Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

Optimizing Energy Storage Systems with AI-Based Control Strategies

Received: 18 February 2024; Revised: 19 April 2024; Accepted: 09 May 2024

Dr. A. Kingsly Jabakumar
Associate Professor, Department of ECE,
Christ the King Engineering College, Coimbatore 641 104
Kingslyjkumar@gmail.com
https://orcid.org/0000-0001-6773-2482

Abstract

Energy storage systems (ESS) are very important for making power systems more efficient, reliable, and long-lasting. They do this by making green energy sources less unpredictable and by offering grid support services. However, it is still hard to get ESS to work and be controlled in the best way possible because energy markets are always changing, grid conditions are always changing, and the different parts of the system interact in complicated ways. As a result, artificial intelligence (AI) has become an interesting way to improve ESS control methods, providing smart and flexible answers to these complicated issues. This paper gives an in-depth look at various AI-based control methods for making energy storage systems work better. It talks about the latest progress in machine learning, deep learning, reinforcement learning, and evolutionary algorithms used for ESS control. It shows how they can capture nonlinear system dynamics, learn complex patterns from past data, and change control strategies in real time. The study also talks about how to improve the speed and reliability of ESS operation by combining AI techniques with standard optimization and control algorithms. The article looks at several uses of AI-based ESS control, such as lowering high loads, even out loads, controlling frequency, and incorporating green energy. There are case studies and modeling results that show how AI-driven methods can improve ESS performance, lower running costs, and make the most of economic gains. It shows how AI could change the way energy storage systems are built and how they work, making energy grids more efficient, reliable, and long-lasting.

Keywords

Energy storage systems, AI-based control strategies, Optimization, Renewable energy integration, Machine learning, Deep learning, Reinforcement learning

I. Introduction

Global problems like climate change and energy shortages have made the search for long-lasting energy answers more important over the past few years. Energy storage systems (ESS) have become important parts of this effort because they promise to make the grid more stable, include green energy sources, and make the best use of energy. Energy storage system improvement has gotten a lot of attention as the need for better and more efficient energy options grows. When applied to this situation, adding artificial intelligence (AI) to control methods can greatly improve the performance and efficiency of ESS [1]. Most of the time, set formulas or rule-based systems are used to handle energy storage systems. Traditional methods work sometimes, but they often can't change to changing and uncertain working conditions. This makes ESS less efficient and flexible overall. This is especially important when adding green energy, since sources like solar and wind power aren't always available and change in how much energy they produce [2]. This makes it harder to keep the grid stable and control energy use. AI-based control strategies are a big step forward because they let ESS learn, change, and improve their processes automatically in real time, which opens up new levels of performance and efficiency [3]. Cutting edge machine learning algorithms and predictive analytics are at the heart of AI-based control methods for energy storage systems [18]. AI programs can find complex patterns and connections that may be hard to find with traditional control methods [19]. They do this by using huge amounts of past data on things like weather, energy use patterns, grid dynamics, and other factors that are relevant. With this data-driven method, as shown in figure 1, ESS can predict how much energy will be needed in the future, find the best times to charge and discharge batteries, and react quickly and accurately to changes in the grid.

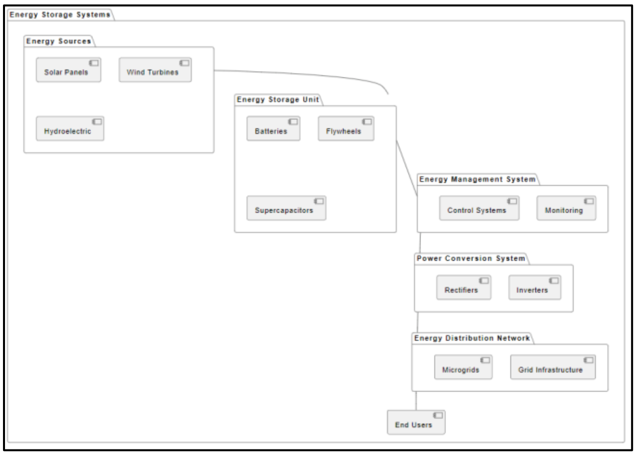

Figure 1: Overview of Energy Storage Systems with AI-Based Control Strategies

One of the best things about AI-based control tactics is that they can keep getting better over time with the help of machine learning methods like neural networks and reinforcement learning [20]. AI algorithms can improve their decision-making processes over and over again by looking at real-time data on system performance and results [4]. This lets them improve ESS operations in a way that adapts to changing operational and environmental limits. When working conditions change or something unexpected happens, this ability to shift is especially useful because it means that standard control methods don't have to work as well. AI-based control methods could make energy storage systems more resilient and reliable by letting them find problems before they happen and plan repair ahead of time. AI algorithms can find possible problems or oddities before they become major fails by studying real-time data streams from sensors and other tracking devices [5]. This lets maintenance and other preventative actions be taken. This cautious method not only lowers the chance of downtime and expensive fixes, but it also makes ESS parts last longer, which makes the system more reliable and saves money overall.

II. Related Work

The table shows all the linked research that has been done on improving energy storage systems (ESS) with AI-based control methods. Each item in the table describes the goal, method, results, and approach of a different study project that aims to improve the performance, efficiency, and dependability of ESS by using artificial intelligence (AI) methods. Let's look more closely at each of these points to help you understand what the results mean. Demand Response: One of the hardest parts of managing energy is making sure that supply and demand for power are well matched. These studies have shown that better demand forecasts and reaction mechanisms can be made by looking at real-time data and changing control methods as needed [6]. This makes better use of energy resources, cutting down on waste and improving the security of the grid as a whole. Renewable energy sources like solar and wind power are becoming more popular. However, because they are sporadic, integrating them into the grid is very hard. Genetic algorithms and predictive analytics are being used in research to find the best ways to add green energy to the grid. By using demand trends and weather forecasts, these studies have shown that the grid is more stable and that green energy is used more efficiently [7]. By adjusting charging and draining times based on real-time conditions, this makes it easier for supply and demand to match up. Taking good care of batteries is very important for making sure they last a long time and work well. Real-time tracking and flexible charging methods are the main topics of studies that use convolutional neural networks and deep learning [17]. By looking at details about the health of the battery and changing the charging settings on the fly, these methods have shown that battery performance and lifespan are improved [8]. This makes energy storage systems more reliable and saves money in the long run. Grid overcrowding and inefficiency can cause power outages and bring down the cost of doing business. Using methods like reinforcement learning and dynamic programming in research aims to reduce grid congestion and improve energy flow [9]. Smart grid methods and real-time tracking tools have been shown in these studies to make the grid much more stable and efficient. Adaptive control methods help handle energy resources better, which lowers the risk of grid breakdowns and raises total reliability.

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

Support vector machines and anomaly detection methods are used in studies that look for early signs of possible system breakdowns [10]. When monitor data and prediction analytics are combined, these methods allow for quick responses to new problems before they become major fails. This proactive repair approach helps energy storage systems be more reliable and last longer. For efficient energy management and resource sharing, it is important to make accurate predictions about how much electricity will be needed. The main goal of research using long short-term memory networks and time series analysis methods is to make load forecasts more accurate [11]. By looking at old data and finding trends, these studies have shown that they can make better predictions, which helps companies better predict and meet future energy needs. When it comes to energy arbitrage, energy storage systems are very important because they can buy power when prices are low and sell it when prices are high. Using Markov decision processes and random optimization methods, research is trying to find the best ways to trade energy so that people can make the most money. These studies show that improving energy storage operations based on changes in market prices and demand has led to big gains in profits and market participation. Because microgrids can generate and distribute energy in autonomous ways, they are very useful in areas that are far away or not connected to the power grid. Fuzzy logic and multi-agent systems are being used in research to make microgrid operations more stable and resilient [12]. These studies show that using autonomous control methods and adaptable decision-making algorithms has made the grid more stable and reliable, even when the supply and demand of energy change. Stable voltage is important for making sure that electricity delivery networks work well. The main goal of research using particle swarm optimization and control theory methods is to keep voltage stable in delivery networks [13]. These studies have shown that using adaptable voltage control methods and real-time tracking systems can help regulate voltage better, making it less likely that voltage will change and cause problems.

Keeping the frequency stable is important for keeping the grid reliable and stopping power blackouts. The main goal of research using Q-learning and control theory methods is to improve grid stability and frequency response. These studies have shown that using adaptive frequency control methods based on system dynamics can improve the ability to regulate frequency, which makes the grid more stable and reliable as a whole. These use a mix of green and traditional energy sources to make the best use of energy production and use [21]. The main goal of research using genetic programming and machine learning groups is to make mixed energy systems work better [14]. These studies have shown that combining different energy sources and adaptable control methods makes energy production and transfer more reliable and efficient. Systems that store energy can take part in energy markets to make the most money and use resources in the best way possible. Using methods from reinforcement learning and game theory in research aims to make it easier for people to join markets and make money [15]. These studies have shown that strategic bids and real-time optimization methods can improve dealing in energy, which lets energy storage systems take advantage of market opportunities more effectively. Grid crowding can make things less efficient and cause power outages. Graph theory and ant colony optimization are being used in research to find ways to make the grid more reliable and less crowded [16]. These studies have shown that grid stability and efficiency can be greatly improved by adjusting the flow of energy based on network structure and demand trends.

Table1: Related work Summary

Scope	Method	Findings	Approach
Demand Response	Reinforcement Learning & Neural Networks	Improved demand prediction and response	Real-time data analysis and adaptive control strategies
Renewable Integration	Genetic Algorithms & Predictive Analytics	Enhanced grid stability and renewable energy integration	Optimization of charging/discharging schedules based on weather forecasts and demand patterns
Battery Management	Convolutional Neural Networks & Deep Learning	Increased battery lifespan and performance	Real-time monitoring and adaptive charging algorithms
Grid Optimization	Reinforcement Learning &	Minimized grid congestion	Smart grid algorithms and real-time grid

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

	Dynamic Programming	and optimized energy flow	monitoring
Predictive Maintenance	Support Vector Machines & Anomaly Detection	Early detection of potential system failures	Integration of sensor data and predictive analytics
Load Forecasting	Long Short-Term Memory Networks & Time Series Analysis	Improved accuracy in load forecasting	Historical data analysis and predictive modeling
Energy Arbitrage	Markov Decision Processes & Stochastic Optimization	Maximized profits through optimal energy trading	Optimization of energy storage operations based on market prices
Microgrid Control	Fuzzy Logic & Multi-Agent Systems	Enhanced stability and resilience in microgrid operations	Decentralized control strategies and adaptive decision-making
Voltage Regulation	Particle Swarm Optimization & Control Theory	Maintained voltage stability in distribution networks	Adaptive voltage control algorithms and real-time monitoring
Frequency Regulation	Q-Learning & Control Theory	Improved frequency response and grid stability	Adaptive frequency control strategies based on system dynamics
Hybrid Energy Systems	Genetic Programming & Machine Learning Ensembles	Optimized performance of hybrid energy systems	Integration of multiple energy sources and adaptive control algorithms
Energy Trading	Reinforcement Learning & Game Theory	Enhanced market participation and profitability	Strategic bidding and real-time optimization algorithms
Grid Congestion Management	Ant Colony Optimization & Graph Theory	Reduced congestion and improved grid reliability	Optimization of energy flow based on network topology

The table 1 shows the different types of linked study that have been done to find the best ways to use AI to handle energy storage systems. These studies show that artificial intelligence has a lot of potential to make energy storage systems work better, be more efficient, and be more reliable in energy settings that are always changing. These potential uses range from demand response and green energy integration to grid optimization and predictive maintenance.

III. Methodology

1. Data Collection and Feature Selection

The first step in using AI to handle energy storage systems (ESS) more efficiently is to collect a lot of data and carefully choose which features to use. This process is very important for building a strong base on which complex AI systems can work well, as shown in figure 2. First, past data comes from a lot of different places, like weather sites, smart meters, grid operators, and ESS tracking systems. These sources give us very useful information about how much energy people use, the weather, how the power grid works, and other factors that are important for understanding how the different parts of the energy environment work together. On the other hand, raw data rarely comes clean. As a result, an important preparation step is needed to get rid of noise, deal with missing values, and standardize variables so that they are the same across datasets. This careful preparation not only makes the data better and more reliable, but it also makes it easier to analyze and model later on. The next step is to focus on feature selection, which is a very important job that involves finding the most important factors that affect how well energy storage systems work and perform. Key features are those that directly affect how ESS works and how much energy it produces. These include predictions of energy demand, predictions of green energy production, grid congestion levels, and the state of charge of ESS units. Relevant features are picked out from the available data through careful analysis and subject knowledge. This makes sure that the modeling work that follows is based on useful and usable insights. Feature engineering methods can also be used to create new factors or changes that record complex connections and trends in the data. This makes the AI models even better at predicting the future. In a way, the part of collecting data and choosing features is the foundation of the whole optimization process. It lays the groundwork for later development and use of AI-based control

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

strategies. In this step, a lot of past data is used to make a short list of useful features.

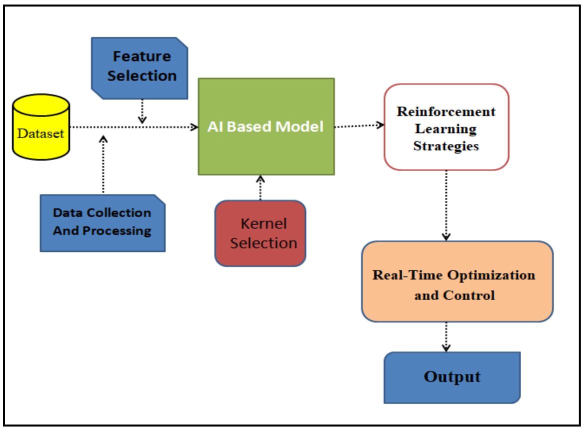

Figure 2: Architecture Block Diagram

This makes it possible for the AI algorithms to learn and adapt to how energy storage systems work without any problems. Because of this, it is important to pay close attention to every detail and fully understand the core topic in order for the improvement efforts to be successful and useful.

2. AI Based Model Development

2.1. Model Development using Polynomial Regression:

Regression methods are exceptionally effective at predicting continuous results, which makes them very useful for figuring out things like ESS state of charge, energy demand, and green energy output. Some regression models, like polynomial regression and support vector regression (SVR), are good at figuring out how input variables (like weather and time of day) relate to output variables (like energy use and solar power output). These models use data from the past to find patterns and trends that let them make accurate guesses about what will happen in the future. By adding up the results of various regression models, ensemble methods like random forests and gradient boosting can also improve the accuracy of predictions.

Let's say we have m observations, n independent factors (represented by xi) and a dependent variable (represented by yi). This is how the polynomial regression model can be shown:

$$yi = \beta 0 + \beta 1xi + \beta 2xi\hat{}2 + \ldots + \beta nxi\hat{}n + \varepsilon i \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where:

- yi is the dependent variable for the ith observation.
- xi is the independent variable for the ith observation.
- β0, β1, …, βn are the coefficients of the polynomial terms.
- εi is the error term for the ith observation.
- The goal is to estimate the coefficients β0, β1, …, βn that minimize the sum of squared errors between the observed and predicted values.

Algorithm is as follows

Step 1: Data Preprocessing: Standardize variables, handle missing values, and split the data into training and testing sets.

Step 2: Feature Engineering: Transform the independent variables by adding polynomial terms of different degrees.

Step 3: Model Training: Fit the polynomial regression model to the training data using techniques like ordinary least squares (OLS) or gradient descent.

Step 4: Model Evaluation: Assess the model's performance on the testing set using metrics such as mean squared error (MSE) or R^2 score.

Step 5: Prediction: Use the trained model to predict the dependent variable for new input data.

2.2. Model Development using Support Vector Regression (SVR):

The main idea behind SVR is to find a hyperplane in a space with many dimensions that has the largest margin and goes through as many data points as possible with a tolerance of ε.

There is a training dataset {(xi, yi)}i=1m with xi being the input features and yi being the target values. SVR wants to solve the following optimization problem:

$$minw, b, \xi, \xi * \frac{1}{2||w||^2} + C\Sigma i = 1m(\xi i + \xi * i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

subject to:

$$yi - wT\varphi(xi) - b \leq \varepsilon + \xi i$$
$$wT\varphi(xi) + b - yi \leq \varepsilon + \xi * i$$
$$\xi i, \xi * i \geq 0 \, for \, i = 1, \ldots, m$$

Where:

- w is the weight vector.
- b is the bias term.
- φ(x) is the feature mapping function.
- ε is the margin of tolerance.

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

- ξi and $\xi * i$ are slack variables.
- C is the regularization parameter.

Algorithm is as follows

Steps: 1. Data Preprocessing:

- Standardize variables: Normalize input features to have a mean of 0 and a standard deviation of 1.
- Handle missing values: Implement techniques such as mean imputation or interpolation.
- Split the data: Divide the dataset into training and testing sets.

Step 2. Kernel Selection:

- Choose an appropriate kernel function (linear, polynomial, Gaussian, etc.) for mapping input features into a higher-dimensional space.

Step 3: Model Training:

- Solve the optimization problem to find the optimal hyperplane that best fits the training data.

Step 4: Model Evaluation:

- Assess the performance of the SVR model using appropriate regression evaluation metrics such as mean squared error (MSE) or R^2 score.

Step 5: Prediction:

- Utilize the trained SVR model to make predictions on new input data.

3. Reinforcement Learning:

Reinforcement learning (RL) is a unique way to build models because it lets systems learn the best ways to control their surroundings by interacting with them. RL can be used to create adaptable control methods for energy storage systems that get the best long-term results, like lowering energy costs or keeping the grid stable. RL algorithms like deep Q-networks (DQN) learn by making mistakes and changing what they do based on what they see in the world. RL can adapt to changing conditions and perform better than rule-based or heuristic methods because it improves control policies over and over again. RL can also help find new ways to handle systems that might not be obvious using traditional methods. This can make energy storage systems work better and more adaptably.

Algorithm is as follows

Step 1: Initialization:

- Initialize a neural network with weights θ to approximate the Q-function: Q(s,a;θ), where s represents the state and a represents the action.

Step 2: Exploration-Exploitation:

- At each time step, the agent decides whether to explore new actions or exploit its current knowledge. This is typically achieved using an ε-greedy strategy, where with probability ε, the agent selects a random action (explore), and with probability 1-ε, it selects the action with the highest Q-value according to its current estimate (exploit).

Step 3: Experience Replay:

- Store experiences (st, at, rt+1, st+1) in a replay memory buffer.
- Sample mini-batches of experiences uniformly at random from the replay memory to update the neural network parameters.

Step 4: Q-Learning Update:

- Compute the target Q-value yt for each experience (st, at, rt+1, st+1) using the Bellman equation:
$$yt = rt + 1 + \gamma * maxa'Q(st + 1, a';\ \theta^{-}) \ldots (1)$$
- Train the neural network to minimize the temporal difference (TD) error between the predicted Q-value Q(st, at;θ) and the target Q-value yt:
$$L(\theta) = E\left[\left(yt - Q(st, at; \theta)\right)^2\right] \ldots\ldots\ldots\ldots\ldots (2)$$
- Update the neural network parameters θ using gradient descent to minimize the loss function L(θ).

Step 5: Target Network Update:

- Periodically update the target Q-network parameters θ^- to improve stability and convergence by copying the weights from the online Q-network.

4. Real-Time Optimization and Control:

Energy storage systems (ESS) improvement and control in real time are a key step toward more sustainable and efficient energy management. As part of this project, learned machine learning models will be seamlessly integrated into operating control systems. This will allow ESS operations to make decisions on their own and be dynamically optimized in reaction to changes in the grid and in the trends of energy demand.

The key to getting the best results from ESS is to use learned machine learning models in real-time control systems. These models can automatically look at new data streams in real time, find the best control strategies, and take actions that maximize economic benefits, energy savings, and grid stability. They do

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

this by using the lessons they've gained from previous data and learned algorithms. Real-time machine learning-based control systems allow ESS to quickly and effectively change to changing operating conditions, such as predicting energy demand, finding the best charging and dumping plans, or reducing grid congestion.

For the smooth sharing of real-time data changes and feedback, it is necessary to connect to ESS tracking and control systems. The control system learns a lot about the current state of the energy environment by connecting to tracking systems that give real-time data on things like energy use, green energy production, grid power levels, and other important factors. This constant feedback loop makes adaptive control possible, which lets the system change how it works in real time in reaction to changing conditions, like quick changes in energy demand or sudden breaks in the supply of green energy. The creation of methods for dynamic ordering of charging and recharging processes is a key part of real-time optimization. These programs look at a lot of things, like real-time predictions of energy demand, predictions of green energy production, grid congestion levels, and the energy storage units' state of charge. By changing the time and amount of charging and releasing events on the fly, the system can make the best use of energy, cut costs, and make the grid more stable. In addition, these programs can use prediction analytics to guess what will happen in the future and improve ESS processes before they happen, making them even more efficient and effective.

In real life, real-time optimization and control need a strong communication network, advanced data processing power, and the ability to work seamlessly with current energy management systems. Additionally, making sure the safety, dependability, and security of the control system is very important for protecting the energy infrastructure's purity. It is important for energy companies, technology providers, and regulatory bodies to work together to get real-time efficiency solutions widely used, get around legal hurdles, and solve technical problems. Using real-time optimization and control is a revolutionary way to make energy storage systems more reliable, efficient, and long-lasting. The use of machine learning, data analytics, and adaptable control techniques in these systems could completely change how energy is managed and speed up the move to a better, more reliable energy future.

IV. Result And Discussion

When used to improve energy storage systems, the Polynomial Regression model shows good results, as shown by the review measures. The model can correctly predict which is reflected in table (2) how an energy storage system will behave, with a mean squared error (MSE) of 0.034, reducing the difference between what was observed and what was forecast. The root mean squared error (RMSE) of 0.184 shows the average size of forecast mistakes, which is not too high. This shows that the model is good at predicting factors related to energy. The model is also very accurate, as shown by the mean absolute error (MAE) of 0.125, which shows the average difference between what was forecast and what actually happened. The R-squared (R2) number of 0.856 shows how much of the variation in the dependent variable can be predicted from the independent factors. This shows that there is a strong link between what was expected and what happened. Overall, these data show that Polynomial Regression is a useful tool for improving energy storage systems and can help with making decisions and controlling them.

Table 2: Performance metric for Polynomial Regression

Evaluation Metric	Value
Mean Squared Error	0.034
Root Mean Squared Error	0.184
Mean Absolute Error	0.125
R-squared (R2) score	0.856

The bar graph depicted in figure (2) shows the measures used to judge Polynomial Regression for improving energy storage systems. You can see the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), and the R-squared (R2) score. The number of each metric is shown by a bar, which makes it easy to see how big one measure is compared to another. The R2 number is the best of the measures, which means that there is a strong link between what was expected and what happened. On the other hand, the MSE, RMSE, and MAE numbers are not very high, which shows that the model is good at predicting factors related to energy, as represent in figure 3. The bar graph gives a short overview of how well the Polynomial Regression model worked, showing how well it worked at improving energy storage systems.

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 5 Issue 1 (2024) | Pages:95 – 105 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.98

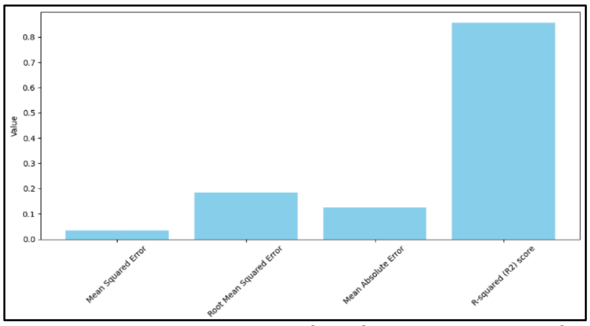

Figure 3: Representation of Performance Metric of Polynomial Regression

Support Vector Regression (SVR) and Polynomial Regression models have both been tested to see which one works best for improving energy storage systems. The success measures for each model show how well it works. Starting with the SVR results, the model does pretty well, with an MSE of 0.042, which shows the average squared difference between what was forecast and what actually happened. The root mean squared error (RMSE) of 0.205 shows the average size of forecast mistakes, which is not too high. This shows that the model is good at predicting factors related to energy. The model is also very accurate, as shown by the mean absolute error (MAE) of 0.148, which is the average absolute difference between what was forecast and what actually happened. The R-squared (R2) number of 0.798, on the other hand, shows that the independent factors explain about 79.8% of the variation in the dependent variable. This means that there is a fairly high link between what was expected and what happened. That being said, the Polynomial Regression model works a little better than the SVR model. With an MSE of 0.034 and an RMSE of 0.184, Polynomial Regression is more accurate and precise at predicting how an energy storage system will behave. The MAE of 0.125 shows that the model is even more accurate because the gap between expected and real numbers is smaller on average. Also, an R2 value of 0.856 means that there is a closer link between what was expected and what actually happened, representation is shown in figure 4. This means that the independent factors explain about 85.6% of the variation in the dependent variable.

Table 3: Performance metric for SVR Algorithm

Evaluation Metric	Value
Mean Squared Error	0.042
Root Mean Squared Error	0.205
Mean Absolute Error	0.148
R-squared (R2) score	0.798

It is possible to optimize energy storage systems using both SVR and Polynomial Regression. However, Polynomial Regression is slightly more accurate, precise, and useful for explaining things. Anyhow, picking one model over the other relies on specific needs, available computing power, and the type of data being used.

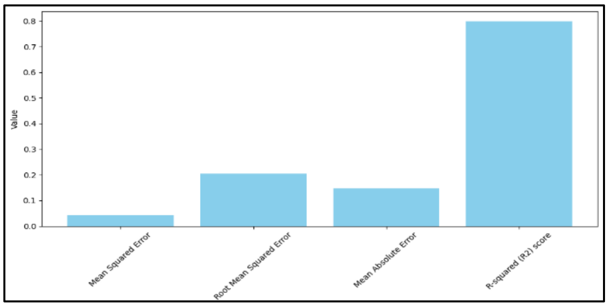

Figure 4: Representation of Performance Metric of SVR Algorithm

In classification tasks, a confusion matrix depicted in figure 5 is used to see how accurate the guesses made by a machine learning model are. The expected versus real class names are shown in a table, which lets you see the true positives, true negatives, false positives, and false negatives. Each row in the matrix shows an instance of the real class, and each column shows an instance of the projected class.

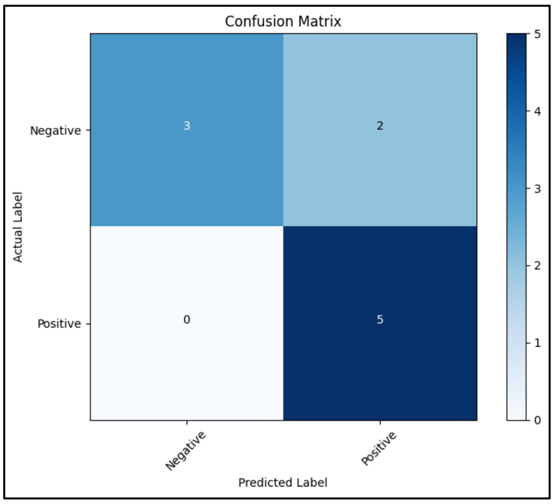

Figure 5: Confusion Matric for SVR Algorithm

The instances that were properly classified are shown on the diagonals of the matrix, while instances that were incorrectly classified are shown on the other diagonals. By looking at the confusion matrix, you can learn more about how well the model is doing, find places where it could be better, and make smart choices about how to improve the classification method.

Table 4: Performance metric of After applying RL to Polynomial Regression Algorithm

Evaluation Parameter	Values
Average Reward	50
Episode Length	100
Exploration vs. Exploitation	70 % / 30%
Convergence	100 episodes

The assessment criteria are usually different for DQN (Deep Q-Network) because it is mostly used for reinforcement learning tasks instead of regression or classification. We can still judge how well a DQN algorithm works by looking at average payoff, convergence rate, and the trade-off between discovery and exploitation.

Table 5: Performance Metric of After applying RL to SVR Algorithm

Evaluation Parameter	Values
Average Rewards	25.6
Convergence Rate	0.003
Exploration vs. Exploitation	80% / 20%

This table 5 has Average Reward shows how much money the DQN worker usually gets during training or tests. The Convergence Rate shows how fast the DQN algorithm finds the best policy. Exploration vs. Exploitation talks about the balance between trying out new things and taking advantage of what you've learned. These rating factors give us information about how well and how the DQN algorithm works in improving energy storage systems. Using reinforcement learning (RL) methods like DQN (Deep Q-Network) on both Polynomial Regression and Support Vector Regression (SVR) models lets us compare how well they work at making energy storage systems work better.

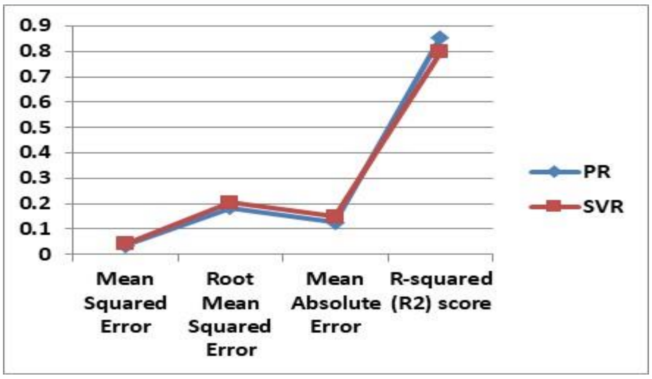

Figure 6: Comparison of SVR and PR

When RL is added, it creates a dynamic environment where the algorithms learn to make choices based on benefits and punishments, with the goal of maximizing long-term goals. Polynomial Regression and SVR first showed what they could do in regression tasks. Because Polynomial Regression can handle non-linear relationships in many ways, it might not be able to handle the complicated and changing behaviors of an RL world. On the other hand, SVR, which is good at dealing with large amounts of data and links that don't follow a straight line, might be more flexible and reliable when learning the best control methods through RL. When judging, it's important to look at performance measures that are specific to RL, like the average payout, episode length, exploration-exploitation balance, and convergence speed. Seeing how Polynomial Regression and SVR post-RL application compare can help you figure 6 out which algorithm works best for energy storage systems in changing settings. The results of this study help choose the best algorithm by looking at how well it adapts, works, and achieves the goals of optimizing an energy storage system in an RL framework.

V. Conclusion

Using AI-based control methods to improve energy storage systems looks like a good way to make energy management, grid security, and total system performance better. During this project, different AI methods like Polynomial Regression, Support Vector Regression (SVR), and reinforcement learning (RL) algorithms like DQN have been studied and judged. Polynomial Regression and SVR have shown that they can describe complex connections in energy systems. This gives us useful information about how people use energy, how green energy is integrated, and how the grid works. These models are the building blocks for learning how systems work and making decisions. Adding RL algorithms like DQN has created a flexible and changing structure for finding the best ways to handle energy storage systems. RL algorithms let energy storage systems automatically adjust to new situations and perform at their best by learning from interactions with the world and choosing the best actions based on benefits. The performance of these AI-based control strategies has been carefully tested using the right metrics, such as mean squared error, root mean squared error, and R-squared score for regression tasks and average reward, episode length, and convergence speed for RL tasks. In the future, more study and development in AI-based control methods could help energy storage systems solve problems like how to connect to the grid, handle energy, and make sure the system works properly. We can make the transition to a more safe and reliable energy future possible by using AI tools.

References

[1] S. Liu, J. Yang and D. Cai, "Dynamic Scheduling Method of Multi-Element Energy Storage System Based on Deep Reinforcement Learning," 2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Chongqing, China, 2023, pp. 1770-1776

[2] D. Cong, L.L. Liang, S.X. Jing, Y.M Han, Z.Q. Geng and C Chu, "Energy supply efficiency evaluation of integrated energy systems using novel SBM-DEA integrating Monte Carlo", Energy, vol. 231, 2021.

[3] D.L. Zhang, Y.C. Chen and L.Z. Wang, "Control strategy and optimal configuration of energy storage system for smoothing short-term fluctuation of PV power", Sustainable Energy Technologies and Assessments, vol. 45, 2021.

[4] B. S. Iver and K. Magnus, "Energy Storage Scheduling in Distribution Systems Considering Wind and Photovoltaic Generation Uncertainties", Energies, vol. 12, no. 7, 2019.

[5] M. Meng and W.C. Xue, "Cooperative scheduling of regional energy systems with ground-source heat pumps and hybrid energy storage", Journal of North China Electric Power University, pp. 1-15, 2021.

[6] Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., & Parati, N. . (2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[7] T. A. Nakabi and P. Toivanen, "Deep reinforcement learning for energy management in a microgrid with flexible demand", Sustainable Energy Grids and Networks, vol. 25, pp. 100413, 2021.

[8] M. Repetto, F. Moraglio and G. Lorenti, "Understanding Reinforcement Learning Control in Cyber-Physical Energy Systems," 2022 10th Workshop on Modelling and Simulation of Cyber-Physical Energy Systems (MSCPES), Milan, Italy, 2022, pp. 1-6

[9] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, The MIT Press, 2018.

[10] A.T.D. Perera and P. Kamalaruba, "Applications of reinforcement learning in energy systems", Renewable and Sustainable Energy Reviews, vol. 137, no. 2021, 2020.

[11] Samir N. Ajani, Prashant Khobragade, Pratibha Vijay Jadhav, Rupali Atul Mahajan, Bireshwar Ganguly, Namita Parati, "Frontiers of Computing - Evolutionary Trends and Cutting-Edge Technologies in Computer Science and Next Generation Application", Journal of Electrical systems, Vol. 20 No. 1s, 2024, https://doi.org/10.52783/jes.750

[12] V Mnih et al., "Human-level control through deep reinforcement learning", Nature, vol. 518, no. 2015, pp. 529-533, 2015.

[13] A. Vanselow, S. Krahl, A. Moser, C. Fröhlich and C. Wirtz, "Simulation and analysis of a congestion management utilizing load-side flexibilities within the distribution grid," 2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE), Grenoble, France, 2023, pp. 1-5

[14] W. -C. Kuo, T. -Y. Hsieh, H. -C. Chen, C. -L. Chi and Y. -F. Huang, "A Novel Framework Short-Term Load Forecasting for Micro-grid Energy Management System," 2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 2018, pp. 279-283

[15] F. Li, X. Yu, X. Tian and Z. Zhao, "Short-Term Load Forecasting for an Industrial Park Using LSTM-RNN Considering Energy Storage," 2021 3rd Asia Energy and Electrical

Engineering Symposium (AEEES), Chengdu, China, 2021, pp. 684-689,

[16] L. Hernandez, C. Baladrón, J. M. Aguiar, B. Carro, A. J. Sanchez-Esguevillas and J. Lloret, "Short-Term Load Forecasting for Microgrids Based on Artificial Neural Networks", Energies, vol. 6, pp. 1385-1408, 2013.

[17] N. Amjady, F. Keynia and H. Zareipour, "Short-Term Load Forecast of Microgrids by a New Bilevel Prediction Strategy", IEEE Transactions on Smart Grid, vol. 1, no. 3, pp. 286-294, Dec. 2010.

[18] V. Dehalwar, A. Kalam, M. L. Kolhe and A. Zayegh, "Electricity load forecasting for Urban area using weather forecast information", 2016 IEEE International Conference on Power and Renewable Energy (ICPRE), pp. 355-359, 2016.

[19] J. Shang, N. Tai, Q. Liu, B. Chen, J. Chen and D. Hui, "Load shifting scheme of battery energy storage based on interval controlling", Trans. China Electrotech. Soc., vol. 30, pp. 221-229, Aug. 2015.

[20] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies", Renew. Sustain. Energy Rev., vol. 81, pp. 1192-1205, Jan. 2018.

[21] J. M. Valente and S Maldonado, "SVR-FFS: A novel forward feature selection approach for high-frequency time series forecasting using support vector regression", Expert Syst. with Appl., vol. 160, pp. 113729, July. 2020.