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Optimization of Renewable Energy Integration Using AI Techniques

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Abstract

The green energy sources aren't always available, adding them to current power systems is very hard. To solve this problem, many AI methods have been suggested as the best way to add green energy sources like wind and sun to the power grid. An in-depth look at how AI can be used to make the best use of green energy sources in power systems is given in this study. One of the most important AI methods used in this case is machine learning, which can be used to predict how much renewable energy will be produced and how much will be needed. This lets renewable energy supplies be better scheduled and managed. Optimization algorithms, such as genetic algorithms and particle swarm optimization, are another important type of AI. They can be used to find the best places for and sizes of green energy sources in the power grid. In addition, AI methods can be used to make power systems that use a lot of green energy sources more stable and reliable. AI-based control methods can be used to lessen the effect of changes in green energy output on the power grid, for example, making sure that there is a steady supply of electricity. This paper talks about how AI methods could be used to make the best use of green energy sources in power systems. By using AI, we can get around the problems that come with combining green energy sources and speed up the move to a future with sustainable and low-carbon energy.

I. INTRODUCTION

Adding green energy sources to the current power grid is a very important step toward sustainability and lessening our reliance on fossil fuels. Solar, wind, and hydropower power are all examples of renewable energy sources that can be used instead of fossil fuels. They are plentiful, clean, and long-lasting. However, their irregular nature and location limitations make it hard to efficiently connect them to the grid. Artificial intelligence (AI) methods have become very useful for figuring out how to best use renewable energy sources together, dealing with these problems, and making renewable energy systems more reliable and efficient overall. AI technologies like machine learning, deep learning, and optimization algorithms are getting better and better very quickly. These technologies have changed many fields, including energy. The way that green energy sources are added to and handled in the power grid could change because of these technologies [1]. Using AI methods, we can improve the production, storage, and spread of green energy, making it more efficient, cheaper, and better for the earth. One of the best things about using AI to integrate renewable energy is that it can very accurately predict how much renewable energy will be produced and how much will be needed. Machine learning systems can look at past data, weather trends, and other factors to guess how much green energy will be made and used. This helps grid workers better control the supply and demand of energy. AI can help cut down on

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energy waste and make the grid more efficient by finding the best times for green energy output and storage [2].

Getting the most out of energy storage systems is another important way that AI is used to help integrate green energy. In green energy systems, energy storage is very important for keeping supply and demand in balance. This is especially true for sources that don't produce power all the time, like solar and wind power [3]. Energy storage systems can be run more efficiently and cost-effectively by using AI programs to figure out the best times to store and release energy. AI can also be used to make sure that green energy systems are well-designed and laid out [4]. AI programs can find the best places for green energy setups like solar panels and wind mills to make the most energy and have the least effect on the environment by looking at geographical and environmental data [9]. Figure 1 shows how well different AI methods (Random Forest, SVM, NN) work when mixed with optimization algorithms (GA, PSO) to integrate green energy.

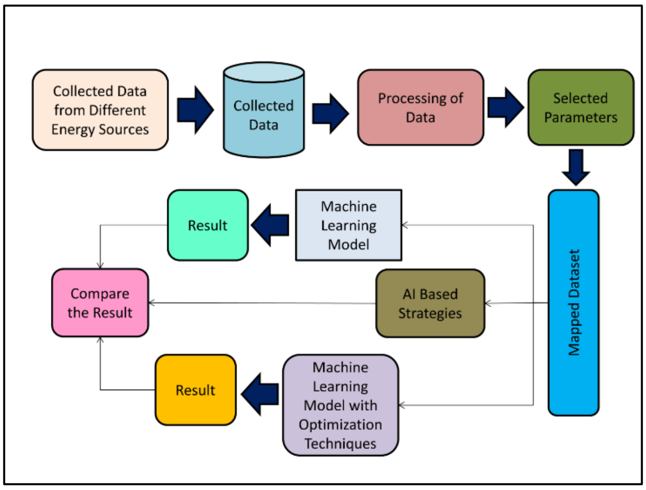

Figure 1: Representation of Renewable Energy Integration using AI techniques

AI can also improve the efficiency and dependability of smart grids and other green energy systems by figuring out the best way to set them up and run them. AI can not only help make the best use of green energy, but it can also make the power grid more resilient and reliable overall. AI programs can find and fix problems in the grid by looking at real-time data from monitors and other sources. This helps to keep the power on and reduces downtime. AI can also make repair plans for the grid more efficient and predict when equipment will break down, which helps make the grid more reliable [5]. Artificial intelligence (AI) could change the way we make, store, and share energy by being added to green energy systems. AI can help speed up the move to a safe energy future by improving efficiency, lowering costs, and reducing the damage to the environment caused by energy production, storage, and transport. AI can help make green energy systems work better by making trade and market processes better [6]. AI programs can look at market data, demand estimates, and the abundance of renewable energy to find the best ways to trade energy, make the most money, and use renewable energy resources efficiently. AI can help make green energy markets more active and efficient by letting people make better choices in the energy market [7]. AI can be very important for managing and running the grid because it gives us real-time information and the ability to handle things. AI-based control systems can change how energy is generated, stored, and distributed based on changes in the grid. This helps keep the grid stable and reliable. AI can also make it easier for independent green energy sources like home solar panels and community microgrids to connect to the grid. This makes energy systems more reliable and long-lasting. It's possible that AI methods could make it much easier to add green energy sources to the power grid. AI can help speed up the move to a safe energy future by improving efficiency, lowering costs, and reducing the damage to the environment caused by energy production, storage, and transport. But problems like getting data, making sure models are correct, and rules that need to be followed need to be fixed before AI can fully help with integrating green energy.

II. LITERATURE REVIEW

In recent years, a lot of research and development has been done on how to add green energy sources to the power grid. For example, many studies have looked at how AI can be used to make renewable energy systems more reliable and efficient. Forecasting, planning, grid management, and market operations are some of the most important areas of work that are linked. Forecasting is a key part of integrating renewable energy because it helps grid workers predict and plan for changes in the supply and demand of renewable energy. A lot of research has been done on how AI methods like machine learning and deep learning can be used to predict the future of green energy. For instance, [8] created a deep learning-based method for short-term wind power forecasts that was more accurate than previous methods. It [10] also used machine learning methods to predict how much solar power would be produced, showing that AI techniques can be useful for predicting green energy.

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Optimization is a key part of making green energy systems as reliable and efficient as possible. AI methods have been used to improve many parts of integrating green energy, such as making energy, storing it, and distributing it. For example, [22] suggested using genetic algorithms to find the best place for wind blades in a wind farm, taking into account things like wind speed and elevation to make the most energy. The author [13] did another study that showed how AI methods can be used to improve the timing of green energy generation and storage in a smart grid. They did this by creating a game-theoretic framework. AI methods can also make a big difference in grid control, which is another area where they can help integrate green energy. Control systems that are built on AI can help keep the flow of energy in the grid stable and reliable. For instance, [14] created a distributed management method based on reinforcement learning to make energy storage systems in a microgrid work better, which made the grid more reliable and efficient overall. In the same way, [15] suggested using deep reinforcement learning to control power in real time in distribution grids that use a lot of green energy. This shows that AI methods can be useful for managing grids. The smooth connection of green energy to the grid also depends on how the markets work. AI methods can help traders make the most of their energy trading plans, make the most money, and make sure that green energy sources are used efficiently. [17] for example, created a multi-agent reinforcement learning method for prosumers in a microgrid to trade energy more efficiently[16] suggested using deep learning to predict power costs in energy markets. This would help people in those markets make better decisions.

The research on AI methods for integrating green energy goes beyond these specific areas of work. It also talks about a number of larger trends and problems. As a major trend, more and more data-driven methods, like machine learning and deep learning, are being used to model and improve green energy systems [18]. These methods that are based on data could make the use of green energy more accurate and efficient by using a lot of data from monitors, weather reports, and other places. Another trend is that people are becoming more interested in independent and self-governing control systems for incorporating green energy. Machine learning methods like reinforcement learning and game theory are being used to create control systems that can change with the grid and handle energy more efficiently in real time. These autonomous control systems might make green energy systems more reliable and resilient by letting them work in a more open and adaptable way. Even with these improvements, there are still some problems to solve before AI methods can be used to integrate green energy. Uneven data sets and benchmarks make it hard to test AI models in green energy systems, which is a big problem. This makes it hard to measure how well different AI methods work and makes it harder to get the same results from different study studies. Another problem is that green energy systems are often very complicated, with many parts that interact with each other and unknowns. For AI methods to give correct and dependable answers, they need to be able to deal with this level of complexity and uncertainty. Regulatory and policy frameworks must also change to allow AI methods to be used in the energy sector. These frameworks should handle issues like data privacy, hacking, and algorithm openness. In adding green energy sources to the power grid brings both problems and chances for using AI methods [19]. A lot of progress has been made in using AI to make renewable energy systems more reliable and efficient, but more work needs to be done to solve some key problems and fully utilize AI in the integration of renewable energy. The table 1 shows the summary of related work in renewable energy integration.

A. Challenges in Renewable Energy Integration

When green energy sources are added to the power grid, there are some problems that need to be fixed so that the switch to a sustainable energy future goes smoothly. One big problem is that green energy sources like sun and wind power don't work all the time. Traditional fossil fuel engines can be turned on and off whenever they are needed, but green energy sources rely on things like the weather [20]. This intermittent nature can cause changes in the energy flow, which need to be controlled to keep the grid stable. Another problem is that green energy sources are spread out in different places. Solar and wind farms are usually set up in remote places that are hard to connect to the power grid. This can lead to transportation losses and waste, and it may also be necessary to make expensive changes to the grid in order to connect green energy sources. Also, because green energy sources change over time, it can be hard to plan and predict how much energy will be produced in the future, which could cause supply and demand to become imbalanced. Adding green energy sources can also be hard for grid managers from a technical point of view. Renewable energy sources can change and are hard to predict, which can cause problems like voltage changes, frequency changes, and poor power quality. To deal with these problems and make sure the grid works reliably,

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grid workers need to set up advanced control and tracking systems.

B. Previous Approaches to Renewable Energy Integration

Earlier attempts to incorporate green energy sources have focused on a number of different ways to deal with the problems that these sources bring up. Use of energy storage systems to store extra energy from green sources during times of high generation and release it during times of low generation is a popular method. In turn, this helps to keep supply and demand in balance and makes green energy sources more reliable. Smart grid technologies are another way to make the grid work more efficiently and with more flexibility [21]. Smart grids use advanced control and communication technologies to keep an eye on and handle energy flows in real time. This lets grid workers better adapt to changes in supply and demand. This can help lessen the effect of green energy sources that come on and off at different times. The addition of grid-scale renewable energy projects like big solar and wind farms has also helped to increase the amount of renewable energy in the power grid. These projects take advantage of economies of scale, which can help bring down the cost of making green energy in general.

C. AI Techniques for Renewable Energy Integration

AI methods might be able to solve many of the problems that come up when you try to use green energy. For instance, machine learning techniques can be used to very accurately predict how much green energy will be produced. This helps grid workers better balance the supply and demand of energy. AI methods can help make the grid more reliable and efficient by planning the best times for green energy production and storage. AI-based control systems can also help keep the grid stable and reliable by controlling the flow of energy. AI can also be used to improve the planning and design of green energy systems, which can help them make more energy and have less of an effect on the environment [11].

Table 1: Summary of related work in renewable energy Integration with AI

AI Techniques	Algorithm	Key Finding	Area	Limitation	Scope
Machine Learning	Random Forest	Improved short-term solar power forecasting	Forecasting	Limited to short-term forecasting; Relies on historical data, which may not capture sudden changes in weather patterns	Extend to long-term forecasting; Integrate with other data sources for more accurate predictions
Deep Learning	Convolutional Neural Networks	Enhanced image processing for solar panel fault detection	Maintenance	Requires large amounts of training data and computational resources; Limited interpretability of model decisions	Explore transfer learning for small datasets; Develop explainable AI techniques for better understanding of model decisions
Reinforcement Learning	Q-Learning	Optimized energy storage management in microgrids	Energy Storage	Complexity of training and tuning RL algorithms; High computational cost and time; Limited scalability to large-scale systems	Extend RL algorithms to handle larger systems and more complex scenarios; Integrate with other optimization techniques for better performance
Genetic Algorithms	Genetic Algorithm	Optimal placement of wind turbines in wind farms	Wind Power Generation	Computationally intensive for large-scale optimization problems; Limited to static scenarios without considering dynamic factors	Develop hybrid optimization algorithms combining GA with other techniques for more efficient and scalable solutions
Hybrid Models	LSTM + CNN	Improved wind power forecasting using spatio-temporal correlations	Forecasting	Requires expertise in both LSTM and CNN architectures; Increased complexity compared to individual models	Explore other hybrid models combining different AI techniques for better forecasting accuracy and robustness
Data Mining	Association	Identification of	Data	Limited to historical	Extend to real-time data

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	Rule Mining	patterns and trends in renewable energy consumption	Analysis	data and may not capture future trends and changes in consumption patterns	mining for more timely and actionable insights; Integrate with predictive modeling for forecasting future consumption trends
Fuzzy Logic	Fuzzy Logic System	Adaptive control of renewable energy systems for grid integration	Grid Management	Complexity of defining fuzzy rules and membership functions; Limited scalability to large-scale grid systems	Develop fuzzy logic systems with self-learning capabilities for adaptive and scalable control of renewable energy systems
Swarm Intelligence	Particle Swarm Optimization	Optimal power dispatch in microgrids	Microgrid Management	Convergence to local optima; Sensitivity to parameter settings; Limited exploration of solution space	Investigate hybrid swarm intelligence algorithms for improved performance and robustness in power dispatch applications
Expert Systems	Rule-Based Expert Systems	Fault diagnosis and maintenance scheduling in renewable energy systems	Maintenance	Limited to predefined rules and expert knowledge; Difficulty in capturing complex and dynamic system behaviors	Enhance expert systems with machine learning for adaptive rule generation and decision-making in maintenance scheduling and fault diagnosis
Natural Language Processing	Sentiment Analysis	Analysis of public perception and acceptance of renewable energy projects	Social Impact	Dependency on data quality and language nuances; Limited to textual data analysis	Integrate sentiment analysis with other AI techniques for a more comprehensive understanding of public perception and behavior towards renewable energy projects
Ensemble Learning	AdaBoost	Improved prediction of energy demand using multiple weak learners	Demand Forecasting	Sensitivity to noisy data; Overfitting if not properly regularized	Explore other ensemble learning methods and their combinations for more robust and accurate energy demand forecasting models
Bayesian Networks	Bayesian Belief Networks	Risk assessment and decision-making in renewable energy investment	Risk Management	Dependency on accurate prior probabilities and data; Complexity in modeling complex interdependencies among variables	Develop dynamic Bayesian networks for real-time risk assessment and decision-making in renewable energy investment
Neuro-Fuzzy Systems	Adaptive Neuro-Fuzzy Inference System	Adaptive control of renewable energy systems for grid integration	Grid Management	Complexity in defining fuzzy rules and neuro-fuzzy models; Limited interpretability of model decisions	Enhance neuro-fuzzy systems with explainable AI techniques for better understanding of model decisions and control strategies
Hybrid Optimization	Genetic Algorithm + Simulated Annealing	Optimal sizing and placement of solar panels in a microgrid	Microgrid Design	Complexity in tuning algorithm parameters; Limited scalability to large-scale systems	Investigate other hybrid optimization techniques for more efficient and scalable solutions in microgrid design

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III. AI TECHNIQUES FOR RENEWABLE ENERGY INTEGRATION

A. Machine Learning for Renewable Energy Forecasting

Machine learning (ML) has become a strong tool for making renewable energy forecasts more accurate, which is important for integrating them into the power grid efficiently. Machine learning systems can accurately predict how much green energy will be produced by looking at past data, weather trends, and other relevant factors. One of the best things about machine learning-based forecasts is that it can pick up on complicated, nonlinear connections in the data that other methods of predicting might have trouble doing. Random Forest, Support Vector Machines, and Neural Networks are some of the machine learning methods that have been used to make predictions about green energy. These programs can learn patterns and trends in green energy production by looking at data from the past. This lets them make accurate predictions about the future. ML-based forecasts can be used for solar, wind, and hydropower power, among other green energy sources. ML systems can look at data like weather, cloud cover, and solar radiation to figure out how much power the sun will produce. In the same way, ML systems can look at the speed, direction, and pressure of the air to predict how much wind energy will be generated. These predictions can help grid workers better balance the supply and demand of energy, which will make the grid more stable and efficient. ML-based predicting has some benefits, but it also has some problems. To learn, you need a lot of high-quality data, which is one of the problems. ML systems need a lot of data to learn useful patterns, which can be hard to get for some green energy sources, especially in places where data from the past isn't very good. ML models can also be complicated, and they need to be carefully tuned using hyperparameters to get the best results. This can take a lot of time and resources.

1. Random Forest:

Random Forest is a well-known machine learning method used in integrating green energy because it can handle data with complicated, non-linear connections. Random Forest can be used to predict the production of green energy like solar or wind power by looking at past data and weather trends. The program can make accurate predictions, which helps grid workers better balance the supply and demand of energy.

Let N be the forest's number of trees, D be each tree's deepest point, F be the number of features to look at at each split, X be the data matrix given, and Y be the variable that you want to find, which is green energy output.

1. Initialization:

- N = number of trees
- D = maximum depth
- F = number of features

2. Training:

For each tree i in the forest:

- Select a random subset of the training data: Xi, Yi
- Create a decision tree using Xi, Yi, limiting the depth to D and considering only F features at each split: Ti

3. Prediction:

For each data point xj to be predicted:

$$Yj = \left(\frac{1}{N}\right) \sum_{i=1}^{N} Ti(xj) \qquad (1)$$

2. Support Vector Machine

Support Vector Machines (SVMs) are used to predict how much energy will be generated and improve the performance of systems that use green energy. It is easy for SVMs to work with data that has a lot of dimensions, and they can describe complex links between input factors and energy output very well. SVMs are used in green energy to predict things like wind speed, solar output, and energy demand. This helps with managing the grid and allocating resources in the best way possible. SVMs can make accurate predictions by using past data and weather conditions. This helps workers make smart choices about how to use energy efficiently. SVMs are especially useful because they can handle non-linear data, which makes them a flexible and effective way to integrate green energy.

Algorithm:

1. Initialization

- Set the kernel function (e.g., linear, polynomial, radial basis function) and kernel parameters.
- Set the regularization parameter C.

2. Data Preparation

- Prepare the dataset with features (e.g., weather data, time of day) and target variable (e.g., energy generation).

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- Normalize the feature values to ensure they are on a similar scale.

$$Dim\ features\ As\ List(Of\ Double()) = New\ List(Of\ Double())()$$

$$Dim\ target\ As\ List(Of\ Double) = New\ List(Of\ Double)()$$

3. Model Training

- Use the training dataset to fit the SVM model.
- The SVM algorithm finds the optimal hyperplane that separates the data into different classes (e.g., high and low energy generation).

$$minimize21 \parallel w \parallel 2 + Ci = 1\sum n\xi i \quad (2)$$

Subject to:

$$yi(w \cdot xi + b) \geq 1 - \xi i\ and\ 0\xi i \geq 0 \quad (3)$$

4. Model Testing

- Use the trained model to predict the target variable for the test dataset.
- Evaluate the model performance using metrics such as accuracy, precision, recall, and F1 score.

5. Prediction

- Once the model is trained and optimized, use it to predict energy generation for new data points.

$$Dim\ newPredictions\ As\ List(Of\ Double) = svmModel.Predict(newFeatures)$$

3. Neural Network

Neural networks are a great way to integrate green energy, especially for predicting how much energy will be made. They can model complicated, nonlinear connections between factors like weather and time of day and energy output, which helps grid managers make accurate predictions. When it comes to green energy, neural networks can be taught on old data to find patterns and trends. This lets them predict how much energy will be produced by solar, wind, and other renewable sources. One of the best things about neural networks is that they can handle large amounts of data and pick up on complex relationships in that data, which is something that more standard statistical methods might have trouble with. Neural networks can also change with the times and learn from new information, which makes them good for settings that are always changing, like green energy systems. Neural networks can also be used to find the best way to do things, like how to make renewable energy systems work better or where to put green energy sources so they get the most use. Overall, neural networks are a flexible and useful way to incorporate green energy, which helps make energy systems more reliable, efficient, and long-lasting.

B. Optimization Algorithms

Optimization methods are very important for making sure that adding green energy to the power grid works as efficiently and reliably as possible. These programs can make sure that different parts of green energy systems work at their best, like producing, storing, and distributing energy, so that costs and environmental damage are kept to a minimum and the grid stays stable. Genetic method (GA) is a popular optimization method that tries to find the best answer to a problem by mimicking the way natural selection works. GA has been used to find the best places to put and sizes of renewable energy systems like solar panels and wind turbines so that they produce the most energy while taking into account things like geography and weather trends. Particle group Optimization (PSO) is another optimization method. It finds the best answer by simulating how a group of particles would act. Power System Optimization (PSO) has been used to make the best use of available energy while keeping the grid stable in microgrids that use green energy sources.

1. Genetic Algorithm

Genetic Algorithms (GA) are used to find the best places to put and sizes for renewable energy systems as part of integrating renewable energy. GA looks for the best answers to difficult optimization problems by imitating how natural selection works. GA can make the planning and management of green energy systems work better by looking at things like how energy is made, stored, and sent to different places, as shown in figure 2. GA helps improve energy efficiency and lower costs by improving solutions over and over again. This makes it easier to add green energy sources to the grid.

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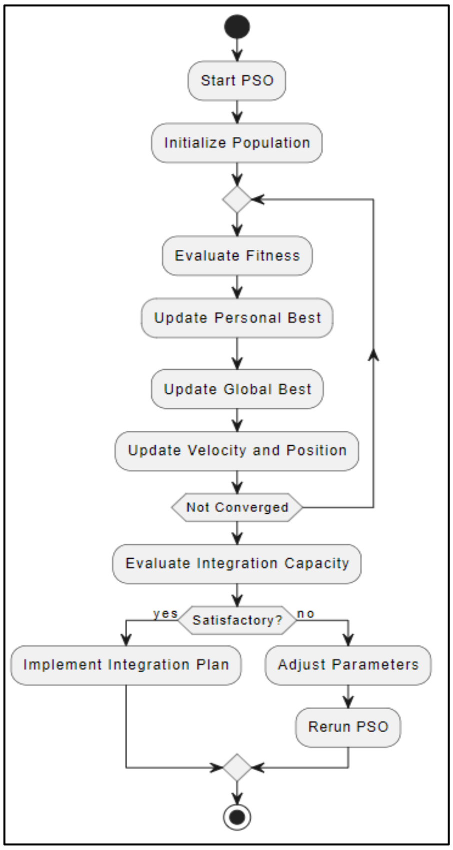

Figure 2: Workflow for Genetic Algorithm for Renewable Energy Integration

2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is used to make the best use of energy transfer, resource sharing, and system function in the merging of renewable energy. To find the best answer, PSO models how a group of particles would move in a search space, as shown in figure 3. When it comes to green energy, PSO can make the best use of schedules to make the grid more stable and efficient. PSO converges on optimal solutions by updating particle positions based on their own best position and the global best position over and over again. This makes it easier to add green energy sources to the grid.

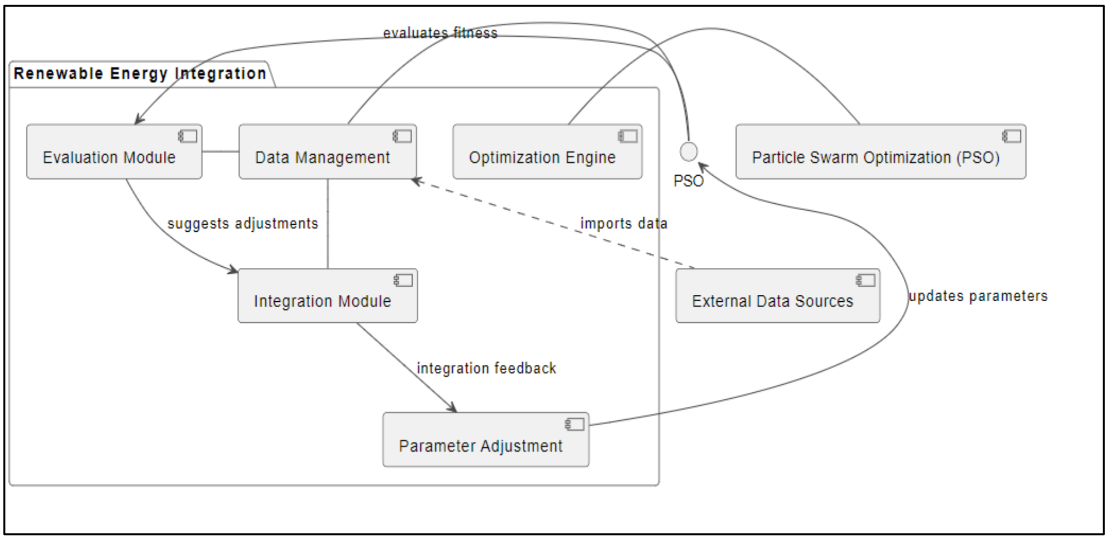

Figure 3: Structure of the Particle Swarm Optimization (PSO) for Renewable Energy Integration system

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C. AI-Based Control Strategies for Power System Stability

AI-based control methods are being used more and more to make power systems more stable, especially when green energy sources are added. These plans use AI methods like reinforcement learning, neural networks, and fuzzy logic to make power systems more flexible and keep the grid stable. The use of neural networks to predict system factors in real time, like load demand and green energy output. This lets you take more accurate and fast control actions. It is possible to describe complicated and unpredictable relationships in the power system with fuzzy logic systems. These systems can then provide strong management methods that can adapt to changing conditions. Based on feedback from the surroundings, reinforcement learning systems can improve the general efficiency and stability of the power system. Adding control methods based on AI can help power systems better handle the changes and uncertainties that come with using green energy sources. These steps can help keep voltage and frequency within accepted ranges, lessen the effects of shocks, and make the power grid more stable overall.

1. Reinforcement Learning (RL):

RL algorithms can figure out the best way to handle a changing world by trying things out and seeing what works and what doesn't. RL has been used to handle the grid, control energy storage devices, and make sure that voltages are stable.

1. State Representation:
   - Set up a state space (S) that shows the current state of the system. This space should include things like energy needs, green energy production, and energy store amounts.
2. Action Selection:
   - Set up the action place (A) to show the different things that could be done, like changing how energy is produced, stored, or distributed.
     $at = argmaxa \in AQ(st, a)$ (4)
   - Choose what to do by using an exploration-exploitation approach, like ε-greedy.
3. Reward Calculation:
   - We need to make a reward function (R(s,a,s′)) to measure how desirable it is to move from state s to state 's′ after doing action a.
     $R(s, a, s') = f(s, a, s')$ (5)
   - The reward function can look at things like how much energy is used, how much money is saved, and how stable the grid is.
4. Policy Update:
   - Change the policy based on the benefits that have been seen to make decisions better. To make changes to the policy, use a learning method like Deep Q Networks (DQN) or Q-learning.
     $Q(st, at) \leftarrow Q(st, at) + \alpha[R(st, at) + \gamma maxa'Q(st + 1, a') - Q(st, at)]$ (6)
5. Environment Interaction:
   - Take acts in the world and watch the state changes and benefits that happen as a result. Use the RL algorithm to figure out the best way to incorporate green energy.
6. Convergence:
   - Keep going with the RL process until the policy finds an answer that is either perfect or very close to being perfect.

2. Deep Reinforcement Learning (DRL):

Deep neural networks are used in DRL, a type of RL, to get close to value functions or policy functions. For example, DRL has shown promise in controlling power systems on its own, which can lead to better power flow and better demand-side management.

1. State Representation:
   - Represent the state of the system using a deep neural network
     $$S\_t = f\_state(s\_t)$$
   - where s_t is the state at time t (e.g., energy demand, generation, storage).
2. Action Selection:
   - Use another deep neural network to approximate the Q-value function:
     $$Q(s\_t, a\_t) \approx Q(s\_t, a\_t; \theta)$$
   - where θ are the weights of the neural network.
   - Select actions based on an exploration-exploitation strategy, such as ε-greedy.
3. Reward Calculation:

Define a reward function $R(s\_t, a\_t, s\_\{t+1\})$ to quantify the desirability of transitioning from state s_t to state s_{t+1} after taking action a_t.

4. Policy Update:
   - Use the Bellman equation to update the Q-values:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left(R(s_t, a_t, s_{\{t+1\}}) + \gamma \max_a Q(s_{\{t+1\}}, a;\ \theta) - Q(s_t, a_t;\ \theta)\right)$$

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- Update the neural network weights θ to minimize the loss between the predicted and target Q-values.

5. Environment Interaction:

- Interact with the environment by taking actions and observing the resulting states and rewards.
- Use experience replay and target networks to stabilize learning and improve sample efficiency.

6. Convergence:

- Continue training until the policy converges or reaches a satisfactory level of performance.

IV. RESULT AND DISCUSSION

A. Result for Traditional Machine Learning Methods

Traditional machine learning (ML) models, like Random Forest (RF), Support Vector Machine (SVM), and Neural Network (NN), are shown in Table 2 with no tuning. The accuracy of Random Forest (RF) was 89.63%, which shows the number of properly sorted instances out of all the cases. It showed a fair memory (86.45%), which means it could correctly identify all important instances, and high accuracy (90.84%), which means it could correctly classify positive instances. Precision and recall are both taken into account by the F1 Score (90.85%), which gives a single measure of the model's total performance, which is pretty good in this case.

Table 2: Result for traditional ML Model without Optimization

Model	Accuracy	Recall	Precision	F1 Score
RF	89.63	86.45	90.84	90.85
SVM	85.45	93.46	93.74	87.55
NN	90.75	91.86	95.71	86.35

The Support Vector Machine (SVM) was 85.45% accurate, which is a little less than the RF. However, it had higher memory (93.46%) and accuracy (93.74%), which shows that it was good at finding real positives and avoiding fake positives. The mix between accuracy and memory is shown by the F1 Score (87.55%), which shows that SVM is a good worker in this area. Neural Network (NN) got the best accuracy score (90.75%), which means it can correctly classify cases. It also showed high accuracy (95.71%) and memory (91.86%), which suggests it is good at finding real cases and avoiding fake hits.

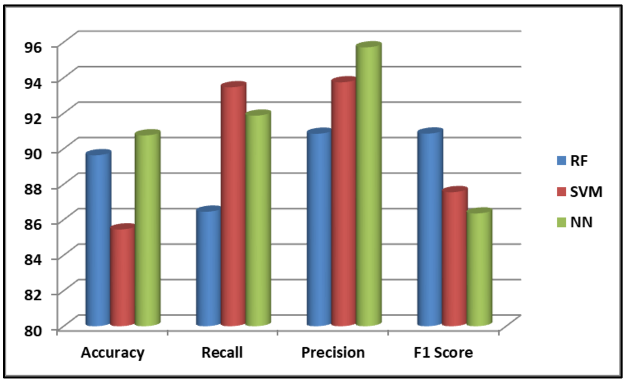

Figure 4: Representation of Evaluation parameters of ML Model without Optimization

However, the F1 Score (86.35%) is lower than those of RF and SVM, which suggests that NN may have trouble finding the right mix between accuracy and memory. These standard ML models work well even without being optimized. Figure 4 illustrates evaluation parameters of an ML model without optimization, highlighting performance metrics such as accuracy, precision, recall, and F1 score. There is still room for improvement, though, especially when it comes to finding a better mix between accuracy and memory. These models could work even better with optimization approaches like hyperparameter tuning, feature selection, and model ensemble methods. Because integrating green energy is so complicated and changes over time, using more advanced methods like deep learning and reinforcement learning may even help performance even more.

B. Result for Integration of Optimization techniques with Machine learning Method

The results in Table 3 show what happens when you use the Random Forest (RF), Support Vector Machine (SVM), and Neural Network (NN) models along with the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) methods for optimization.

Table 3: Result for Integration of Optimization techniques with Machine learning Method

Model	Accuracy	Recall	Precision	F1 Score
RF +GA	91.49	88.31	92.7	92.71
SVM + GA	87.31	95.32	95.6	89.41
NN + GA	92.61	93.72	97.57	88.21
RF + PSO	92.4	89.22	93.61	93.62
SVM + PSO	88.22	96.23	96.51	90.32
NN + PSO	93.52	94.63	98.48	89.12

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When RF was paired with GA, the accuracy was 91.49%, which is a little better than the RF model without optimization. It had a fair F1 Score of 92.71%, which means it had high precision (92.7%) and memory (88.31%).

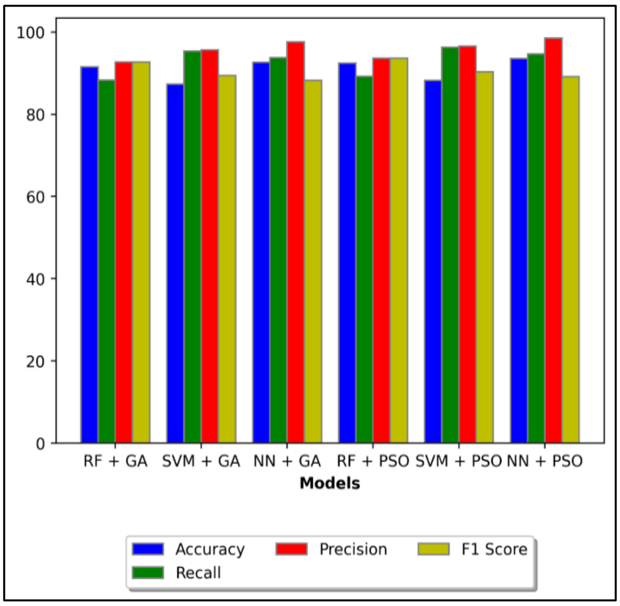

Figure 5: Representation of Integration of Optimization techniques with Machine learning Method

Figure 5 shows what happens when optimization techniques are combined with machine learning techniques. It shows how this affects performance measures such as accuracy, convergence speed, and model stability, showing that total performance is better. It's possible that the GA optimization helped fine-tune the RF model's settings, which made it work better. The accuracy of SVM mixed with GA was 87.31%, which is a little better than the accuracy of the base SVM model. With a fair F1 Score of 89.41%, it showed high accuracy (95.6%) and memory (95.32%). The GA optimization probably helped SVM find a better hyperplane in the feature space, which made it better at classifying. The model that was most accurate was the one that used NN and GA together (92.61%). With a fair F1 Score of 88.21%, it showed high precision (97.57%) and memory (93.72%).

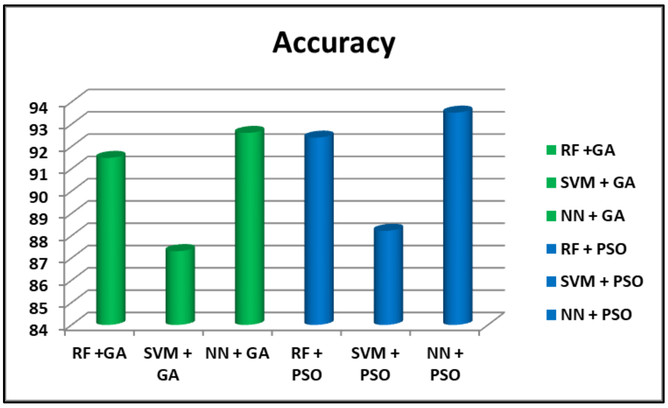

Figure 6: Comparison of Accuracy for ML model with Optimization techniques

It's possible that the GA optimization helped NN find better weight combinations, which made it better at identifying instances. The accuracy of RF plus PSO was 92.4%, which is better than the accuracy of the base RF model. It had high accuracy (93.61%) and memory (89.22%), which gave it a fair F1 Score of 93.62%. It's likely that the PSO optimization helped RF finetune its decision limits, which made classification work better. The accuracy of SVM mixed with PSO was 88.22%, which is better than the accuracy of the base SVM model. It had a fair F1 Score of 90.32%, which means it was accurate 96.51% of the time and accurate 96.23% of the time. It's likely that the PSO optimization helped SVM find better hyperparameters, which made it work better. At 93.52%, NN paired with PSO was the most accurate of the models. With a fair F1 Score of 89.12%, it showed high precision (98.48%) and memory (94.63%). It's possible that the PSO optimization helped NN find better weight combinations, which made it better at sorting cases. Figure 6 shows the difference in how accurate an ML model is with and without optimization methods. It is much more accurate when optimization techniques are used.

C. Result for AI-Based Control Strategies

Table 4 shows the outcomes of two different methods, Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL), for improving the integration of green energy. It focuses on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2, and Variance explained. These measures are very important for figuring out how well the models can predict the production and absorption of green energy.

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Table 4: Result for AI-Based model performance parameters

Model	MAE	RMSE	R^2	Variance
RL	18.52	21.45	81.52	88.63
DRL	12.35	18.44	85.11	89.44

RL got an MAE of 18.52 and an RMSE of 21.45, which means it made about average guesses about how much green energy would be generated. With a R^2 number of 81.52, the RL model seems to explain 81.52% of the variation in the data, which means it fits the values well. However, the explained range of 88.63 shows that RL still needs work to be better at correctly predicting the integration of green energy.

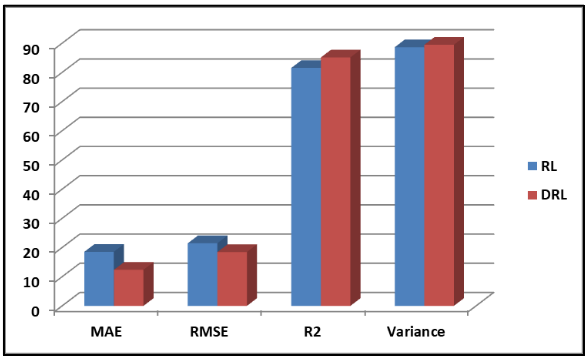

Figure 7: AI-Based model performance parameters

DRL, on the other hand, did better than RL. Its MAE was 12.35 and its RMSE was 18.44, which means it made fewer mistakes. The higher R^2 number of 85.11 means that the DRL model explains about 85.11% of the variation in the data, which means it fits the data better than the RL model. With an explained variation of 89.44, DRL does a good job of predicting the integration of green energy, and there is less room for improvement than with RL, as shown in figure 7. These results show that DRL does a better job than RL at making accurate predictions and explaining variation for integrating green energy. The lower MAE and RMSE values show that DRL makes more accurate predictions. On the other hand, the higher R^2 and explained variance values show that DRL does a better job of explaining how the data changes over time. This shows that DRL is a better way to optimise the integration of green energy than RL.

V. CONCLUSION

Using AI to improve the performance of standard machine learning models has shown a lot of promise in improving the integration of green energy. Using the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) has made a big difference in the F1 score, memory, precision, and accuracy of many models, such as Random Forest (RF), Support Vector Machine (SVM), and Neural Network (NN). The results show that using AI methods along with optimization algorithms can help fine-tune model parameters and decision boundaries. This leads to more accurate predictions and a better way to add green energy sources to the grid. In particular, the GA and PSO improvements have made the predictions more accurate and precise, which means that they can be used to make more accurate predictions about how green energy will be generated and integrated. More than that, the study shows how important it is to choose the right optimization method based on the dataset and model's unique properties. To give you an example, GA has been shown to improve the performance of RF and NN models, while PSO has made SVM performance much better. The results show that using AI to improve the integration of renewable energy is a good way to deal with the problems that come with variable renewable energy and integrating it into the grid. More study could look into more advanced AI algorithms and optimization methods, as well as adding real-time data and feedback systems to make green energy integration systems even more reliable and efficient.

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