Autonomous Energy Grids

Controlling the Future Grid With Large Amounts of Distributed Energy Resources

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THE DRASTIC PRICE REDUCTION in variable renewable energy, such as wind and solar, coupled with the ease of use of smart technologies at the consumer level, is driving dramatic changes to the power system that will significantly transform how power is made, delivered, and used. Distributed energy resources (DERs)—which can include solar photovoltaic (PV), fuel cells, microturbines, gensets, distributed energy storage (e.g., batteries and ice storage), and new loads [e.g., electric vehicles (EVs), LED lighting, smart appliances, and electric heat pumps]—are being added to electric grids and causing bidirectional power flows and voltage fluctuations that can impact optimal control and system operation. Residential solar installations are expected to increase approximately 8% annually through 2050. Customer battery systems are anticipated to reach almost 1.9 GW by 2024, and current forecasts project that approximately 18.7 million EVs will be on U.S. roads in 2030. With numbers like these, it is not unreasonable to imagine a residential electricity customer having at least five controllable DERs. In future

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electric grids, as more DERs are integrated, the number of active control points will be too much for current control approaches to effectively manage.

Imagine, for example, the San Francisco Bay Area, which has a large distribution system with approximately 4.5 million customers. Figure 1 illustrates synthetic distribution systems of the Bay Area made from actual data that have been created to replicate properties of the actual systems, including various voltage levels and both wye and delta connected circuits. What if each customer had a PV system, a battery energy storage system, an EV, a smart thermostat, and controllable lighting loads? This would amount to approximately 10–20 million controllable devices capable of producing, storing, and consuming electricity. Currently, there are no control systems capable of ingesting 20 million data streams and making real-time operation decisions.

In current large-scale grids, such as the Eastern Interconnection in the United States, central station power plants provide power to loads and have on the order of 10,000 points of control. Current control systems work well when there are a limited number of active control points in the system, but to deal with the massive amounts of new DER technologies and the availability of grid measurements, a new control framework needs to be developed. The framework needs to

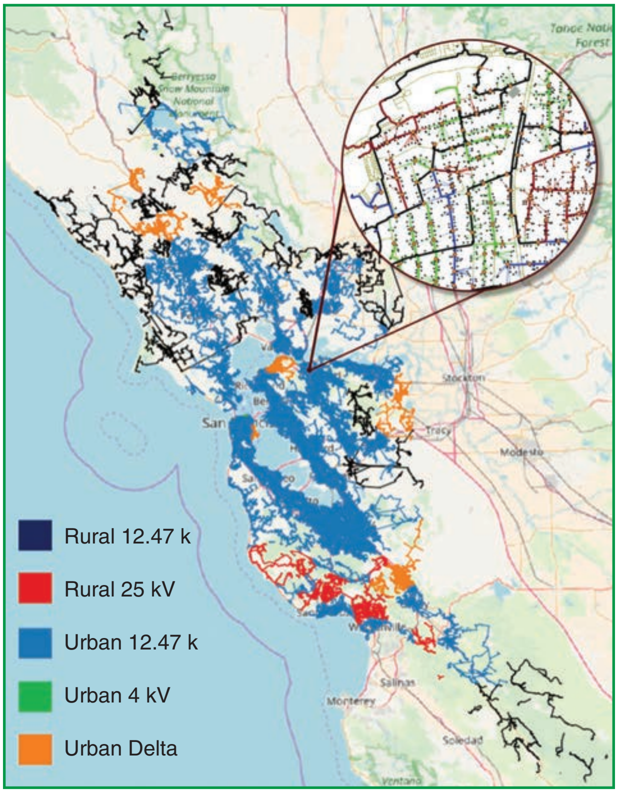

figure 1. This is the San Francisco Bay Area synthetic distribution system, developed under the ARPA-E GRID DATA program. Line configurations are mostly wye with a small amount of delta. (Source: grid data: NREL; map: OpenStreetMap.org.)

monitor, control, and optimize large-scale grids with significantly high penetration levels of variable generation and DERs; it needs to process the deluge of data from pervasive metering; and it needs to implement a variety of new market mechanisms, including multilevel ancillary services. To handle this highly distributed energy future, we propose the concept of autonomous energy grids (AEGs).

Autonomous Energy Grids: The Concept

AEGs are multilayer, or hierarchical, cellular-structured electric grid and control systems that enable resilient, reliable, and economic optimization. Supported by a scalable, reconfigurable, and self-organizing information and control infrastructure, AEGs are extremely secure and resilient, and they can operate in real time to ensure economic and reliable performance while systematically integrating energy in all forms. AEGs rely on cellular building blocks that can both self-optimize when isolated from a larger grid and participate in optimal operation when interconnected to a larger grid. Figure 2 shows how a scalable approach to control can be built from the lowest level of individual controllable technologies (renewable energy, conventional generation, EVs, storage, and loads) and used to control hundreds of millions of devices through hierarchical cells. In the figure, the bottom level consists of individual technologies that are aggregated into small cells. Then, each upper level represents a collection of cells until the entire grid is covered. Within each layer, distributed controls are used to optimize energy production and meet system requirements. There is minimal information passed between layers, and this hierarchical approach enables the control of hundreds of millions of devices.

To make this idea a reality, control algorithms for AEGs will need to be developed and implemented with the following characteristics:

- ✔ *Operate in real time*: Control algorithms must operate fast enough to ensure real-time operations in electric grids that balance load and generation every second.
- ✔ *Handle asynchronous data and control actions*: Data need to be used from a variety of asynchronous measurements and sources, whereas distributed decision making leads to asynchronous control actions.
- ✔ *Robustness*: This covers both reliability and resilience, where reliability is fault tolerance, and resilience is the ability to come back from a failed state. These control systems also must be robust to communications failures, prolonged communications outages, and large-scale disturbances.
- ✔ *Scalable*: Control algorithms must operate in a scalable fashion to ensure control of hundreds of millions of devices.

We will discuss these characteristics in detail in the following sections.

Operate in Real Time

One key challenge with AEGs is the development and implementation of real-time optimization and control methods. We use the term *real time* to indicate that power set points of the DERs are updated within each cell on a *second or subsecond* timescale. Electric grids must maintain energy balance at every time instance. This is required to maximize the operational and economic objectives while coping with the variability of ambient conditions and noncontrollable energy assets and achieving intercell coordination to ensure reliable systemwide operation. Solving optimization problems to convergence every second or every few seconds, however, has been impractical because of the following challenges:

- ✔ *Complexity and convergence analysis.* For large-scale grids, the computational complexity of a centrally defined system could prevent the solution of optimization problems at the required timescales. When an optimization problem is solved in a distributed and/or hierarchical fashion (e.g., with device-to-device or cell-to-cell communications as well as intracellular message passing), multiple communications rounds are necessary to converge to (possibly optimal) solutions. Note that the optimization tasks related to AEGs are markedly different from traditional settings in which energy systems are optimized at the wholesale level using economic- and market-based objectives. In the traditional operation of bulk systems, a few large-scale generators are dispatched, and the noncontrollable net load varies slowly. Such operation is incompatible with AEGs that include a massive integration of DERs or whose optimization models require accurate representations of ac power flows within the DERs' controllability region. In traditional bulk systems, optimization problems are nonconvex, nondeterministic, and polynomial-time hard (NP-hard); therefore, they may be infeasible to solve at the envisioned timescale with hundreds of millions of control points. To address these challenges and facilitate the development of provably stable and optimal distributed solution methods for AEGs, a first step is to develop convex relaxations and linear approximations of pertinent nonconvex problems.
- ✔ *Model inaccuracy.* Approximate linear models or convex relaxation methods might be leveraged to derive convex problems that facilitate the design of computationally affordable solutions. However, approximate/relaxed convex problems might involve only an approximate representation of a system's physics and constraints; therefore, the optimal solutions of the convex problem might not be feasible for the original problem. To begin to address this issue, distributed optimization algorithms have been developed to use measurement information directly, which is known as online optimization with feedback. Measurement-based (or feedback-based) algorithms address the feasibility issue, and they can be distributed or centralized. The design of a distributed version is certainly more challenging than the centralized one, but the distributed version can be implemented on a more flexible communications architecture, which can enhance cyber robustness.

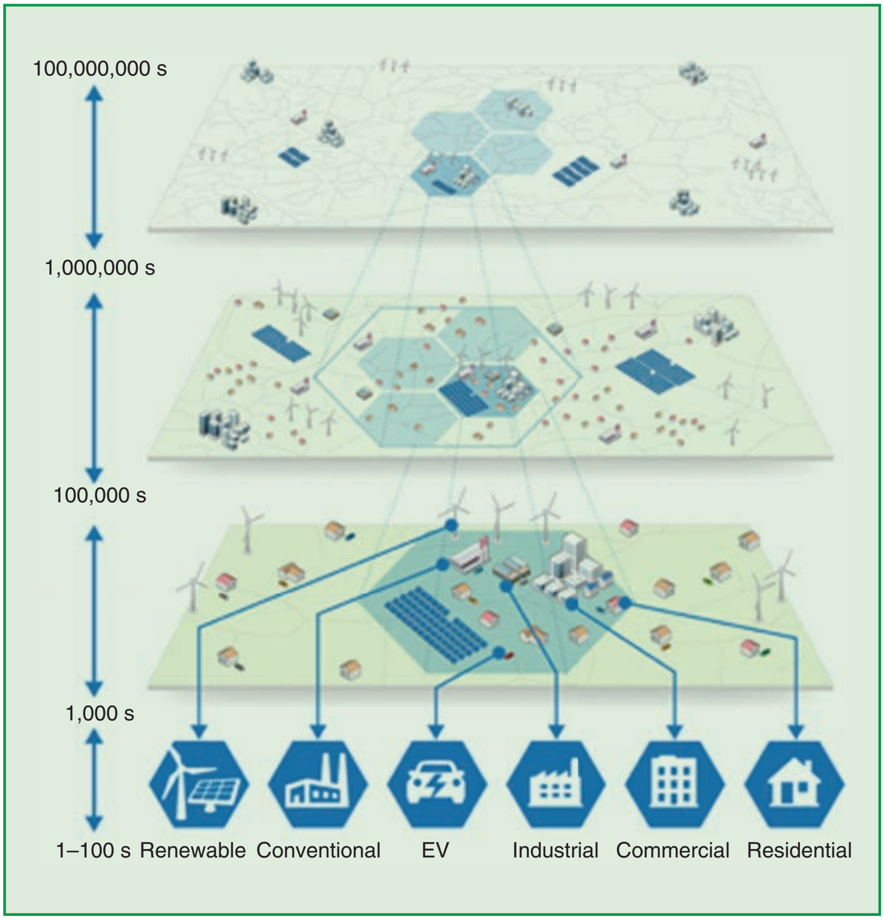

figure 2. The AEGs form a distributed hierarchical control system that integrates individual technologies in a cellular structure to the bulk power system. The scale on the side indicates the number of controllable technologies seen along the bottom level. The lowest level depicts the locations of various generation, storage, and loads.

- ✔ *Pervasive metering.* Solving optimization problems using relaxations/linearizations of the ac optimal power flow (OPF) requires pervasive metering to collect measurements of the noncontrollable loads at all locations in real time, which might be impractical. One way to address this problem in the large-scale grid of the future is to develop and implement distributed state estimation algorithms that can provide insight into the state of the system without having to explicitly measure every point of interest.

To address these challenges within the AEG cells, a real-time optimization framework has been developed at the National Renewable Energy Laboratory (NREL) under the Network Optimized Distributed Energy Systems (NODES) program within the U.S. Department of Energy's Advanced Research Project Agency-Energy (ARPA-E). The framework can model well-defined objectives and constraints of DERs located within each cell as well as consistency constraints for electrical quantities that pertain to the cell-to-cell connections. By using measurements in the system as a feedback mechanism and tracking optimal solution trajectories, the resultant feedback-based online optimization methods can cope with inaccuracies in the representation of the ac power flow and avoid having to measure all the noncontrollable resources. Figure 3 demonstrates how voltage and current measurements are used as feedback to better track the optimal trajectory of a large-scale system by sending a price signal that embeds cost functions, reliability functions, and system constraints.

The algorithm enables DERs to track given performance objectives while adjusting their power [the real power (P) and reactive power (Q) set points] to respond to services requested by grid operators and maintain electrical quantities within engineering limits. The design of the algorithm leverages primal-dual gradient methods that improve the convergence rate of the optimization problem, allowing the algorithms to take advantage of the structure of the problem and be solved in real time. The gradient governs which direction and how fast to search for the next iteration in the optimization, and it can be suitably modified to accommodate appropriate measurements from the distribution network and the DERs. Primal-dual gradient methods can be implemented in real time because every gradient iteration is computationally cheap (very fast to compute); however, this method usually has a fast convergence rate when referred to the number of iterations required for the algorithm to converge. The resulting algorithm can cope with inaccuracies in the distribution system modeling; moreover, it avoids pervasive metering to gather the state of noncontrollable resources, and it naturally lends itself to a distributed implementation. Analytic stability and the convergence of optimally tracking the solutions of the formulated time-varying optimization problem is established. Figure 4 depicts how the real-time algorithm uses active and reactive power set points for a single DER (blue line) to track an optimal trajectory (red line).

Hierarchical Communications and Asynchronous Data

To enable the real-time optimization of AEGs with millions of controllable devices, a hierarchical communications architecture that includes cell-to-cell and cell-to-customer message passing can be formulated to manage these devices. Mathematically, to obtain consistency among cells, constraints are added to the optimization problem to ensure that adjacent cells agree on the power flows from one cell to another. This is known as consensus-based optimization. Overall, the resultant feedback-based online optimization methods need to provably track the solution of the convex optimization problems by modeling well-defined objectives and constraints for each cell as well as the consistency constraints for electrical quantities that pertain to the cell-to-cell connections. The feedback-based method also works for nonconvex problems; however, analytic proof of convergence for the feedback-based method is very tricky and not well established. These cell connections can be geographically

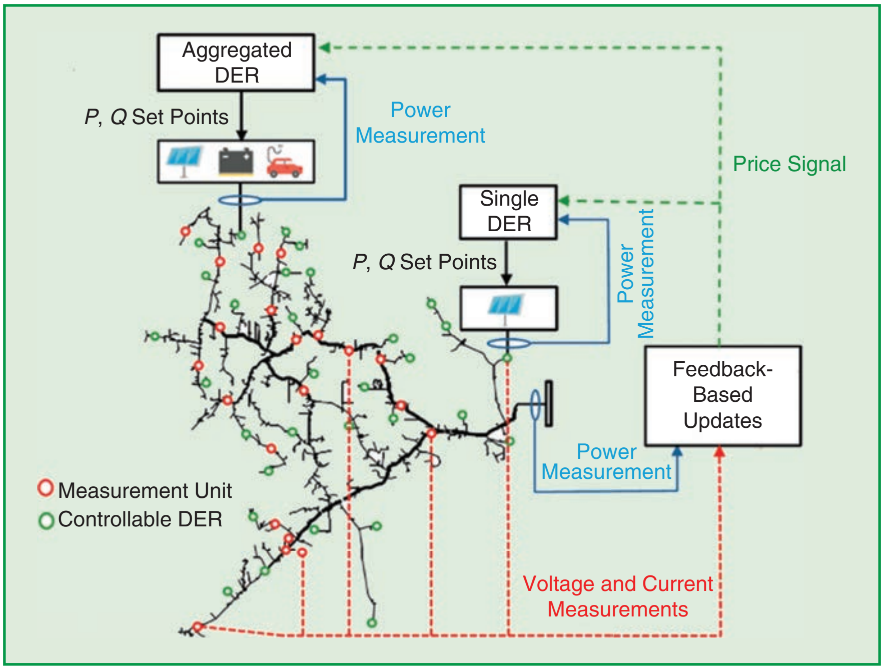

figure 3. These measurements are used as a feedback mechanism for DER control. Real (P) and reactive (Q) power are used to optimize conditions on the distribution circuit.

colocated or based on aggregators, such as smart-home aggregators. In this sense, it is worth emphasizing that the design of the distributed algorithm as well as the overall communications strategy will depend on the types of actors participating in the real-time optimization process (e.g., end customers, cell controllers, or aggregators).

In addition to the influx of DERs, the installation of new sensing and measurement technologies (e.g., smart meters and distribution-level phasor measurement units) will drastically improve the observability of grid conditions at the distribution level. To take advantage of all the available measurements, algorithms must be able to operate in an asynchronous way to account for different communications latencies and for devices that can be controlled at different timescales (e.g., inverter-interfaced devices are controlled at fast timescales, whereas thermostatically controlled loads are controlled every few minutes). Analytic proof of convergence can be tedious, but it is widely accepted that gradient-based algorithms can be implemented asynchronously.

Robustness

In the context of AEGs, robustness includes both reliability and resilience. Reliability is the property to be tolerant to faults, and resilience is the ability to come back from a failure to an operational state. For reliable operation, stability analysis can be used at multiple timescales. Resilience to communications drops and asynchronous operation should be analytically established through pertinent input-to-state stability and tracking results. In other words, the AEGs should be able to continue operating even in the presence of these faults/errors. Mathematically, iterative optimization algorithms have been developed to operate with errors in their estimated parameters, such as gradients. In fact, it can be shown that a packet loss leads to the computation of primal or dual gradient steps with outdated information. Thus, cells that can switch from an islanded mode to a larger grid-connected mode may continue operating amid faults and/or threats to the grid. These properties can be modeled as time-varying constraints in the underlying optimization problem. Similarly, flexible operation, in which a cell (or a portion of a cell) switches to an autonomous control setting during a prolonged communications outage, should be enabled.

Scalability

Figure 5 illustrates an architecture in which communications among cells occur when performing distributed and/or hierarchical control. As mentioned previously, distributed and hierarchical control algorithms are scalable and allow for the control of millions of devices in real time. When using distributed/hierarchical controls, the problem is broken up into smaller "cells," and the interactions among cells can be reconciled using consensus to ensure consistency constraints for electrical quantities that pertain to the cell-to-cell connections. For example, adjacent cells must agree on the real and reactive power exchanges at the points of interconnection or overlap.

Real and reactive power set points from the optimization are sent between levels in the hierarchy. Intracellular communications (on the same level) can be used to ensure that the set points of the DERs are computed to maximize the given operational objectives while ensuring that electrical limits are satisfied within the cell. Communications also

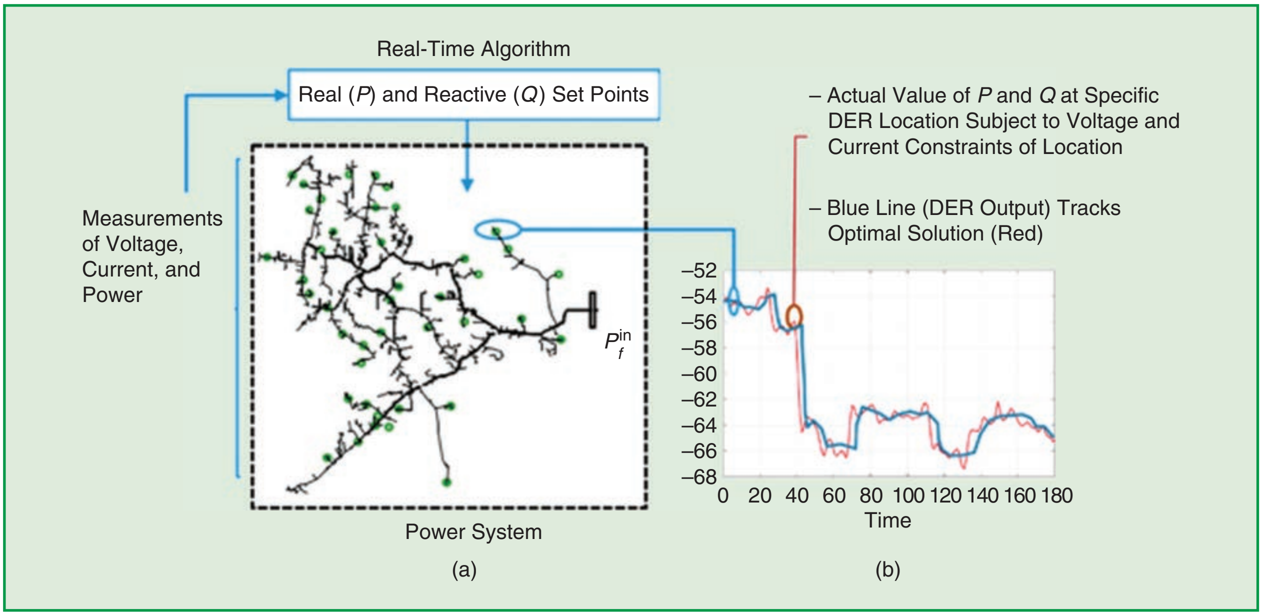

figure 4. The real-time algorithm tracks the optimal solution. (a) Green dots on the map indicate DER and measurement locations. (b) The graph shows only the real power (P) set point in red and the actual DER power output in blue for one DER location.

take place between a cell-level control platform and individual customers; these are necessary to optimize customer-level objectives while respecting electrical limits within a cell. Message passing among cells to optimize the flow of power is based on economic and reliability targets. These levels of hierarchy allow for scalable distributed optimization algorithms to be designed and implemented in AEGs.

Figure 5 presents three levels of hierarchy. The top level, level 3, aggregates neighborhoods to achieve an optimization objective, such as voltage regulation or power balancing. This level communicates to level 2 (e.g., a single neighborhood) about the aggregated power designated for that neighborhood. This information is passed from the neighborhood level down to the homeowner, level 1, as a power set point to track. The homeowners might accordingly coordinate their own distributed wind or solar, smart-home devices, and EVs to optimally balance the grid needs and their own usage preferences. Communications run in both directions, as indicated in Figure 5. For example, if homeowners are unable to meet their power set points, information is passed back up to level 2 (e.g., via monitoring the aggregate power of the neighborhood) to indicate this, and the optimization is repeated until each agent in the cell has reached a feasible solution that achieves the global objective as well as individual satisfaction.

After demonstrating that distributed control concepts can work on a single distribution circuit, the goal is to implement a hierarchical control scheme that would allow true scalability. This work considered a potentially large distribution network controlled cooperatively by several networked AEGs. Figure 6 is an illustration of this work. A regional coordinator communicates with all the dispatchable nodes within each AEG cell, and a central coordinator communicates with all the regional coordinators. Each regional coordinator knows only the topology and line parameters of the cell that it controls, and the central coordinator knows only the topology and line parameters of the reduced network, which treats each cell as a node and connects all the cells. Given such information availability, we explored the topological structure of the linearized power flow model to derive a hierarchical, distributed implementation of the primal-dual gradient optimization algorithm that solves an OPF problem. The OPF problem minimizes the total cost of all the controllable DERs and a cost associated with the total network load subject to voltage regulation constraints. The proposed implementation significantly reduced the computational burden compared with the centrally coordinated implementation of the primal-dual algorithm, which requires a central coordinator for the whole network.

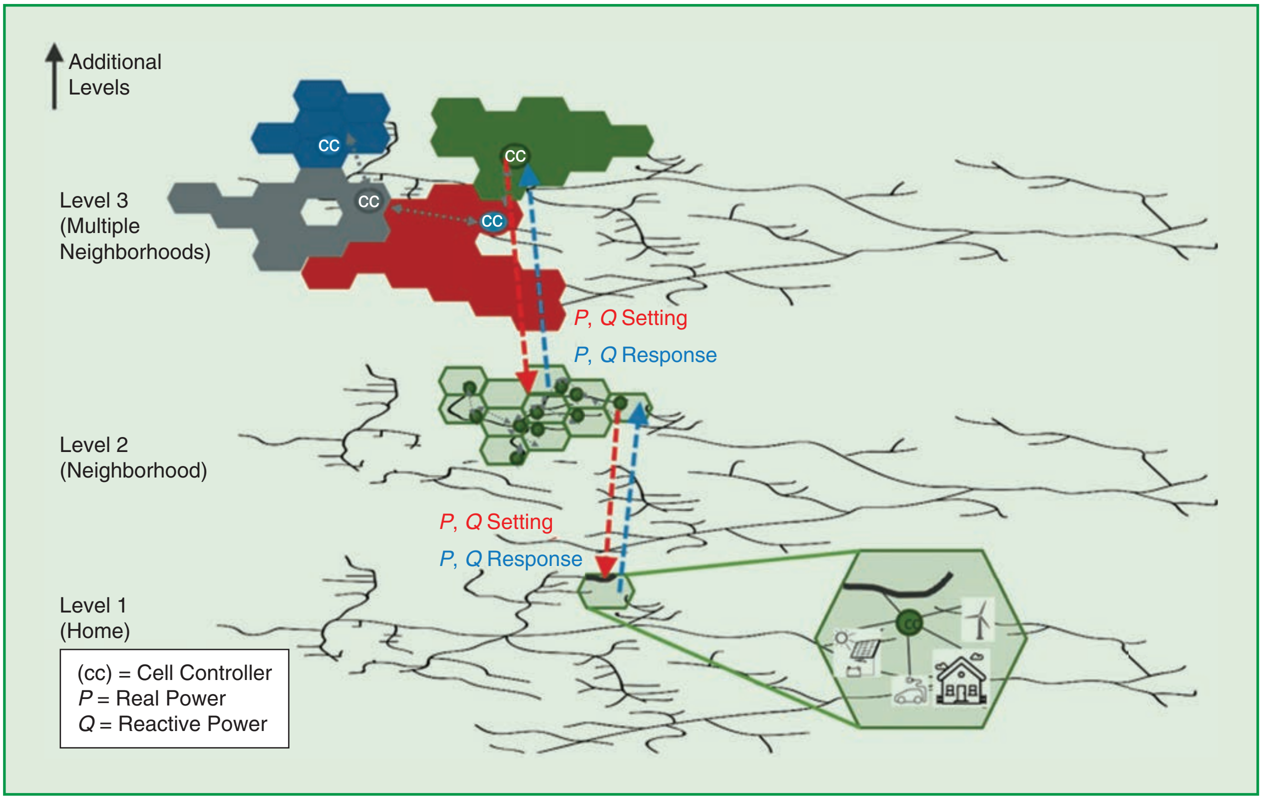

figure 5. The communications architecture for distributed and real-time optimization of AEGs. In the figure, Level 1 would be at a home or business, Level 2 would be at a neighborhood, and Level 3 would be multiple neighborhoods, all on a single distribution circuit.

In this example, a three-phase, unbalanced, 11,000-node test feeder was constructed by connecting the IEEE 8,500-node test feeder with a modified Electric Power Research Institute (EPRI) Circuit 7. In this example, a node is an electrical node where all voltages are equivalent. Figure 6 depicts the single-line diagram of the feeder, where the line width is proportional to the nominal power flow on it, so a thicker blue line has more power flowing through it. The primary side of the feeder was modeled in detail, whereas the loads on the secondary side (which is an aggregation of several loads in this system) are lumped into corresponding distribution transformers, resulting in a 4,521-node network with 1,335 aggregated loads. We grouped the nodes into four large cells (dotted circles) that were physically colocated and into a collection of other scattered nodes not inside these cells, as illustrated in Figure 6. Cell 1 contains 357 nodes with controllable loads, cell 2 contains 222, cell 3 contains 310, and cell 4 contains 154. Cell 4 represents the EPRI test circuit. We fixed the remaining loads on all 292 nodes not included in the four large cells.

To evaluate how well voltage regulation was enabled by the control algorithms, the three-phase, nonlinear power flow model was simulated using OpenDSS, a power flow solver. Figure 7 illustrates the output of the simulations under different voltage controls (voltage without control in blue, voltage with a default local controller in orange, and voltage with the OPF controller in green). The voltage without control (blue) demonstrates a large variation in voltage control between 0.8 and 1.0 p.u. The local controller (orange) demonstrated several locations of undervoltage (lower than 0.95 p.u.). In contrast, the OPF control (green) was able to maintain the voltage magnitudes of all the nodes within the bound from 0.95 to 1.05 p.u. by incorporating global information. In contrast, the default control of the regulators and capacitors could not guarantee that all the voltages were within this bound. Of note in Figure 7 are the nodes located on the right, which present a tight grouping for comparison. These points represent the EPRI circuit and did not have significant voltage changes because their initial conditions were within the normal operating parameters.

The simulation results showed that an improvement of more than 10-fold in the speed of convergence can be achieved by the hierarchical distributed method compared with the centrally coordinated implementation, without losing any optimality. This significant improvement in convergence speed makes real-time grid optimization and control, as well as fast recovery from blackout conditions, possible for large distribution systems.

These results demonstrate how the hierarchical distributed implementation of the primal-dual gradient algorithm to solve an OPF problem achieves the objective to minimize both the total cost over all the controllable DERs and the cost associated with the total network load, subject to voltage regulation constraints. The proposed implementation is scalable to large distribution feeders comprising networked devices, and it reduces the computational burden compared with the centrally coordinated primal-dual algorithm by using the information structure of the AEGs. To the best of our knowledge, this simulation demonstrates the largest optimization-based control of a power system to date, but we are working on even larger simulations.

Large-Scale Simulations

There is a significant challenge to integrate multiple technologies into seamless and resilient operating energy systems with large numbers (10^8) of controllable devices. One of the biggest obstacles to understanding how these systems will function at scale is to create and test a computational framework that enables the design and analysis of optimization and control approaches for these highly distributed energy systems. To enable this vision of AEGs of the future, advanced computational techniques—such as artificial intelligence,

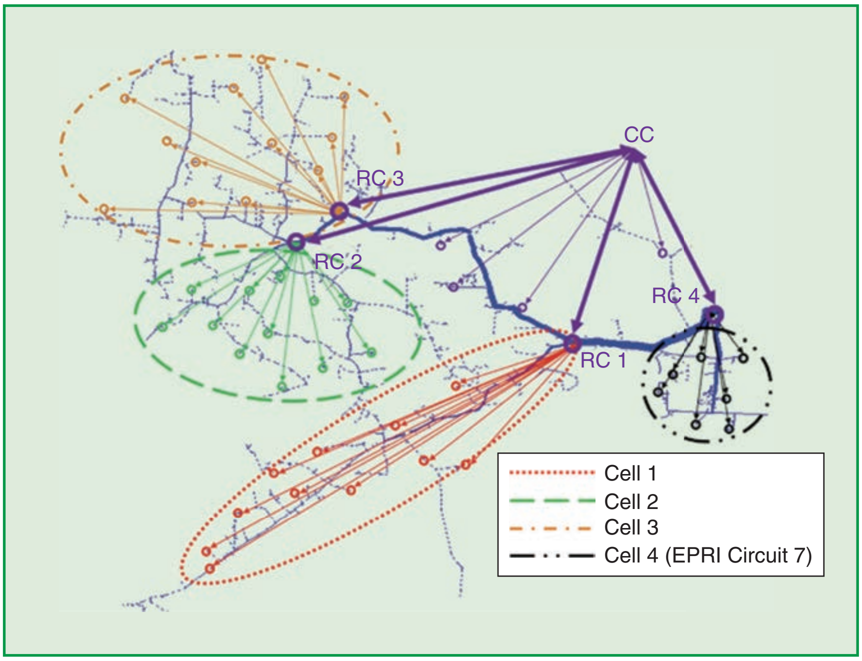

figure 6. The 11,000-node test feeder constructed from the IEEE 8,500-node test feeder and a modified EPRI Circuit 7 (Cell 4). Four AEG cells were formed for this experiment. The higher level cell controller (CC) passes information (purple lines) to the regional cell (RC) controller and to individual nodes that are not located within a cell. The blue lines illustrate the physical layout of the distribution feeder, and the thickness of the line indicates the amount of power flowing through the line.

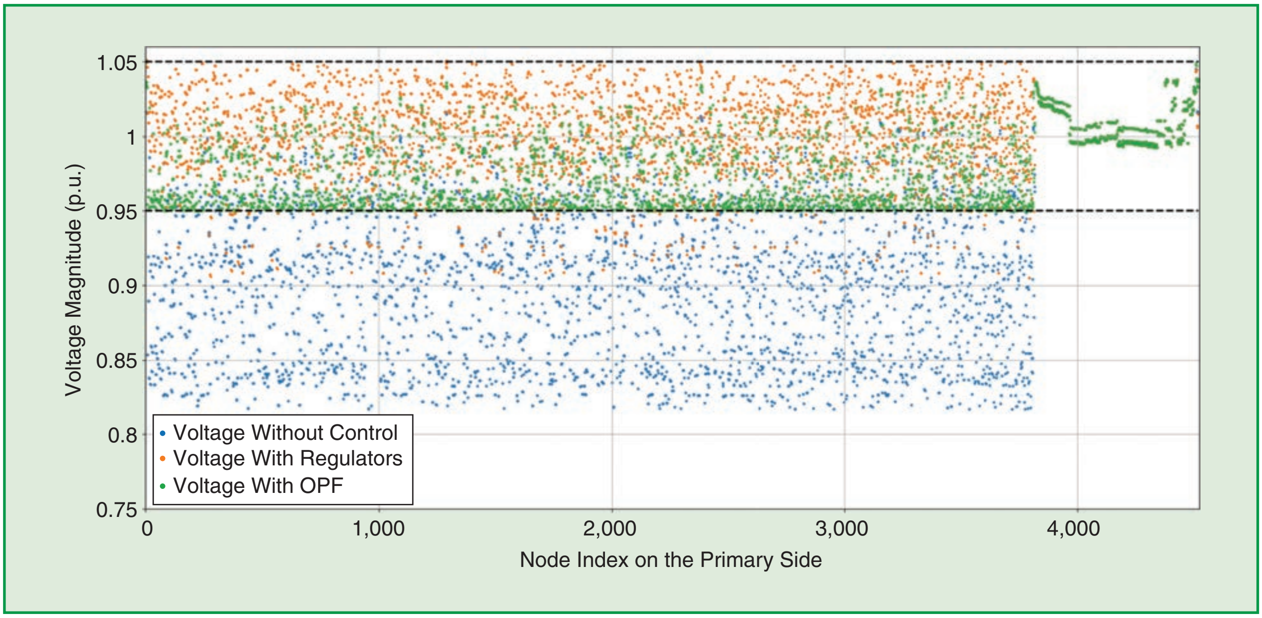

figure 7. The voltages are controlled within 0.95–1.05 p.u. by the OPF algorithm (green dots).

figure 8. A fleet of EVs under distributed control in the NODES experiment at NREL's Energy Systems Integration Facility. (Source: NREL; used with permission.)

machine learning, scalable simulations, and data analytics—are being employed to develop and evaluate these new control and optimization algorithms at large scales to operate millions to hundreds of millions of controllable devices on the grid in real time.

Innovative, secure, scalable, hierarchical, real-time control strategies that are autonomous and make the best use of big and real-time streaming data will be explored to ensure that these complex systems function properly under a wide range of possible conditions. Evaluating deployments through coordinated simulations of 10^8 devices, including high-fidelity models of the system, each component (e.g., residential/commercial buildings, autonomous EVs, solar, wind), and autonomous controllers in both normal and abnormal operations will be carried out to characterize and validate these approaches.

Currently, it takes approximately 1.5 h to run a simulation of feeders with 12,000 DER devices and optimization-based distributed controllers, including high-fidelity solutions of ac power flows for evaluating 24 h at 1-min resolution. This equates to about 23 days of simulation to run an entire year. Scaling to tens of millions of devices will require much more for an annual simulation. In many cases, simulations of critical days and weeks are sufficient; however, this highlights the need for advanced computational resources to fully evaluate these control and optimization approaches for the AEGs of the future. Luckily, in the future, once the algorithms are developed and verified, simulations of their outcomes will not be needed to run in real time on the grid.

Evaluations in the NREL Energy Systems Integration Facility

To evaluate if the software algorithms would work when integrating many real controllable devices, we set up a large experiment at NREL's Energy Systems Integration Facility. NREL's work on the ARPA-E NODES program helped develop the first implementation of the algorithms in hardware and successfully demonstrate the real-time optimization of a single AEG cell. The experiment included simulation of a real distribution feeder from California with 366 single-phase connection points, more than 100 controllable assets at power (inverters, EVs, and batteries; see Figures 8 and 9), and hundreds of simulated devices. The distributed algorithms were implemented in cost-effective microcontrollers that self-optimize and communicate to the central coordinator to attain systemwide goals (voltage regulation and frequency response).

Real-World Applications

We have now started to move out of the laboratory to demonstrate the deployment of AEGs in the real world. The team has been working with Holy Cross Energy (HCE), a utility cooperative near Aspen, Colorado, to deploy the AEG technology in a group of smart homes in Basalt, Colorado. The smart homes in Basalt Vista (Figure 10) are a pilot for an altogether new approach to the grid. These homes optimize energy for residents and their neighbors, but the principles behind Basalt Vista go much further. Within homes, each new connected device or energy resource, such as a residential battery, water heater, or solar PV system, can be controlled for unprecedented energy efficiency. At a larger scale, entire communities could rapidly share power, creating reliable energy for everyone.

HCE had been searching for a solution to managing new devices on its system. This has included a mix of customer energy technologies and bulk generation resources since the decreasing costs of connected customer-owned devices have made these systems much more affordable. HCE's grid has seen 10–15 rooftop solar installations per week, and it has been increasing its solar base for years, planning for a 150-MW summer peaking system through 2030.

In another real-world experiment, we used our real-time optimization algorithms to coordinate assets in the Stone Edge Farm Estate Vineyards & Winery in Sonoma Valley, California (Figure 11). The winery is a microgrid with tens of DERs, including PV systems, batteries, a hydrogen electrolyzer, a gas turbine, and controllable loads. The experiment, conducted in collaboration with the Massachusetts Institute of Technology-born startup company Heila Technologies, showed how our approach can help self-optimize a cell within the future AEG vision, achieving voltage regulation and allowing the microgrid to become a virtual power plant that can provide services to the distribution system.

Conclusion

AEGs of the future will need to control and optimize millions of controllable devices in real time. A traditional central optimization approach to this problem is infeasible because of the computational cost. Therefore, robust, scalable, and predictive hierarchical and distributed control algorithms with provable convergence are needed to optimize the grid in real time. NREL has developed these scalable algorithms to enable the proliferation of DERs on a massive scale.

A fundamental underpinning of AEGs is the ability to accurately model the cellular building blocks and their interactions with the rest of the systems so that control, optimization, and forecasting methods might be applied in operation. NREL is also building computational tools that can cosimulate multiple technologies on the grid to design and evaluate these scalable, distributed control and optimization algorithms using high-performance computing. In addition, NREL has taken the preliminary steps of demonstrating these algorithms in real time for real-world devices in the laboratory and now in smart homes. Additional work will be needed in controls, optimization, data analytics, complex systems, and cybersecurity to implement the AEG across the entire U.S. grid.

Building on the distributed optimization techniques that have been developed, additional thought needs to be given to the design of future market mechanisms to systematically account for payment/rewards to exchange energy and the provision of ancillary services among autonomous cells and devices. The ideas of transactive energy will need to be considerably

figure 9. The inverters under test in the ARPA-E NODES experiment. (Source: NREL; used with permission.)

figure 10. The smart homes in Basalt, Colorado. (Source: NREL; used with permission.)

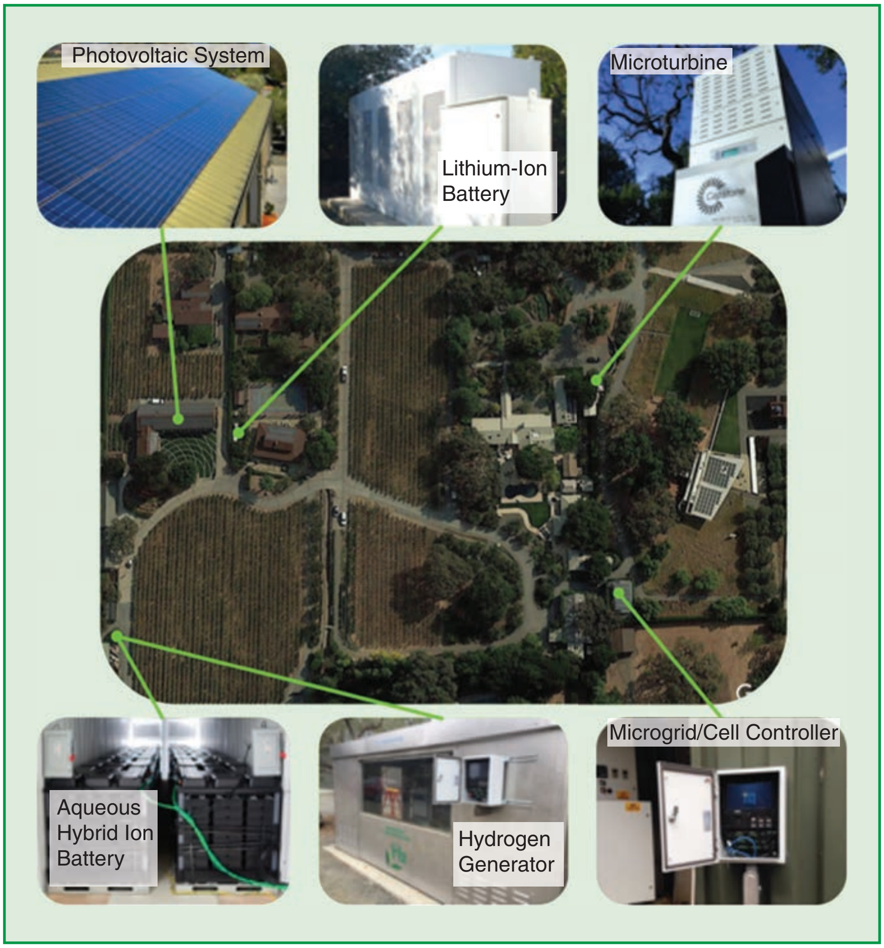

figure 11. The Stone Edge Farm microgrid, Sonoma Valley, California. (Source: Stone Edge Farm; used with permission.)

broadened to accommodate the proposed architecture with millions of controllable devices on the system and to enable rigorous mathematical analysis of system stability and optimality.

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For Further Reading

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