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Behind-the-Meter Resources

Data-driven modeling, monitoring, and control.

BEHIND-THE-METER (BTM) resources are distributed energy resources (DERs), such as rooftop solar photovoltaics (PVs), electric vehicles, and battery storage systems, located on the customer side of smart meters. Driven by monetary incentives, declining costs, and increasing electricity service interruptions, the penetration of BTM resources has been increasing exponentially in the past few years. For example, the small-scale BTM solar PV capacity in the United States has quickly increased from 7,642 MWac in September 2015 to 34,029 MWac in February 2022.

On the one hand, in addition to the energy they produce, BTM resources provide a wide variety of grid services, such as peak capacity reduction, frequency regulation, voltage support, and three-phase load balancing. On the other hand, the rising penetration of BTM resources in power distribution systems causes increased voltage fluctuations, extra wear and tear on the power equipment, the degradation of power quality, escalated cybersecurity risk, and the need for more complex protection systems. The lack of visibility and high uncertainties associated with BTM resources make it challenging for electric utilities to properly model, monitor, and control these DERs. To make matters worse, many electric utilities do not have the data required to develop accurate secondary distribution network models, which include the phase connectivity of the service transformers, transformer-to-meter mapping, and distribution system line parameters.

Most of the existing tools for system modeling, monitoring, and control are based on physical models of distribution systems. These tools rely heavily on accurate models of distribution systems and BTM resources, which could be difficult for electric utilities to develop and maintain. Moreover, model-based tools often depend on optimization and control algorithms that do not scale efficiently with the number of BTM resources and the distribution grid size. Recent advances in machine learning

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(ML) technologies, which are capable of dealing with uncertainties associated with BTM resources and unknown distribution system models, make them suitable tools for managing distribution systems with high penetrations of BTM resources. To improve the modeling, monitoring, and control of power distribution systems with BTM resources, this article introduces state-of-the-art data-driven algorithms that complement model-based approaches.

Data-Driven Modeling for Distribution Systems With BTM Resources

Accurate modeling of distribution systems is crucial to the management and control of distribution systems with BTM resources. To fully take advantage of BTM resources, utilities need advanced tools, such as three-phase power flow, distribution system state estimation, three-phase optimal power flow, network reconfiguration, and volt-var control (VVC). These tools depend on accurate modeling of the distribution system. Inaccurate modeling will cause issues, such as inaccurate power flow analysis, the failure of power system protection, inaccurate hosting capacity analysis, and feeder load unbalance. The modeling information of distribution networks is usually recorded in systems, such as enterprise resource planning systems, distribution management systems, and geographic information systems (GISs). However, for most utilities, these records are either incomplete or inaccurate. During the long history of maintenance and upgrades, GIS records have accumulated errors and missing records due to undocumented network modifications. Thus, how to model the distribution system accurately becomes a significant challenge.

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Figure 1 is an example of a distribution system. The distribution system starts from a substation, which is connected to multiple feeders. Each feeder sends electric power through primary distribution lines in three phases of A, B, and C. Different distribution transformers have different phase connections—they can be single phase, two phase, or three phase. The distribution transformers step down the voltage and send electricity to customers, some of whom have installed BTM resources, such as solar PVs. This example shows the three aspects of a distribution system model: first, the phase connection and topology, i.e., how the lines and components are connected; second, the mapping between transformers and customers, i.e., which transformer serves which customers; and third, the parameters of circuit components, such as the impedance of wires. These three aspects are elaborated in the following sections.

Phase Identification

The goal of phase identification is to determine the phase connectivity of each component, such as customer and distribution transformers, in the circuit. As shown in Figure 1, a customer or transformer can be connected to a single phase (A, B, or C), two phases (AB, BC, and CA), or all three phases (ABC). In primary feeders, the topology and phase connectivity recorded by GISs are mostly correct. However, in secondary distribution networks, the GIS records of the phase connectivity of distribution transformers are usually inaccurate. Thus, the phase connections of distribution transformers need to be correctly identified.

Knowing the phase connectivity of distribution systems is crucial to accommodate the growing number of BTM resources. Unlike transmission systems, which can be treated as balanced systems and analyzed by single-phase power flow, distribution systems are usually unbalanced. In distribution systems, the lines are usually not transposed, and the electric loads in the three phases are usually unbalanced. Thus, three-phase power flow analysis is essential for the accurate management of BTM resources. If the phase connectivity is unknown or inaccurate, then system control will depend on erroneous three-phase power flow analysis, which can further cause severe unbalance and unstable voltage. In traditional practice, to identify phase connectivity, utilities send field crews to measure phase angles and determine the phase connection by using phase meters. Such practice is labor-intensive, time-consuming, and expensive. To identify phase connections more efficiently, data-driven technologies have been developed.

Current data-driven phase identification technologies can be grouped into three ML categories: unsupervised ML, supervised ML, and physics-informed ML, as follows:

- *Unsupervised ML*: Unsupervised ML discovers patterns from data without labels (i.e., correct phase connection samples). There are three typical approaches. In the first approach, customers are assigned to different phases so that, in each phase, the aggregated power consumption measured by smart meters matches the power supply measured at the feeder head. In the second approach, customers' smart meter data are compared with the supervisory control and data acquisition (SCADA) data of each phase at the feeder head. The phase that has the highest correlation is determined to be the customers' phase. In the third approach, the customers whose smart meter data are similar to one another are grouped into one cluster, and they are determined to have the same phase connection.

- *Supervised ML*: In this approach, a small number of customers' phase connections is known (i.e., "labels"). Using the labels, supervised ML algorithms can discover the relationship between smart meter data and phase connections. Based on the discovered relationship, functions are derived to determine the phase connection of unlabeled smart meters.
- *Physics-informed ML*: In this technology, based on the physical model of three-phase power flow, a precise model is developed. In this model, given the phase connections and power measurement data, smart meter voltage data can be calculated. The phase connections are then determined by minimizing the error between the calculated voltages and true values.

Table 1 summarizes the three groups of data-driven phase identification technologies. Utilities can select which technology to use based on their data availability and requirement for accuracy.

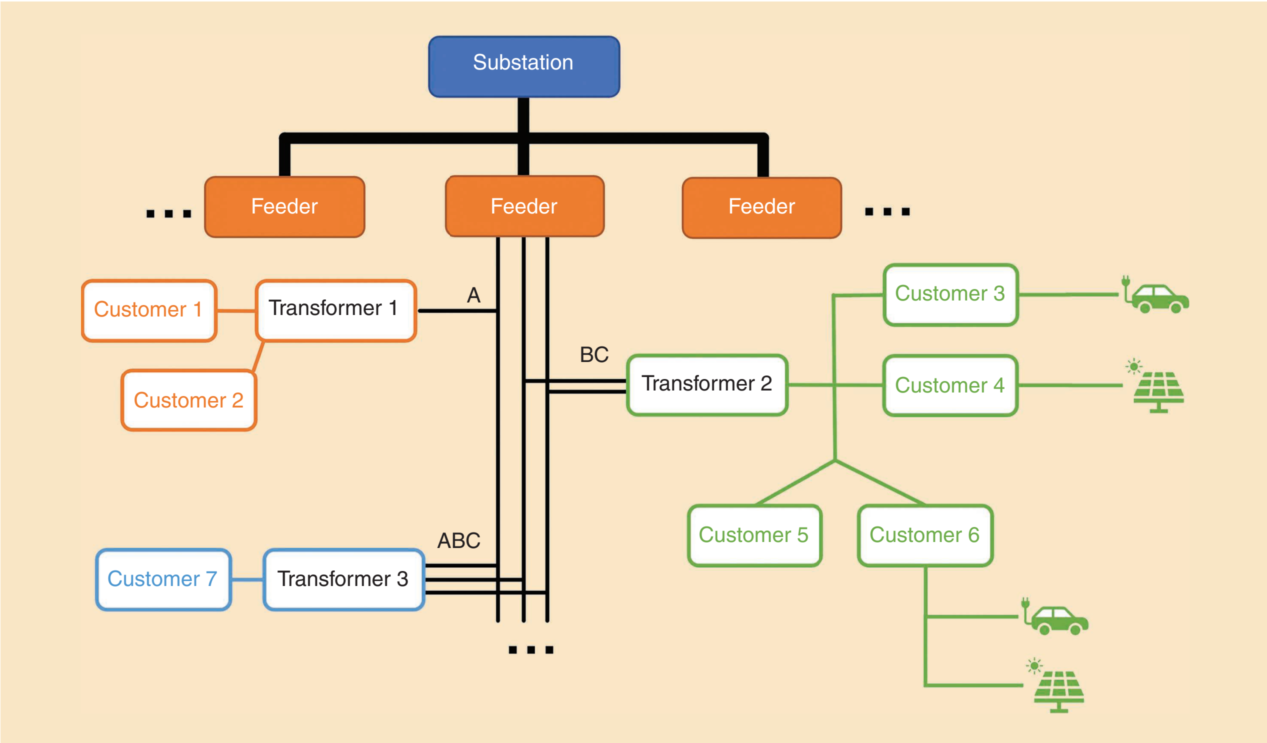

Figure 1. A distribution system model with BTM resources.

TABLE 1. A summary of data-driven phase identification technologies.

	Unsupervised ML	Supervised ML	Physics-Informed ML
Needed data and information	• Smart meter (voltage magnitude and power) • SCADA data	• Smart meter (voltage magnitude) • SCADA data • Samples of correct phase labels for transformers/meters	• Smart meter (voltage magnitude and power) • SCADA data • Physical primary feeder model and locations of smart meters
Advantages	• Accurate phase identification results • Minimum data requirement	• Higher accuracy than unsupervised ML • Does not require physical primary feeder model	• Highest phase identification accuracy • Excellent interpretability
Disadvantages	• Accuracy is not as high as the other two methods • Requires physical primary feeder model	• Less accurate than physics-informed ML • Requires samples of correct phase labels	• Requires more network information than the other two methods

Transformer-to-Customer Mapping

Transformer-to-customer mapping is an important component of the physical modeling of secondary distribution networks. It maps each distribution transformer to the customers being served. Accurate transformer–customer mapping can help analyze and coordinate the increasing BTM resources on secondary feeders. However, in current utility systems, this mapping usually contains errors and missing records. Inaccurate transformer–customer mapping hinders optimal feeder and asset capacity planning. If utilities upgrade distribution feeders on the basis of inaccurate transformer–customer mapping, then some transformers will be overloaded or underutilized. Inaccurate mapping can also impact outage management; locating outages and restoring power can be delayed.

Most of the transformer–customer mapping technologies rely on topology estimations of the secondary distribution networks. Once the secondary topology is discovered, the transformer–customer mapping can be easily determined. Some of the representative technologies are summarized as follows:

- *Voltage correlation-based approach*: In this approach, smart meters with highly correlated voltages are deemed close to one another. The correlation, the voltage level, and the known locations of customers are combined to determine the topology of secondary distribution feeders.
- *Bottom-up regression approach*: In this approach, smart meter measurements of voltage and power are used to fit regression models based on power flow. The topology of the secondary distribution feeder is built by adding customers one by one from the bottom (downstream) to the top (upstream) so that the model's error is minimized.
- *Graphical model approach based on power flow*: In this approach, graphical probability distribution models of nodal power injection and voltage are constructed based on power flow equations. By examining the conditional dependence of voltage measurements in the graphical model, the topology of the secondary distribution feeder is determined.
- *Chow–Liu tree-based approach*: This approach first finds the mutual information (which represents the mutual dependence) between each pair of customers' smart meter voltage. Then, an acyclic tree connecting all customers is built such that the mutual information among neighbors is maximized. In this way, the topology of the secondary network is discovered. The transformer–customer mapping can be determined by combining the topology, the locations of transformers and customers, and existing GIS mapping information.

In summary, the voltage correlation-based approach and the bottom-up regression approach rely on complete data records, such as customer voltage, power, and locations. These approaches may have more errors when the data are incomplete and missing. The graphical model approach based on power flow and the Chow–Liu tree-based approach require less data and are more robust in the presence of incorrect and missing meter data.

Parameter Estimation

The task of parameter estimation is to estimate the parameters, such as line impedances, of components in distribution systems. Without accurate parameters, utilities cannot perform accurate power flow analysis, which will further cause errors in the management and coordination of BTM resources. Parameter estimation in distribution systems is more challenging than in transmission systems. In transmission systems, single-phase models are widely used because the load is very balanced, and the three-phase lines are usually fully transposed. In distribution systems, however, single-phase models are not sufficient for accurate modeling because the load is less balanced, and the lines are rarely transposed. This leads to unequal diagonal and off-diagonal elements in line impedance matrices. Therefore, a three-phase model is required for the distribution system. Thus, instead of estimating one impedance, a 3×3 impedance matrix needs to be estimated for each line section.

Various technologies have been developed for parameter estimation. They can be classified into three groups based on the type of sensor data that they use. The three groups are based on SCADA data, phasor measurement unit (PMU) data, and smart meter data, which are summarized as follows:

- *Technologies based on SCADA data*: These approaches utilize SCADA data, such as power and current injections, to estimate line parameters in a single-phase model. One representative technology is joint state estimation and parameter estimation, in which suspicious parameter values are discovered by analyzing abnormal residuals in the state estimation. The correct parameters are then estimated by expanding the state vectors with suspicious parameters in a reformulated state estimation problem. The drawback is that the method is designed for single-phase transmission systems, and it is not applicable to the three-phase parameter estimation required for distribution systems.
- *Technologies based on PMU data*: These approaches utilize PMU data, such as those from three-phase voltage and current phasors, to build more accurate three-phase power flow models, which are critical for distribution feeders. However, this approach requires widespread installations of PMUs, which is quite expensive for utilities at the distribution level.
- *Technologies based on smart meter data*: These approaches utilize smart meter data, such as the voltage and power consumption of customers. One representative technique is a physics-informed graphical learning method. In this method, a graphical learning model is constructed based on

three-phase power flow. This model links three-phase line parameters and the corresponding smart meter voltage values. The correct parameters values are obtained by tuning these parameters so that the corresponding voltage approximates the actual smart meter voltage. The advantage of this approach is that the needed sensor data are readily available and applicable to three-phase parameter estimation.

To summarize, for SCADA data-based technologies, the data requirement is easy to fulfill, but it is not applicable to three-phase distribution feeders. PMU data-based technologies can work with three-phase distribution feeders, but the required data are usually unavailable. Smart meter-based technologies have advantages in both three-phase applicability and data accessibility.

Monitoring BTM Resources

The operation, control, and planning of modern distribution systems rely on the accurate monitoring of BTM resources. The monitoring of BTM resources can be classified into two domains based on the time horizon: the short term and the long term. In the short-term domain, the power generation of BTM resources needs to be monitored in real time or near real time, which is crucial for real-time control of distribution networks. Without accurate data of BTM resource generation, smart grid technologies, such as three-phase optimal power flow, network reconfiguration, and VVC, cannot be correctly applied, leading to system instability, lower efficiency, and system failures. However, BTM resources are not directly measured by smart meters. Utilities have only the net load measurement, and thus, the power generation of BTM resources needs to be estimated based on the available data.

In the long-term domain, accurate forecasts of the capacity of BTM resources in future years are crucial to the planning of grids. To accommodate the increasing number of BTM resources, distribution systems need to be upgraded and expanded accordingly. System planners need to make sure that the hosting capacity of distribution networks can meet the growth of BTM resources. Details of the two monitoring types are elaborated in the following.

Short-Term Estimation of BTM Resources

Residential solar PV systems are growing rapidly around the world. Increasing solar PV generation brings problems, such as feeder overvoltage, voltage fluctuations, reverse power flow, and protection system malfunction. However, new BTM resources with smart inverters also provide the distribution operator the capability to control the distribution system more effectively. To avoid the problems and take advantage of the new capabilities, utilities need to monitor solar PV generation accurately and then operate the distribution system accordingly.

However, direct monitoring of solar PV generation is difficult. Most residential solar PV systems are connected behind smart meters. Figure 2 presents an example of a house's net load, which is its actual load minus the solar PV generation. From the utility side, only the net load is monitored, and the actual solar PV generation is unknown. The BTM solar generation estimation is also called *net load disaggregation* because it tries to disaggregate the net load into the electric load and solar PV generation. Current net load disaggregation technologies can be classified into two groups: model-based methods and data-driven methods.

The model-based methods are based on the well-studied physical models of solar PV systems. Such models can calculate solar PV generation, given the needed parameters and inputs, including solar irradiation, solar PV size, inverter efficiency, module type, and solar PV geometry data. However, model parameters are often unreliable due to inaccurate records and PV array degradation, making pure model-based methods inapplicable to most residential solar PV systems. In comparison, data-driven methods are more applicable. These methods rely on smart meter data, SCADA data, and weather-related data, which are readily available. Data-driven methods can be further classified into two groups: supervised learning methods and unsupervised learning methods.

The supervised learning for net load disaggregation is similar to the supervised ML for phase identification, i.e., deriving prediction functions based on labeled data. Here, the labeled data are the historical solar PV generation and net load data of customers. Using the labeled data, supervised ML algorithms derive functions that map net load

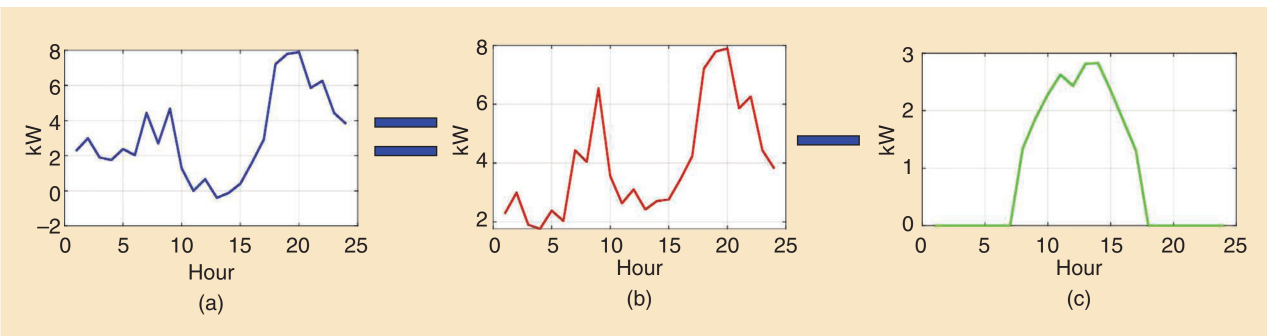

Figure 2. The net load disaggregation of a house. The (a) net load equals the (b) load minus (c) solar PV generation.

data to solar PV generation. These functions are then used to perform net load disaggregation for houses with no labels. Supervised learning methods rely on solar PV generation data, which are typically unavailable for BTM resources. Thus, their applicability is very limited.

Unsupervised learning is more applicable than supervised learning because it does not require historical solar PV generation data. Various techniques have been utilized in this approach, and, here, we describe a few representative methods:

- *Reference to historical load data*: In this method, a customer's historical load data before solar PV installation are used to estimate the disaggregated load data after solar PV installation. This assumes that the electric load patterns before and after solar PV installation are similar. This assumption may not always be true because the customer's energy consumption habits may change after solar PV installation.
- *Customer mixture model*: In this method, a customer's load is modeled as a combination of the consumption patterns of neighboring households that have no solar PVs. The solar PV generation is modeled as a function of solar irradiance. The mixture model's parameters are estimated by approximating the model's net load to the actual net load.
- *Joint estimation of the physical model and solar generation for individual customers*: In this method, the solar PV generation and the customer load are estimated iteratively. In each iteration, the solar PV generation is updated based on its physical model, the customer load is updated by fitting a hidden Markov model, and then, the solar PV physical model is updated accordingly. The method not only improves the net load disaggregation accuracy but also provides accurate estimates of the solar PV physical model's parameters, which are essential for solar PV hosting capacity analysis.
- *Joint estimation of the physical model and solar generation for a community of customers*: This method is an extension of the previous method. The main difference is that, instead of one customer, a community of customers' loads are updated while considering both the individual and population-level customer consumption behavior. This method shows more accurate net load disaggregation results.

In summary, the method based on the use of historical load data may face difficulties if there is not enough historical load data before solar PV installations and if the customer's load behavior changes significantly over time. In comparison, the customer mixture model is more applicable by using readily available data. The methods of joint estimation of the physical model and solar generation are among the state-of-art methods, which not only provide more accurate results but also estimate the parameters in the solar PV physical model, which are essential for solar PV hosting capacity analysis. Some recent research work on net load disaggregation also considered energy storage systems, electric vehicles, and demand response resources. If more granular energy consumption data become available, various nonintrusive load monitoring algorithms can be applied to separate entire electricity usage into appliance-specific individual components.

Long-Term Estimation of BTM Resources

Facing the challenges brought by BTM resources, such as feeder overvoltage, voltage fluctuations, reverse power flow, and protection malfunction, distribution systems need modernization accordingly. This modernization includes infrastructure upgrades and the application of smart grid technologies. The long-term estimation of BTM resources is crucial to feeder planning/upgrades. Utilities need to make sure that the hosting capacity of distribution networks meets the requirements of the fast-growing BTM resources. Overestimating the BTM resources will lead to overinvestment in infrastructures. Underestimating may lead to distribution system malfunction due to an inability to handle the BTM resources. In some cases, BTM resources can also be used to defer some feeder upgrades if the distribution system operator can control those resources appropriately.

The goal of the long-term estimation of BTM resources is to forecast the BTM resource installations in the future. The installation depends on many influential factors, listed as follows:

- *Time*: Adoption rates of BTM resources vary across different years. In recent years, we have seen an ever-increasing number of BTM resources. Typically, the adoption speed will increase in the early-to-middle stage, due to increasing popularity, and then gradually slow down when the market saturates.
- *Location and climate*: These are very influential. For example, places that have a larger number of sunny days have higher potential in solar power generation and solar PV adoptions.
- *Cost and benefit*: The dropping price of solar PV has made solar power more affordable. The net metering programs enable customers to reduce electricity bills and sell excess power to utilities, which further encourages adoption of solar PVs. In addition, government incentives have boosted solar PV adoption. Similar approaches are being used to promote the adoption of other types of BTM resources, such as energy storage.
- *Social and economic conditions*: These conditions include population, education, income, age, and so on. For example, customers with higher income may be more capable of purchasing BTM resources, such as solar PVs and electric vehicles. Education may influence people's recognition of new technologies and awareness of environmental protection.

Existing techniques for long-term BTM resource estimation can be classified into two groups: aggregate diffusion modeling (ADM) and agent-based modeling (ABM). They are explained as follows:

- *ADM*: This approach uses aggregate models to estimate BTM resource adoption under influential factors. It focuses on the behavior of the whole group of customers. These models are estimated by fitting them to the historical adoption data through regression techniques. For example, in the famous Bass diffusion model, the adoption rate is determined by two factors: the innovation factor (representing innovative customers actively buying new products) and the imitation factor (representing customers imitating others). Other influential factors, such as costs, benefits, and incentives, can also be integrated into the model.
- *ABM*: This approach describes customers as unique, autonomous, and adaptive agents. These agent models are assumed to have different characteristics, act independently, and interact with their neighbors. The agents' behaviors are simulated in Monte Carlo experiments, and the model parameters are estimated by minimizing the error between the simulated adoption and the actual adoption data. The estimated models are then used to perform long-term BTM resource estimation.

To summarize these two groups of methods, ADM describes the social dynamics of customer behaviors in a macroscopic view. It has limitations in describing individual customers' characteristics, but it has the advantage of requiring fewer data. ABM is stronger than ADM in describing individual customer's behaviors, but it requires detailed customer data, which are often difficult to collect.

Data-Driven Control of Power Distribution Systems With BTM Resources

As the adoption of BTM resources in power distribution systems and buildings continues to increase, the need to manage the operations of DERs becomes more urgent. From the perspective of distribution system operators (DSOs), the operation of BTM resources needs to be coordinated to ensure system reliability. From the perspective of building operators, the BTM resources should be controlled to lower electricity costs and reduce electricity service interruptions. Due to the lack of reliable distribution network and building models, data-driven control solutions are becoming more suitable alternatives to the physical model-based control technologies. There has been a tremendous amount of research and development in the area of data-driven control for power distribution systems with BTM resources, due to the rapid advancement in ML. The availability of near-real-time data from advanced metering infrastructure systems, SCADA, microsynchrophasor measurement units, and building control systems is making the data-driven control technologies feasible for real-world implementation. We cover a promising data-driven control solution for power distribution systems with BTM resources in the following section.

Data-Driven VVC of Power Distribution Systems With BTM Resources

VVC determines the operation schedule of voltage regulating and var control devices in the power distribution system as well as the real and reactive set points of BTM resources, such as solar PV systems and battery storage systems, to improve voltage quality, reduce network losses, and lessen wear and tear on power equipment. The rapid growth of solar PV systems and electric vehicles makes it difficult for DSOs to keep all voltages within appropriate limits. VVC is typically executed within a two-timescale framework. In the slow timescale, the set points of voltage regulators, on-load tap changers, and capacitor banks are adjusted on an hourly basis to improve the voltage profile and reduce equipment wear and tear. In the fast timescale, the active and reactive power set points of smart inverters connected to solar PV systems and energy storage systems are changed to fine-tune voltages and further reduce network losses on a minute-to-minute basis.

The existing model-based VVC methods can be categorized into two schemes: centralized and distributed. In the centralized approach, the central controller, which has a complete model of the distribution network, collects measurements of the distribution feeder and BTM resources and makes control decisions autonomously. Typical methods used in the centralized VVC scheme include deterministic optimization and robust optimization. In the distributed approach, each voltage regulating device can sense local grid conditions and communicate with neighboring equipment to make coordinated VVC decisions. It is challenging to deploy physical model-based VVC algorithms in distribution circuits, due to the lack of accurate distribution network models. To tackle this challenge, data-driven methods are developed, which learn to choose control actions based on the operational data. In practice, many electric utilities, such as Southern California Edison, are either considering or already switching to data-driven VVC solutions.

Reinforcement learning (RL) is emerging as one of the most promising data-driven approaches to solve the VVC problem, which is essentially a sequential decision-making task. RL teaches the controller(s) to make a good sequence of voltage regulating decisions, which yield proper control outcomes by using historical and/or real-time operational data. RL leverages the framework of the Markov decision process (MDP) to define the interactions between a learning agent (e.g., the volt-var controller) and its environment (e.g., the power distribution grid). The volt-var controller and the distribution system environment interact at each point in a sequence of discrete time steps, as depicted in Figure 3. At each time step, the volt-var controller collects the state of the distribution system and, on that basis, selects the control set points of voltage regulating devices and BTM resources. One time step later, in part, as a consequence of the control actions, the volt-var controller receives a numerical reward, and the distribution system environment transitions into a new state.

The action of the volt-var controller agent is defined as changing the set points of voltage regulating devices and BTM resources to new levels. The state of the distribution system environment could include nodal real and reactive power injections, nodal voltage magnitudes, the current settings of voltage regulating devices and BTM resources, and the global time. The reward function is often defined as the negative of the operational cost, which includes the cost of power losses, device switching costs, and voltage constraints violation costs. The goal of the volt-var controller agent is to learn the optimal policy, which yields the highest sum of discounted rewards within the control horizon. The policy learned by the volt-var controller agent maps states to probabilities of selecting each possible control action. There are two value functions associated with a policy, called the *state value function* and *action value function*, which estimate how good it is for the agent to be in a given state and to take a given action in a given state and follow the policy thereafter.

Once the VVC problem is formulated as an MDP, it can be tackled with a wide range of RL algorithms. The RL algorithms can be divided into three groups: value-based methods, policy-based methods, and actor–critic methods. In value-based methods, the RL agent tries to learn the state and action value functions and use them to make control decisions. In policy-based methods, the RL agent approximates the optimal policy directly without the need to learn the value functions. In actor–critic methods, the actor tries to update the learned policy, while the critic tries to improve the estimates of the value functions.

Although RL has been successfully demonstrated in many complex sequential decision-making problems (e.g., the game of Go), there are many challenges to deploying it to control real-world distribution systems with BTM resources. Some of these challenges and their proposed solutions include the following:

- *Sample efficiency of RL algorithms*: It is expensive to allow the RL-based volt-var controller to interact with the real-world power distribution system. An RL-based volt-var controller requires a large amount of training data to learn a good policy. To improve the sample efficiency of RL-based VVC algorithms, off-policy RL algorithms are developed in favor of on-policy algorithms. Off-policy RL algorithms evaluate and improve the target policy that is different from the behavior policy, which is used for action selection. In on-policy RL algorithms, the target policy and the behavior policy are the same. Thus, off-policy RL algorithms significantly improve the sample efficiency by allowing the use of the historical operational data generated from any controller, which also include the VVC actions taken by the human operators. To further improve the sample efficiency of RL-based VVC algorithms, one could train surrogate models and environment transition functions to emulate the operations of the distribution system. Once trained, surrogate models can be leveraged to generate additional synthetic training samples.
- *Safety of RL algorithms*: RL-based volt-var controllers must be capable of operating the distribution system in a safe manner even during unforeseen operating conditions, such as changes in network topology and BTM resources. The critical operational limits of the distribution system have to be satisfied all the time. To improve the safety of RL-based VVC algorithms, many safe RL algorithms have been developed. One approach to enforce safety constraints is to formulate the VVC problem as a constrained MDP by augmenting the original MDP with a cost function associated with the operating limits. The goal of the volt-var controller is to minimize the total operational cost while ensuring that the expected discounted return with respect to the cost function is less than a limit. The other widely used approach is to add a safety layer to the policy neural network to improve operational constraint satisfaction.
- *Coordination among multiple agents*: When the penetration level of BTM resources is high, the RL-based volt-var controller needs to properly coordinate the operations of conventional voltage regulating devices in the slow timescale, with BTM resources in the fast

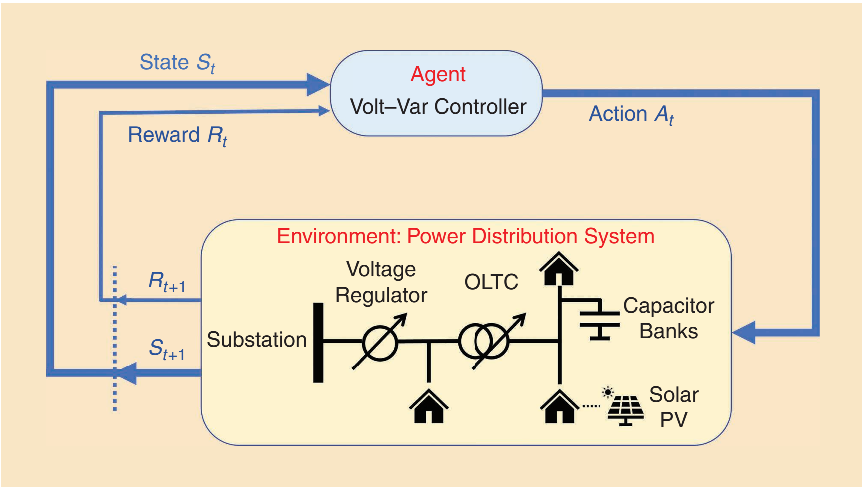

Figure 3. VVC through RL. OLTC: on-load tap changer.

timescale. Crucial state, action, and reward information should be shared between slow timescale agents and fast timescale agents. Two-timescale RL-based VVC algorithms have been developed that allow the control policies of the fast timescale and slow timescale agents to be learned concurrently to maintain the feeder voltage profile. To further improve the scalability of the RL-based VVC algorithm, multiagent RL algorithms have been proposed to coordinate the operations of individual voltage regulating devices. For example, a consensus multiagent RL algorithm has been developed, where each agent (e.g., a BTM resource) learns two parametric models to approximate the global state value function and the local policy.

- *Combining operator intelligence with RL*: Although deep RL (DRL)-based VVC algorithms have been successfully demonstrated in simulation environments, they have not been deployed in real-world distribution systems. One of the bottlenecks of adopting DRL-based VVC is that the learned control policies are represented by deep neural networks, which are difficult for system operators to interpret. To improve the acceptance of DRL-based control in power distribution systems, we must try to figure out a way to synergistically combine operator intelligence with RL algorithms. One promising approach to augment operator intelligence with the RL algorithm is batch-constrained RL. In batch-constrained RL, the RL agent has access only to a fixed amount of VVC experience from the system operator to learn from. To mitigate estimation bias, the volt-var controller will first create a generative model to emulate the decision-making model of the operator or a heuristic controller. Then, the batch RL algorithm will try to learn a VVC policy that not only maximizes the control objective but also minimizes the difference between the learned policy and the control policy of the system operator.

Conclusions

Power grids around the world are transitioning from a scheme that is dominated by large-scale centralized power plants to a network populated with a large number of DERs. Advanced modeling, monitoring, and control tools are critically needed to unleash the full potential of BTM energy resources and mitigate their impacts on power systems. Inaccurate power distribution system models and a lack of visibility make it challenging to deploy physical model-based monitoring and control for BTM energy resources. This article summarized some of the latest developments in data-driven modeling, monitoring, and control techniques for power distribution systems with BTM resources. To improve the modeling of distribution systems' secondaries that directly connect to BTM resources, promising data-driven techniques have been developed to identify phase connections, conduct transformer-to-customer mapping, and estimate distribution network parameters. To better monitor BTM resources, such as solar PV systems, physics-informed data-driven algorithms were developed to estimate solar PV system generation based on net load data. The prediction of the adoption of BTM resources has also been extensively explored. Data-driven control algorithms, such as RL-based VVC, have been shown to be effective in mitigating the impacts of BTM energy resources on the power distribution grid.

Although data-driven algorithms have shown great potential in addressing the integration problems for BTM resources, further research is needed to develop physics-based ML algorithms. Specifically, the physical models of BTM resources and steady-state and dynamic models of the power distribution system may be seamlessly integrated with advanced ML models. The graphical model of power distribution systems can also be explicitly considered in the data-driven solution. The physical models could be used to introduce inductive bias in ML models to make them generalize better to unforeseen scenarios, with a limited amount of training data.

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For Further Reading

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