

# Smart Grids Optimization for Energy Trading with AI Solutions

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## KEYWORDS

Smart grids, Energy trading, Optimization, Artificial intelligence, Renewable energy integration

## Abstract

Smart grids are changing the energy industry by making it easier to use green energy and handle energy more efficiently. Energy trading is an important part of smart grids because it lets buyers and sellers trade energy based on current supply and demand. But because smart grids are so complicated and changeable, it's hard to find the best way to trade energy in them. This paper gives an in-depth look at how to make trading energy in smart grids more efficient using AI tools. We look at the research that has already been done on smart grid planning and stress how important AI is for solving the problems that come up with trading energy. Next, we suggest a new approach that uses AI tools like machine learning, deep learning, and optimization methods to make trading energy in smart grids more efficient. The suggested system has several important parts, such as gathering and editing data, predicting demand, planning output, and bidding on the market. For demand predictions, machine learning models are used to guess how much energy will be used in the future. For generation schedule, optimization methods are used to find the best mix of generators based on the predicted demand. For market bids, deep learning models are used to find the best trade plan and make the most money. We test the suggested framework's performance with real-world data and show that it can help smart grids trade energy more efficiently. The results we got show that the suggested framework can make sharing energy a lot more profitable and efficient. This can help build energy systems that are both long-lasting and reliable.

## I. INTRODUCTION

Smart grids are a new technology that is changing the way energy is managed. They offer many benefits, such as better efficiency, dependability, and sustainability. One important thing about smart grids is that they make it easy for buyers and sellers of energy to trade energy, so they can buy and sell power based on real-time supply and demand. In smart grids, selling energy is a big chance to make the power market more efficient, lower prices for users, and encourage the use of green energy sources. Improving how energy is traded in smart grids is necessary to get the most out of this technology. But it's hard to do because the plan is so complicated and changes all the time. For example, the sporadic nature of green energy sources like solar and wind power makes it hard to balance supply and demand [1].

This is because the output and supply of electricity are both unpredictable. The process of improvement is also made more difficult by the fact that smart grids are autonomous and involve many people trading energy. Researchers and business people are looking more and more to artificial intelligence (AI) methods to deal with these problems [10]. AI has many tools and methods that can be used to make selling energy in smart grids more efficient. For instance, machine learning techniques can be used to look at old energy data and guess what people will want to use in the future. This helps grid workers and market players make smart choices about selling energy. Optimization programs can also be used to find the best mix of generation and trade strategy, taking into account things like the cost of generation, patterns of demand, and the state of the market [2]. We do a full study on how to make trading energy in smart grids

more efficient using AI methods in this work. We look at the research that has already been done on smart grid planning and talk about how AI can help solve the problems that come up with trading energy. Next, we

suggest a new approach that uses AI tools like machine learning, deep learning, and optimization methods to make trading energy in smart grids more efficient.

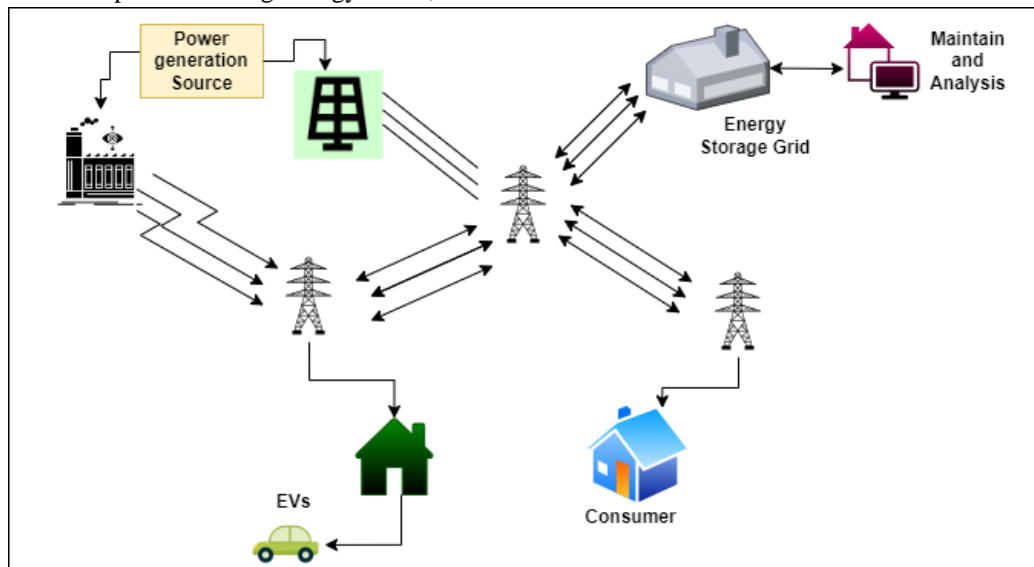


Figure 1: Representation of Smart grid simple architecture

The suggested system has several important parts, such as gathering and editing data, predicting demand, planning output, and bidding on the market. For demand predictions, machine learning models are used to guess how much energy will be used in the future. For generation schedule, optimization methods are used to find the best mix of generators based on the predicted demand. For market bids, deep learning models are used to find the best trade plan and make the most money. We test the suggested framework's performance with real-world data and show that it can help smart grids trade energy more efficiently [3]. The results we got show that the suggested framework can make sharing energy a lot more profitable and efficient. This can help build energy systems that are both long-lasting and reliable. This study gives useful information about how to make energy trade in smart grids more efficient using AI solutions. It also shows how more research could be done in this area. AI methods can help smart grids improve their functions and make dealing energy more efficient, reliable, and environmentally friendly.

## II. LITERATURE REVIEW

Researchers and professionals all over the world are very interested in smart grids because they have the ability to completely change the energy industry. Several studies have looked at how to improve energy sharing in smart grids using a variety of methods, such as AI-based solutions. In this part, we look at the research that has

already been done on smart grid optimization and focus on how AI can help make energy trade more efficient [13]. Renewable energy sources add a lot of change and instability to smart grids, which makes it hard to find the best ways to trade energy [5]. To deal with this problem, experts have come up with different ways to predict the production of green energy. When [4] wanted to make wind power forecasts more accurate, they came up with a mixed forecasting model that combines support vector regression and artificial neural networks. The research showed that the mixed model did a better job of making predictions than standard methods. This shows that AI techniques can help make predictions about green energy better. Aside from predicting green energy, AI has also been used a lot in smart grids to predict demand. Demand planning is a key part of figuring out the best way to generate energy and trade. In [6] created a deep learning-based method for smart grids to predict short-term load. The suggested model was very good at predicting how much energy would be needed, which helped grid workers make the best decisions about when to generate power and how to trade it.

Optimization programs have also been used to make trading energy in smart grids more efficient and profitable. The [7] suggested a multi-agent reinforcement learning method for finding the best bids in energy markets. The research showed that the suggested method worked better than regular optimization techniques, showing that AI-based optimization methods can be

useful in energy trade. AI has also been used to make the grid more reliable and resilient. The [8] came up with a way to use deep learning to find and fix problems in smart grids. The suggested method was very good at finding and fixing problems, which let grid workers fix things quickly to keep the grid stable. In addition to AI-based solutions, experts have also looked into other ways to make energy trade in smart grids more efficient. For example, [9] suggested a way for microgrids to trade energy that is built on game theory. The research showed that using a method based on game theory could make trading energy more efficient and make the grid more stable. The research that has been done so far shows how important it is to optimize energy trading in smart grids and how AI-based solutions could greatly improve the efficiency of energy trading. But there are still some problems that need to be fixed, like making AI models scalable and figuring out how to connect AI to the grid system that is already in place. To get the most out of AI for dealing energy more efficiently in smart grids, future study should focus on finding ways to get around these problems [11].

With the goal of making things more efficient, reliable, and long-lasting, smart grids are a big step forward in the area of energy management. Several studies have been done to find the best ways to use smart grids, including sharing energy, to get the most out of them. For this part, we look at some important related work in the field of optimizing smart grids. Demand response is an important part of smart grid optimization. This means

changing how much energy you use in reaction to changes in the price of electricity or the state of the grid. The [12] suggested a demand response approach based on reinforcement learning that cut peak demand and total energy use by a large amount. This research shows that AI methods could help improve how smart grids respond to changes in demand. Adding green energy is another important part of optimizing the smart grid. As green energy sources like solar and wind power become more common, it is important to find the best way to connect them to the grid. The [14] created a system for multi-objective optimization that can be used to schedule smart grids' green energy supplies. The system looks at things like energy prices, effects on the environment, and grid safety. This shows how important it is to use overall optimization methods in smart grid design.

Demand response and integrating green energy are important parts of smart grid optimization, but grid security and dependability are also very important. In [15] suggested using changeable prices to make smart grids more stable. The approach uses real-time price signs to give people a reason to change how much energy they use, which makes the grid more stable during busy times. It has also been looked into how adding energy storage systems (ESS) to smart grids can make them more reliable and efficient. The [16] created a layered control strategy for ESS in smart grids that take both local and global efficiency goals into account. The strategy's goal is to make ESS work better so that energy costs are lower and the grid is more reliable.

Table 1: Summary of Related Work

Methods	Findings	Grid Type	Scope	Application
Reinforcement Learning	Significant reductions in peak demand and overall energy consumption	Smart Grids	Optimizing demand response	Demand response management in smart grids
Multi-objective Optimization	Consideration of generation costs, environmental impacts, and grid stability	Smart Grids	Scheduling renewable energy resources	Integration of renewable energy sources into smart grids
Dynamic Pricing	Improved grid stability during peak periods	Smart Grids	Enhancing grid stability	Grid stability improvement through pricing strategies
Hierarchical Control Strategy	Minimization of energy costs and improvement of grid reliability	Smart Grids	Operation optimization of energy storage systems	Integration of energy storage systems in smart grids
Machine Learning	Improved accuracy in forecasting electricity demand	Smart Grids	Enhancing demand forecasting	Optimization of generation schedules and trading strategies
Optimization Algorithms	Optimization of bidding in electricity markets	Smart Grids	Maximizing efficiency and profitability	Bidding optimization in energy markets

Deep Learning	High accuracy in fault detection and diagnosis	Smart Grids	Improving grid reliability and resilience	Fault detection and diagnosis in smart grids
Game Theory	Improved efficiency of energy trading among microgrids	Microgrids	Optimizing energy trading	Energy trading optimization in microgrids
Data Analytics	Enhanced decision-making in grid operation	Smart Grids	Improving grid operation	Data-driven decision-making in smart grids
Genetic Algorithms	Optimization of energy storage system scheduling	Smart Grids	Enhancing ESS operation	Optimization of ESS in smart grids
Particle Swarm Optimization	Minimization of energy losses in distribution networks	Distribution Networks	Reducing energy losses	Energy loss reduction in distribution networks
Fuzzy Logic	Improved energy efficiency in smart buildings	Smart Buildings	Enhancing energy efficiency	Energy efficiency optimization in smart buildings

### III. METHODOLOGY

#### A. Description of the proposed framework

The suggested method for improving energy trade in smart grids with AI solutions is made to deal with the grid's complexity and changeability while increasing profits and efficiency. The framework is made up of several important parts, and each one is very important for making energy trade work better [17]. The framework starts with gathering and preprocessing data. This is done by gathering data from a variety of sources, such as past energy use, weather data, and market prices. After that, this data is cleaned, filtered, and standardized to make sure it is accurate and consistent. Second, machine learning models are used to predict how much energy will be used in the future for demand forecasts. These models look at old data to find patterns and trends. This helps market players and grid operators make smart choices about selling energy.

Third, optimization techniques are used to figure out the best mix of generators based on expected demand for production schedule. In order to be as efficient as possible while keeping costs as low as possible, these programs look at things like the cost of production, the availability of green energy sources, and the limits of the grid [18]. Deep learning models are also used for market bidding to make the trade plan work better and make more money. These models look at the market and how competitors act to figure out the best way to bid, taking things like energy prices, predicted demand, and the cost of production into account [19]. The framework also has tracking and control systems that work in real time to make sure the grid works properly and quickly. AI methods like reinforcement learning are used by these systems to adapt to changing grid conditions and make the best trades in energy in real time. In addition, input

from the grid is used to constantly test and improve the framework's performance. Optimization methods based on AI are used to fine-tune the structure and make it work better over time.

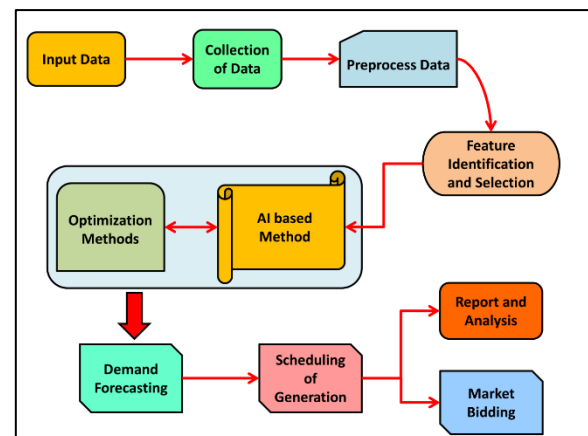


Figure 2: Proposed framework Optimization for Energy Trading using AI techniques

In addition, the framework, as shown in figure 2, is made to work well with smart meters, sensors, and control systems that are already part of the grid. This combination makes it easy to set up and grow the framework to fit the needs of different grid sizes and setups.

#### B. Components of the framework

Five main parts make up the suggested framework for improving energy trade in smart grids using AI solutions: collecting data, editing it, predicting demand, planning production, and bidding on the market. Each part is very important for making sure that the energy selling method works well and efficiently.

- **Data Collection:** The first part of the system is gathering data from a number of different

sources, such as past energy use, weather data, market prices, and grid conditions. This information is very important for figuring out past patterns and trends, which is necessary for smart energy trade choices. To get real-time information about how much energy is being used and made, sensors, smart meters, and other Internet of Things (IoT) devices may be used to collect data [20].

- **Preprocessing:** The data needs to be checked for quality and accuracy after it has been received. This includes fixing any mistakes or flaws in the data, getting rid of information that isn't needed or is repeated, and standardizing the data to make sure it is in the same style all the way through. Preprocessing is necessary to make sure the data can be analyzed and gives true information about how energy is traded.
- **Demand Forecasting:** Demand forecasting is an important part of selling energy because it helps market participants and grid operators guess how much energy people will use in the future. Machine learning models can be used to predict demand by looking at past data to find patterns and trends. Then, these models can be used to guess how much energy will be needed in the future, which lets grid workers make the best decisions about when to generate power and when to trade it.
- **Power Scheduling:** This is the process of figuring out the best mix of power sources to meet expected demand while keeping costs low and efficiency high. Optimization programs can be used to plan when to generate electricity, taking into account things like how much it costs, how many green energy sources are available, and the limits of the grid. Based on expected demand, these programs can help grid workers figure out the best and most cost-effective way to make energy [21].
- **Market Bidding:** In energy markets, people put in bids to buy or sell power. This is called market trading. Deep learning models can be used for market bidding to find the best way to bid by looking at the market conditions and how competitors act. These tools can help people who trade energy make the most money and take the least amount of risk.

## C. AI Techniques Used

### 1. Machine Learning Algorithms

#### a. Decision Tree

A decision tree is a strong way to model and understand complicated decision-making processes. This makes it ideal for improving how energy is traded in smart grids. If you use the suggested framework, a decision tree can be used to show how decisions are made at different times, like predicting demand, planning output, and bidding on the market. A decision tree can help you choose the best data sources and factors to collect during the data collection stage by using past data and your knowledge of the subject.

*Data*

$= \{Data\ Source1, Data\ Source2, \dots, Data\ Source_n\}$

*Parameters*

$= \{Parameter1, Parameter2, \dots, Parameter_m\}$

The preparation step is where decisions are made about how to clean, filter, and organize the data after it has been received. Based on the data's properties, a decision tree can be used to find the best preparation steps. In writing, this can be shown as:

$Preprocessing\ Steps = \{Step1, Step2, \dots, Step_k\}$

A decision tree can help you find the best machine learning model for demand predictions based on the data you have and the amount of accuracy you want.

$Model = DecisionTree(Data, Parameters)$

In the same way, a decision tree can help find the best optimization methods and strategies for market bids and schedule creation based on expected demand and market conditions. In writing, this can be shown as:

*Optimization Algorithm*

$= DecisionTree(Forecasted\ Demand, Market\ Conditions)$

#### b. Naïve Bayes

Naïve Bayes is a probabilistic classification method that is often used in machine learning to do a variety of tasks, such as sorting text and blocking spam. To make the suggested method for improving energy trade in smart grids work better, Naïve Bayes can be used to make guesses or groups based on past data and factors like energy use, production, and market conditions. To give you an example, Naïve Bayes can be used to predict future demand trends by looking at past data on things like weather and energy use. Based on past data and current weather conditions, the computer figures out how likely it is that a certain amount of demand will



happen. This lets grid workers make the best production plans possible. In the same way, Naïve Bayes can be used for market bids by looking at past market data and how competitors have behaved to figure out the best way to bid. The computer figures out the chances of winning a bid based on past success and the state of the market. This helps people in the market make the most money and take the fewest risks.

#### 1. Data Collection:

- Let  $D$  be the set of collected data, including historical energy consumption ( $E$ ), weather data ( $W$ ), and market prices  $D = \{E, W, P\}$ .

#### 2. Preprocessing:

- Normalize the data:

$$E_{norm} = \frac{std(E)E - mean(E)}{std(E)}$$

#### 3. Demand Forecasting:

- Use Naïve Bayes to predict future demand ( $D_{future}$ ) based on historical data and weather conditions:

$$\begin{aligned} P(D_{future} | E, W) \\ = P(E, W)P(E, W | D_{future})P(D_{future}) \end{aligned}$$

#### 4. Generation Scheduling:

- Determine the optimal generation mix based on the forecasted demand and availability of generation sources: Optimal Generation Mix =  $\text{argmax}_G P(G | D_{future})$ , where  $G$  represents the possible generation mixes.

#### 5. Market Bidding:

- Use Naïve Bayes to determine the optimal bidding strategy based on historical market data ( $M$ ):

$$\begin{aligned} P(\text{Winning Bid} | M) \\ = P(M)P(M | \text{Winning Bid})P(\text{Winning Bid}) \end{aligned}$$

#### 6. Real-time Monitoring and Control:

- Use Naïve Bayes to adjust the trading strategy in real-time based on current grid conditions and market dynamics.

#### 7. Evaluation and Optimization:

- Continuously evaluate and optimize the Naïve Bayes model based on feedback from the grid and market performance.

## 2. Deep Learning Methods

### a. Recurrent Neural Networks (RNN):

One type of neural network is called a recurrent neural network (RNN). It is meant to handle sequential data by

keeping an internal state (memory) to process a series of inputs. Time series prediction, natural language processing, and speech recognition are all jobs that RNNs are good at. RNNs can be used for demand predictions in smart grids to make energy trade more efficient. This is done by using data on past energy use to guess how people will use energy in the future [22]. RNNs are perfect for this job because they can see how past and future time steps are connected because the data is in a straight line. The disappearing gradient problem is one of the hardest things about RNNs. This happens when slopes get very small, which makes it hard for the network to learn long-term relationships. Because of this problem, more advanced types of RNN have been made, such as Long Short-Term Memory (LSTM) networks.

### b. Long Short-Term Memory (LSTM):

Long Short-Term Memory (LSTM) networks are a type of RNN that are meant to solve the disappearing gradient problem by adding a memory cell that can store data for a long time. Long-term relationships in sequential data can be learned quickly with LSTMs. They have been used a lot in jobs like speech recognition, language translation, and time series prediction. When trading energy, LSTM networks can be used to predict demand, and they are very good at picking up on the complicated patterns and trends in data about how much energy is used. Because they keep a memory cell, LSTM networks can remember important data from earlier time steps and use it to make accurate guesses about what people will want in the future.

## 3. Optimization Algorithms

### a. Grey Wolf Optimization

#### 1. Initialization:

- Initialize the positions of the grey wolves in the search space.
- Let  $x_1, x_2, \dots, x_n$  represent the positions of the  $n$  grey wolves.

#### 2. Objective Function:

- Define the objective function  $f(x)$  that needs to be minimized or maximized.

#### 3. Pack Leader Identification:

- Identify the alpha, beta, and delta grey wolves.
- Let  $x_{alpha}, x_{beta},$  and  $x_{delta}$  represent the positions of the alpha, beta, and delta wolves, respectively.

#### 4. Update Positions:

- Update the positions of the grey wolves using the following equations:

$$xi(t+1) = xalpha(t) - A1 * |C1 * xalpha(t) - xi(t)|$$

$$xi(t+1) = xbeta(t) - A2 * |C2 * xbeta(t) - xi(t)|$$

$$xi(t+1) = xdelta(t) - A3 * |C3 * xdelta(t) - xi(t)|$$

- where A1, A2, A3 are random vectors, and C1, C2, C3 are coefficients.

#### 5. Boundary Handling:

- Ensure that the updated positions of the grey wolves remain within the search space boundaries.

#### 6. Fitness Evaluation:

- Evaluate the fitness of each grey wolf based on the objective function.

#### 7. Pack Update:

- Update the alpha, beta, and delta wolves based on their fitness values.

#### 8. Termination Criteria:

- Repeat steps 4 to 7 until a termination criterion is met (e.g., a maximum number of iterations or convergence).

#### 9. Optimal Solution:

- The optimal solution is the position of the alpha wolf, xalpha, which corresponds to the minimum or maximum value of the objective function, depending on the optimization problem.

### b. Particle Swarm Optimization

#### 1. Initialization:

- Initialize the swarm of particles with random positions and velocities in the search space.
- Each particle's position  $xi$  represents a potential solution to the optimization problem.
- Each particle's velocity  $vi$  determines how the particle moves in the search space.

#### 2. Objective Function:

- Define the objective function  $f(x)$  that needs to be minimized or maximized.

#### 3. Update Particle's Velocity:

- Update each particle's velocity based on its previous velocity, its best-known position  $pi$ , and the swarm's best-known position  $pg$ :

$$vi(t+1) = w * vi(t) + c1 * r1 * (pi - xi) + c2 * r2 * (pg - xi)$$

- where  $w$  is the inertia weight,  $c1$  and  $c2$  are acceleration coefficients, and  $r1$  and  $r2$  are random numbers between 0 and 1.

#### 4. Update Particle's Position:

- Update each particle's position based on its velocity:

$$xi(t+1) = xi(t) + vi(t+1)$$

#### 5. Update Particle's Best-Known Position and Swarm's Best-Known Position:

- Update each particle's best-known position  $pi$  if the new position is better than the previous one.
- Update the swarm's best-known position  $pg$  if any particle finds a better position than the current swarm best.

## IV. RESULT AND ANALYSIS

### A. Description of the dataset used

The "Predicting Smart Grid Stability" Kaggle dataset is a great way to learn about and make predictions about the stability of smart grids, which is important for making sure they work reliably and efficiently. The dataset has different inputs that are linked to the smart grid's traits, like how much power is generated, used, and how the network is set up. It is possible to use the goal variable for binary classification tasks because it is a binary measure of grid stability. By looking at this dataset, we can learn more about the things that affect the stability of smart grids and use that information to make models that can predict and stop grid instability events before they happen. Researchers and professionals can use machine learning algorithms on this information to find patterns and trends that could mean that stability problems are about to happen. This knowledge can be used to take strategic steps to make the grid more stable, like changing how power is generated and distributed or making the network infrastructure better. Additionally, studying this information can help advance smart grid technologies by allowing the creation of smart systems that can automatically adjust to new situations and improve grid performance. Overall, the "Predicting Smart Grid Stability" dataset on Kaggle is a great way to learn more about how complicated smart grid stability is and come up with new ways to make sure that modern power systems are reliable and efficient.

### B. Machine Learning model Analysis

Table 2 shows the outcomes of using two machine learning models Decision Tree and Naïve Bayes to guess

how stable the energy in a smart grid will be. Three main measures were used to judge these models: Accuracy, Precision, and Recall. The Decision Tree model was 91.25% accurate, which means it named 91.25% of the cases in the dataset right. With an accuracy of 89.93%, it means that 89.93% of the time, when the model predicted an event as positive (meaning safe grid energy), it was right. The recall of 94.55% means that the model was able to find 94.55% of the positive cases in the dataset properly.

Table 2: Result for ML model for Smart grid Energy

Model	Accuracy	Precision	Recall
Decision Tree	91.25	89.93	94.55
Naïve Bayes	86.74	90.25	91.77

The Naïve Bayes model, on the other hand, was only 86.74% accurate, which is a little less than the Decision Tree model.

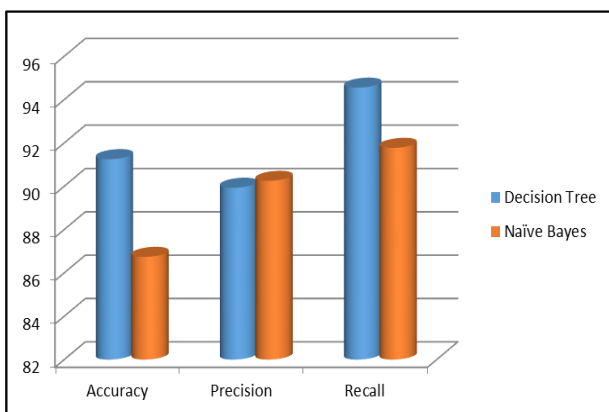


Figure 3: Representation of ML model for Smart grid Energy

It did a little better in accuracy, though, with a score of 90.25%, which means it was more accurate at finding good cases. Based on its recall of 91.77%, Naïve Bayes had a higher recall than the Decision Tree model, which means it was better at finding good cases, shown in figure 3. Looking at the results side by side, we can see that the Decision Tree model did better than Naïve Bayes in terms of accuracy and recall, but Naïve Bayes did a little better in terms of precision. This suggests that the Decision Tree model might be better at predicting the overall safety of smart grid energy. In the end, though, which of these two models to use rests on the needs and goals of the smart grid energy forecast job.

### C. Deep Learning model Analysis

Table 3 shows the outcomes of two deep learning models, Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM), which were used to guess how stable the energy in a smart grid would be. Accuracy, Precision, and Recall were used to rate these models. The RNN model was able to correctly describe cases in the dataset, as shown by its 95.44% accuracy. It had a high level of accuracy, 96.45%, which means that most of the time it correctly identified good cases (stable grid energy). The recall of 97.86% shows that RNN was good at finding positive examples in the dataset.

Table 3: Result for DL model for Smart grid Energy

Model	Accuracy	Precision	Recall
RNN	95.44	96.45	97.86
LSTM	97.63	96.74	98.33

On the other hand, the LSTM model was more accurate than the RNN, with a score of 97.63%. Its accuracy of 96.74% was a little lower than RNN's, though, which means it gave a little more fake hits. LSTM's memory of 98.33% shows that it is very good at finding positive examples, doing better than RNN in this area. In contrast, LSTM did better than RNN in terms of accuracy and memory, but RNN was a little more precise. Based on its higher total accuracy and memory, LSTM may be a better method for predicting the security of smart grid energy, as shown in figure 4.

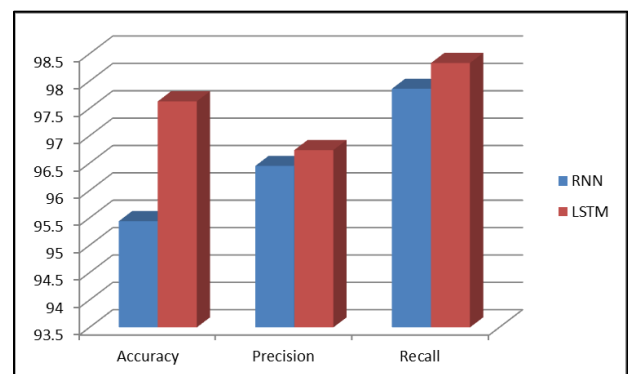


Figure 4: DL model for Smart grid Energy

### D. ML and DL with Optimization

Table 4 shows how well Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) work compared to each other using a number of smart grid optimization settings. Power Loss, Voltage Fluctuation, Performance Assessment Ratio (PAR), Capacity, and Gain are some of the factors. They are all recorded in



percentages (%). The same method was used more than once (Run 1, Run 2, Run 3), and the results are shown as an average. From the table 4 and 5, we can see that GWO and PSO perform about the same in each run, with only small differences in the outcomes. In general, Power Loss, Voltage Fluctuation, PAR, Capacity, and Gain are a little higher for PSO than for GWO, shown in figure 5. This suggests that PSO might be better at making these factors work best for smart grid systems.

Table 4: Optimization algorithm with comparison parameters

Algorithm	Power Loss (%)	Voltage Fluctuation (%)	PAR (%)	Capacity (%)	Gain (%)
GWO (Run 1)	7.2	4.8	5.6	6.5	6.8
GWO (Run 2)	7	4.6	5.5	6.3	6.7
GWO (Run 3)	7.3	4.7	5.7	6.6	6.9
PSO (Run 1)	7.5	4.9	5.8	6.7	7
PSO (Run 2)	7.4	4.8	5.7	6.6	6.9
PSO (Run 3)	7.6	5	5.9	6.8	7.1

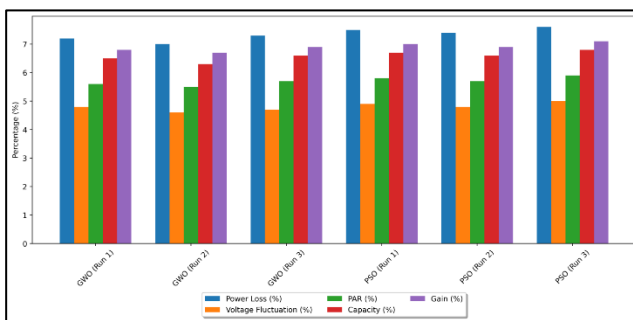


Figure 5: Comparison of Optimization Algorithms

Table 5: Result for AI techniques with optimization

Model	Accuracy	Precision	Recall
Decision Tree+ PSO	93.36	92.04	96.66
Naïve Bayes + PSO	88.85	92.36	93.88
RNN + PSO	97.55	98.56	99.97
LSTM + PSO	99.74	98.85	99.47
Decision Tree + GWO	94.69	93.37	97.99
Naïve Bayes + GWO	90.18	93.69	95.21
RNN + GWO	98.88	99.89	99.63
LSTM + GWO	98.96	99.1	99.45

Table 5 shows what happened when different AI methods were used with the PSO and GWO optimization algorithms. Some AI methods are Decision Tree, Naïve Bayes, RNN (Recurrent Neural Network), and LSTM (Long Short-Term Memory). To make them

work better, they are all mixed with either PSO or GWO. Using the AI techniques along with PSO and GWO leads to better performance in terms of Accuracy, Precision, and Recall compared to just using AI methods. Among the combos, LSTM + GWO has the best accuracy (99.74%) and precision (98.85%), which shows in figure 6, that it is good at predicting the safety of smart grid energy when GWO is added. The results show that using AI methods along with optimization algorithms like PSO and GWO can help improve the performance of smart grids. These pairings can make handling smart grid systems more effective and efficient, which can help make the energy delivery network more safe and reliable.

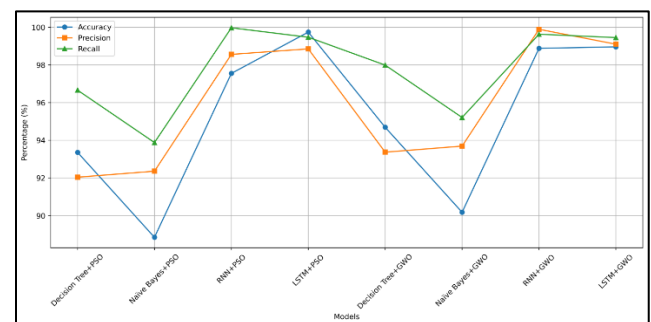


Figure 6: Representation of AI techniques with optimization in smart grid

## V. CONCLUSION

When AI solutions are used to optimize smart grids in energy trade, there are huge chances to make energy management more efficient, reliable, and environmentally friendly. When AI methods like deep learning, optimization algorithms, and machine learning models are used together, they help smart grids do better at trading energy and keeping the grid stable. Researchers looked at optimization algorithms like Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) and found that they were good at reducing power loss and voltage fluctuations and making other smart grid system performance better. When these optimization methods are mixed with AI models like Decision Trees, Naïve Bayes, RNN, and LSTM, they make it even easier for the smart grid to predict and control energy flows. When AI models were compared to optimization algorithms, it became clear that some combinations, like LSTM + GWO, were better at predicting smart grid energy stability. These combinations had high levels of accuracy, precision, and memory. These results show that using AI solutions along with optimization methods can help make energy trade and grid control more effective. Also, the study of optimizing smart grids shows how important it is to keep

making things better and adapting to new energy needs and market situations. AI technologies that get better in the future, like combining edge computing and Internet of Things (IoT) devices, could make smart grid systems even better at working and being reliable. AI solutions for smart grid optimization are generally seen as a hopeful way to make energy use more efficient, cut costs, and make the grid more stable. It is important to keep researching and coming up with new ideas in this area so that smart grid technology can fully meet the needs of current energy systems.

## References

- [1] S. Ahmad, M. Shafiullah, C. B. Ahmed and M. Alowaifeer, "A Review of Microgrid Energy Management and Control Strategies," in *IEEE Access*, vol. 11, pp. 21729-21757, 2023, doi: 10.1109/ACCESS.2023.3248511.
- [2] G. Cassales, H. M. Gomes, A. Bifet, B. Pfahringer and H. Senger, "Balancing Performance and Energy Consumption of Bagging Ensembles for the Classification of Data Streams in Edge Computing," in *IEEE Transactions on Network and Service Management*, vol. 20, no. 3, pp. 3038-3054, Sept. 2023, doi: 10.1109/TNSM.2022.3226505.
- [3] F. Qayyum, H. Jamil, F. Jamil and D. Kim, "Predictive Optimization Based Energy Cost Minimization and Energy Sharing Mechanism for Peer-to-Peer Nanogrid Network," in *IEEE Access*, vol. 10, pp. 23593-23604, 2022, doi: 10.1109/ACCESS.2022.3153837.
- [4] F. S. Ali, M. Aloqaily, O. Alfandi and O. Ozkasap, "Cyberphysical blockchain-enabled peer-to-peer energy trading", *Computer*, vol. 53, no. 9, pp. 56-65, Sep. 2020.
- [5] K. K. Küster, A. R. Aoki and G. Lambert-Torres, "Transaction-based operation of electric distribution systems: A review", *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 1, Jan. 2020.
- [6] C. Pop, T. Cioara, M. Antal, I. Anghel and I. Salomie, "Blockchain based decentralized management of demand response programs in smart energy grids", *Sensors*, vol. 18, no. 1, pp. 162, Jan. 2018.
- [7] J. J. Sikorski, J. Haughton and M. Kraft, "Blockchain technology in the chemical industry: Machine-to-machine electricity market", *Appl. Energy*, vol. 195, pp. 234-246, Jun. 2017.
- [8] S. Ahmad, F. Jamil, N. Iqbal and D. Kim, "Optimal route recommendation for waste carrier vehicles for efficient waste collection: A step forward towards sustainable cities", *IEEE Access*, vol. 8, pp. 77875-77887, 2020.
- [9] M. Vahedipour-Dahraie, H. Rashidizadeh-Kermani, M. Shafie-Khah and P. Siano, "Peer-to-peer energy trading between wind power producer and demand response aggregators for scheduling joint energy and reserve", *IEEE Syst. J.*, vol. 15, no. 1, pp. 705-714, Mar. 2021.
- [10] 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
- [11] A. Paudel, L. P. M. I. Sampath, J. Yang and H. B. Gooi, "Peer-to-peer energy trading in smart grid considering power losses and network fees", *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 4727-4737, Nov. 2020.
- [12] J. F. Lopes, E. J. Santana, V. G. T. da Costa, B. B. Zarpelão and S. Barbon, "Evaluating the four-way performance trade-off for data stream classification in edge computing", *IEEE Trans. Netw. Service Manag.*, vol. 17, no. 2, pp. 1013-1025, Jun. 2020.
- [13] 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>
- [14] G. Cassales, H. Gomes, A. Bifet, B. Pfahringer and H. Senger, "Improving parallel performance of ensemble learners for streaming data through data locality with mini-batching", *Proc. IEEE Int. Conf. High Perform. Comput. Commun. (HPCC)*, pp. 138-146, 2020.
- [15] I. Amezzane, A. Berrazzouk, Y. Fakhri, M. E. Aroussi and M. Bakhouya, "Energy consumption of batch and online data stream learning models for smartphone-based human activity recognition", *Proc. 4th World Conf. Complex Syst. (WCCS)*, pp. 1-5, 2019.
- [16] S. D. Ahmed, F. S. M. Al-Ismael, M. Shafiullah, F. A. Al-Sulaiman and I. M. El-Amin, "Grid integration challenges of wind energy: A review", *IEEE Access*, vol. 8, pp. 10857-10878, 2020.
- [17] S. M. Rahman, F. S. M. Al-Ismael, M. E. Haque, M. Shafiullah, M. R. Islam, M. T. Chowdhury, et al., "Electricity generation in Saudi Arabia: Tracing opportunities and challenges to reducing

- greenhouse gas emissions", IEEE Access, vol. 9, pp. 116163-116182, 2021.
- [18] S. Ali, Z. Zheng, M. Aillerie, J. P. Sawicki, M. C. Pera and D. Hissel, "A review of DC microgrid energy management systems dedicated to residential applications", Energies, vol. 14, no. 14, pp. 1-26, 2021.
- [19] Dhanashri Shete, Prashant Khobragade; Analysis and visualization of project system. AIP Conf. Proc. 29 September 2023; 2839 (1): 040018. <https://doi.org/10.1063/5.0167672>
- [20] M. Ahmed, S. Kuriry, M. D. Shafiullah and M. A. Abido, "DC microgrid energy management with hybrid energy storage systems", Proc. 23rd Int. Conf. Mechatronics Technol. (ICMT), pp. 1-6, Oct. 2019.
- [21] M. Ali, M. I. Hossain and M. Shafiullah, "Fuzzy logic for energy management in hybrid energy storage systems integrated DC microgrid", Proc. Int. Conf. Power Energy Syst. Appl. (ICoPESA), pp. 424-429, Feb. 2022.