Special ReporT: Big Data+Machine Learning for clean coal

# Introduction

Currently, big data and machine learning play a large role in coal-fired power generation. In fact, some companies—such as General Electric (GE) Digital, SAS, and ABB—are already using software and data analytics to help power plants identify operational efficiencies. Fossil energy researchers are increasingly incorporating big data into research programs; and, machine learning is being applied across the coal-fired power industry and coal power research—using big data from sensors and controls to detect patterns that improve operations and predict failures.

Despite the increasing prevalence of big data and machine learning applications for the coal power sector, there are still unrealized opportunities for adopting these tools in the coal industry. To help realize these opportunities, the coal industry should identify research needs for big data and machine learning applications in the coal power sector, as well as perform a crosscutting evaluation of how it can better use these technologies.

To that end, the Office of Clean Coal and Carbon Management (OCCM), within the U.S. Department of Energy’s (DOE) Office of Fossil Energy (FE), has selected big data and machine learning as the special analysis report topic for Fiscal Year 2018. The following document is a first step toward an evaluation of big data and machine learning in the coal industry. It is the product of a scoping exercise that included a one-day workshop attended by a range of experts from utilities, national laboratories, government, and companies that specialize in big data and machine learning applications.

# Relevant Ongoing DOE/FE/OCCM R&D efforts

Power plants and other complex industrial systems generate a significant amount of data associated with every aspect of operations. The volume and intensity of this data is high and only a fraction of what is available is analyzed or used to improve operations. While the term “big data” varies by industry, it is generally defined as data sets that are too large for traditional software tools for visualization, processing, manipulation, analysis, and storage.[[1]](#footnote-1)

Machine learning—one aspect of artificial intelligence (AI)—specifically refers to the ability for machines (computers) to apply algorithms to identify patterns in data. The algorithms adapt in response to new data and become more efficient over time. Machine learning can be used to detect patterns in order to categorize, predict, identify, or detect changes or factors of interest.

FE is already leveraging big data and machine learning throughout the Fossil Energy Research and Development (FE R&D) portfolio and at the DOE national laboratories. In the Crosscutting Research Program alone, there are 20 active projects valued at $19M that focus on advanced power plant controls and predictive maintenance solutions, materials discovery, and model input gathering. Likewise, the Carbon Capture Program is funding the ongoing Carbon Capture Simulation for Industry Impact (CCSI2) project, a roughly $5M/yr effort that employs and refines machine learning approaches for optimal experimental data generation and evaluation. This section describes the primary areas of this research, including predictive maintenance, digital twinning, sensors and controls, materials development, and subsurface. Two specific projects—The Institute for the Design of Advanced Energy Systems (IDAES) and CCSI2—which focus on big data and machine learning are also described.

Predictive Maintenance

R&D on predictive maintenance is focused on the use of data from a diverse set of sensors and the application of machine learning to diagnose faults before they occur—ultimately switching from a culture of preventative maintenance to one of conditioning maintenance. Data analytics can also be used to upgrade sensors and controls with machine learning to identify operational discontinuities and inform decisions on operational efficiency. Doing so would enable plants to operate in an environment where they are required to cycle more frequently than originally envisioned. In this program area, Microbeam Technologies, Inc. is working to predict the impacts of coal quality on boiler operations and Sparkognition is applying machine learning algorithms to detect and diagnose premature equipment failure, among other projects.

Digital Twinning

Digital twinning compliments machine learning. In digital twinning, a computational model is developed, and visualization is used to understand and predict the impact of changes in a digital/virtual environment to optimize the process before application in the real world. A digital twin includes models that replicate usage and wear on engines and turbines to make maintenance more efficient. A commercial example of this is GE’s digital ghost, which combines digital twin and industrial control efforts, using them together to improve cybersecurity.[[2]](#footnote-2) The GE digital twin technology has been applied at more than 600,000 GE facilities, enabling repair at lower costs with less disruption. The National Energy Technology Laboratory’s (NETL) JOULE supercomputer is used to develop digital twins of coal plants to assist in developing the next generation of coal technologies.

Sensors and Controls

Advanced sensors and controls increase coal plant efficiency, reduce forced outages, and avoid downtime related to compliance with environmental regulations.  This work includes the development of sensors and control algorithms, data-driven hybrid models that integrate power plant operations and environmental controls, electrochemical monitoring integrated into the central controls, and application of advanced control systems including artificial intelligence. In addition to the integration of sensors and control systems, there is ongoing research aimed at optimal placement and integration. In this program area, the University of Utah is developing real-time measurement of temperature profiles in different boiler combustion zones; West Virginia University is developing sensors to detect target gasses at high with electrochemical high-temperature sensors; Opto-Knowledge System, Inc. is developing sulfur dioxide (SO2) monitoring for optimal control of alkali injection systems; and the University of Maine is developing wireless harsh-environment sensors.

## Materials Development

Development of future coal systems requires improving the materials needed to operate in extreme environments, such as extreme pressure; high temperature; and states of vibration, fatigue, or stress. High-performance material development concentrates on advanced manufacturing methods and computational materials modeling. R&D of extreme environment materials (EEMs) is underway, incorporating big data and machine learning to accelerate the development of new functional materials. These materials are needed to advance innovative technical approaches and to improve the performance of coal power plants, coal-to-liquids plants, and systems for producing other high-value products from coal. Researchers are overcoming key challenges in developing, modifying, and qualifying new materials by using machine learning and big data, thus, significantly reducing the timeline for a new material to meet the American Society of Mechanical Engineers’ qualifications standards and to be ready for commercial use.

## Subsurface

Research, scientific, and engineering data resources, including subsurface characterization, modeling, and analytical datasets, are increasingly available through online portals, warehouses, and systems. For the subsurface, these resources span petrophysical, geologic, engineering, and geophysical interpretations, models, and analyses associated with carbon storage, water, oil, gas, geothermal, induced seismicity, and other subsurface systems to support the development of a virtual subsurface data framework. Data for subsurface systems is still challenging to access, is discontinuous, and varies in resolution. However, with the proliferation of online data, there are significant opportunities to advance access and knowledge of subsurface systems. One ongoing effort in this area is the Energy Data eXchange (EDX), an online platform designed to address research data needs by improving access to energy R&D products through advanced search capabilities. Recently, researchers successfully integrated EDX and DataBook, giving users the ability to interact with other systems (Earthcube, OpenEI.net, NGDS, etc.) and leverage custom machine learning algorithms and capabilities to enhance user experience.

## The Institute for the Design of Advanced Energy Systems

IDAES is a resource for the development and analysis of innovative advanced energy systems via process systems’ engineering tools and approaches. The Institute develops a rigorous, computational approach for developing new concepts for energy systems. Because of the complexity of energy systems, and the increasing recognition of the importance of understanding uncertainty, IDAES’s models are both multi-scale and dynamic in nature, while incorporating intrusive uncertainty quantification techniques. IDAES builds on existing open-source software tools to the extent possible and, when required, builds new capabilities. When necessary, high-performance computing will be utilized to solve the large systems of equations constituting IDAES models in reasonable time.

## Carbon Capture Simulation for Industry Impact

CCSI2 is a partnership among national laboratories, industry, and academic institutions that develops and deploys state-of-the-art computational modeling and simulation tools. The core of the CCSI2 mission is to accelerate the commercialization of carbon capture technologies from discovery through development, demonstration, and ultimately the widespread deployment in advanced power generation. CCSI2’s open-source, R&D 100 Award-winning computational toolset is designed to provide end users in industry with a comprehensive, integrated suite of scientifically validated models, as well as uncertainty quantification, optimization, risk analysis, and intelligent decision-making capabilities. Among other pursuits, CCSI2 has computational frameworks that develop and deploy machine learning methods for generating optimal design of experiments that produce the most impactful data at all stages of commercialization. CCSI2 can also employ big data and machine learning techniques to develop and apply algorithms for the rational and efficient design of carbon capture materials.

# Future Directions

To determine how the coal industry can further adopt big data and machine learning in the future, an internal scoping effort was conducted between March and June 2018 and the U.S. Energy Association (USEA) convened and a one-day workshop in July 2018. The efforts reviewed ongoing efforts and identified gaps and needs for future R&D in clean coal and carbon management that leverages big data and machine learning. The workshop participants had diverse backgrounds and interests but came together for the common goal of determining how big data and machine learning can shape the future of coal-based systems. Appendices A and B include the workshop agenda and participants list.

“The goal should be to move from descriptive to reactive to predictive to prescriptive and finally autonomous.” –Workshop participant

Although the scoping effort was targeted toward a detailed review of the potential for big data and machine learning within the coal industry, there are a few overarching themes that emerged:

* Although there are tools available to leverage big data and machine learning and improve the efficiency of power plants, application of these tools in the coal sector has been limited.
* Real-world application of big data and machine learning (and other forms of AI) will require diverse teams of data scientists and subject matter experts working together to identify data sets and produce interdisciplinary analysis and solutions.
* Machine learning can be used to target “Smart Data” to cost-effectively improve understanding without the need to process big data sets.
* Data visualization and uncertainty analyses are areas that need additional attention.
* A primary opportunity for big data and machine learning in the coal power sector is to refine and improve physics-based modeling in lieu of traditional empirical approaches. A coal plant is a complex, multi-scale, multi-physics system; improvements for them can be hard to design and operationally challenging. Advanced simulation is a critical component for accurately projecting techno-economic performance. Big data and machine learning provide opportunities to advance simulation and improve future coal plants in the following ways:
	+ A multi-physics model is based on fundamental principles and used to fully characterize or predict performance. However, in advanced R&D, many situations exist where fundamental behavior of materials and processes is not yet known. Integrating fundamental models with machine learning techniques can target data needs to most effectively refine the precision of the model. Machine learning can reveal unknown fundamental behavior to generate models that are more responsive, interpretive, and predictive.
	+ History matching using real data is needed to verify algorithms, including built-in feedback to adjust the model according to observed conditions at key control points.
* Data governance is an important issue. While the research community seeks data to develop and improve algorithms, the data owners have concerns about where and how data will be used. Creating appropriate governance measures will be an important aspect of public-private partnerships efforts.

Together, the workshop and internal scoping efforts, focused on opportunities within the specific strategic objectives outlined in the FE Clean Coal and Carbon Management Strategic Plan:

* **Coal Plants of the Future** – FE aims to create new long-term pathways for coal-fired power generation, supported by the most advanced and innovative technologies.
* **A Competitive, Resilient, and Flexible Existing Fleet** – FE aims to identify ways to improve efficiency, reduce emissions, and allow these existing plants to operate on an evolving grid with more intermittent power sources. Doing so will provide affordable near-term energy security benefits and also support future power and infrastructure needs amidst a changing energy landscape.
* **Capturing New Markets** – FE aims to reduce the cost of carbon capture, utilization, and storage (CCUS) and develop new products and uses of coal and coal by-products to create new businesses and industries and bring CCUS closer to commercial viability.

In addition, there was a second July 2018 workshop convened by NETL and Carnegie Mellon University that focused on subsurface issues. This special report substantially benefited from the discussions and ideas shared during both workshops. Below, the report provides more detail about what this analysis revealed about the potential for each strategic objective to utilize big data and machine learning.

Coal Plants of the Future

For future electricity production with coal, units will need to be efficient, smaller (50–350 MW), more distributed, and closer to load centers, so they can be more modular. These plants must be capable of flexible operations to compete in domestic electricity markets with increasingly diversified smaller-scale energy from renewables. As these systems are designed, many of the system components can benefit from the application of big data and machine learning. For example, big data and machine learning can be leveraged to achieve four objectives, some of which will also help existing plants:

1. **Design new coal plants, including modular coal systems**

Employing machine learning and big data in developing plant simulations—instead of relying solely on physics-based models—can expedite the development of advanced manufacturing processes for modular systems producing electricity and/or other valuable fossil-based products.

The use of big data and machine learning to look for trends and proxy simulation of advanced plant designs will allow plants to learn from existing operating conditions; understand failures, successes, efficiency, and life span; and identify possibilities for hybrid energy production.

1. **Develop next-generation power plant components**

Employing experimental macroscopic data and computational microscopic data to understand and predict material performance can aid the development of high-temperature materials that are capable of operating under ultra-supercritical steam conditions. This application of data includes using computational materials approaches to understand component needs and achieve high-temperature performance with decreased thermal fatigue vulnerability.

The application of motor current signature and electromagnetic signature analysis can improve the understanding of efficiency.

The creation of a library or digital twin that can assist in identifying fault types and signatures and the use of such a tool can help prevent component degradation.

1. **Improve operations under cycling conditions**

Observed and synthetic data for training and machine learning output for finer prediction, uncertainty estimation, etc. can be used to design and operate a plant that responds to dynamic energy needs.

The use of dynamic forecasting can enable flexibility in generation; this includes predicting loads based on societal needs using pattern-derived forecasting.

Machine learning can be applied to achieve predictive dispatch, rather than rules-based (i.e. weather-anticipatory) dispatch.

Management of cycling operating conditions and variable frequency as part of operations (including microgrids, virtual power plants, and distributed energy resources) can enable grid integration for small, modular coal plants or other coal-fueled facilities of the future.

The use of blockchain can help manage frequency and enable decentralized grids where microgrids and large power plants will be required to better co-exist in a single market.

Employing machine learning—using data from multiple regions, owners, and facilities—can help identify patterns and determine optimal size of plant that can load follow.

Big data and machine learning can be used to determine life consumption and life estimation of major components under flexible operation.

Industry should use big data and machine learning to couple models for combustion and degradation, as well as develop new tools that predict how cycling can impact plant component health and performance (including development of neural networks that enable full plant simulation).

1. **Integrate plant components and improve sensors**

The optimization of combustion will improve energy output while minimizing emissions and slagging/fouling (heat integration, improved ramping, etc.).

The integration of operational controls, including the combustion process as well as the emissions control systems, will help to optimize both in real time.

Designing future plants with autonomous control at the component level, including embedded intelligent components, will help predict failure and enable them to work together in an integrated fashion.

The development of sensors with the ability for two-way communication, including system- to component-level sensors for high frequency responses across the entire network, and 5G compatible sensors can provide dynamic prognostics, possibly tying in smart meter data.

A Competitive, Resilient and Flexible Existing Fleet

OCCCM is focused on developing options—particularly technology options—for increasing the reliability, resilience, and efficiency of existing coal power plants. The average efficiency of the U.S. coal fleet is 30 percent (net higher heating value basis), and the efficiencies of individual aging coal power plants are often much lower than this average. This work can be accelerated through applications of big data and machine learning to increase cybersecurity, support and use blockchain, and improve operations at aging units.

1. **Increase cybersecurity**

Big data and machine learning can improve the security of the electric grid, including infrastructure and electrical systems.

Identification, protection, and management of cybersecurity within the plant, including real-time cybersecurity threat, attack monitoring, and early detection is critical.

1. **Leverage opportunities to support and use blockchain**

Blockchain can provide power for servers mining cryptocurrencies.

The application of blockchain can manage supply chain transactions (e.g., fuels, electric vehicle charging, etc.).

The use of blockchain can help manage distributed generation.

1. **Improve operations at existing units**

Machine learning can be used to sanitize sensor data and manage alarms.

Analysis of big data can identify component degradation, quantifying the impact of cycling on various components.

Aggregated data from plants can evaluate inefficiencies at the component and subsystem level. Existing data from independent system operators and real-time operating systems could be leveraged, and machine learning could train a tool with data from plants across the United States. Once aggregated data is part of a neural net, it becomes autonomous and is not proprietary. Operators could compare their plant operations to other plants across the country and the tool could help operators find the lowest cost option to enhance efficiency.

Physics-based models refined by machine learning can be used to upgrade components on existing plants and identify opportunities for efficiency improvements.

The application of image recognition can improve safety and maintenance. This could include something akin to a backpack version of Google Street View for existing plant materials—image recognition for corrosion using simulation and failure records.

Optimizing combustion under different operating regimes can help collect data from a suite of plants and fuels and identify unknown patterns that contribute to efficiency.

New Markets

Innovation in the energy sector is continuously opening new markets. OCCCM’s efforts in leveraging new markets for coal and its by-products will help explore and realize coal’s role in these markets. As a result of more than two decades of R&D, in partnership with industry, DOE has supported some of the world’s largest advanced coal and carbon capture and storage (CCS) demonstration projects.

1. **Enable carbon storage**

Collecting data from distributed sensors and employing machine learning and data analytics can better infer information about carbon storage in the subsurface, including plume location, seismic activity, surface deformation, geochemical and geomechanical interactions, leak detection signatures, and well integrity.

Coupling geophysics with machine learning can help ensure transparency and possibly increase the accuracy of predictive models.

Data fusion should be applied to process big data from multiple sensors as part of seismic processing.

Blockchain can be used to manage data both for accounting and possibly regulatory purposes, including tracking signatures/ownership of carbon dioxide (CO2).

The use of machine learning can reduce monitoring requirements of essential data collected over a limited time period.

Optimizing infrastructure with data mining and visualization will create a digital twin for a CCUS system to assist in a variety of tasks such as predictive maintenance, managed assets, and worker safety.

1. **Accelerate development of rare earth elements (REEs) and critical mineral recovery from coal and coal by-products**

The use of remote sensing at abandoned mine sites, such as gob piles and acid mine drainage, can help identify coal-based material.

Data analytics of the range of possible ash properties can be used to model and optimize systems’ performance using

Data analytics can help identify markers for REEs in overburden, leachate, acid mine drainage, and old mine sites.

Creating a digital library could link data from existing core and coal sample libraries to the presence of potentially recoverable amounts of REEs.

1. **Improve CO2 capture and utilization efforts**
	* Machine learning can guide intelligent design of experiments and design new materials for adsorption.
	* Text analytics tools like IBM Watson or other big data mining algorithms can be employed to search databases on materials for gas separations, solvents for coal to liquids, and catalysts for application for CO2 conversion.
	* The use of simulation tools can accelerate time from discovery of materials to optimization into a process (similar to CCSI2).
	* Developing algorithms based on observations and using a combination of atomistic modeling, physics-based modeling, and machine learning can help model additional parameters while managing high volumes of data.
	* Models can be developed mining existing data sources to understand degradation behavior of materials in high CO2 concentration environments.

# Conclusion

There are significant opportunities to leverage big data and machine learning in ways that will help OCCCM achieve its strategic objectives. In summary, these opportunities fall into three main categories that span the entire coal R&D program: design, operations, and controls.

**Design:** Big data and machine learning can be used to refine fundamental understanding of materials/equipment/systems performance to yield more efficient R&D on extreme environment materials and novel system design, including design of small-scale modular coal-based power plants of the future and CCUS systems.

**Operations:** Big data and machine learning are needed for enhancing predictive capability for identifying materials and component fatigue; understanding and predicting fluid flows in power plant systems and the subsurface; and optimizing dynamic responses to market dynamics.

**Controls:** Real-time machine learning using data gathered by an integrated network of advanced sensors and processed by advanced control algorithms to improve detection, interpretation, controllability, and response.

# Appendix A: Workshop Agenda

Big Data and Machine Learning for Clean Coal and Carbon Management Strategic Initiatives

Date: July 12, 2018

Location: Ronald Reagan Building

1300 Pennsylvania Ave NW, Polaris Suite

Washington, DC 20004

## Background

This workshop was convened to help inform strategic initiatives in the U.S. Department of Energy’s (DOE) Office of Clean Coal and Carbon Management. The discussions aimed to help identify how big data and machine learning can be better leveraged to enable advanced coal energy systems of the future, to build competitive, resilient, and flexible existing fleet; and to develop new products and uses of coal and coal by-products to support creating new businesses and industries.

**8:30–9:00 A.M. Open Registration**

**9:00–9:30 A.M. Welcome from Steven Winberg, Assistant Secretary for Fossil Energy**

**Opening Remarks**

* Overview of workshop objectives, purpose, and expected outcomes
	+ Jarad Daniels, DOE Headquarters
* Summary of relevant work underway in R&D program
	+ Randall Gentry, National Energy Technology Laboratory (NETL)

**9:30–11:00 A.M. Session 1: Lightning Round**

 Non-DOE attendees give a 4-minute introduction outlining perspectives and capabilities in big data and machine learning.

1. Zia Abdullah, National Renewable Energy Laboratory
2. Greg Augspurger, Duke Energy
3. Debbie Bard, Lawrence Berkeley National Laboratory
4. Lee Brenner, Global Blockchain Business Council
5. Grant Bromhal, NETL
6. Sydni Credle, NETL
7. Arindam Dasgupta, Siemens
8. Ken Daycock, GP Strategies Corporation
9. Neva Espinoza, Electric Power Research Institute
10. Justin Fessler, Watson Solutions Consultant, IBM
11. Dan Goldberg, Argonne National Laboratory
12. George Guthrie, Los Alamos National Laboartory
13. Shuangshuang Jin, Clemson University
14. Mike Mateseuski, NETL
15. Bruce Pint, Oak Ridge National Laboratory
16. Carlton Reeves, C3 IoT
17. Kelly Rose, NETL
18. Christopher Sherman, Lawrence Livermore National Laboratory
19. Pamela Tomski, SAS
20. Rich Vesel, ABB Plant Performance & Optimization

**11:00–11:15 A.M. Break**

**11:15–12:15 P.M. Session 2: Industry Panel**What products, processes, tools, and knowledge already exist? What is missing?

Panelists:

* Richard Vesel, ABB Inc.
* Alyssa Farrell, SAS
* Salvatore DellaVilla, Strategic Power Systems Inc.
* Gregory Augspurger, Duke Energy

Facilitator: Geo Richards, NETL

**12:15–1:00 P.M. Lunch Break (Provided by USEA)**

**1:00–3:30 P.M. Session 3: Breakout Group Discussion**Is predictive maintenance commercially available, or the subject of RD&D? Are there applications for blockchain technology that could be applied to fossil energy systems? How can DOE better leverage machine learning and big data to:

1. Enable the advanced coal energy system of the future?
	* Facilitator: Bhima Sastri, DOE and Mike Matuszewski, NETL
2. Realize a competitive, resilient, and flexible existing fleet?
	* Facilitator: Robie Lewis, DOE and Sydni Credle, NETL
3. Leverage new markets?
	* Facilitator: John Litynski, DOE and Grant Bromhal, NETL

**3:30–3:45 P.M. Break**

**3:45–4:30 P.M. Session 4: Recommendations/Goals**This session will include facilitators giving a read out for each breakout topic, followed by a group discussion.

 Facilitator: Sarah Forbes, DOE

**4:30–5:00 P.M. Concluding Remarks from Participants**

Facilitator: Jarad Daniels, DOE

# Appendix B: Workshop Participants

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| --- | --- | --- |
|  | Name | Organization |
| 1. | Zia Abdullah | National Renewable Energy Laboratory |
| 2. | Greg Augspurger | Duke Energy |
| 3. | Debbie Bard | Lawrence Berkley National Laboratory |
| 4. | Laura Biven | U.S. Department of Energy, Office of Science |
| 5. | Lee Brenner | Global Blockchain Business Council |
| 6. | Lynn Brickett | National Energy Technology Laboratory  |
| 7. | Grant Bromhal  | National Energy Technology Laboratory  |
| 8. | Alan Cohen | U.S. Department of Energy, Office of Fossil Energy |
| 9. | Sydni Credle | National Energy Technology Laboratory |
| 10. | Darin Damiani | U.S. Department of Energy, Office of Fossil Energy |
| 11. | Jarad Daniels | U.S. Department of Energy, Office of Fossil Energy |
| 12. | Arindam Dasgupta | Siemens |
| 13. | Ken Daycock | GP Strategies Corporation |
| 14. | Salvatore DellaVilla | Strategic Power Systems |
| 15. | Neva Espinoza | Electric Power Research Institute |
| 16. | Alyssa Farrell | SAS |
| 17. | Justin Fessler | Watson Solutions IBM |
| 18. | Sarah Forbes | U.S. Department of Energy |
| 19. | Charles Freeman | Pacific Northwest National Laboratory |
| 20. | Raj Gaikwad | U.S. Department of Energy, Office of Fossil Energy |
| 21. | Randall Gentry | National Energy Technology Laboratory |
| 22. | Joe Giove | U.S. Department of Energy, Office of Fossil Energy |
| 23. | Dan Goldberg | Argonne National Laboratory  |
| 24. | Heather Greenley | U.S. Energy Association |
| 25. | George Guthrie | Los Alamos National Laboratory |
| 26. | John Hutchinson | Electric Power Research Institute |
| 27. | Shuangshuang Jin | Clemson University |
| 28. | Amishi Kumar | U.S. Department of Energy, Office of Fossil Energy |
| 29. | Robie Lewis | U.S. Department of Energy, Office of Fossil Energy |
| 30. | Youzuo Lin | Los Alamos National Laboratory  |
| 31. | John Litynski | U.S. Department of Energy, Office of Fossil Energy |
| 32. | Mike Matuszewski | National Energy Technology Laboratory  |
| 33. | Colin McCormick | Valence Strategic |
| 34. | Bruce Pint | Oak Ridge National Laboratory  |
| 35. | Carlton Reeves | C3 IoT |
| 36. | Geo Richards | National Energy Technology Laboratory  |
| 37. | Traci Rodosta | National Energy Technology Laboratory  |
| 38. | Kelly Rose | National Energy Technology Laboratory  |
| 39. | Bhima Sastri | U.S. Department of Energy, Office of Fossil Energy |
| 40. | Ann Satsangi | U.S. Department of Energy, Office of Fossil Energy |
| 41. | Christopher Sherman | Lawrence Livermore National Laboratory  |
| 42. | Wei Shi | National Energy Technology Laboratory  |
| 43. | Robert Smith | U.S. Department of Energy, Office of Fossil Energy |
| 44. | Scott Smouse | U.S. Department of Energy, Office of Fossil Energy |
| 45. | Pamela Tomski | SAS |
| 46. | Rich Vesel | ABB Plant Performance & Optimization |
| 47. | Steven Winberg | U.S. Department of Energy, Office of Fossil Energy |
| 48. | Shannon Zaret | U.S. Energy Association |

1. James Manyika, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, and Angela Hung Byers, *Big Data: The next frontier* *for innovation, competition, and productivity* (McKinsey Global Institute, May 2011), <https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Big%20data%20The%20next%20frontier%20for%20innovation/MGI_big_data_exec_summary.ashx>. [↑](#footnote-ref-1)
2. Larry Dignan, “GE aims to replicate Digital Twin success with security-focused Digital Ghost,” ZDNet, March 24, 2017, <https://www.zdnet.com/article/ge-aims-to-replicate-digital-twin-success-with-security-focused-digital-ghost/>. [↑](#footnote-ref-2)