Data Driven Artificial Intelligence Techniques in Renewable Energy System

By

Ke Ning
B.S. in University of Science and Technology of China (1999)
M.S. in Electrical Engineering, University of Minnesota, Twin City (2001)
Ph.D. in Computer Engineering, Northeastern University, Boston (2007)

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Author ……………………………………………………………………………………………
System Design and Management Program
January 15th, 2021

Certified by ……………………………………………………………………………………
Harvey Michaels
Lecturer, System Dynamics and Information Technology
Thesis Supervisor

Accepted by ……………………………………………………………………………………
Joan Rubin
Executive Director, System Design and Management

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Abstract

Today's power grid is composed of different kinds of distributed energy resources (DER) such as solar panels, wind farms, batteries and power transformers. DERs often come with data interfaces and IoT sensors which generate large amounts of data. Besides monitoring device status, those data can be utilized to improve system efficiency and generate additional values. My thesis is to examine the benefits of technologies that incorporate AI algorithms on the growing DER data in a technical perspective;

First, a new field after IoT technology, called AIoT (Artificial Intelligence Internet of Things) is introduced, which are new technologies combining artificial intelligence (AI) and IoT to each other and creating new opportunities in the distributed energy resources (DER) field.

Second, the thesis focuses on three areas of AIoT applications (1) fault prediction in photovoltaic system and power transformers; (2) remaining useful life (RUL) prediction of IoT enabled equipment; (3) AI-enabled algorithms can automate processes and make real time grid system optimization, such as energy storage, demand response (DR) and grid flexibility. The main focus is on data driven AI techniques that differentiate from traditional statistics or knowledge-based systems, present algorithm applicability, compare improvement over traditional method and business value created in each area.

Finally, in the smart grid concept, all AIoT powered distributed energy resources (DER) can be aggregated in terms of virtual power plant (VPP), which enable the management of efficient and reliable power network on a large scale, and coordinate demand and supply in real-time. The AI enabled VPP architecture is presented, which utilized all the AIoT technologies and can provide valuable system capacity, flexibility and reliability.

Thesis Supervisor: Harvey Michaels
Title: Lecturer, System Dynamics and Information Technology

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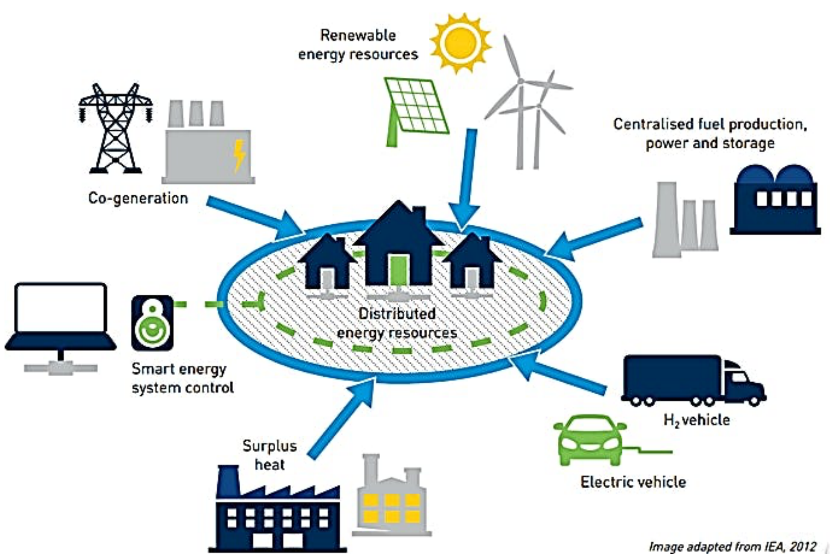
1 Introduction

Today's power grid is composed of different kinds of distributed energy resources (DER) such as solar panels, wind farms and batteries. DERs often come with data interfaces and IoT sensors which generate large amounts of data. Beside monitoring device status, those data can be utilized to improve system efficiency and generate additional values. The thesis is to present technologies that incorporate AI algorithms on the growing DERs data in a technical perspective, including diagnosis and optimization of photovoltaic systems and renewable transformers.

Three trends are happening to revolutionize the energy grid:
First, the traditional power system consists of a network of generation, transmission, distribution, and demand loads of 3 components. With growing technology and market trend, the "smart grid" consists of distributed energy resource (DER) systems, which are many small-scale power generation or storage technologies used to provide an alternative to or an enhancement of the traditional electric power system. DERs are electricity-producing resources or controllable loads that are connected to a local distribution system or connected to a host facility within the local distribution system.

DERs can include solar panels, combined heat and power plants, electricity storage and power transformers. These resources are typically smaller in scale than the traditional generation facilities. Following diagram shows the major components of an DER.



Second, IoT technology continues to advance. The Internet of Things (IoT) is a system of interconnected digital devices, machines and the ability to transmit and receive data over a ubiquitous low bandwidth network. Not only does IoT drive down the cost of sensors and electronic parts, but also the power consumption is reduced drastically. It enables new areas of IoT application that relies on low-cost battery-powered sensors.

Lastly, as vast amount of data is generated and exchanged between grid components. The components can be managed by smart devices from generation to demand loads. For optimal performance, big data analytics and AI-enabled autonomous control can be applied. Artificial intelligence and machine learning algorithms have improved dramatically in the past decade and have proven to be able to solve the previous state of the art problems, which has been a challenge in the traditional methods, for example how to detect faults that is early enough for system operators to act and how to optimize the performance of an interconnected power system to achieve higher efficiency. This thesis dives into the novel technology and emphasizes the improvement over traditional methods.

1.1 AIoT Technology

A new field after IoT technology, recently, more application and technologies combine artificial intelligence (AI) and IoT to each other. The sensors collect information on the system status, based on which the intelligent algorithms in the IoT devices as well as the edge or cloud servers to generate real time actionable insights or make control decisions for the actuators to react. The two fast developing fields have merged into the new application, called "AIoT (Artificial Intelligence Internet of Things)" has created a new pattern among industries. Chapter 2 presents the latest AIoT technology.

1.2 Distributed Energy Resources

An increase in an overall world trend in the awareness of climate change and the need for mitigation efforts is bringing forth huge increases in the deployment of renewable energy in comparison to fossil fuel energy sources. There are several driving factors for the remarkable growth of renewable energy systems (RES) with increasing efforts in research and development in the areas. The yearly growth in the capacity of renewable power plants is becoming greater than the total investment capacity added in power plants based on coal, natural gas, and oil all combined together [1]. RESs have gained significant share of power source (See Figure 1-1) the trend will continue increasing at faster rates as demands for clean energy sources are continuing to grow.

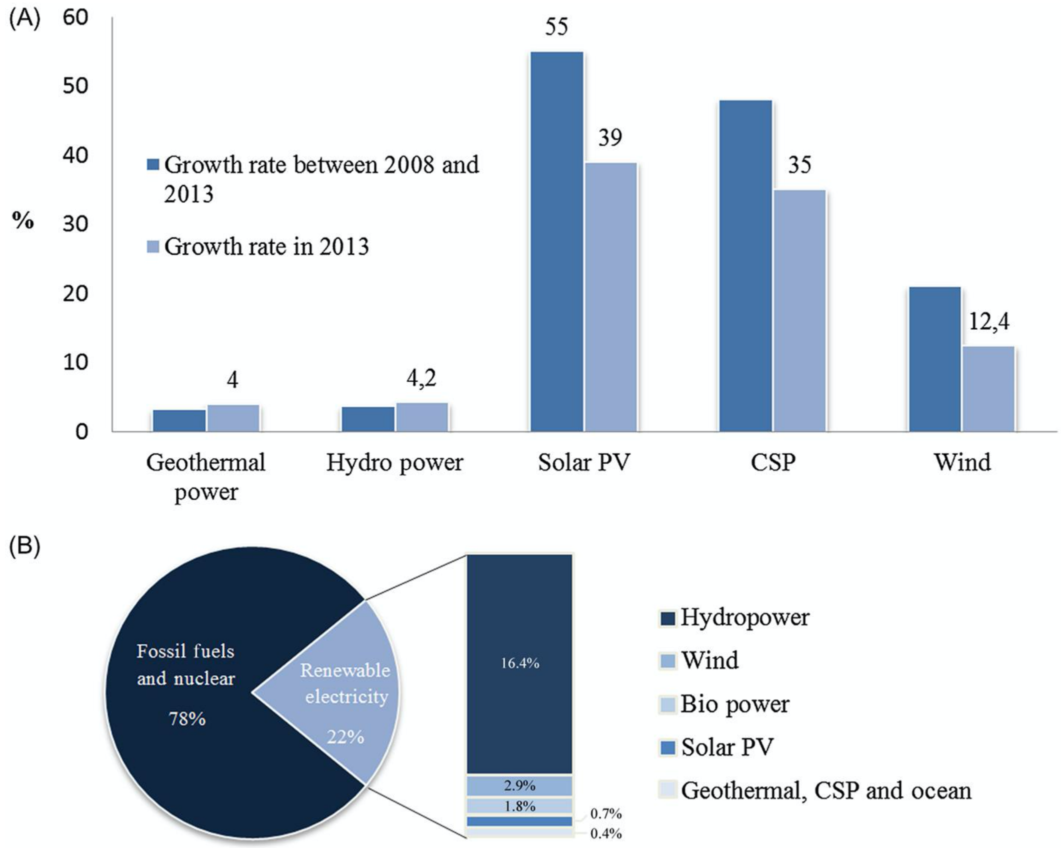


Figure 1-1 (A) Average annual growth rates of renewables (2008–13); (B) global electricity production (2013)

1.3 Thesis Chapters

Based on the aforementioned information, the chapters of this thesis are arranged as follows: Chapter 2 presents AIoT architecture and application; Chapter 3 summarizes all faults that can be found in a photovoltaic system and in renewable transformers, describes the data-driven models, supervisor learning and unsupervised learning algorithms will be presented; Chapter 4 describes a novel type of AI application to predict Remaining Useful Life (RUL); Chapter 5 presents AI driven optimization techniques for photovoltaic systems, energy storage and demand response; Chapter 6 presents the overall virtual power plant (VPP) and present aggregate model of VPP with all AI technologies; Chapter 7 reaches the conclusion.

2 AIoT Distributed Energy Resource

2.1 What is AIoT?

AIoT is short for AI + IoT, the combination of artificial intelligence technology and the Internet of Things in a practical application. The Internet of Things (IoT) connects a huge number of device and machinery to the Internet; in a distributed energy resource (DER) world that includes all the power sources, end node and transformer switches, etc. The IoT sensors generate massive amounts of data to reflect the status of the power system from the generator to the end users. These data are processed and analyzed by software with machine learning (ML) and artificial intelligence (AI) algorithms. The objective of such systems is to make better decisions to operate those systems in the physical world.

IoT is about sensors implanted into machines, which offer streams of data through internet connectivity. All IoT-related services inevitably follow five basic steps called: “collect, aggregate, analyze, insight and act”. Without artificial intelligence, “analyze, insight and act” steps are mostly conducted by humans. Because of the large amount of data information which is beyond human comprehension, most of the important value from IoT data were lost or untouched. This is where the AI technology plays a crucial role to enable the value of IoT. The convergence of mature IoT and artificial intelligence technologies has evolved into "AIoT".

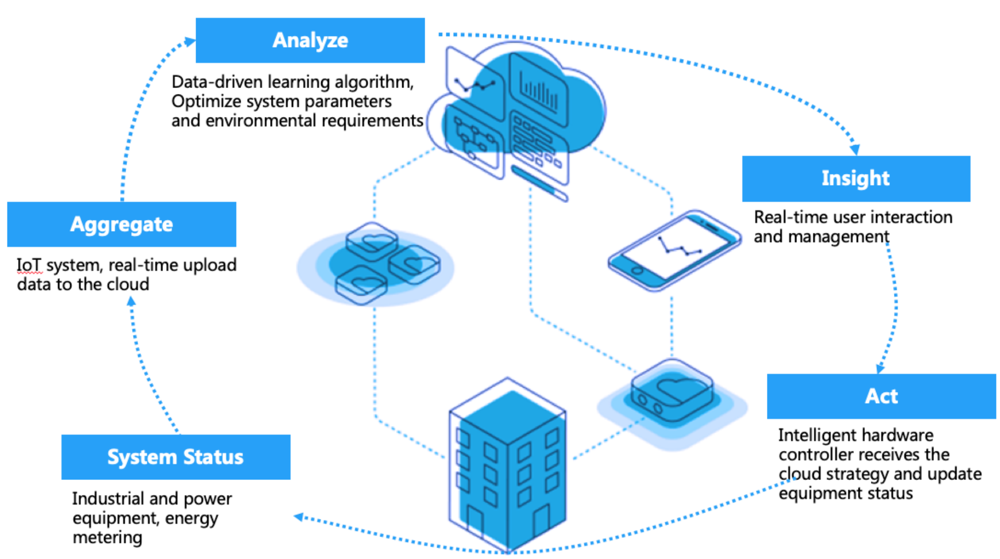


Figure 2-1 AIoT System Data Flow

Massive data from traditional industrial equipment have been collected to the cloud. How to manage and analyze big data and gain insights posts new challenges. In order to make the devices algorithm-driven, it is crucial how the device equipped with artificial intelligence is seamlessly connected to the huge database. Therefore, the networking framework is the key factor for AIoT system. In addition, the equipment has a large number of sensors, but is limited by the quality of the sensors and the lack of original construction, and therefore the data quality is relatively low. Overall, Industrial equipment has low data stability, missing data, incompatible formats, high uncertainty, high dimensionality.

It is important to point out that the advancement of IoT and AIoT cannot be achieved without the development of new communication technologies, such as 5G (fifth-generation mobile communication technology). The 5G low-energy and low-latency is a key feature technology that promotes the AIoT. Some of the distributed energy resources (DER) such as solar farm and transformers, deploying a wired communication is not feasible. With 5G, a large amount of data can be uploaded to the cloud through 5G for artificial intelligence analysis.

For distributed energy resources (DER) systems, it is especially valuable after a large number of connected machinery and sensors are connected via a closed or global network, they are different from the operation mode of previous unconnected generation. Artificial intelligence advances the evolution of DER in addition to the IOT connectivity. They can automatically recognize errors, autonomously optimize system operations and predict future outcome. With AIoT, a DER system can be defined as a "smart energy system".

2.2 Types of AI Learning: Supervised versus Unsupervised

In the artificial intelligence world, learning is a process that improves the behavior of an algorithm by making adjustments based on the observations or training dataset. The more training data are fed into the algorithm, the better the algorithm performs. There are two types of learning. Supervised learning is the most common one. Supervised machine learning algorithms are designed to work with existing datasets. When training a supervised learning algorithm, the training data will consist of inputs paired with the corresponding outputs. Supervised learning is primary used to perform classification and regression. Unsupervised learning refers to a set of artificial intelligence (AI) algorithms to train on data sets which only contain input data. There are no corresponding outputs, which are called unlabeled. Unsupervised learning is primarily used to recognize patterns or behaviors. Following diagram shows the different types of learnings.

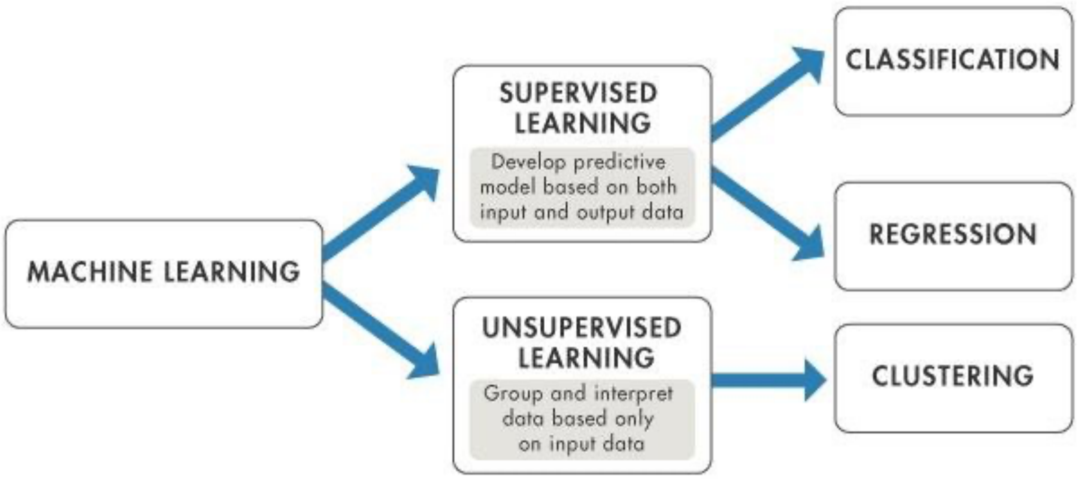


Figure 2-2 Supervised Learning versus Unsupervised Learning

Artificial intelligence technology enables DER systems to learn from its previous data, make predictive analysis, or assist in decision-making after analysis. The low-cost availability of IoT data is very important for the artificial intelligence learning algorithms and generate valuable insights. So, AIoT is the central piece of the modern DER system.

2.3 Benefit of AIoT in Distributed Energy Resources

AIoT leads to a broad range of benefits for energy systems such as proactive actions and real time intelligent automation, which boost the productivity and profitability of the renewable energy industry.

Boosting Operational Efficiency

Accurate and real-time data analytics are required to improve renewable energy generation efficiency and capacity. AIoT will help renewable energy companies to manage the large capacity of assets located in remote and widely distributed areas, which can be very complex. AIoT can analyze asset data in real-time with sophisticated algorithms. In addition, machine learning coupled with AI can predict the operation conditions. Technology can be used to ensure that energy transformation is evenly distributed. AIoT can detect a change in demand and supply and automatically provides operators with information to react to these changes and increase efficiency. Hence, AIoT offers an insight into which processes are redundant and time-consuming, and the productivity of renewable energy assets can be improved.

Better Production Management

Decisions about energy generation, load switching, and network configuration changes are constantly changing in Distributed Energy Systems. Insightful information provided by AIoT data analytics can provide insights to predict power production and asset reliability. For example, AIoT offers real-time access to a solar farm's operation status which can be turned into actionable insights, predict a broad range of risks, and automate for the prompt response.

Reduces Costly Downtime

Renewable energy includes solar panels, wind turbines, and transformer equipment which are remote and difficult to access. The predictive maintenance with AIoT can predict the equipment failure in advance and schedule proactive maintenance procedures. Hence, with AIoT, DERs can reduce unplanned downtime, resulting in lower operating cost.

Deloitte, for example, finds the following results with AIoT:

20% - 50% reductions in their time invested in maintenance planning

10% - 20% increase in equipment availability and uptime

5% - 10% reduction in maintenance costs

2.4 Architecture of AIoT System

AIoT will evolve the existing IoT standards to form autonomous future communication architectures to support the intelligent exchange of data between millions of devices. The architecture AIoT system consists of four layers: IoT hardware, communication layer, cloud infrastructure and data analytics.

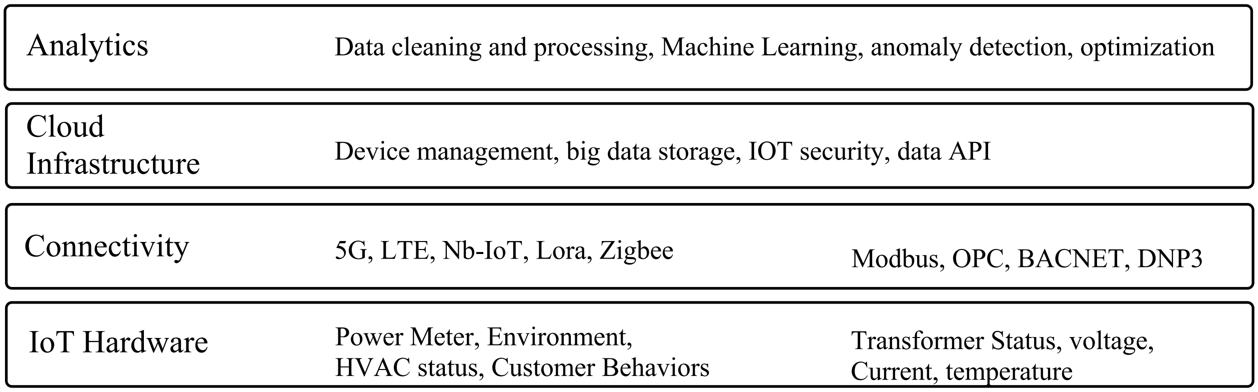


Figure 2-3 AIOT System Architecture

IoT Hardware: The energy assets contain their own data source that require hardware to interface with them. Low cost IoT sensors can also be installed to collect assets' status such as power, flow rate, pressure etc. IoT devices include transducers such as sensors and actuators. With the low cost and low power IoT hardware, the traditional power equipment become connected, such as smart light bulbs, connected valves and pumps, smart meters, connected power plants, smart building components etc. IoT devices are essentially capturing the data, which is the platform of AIoT architecture, the foundation of connected and intelligent solutions. It enables IoT related smart application for the upper layers.

Connectivity Layer: responsible for gathering data and transferring over a network. The main components that complete connectivity layer are sensors and devices. Sensors collect the information and send it off to the next layer where it is being processed. With the advancement of technology, semiconductor technology is used that allows the production of micro smart sensors that can be used for several applications.

The communication layer is considered as the backbone of the IoT systems. It is the main channel between the application layer and IoT hardware layer. AIoT system is loaded with vast amounts of data and information that need to be shared within the network. Therefore, it is needed to set up a low cost and low bandwidth connection network among these nodes. The communication layer needs to interpret all industrial equipment communication protocols such as Modbus, DNP3, and transfer using either wired or wireless protocols such as Lora and NB-IoT and 5G. So, this is a broad layer with multiple devices, technologies, solutions (software and hardware) and functions. Typically, IoT gateways are used for connectivity aggregation, translation of the various protocols, encryption and decryption of IoT data, the management of IoT devices, some advanced edge computing. Moreover, networks are very vital components in AIoT to connect things to the outside world.

Cloud Infrastructure needs to be able to manage a large number of the IoT endpoints in the fields, secure communication, authentication, and verification. With IoT platforms are software infrastructures between hardware-related layers of IoT devices and the business and application layers on the above.

It also provides the infrastructure of big data storage and computation resources. One of the most important components of IoT cloud is database management that is distributed in nature. The cloud basically combines many devices, gateways, protocols, devices and a database that can be analyzed efficiently. These systems are essential of AIoT architecture in order to provide efficient data analysis that can help improve the services and products.

Data Analytics Layer: The most important function of IoT technology is that it supports real-time analysis that discover anomaly and perform optimizations. This layer employs different data science and analytics techniques including machine learning algorithms to make sense of the data, can use data to find trends and gain actionable insights, to evaluate the performance of devices, to help identify inefficiencies, and to create more efficient models for control applications. As shown in Figure 2-4 Data analytics is the brain of the overall AIoT system, which can help improve energy operations, efficiency or even predict future events like machine failure.

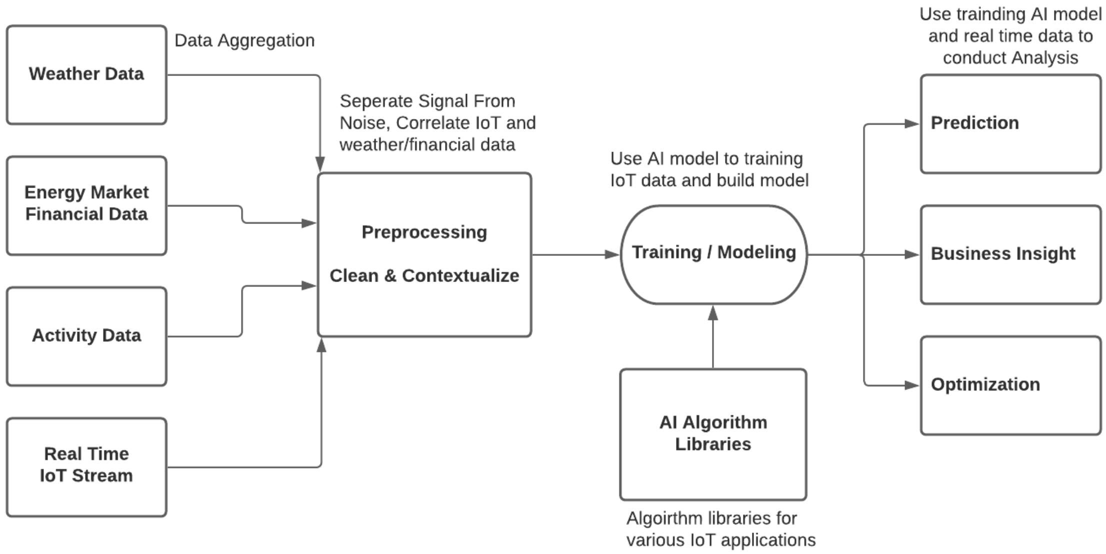


Figure 2-4 AI Data Process Flow for IoT Applications

2.5 Growth Renewable Energy

For all the use cases from the generator, distribution to demand load, which also includes the renewable energy sources and overall power grid balance, the benefits can be categorized as following charts, which consist of energy source site optimization, grid (transmission & distribution) services, and generator & energy trading. Global supplies of renewable electricity are growing faster than expected and could expand by 50% in the next five years, predominantly driven by solar energy. The United States solar energy market is expected to grow at a CAGR of 17.32% during 2020-2025.

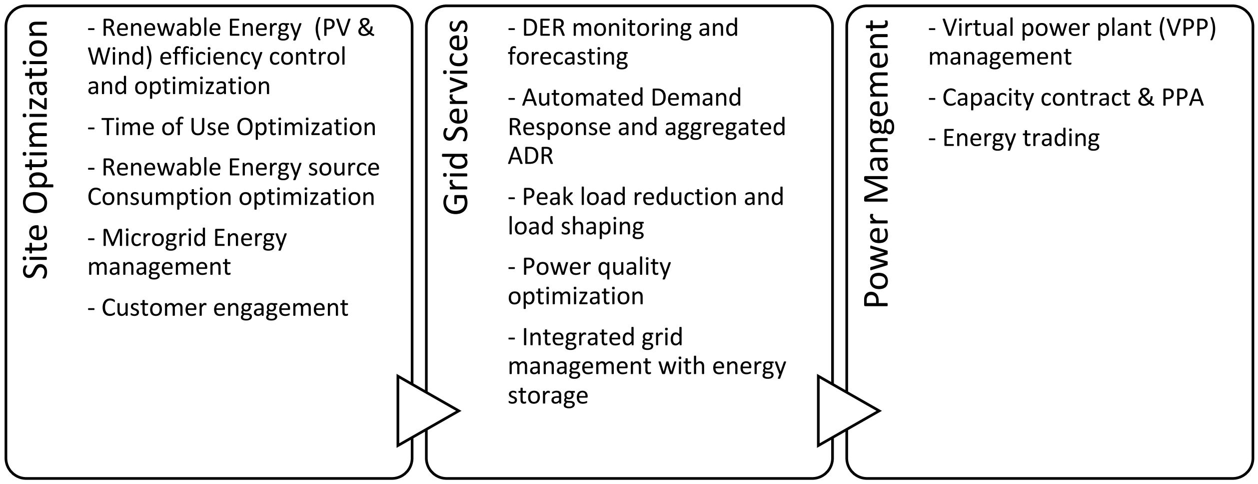


Figure 2-5 Renewable Service Flow Chart

2.6 AI Analytics of AIoT System

Traditionally, IoT devices were all about collecting data. Combining with Artificial Intelligence algorithms, AIoT can analyze data patterns, predict future energy generation and provide business intelligence to enhance operation. In certain cases. In some cases, AIoT can control the system in automatically, which can increase the system capability and reduce human involvement. Following are three areas AIoT can generate values that will be described in the thesis in detail:

Fault Prediction: Using multi-source sensing data to predict grid and machinery failure, to achieve predictive maintenance of energy production and mechanical equipment can remarkably improve the distributed energy resources (DER) grid and energy reliability.

Service Life Prediction: AI algorithm and machine learning technology can take fault prediction one step further. With remaining useful life (RUL) or service life prediction of critical grid components, DER can drastically improve the reliability and reduce cost of maintenance.

AI Enabled Optimization: AI-enabled algorithms can automate processes and make real time system optimization. Not only AI algorithm can make better decisions than human, they are also self-learning and improve and adapt automatically to whatever the grid or energy market environments.

3 Fault Prediction

3.1 Overview

Traditionally, faults of DER components can be detected by constantly monitoring the system performance. With the increasing accessibility of sensor data and artificial intelligence algorithms, fault prediction is a new method that allow the identification of eventual failures before they occur. With development of distributed energy resource (DER), energy demand and supply components are becoming more sparsely located, there is often the need to answer the question: when will the system fail? Fault prediction is data driven reliability algorithms capable of analyzing data, and creating machine learning-based predictive models to critical energy components such as Photovoltaics and transformers.

3.2 IoT Sensor Devices for Photovoltaic Systems

Sensors are the enabling assets of IoT systems. They collect and transmit data in real-time. In DER systems, there are pre-existing sensors and newly installed sensors to sense and collect data, for further processing, analytics, and decision-making. There are following commonly used sensors:

Circuit Sensors are commonly low power IoT Current and Voltage Sensor which measure the basic performance of the device. Current is measured Current Transformer (CT) sensors measure alternating current (AC) flowing through. Some advanced circuit sensors include the capability to measure the harmonic and power factor for AC power.

Environment Sensors are used to detect the fluctuations in environment such as temperature, humidity, solar radiation. Light sensors are used to measure luminance (ambient light level) or the brightness of a light, which are used for solar radiation. Humidity sensors are used to distinguish the amount moisture and air's humidity and temperature sensors are used to detect the fluctuations on the surface. Both humidity and temperature have direct impact of Photovoltaic panel performance.

Activity Sensors are used to measure all human activities external to the IoT equipment themselves. Activities are often related to the load or demands. The common activities are Passive Infrared (PIR) sensors and Proximity sensors which provide feedback to control system output.

Mechanical Sensors are used to measure variables such as position, velocity, acceleration, force, pressure, levels and flow. For example, Inertial sensors, such as accelerometers or gyroscopes can be used to measure position or motion. A popular application is for vibration analysis, which can be used for earlier fault detection. Piezoresistive sensors respond to changes in pressure. Flow sensors can be used to measure liquid flow.

Following is an example diagram to monitor solar panel (PV) performance using wireless IoT devices.

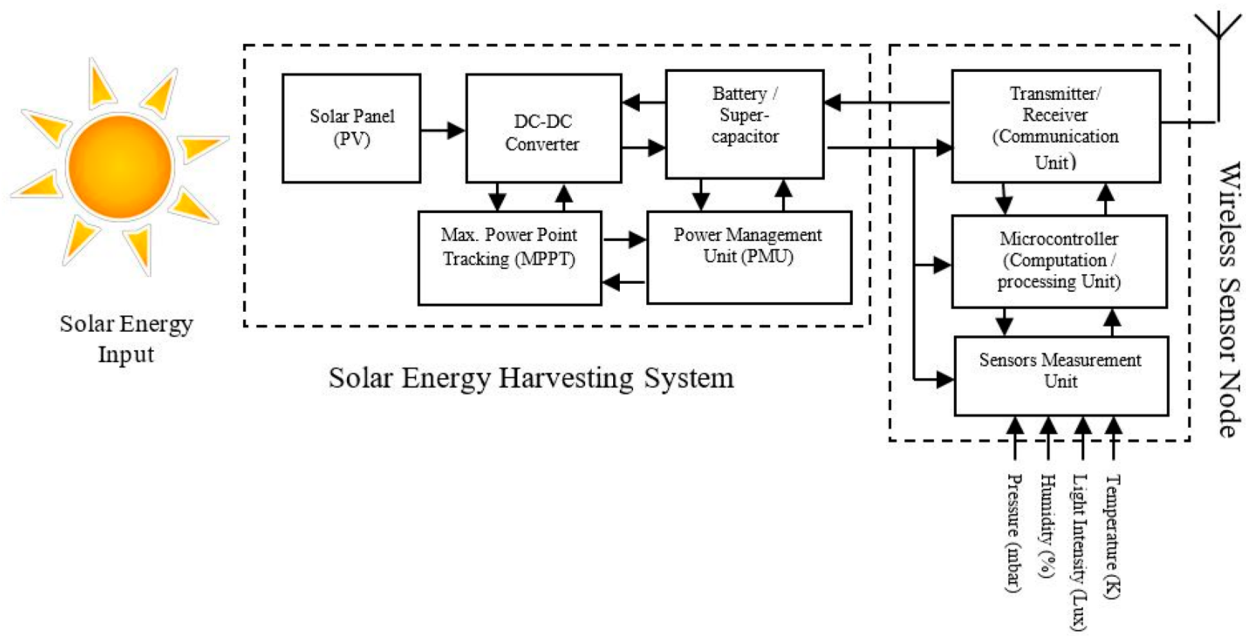


Figure 3-1 Block diagram of Solar Energy Wireless Sensor Network [2]

3.3 Fault Detection of Photovoltaic Systems

Photovoltaic system faults are often considered as the system failure or functional deterioration, and their major consequence is the energy collecting losses or inefficiency, respectively. Even worse, Hot spots or short circuit faults might be further led to fire accidents [3]. Those effects significantly increase the maintenance costs from a long-term perspective and threat the annual photovoltaic system operation. Therefore, many engineers and researchers have attempted to find possible strategies for carrying out the digital fault detection through the monitoring data.

Remote fault detection can replace many investigation and inspection work, which were previously carried out by operation engineers. Since photovoltaic faults are often caused by certain physical reasons, based on the conventional physical model fault detection can be carried out with reliable interpretability. However, due to the uncertainty within the monitoring data and faint environment conditions, the photovoltaic faults can hardly judge only by means of the physical models. To alleviate engineers' workloads and further reduce operation and maintenance costs of enterprise, the fast-growth demand is on the intelligent detection and enhancing the detection accuracy. Together with the fast development of big data technologies and cloudy computation sources, lots of novel data-driven models for handling the photovoltaic fault detection have emerged in last decades. Since physical and data-driven models are suitable for different application scenarios and accuracy, this thesis offers a comparison study between those two types of models; as well an analysis of their hybrid models is also presented.

The probable triggering factor of photovoltaic system faults can be concluded as physical, electrical, environmental, mis-operational and other factors [4]. Mis-operation due to human activities during installation or maintenance is easy to be monitored but difficult to be detected in the light of any physical or data-driven models. Therefore, the impact of mis-operation factor on the photovoltaic systems will be ignored, where the primary focus lies in the inherit physical, mechanical or electronic faults. The environmental factor often comprises of corrosion, rodent chewing, water ingress, mechanical damage and aging, which are also considered as the major trigger factors of causing the mechanical and electrical failure of photovoltaic systems.

The ultimate goal of the fault detection is to reduce maintenance costs and guarantee the secure system operation. To reach those points, many researchers and experts have attempted to find a reliable and accurate solution for the fault detection based on physical or data-driven models in the last decade. Notice that, two key issues should be ascertained through the fault detection, namely the fault type and location, which provide the useful and helpful information to the related maintenance workers of the photovoltaic systems [5].

Successful fault detection can work as an "expert", who possesses reliable and rich experience, for the photovoltaic system and his major task is to identify the fault types as well as to raise the fault signal in real time. According to the literature review, common photovoltaic system faults are accounted in this thesis, which can be generally summarized as five main types, namely open circuit, short circuit, shading, degradation and hot spot faults [4]. Each type of fault corresponds to certain physical phenomenon and can be detected through both I-V and P-V curves. Notice that, the inverse analysis, namely to make conclusions based on I-V or P-V curves, are not totally reliable, since faults are often subjected to certain circumstances. The aforementioned physical and data-driven models are applied for detecting faults and identifying fault types.

From the time series perspective, fault detection can be before or after the failure occurs, corresponding to forecasting or back-analysis, respectively. There were many previous works focused on photovoltaic fault classification, detection and forecast, and among them physical models possessed most part, e.g. one diode model (ODM), the voltage and current characteristics of the PV module (I-V curve), the power and current characteristics of the PV module (P-V curve).

Physical models are often regarded as the major solution for the fault detection and it has strong theoretical support and interpretability, due to the fact that physical models are described by a series of analytic solutions as usual. It is therefore nature to identify the distinction between normal and abnormal states by means of the threshold definitions. The result of using thresholds is stable and for most time is reliable and data independent. Besides, thresholds can be flexibly adjusted depending on the local environment and corresponding photovoltaic systems. In practice, physical models can be applied both on-site and remotely. Nevertheless, physical models are subjected to the cases without target labels and are also hard to conduct in undefined cases, e.g., anomaly detection. Indeed, those types of cases can only be treated by employing the data-driven models.

Artificial Intelligence based data-driven models are often selected as an advanced solution for the fault detection and nowadays it can be combined with big data and cloud computation technologies to facilitate its calculation speed. Besides, data-driven models can also provide more data analysis tools for exhibiting and capturing the faults' behavior of photovoltaic systems than the conventional physical models. Digital insight for the remote monitoring and fault detection can replace lots of the inspection workload. Within data-driven models, artificial intelligent algorithms play an important role and they are often applied throughout procedure of the data preprocessing, processing and post-processing. Based on the analysis of fault phenomenon of photovoltaic systems, the appropriate artificial intelligent algorithms are selected for modeling the fault detection, for instances, artificial neuron network (ANN) [6], probabilistic neuron network (PNN) [7] [8], Bayesian networks (BNN) [9], residual neuron network (ResNet) [10], fuzzy logical ([11] [12], etc. In addition, data preprocessing is another assignable part for artificial intelligent applications in solar energy field. Many researchers and experts have attempted, e.g., Kalman filter [13], fast Fourier transformation (FFT), etc., to gain the clean data.

3.3.1 PV Fault Classifications

Following are the leading faults detected in PV panels.

Open-circuit Faults

Open-circuit faults are directly caused by the disconnection of cables or connector, and leading to power losses of the PV system [10]. Open-circuit faults are easily to identify, since there are no current from the damage PV array even under the illuminated condition.

Short-circuit Faults

Short-circuit faults represent accidental connection or low-impedance among two points in a PV array [14], which may be caused by insulation damage of cables (due to corrosion, rodent chewing, water leakage, aging, etc.), PV module internal damage, mis-operation during installation or maintenance, etc. Short-circuit faults can be further classified into line-line and line-ground faults, and they would lead to a large reverse current flow that obviously reduce power output and even results in electric shock and fire disaster [10].

Line-Line Fault

An LLF is defined as an accidental short circuit between any two points of different voltage potentials [15].

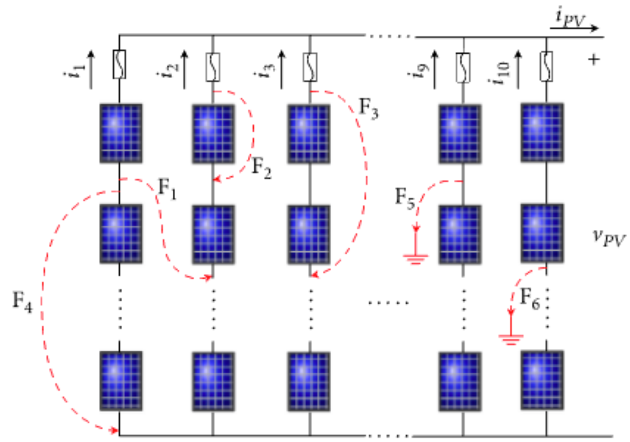


Figure 3-2 PV array configuration showing possible line-to-line faults and ground faults [16]

Arc Fault

AF is a high-power discharge of electricity across an air gap between conductors [17, 18]. Series AF is said to have occurred when the arc is initiated as a result of a discontinuity in any of the current-conducting conductors. Parallel arc faults: parallel faults also occur due to mechanical damage, nesting rodents, or failure within the PV module [4].

Series Arcs Fault

Series arcs can be created across small gaps between two connecting terminals such as busbar-ribbon connection in PV modules and connection in combiner box. The lack of scheduled maintenance, aging effect, weather effect (i.e., corrosion caused by rain), mechanical damage induced by wind, animal bites, improper wiring can cause bad joints. Bad joints decrease the cross-section area, effectively increases the connection resistance, and significantly increase the heat loss. It introduces more thermal stress due to the higher operating temperature, and accelerates the deterioration in connections, which leads to loosen connections [19] [20].

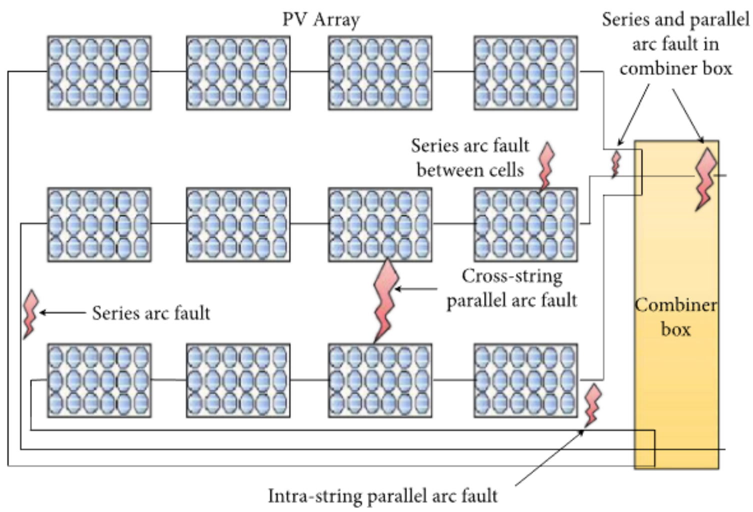


Figure 3-3 Possible locations of AFs in a PV array [16]

Parallel Arcs Fault

Parallel arcs have the similar mechanism as series arc faults. They can be developed between two conductors in the same string, two conductors of two different strings, and conductor and grounding point [21]. The parallel arc faults are mainly caused by degradation and breakdown of insulation because of various reasons such as animal bites, mechanical damage, and aging effect, because most of cables and wires are exposed to the open environment (no protective enclosure) in PV systems [22].

Ground Fault

Due to the existence of a high potential difference between the location and the ground, a substantial amount of current ensues. In contrast, the existence of low voltage between location and the ground leads to a lower fault current. Another indicator of GF severity is percentage mismatch, which specifies the number of PV modules involved in the fault [4]. It is reported that cable insulation failure, accidental short-circuiting of normal conductor and ground, PV module encapsulation deterioration, water corrosion, and impact damage are some of the causes of GF [15].

Partial Shading

Partial shading mainly refers to partly different irradiance input of PV modules in a PV array (due to soiling, dirt, leaves, obstruction by buildings, trees and so on) [23], which may cause power losses and hot spots in PV modules [10].

Degradation Faults

Degradation faults commonly result in an increase of the equivalent series resistance or decrease of the parallel resistance, which would mainly lead to significant decrease of the parallel resistance, which would mainly lead to significant decrease of power [10].

Hot Spot Fault

Hot spot is a condition which occurs in PV cells and modules when the electrical characteristics of series connected cells/modules of PV string become mismatched. A sustained hot spot gives rise to HSF [4].

Table 3-1 Types of PV array faults according to triggering [4]

Fault Reasons	Manifestations	Subtypes	Symbols	Physical Models	Data-driven Models
Disconnection	Open circuit		F_1	√	√
Corrosion, rodent chewing, water leakage, aging, etc.	Short circuit	Line-Line Fault	F_2	√	√
		Ground Fault	F_3	√	√
		Arc Fault	F_4	√	×
Cloudy, trees, buildings, etc.	Shading	Permanent Shading	F_5	√	√
		Temporary Shading	F_6	√	√
Aging	Degradation		F_7	√	√
Manufacturing defects, cracks, shading, degradation, bird droppings, damage to bypass diode, etc.	Hot Spot Faults		F_8	√	×

3.4 Data-driven Models

Physical detection approach often requires an explicit mathematical expression, or physical instruments to depict the component or system circumstance. Data driven model could provide useful and powerful information for revealing the relationship between inputs and outputs, even without the detail knowledge of the complicated systems. Hence, data-driven models provide a novel insight to find the solution for fault detection. In this Section, an overview of what data-driven models were applied in the PV system fault detection is presented, followed by more focus on the link between data-driven algorithm and PV system faults.

An increasing number of researches are investigating on data-driven models used in PV system fault detection. Figure 3-4 shows that the information driven methodologies are increasingly more popular in PV detection. During 2011 and 2014, just 1 or 2 papers were recognized on the utilization of information driven models for PV framework issue identification, and this number drastically increments to 8 or 9 of every 2017 to 2019.

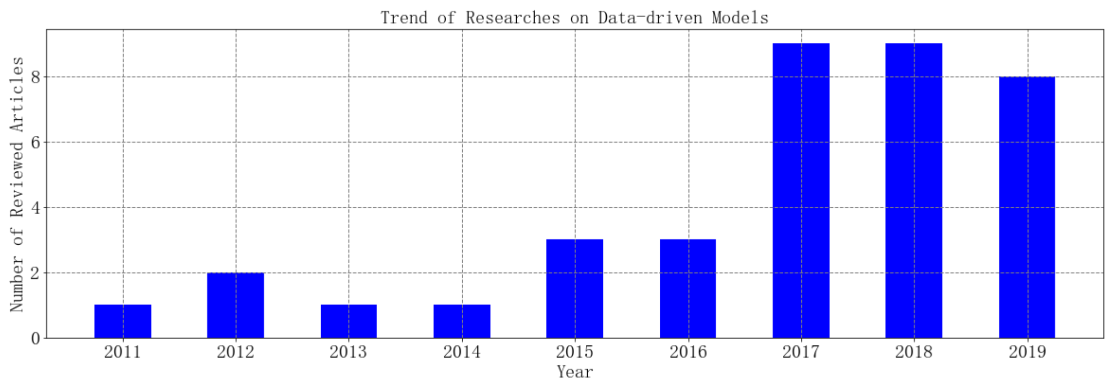


Figure 3-4 Trend of researches on data-driven models used in PV system fault detection

Figure 3-5 illustrates different sub-categories of data-driven fault detection algorithms. Two primary types involved include fuzzy logic and machine learning algorithm. In practice, fuzzy logic approach often converts a binary fault detection process to a fuzzy process, where events can be assessed by the probabilities. Machine learning algorithm, including supervised and unsupervised algorithms, more depends on training data to obtain the internal relationship between measured inputs and expected outputs.

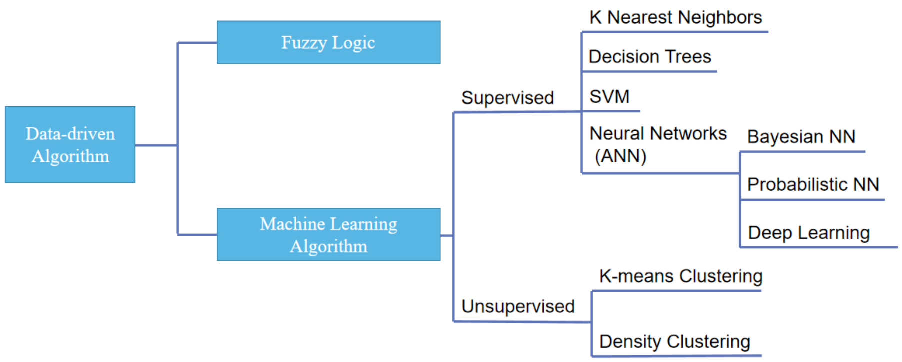


Figure 3-5 Methods used in Data-based fault detection algorithm for PV systems

3.4.1 Fuzzy logic algorithms

Fuzzy logic algorithms were presented in seven articles [11], [24], [25], [8], [26], [27], [12]. Fuzzy logic algorithm turns precise mathematical to mapping the probability of certain events. Used in industrial process for years, fuzzy logic algorithms show pretty good robustness, convenience and fitness for non-linear problem. However, it also requires extensive experience to extract a reasonable and reliable relationship.

3.4.2 Machine Learning and Deep Learning Algorithms

As the hottest type of algorithm nowadays, machine learning algorithms have been successfully applied in computer vision, natural language processing, and man-machine confrontation. When it comes to deployment, machine learning algorithms are also easier to implement with mature developed packages and tools in various programming languages. Inside the group of machine learning algorithms, there are supervised algorithms where labels are required during the training phase, and unsupervised algorithms were not. However, as for the application of PV system fault detection, even the unsupervised algorithms require reference labels to mark the fault type, which makes them close to semi-supervised algorithms. The possible reason that no pure unsupervised algorithm was spotted could be that the fault detection application requires a specific fault output, not only a description (e.g., a most common seen application is, user portrait).

Table 3-2 Summary of Machine Learning Algorithms for PV Diagnosis

Algorithms	Number of Articles	References
SVM	4	Yi 2017 [25], Harrou 2018 [28], Jufri 2019 [29], Alajmi 2019 [30]
Decision tree	3	Zhang 2012 [31], Benkercha 2018 [32], Chen 2019 [10]
ANN	4	Polo 2015 [6], Chine 2016 [33], Mekki 201 [34], Dhimish 2018 [26]
PNN	1	Garoudja 2017 [7]
Deep network	1	Chen 2019 [10]
K-means	1	Liu 2019 [35]
K-nearest neighbors	1	Madeti 2018 [36]
Other neural network	2	Chao 2014 [18], Liu 2019 [12]
Self-developed algorithm	5	Dhoke 2019 [3], Lin 2017 [37], Chen 2019 [10], Zhang 2012 [31], Liu 2019 [12]

Supervised Learning Algorithm

Most of the machine learning algorithms used for PV fault detection fall into the group of supervised approaches, for the reason that labels can ensure an accurate and reliable detection result.

Among supervised algorithms, a large group of researchers turn to neural networks for PV system fault detection, including traditional ANN (including back-propagation neural network), probabilistic neural network [7], [8], and Bayesian neural network [9]. It can be seen that neural networks are able to well fit the non-linear relationship observed largely in PV system fault detection, but still lack comprehensive physical explain of the models. There are also researchers attempting to utilize other algorithm or combine several algorithm ideas to create their own algorithms.

Semi-supervised Learning Algorithm

For those semi-supervised algorithms, the majority of the data used for training were not labeled. Under this circumstance, the basic idea of semi-supervised algorithms is that researchers first applied unsupervised algorithm to find a proper clustering solution, and then use in the light of a small set of reference data to finalize the detection result.

The model inputs for semi-supervised approach are evidently different compared to those for supervised approach. To better differentiate different clusters, normalization of the inputs is inevitable. After the pre-processing step (normalization) and the post-processing step (matching reference labels), different techniques utilized unsupervised algorithm to cluster the data samples. [15], [8], and [12] selected a center-based clustering method, where samples are clustered based on their distance to predefined and adjusted clustering centers. On the contrary, [37] used a density-based clustering method, where each class is extended based on samples' distances between each other.

3.4.3 Hybrid Approach

It was also noted during the research review that data-driven detection approach is not completely separated from physical model approach. Some data-driven intelligent algorithms can intervene in the early design phase of physical detection. [38] and [7] made use of Artificial Bee Colony (ABC) and applied Particle Swarm Optimization (PSO) algorithm, to extract key parameters to fit a physical PV model for fault detection.

3.5 Fault Classification of Renewable Transformer Station

Power transformers are also among the most expensive and complex equipment components. A power transformer is a piece of equipment that is of great importance to the electronic system (See Figure 3-6). Therefore, it is critical to improve the accuracy of fault diagnosis of power transformers. Power transformers are composed of oil, paper, copper, steel, iron and other materials. With the growing renewable energy sources such as photovoltaic, power transformers are becoming more and more towards large-scale and complex, with high complexity integration because of the volatility of the new renewable power sources.

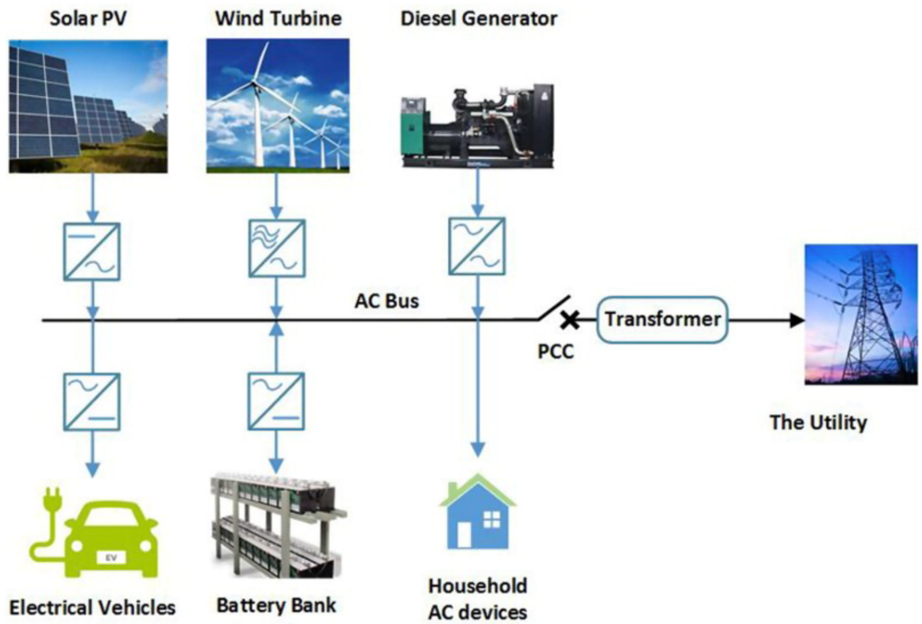


Figure 3-6 Power Transformer and Renewable Energy Resources

Most of traditional fault detection and diagnosis research and analysis methods are based on a certain factor or several factors without comprehensively considering the operating conditions and defects of the transformer. Limitations of testing methods, imprecision of knowledge and other reasons, lead to ambiguity of the detection results, which causes maintenance crew difficulty to rely on the results to decouple interaction and fault evolution of the transformer. The accuracy and timeliness of the traditional diagnosis results are far from the practical requirements. Therefore, it is valuable to explore the new technical system which utilizes data analytics algorithms.

3.6 Transformer Fault Classifications

Power transformer aging is an important factor leading to grid failure. The breakdown cost of any transformer can be catastrophic. There are many types of transformer faults, and the classification methods are different. Generally speaking, according to the location of the fault, it can be divided into internal electrical faults, external mechanical faults and thermal magnetic circuit faults.

3.6.1 Electrical Failure

Short-circuit fault: mainly refers to the short-circuit of the iron core winding outlet and the short-circuit between the winding phases. When the short-circuit fault occurs, a short-circuit current that is dozens of times larger than the normal current will be generated in the transformer, generating a lot of heat, and the winding will break down in severe cases.

Discharge failure: Generally speaking, according to the instantaneous energy density of discharge, discharge failure can be divided into partial discharge, spark discharge, and high-energy discharge. The main discharge part has an air gap in the insulating layer, or when the insulating layer between windings is broken down, there may be time and high-density spark discharge.

3.6.2 Mechanical Failure

Insulation failure: The function of the transformer is determined by the service life of the insulation material. The performance of the insulation material determines the efficiency of the transformer. The factors that affect the insulation performance of the transformer are: temperature, humidity, overvoltage.

Iron core failure: When the transformer is in normal operation, there is only one ground terminal of the iron core. If two points are grounded, the iron core will overheat, and the transformer will be burned in severe cases.

3.6.3 Thermal Failure

The common fault related to transformer is that the oil temperature rises and exceeds the rated temperature. When such a fault occurs, first check whether the transformer load is within the capacity and cooling system is normal. The fault may also be caused by coil eddy current, short circuit of the internal winding of the transformer. The power should be cut off immediately for such case to prevent catastrophic failures.

3.7 Transformer Condition Monitoring Techniques

Transformers condition are commonly depending on the monitoring the tremendous data collected on power stations. Traditional transformer condition monitoring techniques have been developed to uncover issues and ensure the reliability of the power stations. Following are the four common techniques that have been developed [39].

Thermal Analysis of the transformers can provide useful information about its condition and can indicate any incipient fault inside it. Oil temperatures are direct indicator of the condition and capacity of the transformers. [40]

Vibration Analysis has been widely used yet relatively new for conditional monitoring for major machinery. Its research and development for transformer application has been developed. The health condition of the core and windings can be assessed using vibration signature of transformer tank. [41]

Dissolved Gas Analysis (DGA) analyzes gas emission from the oil-based insulation of transformers and their correlation with electrical performance. The problem of the usage of DGA analysis in assessing the condition of the transformer is that it needs special equipment to measure the dissolved gases. [42]

Frequency Response Analysis (FRA) method uses Fourier Transform technique to the signals of a transformer winding, and use the frequency signatures to detect transformer mechanical structure and windings defects. [43]

3.8 Data Driven Models

Traditional methods of diagnosis include dissolved gas analysis (DGA), Thermal/vibration analysis, and frequency response analysis (FRA) have been widely used in industries. However, these methods are complicated to deploy and exabit low detection accuracy [44].

With the continuous development and the deployments of sensor monitoring on transformers in the field and internal status, the data collected presents the characteristics of multi-source and heterogeneous, which are well suited for data analytics. The data collected from transformers according to different data structures, they can be divided into two categories. (1) Structured data, such as temperature, voltage, DGA data, etc. (2) Unstructured data is such as images, videos, logs etc. Research has been developed utilizing both structured and unstructured data. How to use and process collected data continues to be the future development of the research direction of management of transformers.

The first data driven technique for power transformer fault detection has been to apply supervised or semi supervised learning techniques. Bacha etc. [45] developed a fault classification method of power transformer based on support vector machine (SVM) using train data to build a multi-layer SVM classifier. This classifier has superior performance in identifying transformer fault types. [46] presented an intelligent method for power transformer fault diagnosis based on selected gas ratio and SVM. They used a genetic algorithm (GA) to obtain the optimal dissolved gas ratio (ODGR) for DGA ratio selection and support vector machine parameter optimization. Zheng etc. [47] proposed a transformer stability prediction algorithm with an enhanced SVN algorithm called least squares support vector machine (LS-SVM). Their results demonstrated superior results relative to SVM methods.

The second common method for transformer diagnosis is a probabilistic neural network (PNN). Similar methods have been widely used in PV system diagnosis which was reviewed in the previous sections. Wang etc. [48] developed proposed their methods of probabilistic neural network (PNN), and they also applied the technique in Dissolved Gas Analysis. They also use particle swarm optimization (PSO) to optimize the parameters of PNN.

Similar to PV system diagnosis, the third method that was widely used is back propagation Artificial neural network (BP-ANN) or some time deep neural network. Trappey etc. [49] developed their data-driven models based on deep neural network to detect potential faults in transformers. The Principal component analysis (PCA) and BP-Artificial Neural Network (BP-ANN) are used in their models. Zhang etc. [50] developed a method of fault diagnosis for mechanical failures based on deep learning.

Yadaiah and Ravi [51] presented the methodologies for The Dissolved Gas Analysis to detect incipient faults and has been improved incipient fault detection in Power transformers for off-line and on-line method. An artificial neural network (ANN) is used to detect off-line faults and whereas Wavelet transforms are being used for on-line fault detection.

Lastly, there were many fuzzy logic-based techniques proposed. Three and four-digit coding with faulty information and fuzzy logic is used to improve the result by Wagh and Deshpande [52], and they have applied the method to Dissolved Gas Analysis of the transformer. Evsukoff and Schirru [53] proposed fuzzy logic systems for fault detection and isolation.

Table 3-3 Summary of Data Driven Algorithms for Transformer Diagnosis

Algorithms	*Number of Articles*	*References*
SVM	3	Bacha 2012 [45], Li 2016 [46], Zhang 2018 [47]
PNN	1	Wang 2009 [48]
Deep network	2	Trappey 2015 [49], Zhang 2018 [50]
Hybrid	1	Yadaiah 2007 [51]
Fussy Logics	2	Wagh 2014 [52], Si 2011 [53]

4 Remaining Useful Life (RUL) Prediction

As photovoltaic penetration of the power grid increases, accurate predictions of system performance require accurate prediction of decreased power output over time. An extension of fault diagnosis is to predict the failure, enhance the prediction accuracy and hence gradually becomes a major solution. Knowing the remaining useful lifetime (RUL) of particular equipment is of great importance for making good operational and financial decisions. For the aim of improving application of data driven algorithms on fault diagnosis and prediction, Remaining Useful Life (RUL) of photovoltaic (PV) modules and a transformer, RUL prediction can provide many advantages, such as: predicting in advance that something will happen, the time and location of the fault, predicting the life expectancy of the entire system, and improving the system operation reliability [54].

In Figure 4-1, it shows an example of the degradation profiles of historical run-to-failure data sets from an equipment are shown in blue and the current data from the equipment is shown in red. The measured data is converted into a Conditional Indicator. There is a predefined failure threshold, which the equipment Conditional Indicator cross over at the event of failure. Based on the historical Conditional Indicator trend, one can predict the time to failure, which is the Remaining Useful Life (RUL). [55]

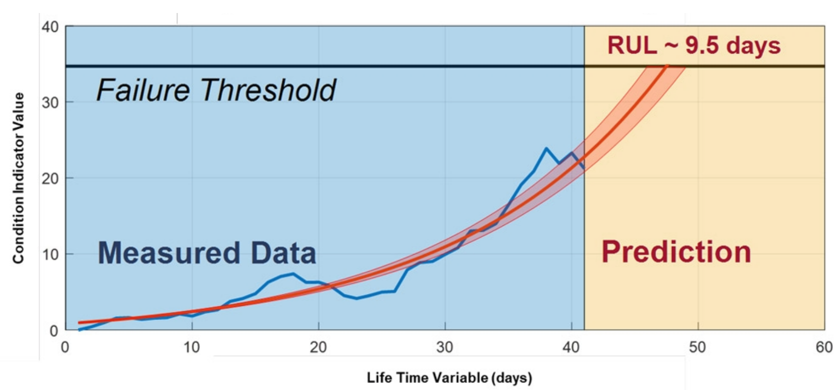


Figure 4-1 Illustration of RUL prediction.

Despite its importance, it is still a challenge to accurately determine how long a PV module or transformer system will continue to operate within its normal condition. The performance of a PV module or transformer system is influenced by multiple factors such as the environment, technology, workload, as well as installation quality. In order to determine the lifetime of a system, continuous monitoring is required and either physical models or mathematical models are utilized to make the prediction.

4.1 Physical Models

The ability to accurately predict system output is of vital importance to the growth of the photovoltaic (PV) industry. As we have described earlier, PV efficiency is mainly determined by sunlight radiation and power conversion. However, this relationship does change, and actually degrades, over time. An accurate quantification of power decline over time, also known as degradation rate is essential. Jordan and S. Kurtz [56] reviewed degradation rates of flat-plate terrestrial modules and systems reported in published literature from field testing throughout the last 40 years. Nearly 2000 degradation rates, measured on individual modules or entire systems, have been assembled from the literature, showing a median value of 0.5%/year. The following section explains several physics-based material degradation mechanisms to quantify the degradation rate of photovoltaic (PV) modules.

4.1.1 Cumulative Exposure Model

Subramaniyan etc. introduced the cumulative exposure model for quantifying the degradation path of PV modules [57]. Their approach starts from the physical fundamental of degradation, which is due to the exposure to sunlight and other environmental stresses. Because continuous exposure to these environmental stress factors initiates defects such as encapsulant browning, solder bond degradation, etc., over time the module power production decreases. The cumulative exposure model uses the information about environmental factors to calculate the instantaneous degradation using physics-based stress-effect function and then accumulate these stress effects over time to study the cumulative damage of environmental stress on module power output. The major assumption of the model is to quantify the degradation using a degradation function. The predicted cumulative degradation should be equal to the actual degradation measurement, which can be used to estimate the degradation function parameters.

4.1.2 Dynamic Covariate Models

Because a degradation process is a stochastic process, time-varying covariates have been incorporated into degradation models. Bayesian linear degradation path models [58], stochastic degradation models [59] and a time-varying model [60] were proposed. They introduced a time-varying component into the cumulative exposure model's degradation function. Hong etc. [61] extended this approach by using B-spline models to incorporate the unknown effect of dynamic covariates on the degradation behavior. Pan etc. [62] also showed that dynamic covariates can be incorporated to model the lifetime of PV modules with known degradation path. The article presents an approach to PV degradation modeling that includes the effects of module-specific stresses (module static temperature, module cyclic temperature) and other environmental stresses including cyclic temperature, ultraviolet (UV) radiation, and relative humidity (RH).

As these factors are material properties, any estimates should be reasonable to the specific material under study. In most cases, the unavailability of these parameters poses a serious hindrance to the determination of acceleration factors for various acceleration tests involving temperature, UV, RH, etc. Since the lifetime of PV modules depends on dynamic environmental factors, these physics-based models could aid in determining the functional form for covariate effects in building the cumulative damage model for PV modules.

In addition, there are other physics-based models such as Arrhenius model, Peck model, Coffin–Manson model, etc., for studying the effects of various environmental factors [63].

Combining the performance information collected over a period of time, as well as the environmental conditions like temperature (activation energy), radiation, etc., degradation function can be estimated. Once the model estimates are known, the degradation of corresponding module technology can then be predicted for other cases.

4.2 Data Driven Models

Degradation rate physical model-based monitoring degradation of existing systems to forecast the remaining lifetime of PV modules have already been used. However, issues related to physical models are that they strongly depend on the availability of data points related to the model. If an insufficient number of data points for the model is available, physical models' capability will be limited. In addition, physical models are not able to capture the underlining trend of the dataset and will be dominated by short-term effects in the dataset, which might not represent the actual performance evolution of a PV system.

Both statistical data-driven and machine learning based approaches were developed, which heavily rely on past observed data and statistical models to predict the occurrence of failures in the future time. RUL can be used to detect the state of PV modules or the transformers. These methods have great fault diagnosis capabilities, there are many intelligent and machine learning methods, they can be used and mathematical models are utilized to determine the lifetime of PV modules and systems in shorter periods. Data-driven techniques can be divided into two categories: statistical techniques (regression methods, autoregressive moving average ARMA model) and artificial intelligence (AI) techniques (neural networks (NNs), fuzzy systems (FSs), etc.).

4.2.1 Regression Model

A smart prognostic method for PV module health degradation and RUL prediction was proposed by Laayouj etc. [64]. The proposed model for prognosis aims to assess the machine's performance degradation, and a data-driven method based on the relevant vector machine (RVM) technique to predict degradation and RUL through the regression of diagnosis and prognosis in a manner that can take the strengths of each. To apply this method, an online monitoring process is first carried out to acquire the system's condition. The data obtained from the diagnosis can be properly managed and utilized by the RVM approach for making a prediction.

Sheng proposed an autoregressive moving average (ARMA) model-filtered hidden Markov model to predict the residual life for complex systems with multiphase degradation and to fit the multi-phase degradation data with unknown number of jump points, together with an iterative algorithm for parameter estimation [65]. They applied the model to predict the residual life of photovoltaic (PV) modules. Their experiment shows a degradation trend with multiple jump points, which are mixed effects of two failure modes: a soft mode of continuous smooth degradation and a hard mode of abrupt failure. Both modes need to be modeled jointly to predict the system residual life

(RUL). This algorithm converges fast with satisfactory parameter estimates accuracy, regardless of the jump point number.

4.2.2 Support Vector Machine (SVM)

Kyeong-Hee Cho etc. [66] proposed failure diagnosis logic using a support vector machine (SVM) classification as a failure diagnosis method that can classify normal vs. failure data. The failure data were processed to be used as the fault diagnosis logic for solar power generators. Their failure diagnosis method uses four years operational data for power generation and solar radiation of an operational 50-kW PV generator. Fault data were generated and the operation data of the PV generators were diagnosed by applying the proposed method to demonstrate improved accuracy.

Van TungTran etc. [67] proposed a novel method for assessing the machine degradation using only normal condition; only the normal operating condition of machine is used to create identification model for recognizing the dynamic system behavior. A “Degradation index” is used for indicating the machine degradation is subsequently created based on the root mean square of residual errors. They combined ARMA, PHM, and SVM in association with time-series techniques with prediction techniques for estimating the RUL. The result shows that the proposed method could be used as a reliable tool to machine prognostics.

4.2.3 Neural Networks

Artificial neural network (ANN) models have been utilized for better renewable energy prediction. They have been emphasis on understanding assets’ reliability issues utilizing ANN networks with prediction techniques for estimating the RUL.

Polo and others [68] have built liability models to incorporate monitoring data on operating assets, as well as information on their environmental conditions based on artificial neural networks models, which allows updating assets reliability analysis according to changes in operational and/or environmental conditions. The ANN models are used for early detection of degradation in energy production due to power inverter and solar trackers functional failures.

Kutylowska's work [69] is to predict failure rate using artificial neural network. failure rate prediction and BFGS algorithm was used to learn the network. The correlation between experimental and predicted data was acceptable.

4.2.4 Hybrid Models

Yan and etc. [70] presented a hybrid method for on-line assessment and performance prediction of remaining tool life in drilling operations based on the vibration signals. Logistic regression (LR) analysis combined with maximum likelihood technique is employed to evaluate tool wear condition based on features extracted from vibration signals using wavelet packet decomposition (WPD) technique. Auto-regressive moving average (ARMA) model is then applied to predict remaining useful life based on tool wear assessment result. In addition, failure risk distribution is discussed. Even though their developed method is used in drilling operation, the same algorithm and method can be also implemented to photovoltaic modules.

4.2.5 Fussy Logics

In previous data driven models, different factors such as outliers in the dataset, seasonal variations, and many other reducing factors (e.g., soiling) should be separated from long-term non-reversible degradation. The lack of a systematic and flexible approach to select parameters of these techniques and their black box character limit the understanding and control of their performance. Ismail Kaaya etc. [71] address this issue by proposing a systematic and flexible approach with adjustable model parameters to evaluate the degradation trend based on the nature of the dataset under evaluation. The proposed method aims to evaluate the irreversible long-term degradation of PV modules and systems. To achieve this, they proposed an iterative algorithm for degradation trends evaluation that allows to separate seasonal variations and other reversible performance reducing effects from irreversible degradation.

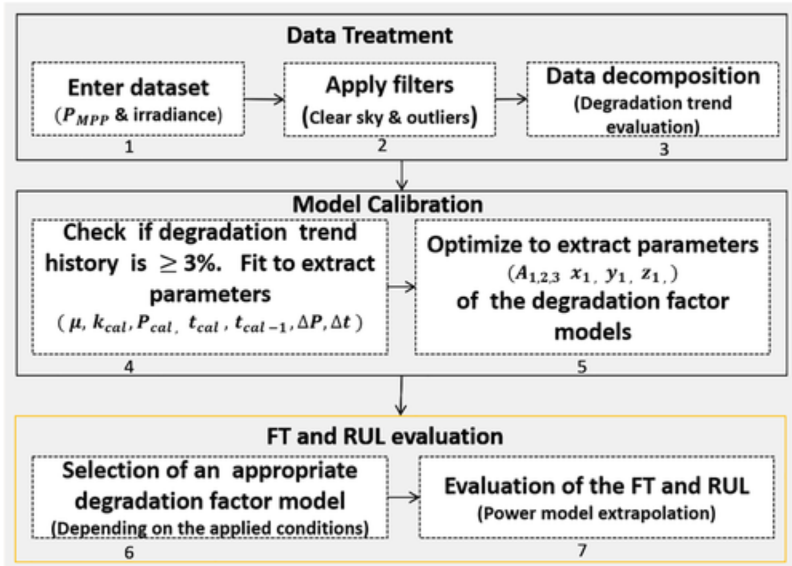


Figure 4-2 Schematic diagram of the modeling approach to evaluate degradation trend, failure time and RUL [71]

Finally, following table summarize all the data driven research articles that were referred in the chapters. The algorithms share significant similarity as data driven model for fault detections.

Table 4-1 Summary of Data Driven Algorithms for RUL Prediction

Algorithms	*Number of Articles*	*References*
Regression	2	Laayouj 2016 [64], Sheng 2019 [65]
SVM	3	Cho 2020 [66], Van TungTran 2012 [67]
ANN	2	Polo 2015 [68], Kutylowska 2015 [69]
Hybrid	1	Yan 2007 [70]
Fussy Logics	1	Kaaya 2020 [71]

5 Optimizing Renewable Energy Systems

Currently, Variable Renewable Energy (VRE) such as solar and wind accounts for 22% of grid generation capacity and 17% of the net power generation. EIA projects that renewables will provide nearly half of world electricity by 2050. The differences between wind and solar power comparing with conventional coal, natural gas and nuclear power is that their output greatly depends on the weather condition. The growing percentage of VRE presents challenges for the power grid to stay balanced. As the proportion of wind and solar energy increases, more changes in grid operation may be required.

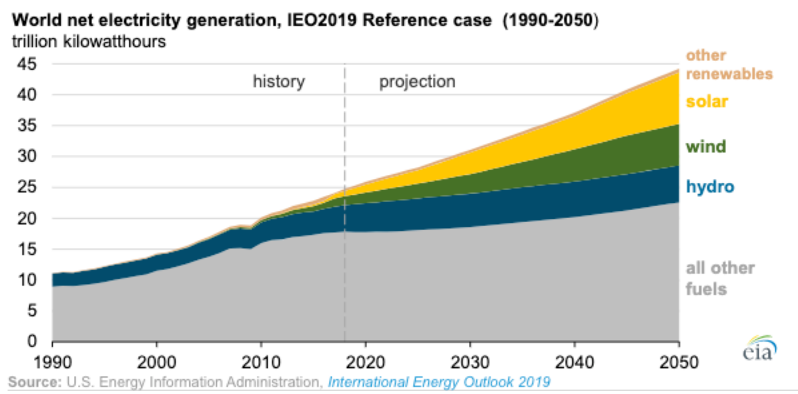


Figure 5-1 World net electricity generation (1990-2050)

5.1 AI Enabled Energy Storage

Energy storage systems (ESS) are expected to play a major role in the future smart grid. They provide a back-up to the intermittent renewable sources and ensure continuous electricity supply to the consumers. Locally, they help in the management of the distribution grid by improving its efficiency and reducing costs. ESS helps in mitigating the peak energy demand on the local grid and bridge the gap for renewable energy supply.

Artificial Intelligence methods mainly focus on the real-time decisions of the best time to charge and discharge the ESS. Optimization helps the system maximize its capacity and its financial returns.

5.1.1 Demand Side Optimization

Utility companies implement incentive or penalty programs to encourage the usage of alternatives, which decreases the stress on the main power grid. Demand charges are additional fees that utilities charge non-residential or commercial customers for maintaining constant supply of electricity. These fees usually amount to a substantial sum of money that businesses must pay on monthly electric bills.

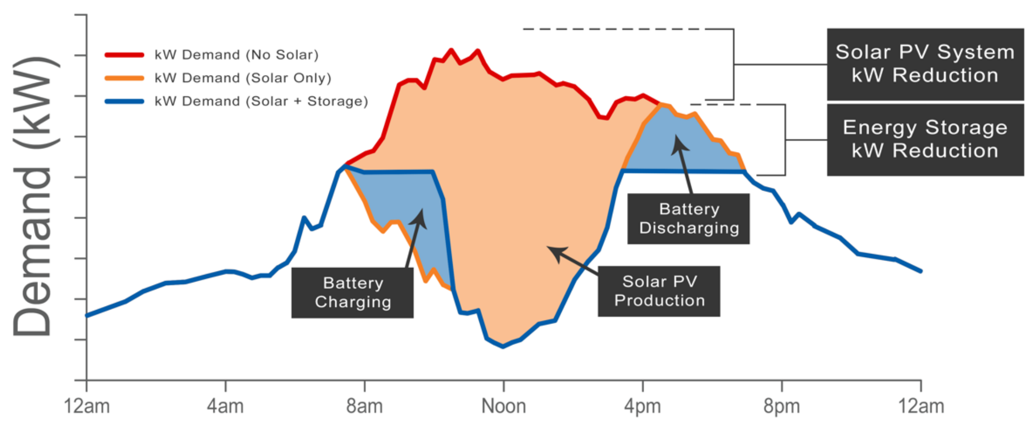


Figure 5-2 Peak Shaving with Energy Storage and Solar PV

Energy storage systems (ESS) can enable flexible bidirectional adjustment with a fine grain time scale of millisecond to control the charge and discharge of the system. As shown in Figure 5-2, ESS combined with Renewable energy can be utilized the perform peak shaving of the energy profile and reduce the demand charges to business. Numerous researches have been done to integrate artificial intelligence algorithms to improve the performance of both ESS and Renewable. In [72], Li etc. proposed a two-stage optimization using Artificial Neural Network (ANN) to solve the established optimal model. It includes the day-ahead plan and the intraday correction to respectively schedule the ESS and Renewable during each dispatch interval. The proposed mothed can effectively improve the integration of wind power and reduce system operation costs. Rahbar et al. [73] propose an algorithm that optimizes the energy-charged/discharged using the shared ESS concept to profit the consumers.

Stem is a technology startup based in California to utilize artificial intelligence software Athena and onsite battery ESS system to optimize commercial customer peak demands [74]. Athena accurately forecasts energy demand onsite and energy demand on the grid, and optimizes energy usage by automatically switching between battery power, onsite generation and grid power. Athena constantly makes economic tradeoffs when determining how much energy to deploy or store up for later.

EnerNOC, acquired by Enel in 2017, is another commercial example of utilizing battery ESS and artificial intelligence software to reduce energy costs for large commercial and industrial (C&I) energy users. Their product promises that customers will save at least 15% on their energy costs after installing their intelligent battery [75].

5.1.2 Supply Side Optimization

Conventional grid designs focus less on energy storage, but with distributed energy system, which commonly accompanied with energy loss reduction voltage fluctuations, less reliability etc. The ESS is an integral component that can transform the current grid structure and operation. ESS combined with intelligent energy management is the most appropriate solutions in this area.

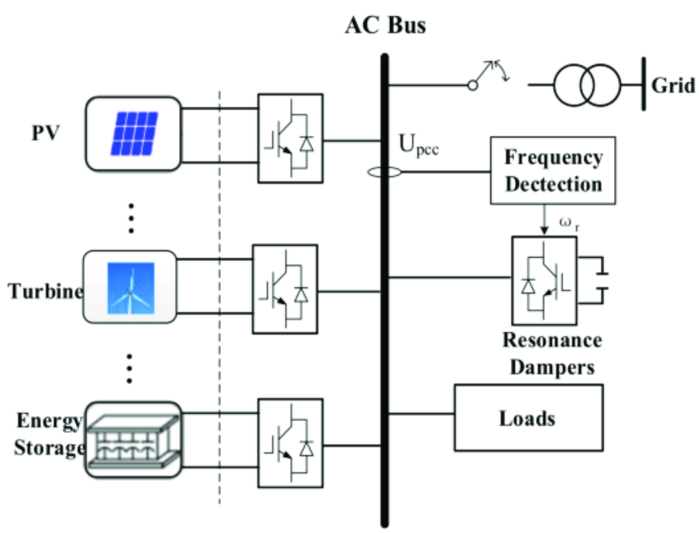


Figure 5-3 Schematic diagram of micro-grid system with Energy Storage

As shown in Figure 5-3, ESS is an integral component that can transform the current grid structure and operation. Artificial Intelligent enabled control software can manage the charging or distribution to the power grid. [76], [77] and [78] all proposed real-time distributed algorithm, to balance the energy demand through charging and discharging of ESS. They can provide targeted energy to all the components of the grid at a different level making the grid reliable and smarter.

5.2 AI Enabled Demand Response

Demand response (DR) is one of the promising approaches for providing demand flexibility to the power grid. The AI enabled DR schemes requires a framework which is automated and smart. It is increasingly apparent that AI can contribute greatly in the success of DR by learning the behavior of both demand side and VRE production, and make the most optimal system wide decision.

The rising interest in AI-based solutions in the DR sector is well illustrated by the sharp increase of research interest in this domain. The number of scientific publications with the usage of AI approaches has increased with the majority using AI techniques for forecasting and scheduling and control tasks [79].

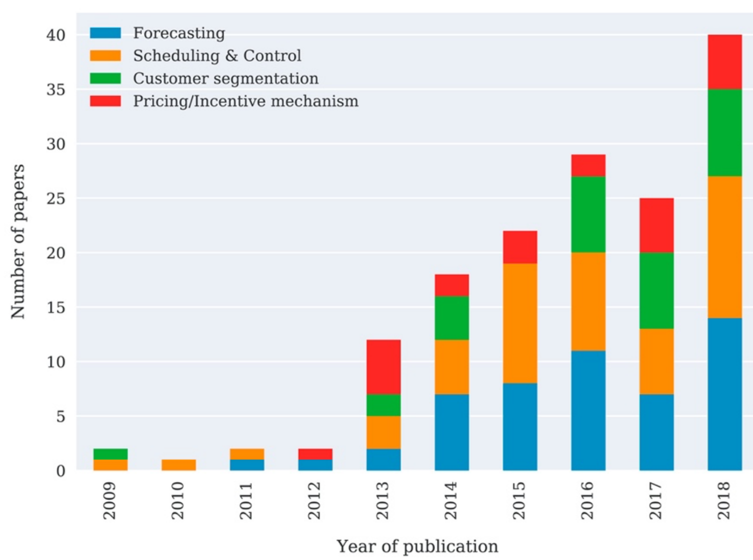


Figure 5-4 Evolution of AI research publications used for specific DR application areas

The most commonly used strategy for Demand Response (DR) is to forecast the load on both demand side and on the power grid. The user can improve their energy usage pattern and provide flexibility to the overall power grid in a cost-effective way. Artificial Intelligence (AI) and Machine Learning (ML) can be used as key technologies to provide real time decision with the use of large-scale data. AI methods can be used to tackle various challenges, ranging from selecting the optimal set of consumers to respond, learning their attributes and preferences, dynamic pricing, scheduling and control of devices. Overall, AI methods can help enhance the DER energy grid to operate in a more efficient way.

Forecasting

Demand forecasting is the process of estimating the forecast of energy demand by analyzing historical energy data. Using a prediction model can lead to more informed decision making in DR, as well as better rewarding of the participants through a more accurate baseline estimation. Traditional forecasting models relies on statistics-based model such as ARIMA, Auto Regression (AR), Integrated Moving Average, and exponential smoothing method. Those type of models are generally linear in nature and have been shown to provide less accurate results in load forecasting [80].

In data driven method of demand forecasting, the most heavily utilized is artificial neural networks (ANN) [81], which have been widely studied. The advantage of ANNs is to learn arbitrary, non-linear, complex functions, which makes it suitable for demand forecasting in demand response (DR) application. Tamizharasi etc. [82] built ANN model for prediction for long term energy consumption producing and demonstrated superior results comparing with ARIMA and SVM methods. As we noted, ANNs can be computationally expensive and usually require a large amount of data in order to outperform other less flexible methods. ANN’s performance can vary greatly depending on the availability of historical data sets, tuning the network structure and parameter selections.

Deep neural networks (DNNs) are also used for the purpose of load forecasting. DNNs are ANNs with several hidden layers, adding complexity to its structure. A Deep Neural Network architecture was proposed for short term load forecasting to integrate deep neural network layers to process energy demand [83]. Another example of DNN is [84] is to use DNNs to predict the monthly electricity demand in Australia based on time series of consumption rates as well as socioeconomic and environmental factors. Figure 5-5 illustrates the schematics of the DNN structure.

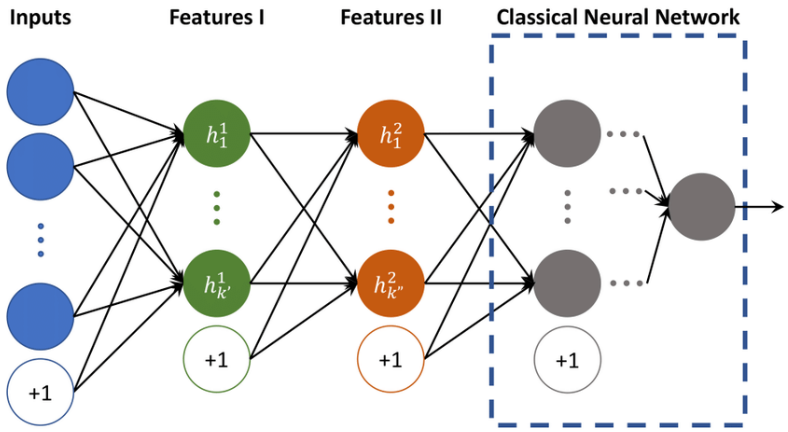


Figure 5-5 Schematic view of a deep neural network with multiple layers of autoencoders stacked with a classical neural network

Unsupervised Prediction

To build an accurate ANN or DNN model requires large amount of training data, in most cases hourly energy data are needed to produced acceptable results. However, in some DR scenarios, there are very limited amount historical data, for example residential energy data. As a result, using unsupervised learning algorithms are the only viable options. The simple unsupervised learning algorithm is clustering. One of more advanced unsupervised learning, reinforcement learning (RL), was introduced in power system area to predict the energy consumption [85] using unlabeled historical data, namely State-Action-Reward-State-Action (SARSA) and Q-learning.

Another type of applications of unsupervised models is to segmenting electricity customers by using only the Advanced metering infrastructure (AMI) data [86]. In the article, they use clusterwise regression model to segment customers to their coincident monthly peak contribution (CMPC), which quantifies the contribution of individual customers to system peak demand.

Dynamic Control and Scheduling

Demand response (DR) is used to encourage end-users to make short-term reductions in energy demand in response to a DR request by grid operator to shift energy usage to periods of low demand, or to periods of high availability of renewable energy. Traditional control mechanisms for DR are in general model-based control where the main problem is intractable and there is no feasible way to model all the involved agents, such as Model Predictive control (MPC). Among all the artificial intelligent methods, reinforcement learning (RL) methods have been mainly successful in controlling system loads and automating DR operations. RL approaches do not require a model of the environment to be applied, and this provides an advantage in designing DR control systems. Moreover, deep RL has been shown to work better in high-dimensional tasks.

In Dusparic etc.'s research [87], the authors propose a multi-agent approach that uses load forecasting for residential demand response, and electoral loads are controlled by reinforcement learning agents which, using the information on current electricity load and load prediction for the next 24 hours, learn how to meet their electricity needs while ensuring that the overall demand stays within the available transformer limits.

The most widely used RL algorithm in DR is Q-learning, researchers have employed multi-agent RL methods to tackle the problem of the large state space. [88] formulates an applied methodology for an agile demand response using mathematical micromodels and simple Q-learning technique in a decentralized fashion is proposed. The optimal strategy chosen by an aggregator is the maximization of the benefits from demand flexibility.

Another optimization when DR is requested from a smart grid is to use direct load control (DLC) by shutting down or regulating part of system to act as an effective means to respond. In [89], a newly proposed power demand optimization scheme predicts the building cooling demand and the power limiting threshold in response to a received DR request, as illustrated in Figure 5-6. A system sequence control resetting scheme determines the number of operating chillers/pumps to be retained. An online control/regulation scheme ensures the system power following the expected profile by regulating the total chilled water flow delivered to the building and therefore the chiller load.

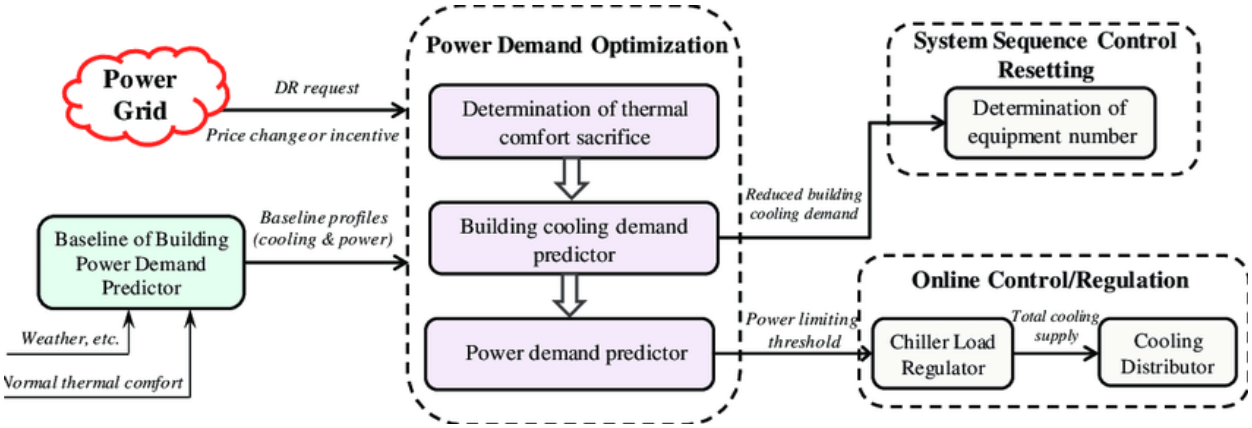


Figure 5-6 Example Flow of fast demand response control strategy during DR events

Controlling power equipment at a DR event primarily operates by shutting down the part of the system that can be sacrificed. Another way to respond to a DR event is by scheduling, where time uncritical tasks are pushed to off peak time to operate. The commonly used methods are GA and PSO.

Overall, when DR-related data sources become more available, AI approaches for controlling are able to provide more advanced and versatile DR services via dynamic control or schedule energy demands.

5.3 AI Enabled Grid Flexibility

The electric grid contains power plants as supply and industrial/residential demands. The grid does not store electricity. The power generated must be the same as the power being consumed. The power grid always maintains flexible resources in order to meet variable electricity demand in every instant. There are many mechanisms available to increase grid flexibility in the short term, as well as the long-term.

The power load profile has changed over the years with more DER recourses are deployed on the grid. In the following Figure 5-7, the “Load” line shows the normal demand variable during a typical day. Because wind and solar energy output varies, the “Net Load” demands (indicated in red line) to conventional generation has drastically changed. The grids must increase its capability to accommodate larger swings during a day.

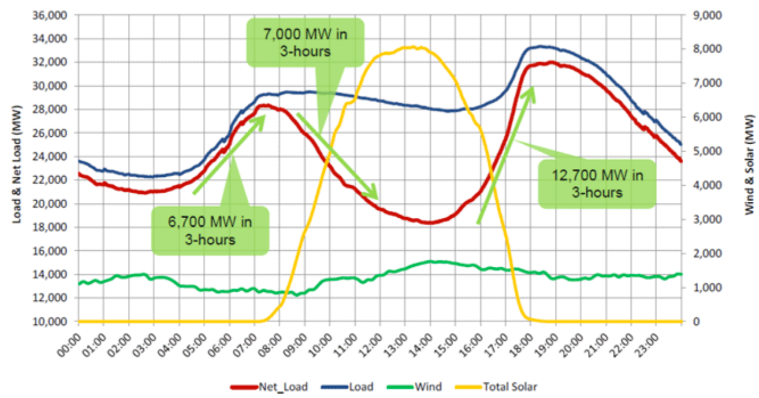


Figure 5-7 Electricity daily demand profile

To solve the problem of variability or any outage from renewable energy, power grid implements reserved power plants, which only used as a backup or insurance of the power grid, is called Ancillary Services. There are currently three types of Ancillary services exist. These options give the grid's Balancing Authority different levels of time granularity to control power supplies. Following table shows the typical balancing operations, and three broad categories of cooperation at the operational level: regulation, primary (spinning) reserve, and supplemental (non-spinning) reserve.

Type of Ancillary Services	**Requirements**
Regulation	Respond <10 seconds Duration 5-30 minutes
Primary (spinning) Reserve	Respond in 10 minutes Duration 30minutes-2hours
Supplemental (non-spinning) Reserve	Respond 10-30 minutes Duration 30minutes-2hours

AutoGrid [90] pioneered the science of flexibility management that enables energy providers to mine and extract data to balance supply and demand in real time. AutoGrid is the leader in flexibility management software for the energy industry. AutoGrid DERMS software uses artificial intelligence (AI)-driven predictive algorithm to control connected, distributed and flexible energy assets in real time and at scale.

Packetized Energy [91] focused on solving energy problems through grid edge flexibility. They developed an innovative research platform, Grid Resilience and Intelligence Platform (GRIP), which focus on leveraging advances in artificial intelligence to improve resilience in power distribution networks. Behind-the-meter distributed energy resources (DERs), like energy storage, PV systems, and even smart thermostats, can work together to enable critical energy services to continue, even when the bulk power grid fails. Packetized Energy leverages AI to enhance grid edge flexibility, which can be a valuable tool in enabling resilience.

6 AIoT Powered Renewable Virtual Power Plant

6.1 Virtual Power Plants (VPP)

Distributed energy resources (DER) account for 22% of grid generation capacity and 17% of the net power generation. EIA projects that renewables will provide nearly half of world electricity by 2050. The differences for distributed energy resource (DER) are that they greatly depend on the weather condition and they operate individually without any coordination. The growing percentage of DER presents challenges for the power grid to stay balanced, which leads to decrease of main grid reliability. Virtual power plants (VPP) aggregate geographically distributed energy resources (DERs) enabling the management of flexible capacity in the power network on a large scale.

For instance, wind, solar and energy storage are internetworked. Controlling these together allows more effectivity and greater grid benefit [92]. The distributed DERs of a certain area constitute a VPP; therefore, the whole VPP is not restricted by the geographical area, and the control mode can be decentralized or centralized. The VPP is proposed to integrate all kinds of DER, including the Distributed Generation (DG), Demand Response (DR) and energy storage (ES) which is shown in Figure 6-1.

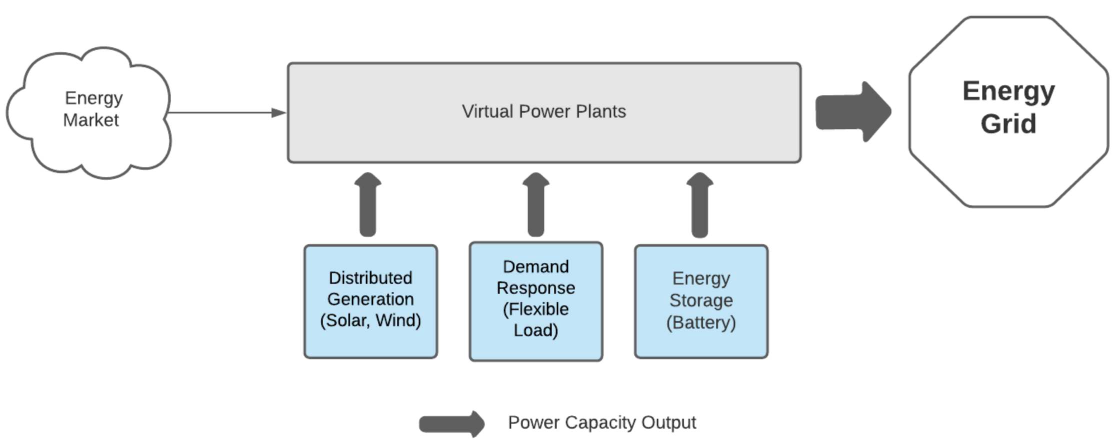


Figure 6-1 Scheme of Virtual Power Plant

A VPP is a flexible representation of a portfolio of DER that can be used to make contracts in the wholesale market and to offer services to the system operator [93]. VPP is characterized by a set of parameters usually associated with a traditional transmission connected generator, such as scheduled output, ramp rates, voltage regulation capability, reserve and so on.

VPPs enable the inclusion of distributed energy resources into ancillary service provision, typically for load-frequency control. Ancillary services demand reliable communication systems for the exchange of relevant information.

6.2 VPP Models

VPP functions as a Cloud-based or SaaS-based platform which governs multiple decentralized power plants through various distribution routes and demand centers. Distributed DERs can be remotely operated and controlled through VPP [94]. Generally, VPP operates as normal plant, with contracted energy which needs to be supplied to the grid. Once connected to power grid, production scheme for specific period of time must be followed in order to keep stability in the network. Following are the three VPP model that shall be addressed the same as traditional power plants.

Power Flow

Optimal power flow (OPF) is an approach to quantify aggregated DER capabilities and maximize capacity of the injected active power and consumed reactive power. OPF also takes into account limitations of the generators, networks and demand [93].

Production Planning

Production of energy in VPP is generally planned for a longer period of time (e.g.,24 or 48 h). This is called offline method. If there is a need for adjusting generation to the changing demand or if one of the generators is corrupted, online method takes place, which means online rescheduling generation between others units. This method is used in the unexpected situation.

Load management

Load management in VPPs are mainly based on demand response (DR). VPP controls many controllable loads like air conditioning systems, electric heaters or freezers. Load control is used for load reduction during requiring peak usage periods These methods generally base on a peak load reduction or minimization of production costs for given period of time [95].

6.3 AIoT enabled VPP Architecture

Figure 6-2 shows a representation of the capacities of DER, distribution and transmission networks as well as central generation of today's system and its future development under two alternative scenarios both with increased penetration of DER. Future (Status Quo) represents simple centralized control and passive distribution networks as today. Where, Future (Active), represents the intelligent system control that fully optimize system supply and demand in real time.

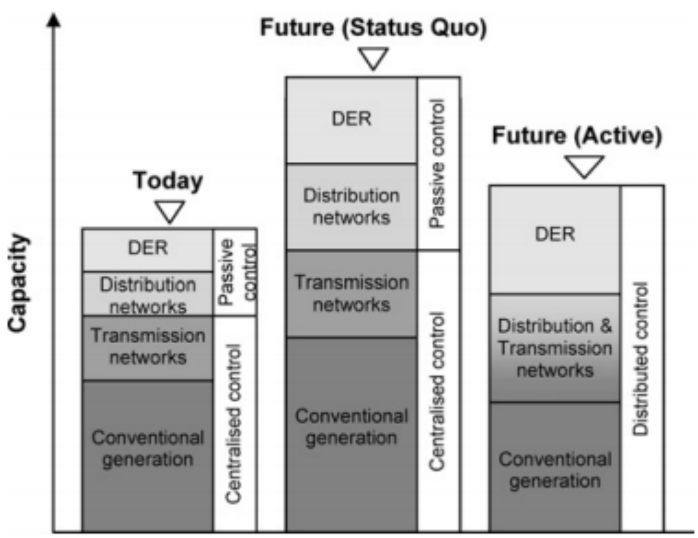


Figure 6-2 Power capacity in different scenarios

To meet the future challenge, VPP must utilize AIoT technique that harness real time DER IoT data, energy market data and power grid data that will enable systems based on DER to become the means for future cost efficient. AI algorithm shall play significant contribution of all three aspects of VPP modes in order to enhance the control capability of the system [93]. This is where AI is able to handle the complexity. VPP utilize load and generation forecasts and feed into optimizers that provide outputs on the best way to operate.

VPP is the center of the optimal management of Distributed Energy Resources (DERs) and upper layer grid operator, also called Independent System Operators (ISO) or Regional Transmission Organization (RTO). VPP and other intelligent control are the key management and integration of the dynamic energy supply and demands in the systems. With all the artificial intelligent algorithms and AIoT technologies, an AIoT enabled VPP architecture is proposed in Figure 6-3 VPP System Architecture with AI Enabled Modules. According to the architecture, each module is capable of making intelligent decisions based on IoT data within the system including advanced scheduling, forecast, scheduling and reliability management.

Demand and Supply Forecast

Photovoltaic are typical DER systems under virtual power plant (VPP). A number of transitional and Artificial Intelligence algorithms have been developed to predict DER power. In present case studies, the widely used forecasting algorithms developed are can be classified into three typical approaches: physical model, statistics model and data driven model.

Demand and Supply Reliability

With AIoT data, fault detection and diagnosis (FDD) can utilize data driven artificial intelligence (AI) algorithms for early diagnosis to prevent severe downtime of DER system and transmission infrastructure. FDD fault detection algorithms can apply to almost all system modules such as DERs (PV, wind farm etc.), energy storage, transformers.

Intelligent Equipment Management

Predictive health monitoring (PHM) are artificial intelligence (AI) techniques to predict the remaining usage life (RUL) of critical grid assets such as transformers. PHM can further guarantee the required health state of the grid and minimize grid level downtime.

Grid Flexibility

Besides production related, there is tremendous potential to create enough grid flexibility with optimal control of DERs. AI algorithms can create the flexibility of the assets and combines them in such a way that they become a reliable and dispatchable source of capacity for grid use.

VPP AI algorithm can then utilize the aggregated DER by shifting energy load from peak hour to off hours, by setback power equipment, or by reducing system peak to avoid turning on fossil-fuel based reserves. Complex solutions like wholesale market trading, ancillary services (such as frequency control), and increasing hosting capacity for renewables may also address this issue.

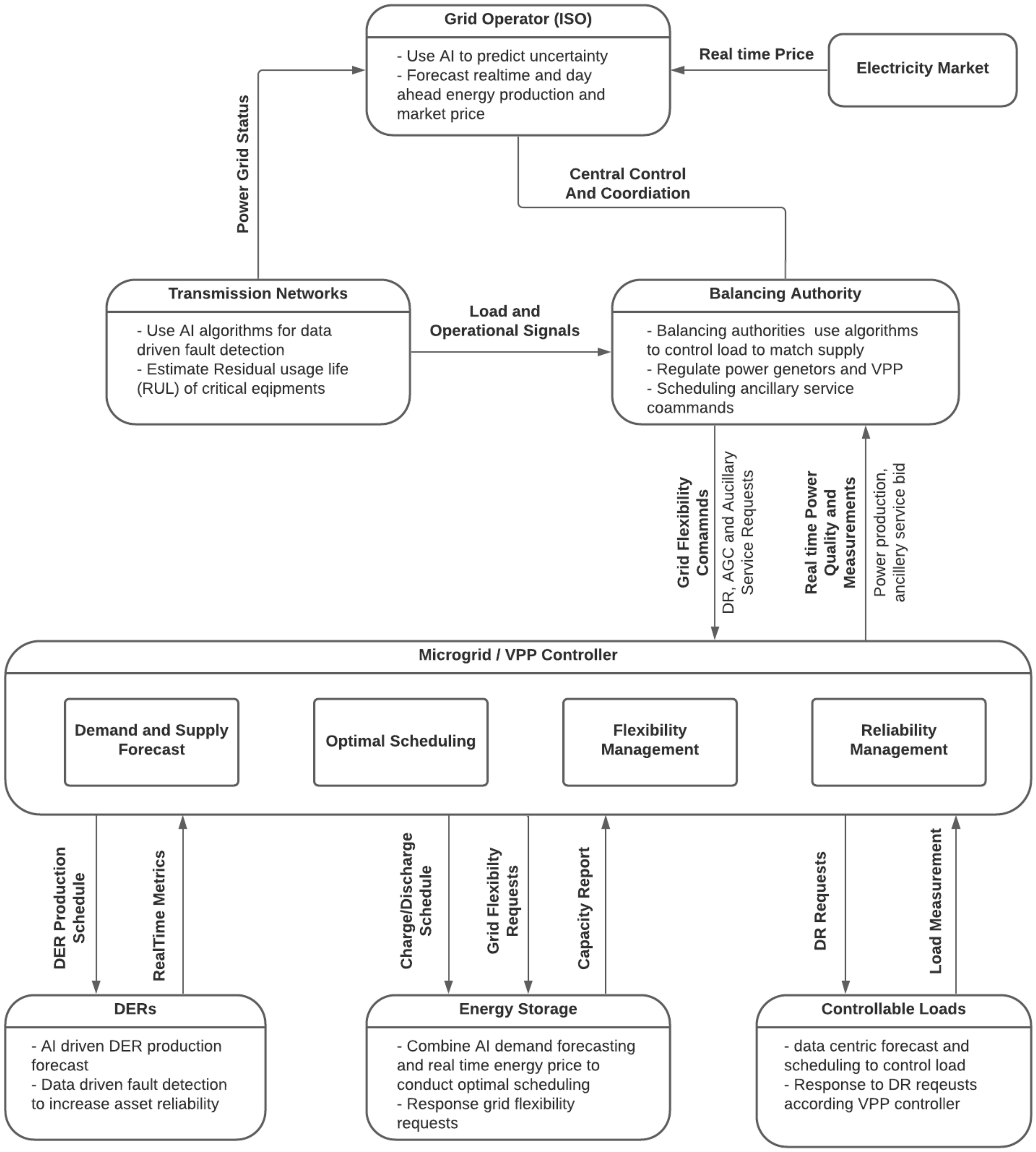


Figure 6-3 VPP System Architecture with AI Enabled Modules

VPP Power Optimization

Currently, many of the operations in the power system are done manually or with a basic level of automation. VPP offers the most important control over all the unpredictable energy resources. Large amounts of IoT data availability with artificial intelligence algorithms will increase the self-learning capability of the VPP controller. It uses all the AIoT data collected combined with AI algorithms to deliver predictive and optimal control. There are four major components for an AI enabled VPP controller: (1) demand and supply forecast; (2) optimal scheduling; (3) flexibility management; (4) reliability management. All of these AI's self-learning algorithms can use predicted demand and supply trend to generate the most optimal system configuration and DR events in order to optimize operations for maximum productivity.

7 Conclusion

Different kinds of distributed energy resources (DER) such as solar panels, storage and power transformers pose increased challenges in microgrid. AIoT-enabled technologies which combine artificial intelligence (AI) and IoT and create new opportunities in the distributed energy resources (DER) field. All the AI algorithms related were reviewed and compared in depth. Their applications mostly focus on three areas: fault detection and diagnosis (FDD), remaining useful life (RUL) prediction, and system optimization and forecast. Finally, the smart grid concept section identifies how all AIoT powered distributed energy resources (DER) can be aggregated in terms of virtual power plant (VPP), which enable the management of efficient and reliable power network on a large scale, and coordinate demand and supply in real-time. The proposed VPP architecture provides guidance to navigate through all microgrid modules and their applicable AI algorithms. In summary, utilizing AIoT technologies for distributed energy resources (DER) system can greatly add to valuable system capacity, flexibility and reliability.

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