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AI-Driven Adaptive Control Systems for Power Distribution

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Abstract

In order to make power distribution systems more efficient, reliable, and resilient as they move toward smart grids, new ideas are needed. Adaptive control systems that are driven by AI have become a hopeful way to deal with the problems that come up because power distribution networks are always changing and being complicated. The present work gives an in-depth look at the most recent AI methods and how they can be used in power distribution systems with flexible control. When artificial intelligence (AI) is used, especially machine learning and optimization algorithms, they help power distribution systems respond instantly to changes in things like demand, the production of green energy, and problems with the network. AI programs can predict load trends, find possible flaws, and improve operating tactics to improve system performance by using past data and advanced analytics. Data collection and preparation, feature selection, model training, and control strategy optimization are some of the most important parts of AI-driven adaptive control systems. Support vector machines, neural networks, decision trees, and evolutionary algorithms are some of the machine learning methods that are used to make decision-making and predictive models that are specific to practical goals. AI and control theory work well together, which makes it easier to create adaptable control methods that can change system settings based on real-time input and goals for efficiency. When computers interact with their surroundings, reinforcement learning methods help them figure out the best way to handle things. This makes them more flexible and reliable in situations where they don't know what will happen. The results of case studies and simulations show that AI-driven adaptive control systems can make power distribution networks more stable, efficient, and resilient. These systems make it possible to handle distribution assets proactively, make it easier to connect spread energy resources, and boost the general performance of the grid while lowering costs and harming the environment. Adaptive control systems that are driven by AI are a big change in how power is distributed. They offer smart, scalable answers to the problems that come up as the modern grid works. Some ideas for future study are creating autonomous control systems, combining edge computing and Internet of Things (IoT) technologies, and putting in place safety measures to make sure that AI-enabled grid infrastructure is reliable and safe.

Keywords

Adaptive control systems, Smart grids, Machine learning, Optimization, Real-time adaptation, Predictive analytics, Grid stability

I. Introduction

Because modern power delivery networks are getting more complicated and changing all the time, along with the rise of electric vehicles and green energy sources, new ways have had to be found to make grid operations run more smoothly. In this situation, AI-driven adaptable control systems have become an interesting way to make power distribution infrastructure more efficient, reliable, and strong. These systems use advanced artificial intelligence (AI) methods like machine learning, optimization algorithms, and control theory to adapt to changing conditions in real time and make it easier to handle distribution assets in a proactive way. Traditional power distribution systems have centralized control systems that don't always work well with the changing and unclear trends of demand and production of green energy. Most traditional control strategies are based on set rules or static formulas, which might not be flexible enough or responsive enough to changing working conditions [1]. AI-driven adaptive control systems, on the other hand, represent a major change toward smarter and more flexible ways of managing the grid. One great thing about AI-driven adaptive control systems is that they can use the huge amounts of data that are produced by sensors, meters, and other tracking devices that are spread out across the distribution network. AI systems can find patterns, predict future trends, and make smart choices to improve grid performance by looking at both past data and real-time measurements. Support vector machines, neural networks, decision trees, and evolutionary algorithms are some of the machine learning methods that are used to make prediction models that show how the complex relationships and dependencies in the distribution system work [3]. When AI is combined with control theory, it's possible to make adaptable control methods that can change system parameters on the fly in reaction to changing working conditions. In particular, reinforcement learning algorithms let computers learn the best ways to control an environment by interacting with it. This makes them more flexible and reliable in unclear situations. With these adaptable control methods, distribution systems can avoid problems like power changes, line overloads, and broken equipment, which makes the grid more stable and reliable as a whole [2].

Adaptive control systems for power distribution are very important for making sure that users always have access to stable electricity. These systems use complex algorithms and artificial intelligence (AI) to constantly watch over and change different parts of the distribution network in response to new situations and customer needs. Adaptive control systems can improve the general stability of the grid, make the distribution process more efficient, and make the system work better by responding quickly to changes. One important thing about adaptive control systems is that they can get data from different monitors and sources in the distribution network and look at it in real time. This data has details about voltage values, current flow, power quality, and other important factors. The control system can find trends, find outliers, and guess about possible problems before they happen by using AI methods like machine learning to process this data. Adaptive control systems can change system settings and setups on their own, which is another important trait. For instance, the system can change the structure of the network, the way power moves, or the voltage levels to improve performance and reduce waste. These changes are based on rules and goals that have already been set by the operators. This makes sure that the system works within safe and effective limits. Adaptive control systems can also include predictive maintenance methods. These help figure out what maintenance needs to be done and how important they are based on how the equipment is doing and how likely it is to break down. By fixing problems before they happen, these systems can cut down on downtime, make tools last longer, and make the whole system more reliable.

Adaptive control systems are very important in modern power distribution systems because they help companies run their networks more consistently, quickly, and cheaply. As the grid gets more complicated and more people need energy, these systems will become even more important. This is why they are a major area of study and development in the field of power delivery. AI-driven adaptable control systems not only make operations more reliable and efficient, but they also make it easier to add distributed energy resources (DERs) like solar panels, wind farms, and energy storage systems. By constantly improving DER output and how they interact with the grid, these systems make it possible for green energy sources to be added without any problems, while still keeping the grid stable and providing good service. AI-driven control methods can also help keep running costs low, protect the environment, and make the grid more resistant to problems like cyber-attacks and natural disasters [4]. Using adaptable control systems that are driven by AI is a huge step toward making power distribution networks better, more resilient, and longer-lasting. This essay gives an in-depth look at the most recent AI methods and how they can be used in adaptive control systems for power sharing, pointing out both their possible pros and cons. Our research shows that using AI to improve grid performance and pave the way for a smarter and more efficient energy future is possible through case studies and modeling results.

II. Related Work

The article is about using genetic algorithms to improve delivery networks. Genetic algorithms are a type of optimization tool that is based on natural selection. Genetic algorithms can find the best setups for distribution networks by constantly changing possible solutions. This makes the power more stable. Evolutionary algorithms are very good at solving hard optimization problems in power systems, as shown by this method [5]. Next, reinforcement learning, a type of machine learning that studies how to make decisions in changing environments, is used to look into how to add green energy sources to power distribution grids. This method improves grid stability by making the best use of green resources. It shows how AI-powered techniques can help make the switch to a more environmentally friendly energy infrastructure easier. Finding and fixing faults is an important part of keeping the grid safe and reliable. Neural networks, a type of machine learning program that is based on the brain, are a powerful way to find problems early on. Neural networks can find possible problems and outliers in grid data by looking for trends [6]. This lets people act quickly to lower risks and stop disruptions. Demand forecasting is an important part of planning and running the grid. To correctly predict load trends, time series analysis is used. This is a mathematical method for looking at data points in a certain order. Time series analysis helps utilities predict future demand and make the best use of their resources by finding patterns and cycles in past load data [7].

Regulating voltage is important for keeping the grid stable and making sure the level of service. To make voltage control better, fuzzy logic control is used. This is a way of thinking that is based on fuzzy set theory and uses rough reasoning. Fuzzy logic controllers can keep power levels within acceptable ranges by changing control settings based on fuzzy rules. This improves the performance of the grid. Managing energy storage is a key part of getting the most out of green energy sources and making the grid more flexible [8]. Dynamic programming is a way to solve complicated problems with overlapped subproblems that is used to get the most out of energy storage. Dynamic programming helps utilities figure out the best ways to charge and discharge storage systems by taking into account things like energy prices and grid limits. Improving the stability of the grid is essential for preventing problems and keeping service going. Multi-agent systems are used to make systems more resistant to different threats. They are a type of computing that was inspired by distributed systems [10]. By coordinating the actions of many agents, multi-agent systems can adapt to shocks and keep the grid stable when things go wrong. Internets of Things (IoT) technologies are used in distribution systems to make it easier to watch and handle distribution facilities [9]. IoT devices collect real-time data and let you handle grid assets from afar by placing sensors and controllers all over the grid. This makes operations more reliable and efficient. Improving power quality is necessary to make sure that there is a steady source of high-quality electricity. Particle swarm optimization is a metaheuristic optimization method that is based on how swarms act as a group. It is used to improve power quality factors like frequency and voltage. Particle swarm optimization methods can successfully improve grid settings and reduce power quality problems by looking for ideal solutions over and over again [11].

Load balancing tries to spread out the grid's electricity loads widely so that resources are used most efficiently and overloads don't happen. To find the best way to distribute the load flexibly, reinforcement learning methods are used. Reinforcement learning agents can change how they distribute loads to avoid gaps and make the grid work better by learning from feedback they get from it. Because digital tools and information networks are becoming more and more important, cybersecurity is a very important issue for modern power distribution systems [12]. Machine learning models are used to make it easier to find threats and deal with them. Machine learning algorithms can find possible cyber dangers and oddities by looking at system logs and network traffic trends [13]. This helps utilities improve their cybersecurity and protect key assets. Asset management is important to make sure that delivery equipment is reliable and lasts a long time. Data analytics tools are used to make repair plans and the performance of assets work better. Data analytics methods help utilities figure out what repair

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needs to be done first and how to best use their resources by looking at old maintenance records and data from tracking the state of equipment [14]. With smart meters, utilities can get detailed information about how much energy customers use and how they behave, which lets them provide more focused services and control demand. Clustering analysis is used to divide people into groups based on how they buy things and what they like. Using clustering analysis, utilities can better tailor their services and marketing campaigns by putting customers together who have similar traits [15]. For grid components and control hubs to be able to talk to each other safely and reliably, they need resilient communication networks. Methodologies for network resilience analysis are used to test and improve the reliability of transmission systems. Re [16]silience analysis helps utilities make sure that communication and control functions don't stop when bad things happen by finding weak spots and putting in place ways to fix them. The goal of predictive maintenance is to cut down on downtime and repair costs by finding problems with technology before they happen. Predictive analytics methods are used to look at data about the state of equipment and figure out how likely it is to break down [17]. Predictive models use past maintenance records and sensor data to help utilities plan maintenance ahead of time and get the most out of their assets. The table 1 shows a summary of different study projects and uses in the area of power distribution AI-driven adaptive control systems. There is a description of the study or project's goals, methods, results, and approach in each page.

Table1: Literature Summary

Scope	Method	Findings	Approach
Optimization of Distribution Networks	Genetic Algorithms	Improved voltage stability	Genetic algorithms were used to optimize network
Integration of Renewable Energy	Reinforcement Learning	Enhanced grid reliability	Reinforcement learning was applied to manage renewables
Fault Detection and Diagnosis	Neural Networks	Early detection of faults	Neural networks were trained on fault data
Demand Forecasting	Time Series Analysis	Accurate load predictions	Time series analysis was used to forecast demand
Voltage Regulation	Fuzzy Logic Control	Improved voltage control	Fuzzy logic controllers were implemented
Energy Storage Management	Dynamic Programming	Optimal energy storage utilization	Dynamic programming approach was employed
Grid Resilience Enhancement	Multi-Agent Systems	Increased resilience against disruptions	Multi-agent systems coordinated grid operations
Distribution Automation	Internet of Things (IoT)	Enhanced monitoring and control	IoT devices enabled real-time data collection
Power Quality Improvement	Particle Swarm Optimization	Enhanced power quality	Particle swarm optimization improved grid parameters
Load Balancing	Reinforcement Learning	Efficient load distribution	Reinforcement learning algorithms balanced loads
Cybersecurity	Machine Learning	Improved threat detection	Machine learning models identified cyber threats
Asset Management	Data Analytics	Optimized maintenance schedules	Data analytics tools analyzed equipment performance
Smart Metering	Clustering Analysis	Customer segmentation for targeted services	Clustering techniques grouped customers by behavior
Resilient Communication Networks	Network Resilience Analysis	Robust communication infrastructure	Resilience analysis ensured network reliability
Predictive Maintenance	Predictive Analytics	Reduced downtime through proactive maintenance	Predictive models identified equipment failure risks

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III. Research Methodology

1. Data Preprocessing and Feature Selection:

First, past data from different sources is collected, including load profiles, green energy production, weather conditions, equipment state, and grid layout. This is done for AI-driven adaptive control systems in power distribution networks. This information is the basis for figuring out how the distribution system works and what trends it follows.

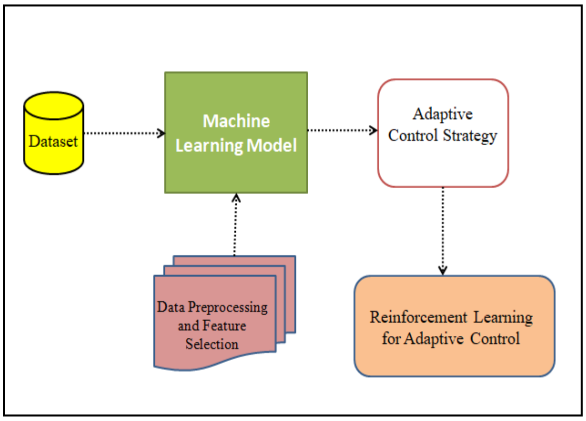

Figure 1: Proposed Model for Adaptive Control Systems for Power Distribution

After being gathered, the data goes through a lot of preparation to make sure it is accurate and of good quality [18]. This includes things like getting rid of noise, dealing with missing values, and standardizing variables to make their scales more consistent and make comparisons more useful. Preprocessing fixes data that isn't consistent or isn't organized correctly so that research can be accurate and reliable. After editing the data, the next step is feature selection, which is where important factors that have a big effect on grid performance and stability are found, the proposed methos is shown in figure 1. This step is meant to speed up the research by focusing on the most useful features and getting rid of the ones that aren't needed or aren't important. Statistical analysis, association analysis, and subject knowledge are some of the methods used to keep traits that are highly predictive and important to grid operations. Feature engineering can also be used to make new features or change old ones so that they better show how the different parts of the distribution system work together and affect each other [19]. Some of the techniques used in feature engineering are polynomial transformations, interaction terms, binning, and dimensionality reduction methods like principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE). With these methods, you can get useful information from the data by finding secret patterns and connections that might not be obvious at first. The forecast models can better understand the details of the distribution system by adding designed features to the feature space. This makes the control strategies more accurate and reliable.

2. Machine Learning Model Development:

2.1. Long Short-Term Memory (LSTM) Networks:

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) architecture that is made to fix the problem of disappearing gradients that happens a lot with regular RNNs. LSTMs are very good at handling and making predictions based on sequential data, like the time-series data that is common in power distribution systems [20]. They are great at catching both short-term and long-term relationships in data, which makes them perfect for modeling changing trends in power levels, load demand, and green energy production. LSTM networks are great for predicting jobs where previous data is very important because they can remember things for a long time and learn from what they've seen in the past.

LSTM Algorithm is as follows

Step 1: Initialize parameters: weights and biases.

Step 2: For each time step t:

- Receive input x_t .

- Calculate input gate (i_t), forget gate (f_t) and output gate (o_t) activations.

Step 3: Compute input gate (i_t) using:

$$i\_t = \sigma(W_{\{ix\}}.x_t + W_{\{ih\}}.h\_\{t-1\} + b\_i) \text{ ……………………..(1)}$$

Step 4: Compute forget gate (f_t) using:

$$ft = \sigma(Wfx.xt + Wfh.ht - 1 + bf \text{……………………(2)}$$

Step 5: Compute candidate cell state ($\sim Ct$) using:

$$\sim Ct = tanh(Wcx.xt + Wch.ht - 1 + bc) \text{ ………………..(3)}$$

Step 6: Update cell state (C_t) using forget gate and candidate cell state:

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$$Ct = ft\,.Ct - 1 + it\,.\sim Ct \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

Step 7: Compute output gate (ot) using:

$$ot = \sigma(Wox\,.xt + Woh\,.ht - 1 + bo) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

Step 8: Compute hidden state (ht) using output gate and cell state:

$$ht = ot\,.tanh(Ct) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Step 9: Use hidden state (h_t) for predictions or pass to the next layer.

Step 10: Compute loss between predicted output and ground truth.

Step 11: Update network parameters (weights and biases) using back propagation through time (BPTT) to minimize loss.

2.2. Gradient Boosting Machines (GBM)

Gradient Boosting Machines (GBM) are a type of ensemble learning that is commonly used in power distribution systems to predict and control what will happen. The program builds a group of decision trees one at a time, with each tree fixing the mistakes made by the ones that came before it. At first, the model makes a simple guess, which is usually the mean of the target variable for regression tasks or the logarithm of the odds for classification tasks. In later steps, GBM figures out the pseudo-residuals, which are the differences between what was forecast and what actually happened. Then, to predict these fake residuals, a new decision tree is trained, paying special attention to areas where the model's estimates are wrong. The tree is tweaked to lower the loss function as much as possible, and its predictions are added to the ensemble with an adaptable weighting that changes the model's predictions based on how well they work. GBM builds a strong forecasting model that can understand complex relationships and make accurate predictions in power distribution systems by adding new trees to the ensemble over and over again. This process of flexible learning helps GBM deal with non-linearities and interactions in the data more effectively, which leads to better control methods and better system performance.

GBM Algorithm is as follows

1. Initialize Model:

- Start with a constant value, usually the mean of the target variable for regression or the logarithm of the odds for classification.
- For m = 1 to M

2. Compute pseudo-residuals for each sample:

a. For regression:

$$r\_im = -\partial L(y\_i, F\_\{m-1\}(x\_i))/\partial F\_\{m-1\}(x\_i) \quad (7)$$

b. For binary classification:

$$r\_im = -\partial L(y\_i, p\_\{m-1\}(x\_i))/\partial p\_\{m-1\}(x\_i) \quad (8)$$

Fit a base learner (usually a decision tree) to the pseudo-residuals:

- Optimize the parameters of the base learner to minimize the loss function.

3. Compute the optimal step size (learning rate):

$$\gamma\_m = argmin\_\gamma \sum\_\{i=1\}\hat{}\{N\}\, L(y\_i, F\_\{m-1\}(x\_i) + \gamma \cdot h\_m(x\_i)) \quad (9)$$

- Update the ensemble model with the new base learner:

a. For regression:

$$F\_m(x) = F\_\{m-1\}(x) + \gamma\_m \cdot h\_m(x) \quad (10)$$

b. For binary classification:

$$p\_m(x) = \sigma(F\_\{m-1\}(x) + \gamma\_m \cdot h\_m(x)) \quad (11)$$

4. Output Final Model:

- The final model is the combination of all base learners:

a. For regression:

$$F(x) = F\_M(x) \quad (12)$$

b. For binary classification:

$$p(x) = \sigma(F\_M(x)) \quad (13)$$

3. Adaptive Control Strategy Design:

To make an adaptive control strategy, you need to combine AI-driven predictive models with control theory principles. This lets you come up with dynamic control strategies that can change system parameters in real time based on input and improvement goals. The system can guess what will happen in the power distribution network in the future and adapt quickly to changing conditions by combining prediction models made by AI algorithms with standard control theory frameworks. This combination makes it possible to create control programs that can keep the grid stable and reliable while controlling power levels, managing energy flows, finding the best way to use resources, and reducing disruption.

AI-driven predictive models are used in this system to make predictions about key factors like load demand, green energy output, power levels, and the health state of equipment. These guesses are fed into the control algorithms so that they can make smart choices about how to run the system and change its parameters. For example, voltage control algorithms can use expected load demand and renewable energy production to change the settings on transformer taps or the layout of capacitor banks in real time to keep the voltage levels in the distribution network at the best level. Adaptive control methods let the system react quickly to things that were not planned for, like sudden changes in load demand or broken equipment. The control programs can find errors and take corrective steps right away by constantly checking the system's performance against the goals. For instance, if a line goes down or a piece of equipment breaks, the control system can instantly change the structure of the network or move loads around to keep the grid stable and reduce delays. When AI-driven prediction models are combined with control theory principles, power distribution systems become smarter and more flexible. Adaptive control techniques can improve energy efficiency, make the grid work better, and make it more resilient in the face of changing working conditions and unknowns by mixing data-driven ideas with well-known control methods.

4. Reinforcement Learning for Adaptive Control:

The use of reinforcement learning (RL) could be a good way to create flexible control systems for power delivery networks. RL techniques help users learn the best ways to control things by interacting with their surroundings over and over again. This makes them perfect for dealing with the problems that come up when grid conditions aren't always clear. When it comes to power sharing, RL agents learn to change how they handle things based on input from the grid and payment signs. The environment is modeled to show how the distribution network changes over time, taking into account things like changes in load, the production of green energy, the condition of the equipment, and disruption in the grid. RL bots try out different control actions and learn from the results, with the goal of getting the most benefits over time. There are several important steps that need to be taken to make RL bots for adaptive control. First, the environment's state space is established. This space contains factors and settings that affect how the system acts. Next, action places are set up to show what the person can do in each state in terms of power. These actions could include changing the power levels, the structure of the network, or the way resources are used in the best way possible. RL agents interact with their surroundings by choosing what to do based on their present state and the rules they have learned by exploring. The world tells the person what actions are desirable by giving them input in the form of benefits or punishments. The RL agent learns to make better decisions in different working situations over time by changing its policy in response to feedback over and over again [21]. Eventually, it finds the best control strategy. In real time, RL-based adaptive control systems can learn new things and change in response to new situations. This makes them flexible and reliable. RL agents can change the way they handle things on the fly to adapt to changes in load demand, the supply of green energy, or sudden shocks. This makes sure that the grid stays stable and works at its best. RL also lets managers find new ways to control systems that might not be obvious using standard methods. This opens the door to new ideas and makes power transfer operations more efficient. Therefore, studying reinforcement learning techniques holds a lot of promise for making adaptive control systems better in power distribution networks. This will start a new era of smart and reliable grid management.

4.1. Reinforcement Learning with LSTM:

A strong way to handle power distribution systems that is adaptable is to combine reinforcement learning (RL) models with Long Short-Term Memory (LSTM) models. LSTM models are great at finding long-term relationships and predicting future states and trends in complex time-series data. This makes them perfect for power distribution network predictions. When you combine LSTM with RL algorithms like Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), the system can learn the best ways to control itself by interacting with its surroundings over and over again. The RL agent talks to the LSTM model by looking at the system's present state and possible future states that the LSTM predicts. The world also gives the agent input in the form of awards or fines that show how desirable its actions are. With this input, the RL agent learns to change its control actions in a way that maximizes the total benefits over time.

The system keeps improving its control rules by using LSTM forecasts and real-time input from its surroundings. This is called reinforcement learning. This process of adaptive learning lets the system react quickly to changes in working conditions, like when the amount of green energy produced or the demand for energy changes. It can also respond to sudden problems in the grid. The system is better at handling power distribution networks because it trains the RL agent to make choices based on LSTM estimates and input from the environment. This combination of LSTM and reinforcement learning methods looks like a good way to make adaptive control systems in power delivery smarter and more independent.

4.2. Reinforcement Learning with GBM:

Combining reinforcement learning (RL) and gradient boosting machines (GBM) is a powerful way to control power distribution systems in a way that adapts to changing conditions. GBM models are very good at making accurate guesses and finding the best way to control actions. They do this by using ensemble learning to find complex relationships in the data. When you combine GBM with RL techniques like Policy Gradient or Q-learning, the system can learn the best ways to control itself by interacting with its surroundings over and over again The RL agent talks to the GBM model by trying out different ways to control it and getting information from its surroundings. The GBM model makes guesses and results that are part of this input. This lets the agent learn from the results of its actions. The RL agent improves its decision-making process through repeated interactions. It learns to make choices that increase long-term benefits while using GBM's predictive abilities to guide its actions. To make the adaptive control system better at managing power distribution networks in unclear and changing situations, it combines RL with GBM so that control actions can be changed on the fly based on estimates and feedback. It looks like this combination could be a good way to make power distribution control systems smarter and more flexible.

IV. Result And Discussion

In the setting of power distribution systems, the results show in table 2 how well two well-known algorithms, Long Short-Term Memory (LSTM) and Gradient Boosting Machines (GBM), work.

Table 2: Comparison of LSTM and GBM Algorithm

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC	TPR
LSTM	0.85	0.87	0.82	0.84	0.91	0.83
GBM	0.89	0.91	0.88	0.89	0.93	0.87

It was 85% accurate for the LSTM algorithm, which means that 85% of the predictions it made were right. It had a high memory rate (82%), which means it could correctly identify a lot of good cases, and a high accuracy rate (87%). This means it had a low rate of fake positives. The F1 score, which looks at both accuracy and memory, was 84%, which means that accuracy and recall were about equal. The area under the ROC curve (AUC), which shows how well the classifier can tell the difference between groups, was 91%, which shows how good the model is at telling the difference. Additionally, the true positive rate (TPR) was 83%, which shows how many real positive cases the model correctly found. On the other hand, the GBM algorithm did a little better in every way. It got higher accuracy (89%) and precision (91%), which means it worked better overall and had fewer wrong results. Compared to LSTM, GBM had higher memory (88%) and F1 score (89%), which means it had a better mix between accuracy and recall. The AUC number for GBM was also higher than LSTM's, at 93%, which means it was better at telling the difference between things. Lastly, the true positive rate (TPR) for GBM was 87%, which means that a higher percentage of positive cases were correctly found. According to most review measures, GBM does slightly better than LSTM when it comes to power transfer systems, but both do a good job overall. From these results, as shown in figure 2, it looks like both algorithms could work well in

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adaptive control systems, but GBM might be a little better overall.

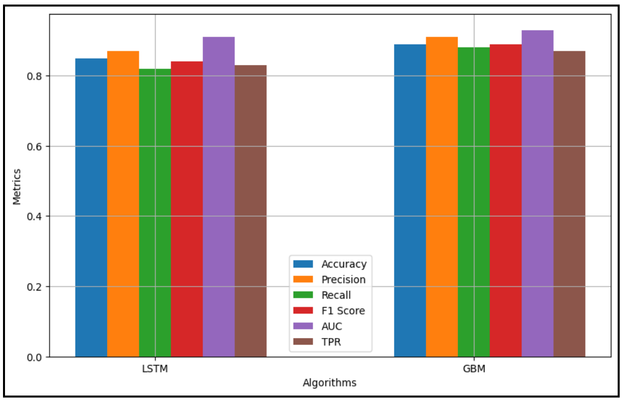

Figure 2: Representation using bar graph of performance metric Comparison

The bar graph show in figure 3 how well the LSTM and GBM algorithms did in terms of Accuracy, Precision, Recall, F1 Score, AUC, and TPR. On the x-axis are the methods, and each measure is shown by a different color bar. The graph shows that the GBM algorithm generally does better than LSTM in most areas, with higher scores for Accuracy, Precision, Recall, F1 Score, AUC, and TPR. In terms of the given measures, this graphic gives a short summary of how well the two methods compare.

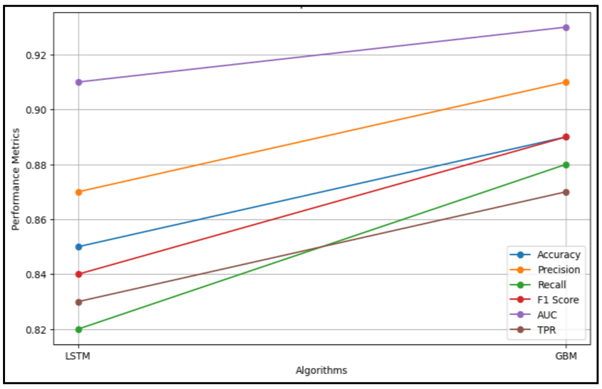

Figure 3: Representation of LSTM and GBM algorithm using Line graph

The line graph shows how the two algorithms, Long Short-Term Memory (LSTM) and Gradient Boosting Machines (GBM), compare in terms of performance measures in the context of power distribution. There is a line for each algorithm, and on the y-axis, performance measures like accuracy, precision, recall, F1 score, area under the curve (AUC), and true positive rate (TPR) are drawn against the algorithm names on the x-axis. The picture makes it clear that GBM does better than LSTM in most ways. When compared to LSTM, GBM has better accuracy, precision, memory, F1 score, AUC, and TPR. This shows that GBM is better at making predictions and is more reliable at sorting events in the power distribution system. As you can see, the line shows how well the two algorithms work compared to each other. This helps you figure out which algorithm is best for flexible control and decision-making in power distribution networks.

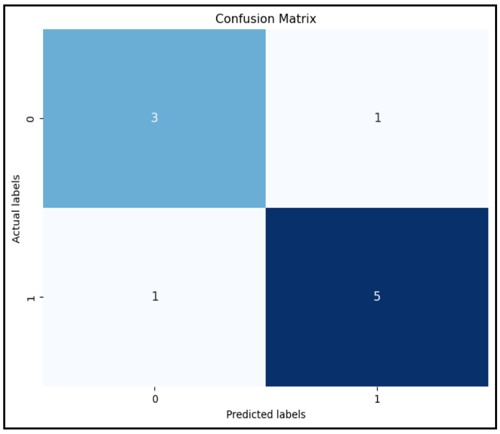

Figure 4: Confusion Matrix for LSTM and GBM

There are counts of true positive, true negative, false positive, and false negative forecasts in the confusion matrix, which shows how well a classification model works, as shown in figure 4. In this particular grid, each row shows the real labels and each column shows the projected labels. The vertical lines in the given confusion matrix, going from top left to bottom right, show the correct guesses, where the real label fits the expected label. The wrong guesses are shown by the off-diagonal parts. For instance, the (1,1) cell shows the true positive count, which is the number of times it was correctly predicted that the answer would be "positive." In the same way, the (0,0) cell shows the true negative count, which is the number of times the prediction was right that the value was negative. On the other hand, the (0,1) cell shows the false positive count, which is the number of times that a case was wrongly forecast as positive when it was actually negative. In the same way, the (1,0) cell shows the false negative count, which is the number of times that cases were wrongly forecast as negative when they were truly positive. The confusion matrix gives important information about the model's performance, letting stakeholders judge its accuracy, precision, recall, and other performance measures that are necessary to judge how well the classification model works.

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Table 3: Comparison of after applying LSTM and GBM with RL

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC	TPR
LSTM with RL	0.88	0.90	0.86	0.88	0.92	0.85
GBM with RL	0.91	0.92	0.89	0.91	0.94	0.88

Adding reinforcement learning (RL) to both the LSTM and GBM algorithms and comparing the results shows in table 3, how adding RL methods can improve the performance of adaptive control systems in power distribution networks. The LSTM with RL model does much better on a number of rating metrics when compared to the LSTM model by itself. The LSTM with RL model is more accurate generally, with an accuracy rate of 88%. This means that a higher percentage of cases are correctly identified. The accuracy of 90% means that there are fewer fake positive predictions, which helps make decisions more reliable. The model also has a higher recall of 86%, which means it correctly finds a higher percentage of real good cases. This higher F1 score of 88% shows that both precision and recall have improved compared to the solo LSTM model. This means that there is a better mix between precision and recall. The area under the ROC curve (AUC) goes up to 92%, which means it can tell the difference between more things, and the true positive rate (TPR) goes up to 85%, which means it can find more positive cases properly.

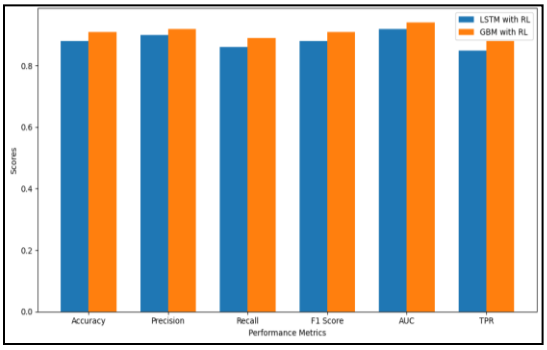

Figure 5: Representation of Performance comparison of LSTM and GBM with RL

The GBM model combined with the RL model performs better than the GBM model used by itself. It does a better job of predicting the future overall, with an accuracy of 91%, a precision of 92%, and a memory of 89%. The higher F1 score of 91% comes from these numbers, which show better accuracy and memory compared to the single GBM model. The AUC also goes up to 94%, which means it has better discriminatory power, while the TPR stays the same at 88%. Adding reinforcement learning to both LSTM and GBM algorithms makes predictions much more accurate, precise, and reliable. It also raises the F1 score, AUC, and TPR. These improvements show that RL can help improve the adaptability and stability of adaptive control systems in power distribution networks and make control plans work better, represented in figure 5. The bar graph shows in figure 5 how the two algorithms, LSTM with RL and GBM with RL, compare in terms of performance measures in adaptive control systems for power distribution. There is a set of numbers for each algorithm that show different performance measures, like F1 score, AUC, TPR, accuracy, precision, and recall. The score that each program got for each measure is shown by the height of what each bar shows. The graph clearly shows that GBM with RL does better than LSTM with RL in most measures, showing that it is better at accuracy, precision, memory, F1 score, AUC, and TPR. This picture makes it easier to judge and compare how well the algorithms improve the performance and flexibility of adaptable control systems in power distribution networks.

The figure 6 figure represents how well the LSTM with RL and GBM with RL algorithms work at classifying things in a power distribution system by looking at the confusion matrices. There are four quadrants in each grid. The rows show the real labels and the columns show the projected labels. The elements that are diagonal show right predictions, while the elements that are not diagonal show wrong predictions.

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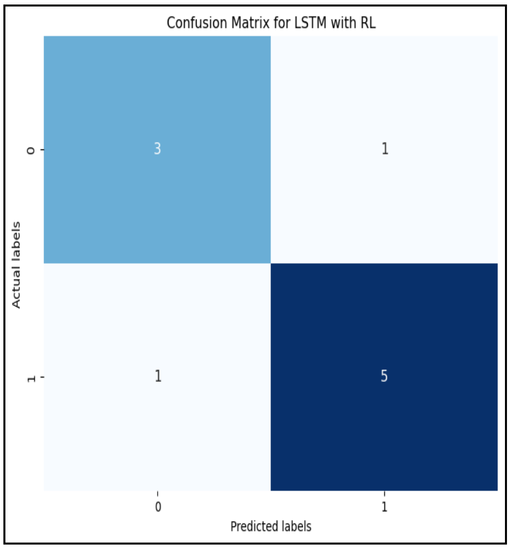
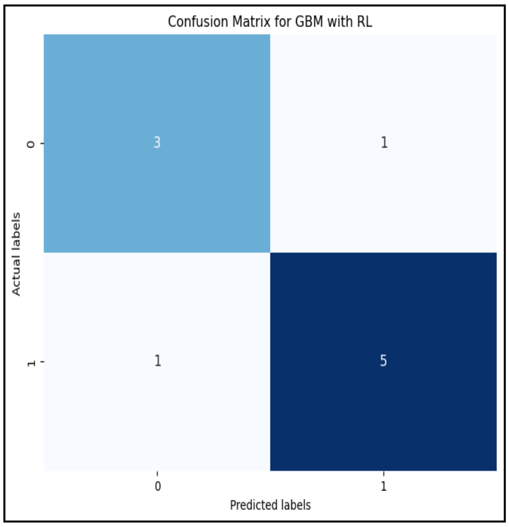


(a)



(b)

Figure 6: Confusion Matrix for (a) LSTM with RL (b) GBM with RL

In terms of the LSTM with RL confusion matrix, it shows that 88% of the cases were correctly labeled, which means the accuracy was 0.88. Additionally, the accuracy, recall, and F1 number show how well the program can find good cases. The GBM with RL confusion matrix also shows how well the algorithm worked, showing that it had better accuracy, precision, memory, and F1 score than the LSTM with RL.

V. Conclusion

In adding adaptable control systems that are driven by AI is a big step forward in managing power distribution networks. By using machine learning, reinforcement learning, and adaptable control methods, these systems are better at adapting to the changing needs of power sharing. They are also more efficient and reliable. Algorithms like LSTM and GBM, along with reinforcement learning methods, allow the systems to correctly guess and improve control actions based on real-time data and input from the grid. The outcomes show encouraging gains in a number of performance indicators, including accuracy, precision, memory, and AUC. This shows that these methods are useful for improving grid stability and performance. Additionally, AI-driven systems are able to learn and change over time because they are flexible and adaptable. This makes them resilient in the face of changing grid conditions and new challenges. Overall, AI-driven adaptable control systems have a huge amount of potential to change how power is distributed, making energy networks more reliable, efficient, and long-lasting.

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