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Artificial Intelligence in Smart Grid Applications
A Brief Review of Different AI Techniques for Critical Grid Applications

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Abstract

The complexities of operation and expansion planning of a power grid in recent time have grown in fast pace primarily due to integration of variable Renewable Energies (RE) and variable load demand. To achieve precise and reliable grid management, two critical functions—prediction and optimization must be executed with high accuracy. Conventional analytical frameworks, however, increasingly fail to deliver robust solutions for these tasks, particularly when processing vast, high-dimensional datasets in real time. This gap underscores the necessity for advanced computational algorithms capable of extracting actionable insights from complex data streams. Artificial Intelligence (AI), a domain focused on developing systems that mimic human cognitive processes, has emerged as a transformative tool for addressing these challenges. Its applications span critical areas such as load forecasting, RE generation prediction, and Economic Load Dispatch (ELD) optimization, where it outperforms traditional statistical methods in scalability and precision. This paper reviews widely adopted AI techniques tailored to core grid applications and industry-standard software solutions that leverage these technologies. By synthesizing advancements in AI-driven tools, the study highlights their potential to redefine grid resilience, efficiency, and operational flexibility in an era of energy transition.

1. Introduction

The Power Grid in recent times has been evolving into Smart Grid which improves the efficient utilization of available resources. A smart grid is a form of electricity network utilizing digital technology. It delivers electricity from suppliers to consumers using robust two-way digital communications to control appliances at consumers' premises. The goal of smart grids is to co-ordinate different parts of system efficiently as much as possible. According to the European Commission Task Force on Smart Grid, the smart grid is defined as "an electricity network that can intelligently integrate the action of all users connected to it - generators, consumers and those that do both - in order to ensure economically efficient and sustainable power system with low losses, high level of quality, security of supply and safety".

[1] Electric power systems worldwide face radical transformation with the need to decarbonise electricity supply, replace ageing assets and harness new information and communication technologies (ICT). The Smart Grid uses advanced ICT to control next generation power systems reliably and efficiently.

[2] The anticipated benefits and requirements of SG are the following:

i) Improving power reliability and quality;
ii) Optimizing facility utilization and averting construction of back-up (peak load) power plants;
iii) Enhancing capacity and efficiency of existing electric power networks;
iv) Improving resilience to disruption;
v) Enabling predictive maintenance and self-healing responses to system disturbances;

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vi) Facilitating expanded deployment of renewable energy sources;
vii) Accommodating distributed power sources;
viii) Automating maintenance and operation;
ix) Reducing greenhouse gas emissions by enabling electric vehicles and new power sources;
x) Reducing oil consumption by reducing the need for inefficient generation during peak usage periods;
xi) Presenting opportunities to improve grid security;
xii) Enabling transition to plug-in electric vehicles and new energy storage options;
xiii) Increasing consumer choice;
xiv) Enabling new products, services, and markets.

Modern power systems are increasingly prioritizing the integration of renewable energy sources (RES), such as solar and wind, into grid. However, the geographically dispersed and inherently intermittent nature of these resources complicates their integration into grid. Smart grid technologies address these challenges by leveraging operational flexibility through strategies like Demand Response (DR) and the deployment of Energy Storage Systems (ESS). These innovations are critical for mitigating the variability and unpredictability of RES output, ensuring grid stability while supporting the transition to sustainable energy ecosystems.

[3] Smart grid solutions emerging to manage continuous balancing of the system include:

- Better forecasting - Widespread instrumentation and advanced computer models allow system operators to better predict and manage RE variability and uncertainty.
- Smart inverters - Inverters and other power electronics can provide control to system operators, as well as to automatically provide some level of grid support.
- Demand response - Smart meters, coupled with intelligent appliances and even industrialscale loads, can allow demand-side contributions to balancing.
- Integrated storage - Storage can help to smooth short-term variations in RE output, as well as to manage mismatches in supply and demand.
- Real-time system awareness and management - Instrumentation and control equipment across transmission and distribution networks allow system operators to have real-time awareness of system conditions, and increasingly, the ability to actively manage grid behavior.

The evolution from conventional electric grid to smart grid has made most of the traditional power management applications and tools inefficient and inadequate which cannot handle the unprecedented scale of data generated by modern smart grids. In response, artificial intelligence (AI) solutions are increasingly being leveraged across smart grid applications, showing substantial promise in enhancing operational efficiency, predictive capabilities, and data-driven insights within these complex energy networks.

[4] AI techniques use massive amounts of data to create intelligent machines that can handle tasks that require human intelligence. In smart grid applications, AI can be defined as the mimicking of grid operators' cognitive functions by computers to achieve self-healing capabilities. [5] AI can handle large amounts of data and utilize them to make power system operations, control and planning more efficient.

The subsequent sections of this paper outline a concise overview of AI and its major categories, analyze AI frameworks best suited for various SG applications, provide a comparative assessment of commercially available AI-driven software and tools, and conclude with key insights and implications for future research and implementation.

2. Artificial Intelligence (AI)

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving. The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal. The broad subsets of AI are

- Machine Learning
- Artificial Neural Network Algorithms.
- Deep Learning Algorithms.
- Swarm Intelligence

2.1. Machine Learning (ML):

Machine learning is mainly focused on the development of computer programs which can teach themselves to grow and change when exposed to new data. Machine learning studies algorithms for self-learning to do stuff. It can process massive data faster with the learning algorithm. For instance, it may be programmed to complete a task, make accurate predictions, or behave intelligently learning from data outcome in the process. [6] In basic terms, ML is the process of training a piece of software, called a model, to make useful predictions or generate content from data.

ML systems fall into one or more of the following categories based on how they learn to make predictions or generate content:

- Supervised learning
- Unsupervised learning
- Reinforcement learning
- Generative AI

The ML is called supervised when it is trained using marked data, where the input and the output are known. It is called unsupervised where unlabeled data are used to train the algorithm, which means it uses data that has no historical labels. Reinforcement learning models make predictions by getting rewards or penalties based on actions performed within an environment. A reinforcement learning system generates a policy that defines the best strategy for getting the most rewards. Generative AI is a class of models that creates content from user input. For example, generative AI can create unique images, music compositions, and jokes; it can summarize articles, explain how to perform a task, or edit a photo.

The following broad subsets of ML are popular which use any or combination of the above mentioned learning categories -

- Linear Regression.
- Logistic Regression.
- Decision Tree.
- Naive Bayes.
- KNN.
- Support Vector Machine (SVM)
- Random Forest

[7] Linear regression algorithms are a type of supervised learning algorithm that performs a regression task and is a type of predictive modeling that discovers the relationship between an input and the target variable.

Logistic regression algorithms are the go-to for binary classification problems. There are two types of logistic regression: binary and multi-linear. The algorithm maps predicted values to probabilities using the Sigmoid function, an S-shaped curve also known as the logistic function.

Decision trees are a type of supervised machine learning algorithm used for classification and regression problems in machine learning. With a flowchart-like structure, decision trees represent a sequential list of questions or features contained within a node. Each node branches into a subsequent node, with a final leaf node representing a class label.

Naive Bayes is a probabilistic classification algorithm based on the Bayes Theorem in statistics and probability theory. The Bayes Theorem is a simple mathematical formula for calculating conditional probabilities.

K-nearest neighbors (KNN) is a supervised machine learning algorithm used to solve classification and regression problems. The algorithm assumes that similar data points exist in close proximity. KNN captures the idea of similarity by calculating the straight-line distance (AKA the Euclidean distance) between points on a graph.

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression problems. The purpose of SVM is to find a hyperplane in an N-dimensional space (where N equals the number of features) that classifies the input data into distinct group.

Random forest is a supervised learning algorithm used for classification, regression, and other tasks. The algorithm consists of a multitude of decision trees—known as a "forest"—which have been trained with the bagging method. The general idea of the bagging method is that a combination of learning models increases the accuracy of the overall result. This method is known as ensemble learning, a technique that combines many classifiers to provide solutions to complex problems.

Machine Learning has the advantages that it has the ability to review large volumes of data and identify patterns and trends that might not be apparent to a human. The main advantages of ML are – [8] It improves accuracy and precision, automates repetitive tasks, enhances decision making, enhances customer satisfactions by personalisation, improves predictive analysis, improves security, provides scalability, reduces cost, drives innovation and competition and enhances human capabilities.

[9] The major disadvantage of machine learning is its Dependency on Data - Inaccurate or incomplete data can lead to incorrect predictions, which can have serious consequences.

2.2. Artificial Neural Network (ANN):

[10]In its most general form, a neural network

is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer. In a neural network, the basic element is the neuron or node which is a processing element. In the network there are many neurons which get information from a source, combine these and perform an operation with them and produce results. This model processes information in a way similar to the biological systems of humans, such as the brain (consisting of millions of neurons), are able to process a certain piece of information and so it is named as Artificial Neuron Network (ANN). An ANN is composed of several interconnected neurons, which change their dynamic state responses with respect to external inputs. In this process, the ANNs try to recognize regularities and patterns in the input data, learn from experience, and then provide generalized results based on their known previous knowledge. The ANN approach was discovered in 1990 by Warren McCulloch and Walter Pitts as an alternative mechanism to the time series forecasting. The ANNs have been successfully applied in many different areas, especially for forecasting and classification purposes. ANN models have been used and studied intensively as a tool to be used for electric load forecasting and gained huge popularity in the last few decades. Basically, the neural network is a non-linear circuit that is capable of doing non-linear curve fitting.

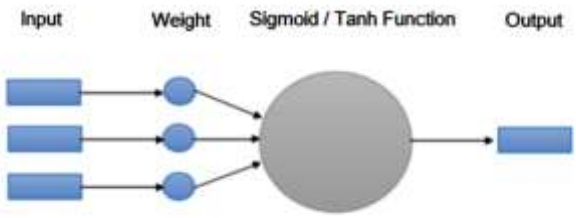

Figure 1. A single neuron ANN

Figure 1 shows a topology of an ANN with one neuron or node. A node consists of an Activation Function either a Sigmoid function or a Tanh function depending on the requirement. The signal sent from each input node travels through the weighted connection, whereby according to internal activation function the output is produced.

Like ML, learning is also the essence of ANN. Neural networks learn (or are trained) by processing examples, each of which contains a known "input" and "result," forming probability-weighted associations between the two, which are stored within the data structure of the net itself. The training of a neural network from a given example is usually conducted by determining the difference between the processed output of the network (often a prediction) and a target output. This difference is the error. The network then adjusts its weighted associations according to a learning rule and using this error value. Successive adjustments will cause the neural network to produce output which is increasingly similar to the target output. After a sufficient number of these adjustments the training can be terminated based upon certain criteria. This is a supervised learning. In unsupervised learning where the algorithm decides to terminate the training when examining additional observations does not usefully reduce the error rate. Even after learning, the error rate typically does not reach 0. If after learning, the error rate is too high, the network typically must be redesigned. Practically this is done by defining a cost function that is evaluated periodically during learning. As long as its output continues to decline, learning continues. The cost is frequently defined as a statistic whose value can only be approximated. The cost function is dependent on the task (the model domain) and any assumptions (the implicit properties of the model, its parameters and the observed variables).

Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge of cats, for example, that they have fur, tails, whiskers, and cat-like faces. Instead, they automatically generate identifying characteristics from the examples that they process.

[11]The commonly used algorithms in ANN are

- Feed-Forward (FF) neural networks,
- Back-Propagation (BP) neural networks,
- NARX (nonlinear autoregressive with exogenous inputs) neural networks,
- Radial Basis Function (RBF) neural networks,
- Random Neural Networks,
- Self-organizing competitive neural networks.

In the Feed Forward network the connections between the nodes do not form a cycle. Based on estimation the input is fixed but if there is any variation in the output then there is no way to adjust the input so as to bring the output to the desired level.

In the back propagation mechanism where the feedback of the outputs are used to adjust the weights of the inputs in some way so that the forecasted outputs approach the desired outputs or in other words the errors (the difference of desired outputs and the forecasted outputs) become minimum. The model with the weights that minimize the error function is then considered as the learning solution.

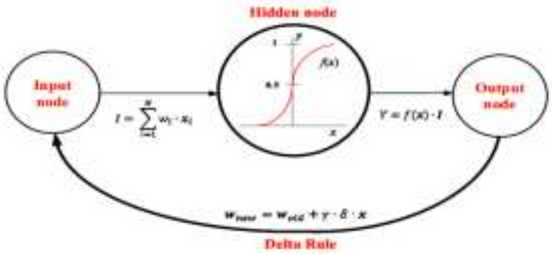

Figure 2. A back propagation ANN

The simplest form of an artificial neural network (back-propagation based) containing input, hidden and output layers is shown in Figure 2. Here, the input values to the hidden node (*I*), associated weights (*wi*), hidden layer function *f(x)*, and the output results (*Y*) can be seen. By changing the weights of the ANNs, the preferred output from a specific input can be achieved. The delta rule is a gradient descent learning rule for updating the weights of the inputs to artificial neurons in a single-layer neural network. The data (*xi*) flows to the input node where it computes to give an output $\sum(wi \cdot xi)$ where *wi* are weights, *xi* are inputs. The output is fed to the hidden node where an activation function is applied. The activation function *f(x)* is generally a sigmoid function whose value lies in between 0 to +1. The sigmoid function f(x) = 1 / (1 + e^(-x)) maps any input *x* to a smooth S-shaped curve, producing outputs strictly between 0 and 1. For neural networks requiring outputs centered around zero (e.g., -1 to 1), the hyperbolic tangent function f(x) = tanh(x) is preferred. The output of the hidden node is *Y= f(x).I* where I is the output of the input node and *f(x)* is the activation or transfer function of the hidden node. After each flow of the data to the output node, a feedback from the output node is fed to the input node where it is used as a new weight for the next flow of data, the feedback value is *wnew = wold+ Y.* $\boldsymbol{\delta}$ *.x* , where *wold* is the weight of the previous flow, the Y is the output of the hidden node, **δ** is the gradient and x is the input variable. The error gradient (**δ)** is the direction and magnitude calculated during the training of a neural network that is used to update the network weights in the right direction and by the right amount. The adjustment of the weight based on the output in each cycle brings the output closer to the desired value. Thus by adjusting the weights, accurate value of the output can be attained.

NARX (Nonlinear autoregressive with external input) networks can learn to predict one time series given past values of the same time series, the feedback input, and another time series called the external (or exogenous) time series. This means that the model relates the current value of a time series to both - past values of the same series and current and past values of the driving (exogenous) series.

RBF networks are a commonly used type of artificial neural network for function approximation problems. It is a type of feed forward neural network composed of three layers, namely the input layer, the hidden layer and the output layer. The Hidden layer of RBF consists of hidden neurons, and activation function of these neurons is a Gaussian function.

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feed forward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. RNNs have gradient-based learning algorithms. Recurrent neural networks recognize data's sequential characteristics and use patterns to predict the next likely scenario.

2.3. Deep Learning

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. The word "deep" refers to the number of layers through which the data is transformed. [12] It uses neural networks with many layers to automatically find patterns and make predictions. It is very useful for tasks like image recognition, language translation, and speech processing. Deep learning models learn directly from data, without the need for manual feature extraction.

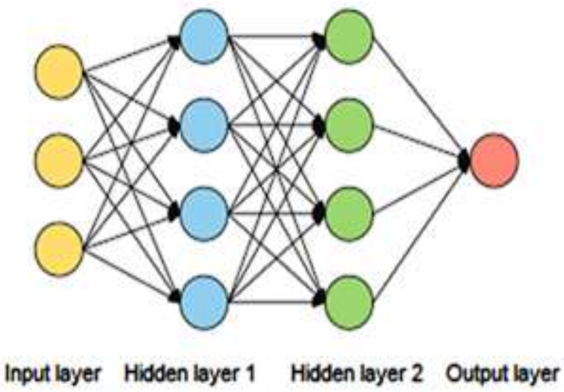

Figure 3. A typical deep learning network with 2 hidden layers.

The different types of Deep Learning algorithms widely used are:

- Convolutional Neural Network (CNN)
- Stacked Auto-Encoders.
- Deep Boltzmann Machine (DBM)
- Long Short-Term Memory Networks (LSTMs)

A Convolutional Neural Network (CNN) is a regulated type of feed-forward neural network that learns features by itself via filter (or kernel) optimization. This type of deep learning network can be applied to process and make predictions from many different types of data including text, images and audio. Convolutional Neural Network (CNN) is built to handle a greater amount of complexity around pre-processing, and computation of data. CNNs were designed for image data and probably be the most efficient and flexible model for image classification problems.

Autoencoders work by automatically encoding data based on input values, then performing an activation function, and finally decoding the data for output. Auto-encoder is useful in applications which require encoding features in massive datasets.

Deep Boltzmann machines don't follow a certain direction. All nodes are connected to each other in a circular kind of hyperspace. It can also generate all parameters of the model, rather than working with fixed input parameters. Such a model is referred to as stochastic and is different from all other deterministic models. Boltzmann Machine is useful in applications like monitoring a system (since the DBM will learn to regulate) and when to work a specific set of data.

[13] An LSTM (Long Short Term Memory) is an improvement of Recurrent Neural Network (RNN), where the same network is trained through sequence of inputs across time. An RNN works like this: First words get transformed into machine-readable vectors. Then the RNN processes the sequence of vectors one by one. While processing, it passes the previous hidden state to the next step of the sequence. The hidden state acts as the neural networks memory. It holds information on previous data the network has seen before. An LSTM has a similar control flow as a recurrent neural network (RNN). It processes data passing on information as it propagates forward. The differences are the operations within the LSTM's cells. The core concept of LSTM's are the cell state, and it's various gates. The cell state acts as a transport highway that transfers relative information all the way down the sequence chain. It can be thought as the memory of the network. The cell state, in theory, can carry relevant information throughout the processing of the sequence. So information from the earlier time steps can make its' way to later time steps, reducing the effects of short-term memory. As the cell state goes on its journey, information get's added or removed to the cell state via gates. The gates form different neural networks that decide which information is allowed on the cell state. The gates can learn what information is relevant to keep or forget during training. Since the LSTM network uses memory modules instead of common hidden nodes to ensure that the gradient will not disappear or expand after passing through many time steps thus it overcomes the difficulties encountered in traditional RNN training. Thus LSTM is suitable for processing and predicting important events with relatively long intervals and delays in time series.

Below is given a brief explanation on working of LSTM network.

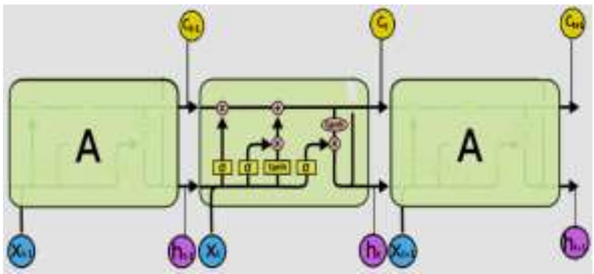

Figure 4. A typical LSTM network showing 3 nodes

Figure 4 shows a typical structure of a LSTM network node. At node (t-1), the input is X t-1 with output function ht-1 and output cell state Ct-1 . At node t, the input h t-1 goes through 4 layers –3 that through Sigmoid (**s**) activation functions (whose outputs numbers between 0 and 1) and tanh activation function (whose outputs numbers between 1 and -1). The top horizontal line in the network is the cell state line running straight down of the complete chain. The state of the cell while moving through the node may be retained or may be subject to change effected by a structured combination of gates. In this diagram there are 2 gates one for multiplying the input Ct-1 by a number ranging within 0 and 1 (output from a Sigmoid function) and in the next stage an addition gate which adds cell state output from the multiplication gate with that of output of a multiplication gate of the 2 activation function Sigmoid and tanh of the node input. The state of the cell after going through the 2 gates is then becomes the input as the cell state of the next node (Ct) in this case. This cell state (Ct) is also subjected to an activation function tanh the output of which is fed to a multiplying gate where another input is taken from a Sigmoid function fed with input. The output of this gate is then become the input (ht) for the next node.

Thus we can see that in a LSTM network the cell state or memory nodes form a separate network running in parallel with the main network and it provides useful information at each node so as to adjust the output to bring it to the desired level. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. The LSTM technique is found to be successful in long term prediction in a time series.

2.4. Swarm Intelligence (SI)

Swarm Intelligence (SI) has since evolved as a new branch of Artificial Intelligence that is used to model the collective behaviour of social swarms in nature. **[3]**Swarm-based algorithms have recently emerged as a family of nature-inspired, population-based algorithms that are capable of producing low cost, fast, and robust solutions to several complex problems.

SI has been found to be very suitable and effective in developing optimization solutions in a complex environment.

To date, several swarm intelligence models based on different natural swarm systems have been proposed in the literature, and successfully applied in many real-life applications. Examples of swarm intelligence models are: Ant Colony Optimization, Particle Swarm Optimization, Artificial Bee Colony, Bacterial Foraging, Cat Swarm Optimization, Artificial Immune System, and Glowworm Swarm Optimization.

3. AI Applications in Smart Grid

The application of AI replacing traditional applications for operation in a grid enables it to obtain higher efficiency, higher reliability and lower cost. There are corresponding application scenarios of AI in every link of power system, such as power generation, power transmission, power transformation, power distribution and power consumption.

Below are some of the areas where AI can be successfully applied:

3.1. Load Forecasting

Forecasting power load makes power production and load match in real-time, which becomes the important work of power grid daily operation. Power load forecasting is the prediction of power demand in the grid. Power load forecasting can be divided into short, medium and long-term forecasting, ranging in time from a few minutes to more than a year.

[15] Machine learning and artificial intelligence-based techniques provide a promising and attractive alternative to the traditional Statistical models used for load forecasting.

While different subsets of ML are increasingly used to develop prediction applications, the SVMs seems to be very popular ML algorithms, maybe because of their amenability to theoretical analysis, and their flexibility in developing predicting applications.

The Artificial Neural Network (ANN) and Deep Learning which are most suitable for time series forecasting and are adopted widely in development of load forecasting applications.

[16] An ANN-based load forecaster is developed by arranging historical data in the form of example patterns. For instance, if next-day load is to be predicted, the example patterns are formed as data pairs (outcome, factors). The outcome is the next day's load, whereas the factors include variables that this outcome is dependent on such as the next day's weather (importantly temperature) forecast, day of the week, and season of the year. Using historical data from the past few years, hundreds of such data pairs are constructed and presented to the ANN system. Using specialized training algorithms, the ANN automatically extracts and learns the underlying relationships that exist between the outcome and factors. Once this learning process is complete, the ANN system can be utilized as a load forecaster for the specific load it has been trained for. Although there could be future situations for

which similar cases do not exist in historical data, the generalization ability of ANN enables it to handle such cases as long as the learned relationships apply to them. Temperature is the most significant variable among the utilized factors. The prediction of a future load requires the corresponding temperature forecasts. The accuracy of weather forecasts has increased significantly in recent years due to the availability of more powerful computational resources as well as improvements in weather models.

[17, 18] Back-propagation ANN algorithms were found to be more accurate for Short Term Load Forecasting (next hour to two weeks) in many studies as it is simple and satisfactory with sufficient samples. In case of limited data availability, the simple Back-propagation model cannot describe a complex function and in such cases other networks namely NARX networks and the RBF networks are better as they possess the ability to create the nonlinear relationships between variables resulting smaller errors.

[19] With the advancement of technology, deep learning is widely used in power system load forecasting. As explained earlier, the Deep Learning based LSTM which predicts well for events with long intervals and delay is suitable for Long Term Load Forecasting (spanning from one to ten years or more).

3.2. Renewable Energies (RE) Generation Forecasting

Precise forecasting of renewable energy generation is a critical necessity to ensure the stable, efficient, and cost-effective operation of power systems. Conventional statistical methods often struggle to handle the nonlinear and non-stationary nature of wind and solar data, resulting in suboptimal prediction accuracy. Mirroring advancements in load demand forecasting, artificial intelligence (AI) has emerged as a more robust solution for predicting renewable energy output.

Given the intricate, nonlinear characteristics of meteorological datasets, deep learning techniques—particularly LSTM and hybrid of LTMS combining with other algorithms models—have gained widespread adoption in this domain. Their strength lies in effectively processing multidimensional data patterns, making them well-suited for capturing the dynamic and complex relationships inherent in renewable energy generation forecasting.

3.3. Economic Load Dispatch [20,21]

Economic dispatch is the short-term determination of the optimal output of a number of electricity generation facilities, to meet the system load, at the lowest possible cost, subject to transmission and operational constraints. To achieve the objective of minimizing the cost, generations are allocated to different generators in such a way that the total cost of generation becomes minimum while operating the grid within the constraints. This process of online allocation of generations is known as economic load dispatch.

[22] In general, the purpose of economic dispatch is to determine at all times the optimum combination of generating units connected to the systems so as to supply the load demand at minimum cost. It is a crucial optimization problem and its main objective is to divide the required power demand among online generators. It is used to minimize the generation cost of units, with satisfaction of constraints namely the equality and inequality constraints.

The objectives of the Economic Load Dispatch (ELD) are:

1. The Fuel Cost Objective
   The aim is to minimize the total fuel cost (operating cost) of all committed plants can be stated as follows:
   Minimize the fuel cost function

$$\mathbf{F(c)} = \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{a_i P_i^2 + b_i P_i + c_i} \tag{1}$$

   Where ai, bi and ci are the fuel cost coefficients of the ith unit generating plant, n is the number of generators, and Pi the active power of ith generator. F(C) is the fuel cost per unit time (hour).

2. To operate within the necessary constraints of the grid which is:
   (i) Equality Constraints:
   This is the basic Load/ Power flow equation.
   The total power generation must satisfy the total required demand (power balance) and transmission losses. This can be formulated as follows:

$$\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{P_{Gi} = D + P_{loss}} \tag{2}$$

   Where D is the real total load demand of the system, PGi is the ith generator's power, and P*loss* is the transmission losses.

   (ii) Inequality Constraints:

These are the constraints or the limits within which the voltage and different components of the grid operate namely

a) Generation constraints
b) Voltage constraints
c) Transformers tap settings
d) Transmission line constraints
e) Network security constraints

Thus the ELD issue involved in solving the equation (1) to find the lowest possible value of the *F(C)* i.e. the cost by varying the value of *P* of each generator within the constraints mentioned in serial no 2 namely the equality and inequality constraints. At this minimum value of *F(C)* the values of *P* for different generators are allocated to the plants.

Optimization algorithms play a pivotal role in addressing grid management challenges, with Particle Swarm Optimization (PSO) standing out as a widely adopted method within the Swarm Intelligence family. As a global optimization tool, PSO addresses challenges where optimal solutions correspond to points or surfaces in *n*-dimensional spaces. Inspired by the collective behavior of bird flocks or fish schools, PSO operates as a randomized, population-based method where individual solutions (“particles”) navigate a multidimensional search space. Each particle adjusts its trajectory based on mathematical rules governing its position and velocity, collectively driving the swarm toward optimal regions.

In Economic Load Dispatch (ELD), PSO is instrumental in determining optimal active power distribution across generating units while adhering to system constraints and minimizing generation costs. Over the past 25 years, PSO has proven highly effective in overcoming practical ELD limitations, with ongoing refinements enhancing its speed and accuracy.

The first practical application of PSO was in the field of neural networks, in 1995, when PSO was able to train and adjust the weights of a feed-forward multilayer perceptron neural network as effectively as the conventional error back-propagation approach. This milestone catalyzed its exponential adoption across diverse fields, including energy systems. Its appeal lies in its simplicity, computational efficiency, and rapid convergence capabilities—qualities that make it particularly suited for complex, multi-objective ELD challenges. Today, PSO remains a cornerstone of modern optimization frameworks, continuously evolving to meet the demands of increasingly sophisticated grid systems.

3.4. Fault diagnosis and protection of equipment [23]

Modern power infrastructure—spanning AC/DC transmission systems, generation assets, energy storage systems, distribution networks, and microgrids—increasingly relies on power electronics-based technologies. However, these systems are frequently impacted by faults stemming from complex, uncertain variables, creating significant diagnostic challenges. Deep learning excels in such scenarios by autonomously extracting hierarchical features from fault data, enabling precise identification and multi-level characterization of fault patterns. This capability enhances diagnostic accuracy despite the nonlinear, dynamic nature of power electronics failures.

3.5. Electricity Consumption Analysis

Analysis of consumer power consumption patterns is essential for detecting abnormal energy usage and enabling non-intrusive load monitoring (NILM). Such analyses play a pivotal role in devising dynamic energy pricing strategies and infrastructure upgrade plans. Leveraging smart meter data—such as power, voltage, and current measurements—AI technologies can decode the unique consumption behaviors of diverse user groups. This enables utilities to tailor pricing strategies and services to specific customer segments, enhancing grid efficiency and customer satisfaction.

Machine learning is uniquely suited for this task due to its robust clustering and pattern recognition capabilities. Consumption analysis and anomaly detection can be distilled into distinct user profiles, which are then classified into groups via mathematical modeling. Advanced multi-layered deep learning networks can be designed as classifiers, outperforming conventional statistical methods by capturing intricate, hierarchical data patterns inherent in energy consumption dynamics.

3.6. Information network security

Smart grid consists of real-time communication and control network. Like any other information network it also faces potential threats. Although the information system attack does not affect the primary equipment directly, the secondary system may be destroyed to disrupt the physical power grid. The malwares or viruses which threaten the network like they do in internet have the characteristics remaining concealed and dormant for long period and so it is difficult to identify and locate them with conventional software. AI technology has the capability to automatically identify network attack features, detect malwares and render them inactive thus providing security to the network.

Since cyber attacks on grids are rare, historical attack data for training models is sparse. Deep learning circumvents this limitation by extracting patterns from unlabeled data, bypassing the need for extensive labeled datasets. This capability makes it superior to rule-based methods, as it can infer complex attack behaviors even with limited examples, enhancing grid resilience against evolving cyber threats.

4. Review of literatures and commercially available applications

AI represents a rapidly evolving field, with a growing suite of algorithms continually being refined and expanded. Beyond foundational techniques like ML, ANN and DL, researchers are actively exploring hybrid models that merge these approaches with traditional statistical methods. Such innovations aim to tailor solutions for specific operational challenges, ensuring adaptability across diverse applications.

In grid management, AI has already gained traction in two critical domains, spurring a wave of commercial software tools – (i) Forecasting Demand and Renewable Energy Generation and (ii) Optimizing Economic Load Dispatch

These applications highlight AI's capacity to transform grid operations, offering scalable, data-driven solutions that outperform conventional optimization frameworks.

In forecasting applications, different forms of ANN are mostly used. [24] , [25] NARX and RBF ANNs are able to provide highly accurate load forecasts for five days ahead, while the relative errors keep their values below the reasonable level (<5%). [26] A RNN-LSTM model is implemented on real time data of ISO New England electricity market with available data of twelve years from 2004 to 2015 and the Electricity demand predicted for a period of five years from 2011 to 2015 on a rolling basis. The proposed model is found to be highly accurate with a Mean Absolute Percentage Error (MAPE) of 6.54 within a confidence interval of 2.25%. Moreover, the model has a computation time of approximately 30 minutes which is favourable for offline training to forecast electricity load for a period of five years.

[27], [28] Particle Swarm Optimization (PSO), along with its modified variants and hybrid algorithms that combine PSO with complementary methods, has gained significant traction in addressing Economic Load Dispatch (ELD) challenges.

ELD frameworks nowadays prioritize dual objectives: minimizing both fuel costs and environmental impacts, so as to reduce the grid's carbon footprint. This shift underscores to maximize renewable energy utilization while balancing economic and environmental goals. In such multi-objective scenarios, Pareto optimality—a concept pioneered by economist Vilfredo Pareto [29, 30]—has emerged as a robust framework for identifying balanced solutions. By combining Pareto principles with Swarm Optimization techniques, researchers achieve more nuanced resolutions to complex optimization problems where competing objectives coexist. Notably, the integration of Pareto optimality into swarm-based algorithms is increasingly becoming a cornerstone in modern ELD strategies, enabling systems to navigate trade-offs between cost efficiency, sustainability, and operational feasibility.

Now, let's have a look at the applications available, the AI techniques used and their manufacturers.

4.1. Load Forecasting applications

Table 1 highlights commercially available tools for Short-Term Load Forecasting (STLF), which enable utilities to predict near-future demand fluctuations and optimize real-time grid operations. These applications are critical for balancing supply-demand dynamics and minimizing operational costs in rapidly changing energy markets.

Table 2 lists prominent commercially available tools for Long-Term Load Forecasting (LTLF), many of which are integrated into comprehensive software suites designed for power system planning. These applications enable utilities to model future demand scenarios, assess infrastructure requirements, and align investment strategies with regulatory or market dynamics. LTLF tools are critical for ensuring grid reliability while balancing economic and sustainability goals.

Table 1. Short Term Load Forecasting applications

Sl.No.	Software	AI Techniques used	Manufacturers
1.	AutoGrid Flex™	ML, DL, reinforcement learning	Schneider Electric (Acquired AutoGrid to enhance energy management solutions)
2.	Verdigris	DL (LSTM, CNN), anomaly detection	Verdigris Technologies (Independent, headquartered in California, focusing on IoT and AI for energy)
3.	Enel X DER.OS	ML, DL, optimization algorithms	Enel Group (Italian multinational energy company; part of their Enel X division)
4.	C3 AI Suite	ML, DL, predictive analytics	C3 AI, Inc. (Publicly traded company founded by Thomas Siebel, offering enterprise AI solutions)
5.	Opower (Oracle)	ML, behavioral analytics	Oracle (Acquired Opower in 2016 for energy efficiency and customer engagement tools)
6.	SparkCognition	DL (LSTM, CNN), anomaly detection	SparkCognition (Independent AI company based in Austin, Texas)
7.	DeepMind (Google)	DL (LSTM, reinforcement learning)	Google (Alphabet subsidiary; DeepMind's AI applied to energy optimization)
8.	NeuroDimension	Neural networks, genetic algorithms	NeuroDimension, Inc. (Independent, specializes in neural network software, based in Florida)
9.	PredictiveGrid™	ML, DL, real-time analytics	Ping Things, Inc. (Independent company focused on grid analytics and IoT)

Table 2. Long Term Load Forecasting applications

Sl.No.	Software	AI Techniques used	Manufacturers
1.	Itron Forecasting Suite	LSTM, ML	Itron
2.	PLEXOS	ML, conventional Mixed-Integer Linear Programming (MILP) , Monte Carlo Simulations	Energy Exemplar
3.	DNV's EnergyPlanner (Synergi Electric)	ML (Reinforcement), Simulation-Based Optimization	DNV (formerly DNV GL)
4.	GE Digital Grid Analytics	ANN, ML (Supervised), Simulation-Based Optimization	GE Digital
5.	ETAP Load Forecasting & Planning	ANN	Operation Technology, Inc.
6.	ABB Ability™ GridOS	ML (Reinforcement), Natural Language Processing (NLP), Cluster Algorithms	ABB
7.	AutoGrid Flex	LSTM, ML (Unsupervised) and Optimisation Algorithm	Schneider Electric
8.	Energy Canvas	ML, Optimisation Algorithm	Ascend Analytics
9.	SAS Analytics for Energy	DL, NLP	SAS Institute
10.	MATLAB/Simulink	ANN tool box, ML (Reinforcement) Tool box. It provides platform to develop and run customized AI applications	MathWorks
11.	PowerWorld Simulator	ML, ANN	Power World Corporation

4.2. Renewable Energy Forecasting

Mirroring trends in load forecasting, Long Short-Term Memory (LSTM) networks—either as standalone models or hybridized with complementary algorithms—have emerged as dominant tools for renewable energy forecasting. Their ability to model temporal dependencies in variable wind and solar generation data makes them particularly suited to this domain. Table 3 highlights commercially available short-term renewable energy forecasting tools, many of which integrate these AI-driven approaches to optimize grid operations and support renewable energy integration strategies.

Table 4 showcases commercially available tools for long-term renewable energy (RE) forecasting, which are instrumental in strategic grid planning, investment prioritization, and policy formulation to address the variable integration of renewables into modern power systems.

Table 3. Short Term Load Renewable Energy forecasting applications

Sl.No.	Software	AI Techniques used	Purpose	Manufacturers
1.	AutoGrid Flex	LSTM, ML(reinforcement)	Wind and Solar generation forecasting	AutoGrid (Schneider Electric)
2.	SolarAnywhere® Forecast	CNN-LSTM Hybrid	Solar generation prediction	Clean Power Research
3.	IBM Renewable Energy Forecasting	Graph Neural Networks (GNNs), LSTM, NLP	Wind and Solar generation forecasting	IBM
4.	Vaisala ForeCast	CNN, ML	Wind and Solar generation forecasting	Vaisala
5.	WindBrain	RNN, ML	Wind forecasting	Wind Brain
6.	AWS Panorama (Renewables Toolkit)	ML, DL	Wind and Solar generation forecasting	Amazon Web Services
7.	MeteoLogic Nowcasting	ANN, ML (Baysian)	Wind generation forecasting	DTU Wind Energy (Denmark)
8.	DeepMind's Wind Forecast	ANN, ML	Wind generation forecasting	Google (DeepMind)
9.	Energy Exemplar's PLEXOS	Hybrid - ML	Solar and wind generation forecasting	Energy Exemplar
10.	Siemens EnergyIP Predictive Analytics	DL, Hybrid	Solar and wind generation forecasting	Siemens
11.	Meteomatics Energy API	LSTM	Solar and wind generation forecasting	Meteomatics

Table 4. Long Term Load Renewable Energy forecasting applications

Sl.No.	Software	AI Techniques used	Purpose	Manufacturers
1.	IBM Watson AI for Energy	Deep learning, hybrid models	Weather, grid, and asset data for multi-year energy yield projections	IBM
2.	GE Digital's Wind Power Forecasting	Digital twins, LSTM networks, predictive analytics	Long-term wind farm performance modeling and resource assessment	GE Renewable Energy
3.	Siemens Gamesa's Energy Forecasting Suite	ML, hybrid physics-AI models	Wind Power prediction	Siemens
4.	Google DeepMind Wind Forecasting	ANN, DL	Wind Power prediction	Google
5.	AWS Forecast for Renewable Energy	ML, DL	Solar and Wind Power prediction	Amazon Web Services
6.	DNV's Renewables Predict	Hybrid ML	Solar and Wind Power prediction	DNV
7.	AutoGrid Flex	DL, Optimisation	Solar and Wind Power prediction	Schneider
8.	Meteomatics' Energy API	ML	Solar and Wind Power prediction	Meteomatics
9.	Open Climate Fix (OCF)	CNN	Open-source ML tools for climate-adjusted renewable forecasts	Open Climate Fix (non-profit)
10.	ArcVera's Forecast	ML	Solar and Wind Power prediction	ArcVera Renewables
11.	Vortex FDC	ML	Solar and Wind Power prediction	Vortex

Analysis of the above tables (Table-1 to Table-4) reveals distinct AI-driven methodologies dominating load and renewable energy (RE) forecasting:

- Load Forecasting
  - Short-Term: LSTM networks and hybrid LSTM-based models (combined with complementary algorithms) are the dominant AI-driven techniques, enabling precise prediction of hourly/daily demand fluctuations.
  - Long-Term: Reinforcement Learning (RL), a subset of machine learning (ML), is gaining momentum alongside LSTM. RL's adaptability to evolving grid dynamics makes it ideal for modeling decade-scale demand trends influenced by socioeconomic and policy shifts.
- Renewable Energy Forecasting
  - Short-Term: LSTM remains widely adopted for its ability to model temporal patterns in solar/wind generation. However, hybrid frameworks integrating ML with Numerical Weather Prediction (NWP) data—leveraging both statistical and physics-based inputs—are emerging as robust alternatives for higher

accuracy.

Long-Term: Hybrid models combining ML with climate projections are increasingly favored. These tools decode nonlinear relationships between climate variables (e.g., temperature, irradiance) and RE output, aiding strategic infrastructure planning for decarbonization goals.

4.3. Economic Load Dispatch

Swarm Intelligence (SI) has emerged as a cornerstone of AI for tackling the intricate optimization challenges inherent in ELD. SI algorithms excel at resolving nonlinear, non-convex optimization problems—common in power systems due to fluctuating demand, generation constraints, and transmission losses—while also enabling simultaneous multi-objective optimization (e.g., minimizing costs and emissions while maximizing efficiency). Their decentralized, adaptive nature allows them to navigate high-dimensional solution spaces, making them indispensable for modern grid management.

Table 5 enumerates some commercially available AI-driven tools leveraging SI and other advanced techniques (e.g., genetic algorithms, particle swarm optimization). These applications empower utilities to automate ELD decisions, balance real-time grid constraints, and align operational strategies with sustainability targets. By integrating SI, vendors address critical industry pain points, such as scalability in renewable-heavy grids and resilience against demand volatility.

Table 5. Economic Load Dispatch applications

Sl.No.	Product	AI technique used	Manufacturer
1	GE Digital’s Predix Platform	Hybrid machine learning (ML) models, reinforcement learning (RL), and optimization algorithms	General Electric (GE)
2	Siemens PSS®E (Power System Simulator for Engineering)	Hybrid models combining particle swarm optimization (PSO) and genetic algorithms (GA)	Siemens Energy
3	ABB Ability™ OPTIMAX	PSO, GA, and neural networks (NN)	ABB
4	Schneider Electric EcoStruxure	Reinforcement learning (RL) and deep neural networks (DNN)	Schneider
5	AutoGrid Flex	RL and swarm intelligence (PSO)	Schneider
6	PowerWorld	Genetic algorithms (GA) and ant colony optimization (ACO)	Power World Corporation
7	ETAP (Electrical Transient Analyzer Program)	GA and PSO	ETAP (Operation Technology, Inc.)
8	Gridmatic Energy Trading Platform	Machine learning (ML) and mixed-integer linear programming (MILP)	Gridmatic
9	OpenELD (Open Source)	PSO, GA, and RL	Research consortiums (e.g., IEEE communities)
10	NREL’s PRESTO	Deep reinforcement learning (DRL) and hybrid ML-PSO models	National Renewable Energy Laboratory (NREL)
11	MATPOWER (Open source tool)	MATLAB-based toolbox with extensions for GA/PSO-based ELD	MATLAB

Table-5 shows that PSO—particularly in its hybrid or modified forms—is the predominant algorithm leveraged by vendors. Its dominance stems from its ability to efficiently resolve the non-linear, multi-constraint challenges inherent in ELD, such as cost minimization, emission reduction, and real-time grid adaptability. These adaptations of PSO enhance convergence speed and solution accuracy, making them indispensable for optimizing modern power systems with renewable integration and dynamic demand patterns.

5. Recent Trend

The Transformer architecture has revolutionized Natural Language Processing (NLP) since its introduction by Vaswani et al.[31]. Unlike earlier models (e.g., RNNs, LSTMs), Transformers rely entirely on self-attention mechanisms to process sequential data, enabling parallel computation and capturing long-range dependencies. Alexandra L'Heureux et al. [32] proposes adaptation of the complete transformer architecture for load forecasting, including both the encoder and the decoder components, with the objective of improving forecasting accuracy for diverse data streams. The study has reportedly provided a 2.571% MAPE accuracy increase when predicting 36 h ahead, and an increase of 2.18% when using a 12 h input. The solution also reportedly performed better on longer horizons with smaller amounts of input data. The study shows increased accuracy more than 90% of the time while having the potential to be parallelized to further improve performance.

Quantum Computing is an emerging field that leverages the principles of quantum mechanics to perform computations far beyond the capabilities of classical computers. Unlike classical bits (0 or 1), quantum computers use qubits (quantum bits), which can exist in superposition, entanglement, and interference states. Though Quantum computing is still in its infancy but holds transformative potential. AI is a potential area which will greatly benefit by adopting Quantum Computing platform. It will accelerate training of large models or solving complex decision-making tasks. [33] Quantum computing can enable more efficient optimization algorithms, allowing for the optimal scheduling and dispatch of electricity generation, load balancing, and resource allocation. Applications such as Phasor Measurement Unit (PMU) placement, unit commitment or facility location-allocation, are among the first expected to be addressed by quantum devices. As this technology evolves, it will also be able to solve more complex issues in power flow and transient analysis, minimizing energy waste and enhancing system performance.

6. Conclusion

Prediction and optimization represent two critical functions in a grid requiring effective execution through the analysis of vast, high-dimensional, and heterogeneous datasets. Load forecasting and renewable energy (RE) generation forecasting emerge as the two principal predictive requirements. Research and commercial tools highlight artificial neural networks (ANNs) and deep learning algorithms as the dominant AI frameworks successfully applied in predictive tasks. For short-term forecasting, deep learning architectures such as Long Short-Term Memory (LSTM) have demonstrated notable accuracy, spurring widespread adoption—many providers now offer LSTM-based solutions. Conversely, long-term forecasting (essential for strategic energy planning, infrastructure investment and policy formulation) relies on complex, nonlinear, and high-dimensional data. Here, hybrid models combining Convolutional Neural Networks (CNNs), LSTM, or other algorithm pairings are gaining traction.

For optimization, Swarm Intelligence (SI) techniques, particularly Particle Swarm Optimization (PSO) and its variants, excel in resolving intricate, multi-objective load dispatch challenges in systems with diverse energy sources. Developers frequently integrate Pareto Optimality principles with SI algorithms to address competing objectives in energy optimization.

Meanwhile, machine learning (ML)-driven AI systems are ideal for applications like electricity consumption analytics and fault diagnosis, where identifying subtle, non-intuitive patterns within massive datasets is paramount.

Looking ahead, advancements in quantum computing hardware and platforms promise to revolutionize AI capabilities. By enhancing computational power and efficiency, quantum technologies are poised to elevate AI-driven solutions in smart grids to unprecedented levels of precision and scalability.

7. Conflict of Interest

The authors declare no conflict of interest.

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