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Original Article

Topology-Aware Federated Multi-Agent Reinforcement Learning for Dual-Level Voltage Regulation in PV-Rich Distribution Grids

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Abstract - *Photovoltaic (PV) generation with high penetration in the distribution networks causes voltage rise, voltage deviation and three-phase imbalance between connected Medium-Voltage (MV) and Low-Voltage (LV) feeders. In this paper, a topology-conscious federated multi-agent reinforcement learning is introduced to subordinated dual-level voltage regulation in PV-rich distribution grids. The given approach represents the network as a graph and implements the state encoding with the help of a Graph Neural Network (GNN) to ensure that every agent is able to represent local electrical state and local topology. Both LV control nodes are considered independent reinforcement learning agents, and the federated aggregation provides the means of updating shared parameters of the model without sharing the raw local measurements. The structure is aimed at minimizing MV voltage violations and LV phase unbalance collaboratively when there are different conditions of PV penetration and communication. The technique is tested on a stochastic load and PV test system on the IEEE 33-bus distribution test system. The findings show that voltage regulation and phase-balancing performance are enhanced when using the centralized RL strategy instead of baseline centralized RL and traditional MARL strategies. The research identifies the promise of topology-conscious learning and federated coordination in the provision of scalable voltage control in privacy-sensitive smart grid systems.*

Keywords - *Federated learning, Reinforcement learning, Graph Neural Networks, Voltage regulation, PV integration, Smart grids, Multi-Agent systems.*

1. Introduction

The rapid integration of renewable energy sources, especially Photovoltaic (PV) systems, is radically changing the way modern power distribution networks work. With the growing objective of decarbonization in the world and the rising usage of distributed energy resources, PV levels in the distribution system have increased by a lot over the past few years. Although this conversion has definite environmental and economic advantages, it has also brought up operational issues, especially in ensuring the stability of voltage and power quality across distribution grids. The intermittent and stochastic characteristics of the PV generation in the distribution system result in variations between active and reactive inputs when there is PV generation. Such fluctuations may lead to an increase in voltage, voltage deviations, and, in worst cases, voltage instability. This issue is increased in a hierarchical distribution network, which is a combination of Medium-Voltage (MV) and Low-Voltage (LV) levels. At the MV level, the reverse power flow and overvoltage are possible when the PV penetration is high. Uneven distribution of the single-phase loads and PV installations at the LV level results in high three-phase voltage unbalance. Such problems have an adverse effect on the quality of power, higher losses in the systems, and shorter life of the electrical equipment. The conventional forms of voltage regulation, such as On-Load Tap Changers (OLTCs), capacitor banks, and voltage regulators, are mainly oriented at comparatively predictive and centralized grid activities. Such strategies are based on a set of control regulations and slow dynamics of response, and thus are less efficient in managing the fast and localized variations brought by distributed PV systems. Optimal power Flow (OPF) and other centralized optimization-based algorithms are capable of achieving better performance but must have system models that are accurate, full network observability and quality communication infrastructure. Practically, such requirements cannot be met in the large-scale distribution systems that have limited sensing and communication properties. To overcome such difficulties,


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data-driven control systems, specifically Reinforcement Learning (RL), have become a perspective option to real-time decision-making in a complex and uncertain setting.

The RL-based methods allow learning the best policies by the controllers through interaction with the environment without the need to have explicit system models. Multi-Agent Reinforcement Learning (MARL) is a generalization of this paradigm, where a coordination of actions by multiple distributed agents is possible to realize system-level goals. Considering the distribution networks, a PV inverter or LV bus can be viewed as an agent that can be controlled. Although they have such benefits, the current MARL-based voltage control techniques either use a centralized training or need to share local operational information, which can include load profiles and PV generation. This brings in overhead issues associated with communication, scalability, and privacy of data. Besides, most of the currently available methods deal with single-level voltage control, that is, one of the two MV and LV networks, not the interactions between the various voltage levels in real-world distribution systems.

Federated Learning (FL) has become one of the decentralized machine learning paradigms, which allows joint training of models without any exchange of raw data. The FL system in FL has individual agents, who train local models with their data, and periodically exchange model parameters with a central aggregator, which estimates a global model. The method minimizes the communication needs and maintains the privacy of data, hence it is applicable in distributed systems like smart grids. Federated reinforcement learning, when used alongside reinforcement learning, allows decentralizing the policy learning but coordinating the agents. Simultaneously, distribution networks by their nature have a graph-structured nature, with buses and lines being nodes and edges of a graph, respectively. This topology has a great impact on the electrical characteristics of the grid since power flows and voltage distributions are determined by connectivity and line characteristics.

Traditional learning-based methods typically ignore the existence of these spatial relationships between system variables, as well as treat the variables as independent. Graph Neural Networks (GNNs) are a good model to capture these relationships, as they allow each of the nodes to learn representations, which use the information of its neighbors. This is due to the fact that when GNNs are introduced to reinforcement learning platforms, control policies are in a position to consider both the local settings and the interactions occurring within the network. Even though the use of reinforcement learning, federated learning, and graph-based approaches in power system control has been significantly developed, there is also a critical practical issue. Improving the voltage regulation of PV-rich distribution networks means that one needs to consider the decentralization of decision-making, privacy-sensitive learning, communication, and the hierarchical nature of the relationship between MV and LV simultaneously. Most of the currently available methods handle these aspects separately, and hence they are not as useful in realistic grids.

Driven by this void, this paper will introduce a topology-based federated multi-agent reinforcement learning architecture that can be applied to coordinate voltage regulation in a distribution system that is highly penetrated by PV. The given strategy is an integration of graphical state modeling and decentralized policy learning, which allows the agents to take advantage of the local measurements and network topography and restrict the transfer of raw data.

The LV nodes are modeled as autonomous agents that learn actions of control of voltages, and the federated aggregation is employed to exchange the model parameters to enhance coordination among the agents. The value of the contribution of this work is that, instead of presenting an entirely new learning paradigm, it presents the combination of topology-aware representation, federated coordination, and dual-level voltage regulation in a single operational framework. The proposed method is analyzed by the research at different levels of PV penetration and when the communication is limited in order to examine the method and its capabilities to survive in the distributed smart-grid control.

The main contributions of this paper are summarized as follows:

- Topology-aware state representation: The encoding is based on a Graph Neural Network (GNN) to encode spatial dependencies of the distribution network and improve the state representation of reinforcement learning agents.
- Federated multi-agent learning framework: It builds a decentralized training architecture where agents are trained to learn local control policies and exchange model parameters by means of federated aggregation and without access to raw data.
- Dual-level voltage regulation: The control objective is developed as a collective effort to resolve the MV voltage deviations and LV three-phase voltage unbalance in one learning context.
- Evaluation under practical conditions: The method is experimented with in different PV penetration levels and communication limitations to study the performance of the voltage regulation, convergence, and strength.

The rest of this paper is structured in the following way. Section 2 is a literature review of reinforcement learning, federated learning and topology-aware techniques in power systems. The proposed methodology is offered in Section 3, which includes the model of the system and the design of the algorithm. Section 4 explains the simulation setup and mentions the results of the performance evaluation. Lastly,

Section 5 will be the conclusion of the paper and give future research directions.

2. Related Work

2.1. Reinforcement Learning for Voltage Regulation in Distribution Networks

Reinforcement Learning (RL) has also been extensively investigated in the context of voltage regulation of distribution systems because it can deal with nonlinear dynamics and uncertainty without any explicit model of the system. Initial research was on centralized RL methods of coordinated voltage control with active and reactive power optimization [1]. These techniques showed better voltage profiles, although they had scaling problems in large distribution systems.

The decentralized and Multi-Agent Reinforcement Learning (MARL) methods have been proposed to overcome the issue of scalability. MARL allows the autonomous control of multiple agents of various nodes and realizes system-level goals [2]. Agents in distribution networks are generally linked to PV inverters or buses in which reactive power can be controlled locally. Multi-timescale learning has also been used in advanced RL-based voltage control strategies to capture slow and fast dynamics in the system [3].

Other more recent works have further improved MARL through the incorporation of domain knowledge and physical constraints. The MARL methods that are informed by physics enhance the stability of learning and ensure consistency of control actions with laws of power systems [4]. Besides this, high-renewable penetration cases have driven the creation of intelligent control systems that are capable of ensuring system reliability when operating in extreme system conditions [5]. Multi-agent learning systems have also been suggested to enhance the coordination and performance of distributed controllers [21].

Even with such developments, many of the RL and MARL-based approaches use centralized training or demand a lot of data exchange among agents, although this introduces overhead to communication and privacy issues. Moreover, the majority of methods are concerned with single-level regulation and do not consider explicitly the dynamics of the MV and LV networks coupled with each other.

2.2. Federated Learning and Federated Reinforcement Learning in Smart Grids

The concept of Federated Learning (FL) has become a potential solution to decentralized learning with the privacy of the data. FL has also been used in smart grid applications to overcome challenges like anomaly detection, load forecasting, and distributed intelligence and enable many entities to jointly train models without exposing raw data to each other [10]. There are more sophisticated methods that involve FL with secure computation (homomorphic encryption) and increase the security of data in a distributed setting [11]. More recent work has applied FL to reinforcement learning to give rise to Federated Reinforcement Learning (FRL), allowing policy learning to be decentralized between two or more agents. FRL-based methods have been used to control voltages and to manage microgrids, and it has been shown that they are more scalable and resilient [15]. Besides this, vertical federated reinforcement learning is also suggested to be used in resilient control of microgrid networks in real-time, and it was tested on real-time testbeds [6].

The recent research, such as survey studies, has emphasized the rise of federated learning in smart grid applications with its advantages and weaknesses in terms of security and reliability in communication links [13]. Privacy-preserving energy forecasting and distributed intelligence of the IoT-enabled grid environment have also been investigated using FL [14]. These trends suggest the growing significance of decentralized learning systems in contemporary power systems. Nevertheless, the current FL and FRL-related methods tend to make homogeneous agents, and they do not take into account the physical topology of the power network entirely. Furthermore, most of the studies are centered on prediction or optimization as opposed to real-time control of voltage in a PV-rich distribution system.

2.3. Graph Neural Networks and Topology-Aware Learning in Power Systems

Graph-based structures. The networks of power distribution are in a natural form of graph structures, with lines and buses being the nodes and edges, respectively. Graph Neural Networks (GNNs) have been popularly used to represent such systems to learn the spatial dependencies and relational information between network components [16]. The GNN-based methods have been implemented in different power systems activities such as state estimation, fault detection, and voltage stability evaluation.

It has been applied to estimate voltage health indices based on Phasor Measurement Unit (PMU) data with the help of graph convolutional networks, and it has been shown that it yields better prediction accuracy due to the use of network topology [17]. On the same note, GNN-based techniques have been utilized in the distributed state estimation, which allows efficient and scalable analysis of large power systems [19]. The initial works on graph-based learning, including dual graph convolutional networks, have formed the basis of learning complex relations in structured data [22].

When it comes to voltage regulation, the inclusion of topology-aware representations in the learning-based control frameworks can help a lot in making decisions. GNN-based methods can control the coordination and effectiveness of the control strategies of the agents more than approaches that make local observations only by enabling them to take into account the impact of neighboring nodes.

2.4. Additional Developments in Intelligent Energy Systems

More recent studies have investigated the issue of intelligent control and energy management of modern power systems, such as hybrid AC/DC microgrids and renewable-integrated networks [8]. The use of AI-based forecasting and optimization models has been created to improve the combination of solar and wind energy with smart grids [9]. Hardware architectures that support edge intelligence have also been developed, which in turn have allowed deployment of AI models in resource-constrained environments [12].

Moreover, studies on the inverter topologies and energy storage systems have also helped to enhance the stability and resilience of the grids that are integrated with renewable sources [18, 20]. These advancements are an addition to the learning-based control methods as they offer the infrastructure and system-level improvements needed to operate reliably.

2.5. Research Gap and Positioning of this Work

Based on the literature available, one can note that three important directions have been achieved: reinforcement learning-based voltage control, federated learning in decentralized intelligence, and topology-aware graph neural networks. Nonetheless, all three methods tend to be created separately, and comparatively less studies have combined all three factors in a single structure of voltage regulation in PV-dense systems.

Specifically, the joint issues of the decentralized control, preservation of privacy, topology awareness, and coordinated MV-LV voltage regulation are not fully covered. The goal of this paper is to fill such a gap by formulating a topology-sensitive federated multi-agent reinforcement learning architecture that combines the idea of graph-based state representation and federated coordination to achieve distributed voltage control.

3. Methodology

It is proposed in this section that Topology-Aware Federated Multi-Agent Reinforcement Learning (TA-FMARL) should be used to coordinate voltage regulation in PV-based distribution networks. It is a framework that combines a graph-based system modeling, the topology-sensitive state representation through Graph Neural Networks (GNNs), decentralized Multi-Agent Reinforcement Learning (MARL), and federated parameter aggregation. The general structure of the suggested framework is presented in Figure 1.

3.1. System Modeling of PV-Rich Distribution Network

The distribution network is represented by a graph-structured system to reflect the electrical connection and spatial constraints of each node. The distribution network is mathematically represented as a graph, \(G=(V,E)\), where \(V\) denotes the set of buses (nodes) and \(E\) represents the set of distribution lines (edges).

Where V is the set of buses (nodes), and E is the set of distribution lines (edges).

The local electrical variables associated with each node $i \in V$are the voltage magnitude, active and reactive power injection, PV generation and load demand.

Local observation vector of node i is given as:

$$x_i = [V_i, P_i, Q_i, P_i^{PV}, Q_i^{PV}, P_i^L, Q_i^L]$$

Where,

- V_i: voltage magnitude at node i
- P_i, Q_i: net active and reactive power injections
- P_i^{PV}, Q_i^{PV}: PV generation and inverter output
- P_i^L, Q_i^L: load demand

Nonlinear relationships of power flows determine the voltage behavior of the system. In PV-rich areas, the dynamic changes in the power injections due to changes in PV generation can cause a rise in voltage and instability.

Also, when loads are distributed unevenly in LV networks, there is a three-phase voltage imbalance.

The phase imbalance index is determined as:

$$U_i = \frac{V_i^{\max} - V_i^{\min}}{V_i^{\text{avg}}}$$

where $V_i^{\max}$, $V_i^{\min}$, and $V_i^{\text{avg}}$are the maximum, minimum, and average phase voltages at node i, respectively.

Every LV node is a modeled autonomous control agent with a PV inverter. The control action of agent iis defined as:

$$a_i = \Delta Q_i^{PV}$$

subject to inverter capability constraints. The general objective of control is to reduce the voltage deviation and the phase unbalance over the network:

$$\min \sum_{i \in V} (| V_i - V_{\text{ref}} | + \lambda U_i)$$

where $V_{\text{ref}}$is the reference voltage and $\lambda$is a weighting factor.

Figure 1 illustrates the overall system architecture comprising PV units, network topology and distributed agents. As shown in Figure 1, every agent is coupled with its local environment and is engaged in federated coordination by means of a global aggregation mechanism.

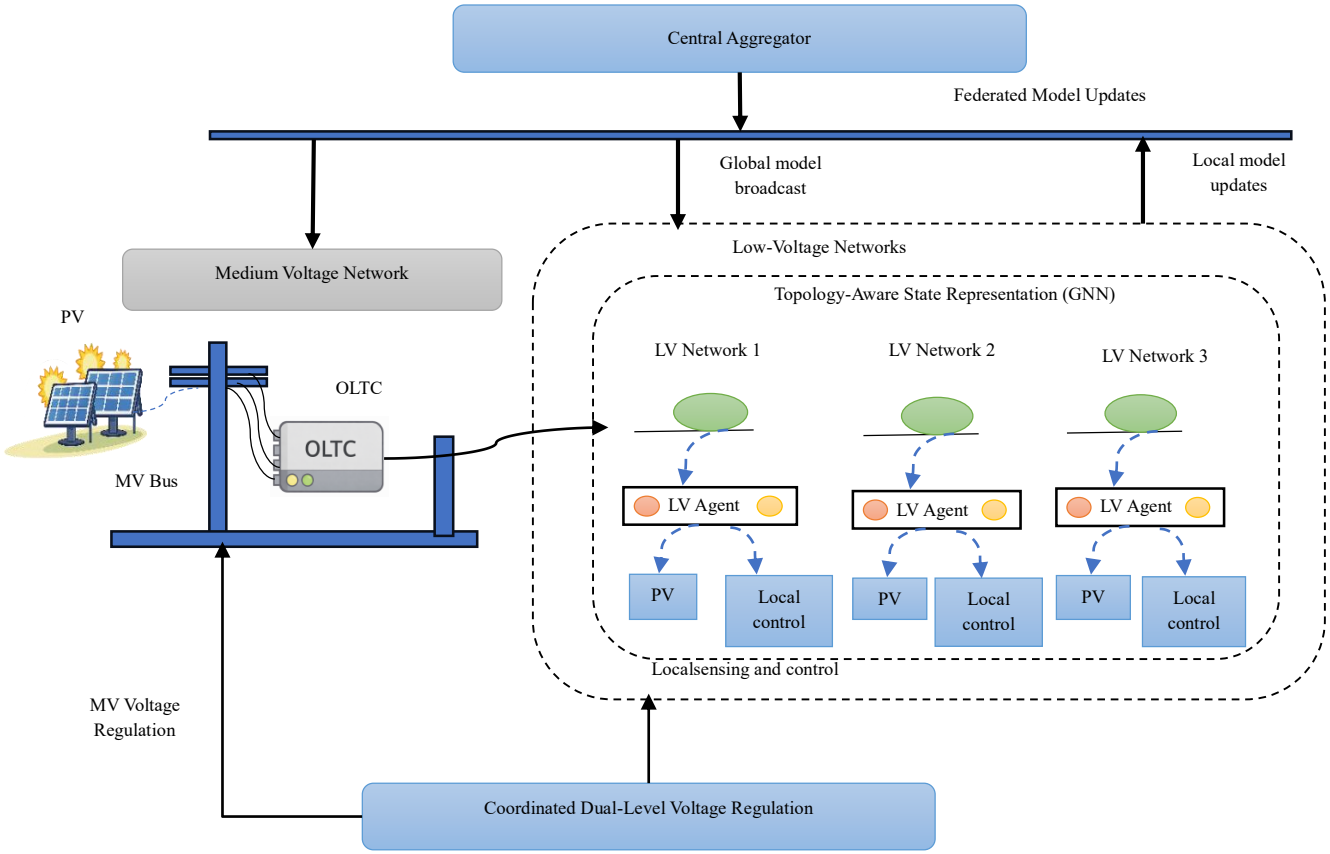


Fig. 1 System architecture of the topology-aware federated multi-agent voltage control framework

3.2 Topology-Aware State Representation using Graph Neural Networks

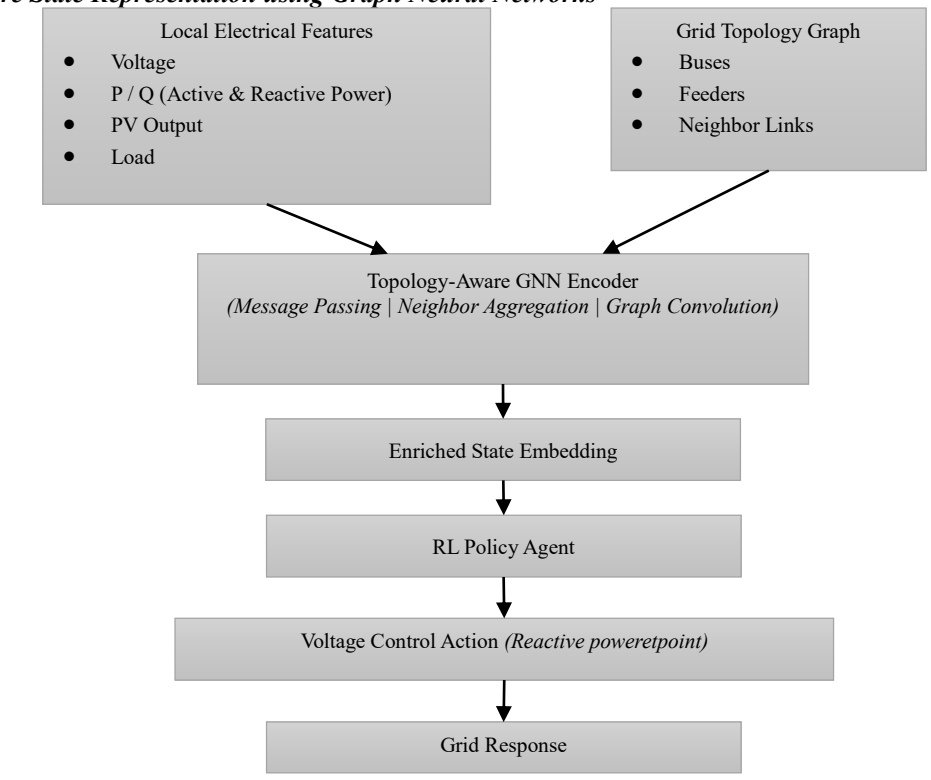


Fig. 2 Graph Neural Network-based topology-aware state representation for reinforcement learning agents

Under traditional reinforcement learning methods, system states have been modeled using local measurements only, thereby restricting the capacity of agents to model network effects. In a power distribution system, however, the voltage of a given node is not only dependent on the local conditions, but also on the neighboring nodes as a result of the electrical coupling. In order to overcome this drawback, a Graph Neural Network (GNN) is used to produce topology-sensitive state representations. The GNN works through the spread of information among the neighboring nodes so that each node is able to learn an embedding that captures the local as well as global characteristics of the system.

The propagation of features of the GNN is given by:

$$h_i^{(l+1)} = \sigma\left(\sum_{j\in\mathcal{N}(i)} W^{(l)}\, h_j^{(l)}\right)$$

Where,

- $h_i^{(l)}$: feature vector of node $i$at layer l
- $\mathcal{N}(i)$: set of neighboring nodes
- $W^{(l)}$: learnable weight matrix
- $\sigma(\cdot)$: nonlinear activation function

A topology-aware embedding h_i (L) is received by each node after L layers and represents the impact of its electrical neighborhood.The reinforcement learning final state of the agent is formulated as:

$$s_i = [x_i, h_i^{(L)}]$$

This representation allows every agent to look at the local electrical conditions as well as the network topology to make control decisions.

The topology-aware learning process is illustrated in Figure 2. As shown in Figure 2, the node features are aggregated through graph convolution layers and are combined with the local measurements to form enriched state representations.

3.3. Federated Multi-Agent Reinforcement Learning Framework

The voltage regulation issue is described as a Multi-Agent Reinforcement Learning (MARL) problem, and each Low-Voltage (LV) node is represented as an independent agent that interacts with the environment of the distribution network. All the agents acquire a local control policy during the process of coordinating other agents via federated learning, as outlined in Section 3.4.

3.3.1. State Representation

At time t, agent $i$observes a state s_i^t consisting of local electrical measurements and topology-aware features provided by the Graph Neural Network (GNN).

$$s_i^t = \left[x_i^t,\ h_i^{(L),t}\right]$$

Where,

- x_i^t: local observation vector (voltage, power injections, load, PV generation)
- $h_i^{(L),t}$: topology-aware embedding obtained from the GNN after layers

This combined state representation allows every agent to factor in local and neighboring network information during its decision-making process.

3.3.2. Action Space

Control action of any agent is proportional to the reactive power adjustment of the corresponding PV inverter:

$$a_i^t = \Delta Q_i^{\mathrm{PV},t}$$

This measure is under inverter operational restrictions, which make sure that the reactive power injections are not over the limit. Local control of reactive power will enable agents to manage the level of voltages and help in system-wide stability.

3.3.3. Reward Function

The reward mechanism is formulated to achieve the aims of voltage regulation, phase balancing and control with minimum effort. Reward of the agent i at time step t is:

$$r_i^t = -\alpha \mid V_i^t - V_{\mathrm{ref}} \mid -\beta U_i^t - \gamma \mid a_i^t \mid$$

where,

- α, β, γ: weighting coefficients
- V_i^t: voltage magnitude at node i
- V_{ref}: reference voltage
- U_i^t: phase unbalance index

The reward function penalizes:

- voltage deviations from the reference value
- three-phase voltage unbalance
- excessive control actions

This formulation promotes the agents to hold constant voltage profiles, and the reason is to reduce unwarranted reactive power changes.

3.3.4. Policy Learning Objective

Every agent intends to discover a policy. $\pi_i(a_i \mid s_i)$ that maximizes the expected cumulative discounted reward:

$$J_i = \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t\ r_i^t\right]$$

Where, $\gamma \in (0,1)$: discount factor; T: time horizon.

The objective function is a measure of the long-term performance of the control policy, a tradeoff between short-term rewards and stability of the system in the future.

3.3.5. Decentralized Learning Mechanism

Agents revise their policies on the basis of locally gathered experience tuples:

$$(s_i^t, a_i^t, r_i^t, s_i^{t+1})$$

Such a decentralized learning enables every agent to adjust to its local operating conditions without the need to have complete system observability. The learnt policies are periodically synchronized with the federated parameter aggregation (Section 3.4), which allows coordination of agents and ensures privacy of data.

3.4. Federated Training and Parameter Aggregation

In order to achieve privacy protection and scalability of distributed voltage control, Federated Learning (FL) is incorporated into the Multi-Agent Reinforcement Learning (MARL) architecture. Under this system, agents are not exchanging raw local information, e.g. load profiles or PV generation measurements.

They instead train a global model jointly by sharing only model parameters, which saves on the cost of communication and maintains the privacy of data. The federated training process operates in rounds, with agents updating their local policy based on the local observations and interaction data they have with the environment. These local updates enable each agent to adjust to its respective operating situations without the need to have centralized control.

In local training, every agent sends its new model parameters. $\theta_i^{(r)}$ to a central aggregation node. A weighted summation scheme is then calculated on the global model:

$$\theta^{(r)} = \sum_{i=1}^{N} w_i \ \theta_i^{(r)}$$

Where,

- $\theta_i^{(r)}$: local model parameters of agent i at federated round r
- w_i: aggregation weight associated with agent i
- N: total number of participating agents

Aggregation weights $w_i$can be chosen according to the size of the data, the quality of learning or the reliability of agents. The flexibility enables the framework to manage the heterogeneous agents who have varying conditions in the distribution network.

After obtaining the world model $\theta^{(r)}$ this is sent via broadcast to all agents. Every agent will update his or her local model with the consolidated parameters such that knowledge acquired at the network is shared without losing local flexibility. This is an iterative process that is repeated through numerous federated rounds until convergence.

The federated training system has a number of important benefits within the framework of PV-rich distribution systems:

- Decentralized learning: The learning of control policies is done by agents individually based on local observations, and no centralized data collection is required.
- Reduced communication overhead: There is also the exchange of only model parameters, which greatly reduces bandwidth requirements as opposed to sharing raw data.
- Privacy preservation: Operation data is sensitive, and thus, it is local to the individual agents, which is responsive to privacy issues in smart grid settings.
- Scalability: The framework is capable of supporting a significant number of agents with little or no significant change in communication or computational complexity.
- Robustness to communication constraints: Because updates are not continuous but periodic, the system will not go down when there is a partial loss of communication.

In general, federated learning can be integrated into the MARL framework as it allows for the efficient coordination of distributed agents without compromising privacy and scalability, which is why it is suitable to be applied to a real-world application, specifically the large-scale PV-rich distribution network.

3.5. Training Procedure

On the whole, the training procedure of the proposed Topology-Aware Federated Multi-Agent Reinforcement Learning (TA-FMARL) is detailed in Algorithm 1. The training is based on an iterative federated learning process in which several agents update their local policies independently and synchronize the global parameters on a periodic basis.

In the initial phase of the training process, global model parameters $\theta^0$are set and shared amongst all agents. At the beginning of the process, each agent initializes its own local model parameters θ_i^0 through the global model. In every federated training round $r = 1,2, \dots, R$, the global model $\theta^{(r-1)}$ is sent to all agents.Given an agent i, a topology-informed state representation s i is produced with the help of the Graph Neural Network (GNN), which is presented in Section 3.2.

According to this state, the agent chooses an action $a_i$based on its current policy π_{θ_i}, which relates to the reactive power control of the corresponding PV inverter. This is actually performed in the environment, and the agent monitors the reward. r_i and the resulting state.The transition tuple

(s_i, a_i, r_i, s_i') is stored by each agent, and local model parameters are updated by learning on the basis of a gradient. Agents send their updated model parameters. θ_i^r to the central aggregator after they have completed local updates.The global model is then computed by the weighted aggregate of the local parameters:

$$\theta^r = \sum_{i=1}^{N} w_i \, \theta_i^r$$

Where $w_i$denotes the contribution of agent i, and N is the number of agents. The new world model is then sent to all the agents, and the same is repeated until the convergence is reached.

The steps of the detailed training can be summarized with the help of Algorithm 1, which underlines the interplay between the topology-aware state representation, local updates in the reinforcement learning, and federated parameter aggregation. The combination of topology-aware representation of states with federated learning, as described in Algorithm 1, makes the coordination between distributed agents efficient and, at the same time, scalable, while preserving data privacy. The training process is especially applicable to large-scale PV-rich distribution systems where centralized control is not feasible because of communication and computation limitations.

Algorithm 1. Training procedure of TA-FMARL

Initialize: global parameters θ^0, local parameters $\theta_i^0 = \theta^0$
For each federated round $r = 1,2, \ldots, R$**:**

- Distribute the global model $\theta^{(r-1)}$To all agents
- **For each agent** i**:**
  - Generate topology-aware state $s_i$using GNN
  - Select action $a_i$using policy π_{θ_i}
  - Execute action and observe reward. r_i
  - Store transition (s_i, a_i, r_i, s_i')
  - Update local model parameters. θ_i
- **End for**
- Aggregate local models:

$\theta^r = \sum_{i=1}^{N} w_i \, \theta_i^r$

- Broadcast the updated global model to all agents

End for
Repeat until convergence.

4. Results and Discussion

In this section, the performance of the proposed Topology-Aware Federated Multi-Agent Reinforcement Learning (TA-FMARL) framework will be assessed in various operating conditions. The analysis is on the accuracy of voltage regulation, reduction of phase unbalances, convergence and resilience under communication limitations.

4.1. Simulation Setup and Test System Description

The given approach will be tested with reference to the IEEE 33-bus radial distribution network that is adapted to have distributed Photovoltaic (PV) units at various terminals.

PV penetration levels vary between 30% to 100% to represent various integration situations of renewable energy. Stochastic time-varying models are used to create load profiles to capture the realistic demand variability. Every Low-Voltage (LV) node is represented as a separate agent that has a PV inverter with the capability of controlling reactive power. The system is designed to work at 1.0 p.u. nominal, whereby the acceptable voltage limits are set at ±5%.The suggested TA-FMARL model is contrasted with the following baseline techniques:

- Centralized RL: One controller that has complete system observability.
- Conventional MARL: Topology-blind, or federated, coordination and state representation of distributed agents.

The evaluations of all methods are done under the same system conditions, control horizons and inverter constraints.

4.1.1. Performance Metrics

The analysis is done on the following quantitative indicators:

- Average Voltage Deviation:
  $\Delta V_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} | V_i - V_{\text{ref}} |$
- Phase Unbalance Index (Average):
  $U_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} U_i$
- Convergence Speed: Number of training episodes required to reach a stable reward
- Robustness: Performance degradation under communication loss.

4.2. Voltage Regulation Performance

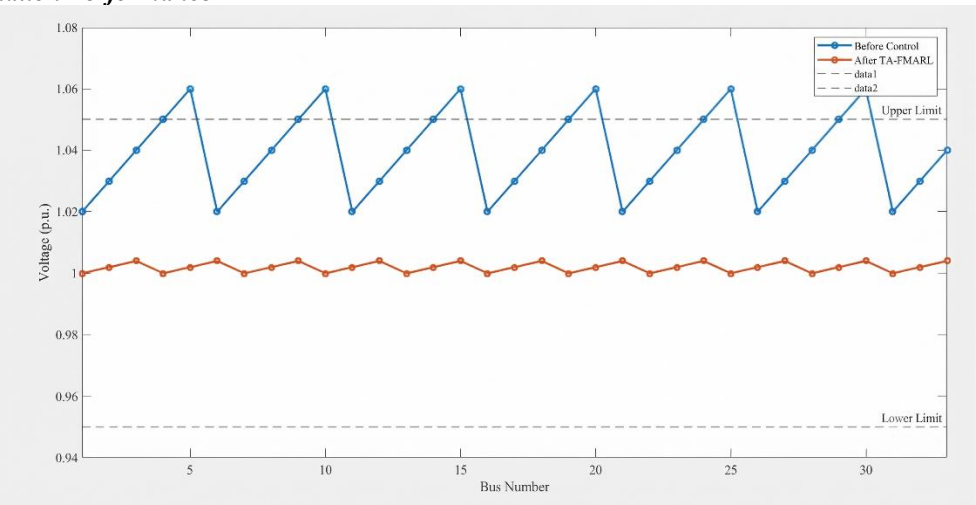


Fig. 3 Voltage profile of distribution network before and after applying TA-FMARL

The efficiency of the suggested approach in stabilizing voltage within acceptable values is assessed at different levels of PV penetration.

The uncontrolled system, as illustrated in Figure 3 shows that there is a high voltage rise in various nodes when PV generation conditions are high, and the voltage magnitudes are far above the upper limit of 1.05 p.u. The voltages of all the nodes are kept within the acceptable range after the implementation of the TA-FMARL framework. The increase in the voltage regulation is numerically defined in the decrease in the overall voltage deviation. The proposed approach has lower deviation values in comparison to centralized RL and traditional MARL, since there are two critical reasons:

1. Topology-conscious representation of states, the representation that allows agents to consider electrical interactions among adjacent nodes.
2. Federated coordination enhances consistency of learned policies among the agents.

The findings reveal that topology-sensitive learning offers superior system knowledge, resulting in superior global voltage control, even in the case of decentralized decision-making.

4.3. Phase Unbalance Mitigation

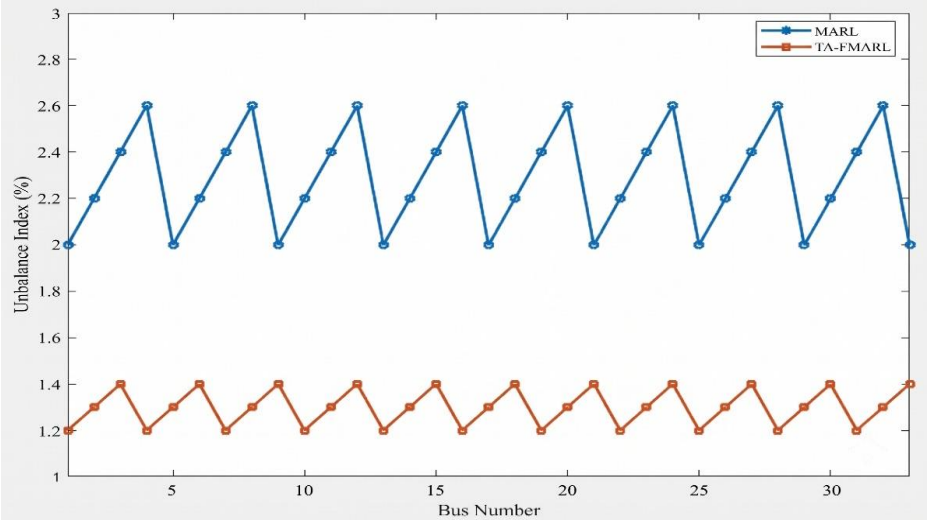


Fig. 4 Reduction in three-phase voltage unbalance using TA-FMARL

The proposed framework is also considered to minimize three-phase voltage unbalance in LV networks, besides regulating the magnitude of voltage in LV networks.

The proposed method greatly minimizes the unbalance index among various nodes as compared to baseline methods, as shown in Figure 4. Without organized control, imbalanced

single-phase load and PV systems are bound to cause high levels of unbalance. The given improvement may be explained by the dual-level control goal that also takes into account:

- MV voltage stability
- LV phase balancing

In contrast to traditional approaches, which maximize the size of the voltage, the presented reward formulation penalizes the unbalance directly, and this allows the agents to learn balanced control strategies.

4.4. Convergence Analysis

Tracing cumulative reward in the course of training analyses the convergence behavior of the proposed framework. The TA-FMARL framework converges much faster and more constantly, as illustrated in Figure 5, than centralized RL and traditional MARL.

It can be attributed to the fact that:

- State representation based on GNNs that gives richer and more informative input features.
- Federated parameter aggregation, which stabilizes learning by exchanging knowledge among agents that are subjected to different operating conditions.

The decrease of the training oscillations means that the process of learning is more stable, and the suggested method is applicable to the real-time control operations.

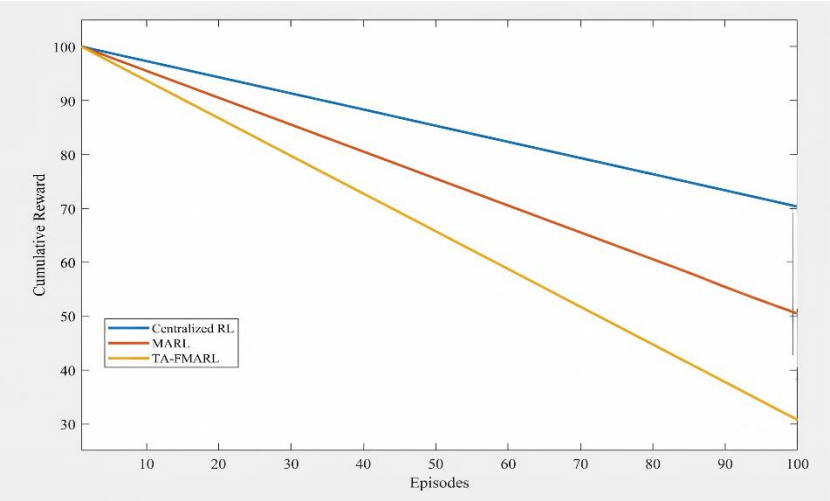


Fig. 5 Convergence curve of TA-FMARL compared to baseline methods

4.5 Robustness under Communication Constraints

In order to measure robustness, the framework is put to the test in communication-constrained environments, such as missed updates and partial loss of data.

As Figure 6 indicates, the performance loss of the proposed approach is still not too high in the case of a substantial loss of communication (e.g., 2030 percent packet loss).

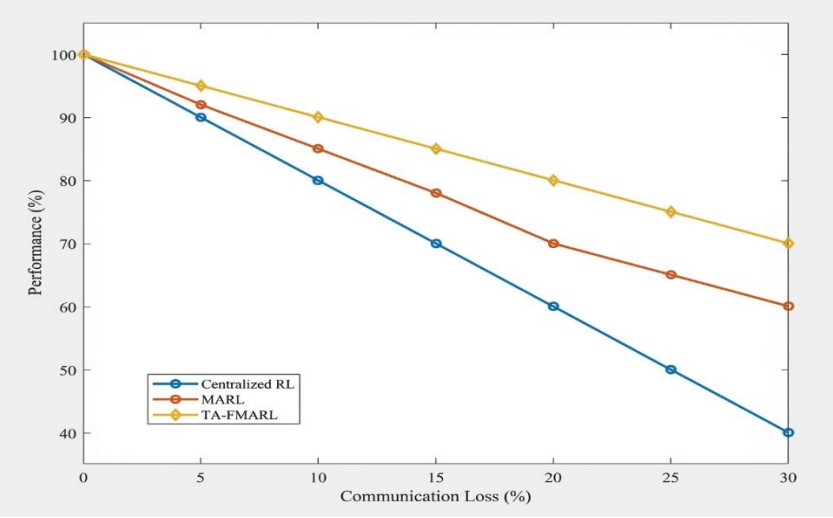


Fig. 6 Performance of TA-FMARL under communication constraints

This strength is mainly a result of:

- Local policy learning in each agent.
- Periodic, as opposed to continuous, parameter exchange.
- Aggregating the federated learning in a weighted fashion.

Contrary to centralized strategies that involve high levels of constant communication, the suggested structure can support a satisfactory performance even in the case of disconnectivity.

4.6. Quantitative Performance Comparison

A quantitative comparison of different methods is presented in Table 1.

The proposed TA-FMARL framework is superior to the baseline methods in all evaluation metrics, as demonstrated in Table 1. Specifically:

- Voltage deviation is reduced by approximately 32% compared to MARL
- Phase unbalance is reduced by approximately 33%
- Convergence is achieved with fewer training episodes
- Performance degradation under communication loss is significantly lower

These findings prove that the combination of topology-sensitive learning with federated coordination can result in better control performance and system resilience.

Table 1. Quantitative performance comparison of voltage control methods

Method	Avg. Voltage Deviation (p.u.)	Avg. Unbalance Index (%)	Convergence Episodes	Performance Degradation (20% Loss)
Centralized RL	0.035	2.8	850	25%
MARL	0.022	2.1	600	18%
Proposed TA-FMARL	0.015	1.4	420	8%

4.7. Discussion

Among the insights that are brought out in the results are:

- Importance of topology awareness: The use of GNN-based state representation enables agents to comprehend network interactions more, resulting in more coordination and voltage stability.
- Effectiveness of federated learning: Federated aggregation increases the effectiveness of learning and, at the same time, maintains data confidentiality and minimizes the communication needs.
- Dual-level control advantage: The simultaneous consideration of MV and LV voltage problems results in more natural control results.
- Scalability and robustness: The framework being decentralized renders it applicable in a large-scale distribution system with limited communication infrastructure.

In general, the offered TA-FMARL model is a feasible and efficient approach to the regulation of the voltage in the PV-contaminated distribution systems.

5. Conclusion

The given paper introduced a Topology-Aware Federated Multi-Agent Reinforcement Learning (TA-FMARL) system to coordinate the process of voltage regulation in Photovoltaic (PV)-rich distribution networks. The growing infiltration of distributed PV systems poses great operational challenges, such as voltage variations, reverse power flow, and three-phase imbalance at Medium-Voltage (MV) and Low-Voltage (LV) systems. The control strategies to handle these challenges need to be decentralized, scalable, and data efficient and can be operated under lower communication and partial observability.In this direction, the suggested framework combines federated multi-agent reinforcement learning with the state representation with the help of a Graph Neural Network (GNN). GNN can be used to ensure that each agent takes into consideration the network topology and interactions between neighboring nodes in its decision-making process, and federated learning can be used so that the policy can be trained in a decentralized manner without exchanging the raw local data. The scheme also uses the dual-level control goal, which reduces the MV voltage aggressions and LV phase imbalance. The results of the simulation of the IEEE 33-bus distribution system show that the proposed method can ensure a better performance of the voltage regulation than the centralized reinforcement learning and traditional approaches to multi-agent reinforcement learning. In particular, it was found that the results indicate a decrease in the average voltage deviation, a decrease in the phase unbalance, accelerated convergence, and enhanced robustness under the communication-constrained conditions. These improvements determine the benefits of combining topology-aware learning and federated coordination in distributed control.

Practically, the given framework has a number of benefits. First, it allows deployment on large distribution networks in a scalable manner through decentralizing control on several agents. Second, it minimizes overheads in communication and ensures data confidentiality by means of federated sharing of parameters. Third, it makes them robust as agents are able to work even in the case of partial loss of communication. The attributes render the method appropriate to smart grid applications in the real world with high penetration of renewables.Although such positive outcomes have been achieved, there are a number of shortcomings. The simulation settings of the current study have pre-determined

system settings, and it does not explicitly represent hardware-level limits, including inverter nonlinearities, measurement noise, or communication latency. Besides that, the network topology is set to be fixed, but in fact, distribution systems can be dynamically reconfigured by switching operations or faulty situations. The processing capabilities of the GNN-based learning and federated aggregation might also be hard to deploy on resource-limited edge devices. The future research will be aimed at overcoming these shortcomings and increasing the scope of the proposed framework. The introduction of dynamic topology adaptation is one of the directions that is considered important so that the learning framework can reconfigure the network on the fly. The other extension that can be considered promising is the addition of other distributed energy resources, including energy storage and electric cars, to the control system to make the system more flexible.

Moreover, communication-effective and safe federated learning mechanisms should be developed in order to guarantee the stable functioning in practice. Hardware-In-the-Loop (HIL) platforms or testbeds of the actual distribution system will also be essential in the experimental validation of the proposed approach in order to determine the real-world viability of the proposed approach. Lastly, explainable reinforcement learning techniques may contribute to a better level of transparency and help the system operators and regulatory organizations to adopt it. Altogether, the presented work has proven that topology-aware learning can be effectively combined with federated multi-agent reinforcement learning to offer an effective and scalable solution to the problem of voltage regulation in PV-rich distribution networks. The suggested framework will lead to the creation of smart grids of the next generation using smart and decentralized control methods.

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