POWER GENXT

Volume : 12

NATIONAL ENERGY EXCELLENCE DRIVE

Published on the day of
12th National Seminar *on*

ARTIFICIAL INTELLIGENCE TECHNOLOGY IN THERMAL POWER STATION : IT'S ADVANTAGES AND DISADVANTAGES

25th February, 2024

ENGINEERS' WELFARE FORUM

THE WEST BENGAL POWER DEVELOPMENT CORPORATION LIMITED

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POWER GENXT

VOLUME : 12

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NATIONAL ENERGY EXCELLENCE DRIVE

Published on the day of 12th National Seminar
(25th February, 2024)
on

Artificial Intelligence Technology in Thermal Power Station : It's Advantages and Disadvantages

Engineers' Welfare Forum

WBPDCL

ISO 9001 : 2015 CERTIFIED

ENGINEERS' WELFARE FORUM

THE WEST BENGAL POWER DEVELOPMENT CORPORATION LIMITED

(Recognised by WBPDCL Vide Letter No. : PDCL/CORP./HR/305/1495, Dated 3.3.2012)

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Aroop Biswas
Minister-in-Charge
Department of Power, Housing,
Youth Services & Sports
Government of West Bengal

Bidyut Unnayan Bhavan
3/C, Block - LA, 6th Floor, Sec - III
Bidhannagar, Kolkata - 700 106
Direct: 2335 0768 / 2339 3269 I Fax: 2335 7331
New Secretariat Buildings
1, Kiron Shankar Roy Road
'A' Block, 7th Floor, Kolkata - 700 001
Direct: 2262 4004
'A' Block, 6th Floor, Kolkata - 700 001
Direct: 2262 4242 I Fax: 2262 7462

2 1 FEB 2024

MESSAGE

I am extremely glad to know that **Engineers' Welfare Forum of WBPDCL** is going to organize a National Seminar on **"Artificial Intelligence Technology in Thermal Power Station : It's Advantages and Disadvantages"** on 25th February, 2024 at Bidyut Unnayan Bhaban, Plot No. 3/C, LA Block, SECTOR-III, Bidhannagar, Kolkata-700106. The main objects of holding this seminar is to inform and motivate all concerned.

I am also glad to know the initiatives taken by the Forum to bring out a Technical journal **POWER GENXT, (Vol.-XII)** to commemorate this special occasion.

I extend my best wishes to all the members of the Forum and wish the Seminar all success.

(Aroop Biswas)

The General Secretary
Engineers' Welfare Forum, WBPDCL,
Bidyut Unnayan Bhavan
Bidhannagar
Kolkata-700 106.

Correspondence : 6/45, Bijoygarh, Kolkata - 700 032 I Mobile : 98300 51484 I E-mail : biswas.aroop@gmail.com

Santanu Basu, IAS
সচিব
বিদ্যুৎ দপ্তর, পশ্চিমবঙ্গ সরকার
Secretary
Power Department
Government of West Bengal

বিদ্যুৎ উন্নয়ন ভবন
কলকাতা-৭০০ ১০৬
Bidyut Unnayan Bhawan (5th Floor)
3/C, LA-Block, Sector-III, Salt Lake City,
Kolkata-700 106
Telephone : +91 33 23351269
Fax : +91 33 23358378
e-mail : powersecy@wb.gov.in

No.: 6 -S(P)/2024

February 20, 2024

MESSAGE

It gives me great pleasure to learn that Engineers' Welfare Forum of West Bengal Power Development Corporation Limited (WBPDCL) is going to organize its 12th National Seminar on **"Artificial Intelligence Technology in Thermal Power Station: It's advantages and disadvantages"** at 10.00 am onwards on February 25, 2024 at WBPDCL Auditorium, Bidyut Unnayan Bhavan, Salt Lake, Kolkata - 700 106 and a Souvenir would be brought out on this auspicious occasion.

I pray for their further prosperity and convey my heartfelt thanks to all of them on this occasion.

20/2/24.

(Santanu Basu)

Santanu Basu, IAS
Secretary
Power Department
Government of West Bengal

Shri Soumen Das
General Secretary
Engineers' Welfare Forum
West Bengal Power Development Corporation Limited
Bidyut Unnayan Bhavan
Bidhannagar
Kolkata – 700 106.

Dr. P. B. Salim, IAS
Chairman & Managing Director

WBPDCL

Date: 22.02.2024

Message

*I am very glad to know that Engineers' Welfare Forum of The West Bengal Power Development Corporation Ltd. is going to organize the 12th National Seminar on "**Artificial Intelligence Technology in Thermal Power Station : It's advantages and disadvantages"** at the auditorium of Corporate Office, WBPDCL, Kolkata – 700 106 on 25th February, 2024 and a Technical journal **POWER GENXT (Vol. – XII)** will be published to mark the occasion.*

My heartiest wishes and congratulations are due to the members of the Forum.

(Dr. P. B. Salim)

The General Secretary
Engineers' Welfare Forum, WBPDCL
Bidyut Unnayan Bhaban,
3/C, Block - LA,
Sector – III, Bidhannagar
Kolkata - 700 106.

The West Bengal Power Development Corporation Limited
(A Government of West Bengal Enterprise)
CIN: U40104WB1985SGC039154
Bidyut Unnayan Bhaban, Plot No. 3/C, Block-LA, Sector-III, Bidhannagar, Kolkata-700106
Phone: 033 2335 0402, 2339 3291 | Fax: 033 2335 0523 | Email: cmd@wbpdcl.co.in
Website: www.wbpdcl.co.in

Machine Learning Paradigms for Thermal Power Plants

Sudeshna Sarkar

Computer Science & Engineering Department
Indian Institute of Technology Kharagpur

Abstract

Artificial Intelligence (AI) and Machine Learning (ML) have been applied to plant operations and various tasks in a power plant. In this talk, we will discuss various ML paradigms that are useful to model various aspects of a power plant and enable higher efficiencies. Supervised Machine Learning is useful for tasks requiring forecasting or prediction based on past labeled dataset. Supervised ML classification systems for computer vision are useful for various tasks involving inspection of the components of a power plant, of the input materials and the output. Unsupervised clustering algorithms are helpful for identifying the patterns in the normal data and can then be used to detect anomalies. Reinforcement learning algorithms are suited to the task of continuous control in order to optimize the objectives of the plant. Today there is a growing emphasis on developing digital twins of a system to maintain high reliability of a plant. Finally there is a great potential of use of Large Language Models (LLMs) to capture knowledge from structured as well as unstructured data such as text and interact with humans in natural language.

□ Introduction

Artificial Intelligence and Machine Learning have in recent years played out a transformative role in every sphere of human endeavor and has impacted industry in a large way. The energy industry has also been benefited by the application of Artificial Intelligence and there are great potential benefits. Artificial intelligence has several applications in optimizing thermal power plants, enhancing efficiency, reducing costs, and improving overall performance.

□ AI Applications in Power Plants

Artificial intelligence (AI) has several applications in optimizing thermal power plants, enhancing efficiency, reducing costs, and improving overall performance.
Optimization of performance of power plants: AI can optimize the operation of thermal power plants by continuously analyzing data from various sources such as weather forecasts, electricity demand, and equipment performance to adjust operational parameters for maximum efficiency.

Predictive Maintenance: AI can be used to analyze sensor data to predict equipment failures before they occur. The ability to detect abnormalities in equipment operation and diagnose the root causes of faults, can prevent costly downtime and extending asset life.

Fuel Efficiency: AI algorithms can optimize combustion processes to extract maximum energy from fuel, leading to lower emissions and fuel costs.

Process Optimization: AI can optimize various processes within the power plant, such as combustion control, fuel management, and emissions control, to improve efficiency and reduce environmental impact.

Emission Reduction: AI can optimize combustion processes to minimize pollutant formation, contributing to cleaner operation and compliance with environmental regulations.

Fuel mix optimization: AI can analyze factors like coal quality and weather conditions to optimize fuel blends for efficient and cleaner combustion.

Asset Optimization: AI can optimize the operation of individual assets within the plant, such as boilers, turbines, and generators, to maximize efficiency and output.

Demand Forecasting and Energy Management: AI-powered models can analyze real-time data on energy consumption and accurately predict electricity demand, enabling power plants to adjust their output efficiently and avoid unnecessary fuel consumption.

Industrial Safety and Autonomous Inspections: Cameras, robots and drones equipped with AI can autonomously inspect critical equipment, reducing risks for human workers. AI-based image recognition can identify early signs of fire or explosions.

□ AI for Power plants

Based on the tasks, different AI methodologies are useful. Machine Learning tools are especially used with various tasks based on collected data. We describe some Machine Learning (ML) tasks and discuss some abstract tasks related to power plants where they can be applied.

Supervised Machine Learning for Predicting Power Output

In supervised ML, we try to predict an output variable based on the values of the input variables. Consider the task of predicting the generated power. We will first have to identify the features or variables that influence the generated power. The data has to be collected under various power generation capacity of the plant. Then we use a ML approach to build a model to predict the power generation. In general, if y is the value of the target variable, and the d variables have the values $x_1, x_1, ..., x_d$, we find a model f such that $y = f(x_1, x_1, ..., x_d)$.

Feature Selection: To identify the useful variables, we need to talk with domain experts to understand the features that affect the power generation. Suppose that we select the following features: steam inlet pressure, exhaust temperature, air temperature, composition of exhaust, boiler temperature.

1. Data Collection: We will now need to collect data from the power plant under different conditions. Thus we construct the training set.
2. Model Building: After collecting the data, we have to choose an appropriate ML algorithm to find a model. Some examples of ML models are Linear Regression, Decision Tree, Neural Network, k-NN.
3. Evaluation: but we have to check whether the model is successful at the task. For this, we keep aside some of the instances in the test set, and use the rest of the data for training. The trained model is evaluated on the held out test set. Mean square error may be used as an Evaluation metric for a regression task.

Computer Vision based Classification

Computer vision based ML classification systems are useful for various tasks in power plant such as anomaly detection, inspection and safety monitoring. Computer vision (CV) based classification systems take an image as an input and produces the class as output. Current CV systems are mostly based on deep neural networks such as CNN or Transformers.

- Detection of leakage of lubricating oil
- Drone based or robot based facility inspection

A typical computer vision system is a neural network whose input is an image and the output is a classification. CNN based Deep Neural networks are often used for the classification task.

Computer vision based monitoring systems have a great potential for monitoring the input materials to the plant and also for monitoring the different components of the power plant. This is especially useful for monitoring those parts of the plant that are not easily accessible by human operators or are hazardous for humans. CV based inspections can detect microscopic cracks or subtle changes that are difficult for human inspectors. The deployment of a CV system also enables continuous monitoring.

Unsupervised algorithms for Anomaly Detection

Anomaly detection algorithms may be supervised or unsupervised. Supervised anomaly detection algorithms using supervised classification algorithms can be uses when we have a dataset containing both normal and anomalous instances.

But often there are very few instances of anomalous examples. Unsupervised algorithms may be used for anomaly detection based on the assumption that most samples are normal.

One of the methods for anomaly detection is to use the normal samples and characterize them, so that a deviation from the normal data can be treated as an anomaly.

Clustering can be applied on the data to identify the normal groups. If an instance is outside a cluster, it may be treated as anomaly.

The task of clustering refers to grouping the instances so that instances within a group are very similar to each other, whereas two instances belonging to two different groups are distant. There are various clustering algorithms such as kmeans and its variants. The kmeans algorithm takes as input the number of clusters k and produces k clusters so as to minimize intra-cluster distance. Autoencoders and GAN based methods are also useful for anomaly detection.

Anomaly Detection for Time Series Data

Since the thermal power plants operate over time, we may need to use the time series data to detect anomaly. ARMA, LSTM and CNN based methods have been used to detect anomaly in time series.

In [4] Hu, Di et al, a Normal benhavior model (NBM) is constructed to model the normal behavior pattern of the equipment as a multivariate time series by using a long short-term memory-based autoencoder (LSTM-AE) neural network.

Reinforcement Learning for Continuous Control

Reinforcement learning (RL) is a framework which models an agent interacting continually with the environment. The agent perceived the current state of the environment and accord-ing decides the actions at the time step. RL is useful in situations where the control actions have to be provided at different time steps. The underlying system is assumed to be a Markov system. The rewards are designed based on the task requirements. The value function is defined considering the cumulative reward. A popular value function is the cumulative discounted sum of rewards which the agent has to optimize. There are various offline and online learning algorithms for different scenarios for learning the optimum policy of the agent.

DeepThermal presents a RL system to optimize the combustion efficiency of a thermal power generating unit. The system uses real plant data collected through sensors as well as synthetic data generated by a data-driven combustion process simulator. This is trained using an offline RL system that uses Deep reinforcement learning.

The system uses the chemical property of the coal and sensor data relevant to the combustion process of a TPGU as states, including temperature, pressure, wind, and water volume along with different sensor readings. The action space includes the key control variables that, such as the adjustment of valves and baffles. A Model-based Offline RL algorithm (MORE) is used. MORE quantifies the risks imposed by the imperfect simulator by proposing a restrictive exploration strategy.

Deep reinforcement learning optimization framework for a power generation plant considering performance and environmental issues.

Digital Twin

A digital twin (DT) is a virtual model of a physical system that behaves identically as the physical system and can be used for simulations of the system, testing, monitoring and analysis. A Digital Twin is created based on the physics-based simulation of the power plant. Since such a complex system cannot be simulated exactly, data driven models are necessary. To develop a digital twin for a process, it is important to deploy various sensors to collect data and use the data for the design of the DT. [7] reviews the FT architectures proposed for power plants and observes that a DT needs to have a Physics-based dynamic system model as well as data-driven model based on Statistics and ML.

Natural Language Processing and Large Language Models

Since a vast amount of reports and logs are in natural language text, Natural Language Processing (NLP) systems can be used to extract knowledge from these sources and use the knowledge for decision making and answering queries. The operation of a complex system such as a power plant requires knowledge of various aspects of the plant and involve different operators and complex decision making. Large Language Models (LLMs) have revolutionized the landscape of NLP as they are trained on massive amount of data and they can capture large and diverse body of knowledge.

LLMs can assist plant operators in making informed decisions by providing insights and recommendations. LLMs can help provide natural language interfaces for interacting with machinery and systems and answer queries related to the operation.

☐ Conclusion

Artificial Intelligence and ML have shown great promise in power plants. Various AI methods can be used in various tasks involved in the plant. It is important to study the task in depth to understand the scope of using AI. But it is clear that the appropriate use of AI is essential to remain competitive.

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Renewable Energy Forecasting Using Machine Learning and Deep Learning Techniques

Kamal Sarkar

Department of Computer Science and Engineering
Jadavpur University

Abstract

Renewable energy sources are gaining popularity in the world's electrical systems because renewable energy is clean and green (low carbon), and is beneficial for environmental protection. However, accurate forecasting of renewable energy is necessary for the proper planning, management, and operation of electric power systems. This is not an easy task because of the chaotic nature of renewable energy. The earlier methods used for this task were physical models and statistical methods. Recently, machine learning and deep learning methods have shown promising results in renewable energy forecasting. In this paper, we will present a brief overview of the traditional machine learning methods like regression and deep learning methods like CNN, and LSTM used for renewable energy forecasting.

1. Introduction

Fossil fuels have been the world's main sources of electric energy. Hydrocarbons or their derivatives, including petroleum, natural gas, and coal, are referred to as fossil fuels. Fossil fuels take millions of years to develop, and the known viable supplies are running out far more quickly than they are being created. Fossil fuels additionally emit greenhouse gases into the atmosphere, expediting climate change and harming the environment that supports human life. As a result, for the development of more sustainable energy systems, renewable energy has received much attention in recent years.

Renewable energy such as solar energy, wind power, tidal energy, and geothermal energy, can be can be recycled in nature. Renewable energy has several important advantages over fossil fuels - (1) renewable energy resources are inexhaustible and renewable, (2) it is clean, green, and low carbon, and thus is less harmful to the environment. By reducing sulfide, carbide, and dust, it also reduces the risk of pollution in the atmosphere, and (3) Exploitation of natural fuels can be reduced by properly utilizing renewable energy.

Due to the immediate benefits of renewable energy, numerous countries, including China and the United States, have created regulations to promote renewable energy. [1]

The reliability and stability of energy systems are significantly impacted by the uncertainty surrounding renewable energy, even though it is thought to be the most viable alternative to fossil fuels, particularly when renewable energy is integrated on a large scale. On the one hand, the high fluctuation, sporadic nature, and unpredictability of renewable energy increases the reserve capacity of electric energy networks (reserve capacity is the difference between plant capacity and the maximum demand) , increasing the power production cost. Therefore, renewable energy forecasting is essential for mitigating the uncertainties of renewable energy sources [2]. For example, wind power forecasting is effective for grid integration and management of wind energy.

For predicting accurately renewable energy for the next few minutes to the next few days, a variety of algorithms have been reported in the literature.' These algorithms can be divided into 4 categories (1) physical methods, (2) statistical methods, (3) Machine learning and deep learning methods and (4) hybrid methods. [3]

Physical methods simulate the atmospheric dynamics according to physical principles and boundary conditions [4] for numerical weather prediction (NWP). The input to this kind of system is taken from meteorological and geographical information, including pressure, temperature, jaggedness, and orography. The main drawback of the physical methods is that it is not robust to unexpected errors during prediction. This makes physical methods unsuitable for short-term forecasting.

Statistical models were used to find out the underlying hidden statistical patterns in online time series data of renewable energy [5]. The widely used statistical methods reported in the literature are: Bayesian approach [6], Auto regressive moving average [7], Kalman filter [8], Markov Chain model. [9]

The development of Artificial Intelligence (AI) techniques, specifically machine learning and deep learning-based forecasting models have shown a better performance than physical methods and statistical approaches due to the potential abilities of the AI algorithm for finding significant patterns from high dimensional data and learning complex nonlinear relationships between input features and output[10]. Moreover, they can handle different types of data such as meteorological data, geographical data, and time series data.

In the subsequent sections, we will discuss the role of Traditional Machine Learning and Deep Learning in Renewable Energy Forecasting.

2. Traditional Machine Learning-based Renewable Energy Forecasting

In this section, we discuss the various machine learning (ML) algorithms used for renewable energy forecasting. Forecasting is by nature a regression problem and a regression algorithm is a supervised learning algorithm.

The goal of supervised is to learn a mapping from inputs x to outputs y, given a labeled set of input-output pairs D = $\{(x^{(i)}, y^{(i)})\}$, where i = 1 to m. Here D is called the training set, and m is the number of training examples. For the regression, output y is continuous valued whereas, for classification, the output y is discrete valued. In general, developing a supervised machine learning system has several important steps- Preprocessing, feature extraction, training for model development, an applying the trained model to the unseen input data for predicting the output. A generic framework for a supervised forecasting model is shown in Figure 1.

The first and most important part of developing ML-based renewable energy forecasting is to collect data for the given problem, pre-process, and label the data. Preprocessing involves noise removal, data normalization, and missing value handling. Feature extraction refers to the identification and extraction of relevant features and the transformation of the raw data into feature vectors which are labelled before submission to a machine learning algorithm. The machine learning algorithm gives a trained predictive model which is applied to unseen data for prediction. Before submission to the trained predictive model, unseen raw data is also passed through multiple steps, namely, preprocessing and feature extraction to convert it to a feature vector.

2.1. Feature Extraction

A feature is the measurable property of an object or a phenomenon. Identifying the appropriate features is important because each input to a machine learning algorithm is a vector of values of the features identified manually or automatically. For traditional machine learning algorithms like Linear Regression, polynomial regression, Logistic Regression, Support Vector Machine, and Decision Trees, the features are designed manually. These features are called hand-crafted features. Through feature engineering, the features are designed. When a feature is chosen, its impact on the output of the concerned ML-based system is taken into account. Therefore, the performance of an ML-based system is highly dependent on the richness of the features crafted by hand. For feature engineering, the designer should spend sufficient time understanding and analyzing the problem. Designing features manually is an art.

Identifying the appropriate features and extracting feature values from a raw input for converting it to a feature vector is called feature extraction. For example, Ibrahim et al. (2012) [11] used three hand-crafted features, namely, average daily maximum and minimum temperatures, as well as the average daily solar radiation for the development of the solar radiation prediction model. In another work, Shi et. al. (2012) [12] used historical data from the previous moment (sunny day, foggy day, rainy day, and cloudy day) and weather report for the next day as the features for forecasting photovoltaic power output.

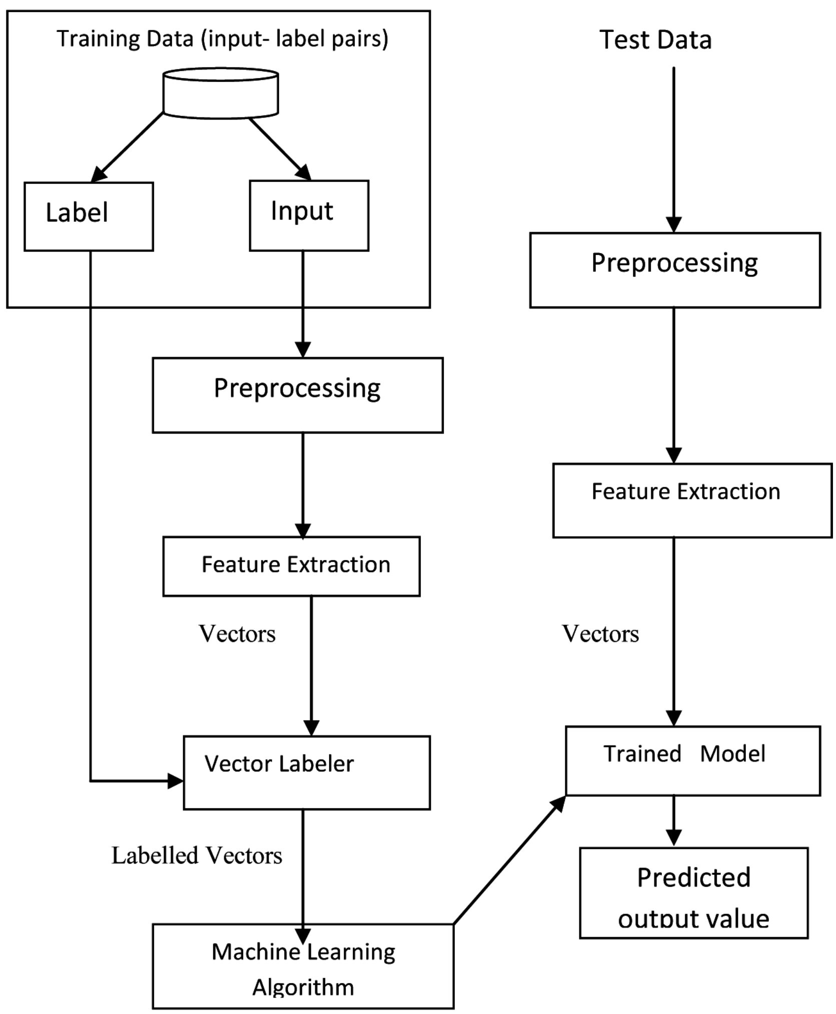

Figure 1: Machine learning framework for renewable energy forecasting.

2.1. Traditional ML Methods for Renewable Energy Forecasting

Many researchers have used traditional ML-based techniques to contribute directly or indirectly to renewable energy forecasting. Ibrahim et al. (2012) [11] used a linear regression model to predict solar radiation which is useful for Renewable Energy Forecasting. The three input features, average daily maximum temperature, average daily minimum temperature, and average daily solar radiation were used for model development.

Ekanayake et al. (2021) [13] used multiple linear regression, power regression models, and artificial neural networks (ANNs) for wind power prediction They used several climate factors such as average wind speed and average ambient temperature as input features. The models were trained on power generation data over five years.

ERTEN et. al (2022) [14] compared several regression models for solar power prediction. Four models, namely, linear regression, logistic regression, Lasso regression, and elastic regression were compared in their study. They used 21 different features which are extracted from the different weather conditions, humidity, temperature, pressure, precipitation, Snowfall amount, cloud coverage, wind speed, wind direction, wind gust, angle of incidence, zenith, azimuth, and generated power. Some features are further subdivided, for example, wind speed 10m above ground and wind speed 80m above ground. They applied Principal component analysis (PCA) to produce low dimensional uncorrelated features.

Li et al. (2016) [15] applied the hidden Markov model (HMM) and Support Vector Regressor (SVR) for short-term solar irradiance prediction. They relied on solar and weather information collected using sensors. Since HMM is good at sequence prediction problems, it is more effective for short-term solar irradiance prediction. In this model, various sensor readings are considered as the observed states, and hidden states are experimentally determined. During testing, new data is submitted to the trained HMM model that calculates the likelihood of the data given the model. Based on this likelihood value, it chooses a range of irradiances which is given as the predicted output. Li et al. (2022) also proposed a solar irradiance gradient regression method for solar irradiance prediction. First, they train an SVR using irradiances of sunny and no cloud days as the training data. Next, for future prediction after an N interval of time (i.e. at time t+N), multiply the gradient of the regressed line by the time interval N and add the current irradiance to it. Gradient information is taken from the past data whereas current irradiance is added to incorporate the current situation at time t (this is done because it changes every moment). However, they finally compared both models and reported that SVM regression performed better than HMM.

SVR and Radom Forest Regressor were used by Mwende et. al. (2022) [16]. In this work, PV module temperature, ambient temperature, relative humidity, the current and voltage of the solar PV system, and Solar irradiance were used as the features. Authors reported that SVR performed better than Radom Forest Regressor.

3. Deep Learning Methods for Renewable Energy Forecasting

Artificial neural networks (ANNs) are a category of machine learning models that are inspired by the biological neural networks in the human body[17]. An artificial neural network has three important components - an input layer, one or more hidden layers, and an output layer. ANN can be used for both classification and regression problems. Depending on the number of hidden layers, ANNs can be categorized as shallow and deep neural networks. ANNs having more than two hidden layers can be called deep neural networks.
ANN acts as a function that maps the input vector received at the input layer to the output vector(for classification) or a predicted value (for regression). It does non-linear mapping of the input to the output. In a fully connected feedforward neural network, each node in a layer is connected to every node in the next layer. There is a weight parameter that signifies the connection between a node at layer L and another node at layer L +1. These connection weights are the parameters of an ANN model. Using the backpropagation (BP) algorithm [18], the weight parameters are trained using the training set which is a collection of (x, y) pairs, where x is the input feature vector and y is the desired output value(s). The BP algorithm modifies the weights within the network during training to ensure that the network generates the intended output for a given training input. The BP algorithm utilizes determines the gradient of the loss function which is a function of the weights and adjusts weights to minimize the total loss (error) on the training set. During prediction, the network is configured with the learned weights, and an unseen input instance is submitted to the network. The values of each node are computed and the predicted y value is obtained from the output node.

The architecture of a shallow neural network is shown in Figure 2. To ensure non-linearity all hidden nodes and the output nodes use non-linear activation functions like Sigmoid. For a highly data-intensive task, ReLU(rectified linear unit) activation functions are used at the hidden nodes for faster training and avoiding overfitting.

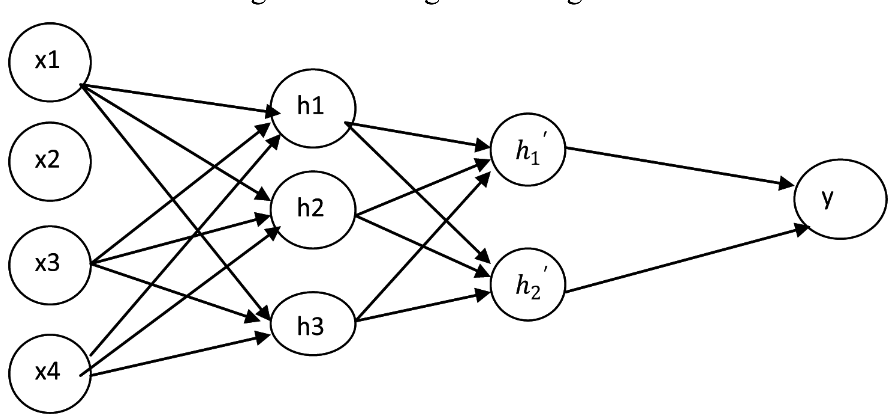

Figure 2. An architecture of a shallow neural network with two hidden layers

The uses of Artificial Neural Networks in renewable energy forecasting have already been studied by researchers. ANNs have been applied for predicting global solar radiation [19][20][21].

ANN was also applied for forecasting wind power generation and load demand. The work presented in [22] used an ANN for forecasting wind power generation and load demand. The different meteorological parameters like wind speed, atmospheric pressure, and temperature were used as input features in this work. Chen et. al. (2019) [23] proposed an artificial neural network (ANN) model for short-term wind power prediction. They considered wind speed at various heights, wind direction, atmospheric pressure, temperature, and relative humidity as the features.

Although many researchers have applied shallow ANN for renewable energy forecasting, deep learning has attracted much attention from researchers in recent years due to its capabilities of automatic feature learning, strong generalization capability, and handling of big data. Deep refers to the fact that the network is organized into many layers and a computation path from the input to the output in a deep neural network has many intermediate steps. Deep learning is a widely used approach for various applications, computer vision, Speech recognition, machine translation, etc. The different types of deep neural networks are available today. Out of them, convolutional neural networks(CNNs), Long Short Term Memory (LSTM) networks, Deep Belief Network (DBN), autoencoder, and combinations of these deep networks have been used for renewable energy forecasting.

LSTM is an improved version of RNN (Recurrent Neural Networks). It is specially designed to handle sequence data. GRU (Gated neural network) is highly similar to LSTM and it has fewer parameters than LSTM. So, GRU has faster training time and overfitting problem is less severe in GRU than in LSTM. Kisvari et al (2021)[24]proposed a GRU-based method for wind power prediction.

An RNN-based model presented in [25], used an adaptive learning rate to predict daily, mean monthly, and hourly solar radiation. It utilizes meteorological data for model development. It was observed by the authors that RNN performed better than the shallow feedforward neural network.

Lim et al. (2022)[26] proposed a hybrid deep learning model that combines CNN and LSTM for stable power generation forecasting in photovoltaic (PV) systems. They considered various environmental factors such as solar radiation and temperature as the features and collected PV power output data from a plant located in Busan, Korea. CNN learns local features from the input sequence and LSTM takes into account the long temporal dependency. Thus the CNN-LSTM model can perform better than the individual CNN or the LSTM-based model. Wu et al. (2020)[27] also proposed a CNN-LSTM model for forecasting very short-term wind power. In this model, CNN extracts spatial correlation features and LSTM extracts temporal correlation features from the input data for effective wind power forecasting within a very short period.

Autoencoder is an unsupervised deep learning model that can be used to extract effective and discriminative features from large unlabeled data. It is often used for feature extraction and data dimension reduction. Some researchers have used autoencoder for renewable energy forecasting. In this case, autoencoder has been used to extract significant features from the input data including weather data, historical energy production data, and other relevant data. Dairi et al. (2015)[28] used a variational autoencoder (VAE) model for feature extraction. Initially, the predictive model was trained in unsupervised mode using layer-wise training and then it was fine-tuned by the training sub-sequences created from time series data where each sub-sequence is in the form $<x(t), x(t+1)>$, $x(t)$ is the subsequence at time t and y value is equal to $x(t+1)$, which is one-step-ahead output at time step t.

Jaseena and Kovoor (2015)[29] utilize a hybrid approach that combines an autoencoder with LSTM for wind speed forecasting. The model utilizes an autoencoder to extract salient features from the input data. Then the LSTM model is trained with the extracted features for forecasting wind speed.

4. Hybrid Models Used for Renewable Energy Forecasting

Ensemble learning (EL) is an ML technique that combines several models to provide more accurate predictions. EL is useful when there is significant variability in the data. The common ensemble techniques are bagging, boosting, and stacking. [29][30]

Guia et al. (2020)[31] applied a bagging-based EL technique for forecasting solar irradiance using weather patterns. In this method, a pre-processed stacked LSTM model is used as a base learner.

The boosting technique is another EL method that was used in renewable energy forecasting Kumari et. al. (2021)[32] proposed an ensemble model that can estimate hourly global horizontal irradiance. In this ensemble method, extreme gradient-boosting forests were combined with deep neural networks.

In the case of Bagging and Boosting, only one base learner is involved. In the bagging method, multiple models are created by changing the training instances sampled from the original training data and in the boosting model multiple weak models are created by making one learner more attentive to the part of the training set that is misclassified by another learner. In the heterogeneous ensemble method [33], several base learners of different types are involved. Such models were also applied to renewable energy forecasting. This kind of hybrid model has some advantages over individual models because it can leverage the strengths of individual models, and reduce bias and variance.

The heterogeneous ensemble model has also been used for renewable energy forecasting, Recently, Lim et al. (2022) presented the hybridization of a LSTM and CNN model for forecasting photovoltaic power generation. In this model, CNN was used to classify first weather conditions and then information given by CNN was utilized in LSTM for forecasting power generation [26].

Various hybrid ML and DL models used for forecasting power are reported in the literature by numerous researchers. An excellent survey on the various hybrid models applied to renewable energy forecasting can be found in [34].

5. Limitations and Challenges

Data is a precious ingredient required for developing an ML or DL-based model for renewable energy forecasting. If data contains errors, the performance and reliability of the developed model is hampered. In electric power systems, collecting quality data is time-consuming and difficult [35]. Errors in input data, communication issues, and sensor malfunctioning can produce inaccurate data in an electric power system. Since deep learning is highly data-hungry, it needs a huge amount of training to achieve accurate performance. If data is inaccurate and insufficient, DL models give poor performance. Even a sufficient amount of data is needed for training the traditional ML algorithms. Data scarcity is one of the biggest problems in developing ML and DL models for power generation forecasting. The second challenge for deploying deep learning models in real-time applications is that DL models require higher training time and demand for sophisticated high-end computing resources. Another problem with the deep learning model is model interpretability and explainability. Deep learning models are often criticized for their "black box" nature. Understanding how and why a model is making decisions is essential for reliability and safety in power systems,

Industry professionals are not very willing to adopt new technologies. They are used to rely on existing tools and technologies. Therefore, bold initiatives are needed to change existing workflows and data exchange protocols and integrate machine learning or deep learning models with electric power systems.

The deep learning algorithms are vulnerable to adversarial attacks that can do minute alterations to the input data to make deep learning algorithms produce erroneous predictions. Therefore, adversarial robustness is crucial in power system applications to prevent models from being exploited to make incorrect conclusions.

Developing deep learning models and deploying the models in real-time electric power systems can be fruitful if collaboration between industry and academia is made possible.

The active participation of both groups is needed to successfully implement ML and/or DL models, and deploy them in the real-time electric power systems.

Safety, reliability, and interoperability are very crucial to the larger power system. Since ML and DL models have some issues, new standards, regulations, and laws are needed for implementing ML and DL models in electric power systems.

6. Conclusion and Future work

Wind, solar power, and other renewable energy sources are attractive alternative energy sources that can be exploited to meet the world's energy needs. However, accurate renewable energy forecasting is still a challenging problem due to the variability and unpredictability of renewable energy sources. Due to this fact, energy system operators face difficulties in for energy system ensuring the stability and reliability of the grid. In this situation, ML and DL-based renewable energy forecasting models can assist the grid operators in effectively managing the system. This survey reveals that the current state-of-the-art ML and DL-based energy forecasting models are effective although there are further scopes of improvement. It is observed that, among the ML algorithms, SVMs, and XGBoost models are better for renewable energy forecasting. Deep learning models CNN-LSTM have also been shown effective.

Despite the progress in ML and DL algorithms, there are still some challenges for renewable energy forecasting. One of the important challenges is the lack of high-quality training and validation data. The data that are publicly available for renewable energy forecasting is often noisy and incomplete. Since security and safety in electric power systems are crucial issues, the data to be used for the development of the models should be authentic. To promote research, data needs to be standardized and data exchange protocols and regulations should framed. This is essential because the scarcity of authentic data makes it difficult to build accurate, reliable, and safe energy forecasting models.

The future research plan can be to promote collaboration between industry and academia for the development of effective ML and DL models, and deployment of them in real time renewable energy forecasting. Combining different types of data collected from multiple sources such as weather data, grid data, and other external data through data fusion and utilizing it in the ML and DL models can be effective in improving renewable energy forecasting.

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Intelligent Renewable Energy for NextGen

Dr. Arindam Ray
Chief Technology Officer
Bangla Sahayata Kendra (BSK)
Personnel & Administrative Reforms Department
Government of West Bengal

Abstract

The renewable energy for the next generation focuses on the transformative potential of clean and sustainable energy sources in addressing global challenges. With an emphasis on mitigating climate change and ensuring environmental stewardship, this highlights the ongoing technological advancements and increased investments in solar, wind, hydro, geothermal, biomass, tidal and wave energy. The shift towards a decentralized and resilient energy infrastructure, coupled with the integration of smart grids and advanced storage solutions, is set to optimize the utilization of renewable resources [1]. Here I underscore the importance of intelligence solar power energy for improved output and the next generation stands to inherit a planet powered by efficient and eco-friendly energy, fostering a sustainable and healthier future.

□ Introduction

Renewable energy is energy derived from natural sources that are replenished at a higher rate than they are consumed. These sources of energy are considered environmentally friendly and sustainable because they do not deplete finite resources and typically have lower environmental impacts compared to non-renewable alternatives. Generating renewable energy creates far lower emissions than burning fossil fuels [2]. The importance of renewable energy is significant and multifaceted, impacting various aspects of society, the economy, the technology, and the environment. According to sustainable development principles, investments in renewable energy need to be widely promoted and supported especially in rural areas. Here are several key reasons highlighting the importance of renewable energy:

- **Reduced Greenhouse Gas Emissions:** The combustion of fossil fuels for energy is a major contributor to greenhouse gas emissions. Renewable energy sources produce little to no greenhouse gases, helping mitigate climate change and reduce air pollution [3].
- **Mitigating the Impacts of Climate Change:** By reducing dependence on fossil fuels, renewable energy plays a crucial role in global efforts to limit temperature rise, mitigate climate change impacts, and transition to a more sustainable future.
- **Less Environmental Impact:** Unlike fossil fuel extraction and combustion, renewable energy sources have a lower environmental impact, minimizing damage to ecosystems, water resources, and landscapes.
- **Diversification of Energy Sources:** Relying on a mix of renewable energy sources reduces dependence on finite fossil fuels, enhancing energy security and resilience against geopolitical uncertainties and supply disruptions.
- **Stable and Predictable Energy Prices:** Renewable energy sources often provide more stable and predictable energy prices compared to fossil fuels, which can be subject to price volatility.

The major identified renewable energy based on how it produces:

- **Solar Energy:** Generated from the sun's radiation, solar energy can be captured using photovoltaic cells to produce electricity or through solar thermal systems for heating water and air.
- **Wind Energy:** Wind turbines convert the kinetic energy of the wind into electrical power. Wind energy is harnessed by large wind farms or smaller residential and commercial installations.
- **Hydropower:** This involves the generation of electricity by harnessing the energy of flowing water. Dams and other water infrastructure are used to control the flow and generate power.
- **Geothermal Energy:** This type of energy is derived from the heat within the Earth. Geothermal power plants use steam or hot water from the Earth's interior to generate electricity.
- **Biomass Energy:** Biomass refers to organic materials, such as wood, crop residues, and animal waste, that can be used as fuel to produce heat or electricity. Bioenergy can also be derived from biofuels like ethanol and biodiesel.
- **Tidal and Wave Energy:** Tidal and wave energy are generated by harnessing the movement of tides or the kinetic energy of ocean waves to produce electricity.

☐ Progress of Renewable Energy

India has set itself the ambitious target of generating half of its electricity from renewables by 2030. Innovations in renewable energy projects have the potential to reshape the global energy landscape and address the challenges posed by climate change. The statistics and projection are mapped in the figure 01 where it clearly indicates the progress.

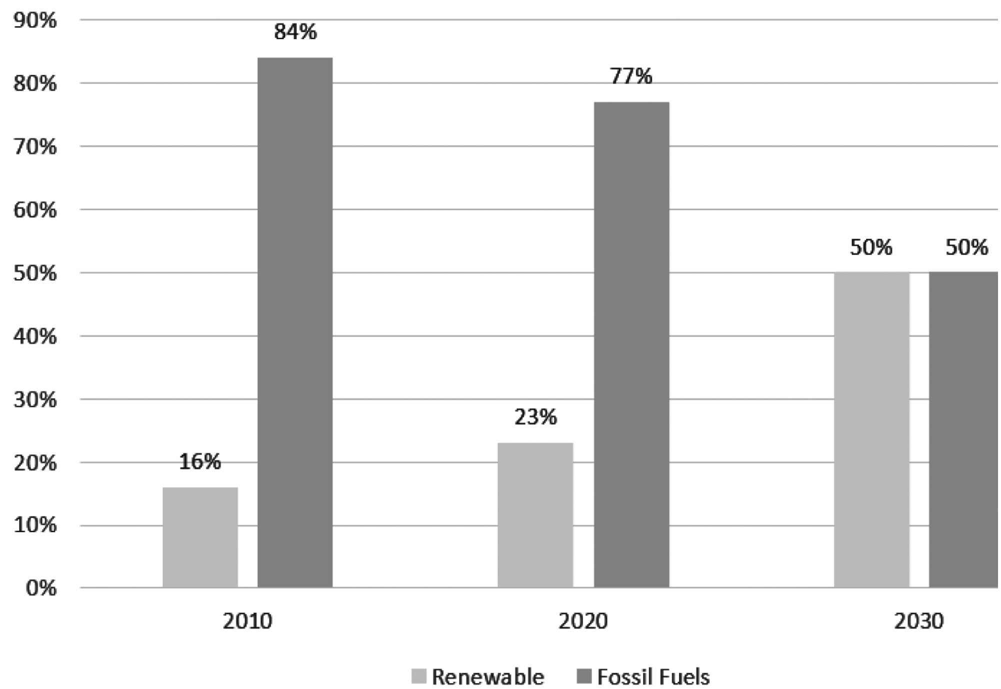

Figure 01: Renewable Energy progress Statistics

Innovations in renewable energy include advancements in solar photovoltaics, wind turbine technology, energy storage solutions like batteries and hydrogen, smart grid integration, bioenergy sources, and sustainable policy frameworks. These innovations drive efficiency, affordability, and scalability, accelerating the global transition towards a sustainable energy future [4].

A. Solar Energy Innovations

- **Next-Generation Photovoltaics -** Innovations like perovskite solar cells, tandem solar cells, and multi-junction solar cells are pushing the efficiency limits and expanding the application possibilities of solar panels.

- **Solar Paints and Coatings -** Solar paints and coatings have emerged as a promising innovation, allowing virtually any surface to harness solar energy. These materials contain photovoltaic properties, enabling buildings, vehicles, and even outdoor furniture to generate electricity from sunlight.
- **Solar Windows -** Solar windows integrate transparent solar cells into the glass, transforming conventional windows into electricity-generating assets. This innovation holds significant potential for large-scale adoption, as it seamlessly combines energy generation with the existing infrastructure.

B. Wind Energy Innovations

- **Floating Wind Farms -** Floating wind farms are revolutionizing offshore wind energy production by enabling installations in deep waters where traditional fixed foundations are not feasible. These floating platforms use advanced mooring systems to harness the strong and consistent winds available in offshore regions.
- **Vertical Axis Wind Turbines -** Vertical axis wind turbines (VAWTs) offer a compelling alternative to traditional horizontal axis wind turbines. VAWTs are designed to capture wind from any direction, making them suitable for urban environments and areas with complex wind patterns.
- **Kite Wind Energy Systems -** Kite wind energy systems utilize large kites tethered to the ground to capture high-altitude winds. The kites generate significant amounts of clean energy while requiring fewer resources compared to conventional wind turbines.

C. Hydroelectric Innovations

- **Run-of-River Hydroelectric Systems -** Run-of-river hydroelectric systems utilize the natural flow of rivers to generate electricity without the need for large-scale dams. These systems have lower environmental impacts and allow for more flexible installation and operation.
- **Underwater Turbines -** Underwater turbines harness the kinetic energy of ocean currents to generate renewable electricity. These innovative turbines can be installed in various locations, including coastal areas and ocean currents, providing a consistent and reliable source of clean power.

D. Geothermal Innovations

- **Enhanced Geothermal Systems (EGS) -** Enhanced Geothermal Systems (EGS) aim to extract heat from deeper and hotter regions of the Earth, expanding the potential for geothermal energy production. By creating engineered reservoirs and utilizing advanced drilling techniques, EGS technologies overcome the limitations of conventional geothermal systems.

- **Geothermal Heat Pumps -** Geothermal heat pumps utilize the stable temperature of the Earth's subsurface to provide efficient heating and cooling for buildings. These systems extract heat from the ground during winter and dissipate excess heat during summer, significantly reducing energy consumption and greenhouse gas emissions.
- **Deep Direct-Use Geothermal Systems -** Deep Direct-Use Geothermal Systems tap into the Earth's geothermal resources to provide direct heating and cooling for residential, commercial, and industrial applications. These systems can efficiently meet the thermal demands of buildings and processes, reducing reliance on traitional heating and cooling systems.

E. Biomass Innovations

- **Bioenergy with Carbon Capture and Storage (BECCS) -** Bioenergy with Carbon Capture and Storage (BECCS) is a novel approach that combines bioenergy production with the capture and storage of carbon dioxide emissions. This innovation not only generates renewable energy from biomass but also removes CO_2 from the atmosphere, contributing to climate change mitigation.
- **Algae Biofuel Production -** Algae biofuel production offers a sustainable alternative to fossil fuels by utilizing the rapid growth and high oil content of certain types of algae. Algae can be cultivated in various environments, including wastewater treatment facilities and coastal areas, providing a versatile and carbon-neutral source of biofuel.
- **Waste-to-Energy Conversion -** Waste-to-energy conversion technologies convert organic waste materials into usable energy, reducing landfill waste and generating renewable electricity or heat. Innovations in this field include anaerobic digestion, pyrolysis, and gasification, which effectively harness the energy potential of organic waste.

F. Tidal and Wave Energy Innovations

- **Storing tidal energy -** In Scotland, an initiative from the European Marine Energy Centre plans to combine tidal power with vanadium flow batteries to produce continuous green hydrogen.
- **Floating tidal system** - Canada's Sustainable Marine has developed a floating tidal energy platform prototype that has already undergone nearly two years of tests on the waters of Grand Passage, Nova Scotia. During comprehensive monitoring, there has not been any evidence of adverse effects on fish or marine life, and construction of

three platforms is set to begin in 2021. They are projected to provide up to 9MW of renewable electricity to Nova Scotia's electrical grid.

☐ Smart Grid with Artificial Intelligent System

AI can manage smart grids, which are electricity supply networks that use digital communications technology to detect and react to local changes in usage. The different components of the smart grid are as shown in the Figure 02.

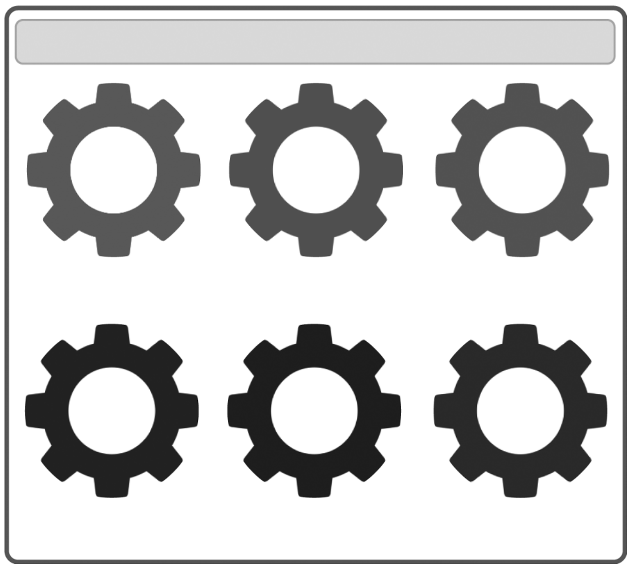

Figure 02: Feature of Smart Grid using Artificial Intelligence.

- **Advanced Metering Infrastructure (AMI):** Smart grids start with smart meters. These devices measure energy consumption in real-time and communicate this data back to the utility company. This helps in better understanding and managing energy usage patterns.
- **Two-way Communication:** Unlike traditional grids, smart grids enable two-way communication between the utility and consumers. This allows for more efficient monitoring, control, and response to changes in electricity demand or supply.
- **Automation and Control:** Smart grids use automation to detect and respond to issues in real-time. If there is a power outage, the system can quickly identify the location and reroute power to minimize downtime.
- **Renewable Integration:** Smart grids facilitate the integration of renewable energy sources like solar and wind power. They can efficiently manage the variability of these sources, ensuring a stable and reliable power supply.

- **Demand Response**: With real-time data, utilities can incentivize consumers to shift their electricity usage during peak and off-peak times. This helps in balancing the load on the grid and avoiding strain during high-demand periods.
- **Grid Monitoring and Analytics**: Smart grids use advanced analytics to monitor the health of the grid, predict potential issues, and optimize overall performance. This proactive approach helps in preventing outages and improving grid reliability.

Overall, the smart grid is all about using data and technology to make the power grid more reliable, efficient, and responsive to the changing needs of the modern world.

☐ Steps of Energy Process

AI plays a crucial role in optimizing and enhancing various aspects of renewable energy. As shown in the figure 03, the execution flows like water fall. The process can be classified in four major sections:

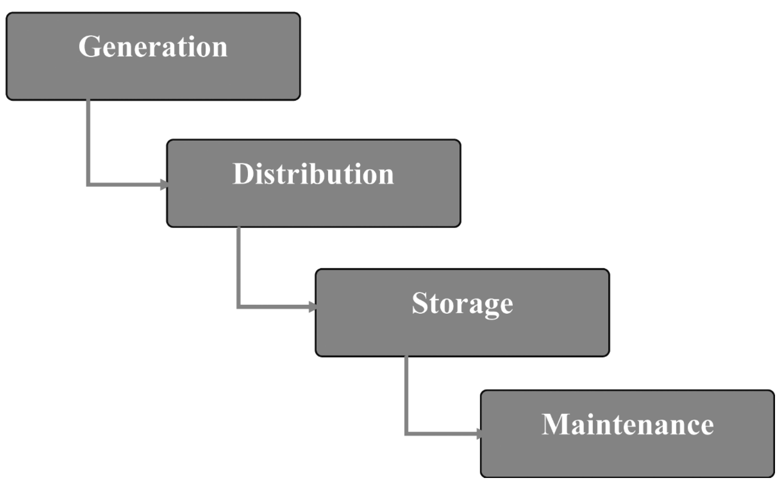

Figure 03: Water fall model of process sequence chain

1) **Generation**
   AI algorithms can predict and optimize energy production by analyzing weather patterns, historical data, and other relevant factors to predict future renewable energy generation. AI algorithms can predict consumption patterns using historical and real-time data, which can help utilities allocate resources more efficiently [4][5]. The process of execution of generation of power is shown in figure 04. Each section has been designed with several AI algorithm for better result.

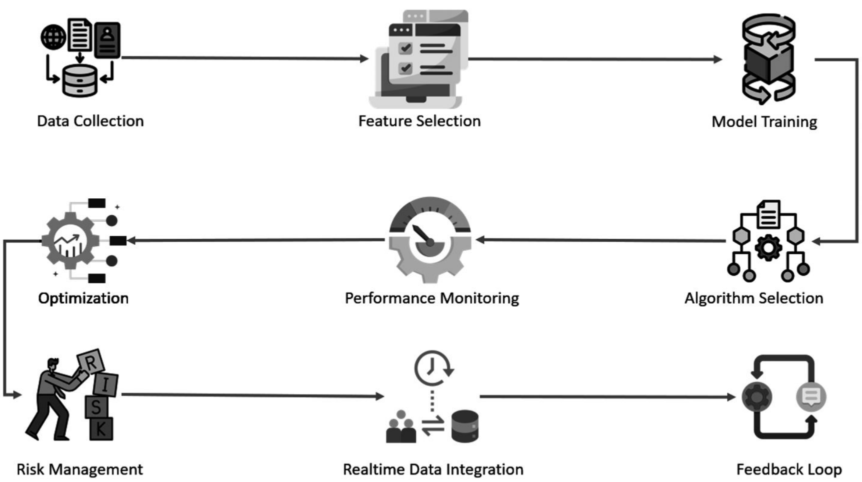

Figure 04: Process of renewable power generation

Data Collection: AI systems gather data from various sources, such as weather conditions, energy consumption patterns, equipment performance, and more.

Feature Selection: Relevant features or variables that impact energy generation are identified. For example, sunlight hours, wind speed, temperature, and equipment status are crucial for solar and wind energy predictions.

Model Training: Machine learning algorithms are trained using historical data to understand patterns and relationships between the chosen features and energy production. This training helps the model learn how different factors affect energy generation [6]. Neural networks, particularly deep learning architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are capable of learning complex patterns from raw data using image recognition and sequential data analysis [7].

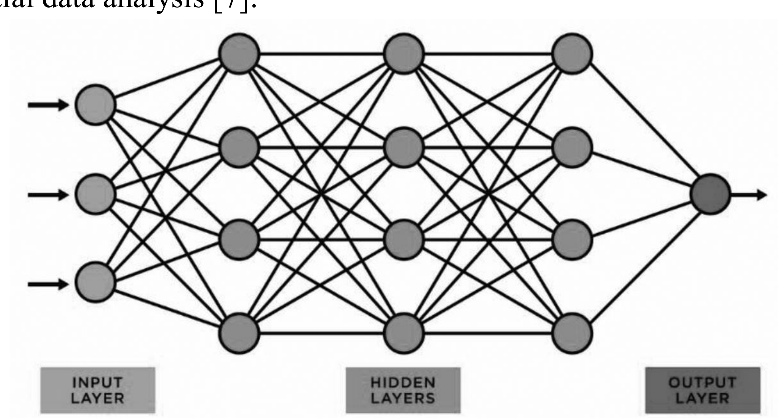

Figure 05: Artificial Neural layer structure

Algorithm Selection: Different algorithms may be employed depending on the type of energy source and the complexity of the system. Common algorithms include regression analysis, decision trees, and neural networks.

Real-time Data Integration: Predictive models continuously integrate real-time data to adjust predictions. For example, if unexpected weather changes occur, the AI system can quickly update its forecasts based on the new information.

Performance Monitoring: The AI system monitors the performance of its predictions against actual energy production. If discrepancies arise, the model may be adjusted or retrained to improve accuracy.

Optimization: AI can suggest optimal operational parameters based on predictions to maximize energy generation efficiency. This may involve adjusting the angle of solar panels, turbine speeds in wind farms, or other operational parameters.

Risk Management: Predictive analytics also help in identifying potential risks and issues before they occur. For instance, anticipating equipment failures or identifying periods of low energy generation allows for proactive maintenance.

Feedback Loop: Continuous learning is crucial. The system incorporates feedback from actual performance, ensuring that it adapts and improves its predictions over time.

2) Distribution

Demand Response Management (DRM) in the energy sector is a crucial strategy for optimising electricity consumption and ensuring the stability of the electrical grid. This practice helps balance supply and demand during peak periods, initiate load shedding to reduce strain on the grid, and avoids the need for expensive infrastructure upgrades. By predicting and managing demand fluctuations, AI can enhance energy efficiency, reduce costs, and help make the shift toward renewable energy sources.

3) Storage

In energy storage, AI algorithms are employed to optimize the charging and discharging cycles of batteries, improving overall efficiency. Smart grids, enabled by AI, enhance the reliability and efficiency of energy distribution, enabling better coordination between energy producers and consumers. However, energy storage allows excess energy generated during peak times to be stored and used when these sources are not producing electricity. This helps to make renewables more reliable and less dependent on weather conditions. Moreover, energy storage is especially crucial for critical facilities like hospitals, data centres, and emergency services, where access to a backup power supply could be life-or-death!

4) Maintenance

AI is used for predictive maintenance of renewable energy infrastructure. By analyzing sensor data and performance metrics, AI can identify potential issues in equipment, allowing for proactive maintenance and minimizing downtime. Energy companies can predict when their equipment is likely to fail or need maintenance. Machine learning can analyse large amounts of data from various sources, such as usage stats, weather data, and historical maintenance records, to predict potential breakdowns before they occur. This approach minimises downtime, reduces repair costs, and improves the overall reliability of energy infrastructure.

☐ Conclusion

The future of renewable energy holds incredible promise for the next generation. As we strive to address the pressing issues of climate change and environmental sustainability, renewable energy sources emerge as key players in shaping a cleaner and more sustainable world. Investments in solar, wind, hydro, and geothermal energy are gaining momentum, driving down costs, and improving efficiency. This shift not only mitigates the environmental impact of traditional energy sources but also creates new opportunities for economic growth, job creation, and technological innovation.

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Energy Demand Forecasting Through Applications of Artificial Intelligence

Rajib Kumar Das

Consultant,
CESC Limited, Kolkata

Summary:

Electricity distribution company requires demand forecasting for power procurement and network development purposes. Long-term forecast is required, generally 3 to 5 years ahead for network planning and associated capital expenditure estimates. Long-term forecast is also required for long-term power procurement. Short-term forecast is for day-ahead (for 15-minute time block) power procurement. Traditionally, demand forecasting was carried out with energy consumption data. With more and more Renewable Energy Sources (Solar and Wind), which are intermittent in nature, accurate prediction of not only demand but also generation from such intermittent sources is inevitable. Moreover, distribution companies are required to provide day-ahead schedule for power procurement. Any deviation of actual power drawal from the schedule may attract penalty. Accurate forecasts can result in efficient use of resources, leading to reduced power purchase cost, optimum capital expenditure for developing network and quality power supply to the consumers. To address the challenge, distribution company can leverage advanced forecasting techniques such as deep learning to develop more accurate and efficient peak load forecasting models.

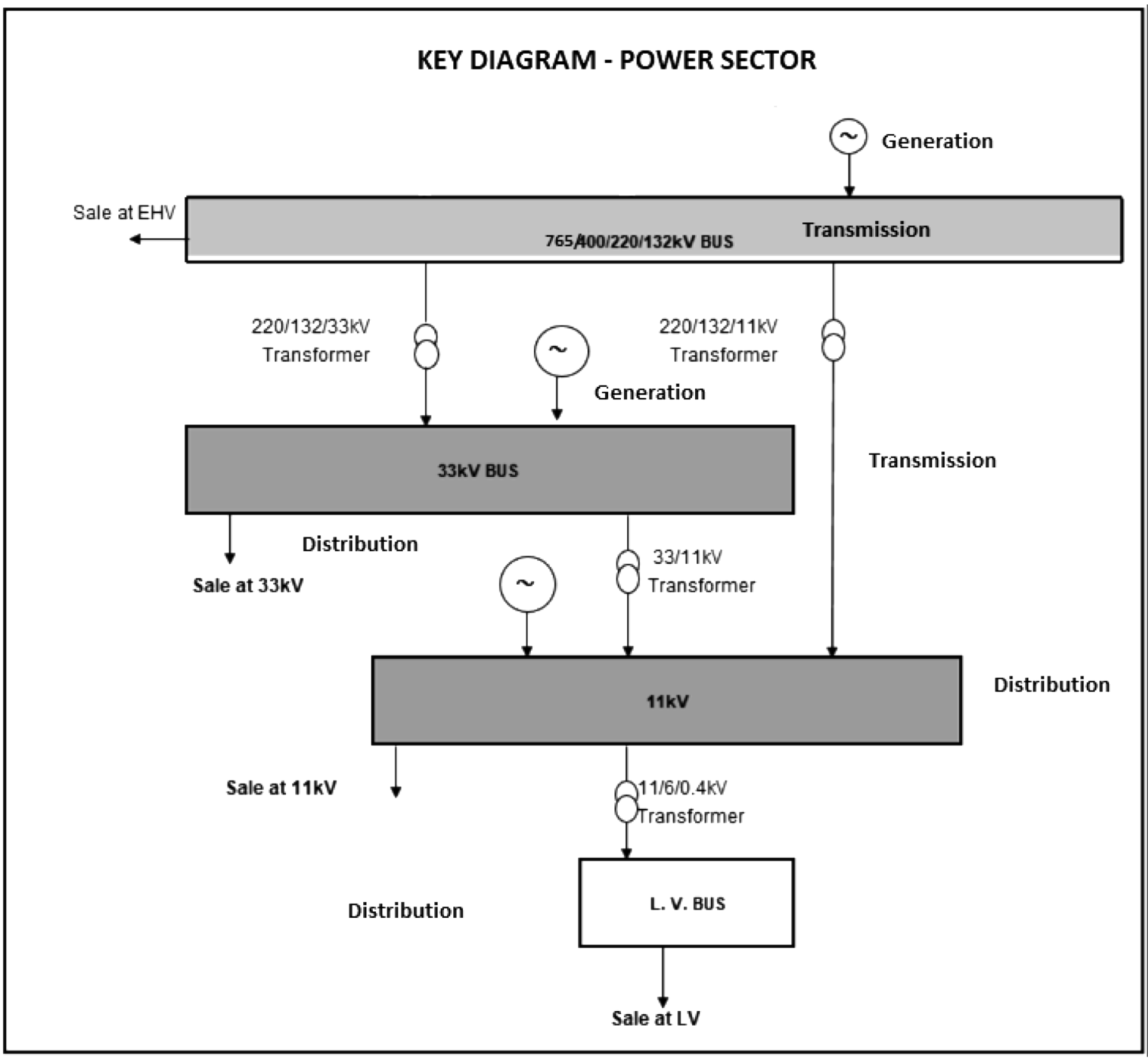
Deep learning is subset of Machine Learning (ML) which is again subset of Artificial Intelligence (AI). Deep learning trains a model using massive amounts of data and complex algorithms. In recent years, deep learning techniques have gained popularity due to their ability to capture complex patterns in the data and generate more accurate forecasts.

Various techniques / models - Multi-layer Perceptron (MLP), Recurrent neural network (RNN), Long-Short Term Memory (LSTM), Gated Recurrent Unit (GRU) or Hybrid model is used for demand forecasting. Energy consumption, Consumer no., Weather data, GDP/

SGDP, Events etc. may be considered as input. Regarding data input, the more the merrier. Explainable and interpretable methods that would enhance stake-holders confidence should be adopted.

☐ Introduction:

"Distribution system" means the system of wires and associated facilities between the delivery points on the transmission lines or the generating station connection and the point of connection to the installation of the consumers :



Duty of a distribution licensee is "*to develop and maintain an efficient, co-ordinated and economical distribution system in his area of supply and to supply electricity*."

Accurate demand forecast is required for developing and maintenance of efficient, co-ordinated and economical distribution system.

Demand forecasting is generally classified as short-term and long-term predictions. Short-term prediction is for hourly and daily and Long-term is for years ahead.

☐ Objective:

Electricity distribution companies procure electricity from generators, generating companies, power market, electricity trader, through bi-lateral arrangements etc. For procurement of power, a distribution company submits day-ahead schedule from different sources of power and this requires day-ahead demand forecasting for every 15-minute time block. Short-term prediction is primarily required for power procurement purposes.

Distribution company in our country incurs about 80% of its total cost towards power procurement. Accurate short-term demand prediction helps in optimum power procurement and reducing cost.

Distribution network is capital intensive and requires long gestation period for its development. Long-term peak demand forecasting is essential for power system planners and operators to ensure that there is sufficient capacity to meet the electricity demand without incurring excessive operational costs or risking power outages.

Traditionally, long-term forecasting was carried out on a bottom-up approach, considering trend analysis consumer category-wise energy consumption as well as per capita consumption over the years. Central Electricity Authority traditionally adopts Partial End Use Method (PEUM) for carrying out Electric Power Survey (EPS) Exercises. Demography, economic factors, weather conditions were hardly modelled in forecasting analysis.

Over the last two decades, electricity demand and price forecasting has become a fundamental decision-making tool for electricity distribution companies. Forecasting is gaining more importance with integration of Renewable Energy (RE) Sources. There is need to be climate resilient by reducing carbon foot print. Government of India has committed to reduce carbon emission and set a target of 500 GW RE capacity by 2030. Both Wind and Solar generation is intermittent and integration of such large scale RE capacity into the Grid is a major challenge for stable operation. Thus, accurate forecasts can result in efficient use of resources, leading to reduced power purchase cost, optimum capital expenditure for developing network and quality power supply to the consumers. To address the challenge, distribution company can leverage advanced forecasting techniques such as deep learning to develop more accurate and efficient peak demand forecasting models.

☐ Deep Learning:

Deep learning is subset of Machine Learning (ML) which is again subset of Artificial Intelligence (AI). Artificial intelligence (AI), the ability of a computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. AI is the backbone of innovation in modern computing, unlocking value for individuals and businesses. Artificial Intelligence, Machine Learning, and Deep Learning have emerged as the most talked-about technologies in today's commercial world, as businesses use these innovations to create intelligent machines and applications.

Deep learning trains a model using massive amounts of data and complex algorithms. In recent years, deep learning techniques have gained popularity due to their ability to capture complex patterns in the data and generate more accurate forecasts. Deep learning techniques can help in peak demand forecasting by providing more accurate and efficient forecasting models. These techniques use neural networks to capture the complex patterns in electricity consumption data, allowing for more accurate predictions of peak demands. Deep learning models can also incorporate additional features such as weather variables and calendar variables to improve their forecasting accuracy.

Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another.

Artificial neural networks (ANNs) are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

Neural networks rely on training data to learn and improve their accuracy over time.

Deep learning can be a powerful tool for time series forecasting, especially for complex and dynamic data by providing more accurate and robust predictions, especially in scenarios where

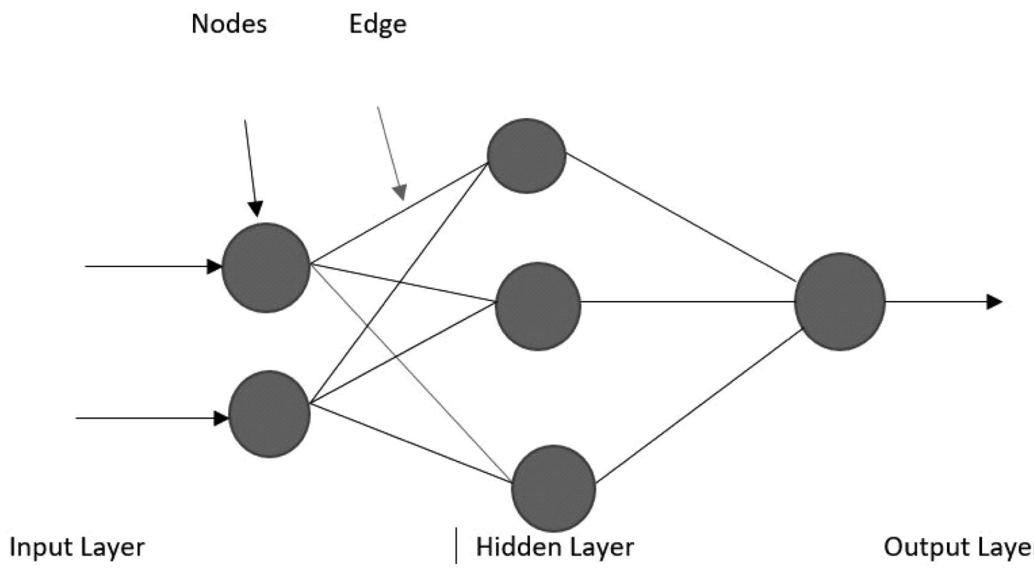
traditional methods may struggle to capture complex patterns in the data. However, it requires a significant amount of data and computing resources to train and fine-tune deep learning models.

☐ Techniques for forecasting:

There are different techniques (Deep learning models) for time series forecasting. Key advantage of deep learning for time series forecasting is that it can automatically identify complex patterns and relationships in the data that traditional time series methods may not be able to capture.

1. Multi-layer Perceptron (MLP)

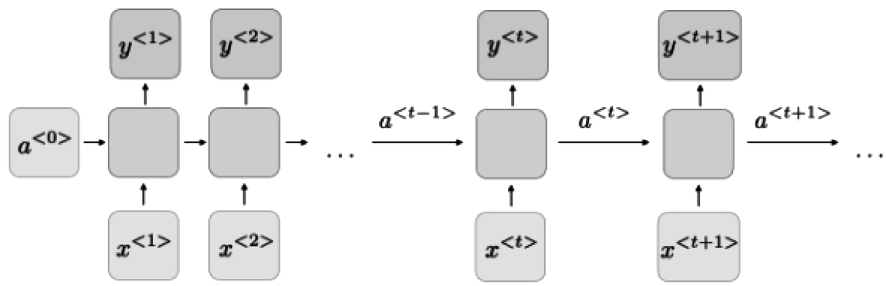
It comprises of an input layer, a hidden layer or layers, and an output layer.



- The input node represents the feature of the dataset.
- Each input node passes the vector input value to the hidden layer.
- In the hidden layer, each edge has some weight multiplied by the input variable. All the production values from the hidden nodes are summed together. To generate the output
- The activation function is used in the hidden layer to identify the active nodes.
- The output is passed to the output layer.
- Calculate the difference between predicted and actual output at the output layer.
- The model uses backpropagation after calculating the predicted output.

2 Recurrent neural network (RNN)

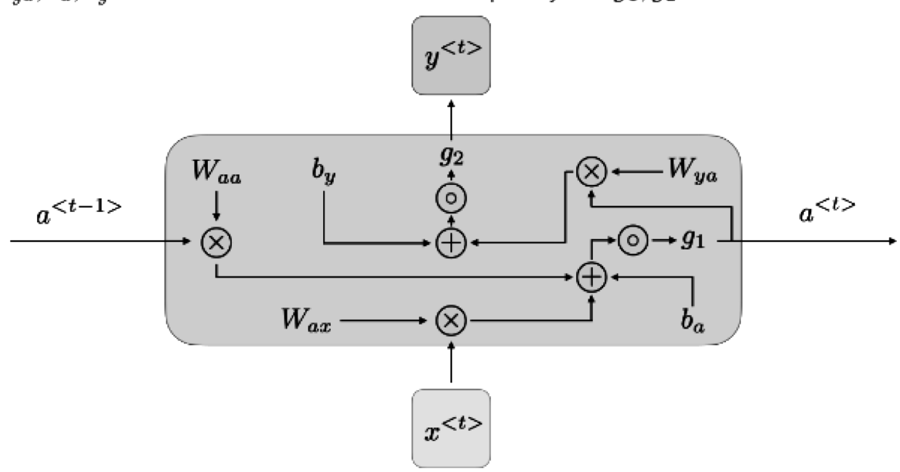
Recurrent neural networks, also known as RNNs, are a class of neural networks that allow previous outputs to be used as inputs while having hidden states. They are typically as follows:



For each timestep t, the activation $a^{<t>}$ and the output $y^{<t>}$ are expressed as follows:

$$\boxed{a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)} \quad \text{and} \quad \boxed{y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)}$$

where $W_{ax}, W_{aa}, W_{ya}, b_a, b_y$ are coefficients that are shared temporally and g_1, g_2 activation functions.



3 Long-Short Term Memory (LSTM)

LSTM is naturally suited for modelling time series. This is due to their ability to capture dependency in a sequential context and preserve past information as they progress through the subsequent time steps in a series. LSTMs accept multivariate inputs.

4 Gated Recurrent Unit (GRU)

The GRU presents itself as an innovative solution to the vanishing gradient problem in traditional RNNs. It incorporates gating mechanisms that enable selective information update and resetting in the hidden state. This mechanism empowers the GRU to retain essential information and forget irrelevant data, facilitating the learning of long-term dependencies.

☐ Factors for undertaking demand forecasting exercise:

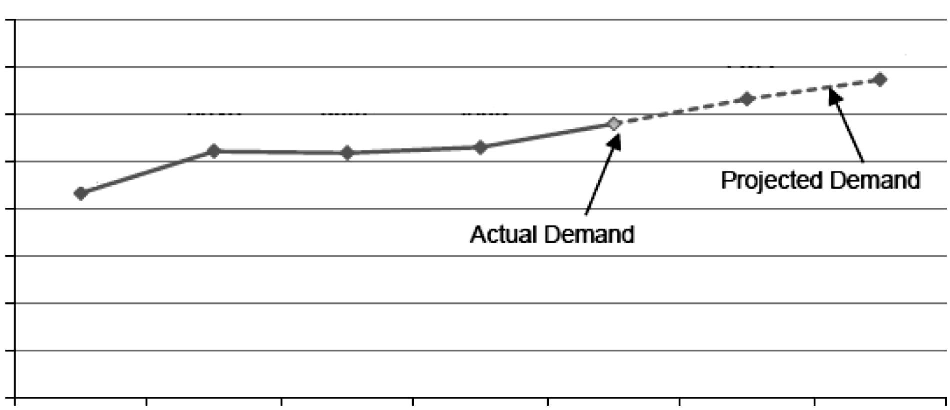
- Energy sales – Consumer category-wise (Domestic, Commercial, Industrial etc.)
- Consumer nos.- Category-wise
- Distribution loss
- Load Factor
- Infrastructure development (Metro Rail, Industrial hub, New township etc.)
- Weather (Temperature, Humidity, Rainfall
- Events dates (Durga puja, Holi, Strike etc.)
- Government Policies / Schemes that may have an effect on electricity consumption
- Technology advancements (Smart Grid, Electric Vehicle, Energy efficiency programs)
- Electricity Retail Tariff
- State (Gross Domestic Product)

☐ Conclusion:

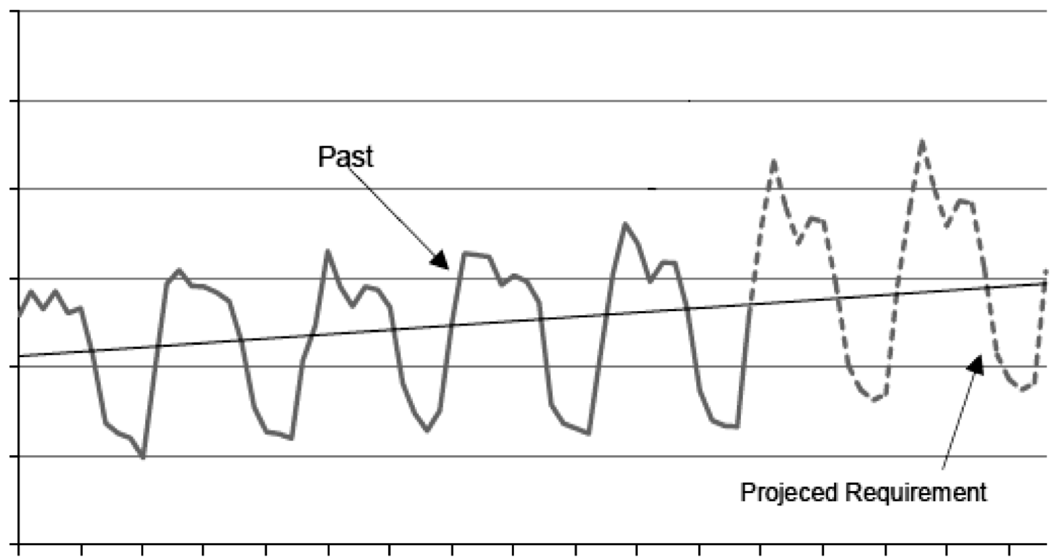
Accurate prediction of load demand along with generation from Solar and Wind generators is required for economic and stable operation of power system. Solar and Wind generation will be integrated in great pace considering commitment towards climate change actions as well economics. Artificial Intelligence / Machine Learning / Deep Learning techniques are increasingly integrated into demand forecasting.

Since the new techniques are increasingly employed into demand forecasting (RE generation as well), the need of transparency and interpretability should be given high importance. Explainable AI methods, which provide insights into how models arrive at specific predictions, enhance stakeholder confidence and foster trust in the forecasting process

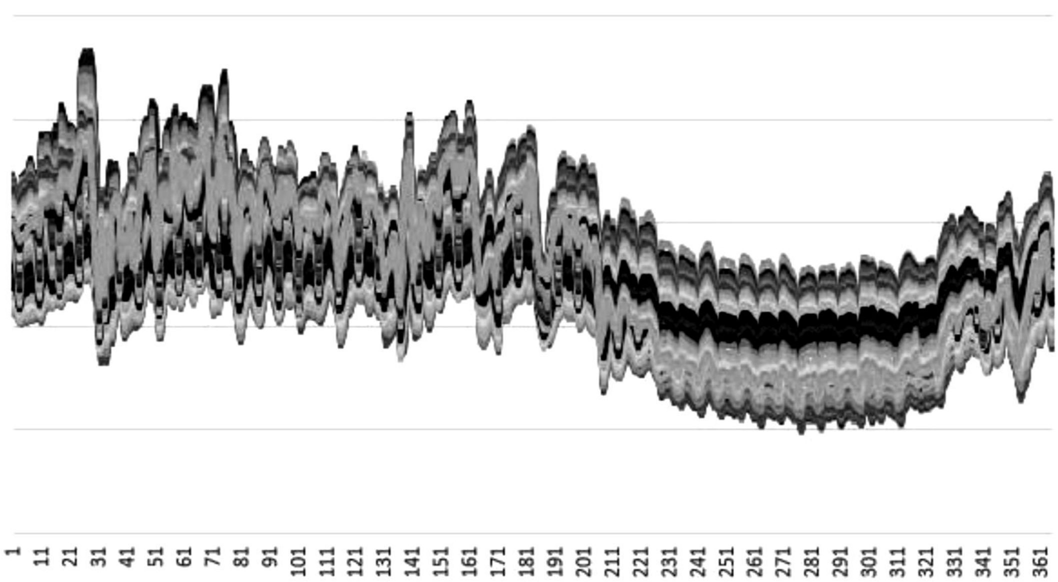
Typical variation in load demand:



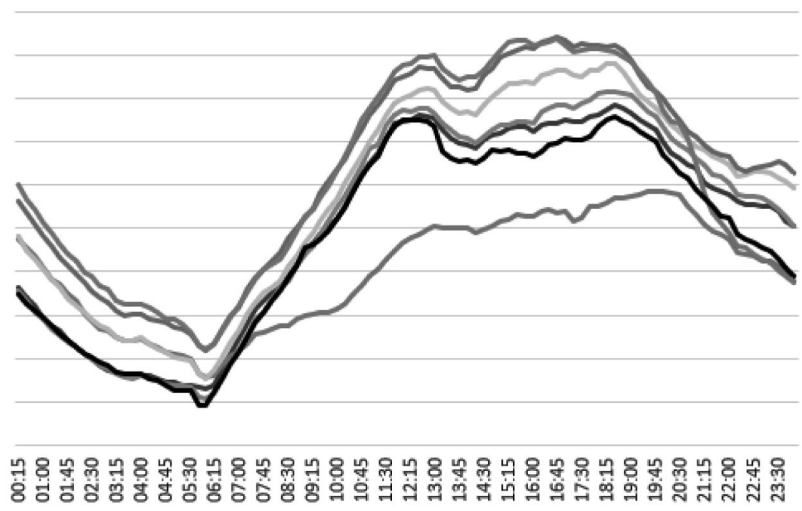
Annual Peak Demand



Monthly Peak Demand over the years



Daily Demand for 365 days



Daily Peak Demand for 7 days

Demand in a day

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AI in Thermal Power Plants: Its Usefulness and Threats

Ashis Dev
Director
Duragen Energy Pvt. Ltd.

1.0. Background:

ARTIFICIAL INTELLIGENCE (AI) is the intelligence of machine or softwares opposed to the intelligence of other living beings, primarily that of Human being. AI Technology is widely used throughout Industry, Government and Science throughout the world. Some high profile applications are Advanced Web search engines (e.g Google search), Recommendation systems (used by YouTube, Amazon, Netflix), interacting via human voice (such as Google Assistance, Siri, Alexa), Self-driving cars, generative and creative tools (ChatGPT, AI Art, CoPilot etc.).

Alan Turing was the first person to conduct substantial research in the field, he called Machine Intelligence. However, AI was funded as an academic discipline in 1956.

The field went through multiple cycle of optimism followed by disappointment and loss of funding. Funding and human interest vastly increased after 2012, when Deep Learning suppressed all previous Technologies.

AI comprises of Artificial neural networks, deep learning and machine learning, among many others. AI & ML Technologies are used in most essential applications of the 2020s, including search engines, autonomous vehicles and drones.

There are many Industry specific tasks, which are used AI software. However, before putting it in use, such software should undergo an exhaustive set of testing to assess its capabilities and implications. With this goal in mind, a large number of experts with specialties encompassing a broad spectrum—spanning the fields of business, economics, education, engineering, healthcare, history, law, mathematics, medicine, mental health, psychology, and the sciences—to explore the capabilities of GPT-4 before its public release and provide their insightful reflections in the form of essays.

2.0. AI applications in Thermal & Gas Power Stations World-wide:

Artificial Intelligence (AI) Technology has been used in Thermal and Gas Power stations world-wide in many areas for improving Safety, Security, Availability, Reliability, Efficiency and Environmental conditions of the Power Plants.

The integration of software driven mechanism not only enhances operational efficiencies but also reshapes company's strategic approach and cultural mindset.

Artificial intelligence (AI) has the potential to make autonomous power plants a reality and knowledge graphs are key to realizing this vision. Energy Stories looks at the applications already developed and the major benefits they bring.

If a pump and a valve that are located close to each other in a power station but have no direct functional connection happen to fail at the same time, that might not be pure coincidence. Something serious impact could have happened that the local monitoring systems didn't detect. Water damage caused by an inconspicuous leak from a pipe, perhaps, or a fire not yet picked up by the smoke detectors on-site. An AI system would be able to detect and alert the standby team accordingly – as long as it had been previously trained using a knowledge graph of the power station. A knowledge graph is a special database capable of being evaluated by a machine. It contains not just the properties of the power station components but also all the connections between them, including those that are non-functional. For the pump in the example, that includes knowledge of all the other components close-by.

- Digitalization of power plants results in generation of operational, enterprise, and other data types, adding an edge to business operation optimization and asset performance management.
- Digital twin solutions backed by IoT, AI, cloud, and advanced data analytics serves as a catalyst to improve the performance of power plants.
- Digital twin employs models that are trained using the past plant data and algorithms to predict the plant behavior at present and make prescriptive decisions for optimizing plant performance.

2.1: Driving Sustainability With Digital Twin:

Power generation alone contributes to over 41% of the global carbon dioxide emissions, largely fueled by coal. Despite several sustainability actions set in motion, coal is expected to provide at least 22% of global power even in 2040, accounting for nearly 68% of emissions. Applying right technologies will help thermal power plants reduce up to two gigatons of CO_2 emissions.

Digital twin solutions backed by internet of things (IoT), artificial intelligence (AI), cloud and advanced data analytics serve as catalysts to improve the performance of power plants across functions. These could include monitoring of equipment and processes, optimizing operations in real time, and improving availability. Digital twin solutions can assist in better operation and maintenance of applications such as boiler, gas turbine, flue gas desulfurization system, selective catalytic reduction system, and air preheater.

The solutions not only reduce CO_2 and greenhouse gas emissions, but also bring down annual operational and maintenance expenses by a large extent.

2.2: Technology to Cut Thermal Emissions:

The need to abate global warming mandates prudent usage of fossil fuels. Coal powered thermal power plants are under pressure to perform efficiently and reduce emissions. Currently, the power generation sector alone is responsible for nearly 41% of global CO_2 emissions, with coal power being the largest contributor of nitrogen oxides (NOx), Sulphur oxides (Sox), mercury (Hg) and particulate matter. Increased deployment of carbon capture, sequestration, and utilization (CCUs) technologies can improve the sustainability quotient but may be insufficient to meet the climate goals set in the Paris agreement. Coal is still expected to provide 22% of global power and account for 68% of carbon dioxide (CO_2) emissions even in 2040.

Leveraging the right technology can help thermal power companies reduce up to 2 gigatons of CO_2emissions. Adoption of the latest digital technologies can help improve thermal plants' performance by reducing the consumption of fuel, auxiliary power, consumables, and greenhouse gas emissions. Existing thermal power plants, therefore, need to be equipped with these technologies to mitigate global warming.

3.0: AI Applications in Indian Power Stations:

Presently AI applications are used by some Power Utilities in India on experimental basis, however, based on its usefulness and impact on complex system, it will be widespread in near future.

Thermal power plants consist of large and complex equipment for power generation such as pulverizers, boilers, steam turbines and gas turbines. Pollution control equipment like selective catalytic reduction (SCR) converters, flue gas desulphurization (FGD) units, electrostatic precipitators (ESP) as well as efficiency improvement equipment like air preheaters (APH), condensers and cooling towers make up its landscape.

Even with advanced control systems in place, monitoring, optimizing performance, and periodic maintenance of these equipment becomes challenging due to:

- Complex plant dynamics
- Interconnected equipment with interacting operations
- Variability in coal quality due to diverse sources and inadequate blending
- Flexibility to accommodate transient and sharp variations in power demand
- Gradual degradation and faults of equipment over time
- Tightening and evolving emission standards and safety regulations

After the introduction of more RE, into the Grid, the Operation of Thermal Plants became more complex. Given the complexities and scale of operations across these plants, it is imperative to take decisions in real-time, as delays lead to huge losses and catastrophic events. There is still considerable dependence on operator expertise for running the plants. Operators take decisions based on heuristics that often result in sub-optimal operation, leading to higher cost of operation and emissions.

3.1: Digital Twin Solutions for Thermal Power Plants:

A digital twin is a cyber-physical system that replicates the behavior of the real-life physical system while maintaining its communication with the actual system in real-time and makes recommendations to improve the plant operations. It employs models that are trained using the past plant data, and state-of-the-art algorithms to predict the plant behavior at present and make prescriptive decisions for optimizing plant performance. It uses physics-based predictive models to improve the accuracy of some complex processes.

Digital Twin solutions address optimization of key performance indicators (KPI) that have conflicting goals and constraints at the equipment, plant, and site levels. Advanced industrial analytics with optimization and control can help solve complex multi-objective decision-making using IoT and the cloud.

3.2: Boiler Digital Twin:

A boiler in a 1,000 MW unit consumes close to 9,000 tons of coal per day and causes nearly 76% of the NOx emissions in the United States. Improving and maintaining the efficiency of boilers and existing thermal power plants can reduce emissions. The challenge is to identify optimum operation settings in real-time, in response to variations in fuel properties and fluctuating power demand.

A digital twin of the boiler can utilize the power of IoT, AI, and digital technologies to detect the change of coal. Sensing environmental conditions and power demand, the twin can identify an optimum operation strategy to maximize heat rate and minimize emissions from the boiler. Boiler digital twins can reduce 8-10% of outgoing NOx and cut coal consumption by approximately a million dollars annually. These improvements also result in reduced load on emission control equipment, lower usage of reagents/chemicals, and lower auxiliary power consumption. Digital twins can benefit industrial boilers as well as captive power plants.

3.3: Integrated Security and Safety for Thermal Power Plants:

An integrated Security system on the concept" Deter, Detect, Delay and Deny" comprising of the following:

Smart CCTV Cameras at Watch Tower, Perimeter and other strategic locations, PIDS (Perimeter Intrusion Detection System for perimeter intrusion alerts, Access Control System (ACS) with Pre-built zones, entry and exit through SMART Cards, Automatic Vehicle Number Plate Recognition (ANPR) system, Under Vehicle Scanning System (UVSS) for inspection of bottom of the vehicle, without stoppingg the vehicle, Thermal Cameras for long distance night time monitoring and monitoring of high value materials through RFID Tags.

3.4: Maximise Availability of Equipment and Unit through Advance Pattern Recognition (APR):

Co-related signals of one equipment are selected as part of one APR Model, e.g. for a Fan, it can be motor current, winding temperature, motor IB/OB Bearing temp and other like Inlet vane position, ambient temp and air flow.

APR Model are predictive and learning model that uses Pattern Recognition methods give expected value of the signal of that model. For each signal, difference of the actually real time value from DCS and the expected values are computed. If the residue exceeds a configurable threshold, an alert (APR Alert/anomaly/catch) is generated. APR Alert is generated much before a DCS Alert.

It gives productive approach and action window for Maintenance person preventing unplanned break-down of equipment and in tern maximize the availability and reducing the O&M cost.

This AI/ML based APR also helps in starting spare-parts planning, Overhauling plan etc.

3.5: AI Based Adaptive Auto Control System for Process Control:

- Artificial Intelligence, with its self-learning capabilities, transforms into a decisive force, actively emulating human cognitive processes to autonomously address challenges without human involvement.
- This is achieved through a combination of rule-based control systems, ML, deep learning, natural language processing (NLP), and Robotic Process automation (RPA).
- The integration of software-driven mechanisms not only enhances operational efficiencies but also reshapes the company's strategic approach and cultural mindset.
- To ensure seamless adaptation, a comprehensive approach includes upskilling and reskillling of personnel, process refinement, and strategic technology deployment.
- AI software add-on to the existing Control system, which is self tuning capabilities in AI Platform.

4.0: Solution Provided By Duragen Energy Pvt Ltd:

Duragen Energy Pvt Ltd is a newly formed startup providing Energy Management, Environment Management and Digital Transformation Solutions to its customers. Under digital transformation solution, it is providing following solutions in partnership with other Technology startups.

- AI based applications for safety: To identify,
    - Unsafe Act,
    - Unsafe condition
    - Safety deviation
    - Headcount during Mock drill
    - Access control
- RFID based Asset monitoring:
    - To track movement of asset across the organization
    - To enable smooth verification of fixed assets
- Coal yard monitoring through SMART Camera
    - Monitoring of hotspot and prevent fire
    - Activation of fire monitors in case of requirement
- Switchyard Hot spot detection through AI enabled Smart camera to enable predictive maintenance
- Battery Health Monitoring System (BHMS): To monitor the health of battery installation to prevent failure and it's impact on the business

Duragen Energy is also looking forward to work with its partners to come out suitable solutions as required by the Energy sector in the future.

5.0: Way Forward:

Although there are few examples of implementation of AI in Thermal Power Plants in India as on date, but, with the pace the AI applications are evolving it is presumed that AI will occupy an important part in the Power Plant technology space to deal with many uncertainties related to process, Equipment health monitoring, Grid variations, Flexibility of thermal plants due to induction of renewable capacities etc.

References: Articles on ChatGPT, Siemens Energy website, Digital Twins from TCS website etc.

Integrating Artificial Intelligence in Thermal Power Plants for Enhanced Efficiency and Sustainability

Er. Arindam Ghosal
Manager (Power Station)
WBPDCL

Abstract:

This technical journal explores the application possibilities of Artificial Intelligence (AI) in thermal power plants to optimize operations, improve efficiency, and enhance overall sustainability. The integration of AI technologies offers advanced monitoring, predictive maintenance, and adaptive control, contributing to a more intelligent and responsive power generation system.

1. Introduction:

Thermal power plants play a crucial role in meeting global energy demands, and the adoption of AI has the potential to revolutionize their performance. This article examines the various applications of AI in thermal power plants and their impact on operational aspects.

2. AI-Based Monitoring Systems:

Implementing AI-powered monitoring systems enables real-time data analysis for identifying anomalies, predicting equipment failures, and optimizing plant performance. These systems leverage machine learning algorithms to analyze vast datasets from sensors and provide valuable insights for proactive decision-making.

3. Predictive Maintenance:

AI facilitates predictive maintenance by analyzing historical data, equipment conditions, and environmental factors to predict potential failures. This approach minimizes downtime, extends equipment lifespan, and reduces maintenance costs, thereby enhancing the overall reliability of the power plant.

4. Adaptive Control Systems:

Intelligent control systems powered by AI algorithms enable adaptive control of various parameters within the thermal power plant. These systems can dynamically adjust combustion processes, optimize fuel consumption, and respond to changes in demand, ensuring efficient and flexible operation.

5. Energy Efficiency Optimization:

AI-driven optimization algorithms help in maximizing energy efficiency by dynamically adjusting operating parameters based on real-time conditions. This not only leads to reduced carbon emissions but also enhances the economic viability of thermal power plants.

6. Environmental Impact Assessment:

AI technologies can aid in monitoring and mitigating the environmental impact of thermal power plants. Through advanced analytics, plant operators can optimize emission levels, comply with environmental regulations, and explore cleaner energy alternatives.

7. Challenges and Future Directions:

While AI presents significant opportunities, challenges such as data security, regulatory compliance, and the need for skilled personnel must be addressed. The article has also indicated potential future developments and emerging trends in AI for thermal power plants.

8. Conclusion:

The integration of AI in thermal power plants offers a transformative path towards enhanced efficiency, reduced environmental impact, and improved sustainability. As technology continues to advance, ongoing research and implementation will play a pivotal role in shaping the future of AI in the power generation sector.

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