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Basic Research Needs for **Autonomous Energy Grids**

Summary Report of the Workshop on Autonomous Energy Grids

September 13–14, 2017

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Summary Report of the Workshop on Autonomous Energy Grids: September 13–14, 2017

Edited by Benjamin Kroposki
National Renewable Energy Laboratory

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15013 Denver West Parkway
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Autonomous Energy Grids: Creating a New Energy Paradigm

Grid modernization is increasingly important to address a range of challenges and enable future energy systems to maintain affordability and reliability while increasing security, resilience, and the ability to integrate energy in all forms. Current frameworks to monitor, control, and optimize large-scale energy systems are becoming increasingly inadequate as higher levels of variable renewable generation and distributed energy resources are integrated into electric power systems. Creating actionable information from extensive sensing and monitoring of grids is bringing additional challenges. Also, a variety of new market mechanisms, including multilevel ancillary services, and interdependencies between energy infrastructures are creating energy systems that are more complex than ever before. To address these challenges, the National Renewable Energy Laboratory (NREL) held a workshop to discuss the basic research needs in four key areas: big data analytics, control theory, optimization theory, and complex systems. This report summarizes the outputs from the workshop and outlines advances in these foundational areas that can be integrated to realize the vision of autonomous energy grids (AEGs). AEGs are supported by a scalable, reconfigurable, and self-organizing information and control infrastructure; are extremely secure and resilient; and can self-optimize in real time to ensure economic and reliable performance while systematically integrating energy in all forms. (See Figure ES-1.) This report discusses the current state of the art, gaps and challenges, and research opportunities for developing AEGs. Presentations from this workshop can be found at: https://www.nrel.gov/grid/autonomous-energy.html.

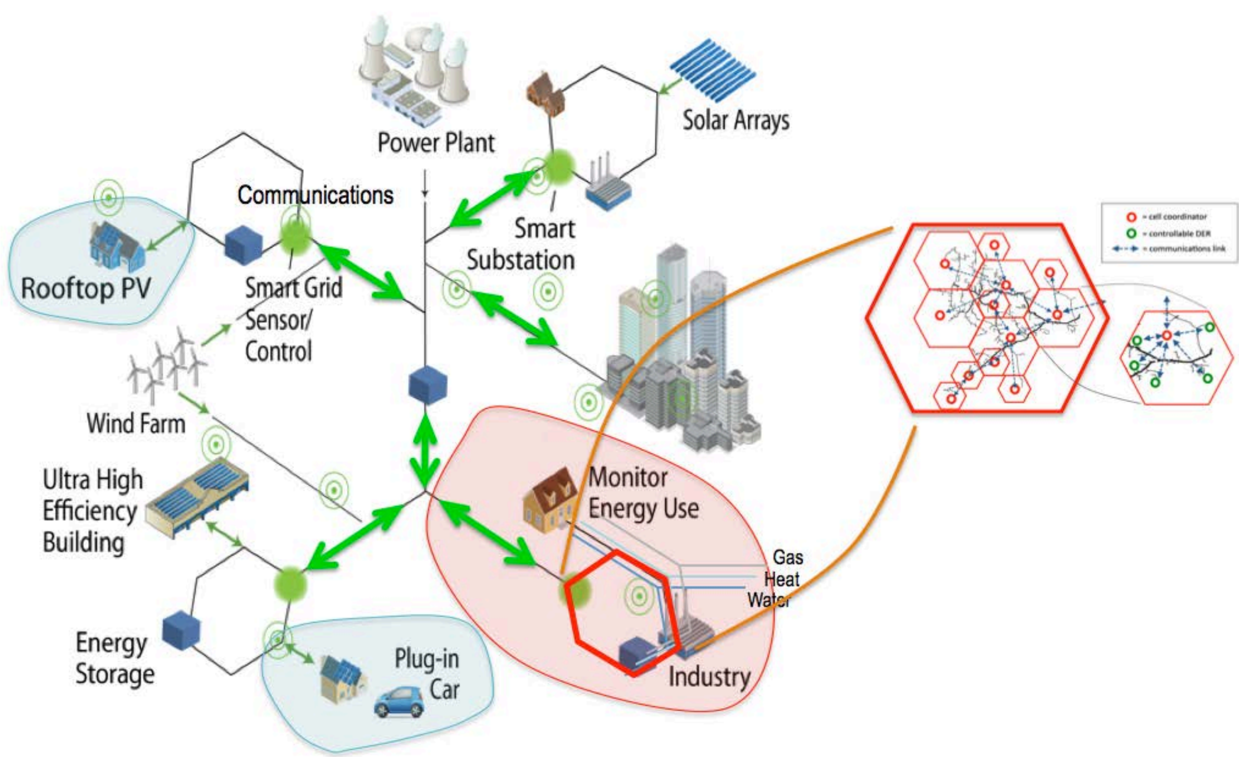

Figure ES-1. Autonomous energy grids organized into self-optimizing cells

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Priority Research Directions

Based on information and discussions from the workshop, the following were developed as priority research directions to enable AEGs.

- Develop innovative data analytics methods that make the best use of available information for grid forecasting and controls.

Key question: How can we use advanced machine learning and artificial intelligence to create actionable intelligence from massive data sets of grid and resource measurements?

Increasing amounts of data are being collected from a variety of heterogeneous sources from the grid and associated systems. These data include information about generation, transmission, distribution, storage, loads, and weather conditions. Some of these data have additional security and privacy concerns. Advanced machine learning techniques are needed to collect and parse data in ways that enable real-time, automated decision-making and forecasting.

- Develop innovative distributed optimization algorithms for real-time and distributed applications.

Key question: How can we develop fundamental mathematics for optimization algorithms for use in real-time and distributed applications?

Currently, grid designers use relatively few parameters to optimize operations and planning. As the number of controllable devices in the grid increases, traditional techniques for optimization in the grid become computationally intractable. New optimization methods are needed that are computationally affordable, stable, and provably optimal across highly distributed applications.

- Develop scalable, nonlinear control methods that work across highly distributed, asynchronous operations and account for heterogeneous grid-friendly devices.

Key question: How can we develop advanced control theory that takes into account inherently asynchronous operations as a result of communications delays, losses, distributed control actions, and heterogeneous devices?

Increasing numbers of controllable devices on the electric grid make traditional techniques for control computationally intractable. These control points also operate asynchronously. New controls methods need to be developed that allow for distributed processing in the extremely short time frames needed to implement real-time controls across an exponentially increasing number of control points.

- Develop modeling and simulation methods that address the integration and interdependencies of many different energy and communications systems at various temporal and spatial scales.

Key question: How can we develop frameworks for modeling and simulation that pass information between temporal and spatial scales while maintaining proper fidelity for the operations and planning of the grid?

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Diverse energy systems have traditionally been modeled using the modeling formalism that most naturally represents the system; however, combining multiple modeling formalisms into a single, coherent simulation over multiple temporal and spatial scales is a foundational topic necessary for the increased optimization and control of these new systems.

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1 Introduction to Autonomous Energy Grids

Current power systems deliver electricity primarily in one direction: flowing from large central plants to customer loads; however, increasing amounts of variable generation (i.e., wind and solar), distributed energy resources (DERs) (i.e., solar, fuel cells, microturbines, generator sets), distributed energy storage (i.e., batteries, ice storage), and new loads (i.e., electric vehicles, light-emitting diode lighting) are being added to electric grids and causing bidirectional power flow and voltage fluctuations that impact optimal control and system operations. In addition, because of increased numbers and types of sensors, massive amounts of new data are being collected on energy grid conditions. Other major changes to the grid include the increasing use of natural gas-fired generation, both at the bulk level and locally through combined heat-and-power applications. Additionally, new types of operations and controls, such as islanded microgrids, are being used locally to disconnect parts of an energy system from a larger system for economic reasons and to improve customer reliability and resilience. On the largest systems, current grid control systems that operate at the bulk-system level typically control approximately 10,000 points. As additional smart, controllable devices are integrated into the grid, the number of control points could easily reach hundreds of millions, significantly increasing the complexity of controlling and optimizing the system.

All these new technologies are increasing the complexity of energy systems to a point at which existing techniques to monitor, control, and optimize them will be inadequate. For example, existing techniques might not offer decision-making capabilities that are consistent with the form and function of future large-scale systems, which will be governed by faster dynamics, include heterogeneous energy assets that are controllable at different temporal resolutions, and accommodate a variety of deregulated energy markets. The National Renewable Energy Laboratory (NREL) has proposed the idea of creating autonomous energy grids (AEGs): a new operational and control paradigm to enable the secure, resilient, and economic operations of future energy systems. Similar to autonomous vehicles—which do not require a physical driver and can make decisions on how to most effectively transport a person from one place to another—AEGs do not require physical operators, can be extremely secure and resilient (self-healing), and can self-optimize in real time to ensure economic and reliable performance while integrating energy in all forms. (See Figure 1.)

Key features of AEGs include:

- **Autonomous:** capable of making decisions and operations without humans in the loop
- **Scalable:** scalable architecture to enable the control of hundreds of millions of devices across many physical scales (distribution to transmission systems)
- **Resilient**: can self-reconfigure (grid-connected and islanded operations) and operate with and without communications
- **Secure:** incorporate cybersecurity and physical security against threats
- **Reliable and affordable:** ensure reliable and economic operations
- **Operate in real-time:** controls, optimization, and data processing use algorithms that are fast enough to make real-time decisions (millisecond response)
- **Allow asynchronous communications:** able to pass information messages between asynchronous sources
- **Robust:** deals with the uncertainty of stochastic resources and forecasts

- **Flexible:** must be able to control and optimize across multi-physics energy flows (electrical, thermal, fuel) and deal with variable resources.

To achieve these goals, AEGs rely on scalable cellular blocks that can self-optimize when isolated from a larger grid and participate in optimal operations when interconnected to the rest of the system. These scalable cells can be areas of the grid that can run independently as microgrids or be sectors of the grid that are segregated from a control perspective but do not have enough local generation to carry the full load of the cell. The AEG concept allows for the use of optimization and control across cells in cases when the cells can form independent microgrids and when they can control assets but not intentionally island.

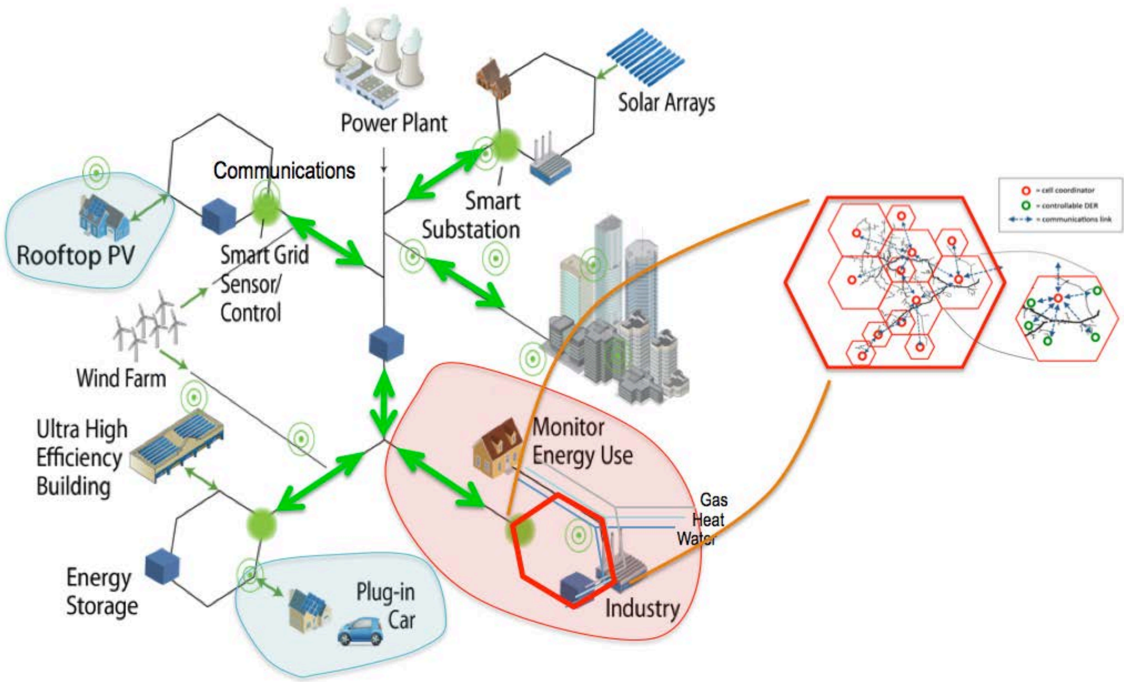

Figure 1. Autonomous energy grids organized into self-optimizing cells

To understand the potential research needs within the concept of AEGs, several technical areas have been identified, including smart grid devices, cybersecurity, nonlinear controls, optimization, complex systems, and big data analytics. (See Figure 2.) The last four of these were the focus of the workshop held in September 2017. The following sections will examine these more closely and evaluate the current state of the art, identify gaps and challenges, and propose research opportunities for creating AEGs.

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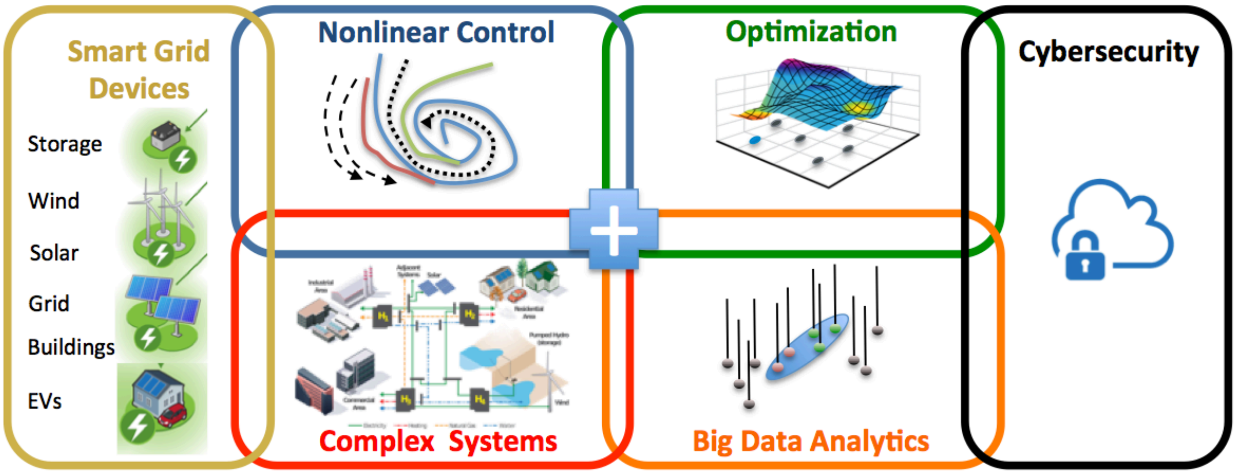

Figure 2. Technical areas needed to achieve autonomous energy grids

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2 Big Data Analytics

Large amounts of heterogeneous data on electric grids are becoming increasingly available from sources such as smart meters, distributed generation, transmission sensors, and smart home energy management systems. Big data analytics—the ability to collect, curate, and create actionable information with these data—will be critical to creating AEGs. AEGs will need to be able to digest data, evaluate data, and make decisions faster than in real time in both centralized and distributed settings to ensure proper grid operations with millions of control points.

2.1 State of the Art

Currently, data use is an important part of power systems planning and operations, and it will become increasingly important as more data and information are available. Metering systems at generators, transmission lines, substations, and end-use devices provide information for asset management, energy management, and market management both long-term and in real time. A wide range of data analytics applications is being used for disaggregation, such as in source separation, device (i.e., switch) configuration detection, forecasting, and power flow and topology estimation.

2.2 Gaps and Challenges

The big data analytics that are needed for the envisioned AEG involve three critical steps:

- Spatial and temporal characterization
- State estimation and forecasting
- Autonomous decision-making.

Spatial and temporal characterization from data sets is a challenge when applied to information peripherally attached to the electric grid. Even with large amounts of available data, it is difficult to infer customer behavior and calculate load flexibility. Theoretical results from big data analytics do not always apply to all conditions, scalable algorithms are needed to focus on feature extraction, and the network of solutions needs to be built; therefore, by mapping the features to the network of solutions, the correct methods can be identified.

In the area of state estimation and forecasting, current research efforts focus on incorporating big data analytics for real-time control solutions (optimal power flow); however, the speed of these analytics is not fast enough for real-time decision-making. This is also influenced by the role of communications and latencies in the control system. Online algorithms are needed to implement big data analytics in an AEG setting. For autonomous decision-making, the challenge is to find enough data to properly train the variety of artificial intelligence techniques.

One of the biggest challenges in big data analytics on AEGs is accessing and selecting the data. Use cases are not well defined or understood by both the industry and research community, which makes it harder for the industry to decide where to put sensors and which types of data are needed. To formulate big data analytics functions, such as optimally selecting and placing sensors, researchers need to understand the objective functions through well-defined use cases.

Additionally, the architecture for big data analytics has not been addressed. With the right architecture, users and developers can manage big data analytics more efficiently and effectively.

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There is also a need for the development of meta-schemas for grid data as well as specifications for AEG big data.

2.3 Research Opportunities

2.3.1 Clustering

System clustering is a key component of an AEG because of the need to organize the massive amount of data. Dynamic analytics methods should be developed using system data to include models to identify features that define the entities for clustering. Data vectors with graphical analytics can then be used to establish links among clusters.

2.3.2 State Estimation

The current state of the systems reflects the true operational conditions of the grid. An AEG's system states will need to potentially include extended states of the network (including topology), devices (i.e., battery state of charge, water heater temperature), and user profile (i.e., occupancy, room temperature). Big data will need to be mined to account for the heterogeneous data input and structure correlation through an analysis process and produce the estimation results for all application needs.

2.3.3 Capability Estimation

With variable renewables and the Internet of Things in mind, the capabilities of certain devices to interact with AEG applications are critical information. Using historical data, models, and real-time sensor data input, data analytics methods can be developed to estimate the potentials of certain devices in terms of energy, power, duration, speed, etc., to provide grid services.

2.3.4 Uncertainty Estimation

Viabilities and uncertainties are critical elements for the applications and decision-making processes in AEGs. Using historical data, real-time input, and learning models, uncertainties can be estimated with statistical attributes.

2.3.5 Better Models or No Models

Big data-based methods can greatly enhance the knowledge of physical models and sometimes challenge the physical models as all-known ground truth. In fact, the models become inputs to the data analytics methods for physical features learning. Physical constraints need to be explicitly considered in big data analytics with robustness margins built in.

2.3.6 Forecasting

For renewable generation load, power flow, and system states, big data analytics will be the key for forecasting future outcomes. Instead of individual methods for forecasting, ensemble learning will be the best approach for forecasting integrated results at all time horizons. The meta-learner that has been trained with historical data together with the system model can aggregate results for better accuracy and interoperability.

Imputation methods need to be developed for forecasting. As systems and data grow, measurement gaps and errors will impose difficulty for forecasting. Features and correlations within the system will provide opportunities to develop methods to replace missing data with substituted values.

2.3.7 Artificial Intelligence and Automatic Decision-Making

Both centralized and distributed decision-making can be enabled by big data analytics. In addition to the results from estimation and forecasting, data analytics methods will consider market behavior, cost benefits, social benefits, and other information for holistic decision-making. Distributed intelligence will make AEGs reliable and resilient under abnormal and extreme events. Garnering feedback from the system and inputting it in the learning process is the key to autonomous decision-making.

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3 Optimization

Challenges and opportunities in the context of optimization methods for AEGs can be divided into the broad areas of planning, operations, and interactions with information and communications infrastructures. Overall, basic research elements in optimization theory are necessary to create new frameworks for the planning and operations of AEGs, to drive new markets, and to contribute to technological leadership.

3.1 Optimization for Operations

3.1.1 Current State of the Art

The complexity of future energy systems and AEGs will render existing control and optimization techniques inadequate. Existing techniques are primarily centralized, and because of underlying computational complexity limits, they do not offer decision-making capabilities that are consistent with future energy systems that are governed by faster dynamics and complex market mechanisms; therefore, they cannot guarantee reliable, resilient, and efficient system operations. The state of the art also lacks tools for solving nonconvex optimization problems (i.e., the AC optimal power flow) in real-time and distributed settings.

3.1.2 Gaps and Challenges

Critical gaps and challenges include how to:

- Formalize key operational concepts for AEGs and identify key operational aspects to optimize the real-time operations of AEGs
- Bypass the need for pervasive metering required by traditional optimization schemes
- Tap into online optimization theory to enable computationally affordable yet optimal real-time distributed control of AEGs.

3.1.3 Research Opportunities

Opportunities include advancing mathematical models, algorithms, and applications for real-time and distributed optimization of large-scale AEGs. The aim is to offer breakthrough formalisms for the synthesis and analysis of computationally affordable, stable, and provably optimal optimization algorithms that lead to significant gains in the resiliency, security, and efficiency of AEGs. System-level coordination enabled by distributed algorithms is essential for AEGs to embrace futuristic, deregulated energy markets while systematically ensuring reliable operations. The development of algorithms that enable the plug-and-play operations of AEGs—wherein each area can disconnect and connect (physically or virtually) from the rest of the grid—is another research problem.

3.2 Optimization for Planning

3.2.1 Current State of the Art

Critical challenges to the development of tools for the long-term planning of future energy systems and AEGs are related to uncertainty quantification, lack of planning tools that accommodate distributed solution methods, and computational scalability. Current tools are primarily centralized, can handle only specific classes of uncertainty and network models, and might not take into account (albeit futuristic) distribution-level market models.

3.2.2 Gaps and Challenges

Uncertainty quantification regarding costs, operational constraints, and extreme events is key to formulating pertinent, robust, chance-constrained, and stochastic optimization problems. The limitation is in the availability of realistic data sets, which prevents researchers from assessing pertinent probability distributions or uncertainty regions. Planning methods will assist in the long-term operations of millions of devices to drive the deployment of new assets; therefore, scalable methods are desirable. The problem is exacerbated when planning is performed across critical infrastructures, such as gas, water, and power networks.

3.2.3 Research Opportunities

There is a high probability that future energy systems and AEGs will no longer be centrally planned. Research needs pertain to the development of new computationally efficient distributed algorithms for robust, chance-constrained, and stochastic optimization methods. These methods can accommodate AEG settings, whereby each area/community pursues individual long-term socioeconomic objectives while coordinating with adjacent areas and system operators to ensure grid-wide reliable and secure operations as well as flexible recovery from extreme events. Robustness to contingencies and extreme events needs to be revisited, formalized, and included in planning methods.

3.3 Integration of Optimization and Other Areas

A fundamental understanding of the impacts of communications and information capabilities on the performance of distributed optimization is still missing. A key research opportunity consists of providing systematic ways to design joint communications infrastructures and distributed optimization methods for AEGs and to assess the performance of distributed optimization methods in case of unreliable communications channels, communications outages, and cyber attacks. The joint design of distributed optimization methods and information infrastructures (i.e., metering) is also essential to uncovering fundamental trade-offs between the performance of the algorithms and data volume. The synthesis of distributed algorithms for AEGs should be cross-fertilized with the design of market models that account for transactions of energy between areas, rewards/payment mechanisms for providing ancillary services within an area and between areas, and provisioning reserves.

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4 Controls

AEGs pose significant challenges in terms of optimal operations and the analysis of their stability. This is particularly the case when distributed or decentralized control algorithms are used to operate the system because these algorithms are inherently asynchronous as a result of communications delays, losses, and distributed (asynchronous) control actions. The typical approach to stability analysis involves analyzing a continuous-time system of differential equations; however, for networked systems with digital controllers, this standard analysis naturally disregards computational and communications latencies as well as asynchronous actions. Another challenge arises because cells must operate autonomously when they are isolated and cannot rely on the frequency and voltage signals from the larger grid. Therefore, scalable control strategies must be developed that can be implemented at both large-grid scales and microgrid scales and be compatible with each other.

4.1 Current State of the Art

The current state-of-the-art approach to control power systems is becoming inadequate for future energy systems and AEGs. The running assumptions are that the system is well modeled, observable, and controllable. In addition, the sensing and control architectures are designed separately, thus leading to suboptimal control architectures. Although there are a lot of sources of data in distribution systems, these data are typically not used for control decisions. Even when phasor measurement units are installed to obtain wide-area measurements, they are frequently not used because they are not trusted. The present approach to control the grid is bi-level: centralized optimal power flow is used to compute the steady state of the network while the controllers do their best to get there. When moving to AEGs, the state of the art has several distributed and decentralized alternatives; however, at present, the work typically does not account for communications and physical delays, and the overall dynamics of the grid under the given control strategy are not modeled. Therefore, overall stability and optimality analysis is limited. Finally, there is a big difference in the state of the art between the research community and industry. Particularly, the industry is taking very simple (linearized) approaches to controls to make them work.

4.2 Gaps and Challenges

4.2.1 Modeling for Control

There is a need for modeling and simulation tools that allow us to develop representations and models of the systems because these are currently significantly lacking.

4.2.2 Observability and Codesign of Sensing and Control

Observability is a crucial question for state estimation. There is no global observability in distribution networks, but is it required? In an AEG setting, local observability might be enough. In this context, one of the challenges is to include state estimation in the feedback loop; this is currently absent even in bulk transmission systems. This leads to the challenge of codesigning the structure of the sensing and control architectures.

4.2.3 Control of a Large Number of Heterogeneous Devices

Another challenge is how to avoid the synchronization of control actions at thousands or millions of devices to ensure stable system operations. In the context of AEGs, how do we prevent intra-area, inter-area, or inter-device oscillation by randomization? How do we control discrete or nonconvex devices? Also, some devices might not be controllable directly (i.e., certain home thermostats or energy storage devices).

4.2.4 Controls and Markets

It is clear that the control problem is not independent of the underlying market. But how are market structures embedded in the controls of millions of devices? On the other hand, systems need to be reliable and not necessarily solely driven by market signals.

4.2.5 Generic Control

When it comes to controlling AEGs, there is currently a lack of an abstraction layer that will allow for the generic control of a building, microgrid, or an aggregation of 100 devices, etc., and corresponding coordination between areas (cells).

4.2.6 Availability of Data

It is very challenging to solve the control problem when the data are not freely available. Most utilities keep their data proprietary for operations and privacy reasons.

4.2.7 Delays

As mentioned, delays are typically not taken into account. The fundamental problem is the ratio of communications speed relative to the speed of the physical dynamics. We need to characterize the delays first to know what the important concerns are.

4.2.8 Separation of Timescales

It will be important to determine whether the design should be based on a separation of timescales or if it should consider multiple timescales.

4.3 Research Opportunities

4.3.1 Aggregation and Scalability of Control

It will be important to design abstraction mechanisms and integrate aggregations of devices (i.e., buildings, neighborhoods, microgrids) into AEG operations. Also, allow the aggregation to curtail, change consumption, and disconnect. The abstraction mechanisms will allow for the scalability of the control architecture. In this context, the value of regionally aggregating microgrids from the points of view of reliability, resiliency, and predictability should be investigated.

4.3.2 Control for System Resilience

Remedial action schemes are an interesting challenge. In this context, real-time control methods are imperative.

4.3.3 Control for Protection

Control schemes on the level of a microsecond are needed.

4.3.4 Nonlinear Stability Analysis

Modeling the nonlinear dynamics under particular control strategies is required to analyze stability.

4.3.5 Communications Aspects

It is necessary to determine the communications requirements to enable distributed/decentralized control with information sharing and to determine how communications affect control design. If the goal is to control the end-user devices, it is not clear whether the communications infrastructure is there.

4.3.6 Real-Time Data-Driven Control of an Area/Cell

Use model-predictive control schemes, reinforcement-learning methods, game-theoretic approaches, and consensus-based approaches. Because the system will be changing rapidly, we need control mechanisms that are able adapt to these changes in real time.

4.3.7 System Design

Design system controls rather than individual controls, taking into account direct delays (both physical and related to communications). The exact level of decentralization must also be taken into account. System designs are needed that allow for some level of both centralized and distributed controls that work in a hierarchical, scalable manner.

4.3.8 Area/Cell Definition

Use controllability and observability as criteria for segmenting the grid. This could be achieved through clustering methods, for example.

4.3.9 Simulation Test Bed

A reliable simulation environment is required to test the different algorithms for AEGs. We need data that everyone trusts. For example, we need to build synthetic testing data that are based on real data (i.e., data that include events that we want to test).

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5 Complex Systems

Energy systems include all energy domains (electricity, fuels, thermal) as well as other domains (communications, water, transportation) that influence how energy is generated, distributed, converted, and used. The connections among these domains create interdependencies that challenge overall system design, planning, control, and optimization. Historically, little attention has been paid to the overlap among these areas, but AEGs will need to be able to account for these interdependencies because of the increasing impacts that each energy and infrastructure domain has on another. Another aspect that increases the complexity of the grid is that a variety of temporal scales are interrelated. Actions happen on the scale from milliseconds in protection systems to longer term planning of the grid.

5.1 Current State of the Art

The current state of the art in complex systems is that extensive work has been done on the detailed modeling of individual systems or applications, but studying the interactions among multiple systems or applications is still in the early stages. The vast majority of previous research has involved the use of a single modeling paradigm to focus on a single issue. Although this has worked well historically, these modeling efforts will need to operate in an integrated fashion to realize the goal of autonomous energy systems. AEGs will need to be able to input the results of actions taken at the lowest level in the system—for example, at the device level—up to the highest layers of the system for an accurate representation of the current system conditions at the various levels where control actions can be decided. This information flow is also critical across applications. For example, a distributed energy storage device that needs to increase its output in response to a local energy consumption increase (i.e., balancing) will have a reduced capacity to respond to an event in the system (i.e., provision of ancillary services). This detailed real-time information sharing is currently not the norm for the majority of power system operations and planning processes, wherein information is often segregated based on the traditional utility boundaries between transmission and distribution, load and generation, and planning and operations. This integration of modeling information becomes even more critical as additional energy systems become increasingly intertwined with the electric grid structure, as will be necessary to realize the goal of AEGs.

5.2 Gaps and Challenges

5.2.1 Combined Power and Communications System Modeling

One of the critical gaps identified was the lack of combined power and communications modeling because information flow within the system is critical to the efficient operations of autonomous systems. This was highlighted in a number of different applications, from security, to preventing blackouts, to the distributed optimization of system actions. This will require interfacing physical models with information infrastructure models, an area that has been underexplored in the energy systems domain.

5.2.2 Information Mapping Among System Actors

A further challenge is understanding the need for information that must be shared by actors in the system while maintaining user privacy and system security. This is critical for more distributed optimization and control of autonomous systems that do not have centralized structures.

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Information mapping is the first step needed to understanding the cybersecurity and privacy concerns that such systems might create, and it should be considered at the design stage to ensure optimal system performance and that costly retrofitting is not necessary.

5.2.3 Identification of Emergent Behavior

Another goal of complex systems modeling for autonomous energy systems will be to identify possible emergent and unexpected system behavior so that it can be identified and corrected during system operations. This is critical for autonomous systems because they need to be able to react to these novel situations without an operator in the loop.

5.2.4 Integrated Systems Test Cases

A major limitation in developing these new technologies for autonomous energy systems is that there are no large-scale test cases that can be used to validate the feasibility of the algorithms necessary for combined energy systems. These test cases serve a critical role in the development, validation, and dissemination of new algorithms before they can be transferred into the operations of real systems. Realistic test cases speed up development efforts and allow for potential roadblocks in implementation to be identified early. For this reason, the early development of realistic test cases is a high priority.

5.3 Research Opportunities

5.3.1 Ontological Descriptions of Energy Systems

One of the critical aspects that will need to be addressed to allow for cooperation among many different energy and communications systems is graph-based ontologies that link different systems at various temporal and spatial scales. This is a critical step that should be addressed in early work in this area because it is a fundamental technology that will be used often later.

5.3.2 Mathematical Basis for Multi-Formalism Modeling

New modeling tools that allow for the expression of complex system interactions in novel manners are also necessary, and the development of these tools should allow for the use of multiple formalisms to most accurately model disparate subsystems. This includes the combination of many different modeling formalisms that have traditionally been treated separately. Examples of modeling formalisms that are critical for multi-energy systems—and thus should be able to be natively represented in such a framework—include discrete event simulation, agent-based modeling, mathematical programming, partial differential equations, and ordinary differential equations.

5.3.3 Scalable Distributed Solvers

Scalable distributed solvers are necessary for the simulation and optimization of these increasingly large and complex systems. This fundamental mathematical work is necessary for all of the modeling formalisms listed in the previous section on multi-formalism modeling.

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6 Integration of Technical Areas

The priority research directions outlined in this report describe the scientific advances in four basic areas that are needed to develop AEGs that are scalable, reconfigurable, and self-organizing. (See Figure 3.) A fundamental underpinning of an AEG is the ability to accurately model the cellular building blocks and their interactions with each other so that control, optimization, and forecasting methods might be applied in cooperative operations. Advanced data analytics will be needed to properly curate and apply information about system operations. Complex system theory will serve as a means to model and simulate the different energy domains and their interactions. These models can then be used for the real-time optimization and control of systems and subsystems using information gained from big data analytics to provide forecasts that serve as parameters in the control and optimization algorithms as well as the algorithmic computational awareness to apply regime-switching approaches.

Advances in controls, optimization, big data, and complex systems theory can find immediate impact in applications on the electric grid in addition to many other sectors, including transportation and building systems. The convergence of knowledge, techniques, and innovation in these areas can provide unprecedented opportunities to advance next-generation grids and improve their relationship with interconnected domains through innovative and powerful scientific research in these areas.

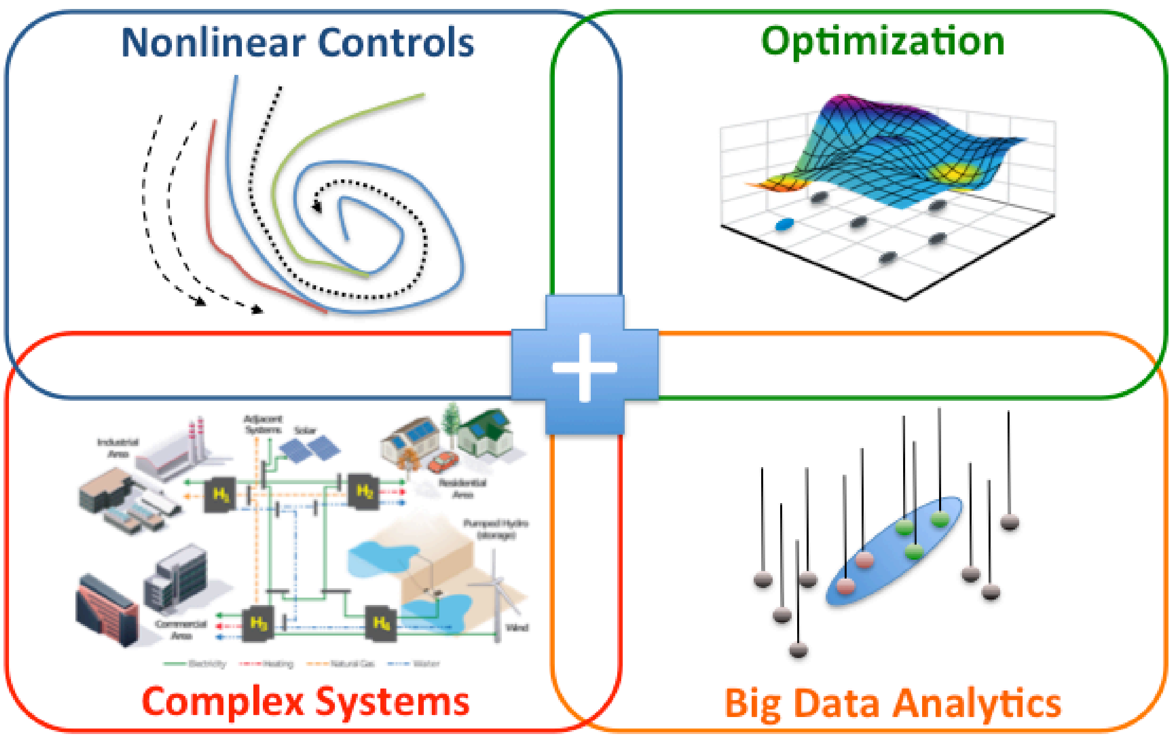

Figure 3. Four basic research areas to enable autonomous energy grids

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Appendix A: Workshop Participants

Basic Research Needs for Autonomous Energy Grids
Denver West Marriott, Golden, Colorado
September 13–14, 2017

Chair: Benjamin Kroposki, National Renewable Energy Laboratory

Organizing Committee:

Andrey Bernstein, National Renewable Energy Laboratory

Emiliano Dall'Anese, National Renewable Energy Laboratory

Bri-Mathias Hodge, National Renewable Energy Laboratory

Yingchen Zhang, National Renewable Energy Laboratory

Plenary Speakers:

Big Data Analytics

Georgios Giannakis, University of Minnesota

David Culler, University of California, Berkeley

Optimization Theory

Steven Low, California Institute of Technology

Angelia Nedich, Arizona State University

Control Theory

Sean Meyn, University of Florida

Mihailo Jovanovic, University of Southern California

Complex Systems

Gil Zussman, Columbia University

Daniel Kirschen, University of Washington

Autonomous Energy Grids

Ian Hiskens, University of Michigan

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Participants

Person	Affiliation
Adam Wierman	California Institute of Technology
Andrew Puryear	Sandia National Laboratories
Andrey Bernstein	National Renewable Energy Laboratory
Angelia Nedich	Arizona State University
Ben Kroposki	National Renewable Energy Laboratory
Bokan Chen	Google
Bri-Mathias Hodge	National Renewable Energy Laboratory
Brian Bush	National Renewable Energy Laboratory
Bryan Palmintier	National Renewable Energy Laboratory
Changhong Zhao	National Renewable Energy Laboratory
Chris De Marco	University of Wisconsin
Christopher Bay	University of Colorado Boulder
Dan Molzhan	Argonne National Laboratory
Daniel Kirschen	University of Washington
David Culler	University of California, Berkeley
David Lawrence	Duke Energy
Devon Sigler	National Renewable Energy Laboratory
Dylan Cutler	National Renewable Energy Laboratory
Emiliano Dall'Anese	National Renewable Energy Laboratory
Emre Cara	Stanford National Accelerator Laboratory
Georgios Giannakis	University of Minnesota
Gil Zussman	Columbia University
Gonzalo Mateos	University of Rochester
Gregor Henze	University of Colorado Boulder
Guannan Qu	Harvard University
Hamed Mohsenian-Rad	University of California, Riverside
Hao Zhu	University of Texas at Austin
Ian Hiskens	University of Michigan
Jean Paul Watson	Sandia National Laboratories
Jeffrey Hokanson	Colorado School of Mines
Joanna Mathieu	University of Michigan
Juan Torres	National Renewable Energy Laboratory
Karan Kalsi	Pacific Northwest National Laboratory
Li Na	Harvard University of Texas at Austin
Lijun Chen	University of Colorado Boulder
Lucy Pao	University of Colorado Boulder
Mads Almassalkhi	University of Vermont
Mariko Shirazi	National Renewable Energy Laboratory
Matthew Reynolds	National Renewable Energy Laboratory
Mihai Anitescu	Argonne National Laboratory
Mihailo Jovanovic	University of Southern California
Nikolai Matni	California Institute of Technology
Nikos Gatsis	University of Texas at San Antonio
Peter Graf	National Renewable Energy Laboratory

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Peter Green	National Renewable Energy Laboratory
Rush Robinett	Michigan Technological University
Sairaj Dhople	University of Minnesota
Sakis Meliopoulos	Georgia Institute of Technology
Sean Meyn	University of Florida
Sila Kiliccote	Stanford National Accelerator Laboratory
Sonja Glavaski	U.S. Department of Energy, Advanced Research Projects Agency-Energy
Steven Low	California Institute of Technology
Tim Heidel	National Rural Electric Cooperative Association
Tyler Summers	University of Texas at Dallas
Tyrone Vincent	Colorado School of Mines
Vassilis Kekatos	Virginia Tech
Wei Ren	Eaton
Xiaoming Feng	ABB
Yashen Lin	National Renewable Energy Laboratory
Yingchen Zhang	National Renewable Energy Laboratory
Zachary Pecenak	University of California, San Diego

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