procurement decisions [1, 6, 8].

3.1.1 Inputs for Trend Prediction

- Time
- Selling bid
- Purchase bid
- MCP
- MCV
- Weather conditions

Dataset

MCP (Rs/N	Final Sche	MCV (MW	Sell Bid (M	Purchase E	Time Block	Hour	Date	temp	dwpt	rhum	prcp	snow	wdir	wspd	wpgt	pres	tsun	coco
3800.44	7513.77	7513.88	13859.2	12839.5	00:00 - 00:	1	8/3/2024	17.3	5.6	46	0		360	5.4		1013.9		1
3658.26	7763.76	7862.64	14858.1	12751.1	00:15 - 00:	1	8/3/2024	17	5.975	48.25	0		355	4.95		1014.35		1
3634.93	7622.56	7721.43	15345.4	12530.8	00:30 - 00:	1	8/3/2024	16.7	6.35	50.5	0		350	4.5		1014.8		1
3634.34	7536.26	7635.13	15570.4	12344.8	00:45 - 01:	1	8/3/2024	16.4	6.725	52.75	0		345	4.05		1015.25		1
3634.02	7584.75	7662.99	15987.8	12194.1	01:00 - 01:	2	8/3/2024	16.1	7.1	55	0		340	3.6		1015.7		1
3506.65	7520.78	7556.53	16293.4	11981.5	01:15 - 01:	2	8/3/2024	16.6	7.125	53.5	0		255	2.7		1015.9		1
3499.28	7235.53	7332.53	16370.7	11624.2	01:30 - 01:	2	8/3/2024	17.1	7.15	52	0		170	1.8		1016.1		1
3316.98	7141.83	7206.55	16531.8	11468.3	01:45 - 02:	2	8/3/2024	17.6	7.175	50.5	0		85	0.9		1016.3		1
3310.01	7042.2	7046.77	16824.5	10905.7	02:00 - 02:	3	8/3/2024	18.1	7.2	49	0		0	0		1016.5		1
3300.31	6876.38	6952.53	16928.8	10670.1	02:15 - 02:	3	8/3/2024	18.6	7.35	48	0		17.5	2.8		1016.35		1
3298.38	6790.84	6886.19	17046.9	10450.5	02:30 - 02:	3	8/3/2024	19.1	7.5	47	0		35	5.6		1016.2		1
3260.04	6810.25	6881.77	17198.7	10183.9	02:45 - 03:	3	8/3/2024	19.6	7.65	46	0		52.5	8.4		1016.05		1
3190.82	6840.33	6907.52	17423.4	10128.4	03:00 - 03:	4	8/3/2024	20.1	7.8	45	0		70	11.2		1015.9		1
3185.84	6901.41	7000.35	17650.6	10189	03:15 - 03:	4	8/3/2024	20.85	7.125	41.5	0		72.5	11.2		1016.325		1
3185.32	6792.09	6881.07	17751.2	9942	03:30 - 03:	4	8/3/2024	21.6	6.45	38	0		75	11.2		1016.75		1
3185.32	6754	6853	17643.9	9836.1	03:45 - 04:	4	8/3/2024	22.35	5.775	34.5	0		77.5	11.2		1017.175		1
3184.83	6754.4	6853.4	17780.3	9879.2	04:00 - 04:	5	8/3/2024	23.1	5.1	31	0		80	11.2		1017.6		1
3272.43	6766.39	6772.25	16819.8	10100.4	04:15 - 04:	5	8/3/2024	23.6	5.15	30.25	0		75	11.2		1017.525		1
3287.91	6729.86	6734.65	16494.5	10213.9	04:30 - 04:	5	8/3/2024	24.1	5.2	29.5	0		70	11.2		1017.45		1
3305.56	6626.46	6638.55	15582.8	10312.8	04:45 - 05:	5	8/3/2024	24.6	5.25	28.75	0		65	11.2		1017.375		1
3658.33	6603.7	6686.6	13710.8	10278.1	05:00 - 05:	6	8/3/2024	25.1	5.3	28	0		60	11.2		1017.3		1
3658.65	6837.8	6920.7	13198.6	10511.8	05:15 - 05:	6	8/3/2024	25.55	5.55	27.75	0		62.5	12.1		1016.675		1
3749.64	7000.8	7052.1	12548.4	10875.4	05:30 - 05:	6	8/3/2024	26	5.8	27.5	0		65	13		1016.85		1
3850.49	7234.61	7307.69	12249.3	11231.7	05:45 - 06:	6	8/3/2024	26.45	6.05	27.25	0		67.5	13.9		1015.425		1

Table 01: - Dataset Creation Using CSV File for training LSTM Model

Training

```
<ipython-input-7-1d4628d3598f>:35: FutureWarning: DataFrame.fillna with 'method' is deprecated and will rais
  data = data.fillna(method='ffill')
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_
  super().__init__(**kwargs)
Epoch 1/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - loss: 0.0463 - val_loss: 4.3204e-04
Epoch 2/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 0.0025 - val_loss: 4.3477e-04
Epoch 3/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 0.0018 - val_loss: 1.4759e-04
Epoch 4/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 0.0013 - val_loss: 3.5412e-04
Epoch 5/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 0.0011 - val_loss: 5.5707e-05
Epoch 6/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 5s 4ms/step - loss: 8.9666e-04 - val_loss: 8.8363e-05
Epoch 7/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 7s 6ms/step - loss: 7.8113e-04 - val_loss: 8.1545e-05
Epoch 8/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 7.1456e-04 - val_loss: 2.3754e-04
Epoch 9/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 5s 4ms/step - loss: 7.2939e-04 - val_loss: 1.6120e-04
Epoch 10/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 6.9810e-04 - val_loss: 6.2109e-05
Epoch 11/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 6.5635e-04 - val_loss: 3.6923e-05
Epoch 12/50
879/879 ━━━━━━━━━━━━━━━━━━━━ 5s 4ms/step - loss: 6.3347e-04 - val_loss: 2.7044e-04
Epoch 13/50
```

Table 02: - Model Training & Epochs

Model summary

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 1, 50)	13,000
dropout (Dropout)	(None, 1, 50)	0
lstm_1 (LSTM)	(None, 50)	20,200
dropout_1 (Dropout)	(None, 50)	0
dense (Dense)	(None, 1)	51

Total params: 99,755 (389.67 KB)
Trainable params: 33,251 (129.89 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 66,504 (259.79 KB)

Table 03: - Summary of Model

3.1.2 Output

• Predicted DAM procurement percentage

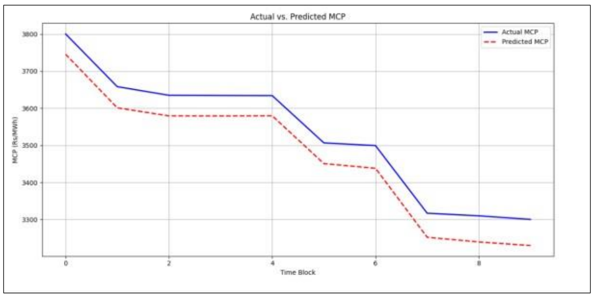


Table 0 4 : - Actual v/s Predicted Graph

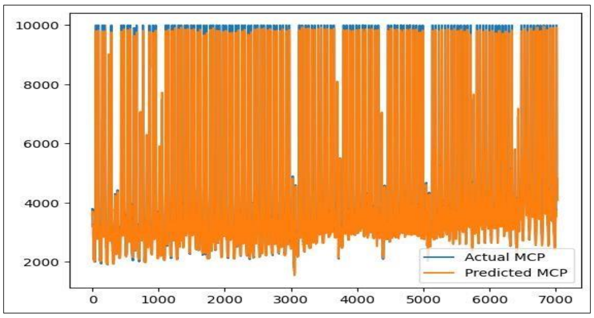


Table 0 5 : - Actual v/s Predicted Trend

3.1.3 Purpose

The LSTM model aims to provide an accurate forecast of the DAM trend, taking into account both market trends and external factors such as weather, which directly affect electricity demand and generation.

3.2 Hybrid PPO +DQN Model for DAM and TAM Procurement

This hybrid model adjusts the procurement mix between DAM and TAM to minimize overall costs while considering the LSTM's predictions. It combines the algorithm, with DQN to optimize the procurement decision-making process and learn from it using DQN model. [7, 8]

3.2.1 Inputs

- LSTM's DAM prediction
- DAM price
- TAM price
- Load categories (critical, non-critical, priority)

3.2.2 Output

• Adjusted DAM and TAM procurement percentages

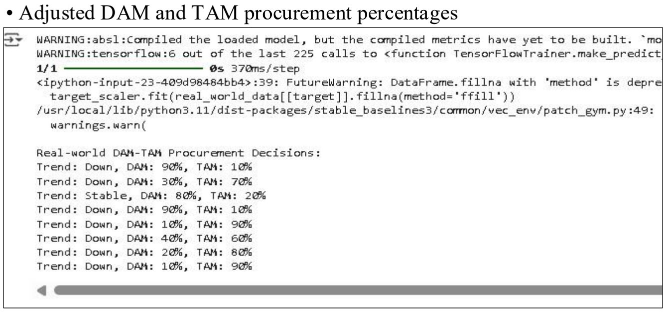


Table 0 6 : - DAM and TAM Predicted percentages

3.2.3 Purpose

The PPO state action

actions = [(0.9, 0.1), (0.8, 0.2), (0.7, 0.3), (0.6, 0.4),

(0.5, 0.5), (0.4, 0.6), (0.3, 0.7), (0.2, 0.8), (0.1, 0.9)]
adjusts the procurement mix between DAM and TAM based on favorable pricing conditions, while DQN learns optimal strategies for minimizing procurement costs based on historical data and cost feedback.

3.3 RTM Adjustment Model (DQN + PPO)

The RTM adjustment model is designed to optimize real-time procurement strategies and manage deviations. It uses a combination of DQN and PPO to determine immediate actions to correct supply imbalances and adjust the procurement mix.

3.3.1 Inputs

• Real-time grid parameters: frequency, voltage, current, power factor, active/reactive power

3.3.2 Output

Optimal RTM procurement percentage
Load corrections to maintain grid stability 3.3.3 Purpose
The DQN model decides the optimal procurement strategy based on immediate market conditions, while PPO ensures that the system learns stable policies under fluctuating market conditions, avoiding penalties and ensuring supply stability.

4. Key Features of the System

4.1 Deviation Penalty Minimization

The system minimizes deviation penalties by adjusting the DAM/TAM/RTM procurement mix based on forecasted vs. actual demand and real-time grid parameters. The models are trained to ensure that any discrepancies between predicted and actual demand are corrected in real-time. [7, 8]

4.2 Cost-Effective Procurement

By using the State action logic in conjunction with the LSTM and DQN models, the system reduces the dependency on TAM, especially when DAM pricing is favorable. This results in significant cost savings and more efficient procurement strategies.

4.3 AI Adaptability

The system evolves over time using reinforcement learning, ensuring that it adapts to changing market conditions. This adaptability is critical for maintaining the effectiveness of the system in a volatile and uncertain market environment.

4.4 Load-Aware Scheduling

The system intelligently schedules loads based on their priority (critical, non-critical, or priority loads) and the available energy sources. This ensures that critical loads are always met while non-critical loads can be adjusted based on available supply.

5. Experimental *Results* and Discussion

In this section, we present the simulation results of the proposed model, utilizing real-world electricity market data. The model's performance was evaluated based on its effectiveness in predicting the optimal procurement mix, minimizing deviation penalties, and reducing overall procurement costs. The results demonstrate that the hybrid AI model significantly outperforms traditional approaches, achieving superior cost optimization and enhancing grid stability. [1]

5.1 Cost Optimization

The proposed system achieved a notable reduction in overall procurement costs by effectively optimizing the procurement mix across the Day-Ahead Market (DAM), Term Ahead Market (TAM), and Real-Time Market (RTM). By integrating LSTM-based forecasting with a hybrid reinforcement learning model combining Proximal Policy Optimization (PPO) and Deep Q-Network (DQN), the system was able to make more informed and adaptive procurement decisions. This approach significantly reduced reliance on highercost markets such as TAM, resulting in improved costefficiency and better alignment with real-time market conditions.

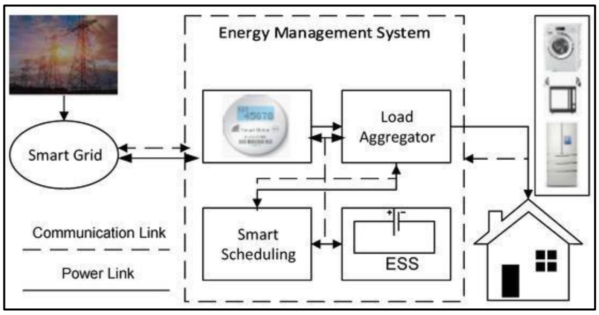
5.2 Penalty Minimization

The Real-Time Market (RTM) adjustment model proved highly effective in minimizing deviation penalties by dynamically refining procurement strategies in response to real-time fluctuations. The integration of Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) enabled the system to swiftly and accurately correct supply-demand imbalances, thereby enhancing operational responsiveness and contributing to stable grid performance.

5.3 System Scalability

The AI-based approach demonstrated strong scalability in handling larger datasets and more complex market scenarios, showcasing its robustness and practical applicability. As the system continues to evolve through reinforcement learning, it is expected to retain a high degree of adaptability, enabling it to respond effectively to emerging trends and future dynamics in electricity markets.

5.4 Energy Management System (EMS)



Smart Grid

A **Smart Grid** is an advanced electricity network that utilizes digital communication technologies to detect and respond to localized changes in electricity consumption.

It facilitates the integration of renewable energy sources, continuously monitors the flow of electricity, and enables real-time communication between utilities and consumers.

The Smart Grid supports bidirectional power and communication flows, optimizing the generation, distribution, and consumption of electricity for enhanced efficiency.

Energy Management System (EMS)

The Energy Management System (EMS) serves as the central decision-making unit within this framework, incorporating various components designed to optimize energy usage. Key components of the EMS include:

Smart Meter

Continuously measures energy consumption in real-time.

Facilitates data exchange between the smart grid and household devices.

Enables time-of-use pricing and supports demand response operations to adjust energy usage based on pricing and grid conditions.

Load Aggregator

Collects data on energy consumption across all household appliances.

Makes decisions on which appliances to operate and when, based on usage patterns and energy availability.

Optimizes energy consumption by balancing user comfort, cost, and efficiency.

Smart Scheduling

Uses advanced algorithms to schedule appliance usage during off-peak hours, reducing energy costs.

Considers factors such as user preferences, appliance priority, and signals from the grid.

Helps lower energy bills and reduces peak load demand, contributing to overall grid stability.

Energy Storage System (ESS)

Stores excess energy, often generated from renewable sources or during off-peak periods.

Provides stored energy during times of high energy costs or power outages.

Acts as a buffer, enhancing energy reliability and supporting grid stability by smoothing out fluctuations in supply and demand.

3. Home Appliances

These are the connected electrical devices within a home, including appliances such as washing machines, refrigerators, and HVAC systems.

The EMS controls these appliances to optimize their energy consumption.

Appliances communicate with the EMS either through smart plugs or built-in Internet of Things (IoT) features, enabling seamless coordination for energy optimization. [12]

4. Communication Link (Dashed Lines)

Represents the data communication pathways between the smart grid, EMS, and home devices.

Facilitates real-time data exchange, enabling timely decision-making and system adjustments.

Utilizes technologies such as Wi-Fi, ZigBee, or Power Line Communication (PLC) to ensure seamless connectivity and efficient communication. [13]

5. Power Link (Solid Lines)

Represents the physical flow of electricity from the grid to the home.

Includes connections to and from the Energy Storage System (ESS) and home appliances, facilitating the distribution of power throughout the system. [14]

5.5 IEX Load Scheduling & Prediction Table

Date	Hour	Time Block	Purchase Bid (MW)	Sell Bid (MW)	MCV (MW)	Final Scheduled Volume (MW)	MCP (Rs/MWh) *
21-04-2025	1	00:00 - 00:15	16842.70	5227.70	5227.70	5227.70	10000.00
		00:15 - 00:30	16732.00	5271.50	5271.50	5271.50	10000.00
		00:30 - 00:45	16373.10	5298.20	5298.20	5298.20	10000.00
		00:45 - 01:00	16169.00	5491.80	5491.80	5491.80	10000.00

Table 7 : - Load Scheduling & Prediction Table

•The IEX Load Scheduling & Prediction Table presents real-time data, including demand, generation, pricing, and weather information, organized in 15-minute intervals. This data supports AI-driven forecasting and smart load management, enabling cost optimization, improved grid stability, and enhanced integration of renewable energy sources. [5]

5.6 Energy Management Scheduling Algorithm[11]

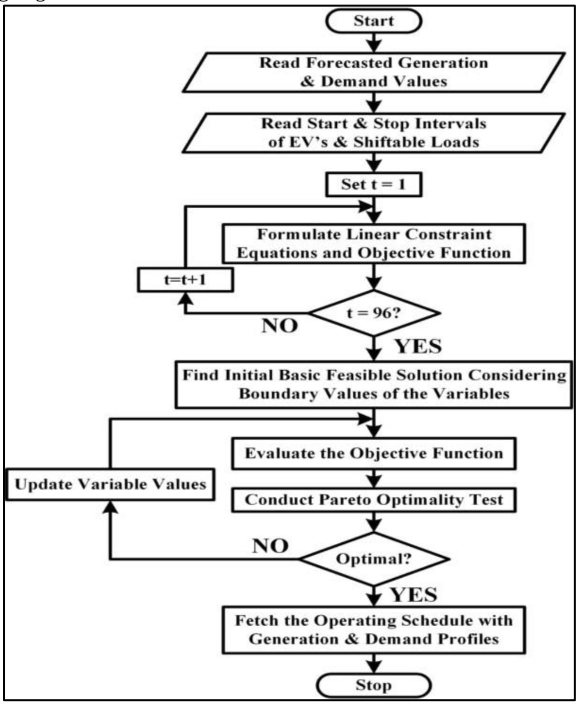


Table 8: - Flowchart Energy Management Scheduling Algorithm

6. Conclusion

This research introduces a novel AI-driven approach to optimizing load scheduling for electricity procurement. By combining LSTM forecasting, hybrid DQN + MPPT for cost optimization, and DQN + PPO for realtime adjustment, the proposed system ensures cost effective procurement while maintaining grid stability. The system's adaptability to dynamic market conditions and its ability to minimize deviation penalties make it a valuable tool for modern energy trading applications. Future work will focus on further refining the system's ability to handle larger-scale markets, incorporate more diverse data sources, and enhance the real-time decision-making capabilities. [14]

REFERENCES :

1. R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed., MIT Press, 2018.
2. J. Schulman et al., “Proximal Policy Optimization Algorithms,” arXiv preprint arXiv:1707.06347, 2017.

3. V. Mnih et al., "Human-level control through deep reinforcement learning," Nature, vol. 518, pp. 529–533, 2015.
4. S. Hochreiter and J. Schmidhuber, "Long Short-
5. Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
6. Indian Energy Exchange (IEX), "Real-Time Market
7. Snapshot." [Online]. Available: https://www.iexindia.com
8. OpenWeatherMap, "Weather API." [Online]. Available: https://openweathermap.org/api
9. Stable-Baselines3 Documentation. [Online]. Available: https://stable-baselines3.readthedocs.io
10. Scikit-learn: Machine Learning in Python. [Online]. Available: https://scikit-learn.org/stable/
11. Y. Zhang et al., "Smart load forecasting using deep reinforcement learning," Energy Reports, vol. 7, pp. 1056–1064, 2021.
12. A. Kumar et al., "Multi-agent reinforcement learning for smart grid scheduling," IEEE Access, vol. 9, pp. 33421–33434, 2021.
13. S. Wang et al., "Hybrid deep reinforcement learning for energy management in microgrids," Applied Energy, vol. 300, 2021.
14. Energy Management System - https://images.app.goo.gl/UxSVbbDRb9j7EgGz7
15. Communication Link (Dashed Lines) - https://core.ac.uk/download/pdf/37831683.pdf
16. S. Galli, A. Scaglione, and Z. Wang, "For the grid and through the grid: The role of power line