Deep Reinforcement Learning for Control of Microgrids: A Review

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Abstract— *A Microgrid is widely recognized as a prominent solution to enhance the resilience and performance of distributed power systems. Microgrids offer a unique advantage in that they can easily incorporate distributed energy resources into the existing electrical networks. The unpredictable nature of distributed energy resources (DERs) makes it difficult to coordinate their activities, so control techniques are employed to bring them into synchronization. Recently techniques based on artificial intelligence are being applied to the problems that arise in the operation and control of the latest generation Microgrid. Machine learning and deep learning are two of the most commonly used techniques in the field of artificial intelligence. Both of these approaches are effective in providing intelligent solutions to complex problems. The objective of this research is to survey the latest strategies of control in microgrids using the deep reinforcement learning approach (DRL). Other techniques of artificial intelligence had already been reviewed extensively but the use of DRL has increased in recent years. To bridge the gap for the researchers, this survey paper aims to provide an overview of the current strategies for controlling Microgrids using DRL. It specifically focuses on voltage control and frequency regulation with distributed, cooperative and multi-agent approaches.*

Keywords — Deep Reinforcement Learning Approach (DRL), Microgrids, Multi-Agents, Control

1. INTRODUCTION

The development of microgrids and smart grids can have the potential to address the shortcomings of traditional energy generation and distribution networks. This new system provides a more efficient and reliable energy source than its predecessor, making it an attractive option for many. Distributed energy resources (DERs) based systems reduce the cost of electricity and enhance reliability and efficiency along with the benefits of reduction in carbon emissions. Artificial intelligence (AI) is widely used to solve problems in almost every field in modern times i.e. healthcare, transport, communication and the power sector. The current application of AI is widespread, ranging from autonomous cars to drones. It has also been used to tackle complex problems encountered in the operation of microgrids due to fluctuations in the frequency of DERs. This review paper will provide a brief overview of AI, microgrids and their associated control strategies.

1.1 Machine Learning (ML)

The buzzword of machine learning (ML) has been around the scientific world since 1959 as the term was invented in 1959 by A. Samuel and who was a leading computer scientist in the area of artificial intelligence. As defined by him, in machine learning, computers gain the capability to learn even if they are not programmed explicitly. Machine Learning (ML) algorithms allow for accurate predictions to be made without relying on traditional programming approaches. The fundamental concept of ML is to anticipate the output by inputting data and performing analysis based on statistical methods. A summary of machine learning techniques is given in [1].

ML algorithms can be divided into three main types.

I. “Supervised Learning”

II. “Unsupervised Learning”

III. “Reinforcement Learning”

I. *Supervised Learning*

In this class of machine learning technique, the system is provided with data that is labeled correctly i.e., the input data or reference data which is tagged with some meaningful labels. This data is then used to train a function that can identify and predict data as the output of the system. A model for supervised learning is showed in ***Figure 1***.

In supervised learning, the system is inputted with a set of data that is characterized with labels, which means the data set is tagged with the right label. When training is complete under the supervision of labeled or tagged data, it’s time to assess the model using a new data set. Hence this model can predict the outcome based on some referenced data sets. This type of learning can be used for two types of problems: classification and regression. Classification problems involve predicting the output as a category, for example, categorizing a population as healthy or unhealthy. Regression problems involve predicting the output as a real value, such as height or currency.

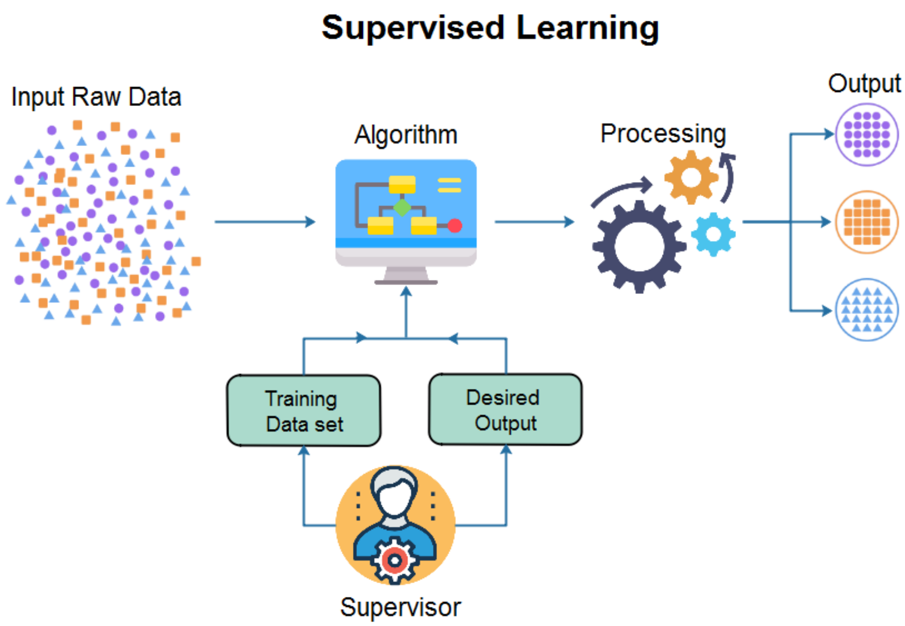

Figure 1 Supervised Learning Model

II. *Un-Supervised Learning*

Un-supervised learning is the opposite of supervised learning in the manner that the provided data is without labels and there is no training involved initially. This system is kind of a model to test artificially intelligent algorithms. It requires the coded algorithm to provide output and concludes the data based on the primary structure of the elements in the input. This model can efficiently categorize elements into two types. Clustering is used to make predictions based on the inherent behavior of the data, such as grouping retailers according to the availability of products. Association, on the other hand, involves learning rules to make predictions based on the rules that are observed in the data set. For example, people who buy mobile phones (X item) might also purchase protection cases (Y item).

There is also a special type of machine learning called semi-supervised learning, in which the training data is incomplete or missing some information. The model for supervised learning is shown in ***Figure 2***.

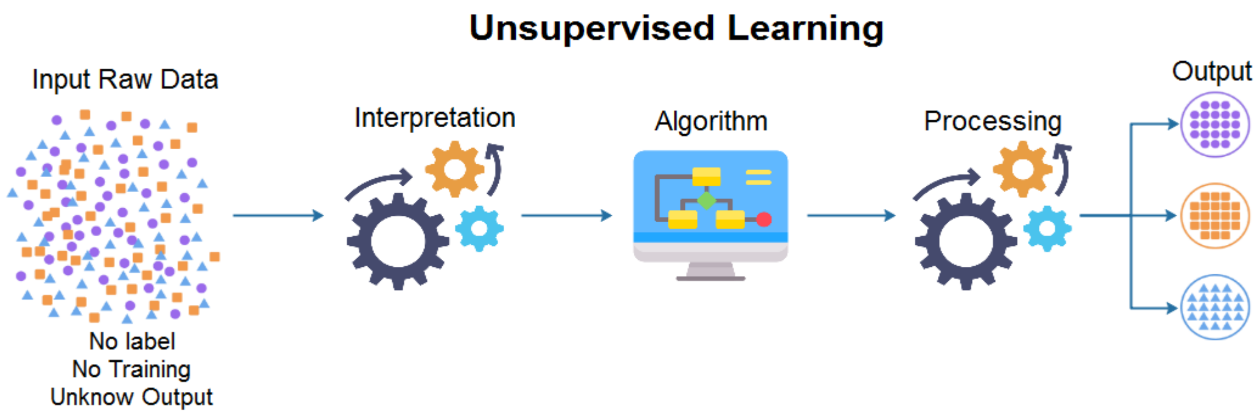

Figure 2 Unsupervised Learning Model

III. Reinforcement Learning

Reinforcement Learning (RL) is a type of learning in which the agent is trained itself by interacting with the environment. It is an algorithm that allows the agent to interact with its environment and receive either positive or negative rewards depending on their performance. Unlike other types of learning, RL does not require any human intervention and is based on dynamic programming that maximizes rewards and minimizes punishments.

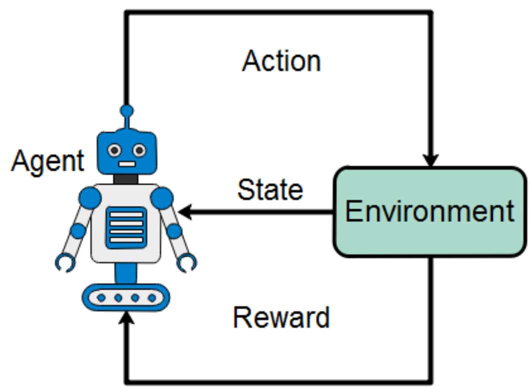

Figure 3: Reinforcement Learning Model

Reinforcement Learning (RL) is an approach where an agent is rewarded or penalized based on the choice it makes. For example, if the agent decides to take the path of fire over the other path of water, it is penalized by losing rewards so that agent learns to avoid the wrong path i.e., the fire path. However, if the agent chooses the path of water, it is rewarded with certain points. This technique allows the agent to improve its policy and optimize its performance in the environment. The model for reinforcement learning is shown in ***Figure 3***.

1.2 Deep Learning (DL)

Deep Learning (DL) is a part of AI that is designed to simulate the human brain for predicting model functions and structure [2]. It relies on Artificial Neural Networks (ANNs) to process large amounts of data. The ANNs are organized in layers, including input, hidden and output layers. Each layer contains nodes, which are analogous to neurons in the brain. A deep learning model depicting the layered structure of the system is shown in ***Figure 4***.

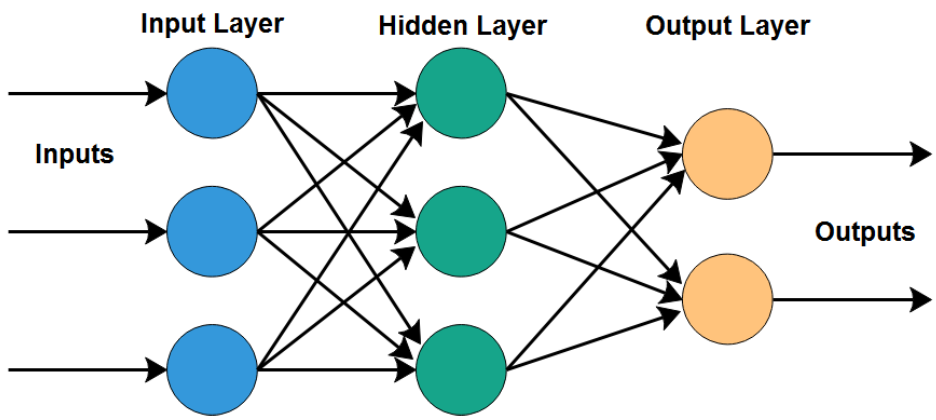

Figure 4 : Layered Structure of Deep Learning Model

At each node, a data set is provided as input. This node is multiplying the inputs with various random weights and adds a bias in the hidden layer afterward. An activation function is employed to activate the desired neuron. Several of the most frequently used algorithms in DL are

- Recurrent Neural Networks (RNNs)
- Generative Adversarial Networks (GANs)
- Convolutional Neural Networks (CNNs)
- Long Short-Term Memory Networks (LSTMs)

1.3 Deep Reinforcement Learning (DRL)

This paper provides a review of Deep Reinforcement Learning (DRL) for the control of microgrids. DRL is a powerful technique that can be used to optimize the operation of microgrids by considering both the energy supply and demand. It has the potential to improve the efficiency of energy management in microgrids and provide a more reliable electrical supply. DRL, a deep learning algorithm, merges the strengths of reinforcement learning to find solutions to problems that require a sequence of decisions that have a direct impact on the agent's environment. Both of these approaches have already been explained in detail in this article. A sample model for deep reinforcement learning is shown in ***Figure 5***.

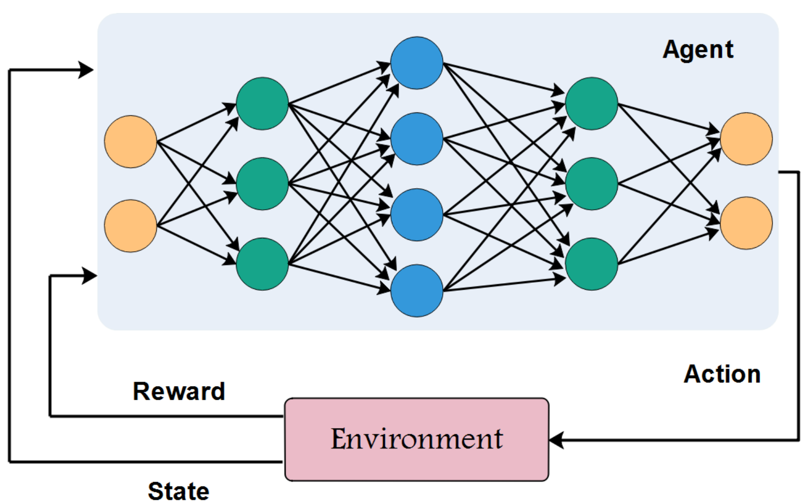

Figure 5 : Model for deep reinforcement learning

Solving problems using DRL algorithms can be achieved through the use of control theory, optimization and management. The application of model based and model free DRL algorithms have been discussed for electrical power systems in [3]. Apart from these two types, other reviewed approaches include value based and gradient type algorithms. DRL methods are classified into three main categories: value-based, policy gradient-based and model-based. One of the most popular value-based methods is Deep Q Learning, known as Deep Q Network or DQN. It uses the deep learning technique of Convolution Neural Networks (CNNs) to approximate the value function Q. Further reinforcement techniques are employed to develop a reward based policy, as described in [4].

Policy gradient algorithms are used to maximize performance and reward by learning an optimal policy. This type of algorithm requires a gradient theorem, and the value function is determined by the current policy [5]. Principle aspects of reward functions i.e., environment models in combination with optimal algorithm affect the model-based category methods of DRL. These methods are known for their fast processing [6]. There are five algorithms available for each DRL category, and further details can be found in [7].

2. AN OVERVIEW OF MICROGRIDS AND THEIR CONTROL

A Microgrid (MG) is an advanced electrical grid system that has the capability to independently operate, even when disconnected from the larger power grid. This is possible because of the smart control abilities built into the architecture of the Microgrid. Outlook of a migrogrid is shown in ***Figure 6***.

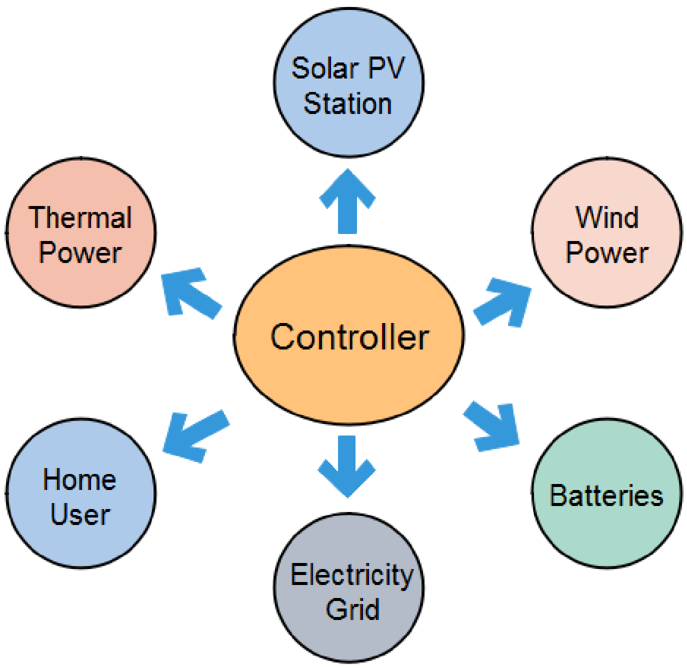

Figure 6 : A Sample Outlook of Microgrid Blocks

A grid is a network connected by a central power source with transmission and distribution mechanisms. The smart grid technology offers improved monitoring, protection and optimization of the generation, transmission, distribution and consumers of all grids. This is achieved through two-way communications, digital technologies, advanced sensing and computing infrastructure and software capabilities. These features make the smart grid a valuable asset for the efficient functioning of all grids. A microgrid is an isolated system that is capable of operating with or without the main grid. When the microgrid didn't connect to the main grid, the situation is called islanding. An islanded microgrid can provide energy to its connected users and is beneficial in times of power outages. A microgrid is connected to a grid with the point that couples both grids at the same voltage and frequency. This technology is currently being researched extensively and is becoming increasingly popular in the energy sector [8].

Micrograds can be connected to a main grid or operated independently, depending on the source of their energy i.e., by central source or locally distributed renewable energy sources. While connected to the main grid, the controller of a Microgrid only needs to manage energy, but when it is in its isolated state, it must also synchronize frequency and regulate voltage in addition to management of energy load. Inverters are responsible for the control systems in Microgrids. This provides a more reliable and efficient source of energy [9][10][11].

There are three main ways to control microgrids, centralized, decentralized, or distributed and hierarchal control. The centralized approach has been employed on the generation side and planned before the implementation phase. In this approach, a controller is connected with load balancing and sensing devices through a network to communicate data regarding control variables [11][12].

The decentralized control is a system where the control is distributed across a series of small networks called microgrids. Each microgrid has its controller or a single controller can be used to control several microgrids. This type of control is especially useful when there are numerous local control machines connected to each other. Distributed control is especially challenging as renewable energy sources are highly unpredictable and difficult to manage [12][13]. The three main approaches used for distributed control are consensus based, predictive models and agent based. Moreover, hierarchical control operations can be used at tertiary, secondary and primary levels. Recent research has focused on optimizing distributed control for islanded microgrids [14].

Primary control is related to the regulation of frequency and control of converters and distributed energy resource elements within a microgrid. While secondary control is used to reduce any frequency fluctuations which may arise from primary control, by coordinating the local controllers of a distributed microgrid also called the consensus-based approach. Finally, tertiary control is the highest level of hierarchical control or overall control of power flow, aiming to optimize solutions and consider all potential uncertainties to optimize solutions [15].

3. METHODOLOGY

Deep reinforcement learning for the control of microgrids has not been implemented properly before 2019. This study focuses on the period between 2019 and 2022 since the majority of related research has been done in that time frame. The sources examined in this review are only from journals that are indexed in International Scientific Indexing (ISI) and Scopus. Conference papers are not included due to the page limit, and also because most of these works were usually further developed and published in journals. The keywords used for filtering the research data were deep reinforcement learning for control, DRL and Microgrids, Smart grid control using Deep Q networks, Microgrid management based on deep Q learning, Deep forest reinforcement for microgrid control, deep learning and reinforcement learning, voltage control in Microgrid and frequency regulation Microgrid.

This paper reviews research based on DRL used for certain control problems of microgrids. To ensure the quality and relevance of the material, only papers from reputable journals were chosen. A few preliminary versions (pre-prints) are also included from free repositories which are not yet been published in any peer reviewed journal. The summary of published work is organized according to year, starting from 2019 until 2022, and will be presented in the following section.

4. APPLICATIONS OF DRL IN CONTROL OF MICROGRIDS

A comprehensive summary of the operation, application and control of microgrids is given in [16]. The authors have provided an in-depth overview of microgrids, exploring their architecture, functioning, and applications. They have also highlighted the importance of economic feasibility and optimization for the successful implementation of microgrids.

Sequential attributes like heuristic, programming, and convex optimization methods have been used to solve decision-making problems. These methods have been widely employed for problem-solving in power systems. However, the introduction of distributed generation and its control, particularly in the form of microgrids, has raised the complexity of the system and necessitated the use of new models that can manage larger data spaces in real-time environment. Glavic [17] provided an overview of control-related issues in electrical systems and their potential solutions through deep reinforcement learning techniques.

DRL technologies are far more robust to handle complex control issues of the distributed power system than the traditional methods used previously without the use of artificial intelligence. The advantages of DRL over traditional methods have been discussed in [18]. DRL does not require a proper objective function and can handle more data than convex optimization techniques. A detailed survey is available in [19] to study the applications of artificial intelligence for the management and control problems of the microgrid. In this research, almost every aspect of microgrid applications has been reviewed based on different artificial intelligence techniques. What makes DRL especially useful is its ability to make decisions in real time, as its reward policy is only dependent on the current state. Heuristic methods cannot match the stability and robustness of DRL for convergence and decision making.

4.1 Relevant Published Work in the Year 2019

Manufacturing plants require a consistent energy supply, which can be provided by renewable energy sources integrated into on-site microgrids. To implement optimal energy control, reinforcement learning combined with neural networks is employed. The results have shown energy cost savings with no constraints on manufacturing output [20]. Other research has also demonstrated the superior performance of the Adaptive Deep Dynamic Programming (ADDP) algorithm, which integrates three deep learning algorithms. For multi-microgrid architecture, the designed control system was simulated against 157 other algorithms in six different environments, with improved frequency control results [21].

Proactive risk management and effective decision making in real-time are achieved through reinforcement learning integrated with a convolution neural network. This is also used in stabilizing voltage in grids with distributed energy sources in islanding situations [22]. Value based policy learning algorithm along with deep neural networks is applied in stack mode to solve problems in huge data space. This is done by creating a model with subnetworks of grids [23]. A summary of this research is presented in table 1 below.

Table 1:Relevant Published Work in the Year 2019

Reference	Objective	Application	Architecture	DRL Algorithm	Q function estimator
[20]	To reduce energy cost for production without sacrificing production throughput while addressing the “curse of dimensionality”.	Optimal Control	On-Site Microgrid Generation System and Manufacturing Plant Simultaneously	Deterministic Policy Gradient (DPG) With On-Policy Temporal Difference Control	Neural Networks
[21]	To regulate the frequency of the system to its standard value.	Secondary Control in Terms of Frequency Control.	Microgrid Systems Based on Multi Area and Multi-Level	Adaptive-Deep Dynamic-Programming with Deep Learning	Neural Networks Based on Deep Prediction, Deep Critic and Deep Action
[22]	Stability of high voltage buses with efficient decision making.	Transient Voltage Control	Islanded Mode, Distributed Energy Resources	Reactive Power Compensation Decision Optimization Algorithm	Convolutional Neural Network
[23]	To resolve high dimensional, hierarchical control tasks.	Optimal Control	Multi-Stage Grid	Stacked DQN	Deep Neural Networks

4.2 Relevant Published Work in the Year 2020

Photovoltaic (PV) systems are an essential element of microgrid generation as a renewable energy source in smart grids. Model free DRL algorithm has been designed for maximum power point tracking (MPPT) control problems in varying weather conditions when the state of each PV layer is different and requires online modeling. Open source simulation environments have been developed by the authors to test their algorithm and further support research progress [24]. Additionally, the complex problem of bus voltage stability in DC microgrids is being tackled through the development of a DC-DC Converter, which is designed using a deep reinforcement learning approach. Simulations have demonstrated improved voltage control through an enhanced self-learning process [25].

Frequency deviation control is an important component of microgrid architecture. To address instability issues due to the unpredictable nature of renewable energy resources, fuzzy control with online learning via an Actor-Critic Framework based deep reinforcement learning scheme has been employed [26]. Active distribution networks (ADNs) similar to microgrids, also have a majority of their energy sources based on renewable energy sources. A DRL based optimal control scheme with additional safety features for voltage control problems has been developed as a continuous action space [27]. Furthermore, a Policy Approximation based on a multilayer perceptron neural network and feed forward algorithm was proposed to synchronize frequencies and solve control problems in interconnected microgrids [28].

Frequency regulation in an islanded mode of AC microgrids can be improved through the use of a controller based on a deep deterministic policy gradient algorithm. This approach has been shown to be more reliable, even in extreme conditions, compared to a proportional-integral controller (PIP) [29]. A model free solution based on DRL has also been used to address the Volt-Volt Amp reactive (VAR) control problem, producing superior results in comparison to traditional optimization techniques and other reinforcement learning methods [30]. Moreover, the integration of Long Short-Term Memory (LSTM) neural networks with reinforcement learning have been proposed for the protection layer in overcurrent scenarios, resulting in a faster, more robust solution than existing relays designed for the same objective [31].

The traditional approach of centralized control fails to deal with the increasing integration of distributed energy generation in power systems. To address this limitation, distributed control is implemented in such systems to support automated control. The Action Discovery based Dual Deep Q Network, a deep reinforcement learning technique has been applied [32]. Moreover, Voltage deviations due to distributed energy generation in modern distributed grids create huge power flow problems. To solve this, a Deep Q Network based solution has been employed, making use of convolutional neural networks (NNs) to stabilize the voltage in distribution grids with renewable energy generation [33]. Additionally, the Volt-VAR Optimization (VVO) algorithm has been applied to the distribution network to adjust varying conditions over time. The proposed DRL scheme provides power flow with accuracy. Numerical results based on simulations validate exceptional performance in terms of reduced power loss and enhanced voltage stability [34]. A summary of the relevant research papers is presented in Table 2.

Table 2 Relevant Published Work in the Year 2020

Reference	**Objective**	**Application**	**Architecture**	**DRL Algorithm**	**Q function estimator**
[24]	To resolve the problem of maximum power point tracking (MPPT) of photovoltaic (PV) systems for partial shading conditions.	MPPT control	Microgrid based of PV arrays	Deep Deterministic Policy Gradients algorithm	Deep Neural Network
[25]	To design a converter for DC-DC control with self-optimization ability.	Bus Voltage Stability	DC Microgrid	Deep Q Network	Neural Network

[26]	To Restore Stability with Efficient Load Frequency Control.	Frequency Regulation/Secondary Control	Hybrid Distributed Power System as Isolated Microgrid	Actor-Critic Framework Based Algorithm	Neural Network
[27]	To address control issues with the additional characteristic of the safety layer.	Voltage Control	Distributed Generators and Smart Transformers	Deep Deterministic Policy Gradient Algorithm	Deep Neural Network
[28]	To regulate of frequency by eliminating the deviations in frequency that occur during transients in microgrids.	Primary Frequency Regulation	Interconnected Microgrids Simulated in Grid LAB-D™	Policy Approximation Algorithm	Multilayer Perceptron Neural Network
[29]	To design robust controller for AC microgrid to regulate frequency under stochastic conditions.	Frequency Regulation, Primary/Secondary Control	Islanded AC Microgrid	Deep Deterministic Policy Gradients Algorithm	Deep Neural Network
[30]	To resolve control problem related to Volt-VAR based on model free method.	Volt- volt Amp reactive (VAR) control	Distribution Test Feeders Based on IEEE 4-Bus And 123, 34-Bus	Deep Q-Network	Policy Neural Network
[31]	To design and implement protective relays in the distribution grid.	Over Current Protection in Distributed Control	Distribution Grids	Deep Q Network	Long Short-Term Memory (LSTM)
[32]	To develop a more effective automatic generation control (AGC) strategy.	Distributed Control	Connected Small Microgrids	Dual Deep Q Network-Action Discovery	Deep Neural Network
[33]	To implement voltage regulation by focusing on the reactive control abilities of inverters and capacitors.	Voltage Regulation	Distribution Grid	Deep Q-network	Convolutional NN
[34]	To enhance the performance of the control in distribution feeders with large-scale	Voltage Control	Unbalanced Smart Distribution Systems	Soft Actor-Critic Algorithm	Neural Network

4.3 Relevant Published Work in the Year 2021

To allow local autonomy in microgrids without the need for human personnel or central control, an edge computing-based deep reinforcement learning distributed multi-agent intelligent control algorithm has been proposed for power flow management [35].

A decentralized control scheme based on a cooperative approach has been proposed to improve scalability and smooth communication among agents [36].

The preservation of electricity consumer privacy and peak power load handling in residential microgrids is a complex task. For this, a distributed model free technique based on multi agent DRL has been simulated to achieve better results [37]. Transfer learning integrated deep learning algorithms have also been successfully used with scheduling knowledge to effectively optimize the operations of microgrids [38]. Furthermore, a novel approach has been proposed to control voltage and frequency in an islanded mode with the integration of electric vehicles [39]. Additionally, the stability of DC microgrids is endangered by the presence of Constant Power Loads (CPLs) due to their impedance. To address this issue, a converter based on the Deep Deterministic Policy Gradient Algorithm has been designed.[40].

To protect against different types of cyber-attacks, two algorithms based on multi agent DRL have been implemented for DC microgrids in islanding mode [41]. A novel technique has been proposed to manage the control problems between power distribution nodes and controllers in an islanded microgrid, which is based on ensemble, imitation, and curriculum learning. The proposed technique is validated through simulation to improve frequency control and cost savings [42]. Moreover, a robust controller has been designed to control bus voltage fluctuations by formulating the Markov chain problem [43]. An online distributed control strategy has been developed to regulate Volt/Var control issues through DRL [44].

The Internet of Things combined with deep learning group control methods can be used to manage the regulated power output from multiple distributed energy sources [45]. A load control scheme with the extra feature of privacy has been applied in microgrid based residential buildings with home appliances and electric vehicles. This goal is achieved due to the use of a recurrent neural network to partially observe the states [46]. A control method for load frequency management has been proposed for all layers of microgrid control with no communication required between operating nodes, providing an extra security layer. This proposed DRL method is implemented with central learning, but in a distributed manner [47].

Optimizing a microgrid in real-time is a challenging process that can be achieved through the use of a double deep Q network based algorithm [48]. To accurately forecast scheduling problems and power flow from distributed energy sources, a combination of long short-term memory deep learning and model-based reinforcement learning can be used for residential microgrids [49]. Active distribution networks with renewable energy sources are implemented with DRL based techniques to resolve problems of power losses and voltage violations. This proposed method is implemented in two stages; first, to the capacitor nodes and on-load tap changer (OLTC) to achieve minimum power loss, and then secondly, to regulate the reactive power of photovoltaic systems to mitigate voltage fluctuations [50]. Additionally, a converter for secondary voltage control based on DRL has been designed to assess the flexibility of the voltage capacity of the power grid, allowing it to host renewable energy sources without causing voltage instability and overcurrent scenarios [51].

Research has been conducted to apply DRL based control methods to physical architectures with photovoltaic energy generation [52]. In particular, multi-agent DRL techniques have been proposed to solve the problem of load frequency control in power systems with distributed energy resources [53]. Quantum learning combined with DRL is applied to optimize real time control in electrical systems featuring high penetration of alternative energy sources [54]. A double deep Q-learning technique has been applied to an islanded microgrid with energy storage capabilities for cooperative control and energy management in different weather conditions [55]. A summary of this section's research is presented in table 3.

Table 3 Relevant Published Work in the Year 2021

Reference	Objective	Application	Architecture	DRL Algorithm	Q function estimator
[35]	To enhance the efficiency and scalability of the system.	Power Flow Control	Sub-grid partition based	Asynchronous Advantage Actor-Critic(A3C) algorithm	Value Networks
[36]	To avoid the effects of system uncertainty and random noise for cooperative control.	Secondary Voltage Control	Power grid With Distributed Generation, Microgrid	Independent Actor-Critic (IA2C)	Long Short-Term Memory (LSTM)
[37]	To reduce the cost of management of the grid and cost of electricity.	Load Control	Residential Smart Grids	Actor Critic-Based Algorithm	Deep Neural Network
[38]	To effectively accumulate and utilize the scheduling knowledge at present to control scheduling in microgrids.	Scheduling	Microgrid With Distributed Energy Resources	Deep Deterministic Policy Gradient	Neural Networks based on Transfer Learning based
[39]	To solve the problem of stability of islanded microgrid.	Frequency and voltage regulation/Secondary Control	Island Microgrid with Electric Vehicles	Deep Deterministic Policy Gradient (DDPG)	Critic Target Network
[40]	To develop an advanced regulatory mechanism for DC-DC converters implementation in microgrids.	Power Conversion, Voltage Regulation	DC Microgrid Scenario	Deep Q Network	Deep Neural Network
[41]	To address issues related to cyber security in microgrids for the secondary control layer.	Detection of Cyber Attacks through Distributed Control	DC Microgrids in Islanded Mode	Deep Deterministic Policy Gradient (DDPG)/ DQN	Not mentioned
[42]	To minimize the cost of power generation and achieve improved frequency stability.	Secondary Control in Frequency Regulation	Islanded Microgrid	Variant of Deep Deterministic Policy Gradient	Critic Network
[43]	To reduce network power losses and bus voltage deviations for optimization problems in Volt/Var control	Voltage Control	Active Distribution Networks based on PV	Multi-Agent Deep Deterministic Policy Gradient	Behavior Cloning Based Q Learning
[44]	Online Decentralized Control framework to improve the stability and efficiency of Volt-VAR control.	Voltage Control	Active Distribution Networks	Multi-Agent Actor-Critic Based Algorithm	Deep Neural Network
[45]	To attain economic operation of the power grid by regulating the coordination in the output of distributed energy sources.	Group Control	Connected Microgrids Based on IoT Model	Edge-Side Training Learning Based	Deep Neural Network

[46]	To improve the operating efficiency with privacy preserving mechanism.	Load Control	Residential Microgrid Based Home Appliances and Electric Vehicles	Vectorized Advantage Actor-Critic (Va2c) Algorithm Based DQN	Recurrent Neural Network (RNN)
[47]	To design an algorithm to control load frequency without the need for a central controller.	Primary, Secondary, And Tertiary Control	Distributed Microgrids	Deep Q Network	Long Short-Term Memory (LSTM)
[48]	To operate microgrid with power flow constraints in real-time.	Optimization	10-Bus Microgrid System with Modified IEEE 69-Bus Microgrid System	Double Deep Q Network	Long Short-Term Memory (LSTM)
[49]	To forecast Accurately renewable power generations with online scheduling.	Optimal Power Flow and Economic Operation	Residential Microgrid	Model-Based Deep Reinforcement Learning	Long Short-Term Memory (LSTM)
[50]	To eliminate violations of fast voltage and minimalization of power loss in the network.	Voltage Control	Active Distribution Networks	Deep Deterministic Policy Gradient	Deep Neural Network
[51]	To enhance the efficiency of converter-interfaced generators in electrical networks.	Secondary Control	Modified IEEE 34-bus test feeder with six inverted-based DGs	Deep Recurrent Q-Network (DRQN	Long Short-Term Memory (LSTM)
[52]	To Design a control based on closed-loop for optimization in Distributed Energy Resources based systems	Control Of Load And Efficiency of Energy	Physical Test Building for Distributed Energy Resources (DER)	Deep Deterministic Policy Gradient	Two Neural Networks
[53]	To achieve an optimal resolution by a collaboration of multi region grids and overcome issues in classical deep reinforcement learning techniques.	Load Frequency Control	Hubei Power Grid Model Combined with IEEE Standard	Double Deep Q-Network Context-dependent processing (DDQN-CDP)	Backpropagation Neural Network (NN)
[54]	Avoiding the curse of dimensionality	Online Control	Grid Connected Wind Turbines Based Distributed Network	Quantum Deep Reinforcement Learning	Deep Belief Networks
[55]	To develop real-time charge and discharge strategy, and calculate the timing arrangement scheme of the storage system.	Optimization Control and Energy Management	Island Micro-Grid System	Double Deep Q Network (DDQN)	Long Short-Term Memory (LSTM)

4.4 Relevant Published Work in the Year 2022

A coordinated approach is implemented in the multiple area model architecture of "China Southern Grid (CSG)" with integrated renewable energy sources. The proposed method efficiently improved frequency regulation decision making in real time [56]. The virtual combination method has been tested and found to be effective in correcting unbalanced load voltage problems in three phase systems with single phase loads. Deep Q network learning was also tested to manage unintentional load shedding in an islanded microgrid with successful results. These techniques have been found to be reliable and effective [57].

A control method based on deep reinforcement learning (DRL) was proposed for reconfiguring islanded hybrid microgrids with AC/DC distribution networks [58]. Distributed frequency control method for islanded microgrids is proposed by combining DRL with quantum learning [59]. For islanded microgrids an optimal control strategy is proposed using deep reinforcement learning by deploying microgrids as multiagent systems [60]. A decentralized control method for frequency deviations is proposed in [61]. It is capable of restoring system frequency with minimum cost. In [62] challenge of recurrent fluctuation produced in microgrids due to renewable energy resources is presented with the solution through a self adaptive model free algorithm. A summary of this section's research is presented in table 4.

Table 4 Relevant Published Work in the Year 2022

Reference	Objective	Application	Architecture	DRL Algorithm	Q function estimator
[56]	To improve the performance of frequency regulation using coordinated control.	Load frequency control	Multi-Area System Integrated with Renewable Energy	Multi-Agent Deep Deterministic Policy Gradient	Neural Network
[57]	To mitigate shortage of power issue while transitioning to islanding mode unintentionally.	Frequency Regulation	Hybrid Multi-Microgrid	Deep Q-Learning Network	Convolutional Neural Network
[58]	To reconfigure microgrid after unintentional islanding	Restoration Through Coordinated Control	Hybrid Distribution Networks with AC and DC sources as Microgrid	Soft Actor-Critic Algorithm with Multi-Agent Approach	Deep Neural Network
[59]	To regulate frequency in islanded microgrids with improved performance regarding training.	Frequency Control	Islanded Microgrids	Deep Deterministic Policy Gradient Algorithm	Quantum Neural Network
[60]	Development of Global Cost Function	Secondary Control	Islanded Microgrids	Deep Deterministic Policy Gradient Algorithm	Deep Neural Network
[61]	Optimal Control under varied frequency and load	Frequency Control	Networked microgrid	Soft Actor-Critic Algorithm	Neural Network
[62]	To minimize the deviation of the frequency	Frequency Control	Islanded AC Microgrid	Deep Deterministic Policy Gradient Algorithm	Deep Neural Network

5. DISCUSSION & CONCLUSION

Distributed Energy Resources that contain various AC, DC, and hybrid loads with energy storage systems have become increasingly popular in managing the energy flow in Microgrids. This combination of technology has proven to be an effective way of controlling energy usage. Traditional control approaches are not sufficient for this purpose, and therefore, distributed and central approaches are implemented to regulate frequency and voltage. Artificial Intelligence has been used in forecasting problems and providing solutions to tackle the complexity of energy demand and supply, as rapidly fluctuating prices of energy in the renewable power sector.

This paper has presented an overview of artificial intelligence and its sub-categories to provide oversight to researchers about machine learning, such as deep learning, reinforcement learning, and the combination of both. It then proceeds with an overview of microgrids and their control. The background and limitations of traditional control methods used in the control of microgrids are discussed, along with the advantages of implementing deep reinforcement learning-based schemes. These techniques are highly suitable for scenarios where control problems have a larger database and previous methods based on deep learning can cause a curse of dimensionality. By combining reinforcement learning with neural or deep networks, this issue can be successfully addressed.

Real time decision making, effectiveness and robustness are improved dramatically through the use of the techniques surveyed in this paper. Moreover, deep reinforcement learning (DRL) can provide effective support for microgrids in terms of handling large data sets and solving problems in real time. By forecasting and decisions making in advance, energy utilization in the future can be optimized. To further advance this research, energy and demand side management should be incorporated.

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