ADVANCES IN AI FOR SIMULATION AND OPTIMIZATION OF ENERGY SYSTEMS

EDITED BY
QASEM ABU AL-HAIJA, OMAR MOHAMED,
AND WEJDAN ABU ELHAIJA

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Advances in AI for Simulation and Optimization of Energy Systems

Advances in AI for Simulation and Optimization of Energy Systems explores AI's groundbreaking role in the future of energy. As the demand for cleaner, more efficient energy systems grows, AI-driven methodologies are leading the way in simulating and optimizing critical processes across the power generation, transmission, and storage sectors. Whether applied to traditional power grids, renewable energy systems, or energy markets, AI techniques such as neural networks, reinforcement learning, fuzzy logic, and metaheuristic optimization are revolutionizing how energy systems are modeled and managed.

This comprehensive volume offers:

- In-depth chapters on AI-driven simulation and optimization strategies
- Case studies that demonstrate real-world applications of AI in energy systems
- An examination of the ethical concerns and legal frameworks surrounding AI
- Cutting-edge methodologies for improving energy technologies' accuracy, efficiency, and performance

Bringing together leading researchers and practitioners in AI and energy systems, this book is an invaluable resource for academics, engineers, and professionals who want to stay ahead of the curve in this rapidly evolving field.

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Wejdan Abu Elhaija

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Contents

Preface

This book contains nine peer-reviewed research articles organized and formatted as chapters. These chapters have been written by prominent researchers in the interdisciplinary field of AI advances in energy systems. Chapter 1 introduces the fundamentals of AI models, which explains the core tool for the rest of the chapters. Chapter 2 presents some of the salient AI applications in power systems. Chapter 3 explains the intelligent techniques in hybrid renewable energy systems. The smart grid applications of AI have been reported in Chapter 4. Chapter 5 reviews algae-based carbon sequestration through optimizing renewable energy and climate strategies. Chapter 6 demonstrates the effect of the Black-Widow Optimizer for improving the load-frequency control of interconnected power systems penetrated by real-life wind power signals. Chapter 7 explains the state-of-the-art advances in biofuel production. Chapter 8 reports machine learning techniques for hierarchical robust optimization of chemical processes, emphasizing energy systems. Finally, Chapter 9 explores the applications of machine learning techniques in developing smart cities, mainly the 5G-enabled Smart Cities and Energy Grid Cyber-Defense. The book can be used for research and education purposes, specifically for senior undergraduate and postgraduate students to upgrade their knowledge and insights toward meaningful and useful applications of AI.

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About the Editors

Qasem Abu Al-Haija received his Ph.D. from Tennessee State University (TSU), USA, in 2020. He is an assistant professor in the Department of Cybersecurity, Faculty of Computer & Information Technology, Jordan University of Science and Technology, Irbid, Jordan. He authorizes more than 250 scientific research papers and book chapters. His research interests include artificial intelligence (AI), cybersecurity and cryptography, the Internet of Things (IoT), cyber-physical systems (CPS), time series analysis (TSA), and computer arithmetic. Recently, he was listed as one of the world's top 2% of scientists, and his list was released publicly by Stanford University and other publishing houses.

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1 Fundamentals of Machine Learning Models

Rahmeh Ibrahim and Qasem Abu Al-Haija

1.1 INTRODUCTION TO MACHINE LEARNING (ML)

ML is a subset of artificial intelligence through which computers are modeled to carry out several tasks without necessarily being programmed. They learn from patterns and inferences from the data. The element key to this process is the assertion that systems can automatically improve from experience, thus enabling the creation of adaptive models that will predict the outcome or show any pattern from the large dataset [1]. ML is generally defined as a computer's ability to mimic cognitive functions like learning and problem-solving.

The importance of ML cannot be overemphasized. It disrupted many spheres with advances that used to be incomprehensible. For example, ML models were made possible in health care for outcome prediction, early disease diagnosis, and treatment personalization through data on individual patients. ML within the financial industry is also used to detect fraud, predict market trends, and automate trading strategies. ML has also transformed marketing by making personalized advertising, customer segmentation, and sentiment analysis possible, enabling greater customer engagement and satisfaction.

ML has several types that are unique in their methodologies and applications. The standard type of ML includes supervised learning, where a model is trained using a labeled dataset with an input–output pair whose response is known [2,3]. This kind of supervised learning is appropriate when solving classification and regression problems. Some supervised learning algorithms frequently used include Linear Regression (LR), Logistic Regression (GR), Decision Trees (DT) and Neural Networks (NNs). In application, for example, supervised learning can be carried out to classify emails as either spam or non-spam, to predict the price of a house, or in medical imaging to diagnose diseases. On the other hand, unsupervised learning deals with unlabeled data.

Unsupervised learning aims to extract hidden patterns or inherent structures within the data. The most important techniques within unsupervised learning are clustering and dimensionality reduction.

Well-known algorithms in this subfield include K-means clustering and PCA. These group similar data points or reduce the dimensionality to plot the points for easier visualization and analysis. For instance, unsupervised learning can segment customers based on purchase behavior and simplify the complexity of data in genomic studies [4]. Semi-supervised learning falls between labeled and unlabeled data training. This comes in handy, as sometimes acquiring a fully labeled dataset can prove to be very expensive or consuming in terms of time. Utilizing massive

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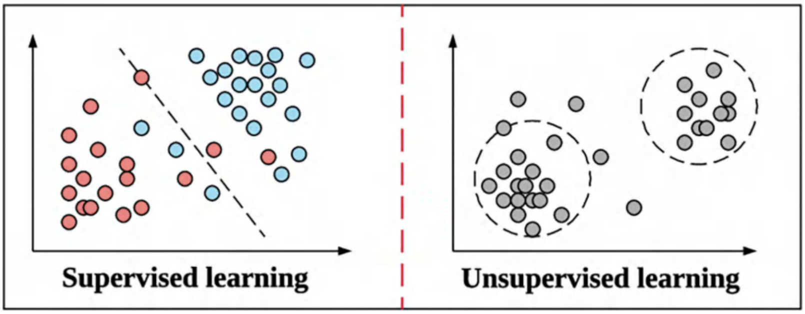

FIGURE 1.1 The supervised and unsupervised learning.

unlabeled data will boost the performance level of the model. It is widespread in tasks requiring a large amount of labeled data to develop a highly accurate model, for example, in natural language processing or image recognition tasks. Reinforcement learning is another form of distinct ML [5], where an agent learns to make decisions by acting in an environment to maximize cumulative rewards. In contrast to supervised and unsupervised learning, reinforcement learning is dynamic and interactive; it implies trial and error directed toward obtaining the best results possible. Its application can be seen in various fields, from robotics and game playing to autonomous vehicles, where the agent is concerned with changing environments and learning optimal strategies through time [6]. Figure 1.1 shows the difference between supervised and unsupervised learning.

1.2 SUPERVISED LEARNING

Supervised learning is the most basic form of ML; it learns a model to fit data described by labeled examples. There is a training dataset where one has pairs of input–output, and this correct output is known and given. The critical goal of supervised learning is developing the general rule, a mapping of inputs into outputs, which will work on new, unobserved data. This type of learning is relevant when there is historical data with known outcomes, and the information is used to predict the future events that a model will cover. Supervised learning can be classified into one of two categories: classification or regression [1].

1.2.1 Types of Supervised Learning

1.2.1.1 Classification

Classification, a supervised learning method, groups the outcome variable into categories. It's about categorizing input data into already defined classes or categories. For example, an email can be classified either as ‘spam’ or ‘not spam,’ a tumor can be classified as either ‘benign’ or ‘malignant,’ and an image can be classified into different objects like ‘cat,’ ‘dog,’ or ‘car.’ In essence, classification models learn how to distinguish between various classes based on the features of the input data.

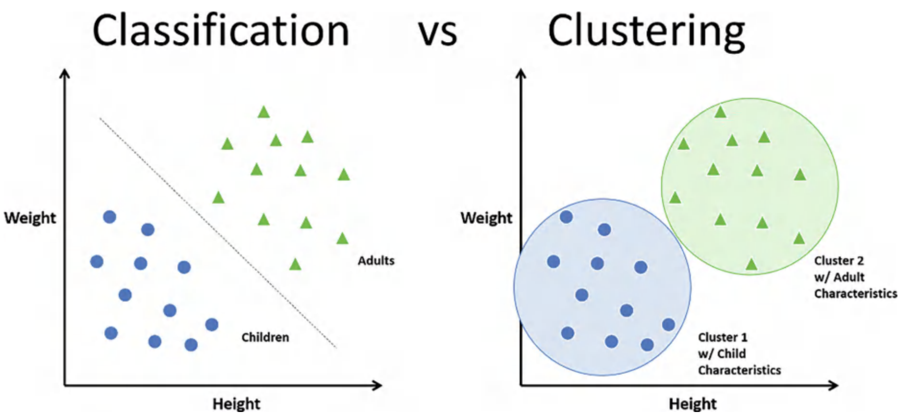

FIGURE 1.2 Classification vs clustering [7].

According to Goodfellow et al. [2], DT, GR, and SVM are popular classification techniques. Figure 1.2 shows the differences between classification and clustering.

1.2.1.2 Regression

On the other hand, regression is applied to work on continuous output variables. Prediction of a numerical value based on input data is the main task in regression. Examples of regression tasks are the prediction of house prices, stock price predictions, and estimation of the amount of rainfall. In regression tasks, a model learns relationships between input features and the continuous output variable so that new data allows for accurate predictions. Some standard regression algorithms are LR, ridge regression, and polynomial regression [3].

1.2.2 Common Algorithms

1.2.2.1 Linear Regression (LR)

LR is one of the simplest and most widely used algorithms in supervised learning. It is, in fact, a model that attempts to fit the relationship between input features and the output variable as an equation of a straight line. It tries to find a line of best fit, thereby implying minimization of the difference between the predicted and actual values. It relates an LR function between the independent variable x and dependent variable y as follows: $y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_n \cdot x_n + \epsilon$ where y is the predicted output, x_i are input features, β_i are coefficients, and ϵ is the error term [8]. Although simple, this approach to LR is quite powerful in many regression tasks and works as a baseline for other complex models. It would be best used when the relationship between input variables and output is roughly linear.

1.2.2.2 Logistic Regression (GR)

GR is a misnomer; it should classify tasks. It works on modeling the probability that a given input belongs to a particular class. GR is an output: a value between 0 and 1, interpreted as the probability of this input belonging to the positive class. The logistic function (also called the sigmoid function) is defined as the mapping of the linear combination of input features to the probability: $P(y=1|x)=1/(1+e^{-(\beta 0+\beta 1\cdot x1+\beta 2\cdot x2+\cdots+\beta n\cdot xn)})$. This algorithm is particularly effective for binary classification problems, such as determining whether a piece of email is spam. GR can be extended in that line to multiclass classification with techniques such as one-vs-all and softmax regression [9].

1.2.2.3 Decision Trees (DT)

DT is a general-purpose, versatile algorithm used mainly for classification and regression problems. They work by recursively partitioning the input data into subsets based on values of input features [10]. Each internal node in the tree represents a decision that would be made based on some feature, and each leaf node gives the final output or class. The general procedure in creating a decision tree is choosing the best feature to split the data at each node. Classification usually employs measures like Gini impurity and information gain; regression typically uses mean squared error. An essential strength of DT is that they are easy to interpret and visualize. Consequently, they are trendy for exploratory data analysis. However, they tend to overfit considerably, especially with complicated data sets.

1.2.2.4 Support Vector Machines (SVM)

SVM is one of the practical algorithms used mainly for classification, as shown in Figure 1.3. These hyperplanes separate the data so that the margin between points from two different classes, also called support vectors, is maximized. This aids in the generalization of new data. The optimal hyperplane is mathematically found by: min $1/2\ ||w||^2$ subject to $y_i(w\cdot x_i+b)\geq 1\ \forall_i$, where w is the weight vector, b is the bias term, x_i are the input features, and y_i are the class labels. SVMs are very good in high-dimensional spaces and flexible with different kernel functions, so they can treat non-linear classification problems by implicitly mapping input features into the higher-dimensional space than that of input features originally [11].

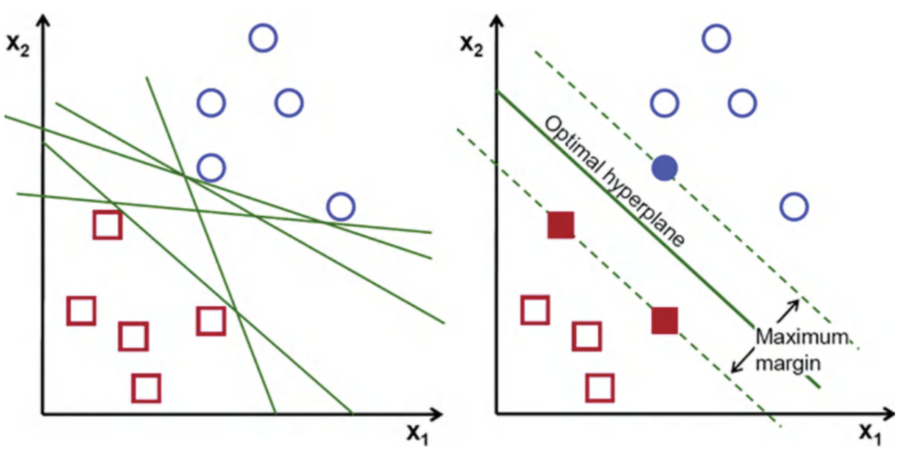

FIGURE 1.3 Support vector machines (SVM) [7].

1.2.2.5 K-Nearest Neighbors (KNN)

KNN is a very intuitive and straightforward algorithm used in classification and regression. This algorithm obtains the 'k' data points closest to the input in the training set, and its predictions are based on the majority class or average value in case of regression from these neighbors. The distance between data points is usually computed through Euclidean distance, although other distance metrics may be applied equally. Despite its simplicity, KNN can be very effective, especially for small datasets. Its performance can degrade when handling a large dataset because of the high computational costs, as all training samples must be calculated for the distance of a particular prediction [12].

1.2.2.6 Neural Networks (NNs)

An NN is a set of algorithms modeled around pattern recognition with the workings of the human brain. It has great potential for complex and non-linear relations between input and output. NNs are a class of interconnected nodes arranged in layers, where each node, or neuron, connects to another and influences it, like synaptic links. All of these involve networks trained to learn hierarchy-aware representations of the data, making them suitable for an extensive range of tasks, from image and speech recognition to natural language processing. Arguably, deep learning—as a subfield of ML in general—through many hidden layers has enabled state-of-the-art performance on many complex problems. The basic building block of a neural network is the perceptron. Mathematically, it can be represented as $y = f(\sum i = 1^n \, w_i{\cdot}x_i + b)$, where y is the output, x_i is the input features, w_i represents the weights for the feature vectors, b is the intercept term, and f is an activation function—commonly a sigmoid or ReLU function. The weights and biases in a trained neural network are adjusted to minimize the mismatch between predicted and actual outputs, usually employing gradient descent and backpropagation algorithms [13]. This overview of supervised learning and standard algorithms is very detailed because it underpins how machines can be taught from labeled data to produce accurate predictions and classifications. Mastering these concepts and techniques enables the practitioner to effectively deal with ML and solve real-life problems.

1.3 UNSUPERVISED LEARNING

Unsupervised learning is a category of ML where data with no labeled responses are dealt with. In supervised learning, our task is to predict an output based on input–output pairs; in unsupervised learning, the task is to deduce underlying structures and patterns from the data. This is particularly important when working with datasets that could be impossible or too expensive to label. The main objective of unsupervised learning is to learn the data structure. It broadly applies to exploratory data analysis, pattern recognition, and compression. The two primary flavors of unsupervised learning are clustering and dimensionality reduction [14].

1.3.1 Types of Unsupervised Learning

1.3.1.1 Clustering

Clustering is a process where all data are grouped according to a similar trend. The primary objective of clustering is to partition a data set into different clusters, each being different, such that the points belonging to a similar group are much closer to one another than those in another group. Clustering is commonly applicable in customer segmentation, image segmentation, anomaly detection, and social network analysis. Distance metrics include Euclidean distance, Manhattan distance, or cosine similarity [14]. The most popular algorithm for clustering can uncover natural groupings in the data. For instance, using a customer segmentation approach, one can enable the business to create distinctive customer clusters based on their purchase behavior. This information can be implemented for market targeting and for improving customer satisfaction. In image segmentation, clustering can also be applied to break down an image into meaningful regions that can be analyzed further, as in object identification in an image.

Clustering algorithms can be broadly categorized into partitioning, hierarchical, density-based, and grid-based methods. Each category has its specific algorithms and techniques, among which many others have different strengths and weaknesses. For instance, in the category of partitioning methods, we find K-means clustering, which is quite simple and fast but requires users to pre-define the number of clusters. Agglomerative and divisive clustering belong to the hierarchical methods. They don't have to specify the number of clusters a priori, which is pretty helpful in finding the nested data structures. Density-based methods, such as DBSCAN, can discover clusters with arbitrary shapes and are highly robust to noise, making them useful in complex datasets. Grid-based methods such as STING decompose the data space into a grid structure and perform clustering on the grid cells to balance computational efficiency and clustering quality.

1.3.1.2 Dimensionality Reduction

Dimensionality reduction reduces the number of random variables under consideration by obtaining a set of principal variables. This is an essential technique because high-dimensional data requires some form of dimensionality reduction. It helps reduce computational costs and avoids the curse of dimensionality [15]. Increased dimensions for high-dimensional data create increased sparsity and complexity, making this kind of data visual and analytical challenging. Dimensionality reduction techniques help simplify the data to be easy to work with and comprehend. Feature selection and feature extraction facilitate this process of dimensionality reduction. Feature selection is the process of selecting a subset of relevant features. At the same time, feature extraction is considered a data projection into subspace. Some popular approaches to dimensionality reduction include PCA and ICA.

PCA finds the directions of maximal data variance, extracting its most dominant features from the data. On the other hand, ICA deals with finding independent components in the data. It has so far been applied to problems like source separation and source coding. These techniques alleviate the problem of overfitting, help improve model performance, and reduce computational resources. Dimensionality reduction also improves the interpretability of the data by focusing on important variables and relationships.

1.3.2 Common Algorithms

1.3.2.1 K-Means Clustering

One of the most popular and commonly used clustering algorithms is the K-means clustering algorithm, which groups a dataset into K clusters in which a point belongs to the cluster with the closest mean. The algorithm works in the following manner: it initializes randomly K centroids; then, iteratively, the data point is assigned to the nearest centroid, followed by updating the centroids with the mean of the points assigned to them. This process goes on until the centroids change very little [16].

Here is an overview of the general steps of the K-means algorithm:

1. Randomly initialize K centroids.
2. Then, assign each data point to the centroid to which it is closest.
3. Update the centroids by computing the mean of the assigned points.
4. Repeating steps 2 and 3 to convergence of centroids.

Since K-means is computationally effective and very simple to implement, it is suitable for huge datasets. The main drawbacks include the fact that the number of clusters (k) must be predecided, and initialization significantly influences the algorithm. Here, the choice of the value for K is sensitive and determinant as to how well the algorithm will perform; techniques have been developed for this, including the elbow method and silhouette analysis.

While K-means is simple, it comes with its significant drawbacks. One such is that it assumes the spherical shape of clusters and that the clusters are equally sized. This is a deviance from actual data observations. Moreover, K-means will be sensitive to outliers and noise, as points with these attributes will cause the mean calculation to shift significantly, influencing the cluster formation. Therefore, these have resulted in various forms and extensions of K-means, for example, K-medoids using medoids, actual data points, not centroids, and K-means++ for better initialization by picking more informative starting points.

1.3.2.2 Hierarchical Clustering

Hierarchical clustering is a cluster analysis technique used to create a sequence of hierarchical clusters. It is an agglomerative (bottom-up) method where the algorithm initially considers all data points to be individual clusters. The two nearest neighboring clusters are consolidated into a new cluster at each subsequent merging step. Divisive clustering, on the other hand, starts with all data points in one cluster and recursively splits them into smaller clusters [17].

The overall result of hierarchical clustering is a tree structure, a dendrogram, representing the nested grouping of data points and the ordering in which clusters are merged or split. This kind of tree-based visualization represents the formation of the cluster graphically. It can be utilized to determine the ideal number of clusters by cutting the tree at the desired level.

Hierarchical clustering outperforms partitioning methods such as K-means in numerous ways. No specification of the number of groups is required, unlike what happens in partitioning; hence, it is more flexible in exploratory data analysis.

This feature also helps hierarchical clustering be sensitive to nested data structures and provide more detailed insight into data organization.

However, hierarchical clustering does have its drawbacks. It can be computationally expensive: agglomerative clustering has a time complexity of $O(n^3)$, and divisive clustering is $O(2^n)$, thus unsuitable for large datasets. Furthermore, minor modifications in the data may significantly influence the obtained dendrogram, so the process is sensitive to outliers and noise. This way, several linkage criteria, such as single, complete, and average linkage, can determine the distance between clusters to smooth out the process, making the results more reliable.

1.3.2.3 Principal Component Analysis (PCA)

PCA is a widely used technique for dimensionality reduction. This method works by calculating the eigenvalues and eigenvectors of the data covariance matrix [18]. The eigenvectors determine the directions of the principal components, while the eigenvalues represent the magnitude of variance in these directions.

PCA technique reduces the dimensionality of a dataset while retaining as much variability as possible. This makes it highly useful for visualizing high-dimensional data. PCA is commonly applied in image compression, gene expression analysis, and finance. By reducing the number of dimensions, PCA helps improve the performance of ML algorithms by decreasing overfitting and computational complexity.

1. Standardize the data.
2. Compute the covariance matrix from the standardized data.
3. Calculate the eigenvalues and eigenvectors of this covariance matrix.
4. Sort eigenvalues and their corresponding eigenvectors in decreasing order.
5. Pick k eigenvectors corresponding to the k largest eigenvalues to obtain the principal components.
6. Map the data into this new coordinate system founded by these principal components.

However, despite the capability of PCA, it has a few limitations that make it assume linearity in data and often not work well with non-linear distributions in data. Moreover, PCA can be sensitive to scaling; therefore, the data should always be standardized before applying the PCA algorithm.

1.3.2.4 Independent Component Analysis (ICA)

ICA is another powerful method for dimensionality reduction. It has far-reaching applications in separating a multivariate signal into additive, independent components. Much like PCA, this method is similar. Still, it differs from the latter since ICA tries to maximize statistical independence among the components, unlike the former, which maximizes variance. ICA has been applied to many problems, including blind source separation, for example, the famous 'cocktail party problem,' where mixed audio signals are separated, and more recently, even brain imaging data from neuroscience.

ICA assumes that the observed data is a linear mixture of independent source signals, and its goal is to unmix the data into sources. This can be expressed mathematically as follows: $X = AS$

X is the measured data matrix, A is the mixing matrix, and S is the source matrix. One of the key objectives of ICA is to estimate the mixing matrix A and the source matrix S so that the components in S are as statistically independent as possible.

ICA especially works fine in applications where the underlying sources are assumed to be non-Gaussian and independent. This aspect is achieved by using higher-order statistical properties of the data, like kurtosis or mutual information, which makes evidence for independent components. The ICA can be used with several kinds of data, from simple image and audio signals to large financial time series.

The main ICA process is as follows:

1. Centering and whitening the data to remove correlations and standardize the variance.
2. Running an optimization algorithm, like the FastICA algorithm, where the maximization of non-Gaussianity gives an estimate of the mixing matrix and independent components.
3. Projection of data in this new coordinate system using the estimated mixing matrix.

ICA has more advantages over PCA, especially when dealing with data that is non-Gaussian and independent sources exist in it. However, ICA also has some limitations. This approach requires the number of independent components to be fixed in advance. It can also be sensitive to initialization and convergence criteria. In addition, ICA assumes that the source signals are mixed linearly, although this may not be true in real data. Proposals for some extensions or even modifications of ICA have been put forward in trying to deal with some of these challenges, such as non-linear ICA and robust ICA.

1.3.3 Applications of Unsupervised Learning

Unsupervised learning has been applied to domains [14,19]. Notable applications include:

1.3.3.1 Customer Segmentation

Customer segmentation in marketing makes broad use of unsupervised learning. Businesses can cluster customers buying behavior, demographics, and other features, establishing, in turn, distinct groups of customers to whom appropriate marketing strategies are built. This aids in improving customer satisfaction, increasing sales, and enhancing customer retention. Clustering algorithms that are mostly used include K-means and hierarchical clustering.

1.3.3.2 Anomaly Detection

Another application of unsupervised learning is anomaly detection, wherein unusual or abnormal data points in a dataset must be identified. This will have a high utility value in fraud detection, network security, and industrial monitoring applications. Identifying anomalies enables a business to take preventive measures against risks and improve operational efficiency. One common anomaly detection technique is density-based clustering algorithms like DBSCAN, which can identify clusters of arbitrary shapes and densities.

1.3.3.3 Image Segmentation

The task of computer vision that uses unsupervised learning is image segmentation, which involves partitioning an image into meaningful regions. It finds many applications in object detection, medical imaging, and image compression. Clustering algorithms like K-means and hierarchical clustering can be applied to group together similar pixels, and dimensionality reduction techniques like PCA can help simplify the image data.

1.3.3.4 Topic Modeling

Topic modeling belongs to such applications of unsupervised learning in natural language processing that aim at identifying the underlying topics within a collection of documents. It enables the organization and summarization of huge text corpora by grouping similar documents and identifying common themes. Techniques such as latent Dirichlet allocation (LDA) and non-negative matrix factorization (NMF) are commonly used for topic modeling.

1.3.3.5 Gene Expression Analysis

In bioinformatics, unsupervised learning finds its application in gene expression analysis for detecting patterns and correlations in gene expression data. Clustering based on similar gene expression profiles should allow inference about gene function, mechanisms of diseases, and even the identification of potential therapeutic targets. Dimensionality reduction techniques like PCA and ICA are normally used to lower the complexity of gene expression data and further analyze them.

1.4 SEMI-SUPERVISED LEARNING

Semi-supervised learning combines both, as shown in Figure 1.4, where supervised and unsupervised techniques are combined. The central concept in this strategy is the application of available labeled data in combination with much larger unlabeled data to improve learning so that it's quite effective in producing results accurately. The basic idea that revolves around using these semi-supervised learning techniques is the rigorous nature of acquiring labeled large datasets. This process, once entered, can be very time-consuming, expensive, and sometimes very labor-intensive [20].

Semi-supervised learning uses labeled and unlabeled data to improve learning, especially when the labeled data is insufficient. One of the most important underlying principles of semi-supervised learning is that the unlabeled data can prevent the learning algorithm from getting stuck in a less effective generalization mode. This is achieved through various methods, such as self-training, co-training, and graph-based approaches. The model first goes through training using labeled data before making predictions on the labels of the unlabeled data, some of which are added to the training set for retraining. Co-training involves training two or more models on different views with the ability to teach each other, usually by exchanging labels for the unlabeled data. Graph-based methods create a graph in which nodes are

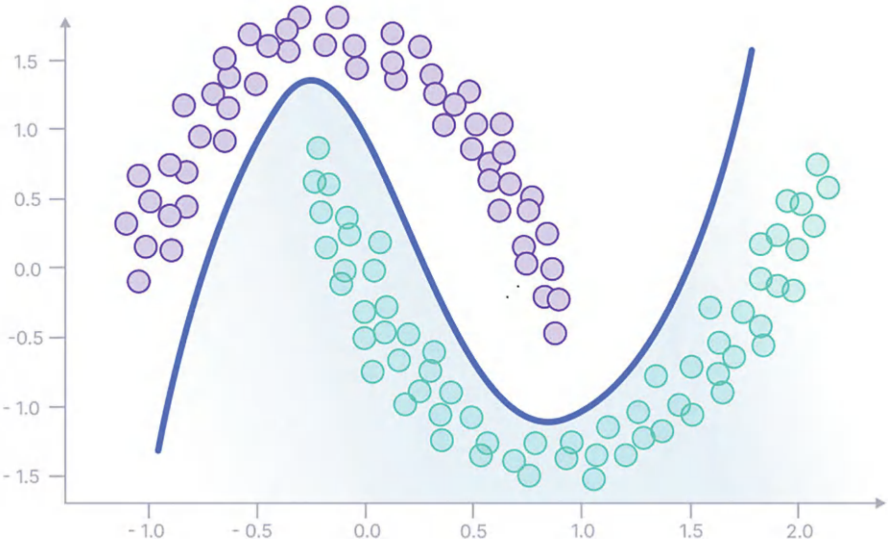

FIGURE 1.4 Semi-supervised learning.

the data points, the edges represent the similarity, and the labels propagate from the labeled to the unlabeled nodes based on their connections [21].

Semi-supervised learning has diverse applications in domains characterized by an absence of labeled data. Natural language processing, for instance, is used to enhance the performance of tasks like text classification or sentiment analysis by using large corpora of unlabeled text. In computer vision, semi-supervised learning has found application in object detection and image segmentation, where annotating images can be extremely expensive. In healthcare, semi-supervised learning allows medical diagnosis and treatment planning through labeled medical records and an enormous volume of unlabeled patient data. Semi-supervised learning helps implicitly bridge the gap between supervised and unsupervised learning methods in handling real-world challenges posed by ML, realizing an approach concerning the ability of labeled and unlabeled data combined [22].

1.5 REINFORCEMENT LEARNING

Reinforcement learning is an ML technique where an agent learns how to make decisions over time from selections made in an environment it interacts with, driven by the desire to maximize overall rewards. This contrasts with supervised and unsupervised learning, in which the learning algorithm is non-interactive with the data or the environment and deals with time and improvisation to achieve the best outcomes. The agent learns to interact within the environment, receives feedback through rewards or penalties, and uses this feedback to adapt its behavior during successive interactions in the future. In RL, the goal is to devise a policy describing the best action to take in each state to maximize long-term rewards [23].

So, in reinforcement learning, we pretty much have the same setting: a Markov decision process (MDP), which includes a set of states, a set of actions, a transition function, and a reward function. The agent must learn a policy to maximize the expectation of the cumulative reward over time. Important concepts in reinforcement learning are state, action, reward, policy, value function, and Q-function. The state represents the current situation of an agent, the action is the choice taken by the agent, and the reward is the feedback from the environment. The policy determines the agent's behavior, the value function predicts the expected reward for being in a state, and the Q-function predicts the expected return for taking a particular action for a state.

1.5.1 Common Algorithms

1.5.1.1 Q-Learning (QL)

QL is a relatively elementary and popular algorithm within reinforcement learning. It learns off-policy learning estimation directly through the value of the policy realization, not under the available policy. The basic idea of QL is to learn a Q-function, $Q(s, a)$, which estimates the expected cumulative reward of acting (a) in the state (s) and following the optimal policy after that.

1.5.1.2 Deep Q-Networks (DQN)

DQNs extend QL to handle high-dimensional state spaces using deep NNs. Traditional QL has performance issues in the face of large or continuous state spaces because it needs to compute a Q-value for every state-action pair. In DQN, the Q-function is approximated using a neural network that can generalize over some notion of state-action space [24].

Q-values are approximated using a neural network with the DQN algorithm, and the network parameters are updated using gradient descent. Techniques that involve experience replay and target networks are applied to stabilize training. This will record an agent's experience into a replay buffer and sample from it in random batches, thus breaking the correlation between consecutive updates and benefiting from learning stability. Target networks, which are periodically updated with the weights of the Q-network, are used to generate stable targets for the Q-value updates.

1.6 PRACTICAL IMPLICATIONS OF AI AND ML IN ENERGY AND POWER SYSTEMS

Artificial intelligence and ML can potentially lead to significant changes in the energy and power systems sector. Their applications cover transformational aspects of energy production, transmission, and consumption stages, opening opportunities to ensure better effectiveness, reliability, and sustainability.

1.6.1 Improving Energy Efficiency

AI and ML hold huge promise for improving efficiency in the functioning of energy systems. For example, smart grids use various algorithms from ML to analyze the available consumption patterns and forecast demand. Forecast demand will allow utilities to plan accordingly, thus avoiding energy wastage through streamlining energy distribution. Artificial intelligence predictive maintenance can detect equipment failure in advance, cutting downtime and maintenance costs [25]. Moreover, ML optimizes renewable energy sources, such as solar and wind farms, by weather forecasting and adjusting the mode of operations to obtain maximum output in terms of energy, as indicated by [26].

1.6.2 Integrating Renewable Energy

Integrating renewable energy sources into the power grid brings several challenges relating to variability and unpredictability. AI and ML combat the variables associated with renewable energy by enhancing the forecasting of renewable energy sources. For instance, ML algorithms can consider long-term weather data besides meteorological information in real-time, enabling highly accurate solar and wind energy production predictions. This appropriately balances supply and demand; in return, this ensures grid stability and minimizes the dependency on fossil fuels, which is explained [26].

1.6.3 Smart Grid Management

Smart grids are AI and ML power systems that improve the reliability and resilience of the grids. AI, through its real-time monitoring and analysis data, can detect anomalies, identify fault conditions, and trigger corrective actions autonomously. Finally, deploying ML algorithms also enables advanced load forecasting, demand response, and energy storage management; hence, it optimizes operational costs attached to grid operations. For example, AI can dynamically adjust power flows to ensure no load conditions are reached, and energy storage management is carried out to keep the power state stable [27].

1.6.4 Consumer Energy Management

AI and ML applications are further associated with empowering consumer energy management. AI-embedded smart home systems learn user preferences and habits and optimize energy use for heating, cooling, lighting, and appliances. Such systems could even communicate with a grid, enabling a demand response, meaning low-usage energy at peak periods, thus adding to home and grid stability. Moreover, ML algorithms can help visualize energy consumption patterns so consumers know how to use and conserve energy through their decisions [26].

1.6.5 Energy Trading Enhancement

Artificial intelligence and ML are revolutionizing energy trading. This is through the utilities essential in generating comprehensive market insights for decision-making. For instance, ML algorithms analyze broad market data to detect trends and price movements, which help offer predictive ability that inevitably allows traders to make an informed decision. AI-based trading platforms can automate several trading strategies, thereby providing optimized buy and sell orders with profit. Furthermore, AI, alongside blockchain, will assist peer-to-peer energy trading that allows consumers to buy and sell any surplus of energy to one another. Therefore, this will make the market efficient [26,27].

1.7 FUTURE DIRECTIONS AND ETHICAL CONSIDERATIONS IN AI APPLICATIONS IN POWER SYSTEMS

Growing deployment of AI and ML in power systems to ensure they are applied responsibly and are of good use.

1.7.1 Data Privacy and Security

AI and ML depend extensively on data; thus, ensuring this feature is put in place becomes essential in ensuring data privacy and security. Power systems collect vast volumes of data from the consumers, which in some cases may contain sensitive information on the habits and behaviors of the consumers. This is sensitive, substantive data that must be protected from leaks and other abuse. Strong encryption protocols and systems for storing data must be packaged with stringent access controls over consumer data. Finally, regulatory frameworks must be implemented regarding how data is collected, harnessed, and shared across the energy industry.

1.7.2 Transparency and Accountability

Stakeholders need to trust AI and ML systems, which call for transparency in the systems. AI algorithms should be explainable, enabling the stakeholders to understand how decisions are made. This becomes too critical in such critical infrastructures as power systems, where the ramifications might be huge. Cleanliness of accountability can be ensured by setting up well-engineered protocols of human oversight and intervention, with particular emphasis placed on instances in which AI decisions could result in adverse effects.

1.7.3 Bias and Fairness

The AI and ML systems can unknowingly pick up or accentuate biases in the training data sets within the power system without the system designer's knowledge. For example, inappropriately lower or higher tariffs could be charged for a certain category of consumers or region. Developers and implementers must ensure that algorithms are fair and unbiased while their performance is monitored and evaluated to identify and reduce biases. This is enabled through, first, the use of diverse and representative datasets during training in addition to the use of fairness-aware algorithms and evaluation metrics [28,29].

1.7.4 Environmental Impact

AI and ML can improve the efficiency and sustainability of the power system; they, in an initiative, impact the environment, specifically on power consumption during data processing and storage. There is a need to develop energy-efficient AI algorithms and such corresponding hardware while factoring in the impact such AI deployments have on the environment. One such optimistic direction for the future is green AI, which reduces the environmental impact of AI technologies [28].

1.8 CONCLUSION

In conclusion, inside ML, many techniques and approaches are oriented to some data and problem domains. Supervised learning techniques act on labeled data and can provide good predictions because, for most day-to-day strategies, historical data with known outcomes are used. On the other hand, unsupervised learning is quite effective in finding hidden patterns and structures, which usually come in handy in unlabeled datasets. While supervised learning deals with labeled data and unsupervised deals with unlabeled data, semi-supervised learning deals with labeled/annotated and unlabeled/unannotated data to create a system with better quality learning and learning performance. Reinforcement learning differs in the main dynamic and interactive approach in which agents learn to decide through the trial and error of these decisions, optimizing their decisions given the cumulative effect of rewards perceived. Smaller explorations, such as the play of algorithms like QL, DQNs, and PG Methods in Reinforcement Learning, show the great adaptability of the various ML techniques within these learning paradigms and their application domains. Each has strengths and applications with major contributions to research areas varying from natural language processing and computer vision to robotics and healthcare. The continued evolution of ML will finally be reflected by the further development and refinement of these algorithms to meet the more sophisticated and differentiated challenges. Integrating advanced ML models in real-world applications promises to drive innovations and increase efficiencies in various industries. ML can enable the unlocking of new opportunities to get closer to understanding truly deep volumes of data generated in the Information Age.

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2 Applications of Artificial Intelligence Techniques in Power Systems

Mostaan Khakpoor

2.1 INTRODUCTION

2.1.1 BACKGROUNDS

As a demanding technology, AI has demonstrated various applications in many fields including medicine, finance, marketing, customer service, transportation, cybersecurity, and power systems. Whether we admit it or not, AI will permeate our daily lives in many ways and will have a significant impact on addressing societal needs. In today's society, AI is developing in many ways, targeting all ranges of audiences. It can range from our daily Google searches, which recommend lovely jackets, to suggesting food recipes. All have been made possible with the advent of science and research in hardware and software engineering. The introduction of open source code and libraries also effectively helped in shifting fast toward more intelligent and smarter tools.

With advancements in AI and machine learning (ML) algorithms, it becomes crucial to understand how AI works, its impacts, how it contrasts with other technologies, and the opportunities it may foster in the future. In addition, the advances in AI-powered techniques in recent years have attracted great attention in industry and academia. Our industry has been revolutionized several times over the years, starting back from the agricultural revolution in 1760, which introduced mechanization, water power, and steam-powered machinery by 1840. This led to mass production and long assembly lines and evolved to the more recent emergence of computers and automation. Throughout history, humans have embraced new technologies that change the world, making life easier and more pleasant by providing various services and comforts.

Artificial intelligence (AI) is a powerful tool that can revolutionize various services in our daily lives. AI is also recognized as the driving force behind the fourth industrial revolution. It has the potential to redefine future objects from our cellphones to large power plants and propel the digitalization of our society. Although AI applications are considered controversial by some industry magnets, they have demonstrated strong potential for making a difference.

The rapid changes are caused by two main reasons. On one hand, the advancements of high-performance hardware like GPU processors have increased computational power, consequently, computers can perform complex and sophisticated tasks

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in a more effective and efficient fashion. On the other hand, the abundance of data shared on the internet, YouTube, cellphone applications, etc. has paved the way for using them as AI inputs. These achievements have allowed AI to excel progressively in recent years. AI has demonstrated potential and strong impacts in areas such as healthcare [1–4], finance and marketing [5,6], customer services [7–9], transportation [10,11], cybersecurity [12–14], and beyond.

2.1.2 Introduction of AI and Power Systems

Witnessing promising solutions powered by AI in worldwide applications has attracted the attention of researchers and engineers working in various areas. One of the focal points in investigating AI applications is within the domain of power systems. Power systems are always receptive to positive changes, such as restructuring their environment and reducing air pollution by utilizing renewable energy sources. They consistently welcome new technology, making them ever-evolving infrastructures. In addition, many sensors have been installed in the different sectors of power systems, preparing the potential for integrating with AI-powered techniques. Nowadays, power systems are equipped with smart meters, phasor measurement units, and supervisory control and data acquisition (SCADA) which provide abundant data for AI usage. Additionally, being exposed to various uncertainties and ever-evolving challenges in our electricity networks, AI can bring considerable benefits to the system and tremendously ease the so-called hard decision-making within it. Current technologies may not be adequate for the complex and ever-changing future power systems. As we move toward a greener world, mindful of air pollution and limited fossil fuels, we deal with a large influx of unpredicted renewable energies penetrations and their role in meeting demands and maintaining power balance equation [15].

AI models have provided a new era of efficiency, innovation, and reliability. AI will inevitably become pervasive in our power systems over the next few decades. Therefore, it is necessary first to identify the potential applications on power systems and then to use AI accordingly while appropriate. AI has the potential to be applied in both traditional power systems and smart grids. Therefore, AI applications can be investigated and accordingly applied to different power grids' issues. AI algorithms are usually better adapted to power system uncertainties, are robust against various system models, and are less dependent on complete system information for their implementation. Therefore, AI is a valuable asset for power system engineers and operators in addressing power system issues.

2.1.3 Chapter's Contribution

AI may be utilized in numerous applications in power systems such as uncertainty management, anomaly detection, forecasting and predictions, cybersecurity, and optimizations. AI has effectively demonstrated capabilities in topics that are also central to discussions in the power systems area. Having this in mind, a comprehensive review of AI applications in power systems, ranging from smart grids to traditional grids, is paramount for researchers and engineers. A survey that investigates the impacts of AI on power systems and explores the current and future trends in

AI-powered algorithms in this field is yet scarce in the technical literature. Therefore, this chapter tries to fill this gap and shed light on the extensive impacts that AI can have on our power systems. The main contributions of this chapter are as follows:

- The chapter provides a comprehensive overview of the state-of-the-art AI applications within power systems, examining both the current landscape and future potential. It delves into various application areas where AI and ML can make a significant impact, exploring several primary applications of AI in detail.
- A range of ML algorithms is discussed, highlighting different techniques and the potential each holds for specific power system applications. The chapter also addresses concerns and challenges associated with the full deployment of AI in power systems, offering insights that can assist in making informed decisions and strategies for integrating AI into power grid enhancements.
- Furthermore, the chapter explores potential future developments and identifies research gaps in AI-powered techniques. This forward-looking perspective directs scholars and practitioners toward areas needing further action to expand AI applications, particularly for safety-critical power system problems.

2.1.4 Chapter's Organization

The chapter is organized as follows. Section 2.2 provides a preliminary discussion on electric power systems. Section 2.3 provides fundamental information about traditional power systems and smart grids, stating their principles and differences. Section 2.4 delves into showing and comprehension of AI opportunities in power systems. Additionally, the opportunities that AI can take part in will be introduced. Section 2.5 discusses the most prevalent inputs and parameters in power systems, used by AI-powered algorithms as data sets for training purposes. Section 2.6 presents several AI applications in power systems and explores them in detail. In Section 2.7, the challenges and limitations of using AI in power systems are highlighted. Section 2.8 provides a discussion of the research opportunities in AI and possible avenues for developing and exploiting its benefits within the power sector. Section 2.9 draws the conclusions.

2.2 PRINCIPLES OF ELECTRIC POWER SYSTEMS

Before exploring AI applications, it is essential to understand the fundamental components of electric power systems. These systems are interconnected and complex networks comprising various sectors and equipment. The following are the main components [16]:

- **Generation sector:** This is where electricity is created. This sector encompasses all the power plants, including those powered by gas, coal, wind turbines, photovoltaic cells, and hydropower, where electricity is produced.

Therefore, the goal of this sector is to generate electricity while considering cost and reliability.
- **Transmission sector:** The transmission system is considered the backbone of power systems, facilitating the delivery of electricity over long distances. This sector includes high-voltage transmission lines and high-voltage substitutions and transformers.
- **Distribution sector:** This is the final part of the electricity journey. The distribution system manages the final step of delivering electricity to residential, commercial, and industrial customers. The low-voltage lines, step-down transformers, and low-voltage substations belong to this sector.
- **Control and monitoring sector:** This sector is responsible for controlling power systems so that the operation of the network is done in a reliable and secure manner. Smart meters, phasor measurement units and SCADA, and energy management systems are among the facilities in this sector.

The power system structure is depicted in Figure 2.1. The ultimate goal of power systems is to generate, transmit, distribute, and deliver electricity to end-users while maintaining reliability, security, and efficiency with the optimal operational cost.

2.3 FUNDAMENTALS OF TRADITIONAL POWER SYSTEMS AND SMART GRIDS

Power systems can be subject to different regulations and rules throughout the world. Based on their policies and structure, they may be classified as traditional power systems or as modern power systems, commonly referred to as smart grids. Traditional power systems are generally known as centralized electricity networks where electricity produced by power plants is distributed to end-users through transmission and distribution lines [17]. These systems are characterized by a so-called vertical structure with typically unidirectional power flows. On the other hand, modern power systems or smart grids revolutionize traditional

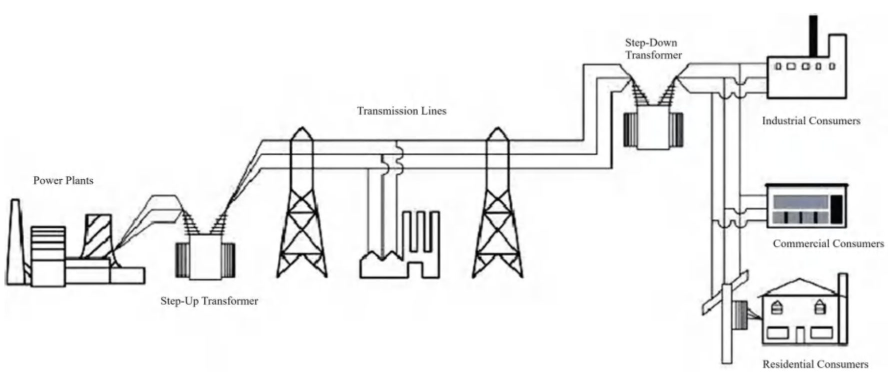

FIGURE 2.1 Power system structure.

TABLE 2.1
Comparison between Traditional Power Systems and Smart Grids

Characteristics	Traditional Grids	Smart Grids
Electricity production	Centralized	Distributed
Power flow	Unidirectional	Bidirectional
Consumer participation	Passive	Active
Environmental pollution	Higher	Lower
Sensors' deployment	Lower	Higher

power systems, bringing different benefits such as increased efficiency, reliability, and environmental-friendly technology, combined with a greater integration of Distributed Energy Resources. Furthermore, smart grids authorize consumers to participate in energy production, thereby advancing them to "prosumers". Unlike traditional power systems, smart girds deploy a large number of sensors and smart meters. Table 2.1 shows the main differences between traditional power systems and smart grids [18].

Despite these differences between traditional power systems and smart grids, they still share many features and services. As such, AI can be applied to both systems to enhance customer satisfaction and improve the services they provide. For the sake of generality, we use the term "power systems" throughout this chapter as a general term to refer to both traditional power systems and smart grids. Note that certain services or problems may pertain specifically to one of these two structures. Nonetheless, AI applications are broad and can be implemented in numerous areas within both traditional power systems and smart grids. In the following sections, we will discuss various applications that AI either can be a part of or currently are being used.

2.4 REALIZING AI OPPORTUNITIES IN POWER SYSTEMS

The initial use of AI can be dated back to 1950 when Alan Turing created the "Turing Test" [19]. Afterwards, many researchers and computer scientists worked on developing AI-powered platforms for different purposes. Therefore, ML and deep learning (DL) algorithms have emerged. Although AI and ML are interconnected and used interchangeably in the literature, it should be noted that they are not the same [20]. Indeed, ML is a subset of AI. In other words, all ML and deep learning algorithms are an example of AI, but not all AI is ML or DL [21], see Figure 2.2. AI represents a broader spectrum of technologies including planning, robotics, and rule-based algorithms which may not necessarily involve learning from data.

Furthermore, the advent of large language models (LLMs) (e.g., ChatGPT [22] and Gemini [23]) has reformatted the field of natural language processing. ChatGPT, introduced by OpenAI, has received great attention and interest from engineers and researchers around the world. It has shown the ability to generate coherent and

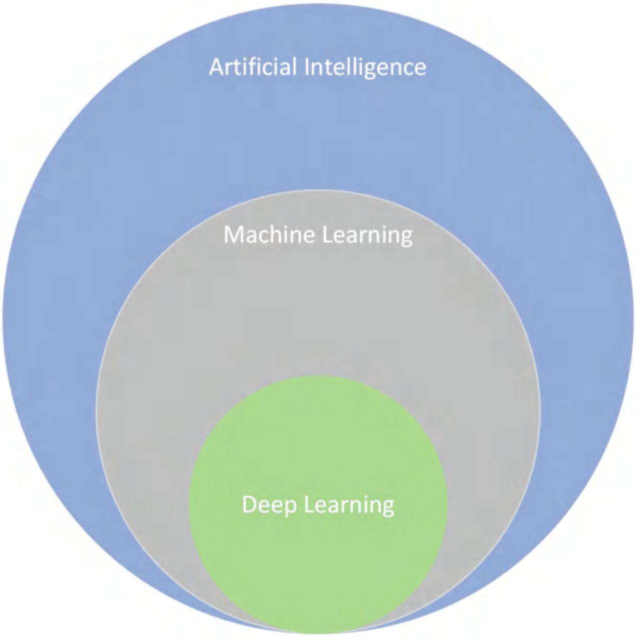

FIGURE 2.2 The Venn diagram of artificial intelligence, machine learning, and deep learning.

contextually relevant responses. This feature underscores the prowess of LLMs which makes them valuable tools for numerous applications.

ML involves the algorithms' development that can learn, predict, and make decisions based on data. ML allows systems to learn and improve from data or experience without being explicitly programmed. Given the power grids' nature, ML and DL algorithms are a perfect fit when trying to leverage the benefits of AI. Generally, ML algorithms can be categorized into three main groups: supervised, unsupervised, and reinforcement learning. In the following, each group is defined.

- **Supervised learning:** Supervised learning is a type of ML algorithms, provided with a specific set of input-output pairs and a collection of labeled training data. The algorithm employs machine inference to develop a function that can replicate the mapping process for new data. Supervised learning is a branch of ML in which the system learns from pre-classified or pre-labeled existing data. A classic example of a supervised learning task is the classification problem, where the goal is to automatically classify objects based on certain known input features after it has been properly trained.
- **Unsupervised learning:** Unsupervised learning is another type of ML algorithm. It requires very little prior information about the model. This type is often referred to as clustering algorithms. The primary clustering approaches can be categorized as partitioning, density-based, grid-based, and hierarchical, although different researchers may use slightly different

terms. No single approach has been shown, either theoretically or experimentally, to be applicable to all problems. Instead, different clustering approaches have their own advantages and limitations, making them suitable for different types of problems.

- **Reinforcement learning:** The reinforcement learning approach is well-known for tackling problems where information is incomplete or hidden. RL focuses on making a sequence of optimal decisions over time within an uncertain environment. This is achieved through ongoing interactions between the decision-maker (known as the "agent") and the environment. Throughout this learning process, the agent improves its performance by continuously learning from the environment and taking actions that influence the environment to achieve its goals.

This is an introductory description for each group. Diving deep into each group is beyond the scope of this chapter. Interested readers may refer to Sarker [24] for more information.

Power systems, which are among the largest infrastructures, frequently deal with uncertainties stemming from various sources including renewable energy resources (RES), load forecasting, generation and consumption volatility, demand-side management, price incentives programs, and more. The manifold stochastic nature of participants and facilities in the electricity networks combined with unpredicted equipment failures and weather conditions, render power systems highly complex and intermittently unpredictable. Thus, reliable and efficient operation by network operators is a challenging task.

Power systems have utilized various methods to meet customers' demand [25,26]. Figure 2.3 illustrates a range of generic uncertainties with regards to different time horizons [27]. It should be noted that uncertainties in a typical power grid can span from millisecond scale for transient studies to several years for expansion planning [28].

In exploring AI opportunities within power systems, addressing uncertainties is critical yet worthy avenue of research since decision-making under uncertainties is always a desideratum across many engineering disciplines including power system problems. Table 2.2 provides an overview of various opportunities of AI-powered models in power systems. It should be noted that based on the specific characteristics of the topic, these models may be utilized in one or more types of techniques.

2.5 INPUTS OF AI IN POWER SYSTEMS

It is obvious that data is very important when working with AI-based algorithms. A lack of data or an abundance of it can significantly impact ML performance. In power systems, a variety of measurements and parameters can be utilized as the required inputs for AI-powered techniques and ML algorithms. Some of the most frequently used inputs and parameters are as follows:

- **Customer demand:** It can indicate the required power to be produced and delivered. It can also aid in load forecasting and predicting future load growth.

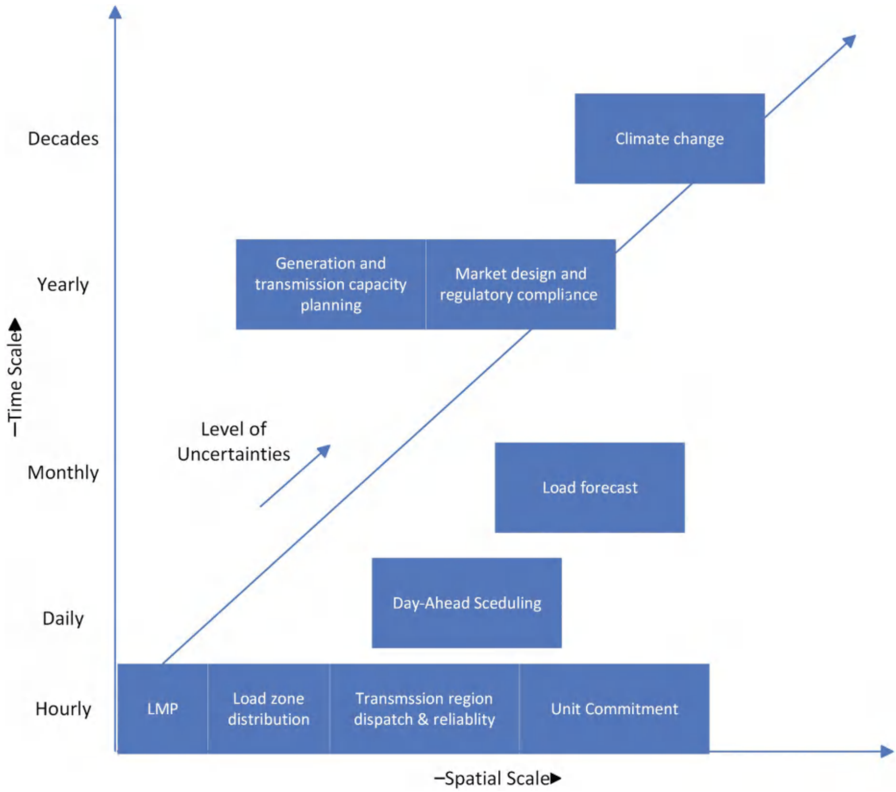

FIGURE 2.3 Levels of uncertainties with respect to the time horizon.

- **Generation capacity:** This input is useful for both short-term operational scheduling and long-term planning. For renewable energy sources like wind turbines and solar cells, the generated amount can also help predict system behavior and the expected amount of green energy participation.
- **Current and voltage measurements:** These are frequently used as inputs for ML algorithms to train models that detect anomalies or faults in different parts of the system and project power loss during operation.
- **Equipment data:** Analyzing operational data of different equipment in the power system can predict the likelihood of failure and suggest routine maintenance to prevent unexpected breakdowns.
- **Seasonal changes and weather data:** These datasets are important for determining variations in load, generation, and power system stress. They can also inform predictions about power system management and operational consequences. Additionally, weather data are crucial in forecasting the next hour's electricity generated by renewable sources.
- **Transmission capacity:** As an input for AI-powered techniques, it can help predict congested lines during specific hours and assist in unit commitment scheduling and power loss reduction.

TABLE 2.2
Opportunities for AI-Powered Techniques in Power Systems

AI-Powered Technique	Opportunities in Power Systems
Supervised learning	• Security assessment in power system • Asset class failure prediction • Electric vehicle charging profile • Optimal power management of microgrids • Trade-off between operation cost and security risk • Collusion detection in electricity markets • Forecast the operational modes of photovoltaic cells • Forecast battery systems • Harmonic management in distribution system • Anomaly detection in smart meters in distribution systems • Making smart grids more transparent • Non-intrusive load monitoring • Automated residential appliance annotation • Optimal demand response of HVAC systems • Dynamic security assessment • Screening power system contingencies • Short-term (i.e., next hour/day) load forecasting in power systems • Substations sitting and sizing problem • Detection of unobservable false data injection attacks • Application of micro-phasor measurements in network event type identification • Electricity consumers' characterization • Wind speed forecasting • Demand-side management
Unsupervised learning	• Harmonic management in distribution system • Non-intrusive load monitoring • Screening of system disturbances • Detecting the correct direction of Photovoltaic array • Optimal grid reconfiguration problem • Forecast of the plug-in electric vehicles (PEV) travel behavior • Detecting types of events in micro-PMU measurements • Data anomaly detection • Assessments of voltage fluctuations in the power systems • Detecting and classifying faults in the transmission lines • Disturbance event identifier • Short-term load forecasting in a day-ahead load profile • Electricity consumers characterization • Estimate the missing data from PMU • Impedance and topology estimation of distribution networks • Dynamic security assessment • Detecting non-technical losses • Operational risk assessment • Preventive dynamic security control • Congestion status identification

(*Continued*)

TABLE 2.2 (*Continued*)
Opportunities for AI-Powered Techniques in Power Systems

AI-Powered Technique	Opportunities in Power Systems
Reinforcement learning	• Cascade failure damage control • Estimation of the system voltage status • Load frequency control • Demand-side energy management • Intelligent power system flow • Increasing profits of a market investor • Scheduling of electric vehicles charging • Minimizing system operator cost • Demand response control • Operational efficiency of energy system storage • Maximizing power extraction from PV array • AC optimal power flow • Alleviation of battery energy system storage systems capacity • Maintaining security and resiliency in power grid • Residential building energy management • Day-ahead scheduling to charge an EV fleet • Volt-VAR control of power distribution system • Tap setting of load tap changers
LLM (ChatGPT, Gemini, Llama, …)	• Co-planner in planning study • Tool for power utility companies • Designing Chatbots for engineers and practitioners • Creation of workshops and learning platform for electricity employees • Support for inquiries about information technology and staff-related issues • Customer services and customer awareness programs

- **Charging and discharging data:** This information can be utilized in ML algorithms to predict total demand at electric vehicle (EV) charging stations, the required energy purchase, the net revenue for station operators, and more. Optimal charging and discharging schedules can also be recommended to EV owners to help reduce system peak load.
- **Network traffic data:** ML algorithms can analyze these data sets, acquired by SCADA systems, for abnormalities which can indicate cyberattacks. Compromised data may also be used to train models to recognize such attacks.

  It should be noted that the above-mentioned data are among the most prevalently used inputs for ML algorithms in power systems. However, there are also other data sets that can serve as additional inputs for various applications, such as special events data, phasor measurement unit data, and so on.

2.6 AI APPLICATIONS IN POWER SYSTEMS

The utilization of AI-based algorithms in power systems traces back to the last three decades [29]. While the concept of AI did not make significant strides forward in power systems for a long time, it has experienced a surge of investigation over the last decade. These models are equipped to deal with sophisticated problems with non-linear mathematical characteristics. The deployment of AI in power systems is aligned with the challenges inherent in their environment. In general, ML algorithms can predict, classify, and optimize data based on the problem's requirement. In this context, each algorithm can play an important role in resolving current issues in power systems.

The applications of AI in power systems can be broadly classified into two critical areas: operation and planning. Power system operation refers to the tasks involved in meeting demands reliably and securely during real-time power generation. Power system operation can range from power plants, transmission lines to local distribution systems. The problem encompasses unit commitment, optimal power flow, generation scheduling, reactive power dispatch, charging and discharging of EVs from/to main grid, voltage and frequency control, security assessments, and so on. Therefore, power system operation represents a large domain with challenges. In the following sections, some major power system issues are explored in detail where AI algorithms have been effectively employed.

2.6.1 Power System Expansion Planning

A typical power system is a large and complex infrastructure. It consists of power plants, transmission lines, AC and DC distribution lines, residential and commercial demands, FACTS devices, wind farms, etc. The primary goal of power system expansion planning is to optimally determine where, when, and what size for new equipment should be installed while considering planning indices [30].

In power system expansion planning, a variety of factors may be optimized including investment cost, congestion cost, reliability index, social welfare, etc. Types of power system planning encompass generation expansion planning, transmission expansion planning, and reactive power planning. Since the expansion planning problem seeks an optimal plan within a given case study, reinforcement learning algorithms are well suited to this problem and have been used [31,32].

2.6.2 Fault Protection

The main objective of fault protection is to detect, and potentially locate, faulty sections and isolate them from healthy sections so that the rest of the system continues operating normally. Fast fault detection is crucial because the fault currents can exceed several times of rated conditions within a second.

Failure to detect faults promptly may interfere with the healthy parts of the system and therefore propagate throughout the system and even collapse the whole system or cause blackouts. Therefore, fault protection is a critical task that should be done quickly and accurately. Additionally, faults can have different types and each presents different behaviors and impacts on the system. Generally, designing a versatile fault detection scheme that can work with different types is a complex task that requires solid electrical engineering knowledge and system modeling. Due to the inherent nature of the fault protection problem, one of the supervised learning algorithms, semi-supervised or unsupervised algorithms are suitable for addressing this problem [33–35].

2.6.3 Demand Forecasting

Demand forecasting is a key predictor of future electricity needs for both consumers and industrial entities. It takes two primary shapes: short-term, which looks hours to days ahead, and long-term, which projects months to years into the future. Achieving precision in demand forecasting is critical since it guides real-time decision-making on the amount of power generation that must be deployed. Therefore, everything from operational efficiency to the stability and reliability of power grids depends on accurate forecasting.

AI/ML algorithms can analyze historical demand data considering influencing factors such as weather conditions, economic indices, social events, and behavioral trends of consumers, among others [36,37]. ML algorithms can enhance their forecasting accuracy by adjusting to new patterns over time.

2.6.4 Renewable Energy Integration

Integrating RES into the power system can be challenging due to their variable and intermittent nature [38]. This integration requires a careful balance between power production and power consumption.

ML can predict renewable energy output power by analyzing weather data and historical patterns of production (i.e., wind farms or solar panels.) [39]. Thus, it can optimize the operation of conventional power plants and manage energy storage systems in order to relieve renewable energy fluctuations inherent in RES.

2.6.5 Prosumer Risk Management

Prosumers generally refer to consumers, or end users, who also contribute to electricity production through their installed rooftop photovoltaic cells or small-scale wind turbines. Therefore, prosumers engage in both buying and selling electricity with utilities or smart grids. Due to price volatility and changing regulatory, prosumers must manage their risks when participating in the market. ML can build models for predicting market prices and optimizing bidding strategies [40].

2.6.6 Predictive Maintenance

Predictive maintenance means routinely inspecting and repairing power system equipment to prevent any failures before they occur. This is a crucial practice to avoid unplanned outages and to extend the lifespan of assets. Moreover, it also aids in properly addressing unexpected power outages in the power systems.

The use of ML algorithms can improve predictive maintenance by analyzing data. It detects anomalies that could indicate impending equipment failures. Thus, ML enables the early identification of required maintenance for specific assets [41,42]. AI algorithms can learn to identify and detect deviations from normal operation patterns as an indicator of potential issues.

2.6.7 Electric Vehicles Integration

EVs are becoming increasingly prevalent in the automobile industry. Many companies now offer their EV models to consumers. EVs can potentially add a significant load to the power grid and change the load duration curve. Hence, integrating this new load in a manageable way is crucial.

AI algorithms have shown effectiveness in managing when and how EVs are charged optimally [43,44]. Consequently, they help smooth out potential peak points on the load duration curve. They have also demonstrated their ability to optimize the use of EV batteries as distributed storage resources within the power grid [43].

2.6.8 Stability Monitoring

Monitoring the power system stability involves continuously assessing the status of the power system to maintain stable operating conditions under various situations. This process is critical to ensure that the system can reliably withstand disturbances like faults, demand changes, or fluctuating generation levels [45].

Utilizing AI-powered models to analyze data enables the early detection of signs indicative of instability, prediction of potential threats, and execution of preventive course of corrective actions to mitigate the risk of cascading blackouts or other failures. ML algorithms have contributed significantly to improving the overall stability of power systems [46,47].

2.6.9 Cybersecurity

The shifting toward digitized power systems increases the vulnerability of the system to cyberattacks. Therefore, this may disrupt normal operations and compromise data. AI can monitor network activity and detect any unusual pattern that may indicate a security breach. Consequently, it allows rapid response and mitigation of threats. Deep learning methods because of their enhanced algorithm structure have shown well suited to deal with these cybersecurity challenges [48,49].

2.6.10 Residential Building Energy Management

Residential building energy management is the process of monitoring and controlling energy use in homes or apartments. Activities include turning off unnecessary lights and managing internal temperatures and more. Therefore, the goal is to optimize energy efficiency and consumption in the building.

AI algorithms can analyze consumption patterns and accordingly recommend energy-saving strategies, tailored to the usage profiles of a household. Furthermore, these systems can dynamically control Heating, Ventilation, and Air Conditioning (HVAC) systems and adjust thermostats based on the occupancy or external weather conditions. With real-time monitoring and controlling of the system, AI algorithms can guide to make more energy-efficient decisions [50,51].

Note that the topics mentioned represent some of the most prevalent applications of AI in power systems. It is evident that AI has the potential to be adopted across various aspects of the power system. These algorithms are continuously improving, enabling them to handle increasingly large-scale and complex power systems. Such enhancements accommodate the growing number of participants and uncertainties in both traditional power systems and smart grids.

2.7 AI CHALLENGES IN POWER SYSTEMS

With AI becoming more pervasive in our daily lives, understanding, and preparing for all the risks associated with this technology is crucial. Despite all the remarkable merits of AI, it still should not be considered as a panacea for problems in power systems. The full applicability of AI-powered algorithms in power systems has encountered certain considerations and challenges. These challenges can be categorized into four main areas which can also be considered as future works in improving and developing AI applications in power systems issues.

1. **Training issue:** AI applications are dependent on the availability of data for the problem under study. The training phase often requires a large number of samples and high-quality training data sets to ensure the performance is reliable enough to be adopted. Traditional power systems still use the old measurement sensors with partially observable data. Although smart grids offer a better environment with more sensors and therefore more real-time data, training data can still be scarce and costly to collect in many situations and operational scenarios.
2. **Lack of explainability:** The use of AI is frequently identified with the black-box characteristics of its algorithms. Indeed, the absence of theoretical analysis and clear formulations can make electrical engineers skeptical and doubtful about AI performance. This is particularly true when the applications are related to safety-critical applications concerning the safety and security of power systems. In such cases, the black-box nature of the AI models may cast doubts on the reliability of results. Therefore, still more research is needed to enhance the transparency and trustworthiness of the AI models in power systems. The ability to elucidate the reasoning behind decisions is necessary to gain the trust of power system engineers when applying such an algorithm in safety-critical applications.
3. **Infeasible results:** AI models can produce infeasible results in power systems issues. Many AI models work solely with the data they receive regardless of underlying problems they aim to solve. Hence, in physics-based problems, common in the field of power system engineering, AI models may generate entirely infeasible solutions. A carefully crafted design

requires domain-specific knowledge. Therefore, this should be considered while choosing an algorithm in the first stage of modeling.

4. **Security concerns:** As power systems become more reliant on AI models, they are increasingly susceptible to the risk of system failures due to malicious attacks. AI-powered power systems are vulnerable to adversarial attacks and various forms of manipulation. Unauthorized parties may infiltrate the power system to cause intentional black-outs or provide deceptive inputs for the systems. They may also steal the data related to producers and customers. Furthermore, it can pose a significant threat to privacy and security issues for all power systems participants.

   It is important to note that the challenges discussed here relate to technical aspects. There are also other challenges from a different perspective including economic, sociopolitical, and regulatory challenges which may also need to be considered when integrating AI in power systems.

2.8 FUTURE DIRECTIONS

Each of the aforementioned challenges represents a significant gap that avoids the full integration of AI in power systems. Future research can be built upon addressing these challenges. The future works and research can be considered in one of the following main directories:

- **Increasing interpretability:** Enhancing the interpretability of AI methods can support the trust of the power system engineers and encourage them to adopt these methods for various issues. Research aimed at better understanding the decision-making behavior of AI models can boost confidence in their utility and, consequently, expand their applicability within power systems. Therefore, this area requires further investigation.
- **Physics-aware algorithms:** physics-informed AI (PI-AI) is an emerging paradigm that has demonstrated impressive performance by aligning with the underlying physics of problems [52]. Despite this, PI-AI algorithms have not been widely applied in power system contexts, where issues are often characterized by complex formulations and governed by mathematical equations. Utilizing PI-AI can potentially yield improved results and therefore expand its applications among researchers, engineers, and industry practitioners. Future studies in the power systems field should consider adopting more PI-AI models.
- **Deep learning algorithms:** While DL algorithms have shown promising results in image and video analysis, their application in power systems remains limited. Future research may explore converting power system measurements into image or video formats to capitalize on the sophisticated capabilities of DL methods to overcome power systems issues.

2.9 CONCLUSIONS

AI models have been employed across various industries and services. Power systems stand out as one of the largest infrastructures that can significantly reap the benefit of AI applications in operation, planning, and monitoring. This chapter explored numerous AI applications and opportunities in power systems. Additionally, some of the most prevalent uses of AI-powered applications have been addressed. It has been demonstrated that integration of AI-powered methods into the power grids is yet to come and many potential applications are under development. This chapter also addressed some of the main challenges and limitations associated with full exploitation of AI models in the power sector. Furthermore, it has been discussed that the application of AI models in power systems may not be feasible for all power system problems considering the inherent challenges of the methods themselves. Accordingly, new paradigms are necessary to establish a secure, explainable, and trustworthy framework that encourages policymakers, practitioners, and engineers to adopt AI-powered algorithms for policy-related and market-based issues. Consequently, the development of reliable and interpretable AI models is a crucial area for future research. By employing such algorithms, AI's application scope could broaden to encompass more power system issues, particularly privacy-sensitive and financially incentivized programs. Despite these hurdles, as discussed in this chapter, AI holds great promise to leave a meaningful impact on power system issues. The learning capabilities of AI models offer significant improvements in addressing a variety of issues within power systems, and consequently, it is likely to lead to increased adoption by power system engineers in the future.

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3 Applications of Artificial Intelligence Techniques in Hybrid Renewable Energy Systems

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3.1 INTRODUCTION

3.1.1 Artificial Intelligence in Hybrid Power Systems Integrating Renewable and Traditional Energy

As a hybrid system in renewable energy systems relies on more than one energy source, one of which is renewable, it is considered an integrated system for supplying electricity to facilities. It may be possible for the hybrid system to contain a method of storing energy [1], which makes it flexible and highly reliable, enhancing the idea. In remote areas and rural areas, especially places outside of the electrical grid, these systems have been used for a long time to meet energy needs [2]. It is proven that integrating multiple types of renewable energy and enhancing them with a storage system confirms the comprehensive nature of utilizing renewable energy continuously which in turn results in overcoming restrictions and increasing confidence in these systems, especially in areas with difficulty delivering electricity and relying mostly on fossil fuels and traditional energy sources. In addition to wind/PV systems, PV/Battery/Wind systems, PV/Diesel/Wind systems, and PV/battery/Diesel systems, PV/Hydrogen/Wind systems are also examples of hybrid systems. As more than one source of energy is needed to ensure that the energy supply is not interrupted in different weather conditions, hybrid systems for renewable energy are becoming increasingly popular in places outside of the grid. A sustainable energy supply can be ensured, for instance, by using wind energy and solar energy together [3]. In addition, you should have a backup generator, such as a diesel generator, or an energy storage system, such as batteries and fuel cells. The fact that some communities are located a long distance from energy supply centers and that it is difficult to deliver electricity to them from a technical standpoint makes the need for a hybrid system in energy supply essential. As they provide energy sources through diesel

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generators, which are considered highly expensive, and require long distances of transportation, it is very costly. Additionally, because fuel prices are on the rise, it has a high operational cost, and it also contributes to global warming by emitting greenhouse gases and emissions such as carbon dioxide that are harmful to the environment. As a result, hybrid systems provide sustainable energy and continuity of supply to these communities [4].

When conventional and unconventional systems are combined, there are benefits, such as adding a diesel generator to operate if the renewable system is not working or if there are circuit shortages in the battery system, and the system has several advantages, such as: reducing fuel use and protecting the environment; eliminating disconnections from the electrical system; and treating hybrid problems directly [5]. Increasing petroleum prices have led to hybrid renewable energy systems becoming more prevalent. Essentially, a hybrid system is composed of two or more sources of energy that work together to provide uninterrupted electricity at high efficiency. Natural resources such as the sun, wind, and water are used to power hybrid renewable systems. Additionally, batteries can be used to store this energy, and diesel generators can be used to support the system when needed. In rural areas far from city centers, hybrid renewable energy systems are common since they meet the energy needs of these areas efficiently and at a low cost. It relies on diesel generators, which are considered environmentally unfriendly and high-cost. Because of the significance as well as the upswing performance of AI in hybrid power systems, this chapter makes knowledge addition by reviewing leading approaches used so far with an emphasis on targeting the preliminary and prominent researchers in this area of research to thereby provide a wider readership with a brief educational guide for advanced and novel concepts in this specialism.

3.2 HYBRID ENERGY RESOURCES SYSTEMS

Solar and wind energy sources are the most widely available sources of renewable energy in the world, and they have a wide range of applications that can be tapped into. Special devices and special maps can be used to study the availability of energy sources, for example, to predict the suitability of an area to apply these systems: Anemometers and Wind Rose maps are used to measure the wind speed of an area and ensure that wind energy is efficient throughout the year. In addition, to measure solar radiation, pyranometers are used, as well as atlas maps that use satellites to provide real-time solar radiation information.

3.2.1 Hybrid System Components

Solar panels: In hybrid systems, solar panels are considered one of the most important renewable energy systems. In comparison with their cost, they produce an appropriate amount of electrical energy due to their high efficiency. Due to their availability in most countries, they have been widely used for a long time. Here is an equation that can be used to calculate the power of solar panels [6].

$$P_{\text{PV-Out}} = P_{\text{N-PV}} \times \frac{G}{G_{\text{ref}}} \left[1 + K_t \left(\left(T_{\text{amb}} + (0.0256 \times G)\right) - T_{\text{ref}}\right)\right] \tag{3.1}$$

Where, $P_{\text{N-PV}}$: the power with ideal conditions, G_{ref}: 1 kW/m^2, G: solar radiation, K_t: constant, -3.7×10^{-3} (1/°C), T_{amp}: ambient temperature, and T_{ref}: Standard temperature 25°C.

Wind turbine: The wind turbine has a high efficiency because it rotates using the kinetic energy of the air, which moves the blades, making them rotate. In contrast to solar energy systems, this system can operate at any time of day or night, and the energy output of the turbine can be calculated. This relationship can be explained as follows [7]:

$$P_{\text{WT}} = \frac{1}{2} \times \rho_a \times A \times v^3 \times \eta \tag{3.2}$$

Where, ρ_a: air density (kg/m^3), A: wind turbine blades swept area (m^2), v: wind speed (m/s), and η is the efficiency of wind turbine.

Fuel cell: In a fuel cell, hydrogen is combined with oxygen to produce water and heat, instead of generating electricity. The components of a fuel cell are an anode (−), a cathode (+), an electrolyte, and a catalyst [8]. Anode (−): This is the negative post of the fuel cell that conducts the electrons that are released from the hydrogen molecules. Cathode (+): Oxygen is distributed to the surface of the catalyst by the positive post of the fuel cell and etched channels, electrons are conducted back from the external circuit to the catalyst, and water is formed by recombined hydrogen ions and oxygen. Electrolyte: proton exchange membrane and specially treated material that conducts only positively charged ions. As a result, electrons cannot pass through the membrane. Catalyst: A material that facilitates the reaction between oxygen and hydrogen. Using platinum-coated carbon paper or cloth. As shown below, hydrogen consumption is related to electrical energy production:

$$H_{2\text{FC}} = H_{2C} * P_{\text{FC}} \tag{3.3}$$

Where, $H_{2\text{FC}}$: fuel cell consumption of hydrogen, H_{2C}: constant of hydrogen consumption, P_{FC}: fuel cell output power.

Diesel generator: A diesel generator is one of the most important components of a hybrid system since it provides energy when a shortage or defect occurs in the network. The hybrid system operates automatically according to its design method. Through the equation, you can calculate how much diesel is consumed based on the generator's capacity [9]:

$$q(t) = aP(t) + bP_{\text{rated}} \tag{3.4}$$

$q(t)$: diesel generator fuel consumption, a and b: are the fuel consumption coefficients, and $P(t)$: energy produced (kWh).

3.2.2 Hybrid Energy Storage Components

Batteries: In hybrid systems, especially those located outside the grid, batteries are the most important component, since they store energy until needed and also store surplus energy. As they provide the hybrid system with energy, they also increase its reliability. These batteries come in a variety of types, including those that contain lithium ions, nickel ions, and others. The following equation shows the battery capacity [10]:

$$P_{\text{Batt,Cmax}} = \frac{\min\left(P_{\text{Batt,Cmax,kbm}} P_{\text{Batt,Cmax,mcr}} P_{\text{Batt,Cmax,mcc}}\right)}{\Delta_{\text{Batt,C}}} \tag{3.5}$$

$$P_{\text{Batt,Cmax,kbm}} = \frac{KQ_1 e^{-k\Delta t} + QKC\left(1 - e^{-k\Delta t}\right)}{1 - e^{-k\Delta t} + c\left(k\Delta t - 1 + e^{-k\Delta t}\right)} \tag{3.6}$$

$$P_{\text{Batt,Cmax,mcr}} = \frac{\left(1 - e^{-\alpha c\Delta t}\right)\left(Q_{\max} - Q\right)}{\Delta t} \tag{3.7}$$

$$P_{\text{Batt,Cmax,mcc}} = \frac{N_{\text{Batt}} \times I_{\max} \times V_{\text{nom}}}{1000} \tag{3.8}$$

$\eta_{\text{Batt,C}}$: Efficiency storage, Δt: Period time (hour), K: Storage constant (hour^{-1}), Q: first available energy (kWh), Q_1: Energy available in battery (kWh), C: ratio of battery capacity, $Q_{\max}$: Total storage of the battery, N_{Batt}: the number of batteries, $I_{\max}$: highest current in the battery (A), and V_{nom}: battery voltage (V).

Hydrogen tank: During periods of excess electrical energy, hydrogen is produced through the fuel cell through electrolysis through the fuel cell. It is believed that this method is effective for exploiting excess energy and storing it in pressurized tanks as hydrogen.

Technology development, especially artificial intelligence, has become a key component of predicting the future of hybrid renewable energy. Scientists are conducting a great deal of research in this field and in what artificial intelligence can offer to renewable energy in the future. As part of the application of artificial intelligence to hybrid energy systems, artificial neural networks (ANN) are widely used to improve the response of hybrid renewable energy systems and to activate their roles intelligently [11].

A summary of all previous components of hybrid renewable energy systems is shown in Figure 3.1.

Many countries are working on introducing artificial intelligence systems into most technological applications, especially in managing energy files, because they require extensive effort to develop. It is here that artificial intelligence can be used to develop and improve energy management programs through its various algorithms. By developing smart grids and by providing citizens with support for building their future projects, developed countries have made laws and enacted legislation that facilitate the development of energy systems and connecting them to the grid.

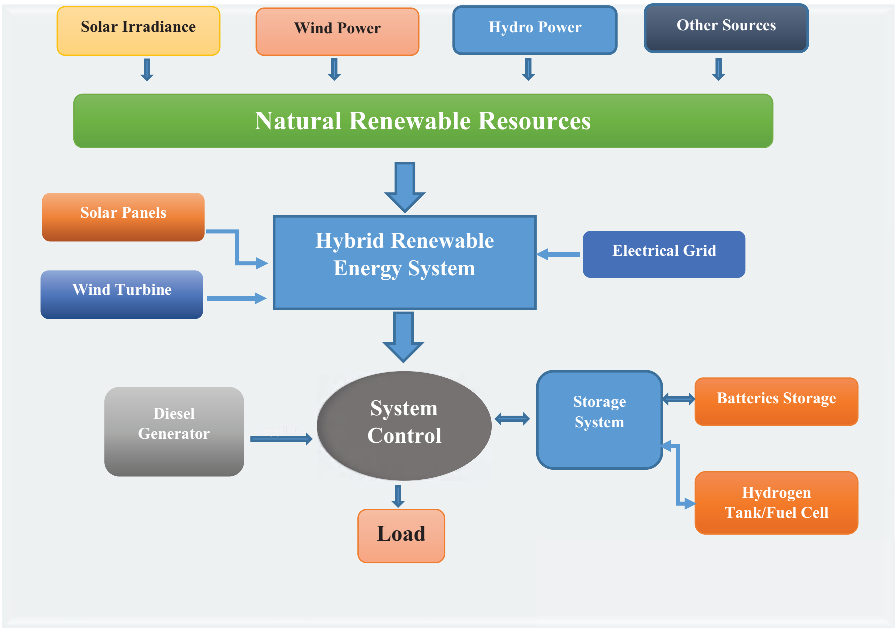

FIGURE 3.1 Hybrid renewable energy systems components.

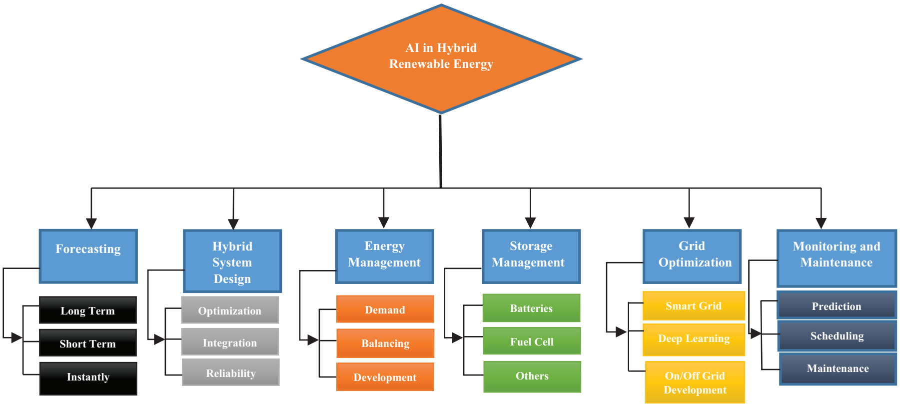

FIGURE 3.2 Role of AI in hybrid renewable energy systems.

Hybrid renewable energy systems can be improved by artificial intelligence through its various strategies, such as design and forecasting algorithms that are established. Based on stored memory and approximate values for each region, it builds probabilities based on stored information and weather conditions throughout the day and year; see Figure 3.2 [12].

Artificial intelligence is responsible for arranging the energy systems in terms of working time and using their appropriate capability. As part of the storage and support system, diesel generators are also integrated. In response to changing conditions, it directs the components of the hybrid system to act intelligently and flexibly based on machine learning. The system is therefore able to accomplish ideal results by acting intelligently and professionally. In a hybrid system, artificial intelligence assists the machine in programming the components to be more intelligent and interactive, so they can perform their tasks as efficiently as possible. Artificial intelligence is used to track solar radiation on solar panels. Allowing solar panels to receive sunlight at the right angle. Atmosphere sensors are connected to this control system, which gives readings to it and provides information on weather conditions and the movement of the sun, and the movement devices are informed accordingly by directing these solar cells in the direction of the most efficient solar radiation. The development of smart dust sensing systems has been linked to a computer, which sends signals to dust cleaning machines if those panels are dusty [13].

Artificial intelligence also works through several strategies to develop the operation of wind turbines used in hybrid systems. In the beginning, it will assist in selecting the best location for installing these turbines by linking them to interactive and aerial maps, and by providing real-time and future information for the region. Thus, wind turbines will be made more intelligent by interacting with wind speed and direction to attract and transfer kinetic energy. As a result, weather monitoring and humidity measurement systems are linked to the part of the turbine that controls its direction, where they operate efficiently and reliably to deliver the best results. By using special equations and algorithms, artificial intelligence works to harmonize the components as a whole, not only at the level of the component that makes up the hybrid system, but also as a whole, arranging orders and systems both at the level of the individual components and at the level of the elements as a whole. An intelligent storage system is designed to meet the hybrid system's capacity and quality needs. A surplus of energy can be stored until needed by the system if production is abundant. Artificial intelligence selects the best storage system based on the information it possesses, whether it be batteries, fuel cells, or others, and controls charging, supply, energy supply times, optimal charging, and optimal discharging of the storage unit. It is possible to sustainably supply the hybrid system without interruption to the energy sources by using technical algorithms that allow the storage system to interact with the state of the system. It is therefore possible to integrate hybrid systems. The purpose of this is to provide a viable alternative to energy and artificial intelligence since these components can be controlled and given orders to achieve unbelievable and practical results [14].

3.3 METHODOLOGIES/THEORY

3.3.1 Artificial Intelligence in Energy Management

The concept of artificial intelligence was developed by humans to help machines comprehend human thinking and solve problems and find ideas and solutions with a high level of efficiency so that humans would not have to exert physical effort or calculate as much [15]. Most aspects of life are affected by artificial intelligence, such as industry, medicine, information technology, education, etc., since it has improved quality and reduced time to accomplish tasks. As is the case in other fields, artificial

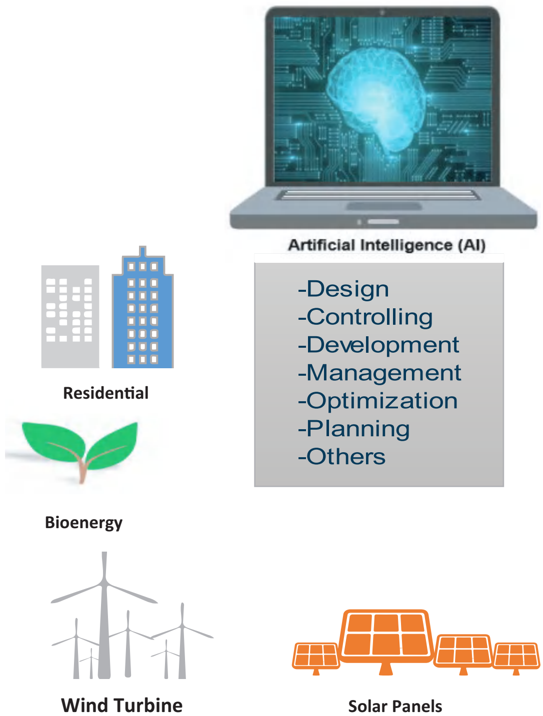

FIGURE 3.3 Applications AI with energy resources.

intelligence has entered renewable energy applications, where it has been used to maximize the use of energy resources and improve their performance, as we can see in Figure 3.3. In addition, hybrid renewable energy systems can be managed better and at a lower cost, as well as providing better outputs. Several engineering fields have used artificial intelligence algorithms in recent years, especially in the energy sector, as the best design is determined by artificial intelligence algorithms. Through these techniques, practical and scientific solutions have been found to predict energy production and probabilities of system success or failure. In order to achieve full sustainability, these techniques allow smart applications to reduce costs, improve systems, and integrate them with hybrid methods [16].

It is possible, for example, to forecast wind speed, weather conditions, and solar radiation using artificial intelligence, but this requires data for that region in addition to advanced sensor technology [17]. A machine learning algorithm is applied to the system to provide optimal solutions to these variables. In this task, the design of the energy system based on the algorithms used in artificial intelligence plays a large role, as it can provide data and readings to the energy system before it is implemented and before it produces energy. Additionally, artificial intelligence has been applied to climate forecasting, which is the most significant global issue. By monitoring future drought rates, some pre-disaster measures can be taken, such as storing additional energy or integrating renewable systems with hybrid systems to guarantee sustainability.

Massive population growth will inevitably lead to increased energy demand, since fossil fuels cannot satisfy this demand [18]. There are many fields in which machine learning is applied, such as programming systems, artificial intelligence, and data improvement. Machine learning aims to reach appropriate and ideal solutions by finding relationships between inputs and outputs. In machine learning, equations and mathematical forms can be used to train various systems to predict, influence decisions, and influence results directly. Deep learning, a part of machine learning, has gained importance as technology continues to advance rapidly. It is the responsibility of machine learning systems to work with their own data. It selects and verifies the appropriate systems, processes, manages, and makes predictions to provide intelligent outputs. In many fields, deep learning contributes to realistic and satisfactory performance as machine learning systems predict renewable energy system performance indicators. In order to forecast renewable energy, hybrid systems have been developed with clear indicators and results. As renewable energy sources are widespread and environmentally friendly, the demand for renewable energy has increased enormously. The use and development of them in the future have been studied, therefore attention has been paid to them. In the future, renewable energy will depend on whether fossil fuel-based systems can replace this new form of energy. We need to ensure the continuous supply of this energy and ensure its reliability. Therefore, these volatile sources must be managed and dealt with in a way that maximizes their benefits. Technology plays a significant role in forecasting and managing renewable energy, storing energy, and developing efficient systems and tools. Thus, machine learning has been applied to forecasting and managing renewable and hybrid energy systems by integrating data and inputs from high-precision systems to find possible solutions and to manage and build renewable hybrid systems. Off-grid and on-grid hybrid renewable energy systems can be managed efficiently with the machine learning system. It is also capable of analyzing and organizing renewable energy resources and conventional energy sources to link them, as machine learning manages hybrid energy systems by:

- There is a predictable outcome to renewable energy. In energy production, it is important to predict these results and outputs, so machine learning has been used to predict solar incidences and wind energy information, for example, based on previous data. This process has some problems, however, because the reading of energy sources changes with the environment [19].
- An abundance of energy sources and a good location on the map. As with any project, hybrid energy plants are built based on the conditions in the area where they will be established, including conditions such as geography, weather, temperature, humidity, etc. Additionally, there are general expenses and costs associated with the area. As a result of machine learning, the best option can be filtered based on the inputs provided for the area.
- Intelligent and integrated operating and managing the system. As soon as the energy source is received, it works to improve all parts of the system, from the point where the energy source is received to the point where the energy is produced and stored. In order to build a smart and highly efficient network, artificial intelligence and advanced systems are needed to manage

these complex and overlapping processes. Through this smart technology, solutions are found, networks are managed, and networks are controlled professionally.

- Forecasting the energy future. This is challenging because it depends on estimates so machine learning assists in estimating the amounts of energy needed at a particular stage or for a particular system. It is also useful for smart grids to know how much energy is consumed and how much is needed for a specific period of time, which increases their reliability and efficiency to boost production in the future [20].

3.3.2 Artificial Intelligence Strategies to Improve Hybrid Renewable Energy System

This section will comprehensively describe the most common artificial intelligence (AI) strategies used in optimization within hybrid energy systems. It is essential to optimize such a system for energy efficiency, reliability, and sustainability because these systems combine quite several sources like solar, wind, and conventional fossil fuels. For clarity's sake, the strategies used have been grouped under the following subheadings:

3.3.2.1 Genetic Algorithms (GA)

A single-objective optimization and management algorithm as well as a multi-objective optimization algorithm work to find the best solutions within the existing data. A single-objective optimization gives one result for the upper and lower bounds of the problem, whereas a multi-objective optimization manages and develops many functions and tasks within the problem space. It provides a set of smart solutions that are reasonable and controlled. As a first step, we enter the population number, and the children are linked with their parents by the intersection of mutations, since mutations result in characteristics that are different from those of the parents. In this way, this mutation may provide a good set of possibilities for the same source. Consequently, the process continues until a reliable and accurate solution has been obtained. The algorithm searches and analyses the required pattern through orders within a specific time frame and stops when it reaches the desired result [21]. In the field of hybrid renewable energy, artificial intelligence was integrated into this strategy, where it was used to determine how much wind energy is needed and link it with solar power, for example, and calculate how much energy is needed and how much it will cost. Additionally, GA was used in forecasting to design hybrid renewable systems combining fossil fuels, batteries, and energy. By analyzing size, costs, and choosing the best options, GA contributed to generating the best hybrid renewable systems. A common strategy used in hybrid systems that use diesel generators and serve areas outside the grid is the GA strategy, which works by organizing the interconnections between the components of renewable energy systems and their storage in a way that considers cost and environmental impacts. A large number of traditional possibilities are examined until the maximum limit is reached to achieve the best results.

3.3.2.2 Particle Swarm Optimization

Swarm systems are used by birds and fish and are based on particle swarm optimization (PSO). An optimization system based on stochastic processes is called stochastic optimization. Whenever we are not able to achieve a satisfactory and ideal solution, this method is used. Based on a set of random options and data, it represents finding the most logical and optimal solution [22]. Cost, sustainability, and reliability are factors considered when determining the optimal design. This strategy can output optimal results more quickly and easily than GA in independent and networked hybrid systems. PSO is an effective way to deal with random targets and find the most appropriate ones when it comes to increasing energy consumption and providing power to remote networks. PSO was developed by Eberhart and Kennedy and is based on the movement of fish and birds. Controlled by a number of algorithms with overlap in locations, it can be controlled in various ways. Compared with GA, the PSO finds solutions faster with fewer possibilities.

3.3.2.3 Artificial Neural Network (ANN)

An artificial neural network links a large number of input elements with their inherent data without requiring complex algorithms and mathematical equations that require extensive analysis. There is a great deal of cells in this system, which are linked to each other to represent elements, like neurons in the human brain. To reduce error rates and obtain accurate prediction results, these inputs are subjected to training and follow-up. It is possible to enter large amounts of data into the input layer, and then to link these elements together using a number of mathematical possibilities and simplified mathematical relationships into hidden layers, until a final, ideal system is chosen based on the previous processes. As ANNs reduce expected errors and make output selection more precise, they work to implement tasks and applications specified for them. Additionally, it can learn self-learning like brain cells, so it does not require complete knowledge. Thus, it is used for network management and monitoring. A controller is considered to be the main controller for renewable and hybrid systems [23].

3.3.2.4 Fuzzy Logic (FL)

A fuzzy logic system deals with many ranges of inputs and elements, which makes prediction values more accurate. Ranges of data are entered, and inputs are grouped into groups. In fuzzy logic engines, probabilities are managed based on pre-set rules, and the results are displayed after the fuzziness is removed from input elements and the elements are sorted. Show the outputs that are required. Based on certain iterations within specific periods, this basic model will work with this system [24,25].

Table 3.1 shows the advantages and disadvantages AI with different strategies.

3.4 RECENT STUDIES AND OUTCOMES

The following section presents the synthesis of the prospects for coupling artificial intelligence in hybrid renewable energy systems with smart grids. Reliability and efficiency will be improved with AI through a reduction in costs that may be incurred during mismatching between interfacing renewable power demand and the primary grid.

TABLE 3.1
Advantages and Disadvantages AI Strategies

AI Strategies	Advantages	Disadvantages
GA	• Easy to dealing with • Ease of completion • Uncomplicated working mechanism • It handles the output in the form of a string	• Long time to make calculations • Complex problems are more complex • The possibility of convergence between the results
ANN	• The possibility of self-learning without follow-up • Ability to work in the event of a network connection interruption • Nonlinear elastic simulation • Uncomplicated system • Dealing with noise	• Complexity in trends and reduction of necessary input data during the entry process • The ability to train for a given volume of data, focusing on the necessary ones • The optimization process takes a long time
PSO	• Faster data convergence and rate • It takes relatively less time than GA • The ability to solve multiple non-linear coefficients • Ability to work effectively in improved versions	• The possibility of convergence in distant space • It needs constant adjustment compared to GA • Presentation and marketing
FL	• Use archived and dated data • Work successfully in complex and irregular situations • Easier interpretation of outputs and models • The possibility of building rules from failure and self-learning processes	• Lack of accuracy in timing • Having trouble with complex elements • Failure to autophagy

Therefore, integration of this kind can lead to minimized electricity energy costs, increased sustainability, and wider user adoption of renewable technologies.

3.4.1 AI in Hybrid Renewable Energy Systems and Smart Grids

As a result of interactive and smart grids, the system can accommodate renewable energy sources as well as the main current, thus increasing reliability. Smart grid reliability has increased reliance on renewable energy sources, and users are more willing to implement their renewable energy systems due to the reduction in energy costs and the possibility of storage in some cases [26]. As one of the most developed renewable energy sources in the world, wind energy plays a significant role in making the electrical grid smart by contributing a variety of sources such as solar energy and wind energy. It has also gained popularity due to its high efficiency. Renewable energy sources must be integrated into the smart grid so that they can communicate with it. There is a need for smart electrical grids to be flexible when it comes to adjusting energy fluctuations caused by renewable energy, since a large amount of reserve energy is sometimes present, and sometimes a storage system is required to compensate for weather-related fluctuations. Thus, this network should be interactive according to user requirements and energy regulation. In the provision of electrical services, the smart grid is considered an interactive network that allows the integration of multiple energy sources in a sustainable, economical, and reliable manner. A coordinated and planned energy supply between the energy consumers and the devices and systems supplied is important for ensuring an optimal supply of energy, as well as dealing with variations in energy loads [27]. Smart grids have become an urgent necessity due to their benefits. The following are some of the most important benefits of renewable energy systems that help this network achieve satisfactory results:

- Enhance and enable renewable energy sources and increase reliability.
- Consumers can be integrated effectively into the grid energy supply system.
- Maintaining a healthy environment by reducing harmful carbon emissions and greenhouse gases.
- Using renewable energy sources to reduce electricity production costs.

It also focuses seriously on AI developing or introducing HRES into smart grids that are to be sustainable energies, among other targeted solutions. The application of AI tools creates significant potential for such systems to be optimized in terms of their design and operation, therefore lowering total life cycle costs and increasing sustainability as well as reliability [28]. In addition, their research indicates that the application of AI methodologies in energy prediction and distribution is bound to experience improved overall system performance while reducing both implementation barriers and costs in the process of making HRES more viable and practical. Further, into engagement with AI, Al-Othman et al. go on to explore its application in hybrid systems incorporating fuel cells and improvements in performance and efficiency. They do show that the adequacy of better prediction models supported by real-time monitoring and adaptive control strategies will make AI necessary for accurate and practical progress to be reached in terms of improved reliability with low costs and better scaling, particularly in the context of hydrogen and associated fuel cell technologies [29]. Furthermore, Shenglin Su et al. have analyzed how AI techniques can be applied in a hydrogen-based HRES and developed case studies to underline the development and implementation of these techniques for optimization techniques in performance, storage, and distribution systems [30]. It is necessary to review the optimization methods—both the classical techniques and AI or hybrid algorithms—whenever the powerfulness of AI implementation into optimization as well as the implications toward the efficiency and viability enhancement for HRES and intelligent grids. These two studies explain another workable option of implementing AI technology for changing the energy scenario to be sustainable [31].

The transition to alternative energy requires the use of renewable energy and hybrid energy to reduce costs. This will facilitate rapid and efficient transformation and develop the process of switching to alternative energy. In all cases, sustainable development in renewable energy and its integration into the smart grid are successful investments, as energy reliability is guaranteed and the user's support for the grid increases, directly impacting the environment. Several factors contribute to the development of smart grid systems and their connection to renewable energy:

- It is considered a practical solution to this problem given the rise in global fuel prices, since the smart grid offers lower electricity prices than the traditional grid.
- As global industries, especially in developing countries, grow, the energy gap between supply and demand needs to be filled, and it is a major problem.
- Government support and motivation are key, as this reduces the cost of capital, which increases the number of systems supporting the network.
- As opposed to fossil fuel-based energy, smart systems contribute to reducing emissions, reducing pollution and environmental problems.
- The use of smart and hybrid systems can provide energy to distant and remote locations as long as renewable energy sources are available, both inside and outside the grid. Thus, they can be implemented in a variety of locations.
- The combination of renewable energy and smart grid provides continuity of supply by addressing the issue of intermittent and irregularity of renewable energy.
- Future energy systems will be based on developing energy technology and electrical connections.

The use of AI improves the efficiency and accuracy of the smart grid's work. Since smart grid management is complex, it requires many processes and commands to maintain the network's performance. Figure 3.4 explains the behavior of AI in

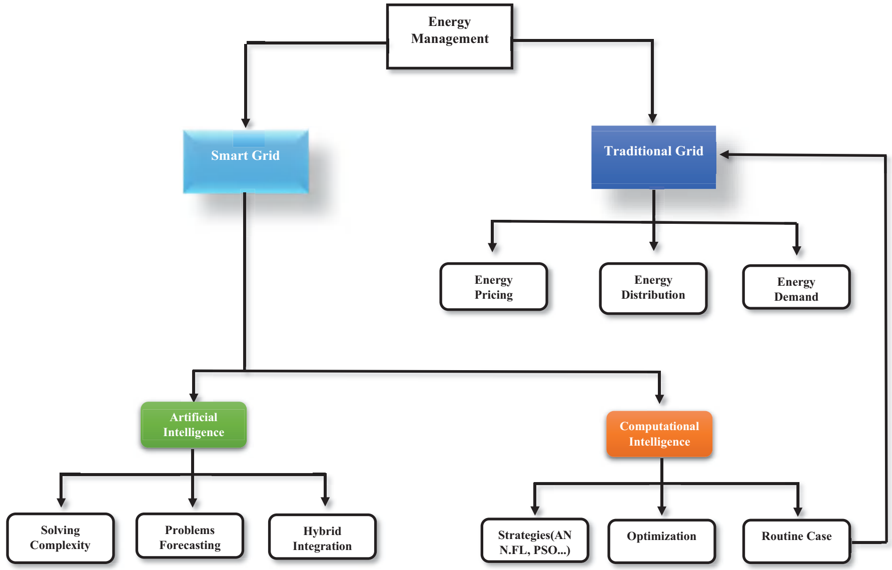

FIGURE 3.4 The impact of AI on energy management.

energy management, smart programs work effectively in networks to monitor and follow up on network disturbances to mitigate them and control them using artificial intelligence. Furthermore, algorithms are used to predict errors and the totality of data added to the network. The use of renewable energy sources results in unstable loads in the network, while demand exceeds the network's capacity, resulting in disturbances [32].

Additionally, it contributes to enhanced integration and speed of decision-making by exchanging information and communications between systems. The benefit of this feature is that it enhances an efficient and homogeneous working mechanism in renewable energy systems, especially hybrid ones. As compared to the traditional grid, the smart grid collects and processes a great deal of data.

It is therefore necessary to use an intelligent system to handle these data and determine consumption quantities. Afterward, it links them to prices, calculates peak demand for energy, and solves all energy problems. Artificial intelligence has a challenging task ahead of it to produce ideal results and conclusions in the shortest amount of time and with as little effort as possible.

A smart grid, on the other hand, coordinates hybrid renewable energy systems like wind turbines, solar cells, and storage units. Integrating energy system information with a control system, FL and ANN algorithms are used in the process of managing and distributing tasks between those systems. Whenever a smart network is controlled, it works much like a human brain since the number of system components and how they are provided to the network make it more complex than a traditional network.

3.4.2 A Cleaner Environment with Artificial Intelligence and Renewable Energy

As the demand for energy increases at a high rate, coincident with the climate change that the world is currently experiencing, the sustainability and continuity of energy in the future are crucial. Thus, it is crucial to consider the future of energy, both renewable and non-renewable, and find solutions to the impacts and restrictions that will affect energy in the future [33]. In terms of sustainability, sustainable energy is defined as energy that meets the need for energy naturally and without interruption without harming the environment or causing harmful emissions. Wind energy, solar energy, and other renewable sources are the most common. They summarized the idea of energy sustainability to meet daily energy needs without affecting or compromising energy reserves for future generations. In addition to protecting their futures from interruptions of energy sources, sustainable energy is also an essential part of reducing climate change, since its extensive use protects them from harmful emissions and prevents interruptions of energy sources.

Renewable energy sources enable energy independence by enabling the process of relying on energy as a sustainable source. A renewable energy source differs from a nonrenewable energy source in terms of sustainability, continuity, and environmental impact. Because fossil fuels emit harmful carbon dioxide as a result of their use as energy sources, non-renewable energy sources, like fossil fuels, have a significant impact on the issue of climate change. A renewable energy source, on the other hand, does not emit harmful emissions and has a minimal impact on the environment. AI and renewable energies will make sustainability and energy saving a new space. Machine-learning algorithms, in particular, have demonstrated near-real potential for optimizing energy systems in predicting energy demand and ensuring grid stability to increase efficiency in renewables such as wind power and solar photovoltaic power. AI can predict production and consumption patterns very accurately, through the use of vast data, and consequently enable the management of energy resources in a better way and waste reduction [34]. Intelligent energy systems, designed for a low-carbon economic change, have emerged with the development of AI technology toward intelligent energy. Such AI-based systems can optimize performance and reliability related to equipment used for energy generation from renewable sources by intelligent monitoring and control, ensuring a more stable and efficient energy supply. Besides, AI applied to energy storage and smart grids would accommodate even larger shares of renewable energy sources into the existing infrastructure, promoting a cleaner and more sustainable energy landscape simultaneously [35]. Artificial intelligence has played an invaluable role in addressing the challenges of energy efficiency and environmental sustainability. The application of AI in the energy sector has moved from rudimentary research and an experimental stage to very sophisticated data-driven methods. Examples here include load forecasting, forecasting energy market prices, and managing distributed energy resources.

The country emphasizes the direction of AI-driven innovation: this is in line with the realization of economic development of high quality and a decrease in carbon emissions. Together, AI and renewable energy, in particular, will represent a giant leap forward for a cleaner environment. It is the power of AI that will be harnessed to increase power system operational efficiency and support the broad penetration of energy sources based on renewables, hence contributing to a sustainable future [36].

Energy sources that rely on traditional sources of energy are diminishing, as they are no longer considered to be primary energy sources. This has resulted in an increase in interest in renewable energy as the only solution to the problem of energy decay, as it is one of the forms of energy that can be used successfully [5]. In places with frequent power outages, renewable energy is particularly attractive for use. Hybrid renewable energy is also highly reliable when integrated with a storage system or generator.

The most important advantages of integrating renewable energy systems into hybrid systems are [37]:

- Utilizing energy sources that are most environmentally friendly will result in a significant reduction in carbon emissions.
- The design and implementation of most systems are simple, especially when used at home.
- Compared to other sources of energy, its prices are considered relatively inexpensive.
- Due to its reliability and ability to supply energy over time, hybrid renewable energy systems are the best choice for remote areas far from power centers.

There are approximately one billion people in the world who do not have access to electricity. The importance of sustainable energy dictates that the sources of energy be close to the end user due to the long distances involved in energy supply [38]. Sustainable energy has become more important because of its ability to solve energy problems. As a result, it increases the cost and decreases efficiency. Recent declines in the price of technologies used in renewable energy have encouraged the trend toward renewable energy and made it more competitive than other sources of energy. Examples of this are solar panels and wind energy. Hybrid systems are most successful in a given area when they are reliable and cost-effective. This will make the hybrid system a reliable source of energy if it achieves its objective.

Several factors and programs can improve hybrid renewable energy systems that give reliable results at reasonable costs. These factors can be applied to both grid-connected and off-grid systems. Graphical construction is one of the improvement techniques, which involves examining the design variables graphically to find the optimal point in the possible area. Probabilistic methods consist of collecting random data, where these data do not have specific values, and using such data, finding the optimal system through statistical equations aimed at finding energy rates for each month or for any other period. Load data can be collected at a low cost and in a short amount of time with this method. By using artificial intelligence strategies such as (FL), (ANN), (PSO), and others, the most appropriate design is selected using machine intelligence and specialized programs and algorithms. Through the use of these methods, good results can be obtained, which are not possible with traditional methods. As a constituent of 72% of greenhouse gases, carbon dioxide is one of the most significant gases contributing to global warming caused by hybrid renewable energy systems [39–41].

Technological advances have been made in all aspects of life thanks to artificial intelligence and machine learning; developments have been made in the fields of technology, health, industry, education, and environmental protection. As with factories, companies, and homes, artificial intelligence systems have also been integrated into the production of smart and interactive devices. Artificial intelligence tools are being harnessed by scientists. Our lives can be made easier and more enjoyable by making it easier and more efficient.

The future of hybrid energy management will involve the development of artificial intelligence systems to address data and inputs related to the nature of the system, its location, and the method of its operation [42]. Due to network fluctuation and continuous updates, hybrid systems will face an array of challenges in the future that will require the development of advanced artificial intelligence algorithms and systems. A key component of artificial intelligence development in the future will be integrating design with digital communication networks, as the Internet of Things (IoT) and energy connectivity fields make room for the introduction of advanced communications technologies and modern networks. Through machine learning, artificial intelligence increases the efficiency of communication between systems. By improving energy quality and reducing harmful carbon emissions, artificial intelligence directly impacts the ecosystem and biological system and reduces diseases related to pollution. It provides opportunities and designs for a clean, free future by using artificial intelligence for designing smart and environmentally friendly cities. Energy

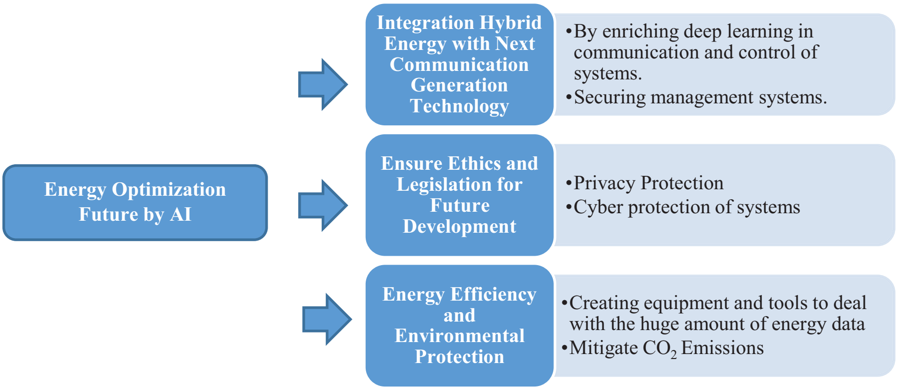

FIGURE 3.5 Energy future with AI.

predictions will be pollution-free and health-friendly through the use of algorithms and strategies. Figure 3.5 summarizes the energy future of artificial intelligence.

Artificial intelligence is rapidly developing, and legislation is needed to regulate the ethics of its use, especially in the areas of privacy and infringement on protected information. Therefore, programming companies must protect their systems and information from artificial intelligence penetration. Consequently, the use of artificial intelligence is a two-sided weapon, so it is important to ensure the development of smart systems in conjunction with the creation of ethical protocols to deal with developments in this field [43].

3.4.3 Economic and Regulatory Dynamics in Hybrid Power Generation

As climate change and environmental problems have intensified, the need for energy has become increasingly urgent, and the demand for renewable energy has grown [44]. Information management readings show that the global trend toward hybrid renewable energy has increased, which is why hybrid renewable energy has become a prominent and effective solution. According to the Energy Information Administration (EIA) [45], renewable energy consumption reached 1240 terawatt-hours in 2010 and 2960 terawatt-hours in 2020, indicating an increased demand for renewable energy. Renewable energy adoption has increased significantly due to public policies supporting sustainable energy and legislation that encourages its use. To enhance the concept of uninterrupted and highly reliable renewable energy, a supportive and adaptable environment was required for this type of environmentally friendly project and hybrid energy. Using more than one renewable energy source is what hybrid energy is all about. Solar energy, for example, operates during daylight hours when the sun is present. This helps to continue the supply of solar energy and reduce problems when the supply is interrupted. This in turn helps to continue the supply and reduces problems. Power outages in different weather conditions, and there are also storage technologies that conserve energy until it is needed.

What are the benefits of hybrid renewable energy? They enhance the reliability and effectiveness of renewable energy systems by providing the following qualitative additions:

- In order to increase reliability, it is necessary to combine types of renewable energy to ensure a stable grid and continuity of supply, which makes hybrid energy a stable and integrated energy source [46].
- Having multiple sources of energy supply and providing energy according to demand, hybrid systems increase energy abundance: Since renewable energy is dependent on weather conditions, hybrid systems provide reliable energy supply continuously [47].
- In a hybrid energy system, surplus energy can be stored in various storage units and supplied to the system when required, which contributes to maintaining the efficiency of renewable energy systems. This maximizes the efficiency of renewable energy systems by utilizing all their products.
- Off-grid areas benefit from a hybrid system: In villages and remote areas, hybrid systems are a reliable source of energy since they replace expensive and harmful diesel generators.
- In order to access clean energy, renewable energy needs to be integrated with storage and support units, which are lower in carbon emissions than fossil fuels and their emissions, paving the way for the elimination of fossil fuels gradually.

3.4.4 Technical Problems

It is important to consider the degree to which the new network from renewable energy is compatible with the electrical grids when there is infrastructure that facilitates the integration of the two grids, especially when there is a hybrid system or the possibility of storing energy. Additionally, network managers must be trained to a high level of skill in order to manage grids effectively. Hybrid renewable energy systems face a number of technical challenges, including:

- In this case, a hybrid system addresses the problem of intermittent renewable energy resources by storing energy or supported by generators, which increases the system's cost.
- Storage of electrical energy is a challenge in hybrid systems since the technologies used for storing electrical energy are limited and lose efficiency over time, not to mention being costly to implement, as well as needing to be replaced when they reach their end of life.
- As a result of varying load, renewable and hybrid energy systems must be integrated into the electrical network. However, integrating those systems into the electrical grid requires technology that is available in the grid. For this reason, the network must be capable of receiving the generated loads and creating a balance between inputs in order to avoid interruptions in the electricity supply, especially in older networks that do not have modern technology.

- A large number of hybrid renewable energy projects are being applied in the form of units or relatively small projects. However, if it is applied at a larger scale, it will require sophisticated technology and control tools as well as complicated communication and control tools, which in turn raises project costs significantly [39].

Numerous renewable energy sources and different storage and distribution systems result in high costs, which present economic challenges. Because hybrid projects contain multiple components and storage systems, they require high investment capital to analyze their initial costs. The cost of these projects consists of the purchase of land, the installation of renewable energy systems, including wind turbines, solar cells, and others, as well as operating costs, installation fees, and the cost of batteries and generators, as well as the creation of a hybrid energy control system as well as communication and control systems for maintaining a continuous supply of energy. It is predicted that renewable hybrid energy will grow and spread in the future. In addition to being able to expand and keep pace with rapid technological progress, it provides diverse and attractive opportunities to solve energy problems. Our world is experiencing smarter technology than ever before, which makes the hybrid system an appealing solution to our high energy demands. Hybrid energy production is directly impacted by network control, ensuring a promising future for future generations of energy [48]. Increasing the use of renewable energy sources is the most sustainable solution to energy supply problems because this energy is widely available in most countries and has a lower carbon footprint than fossil fuels. The use of wind and solar energy is widespread throughout the world and suggests the possibility of replacing traditional energy with clean energy. It is challenging to expand the use of renewable energy sources due to the fact that it affects the social and political aspects that play a key role in encouraging the use of clean energy sources, and the expansion process faces obstacles due to competition with the local industries and companies a country relies on for energy security.

3.5 CONCLUSION

3.5.1 The Review Outcomes

There is no doubt that the future of the world is facing a transition toward a clean and more economical energy either by renewables or advancing conventional resources. Hybrid renewable energy has emerged to enhance the reliability of energy use with realistic expansion. The increasing growth in energy demand requires carefully studying the types of energy and predicting the future to provide energy security for generations by artificial intelligence techniques and strategies. Renewable energy sources can be utilized optimally and at a lower cost, as the continuous development of renewable energy reduces the demand for energy produced by burning fossil fuels, thus protecting our planet from climate change and the harmful carbon effects that destroy nature.

The role of artificial intelligence techniques in control, protection, optimization, and decision-making is fundamental in the optimization of renewable energy systems.

In the renewable energy sector, AI is proving to have great potential for optimizing energy management. Future research in renewable energy sources, especially in hybrid systems, will require its effective application. The application of IA in the different control strategies of hybrid renewable energy systems is important to optimize the performance of the system. This allows the reduction of harmonics, power fluctuations, efficient energy management, etc.

More studies are implementing AI models to demonstrate their effectiveness in forecasting the variability of renewable energy sources. This article also reviews existing studies on AI methods used to predict the variability of solar and wind energy systems.

3.5.2 Future Studies on AI in Energy Systems

The opportunities are considerable in including AI for purposes of efficiency, reliability, and sustainability in energy systems. The following section presents some areas of further research and development operationalizing to fill the present gaps and offer solutions to contemporary issues.

- **Making Artificial Intelligence work in SCADA systems**
  The application of advanced AI algorithms in SCADA systems integrates real-time analytics, predictive maintenance, and automated decision-making to enhance the resiliency and cybersecurity of power systems.
- **AI-based smart grids**
  Future work will involve AI algorithms that will compensate for the energy dispatch, forecast the demand, and handle storage in the smart grids as much as possible so their adaptability to a fluctuating power supply is enhanced with integrated distributed energy resources.
- **Energy Storage Management with AI**
  Develop AI algorithms that tune charge-discharge cycling for longer life of storage components and higher efficiency in general.
- **AI-based forecasting for renewable energy**
  Allow more sophisticated AI models to make reasonable forecasts of solar and wind energy in grid stability and proper energy planning when coping with their variability and intermittency.
- **AI for energy-efficient buildings**
  Emphasize AI-powered building management systems for optimization in the use of space and resources in buildings, including HVAC, lighting, and appliances, to minimize wastage along with energy consumption and greenhouse gas emissions.
- **AI Integration into the Internet of Things (IoT)**
  Look for AI algorithms in processing sensor data with the Internet of Things to make energy systems more efficient, perform predictive maintenance, and detect anomalies.

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4 Applications of Artificial Intelligence Techniques in Smart Grid Systems

Abdallah A. Smadi and Amani A. Alomari

4.1 INTRODUCTION

Conventional power grid is transitioning from an electromechanically managed network to a digitized controlled system. The SG functions coordinate interoperability between various technological devices and equipment, such as smart sensing, management systems, control devices, communication infrastructure, and electronic devices. The planning and operation of the SGs have revolutionized the conventional grid in several areas: (a) Monitoring and measurement, SGs employ smart sensing devices and communication infrastructure to monitor and measure grid performance continuously; (b) Transmit information, SG communicates real-time data among devices and back to operation centers; (c) Automatic response, SGs process, analyze, and respond automatically to changing conditions such as detecting faults and predicting potential issues; (d) Optimization, SGs apply optimization methods to help control centers in situation awareness and implementing corrective actions.

The growing integration of Renewable Energy Sources (RESs), such as PV systems and wind energy, into the power grid is a result of digitization, global warming, climate change, and the depletion of fossil fuels. This high penetration of stochastic and intermittent resources reduces pollution and other additional characteristics, as shown in Figure 4.1: (a) Flexibility to bidirectional power flow, where end users can contribute to energy production; (b) Power system stability, where the network can be divided into multiple microgrids using localized control and management, which can be isolated/islanded during outages to mitigate issues without affecting the entire grid; (c) EV and Energy Storage Systems (ESS), where they can charge from and discharge to the smart grid (SG), enhancing energy efficiency and storage capabilities; (d) Power and energy marketing, where SGs improve energy management efficiency and boost economic welfare by adopting dynamic pricing and energy trading; (e) Decision-making, where SG equipped with advanced methods are capable of autonomous decision-making based on real-time data and predictive analytics; (f) Self-Healing, where SGs are able to detects different types of faults and able to automatically isolate and resolve without human intervention. During faults or outages, the advanced control of the SG can automatically change the grid configuration to isolate the affected areas and maintain healthy areas [1,2]. These characteristics

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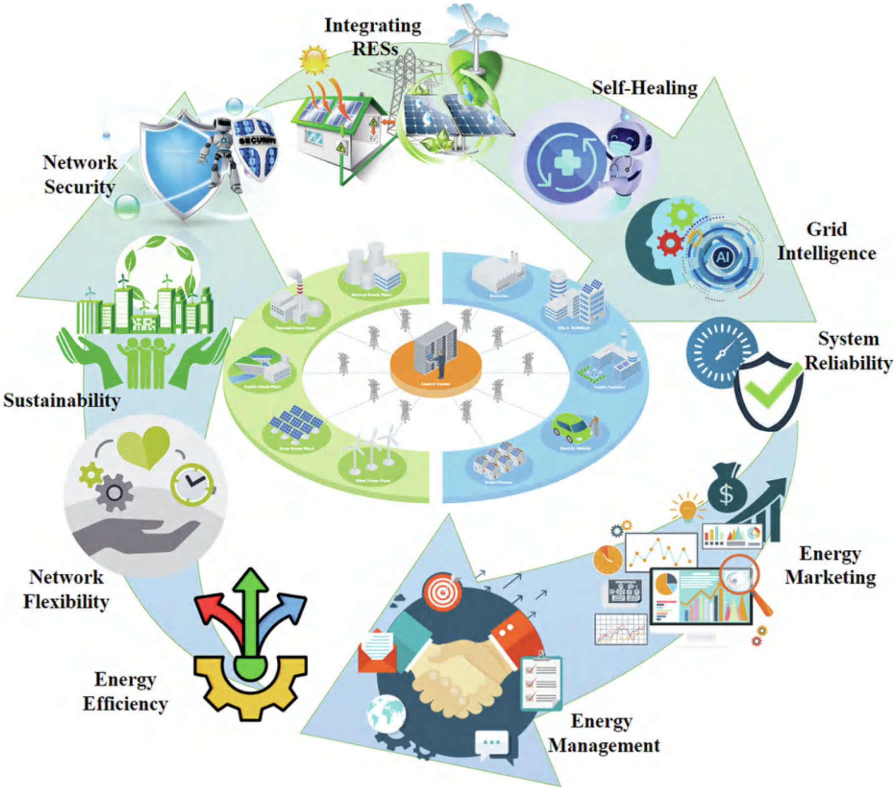

FIGURE 4.1 A schematic of the main characteristics and features of the SGs.

provide a more secure and stable power system that improves the system's resiliency and sustains the power delivery.

However, the unpredictable nature of RESs has presented serious issues to the power system: (a) RESs are not dispatchable sources (their output power cannot be controlled), and RESs cannot be predicted with precision, leading to grid management complexity; (b) Unpredictability nature can lead to difficulties in maintaining a balanced and stable grid, especially during periods of high demand or low generation; (c) The incorporation of advanced communication and control technologies increases the grid's vulnerability to cyberattacks, necessitating robust security measures; (d) The high initial costs of deploying SG infrastructure and the need for continuous updates and maintenance can be a financial burden for utilities and consumers alike; (e) Massive information, these advanced components provide massive, high-resolution, dimensional, and multivariate data about the power system operations. However, conventional modeling, control, and optimization approaches have numerous limitations and restrictions in processing the huge number of datasets provided by smart devices. Thus, the application of AI techniques in the SG has become more apparent [3,4].

The latest Artificial Intelligence (AI) technologies have revolutionized many sectors, such as business, economy, and industries, by solving numerous complicated problems in autonomous driving, computer calculations, computer language processing, and other fields. Massive data sets are used in AI approaches to build intelligent machines that can perform tasks that need human intelligence. AI refers to the computer mimicking the cognitive functions of grid operators to attain self-healing capabilities. AI methods applied in SGs enable fast and accurate decision-making and help SG strict standards for stability, security, and dependability. However, AI techniques may not replace human intervention in the near future as there are many challenges prohibiting AI methods to control SG applications comprehensively.

In this chapter, we examine and summarize the definitions of SGs, advances, and developments that have transformed the conventional power grid into the present form of SG. Then, we give an overview of the state-of-the-art AI techniques employed to improve the speed and accuracy of the SG response. This chapter also presents an overview of the applications of AI techniques to energy management systems (EMS), load forecasting (LF), SG stability analysis, fault diagnosis, and security.

4.2 TECHNOLOGICAL ADVANCEMENTS IN SMART GRID: FROM CONVENTIONAL TO FUTURE GRID

Significant advances have been made in the power grid driven by rapid technological innovation, which has led to a change in energy management. The evolution and trends that have led to a more resilient, adaptive, and interconnected SG infrastructure are discussed in this section. As shown in Figure 4.2, improvements have been based on incremental improvements in generation and distribution, as well as the introduction of computing concepts.

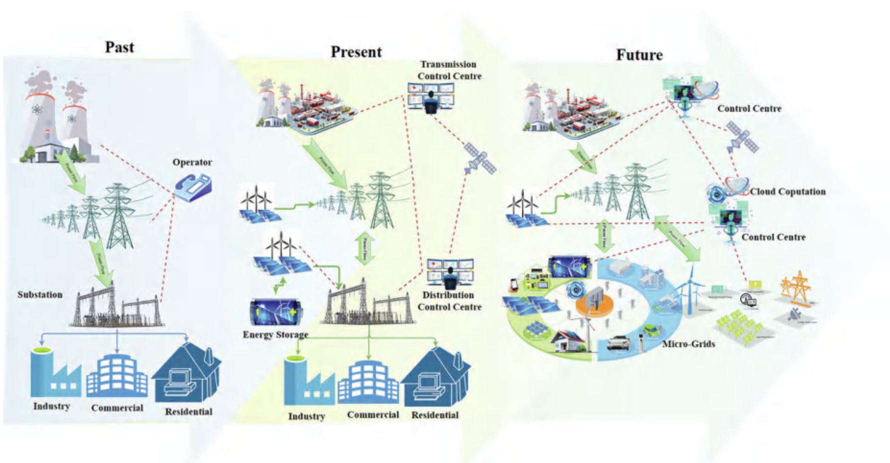

FIGURE 4.2 A generalized schematic of the trends of evolution of the smart grid.

4.2.1 Classical Power Systems

The power grid has experienced a substantial evolution, transitioning from its conventional hardwired to a semi-automatic and then to a fully integrated smart network. The electric power grid was initially established as a district-oriented wire grid and terminals approach, as shown in Figure 4.3. These power networks serve local communities clustered around fuel resources [5]. Over time, these localized grids expanded and interconnected, forming large and more sophisticated structures. Rapid industrialization and infrastructural growth in recent decades have driven the development of the present power grid. Power grids exist in diverse topographies that maintain clear distinctions between generation, transmission, and distribution systems. However, the existing grid operates on an absolute hierarchical architecture, with power plants at the top of the value chain distributing power to customers at the bottom, as shown in Figure 4.3. This architecture scheme has been lacking real-time information exchange between generation and distribution. This hard-wired system, designed to withstand maximum peak demand, has become increasingly ineffective due to rising electricity demand and inadequate financial support for infrastructure. The tolerance limits of the power grid have been reached, which makes it susceptible to catastrophic shutdowns in the event of unanticipated demand surges or irregularities. Power utility corporations have proposed central controllers, such as supervisory control and data acquisition (SCADA) systems, to address these challenges to enable auto-diagnosis and maintenance of upstream assets. While advances have primarily focused on improving generation and distribution, operational changes beyond the substation have only recently occurred, with the core grid computing concept remaining largely unchanged [6].

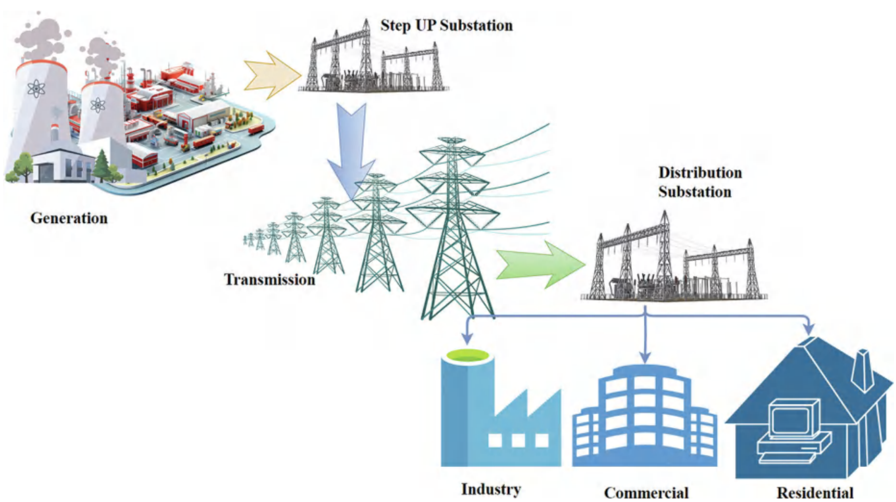

FIGURE 4.3 Overview schematic of the classical power grid.

4.2.2 Smart Power Grid

The SG indicates the shift from the conventional electromechanically controlled power network to a digitally automated control grid. The advancement in infrastructure investment led to the introduction of Automated Meter Reading (AMR) schemes in the distribution system. AMR allows the utilities to read the utilization data, warnings and alarms, and status remotely from customers' premises equipment [6,7].

Various technological, social, and policy trends have stimulated the conceptualization of innovative grid design, operations, and management approaches. An example of these trends is the expanded integration of RESs. This leads to the increased use of smart devices and a rise in Distributed Energy Resources (DERs) such as Electric Vehicles (EVs), rooftop solar, and ESSs. While these practices improve system capabilities for energy producers and consumers, they also carry considerable complexity in power system controls and EMS [8]. This heightened complexity appears when the power system is expected to be more efficient, secure, reliable, adaptable, and resilient to keep up with the rapid growth in energy demand. Handling and regulating such a complex system using the existing centralized control framework has nearly reached its scalability limits. This highlights the need for a more efficient energy grid for a smarter future.

The SG incorporates various control techniques and field-sensing devices communicating information and coordinating diverse electrical functions. The introduction of SG technologies has transformed traditional grid architecture and addressed operational challenges in three primary areas: Monitoring and measurement processes by transmitting data back and forth between the smart sensing devices and the energy management and control centers to make responses and necessary adjustments automatically. Moreover, processes involve evaluating and supporting operators in accessing and utilizing information generated by automated techniques throughout the power grid. Nevertheless, there were drawbacks to these developments, including LF, cybersecurity, grid dependability, and fault detection and monitoring. These crucial elements generate substantial volumes of high-dimensional, multiclass data related to SG functionalities and operations [9]. Hence, integrating AI algorithms into the SGs has become increasingly adopted. Therefore, deploying AI approaches improve precise control, and life-monitoring, decision-making, and analysis are imperative.

4.2.3 Advanced Smart Grid

The future grid has not only evolved from advancements in science and engineering. Nevertheless, it has also been forced by investors and investment motivation to address critical challenges the existing SG faces. The future SG architecture integrates some advances to the current SG, such as an advanced meter reading scheme. However, while AMR represents considerable progress, it must fully address key challenges necessary for effective demand-side management. The ability of AMR to read meter readings with any form of data logging is restricted due to the Simple communication exchange framework. This limitation cannot allow the power companies to take corrective action based on data gathered from their meters. This means that

AMR systems restrain the possible transition to the SG, where universal control and management are at all levels [10]. Consequently, power corporations shifted toward Advanced Metering Infrastructure (AMI).

The advancements of AMI have marked a collaborative effort by investors to enhance ideas surrounding the SG. As the SG paradigm continues to evolve, future SG will be characterized by full-scale automation, intelligent applications, and support from intelligent agents. Sensors for future grids are not just hard-wired but intelligent; the applications are smart, and smart operators support field equipment, which helps with accuracy, information reporting, and monitoring. Transmission and distribution networks will be fully automated, with reliable outage detection and response and support for load balancing [3].

As shown in Figure 4.4, the future SG will be software-driven, with smart sensors incorporating AI techniques to form the Internet-of-Things (IoT) foundation, enabling semi-decision-making and automated management centers. This integration will allow programmable sensors to interface with various platforms, such

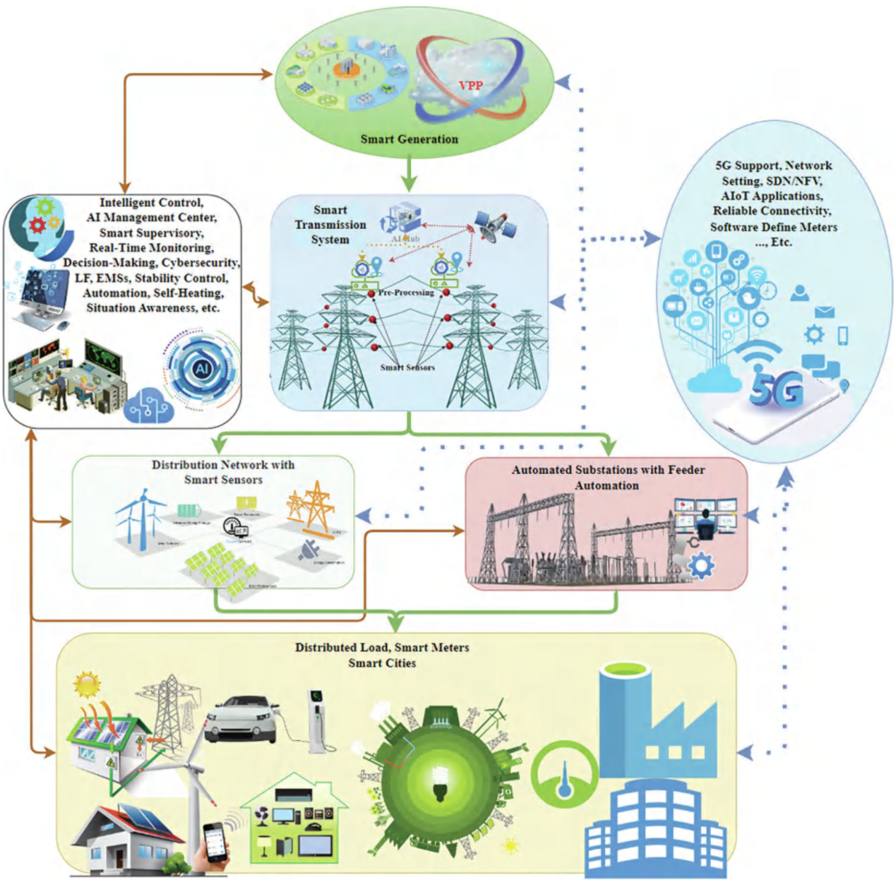

FIGURE 4.4 Generic schematic of the advanced SG functions.

as cloud computing and advanced communication networks. Unlike conventional smart meters, AI meters will make micro-decisions, such as remotely monitoring consumption levels, reporting to authorities, and independently suggesting which appliances need to be disconnected to save energy [3,9]. Additionally, AI meters will offer enhanced security and data privacy to withstand hacking attempts and false data injections. The future grid will feature a sophisticated communication network that is resilient against hackers, utilizing technologies such as network slicing and network function virtualization. Furthermore, the future grid will be software-defined or software-driven with network slicing and network function virtualization capabilities, supported by cloud computing and storage. These networks combine machine learning, language processing, and other cutting-edge technologies to provide AI-enabled services, guaranteeing efficiency, scalability, and resilience [3,10].

4.2.3.1 Power Generations

Two new and innovative cutting-edge concepts are under discussion in energy generation research: Microgrids and Virtual Power Plants (VPPs). Microgrids can operate separately during emergencies, where the control can isolate the microgrid from the main grid and independently generate power to provide services for local loads. Conversely, VPPs are cloud-based control distributed power plants that combine various energy sources to increase generation and ease trading on the electricity market.

The microgrid control technique can autonomously isolate from the national grid during crises, which improves the SG's resiliency, reliability, robustness, flexibility, and sustainability. Isolating or islanding a healthy grid from the affected one due to any outage or crises, such as natural disasters or unexpected events, can help continue serving its customers and support other healthy neighboring grids. Microgrids provide different benefits to the power grid, such as affordable and clean energy, higher efficiency, improved resiliency, dynamic situational awareness, and enhanced operation and reliability [7,10].

The VPP is different than microgrids in many aspects. A VPP, as shown in Figure 4.5, is a cloud-based distributed system combining various heterogeneous DERs energy production. The Aim is to get the maximum possible power generation and facilitate power electricity market trading. A VPP unifies multiple small-scale distributed generation units into a cohesive entity. Despite their various locations, these small-scale sources can be efficiently managed and coordinated through Information and Communication Technology (ICT), allowing them to collectively meet and support peak power demands. This concept of a VPP assists large power utilities operating centralized power plants and centralized control systems by integrating microgrids and distributed energy sources to form a holistic computer-controlled power management system. This fully controllable network can be managed from a central grid control center, allowing the combination of various energy generation sources and large energy users to function as a single and unified supplier [11]. The main differences between the VPP and the microgrids are:

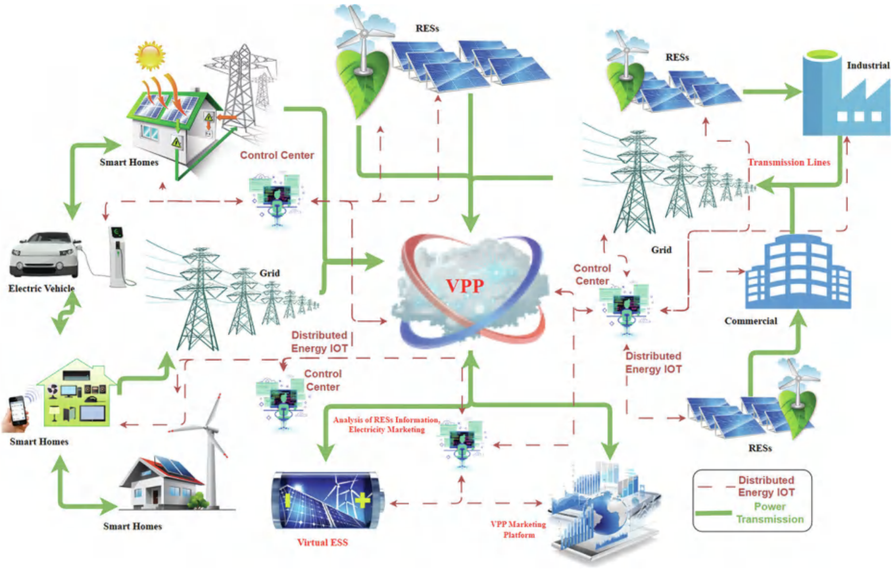

FIGURE 4.5 Generalized conceptualization of the virtual power plants.

1. Microgrids can typically work off-grid and operate independently (islanded) during grid outages, whereas VPPs are integrated into the power grid system.
2. Microgrids are confined to a specific location, such as a region, while a VPP utilizes resources connected to part of the grid.
3. The control, operation, and management systems of VPPs and microgrids differ significantly.
4. VPPs target wholesale markets, and microgrids focus on end-user power supply.

4.2.3.2 Smart Transmission Line

Transmission lines are current-carrying conductors that transmit energy from the generating site to the substations and end at the electric grid. Transmission lines could be long, medium, or short transmission lines. The traditional transmission grid faces several challenges in conveying energy from generation to the customer. Aging infrastructure and transmission losses reduce efficiency, while balancing supply and demand is difficult, especially when integrating RESs. Significant issues include environmental pollution from traditional power generation and the prohibitive costs of upgrading infrastructure. Additionally, engaging consumers in energy-saving programs and adopting innovative technologies remains challenging. Therefore, a robust real-time monitoring and fault detection scheme is essential for transmission and distribution lines. The future power grid will have intelligent, programmable sensors with advanced smart transmission lines. As shown in Figure 4.6, these smart sensors will provide immediate and accurate real-time measurements of the status of transmission lines [3,6,9].

Additionally, augmenting the transmission lines with smart sensors and operated by AI techniques allows the network management control centers to oversee the

FIGURE 4.6 Smart and programable sensors used in transmission lines.

entire grid. This will be the foundation of an internet-oriented transmission network and help utilities monitor and detect faults and address challenges such as cable theft and vandalism. Overall, this technological approach enables two-way communication between utilities and customers, with intelligent sensing enhancing the grid's efficiency and responsiveness.

4.2.3.3 Smart Distribution Networks

4.2.3.3.1 Smart Feeders

Distribution feeders transmit energy from substations or DERs to other distribution substations or end users. Distribution automation is a comprehensive data management network that utilizes AI and ML techniques, smart agents, a secured and high-speed communication network, and smart sensors. These smart feeders improve system reliability, boost energy delivery, provide high-quality services to consumers, and reduce operating and labor costs [2,8,12]. The distribution automation progresses in three stages, as illustrated in Figure 4.7

1. Conventional distribution switching devices like reclosers lack communication infrastructure and computerized control processes. However, smart switching devices such as Intelligent Electronic Devices (IEDs), reclosers, and sectionalizers operate collectively with IOT-based functions. These advanced applications can isolate or island neighboring grids during faults in real time, ensuring continuous energy delivery to unaffected areas. AI sensors monitor and analyze failure patterns using ML algorithms for future reference. Additionally, smart reclosers and auto-switch devices are utilized alongside other intelligent operations and supervision, eliminating the labor-intensive processes currently used in existing SGs [13]
2. Distribution smart supervisory agents can monitor the electricity distribution grid's operational state in real time through this stage. Moreover, remotely

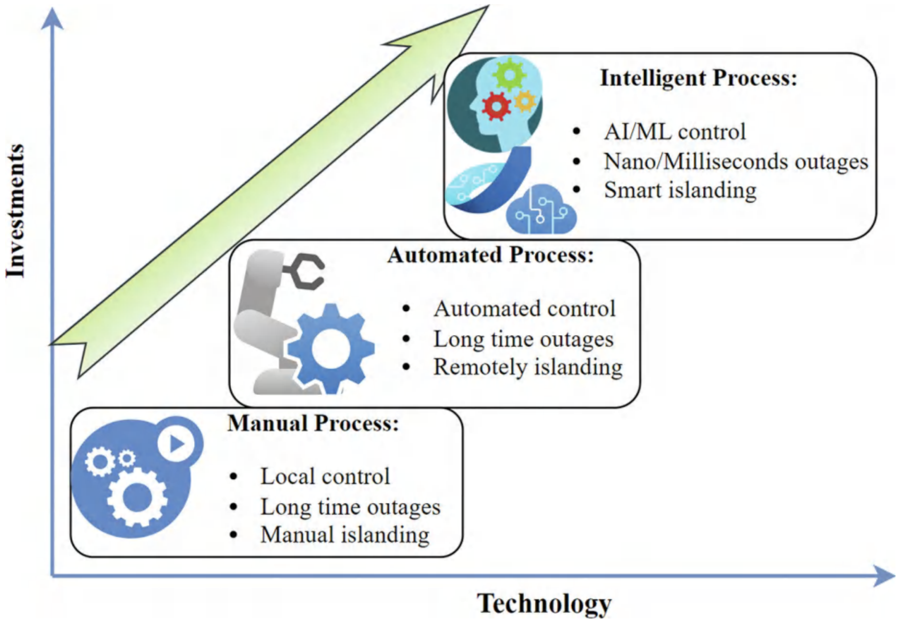

FIGURE 4.7 Stages of advancements in distribution automation.

adjust operational parameters with SG systems and installed radio communication networks. This enables quick fault detection, and dispatchers can remotely isolate impacted communities and bring other areas back online. The communication network transmits vital data, including telemetry and tele-indication data, as well as remote control commands from primary sites to substations for line-fault isolation and restoration. In an intelligent distributed feeder, the processing logic shifts to an intelligent mode via mesh interactions (peer-to-peer communication). These automated processes facilitate intelligent decision-making, fault location, islanding, and power supply recovery in non-faulty areas, which reduces the possibility and duration of power failures.

3. Smart devices embedded with intelligent control functionalities are deployed, integrated, and activated. The incorporation of AI/ML algorithms in future SGs will add more capabilities and features to the present SGs. Firstly, it enables the integration of fully automated and supervised control systems that are smarter than the current SCADA systems used in the present SG networks. Secondly, it incorporates work management, dispatcher scheduling simulation, a defect call service system, and a power distribution geographic information management system. Lastly, remote meter reading, feeder segment switch controller, customer load controller, capacitor bank parameter controller, and substation automation.

4.2.3.3.2 Smart Programable Sensors

AI-powered sensors represent the future of grid management due to their decision-making capabilities and programmability. These smart sensors will play a significant role by gathering raw data about grid status, such as faults and outages, and transmitting it to computationally capable nodes within the grid known as sensor hubs. These local hubs will collect and pre-process the data, making micro-decisions for local intelligence. As shown in Figure 4.8, these localized hubs will communicate data with one another and with the network management center to receive accurate real-time feedback on the grid status. This center works as a global intelligence of the grid, located in the cloud, and organizes the overall management and operation of the grid [3,13].

4.2.3.3.3 Smart Loads

Integrate intelligent loads utilizing AI-driven networks to enhance energy consumption efficiency and reinforce grid performance. These sophisticated loads can autonomously modulate their energy consumption, particularly during peak demand periods, thereby alleviating stress on the grid. Through real-time communication with network management centers, these smart loads are continuously informed of and can respond to dynamic operational conditions. This bidirectional flow of information and control augments the grid's adaptability and resilience to fluctuations and disruptions [2,14]. The intelligent loads, with their adept data processing and decision-making ability, play a critical role in managing the complexity and decentralization of the power network. This, in turn, enhances the grid's reliability, flexibility, and responsiveness to both consumer needs and utility objectives.

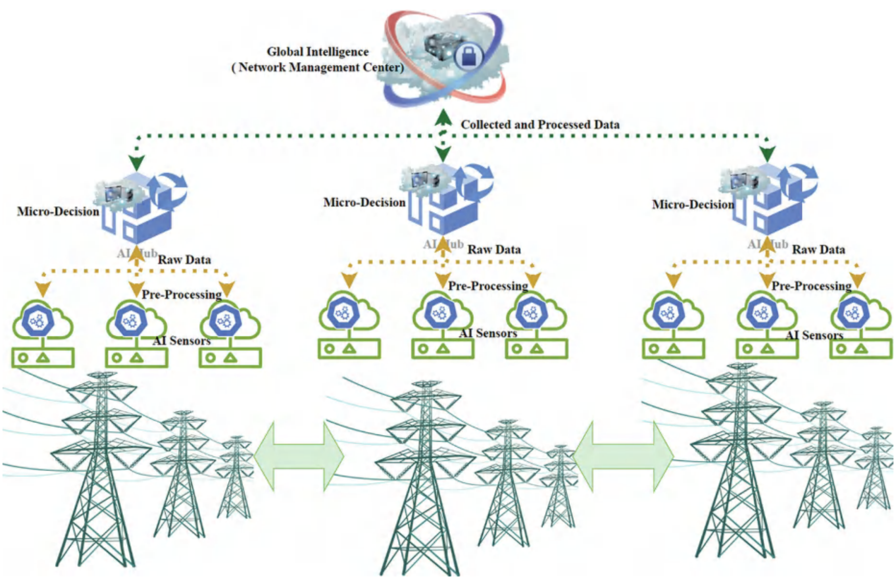

FIGURE 4.8 Generalized architecture of AI-powered sensors.

4.3 AI APPLICATIONS FOR SMART GRIDS

AI techniques have enabled the smart energy markets to facilitate market regulations and policies and benefit the end users to contribute to generation/consumption decision-making. To efficiently manage the power systems and accurately make decisions, sophisticated procedures are required for more complex systems. In general, AI methods are used in SG applications to overcome many issues related to load and generation forecasting, power market pricing, fault diagnostics, control operation techniques, system optimization, decision-making, etc. However, most of the grid operations are still, and field devices are still manually executed, and field devices are semi-autonomous, which needs human intervention.

With the continuous adoption of new technologies, more AI techniques will be implemented in the field, introducing innovative directions to power system operations, security, design, and planning. However, several challenges appear when using AI approaches in power system networks, including developing communication channels between the end user and the generation sides, designing autonomous techniques to adapt and change their configurations under different operation and consumption conditions without the intervention of humans, Developing simulation software and prediction tools that are capable of representing the response of field devices [3,15].

4.3.1 Energy Management System

EMS is a critical component in the control operation centers of the SGs that integrates both technical and economic aspects. It is essential for optimizing grid performance and integrating power resources. EMSs can be divided into two primary categories: model-based and model-free. Model-based EMS relies on domain expertise to develop accurate models and parameters. However, the development of this approach is costly because it is often non-transferable and non-scalable. Moreover, updating the design of the parameters is frequently required due to their inherent uncertainties, which increase the maintenance expenses [16].

On the other hand, ML algorithms are employed by model-free or data-driven EMS techniques to generate optimal control schemes straight from operational data. Model-free EMS enhances scalability and reduces costs by eliminating the need for precise system models. This is because model-free EMS operates by deriving near-optimal control approaches from real-time data. AI techniques are employed in different sectors of the EMS to improve system security, flexibility, reliability, resiliency, etc. For example, Artificial Neural Networks (ANNs) are employed to model the power output uncertainties of the RESs. This aids in stochastic programming formulations for optimal energy management. ANNs are used to minimize production costs, maximize renewable energy utilization, and effectively address the intermittency of RESs and the stochastic nature of market prices and loads. Figure 4.9 Summarizes the main functions of the EMS in the smart power network.

Through demand response (DR) programs, end users are encouraged to modify their energy usage in response to feedback from markets or grid operators. DR increases grid stability and dependability by incentivizing users to cut back on or modify their electricity usage during peak demands [17]. Advances in ICTs have

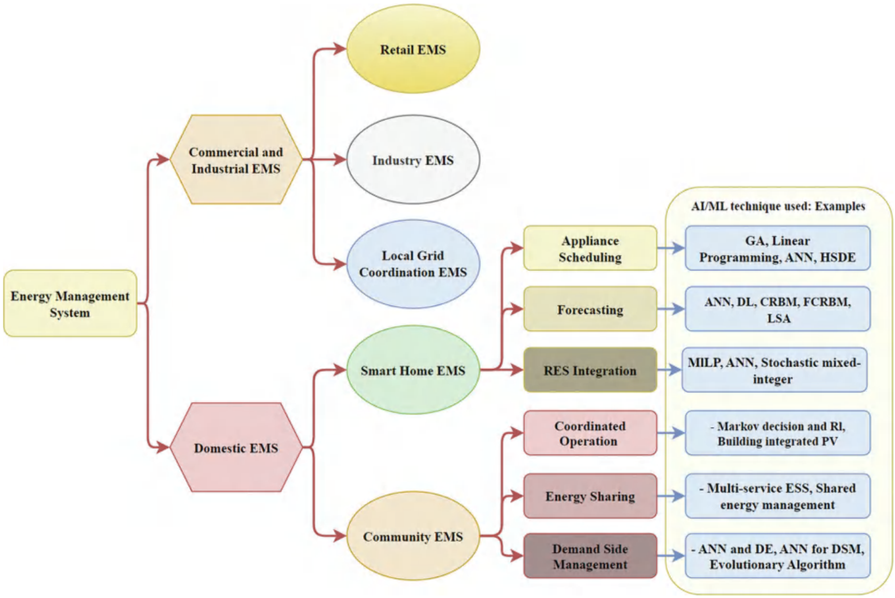

FIGURE 4.9 Energy management system in the SG system.

made it possible for AI algorithms to properly estimate energy prices, facilitating the digitalization of demand response and supporting demand prediction and optimal resource usage. AI tools utilize customer and utility data to optimize grid operations, facilitate decision-making, and load predictions.

4.3.2 Load Forecasting

Future SGs will be characterized by the incorporation and management of diverse DERs. This includes the integration of microgrids and VPPs. However, urbanization and exponential growth in electricity demand are driving the complexity of grid operation. LF emerges as a critical component to ensure grid stability and intelligence. The LF is an EMS tool used to help in scheduling and strategic decision-making. Therefore, accurate LF helps minimize energy generation costs and conserve electric power, particularly in scenarios of fluctuating load demand [18,19].

LF is classified into three categories, as shown in Figure 4.10: Short-Term LF (STLF), which predicts load variations from seconds to hours; Mid-Term LF (MTLF) predicts variations in load from hours to weeks; and Long-Term LF (LTLF), which estimates load patterns from months to years. Numerous factors influence LF, including time, user types, weather conditions, seasons, events, and the applied algorithms. MTLF and LTLF predictions rely on historical power consumption data. Moreover, other key factors, such as customer demographics and weather conditions. STLF is used in applications related to power flow planning, demand response, and real-time monitoring, control, and decision-making. On the other hand, MTLF and LTLF will play an essential role in future SG planning and design.

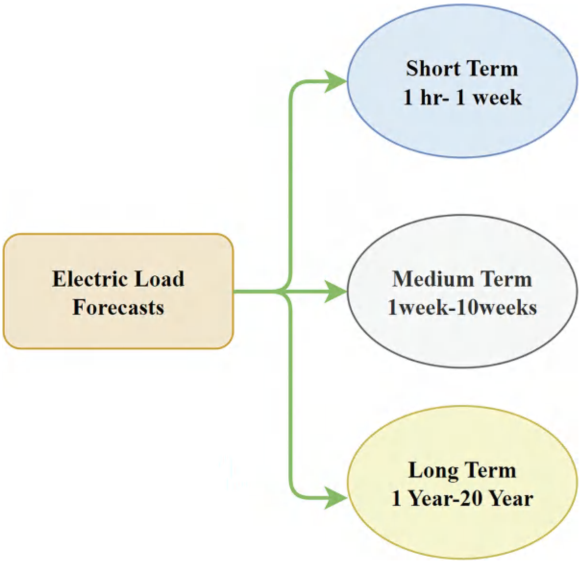

FIGURE 4.10 Basic load forecasting techniques.

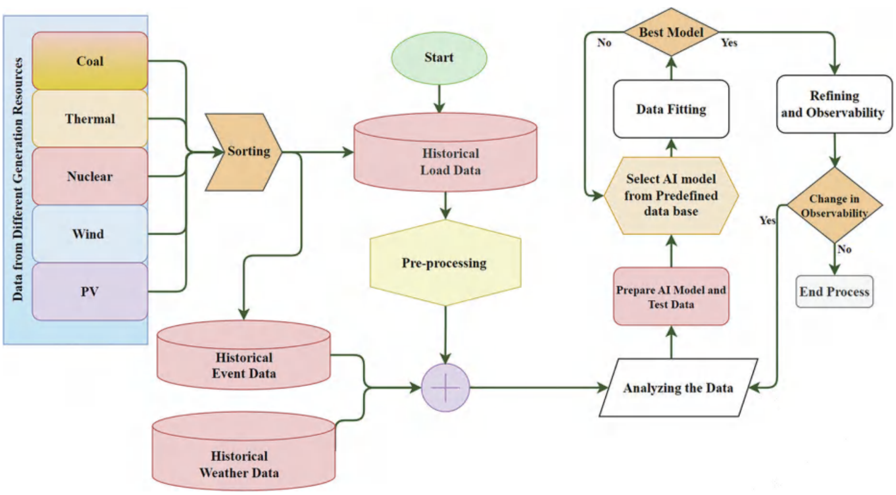

FIGURE 4.11 Generalized flowchart of LF techniques process.

The design of LF models involves several steps, as shown in Figure 4.11. The techniques start with data preprocessing to reduce noise and isolate biased data for a more reliable dataset. Subsequently, AI algorithms are utilized to develop or improve existing algorithms. AI-based hybrid methods, combining multiple algorithms, aim to enhance efficiency and performance. They often employ metaheuristic or trial-and-error approaches for parameter optimization. Another important aspect of effective SG management and control is forecasting RESs such as wind and solar. Studies utilize various AI-based techniques, including ANN and SVM, as well as hybrid methods, to improve forecast accuracy for these intermittent energy sources.

4.3.2.1 Short-Term Load Forecasting

STLF methods are applied to predict the power consumption of the end-users within a time period from 1 hour to several days. STLF is an essential part of the EMS, and it helps control center operations for appropriate load and generation scheduling. The main requirements of the STLF are high forecasting accuracy and speed. At the same time, many factors that can affect the LF have simple or complicated relationships with the loads, such as weather conditions, part of the year and days, and electricity market pricing. Various STLF approaches have been applied in the field to improve prediction accuracy and decision-making efficiency. Generally, these approaches can be categorized as conventional or modern methods.

Conventional methods have demonstrated that predicting accuracy depends on the system, and by combining them with weighted multimodel techniques, more suitable outcomes can be obtained in real-world systems. However, these methods cannot represent the nonlinearity between the load and dynamic system change. Various AI/ML techniques are employed in STLFT to enhance forecasting accuracy. For example, AI approaches combining multiple techniques have shown promise to overcome the limitations of traditional methods. Ultimately, integrating AI techniques offers an opportunity to optimize grid operations, minimize costs, and ensure reliable power delivery within SGs [20].

4.3.2.2 Mid-Term Load Forecasting

MTLF is used for strategic planning and decision-making processes of utilities within SGs. MTLF provides insights into load trends and patterns over a medium-term horizon spanning days to weeks. Moreover, the MTLF is employed in various applications such as managing maintenance planning, load balancing, load demand, and load dispatch. This longer study helps utilities make strategic resource allocation and demand-side management decisions. With the increasing integration of DERs, accurate MTLF becomes essential for ensuring grid stability, optimizing generation, and meeting future energy demand [18].

Adopting AI-enabled MTLF significantly enhances the accuracy and robustness of future SGs. AI techniques can harness vast amounts of historical load data, weather forecasts, economic indicators, and other relevant factors to generate precise forecasts. AI-driven MTLF models can capture complex and nonlinear relationships within the data. This will allow operators to anticipate load variations with greater accuracy. Therefore, corporations can improve long-range planning and proactively address challenges posed by evolving grid dynamics. Furthermore, AI facilitates adaptive forecasting models that can continuously learn and develop to stay ahead of the prediction curve [4].

4.3.2.3 Long-Term Load Forecasting

LTLF is essential for predicting power consumption and expansion scheduling that spans several years to decades. LTLF facilitates substantial investment in the future SG. It plays a significant role in grid planning, power consumption prediction, and load and generation scheduling. AI and ML algorithms are utilized in EMS to improve the accuracy of LTLF models and lead to more precise forecasts. Various AI and ML techniques have been developed to address LTLF challenges. For instance, the multivariate adaptive regression spline approach has shown great precision and consistency compared to ANN and LR models in predicting load demand and environmental variables [18,20]. Innovative approaches like the hybrid fuzzy-neuro model and the Long Short-Term Memory model have captured long-term dependencies.

4.3.3 Power Grid Stability Assessment

System stability relies on the synchronous generator to maintain the system synchronized under and after fault conditions. The three main types of power system stability depend on the magnitude of the disturbance, as shown in Figure 4.12. The power grid stability is assessed based on their behavior, encompassing transient, frequency, and voltage stability.

Traditionally, stability assessments have relied on complex models that are based on real-time dynamic models of the power system. However, the growing electricity demand, integration of renewable energy, and advancements in power electronics devices have raised critical concerns about power grid stability [21,22]. Advancements such as phasor measurement units (PMUs) and wide area measurement systems have also facilitated the application of data-driven AI methods for stability analysis in SGs. Monitoring and early detection of instability are crucial for maintaining secure and stable grid operations. It can be divided into two stages: offline training and online application framework, as shown in Figure 4.13. The processing of the AI-driven grid stability is done offline training while the online process takes care of

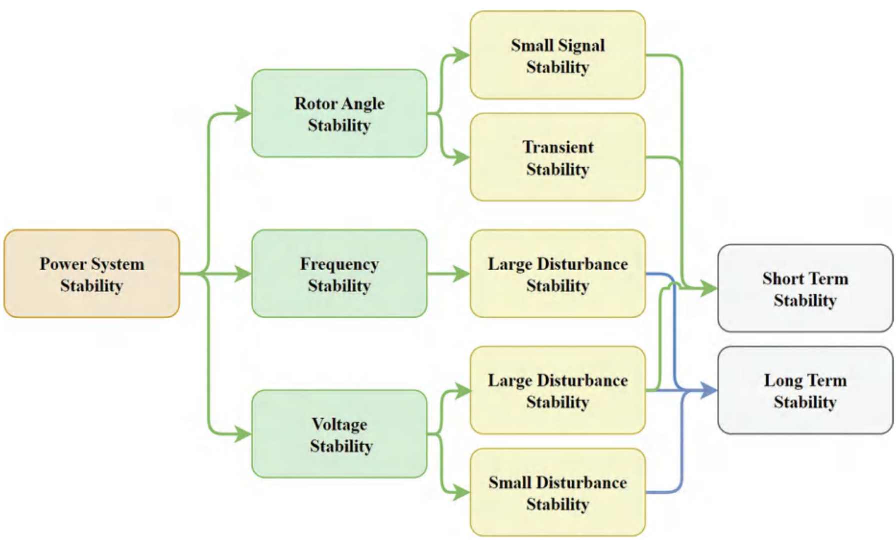

FIGURE 4.12 A general framework of security or stability assessment using AI techniques.

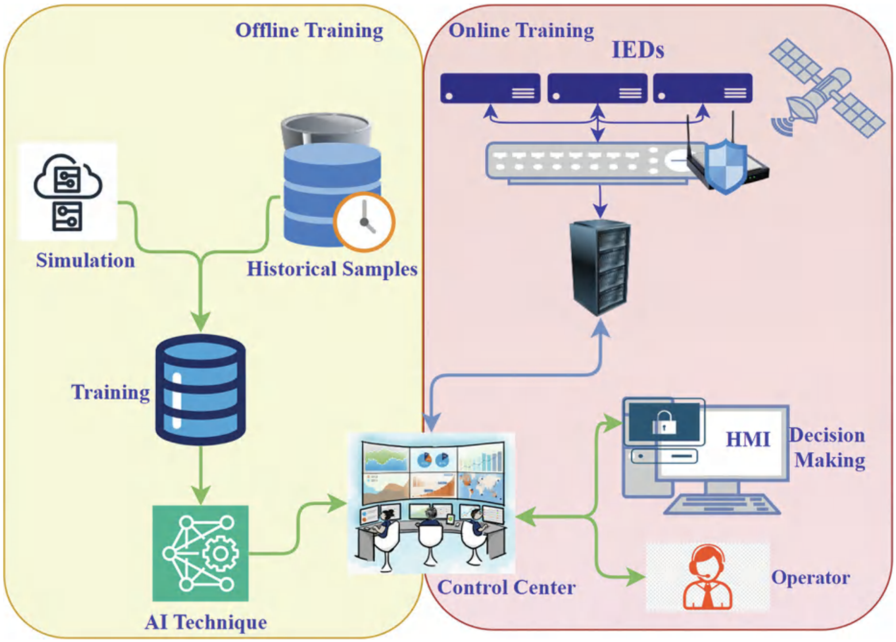

FIGURE 4.13 A general framework of security or stability of the smart grid using AI techniques.

collecting the measurements and the decision-making. AI has been applied to all of these areas for its effective speed, accuracy, and adaptability advantages.

4.3.3.1 Rotor Angle Stability Assessment

4.3.3.1.1 Transient Stability

Transient stability is referred to as rotor angle stability, which is achieved by maintaining synchronism in the synchronous generator. Transient stability represents the large disturbance in the rotor angle stability. Conventional techniques face many challenges in stabilizing the power grid. These techniques rely on detailed models of the power system. These methods require significant resources to simulate the dynamic behavior of the power system. Moreover, they are sensitive to parameter values and susceptible to parameter uncertainties [23]. These issues emphasize the need for more advanced methods, such as data-driven approaches and AI-based techniques. AI and ML approaches are capable of mapping between the stability status and the variables of the power system network. In practice, modern SGs are more stabilized than conventional grids due to their controllability and advanced EMS. Hence, unstable conditions are less likely to happen, which may significantly deteriorate the performance of AI.

4.3.3.1.2 Small-Signal Stability

Small-signal stability refers to the ability to maintain power system synchronism under small disturbances. A small disturbance is considered when minor load changes or small variations in generation occur. The disturbance is classified as a small signal when the power system can return to a stable operation condition without experiencing long-time oscillations. Conventional techniques used in assessing small-signal stability have relied on linearizing the power system models around their operating points [24]. They usually use eigenvalues to represent the model analysis. However, these methods have limitations, including their need for accurate system models and parameters.

4.3.3.2 Frequency Stability

The frequency stability of the SG refers to the capability of the power system to maintain or stay at the equilibrium frequency regardless of the intensity of the system disturbance. The use of renewable energy sources and the use of IEDs in modern SGs have raised more concerns about keeping the system frequency within limits. Frequently, instability of the power system arises from a significant mismatch between energy generation resources and load demand. This issue often becomes more noticeable when a large frequency divergence occurs, causing the corporations to respond in a manner that ultimately affects the system's stability. Due to their speed and accuracy, some interactive and dynamic measures have been proposed using AI and ML techniques to restrain system stability. Additionally, AI and ML algorithms are used for load shedding to help regulate the system frequency as a contribution to proactive measures [25].

4.3.3.3 Voltage Stability Assessment

Environmental constraints, the prohibitive cost of transmission line construction, and deregulation policies drive conventional power networks to operate under stressed conditions. At this point, even minor disturbances could result in a voltage breakdown. Voltage stability analysis is therefore crucial for a safe and dependable power system. Both dynamic and static approaches are used to analyze the voltage stability of the power system. Static techniques capture system snapshots at various intervals, while dynamic methods need more computational time [26]. Corporations developed and adopted methods based on voltage stability indices to speed up the estimation.

The voltage stability indices use the power flow solution to calculate a numerical representation of the voltage stability. Conventionally, the Jacobian matrix is applied to solve the system indices. However, due to non-linearity close to the voltage collapse point, these indices are unable to determine the voltage collapse point with any degree of accuracy. In response to these challenges, AI models trained on simulation or measured data are utilized to determine the indices under the nonlinear relationship between power system variables and voltage stability status.

4.3.4 Smart Grid Security

The future SG will include various IEDs and smart devices such as smart appliances, DERs, smart meters, and energy storage systems spread across vast locations. The security of the physical layer of the SG is just as important as the cyber layer to withstand disasters. SGs are equipped with advanced control infrastructure and communication networks to maintain the stability and reliability of the networks.

However, due to the complexities of real-world power systems, they are prone to diverse types of vulnerabilities to cyberattacks. These vulnerabilities include human behavior, regulatory and political policies, and commercial interests. Incorporating and implementing ICTs into the SG to collect, store, and evaluate data through various sensors and IEDs attracts intruders to the grid to alter its operations.

4.3.4.1 Cybersecurity Root Causes and Surface

The wide emergence of low-cost semiconductor and microprocessor technologies in power systems. These devices can send and receive measurements and control functions between each other, with the control centers at low latencies over digital communication channels. While the increased use of IEDs has lowered the processing and decision-making times during contingency events, they have also increased the cybersecurity vulnerabilities of the power system.

While there are diverse types of cyberattacks, one of the most common is the man-made manipulation of power system functions by intruders and the improper redirection of power flow. Table 4.1 reviews modern power systems' attack surfaces, including the domain and types of common attacks [27].

4.3.4.2 Cyber Vulnerabilities of the Smart Power Grid

The expansion of the power system network led to the integration of communication infrastructure and cyberinfrastructure, which in turn widened the cyberattack surface characterized by intensified complexity, heterogeneity, and number of resources. These incorporations of IEDs and smart devices have launched new cybersecurity vulnerabilities in the following areas [7,14].

- **Communication network:** The integration of IEDs into the power networks increased the complexity, which makes it harder to maintain situational awareness and faster respond to system disturbances.
- **Control functions:** The control vulnerabilities in the SG include a lack of coordination between different grids. This leads to the development of advanced control algorithms to manage the integration of DERs in real time.
- **Cyber-physical system:** Intruders might perform a coordinated attack that targets the physical components of the power grid, such as transmission

TABLE 4.1
Several Types of Cyberattacks on Smart Grids

System/Device Name	Attacks
SCADA	DoS/FDI
HVDC Control System	DoS/FDI
State Estimation	FDI
Communication Media	Delay/DoS/Jamming
RTUs	Delay/DoS/Jamming/FDI
PMUs	Delay/Jamming/FDI
IEDs	Jamming/FDI

lines or transformers, and at the same time attack the measurement data. These attacks can have profound consequences, as the operators do not realize that equipment is out of service.

- **Supply chain:** Adopting smart sensor technologies, combined with modern hardware and software development practices, increases the dependence on third-party providers. This can create supply chain vulnerabilities, such as a lack of security testing, poor software development practices, and a lack of security in the supply chain.

Figure 4.14 shows a generalized view of the power grid cyber vulnerabilities.

4.3.4.3 Impact of Cyberattacks on Power Grid

As previously mentioned, the integration of IEDs to form ICTs has driven the power systems to become more vulnerable to diverse types of attacks. Moreover, faster control algorithms and functions contributed to making the equipment operate closer to its thermal and stability limits. Therefore, cyberattacks can have a variety of effects on the SG depending on the detailed nature of the cyberattacks and the impacted devices [15]. Some of the main impacts that target the SG are as follows:

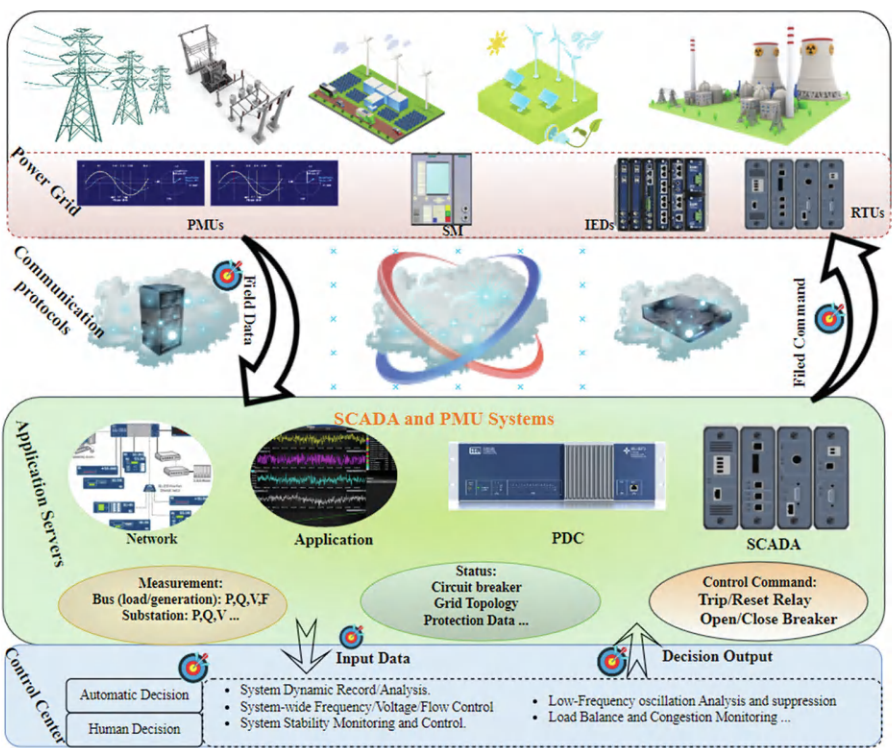

FIGURE 4.14 General overview of potential cyberattack vulnerabilities in smart grid paths.

- **Power outages:** Cyberattacks have the potential to disrupt the operation of the power network, leading to blackouts of the power system.
- **Equipment damage:** Cyberattacks can cause damage to equipment in the power grid, such as generators, transformers, and substations.
- **Threat:** Cyberattacks on the power grid can be used as a tool of espionage or sabotage by nation-states.
- **Financial losses:** The power grid operators, regulators, and the general public can face financial losses due to power outages, equipment damage, loss of personal and sensitive data, loss of intellectual property, and other impacts.

4.3.4.4 AI Techniques in Cybersecurity

Due to the complexity of the power system and the fact that sophisticated attacks are difficult to identify, it is impossible to include every potential hazard in the SG. Malicious attacks can be divided into three main types: information privacy, network availability, and data integrity. In addition to its technical difficulties, the SG presents regulatory challenges. These difficulties are the results of the competition between policymakers and stakeholders competing for dominance in the markets and the regulations [28].

As power systems become more interconnected and reliant on digital technologies, they are exposed to many cyberattacks. Diverse cyberattack types can target power system networks, such as False Data Injection (FDI), sensor attacks, communication latency, denial of service attacks, control system attacks, etc. [27]. Due to their efficiency and accuracy, AI-based techniques offer robust cyberattack detection, prevention, and mitigation solutions. AI approaches can continuously monitor network activities, identify anomalies, and respond to threats in real time. This proactive approach enhances the resilience of power systems, ensuring reliable and secure operations against sophisticated cyberattacks [29].

4.4 CONCLUSION

The power grid has experienced a substantial evolution, transitioning from its conventional hardwired electromechanical system to a semi-automatic and then to a fully integrated smart network. Huge technical innovations have driven this transition to implement various integrated techniques in the power grid. While these innovations provide a sustainable, clean, efficient, and reliable SG, they also accompany new challenges and limitations in processing and analyzing massive amounts of data that make the power grid more complex and susceptible to various drawbacks. Under these circumstances, conventional power system operation control, communication, etc. techniques are ineffective in satisfying the needs for a stable, secure, accurate, resilient, and reliable SG.

With the recent advancements in AI algorithms and the incorporation of digitized electronic devices and communication infrastructure in the SG, AI methods provide powerful tools for SG applications such as EMS, LF, cybersecurity, stability, etc. Hence, AI techniques are being developed and used with promising outcomes in various SG applications.

In this chapter, we presented an overview of the definitions of the power grid, advances, and developments that transitioned the classical power system into a SG. Moreover, it summarizes the enhancement of the present SG toward a future grid that includes unique functions like smart generation, smart transmission lines, smart feeders, smart programmable sensors, and smart loads. Then, we discussed the utilization of AI approaches to improve EMS, LF, SG stability analysis, and security. These improvements will enhance the power system's reliability, robustness, performance, security, and resiliency.

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5 Algae-Based Carbon Sequestration

Optimizing Renewable Energy and Climate Strategy

Pourya Bazyar and Ehsan Sheidaee

5.1 INTRODUCTION

An expanding global population has resulted in the need for more energy. Consequently, more CO_2 enters the air, which increases the global warming hazard. The CO_2 makes up approximately 68% of the greenhouse gases emitted into the air [1]. Reaching an acceptable level will not be achieved unless there is a significant reduction in the level of CO_2 emitted into the atmosphere. Various nations and organizations that are concerned about the environment have looked into alternative energy sources that have low carbon emissions to reduce harmful emissions.

Also, the use of technologies to capture carbon and sequestration has become a critical tool to reduce atmospheric carbon emissions sustainably [2]. Research must be done on strategies for the reduction of the amount of carbon emitted using capturing and sequestering carbon. Lowering CO_2 levels in the environment and sequestering CO_2 can mitigate the pace of global warming. This technology allows for the capture and storage of carbon, as well as its use for other things. Physical and biological methods can be broadly categorized as sequestration and capture strategies have become increasingly popular in final few years [1,3,4]. Physical methods of CO_2 sequestration have drawbacks and are expensive, so it is necessary to develop the appropriate technologies. Despite showing much promise, the method of capturing and sequestering carbon has several drawbacks including high operation expenses due to the high amount of energy consumed. Additionally, it costs a lot of money to capture, move, and store CO_2. Physical methods can be substituted with biological ones for CO_2 sequestration. For instance, it was discovered that the capturing carbon department at the Shanghai factory located in China consumed roughly 40% of the total energy required to run the plant [5]. In addition, carbon isolation frequently entails reservation, mineralization, transportation, and sending carbon thousands of meters below the surface of the ocean which makes this method a complicated process causing numerous concerns including financial, environmental, safety, and technical ones [6]. The technique for capturing and sequestering carbon and isolation method faces many difficulties [5]; on the other hand, the biological method

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has been proved to be sustainable and practical for achieving these goals. Utilizing organisms including plants, the biological techniques to capture carbon turns CO_2 into the energy plants need to survive. In the past, this process has been carried out by terrestrial plants such as trees and new methods of nano-agrochemical grows [7], but algae have been discovered to be more effective than such plants in capturing and sequestering carbon. Algae species are more effective than terrestrial plants at absorbing and storing carbon up to 10–50 times [4].

The reduction of CO_2 and production of biofuels, and other intriguing specialized metabolites are among the benefits of using algae for CO_2 sequestration. Algal dry cell weight uses approximately 1.83 kg_{CO2}/kg while raceway ponds can sequester between 54.9 and 67.7 tonnes of CO_2 annually that is, 30–37 tonnes (d.w.) of biomass are produced per hectare [8]. Biofuels and other scientifically and commercially significant goods, such as industrial food items, biofilters, and water quality testing products can be made from algae biomass [9]. When these organisms reach a certain size, they can be used as feedstock materials in producing biofuels. They grow faster than land plants and efficiently fix carbon through photosynthesis [10]. A drawback of an open system is it cannot be controlled for factors like temperature, pH, nutrient concentrations, pH availability, or agitation. In open systems, seasonal and daily temperature fluctuations and varying light availability pose significant challenges [8]. Additionally, because of its high susceptibility to contamination, these systems are less productive when used to produce commercially significant goods and have a lower productivity overall. In a closed system, there is a very high degree of control and the ability to manage key variables that affect culture [11].

This chapter primarily explores algae's role in CO_2 sequestration. It covers diverse mechanisms and equipment employed for CO_2 sequestration and biomass production. Additionally, the chapter discusses algae's life cycle, performance, economic evaluation, environmental impact, and its significance in carbon capture and sequestration.

5.2 THE METHOD OF MICROBIOLOGY CONCERNING ALGAE

In the sequestration of carbon and photosynthesis, algae are among the most useful organisms and are divided into multicellular and unicellular, which differ in morphology and size [12]. Algae are primarily classified based on the life cycle cellular structure and color [8,13]. The photosynthetic ability due to possessing chlorophyll in a single algal cell, facilitating the generation of biomass, and doing effective metabolic and genetic research in another period shorter compared to conventional plants is what differentiates them from other microorganisms.

Algae possess key features such as chloroplasts with chlorophyll and other pigments, cell walls, starch granules concentrated on their surfaces, pyrenoids, flagella, and a stigma. Filamentous colonies of cyanobacteria (blue-green algae) can be grouped into types of cells including akinetes, cells vegetative, and heterocysts. Resisting climate, carrying out complete oxygenic photosynthesis, and fixing nitrogen are general functions of vegetative cells, heterocysts, and akinetes respectively. The nitrogenase enzyme complex in heterocysts converts atmospheric nitrogen into ammonium, a unique capability among oxygenic photosynthetic microorganisms.

These are the unique prokaryotes that, similar to eukaryotic algae and plants, are known to have oxygenic photosynthesis for CO_2 fixation. These organisms are remarkably able to produce value-added products and biofuels [14,15].

Algae are classified based on their environment and morphology as well. A vast group of photosynthetic organisms are known as cyanobacteria and green algae. They can be found and grow in many conditions from aquatic to terrestrial places. As the wide range of cellular lipids obtained from algae shows they can survive in various carbon-rich surroundings.

5.2.1 Algae Species for CO_2 Sequestration

A majority of species of algae can withstand high concentrations of CO_2 and can be withstood by many species of algae as a result they can use the CO_2 from the exhaust systems of factories [4,16]. Numerous algae are known to use carbonates including Na_2CO_3 and $NaHCO_3$ for their growing themselves [17]. Different species have different oil concentrations up to 80%. Algae can therefore be used to keep CO_2 and change it into energy [18]. How high levels of CO_2 affect their species has been analyzed in investigations that focused on the species that sustain high CO_2 concentrations and produce biomolecules such as triglycerides and lipids meanwhile [19]. Some various types of algae including green, brown, blue-green, and yellow-green from both groups of unicellular and multicellular have been investigated for biosequestration. Scenedesmus obliquus unicellular green algae, Arthrospira (Spirulina) platensis (SP) a blue-green microalgae, and Chlorella a single-celled green algae are generally used for capturing carbon [20,21]. Cheah et al. presented that cultivation of unicellular algae can remove 1.83 kg_{CO2}/kg and it can create high-performance for sequestering CO_2. Chlorella vulgaris (green, single-celled microalgae) and Anabaena sp. [22] (a filamentous cyanobacteria) with speed of 6.24 g/L/d may remove CO_2 [23]. For comparison, the amount of CO_2 in the air changes between 0.03% (V/V) and 0.06%; however, in the flue gas it can change between 6% (V/V) and 20% [24–26]. The CO_2 biofixation and the algal biomass production oscillate greatly controlled by characteristic algae species, impacts of the cultural system, and effects of the physicochemical process. The cultivated process of selected species of algae is significant for the successful biomass production of CO_2 bioconversion. CO_2-tolerant Scenedesmus sp. allows an increase in the amount of CO_2 from 10% to 20% (V/V), however, the ideal concentration of CO_2 is just 2% (V/V). The CO_2 amount that the algae species is exposed to has a significant effect on the obtained biomass [27]. Cultivated Nannochloropsis sp. at 15% (V/V) in a day, CO_2 grew faster at a rate of 58%, from 0.33 to 0.52 [28]. If the amount of CO_2 exceeds 5%, it is fatal for the growth of certain types of algae.

5.2.2 Different Metabolisms for CO_2 Sequestration

Algae, responsible for over half of global CO_2 absorption, are primary producers of oxygen through photosynthesis. On the other hand, some algae species can endure in dim surroundings because they have heterotrophic metabolisms. Under some circumstances, some algae strains can develop mixotrophically. Algae must be able to grow in heterotrophic, auto-phototrophic, or mixotrophic environments to absorb the carbon of organic matter (TOC) from waste that if not, will be emitted into the air.

Dissolved inorganic carbon (DIC) including CO_2, H_2CO_3 and HCO_3 can be taken up by algae. The spectrum of DIC assimilation in terrestrial plants, in contrast, is considerably less [29,30]. *Chlorella miniata, Monodus subterraneus and Chlorella vulgaris* are examples of algae strains that can only absorb CO_2, while marine eustigmatophyte algae like *Nannochloropsis oculata* and *Nannochloropsis gaditana* are actively able to transport HCO_3^- [31]. Contrarily, several species, including *Chlamydomonas reinhardtii, Auxenochlorella pyrenoidosa, Scenedesmus obliquus*, *Chlorococcum littorale* has an external carbonic anhydrase (CA) and can utilize both CO_2 and HCO_3^-. Some strains, like *Chlorella ellipsoidea* and *Chlorella kesslerii*, don't have an external CA but can still use CO_2 and HCO_3^- [32–34]. Algal CO_2 fixation requires both Nicotinamide-adenine dinucleotide phosphate (NADPH) and Adenosine triphosphate (ATP), both of which are produced during photosynthesis abundantly. The three stages of the Calvin cycle – carboxylation, reduction, and then regeneration – describe how CO_2 is absorbed. During carboxylation phase, ribulose-1,5-biophosphate (RuBP) is formed from ribulose-1 and is absorbed by 5-bisphosphate carboxylase (RuBisCo). Following chemical reduction and 3-phosphoglycerate kinase action, converts 3-phosphoglyceric acid to glyceraldehyde 3-phosphate and glyceraldehyde phosphate dehydrogenase, respectively. The fixation cycle moves on to the next stage as a consecutive series of chemical processes replenish RuBP. Yet, when some algae strains eat HCO_3^-, carbonic anhydrase can create CO_2. An abstract of the auto-phototrophic metabolism for CO_2 assimilation can be seen in Figure 5.1.

In heterotrophic metabolism, the pentose phosphate pathway (PPP) enables the respiration of organic molecules to produce lipids and other metabolites as they pass through cell walls [35]. Certain strains can display heterotrophy when exposed to light. Photoheterotrophy is a process that uses light as a source of power, heterotrophs can grow more quickly and produce more biomass, lipids, and proteins while also operating more simply than autophototrophs. Also, heterotrophs avoid the light restrictions that occur during autophototrophic development, resulting in faster growth of protein, lipid, and biomass production as well as more straightforward processes. However, the diversity of the high capacity of heterotrophic is constrained, and bacterial activities could be detrimental to the survival of the culture. The majority of carbon used in the extension of heterotrophic algae is glucose. Organic molecules in wastewater represent a significant carbon sequestration target and a low-cost source of carbon [36,37].

More glucose is produced by mixotrophic metabolism, which combines respiration and photosynthesis. Due to the possibility of using carbon, mixotrophic metabolism can produce a lot of biomass. Mixotrophic cultures of algae yield cells per unit of energy input than other kinds of cultures [38]. Shorter growth cycles, greater growth rates, higher overall biomass output, and less biomass loss in the dark are some advantages that mixotrophic farming provides over photoautotrophic cultivation [39,40]. Conversely, mixotrophic metabolisms contain some drawbacks, including the fact that they are relatively costly because of the high requirements for organic carbon as well as vulnerable to invasive heterotrophs in exposed pond settings [41].

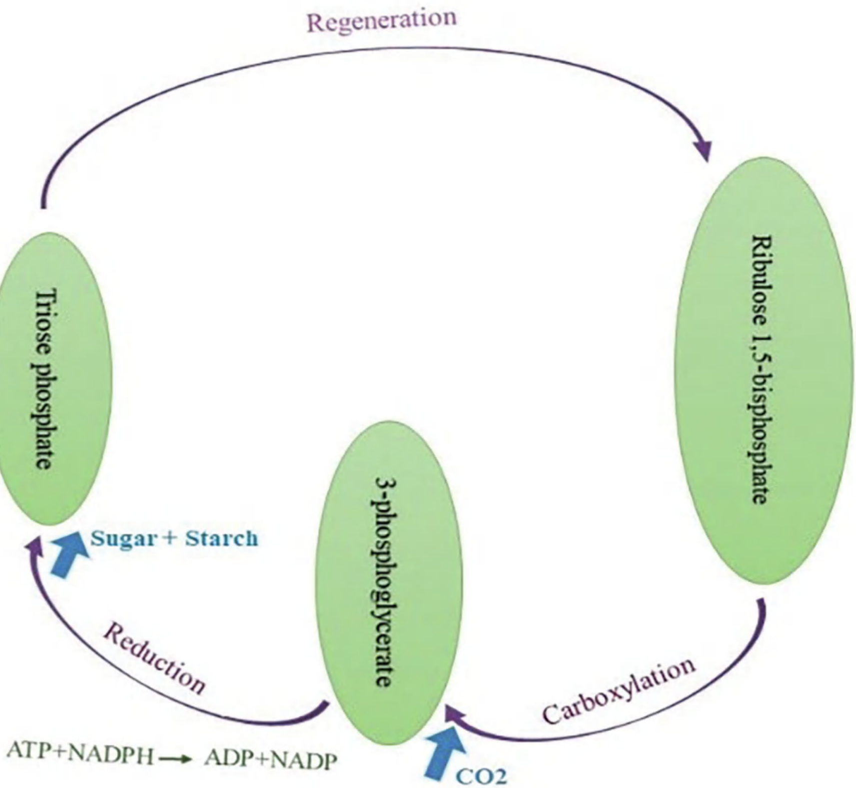

FIGURE 5.1 The auto-phototrophic metabolism for assimilation of CO_2.

5.2.3 Carbon Fixation and Concentration Mechanism (CCM)

Photosynthesis is a biological mechanism that fixes carbon. The general equation for photosynthesis is:

$$CO_2 + H_2O + \text{light} \rightarrow (CH_2O)_n + O_2$$

Although 467 kJ of energy is produced per mol of CH_2O rather than the 1744 kJ needed to make it, photosynthesis transforms around 27% of solar energy into chemical energy [8].

Algae can use a carbon-concentrating mechanism (CCM) to continue growing when there is insufficient CO_2 for photosynthesis. This mechanism of concentrating CO_2 at Rubisco enables algae to improve the efficiency of photosynthesis, while also boosting reducing photorespiration and carbon fixation [42]. Elevated carbon concentrations around enzymes [43], the metabolism of C4+crassulacean acid and carboxysome metabolism [44] are a few of the pathways that have been identified as contributing to this mechanism. This method not only offers a choice for the removal of greenhouse gases, but it also produces valuable byproducts [45].

5.3 PROCEDURE OF ALGAE-MEDIATED SEQUESTRATION BY ALGAE: PERFORMANCE AND FACTORS

Also, greenhouse gas emissions (GHGs) have been projected to be between 40.3 and 50 Gt by the end of half century [46,47]. Due to algae's exceptional fixation capacity in comparison to terrestrial plants (10–50 times greater) and the fact 1 kg of biomass (d.w.) uses around 1.83 kg_{CO2}, algae-mediated CO_2 sequestration has garnered considerable interest [46,48]. The issue can be resolved by the idea known as the Bicarbonate-based integrated carbon capture and algae production system (BICCAPS). The most promising species for both the production of biofuels and carbon sequestration include microalgal *Nannochloropsis oculate, Botryococcus braunii, Scenedesmus obliquus,* and *Chlorella vulgaris* [6]. BICCAPS offers the dual advantage of recycling of solvent and accumulation of value-added bioproducts, which lowers the operational cost of CO_2 mitigation [49]. This solution serves as a feedstock for the algae growth [50]. Because they swiftly transform CO_2 into bicarbonate, amine solutions like mono-, di-, and tri-ethanolamine have occasionally been used [51,52]. Integrated algal bioenergy carbon capture and storage (Integrated Algal BECCS) is the other cutting-edge sequestration technology. Combining energy production with capturing and long-term storage of CO_2 in geological reservoirs, as well as biomass gasification and ethanol production, this technology can also be used to treat waste incineration and flue gas streams from the paper industry [53]. In order to gain net negative CO_2 emissions without compromising food security, BECCS can be combined with produce algae. This system produced as much protein as soybeans grown in the same area, yielded 61.5 TJ of electricity, and annually sequestered 29,600 tonnes of CO_2. A significant step toward achieving environmental sustainability is BECCS potential to produce energy while lowering carbon emissions [54].

Algae and other aquatic photosynthetic organisms are a major contributor to the global CO_2 uptake. At least half of Earth's annual carbon fixation is produced by the photosynthetic activity of marine algae [46,53]. Ocean Macroalgal Afforestation (OMA) is a method to increase natural populations of microalgae by the year 2085 in order to lower the atmospheric CO_2 concentrations to below 350 ppm [55]. OMA has additional benefits besides carbon sequestration and contaminant bioremediation, such as the ability to reduce ocean acidification, mitigate coastal eutrophication, and manage the harmful spread of algal blooms. The Coastal CO_2 Removal Belt consists of both naturally occurring and artificially created Ecklonia cava kelp forests in southern Korea with a capacity of about 10 tonnes/ha annually [56].

5.3.1 Performance Evaluation of Algae for CO_2 Sequestration

This section provides an overview of how algae can be used to sequester CO_2. Analyzing the data in Table 5.1, the highest CO_2 capture rate is 93.7%. Through a process called bioconcentration during photosynthesis, CO_2 is captured and stored through the CO_2 sequestration mechanism [57]. Big amounts of carbon fixation occur in the Calvin-Benson cycle, and the majority of CO_2 capture occurs through photoautotrophic metabolism, which uses light to convert inorganic carbons into carbohydrates [58].

TABLE 5.1
Effectiveness of Various Algae Strains in CO_2 Sequestration

Algal Strain	CO_2 Capture Efficiency	Product Yield	Biomass Yield	References
Chlamydomonas reinhardtii	0.113 g/L/day	0.46–0.49 g/g (Bioethanol)	0.512 g/L	[87]
Chlorella sp. L166	93.7%	0.0069 g/L (Lipid)	—	[88]
Chlorella vulgaris	75%	—	1.28 g/L	[89]
Chlorella vulgaris UTEX 2714	0.182 g/L/day	—	0.219 g/L/day	[90]
Chlorella sorokiniana, Coelastrella sp., Chlorella pyrenoidosa	0.567 g/L/day	—	1.1 g/L	[91]
Chlorella sorokiniana	—	—	12.2 g/L/day	[92]
Chlorella sp.	—	—	0.682 ± 0.007 g/L	[70]
Anabaena sp. ATCC 33047	—	—	0.31 g/L/day	[93]

Algae biomass yield is higher than that of any other crop. *C. vulgaris*, which has a 40% removal efficiency, produced a yield of up to 2.12 g/L of algae during CO_2 sequestration. The biomass yield of a continuous reactor using *C. pyrenoidosa* was 90.25 g a day with a 92% efficiency of removal [59–61]. Numerous valuable compounds found in biomass produced from algae can be used to create pharmaceuticals, renewable energy, and food products [62]. The amount of protein in algae is used to make pharmaceuticals and food, while the lipids in them can be used to make biodiesel or other oil-based biofuels [63]. According to Jha et al., some personal care products contain *Chlorella sp.* as one of the ingredients [64]. Also, *Prymnesium parvum* and *Ochromonas sp.* play key roles in the production of phycotoxins used in pharmaceutical applications. Studies on *C. reinhardtii* have shown that it may be used as a supplement for fibronectin, protein, and human growth factor [65]. In spite of their specific uses, a number of *Chlorella* and *Spirulina sp.* have also been cited as being important in the food industries [66,67]. Table 5.1 represents the produce yield and capture efficiency of several algae strains in CO_2 sequestration process.

5.3.2 Factors Affecting the Algae-Based CO_2 Sequestration Process

The key factors in determining whether an algae strain is suitable for CO_2 sequestration include high rates of growth, resistivity to shear stress, and a wide temperature range. The sequestration efficiency is said to be significantly impacted by several factors, including CO_2 concentration, light intensity, temperature, and pH. The rate of inorganic carbon supply to phytoplankton is influenced by many environmental factors, including pH, temperature, alkalinity, and others. The slower diffusion rate of CO_2 in water can sometimes lead to CO_2 deficiency, which reduces the amount of HCO_3 that is available in the aquatic surroundings.

5.3.2.1 CO_2 Concentration

Carbon metabolism by algae is positively influenced by high CO_2 concentrations, which leads to Chlamydomonas reinhardtii accumulating more biomass and fatty acids. The MDH3, FBA2, GAP1, and GLYK genes, which can adapt to changes in carbon flux, are responsible for this phenomenon [68]. It has also been noted that the acidification of the water caused by increased CO_2 concentrations caused a more toxic effect in the algae [69]. Optimum CO_2 sequestration is highly dependent on the strain and the amount of CO_2 concentration varies from 2% to 10% depending on species. The dissolved CO_2 concentration in an aqueous environment depends on the pH and temperature and is always in equilibrium with H_2CO_3, HCO_3, and CO_2. Consumption of any inorganic carbon has no impact on the equilibrium because of its rapid interconvertible reactions. Although HCO_3 is a poorer source of carbon than CO_2, microalgal cells prefer to absorb it over CO_2 [11]. Also, at high CO_2 concentrations, the pH of a culture decreases due to the formation of bicarbonate buffer. Biomass productivity has an increase in the percentage of CO_2 in the mixture of gas up to a certain value before it starts to decline. Chiu et al. [70] found that 2% of CO_2 (v/v) is ideal for *Chlorella* growth, while 10% (v/v) results in an insignificant specific growth rate. *Chlorella sp. T-1* may tolerate CO_2 concentrations up to 100%, according to Maeda et al. report on the CO_2 sequestration from flue gas by power plants, but its growth rate was at its highest when using 10% CO_2, with no discernible decline occurring up to 50% CO_2 concentration [71]. They concluded that cells adapted to higher CO_2 concentrations are more tolerant due to precipitation from cells accustomed to lower CO_2 concentrations.

The coefficient of volumetric mass transfer (K_La), which is a property of the bioreactor, establishes its capacity to maintain optimal cell growth. The different regions of liquid flow affect K_La behavior and cell growth rate differently. According to the gas velocity, the photobioreactor (PBR)'s liquid flow region can be classified as a transition zone, heterogeneous zone, or bubble flow. Gas hold-up, interfacial area, and K_La in the bubble flow region are all inversely correlated with gas superficial velocity. Even though the interfacial area starts to decrease as you move from the heterogeneous zone to the transition zone, gas pressure holds steady and K_La reaches a plateau. Initially, the specific growth rate rises following an increase in K_La, but it begins to decline as soon as the transition zone ceases to exist. Also, shear stress could be the cause of the decline in specific growth rates [72]. A comparative analysis of K_La in various photobioreactors with varying CO_2 percentages was conducted by Zhang et al. who came to the conclusion that the amount of critical K_La needed to satisfy the needs of the algal cells for CO_2 increases as the CO_2 concentration in the inlet gas stream decreases [73].

5.3.2.2 Light

Light-dependent photoautotrophic metabolisms played a main role in the illumination period of the day [74]. The main factor affecting productivity outdoors is the amount of light available. According to Morales-Sánchez et al., photoautotrophic and mixoautotrophic species require longer illumination periods [75]. According to Liang et al., the Calvin-Benson cycle, which contains Rubisco, uses light-dependent reactions to convert photons into NADPH and ATP [74].

A reliable estimate places the range of saturation light intensity between 30 and 45 W/m^2 [76]. According to Torzillo et al., the relationship between saturation light intensity (I_s) and incident light intensity (I_o) has a significant impact on both overall photosynthetic efficiency (E_r) and light utilization efficiency (E_s) [77]. It can be described mathematically in this way:

$$E_s = l_s / l_o \left(\ln\left(l_o / l_s \right) + 1 \right) \tag{5.1}$$

This equation (equation 5.1) is valid for the value $I_o/I_s > 1$. For $I_o/I_s \leq 1$, E_r and E_s are 0.2 and 1, respectively. While productivity maintains a maximum value when $I_o/I_s \leq 1$, the equation explains the efficiency of light utilization. Thus, productivity is not always dependent on light utilization effectiveness. For better light utilization, photo bioreactors should be built to minimize (I_o/I_s), achieved by either lowering Io or raising I_s. Choosing an algal strain with a high value of I_s is advised. It reduces Io and makes use of the effect of flashing lights. According to Ugwu et al., this effect boosts tubular photo-bioreactor productivity by up to 40% [78].

As a result of the incoming light overload on the photosystem's pigments, the degradation and synthesis of light-harvesting complexes are halted. According to Torzillo et al., this causes the production of reactive oxygen strains, which can lead to photoinhibition or photooxidative death [77]. Using algae strains with small antenna sizes allows for uniform and impartial distribution of Io to all cellular layers. In a typical situation, the first layer of cells receives the most light, which dramatically decreases as it moves through the subsequent layers of cells. Small antenna strains minimize light loss and shield cells from photo inhibition and light dissipation in non-photochemical quenching [77]. Another approach is to lower the chlorophyll content. This approach can be used to increase biomass production, aerial CO_2 sequestration, and other outcomes, like hydrogen production in photo-bioreactors. By using spirulina as a model microorganism, it is claimed that open ponds can have aerial productivity that is ten times higher.

5.3.2.2.1 Considerations Regarding Light in a Photobioreactor Design

The photobioreactor's geometry, cell density, light penetration distance, and wavelength all affect how much light is attenuated. Red and blue light penetrate algae suspensions less than green light because they are primarily absorbed by algae. In the densely populated areas, this effect is more noticeable. Reactor geometry can, from an engineering perspective, lessen light attenuation in a suspension of algae. One crucial factor that affects the effectiveness of how well light is used as well as the overall photosynthetic efficiency is saturation light intensity (I_s).

In photobioreactors having larger optical cross-sections, light is effectively distributed throughout the entire culture area. Numerous photobioreactors with specially designed lighting systems have been tested in an effort to effectively capture CO_2 and form biomass while utilizing intense light [79]. With the assist of *Synechococcus sp.* PCC 6301, to determine the best light dispersion for the growth of photosynthetic cells, Suh and Lee developed an internally lighted airlift photobioreactor [80].

5.3.2.3 Temperature

Flue gas is heated to a temperature of around 120°C and is released from power sources. Installing a heat exchanger system or utilizing thermophilic strains is required for the CO_2 sequestration from flue gas to be feasible. The algae species significantly influence the optimal temperature effect, for instance, *C. vulgaris* has a 30°C optimum temperature [81], *Scenedesmus sp.* at 25°C [82], *N. oculata* at 20°C [81], and *S. obliquus* at 30°C [83]. There are a few species that can endure temperatures up to 60°C. The overall CO_2 removal is impacted by the temperature's antagonistic relationship with the CO_2 dissolution in the aqueous solution [43,48].

Temperature has an impact on algae's ability to sequester CO_2 by affecting the activity of the enzymes Rubisco and carboxylase. Since an enzyme is a unit of protein, changes to the structures of amino occur at low temperatures, whereas the polypeptide chain is stretched and broken at high temperatures [84], disrupting the process of the sequestration of CO_2. When the unicellular cyanobacterium *Synechococcus elongatus* was exposed to different CO_2 concentrations and temperatures, a pH decrease at 52°C with 60% CO_2 was similar to that at 25°C with 20% CO_2. A significant amount of oxygen is fixed by RuBisCO's oxygenase activity as the ratio of solubility of O_2 to CO_2 rises with temperature. Additionally, the affinity of RuBisCO for CO_2 decreases with rising temperature [85].

5.3.2.4 pH

For the best algae growth a neutral pH (6.5–8) is advised. Dissolving SO_x and CO_2 of flue gas can change the medium's pH. pH decreases to pH 5 at higher CO_2 concentrations and reports have been made of pH 2.6 at higher SO_x concentrations [86].

The pH change brought on by CO_2 has a negligible impact on growing algae, but the change in pH brought on by SO_x will completely prevent any growth [48]. There were essentially no variations in growth rates as ompared to lower amounts of SO_x when utilizing a buffered medium, which prevented the pH drop [71]. Accordingly, it can be concluded that the effect of SO_x is, within certain bounds, primarily caused changes in pH value rather than sulfate medium's concentrations, avoided by buffering [48]. *Chlorella sp. AT1* [94] and *C. sorokiniana str. SLA-04* are examples of alkaline-tolerant and high-CO_2 species that will benefit from an increase in CO_2 solubility due to an alkaline pH [43,95]. Furthermore, as free CO_2 becomes more concentrated at acidic pH levels, acid-tolerant species such as *Scenedesmus sp.* and *C. sorokiniana* benefit [96]. Along with high temperature and CO_2 levels, NO_x and SO_x also have an impact on the growth of algae. There is many strains with tolerance to NO_x and SO_x. For example, *Nannchloris* can grow in conditions as low as 100 NO_x ppm [97], and *Tetraselmis sp.* can flourish when exposed to a mixture of 185 SO_x ppm and 125 SO_x ppm [98].

5.3.2.5 Culture Density and Strain

Selecting the appropriate culture strain is the most critical factor for effective CO_2 mitigation. Dunaliella is a very delicate species in terms of cellular fragility because it lacks cell walls. The cell cycle affects how sensitive Haematococcus is to secondary metabolites like the carotenoid astaxanthin. From the green to the red phase, shear stress resistance increases significantly.

Due to deflagellation, Haematococcus is sensitive in the green phase, whereas the presence of immobile aplanospores in the red phase confers resistance. *Scenedesmus sp.* is better for C-fixation [83]. The capacity of algae for the growth of a cell and their capacity for CO_2 metabolism, among other physiological factors, influences the efficiency of CO_2 removal [83]. According to López et al., strains that are good for CO_2 sequestration should produce high-quality products with little chance of contamination [93]. In order to effectively sequester CO_2, the best cell configuration must be chosen. Not all light can be absorbed by cells below the optimal concentration, and because of self-shading, a greater percentage of cells are in the dark above the optimal cell concentration [99]. Vertical flat plate and inclined modular and photobioreactors both exhibit a bell-shaped relationship between cell concentration and the productivity of biomass [100].

5.4 DIFFERENT TECHNOLOGIES OF PHOTOBIOREACTORS

The flexibility of CO_2-rich gas allows bioreactors designed for CO_2 sequestration to be used for mixing and supplying nutrients for the growth of algae. Typically, non-mechanical agitation methods including flat panels, airlifts, bubble columns, tubular reactors, etc. are used in this type of reactor. Few bioreactors also allow for mechanical agitation in addition to bubbling through CO_2-rich intake gas such as found with a stirred tank reactor. The requirement for the bioreactors created specifically for CO_2 sequestration is high mass transfer. Photobioreactors operate differently in the CO_2 sequestration process depending on their geometric properties.

5.4.1 Vertical Tubular Photobioreactors

Vertical tubular photobioreactors are made of transparent vertical tubing to allow light penetration. The sparger, attached to the reactor's bottom, converts the sparged gas into tiny bubbles. In addition to removing the O_2 created during photosynthesis, sparging with gas mixtures enables the general mass transfer of CO_2. Depending on how the flows of liquids through vertical tubular photobioreactors, they can be classified as bubble column or airlift reactors [48]. The bubble column reactors' height is larger than double their diameter. It benefits from low initial cost, the absence of moving components, good heat and mass transfer, a high surface-to-volume ratio, and effective residual gas mixture and O_2 release. To disperse and break up collected bubbles in scale-up, long bubble columns are covered with perforated plates [101]. Because there is no back mixing when the flow rate of gas is below 60.01 m/s, there is no circulation flow pattern [102]. Shorter light and dark cycles can be achieved by increasing the gas flow rate (≥0.05 m/s), which will considerably boost photosynthetic efficiency (blue article reference). The vessel known as an airlift reactor has two interconnected zones. The gas mixture gets sparged in the section of one of the tubes known as the riser. There are two kinds of airlift reactors: internal loop and external loop. In an internal loop reactor, a split cylinder divides the regions, while in an external loop reactor, the downcomer and riser are physically separated by two different tubes. The gas is simply bubbling through the sparger in the riser tube to mix. The sparged gas moves up the riser similar to how it moves up a bubble column. The riser's gas hold-up helps to support this upward movement [48].

An airlift reactor's advantage lies in its ability to create a circular mixing pattern, allowing the liquid culture to cycle through dark and light phases, resembling flashing lights for algal cells [103]. Another option is the rectangular airlift photobioreactor, which has higher photosynthetic efficiency [102]. Loubière et al., also, developed an airlift photobioreactor that has an external loop and stirs the fluid [9].

5.4.2 Horizontal Tubular Photobioreactors

As a result of their orientation toward the sun and high light conversion efficiency, the shape of the horizontal tubular reactor is advantageous in outdoor cultures. A disadvantage is the efficiency of photosynthesis is decreased by photo bleaching, which is brought on by oxygen buildup during photosynthesis [104]. The temperature is controlled automatically by an evaporative cooling system. Also, the light-weight-harvesting unit has been placed inside a pool of water with controlled temperature, tubes have been overlapped, water is sprayed on the surface of the tubes to cool the system, and the feed or recirculation stream's temperature is adjusted. Another significant disadvantage is the photobioreactor's high energy consumption, which is around 2000 W/m^3 as opposed to 50 W/m^3 for the flat plate and bubble column photobioreactors [105]. The near horizontal tubular reactor despite having a slight inclination toward the sun is nearly similar to horizontal tubular reactors. This tendency aids in the more effective use of solar energy [106].

5.4.3 Flat Panel Photobioreactors

A cuboidal shape with a short light path characterizes the flat panel reactor which is made of materials transparent enough to allow visibility. This includes glass, plexiglass, and polycarbonate. Air bubbles are introduced into one side of the flat panel reactor via a perforated tube.

When *Chlorella sorokiniana* was continuously cultured on a flat panel with a short path length and high irradiance conditions volumetric productivity was 12.2 g/L/d. By placing several plates on a surface, the flat panel's size can be increased. The solution for scaling up does not involve lengthening the reactor; rather, it involves increasing the liquid's height and widening the light path [73]. The airlift mode of circulation was used in the flat panel [107]. It contains two air-injection zones: a sizable riser zone and a smaller downcomer zone. Baffles were also one of their reactor's additional features and they were alternately attached to the panel's larger faces on the front and back. The reactor's front illuminated side also has a transparent cooling jacket attached. Comparable bubble column reactors had volumetric productivity of biomass that was 1.7 times higher.

5.4.4 Helical-Type Photobioreactors

The culture in a helical photobioreactor is conveyed to the degassing unit via a lengthy tube and a centrifugal pump. This system consists of a coiled, flexible tube with a small diameter, either separate from or integrated into the degassing unit. Two advantages of this type of photobioreactor are the long tubes are mounted on a low rise and this type unit takes up little ground space [108]. Moreover, enhanced CO_2 transfer from gas to liquid occurs due to a larger CO_2-absorption surface area. However, the energy requirements of the centrifugal pump for recirculating the culture and the resulting shear stress have hindered widespread industrial adoption, despite the potential scalability by integrating a light-harvesting unit. Another drawback of this system is fouling on the interior of the reactor.

Conical helical systems (60° cone angle), created by Morita et al. [109], have very specific height and angle requirements. This system also has a heat exchanger and a degassing system attached. The amount of light that is received increases by a factor of two at an angle of 60°, as does the productivity of photosynthetic processes. The highest photosynthetic efficiency measured for this kind of reactor was 6.84%, which was higher than all other cone angles [109]. The primary benefit of a cone shape is its ability to harvest light with a similar basal area [110]. When balancing energy input and photosynthetic efficiency, photobioreactors have an advantage. Other benefits of this reactor include less mechanical stress placed on algal cells and a lower energy requirement for operation. Due to its defined angle and size, scaling up requires more light harvesting units, but this also causes more energy to be lost in the intricate branches of the flow networks [48].

5.4.5 Stirred Tank Photobioreactors

In a stirred tank reactor, which is the most common type of reactor, mechanical agitation is provided by variously sized and shaped impellers. To lessen vortex, baffles are used and to provide algae growth with a carbon source, air that has been enhanced with CO_2 is bubbled at the bottom. This bioreactor can be converted into a photobioreactor through external illumination using fluorescent lights or optical fibers. However, its primary limitation lies in its low surface-area-to-volume ratio, which reduces its effectiveness in harvesting light. It has also been tried using optical fibers, but this has drawbacks because it interferes with the mixing pattern, which makes it unsuitable for illumination [111]. Commercially available fermentors with external light systems include the New Brunswick Bioflo 115 and Bioengineering models. The oxygen produced during photosynthesis is separated from the used sparged gas and gassed liquid phase by a sizable disengagement zone [48].

5.4.6 Hybrid-Type Photobioreactors

The hybrid photobioreactor, which integrates advantageous features from two distinct reactor types while mitigating their respective disadvantages, is highly interesting. As it regulates the culture's temperature and also provides a high surface area to volume ratio, the external loop functions somewhat like a light-harvesting device. On the contrary, the airlift system serves not only as a degassing mechanism but can also incorporate probes to control other variables within the culture. The hydrodynamics of the airlift section of the reactor were additionally utilized to regulate flow velocity through the solar receiver [48]. Its benefits can be better control over cultural variables, increased productivity, and decreased power consumption [112]. Similar integrated systems were developed by Richmond et al. and Grima et al., but the latter's external light-harvesting unit is a loop-like structure while the former's is a horizontal parallel tube [113,114]. The external light-harvesting unit's temperature is controlled using a water spray. Horizontal tubes have the benefit of being inexpensive and highly effective at photosynthetic activity. The main drawbacks are the limited light-harvesting area and the size of the occupied land area. Because of the expense of the necessary land area and a bundle of tubes, it is not economically feasible. Another type of hybrid system created by Lee et al. is the alpha-shaped reactor, which was built using principles from algal physiology and sunlight [79]. In this reactor, the culture is raised 5 m by air to a receiver tank, where it flows down a 25-m-long inclined PVC tube with a 2.5-cm ID at a 25° angle to another set of air riser tubes. Low air flow rates can still result in a unidirectional flow of liquid at high rates. The high photosynthetic efficiency is also a result of the large area-to-volume ratio. Approximately 10 gdw/L was said to be present [79].

5.4.7 Promising Photobioreactors

The most frequent issues with this reactor are fouling within the helical reactor and fluctuations in the hydrodynamic stress. The airlift reactor operation is the high effective photobioreactor for removing CO_2 from flue gas among all those currently on the market. This reactor's characteristics include high gas transfer rates, uniform mixing, low hydrodynamic stress as well as simplicity of control. Incorporating an airlift photobioreactor with a tubular loop reactor will make up for the photobioreactor's limited S/V ratio and scalability drawback [48]. Figure 5.2 shows several kinds of algal cultivation both open and closed systems.

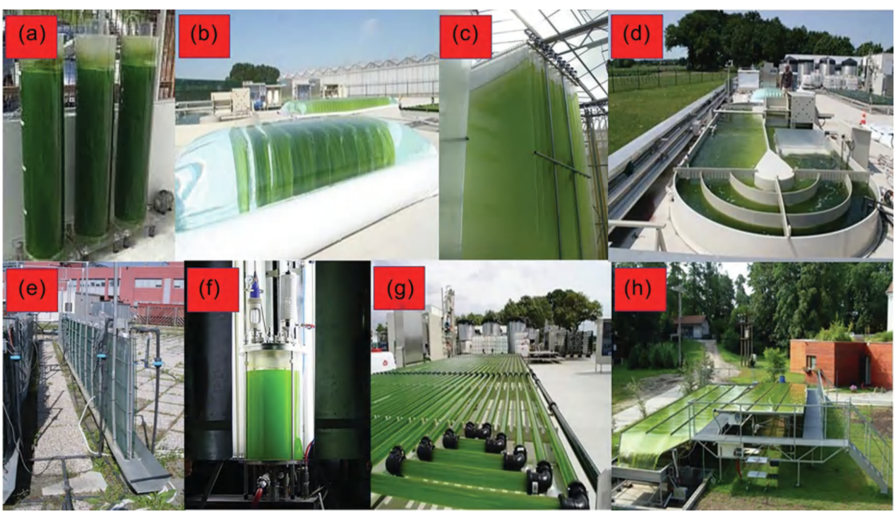

FIGURE 5.2 Showing different technologies for algal cultivation; (a) annular PBR [115], (b) flat panel PBR [116], (c) an innovative flat-plate PBR [117], (d) raceway pond open system [116], (e) vertical flat-panel photobioreactor [117], (f) stirred tank PBR with external illumination [118], (g) horizontal tubular PBR [116], (h) inclined-surface system [117].

5.5 ALGAE-POWERED RENEWABLE ENERGY: SUSTAINABLE SOLUTIONS

5.5.1 Environmental Aspects of Algae-Mediated CO_2 Sequestration

Using algae to sequester CO_2 is a viable solution for reducing the amount of carbon throughout the atmosphere and assisting in reversing the trend toward increasing global warming [119,120]. Yet, the process's effects on energy and the environment determine its applicability and viability. The impacts of using algae for CO_2 sequestration on energy and the environment have been shown in several studies. From a mechanistic standpoint, Xu et al. investigated the effectiveness of carbon fixation during photosynthetic processes in algae [5]. Such a study is intriguing because it demonstrates how this technology might simultaneously have a positive impact on the energy-environment nexus. Algae, also, are useful as biomass but also have other uses, including the treatment of wastewater and CO_2 capture. It is possible to use algae as a wastewater treatment agent because of their high capacity to absorb nitrogen and phosphorus which enables them to grow quickly [61,121].

According to statistics, for every 1% increase in gross domestic product, resource use climbs by an average of 0.4% (GDP) [53]. Rapid urbanization, industrialization, and urban population increases have created concerns about food and energy insecurity, pollution, and climate change. The current industrial community is now moving toward a resource-conserving bioeconomy in response to pressure from governments and society to ameliorate these concerns. A closed-loop system of cascading and recycling energy and material flows can be used in a circular bioeconomy to achieve sustainable production. The biorefinery concept, which involves the coordinated extraction of all biomass components to produce bioenergy and high-value products with little to no waste, can help to further improve this integrating unit operations into the bioprocess framework can increase cost-effectiveness, process efficiency, and resource recovery by creating high-value products. Algae are photosynthesis-powered cell manufactories, converting inorganic or organic carbon into precious products, and are becoming more and more important in the aforementioned problems due to their enormous potential. Algae can serve as a source of feedstock for biofuels, a food source for animals and humans, a source of commodity and fine chemicals (cosmetics, pharmaceuticals, and nutraceuticals), and a means of pollution treatment, remediation, and sensing Due to their ability to adapt to and thrive in challenging surroundings (such as greywater, brackish water, seawater, etc.), they can also recover nutrients and absorb CO_2 from wastewater, allowing for the reduction of the usage of arable land and the creation of low-carbon feedstock. These elements make algae promising participants in circular bioeconomy models that are integrated and low-carbon. Algae have shown promise as a clean energy solution to these problems and can produce a wide range of biofuels [53].

Algae exhibit stronger lipid productivity and photosynthetic efficiency than terrestrial plants or oleaginous crops 58,700 L/ha for maize (Zea mays L.) versus 172 and 446 L/ha for soybean (Glycine max L.). Algae also grow more quickly and produce more biomass and also have an advantage over maize and soybeans in that they don't contain lignin, which facilitates pretreatment and enzymatic hydrolysis in the production of biofuel. Algal bioenergy is currently being used on a large scale, but there are a number of barriers standing in the way of its widespread commercialization including costs associated with harvesting, pretreatment, operation and conversion, and maintenance. Algae can also convert the carbon they take in during photosynthesis into carbohydrates, which can then be processed into biodiesel or bioethanol [122]. Algae are the most prevalent biotics in oxidation ponds used in sewage treatment ponds and wastewater treatment plants [22]. Zhao and Su claim that algae have the potential to produce 324.33 m tonnes of biomass annually, and an average of 0.5393 Gt CO_2 can be sequestered [123]. According to Chen et al., CO_2-sequestering algae could produce 280 tonnes (d.w.) of biomass a year while consuming 513 tonnes of CO_2 by capturing about 9% of solar energy through photosynthesis [124]. Cost is another crucial component of sustainability, even though it is not directly connected to the energy-environment nexus. The results of the energy and environmental studies, which were based on the reviewed literature, indicate that using algae for CO_2 sequestration can be an environmentally friendly as well as cost-effective way [1].

5.5.2 Economic Analysis of CO_2 Sequestration

Attention has recently switched to third-generation feedstock, or aquatic biomasses like algae and seaweeds, in an effort to reduce the likelihood of a land and fodder shortage for the production of biofuels [125]. Yet, there are difficulties with algae CO_2 sequestration including (but not restricted to) algae species, CO_2 supply composition and tolerance capability as well as growing systems [6]. As a result, expanding algae cultivation to produce commercial amounts of biomass is difficult and necessitates a feasibility study of a lab-scale growing procedure. In order to produce algal biomass, researchers have investigated a variety of growing methods and put them to the test on both a small and large scale [126]. In terms of capturing and storage of carbon, life-cycle assessments (LCA) as well as technoeconomic analysis of BECCS revealed that a 2680 ha eucalyptus forest is equivalent to a 121 ha algal facility [53].

5.5.2.1 Lifecycle Analysis of Algae-Mediated CO_2 Sequestration

LCA is a helpful technique for assessing how well systems for producing algae from end products operate environmentally. Several LCAs of the algae-mediated production of biofuels do not account for the entire "cradle-to-grave" cycle. This research overlooked water- and land-use aspects, which are crucial in an algae production system and focused on a few environmental effect elements, primarily the potential for global warming. While evaluating the commercial uses of algae-mediated biofuel, it is also important to take social impact (such as employment) into account. The LCA approach has developed into a potent tool for evaluating the entire life cycle of products [29]. For instance, an LCA technique helps analyze different diverse arrangements for the characteristics of cultivation for sustainable growth when it comes to algae production [127]. Also, pond systems and photobioreactors have both been the subject of LCAs to evaluate the efficacy of algae cultivation [90]. LCA is assisted to resolve issues with the economics, lifecycle metrics, and commercial-scale logistics of raceway pond systems and helical photobioreactors in another study [128]. Additionally, it helped compare the eco-performance of various methods and the potential effects of algae producing [127]. Moreover, LCA has been successfully utilized to analysis the environmental effects of the algal biofuel generation, and food [129,130]. The LCA used for processing of growing algae is the section's main focus because algae cultivation has a big impact on downstream production and CO_2 sequestration.

We concentrate on the LCA research that examined the cultivation-based CO_2 sequestration of algae without considering the biomass application procedure. Also, a cogent comparison of the methods for growing algae for use in a product was intended by the various LCAs. For example, a comparative LCA for farming methods, approaches, scenarios, frameworks, CO_2 sources, and system design alternatives was carried out. Even though algae are grown for many uses, including bioenergy, food, and cosmetics, the articles' LCA focus is the same. The processes that supply energy and any materials and are considered the foreground processes, and the processes that typically influence those stages are considered the background processes [131]. Together, these processes make up the system boundaries. This LCA's system boundaries can be applied to other LCAs for growing algae. Algal nutrients, cultivation methods, and strains might alter, nonetheless, depending on the analysis's scope and objective. It has been noted that some research that used PBR to cultivate algae began the process by cleaning and sterilizing the reactors. A limited comparison of LCA studies is thus made possible by providing all relevant information about the system boundaries.

The Life Cycle Inventory (LCI), as depicted in the system boundary, is made up of all main key inputs (energy, nutrients, water, and gases) and all output streams (such as gases and wastewater) generated throughout the cultivation process. The main system inputs, for instance, are flue gas CO_2, tap water, growth nutrition, and electrical energy [89]. Similar to this, Peter et al. analysis of LCIs in 2022 took into account air input, CO_2, water availability, and sources of electricity and CO_2 [127]. By recycling nutritional medium, the amount of externally acquired nutrients that are needed are reduced, along with the costs and environmental effects of manufacture and transportation that go along with. Actual data is necessary during the cultivation phase to effectively perform an LCA of an algal product because any assumptions could affect the general process of growth. In the same way, assuming that a species of algae is superior in terms of growth rate may make the species appear to be acceptable without taking into account the conditions or nutrients necessary to achieve that growth rate [1].

The cultivation stage was the main hot area, having an influence of 80% or more across all categories that were examined [131]. An impact of at least 75% was also observed by another study which used the outcome of characterization of the centrum milieukunde lieden (CML) technique to compute subsystems, such as flue gas compression, waste treatment, and transport [89]. Also, the increased electricity needed per kilogram of the torrefied algal biomass in the aforementioned scenario contributed to the elevated impact of torrefaction. Since practically every process subsystem uses energy and adds significantly to the environmental burden, it is imperative to evaluate the impact of energy use in the algae production.

For the PBR and open race pond (ORP) production systems, respectively, the cumulative energy demand (CED) was 17,854.7 and 37,203 MJ, taking into account all the meteorological conditions [131]. Similarly, it is found that 36,943.3 MJ was consumed from non-renewable fossil and nuclear energy, together accounting for around 85% and 10% of total CED, respectively [89]. The open raceway ponds' aeration and mixing may be to blame for the close ties and higher energy consumption values in both experiments. Contrarily, the estimated average energy for PBRs (5323.4 MJ) suggests that energy consumption during the production of biomass in ORPs may exceed that of PBRs, regardless of location [132].

As algae are produced, greenhouse gasses are produced which are related to climate change, especially when non-renewable energy sources are used. As a result, the influence of the GWP can be related to the emissions of GHGs. The calculated average GWP impacts of biomass production per kilogram in PBRs are 1086.8 kg CO_{2eq} [131], 278 kg CO_{2eq} [133], and 331.5 kg CO_{2eq} [132]. This value for open raceway ponds is reported as 2256 kg CO_{2eq} [131] and 914.3 kg CO_{2eq} [89]. Undoubtedly, CO_2 is sequestered during the ORP's period of algae development, which should greatly reduce the influence on global warming.

According to the information above, it would seem that producing a kilogram of biomass using a raceway pond as opposed to a photobioreactor will result in a greater environmental load for the impact categories stated. Nonetheless, given the variances in the studies' objectives, algal species, production levels, Life Cycle Impact Assessment (LCIA) methodology, and data sources, it might be an incorrect conclusion. Hence, more comparable research (in terms of objectives and methodology) is needed in order to make sound judgments about the likelihood of creating algae in a sustainably responsible way.

5.5.2.2 Cost Considerations of Algae-Mediated CO_2 Sequestration

Studying the impact of algae production and its characteristics on algae pricing is essential. However, due to market changes and uncertainties, a number of variables, including the price of raw materials and equipment, may fluctuate [127]. Interestingly, each subsystem's input flows within the system boundary have a cost associated with them. For example, the price of the land needed for building, the price of the borosilicate glass used to make PBR systems, the price of water, energy, and cleaning supplies, the price of water, energy, fertilizers, and pesticides used during cultivating, and the price of energy used during drying. Additionally, the cost of a glass tube system represents the most investment cost for the production of 1 kg (d.w.) biomass (24%–31%), followed by the drying system cost (21%–24%), and finally the cultivation construction cost, which is 18%–21% of all investment costs. When it comes to operational expenditures, the cost of labor accounts for 39%–42% of the whole operating costs [134]. Researchers also noted that plant infrastructure for manufacturing algae biomass remained the same regardless of the process alternatives. A 14,000 L PBR was anticipated to cost $451,000 in capital expenses overall [127].

Based on research on algal biomass production employing open and closed systems, open systems have higher operating costs than closed systems, but closed systems have higher production costs. Furthermore, the closed cultivation system necessitates a smaller plant capacity compared to the open system, yet achieves significantly higher algal productivity. According to the research, closed systems have higher manufacturing as well as operational costs. Also, in comparison to the open culture technique, the closed cultivation system uses fewer plants and has a greater algal yield [135].

5.6 FUTURE PERSPECTIVES

Algal-based technology is pivotal for advancing toward a low-carbon bioeconomy, with significant environmental and socioeconomic implications. However, to establish and expand the algal bioeconomy several significant obstacles must be removed. Industrial symbiosis systems, sometimes known as eco-industrial parks, are industry clusters that include a number of different businesses and in which resources, technology, energy, and even knowledge can be shared and used by and/or between the companies of the system. Algal development and intracellular chemical accumulation can be improved with the use of cutting-edge technologies like bioelectromagnetic and ultrasonic stimulation. An algae bioeconomy's life cycle has shown the potential of these ground-breaking technologies, which calls for more investigation and development. As an illustration, the output of one industry may be used as the input for another (for instance, algal biomass as an input for the production of biofuels, biochemicals, biomaterials, etc.), lowering costs and the carbon footprint. Similar to this, extra heat and power can be generated and distributed to other parts of the system.

5.7 CONCLUSION

In the foreseeable future, as human society evolves, the enormous potential shown by an algae-based bioeconomy will be important. Algae can be used for bioproducts as a feedstock to meet our needs for food, energy, and chemicals. It also plays a crucial role in carbon capture processes, wastewater phyco-remediation, and the conversion of waste into products with added value, and addressing sustainability and pollution issues. Many information gaps have been discovered because of the assessment of the energy and environmental impacts of CO_2 sequestration using algae, which opens up more possibilities for future research in this field. Algae are an environmentally beneficial and CO_2-sequestering media, according to the majority of the research we studied. Yet, it is still unclear how well algae function at a macro level in reducing carbon emissions. These investigations about the suitability of different algae strains for CO_2 sequestration are necessary. Open systems have a higher running cost than closed ones, although their production costs are lower. To properly explore the potential of algae, major action needs to be taken by governments, industry, and researchers. Government assistance can be used to overcome the inherent difficulties and constraints and create an algae-mediated low-carbon bioeconomy on a commercial scale. Algae can help decouple economic growth from greenhouse gas emissions, paving the way for a more sustainable future.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Data will be made available on request.

AUTHOR CONTRIBUTION

P.B and E.S: methodology, P.B: writing —original draft preparation, E.S: writing —review and editing. All authors have read and agreed to the published version of the manuscript.

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6 The Use of BWO for Calibration of LFC of a Multi-Area Power System with Real-Life Wind Energy Penetration

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6.1 BACKGROUND AND AIMS

The planning for defense against frequency instabilities is subject to regular updates from the planning departments of electric utilities, which result from experience acquired by the data of system events that include disturbances or blackouts [1,2]. On the other hand, metaheuristic optimization algorithms are capable of solving many engineering problems [3]. Interdisciplinary studies on different energy sources have combined the two disciplines of system parameter updating and metaheuristics [4–7]. Despite intensive research for handling the issue of frequency disturbance due to wind penetration, some practical and easy-to-implement techniques can still be investigated. It is well-known that wind power dynamics introduce additional influencing factors to the power system frequency fluctuations and decrease the equivalent inertia of the system. It has also been reported that high wind energy penetration causes grid failure due to misplanned or poor frequency stability and overvalued existing controls [8,9]. One of the most significant and least-cost solutions is to upgrade and calibrate the parameters of existing centralized Automatic Generation Control (AGC) by online or offline advanced optimization algorithms. There is already a standard model for Load Frequency Control (LFC), augmented by AGC, which is published in many textbooks and articles [10–12]; this model can be upgraded with multiple sources (e.g., wind) to provide insight for the system under investigation and show the effect of wind penetration on the frequency responses. Then, several thoughts shall be given to reduce the effect of including wind power on the system frequency. The options are open for many strategies; however, retuning or calibrating the parameters of the controllers optimally on the primary and secondary levels of LFC can be a leading option. With the emergence of modern metaheuristic optimizers, any modification in the existing system or addition of new devices could be identified using metaheuristic optimization algorithms. In the past

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years, the contribution of renewable energy resources (RES) has increased due to its clean and environmentally friendly advantages. With that increase in RES, the random dynamic of these sources makes a stability challenge, especially for wind energy sources, which need to be understood in terms of how wind energy impacts frequency response. Robust primary and secondary LFC ensures smooth integration for wind energy and other RES. In multi-area power systems, the LFC study helps to optimize the power flow and ensure stability between different areas. LFC in multi-generation-source and multi-area connection power systems became more complex. Figure 6.1 below depicts the problem as an interconnected two-region power system penetrated by intermittent wind energy.

The stochastic nature of wind affects the power system frequency, especially in the upper area in the figure. Therefore, system improvement emphasizing frequency response is mandatory for considerable wind penetration. These improvements include calibration of the parameters of existing controllers (PI and PID controllers and primary governors) or adding hierarchical controllers such as the model predictive control (MPC). As a result of these problems, the researchers are interested in improving the performance of the load frequency response by finding the optimal parameters of the governor and the LFC, like the PI/PID controller, by using a metaheuristic optimization algorithm. AGC is critical to the power system's stability by maintaining the balance between generated power and the load with a high level of automation. Metaheuristic optimization methods are algorithms used to solve problems that conventional approaches can't solve. Natural behaviors like biology, animal,

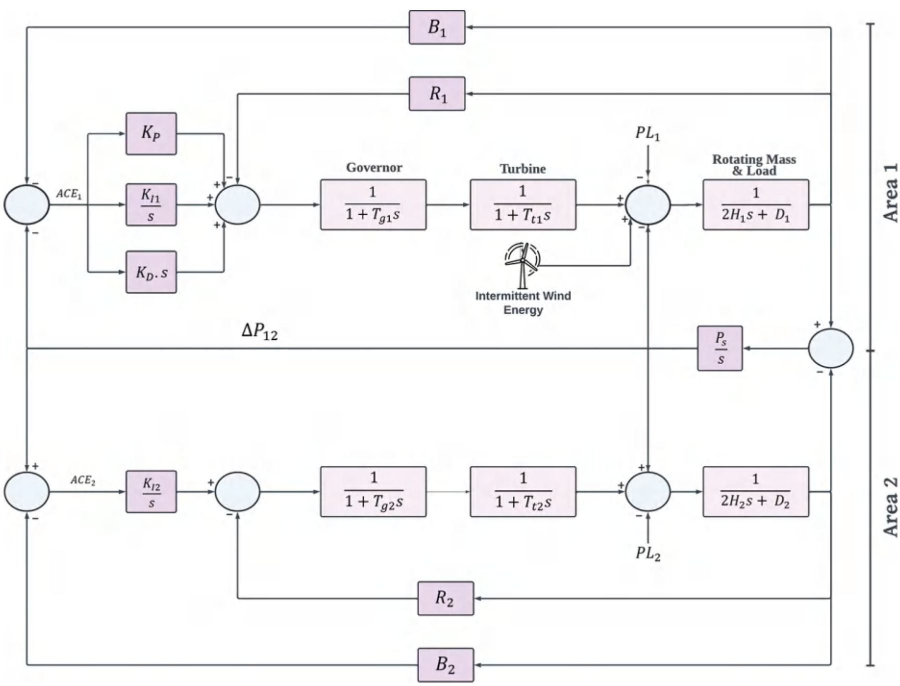

FIGURE 6.1 Two-region power system penetrated by wind power in area 1.

and human behaviors inspire these algorithms. Metaheuristic optimization provides the best and most flexible optimization, helping us find the optimal parameters. Such integration of metaheuristic optimization with AGC for an improved automatic LFC optimization is shown in the schematic in Figure 6.2. Without unnecessary details of essential metaheuristics, the Black Widow Optimization Algorithm (BWO) is a salient technique proven superior to other metaheuristic algorithms [3].

The objectives of this study are as follows:

- To demonstrate the impact of wind energy penetration on a conventional power grid as described by a standard AGC model for a two-area coupled tie-line system.

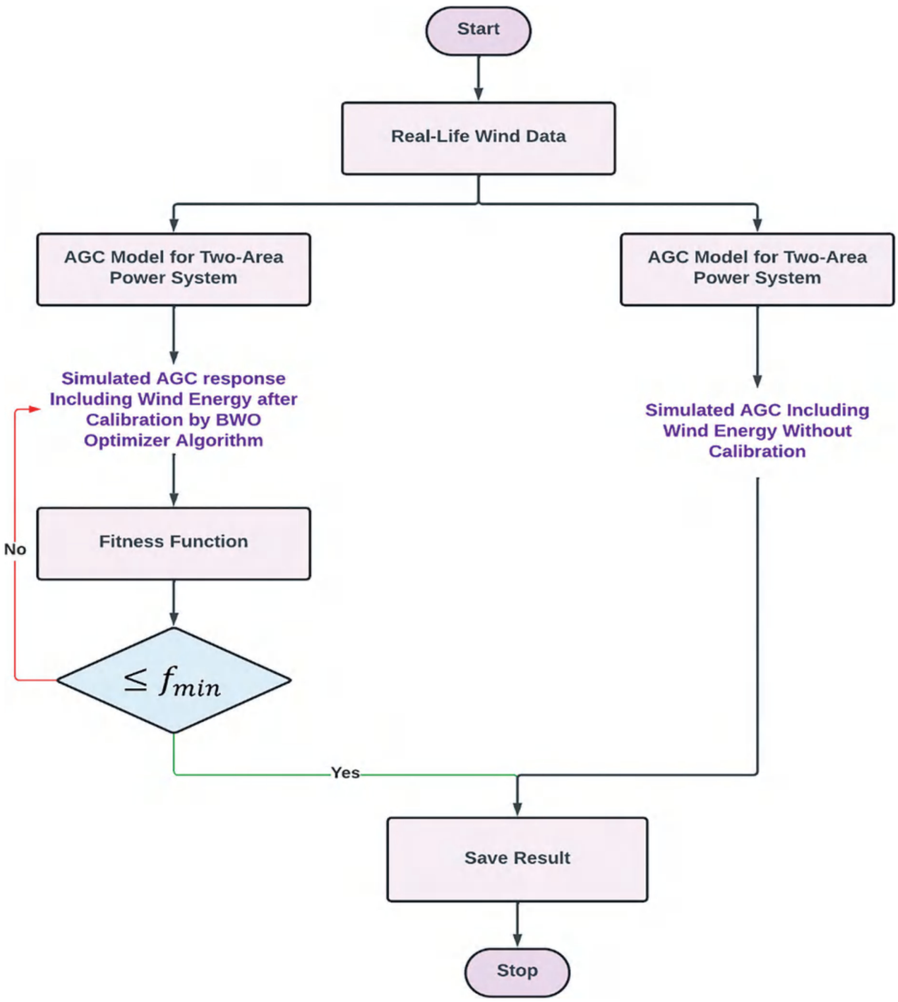

FIGURE 6.2 Metaheuristic applications to enhance the AGC for power systems penetrated by wind energy.

- To demonstrate the enhancement of power system frequency responses that are probable due to wind energy penetration using a workable control strategy.
- To evaluate the practicability of the calibrated controller through dynamic time-based simulation.

The rest of the sections have been organized as follows. Section 6.2 represents the literature review and paper contributions Section 6.3 discusses the simplified LFC model of interconnected power systems with the inclusion of a wind penetration Section 6.4 explains the BWO algorithm, Section 6.5 shows the simulation results and discussion, and finally, Section 6.6 presents the conclusion of the paper.

6.2 LITERATURE REVIEW AND THE PAPER CONTRIBUTIONS

To identify the research gap in LFC, including wind penetration, a review of the most recent and most necessary published research is necessary. It is also more reasonable to confine our review to LFC, including renewable power participation, to avoid too much widening of the topic, including many other research objectives.

They are starting with Zhao et al. [13], who presented H_inf and Linear Matrix Inequalities (LMIs) controllers to improve the response of LFC with the inclusion of renewable resources. The simulation results of the proposed LFC method, demonstrated by a two-area interconnected power system, show the effectiveness of the proposed method and that the co-controller effectively reduces frequency deviation.

Wang et al. [14] have proposed a cloud PI controller to improve the response of the LFC due to the randomness of the wind energy power penetration and compare it with conventional PI and fuzzy PI controllers. The result of the proposed control shows better performance in tie-line and frequency deviation, especially in regions with high wind power fluctuations. The application of the suggested control method to networked systems that include multiple renewable power generation types will be the primary area of future research.

Xu et al. [15] have proposed an area-based event-triggered sliding mode control scheme for LFC in a multi-area power system with a wind farm. They studied the proposed control via a three-area power system and the IEEE 39-bus system. The simulation result shows the proposed control effectiveness in restoring the nominal frequency and maintaining tie-line power at its scheduled value. Given the growing focus on cyber-security concerns in multi-area power systems, future research may further examine the topic of robust control design and attack detection.

El-Bahay et al. [16] have proposed a new optimization algorithm to support frequency in multi-area systems with renewable energy sources (including wind) penetration called the Coot Optimization Algorithm (COA). COA determines the optimal parameters of the fractional order proportional integral derivative (FOPID) controllers, droop, and auxiliary storage controllers. They compared the proposed Algorithm with other algorithms like particle swarm optimization, honey badger algorithm, atomic orbital search, and water cycle algorithm. Different scenarios, such as load disturbances and fluctuating weather, are tested for the controllers. Based on the results, it can be concluded that the coot optimization technique minimizes frequency and tie-line power variations the best.

Mi et al. [17] have presented a frequency control method for a multi-area hybrid power system that integrates battery energy storage systems (BESS) with renewable energy sources. This approach divides area control error (ACE) and active power disturbances into their high-frequency and low-frequency components. A specially developed disturbance observer identifies and handles high-frequency disturbances, which adjusts the BESS. Traditional thermal power units were designed to react to low-frequency components using a sliding mode (SM) load frequency controller. The technique minimizes deviations and enhances frequency quality while optimizing the required BESS capacity, according to the results of simulations.

Gulzar et al. [18] have proposed a cascaded fractional model predictive controller coupled with a fractional-order PID controller (CFMPC-FOPID) for LFC in a multi-area hybrid power system containing photovoltaic (PV) and wind power sources. Under various load conditions and uncertainties in the system parameters, the proposed controller reduces frequency deviations and tie-line power fluctuations. They have optimized the parameters of the controller by using a sooty-tern optimization. The outcome shows that, in comparison to alternative controllers, the one proposed more effectively restores the system frequency and enhances the stability of the power system under various testing scenarios, including similar load variations and distance load variation in multi-area, uncertainty in the power system's parameters, nonlinearities in the power system, and sensitivity analysis. Investigating linked models and how well they function under different loads in the future would be feasible.

Gulzar et al. [19] have reviewed various LFC strategies used in hybrid power systems consisting of renewable energy sources and conventional power plants. The review covers single-, multi-, and multi-stage power system setups, among many more; it included the study and discussion of using PID, fuzzy logic, neural networks, and other control methods in developing LFCs and optimization methods to boost LFC performance. The study evaluates and contrasts the performance of various LFC designs. Also, highlight the areas that require more investigation, such as improving the resilience and flexibility of LFCs for intricate hybrid power systems.

Ojha and Maddela [20] have studied an optimization technique known as the brown bear optimization algorithm (BOA) to tune the PID and cascade PI-PDN controller parameters for the LFC of an interconnected power system with two areas that are integrated with RES like PV and wind power under normal and varying load conditions. They compared the BOA algorithm with differing optimization techniques, such as grey wolf optimization (GWO) and particle swarm optimization (PSO). The results of the simulations show that under four distinct scenarios, the implementation of the BOA-tuned PID controller has better performance in terms of peak overshoot (+ve) values, the peak overshoot (−ve) values of system frequency deviation, and settling time of fluctuations in a RES integrated power system as compared to other optimization techniques.

Pradhan and Bhende [21] have proposed a modified version of the Jaya algorithm using two different techniques for the basic version of (w): one is the linear weight (LW)-the based variation, and another is a fuzzy-based variation, then they test the algorithm of different benchmark functions. The simulation result shows that fuzzy-based variation performed better in faster convergence and optimal value than different optimization methods like PSO, FA, CS, original Jaya, and LW-based Jaya algorithm.

Tavakoli et al. [22] have discussed the contribution of wind farms in frequency control during power grid integration compared with thermal, gas, and hydro unit contributions. The study considered system constraints like GRC, reheat turbine, governor dead band, and time delay for a more practical power system. They used inertia and droop control for wind farms because of the lack of frequency contribution. Under the assumption that wind energy is constant, they studied a single-area power system and a two-area power system by optimizing the parameters using the practical swarm optimization algorithm PSO. The outcome showed that the performance of LFC improved significantly in the two-area power systems integrated with wind energy. Further work using more realistic wind energy data is needed.

Arya [23] has proposed a control strategy called a fuzzy-aided integer order proportional integral derivative with filter-fraction order integral FPIDN-FOI controller for the LFC of multi-area power systems. The study used an imperialist competitive algorithm ICA to find different optimal parameters of the proposed controller. They studied the controller under various scenarios like load variations, the integration of renewable energy sources, and different conventional power systems to test the controller. The result improves LFC in two-area power systems under different challenges.

Guo [24] has presented a new approach to full-order sliding mode control (SMC) in (LFC) systems. This method aims to overcome the limitations of the traditional SMC. The proposed method combines terminal sliding mode method (TSM) and linear sliding mode control (LSM). This method has proven effective in maintaining zero frequency deviation under load disturbances in power systems combining different types of turbines. Based on the result, the proposed TSM and LSM methods show better response times and reduced chattering effects than traditional SMC. The study also extends the methods to a three-area power system, which is mathematically proven to be stable and effective, highlighting the method's potential for future work in power electronics applications (Table 6.1).

TABLE 6.1
The Predefined Parameters of the Utilized Algorithms

Year	LFC Method	Optimizer	Contribution
[13], 2020	H_inf and Linear Matrix Inequalities (LMIs)	—	Improved response of LFC with renewable resources, reduced frequency deviation
[14], 2023	Cloud PI controller	—	Improved response of LFC due to randomness of wind energy power penetration, better performance in tie-line and frequency deviation, especially in regions with high wind power fluctuations

(*Continued*)

TABLE 6.1 (*Continued*)
The Predefined Parameters of the Utilized Algorithms

Year	LFC Method	Optimizer	Contribution
[15], 2022	Area-based event-triggered sliding mode control scheme	—	Effective restoration of nominal frequency and maintenance of tie-line power at scheduled value, potential for robust control design, and attack detection in multi-area power systems
[16], 2023	PID, fractional order proportional integral derivative (FOPID), auxiliary storage	COA	Minimization of frequency and tie-line power variations.
[17], 2019	Frequency control method for a multi-area hybrid power system with battery energy storage systems (BESS)	—	I am minimizing deviations, enhancing frequency quality, and optimizing required BESS capacity.
[18], 2023	A cascaded fractional model predictive controller coupled with a fractional-order PID controller (CFMPC-FOPID)	Sooty-Tern	Reduction of frequency deviations and tie-line power fluctuations, restoration of system frequency, enhancement of power system stability
[19], 2022	Various load frequency control strategies reviewed	—	We evaluate and contrast LFC designs and identify areas requiring more investigation to improve resilience and flexibility in hybrid power systems.
[20], 2023	PID and cascade PI-PDN controller	BOA	Enhanced performance in peak overshoot values, system frequency deviation, and settling time.
[21], 2019	Jaya algorithm modified with linear weight-based and fuzzy-based variations	—	Fuzzy-based variation showed faster convergence and optimal value than other methods.
[22], 2018	Standard AGC for multi-area	PSO	Improved LFC performance in two-area power systems integrated with wind energy
[23], 2018	Fuzzy-aided integer order PID with FPIDN-FOI	—	It improved LFC in two-area power systems under various scenarios and challenges.
[24], 2019	Full-order SCM combining TSM and LSM	—	Showed maintained zero frequency deviation, better response, and reduced chattering effects in power systems.
Proposed work	Standard AGC for multi-area	BWO	—

From the above literature, it can be deduced that LFCs with a penetration of renewable energy still have more opportunities for further practical improvements, such as including the newest metaheuristic optimizers to revisit the parameters of primary and secondary LFCs. The main contributions of this paper can be then stated as follows:

- Simulating the impact of wind penetration on the frequency of existing LFC.
- Applying BWO to the standard model of LFC with real-life wind energy penetration to find the optimal parameters of primary and secondary LFCs.

A more thorough examination of the current LFCs of power systems is essential to enable greater wind energy penetration, as was determined by numerically comparing frequency drops with and without BWO turning.

6.3 THE STANDARD LFC IN INTERCONNECTED POWER SYSTEM PENETRATED BY WIND

LFC is a critical aspect of power system operation. The main objective of LFC is to maintain the balance between power supply and demand while keeping the system frequency within acceptable limits. In a two-area power system, each area has its generation and loads and is connected through tie-lines. The idea behind LFC is to adjust the power output of generators in response to the change of loads to keep the frequency system stable and power exchanges between interconnected areas. They can be briefly outlined as follows: Figure 6.1 shows the system components of this system. Each area has the following components, with wind energy penetrated in area 1. The first-order transfer function is used to simplify the analysis. The transfer function of each block is represented as follows in addition to some equations of the system:

1. **Generator and Load Model:**

   A generator converts the energy from mechanical energy to electrical.

$$G(s) = \frac{1}{H_i s + D_i}$$

   Where:
   - H is the inertia constant of the rotating masses.
   - D is the frequency dependency parameter expressed as the percent change in load divided by the percent change in frequency.
   - i is number of areas.

   In Figure 6.1, the R_1 and R_2 represent the speed regulation of the governor.
2. **Governor Model:**

   The valve position is controlled to control the flow of steam or water into the turbine. This is done based on fluctuations in frequency and power exchanges between interconnected areas.

$$G_g(s) = \frac{1}{1 + T_{gi}s}$$

Where:

- T_g is the governor's time constant.
- i is the number of areas.

3. **Turbine Model:**

   Converts the kinetic energy of water to steam to mechanical energy to drive the generator.

$$G_t(s) = \frac{1}{1 + T_{ti}s}$$

Where:

- T_t is the turbines's time constant.
- i is the number of areas.

4. **Area Control Error (ACE):**

$$\text{ACE} = \Delta P_{\text{tie}} + B \cdot \Delta f$$

Where:

- ΔP_{tie} is the deviation in tie-line power from its scheduled value.
- B is the frequency bias parameter, where $B = 1/R + D$.

5. **PID Controller for LFC:**

   The PID controller equation for the LFC can be expressed as:

$$\Delta P_{\text{ref}} = K_P \cdot \text{ACE} + K_I \int \text{ACE}dt + K_D \frac{d(\text{ACE})}{dt}$$

Where:

- ΔP_{ref} is the adjustment to the reference control.
- K_P, K_I and K_DRe the controller's proportional, integral, and derivative gains, respectively.

The main objective of LFC controlling the output power to keep the system frequency stable is accomplished through a feedback control loop that involves ACE. The ACE generates a control signal (ΔP_{ref}) combining the deviation in frequency and power is used to change the setpoints of the turbine by controlling the governor. This allows the power output to resist any disturbances.

Properly tuning the system's primary parameters, such as the governor time constant, is critical to effectively dampen oscillations and restore balance after sudden changes in wind energy production. T_g, as well as secondary parameters of the PID controller (K_P, K_I, and K_D). Adding wind energy to the power system adds another layer of complexity to control, which needs a helpful tool such as a metaheuristic algorithm to tune the parameters to ensure reliable power system operation. The wind power signal has been publicly available [25]. It has been redrawn via MATLAB® to observe and ensure significant changes in wind speed and power (Figure 6.3).

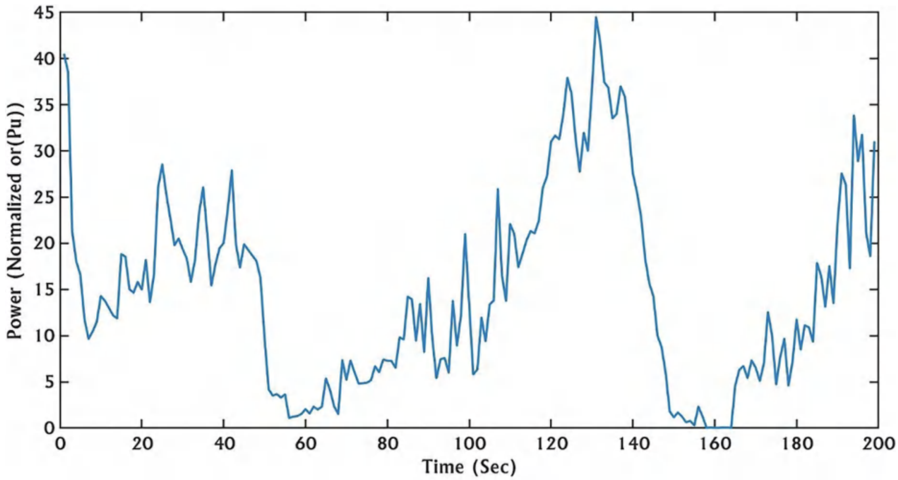

FIGURE 6.3 The practical wind power signal (before resampling). (The data is publicly available under Attribution 4.0 (CC BY 4.0 with unique doi: see Ref. [25].)

The data was then resampled to represent time scaling in seconds before being injected into the LFC model. Figure 6.1 in Section 6.1 indicates the location of wind penetration, which is sufficient to emulate the effect of wind. The next section explains the mechanism of BWO.

6.4 BLACK WIDOW OPTIMIZATION ALGORITHM

The Black Widow Optimization Algorithm (BWO) is an innovative meta-heuristic strategy inspired by black widow spiders' behavior and cannibalistic habits. This algorithm has a fresh and unique way of dealing with problems like solutions converging early and not being optimized, issues often found in other optimization algorithms.

The primary foundation of BWO is the mutation of the black widow spider's lifestyle, mainly focusing on their unusual mating ritual and the cannibalistic behavior afterward. Female black widows are known for their tendency to consume their mates post-mating, an act as young siblings participating in sibling cannibalism. The BWO algorithm improves algorithmic performance and the solution quality generated by using these inherent behaviors of the black widow metaphors.

6.4.1 Algorithmic Structure

The BWO algorithm randomly creates a population, each representing a potential spider, then goes through processes similar to procreation, cannibalism, and mutation. The structure of the process is as follows in Figure 6.4:

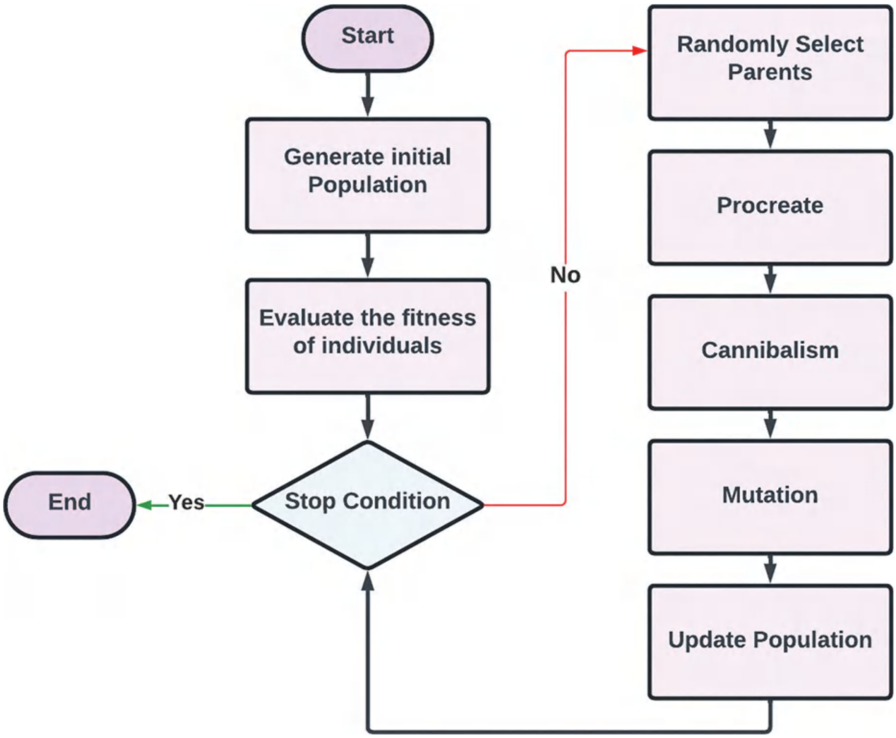

FIGURE 6.4 Basic flowcharts of the black widow optimization algorithm.

- **Procreate:** After randomly selecting the solution to pair. A new solution is created. This process is similar to another algorithm called crossover.
- **Cannibalism:** The algorithm evaluates the fitness of the new solutions. Solutions with lower fitness are discarded, resembling the behavior of cannibalism of the black widow's spider. This step helps focus on potentially superior solutions by effectively reducing the population size.
- **Mutation:** In this step, random alteration is made into the surviving solutions, which increases the diversity of the population and helps to explore new areas of the solutions.
- **Convergence:** The algorithm continues to iterate through the steps until the stopping criterion is met. This criterion could be (a) a specific number of iterations, (b) achieving the desired level of accuracy, or (c) there being no change in the fitness value of the best solution multiple iterations.
- **Fitness function:** Each spider, also called a widow (solution), has a fitness value that determines the ranking of the solutions. The fitness value is determined by evaluating a fitness function, where the fitness function typically depends on the problem's objective and constraints.

The fitness function mathematical model is:

$$\text{Fitness} = f(\text{widow}) = f(x_1, x_2, \ldots, x_{N\text{var}})$$

Where N_{var} Represents the number of variables in the solution.

6.4.2 The Integration of BWO to LFC Control Problem

MATLAB® is an excellent tool for testing and developing optimization algorithms. It provides a wide range of mathematical functions, can work with matrix operation, and its Simulink feature.

Fortunately, the codes necessary to execute the BWO routine are publicly available [26]. The scripts or functions are run sequentially, as described in Figure 6.5, and are mentioned as **initialization.m**, **main.m**, **Get_Function.m**, **BWOA.m**, **getPheromone.m**, and **getBinary.m**. However, some important modifications are needed to make it fit the case study in this paper. The programs have been correctly modified. First, the number of variables is changed to match the elastic parameters of LFC primary and secondary control systems: the governor time constant and the PID control system parameters.

The parameters have been defined in a separate file named (**Error.m**) file, which is called by another file or script in the original code (named **Get_Function.m**). The dimensions are now defined, but the error function needs more elaboration. The error function is the frequency deviation, which can be known only if the SIMULINK® LFC file is run. The calling command for the SIMULINK file is added to the '**Error.m**' script, and then the command for frequency deviation computation is added. The details of the code modification, including the '**Error.m**,' have been mentioned in the appendices. Therefore, the parameters are changed, and the error is calculated in each iteration to obtain the optimum results progressively.

Mathematical formulation of the problem is also necessary to give the reader clearer insight into the optimization problem. Mathematically, the problem is formulated as:

$$\Delta f = f\left(\tau_g, K_i, K_p, K_d, t\right)$$

This above equation expresses the highly uncertain function to be minimized, which leads to the following optimization problem,

$$\text{minimize } \Delta f$$

subject to the following inequality constraints

$$0.1 \le \tau_g \le 0.5 \text{ second}$$

$$\min \le K_i \le \max$$

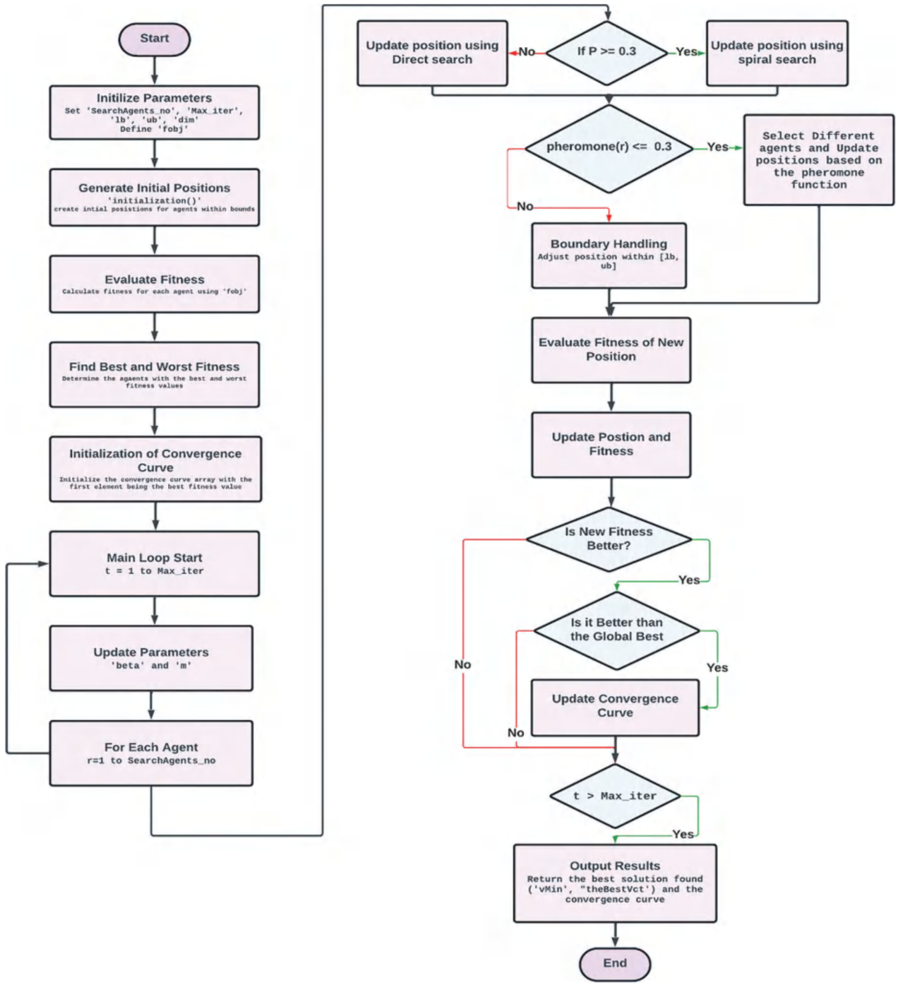

FIGURE 6.5 Flowchart of Implementation of black widow algorithm in MATLAB®.

$$\min \le K_p \le \max$$

$$\min \le K_d \le \max$$

The constraints of the governor's time constant (the primary LFC) have been known In some books, the lowest value of τ g could be 0.2 seconds, not 0.1. However, the cited reference is highly appreciated [27–29], which widens the governor constraints to include modern governors to get further improved results.

The constraints parameters of the PID controller are preferred to be set unknown and determined later by trial and error because there were no practical limits for them, in this case, reported in textbooks or articles. The other LFC and power system parameters cannot be modified because they lead to the replacement of the entire generation or even the power system, which is not practical. Therefore, parameters such as system inertia, turbines' time constants, and D factors are left as the base case for fair comparison and improvement in a practical sense.

6.4.3 Simulation Result and Analysis

This section provides the results of the LFC performance simulation illustrated by MATLAB/SIMULINK R2023a. The main goal is to analyze the LFC under different system conditions and determine how effective the black widow optimizer BWO is in optimizing traditional LFC. The study is divided into two scenarios. The first scenario studies the system's frequency response without the BWO optimizer, dividing it into two cases: changing the system inertia constant (H) for case 1 and changing the time constant of the governor for case 2. The frequency response is studied in the second scenario, where the BWO optimizer is applied to the primary and secondary parameters and compared with the previous scenario.

6.4.4 Scenario 1: Traditional LFC Performance Without BWO Optimizer

6.4.4.1 Case 1: Variation of Inertia Constant (H)

This case observes how modifying the inertia constant (H) affects the system's frequency response. The value of H is adjusted from 3 to 9 seconds in 2 seconds increments. The system's performance is determined using the frequency deviation and settling time.

Figure 6.6 shows the system's more damped response due to the increasing inertia constant H. Stability is reached faster for higher values of (H), such as 7 and 9, which means they oscillate less and have a shorter settling time. Lower values of (H) curves, such as 3 and 5, take longer to reach steady-state values, indicating a slower response before stabilizing the system after disturbances.

This graph clearly shows the important role of the inertia constant in the dynamic response of power systems and stability due to disturbances.

6.4.4.2 Case 2: Variation of Governor Time Constant (T_g)

In Figure 6.7, the governor's time constant T_g As changed from 0.2 to 0.5 seconds in 0.1 seconds intervals to study its effect on the system's performance.

The result shows a direct relationship between the system's damping performance and the governor's time constant, as shown in Figure 6.7. The higher governor's time constant reduces effectiveness in the damping performance, as shown by the increased oscillations in the frequency response.

The adjustment, based on new references, may increase the flexibility and speed of response in the LFC systems, especially in cases where they face massive variable generation penetration like wind requiring immediate response to power fluctuations.

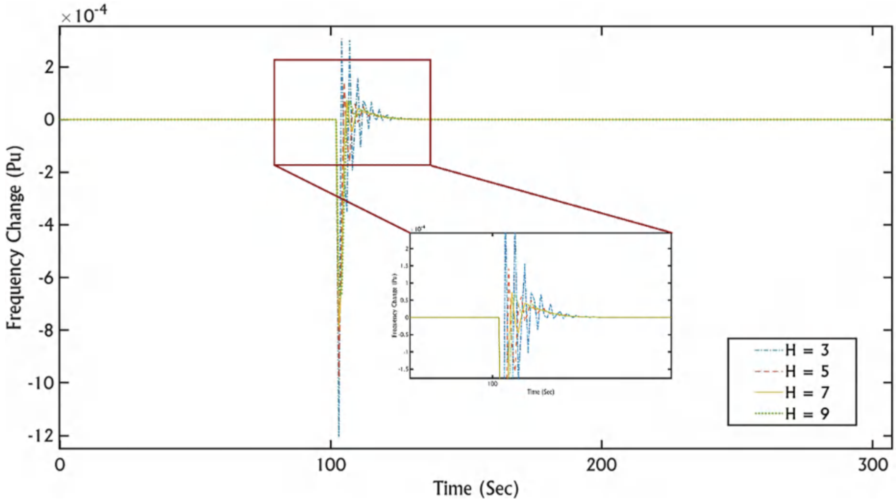

FIGURE 6.6 Frequency response vs. inertia constant after wind energy changing.

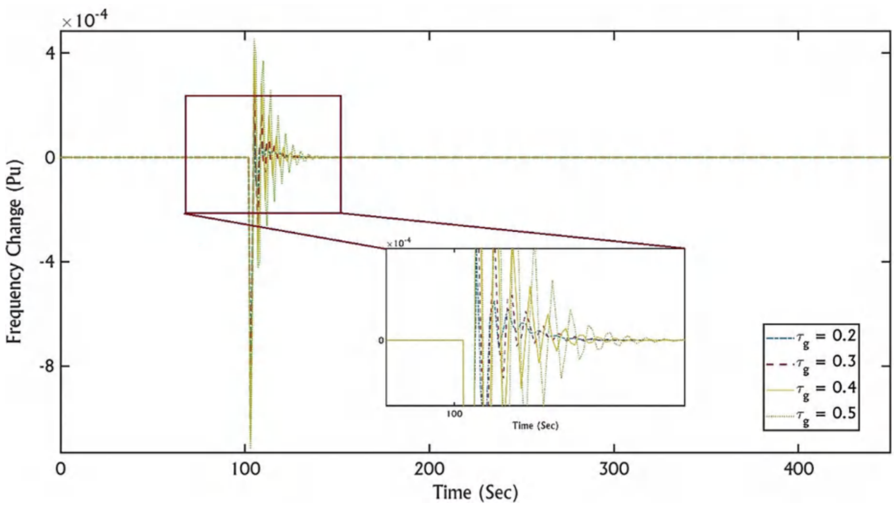

FIGURE 6.7 Damping performance vs. governor time constant (T_g) after wind energy changes.

According to recent publications, the governor time constant could be as low as 0.1 seconds for today's digital electrohydraulic governors[27–29].

6.4.5 Scenario 2: Traditional LFC Performance with BWO Optimizer

The BWO algorithmBWO was used to optimize the parameters of traditional LFC systems while maintaining a fixed value for the inertia constant *H*. The aim was to improve the system's frequency stability and response time while integrating wind energy. The frequency deviation was taken as the cost function for the BWO to minimize and adjust the LFC parameters. The optimization process ran for ten iterations to ensure convergence to the optimal solution.

Figure 6.8 shows the system's response over 75 minutes, with multiple wind variations every 10 minutes with and without BMO applied. The system enhanced frequency stability after optimization. The frequency deviation and frequency drop were reduced significantly, which means the system doesn't need a defense action against the disturbance of the wind energy integration. Also, the settling time showed a good improvement.

Figure 6.9 shows when wind generation sharply decreased. The frequency initially drops but quickly recovers to a stable state when BWO is applied, emphasizing the BWO algorithm's ability to stabilize the frequency and minimize fluctuations quickly. This is crucial for managing sudden decreases in wind energy input.

Figure 6.10 represents a scenario where the wind generation increases, leading to a noticeable spike in frequency. The BWO algorithm can handle this disturbance and quickly restore the frequency to the normal range.

However, a quantified analysis of the results will increase the clarity of the work. The frequency responses have been recorded on p.u scaling, where they should be in Hz to confirm the controller's validity. Recalling Figure 6.8, the response has been translated to Hz quantities. Over a considerable time, the largest decrease in wind power penetration has been from 38% to 23% due to wind speed decrease; an enhancement in frequency excursion has been obtained via BWO, which can be changed to actual Hz quantifies through investigating the initial drops of frequencies from 49.74 Hz in existing case to 49.97 Hz in the improved case, respectively. On another operational time window in Figure 6.10, a sudden wind energy increase from 12% to 18.5% due to wind speed increase leads to an informative conclusion

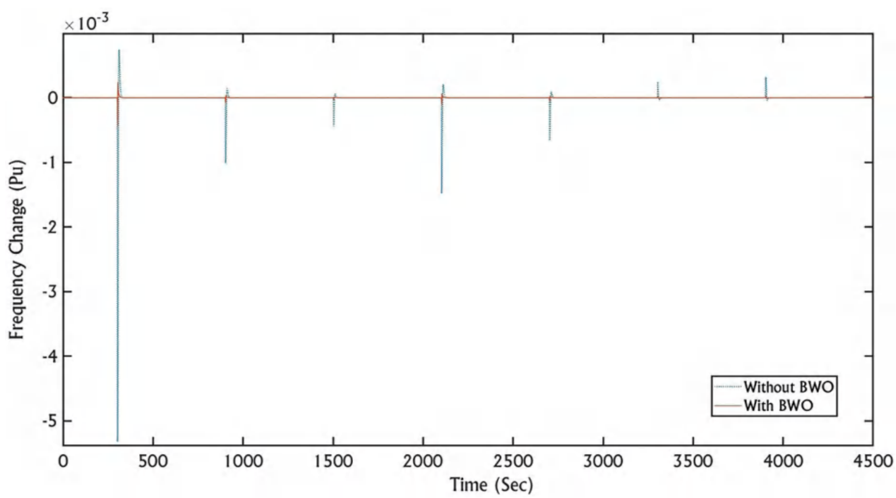

FIGURE 6.8 Wind changes within 75 minutes assumption.

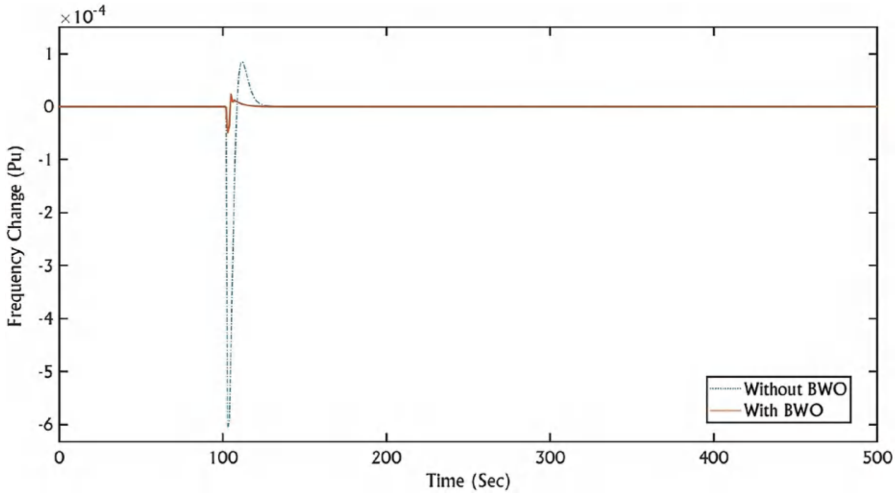

FIGURE 6.9 Frequency response before and after BWO optimization after wind energy decrease.

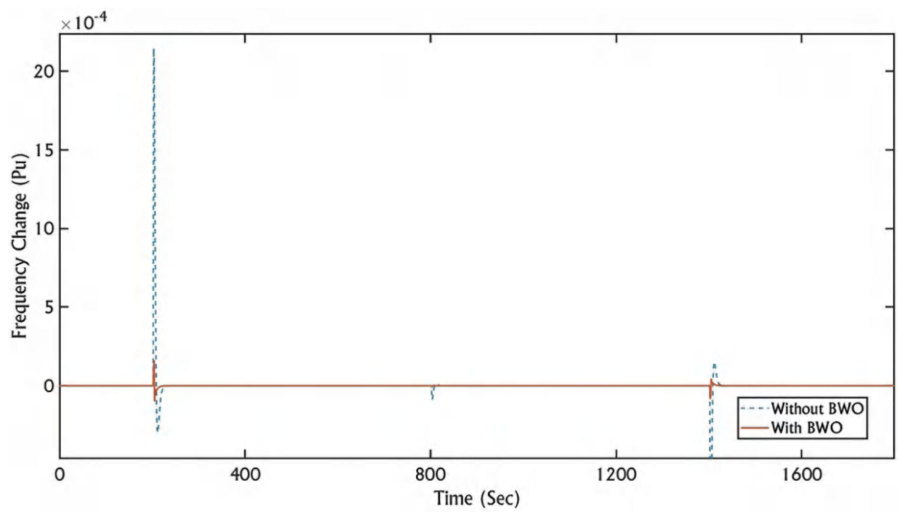

FIGURE 6.10 Frequency response before and after BWO optimization after wind energy increase.

of confirming the system robustness with frequency improvement from 50.1 Hz in the existing case to 50.01 Hz in the BWO-based improved case, respectively. Hence, metaheuristics are promising techniques for improving defense actions against frequency instabilities, which comply with the system authority's ground rules [30].

6.4.6 Conclusion

The findings and outcomes of this paper have been summarized as follows:

- Wind energy systems negatively affect the power system's frequency stability. Consequently, the existing controller's parameters must be revisited for better time domain performance.
- There are many tuning strategies for primary and secondary controller parameters. However, BWO was selected because of its modernity and performance superiority when compared with other algorithms.
- Form a practical signal of wind power injected to a simplified model of load frequency controller in a two-area power system, the effect of inertia (H) and governor time constant (τ_g) Are considered.
- Simulation results have shown improved controller performance on the frequency response, quantified and discussed in previous chapters.

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7 Advanced Biofuel Generations

Optimizing Sustainable Agriculture and Renewable Energy Transition

Pourya Bazyar and Ehsan Sheidaee

7.1 INTRODUCTION

Sustainable development of agriculture is the main criterion of economic expansion in development areas and food security in the world. The protection of natural resources and the value of nature are of fundamental importance to all societies. The major changes initiated in the 18th century, associated with the title of the Industrial Revolution, were caused by the efficient use of petroleum products, involving the carbon structure instead of human and animal labor [1]. It is the main contributor to air pollution from industrial development and factory expansion, caused by excessive use of natural and petroleum resources. Therefore, it's important to access sustainability and protect the environment, it is essential to comply with the standards. The urgency to address climate change, fuel price volatility, food security, and global economic instability has spurred global interest in biofuels, particularly in developing countries where they offer potential for self-reliant energy sources at national and local levels, though 42 African nations' vulnerability as net oil importers underscore the need to reduce dependence on imported petroleum through sustainable domestic alternatives, posing questions about achieving this goal without compromising social and environmental considerations in a nascent renewable energy sector promising substantial economic, ecological, and security benefits, amidst varying performance of biofuels in reducing non-renewable energy use and greenhouse gas emissions across their lifecycle, necessitating policies and technologies to enhance efficiency and sustainability in biofuel production [2].

7.2 RELATED WORK

Due to the development of industry and the growth of population in the world, it will increase per capita energy consumption in the next decade. Fossil resources, including coal, oil, and derivatives, are decreased over time, so it is important to pay attention to biofuel [3]. As a result, carbon dioxide emissions increase during peak consumption, and numerous researchers have published variant dimensions to neutralize the negative

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environmental impact. While the constantly increasing energy consumption, it's necessary to change fossil resources to renewable energy must be considered. In recent years, a sustainable revolution in agriculture with extra renewable biomass resources, equivalent to five times the world's energy consumption, has been maintaining food security, energy independence, and a green economy [4,5]. The importance of food security and maintaining the qualitative and quantitative amount of agricultural production will be necessary for the usage of biofuel and renewable energy resources. The ascending demand for energy in recent years has led to investments in biofuels, it will be increasing more than 50% by 2050 without jeopardizing of food security around the world [6]. Biofuels have been developed from various chemical aspects, including alkanes [7], fatty acid esters [8], nano agro-chemicals [9], hydrogen [10], hydrocarbons [11], wax [12], cellulosic ethanol [13], iso-butanol [14], long-chain alcohols [15] and electrical [16]. The main benefit of biofuels as a fuel for diesel engines without engine modifications on it, so it has been decreased harmful gas emissions with the high rate of beneficial energy resources due to the renewable tools [17]. The goals will be achieved the maximum biofuels of biomass, the preventive indexes on the global decisions, and the available technologies for the transition to biofuels.

According to the past, the Plant *Euphorbia Abyssinia* was used as biofuel in 1830, then alcohol was used as fuel for lamps in 1834. The main sources of biomass are wheat and rice straw with Corn Stover and Sugarcane bagasse, listed in Table 7.1 [18]. The basic component in biomass is the lignocellulose compound in whole production, so the volume of biomass production in the European continent is about 950 million tons, which can cover 300 million tons of fuel, which has a high rate of oil consumption in Europe, the equivalent of the total production is 65% of all biofuels [19]. Advanced technologies are targeting the use of cellulosic biomass from wastes, residues, and dedicated energy crops to produce ethanol, yet sustainability challenges still need to be fully understood [20].

Agricultural biomass will be generated through essential chemical and physical processes to expand the products for consumers, such as Combustible fuels [21], Gaseous [22], liquid [23], solid fuel [24], and generating electric power [25].

7.3 COMBUSTIBLE FUELS, GASEOUS, LIQUID, SOLID FUEL AND GENERATING ELECTRIC POWER

The benefits of using biomass for heating, lighting, and cooking processes are more than 30% globally and about 37% in China, and more than 190 million people use biomass gas stoves. In this Central Asian country, rice straw is one of the ingredients

TABLE 7.1
Annual Distribution of Agricultural Waste [18]

Agricultural Waste Section	Crop	Amount (Million Tons)
Straw & stubble	Wheat	354.3
Straw & stubble	Rice	731.3
Stover	Corn	128.0
Bagasse	Sugarcane	180.7

used in the production of biomass [26,27]. The energy supply for households and industry takes place in gaseous, liquid, and solid forms. Methane (CH_4) is mainly used in gas consumption, so straw and stubble of different plants are abundant agricultural waste material for biogas production [28]. The trend toward increasing use of biogas in Europe is high and in Poland country, this amount is used more than 1.5 billion m^3 biogas [29]. By accessing biofuel in the form of a liquid state with a structure of cellulose and hemicellulose, it was converted into bioethanol production and it was decomposing wheat straw with 80% of this structure a rich source for biofuel production [30]. Developed countries, including Canada, with annual worldwide production of ethanol as highly numerate 5336 million L in the years between 2001 and 2004 and it tended to increase from 30 to 94 GL (Giga Liters) [31]. Another form of biofuel is the use of solid fuel pellets to produce this type of fuel from tree bark, plant residues, and dry leaves, which have a high calorific value and are suitable for cooking [32,33]. This kind of bullet has an energy efficiency of 91.67% and an index of Torrefaction with a value of 1.379. The ever-increasing generation ofelectrical energy from biomass is an inseparable phenomenon for electricity production. Therefore, straw has been used as an effective component of agricultural biomass with high energy capacity waste in an advance powerhouse converter to generate 21.5 MW electric power plant in England [34]. Forecasts show that by 2030, 16.1% electric energy, 72.3% heat, and 11.6% biofuel can be developed from biomass [35].

In recent decades, the high rate of fossil fuel is the undeniable of human consumption, so it caused air pollution, proliferation of pollutants in the environment and increased amount of greenhouse gases as the excessive consumption of natural resources has a negative impact on the climate and agricultural production worldwide. Water and soil resources are deteriorating day by day as cities expand and factories grow, factors such as drought, rising global temperatures, and variable rainfall patterns also play a role. Therefore, the increase of average global temperature worldwide has caused a 7% decrease in the production of cereals and legumes [36]. Climate change will continue to affect agricultural productivity and food production processes. Over time, it is important to implement computer algorithms and intelligent management to increase the annual output of future products [37]. Comparing available statistics on greenhouse gas emissions, biofuels are inferior to fossil fuels, reducing emissions of unburned hydrocarbons, aerosols, and carbon monoxide by 30%, 25%, and 20%, respectively [3]. In addition, with the combination of ethanol, the amount of NO_x emission decreases by 10% compared to mineral fuel. According to the statistics announced by the national American agriculture society (USDA), it was reached to the number of 79 million m^3 of biofuel products, which is 11.4% of the agricultural lands in the southeastern U.S, including THP, is needed for the production of biofuel [38]. Sustainable development of agriculture using perennial plants is very important to increase food, biofuel, and food security. In recent decades, the need for energy has been increasing to use of systems from human to animal, engine power, liquid fuel, hydrogen, and electricity (Figure 7.1) with high efficiency for agricultural tools could be necessary [39–41].

More recently, perennials have been used for the high impact of biofuel efficiency on the environment and the ratio of output energy according to input (Table 7.2). These plants absorb sunlight effectively, have a long growing season, deep and wide roots, and efficiently take up water, nitrogen, and phosphate.

FIGURE 7.1 The history of main agricultural machinery tools powered by animal, fuel, and electricity [39–41].

TABLE 7.2
Aspects of the Perennial Crop on Environmental and Energy [42–46]

Benefits	Reasons
Environmental benefits	
Benefits	**Reasons**
More carbon fixation	Less seedbed preparation
Less water consumption	Mixed cultures
Very low soil erosion	Deeper root systems
Better biodiversity	
minimum pollution of water	
High resistance to abnormal climate changes	
Energy benefits	
Benefits	**Reasons**
High biomass (energy) the output	More sunlight intercept
Minimum input energy requirement	Longer growing season
	The ability to absorb nutrients and water in the different depths of the soil bed
	Nearly no pesticides or herbicides
	High nutrient utilization efficiency (i.e., low fertilizer inputs)
	Few seeds needed
	Few passes of farm machinery
	Less or almost no irrigation

In the investigation of the growth rate of the roots of various types of plants in the field of biofuel, the amount of perennial plants is higher than annual plants, so the length of root penetration into the soil depends on drought stress and the amount of fertilizer. Plants like large clumps of switchgrass, a tall poplar tree, high energy palm oil in cane plants, and reed on grass gens plant [47] and the plant willows from the species-genus *Virginia fanpetals Sida hermaphrodita Rusby*, variant type of *Miscanthus and Spartina pectinate*, the abundant poplars from *Populus L* specious are very bioenergetics.

The main feature of second-generation biofuel refineries where non-food biomass has become important to increase food security [48]. Researchers developed catalytic, pyrolysis, fragmentation, polymerization, and Fisher–Tropsch processes aimed at sustainable second-generation biofuel products [49,50]. This generation of biofuel production can use crops grown in less demanding water and fertile soil, such as Jatropha, which requires less water and algal biomass is a type of non-food Consumption [51].

7.3.1 Sustainable Agriculture in Different Concepts

In the significant field of natural resource development, there are two terms, "sustainability" and "sustainable development", which are synonymous but have conceptual differences. In this way, sustainability means a constant rate, stagnation, and plateau. The terms "sustainability" and "sustainable" were developed structures in mid of the 20th-century, which are available in the Oxford dictionary. Therefore, this phenomenon is due to the existence of different crop cultivation environmental issues such as land salinization, soil erosion and cut the trees over many years, which include sustainability problems owing to excessive agricultural activity, mining and urban growth, and the lack of implementation of disciplines [52]. Meeting the multifaceted demands on soil resources in the 21st century—such as increasing food production, producing bioenergy crops, restoring degraded lands, sequestering carbon, improving water use efficiency, and creating reserves for biodiversity—requires an interdisciplinary approach involving soil scientists and experts from various fields to address these global challenges [53].

Sustainable development is the main section of social relationships and development on specific environmental and economic conditions (Figure 7.2). In the conditions of unlimited natural resources, the stability and transfer rate have a constant rate, but if the resources are limited, the speed of the process changes and it will be decreased during the time. Sustainable agriculture methodologies such as precision agriculture, integrated pest management, and soil carbon and nitrogen cycling are crucial for optimizing harvests while minimizing economic and environmental costs, contributing significantly to the potential of biofuels to replace fossil-fuel-based products and mitigate global warming [54]. Recent biotechnology breakthroughs in fractionation and conversion processes, along with the cultivation of perennial high-biomass yield plants, highlight the potential for sustainable agriculture and biorefineries to address the energy–food–water nexus while reducing environmental impacts associated with traditional annual grain crops [55]. The increase in greenhouse gas emissions has spurred the search for renewable biofuels, with sweet sorghum emerging as a promising feedstock due to its low input requirements and adaptability to semi-arid regions, and conservation agriculture potentially offering a sustainable production system to enhance its cultivation in South Africa [56].

7.3.1.1 Economic Sustainability

The economy of biofuels, which competes with fossil fuels, has been high profitability in the long term with the support of governments. However, it has a high efficiency and significant impact on reducing economic barriers and developing

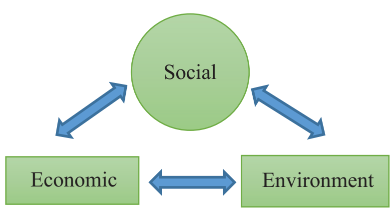

FIGURE 7.2 Three aspects of sustainable development [57].

marketing and diverse products in the sustainable development of agriculture. The main need of humans is to provide food security and agriculture development, it is the basis of civilization of food production, so according to Henry Kissinger "control the country and people by controlling oil and food respectively" and by investing in biomass, the transfer of wealth between countries is reduced and food security will be provided for 7 billion people [4]. Most recently, due to the increase in the appeal of the raw materials of biofuels, there is an upward trend of several roles in the global fuel market, including the competition over common resources in order to produce essential food for human life or its use to be fuel on the industry, which increase the price of food in the world. The other study employs bibliometric analysis to explore the economic potential of biofuels and their implications for achieving a sustainable economy, revealing positive correlations between biofuel research and production growth, particularly in major markets like the United States, India, China, and Europe, with emphasis on sustainable development and various socio-economic impacts [58]. Other research emphasizes how escalating global energy needs and environmental issues propel the shift toward cleaner energy solutions, specifically highlighting solid biofuels as sustainable resources. These studies examine their attributes, and energy recovery techniques, contrast them with fossil fuels, and evaluate their sustainability and economic viability using methodologies such as LCA and LCSA, while also considering certification frameworks like RSB and RSPO [59]. Although, researchers introduce an optimization framework for designing a sustainable hybrid first/second-generation ethanol supply chain, addressing issues like food crop use, land requirements, and biomass competition, with a case study on UK ethanol production [60]. The utilization of sugarcane trash and bagasse, derived from harvesting and processing, as fuel for electricity generation or feedstock for second-generation ethanol, presents an opportunity for revenue maximization through flexibility in diverting these materials based on favorable electricity or ethanol prices, demonstrating economic and environmental benefits in an integrated first and second generation ethanol production process from sugarcane [61]. In this way, allocating part of the fuel income to reduce the price of food is necessary and ultimately requires a more detailed analysis of policymaking and forecasting food security in the lives of communities.

7.3.1.2 Environmental Sustainability

Environmental sustainability is one of the three elements of agricultural sustainable development, so this part indicates reducing greenhouse gases, climate change, soil erosion, and climate pollution. The important point of agricultural sustainability is to improve soil quality and renewable energy from a farm to the whole world. The important criterion for the sustainable development of agriculture is water management. However, with the global water crisis, it is important to control water use and conserve it for the security of the future agricultural industry. Among the important roles of biofuels in the environment, that pointed out the factor of reducing greenhouse gases, including CO_2, methane N_2O. By replacing petroleum products with 1 L of bio-oil or bio-alcohol, so the amount of carbon dioxide gas decreases to 2.68 for bio-oil and 2.31 for bio-alcohol. One of the essential resources of biofuel products is the existence of forest and grassland with high density, which was discussed with the analysis of the life cycle (LCAs) description to the importance of this cycle and the amount of greenhouse gas emission, encompassing all phases including production, storage, transport, and consumption, is associated of environmental sustainability. One of the important factors of biofuel is the amount of energy required to cultivate and harvest raw materials. In agriculture, activities such as plowing, irrigation, and spreading fertilizers and poisons, where the necessary energy comes primarily from fossil fuels. Then a conversion process for production and distribution is carried out, which includes energy production and use of fossil energy, which is considered as an energy balance and indicates the need to replace biofuel instead of fossil fuel. This energy balance ranges from 1 to 4 for wheat and 3–10 for cellulosic ethanol and 0.8–0.9 for diesel and petrol. Another important criterion for the sustainable development of agriculture is water management. However, with the global water crisis, it is important to control water use and conserve it for the security of the future agricultural industry. However, it is an important part of preserving crop biodiversity because if you grow any type of crop it will result in a loss of biodiversity and spread pollution from herbicides, fertilizers, and insects.

The important part of burning biomass in agricultural lands for increase soil fertility and reduce pests, so it causes to increase in methane and carbon dioxide gas in atmosphere. The main material in the production of bioethanol is lignocellulose from raw material, so this material is analyzed with the consumption cycle of raw material as a fuel, then the meaningful result to increase eutrophication, radiation of phosphorus and nitrogen gas from the plant and acidification of the environment. According to the existing solution in biofuel production from four generations of biofuel refineries, it is possible to extend the third generation of algae material production of materials with a combination of micro and macro as a stable raw material is effective in reducing environmental pollution and food safety problems.

7.3.1.3 Social Sustainability

Aspect of the development of biofuel, this will lead to increased rural development and reduced poverty in agricultural areas. The introduction of common land possession policies and it's necessary to generate high legal to reduction of this type of useless land. One of the benefits of this energy source is the creation of jobs in various biofuel production processes and it is a major motivation of the agricultural employment discussed in high awareness regions. Biofuel production across the Americas is shaped by diverse factors such as geographic conditions, land tenure history, and government policies, leading to varied roles and impacts in different nations, with key social issues arising from the recent expansion in Mexico, Colombia, and Brazil, highlighting the need for better incorporation of local needs and expertise in sustainability governance [62]. A comprehensive social sustainability evaluation of three potential aviation biofuel supply chains in Brazil—sugarcane, eucalyptus, and macauba—reveals that each feedstock results in distinct social impacts, with macauba generating the highest job creation and GDP value, eucalyptus providing better employment opportunities for women, and sugarcane having moderate social effects [63]. The prospect of biofuels going "mainstream" has highlighted the social impacts of their production and use, with media reports since 2007 contrasting alleged negative effects such as increased food prices and land grabs with the optimistic views of some academics, suggesting that while negative social impacts are likely under certain conditions, positive impacts could be achieved through tailored social innovations and robust certification of supply chains [64]. Ultimately, politicians are discussing ways to improve the livelihoods of rural communities, including women and children, by providing access to power tools and water resources and reducing the difficulties of working on the farm.

7.3.2 Analysis of Sustainable Development

In research by Wasiak, by presenting a mathematical model for economic and technological processes under the limited resource condition, it is a kinetic function to describe physical, chemical, or biological processes [65]. The coefficients of the formula are such that a, k, n are constant which is indicated in half time ($t_{1/2}$) period of the whole process. While the value of "a" indicates the amount of transfer into the substrates, "n", and "k" are factors affecting time. The function $x_{(t)}$ the coefficient of the process in terms of time. According to the formula, the amount of changes in the reaction process per unit of time in this method is as equations (7.1) and (7.2).

$$x_{(t)} = a\left[1-\exp\left(-kt^n\right)\right] = a\left[1-\exp\left(-\frac{\ln 2}{t_{1/2}^n}t^n\right)\right] \tag{7.1}$$

$$\frac{dx(t)}{dt} = a\ \left[1-x(t)\right]nkt^{n-1} \tag{7.2}$$

According to the above formula, the process of growth rate reached a maximum value at $t_{1/2}$ and equals zero at the beginning to end. According to equation (7.2), a value of $[1-x_{(t)}]$ in time represents a conversion factor of remaining in the feedstock fraction and a value of α in the instant time t_z, being fed back to the system. Equation (7.3) describes the recycling source over time, and adding the raw material rate to the recycled material flow yields the recirculation rate represented by equation (7.4).

$$X_r = \alpha\ a\left\{1-\exp\left[-k\left(t-t_z\right)^n\right]\right\} \tag{7.3}$$

$$\frac{dx_m}{dt} = a\left\{nkt^{n-1}\exp\left(-kt^n\right)+\alpha\ \left[1-\exp\left[-k\left(t-t_z\right)\right]^n\right]\right\} \tag{7.4}$$

In developing the process in the mentioned equation, the consideration of $x_{(t)}$ means the current time dependent on τ, which has two main parts, the first relates to the main substrate and the second to the retrieval layer affected by the criterion α, shows on the equation (7.5).

$$X_m^{(t)} = a\int_0^t nk\tau^{n-1}\exp(-k\tau^n)\,d\tau + \alpha\ a\int_0^t \left\{1 - \exp\left[-k\left(\tau - \tau_z\right)^n\right]\right\}d\tau \tag{7.5}$$

The results obtained from the formula show that biofuel production through carbon recycling has a positive effect in terms of sustainable agricultural development.

7.3.2.1 Impact of Energy

One of the models stated by Zhang and Colosi, introduces of ERORI index to calculate effective energy in the complex system for agricultural products during the year [4,66]. The amount of energy was expressed by Wasiak and Orynycz of energy efficiency (ε) from equation (7.6) [67].

$$\varepsilon = \frac{E_{\text{bio}}}{E_{\text{ex}} + E_{\text{tr}} + E_{\text{emb}}} \tag{7.6}$$

According to the formula (7.6), the factors mentioned include E_{bio}, E_{ex}, E_{tr}, and E_{emb}, which respectively represent the energy consumed by the soil, the energy used for tillage, the energy required for transport and the part of the existing embodied energy that finds a place in tillage operations.

Therefore, the direction of increased energy efficiency according to the coefficients E_{bio}, E_{ex}, and E_{agr} are related to the farm area, while E_{tr}, E_{mik}, and E_{mtr} are not related to the farm area [65]. Therefore, it has more complex properties to obtain ε, and therefore ε_{tot} can be obtained by using many subsystems ε_1 and ε_2 in a large system of formula (7.7).

$$\frac{1}{\varepsilon_{\text{tot}}} = \frac{1}{\varepsilon_1} + \frac{1}{\varepsilon_2} \tag{7.7}$$

According to the mentioned formulas, it is aimed at achieving maximum energy efficiency in cultivated farms. In this method, it is important to provide hardware and software technologies for recycling carbon dioxide and the extent of sustainable agriculture in the future. However, the principle section of appropriate technology in the fertile lands for cultivation and conversion to biofuel and used agricultural wastes instead of useful products such as straw instead of corn seeds in potential processes.

7.3.3 Biofuel Production Technologies and Energy Transition Strategies

There are several methods for biofuel production in different methods such as combustion, gasification, pyrolysis, hydrothermal liquefaction, enzymatic hydrolysis, anaerobic digestion, and transesterification. Combustion is one of the methods used directly from agricultural biomass as energy for heating and domestic use, so the consumption of energy isomer used from petroleum products in the world reaches more than 96% and the cost of generating electricity with this method is lower than with coal [68,69]. Researchers presented two methods of converting biomass to a gaseous state for fuel, including atmospheric oxidation with a lower calorific value and the carbonization pyrolysis gasification process to obtain a higher calorific value. This main process for pyrolysis, which is a thermal decomposition through the process of the extraction of more bio-oils at a high-temperature range [70]. Process steps can produce petroleum products such as kerosene oil, petrol, bio char, and diesel with high quantities of oxygenate that cause more alcohol, aldehydes, and ether in molecular structure [26]. The research on producing biofuels by this method was carried out on wheat, maize, and rice straw with husk products at a temperature above 400°C, the highest yield is achieved with a yield of 43.8% from rice straw [70]. This process was carried out under the temperature condition of 280°C and under catalytic and non-catalytic conditions on products such as kind of pinewood in the jungle, wheat stubble, and kind of sugarcane bagasse, so the best characteristic result of sugarcane bagasse was obtained with the higher conversion rate of 95% [71]. This essential method in the intention of biomass to the decomposition process, such as fragmentation way to increase the contact surface of the material, biochar, enhance the enzyme process, electron beam radiation, and thermal decomposition [72,73]. This process has a good reputation in biodiesel production as having lower sulfur emissions and acceptable ignition point and lubrication [3]. Current biofuel refinery technologies have emphasized that the direct liquefaction of biomass using hydrolysis, fermentation, and thermodynamic liquefaction processes promotes higher energy efficiency and economic value [74].

7.3.4 Generation of Bio Refineries of Agriculture Product

Biofuels, categorized into first through fourth generations, serve as an alternative energy source aimed at reducing greenhouse gas emissions and addressing global warming, with each generation striving to meet global energy demands while minimizing environmental impacts [75]. Biorefineries have been developed in four generations (Figure 7.3) and the first generation is efficient with the raw materials stock in farms such as corn, wheat cassava, sorghum, and cassava to produce biofuel. First-generation bioethanol, primarily derived from corn and sugarcane in the United States and Brazil, constitutes the majority of global bioethanol production as of early 2016, despite concerns over sustainability due to impacts on land use, water resources, and competition with food production [76]. The EU's ambitious climate change mitigation and sustainable development goals by 2030 are supported by the European Commission's 2012 bioeconomy strategy, which emphasizes sustainable biorefineries converting lignocellulosic biomass into bioenergy and bioproducts while addressing sustainability issues of first-generation biorefineries and exploring advanced biorefining challenges and future directions [49]. Excessive optimism regarding crop-based biofuels, notably first-generation types, has impeded the future of biofuel development in Southeast Asia, underscoring the need for transitioning to second-generation biofuels to enhance sustainability and uplift rural living standards [77]. The EU economy faces the forthcoming issue of ensuring the availability of bio-based chemicals, materials, and energy at reasonable costs, with the European research and innovation strategy promoting the development of technologies utilizing alternative resources to fossil fuels, particularly second-generation biorefineries that use bio-waste and avoid the ethical, social, environmental, and economic issues of first-generation biorefineries [78]. The ethanol production process in this generation for products such as wheat and corn requires more processing steps, and for products such as sugar cane and beet, the amount of sugar is extracted, then with the catalytic process is decomposed of chemical and biological structure from the raw materials in the state of lactic and propionic acid or Fuels such as ethanol, methanol, and butanol are converted into biofuel [79]. Integrating second-generation ethanol production from C5 sugars in bagasse and cane trash with first-generation sugarcane biorefineries in Brazil could significantly increase ethanol yield by co-fermenting C5 sugars with cane juice and molasses, enabled by recent biotechnological advancements [80]. The universal method of this biofuel generation has been developed more than 20% in the American continent and that's more popular in other countries such as Brazil, France, Japan, and China [81].

Second-generation biofuel refineries use non-edible feedstocks such as domestic waste, municipal solid, and factory waste to produce biofuels [83]. This type of process involves the gasification or pyrolysis of a feedstock to biological transformation for implementing the mixture of hydrogen and carbon monoxide with catalyst operation and Fisher–Tropsch method to extract biogas [85]. Therefore, the challenges associated with the function of lignocellulosic materials in the biofuels generation, especially the second generation of biofuels consumption, feedstock organization, increasing economic and social capacity to use this species of biofuel, benefiting from energy with chemical, microbial, and biological processes with reducing environmental risks [86]. Products containing lignocellulosic feedstock are likely to be wheat straw [87], corn pile [88] and the numerous parts of rotting plants in the garden [89] and small fields [90], grasses [91], and leaves [92,93]. New technologies for producing second-generation ethanol from sugarcane bagasse and other raw materials have been developed to meet global demand for renewable energy, integrating biorefinery processes using Pinch analysis to significantly reduce energy consumption by over 50% compared to non-integrated cases and more than 30% compared to traditionally designed Brazilian industrial plants, thereby enhancing second generation ethanol production and economic viability [94].

Due to the more need for biofuels, it's led to the use of micro algae and the kind of seaweed macro algae in the next generation of biofuels, and other types include cyanobacteria (blue-green algae), are highly energy-intensive in the efficiency of biofuel from the previous generation. The numerate of algal along more diversity of over 72,000 species in different water areas such as fresh, waste and exhibit high growth rates under conditions of temperature, acidity, and nutrient abundance. Algae can be used in the third-generation biorefinery to produce various biofuel outputs. Therefore, it's mainly used as fertilizer additives and chemicals for the process of biodiesel and bio-oil extraction [95,96]. The algae was converted into biofuels by biochemical and thermochemical processes and it was extracted metabolites and algal secretions for a usable bioenergy source. Third-generation biorefineries use microbial cell factories to convert renewable energy sources and atmospheric CO_2 into fuels and chemicals, offering a carbon-neutral alternative to fossil fuels. To compete with the petroleum industry, these biorefineries must evaluate CO_2 fixation pathways, utilization models, and productivity levels [97].

The fourth-generation biofuel refinery uses transgene algae as a feedstock because of their high photosynthetic properties, higher light transmittance, and reduced photoinhibition in genetically engineered micro algae. According to studies, Table 7.3. shows different aspects of using biofuel generations. The other study presents an integrated framework that evaluates and enhances the performance of fourth-generation

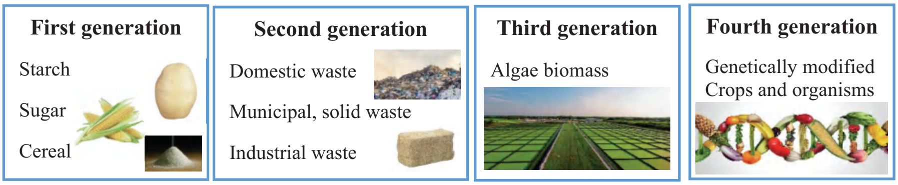

FIGURE 7.3 Different bio refineries [75,82–84].

TABLE 7.3
Features of Different Biofuel Generations

	Generation				
Subject	**First**	**Second**	**Third**	**Fourth**	**References**
Food security	Raw materials with the structure of starch and edible oil	Without overlapping of food and energy product	Without overlapping of food and energy product	Without overlapping of food and energy product	[99]
Crop land	arable ground	arable and forest ground	Any type of land	Any type of land	[100]
Aspect of environmental	Exist of fertilizer and pesticides	deforestation phenomenon	No cost for fertilize, reliable water treatment and engender marine eutrophication cons	Water and Co_2 treatment, exist of GM organism phenomenon	[101]
Sustainability manager	Insensitivity to water and soil sources	Insensitivity to forest resources	There is no economic justification	Damage of diffusion GMO	[102–104]
Financial aspects	Low capital required	Low capital required	High cost for large scale	High cost for large scale	[99]
Environmental circumstance	Control temperature and humidity range	Control temperature and humidity range	Cultivable in salty soil, high PH soil, and intensive light	Cultivable in salty soil, high PH soil, and intensive light	[105,106]

biorefinery departments, emphasizing macroergonomics and sustainability indicators. It employs methods like the best-worst method, data envelopment analysis (DEA), and sensitivity analysis, while also formulating strategies through SWOT analysis [98].

7.4 CONCLUSION

The results indicate the increasing demand for energy, food, and fuel, the field of modern and sustainable agriculture will undergo major changes in the coming decades. Therefore, the cultivation and development of perennials, the cultivation of annual grains, the growing of algae, and the benefit of genetic modification in human diet products, biomass feedstock, the reduction of toxic pollutants, and the creation of new fields for many job opportunities will revolutionize agriculture. The model was mentioned for the energy requirements of biological applications and it was made possible method by the correct choice of plants, tillage, and conversion techniques. According to the present study, biodiesel fuel should be used for operational and thermal stability to achieve sustainable development. Improving the next generation of biofuels, where different feedstock must be blended to achieve high-value, low-cost biofuels, use of new standards and development of fuel refineries, use of genetically modified biomaterials, The application of useful policies of various countries in the aspect of thermal and bio base on chemical conversion of lignocellulosic materials and, ultimately, the mandatory use of biofuels, the implementation of tax exemptions and the granting of subsidies is of superior importance.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Pourya Bazyar: Conceptualization, Writing – review draft. Ehsan Sheidaee: Methodology, Visualization, Writing – review and editing.

DATA AVAILABILITY

No data was used for the research described in the article.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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8 Hierarchical Robust Optimisation of Chemical Processes and Energy Systems through In-Depth Industrial Data Analysis and Machine Learning

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8.1 INTRODUCTION

The integration of Industry 4.0 technologies, artificial intelligence (AI) and advanced optimisation methodologies significantly enhance the operational efficacy of contemporary industrial assets. These technologies facilitate the optimisation of performance, maintenance and inventory management, thereby catalysing cost-efficient solutions and fostering substantial reductions in carbon emissions and other environmental pollutants [1,2]. Industry 4.0 enables the deployment of sophisticated AI and machine learning (ML) algorithms for process monitoring, strategic execution of predictive and preventive maintenance, operational optimisation and enhancement of productivity and product quality [3,4]. Decarbonisation of sectors including the conventional power sector, large industrial complexes and maritime transport necessitates the adoption of greener technologies and optimisation of operations at various levels. These changes result in improved environmental metrics and enhanced energy performance [5]. Furthermore, the need for decarbonisation in manufacturing industries to meet emission reduction targets requires a complex optimisation of measures, considering individual situations and available resources during product development, process development and large-scale manufacturing [6].

We are currently transitioning from the fourth industrial revolution to the fifth industrial revolution within the framework of human techno-economic evolution [7].

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Concurrently, this transition encompasses a shift from the fourth research paradigm (Data-Driven Sciences) to the fifth (The Age of Artificial Intelligence) in the sphere of human techno-scientific advancement [8,9]. Research paradigms have traditionally preceded their respective industrial revolutions, yet we have witnessed significant lags in the translation of research findings into industrial applications across earlier paradigms. However, the fourth research paradigm and fourth industrial revolution have exhibited temporal overlap. The primary reason for that is the monumental developments in portable computational capabilities and information and communication technologies (ICT). This convergence has significantly narrowed the gap between industry and academia, thereby reshaping interactions between the customer (industry) and the supplier (academia and R&D institutions). This enhanced proximity is bound to revolutionise the industry's approach to product and service design [10], development, process modelling and optimisation [11–13], operational management [14–16] and marketing strategies [17,18].

Although the impact of the fifth research paradigm on industry in the fifth industrial revolution is anticipated to permeate across all industries and almost all aspects of their operations, one particular industrial segment i.e., large process industrial complexes and their operational productivity and maintenance regimes are the lowest hanging fruits. The operational efficiencies and maintenance practices within these complexes are intricately linked to their carbon footprint and emissions metrics. Often, enhancements in operational efficiency directly translate into quantifiable decarbonisation and reductions in emissions. Recently many researchers have demonstrated successful applications of AI for robust modelling and optimisation of large process industry complexes yielding promising improvements in various operational efficiencies and reductions in emissions, sometimes coupled with reductions in operational costs [19,20].

Large process industrial complexes constitute typically integrated systems comprising multiple multidisciplinary subsystems. A fossil fuel-powered combined cycle power plant can be taken as a typical example. This integrated electrical energy generation system may comprise subsystems including (a) a fossil fuel thermal combustion unit (typically a boiler), (b) a mechanical energy generation unit (an internal combustion engine, gas turbine or steam turbine) and (c) an electrical energy conversion unit (typically a generator). Another example could be a fertiliser plant which is an integrated chemical processing unit. The subsystems may include (a) a thermo fluid management unit (controlling temperature and mass/volume flows of reactants), (b) a chemical reaction or catalysis unit (to maximise reactant yield through accelerated reactions) and (c) a thermal drying or prilling unit (transforming wet reactants into more valuable dry granular products).

All the subsystems mentioned in the above examples belong to different disciplines of engineering and hence separate bodies of knowledge, yet they are physically very closely interfaced rather inseparably integrated in large process industrial complexes. This situation presents two principal challenges. First, the bodies of engineering knowledge across various disciplines consist of first-principle mathematical models that do not effectively address the critical interfaces. Second, even the most sophisticated first-principle mathematical models of individual engineering subsystems are limited by the inclusion of only a few operationally relevant variables. Consequently, industrial operations management frequently encounters scenarios such as (a) actual yields and efficiencies of subsystems are significantly different from the theoretical yields and efficiencies calculated by first-principle mathematical models built on very limited dimensional input spaces, (b) variations in performance across geographically or climatically distinct locations and (c) reliance on empirical optimisation approaches by engineering managers.

In the perspective of the fifth research paradigm and fifth industrial revolution; our research group has reported the role of AI in transforming the engineering management of large industrial complexes as a three-level stack shown in Figure 8.1 [21]. These three operating levels are unique in three ways: (a) the concerns and the key performance indicators (KPIs) of the concerned engineering manager (EM) are interested in modelling, control and optimisation, (b) the type and distribution of data of individual variables/parameters involved in the problem and (c) the nature of ML problem they pose. The explanation of the classification of the industrial system on the three levels as well as the KPIs associated with the operating levels, the nature of data and the choice of the ML algorithm are summarised in Table 8.1. It is conspicuous from the information presented in Table 8.1 that as we move from component to system and strategic levels, the nature of problem progressively transitions from an engineering textbook-type continuous data, quantitative, first principal function approximation problem to a mixed data-type qualitative classification problem. However, a careful review of the literature reveals that it very rarely becomes a typical categorical data classification problem in the case of large industrial complexes for mechanical, chemical, electrical and interfacial problems of these disciplines.

We have taken three problems corresponding to component, system and strategic level operation of coal power plant. The #1 bearing is mounted on the shaft rotor that supports the steam turbine system. The vibration of the bearing serves as a component-level problem [22]. The system-level problem corresponds to the industrial process

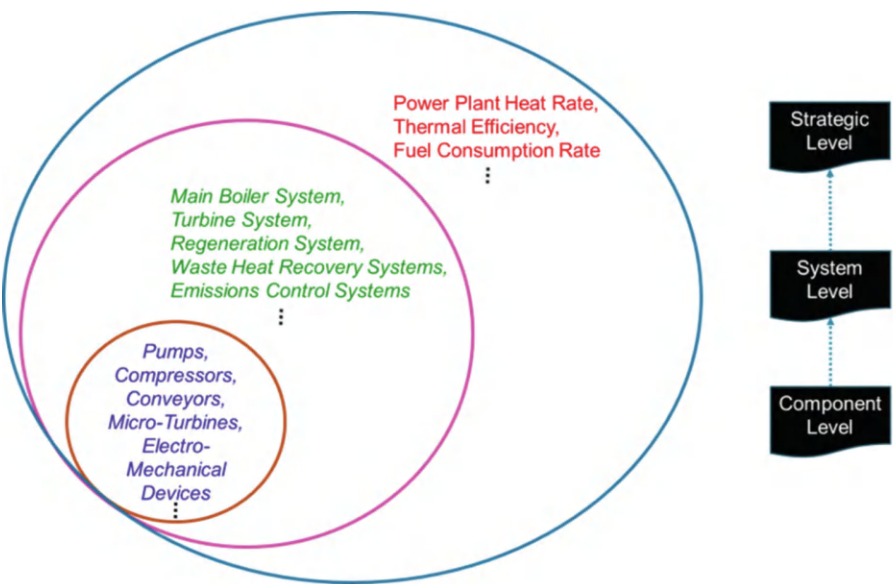

FIGURE 8.1 The three-level stack of engineering management problems in large industrial complexes [21].

TABLE 8.1
The Three-Level Characterisation of the Operation of the Industrial System

Level	Concerns of EM	KPIs	Nature of Data	Nature of ML Problem
Component level	i. Preventive, predictive and shutdown maintenance planning ii. Component inventory levels iii. "Useful life" assessment of components iv. Process quality variance investigation v. Product quality variance investigations	i. **Housing/Casing** Vibrations, stability, etc. ii. **Shafts** Vibrations, alignment, camber, etc. iii. **Bearing** Vibrations, wear, alignment etc. [1]. iv. **Impellers** Vibrations, rpm, wear etc.	i. Mostly continuous variables on the input/ control sides and output side ii. Rarely qualitative numerical variables on output/KP I side	i. Mostly numerical function approximation problems, ii. Often extended equivalent of some first-principle models for analysis
System level	i. Technology upgradation investment and breakeven calculations ii. Operational recipes to control work in process inventory, rejection or rework from systems iii. Optimisation of operational parameters of the system for different types of efficiency/cost tradeoffs	i. **Energy outputs** Thermal, or electrical [19,25] ii. **Mass outputs** Process yields fluid or solid iii. **Flow outputs** Liquid, vapour or gas flows from heat exchangers, compressors or boilers etc. iv. **Emissions** CO_2, NO_x, SO_x, Hg, Dust etc. [23]. v. **Efficiencies** Thermal or electrical [24]	i. Mostly continuous variables on the input/ control sides and output side ii. Rarely qualitative numerical variables on out/KPI side	i. Mostly numerical function approximation problems, ii. At times classifier versions of function approximators required for effective modelling (ANN/SVM for reg/class) iii. Almost no first-principle model available for comparison

(*Continued*)

TABLE 8.1 (*Continued*)
The Three-Level Characterisation of the Operation of the Industrial System

Level	Concerns of EM	KPIs	Nature of Data	Nature of ML Problem
Strategic level	i. Emissions control in compliance of International Energy Agency (IEA) and Net Zero targets ii. Energy generation efficiency of a power plant iii. Material throughput of a fertiliser plant iv. Gasoline or diesel yield of an oil refinery	i. **Compliance with environmental regulations** Overall carbon footprint, carbon credits etc. [26 27] ii. **Enhancing overall energy/material yields without inflating costs** Costing workouts for financial and management accounts, energy efficiencies, energy management metrics iii. **In pocket capacity/ capability margins while negotiating with tariff regulators, trade deals and government agencies** Optimising the heat rate of the power systems [21] iv. **Enhancing the performance of manufacturing systems** Increasing the material removal rate and reducing the process-related CO_2 discharge [12,13]	i. Mostly continuous variables on the input/ control sides and output side ii. Some qualitative numerical variables on out/KPI side	i. Mostly numerical function approximation problems, ii. Classifier versions of function approximators or typical classifiers required for effective modelling iii. No first-principle model available for comparison

for the removal of SO_2, Hg, NO_x and dust from the flue gas [23]. Whereas, thermal efficiency, power and turbine heat rate represent the strategic-level performance parameters of the power plant [24]. The three operation-level problems are analysed by data-driven modelling and optimisation approaches. More details about the workflow and framework utilised to analyse the problems are provided in the following.

8.2 PROBLEM IDENTIFICATION CORRESPONDING TO THE POWER PLANT

A focused approach to utilising AI methodologies is often beneficial in the decision-making process. This process begins with the proper identification of the problem, including its relationship with the main system, auxiliary systems and the environment. Consequently, it is challenging to identify an isolated problem or solution that does not impact its surroundings. Therefore, problem considerations must be handled responsibly.

8.2.1 Problem Categorisation, Modulation and Selection of Variables

The identified problem is categorised into two stages: problem level and problem direction. The problem level pertains to the definition of the problem at a strategic, system, or component level. The problem direction involves the designation of the problem's objective, such as optimisation, forecasting, or decision-making. Selecting the correct category aids in the relevant variable selection for AI-based process modelling. If necessary, the selection and categorisation of the main problem are followed by breaking it down into a series of smaller, logical problems. It is impractical to model a process using a large number of variables or variable combinations. Therefore, variables are selected based on process understanding, experience and literature reviews.

8.2.2 Type of Variables

Numeric variables (continuous and discrete) and categorical variables (nominal and ordinal) are two main types in which a selected variable can be segregated. Each selected variable is identified with respect to the mentioned categories. The understanding of variable type has a significant effect on the selection of AI modelling algorithms. Moreover, different statistical tests can be performed to find out the health of data depending upon the variable type.

Figure 8.2 presents three examples of the problems reported by our group in the literature whereas Figure 8.2a presents the listing of the input variables for modelling #1 bearing vibration mounted on the steam turbine shaft bearing (component level problem) [22]. Four variables namely outlet SO_2 conc. (mg/Nm^3), outlet NO_x conc. (mg/Nm^3), outlet Hg conc. (μg/Nm^3) and outlet dust conc. (mg/Nm^3) are the representative output variables corresponding to the flue gas desulphurisation system-level modelling which are mentioned in Figure 8.2b and details are provided in Uddin et al. [23]. Two strategic-level problems are considered from the coal power plant operation where thermal efficiency, power and turbine heat rate are modelled by the relevant input variables as mentioned in Figure 8.2c [24] while generator power is modelled on the comprehensive list of the input variables as depicted on Figure 8.2d [28]. However, the distribution of individual variables, the dimension compressed distribution of the input space and the level of problem can result in different types of machine learning architecture for the modelling tasks.

8.2.3 Variable Processing and Assessing Health of Data

The list of variables selected for the AI training process requires careful preprocessing to prevent skewed results due to differing variable ranges. AI models are initially trained under the assumption that all factors or variables contribute equally to the output. Therefore, it is necessary to standardise variables with very high or very low

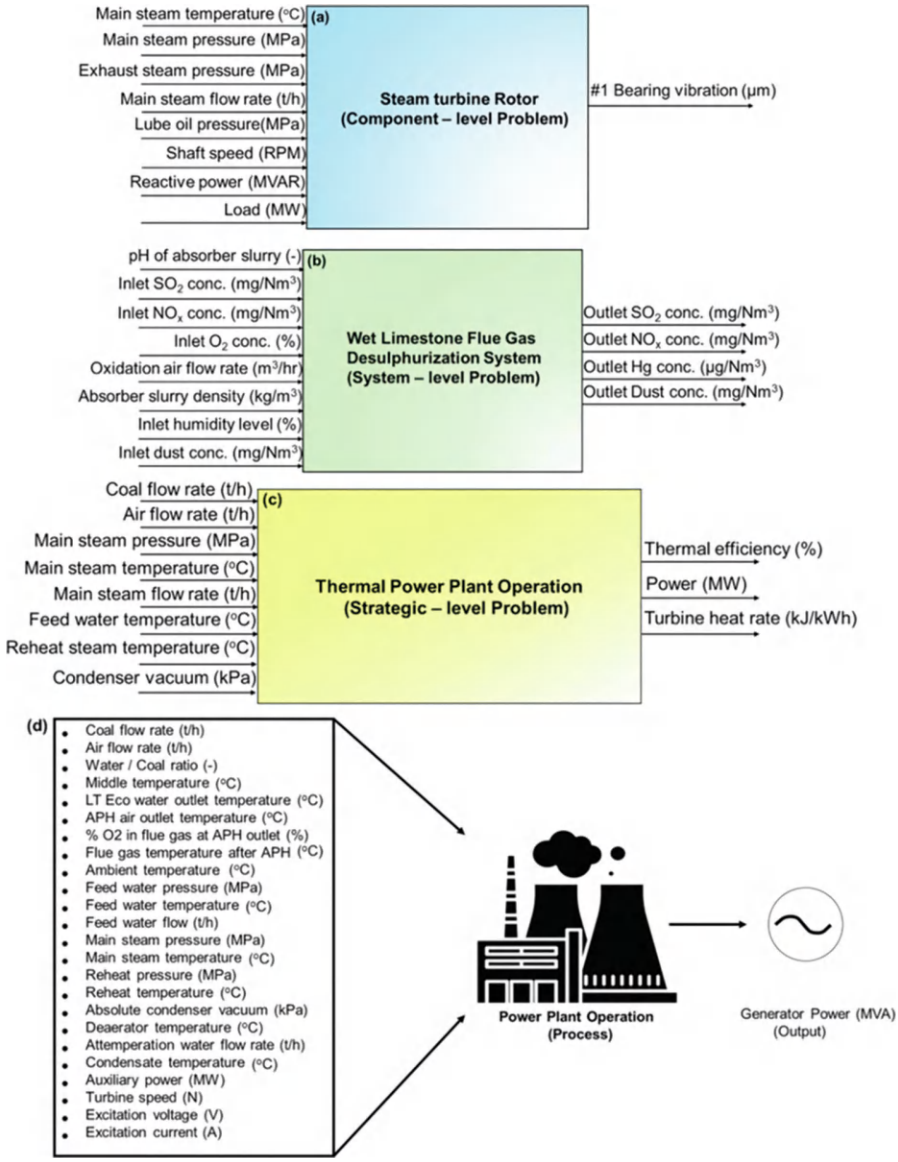

FIGURE 8.2 Input process output diagrams of (a) component level problem, (b) system-level problem and (c–d) strategic level problem. The input variables are listed on the left while output variables are mentioned on the right side of the figure.

ranges to an equal scale. Training models without normalisation can adversely affect the performance of AI-based algorithms. For instance, distance-based algorithms such as support vector machines (SVMs) are particularly sensitive to this issue.

One widely used data-processing technique is the min-max approach; other well-known techniques include robust normalisation, log normalisation and

z-score normalisation. The selection of the most appropriate normalisation technique depends on data characteristics, such as the presence of outliers, large-magnitude data, or distributed data.

It is well-established that the decision-making capabilities of AI models depend heavily on the quality of the training data. Therefore, it is essential to assess data quality or "data health" before training AI models. This assessment can be performed using statistical tools, either numerically or visually. Depending on the process being studied, various data health issues can be identified, such as outliers, repeated data, delayed data, abnormal data clusters, empty or missing data etc. A particularly challenging issue to detect is a faulty sensor that consistently produces erroneous data within an expected range at regular intervals, without any delays or missing data. The variable from such a faulty sensor will be mixed with the data stream from other non-faulty sensors, making the erroneous data appear legitimate. This can lead to the training of an AI model that does not accurately represent the process.

8.2.4 Data Collection and Visualisation

After deciding on the variables' range selection, the next critical task is the data collection process. Two data sampling methods are commonly used: (a) collecting a large chunk of data from the industrial system, or (b) sampling a representative dataset from the larger chunk. AI models can be trained with the full dataset or with a representative dataset. For example, temperature data for the whole year (full dataset) or features such as high, low and changing temperatures representative of the entire year's temperature data. The frequency of data collection within the selected range is also crucial. Data can be collected at different intervals, such as every hour or every second, depending on the resolution window required for model-based predictions. This frequency impacts the granularity and accuracy of the AI model's predictions.

Data visualisation is one of the most powerful tools for evaluating data at both stages: (stage 1) raw data obtained for training (pre-training data), and (stage 2) results obtained after training (post-training data). Typically, emphasis is placed on visualising data distribution profiles. However, visualising the input data is crucial for assessing input data quality and health. This visualisation provides intuitive insights that are essential for evaluating modelling accuracy within the operating ranges of the variables.

8.2.5 Different Visualisation Techniques

Various visualisation techniques can be employed to evaluate the behaviour of input data, such as line charts, bar graphs, scatter plots, histograms, hierarchical parallel coordinate systems, RadViz or PolyViz methods and self-organising feature maps (SOFM). Line graphs, bar graphs and scatter plots are particularly useful for understanding the behaviour of individual variables. Line and scatter plots are effective for identifying outliers in the input data, while bar graphs are especially helpful for identifying interdependencies between input variables. Histograms can be used to distribute data into sub-ranges or classes, allowing the identification of the distribution's shape or type (e.g., normal, positively skewed, negatively skewed, or discrete distribution).

The aforementioned techniques treat variables individually, whereas SOFM can be used to visualise input combination distributions in lower-dimensional space.

Figure 8.3 presents the individual distribution of variables in the training data of the problem summarised in Figure 8.2. It is important to note that real-world industrial data like this has distribution of critical variables biased towards either extremes or the mean value based on the specific process control regimes implemented in the operations with less concentration of data in other zones. It is very important for AI process modelling engineers/experts to take cognisance of the high data concentration zones and the low data concentration zones so that they know the areas in which their models may be expected to be more reliable. Moreover, as a rule of thumb, a normally distributed variable is less desirable than a uniformly distributed variable as it offers a higher probability of capturing linearity, nonlinearity and interaction of causation.

8.2.6 Compressed Dimensional Space

In many industries, dealing with high-dimensional data poses a challenge for direct visualisation methods. However, this issue can be addressed by reducing the dimensionality of the data. Techniques such as principal component analysis (PCA), linear discriminant analysis (LDA) and self-organising feature maps (SOFM) are commonly employed to transform high-dimensional data into low-dimensional space. Data visualisation, particularly the representation of high-dimensional data in low-dimensional space, is invaluable for qualitatively analysing the health of the data. Sections of high data density provide more confidence in predictions made by trained networks within those high-density data ranges. This enables better understanding and interpretation of complex data structures, facilitating more accurate decision-making in various industrial applications.

The SOFM is a very useful data dimensionality reduction tool for data visualisation especially when analysing data topological features. It is a neural network-based competitive unsupervised learning algorithm relying on distance calculations. A connected rectangular or hexagonal structure is usually formed. At each connection, a node or neuron is created initially with random weight that updates as the training progresses. Each time an input vector is presented to the neurons, Euclidean distance is calculated and the neuron with the minimum distance or closest to the input vector wins the competition. The process runs iteratively until the stopping conditions are met. Finally, the neurons with maximum winnings on presented input vectors show a larger data cluster compared to the other neurons. Figure 8.4 presents the compressed dimensions distribution of input space in the training data of component (Figure 8.4a) and system-level problem (Figure 8.4b). The SOFM offers a summarised vision of the training data input space to the process modelling engineers/experts to assess the probability of capturing linearity, nonlinearity and interaction of causation.

8.3 BASIC INTRODUCTION OF SUPERVISED LEARNING

The AI models are usually differentiated into two major categories i.e., supervised machine learning and unsupervised learning. The difference explained in simplest form between supervised and unsupervised machine learning is how data is fed to the models.

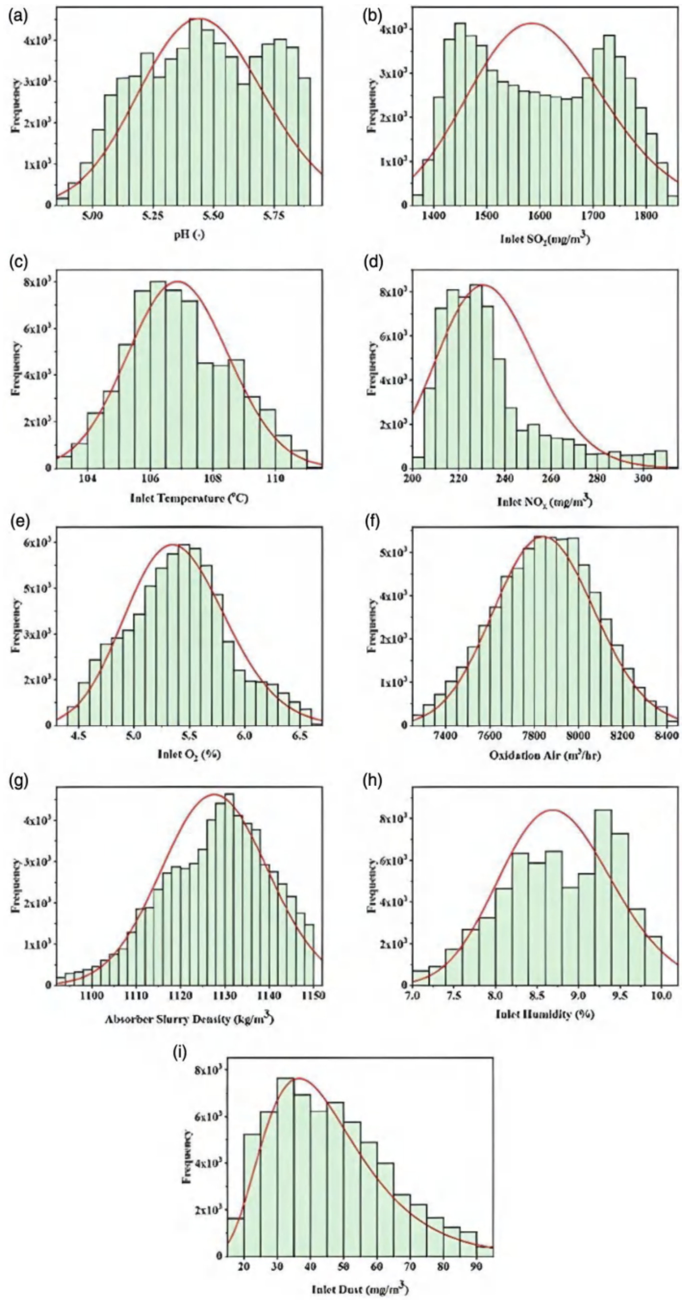

FIGURE 8.3 Visualising the data-distribution space of the input and output variables taken from the system-level problem of flue gas desulphurisation system. Continuous and asymmetric data distribution profiles of the variables are observed indicating the tendency of the operation engineers to maintain the operating variables in the given operating ranges of the variables [23].

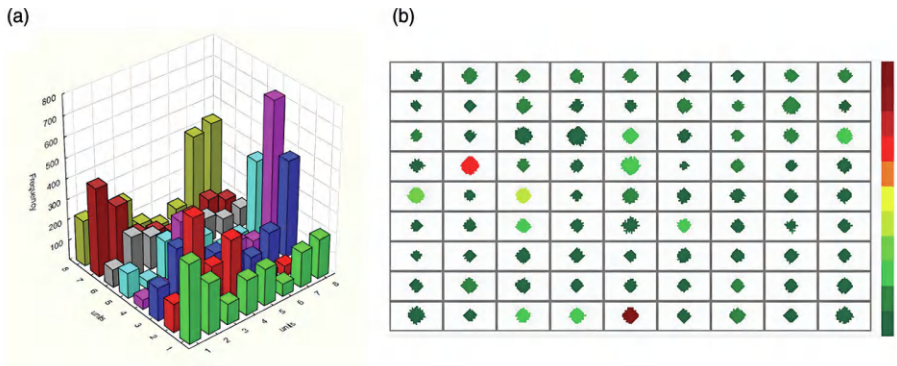

FIGURE 8.4 SOFM plotted for (a) component-level [22] and (b) system-level problems of the power plant [23].

Training data with inputs and the corresponding output is required in supervised learning whereas, in unsupervised learning raw data is fed to the model to deduce meaningful/useful results. In supervised learning, the architecture is made to support data that includes inputs with specified outputs, a data processing algorithm and an error quantifying/communicating mechanism.

8.3.1 Introduction to Artificial Neural Network

The artificial neural network (ANN) lies under the umbrella of both supervised machine learning and unsupervised machine learning (radial basis function networks RBFNs). It is inspired by the human brain's neural network working. Although ANN is not able to fully mimic the human brain's neural network, yet still approximates the information processing mechanism of the brain. The following section explains the working of ANN.

8.3.1.1 Architecture of ANN

The architecture of ANN needs to support all the fundamentals described earlier for supervised machine learning i.e., data that includes inputs with specified outputs (training data), a data processing algorithm (handled by input-hidden-output layer) and an error quantifying/communicating mechanism (backpropagation algorithm that communicates between output to hidden to input layer).

8.3.1.2 Neurons

A neuron is a node to collect data signals, process it and distribute it according to specified instructions. In fully connected ANN, the normalised input data arrives at the input neuron. Each input neuron usually collects one specified input data that is sent to all first hidden layer neurons. Each input data signal is multiplied with a weight, then the result of each input is summed up with the addition of a bias value (bias value includes bias multiplied by a weight). The summation of all input weights with bias is collected at the hidden layer. The signal collected at each hidden layer neuron is presented in a mathematical form in equation (8.1). The summed data function is passed through an activation function. Similarly, the signal from each hidden layer neuron is collected at the output layer neuron, multiplied with weight, summed and passed through a function.

$$\xi = \sum_{i=1}^{N} w_i x_i + w_0 x_0 \tag{8.1}$$

8.3.1.3 Activation Function

An activation function is used to map the data behaviour of the system through the introduction of mathematical operation. It is vital to select a mathematical function that has the ability to map systems behaviour. If a system behaves linearly then a linear mathematical function is appropriate. Similarly, non-linear mathematical functions can be used to map complex system behaviour. Popular activation functions include linear, sigmoidal, tangent hyperbolic, exponential and ReLU. There is no special restriction on the usage of particular activation functions. Any mathematical expression; suitable for the solution of a problem, can be exercised. Equation (8.2) represents the sigmoidal activation function as one such example.

$$\varphi(\xi) = \frac{1}{1+e^{-\xi}} \tag{8.2}$$

8.3.1.4 Layers

The computational stages of ANN are distributed into three layers i.e., input layer, hidden layer and output layer. Each layer has its own significance however, the hidden layer is the most important layer where most of the calculations happen. A network can have a single hidden layer or multiple interconnected hidden layers. The number of hidden layers and the neurons embedded in the hidden layer introduces the complexity to approximate the function space of the output variable. The ANN is described as a shallow neural network for having a single hidden layer or deep neural network possessing multiple hidden layers in the architecture. The number of neurons in the hidden layer are selected by the hit and trial method and the modelling performance of the model is evaluated on the performance metrics as mentioned in Section 8.3.3. The graphical visualisation of a fully connected artificial neural network is depicted in Figure 8.5.

8.3.1.5 Training Algorithms for Parameters Optimisation

The training algorithms refer to the over-all steps followed to update the parameters (weights and biases) in the network. The backpropagation algorithm is a widely used training algorithm for ANN. Other examples of training algorithms include but are not limited to gradient descent, gradient descent with momentum, quasi-newton method, scaled conjugate gradient method, Levenberg Marquardt algorithm, Hilbert-Schmidt independence criterion algorithm, evolutionary algorithms including genetic algorithm, particle swarm optimisation etc. In backpropagation, the error calculation (difference between model-predicted output and actual output is calculated) and how much weights need to be updated, is calculated using a training algorithm.

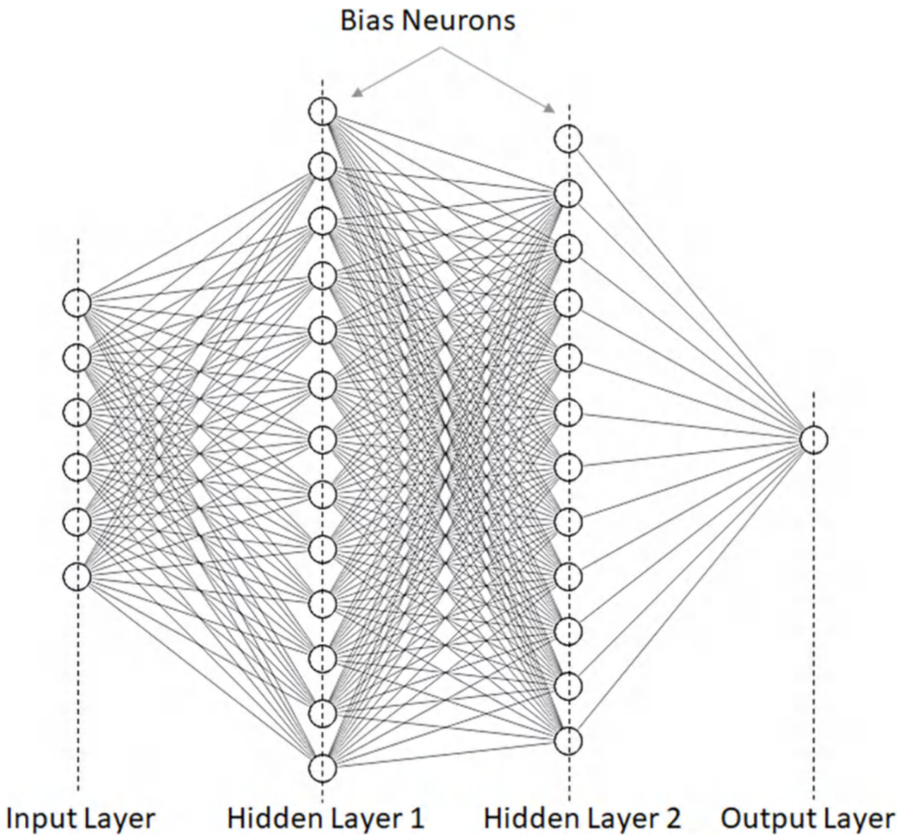

FIGURE 8.5 Fully connected artificial neural network example architecture.

8.3.1.6 Learning Rate

The learning rate is the step size that tells how large the jump should be in the direction of error minima. A larger step size may lead to missing the target or global minimum, and very small step size leads to high computational time and cost.

8.3.2 Introduction to Support Vector Machine

Support Vector Machine (SVM) is an advanced supervised learning algorithm extensively utilised for classification, regression and outlier detection. Based on the principle of structural risk minimisation as proposed by Cortes and Vapnik [29]. SVM aims to minimise generalisation error, thereby enhancing model robustness, particularly in high-dimensional spaces. By constructing hyperplanes in a higher-dimensional space, SVM effectively classifies and regresses data points. In classification tasks, SVM establishes a decision boundary or hyperplane that maximises the margin between different classes, which can be represented as:

$$w \cdot x + b = 0 \tag{8.3}$$

Soft margin classification addresses the balance between maximising the margin and limiting margin violations (i.e., data points that fall within the margin or are misclassified) using a hyperparameter C. This parameter controls the penalty for margin violations, aiming to find a balance between a large margin and minimal classification errors:

$$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{i}^{N}\zeta_i\right) \tag{8.4}$$

where ζ_i are slack variables representing the degree of misclassification of the data x_i.

On the other hand, in SVM regression, or support vector regression (SVR), the model fits ε-tube hyperplane allowing deviations beyond the boundary of the tube. The objective of SVR is to minimise deviations larger than ε while keeping model complexity low:

$$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\zeta_i + \zeta_i^*)\right) \tag{8.5}$$

Subject to

$$\left|y_i - (wx_i + b)\right| \leq \varepsilon + \zeta_i$$

$$\zeta_i \geq 0$$

In the optimisation of SVM parameters, quadratic programming is critical as it involves solving a convex quadratic optimisation problem with linear constraints. The dual problem in SVM transforms the problem into a dual formulation, simplifying the computation using kernels based on Mercer's theorem [30]:

$$\left(\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{N}y_i y_j \alpha_i \alpha_j x_i \cdot x_j\right) \tag{8.6}$$

Subject to

$$\alpha_i \geq 0$$

$$\sum_{i=1}^{N}\alpha_i y_i = 0$$

SVM also extends to non-linear functions using the kernel trick, which allows the SVM framework to accommodate non-linear boundaries [31]. This is achieved by transforming the feature space using kernel functions such as:

$$\text{Polynomial Kernel: } K(x,x') = (\gamma x \cdot x' + c)^d$$

$$\text{Gaussian RBF Kernel: } K(x,x') = \exp\left(-\gamma \|x - x'\|^2\right)$$

where d is the degree of the polynomial, c is a constant term and γ controls the kernel's width while acting as a regularisation hyperparameter. The hyperparameters are tuned during the training of the SVR model to avoid overfitting and ensure the generalisation performance of the model.

This SVR approach significantly enhances predictive accuracy, particularly in engineering applications where processing continuous data streams with high computational efficiency and robustness is vital. Utilising quadratic programming and strategic optimisation constraints, SVM exhibits remarkable versatility, proving indispensable in specialised applications. For instance, SVR models are employed to optimise operations in thermal power plants and energy systems [19,20,32]. In the maintenance of mechanical components like bearings and gears, SVR contributes to the early detection of faults and system failures, thereby substantially reducing machinery downtime and maintenance costs [22,33]. SVR's adaptability to time series data and the capability for online SVM implementation facilitate real-time monitoring and predictive maintenance in complex mechanical systems, promoting continuous operational efficiency and preemptive troubleshooting. This strategic utilisation of SVR exemplifies its competence in handling, analysing and predicting intricate data patterns, thereby cementing its status as a critical tool for optimising system performance. The comparative demonstration of two SVR models in Figure 8.6, one employing a linear kernel and the other a polynomial kernel, highlights the flexibility of SVR techniques. These models adeptly capture complex data patterns within specified tolerance levels, illustrating SVR's versatility across varied scenarios and affirming its value in both academic research and practical applications.

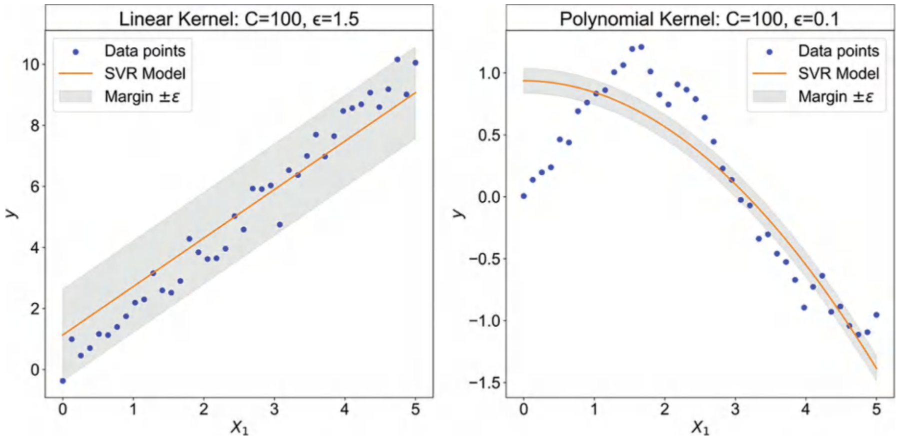

FIGURE 8.6 Visualising the curvature of the hyperplane along with the margins. The data points trained by the SVM model are also shown.

8.3.3 Choices of Performance Metrics

The AI models need to be evaluated on the basis of their performance and robustness. It is advisable to not rely on a single matrix to evaluate AI model performance and robustness as it may be misleading sometimes. R^2 is one of the most commonly used AI model performance evaluation metrics. Technically, R^2 tells about how much the variability in the system response can be accurately predicted or explained by the trained model. In simple words R^2 is a measure of goodness of fit i.e., how well the model can fit the data. The R^2 is calculated by equation (8.1).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \overline{y}_i\right)^2} \tag{8.7}$$

where, N is the number of samples, y_i represents the actual response, $\hat{y}_i$ indicates model-predicted response and $\overline{y}_i$ is the mean of the actual response. R^2 measures the modelling accuracy and varies from zero to one. The error-based metrics are used along with R^2 to evaluate the predictive performance of the AI-based process models. Some of the commonly used error metrics are mentioned in Table 8.2. Mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), root mean square error (RMSE), normalised root mean square error (NRMSE) and weighted mean absolute percentage error (WMAPE) are summarised in Table 8.2.

TABLE 8.2
Error Based Model's Performance Evaluation Metrics

No.	Criteria	Mathematical Form	Comment
1	Mean absolute error (MAE)	$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left\lvert y_i - \hat{y}_i\right\rvert$	MAE tells about average error between model predicted and actual response. It is useful when the error range is tight, or error distribution is uniform. In case of outliers (large value or very small value) the MAE will be misleading
2	Mean absolute percentage error (MAPE)	$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{\hat{y}_i - y_i}{y_i}\right\rvert \times 100\%$	MAPE also depends upon average error. Care should be exercised while using MAPE when the actual response has few extremely low, high or zero values
3	Mean squared error (MSE)	$\text{RMSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2$	This criterion is usually used when we want to penalise a larger error in model prediction more as compared to smaller model-based predicted values
4	Root mean square error (RMSE)	$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}$	RSME is used instead of MSE when the error in the same units as actual response is required. This also penalises a larger error in model prediction compared to smaller ones

(*Continued*)

TABLE 8.2 (*Continued*)
Error Based Model's Performance Evaluation Metrics

No.	Criteria	Mathematical Form	Comment
5	Normalised root mean square error (NRMSE)	$NRMSE = \frac{RMSE}{y_{max} - y_{min}} \times 100\%$	NRSME is useful for comparing prediction accuracy of two or more models with different ranges or scales
6	Weighted mean absolute percentage error (WMAPE)	$WMAPE = \frac{\sum_{i=1}^{N}(w_t \lvert \hat{y}_i - y_i \rvert)}{\sum_{i=1}^{N}(w_t \lvert y_i \rvert)}$	Whenever certain values or ranges are more important compared to others, WMAPE is implemented as a model prediction accuracy measure. For example a lower weight can be associated with a large outlier value to diminish its effect or vice versa

It is evident that special attention needs to be given based on the problem, expected error distribution and particular error significance to select model evaluation criteria.

8.3.4 Comparison of AI Based Modelling Performance on the Identified Problem

The output variables of the three problems associated with the power plant operation are modelled by AI-based modelling algorithms like ANN and SVM and the modelling performance is shown on Figure 8.7. The bearing vibration problem is analysed by ANN and SVM-based algorithms and the comparison of the modelling performance on the test dataset reveals the superior performance metrics

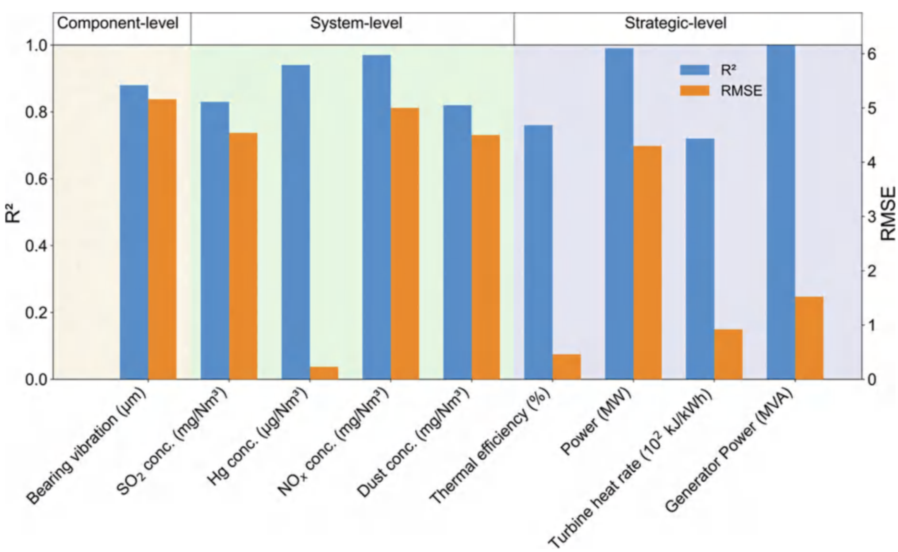

FIGURE 8.7 The performance metrics computed for the component, system and strategic level problems of the power plant.

($R^2 = 0.88$, RMSE = 5.16 μm) of the ANN model trained for the modelling task. The four output variables taken from the flue gas desulphurisation system are modelled by ANN algorithm and it is noted that an R^2 value of more than 0.8 is observed on the test dataset for the variables indicating the good generalisation of the models trained for the output variables. Similarly, an R^2 value of more than 0.70 is observed for the three strategic-level output variables including thermal efficiency, power and turbine heat rate modelled by Data Information integrated Neural Network (DINN) model – a variant of ANN. Moreover, reasonable values of RMSE are computed for the three output variables in comparison with the operating ranges of the output variables. For generator power output, both ANN and SVR models are trained, and the predictive performance comparison of models confirms the higher modelling performance capability of the SVR (RMSE = 1.52 MVA) than those of ANN (RMSE = 2.1 MVA). The comparison of the performance metrics on the three operating levels of the problem suggests using ANN for the quantitative nature of the problem. Whereas, SVM is expected to perform better for the strategic level problem analysed on large number of input variables.

8.4 VARIABLE SIGNIFICANCE ANALYSIS

AI-based process models are typically black-box systems, making it crucial to investigate the significance of variables influencing model-based predictions. Variable significance analysis is commonly conducted in AI-based studies to establish the relative order of significance among variables. Identifying and understanding critical variables that significantly impact the output variable corresponding to the system's operating level is essential. This holds true for both forecasting and decision-making problems, as they directly involve identifying significant variables or determining the magnitude and order of significance. Moreover, variable significance analysis helps focus efforts on system improvement by identifying less meaningful or insignificant variables. Additionally, starting with a large number of variables initially, the analysis can be reduced to studying only the most significant ones.

Several techniques are available for determining the significance of individual variables through trained AI models. Some of these techniques include correlation analysis, one-factor-at-a-time (OFAT) analysis, regression-based and AI-based response surfaces, game theory-based techniques (such as SHapley Additive exPlanations – SHAP) and Monte Carlo-based techniques. A discussion of a few of these techniques is provided here for reference.

8.4.1 OFAT

One factor at a time (OFAT) is a fundamental technique used to identify the significance of independent input variables. In this method, one factor or variable is varied within its respective range while keeping all other factors constant at specific values. The response of the AI-based system is observed under these conditions. This process is repeated for each remaining input factor or variable, changing one factor within its range while holding all others constant and observing the system response. The factor that creates the maximum disturbance in the system response is considered the most significant.

OFAT analysis is advantageous when the system is less complex, and the output is not influenced by combinations of input factors. It is particularly useful when main effects are important, rather than interactions between variables. However, the main disadvantage of this analysis is its inability to represent the significance of factors in complex interactive systems. Additionally, fixing the value of input variables except one can lead to critical decisions regarding which value or condition of each variable is most important for the analysis purpose.

8.4.2 Response Surfaces Technique

In response surface analysis, response surfaces are constructed to analyse the relationship between inputs and outputs. In this method, two, three, or more input factors are systematically and simultaneously varied, while the remaining input factors are kept constant, and the system response is measured. The system output, varying with input, is then plotted as response surfaces and analysed. This type of analysis is particularly helpful for systems with interactive input factors concerning output. It allows the identification of system responses to changes in two, three, or more variables simultaneously, enabling critical decisions for system improvement.

However, one disadvantage of this technique is the need to fix some factors at specified values when the number of factors is large. If values are not fixed for certain variables, then methods are required to visualise the causal relationship between input and output factors in multi-dimensional space. This can be challenging and may require advanced analytical techniques to accurately interpret the results.

8.4.3 Monte Carlo Simulation Based Significance Analysis

The Monte Carlo simulation-based significance analysis technique provides an opportunity to assess system response and factor/variable significance from a trained AI model. Monte Carlo is a very powerful technique to solve various problems. Different statistical techniques can be used to evaluate factor/variable significance from a trained AI model. One such technique includes changing one factor/variable from the minimum to the maximum value while varying all remaining factors/variables randomly. It is important to note here that the variable whose significance is to be determined is kept constant at an operating level while the remaining input variables are changed randomly within their operating ranges. This provides an opportunity to investigate the variable significance comprehensively and mean variable significance can be computed. More details about the working of the Monte Carlo technique can be found in Ashraf et al. [21].

Ten-thousand randomly distributed observations are generated corresponding to the 100-step changes in the variable for the variable significance analysis. The Monte Carlo technique-based variable significance is computed for the three performance parameters taken at the strategic-level performance of the power plant as shown in Figure 8.8. Feed water temperature (FWT) is estimated to be the most significant variable having percentage significance of 29.6% and 54.4% for thermal efficiency and Power respectively. Whereas, air flow rate (m_a) turns out to be the most significant variable for the turbine heat rate with a percentage significance of 32.1%. FWT is critically controlled by the feed water regenerative system to maintain the thermodynamic conditions of the FWT. The heat duty of a boiler is strongly dependent on the FWT conditions and thus,

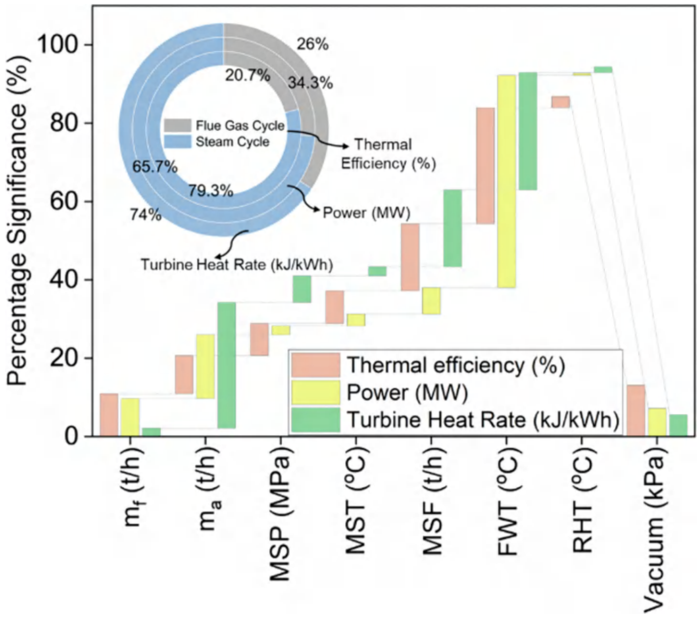

FIGURE 8.8 Monte Carlo technique based variable significance analysis at the strategic-level problem. The percentage significance of the variable is computed for thermal efficiency, power and turbine heat rate of the power plant. The significance of the flue gas cycle and steam cycle on the three performance parameters is also computed [24].

fluctuation in FWT drives the unstable boiler operation impacting the thermal efficiency and power generation. Whereas, larger volume of m_a than the optimal operating level corresponding to the plant operation increases the energy input to preheat the air and the latent load that increases the heat rate of the turbine. The variables taken for the modelling of three performance parameters associated with the flue gas cycle and steam cycle of the coal power plant allow us to compute the percentage significance of the two power cycles on the plant operation. It is noted that the steam cycle has comparatively the higher significant impact on the three performance parameters computing percentage significance of 79.3%, 65.7% and 74% towards thermal efficiency, power and turbine heat rate respectively. The high significance of the steam cycle is explainable considering the thermodynamic conditions of the steam being discharged in the steam turbine system and also complies with the working of the Rankine cycle [34].

8.5 MULTI-OBJECTIVE ROBUST OPTIMISATION OF THE COAL POWER PLANT

The energy-efficient operation of the coal power plant can be maintained by setting the operating levels of the input variables at the optimal conditions that maximise the thermal efficiency and minimise the turbine heat rate at the sustained power generation mode. The function space built on three performance parameters is essentially nonlinear and required to conduct the nonlinear programming-based optimisation analysis to determine the optimal solution for the multi-objective optimisation problem. The multi-objective problem formulated for the operation optimisation of the coal power plant is given as:

$$f = -f_{\text{Thermal Efficiency}}(x) - f_{\text{Power}}(x) + f_{\text{Turbine Heat Rate}}(x) \tag{8.8}$$

Subject to:

$$\begin{aligned} &h(x) = 0 \\ &x = x_1, x_2, \ldots, x_m \\ &x \in X \subseteq R^n \\ &x^L \le x \le x^U \end{aligned} \tag{8.9}$$

Here, −ve sign means that the term in the objective function is to be maximised and vice versa. $h(x)$ is the equality constraint and represents the ML-based models and is also deployed to define the multi-objective function. x is the set of input variables and is bounded on the lower (x^L) and upper bounds (x^U) that serve as the search space to explore the feasible solution in the face of the constraints. A sequential quadratic programming solver is used to solve the multi-objective optimisation problem corresponding to different initial points and the feasible solution (x^*) is determined.

The Monte Carlo technique is used to explore the impact of operational uncertainty that is associated with the sensor-based uncertain measurements, aleatoric and epistemic uncertainty associated with the industrial operation, and degradation in the health of the equipment. The experiments are constructed by adding the Gaussian noise generated on the 1% range of the input variables (δ_k) with x^*. The experiments ($x^* + \delta_k$) explore the vicinity of the solution to investigate the sharp fluctuation in the multi-objective function space and are simulated by the multi-objective function to numerically approximate the mean response and variance. The mean ($F(x^*)$) and variance ($V(x^*)$) produced in multi-objective function around x^* are computed as:

$$F(x^*) = \frac{\sum_{k=1}^{H} f(x^* + \delta_k)}{H} \tag{8.10}$$

$$V(x^*) = \frac{\left\| F(x^*) - f(x^*) \right\|}{\left\| f(x^*) \right\|} < \varepsilon \tag{8.11}$$

Here, ε is the threshold limit as defined by the user to account for the robustness of solution. x^* is regarded as robust if $V(x^*) < \varepsilon$. We have analysed the plant operation under three power generation scenarios i.e., 358–365 MW for scenario-1, 495–500 MW for scenario-2 and 655–660 MW for scenario-3 and the feasible solution is determined by solving the multi-objective function corresponding to different initial guesses. Monte Carlo experiments are constructed on 10,000 noise observations and ε is set as 0.01.

The two-stage robust optimisation approach is applied to estimate the robust optimal solutions under three power generation scenarios for thermal efficiency, power and turbine heat rate, and are depicted in Figure 8.9a–c. The highest thermal efficiency is estimated to be 42.12% ± 0.31% while the minimum turbine heat rate is found to be 7643 ± 71 kJ/kWh corresponding to scenario-3. The estimated

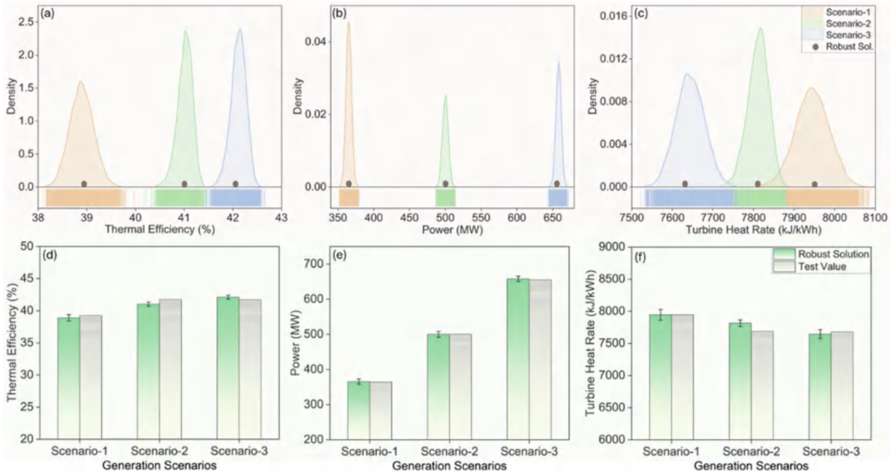

FIGURE 8.9 The multi-objective robust optimisation of coal power plant on maximising (a) thermal efficiency, (b) power and minimising (c) turbine heat rate on three power generation scenarios [24]. The robust optimal solutions corresponding to the generation scenarios are verified on the plant operation and the experimental results are compared with those of the estimated robust solution for (d) thermal efficiency, (e) power and (f) turbine heat rate.

robust solutions are verified on the plant operation and a good agreement between the model-based robust optimal solutions and those of the experimental observations is observed under three power generation states of the power plant as mentioned in Figure 8.9d–f. The verification of the robust optimisation results on the plant's operation demonstrates the accuracy of the model-based analytics starting from the problem identification to model development and estimating the robust optimal solution by hybridising the mathematical-stochastic approaches.

8.6 CONCLUSION

We have presented the framework to carry out the AI-based modelling and optimisation analysis for the optimisation of industrial processes and systems. The problem definition on the selection of input-output variables is the crucial step and requires consulting with domain experts and literature. The dataset collected corresponding to the selected variables should be visualised to investigate the health and quality of the data. The AI-based modelling algorithms should be selected considering the operating levels of the problem and/or quantitative or qualitative nature of the dataset. The models are trained on the extensive hyperparameters tuning and modelling performance is evaluated on the rigorous statistical parameters. The modelling performance of the AI model is found to be around 70% minimum on the test dataset corresponding to component, system and strategic level problems taken from the coal power plant. The model-based robust optimisation results are estimated to correspond to strategic-level problems and are verified on the plant operation. The AI-based process models demonstrate the potential for the optimisation of industrial processes and systems that can enhance the performance of the industrial systems, promoting energy-efficient operation and contributing to net-zero goal.

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9 Ethical and Legal Aspects of Machine Learning in 5G-Enabled Smart City and Energy Grid Cyber-Defense

Vinay Aseri, Sumit Kumar Choudhary, Adarsh Kumar, and Aayush Gupta

9.1 INTRODUCTION

By 2050, 60%–70% of the global population is projected to reside in urban areas. This rapid urbanization will significantly impact ecology, security, and city administration. To address these challenges, many nations are adopting the innovative city model to efficiently allocate resources and optimize energy consumption [1,2]. Smart cities aim to manage urban growth, reduce energy usage, protect the environment, enhance citizens' socioeconomic status and quality of life, and effectively use modern information and communication technology (ICT). ICT is pivotal in policy creation, decision-making, implementation, and service delivery within intelligent cities [3].

The concept of intelligent cities integrates sensors and Big Data through the Internet of Things (IoT), providing new opportunities for city governance and economic enhancement. However, it is crucial to balance technological advancements with sustainability and livability [4]. Smart cities strive to improve residents' services, addressing social and economic needs [5]. Practical data analysis, communication, and implementation of complex plans are essential for smart cities' smooth and secure operation, and ICTs are critical to this process [6–8].

The IoT is fundamental in innovative city applications, generating vast data [9,10]. Managing these extensive datasets requires advanced techniques like deep reinforcement learning (DRL), machine learning (ML), and artificial intelligence (AI), which can analyze data and make optimal decisions considering long-term objectives [2,9]. Increasing the quantity of training data can enhance the accuracy and efficiency of these automated decision-making processes [11].

AI has become increasingly prevalent in intelligent city operations, replicating human cognitive functions through voice recognition, advanced systems, machine learning, and natural language processing applications. ICT in intelligent cities promotes better governance, improves human welfare, and boosts the economy. AI can

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make cities safer and more livable by enhancing home management, traffic monitoring, and waste management [12,13].

The widespread use of ICT and related technologies, such as Cyber-Physical Systems (CPS), Cloud and fog computing, and IoT, has led to rapid data generation and collection [14]. This data often contains sensitive information about citizens, raising privacy concerns. While proper data handling can mitigate risks and offer significant benefits, real-world data management presents challenges. Ethical considerations and data privacy remain critical issues that must be addressed [15]. Our research examines the moral dimensions of intelligent cities, drawing on scholarly articles that focus on these issues.

Overview of Machine Learning Techniques Unmanned aerial vehicles (UAVs), smart cities, IoT, blockchain, and the application of AI, ML, and DRL-based techniques are still developing but promise significant future opportunities [16]. The growth of smart cities and advanced data analysis methods for Big Data have progressed simultaneously. AI, ML, and DRL methodologies significantly impact intelligent city sectors, enhancing their efficiency and adaptability [17].

Smart grids (SGs), cybersecurity, intelligent transportation, and UAV-assisted fifth-generation (5G and B5G) connectivity are critical in innovative city initiatives. ML and DRL techniques are crucial in developing self-driving vehicles, ensuring vehicle security, and improving passenger search and travel safety within intelligent transportation systems (ITS) [18].

Machine learning (ML), a critical AI application, involves developing algorithms to recognize and interpret complex patterns from data. ML models can be analytical for predictions or descriptive for extracting information [19]. Initially, ML aimed to overcome the knowledge-acquisition barrier in expert systems. Today, ML techniques are also tools for data analysis and information mapping, akin to traditional statistical methods [20,21]. ML can be divided into supervised and unsupervised learning based on training data. Its non-parametric nature allows for fewer data assumptions but requires more computations. ML development typically involves training, validation, and testing phases to ensure model accuracy.

In supervised learning, an AI network is trained using input-output data pairs to map inputs to outputs. This method includes regression and classification tasks. Examples include random forest, support vector machines, and linear regression. On the other hand, unsupervised learning involves discovering patterns in unlabeled data, with everyday tasks including clustering and association. Techniques like auto-encoders and K-means use unsupervised learning [22].

To solve problems using machine learning, algorithms must be developed, drawing on methodologies from various fields like statistics, pattern recognition, data mining, and signal processing. This interdisciplinary approach enables the creation of robust solutions by leveraging diverse knowledge domains [22].

9.2 DATA-DRIVEN ANALYTICS AND ETHICS IN SMART SCIENCE AND SMART CITIES

The widespread availability of comprehensive and indexed data, combined with the effort to extract meaningful insights, underscores the importance of addressing ethical concerns related to datafication, geo-surveillance, dataveillance, privacy, and various applications such as social sorting and anticipatory governance. While advancing intelligent cities and using science and technology to understand urban environments remains crucial, it is essential to reimagine and rethink these initiatives to mitigate their negative impacts, emphasize rationality and epistemology, and consider alternative approaches to urban systems [23].

9.2.1 Datafication and Privacy

In democratic societies, privacy includes the right to control how much personal information is shared publicly. This right is recognized as fundamental and protected by national and international laws. However, perceptions of privacy can vary across different cultures and contexts. Legal discussions often focus on the standards for collecting and sharing sensitive personal information [24]. This sensitive information can encompass various aspects of an individual's life, leading to different forms of privacy, such as [25,26]:

- **Territorial privacy:** Protecting one's personal space and possessions.
- **Bodily privacy:** Maintaining physical integrity.
- **Mobility and location privacy:** Preventing the monitoring of spatial activities.
- **Confidentiality of transactions:** Preventing the surveillance of searches, payments, and other transactions.
- **Communications privacy:** Protecting conversations and correspondence from being monitored.

9.2.2 Datafication, Dataveillance, and Geo-Surveillance

With the increasing datafication of daily life, individuals face heightened scrutiny. It is nearly impossible to navigate daily routines without leaving digital traces—both self-generated and those left by others. The rise of unique identifiers and personally identifiable information (PII) for accessing services, surveillance, and digital transactions contributes to this trend. These identifiers include credit card numbers, license plates, intelligent card IDs, names, usernames, passwords, account numbers, addresses, emails, phone numbers, and facial recognition technology [27]. Data surveillance, particularly in smart cities, and geo-surveillance are becoming increasingly common. Data surveillance involves creating, sorting, and filtering datasets to detect, monitor, control, predict, and prescribe behaviors. Geo-surveillance tracks the movements of people, vehicles, objects, and services and monitors spatial relationships [28–30].

9.2.3 Inferencing and Predictive Privacy Harms

Predictive modeling using urban big data can generate inferences about individuals that are not explicitly recorded in a database yet still represent personally identifiable information (PII) and cause "predictive privacy harms" [31,32]. For example, tracking data that shows a person frequently visits gay clubs can suggest their sexual orientation, which many consider private and sensitive. This issue is particularly pronounced in anticipatory governance and predictive policing, where profiling based on poor data or models can reinforce stigmas and cause distress.

9.2.4 The Ineffectiveness of Notice and Consent

Innovative city technologies severely undermine privacy and data protection principles—notice and consent—and render data/urban science largely ineffective. Everyday interactions with various intelligent city technologies generate vast amounts of data. Given the sheer volume and variety of these interactions, it is overwhelming for individuals to manage their privacy across multiple entities, weigh the pros and cons of agreeing to terms, understand how their data might be used in the future, or assess the overall impact of their data when combined with other information [33].

Even when individuals attempt to control their personal information across these platforms, they often face lengthy, complex legal agreements that are essentially non-negotiable—requiring acceptance to use the service. Consequently, consent frequently involves individuals relinquishing their rights without fully comprehending the extent or consequences of their actions [34].

9.2.5 Data Use, Sharing, and Repurposing

One of the critical characteristics of the data revolution is the total disregard for the principles of purpose specification and usage limitation. These principles state that data should be collected only for a specific task, retained only as long as necessary, and used solely for that purpose. However, the objectives of big data and the operation of data markets, which aim to collect and amass vast amounts of information to extract more excellent value, often conflict with these principles [35]. Many companies repackage data, de-identify it (using pseudonyms or aggregation), and apply data reduction to the original dataset. The repackaged data may then be shared and used in various ways unrelated to the original purpose for which the data was collected without informing or obtaining the consent of the individuals to whom the data belongs [36].

9.3 RENEWABLE AI IN POWER GRIDS—COMMUNICATION INFRASTRUCTURE

Power grids have evolved from local to large-scale networks spanning multiple countries or continents [37]. Despite its crucial role in modern society, the energy sector has been slower to adopt digital technologies than other industries due to the high demand for reliability and the scale of operations. Many countries view Power grids as critical infrastructure from a legal perspective [37]. The need for higher efficiency has led to integrating digital technologies, resulting in renewable and sustainable energy sources (e.g., offshore wind farms and household-based solar grids) supplementing traditional power plants. This has made power generation more distributed and less predictable, complicating energy distribution and transmission organization.

9.3.1 Managing Power Consumption and Generation in Smart Cities

Electrical power grids require a stable frequency range of 50–60 Hz, as alternating current is used. This frequency stability is maintained when power consumption and generation are balanced. When generation exceeds consumption, the frequency increases, and vice versa. Ensuring this balance requires constant monitoring and adjustment. In Europe, operational reserves are divided into primary, secondary, and minute reserves. Primary control involves continuous frequency regulation, with control distributed among various power plants. For instance, 3GW represents the primary reserve, equivalent to the power output of several nuclear power plants.

9.4 REQUIREMENTS OF AN ETHICAL FRAMEWORK

In the last decade, the rapid changes driven by the digital data revolution, predicted in the early 2010s, have transformed decision-making systems worldwide. The interconnected nature of global processes, real-time information, and societal responses to events and crises has created a complex global network [38]. As humanity introduces the metaverse, the foundation of the Fifth Industrial Revolution (FIR), it is crucial to translate ethical principles into practice to avoid repeating past mistakes. This transformation requires a top-down approach using diverse information combined with a bottom-up system of interindividual consensus. By establishing a comprehensive framework applicable to various cities and identifying shared values, an evidence-based consensus can determine which values should be universally recognized and promoted [39].

Digitalization and computers can serve as tools for moral reasoning within evidence-based ethical frameworks. In environmentally conscious and smart cities, this includes collecting data for precise pollution measurements or utilizing self-driving cars. Although data-driven methods can gather objective data, they also pose ethical challenges that must be addressed to protect citizens' privacy and sensitive information. Ethical frameworks must consider systemic and conceptual risks to address issues stemming from industrialization and automation. Digital technologies have proven to be unique tools for developing rights-protecting processes and enabling swift recovery, essential for sustainable development [37,41,42]. To minimize disparities caused by industrialization, it is necessary to address the significant challenges digitalization poses to individual rights, values, and cultural diversity. Complexity, climate change, and computational methods introduce new systemic risks, highlighting the need for a construct that fosters interindividual agreement through collective intelligence [43–45]. Unlike the current trajectory of digitalization, societal models should be informed by the concept of humanity, using innovation and deductive processes to define principles. A virtual congress is an example of how digitally connected groups can use technology to reach conclusions and share them with other groups [40]. Reducing the risks of digitalization and enhancing social systems through digital technologies must be conducted within an ethical context, articulated as both actionable general standards and protective rights [46]. These principles should encourage local actions to implement appropriate procedures in line with local traditions rather than accelerating the globalization of digitalization.

9.5 FEATURES OF THE ETHICAL FRAMEWORK

Ethics must integrate scientific terms and concepts to achieve the goal above. A common language and vocabulary are essential to incorporate traditional wisdom into the global digitalization paradigm naturally. Given the current use of digital technology, it is crucial to reevaluate ethical concepts like truth, liberty, and solidarity and embed them into the digital core, design, and implementation across the real world. Conversely, digitalization is driven by various fragmented ethical concepts [47] and technological and industrial principles [48]. AI and data improve decisions, streamline processes, personalize services, identify trends, and understand society. Several principles have been proposed to ease AI integration and address ethical issues. However, for sustainable industry and digital compact areas, universal moral standards found in transcendental ethics [49] must be prioritized. Understanding technology's catalytic or hindering roles is vital to prevent the misuse or underuse of digital technologies [50]. Thus, a moral framework based on new governance principles is necessary [51].

While there is a trend toward ethical standards in AI and digitalization, a more comprehensive view of humans and sociotechnological models from a moral perspective is needed. Various strategies have been proposed, such as human rights-based digitalization or systematically incorporating diverse ethical frameworks [43]. These strategies rely on consensus but do not ensure that actual initiatives and actions will lead to a better and more ecological society. A universal human perspective is required to understand the agreement. Current initiatives in digital governance, such as AI audits, trustworthy AI, machine behavior, assessment algorithms, and macro tech indexes, can be supported by this vision. The Sustainable Development Goals (SDGs) are a step in the right direction toward achieving such a vision. Still, their implementation and the creation of structures for future ethical governance are hindered by the lack of a long-term human vision and non-ethically motivated crisis responses [51].

All SDGs, including SDG-11, impact people (e.g., reducing hunger and poverty and promoting gender equality) and suggest structural changes in social norms, economic relationships, and societal behavior. The relationship between SDGs and digitalization is complex. Digital innovation has potential in various sustainability growth projects [52,53].

The foundation of a comprehensive framework based on the SDGs is moral principles. The two main tasks for this mission are: first, recognizing the moral and ethical implications of actions, roadmaps, and technological advancements needed to achieve the SDGs, and second, employing and deriving structures from principles that provide reassurance and enforceable standards while portraying the future as crucial components of policies and governance. Lovely technology is needed to shed light on facts and serve as the basis for accountable management in today's society, alongside formal technology-based frameworks to address vulnerabilities and individual-level issues.

An ethical framework should encompass how society is structured, soft regulations, new forms of governance, and the application of digital technologies to advance public good or build powerful private platforms. These techniques and the ability to receive criticism are not yet fully established. To achieve future societal goals, especially in city science, computational socioeconomics, and city dynamics, cooperative initiatives, practitioner- and citizen-led educational programs, and platforms and initiatives for collective intelligence are crucial [54,55].

9.6 CYBER STRATEGIES AND PLANNING FOR APPLICATIONS

Smart cities are expected to comprise a network of connected sensors, actuator systems, and relays to provide efficient and reliable digital services. This interconnectivity of various devices introduces cybersecurity vulnerabilities that need to be addressed [56]. Much of the data in smart cities is generated by cloud-based IoT devices and IIoT, which play a crucial role in numerous applications [57]. Key issues include maintaining data privacy and security, protecting networks from cyber-attacks, fostering an ethical and accountable data-sharing culture, and enhancing the usability of ML, AI, and DRL methods.

From communication, privacy, and security perspectives, intelligent city design should be considered. This includes addressing the challenges of integrating existing infrastructure, sensors, and actuators. The authors proposed a DRL-based strategy to protect against jamming attempts on flying UAVs. This method can be modeled regardless of the jammer's location, channel type, or UAV channel model. The approach determines the trajectory and power transmission level based on the UAV's quality. Simulation results show that this method improves the quality of service (quality of service) for mission-specific UAVs.

9.7 SMART GRID OPERATION

Big data revolutionizes intelligent city operations and enhances energy consumption efficiency [58]. Smart Grids (SGs) are built on large volumes of data, IoT devices, and modern information and communication networks [59]. SGs receive heterogeneous data from various sources, which can be efficiently processed to inform operational and management decisions. In smart cities, big data analytics can enhance power grids' performance, management, and efficiency. Recent developments show SGs successfully utilizing big data from smart meters for multiple purposes, including demand response, load clustering, load assessment and prediction, baseline estimation, and addressing malicious data deception attacks [55, 60–65].

9.8 APPLICATIONS OF DRL-BASED UAVS IN 5G AND B5G COMMUNICATION

The increasing demand for high data efficiency, reliability, and low latency has driven mobile wireless communication systems toward 5G and B5G communications. AI, ML, and DRL-based approaches are recognized as practical tools for managing complex communication challenges involving large volumes of network data [66–69]. While these tactics were crucial for 5G communication, we focus on UAVs' role in B5G and 5G communication, which is essential for developing smart cities and environmental sustainability. A novel method has been developed for analyzing and detecting cyberattacks in 5G and B5G communication networks using DRL techniques to examine network traffic.

Despite their promising applications, UAVs face several unresolved challenges. For instance, LTE cellular service is not widely available, especially in the air. LTE's down-tilted, ground-focused BS antennas primarily serve UEs. Issues with interference and LoS and financial limitations make achieving ubiquitous sky coverage challenging even with 5G and B5G connectivity.

9.9 DRL-BASED UAVS-ASSISTED MMWAVE COMMUNICATION

UAV-supported WSNs can support higher data rate transmission using mmWave bandwidth technology for wireless network communication. The smaller wavelength of the mmWave spectrum facilitates the construction of efficient short antennas on a single chip, creating beamforming antenna arrays suitable for UAV-aerial-assisted communication. Additionally, the directed nature of the mmWave beam reduces interference and enhances data security [70]. Figure 9.1 [71] illustrates an aerial UAV providing mmWave communication-based network coverage and how a mmWave link can be disrupted by human presence. Various strategies have been developed to address current challenges and improve mmWave communication. The following sections will focus on a DRL-based strategy for creating effective UAV-assisted 5GmmWaves networking.

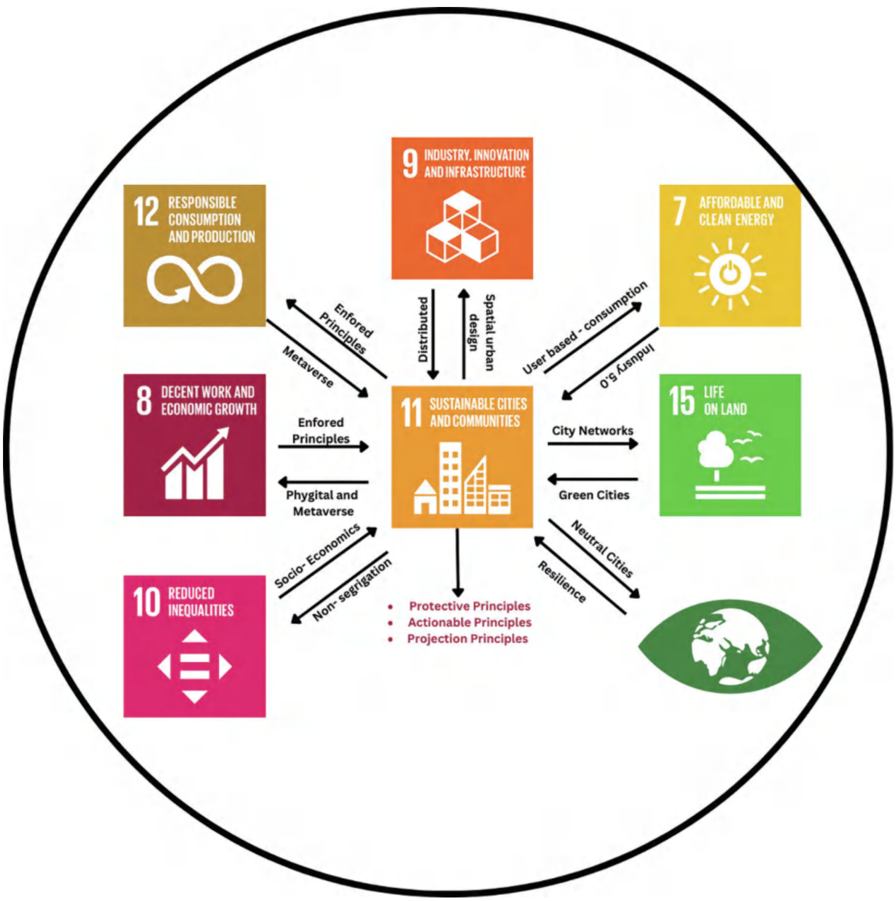

FIGURE 9.1 Ethical framework constructed for sustainable smart cities.

9.10 SMART CITY HEALTHCARE AND MACHINE LEARNING

Health intelligence, which refers to improved healthcare procedures, has seen broader use of DRL, ML, and AI techniques due to enhanced sensors, cloud computing, high-performance IoT devices, and increased data rates [72–74]. Recent developments in healthcare research and related efforts for intelligent cities are discussed here.

A comprehensive analysis of the use of DRL, ML, and AI applications in big data analytics in healthcare systems highlights the benefits of these methodologies for complex data processing, classification, diagnosis, disease risk assessment, optimal therapy, and patient survival predictions. However, implementing these methodologies presents challenges, such as precise model training, addressing genuine clinical concerns, physicians' understanding of data analysis tools and data, and ethical considerations that must be appropriately managed.

Accurate information related to the field would form the basis for developing an efficient AI-enabled system [72]. The authors of Fallah et al. [73] examine how AI is perceived for achieving drug discovery objectives, potentially transforming current pharmaceutical research and development. Tureczek et al. [74] discuss various potential AI, ML, and DRL protocols that could benefit the IoT-based healthcare market.

9.11 CONCLUSION AND FUTURE OUTREACH

This chapter examined the latest advancements in smart city research, focusing on various complex problems and applications developed by academic and corporate sectors. The thematic concepts of Artificial Intelligence (AI), Machine Learning (ML), and Deep Reinforcement Learning (DRL) techniques were briefly explored. We discussed how these methodologies have effectively contributed to developing nearly optimal procedures for various applications crucial for intelligent city operations.

Our chapter covered the current use of AI, ML, and DRL in designing innovative governance, emphasizing the need for new policy frameworks compatible with AI and their applications in Smart Grids (SGs), cybersecurity, sustainable energy practices, Intelligent Transportation Systems (ITS), and UAV-assisted 5G and Beyond 5G (B5G) communication networks within intelligent city contexts.

The authors also highlighted the growing importance of these techniques in enhancing healthcare services within intelligent cities, including their role in efficient diagnosis and health recovery processes, addressing security concerns related to health-focused IoT devices, and potentially contributing to drug discovery efforts.

In conclusion, we explored current research inquiries within intelligent cities, identifying potential future research domains ripe for exploration and innovation.

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