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FRONTIERS OF **ENGINEERING**

Reports on Leading-Edge Engineering from the 2017 Symposium

NATIONAL ACADEMY OF ENGINEERING

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Preface

This volume presents papers on the topics covered at the National Academy of Engineering's 2017 US Frontiers of Engineering Symposium. Every year the symposium brings together 100 outstanding young leaders in engineering to share their cutting-edge research and innovations in selected areas. The 2017 symposium was hosted by United Technologies Research Center (UTRC) in East Hartford, Connecticut, September 25–27. The intent of this book is to convey the excitement of this unique meeting and to highlight innovative developments in engineering research and technical work.

GOALS OF THE FRONTIERS OF ENGINEERING PROGRAM

The practice of engineering is continually changing. Engineers must be able not only to thrive in an environment of rapid technological change and globalization but also to work on interdisciplinary teams. Today's research is being done at the intersections of engineering disciplines, and successful researchers and practitioners must be aware of developments and challenges in areas that may not be familiar to them.

At the annual 2½-day US Frontiers of Engineering Symposium, 100 of this country's best and brightest engineers—ages 30 to 45, from academia, industry, and government and a variety of engineering disciplines—learn from their peers about pioneering work in different areas of engineering. The number of participants is limited to 100 to maximize opportunities for interactions and exchanges among the attendees, who are chosen through a competitive nomination and selection process. The symposium is designed to foster contacts and learning among promising individuals who would not meet in the usual round of professional

meetings. This networking may lead to collaborative work, facilitate the transfer of new techniques and approaches, and produce insights and applications that bolster US innovative capacity.

The four topics and the speakers for each year's meeting are selected by an organizing committee of engineers in the same 30- to 45-year-old cohort as the participants. Speakers describe the challenges they face and communicate the excitement of their work to a technically sophisticated but nonspecialist audience. They provide a brief overview of their field of inquiry; define the frontiers of that field; describe experiments, prototypes, and design studies (completed or in progress) as well as new tools and methods, limitations and controversies; and assess the long-term significance of their work.

THE 2017 SYMPOSIUM

The topics covered at the 2017 symposium were (1) machines that teach themselves, (2) energy strategies to power our future, (3) unraveling the complexity of the brain, and (4) megatall buildings and other future places of work.

The first session described machines that process information into useful output by learning their own models. The first speaker discussed the application of interactive machine learning to self-optimizing tutoring systems in classrooms, work that advances reinforcement learning—an important foundation for building machines that teach themselves. The next speaker focused on machine systems that utilize highly heterogeneous data (e.g., sensor streams, genomic data, text) to make inferences that improve health care through predictive models and individualized treatment. The session concluded with a talk on machine learning qualities such as question-answering AI that are necessary for a future where machines interact naturally with humans.

The next session addressed the question, “How will we power our future?” The answer will be multifaceted and involve power generation and storage, new grid technologies, and transportation electrification. The first speaker set the stage by discussing “deep decarbonization” and what it will take to move from a carbon-based energy system to one based on renewable energy. Because this will require substantial changes to how electric power systems are planned and operated, the talk described emerging technologies that will improve real-time grid state awareness, achieve more robust control over power flows, and enable comprehensive approaches to power system optimization. This was followed by a presentation on the merger of advanced physical models for wind energy with big data and analytics to enable a reduction in the cost of energy supplied by the next generation of wind plants. The third presenter talked about how imaging and machine learning will help design tomorrow's energy conversion devices. The final speaker described the state of the art for stationary and dynamic wireless charging of electric vehicles and the challenges in performance, cost, and safety that need to be overcome for wide-scale adoption of wireless power transfer systems.

Because the brain is a complex system consisting of microscopic and macroscopic networks, understanding it requires simultaneous measurements at multiple spatiotemporal scales. In the session *Unraveling the Complexity of the Brain*, speakers outlined the advances that engineers have made in the quest to understand the brain, treat its disorders, and enhance its functions. The presentations described technologies to interface with the brain for recording and modulation, the neural basis of skill learning using brain-machine interfaces, new models for neuroscience, and efficient feature extraction and classification methods in neural interfaces.

This decade launched the rise of a new breed of skyscrapers, megatall buildings, defined as being more than 600 meters tall. The session began with an overview of fundamental design transformations in the construction of megatall buildings and how their distinctive spatial characteristics influence the quality of life inside and outside the building. The next speaker addressed the role of digital interaction, physical-human interface, and intuitive behavior in the transformation of vertical transportation. This was followed by a talk on the functional natural materials such as bamboo that challenge the status quo of structural systems in high-rise buildings. The final speaker described the applications of insights from biology and mathematics to the design of material structures in the form of adaptive building skins, material assemblies, and architectural interventions.

In addition to the plenary sessions, the attendees had many opportunities for informal interaction. On the first afternoon, they gathered in small groups for “Meet and Connect” sessions during which they presented short descriptions of their work and answered questions from their colleagues. This helped them get to know more about each other relatively early in the program. On the second afternoon, UTRC arranged tours of its state-of-the-art “innovation hub” that highlighted several research areas: digital service for Otis Elevator, measurement sciences and microscopy, human-machine interaction, machine learning, and additive and advanced manufacturing.

Every year a distinguished engineer addresses the participants at dinner on the first evening of the symposium. The 2017 speaker, Dr. David E. Parekh, corporate vice president and director of UTRC, gave the dinner speech titled, “Navigating Innovation’s Uncertain Course.” He compared the ability to know where innovation is heading to an autocross competition—one does not know the race course, it is constantly changing, and others are in fast pursuit. He noted that the transitions from film to digital imaging and from taxis to shared transportation exemplify the challenges of managing disruptive technological change. Dr. Parekh closed his presentation by observing that innovation is best served when it is developed by people with different perspectives.

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We also thank the members of the Symposium Organizing Committee (p. iv), chaired by Dr. Robert Braun, for planning and organizing the event.

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MACHINES THAT TEACH THEMSELVES

Machines That Teach Themselves

RAJAN BHATTACHARYYA
HRL Laboratories

The human race has been using tools for more than 2.5 million years, and building machines for just more than 2,000 years. Over the past 200 years, humans developed machines to do physical work during the Industrial Age, and in the past 50 years innovations in technology areas such as electronics and computer science spawned the Digital Age.

Until now, machines were designed by hand to perform specialized functions in a highly efficient way using engineering principles. In the Information Age, data volume is increasing by 40 percent annually and streaming at faster rates each year. Moreover, this exponential growth is dominated by an acceleration in unstructured data due to the variety of sources, which include documents, video, audio, and embedded sensors. Finally, high dimensionality and uncertainty in data require new computational methods to extract latent patterns and semantics. Taken together, these challenges necessitate a new way to build machines to make Information Age data useful.

In this session the speakers explored machines that process information into useful output in a variety of applications but that are optimized in a very different way: by learning their own models. Emma Brunskill (Stanford University) opened the session with a presentation on how interactive machine learning can be applied to self-optimizing tutoring systems in classrooms.¹ Her work advances the paradigm of reinforcement learning, an important pillar in building machines that teach themselves. Suchi Saria (Johns Hopkins University) focused on machine systems that utilize highly heterogeneous data, ranging from sensor streams and genomic data to unstructured data, such as text, to perform inference.¹ She

¹ Paper not included in this volume.

explained how she applies a variety of machine learning methods and computational statistics to improve health care through predictive models and individualized treatment. Jordan Boyd-Graber (University of Maryland) discussed qualities that ubiquitous machine learning should have to allow for a future filled with “natural” interactions with humans. He explained the use of question-answering artificial intelligence (AI) as a way of evaluating how well AI systems can communicate what they are “thinking” to humans.

Humans and Computers Working Together to Measure Machine Learning Interpretability

JORDAN BOYD-GRABER
University of Maryland

Machine learning is ubiquitous: it is involved in detecting spam emails, flagging fraudulent purchases, and providing the next movie in a Netflix binge. But few users at the mercy of machine learning outputs know what is happening behind the curtain. My research goal is to demystify the black box for nonexperts by creating algorithms that can inform, collaborate, and compete in real-world settings.

This is at odds with mainstream machine learning. Topic models, for example, are sold as a tool for understanding large data collections: lawyers scouring Enron emails for a smoking gun, journalists making sense of Wikileaks, or humanists characterizing the oeuvre of Lope de Vega. But topic models' proponents never asked what those lawyers, journalists, or humanists needed. Instead, they optimized held-out likelihood.

THE NEED FOR IMPROVED INTERPRETABILITY

When my colleagues and I developed an interpretability measure to assess whether topic model users understood the models' outputs, we found that interpretability and held-out likelihood were negatively correlated (Chang et al. 2009)! The machine learning community (including me) had fetishized complexity at the expense of usability.

Understanding what users want and need offers technical improvements to machine learning methods, and it improves the social process of machine learning adoption. A program manager who used topic models to characterize National Institutes of Health (NIH) research investments uncovered interesting synergies and trends, but the results were unpresentable because of a fatal flaw: one of the

700 clusters lumped urology together with the nervous system, anathema to NIH insiders (Talley et al. 2011). Algorithms that prevent nonexperts from fixing such obvious problems (obvious to a human, that is) will never overcome the social barriers that often hamper adoption.

These problems are also evident in supervised machine learning. Ribeiro and colleagues (2016) cite an example of a classifier to distinguish wolves from dogs that detects only whether the background is snow. More specifically for deep learning, Karpathy and colleagues (2015) look at the computational units responsible for detecting the end of phrases in natural language or computer code.

These first steps at interpretability fall short because they ignore utility. At the risk of caricature, engineers can optimize only what they can measure. How can researchers actually measure what machine learning algorithms are supposed to be doing?

QUESTION ANSWERING

A brief detour through question answering (QA) can shed light on the answer to that question. QA is difficult because it has all the nuance and ambiguity associated with natural language processing (NLP) tasks and it requires deep, expert-level world knowledge.

Completely open-domain QA is considered AI-complete (Yampolskiy 2013). Short-answer QA can be made more interactive and more discriminative by giving up the assumptions of batch QA to allow questions to be interrupted so that answers provided earlier reward deeper knowledge.

Quiz Bowl

Fortunately, there is a ready-made source of questions written with these properties from a competition known as Quiz Bowl. Thousands of questions are written every year for competitions that engage participants from middle schoolers to grizzled veterans on the “open circuit.” These questions represent decades of iterative refinement of how to best discriminate which humans are most knowledgeable (in contrast, *Jeopardy*’s format has not changed since its debut half a century ago; its television-oriented format is thus not considered as “pure” a competition among trivia enthusiasts).

Interpretability cannot be divorced from the task a machine learning algorithm is attempting to solve. Here, the existence of Quiz Bowl as a popular recreational activity is again a benefit: thousands of trivia enthusiasts form teams to compete in Quiz Bowl tournaments. Thus far, our algorithm has played only by itself. Can it be a good team player? And can it learn from its teammates? The answers to these questions can also reveal how useful it is at conveying its intentions.

BOX 1 Sample Quiz Bowl Question

The question begins with obscure information and incorporates more well-known clues as it progresses. In our exhibition match, Ken Jennings answered (*) this question before the computer could (**), showing he had deeper knowledge on this topic.

Q: This man ordered Thomas Larkin to buy him 70 square miles of land, leading him to acquire his Mariposa gold mine. He married Jessie, the daughter of Thomas Hart Benton, and, during the Civil War, he controversially confiscated () slave-holder property while acting as the leader of Missouri. Kit Carson served as the guide for the first two of his expeditions to survey the American West. For 10 points, name this explorer known as “the Pathfinder” (**) who was also the first presidential candidate of the Republican Party.*

A: John C. Fremont

Box 1 shows an example of a question written to reward deeper knowledge and the places in the text where our system (**) and Ken Jennings¹ (*) answered the question.

A moderator reads the question word by word and the first player who knows the answer uses a signaling device to “buzz in.” If the player has the correct answer, he earns points; if not, the moderator reads the rest of the question to the opponent. Because the question begins with obscure clues and moves to more well-known information, the player who can buzz first presumably has more knowledge.

We have good evidence that Quiz Bowl serves as a good setting for conveying how computers think. Our trivia-playing robot (Boyd-Graber et al. 2012; Iyyer et al. 2014, 2015) faced off against four former *Jeopardy* champions in front of 600 high school students.² The computer claimed an early lead, but we foolishly projected the computer’s thought process for all to see (Figure 1). The humans learned to read the algorithm’s ranked dot products and schemed to answer just before the computer. In five years of teaching machine learning, I have never had students catch on so quickly to how linear classifiers work. The probing questions from high school students in the audience showed that they caught on too.

¹ Ken Jennings holds the record for longest winning streak—74 consecutive games in 2004—on the quiz show *Jeopardy*.

² See <https://www.youtube.com/watch?v=LqsUapRYMOW>.



FIGURE 1 When opponents can see what a computer is thinking in a trivia game, they can more easily defeat it.

(Later, when we played against Ken Jennings,³ he was not able to see the system's thought process and our system did much better.)

“Centaur Chess”

A growing trend in competitive chess is “centaur chess” (Thompson 2013). The best chess players are neither a human nor a computer but a computer and a human playing together. The language of chess is relatively simple; given a single board configuration, only a handful of moves are worthwhile. Unlike chess, Quiz Bowl is grounded in language, which makes the task of explaining hypotheses, features, and probabilities more complicated.

I propose a “Centaur Quiz Bowl” as a method of evaluating the interpretability of predictions from a machine learning system. The system could be part of a team with humans if it could communicate its hypotheses to its teammates.

³ See <https://www.youtube.com/watch?v=kTXJCEvCDYk>.

EFFORTS TO EXPLAIN MACHINE LEARNING ANSWERS

At our exhibitions, we have shown ordered lists of predictions while the system is considering answers. This is effective for communicating *what* the system is “thinking,” but not *why* it provides an answer. Thus, a prerequisite for cooperative QA is the creation of interpretable explanations for the answers that machine learning systems provide.

Linear Approximations

Deep learning algorithms have earned a reputation for being uninterpretable and susceptible to tampering to produce the wrong answer (Szegedy et al. 2013). But, instead of making predictions based on explicit features, one of their strengths is that they embed features in a continuous space. These representations are central to deep learning, but how they translate into final results is often difficult—if not impossible—to determine. Ribeiro and colleagues (2016) propose local interpretable model-agnostic explanations (LIME): linear approximations of a complicated deep learning model around an example.

LIME can, for example, create a story of why a particular word caused an algorithm to provide a specific answer to a question. A logistic regression (a linear approximation of a more complicated predictor) can explain that seeing the words “poet” and “Leander” in a question would be a good explanation of why “John Keats” would be a reasonable answer. But individual words are often poor clues for why the algorithm suggests a particular answer. It would be even better to highlight the phrase “this poet of ‘On a Picture of Leander’” as its explanation.

Human-Computer Teamwork

I propose to extend LIME’s formula to capture a larger set of features as possible explanations for a model’s predictions. For example, “And no birds sing” is a well-known line from Keats’ poem “La Belle Dame sans Merci,” but explaining the prediction by providing a high weight for just the word “sing” would be a poor predictor. The algorithm should make itself clear by explaining that the whole phrase “no birds sing” is why it cites “La Belle Dame sans Merci” as the answer. While recurrent neural networks can discover these multiword patterns, they lack a clear mechanism to communicate this clue to a user.

Fortunately, Quiz Bowl provides the framework needed to measure the collaboration between computers and humans. The goal of a Quiz Bowl team is to take a combination of players and produce a consensus answer. It is thus the ideal proxy for seeing how well computers can help humans answer questions—if it is possible to separately assess how well the computer aids its “teammates.”

Statistical Analyses and Visualizations

Just as baseball computes a “runs created” statistic (James 1985) for players to gauge how much they contribute to a team, Quiz Bowlers create statistical analyses to determine how effective a player is.⁴ A simple version of this analysis is a regression that predicts the number of points a team will win by (a negative number if it is a loss) with a given set of players.

There are two independent variables we want to understand: the effect of the algorithm and the effect of visualizations. We analyze the effect of a QA system and a visualization as two distinct “team members.” The better a visualization is doing, the better its individual statistics will be. This allows us to measure the contribution of a visualization to overall team performance and thus optimize how well a visualization is communicating what a machine learning algorithm is thinking.

CONCLUSION

Combined with the renaissance of reinforcement learning (Thrun and Littman 2000) in machine learning, having a clear metric based on interpretability allows algorithms to adapt their presentations to best aid human collaboration. In other words, the rise of machine learning in everyday life becomes a virtuous cycle: with a clear objective that captures human interpretability, machine learning algorithms become less opaque and more understandable every time they are used.

Despite the hyperbole about an impending robot apocalypse associated with artificial intelligence killing all humans, I think a bigger threat is automation disrupting human livelihood. In juxtaposition to the robot apocalypse is a utopia of human-computer cooperation, where machines and people work together using their complementary skills to be better than either could be on their own. This is the future that I would like to live in, and if we are to get there as engineers we need to be able to measure our progress toward that goal.

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⁴ The Quiz Bowl Statistics Program (SQBS), <http://ai.stanford.edu/~csewell/sqbs/>.

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ENERGY STRATEGIES TO POWER OUR FUTURE

Energy Strategies to Power Our Future

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Power consumption is a good proxy for quality of life, and societies around the world currently consume about 18 terawatts (TW) globally. Greater than 60 percent of that power is derived from fossil fuels. In many countries, there has been increasing use of renewable energy, due to both declining costs of renewable energy and national policies that seek to increase energy security and decrease the environmental footprint of the energy sector. This session aimed to address the question, “how will we power our future?” Answers were multifaceted and involved not only power generation and storage but also new grid technologies and transportation electrification.

Over the next few decades, new power generation technologies will be deployed at a large scale to match power demand with the lowest cost and environmental impact. As a resource, solar power is abundant ($>10^5$ TW at Earth’s surface), although it makes up only about 1 percent of US electricity generation. Challenges to widespread adoption include the need for reduced cost, improved efficiency, and storage solutions over a range of time scales (hourly to seasonal). For wind energy, a substantial US market has developed and wind now supplies nearly 6 percent of US electricity demand. However, the complexity of mesoscale flow as it makes its way down and through the plant, transforming into electricity as it goes, involves many open research challenges.

Both solar and wind energy promise to become prominent sources of electricity generation. But their variable nature means that the current grid system needs to be flexible in order to adapt as solar and wind energy are added. Such adaptability necessitates substantial technology innovation to transform the grid to support high levels of variable generation.

Furthermore, the grid of the future is likely to support a significant amount of electric transportation on the distribution side. The transportation sector consumes nearly 30 percent of US energy production, with 90 percent from fossil fuels. While electrification could significantly reduce petroleum use, it affects the grid in terms of power generation and distribution. Concurrently, new opportunities are emerging in storage and new grid technologies, with high renewable penetration and dynamic distribution systems.

The first speaker, Tim Heidel (National Rural Electric Cooperative Association), set the stage by discussing “deep decarbonization” and what it will take to move from a carbon-rich energy system to one dominated by renewable energy, a transition that will require substantial changes to how electric power systems are planned and operated. He described technologies emerging from the research community that promise to improve real-time grid state awareness, achieve more robust control over power flows, and enable comprehensive approaches to power system optimization. Next, Bouchra Bouqata (GE Global Research Center) discussed how the merger of advanced physical models for wind energy with big data and analytics will enable a new generation of wind plants with substantially reduced energy costs, increasing the competitiveness of wind with fossil fuels even at very low cost levels. Mariana Bertoni (Arizona State University) explained how imaging and machine learning will help design tomorrow’s energy conversion devices. Khurram Afridi (University of Colorado Boulder) discussed wireless power transfer that allows self-driving vehicles to be fully autonomous. He described the state of the art for stationary and dynamic wireless power transfer for electric vehicles, and identified performance, cost, and safety challenges that need to be overcome for wireless power transfer systems to be widely adopted.

Agile Fractal Systems: Reenvisioning Power System Architecture

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The methods used to plan and operate the grid since the dawn of electrification have worked well. Indeed, the US grid has set the absolute standard for scale and performance of engineered systems for more than a century, but new technologies, economics, social attitudes, and environmental sensibilities are calling this model into question.

Rapidly falling costs of distributed electricity generation methods such as solar photovoltaics and storage technologies coupled with the growing emphasis on improving electric power system resiliency have motivated the investigation of alternative architectures for planning and operating electric power systems.

In addition, recent advances in power electronics, computation, and communication technologies could provide the opportunity to optimize and control grid operations closer to the locations where power is consumed (Kassakian et al. 2011), offering significant efficiency, cost, reliability, and emissions benefits.

But the methods that have historically been relied on for designing and operating power systems will prevent the full realization of the potential benefits associated with the newer technologies. Power system design and control methods that are both agile and fractal are needed to fully realize the benefits offered by distributed generation and storage technologies.

BACKGROUND

In a 2014 speech, then US Secretary of Energy Ernest Moniz defined the electrical grid of North America as “a continent-spanning machine of immense complexity that is at its best when it is invisible” (Moniz 2014). There has prob-

ably never been a more succinct and accurate definition of the grid that has grown from the first central power plant opened in 1882 in Manhattan.

For more than a century the electric power delivery system has evolved continuously as generations of engineers have identified improvements enabling greater reliability, resilience, and lower cost. Over time, every component and procedure has been refined and polished. Today, the grid operates with impressive reliability, often making it invisible.

The grid's generally routine reliability is largely a consequence of the system's scale, literally its angular momentum. Titanic power flows from the Hoover Dam and its kin, an immense fleet of large-scale central power generation stations throughout the country. Small generators and loads are effortlessly swept into synchronicity by the current flowing from these huge turbines. This has proven to be a very good way to design a system, especially given the economies of scale and increased efficiency of most electricity generation technologies.

RECENT CHANGES MOTIVATING NEW ADAPTATION

The recent rapid growth of distributed energy resources located at the far, thin edge of the grid is calling the existing model into question. As these resources continue to proliferate, individual homes, businesses, and factories will begin to have a far larger influence on the operation of the grid both locally and throughout the system (Kristov 2015).

Distributed and, particularly, customer-owned generation, thermal and electrical storage, and load control technology such as communicating thermostats and building management systems all raise the question of what constitutes a grid. Is the grid the continent-spanning totality, or is it one utility, one feeder, one portion of a feeder, or one building? The answer is, increasingly, all of these. A useful working definition of a grid is a collection of electrical assets (generation, load, storage, transport) that can be controlled by a single entity. By this definition, grids range from individual buildings to regional transmission organizations (RTOs) spanning multiple states.

A building energy management system may control rooftop photovoltaic or gas-powered combined heat and power technologies, loads, energy storage, and purchases from or sales to the grid. It is an electrical grid in every sense except scale and presents many of the same problems in optimal control. It must also act in harmony with all the other actors in the grid. This will become increasingly critical as the electric power system as a whole evolves to rely ever more heavily on distributed energy resources.

This is a unique time of challenges to adapt the grid for new and changing needs. The challenges present an opportunity to think beyond incremental improvement to a fundamental reimagining and reinvention, building on emergent technology in distributed generation and sensor technology and advances in communications and industrial controls.

AGILE AND FRACTAL GRIDS

The hierarchical model of the grid challenges the old simplifying dichotomy in which generation and transmission companies thought of the distribution system as an exogenous, slowly varying, uncontrollable load, and distribution companies treated the transmission systems as an infinite bus. With many systems and actors involved, the fundamental problem in operations moves from pure control to harmonization.

A conglomeration of today's distinct and incompatible methods of operating buildings, campuses, feeders, distribution systems, generation and transmission systems, RTOs, and independent system operators (ISOs) will not enable high potential agility. Furthermore, it will create a morass of interoperability standards and local, ad hoc, idiosyncratic methods of coordination.

Efforts to establish commonality in the problems of grid operations across many scales can move the system closer to a grid that continuously adapts, collaborates, and harmonizes to achieve greater reliability, resiliency, and efficiency. We believe that such a grid must be agile and fractal.

What Is an Agile Grid?

To be agile in this context, a grid must be capable of dynamically reconfiguring and optimizing based on rapidly changing local conditions.

Even under ideal conditions the grid is constantly changing—components are installed and retired every day, and load varies with weather, season, and the vagaries of human activity. Beyond these (literally) “blue sky” variations, storms, natural disasters, equipment failures, and other factors disrupt normal grid operations.

Variations have always been present, but they are poised to have more significant impacts as new weather-dependent generation sources (such as solar and wind) and new electricity uses (such as electric vehicles) become ubiquitous. Efforts to design and build the grid of the future must therefore be based not on a static approach but on a design process that is constantly evolving and that allows the routine and continuous adaptation of operations to account for changing conditions and circumstances.

As new technologies enable a more efficient grid, the fiction of a static grid—designed to a fixed point and then simply operated as designed—will be further undermined. A campus or individual building in an office park may sometimes operate autonomously, sometimes focus on local coordination, sometimes operate as part of a much larger whole. The future grid must be envisioned as a grid of grids of grids, dynamically adapting when challenged.

What Is a Fractal Grid?

Fractal design is an essential element to achieve desired grid agility. Taking inspiration from fractal geometric figures, fractal grids will exhibit the same control and operational characteristics at every scale.

In a fractal grid, any part of the overall power system will be capable of performing all of the functions of the full grid today. With fractal design, parts of the grid can safely isolate from the rest of the power system if and when it is optimal to do so (e.g., in response to local weather conditions, changes in fuel costs) but return to the broader system when conditions change. Decisions on how and when to segment parts of the system will be based on economic, engineering, and business considerations.

Figure 1 illustrates the concept of an agile, fractal grid. Figure 1a illustrates the current operation of a distribution grid. Energy flows to customers from two substations and the system operates with a tree structure. A normally open switch isolates the green and blue portions of the distribution system. Individual customers with generation or storage can use power generated locally and may in some circumstances be able to feed that power back to the local grid.

Figure 1b illustrates how the grid might be reconfigured after an equipment or line failure. In this scenario, energy is still fed from two substations, but certain customers are now receiving power from Substation B instead of Substation A. This scenario is becoming increasingly common as utilities install automated switching technologies in distribution systems.

Finally, Figure 1c illustrates the potential for a portion of the grid, corresponding to a small group of customers, to further isolate from the rest of the system for business or economic reasons. That portion of the system would consume power, in this specific scenario, purely based on locally available generation resources. Eventually, one would generally expect the operation of the system to return to that shown in Figure 1a.

TECHNICAL CHALLENGES

Rearchitecting the control of electric power systems will not be achieved quickly or simply. Indeed, the study of grid architecture is emerging as an important new research domain (e.g., Taft and Becker-Dippmann 2015). But the technology needed is there or nearly there.

Achieving the transition to an agile and fractal future grid will rely primarily on three classes of innovation:

- (1) precise state awareness,
- (2) precise controls, and
- (3) advanced analytics (including forecasting and optimization technologies).

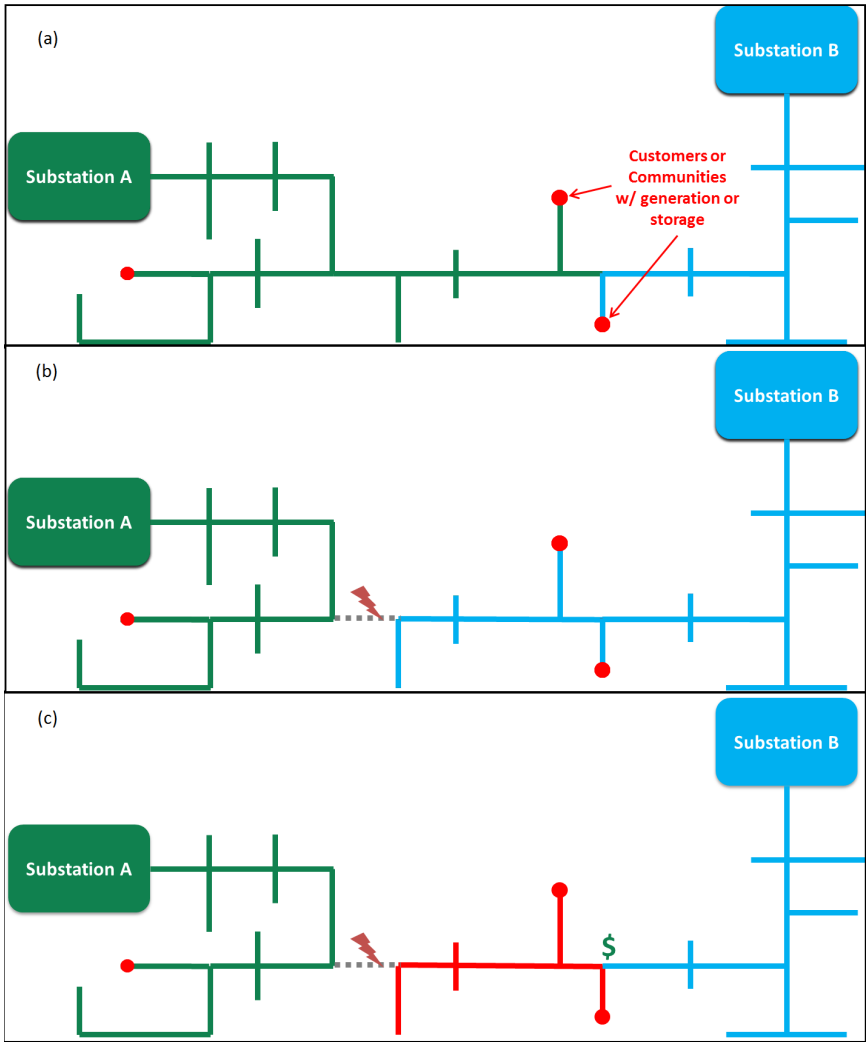


FIGURE 1 Agile, fractal grid scenarios. (a) Normal distribution system operations with power fed from two substations. The green and blue portions of the feeders are electrically isolated by a normally open switch. (b) Distribution system reconfiguration, widely used today, transfers some customers to a new substation feed in the case of an outage in a portion of the network to minimize the scale and duration of the outage. (c) Agile, fractal grid design enables portions of the system (shown in red) to operate independently in order to satisfy objectives for reliability and economics. Decisions on when and how to segment networks can be made centrally or in a distributed fashion.

Precise State Awareness

Successful grid operations in an agile, fractal environment will require precise knowledge of the state of the grid at all times and locations. Grid operators need to understand the operating state and the real-time capability of loads, generators, and storage devices. Ensuring the safety of utility personnel and customers will also require a precise understanding, at all times, of what parts of the system are connected to each other (and what reconfiguration options are permitted).

Fortunately, recent years have seen dramatic advances in sensor technologies that can contribute to state awareness, such as communicating digital consumption meters and distribution system phasor measurement units (von Meier et al. 2017). The rapidly falling costs of communication technologies also enable grid operators at all levels to communicate state-related information more often and on a more granular basis.

Precise Controls

Many companies are developing advanced switching and power electronics technologies that can enable more rapid and precise control (Bhattacharya 2017). More advanced protection system devices, reactive power controllers, networked switches, and disconnect-capable meters can enable more agile volt/voltage-ampere reactive (VAR) control throughout the system and a wider range of feasible system reconfiguration options.

Many of these technologies are already being adopted in the utility community to reduce system losses, enhance efficiency through conservation voltage reduction, or improve resiliency during and after storms. The power electronics-based inverters that interface with distributed energy resources such as photovoltaics or storage devices will play an increasingly important role in enabling more precise control of the system.

ADVANCED ANALYTICS

A new generation of electricity system data analytics is needed (National Academies 2016), with more precise and accurate algorithms for forecasting the evolution of customer needs and generation resource capabilities. Scalable algorithms will also need to be developed to optimize large, diverse fleets of controllable resources (Panciatici et al. 2014). These algorithms will help translate improved state awareness into decisions on how best to deploy distributed energy resources and other controllable devices.

Effectively and securely managing the transport, storage, and analysis of data among a large number of diverse stakeholders will be a key architectural design challenge. Advances in the analysis of corrupted or incomplete data will also be critically important. Many of these advances will rely on techniques for making decisions in the face of significant uncertainty.

CONCLUSION

Analytically driven and agile control of the grid is being made technologically possible by declining costs of renewable and distributed generation technologies, higher-performance computing, and high-bandwidth communications, coupled with advances in power electronics and related control technologies. Indeed, many of the individual components required to realize agile, fractal grid operations are either already available or in advanced development.

But significant research and development are still needed to determine how to optimally integrate all the required component technologies. A particular challenge will be harmonization of this vision for future grid operation with the reality of continuous incremental change, which is necessary to the engineering of all critical infrastructure technologies. Control systems that are consistent with agile, fractal operation will have to coexist for some time with the control approaches that are used widely today.

As this new architecture for the control of electricity delivery infrastructure becomes widely used, we expect it will be possible to achieve greater reliability, resiliency, and efficiency while also easing the challenge of adapting to future changes. Finally, we believe insights gained throughout this transformation could have important implications for the design of other highly distributed engineered systems.

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Big Data and Analytics for Wind Energy Operations and Maintenance: Opportunities, Trends, and Challenges in the Industrial Internet

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Clean renewable energy from sources such as the wind has been moving to the forefront of social awareness and public policy. And major tech corporations such as Google and Apple are increasing their investments to achieve 100 percent power for their data centers from renewable energy (Etherington 2016; Moodie 2016; Saintvilus 2016).

As wind energy becomes more economically competitive, wind farm operators must understand and manage the performance analysis of their farms in order to achieve desired production and revenue goals. But farm operators face a deluge of data from multiple sensors connected to wind turbines' complex systems.

Big data and analytics are resulting in disruptive innovation across many industry sectors. Given the uncertainty and complexity associated with wind energy systems, there is huge potential for these techniques to significantly improve the performance and reduce the costs of wind energy systems.

There is also a paradigm shift with the Internet of Things (IoT)—connecting machines to machines through networks, data, and analytics—as an important technology to deal with challenges of big data analytics for wind energy operations and maintenance (O&M). Through emerging technologies in the IoT's advanced analytics capabilities, it is possible to reduce operating expenses and move away from traditional reactive O&M to sophisticated predictive and proactive O&M solutions.

This paper provides an overview of big data analytics trends, challenges, and enabling technologies both generally and as they relate to wind energy O&M. Next, it describes the IoT as a technological tool for dealing with the challenges of big data analytics for wind energy O&M. It then reviews opportunities and

challenges of this new paradigm to address wind energy O&M expenses and move from reactive to proactive O&M.

INTRODUCTION

As wind energy grows in market share, the more it needs to increase its output (performance) and reduce its cost (maintenance).

Wind energy systems stand out from other complex technical systems because of the combination of large levels of wind uncertainty and high levels of interaction of wind farm physics. Big data analytics techniques can significantly improve wind farm performance and reduce costs.

Data are estimated to be created at 2.5 quintillion bytes/day from sensors, social media, images, and myriad other sources. The growing use of big data in wind power operations and maintenance generates an estimated 25 trillion bytes/day. The ubiquitous availability of data has created a paradigm shift from information-poor to information-rich management and impacts virtually every area of modern life.

TRENDS IN BIG DATA ADVANCED ANALYTICS

The use of big data advanced analytics for knowledge discovery, especially machine learning (ML), has emerged as a means to enable smart decisions. It has been successfully used to address problems in many industrial domains, resulting in disruptive innovation that can be leveraged to solve challenges such as those in performance and maintenance costs of wind energy.

The design and development of high-quality large-scale analytics are complex, involving big, “noisy,” structured and/or unstructured datasets as well as a large pool of diverse models. Evaluating just a single model involves a search across all combinations of structures and parameter values, and finding the right scalable ML approach can require many attempts.

The availability of new infrastructures at scale, such as cloud platforms, has provided a new direction for efforts to solve these challenges. The emerging paradigm needs to involve automation of a significant portion of the current manual process involved in problem formulation (to select the appropriate ML algorithms) as well as data preparation, model selection, model tuning, and so forth. In addition, it is important to leverage parallel computing environments—through cloud computing (such as Hadoop), high-performance computing, and large-scale optimizations—to create, maintain, and deploy large-scale machine learning on big data.

Good-quality data are essential to the development of an effective predictive model. There are two main challenges when dealing with data quality: (1) The data are unlabeled even when there is a large pool, and (2) the features do not have predictive power.

In the first scenario, the data could be annotated by subject matter experts. Since their time is very expensive, the challenge is to determine what data points are the most informative to focus their time and effort. ML techniques, such as active learning (Settles 2010), can interactively query the expert to obtain the desired outputs at new data points and solve an optimization problem in order to get the highest performance from the predictive model with the smallest training set.

The second scenario is common when the predictive problem is very complicated and predictive features are missing. In this case, feature engineering (Heaton 2016) can be used for the design of the best (or at least a better) representation of the sample data to yield the necessary information for the predictive algorithm.

BIG DATA ANALYTICS AND THE IOT

The IoT, connecting machines both to machines and to people through networks, data, and analytics, is an important technology for dealing with challenges of big data analytics. As it shapes modern businesses from manufacturing to marketing, the IoT promises to remake global industry, boost productivity, and launch a new age of prosperity and growth.

Machines and other objects have long been used to issue early warnings, but in an inconsistent and unactionable way. The advent of networked machines with embedded sensors and advanced analytics tools has changed that reality. Most machines now either have or are in the process of getting multiple sensors and being connected. The sensors constitute a plethora of data sources that are often neither connected nor integrated, yielding a deluge of data from wind turbines.

To harness the power of data integration and systems-level analytics and optimization in applications such as wind energy O&M, it is critical to ensure interoperability among data sources. But concerns about privacy and cybersecurity are raised by both industry and government. The risk of connecting insecure devices to the Internet should be properly mitigated through a combination of cyber- and physical security solutions. To accelerate secure data-driven innovation and discovery, new technologies, infrastructure (for networking, storage architecture, cloud computing), new platforms, and cybersecurity technologies are needed to enable industry to effectively tackle the flow of data from machines and objects.

CHALLENGES AND OPPORTUNITIES

The Industrial Internet—the combination of big data analytics with the IoT—is producing huge opportunities for companies in all industries, and renewable energy is no exception. But as one analysis put it, “Not all Big Data is created equal” (Kelly and Floyer 2013). According to the authors, “data created by industrial equipment such as wind turbines, jet engines and MRI machines . . . holds more potential business value on a size-adjusted basis than other types of Big Data associated with the social Web, consumer Internet and other sources.”

To support and accelerate data-driven innovation and discovery, new technologies and infrastructure are needed to empower industry. To that end, GE has invested significantly in a new Industrial Internet platform, Predix Asset Performance Management (Evans and Annunziata 2012; Floyer 2013),¹ to enable big data analytics to address complex systems such as wind farm O&M. Through the diagnostic and prognostic capabilities of GE's new platform, it is possible to reduce operating expenses and move away from traditional reactive O&M to sophisticated predictive and proactive O&M solutions.

For wind energy O&M, this approach extensively leverages physics-based modeling of the system and fuses it with data-driven models and statistical and ML techniques to increase performance and reduce maintenance costs in wind energy O&M. It does so by

- continuously collecting data from assets combined with other operational data to monitor, analyze, and improve performance and maintenance;
- delivering insights from asset-specific advanced analytics models; and
- providing the asset issues to enable smart decisions and the best course of action.

Wind farm operators can thus better understand what is happening in the field, plan ahead, and properly predict extended operating life, resulting in reduced maintenance costs and improved performance.

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Across Dimensions and Scales: How Imaging and Machine Learning Will Help Design Tomorrow's Energy Conversion Devices

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Energy is the single most important factor that impacts the prosperity of any society, underpinning advances on which all depend. To supply the more than 7 billion people on this planet at the level of energy that the developed world is accustomed to, 60 terawatts would need to be generated—the equivalent of 900 million barrels of oil per day. Where could this astonishing amount of energy come from? The term “terawatt challenge” refers to the endeavor to produce energy at the level needed in an economically, socially, and technologically sustainable way.

When one searches for potential sources of energy at the terawatt (TW) scale it is striking to find that the biggest resources and most technically exploitable options are those that barely make up 10 percent of the energy mix today—solar, wind, and geothermal. If the TW challenge is solved, though, the world energy breakdown will look quite different by 2050.

It is not unreasonable to think that renewables can handle heavy loads. Reports have proposed that 100 percent of the world's energy needs by 2030 (11.5 TW) can be fully achieved with an energy mix of roughly 50 percent wind, 40 percent solar (concentrated solar power and photovoltaic [PV]), 4 percent hydroelectric, 4 percent geothermal, and 1 percent tidal turbines (Jacobson et al. 2015).

No renewable energy source is as abundant as the Sun, and in recent years its potential has been capitalized to the point that solar has moved from a niche source toward a mainstream electricity generation source with grid parity. With 15 gigawatts (GW_{DC}) installed, solar was the number one source of new US capacity in 2016—an unprecedented 39 percent. That momentum carried into 2017, as solar accounted for 30 percent of all new electric capacity installed in

the first quarter. Global PV shipments reached an astonishing 75 GW in 2016, arguably making the solar industry the largest optoelectronic sector in the world, worth \$110 billion/year (Perea 2017).

The aspirational goal set by the US Department of Energy Sunshot initiative to meet \$1/watt by 2020 initially seemed unrealistic and even comical to many in the industry (US DOE 2010). But 6 years later and 3 years ahead of schedule, module prices have dropped to \$0.99/watt for fixed-tilt utility-size installations (Perea 2017).

For 18 states the levelized cost of solar energy is below gross electricity bill savings in the first year of a solar PV system's life. This means grid parity under business-as-usual conditions is a reality, and 32 more states are expected to follow suit by 2020 (Munsell 2016). If PV reaches grid parity it will be an important milestone, but it is just the beginning. High market penetration will require that PV system costs drop to offset the additional costs of storage and transmission so that solar generation can be distributed to meet electricity demand both cost effectively and more broadly in time and space (Kurtz et al. 2016).

The rapid pace of change brings its own challenges and opportunities. For example, there are concerns about the maximum penetration possible with PV power because of its impact on utility demand, lowering its value as PV penetration increases and requiring further cost reductions. In addition, the important metrics of photovoltaics for sustainable energy are expanding to include factors previously not analyzed, such as the impact of capital expenditures on realizing sustained high growth rates (Haegel et al. 2017; Powell et al. 2015).

Technological barriers to PV have in some ways increased. Cost reductions from economies of scale are plateauing, the cost of photovoltaics is a moving target, and efficiency from single-junction technologies is approaching its technological limits, hampering the ability to use efficiency boosts as the lever to overcome previous barriers.

In this context, like Moore's Law, an underlying law based on fundamental physics can help make a specific, quantitative prediction about innovation as a function of time. For semiconductors, the technical parameter has been transistor density; for photovoltaics the analogue is energy produced per unit volume.

Figure 1 puts a lot of this discussion in perspective. It shows that computing and photovoltaics have seen significant and steady cost reductions during the past 20 years by "packing more in a smaller volume," while oil and natural gas have remained relatively constant despite shorter-term price fluctuations. It also depicts how competitive today's solar energy prices are (light blue inset data in \$/kWh) compared to other electricity sources, that unlike solar benefit from federal and state subsidies. The achievement of silicon module prices below \$1/W—and projections of \$0.50/W—has fundamentally changed solar R&D.

Slim margins have pushed some companies into bankruptcy and challenged the annual profitability of others. Cost, intermittency, and dispatchability have been major challenges in the pursuit of utility-scale solar energy generation. More

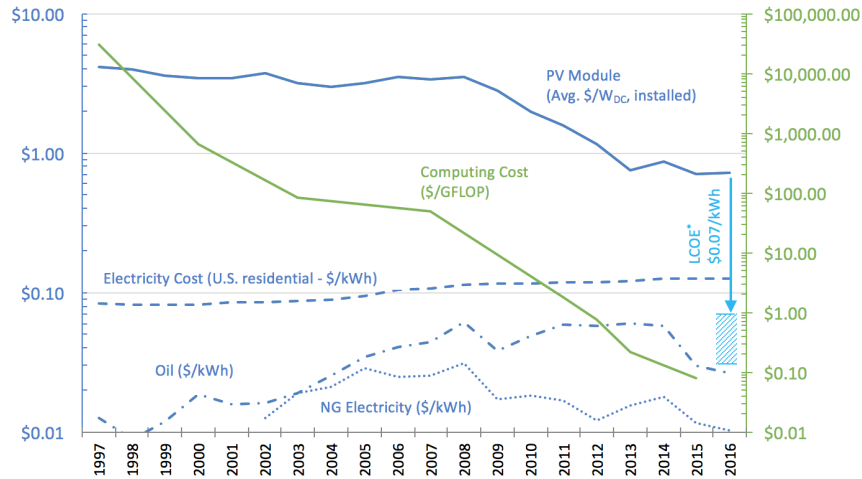


FIGURE 1 Photovoltaic (PV) module, natural gas, and oil price trends (blue, left axis) compared to computing cost trend (green, right axis), 1997–2016. Data taken from annual reports of the US Energy Information Administration (www.eia.gov). Light blue inset: *Solar levelized cost of electricity (LCOE) estimated for 0.72 \$/W PV Module peak nominal, 100 MW_{DC} fixed-tilt system installation with 0.5%/yr. and financial parameters from Jones-Albertus et al. (2016).

recently, materials’ degradation studies and long-term system performance R&D have become crucial for the bankability of projects. However, the standard business model of the solar industry, with each company eager to outcompete the next in price, has made the industry very risk averse when it comes to implementation of innovation.

What are the next steps? Movement toward an “electric-powered world” and increased demands for clean and efficient electricity (e.g., electric vehicles, portable electronics, rural electrification) raises new challenges.

The first of these challenges concerns portability: the availability of light-weight and flexible modules necessary for implementation in everyday life. Additional challenges involve the achievement of high power in small areas and the use of sustainable materials for device manufacturing.

As with other consumer applications, solar margins will improve and engineering hurdles associated with aesthetics, customization, and functionality will become standard R&D considerations. An analogy is the introduction of Ford’s Model T car: photovoltaics has demonstrated its affordability, impact, and potential, and now a whole new technology is taking off.

The path for improved PV is to make cells thinner and more efficient. The industry is maturing, costs are becoming dominated by those of materials, and

expensive process changes are yielding very small incremental benefits. Fundamental scientific breakthroughs are necessary to propel this energy source to next-generation levels.

Higher-power cells can be achieved by stacking cells with different bandgaps to efficiently capture a wider portion of the solar spectrum. The efficiency limits rise from 33 percent for a single-junction cell to 43 percent for two junctions under no concentration, 49 percent for three junctions, and 66 percent for all greater numbers of junctions. This approach is not novel; multijunction cells are well known in space applications, where very high quality single crystals are epitaxially grown and cells are engineered to withstand radiation and high levels of illumination (Takamoto et al. 2005). The automotive analogy would be a limited-edition Ferrari.

Although these modules are very expensive, epitaxial liftoff techniques enabling substrate reuse have demonstrated a path to lower costs. The future of solar lies in merging the ubiquitousness of the Model T solar cells with the performance of the limited-edition Ferrari cells.

The first thing to realize is the necessity of relying on the mass-production low-cost manufacturing lines of the Model T cells, which most likely means a silicon cell will be the bottom cell and high-quality single-crystal films will not be available for the multilayer stack. Instead faster deposition methods, like evaporation or sputtering, and defect-engineered top films will have to be used to achieve the desired electrical and optical properties (Bobela et al. 2016). This is crucial to the success of next-generation solar absorbers; engineered defect-tolerant materials are the best way to enable ultra-low-cost manufacturing technology for high-efficiency devices. A top-cell bandgap of 1.7 electron volt (eV) and an efficiency comparable to standard silicon cells today (20 percent) can enable 32 percent efficient tandems (Yu et al. 2016).

The task seems daunting, especially when one considers that the performance of a full device is usually governed by the concentration and distribution of nanoscale inhomogeneities and defects throughout the solar cell.

How can discovery and defect engineering be accelerated to facilitate a high-power, portable, and economic solar industry? The paradigms for materials discovery have to be redefined, especially for systems with complex functionalities, to move beyond serendipitous discoveries, Edisonian approaches, and the classical synthesis-characterization-theory methods. The answer lies in highly correlative imaging methods under operating conditions combined with big data analytics.

Understanding the fundamental relationships between composition and structure properties on a nanopixel basis, under real operating conditions and in situ (with both controlled and ambient temperature) is necessary to unravel the causes and effects of certain defects, including their impact on performance.

Current imaging techniques do not merely provide a picture of the system under study, they actually contain compositional, structural, and functional infor-

mation. The correlation of multiple 2D or 3D mapping modalities on a pixel-to-pixel basis and the multiple dimensions of these maps, based on time, temperature, and ambient conditions, creates a big data challenge.

In situ and operando measurement techniques combined with nanoscale resolution have proven invaluable in multiple fields of study. I argue that correlative hard X-ray microscopy (HXM) with <100 nm resolution can radically change the approach for optimizing solar absorbers, interfaces, and full devices in solar cell research.

Unlike other fields of microscopy, HXM has excellent penetration through layers and entire devices, yielding 3D imaging of buried structures. It can easily penetrate gases and fluids, enabling studies at pressure and under process conditions. It also enables quantitative studies of sample composition with trace element sensitivity in structured materials and devices. Chemical state information of individual atomic species can be obtained using X-ray spectroscopic techniques. X-rays do not interact with external fields and are therefore useful for studies in electric or magnetic fields (Stuckelberger et al. 2017).

As acquisition speeds and resolution increase, providing more density of data points, and the functionality of measurements adds more dimensions to be analyzed, the handling, management, and analysis of datasets become more and more complicated. Operando measurements as well as in situ studies pose a new challenge: Finding correlations in the 3D+ datasets that result from many of these measurements is not straightforward, and the possibility of missing connections, relationships, and trends is cause for concern.

Machine learning techniques, including principal component and cluster analyses, have been widely used in fields plagued with tremendous amounts of data (Hastie et al. 2013). A key benefit of these approaches is the ability to identify trends in highly dimensional data, a task that is otherwise difficult and sometimes even impossible.

The first step toward full information recovery from high-resolution multifunctional imaging data is the adoption of big data analytics (Kalinin et al. 2015; Rajan 2012, 2015; Runkler 2016). This requires implementation of dimensionality reduction, clustering techniques, and statistical unsupervised learning (Hastie et al. 2013). Unsupervised image analysis tools targeted to high-performance computing platforms can analyze high-resolution scanning and electron microscopy data in 2D in real time (Belianinov et al. 2015). Advances in high-resolution experimental imaging and high-performance computing (Dongarra et al. 2011) will undoubtedly propel materials discovery and ultimately “materials by design.”

However, just because a statistical correlation is observed does not imply an accurate understanding of the underlying physics in the multimodal imaging. Transitioning from big data to “deep data” is the next step. All the structure-property relationships at the nanoscale retrieved from big data can be examined with real physical models, allowing for verification and improvements in predictive modeling (Kalinin et al. 2015). This step makes it possible to close the loop and

propose design guidelines to develop or process a material with desired properties and functionalities.

Materials informatics is ready to lay the foundation for a new paradigm in materials discovery, especially for complex functional systems like solar cells. It could very well end up being data that ultimately push the cost of solar power to the levels of subsidized fossil fuel.

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Wireless Charging of Electric Vehicles

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Road transportation, which accounts for 23 percent of US total energy consumption, 59 percent of petroleum consumption, and 22 percent of greenhouse gas emissions (Davis et al. 2016), is undergoing a major transformation with the advent of ridesharing, autonomous driving, and vehicle electrification. Collectively these technologies, in conjunction with renewable sources of electricity, have the potential to dramatically reduce the negative impact of road transportation on the health of the planet.

The successful convergence of these technologies will require electric vehicles (EVs) that are low cost and fully autonomous. These attributes can be realized through wireless charging.

INTRODUCTION

Consider a future in which a driverless ridesharing EV pulls over as you exit a building, takes you to your destination, and proceeds to drive passenger after passenger without ever needing to stop to recharge its battery. Instead, power generated by nearby wind and solar resources is delivered wirelessly from the roadway to the vehicle while it is in motion.

Not having to stop for recharging will make EVs truly autonomous, and, because the vehicles can thus remain in service for more hours, fewer vehicles will be needed to meet passenger demand. Furthermore, EVs with in-motion (dynamic) wireless charging can have much smaller batteries, an option that can reduce their cost and accelerate adoption.

While the concept of medium-range wireless power transfer (WPT), achieved using near-field (nonradiative) electromagnetic coupling, has existed since the

pioneering work of Nikola Tesla (1891) more than a century ago, the technology to enable effective dynamic WPT for EVs is still in its nascent stage. Numerous challenges related to performance, cost, and safety need to be overcome before the vision of wirelessly powered EVs can be realized.

NEAR-FIELD WIRELESS POWER TRANSFER

Near-field WPT systems are of two types: inductive, which use magnetic field coupling between conducting coils, and capacitive, which use electric field coupling between conducting plates to transfer energy (see Figure 1). For medium-range applications (in which the distance between the transmitter and the receiver couplers is comparable to the size of the couplers, as in EV charging), inductive WPT systems have traditionally been preferred.

Inductive WPT Systems

Building on work done for material handling applications during the 1990s (Green and Boys 1994), the past decade has seen tremendous progress in inductive WPT technology for stationary charging of EVs (Bosshard and Kolar 2016). Aftermarket stationary chargers are already available, and some EV manufacturers have announced plans to introduce built-in stationary inductive WPT systems as early as 2018.

However, for magnetic flux guidance and shielding, inductive WPT systems require ferrite cores, making them expensive and bulky. Also, to limit losses in the ferrites, the operating frequencies of these systems are kept under 100 kHz, resulting in large coils and low power transfer densities. The high cost and low power transfer density are particularly problematic for dynamic WPT, as these systems need to have very high power capability to deliver sufficient energy to the vehicle during its very brief time passing over a charging coil.

For these reasons dynamic inductive WPT is yet to become commercially viable, although a few experimental systems have been demonstrated (Choi et al. 2015; Onar et al. 2013).

Capacitive WPT Systems

Capacitive WPT systems have potential advantages over the inductive systems because of the relatively directed nature of electric fields, which reduces the need for electromagnetic field shielding. Also, because capacitive WPT systems do not use ferrites, they can be operated at higher frequencies, allowing them to be smaller and less expensive. Capacitive WPT could thus make dynamic EV charging a reality.

But because of the very small capacitance between the road and vehicle plates, effective power transfer can occur only at very high frequencies, making

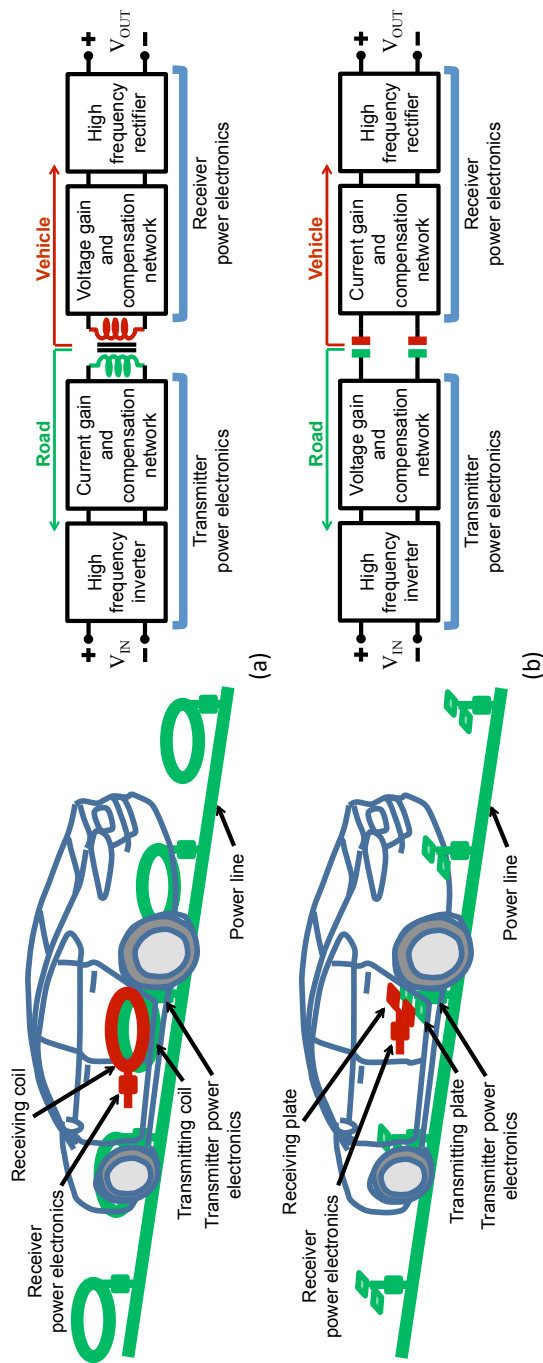


FIGURE 1 Physical implementation (left) and block diagram representation (right) of two approaches to deliver energy wirelessly to electric vehicles from an electrified roadway: (a) inductive wireless power transfer (WPT) using coils (embedded in the roadway and in the vehicle) that are coupled through magnetic fields, and (b) capacitive WPT using plates coupled through electric fields. In both cases, power electronics (comprising a high-frequency inverter and rectifier with semiconductor devices, and gain and compensation networks with inductors, capacitors, and/or transformers) is the enabling technology.

the design of these systems extremely challenging. With the recent availability of wide-bandgap (gallium nitride [GaN] and silicon carbide [SiC]) power semiconductor devices that enable higher-frequency operation, high-power medium-range capacitive WPT systems are becoming viable (Regensburger et al. 2017; Zhang et al. 2016).

Two major challenges associated with capacitive WPT for EV charging are (1) achieving high-power transfer density at high efficiencies while meeting electromagnetic safety requirements, and (2) maintaining effective power transfer even as the couplers' relative position changes. These challenges have been a focus of my group's recent efforts.

ACHIEVING SAFE AND EFFICIENT HIGH-POWER TRANSFER

The size of the couplers in WPT systems can be reduced and the power transfer density increased by designing the systems to operate at higher frequencies. In inductive systems the increase in induced voltage with higher frequency compensates for the reduced mutual inductance of the smaller coils, and in capacitive systems the increase in displacement current with higher frequency compensates for the smaller plates' lower capacitance. Higher operating frequencies also enable smaller power electronics associated with WPT systems (see Figure 1) thanks to a decrease in energy storage requirements.

But achieving high efficiencies at high switching frequencies is very challenging. And the fringing fields of WPT systems must be within safe levels (as defined by the International Commission on Non-Ionizing Radiation Protection; ICNIRP 1998) in areas occupied by people and animals (e.g., the vehicle cabin and outside the perimeter of the chassis). These requirements for capacitive WPT systems can be met through circuit stages that provide appropriate voltage and current gain (to reduce displacement currents) as well as reactive compensation (Figure 1). An active area of research is the design of these circuit stages (Lu et al. 2015; Theodoridis 2012).

Multistage Matching Networks

Our work in this area has explored approaches utilizing multistage matching networks that can simultaneously provide gain and compensation (Sinha et al. 2016). We have discovered that, depending on the ratio of the system input and output voltages, there is an optimal number of stages that maximizes efficiency, and we have identified the optimal distribution of gain and compensation among these stages.

To further reduce fringing fields in capacitive WPT systems, various coupler design approaches have been considered. Those that use dielectric materials for field guidance introduce additional losses and have limited success in medium-range applications.

Phased-Array Field Focusing

We have been exploring techniques traditionally used for beamforming in radars and other far-field applications (Hansen 2009). We have developed a near-field phased-array field-focusing approach that uses multiple phase-shifted capacitive WPT modules to achieve dramatic reductions in fringing fields (Figure 2). We have shown that a 180° -outphased configuration yields a progressive reduction in fringing electric fields as the number of modules increases (Kumar et al. 2015).

Phased-array field focusing provides opportunities for innovation, for example in the exploration of methods that incorporate parasitic interactions between multiple coupling plates in the design of the matching networks. Such phased-array approaches could also be adapted for inductive WPT to help eliminate ferrites (Waters et al. 2015).

ACHIEVING VARIABLE COMPENSATION

To achieve effective power transfer, WPT systems need to operate close to the resonant frequency of the resonant tank formed by the reactances (capacitive and inductive) of the coupler and compensating network. However, the coupler reactance depends on the vehicle's road clearance, and varies as the vehicle moves across the charger (Figure 3). The drift between resonant and operating frequency causes a reduction in power transfer and WPT system efficiency.

In WPT systems that operate at frequencies below 100 kHz, where bandwidths are not restrictive, the traditional way to deal with variations in coupling is to change the operating frequency to track the resonant frequency (Covic and Boys 2013; Shekhar et al. 2013). But in high-frequency WPT systems the operating frequency must stay within one of the designated, very restrictive industrial, scientific, and medical (ISM) bands (e.g., 6.78 MHz, 13.56 MHz, and 27.12 MHz; FCC 2014).

One solution, employed in low-power inductive WPT systems, is to use a bank of capacitors that can be switched in and out of the compensating network, to keep the resonant frequency roughly unchanged as the transmitter and receiver move relative to each other (Lim et al. 2014). But this is not an effective approach for higher-power WPT systems as the switches have to be much bigger and more expensive to keep the system efficient. This approach is also less suited to capacitive WPT because it requires multiple switchable compensating inductors, which are bigger than capacitors.

Other adaptive impedance matching techniques include the use of saturable and variable inductors (James et al. 2005), but these techniques reduce system efficiency and do not scale well with power.

We have developed new high-frequency rectifier and inverter architectures that compensate for coupling variations while operating at fixed frequency and maintaining high efficiency. An example is the active variable reactance (AVR)

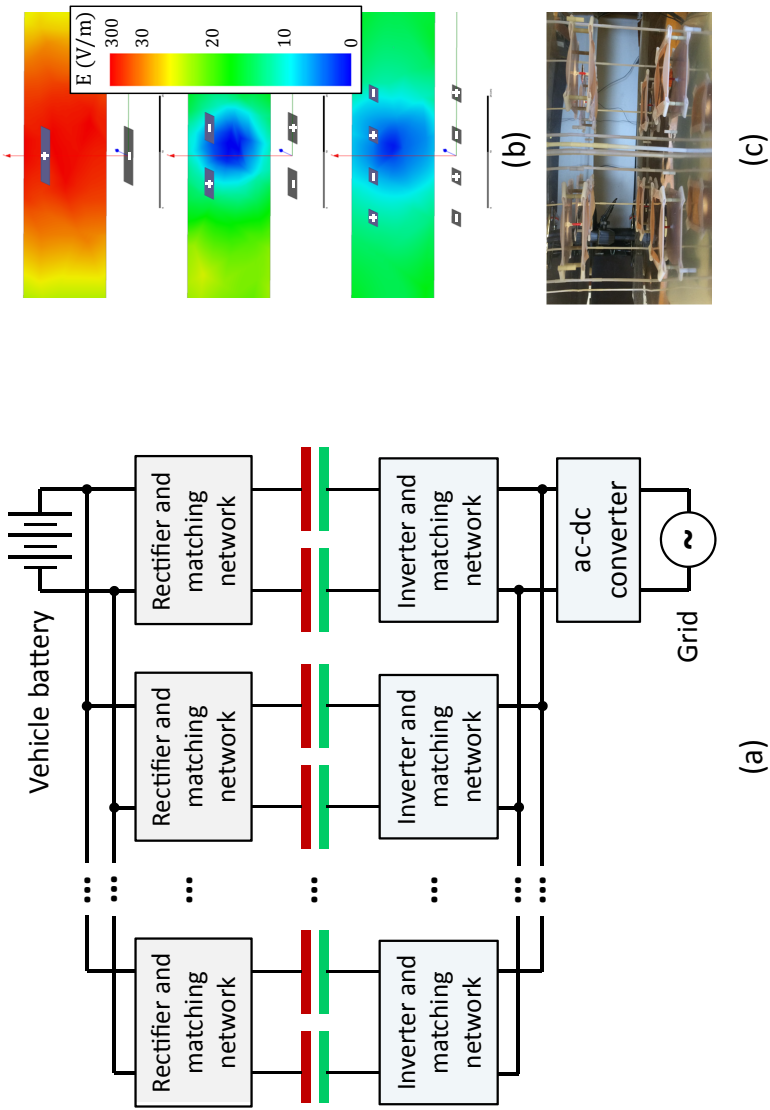


FIGURE 2 Multimodular near-field phased-array capacitive wireless power transfer (WPT) system: (a) block diagram representation, (b) simulated performance showing fringing field reduction with progressive increase in the number of modules, and (c) photograph of a prototype system. E = electric field strength; V/m = volt per meter.

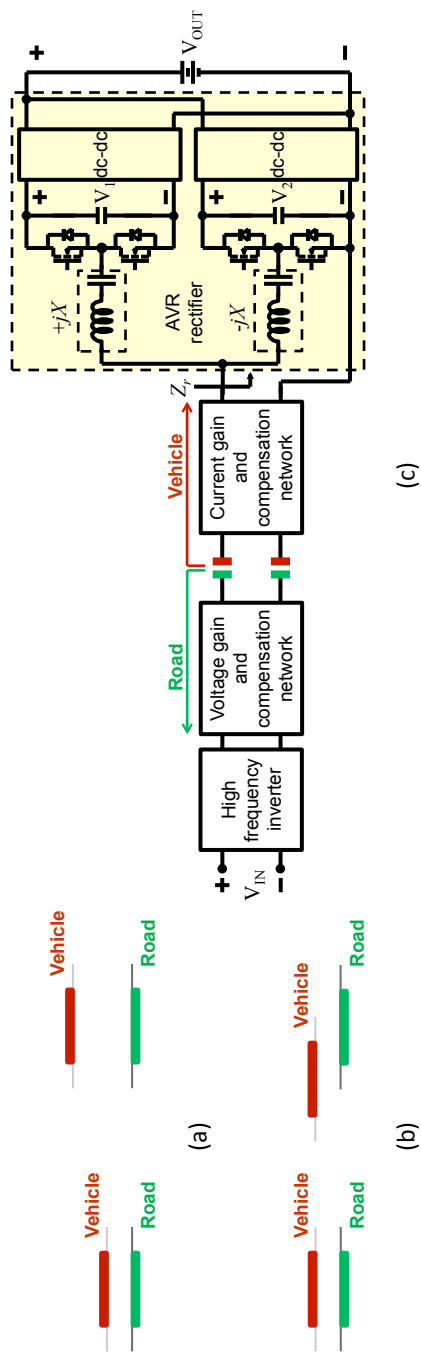


FIGURE 3 Coupling variations and an approach to compensate for these variations: (a) variation in coupling due to different vehicle road clearances, (b) variation in coupling due to change in vehicle position as it drives over the charger, and (c) a capacitive wireless power transfer (WPT) system with an active variable reactance (AVR) rectifier that can provide continuously variable compensation by controlling the voltages V_1 and V_2 . jX = tank reactance; Z_r = rectifier input impedance.

rectifier shown in Figure 3 (Sinha et al. 2017). By appropriately controlling the output voltages of its two coupled rectifiers, the AVR can provide continuously variable compensation while maintaining optimum soft switching to ensure high efficiency. This compensation architecture ensures that the output power of the WPT system is maintained at a fixed level across wide variations in coupling and is applicable to both capacitive and inductive WPT systems.

CONCLUSIONS AND FUTURE DIRECTIONS

High-performance, safe, and cost-effective dynamic electric vehicle charging has the potential to revolutionize road transportation. What combination of capacitive and inductive WPT will enable this revolution is an open question. Both systems offer tremendous opportunities for research, especially in high-frequency power electronics and near-field coupler design. Research is also needed on

- health effects of long-term exposure to weak electric and magnetic fields,
- mechanisms to detect living and foreign objects in the proximity of WPT systems,
- methods to determine optimal charger power levels and spacing for cost effectiveness,
- techniques to embed WPT technology in roadways, and
- approaches to analyze impacts of large-scale WPT system deployment on the electric grid.

The technologies developed for dynamic EV charging are foundational—they can also enable wirelessly powered biomedical implants, humanoid robots, and supersonic hyperloop transport. The technological challenges are exciting and the possibilities endless.

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UNRAVELING THE COMPLEXITY OF THE BRAIN

Unraveling the Complexity of the Brain

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The brain is a complex system consisting of microscopic and macroscopic networks that give rise to its function. Efforts to understand the brain require simultaneous measurements at multiple spatiotemporal scales. Over the years, technology has been established to record high-dimensional electrical activity from a network of brain cells at small (single neurons) and large (local field potentials and electrocorticography [ECoG]) scales. Recent advances in optogenetic techniques have further enabled the possibility of imaging and controlling a large number of neurons.

The ability to collect high-dimensional neural activity introduces the great challenge of analyzing and modeling this activity to understand the brain's function and dysfunction, to devise novel treatments for various neurological disorders, and to enhance brain function. Advanced mathematical techniques are being developed spanning the fields of machine learning, signal processing, control, and information theory. Novel photonic and genetic techniques are being explored for increasingly precise optogenetic imaging and control. Finally, development of the next generation of neurotechnologies requires the design of low-power biocompatible electronic implants that can simultaneously record and stimulate the brain, and wirelessly transmit the recorded data to the outside world.

This session explored these challenges and the advances that engineers have made to tackle them. It began with a talk by Ellis Meng (University of Southern California) on technologies to interface with the brain for recording and modulation. She was followed by Jose Carmena (University of California, Berkeley), who discussed efforts to understand the neural basis of skill learning using brain-machine interfaces. The third speaker, Konrad Kording (University of Pennsylvania), described new models for neuroscience. The session concluded

with a talk by Azita Emami (California Institute of Technology) on efficient feature extraction and classification methods in neural interfaces.

Together these efforts will help pave the way to understand the brain, treat its disorders, and enhance its functions.

Technologies to Interface with the Brain for Recording and Modulation

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“The history of electrophysiology has been decided by the history of electrical recording instruments.”

Edgar Douglas Adrian (1932)

The desire to decipher targeted neural activities in the mammalian nervous system has inspired the development of many innovative technologies that incorporate a variety of signaling modalities (electrical, chemical, and mechanical). While decades of neural engineering have been dedicated to electronic interfaces with neural tissue, more recent advances acknowledge the multiple modalities of neural activity and make use of other interface methods. Scaling of such technologies to acquire data from large numbers of neurons remains a challenge, as is the long-term stability of the recording interface, which is susceptible to foreign body response. The goal of advancing interface technologies is both to better understand proper functioning of the brain and to address a variety of neurological, neurodegenerative, psychiatric, and neuromuscular conditions and deficits.

BRAIN COMPOSITION AND ANATOMY

The anatomical and functional complexity of the brain poses a great challenge for engineering the interfaces needed to record and modulate its activity with precision and over short and long time scales. The human brain ($\sim 1.3 \text{ cm}^3$) has 100 billion (10^{11}) electrically active neurons (cell body $\sim 20 \text{ nm}$ diameter) that are interconnected to one another via chemically active synapses (20–40 nm wide gaps). Each neuron possesses about 10^3 synapses and therefore 100 trillion (10^{14}) such connections exist in the brain. Furthermore, chemical synapses communicate

via 10^2 different neurotransmitters, with events occurring at a rate of 0.1–200 Hz (“firing” rate). For comparison, the number of estimated stars in the observable universe is on the order of 10^{22} – 10^{24} .

Electrically active neurons account for only 50 percent of the cells in the brain. The other 50 percent are electrically inactive support cells (e.g., oligodendrocytes, astrocytes, and microglia; Chen et al. 2017). To support all the cell types, the organ is bathed in and cushioned by cerebrospinal fluid and nourished via blood vessels.

Neurons are anatomically organized into different regions, each with specific functions. Interfaces to neurons target specific brain regions associated with functions of interest. While it is possible to engineer devices that are smaller and computationally faster than neurons, it is not possible to fully recreate functional neural tissues. Hence, the ability to reliably interface with different brain regions is of immense scientific and clinical interest.

THE NATURE OF BRAIN ACTIVITY

Brain activity can be recorded from single neurons (single unit spikes or action potentials, APs) or from groups of neurons (multiunit recordings or local field potentials, LFPs) in a particular region. An inactive neuron has a resting potential of -70 mV (cell membrane voltage). An active neuron exhibits an AP of 80 – 100 mV, lasting a few milliseconds, that propagates down a neuron. This measurable electrochemical gradient results from the cell’s selective permeability to specific ionic species mediated by voltage-sensitive ion channels in the membrane and produces a measurable electrochemical gradient.

At the synapse, the AP induces the release of neurotransmitters, which cross the gap and bind to receptors on the cell membrane of the recipient neuron, triggering the opening of its ion channels. Signal transmission between two neurons connected by such a chemical synapse goes from electrical to chemical to electrical, where electrical signaling involves the movement of ions and not electrons. It is possible to modulate this natural activity using artificial stimuli such as electrical current or chemical agents.

The AP or “spike” from a single neuron (single unit) represents communicative activity and is measurable using invasive electrodes placed in (intracellular) or next to (extracellular) neurons. The “recording” electrode can be used in conjunction with a distant reference electrode to enable measurement of current or potential difference. Given the difficulty of targeting the interior of a single neuron, the destructive nature of such an interface, and the limited information it provides, the focus here is on extracellular interfaces.

Extracellular interfaces can also be used to record the LFP, the collective activity of a nearby group of neurons. Less invasive FPs can be recorded on the surface of the brain or through the protective dura membrane covering via electrocorticogram (ECoG) or exterior to the skull via electroencephalogram

(EEG). The less invasive the interface, the lower the resolution and the higher the tissue volume from which recordings are obtained (e.g., ~ 0.1 mm for an invasive penetrating electrode, compared to 2 mm for ECoG and 10 mm for EEG; Borton et al. 2013). With advances in recording interfaces, multiple penetrating electrodes can be placed to obtain recordings from multiple single units, thus achieving both high resolution and access to information from different regions of the brain.

It should be noted that while most synaptic transmission is chemical in nature (involving neurotransmitters), there are also electrical synapses that form a mechanical and electrically conductive link via a structure known as a gap junction ($\sim 3\text{--}4$ nm). And some neurons possess specialized ion channels that respond to physical stimuli such as pH, temperature, pressure, and tension (Chen et al. 2017).

HISTORY OF ELECTRICAL STIMULATION AND RECORDING

Early Explorations and Applications

Electrical interfaces that interact with the nervous system have been used since ancient times, when Egyptians and Romans used electric shocks delivered by electric eels to treat pain. The foundations of bioelectricity and electrophysiology were laid much later in experiments conducted by Luigi Galvani in the 1780s, in which dead frog's leg muscles moved in response to current applied to nerves via metal wires, a phenomenon dubbed "animal electricity."

With the discovery of the effects of electricity on the human body (often the investigator's own body), "medical electricity" research commenced shortly thereafter (Bresadola 1998). Giovanni Aldini, nephew of Luigi Galvani, discovered that electrical stimulation of the cerebral cortex could elicit physical responses (facial grimaces on decapitated prisoners; Aldini 1804). This discovery inspired work on brain stimulation both to understand function and as a means of therapy. In 1938, Ugo Cerletti applied electric current to the skull to induce "therapeutic" epileptic seizures to treat severe psychosis (Cerletti 1940).

Another paradigm shift occurred in 1947 when electrodes were used for intraoperative electrical stimulation to determine the location of lesioned targets with the assistance of stereotactic techniques; until that point, electrodes were used clinically to lesion the brain in neurosurgery (Spiegel et al. 1947). Brain stimulation was also investigated for pain control in the 1950s.

Together these efforts provided the foundation for new clinical therapies such as transcranial magnetic stimulation, cortical brain stimulation, and deep brain stimulation (DBS). DBS has borrowed heavily from cardiac pacemaker and defibrillator electrode concepts that were developed earlier.

Evolution of Technologies

Recordings of animal electricity were first reported by Leopoldo Nobili in 1828 using an electromagnetic galvanometer, but the first true recordings of the resting and action potentials were made in 1868 by Julius Bernstein using a differential rheotome that allowed measurement of fast electrical processes (Verkhatsky et al. 2006). The detection of currents from the brain was achieved using an early form of EEG by Richard Caton in 1875 (Grimnes 2014). Wire electrodes were used to record from behaving animals in the 1950s.

Advances in microelectronics led to the development of miniaturized multi-electrode arrays on planar surfaces in the 1970s. They interfaced with cell and tissue cultures and demonstrated that electrodes could be made at the scale of a single neuron. At about the same time, microelectrodes on penetrating probes were introduced. The technology was independently developed by multiple groups, leading to commercially available products for research in animals and investigational studies in humans, including use in clinical trials in 2004 (Chen et al. 2017). But while silicon microelectrode arrays have been developed over several decades, the inability to achieve reliable and stable long-term device-tissue interfaces has spurred interest in the development of more compliant polymer probes.

Electrodes used for stimulation and recording have opposing requirements, which prevent their simultaneous use. Smaller recording electrodes are preferred to isolate activity from single cells, whereas stimulation electrodes should have larger surface area to increase the charge injection capacity available to excite neurons. Because electrical stimulation indiscriminately activates nearby neurons and produces a large artifact that interferes with recording, its use in understanding brain activity and therapy is limited; but lowering the electrode area to minimize activation proportionately increases the input charge densities and the risk of tissue damage. Electrical stimulation is unable to inhibit activity. These drawbacks of electrical interfaces have given rise to alternative interface modalities.

NONELECTRICAL INTERFACES

Advances in genetic engineering of cells have opened new avenues to interface with neurons. In optogenetics, a neural population is genetically manipulated so that it can be selectively perturbed optically and probed electrically at the same time. This is accomplished by injecting a cell with light-sensitive microbial ion channels (opsins), which can change their conformation in response to light and affect ion transport. Unlike electrical stimulation, optogenetic approaches can both excite *and* inhibit neural activity.

Chemical stimulation, whether excitatory or inhibitory, can be achieved by infusing (through conventional cannulae or microfluidics) chemical agents or biological (genetic) agents to modulate activity. Electrochemical sensors provide a means of detecting neurotransmitters and can be specific to particular

electroactive neurotransmitters. They may be located nearby conventional micro-electrodes, even on the same supporting substrate, and provide information about the concentration of molecules.

Nanoscale transducers introduced into brain tissue can modulate brain activity through the conversion of optical, acoustic, and magnetic stimulation into voltage or electric fields. These nanotransducers include quantum dots, gold nanoparticles, up-conversion nanoparticles, and magnetic nanoparticles. The latter can activate mechanosensitive ion channels by producing the required piconewton-level forces in the presence of a magnetic field gradient. The delivery of these nanomaterials and control of their targeting remain a challenge.

Interfaces need not be invasive. Acoustic waves and magnetic fields can be harnessed to modulate activity in the brain. Whereas electromagnetic waves in the visible and infrared spectrum have limited penetration depth (1 mm), transcranial focused ultrasound can access deeper regions (>50 mm), although at inferior spatial resolution (1 mm³). Transcranial magnetic stimulation can access the upper 10 mm but with reduced spatial resolution (Chen et al. 2017).

Although electrical and nonelectrical interfaces are discussed separately here, several have been combined to leverage the advantages of the particular technique for research purposes.

CHALLENGES AND OPPORTUNITIES

The availability of appropriate interface technologies for the brain strongly affects the ability of researchers and clinicians to understand it and develop new therapies. Yet even the limited and imperfect information currently available has resulted in clinically implemented technologies with only a few stimulating electrodes that have dramatically improved lives. DBS, for example, has been approved by the US Food and Drug Administration for the treatment of tremor (1997), Parkinson's disease (2002), dystonia (2003), and obsessive compulsive disorder (OCD; 2009) (Sironi 2011).

Future advances seek to seamlessly integrate neural interfaces with the brain to enable *both* long-term recording and modulation of neurons with a higher number of input and output channels (Wellman et al. 2017). To achieve this, the health of the tissue-device interface needs to be improved by addressing tissue damage related to surgical delivery, the biological immune response, and the stability of the materials used in the construction of the interfaces. More information is needed about the effects of the complex interplay between material selection, device design, and fabrication methodology on the long-term performance and function of the device in the body. These advances are critical to obtain chronically stable high-density and large-scale recordings.

In addition, modulation technologies need improvements in reliability and precision. When used together, recording and modulation can achieve exciting new concepts in closed-loop therapeutic systems of the future. With rigorous

engineering focused on reliability, the next generation of life-changing medical technology breakthroughs can be realized.

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Brain-Machine Interface Paradigms for Neuroscience and Clinical Translation

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The brain-machine interface (BMI) is a novel technology that holds great potential to aid large numbers of people with sensory, motor, and cognitive disabilities. The goal of cortically controlled BMIs is to reliably, accurately, and robustly convey enough motor control intent from the central nervous system (CNS) to drive multi-degree-of-freedom (DOF) prosthetic devices by patients with amputated, paralyzed, or otherwise immobilized limbs for long periods of time (decades). Two main challenges need to be addressed in order to achieve this goal: (1) how to make viable neural interfaces that last a lifetime, and (2) how to enable skillful control and dexterity of a multi-DOF prosthetic device comparable to natural movements.

In a BMI system, neural signals recorded from the brain are fed into a machine that transforms them into a motor plan. This is the subject's "intention of movement," which is then streamed to the prosthetic device. A closed control loop is established by providing the subject with visual and sensory feedback of the prosthetic device.

BMIs also provide a framework for examining basic neuroscience questions, especially those related to the understanding of how neural plasticity relates to the acquisition and consolidation of skills.

We postulate that achieving skillful, natural control of a multi-DOF BMI will entail synergizing two types of adaptation processes—natural (brain plasticity) and artificial (decoder adaptation)—as well as providing realistic sensory feedback from the prosthetic device. Recent work shows that (1) neuroplasticity facilitates consolidation of neuroprosthetic motor skill in a way that resembles that of natural motor learning, (2) corticostriatal plasticity is necessary for neuroprosthetic skill learning, and (3) closed-loop decoder adaptation (CLDA) techniques can expedite

the learning process by adapting the decoder parameters during closed-loop BMI operation (i.e., while the subject is using the BMI).

The design process of a CLDA algorithm requires important decisions not only about *which* parameters of the decoder should be adapted and *how*, but also *when* (i.e., how often), as the rate at which the decoder changes can influence performance. We believe that BMI systems capable of exploiting both neuroplasticity and CLDA will be able to boost learning, generalize well to novel movements and environments, and ultimately achieve a level of control and dexterity comparable to that of natural arm movement.

Next we discuss how to use BMIs to study skill learning and consolidation. In addition to holding great therapeutic potential as assistive and rehabilitation technology, BMIs provide a powerful framework for examining basic neuroscience questions, especially those related to the neural correlates of learning behavior, as it offers researchers the unique opportunity to directly control the causal relationship between neuronal activity and behavioral output. In particular, we focus on the question of how neuroplasticity relates to the acquisition and consolidation of skills. This question is paramount as it affects both brain function and dysfunction.

We examine the question of how a task-relevant neural population explores and consolidates spatiotemporal patterns supporting neuroprosthetic skill learning. In the early stages of motor skill learning, movements are variable from attempt to attempt. This variability can be beneficial to learning, permitting the motor system to explore actions and their consequences. Gradually movement variability decreases as the motor system consolidates the movements that lead to success.

Neurophysiological motor learning studies have found that neural activity in various species and brain areas follows a similar trend, exhibiting high variability in early training and reducing variability as particular activity patterns are consolidated in late training. These studies have focused on overall changes in neural variability. Given the large dimensionality of possible activity patterns available to a neural population, and the possibilities for interaction among cells, it is critical to understand how different sources of neural variability contribute to motor learning. If the variability in a neural population is driven mostly by private independent inputs, then each neuron produces independent activity and the population fully explores high dimensional activity space. If, on the other hand, cells receive coordinating inputs (input activity that drives multiple cells simultaneously), then activity becomes constrained to a coactivation manifold.

Because the motor system is a distributed and redundant dynamical system, with parallel degenerate pathways and many more neurons than muscles, a fundamental challenge of neuroscience has been to ascertain the causal relationship between observed neural activity patterns and motor output. This apparent complexity and degeneracy makes the question of how neural plasticity changes movement production difficult to answer.

We took advantage of a paradigm in which we could identify the output neurons that control behavior and identify the explicit transformation between output neuron activity and behavior. We used an operant learning BMI paradigm in which stable recordings from ensembles of primary motor cortex neurons in macaque monkeys are fed through a constant mathematical transform, referred to as a decoder, to transform neural activity into prosthetic movements. The BMI provided a closed-loop feedback system operating within the natural motor system, called the neuroprosthetic circuit.

Under the condition of a fixed decoder and fixed neural population over training, subjects acquire proficient neuroprosthetic control that is stable and readily recalled over days. This neuroprosthetic skill learning paradigm is uniquely advantageous to investigate how task-relevant neural populations explore and consolidate activity patterns that support skill learning.

By selecting the stable cells whose activity is fed through the decoder (known as direct cells), we define the direct cells as task relevant. By designing the decoder and task goals, we define the neural activity space that is relevant for behavioral output as well as the possible activity patterns that can lead to success. By holding the neuroprosthetic circuit fixed, we can investigate how variability from different sources in a task-relevant neural population evolves with training, contributes to the consolidated activity and neuroprosthetic patterns, and ultimately drives neuroprosthetic learning.

We used factor analysis to model independent and coordinated sources of variability in a neuroprosthetic skill learning task, and revealed that population dynamics became more coordinated and low dimensional with training. We leveraged the decoder structure to interpret the observed changes in dynamics and found that task-relevant coordinating input signals were consolidated.

Previous studies have shown that motor learning is accompanied by a decrease in total trial-to-trial neural variability. We found that private and shared sources of variability evolve differently over training. While private variability is important early in training and then decreases, shared variability slowly consolidates to produce faster and straighter movements. Hence, our findings describe neuroprosthetic skill learning as a process of spatiotemporal neural pattern consolidation, whereby the strengthening of task-relevant input signals coordinates initially variable, high-dimensional activity.

A greater understanding of the neural substrates of neuroprosthetic skill learning can provide insight into the mechanisms of natural sensorimotor learning as well as help guide the design and development of neurobiologically informed neuroprosthetic systems to aid people with devastating neurological conditions.

Finally, in the last part of the talk I discuss the emerging field of mind prosthetics, which has applications to mental health. The current paradigm for the treatment of neuropsychiatric disorders, such as addiction and depression, relies heavily on pharmacological and behavioral therapies. This paradigm is inherently limited by its palliative rather than curative approach. Prospective corrective ther-

apies must target the etiology of neuropsychiatric disorders, and this approach can be realized using neurotechnologies that are capable of leveraging neurofeedback to construct targeted mechanisms that ameliorate pathological activity.

BMI technologies are ideal for neuropsychiatric treatment therapeutics. In combination with new physiological biomarkers and animal models, future BMI neurotherapeutic devices will have the potential to cure people suffering from psychiatric and mood disorders. Toward this goal, we have developed a novel animal model for assaying correlates of acute anxiety and closed-loop strategies for mood modulation with strong anxiolytic effects.

The Roles of Machine Learning in Biomedical Science

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While the direct goal of biological modeling is to describe data, it ultimately aims to find ways of fixing systems and enhancing understanding of system objectives, algorithms, and mechanisms. Thanks to engineering applications, machine learning is making it possible to model data extremely well, without using strong assumptions about the modeled system. Machine learning can usually better describe data than biomedical models and thus provides both engineering solutions and an essential benchmark. It can also be a tool to advance understanding.

Using examples from neuroscience, we highlight the contributions, both realized and potential, of machine learning, which is becoming easy to use and should be adopted as a critical tool across the full spectrum of biomedical questions.

INTRODUCTION

The goal of nearly all of computational biology is to numerically describe a system, which is often quantified as the explained variance. In some cases, only the explained variance is of interest—for example, to make predictions. But in most cases, just describing the data successfully is not sufficient. There has been much discussion of objectives in the neuroscience community (e.g., Dayan and Abbott 2001; Marr 1982).

Uses of Models

The typical model is designed not only to numerically describe data but also to meet other objectives of the researcher. In some cases it is used to inform how to fix things—to predict what would happen based on certain interventions. In

others, the goal is to determine whether the system optimizes some objective; for example, whether the intricate folds of the brain minimize wiring length (Van Essen 1997). Or the aim may be to understand the system as an algorithm—for example, which algorithms the brain uses to learn (Marblestone et al. 2016). Probably most commonly, a model is used to understand underlying mechanisms—for example, how action potentials are enabled by interactions between voltage-dependent ion channels (Hodgkin and Huxley 1952).

So far, progress in the modeling field comes mostly from human insights into systems. People think about the involved components, conceptualize the system's behavior, and then build a model based on their intuitive insights. This has been done for neurons (Dayan and Abbott 2001), molecules (Leszczynski 1999), and the immune system (Petrovsky and Brusica 2002).

Biomedical researchers are starting to use computational models both to describe data and to specify the underlying principles. However, understanding such complex systems is extremely difficult, and human intuition is bound to be incomplete in systems with many nonlinearly interacting pieces (Jonas and Kording 2017).

What Is Machine Learning?

The vast field of machine learning is a radically different way of approaching modeling that relies on minimal human insight (Bishop 2006). We focus here on the most popular subdiscipline, supervised learning, which assumes that the relationship between the measured variables and those to be predicted is in some sense simple (Wolpert 2012), with characteristics such as smoothness, sparseness, or invariance.

Supervised algorithms receive vectors of features as inputs and produce predictions as outputs. Machine learning techniques mostly differ by the nature of the function they use for predicting (Schölkopf and Smola 2002). Rather than assuming an explicit model about the relationship of variables, ML techniques assume a generic notion of simplicity.

The field of machine learning is undergoing a revolution. It has moved from a niche discipline to a major driver of economic activity over the past couple of decades as progress revolutionizes web searching, speech to text, and countless other areas of economic importance. The influx of talent into this field has led to massive improvements in algorithm performance, allowing computers to outperform humans at tasks such as image recognition (He et al. 2015) and playing Go (Silver et al. 2016). These developments in machine learning promise to make it an important tool in biomedical research. Indeed, the number of ML-related papers and patents in biomedical research has grown exponentially (Figure 1).

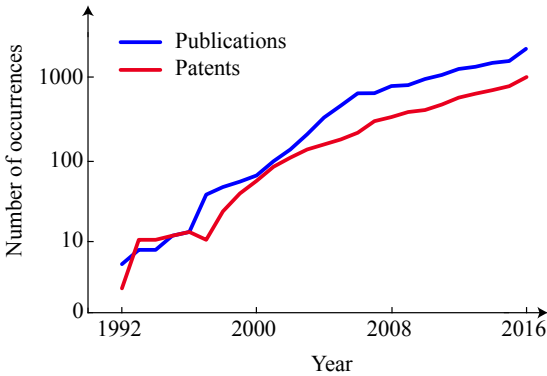


FIGURE 1 Trends in use of machine learning (ML) for biomedical sciences, 1992–2016. Publication data (blue) were collected from the Semantic Scholar website using the keywords “biomedical” and “machine learning.” Patent data (red) were collected from Google Patents using the same keywords.

USES OF MACHINE LEARNING FOR BIOMEDICAL RESEARCH

Many kinds of questions can be answered using machine learning techniques. In some cases they are useful for predictions, such as whether a drug will cure a particular cancer. In others they set a benchmark—for example, what are the shortcomings of the human-thought-out model relative to what may be possible? In yet other cases machine learning may enhance understanding of a system by revealing which variables are shared between components of a system.

Description and Prediction

The standard use for machine learning is to make a prediction based on something that can be measured. For example, in psychiatric medicine, studies have used smartphone recordings of everyday behaviors (e.g., when patients wake up or how much they exercise) to predict mood using machine learning (Wang et al. 2014).

A typical problem in neuroscience is the decoding of neural activity (Velliste et al. 2008) to infer intentions from brain measurements. This application is useful for developing interactive prosthetic devices, in which one uses measurements from the brain of a paralyzed subject to enable a robot to execute the movement. Many algorithms have been developed to solve such problems (Corbett et al. 2012; Yu et al. 2007); for this application, general purpose machine learning tends to do extremely well (Glaser et al. 2017).

Computationally similar problems exist throughout biomedical research, in areas such as cancer (Kourou et al. 2015), preventive medicine (Albert et al.

2012), and medical diagnostics (Foster et al. 2014). In these areas only the quality of the predictions is of interest. Similarly, many engineering problems are mainly concerned with the error size of predictions. When the main goal is to obtain accurate predictions, it is best to first try machine learning methods.

Benchmarking

Often the goal is not only to describe and predict data but also to produce models that can be readily understood and taught. Machine learning can be extremely useful by providing a benchmark.

One problem when evaluating a model is that it is hard to know how much its errors are due to noise versus the insufficiency of the model. Because machine learning is a useful tool for making predictions, it may provide close to an upper bound for human-produced models. If a human-generated model produces results that are very different from the ML benchmark, it may be because important principles are missing or because the modeling is misguided. If, on the other hand, a model based on human intuition is very close to the ML benchmark, it is more likely that the posited concepts are, indeed, meaningful.

But how is it possible to know whether a model is missing important aspects? We argue that ML benchmarking can help answer those questions (Benjamin et al. 2017).

Understanding

Machine learning can also directly help understanding. One important question is whether a system carries information about some variables (for example, whether neural activity contains information about an external stimulus), but it may not be clear whether the relation between the variables is linear or nonlinear. With machine learning it is possible to determine whether information is contained in a signal without having to specify the exact nature of the relationship.

Another important question concerns the information shared between two parts of a system. For example, which aspects of the world (high dimensional) are shared with which aspects of the brain (also high dimensional)? Machine learning makes it possible to ask such questions in a well-defined way (Andrew et al. 2013; Hardoon et al. 2004).

For many questions in biology, machine learning promises to enable new approaches to enhance understanding.

MACHINE LEARNING: A NECESSITY FOR EVER-GROWING DATASETS

Datasets are rapidly growing and becoming more and more complex as they become multimodal and multifaceted (Glaser and Kording 2016). In neuroscience,

the number of simultaneously recorded neurons is increasing exponentially (Stevenson and Kording 2011), as is the amount of electronic health record data (Shortliffe 1998).

Challenges in Modeling for Complex Datasets

There are several ways in which these changes in datasets will create new problems for modeling. First, we humans are not very good at thinking about complex datasets. We can only consider a small hypothesis space. But in biology, as opposed to physics, there are good reasons to assume that truly meaningful models must be fairly complex (O’Leary et al. 2015). While humans will correctly see some structure in the data, they will miss much of the actual structure. It could be argued that it is nearly impossible for humans to intuit models of complex biological systems.

Second, nonlinearity and recurrence make it much more difficult to model complex systems (O’Leary et al. 2015), which require complex models. It can be hard to falsify models that are very expressive or have many free parameters. One needs to both explain complexity and ensure that the model will fail if the causal structure is dissimilar to the model. For full-cell interactions or full-brain modeling, the design of models that strike this delicate balance seems implausible.

Finally, in the case of the large complex systems that are characteristic of biology, a major problem is the lack of understanding of how many different models could in principle describe the data. Models can explain some portion of the variance, but not necessarily the mechanism (Lazebnik 2002). Comparing models is pointless if they are not good at describing the relevant mechanisms.

Given all these arguments, it may be that physics-based non-ML-based approaches can only partially succeed. Any reasonably small number of principles can describe only part of the overall variance (and potentially a relatively small part). It is unclear how far the typical approach in biomedical research, drawing on concepts of necessity and sufficiency, can help to enhance understanding of the bulk of activity in complex interacting systems (Gomez-Marin 2017). Machine learning has the potential to describe a very large part of the variance.

A Note about Model Simplicity and Complexity

Machine learning also changes the objectives of data collection. In traditional approaches, measuring many variables is unattractive as, through multiple comparison testing corrections, it is not possible to say much about each of them. But with machine learning, using many variables improves predictions—even if it is not clear which variables contribute—making it attractive to record many variables.

This is not just a vacuous statement about information processing. It reflects the fact that the brain and other biological systems are not simple, with few

interactions, but highly recurrent and nonlinear. The assumption of simplicity in biology is largely a fanciful, if highly convenient, illusion. And if the systems subject to machine learning are not simple, then biases toward simple models will not do much good.

Based on their intuitions, researchers are starting to fit rather complex models to biological data, and those models usually fit the data better than simpler models. However, a complex model based on a wrong idea may fit the data extremely well and thus negate the advantage of an interpretable model.

A good fit does not mean that the model is right. For example, Lamarckian evolution explains a lot of data about species, but it was based on a fundamentally misleading concept of causal transmission of traits. The problem of apparent fit affects human intuition-based models, but not ML models, which, by design, do not produce a meaningful causal interpretation.

SPECIALIST KNOWLEDGE NOT NECESSARY FOR MACHINE LEARNING

There are countless approaches in machine learning, certainly more than most biomedical researchers have time to learn. Kernel-based systems such as support vector machines are built on the idea of regulating model complexity (Schölkopf and Smola 2002). Neural networks are built on the idea of hierarchical representations (Goodfellow et al. 2016). Random forests are built on the idea of having many weak learners (Breiman 2001). One could easily fill books with all the knowledge about machine learning techniques.

Yet the use of ML techniques has actually become very simple. At application time, one requires a matrix of training features and a vector of the known labels. And given the availability of the right software packages (Pedregosa et al. 2011), generally only a few lines of code are needed to train any ML system.

Moreover, ensemble methods obviate the need to choose a single machine learning technique (Dietterich 2000). The idea is that a system can run all techniques and then combine their predictions using yet another ML technique. Such approaches often win ML competitions (e.g., kaggle.com).

Furthermore, a new trend has developed rapidly in the past few years: automatic machine learning (Guyon et al. 2015). The idea is that most ML experts do similar things: they choose one of a number of methods (or all of them if they use ensembling) and then optimize the hyperparameters of those techniques. They may also optimize the feature representation. Although this can take a significant amount of time via trial and error, the process is relatively standard and several new packages allow automation of some or all of it.¹

¹ Examples of these packages are available at <https://github.com/automl/auto-sklearn>, www.cs.ubc.ca/labs/beta/Projects/autoweka/, <https://github.com/KordingLab/spykesML>, and https://github.com/KordingLab/Neural_Decoding.

These developments are likely to pick up speed in the next year or two, making it less necessary for biomedical scientists to know the details of the individual methods and freeing them to focus on the scientific questions that machine learning can answer.

EXAMPLES OF STATE-OF-THE-ART MACHINE LEARNING IN NEUROSCIENCE

With examples from neuroscience we illustrate two uses of ML approaches, predictions and benchmarking.

Neural Decoding

In neural decoding the aim is to estimate subjects' intentions based on brain activity—for example, to predict intended movements so that they can move an exoskeleton with their thoughts. A standard approach in the field is still the use of simple linear techniques such as those used in the Wiener filter, in which all previous signals during a given time period are linearly combined to predict the output.

There has recently been a lot of interest in improving this and similar approaches using modern machine learning. For many applications the goal is simply good performance. To analyze the advantages of using standard machine learning, we implemented many approaches: the linear Wiener filter, the non-linear extension called the Wiener cascade, the Kalman filter, nonlinear support vector machines, extreme gradient-boosted trees, and various neural networks (Figure 2).

The modern neural network-based techniques did very well (Glaser et al. 2017), and a combination of all the techniques, using ensemble methods, performed even better. The same phenomenon was seen when decoding from different brain regions. Thus we conclude that, to solve biomedical engineering problems, use of standard machine learning should be the starting point.

In this sense, machine learning also sets a benchmark for other decoding approaches. When neuroscientists write decoding algorithms they are often based on their insights into the way the brain works (Corbett et al. 2012). However, without a comparison to modern machine learning, it is not possible to know whether or to what extent these insights are appropriate.

As machine learning becomes automatic and easy to use, we argue that it should always be used as a benchmark for engineering applications.

Neural Encoding

Neural encoding, or tuning curve analysis, involves the study of signals from a neuron or a brain region to understand how they relate to external variables.

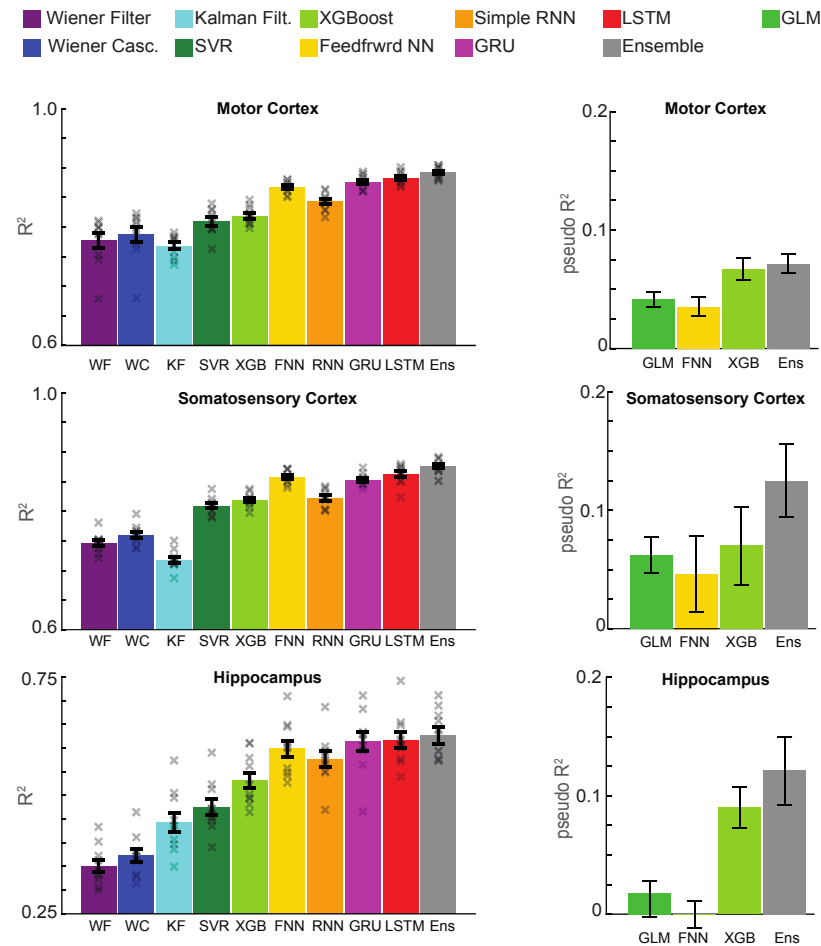


FIGURE 2 State-of-the-art machine learning decoding (left) and encoding (right). Left: Predicting state based on signals from three brain areas using various machine learning techniques and then ensemble analysis. Right: Predicting spikes using signals from three brain areas. Motor cortex data are from a study of macaques; somatosensory cortex and hippocampus data are those of humans. Data replotted with permission from Glaser et al. (2017), Benjamin et al. (2017). Casc. = cascade; GLM = generalized linear model; GRU = gated recurrent unit; LSTM = long short-term memory; NN = neural network; RNN = recurrent neural network; SVR = support vector; XG = extreme gradient.

Such a characterization can yield insights into the role of a neuron in computation (Jonas and Kording 2017).

Typically, the neuroscientist chooses a model (often implicitly) and the average signal is plotted as a function of external variables such as visual stimuli or movements. This approach generally assumes a simple model. Would machine learning give better results?

For such applications it is impossible to know whether poor model performance is due to external variables unrelated to neural activity or to the choice of model form. In principle, input variables may affect the neuron’s activity in highly nonlinear ways. This hypothesis can be tested with machine learning.

When we compared the generalized linear model (GLM; Pillow et al. 2008), it performed considerably worse than neural networks or extreme gradient–boosted trees (Figure 2). And again, the combination of all the methods using ensemble techniques yielded the best results. It can be difficult to guess features that relate to neural activity in exactly the form specified by the GLM.

Interestingly, despite the fact that the space was rather low dimensional, GLMs performed poorly relative to modern machine learning. This may suggest that the tuning curves measured by neuroscientists are rather poor at describing neurons in real-world settings.

In this context, machine learning can conceptually contribute in the following ways:

1. It can detect that a variable is represented, even if there is no linear correlation.
2. It can set a benchmark that humans can strive for.
3. It offers a possibility of replacing the common cartoon model of neural computation with a complex (although admittedly hard to interpret) alternative.

CONCLUSION

The incorporation of machine learning has profound implications for neuroscience and biomedical science.

For biomedical modeling, traditional modeling and machine learning cover opposite corners. Traditional modeling leads to models that can be compactly communicated and taught, while explaining only a limited amount of variance. Machine learning modeling explains a lot of variance, but is difficult to communicate. The two types of modeling can inform one another, and both should be used to their maximal possibility.

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Efficient Feature Extraction and Classification Methods in Neural Interfaces

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Brain disorders such as dementia, epilepsy, migraine, and autism remain largely undertreated, but neural devices are increasingly being used for their treatment. Such devices are designed to interface with the brain, monitor and detect neurological abnormalities, and trigger an appropriate type of therapy such as neuromodulation to restore normal function.

A key challenge to these new treatments is to integrate state-of-the-art signal acquisition techniques, as well as efficient biomarker extraction and classification methods to accurately identify symptoms, using low-cost, highly integrated, wireless, and miniaturized devices.

THERAPEUTIC NEURAL DEVICES

A general block diagram of a closed-loop neural interface system is shown in Figure 1. The neural signals recorded by an array of electrodes (intracranial, scalp, or other types) are initially amplified, filtered, and digitized. A feature extraction processor is then activated to extract the disease-associated biomarkers. Upon abnormality detection, a programmable neural stimulator is triggered to suppress the symptoms of disease (e.g., a seizure, migraine attack, Parkinson's tremor, memory dysfunction) through periodic charge delivery to the tissue.

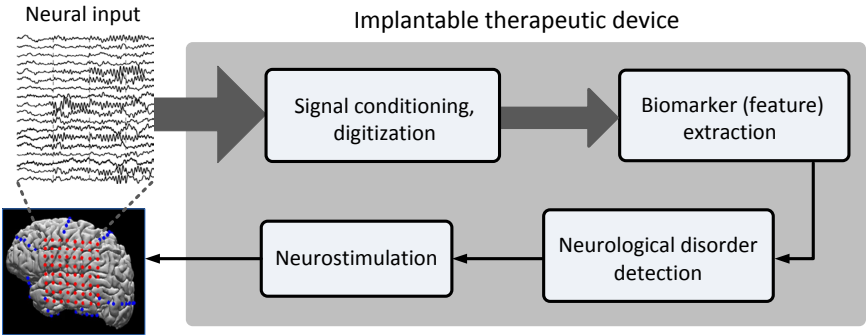


FIGURE 1 General block diagram of a closed-loop therapeutic system for detection and suppression of disabling neurological symptoms.

The abnormality detector device must demonstrate high sensitivity (true positive rate), sufficient specificity (true negative rate), and low latency. It also has to satisfy the safety, portability, and biocompatibility requirements of the human body.

AN EXAMPLE OF NEUROENGINEERING TREATMENT: EPILEPSY

The emerging field of neuroengineering uses engineering technologies to investigate and treat neurological diseases. Epilepsy has been one of the primary targets, along with movement disorders, stroke, chronic pain, affective disorders, and paralysis (Stacey and Litt 2008).

Approximately one-third of epileptic patients exhibit seizures that are not controlled by medications. Neuromodulation offers a new avenue of treatment for intractable epilepsy.

Over decades, research on epilepsy has led to fundamental understandings of brain function, with strong implications for other neurological disorders. In addition, because of the severity of refractory epilepsy and the need for surgery, human tissue and epileptic EEG datasets are largely available. Most therapeutic neural interfaces reported in the literature have therefore focused on extracting epileptic biomarkers for automated seizure detection (Shoaran et al. 2015; Shoeb et al. 2004; Verma et al. 2010).

The spectral energy of neural channels in multiple frequency bands as well as various time and frequency domain features have been used as potential seizure biomarkers. To improve the power and area efficiency in multichannel systems, a spatial filtering technique was proposed to precede the seizure detection unit (Shoaran et al. 2016b). But in most devices the classification of neural features is performed either remotely or by means of moderately accurate thresholding techniques.

For one patient-specific support vector machine (SVM) classifier (implemented by Yoo et al. 2013), the classification processor contributes to a significant portion of chip area and power. To improve the accuracy of detection, resource-efficient on-chip learning is becoming an essential element of next-generation implantable and wearable diagnostic devices.

**MACHINE LEARNING IN NEURAL DEVICES:
SCALABILITY CHALLENGES**

Conventional classification techniques such as SVMs, k-nearest neighbors (KNNs), and neural networks (illustrated in Figure 2) are hardware intensive and require high processing power and large memory units to perform complex computations on chip.

Numerous studies show that a large number of acquisition channels are required to obtain an accurate representation of brain activity, and that the therapeutic potential of neural devices is limited at low spatiotemporal resolution. It is expected that future interfaces will integrate thousands of channels at relatively high sampling rates, making it crucial to operate at extremely low power. The device must also be very small to minimize implantation challenges.

Despite a substantial literature on machine learning, hardware-friendly implementation of such techniques is not sufficiently addressed. Indeed, even the

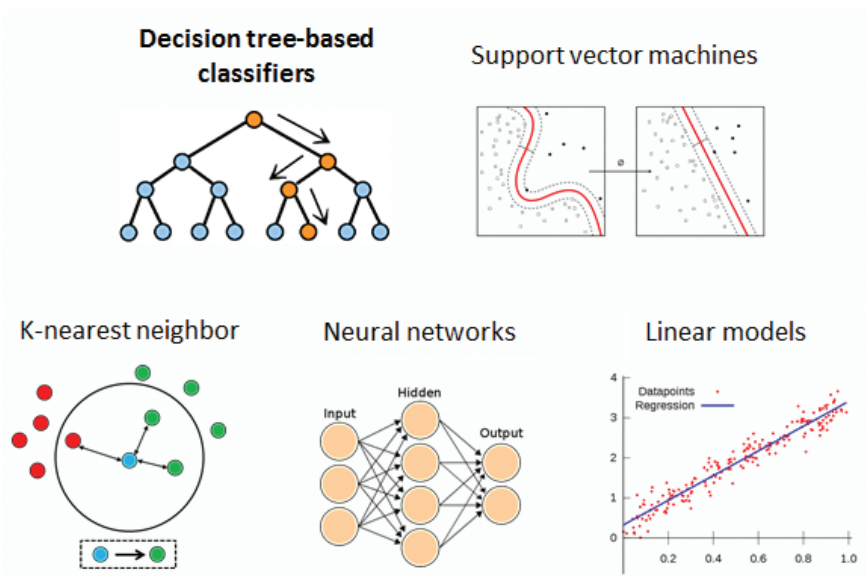


FIGURE 2 Schematic of common learning models as potential candidates for hardware implementation.

simple arithmetic operations performed in conventional classification methods can become very costly with an increasing number of channels.

Finally, filter banks and, in general, feature extraction units can be hardware intensive, particularly at higher frequencies associated with intracranial EEG. Extensive system-level design improvement is needed to meet the requirements of an implantable device while preserving high-resolution recording capability.

DECISION TREE-BASED CLASSIFIERS

We present and evaluate a seizure detection algorithm using an ensemble of decision tree (DT) classifiers. The general schematic of a single decision tree is shown in Figure 2.

With only simple comparators as their core building blocks, DT classifiers are a preferable solution to reduce hardware design complexity. Using a gradient-boosted ensemble of decision trees, we achieve a reasonable tradeoff between detection accuracy and implementation cost.

Gradient boosting (Friedman 2001), one of the most successful machine learning techniques, adaptively combines many simple models to get an improved predictive performance. Binary split decision trees are commonly used as the “weak” learners. Boosted trees are at the core of state-of-the-art solutions in a variety of learning domains because of their accuracy and fast computation and operation.

Combined with an efficient feature extraction model, we show that, with only a small number of low-depth “shallow” trees, the boosted classifiers quickly become competitive with more complex learning models (Shoaran et al. 2016a). These ensembles of axis-parallel DT classifiers are excellent candidates for on-chip integration, eliminating the multiplication operation and offering significant reductions in power and chip area.

Performance Evaluation and Hardware Design

As a benchmark, we compare a boosted ensemble of 8 trees with a depth of 3 to linear SVM, cubic SVM, and KNN-3 models proposed for on-chip classification, using the following features: line length, time-domain variance, and multiple band powers. The proposed approach is tested on a large dataset of more than 140 days of intracranial EEG data from 23 epileptic patients.

Figure 3 (left) shows the average F1 measure of classifiers. This benchmark is already competitive with its peers and can outperform using larger ensemble sizes. It achieves an average seizure detection sensitivity of 98.3 percent.

Decision trees are very efficient, but also susceptible to overfitting in problems with high feature space dimensionality. To address this, we limit the number of nodes in each tree—that is, we design shallow trees with a small number of features. These shorter trees are also more efficient in hardware and, equally

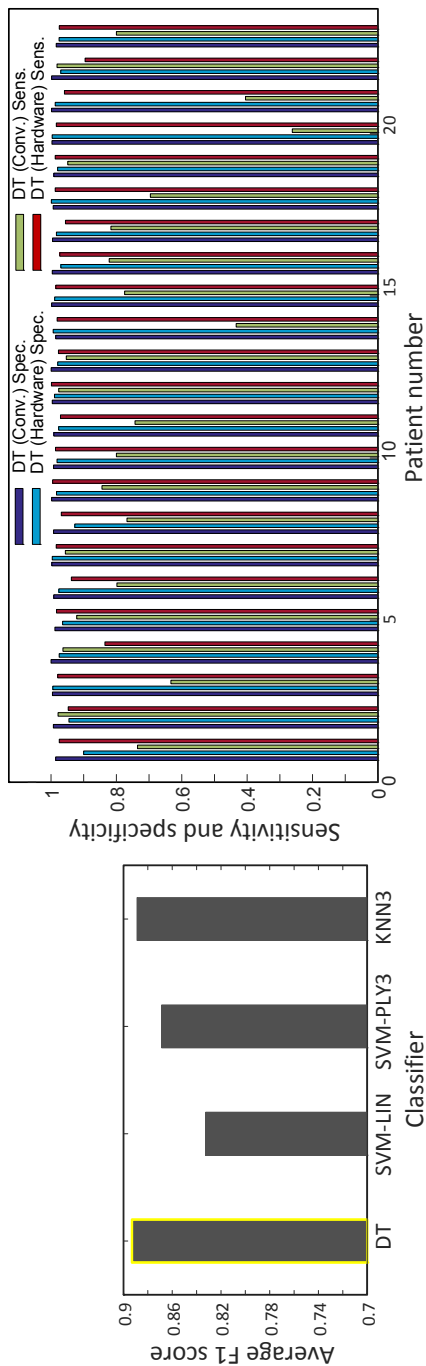


FIGURE 3 Comparison of predictive ability of different classification methods with an ensemble of 8 decision trees (DT) of depth 3 (left), and the classification performance of the asynchronous hardware model compared to a conventional (conv.) DT (right). KNN = K-nearest neighbor; LIN = linear; PLY3 = polynomial kernel of order 3; SVM = support vector machine.

important, incur less detection delay. In our simulations, the detection accuracy is not significantly improved (<0.5 percent) with DT depth values of 4 or more.

Proposed Decision Tree Architecture

We propose the architecture shown in Figure 4 (top) to implement ensembles of decision trees. At each comparison step, only the features appearing in the active nodes of trees are needed; the rest of the recording array can be switched off to save power.

Because the final decision is made upon completing decisions at prior levels, a single feature extraction unit can be sequentially used per tree. This results in a significant hardware saving, in contrast to SVM, which requires all features from the entire array.

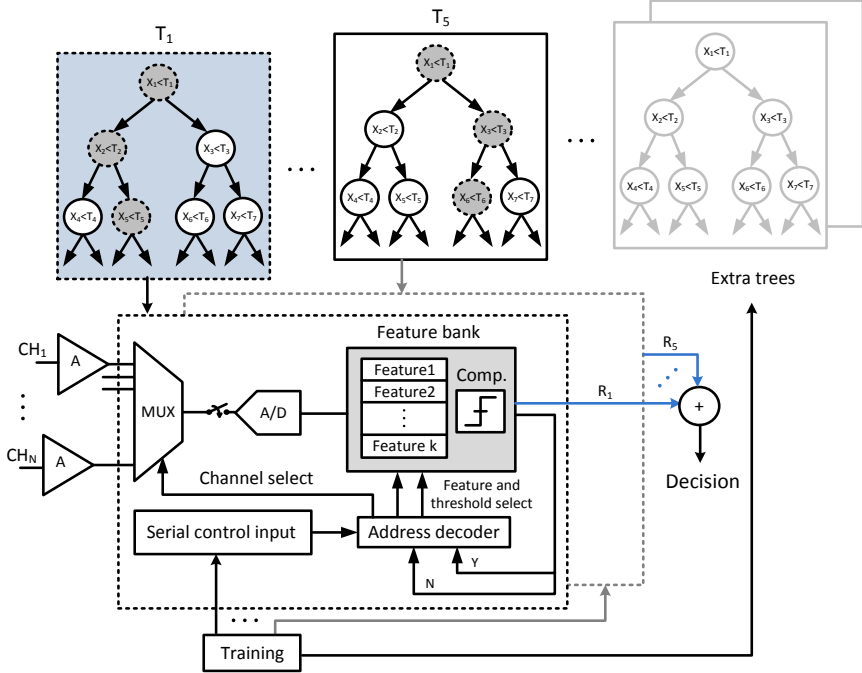
For example, the memory required to classify 32-channel neural data with 8 trees (a maximum depth of 3 and threshold resolution of 8 bits) is as low as 100 bytes, while SVM and KNN-based arrays would need more than 500 kB of memory. Depending on the specific patient and the difficulty of the detection task, additional “supportive” trees can be used to further boost the classification accuracy.

The proposed architecture faces a practical challenge of designing decision trees under application-specific delay constraints. Given any DT ensemble $\tau = \{\tau_1, \dots, \tau_k\}$ obtained from our original method, we need to ensure that each tree τ_i satisfies the delay constraint: $\sum_{i \in \pi(h)} d_i \leq \Delta T$, where d_i is the time required to compute feature f_i , ΔT is the maximum tolerable detection delay, and $\pi(h)$ is the set of all predecessors of node h . We propose a “greedy” algorithm to solve this practical constraint by building trees that satisfy the delay requirement, as illustrated in Figure 4 (bottom).

However, this algorithm may result in a suboptimal solution. We therefore investigate a novel asynchronous model to learn from neural data streams, the results of which are shown in Figure 3 (right). In this model, the trees are built with features that maximize accuracy regardless of their computational delay. Based on averaged results of completed trees and previous results of incomplete trees, decisions are frequently updated (over 0.5-sec intervals) to avoid long latencies and maximize sensitivity. Once completed, longer trees contribute to decisions at future time steps.

CONCLUSIONS

Based on a simple yet sufficiently accurate (98.3 percent) decision tree model, we introduce efficient hardware architectures and related training algorithms to predict the abnormal neurological states in various disorders, such as epilepsy, Parkinson’s disease, and migraine. Such classifiers may allow the full integra-



Input: Original trained tree ensemble $\mathcal{T} = \{\mathcal{T}_1, \dots, \mathcal{T}_k\}$
Output: Delay-constrained ensemble $\mathcal{T}' = \{\mathcal{T}'_1, \dots, \mathcal{T}'_k\}$
Data: training set: $S = \{(x_i, y_i)\}$
 feature set: $F = \{f_i\}$, each with delay d_i
 delay tolerance: ΔT
 set of predecessors of node h : $\pi(h)$

```

for all trees  $\mathcal{T}_i$  in  $\mathcal{T}$  do
  for each node  $h \in \{1, \dots, |\mathcal{T}_i|\}$  do
    if  $\sum_{i \in \pi(h)} d_i > \Delta T$  then
       $\forall f_i \in F$  find feasible  $f$  that obtains the best
         $SplitCriterion(f_i, S)$ 
      Label node  $h$  with  $f$ 
      Grow  $Subtree(h)$ 
    end
  end
end
    
```

FIGURE 4 Hardware-level architecture for an ensemble of decision tree classifier with primary and supportive trees (top) and a greedy training algorithm to meet the delay constraints (bottom). A = amplifier; A/D = analog to digital converter; CH = channel; Comp. = comparator; k, N = number of features and channels; MUX = multiplexer; R = result.

tion of processing circuitry with the sensor array in various resource-constrained biomedical applications.

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MEGATALL BUILDINGS AND
OTHER FUTURE PLACES OF WORK

Megatall Buildings and Other Future Places of Work

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MARIJA TRCKA
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In 2015 a record-breaking 106 skyscrapers above 200 meters high emerged across the globe; the Council on Tall Buildings and Urban Habitat (CTBUH) reported that 62 skyscrapers were built in China alone. The growth is exponential in both number and height—CTBUH forecast an increase from 18 percent to 27 percent in supertall buildings from 2015 to 2016.

Of the 100 tallest buildings in the world, all are at least supertall, rising more than 300 meters. This decade launched a new breed of skyscraper, the megatall building, which rises 600 meters or more; in 2016, 6 megatall buildings were either fully completed or under way. This scale challenges conceptions and notions of livability at great heights. The new record for a megatall building will be set by the *kilometer-high* Jeddah Tower, by Adrian Smith and Gordon Gill Architecture, in Saudi Arabia; it is scheduled for completion in 2020.

Megatall buildings elicit mixed reactions. They are seen as towering masterpieces that serve as icons and symbols of power—or destroyers of urban quality of life. They are praised as efficient green construction models for vertical densification—and denounced as consumers of resources that cannot possibly be sustainable.

The mega-high structures are more than aesthetic and structural advances that establish urban and corporate statements. Their scale challenges fundamental inhabitation models and affects multiple spheres of urban life and society, from geography and zoning regulations to economics and cultural beliefs. It is therefore essential to understand the role of science, technology, and development in addressing the complex environmental and sociocultural challenges inherent to megatall constructions.

How does scientific research enable and influence the design of megatall buildings? What are the scientific and technological innovations that will best support environmental sensibility and quality of life? What key driving factors will shape how engineers, architects, and scientists pursue new models that can be truly sustainable?

Megatall constructions will influence potential paradigm shifts in intelligent buildings and transportation systems, materials, structures, and the very future of the workplace. This session aimed to prompt discussion of the critical role of advances in sustainability and energy, intelligent transportation, functional natural materials for structural innovation, and spatial quality of the future of work in megatall buildings.

The session began with a review of fundamental design transformations in the making of megatall buildings and the impact of their distinctive spatial characteristics on daily life. Stephen Nichols (Otis) surveyed the role of digital interaction, physical-human interface, and intuitive behavior, spanning the disciplines of computer science and electrical, mechanical, and systems engineering as vertical transportation continues to evolve in taller buildings. The next presenter, Michael Ramage (University of Cambridge), looked at functional natural materials for structural systems in high-rise buildings. He is a research leader in such materials, in particular engineered timber and bamboo for high-rise structures. The session concluded with a talk by Jenny Sabin (Cornell University) on the applications of insights from biology and mathematics to the design of environmentally adaptable material structures.

As population concentration in urban settings continues to grow, so will vertical densification at unforeseen scales. It is essential to prepare for this outcome through fundamental research and development in potentially transformative models, in order to design and construct megatall buildings that exist in synergy with nature while promoting health and overall urban quality of life.

The Evolution of Elevators: Physical-Human Interface, Digital Interaction, and Megatall Buildings

STEPHEN R. NICHOLS
Otis Elevator Company

For more than 160 years advances in vertical transportation and elevator technology have been key enablers of the increasingly high-rise buildings that define cities around the world. Improvements in elevator safety, robustness, quality, space efficiency, and performance have allowed buildings and cities to grow megatall.¹ The design and construction of such buildings and their vertical transportation systems need to be balanced with improvements that reduce passengers' anxiety while increasing convenience and efficiency.

This article reviews the history of elevators and their technologies. It then examines specific considerations for megatall buildings, such as building traffic, lobbies and layout, and evacuation. The discussion considers the incorporation of new technologies and user-centered design to improve passenger experience.

BRIEF HISTORY OF ELEVATORS

The functional “job to be done” (Christensen 2011) of an elevator is simple: transport passengers and cargo safely and quickly from one altitude to another.

Early Methods

Elevators have been part of human history as far back as the pyramids of ancient Egypt (Gavois 1983), when the construction of large structures required

¹ Megatall buildings are 600 meters or more. For reference, the original 110-floor World Trade Towers in New York were just over 540 meters. The world's tallest building, Burj Khalifa in Dubai, is 828 meters.

the capacity to raise materials to greater heights than humans could lift without mechanical advantage. The Egyptians, Romans, Babylonians, and others devised increasingly sophisticated rope and pulley systems, capstans, and other hoists for construction purposes—and there is evidence of an elevator hoistway in the Roman Colosseum completed in the year 80.

The first counterweight, used to balance and counteract the effects of gravity, did not appear before 1670, and hoists were not widely applied to industry until 1830 (Goodwin 2001). Elevators were generally not successful because of their unreliability and lack of safety. Fraying rope and other mechanical failures due to wear and excessive weight were common causes of dangerous accidents that made factory owners reluctant to use elevators for cargo. Passenger use was all but unthinkable.

Invention of the Elevator Safety Brake

The use of levers, ropes and pulleys, and other lifting means persisted without many significant improvements until the invention in 1852 of the elevator safety brake by Elisha G. Otis (1811–61). He demonstrated it at the New York World's Fair (Figure 1²) in 1854 (Goodwin 2001), and it was patented in 1861.

Otis's invention took a simple flat-leaf spring from a cart and applied it to the roof of an elevated hoist such that, in the event of the hoist rope's failure, the tension in the spring would cause shoes on either end of the spring to engage with notches in the guide rails at either side of the hoist. As dramatically demonstrated at the World's Fair, when the rope was cut, the safety brake activated and brought the hoist to an abrupt halt with no harm to the cargo or passengers.

The safety brake quickly transformed an unreliable, little-used industrial tool into a viable means of transporting not only cargo but also people. The first-ever safe commercial passenger elevator was installed in 1857 in a Manhattan department store owned by E.V. Haughwout and Co.

With the commercial success of safe passenger elevators, architects and builders started constructing taller buildings. Prime real estate in buildings and cities quickly moved from the first few floors that were conveniently close to the building entry to the top floors and penthouses away from the dust and clamor of the city street.

The breakthrough in elevator safety prompted the evolution toward taller and taller cities and, eventually, today's megatall buildings.

² All figures and images are provided from the Otis Historical Archive: Historical Photographs, Illustrations and Ads; Digital Image Collection.



FIGURE 1 Elisha Graves Otis performs his safety elevator demonstration in the dome of the Crystal Palace at the World’s Fair in New York City (May 1854). Hired by showman PT Barnum to perform the feat, Otis rode up on the platform, had the rope cut, and, when the car did not fall in front of the stunned crowd, proclaimed: “All safe, ladies and gentlemen! All safe!” Courtesy Otis Elevator Company.

ELEVATOR TECHNOLOGY DRIVERS

The competing benefits and disadvantages of gravity and friction, coupled with continuous improvements in power management, building materials, and other factors, transformed elevators from purely functional devices to a central component of urban buildings and city life.

Harnessing Gravity

The art of elevating—moving people vertically through buildings—is fundamentally about controlling gravity, which is both the elevator’s enemy and friend. It must be overcome to move people safely and smoothly, and harnessed (through counterweights and other means) for control and energy savings.

Early advances focused on propulsion technology. Steam engines in the 1850s and 1860s, hydraulic systems in the 1870s, and electric motors in the 1890s (installed at either the top of the elevator hoistway or the bottom of the elevator pit) powered elevators through a variety of arrangements and layouts to enable higher rises, different building configurations, and efficient vertical motion. Rotating machinery and ropes, hydraulic pistons, or the combination thereof created the upward force to pull or push the passenger and cargo compartment up and to stop it safely, smoothly, and accurately at a desired destination.

Improvements in propulsion technology enabled the control of gravity, fostered public confidence in elevators, and led to widespread success. Advertisements initially showed the elevator’s industrial roots with a focus on machinery (Figure 2), but soon luxurious elevator interiors shifted the focus to passengers and elevators became part of the architectural intention of a building.

Controlling Friction

The safe, controlled, smooth deceleration and stopping of an elevator are of paramount importance.

Traction elevators balance friction and the interface between the rope (or belt) and the drive sheave, whether the “rope” is a hemp rope, steel cable, polyurethane-coated steel belt, or carbon-fiber suspension member. Innovations in roping (with one-to-one and two-to-one roping, under- and overslung, and roped hydraulic arrangements) and other technological advances yielded a series of inventions from the latter half of the 19th century into the 20th (see Figures 3, 4). These improvements in elevator machinery and propulsion benefited both passengers and architects as elevators became faster and larger.

Systems in which propulsion did not rely on frictional interfaces were introduced in the 1990s: the first linear motor elevator system was commercially offered by Otis in Japan (Janovský 1999). This system, with the motor mounted on the counterweight, reduces the complexities of controlling friction for propulsion while retaining the counterweight for the advantages of working with gravity. Advances in linear motors will eventually make it possible for multiple elevator cars to travel simultaneously in individual hoistways.

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AND POWER, CONSTANTLY ON HAND AND IN PROCESS OF MANUFACTURE.



Union Hoisting Engine. Cut A.
Our Patent Double-Turn Hoisting Engine, adapted for use in connection with Safety Hoisting, for Storage Warehouses, Packing Houses, Shipping Docks, Mines, &c. Motion of Platform as will of attendant, up to 300 feet per minute.



Union Hoisting Engine. Cut B.
Our Patent Double-Turn Hoisting Engine, showing application of Patent Automatic Stop Mechanism, by which the engine automatically stops after making any desired number of revolutions. Motion of Platform as will of attendant, up to 300 feet per minute.



Automatic Safety Drum. Cut C.
Our New Patent Safety Mechanism for stores and high buildings where the excessive weight of the Wire Lifting Rope tends to prevent the Safety Spring from acting in the critical moment. Instantly releasing a safety device, immediately as between the Hoisting Engine and Safety Platform necessary. This "Safety Drum" is mounted directly upon the lead-way and acts as a counter to the entire machine, instantly stopping the Platform upon any approach to an unsafe position.

DEALERS in all kinds of Machinery required in the application of Steam for Hoisting Purposes.
STEAM BOILERS, STEAM PUMPS, STEAM & WATER GAUGES, STEAM & WATER PIPES, DAMPER REGULATORS, SHATTING, IRON CASTINGS, PULLEYS, &c.

WIRE ROPE

Of the best quality, manufactured expressly for Hoisting, constantly on hand and supplied to order.



Lifting Power-screw combination. Cut D.
For Manufacture and all general purposes of hoisting by bolts. A strong, compact machine, simple in construction, and readily attached to work with or without Safety Platform.



Lifting Power-gear combination. Cut E.
Our Universal Hoisting Machine, as illustrated below, showing "The Bell Mechanism," by which the machine is instantly stopped in case the power ceases on a sudden motion from any cause, or in the breaking of a bolt while the machine is in motion.

DESCRIPTIVE CIRCULARS
Of our Machinery, with any information required, will be furnished on application by Mail or in person.



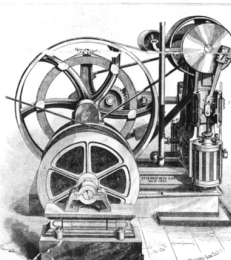
Metropolitan Hoisting Engine. Cut F.
Our Patent Horizontal Bell and Four Hoisting Engine, Safety Platform and connections, for Mills, Manufacture Houses, &c. Platform or Car moves any speed, as will of attendant, up to 300 feet per minute.



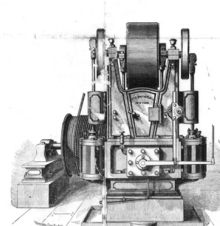
Relief Hoisting Engine. Cut G.
Our Patent Reversible Relief Hoisting Engine, adapted for use in connection with Safety Platforms. The ordinary overhead Hoisting Machine, 30 to 60 feet per minute motion of Platform.



Universal Hoisting Machine. Cut H.
Our Patent Lifting Frame, Safety Platform and connections, for Factories, Mills, Shipyards, Bakeries, and all general hoisting purposes where steam, water or other power is to be used. Motion of Platform 30 feet per minute.



National Hoisting Engine, Front View. Cut J.
Our Patent Stationary Cylinder Hoisting Engine. Side View. See Cut J.



National Hoisting Engine, Side View. Cut J.
In this Hoisting Engine are realized many novel and useful features, which will command it to make its position as a hoisting machine, strong, and compactly built, efficient, and simple in appearance, and easy to run without noise. The valve-gear is constructed upon an entirely new principle, by which a direct-acting and very simple motion is obtained with less loss by friction than in any other mechanism for the purpose in use.



Metropolitan Hoisting Machine, showing Corner Platform. Cut K.
This "Corner Platform" is adapted to buildings where it is necessary to hoist goods to and from the platform on all sides or on any two sides at right angles at any of the different floors.

Printed by H. J. BERRY, 174 W. 4th St., N. Y.

FIGURE 2 This 1869 Otis Brothers ad illustrates advances in steam engines and belt-driven hoist machinery for early elevator propulsion. Hydraulic piston-powered elevators were adopted in the 1870s and electric elevator motors in 1889. Courtesy Otis Elevator Company.

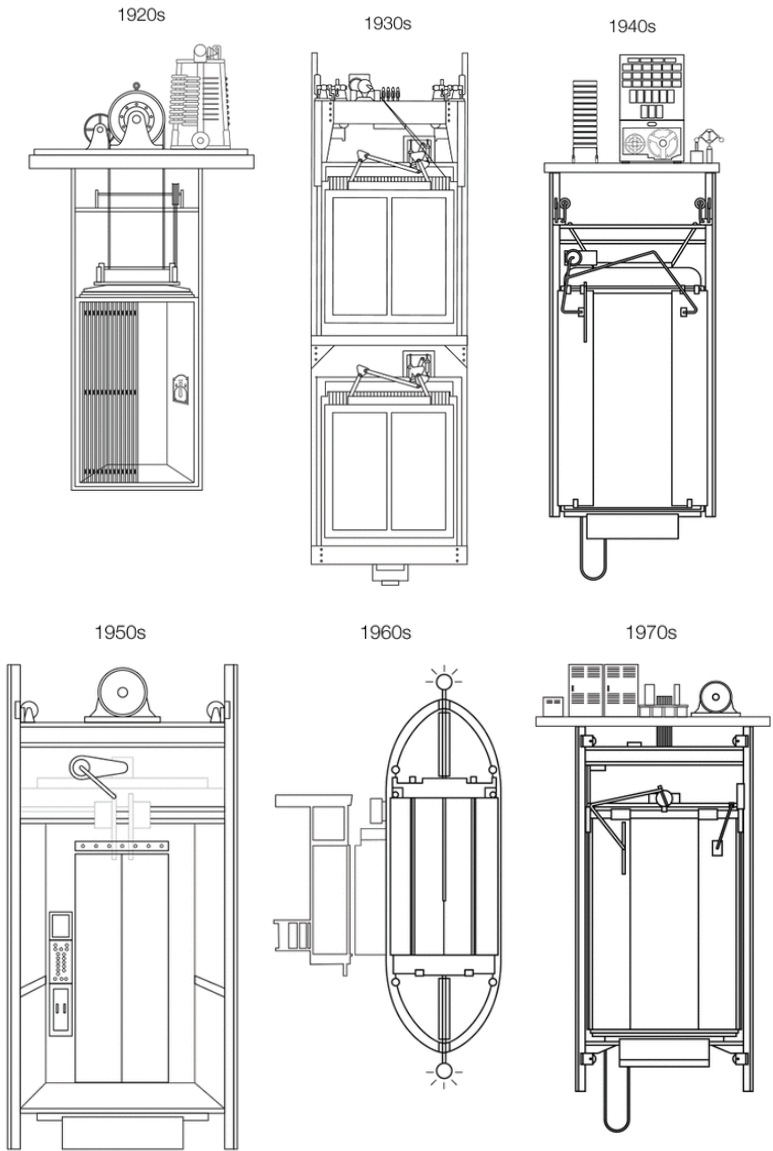


FIGURE 3 Elevator innovations in the mid-20th century looked beyond propulsion and hoisting technology. In the 1920s signal control and push buttons start to pave the way for automated control that, with the introduction of automatic doors, is realized in the 1950s (car operating panel shown to the left of the doors). In the 1970s the first integrated circuit, electronic, controlled elevator is introduced by Otis as the technology continues to shrink. Courtesy Otis Elevator Company.

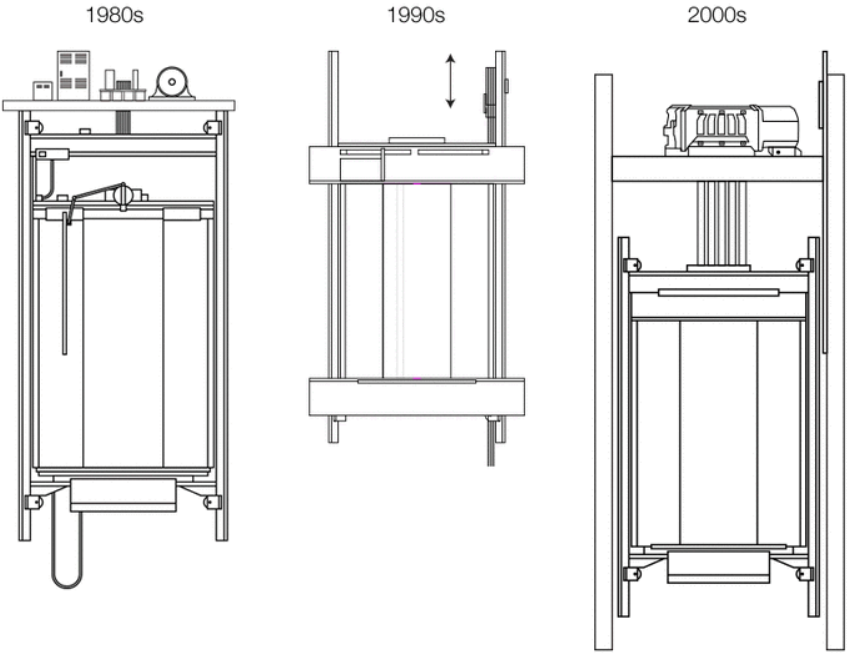


FIGURE 4 Elevator innovations in the late 20th century. Looking beyond the elevator shaft, remote service was introduced in the 1980s. In the 1990s space-saving linear magnetic motors (shown to the right along the counterweight rail) remove the need for an elevator machine room. The turn of the century ushers in machine-roomless (MRL) elevators with flat coated steel belts and other more sustainable technologies. Courtesy Otis Elevator Company.

Managing Power

Rotating machinery, whether powered by steam or electricity, and linear motors all require power. Careful management of that power is required for both the elevator system and the building system as a whole.

Innovations like the counterweight and two-to-one roping are advantageous because they require lower power. Reduced power consumption allows propulsion components to be smaller and more efficient, benefiting both the building owner and the architect in the long-term operational cost of the elevator and the building’s overall energy footprint. Linear motors may offer some benefits, but they require significantly higher amounts of power than traditional means (Janovský 1999).

An elevator system’s power use, environmental impact, and sustainability must be considered in the context of the building system and the city itself. Recent

innovations in battery-, solar-, and even hydrogen-powered elevators (Auditeau 2007) are intended to help elevator systems coexist in the environment where they operate.³

Building Construction, Materials, and Use of Core Space

An elevator system must adapt to a building's construction methods and materials (e.g., concrete, steel, timber). Steel construction in North America may yield different optimal configurations than concrete or prefabricated buildings in Asia. Advances in timber construction for sustainability or seismic advantage will require elevators to innovate along with the building material.

In addition, architects must consider a building's core space (allocated to elevators, machine and utility rooms, ventilation shafts, and the like) and the percentage of rentable space consumed by an elevator system. Developments such as the ability to use multiple cars in a hoistway can optimize both core space use and traffic flow through a building, as explained below in the discussion of double-deck elevators.

THE PASSENGER EXPERIENCE AND HUMAN BEHAVIOR

Passenger experience is the art and science of matching the elevator experience to the expectations of the people riding the elevator. It is a true human-machine interface that requires enhanced technology, an understanding of human behavior, and the smooth interaction between the two. A user-centered design approach helps to adapt beyond the functional “job to be done” in order to meet new social and emotional requirements.

Personal Expectations

One important dimension of this experience is ride quality. The quality of an elevator ride—the noise and vibration experienced by passengers—is another area where technology has progressed steadily to provide smoother and quieter rides.

Social, circumstantial, and ethnographic differences, however, are associated with different expectations of what constitutes a “good ride.” Residential passengers may think of the elevator as an extension of their living space. Hospitality passengers may want their visit to be better than their home. Commercial passengers may simply expect an efficient and secure journey that does not impinge on their valuable time. Passengers in New York City may want to feel the rush of moving quickly up the building. Passengers in Tokyo may look for the experience

³ Also see “Gen2 Switch” brochure and information from the Otis Elevator Company (www.otis.com/site/lb/Pages/Gen2-Switch.aspx).

of leaving one space, entering the elevator, and a moment later having the doors open in an entirely new space with little physical feeling of movement.

Technological Enhancements

For much of the early history of elevators, the experience was simple and very personal. Passengers would communicate directly with elevator operators who guided traffic, opened and closed doors, and directed the movement of the elevator car.

Elevator buttons were introduced in 1892, electronic signal control in 1924, automatic doors in 1948, and in 1950 the first operatorless elevator was installed at the Atlantic Refining Building in Dallas. Full automatic control and autotronic supervision and operation followed in 1962, and elevator efficiency has steadily increased in other ways.

Yet questions associated with personal interaction remain. Where is the passenger in relation to the elevator? Is the passenger ready to ride or leave the elevator? Is the passenger allowed to go to his desired destination? How does the machine interact with the passenger to communicate valuable information?

Integration of the Two

Many of the challenges in modern passenger experience involve providing intuitive interactions and behavior solutions, and these can largely be achieved through new technologies and the application of connected and Internet of Things (IoT) technologies from other industries (Gulan et al. 2016). Digital interaction technology such as smartphones, wearables, video analytics, and other sensors, as well as advances in physical-human interfaces (e.g., touchscreens instead of buttons), will greatly improve intuitive behavior.

Technologies can be combined and introduced to lower anxiety and increase convenience and efficiency. Ensuring that passengers feel safe, trust equipment reliability, reduce or eliminate their wait time, get to their destination faster, and travel in a secure, comfortable, personalized space is of paramount importance to elevator technology well beyond the early physics-based problems.

CHALLENGES OF MEGATALL BUILDINGS

The growing height of buildings and the desire for people to live and work at higher altitudes amplify all the challenges discussed.

- Propulsion systems must be devised to carry increasing duty loads of passengers and cargos, yet fairly quickly in high-rise buildings the combined weight of the ropes and suspension components outweighs the desired movable mass.

- Safety and braking technology that works well at low speeds must combat increasingly high forces, thermal loads, and more demanding friction environments.
- Physically moving larger and larger elevator machinery to the top of the building during construction and providing power to those machines throughout the life of the building are monumental challenges for both the elevator and the building itself.

All the challenges in elevator design, from ride quality to seismic concerns, must be considered and optimized, in addition to new, unique challenges such as building sway due to wind. Challenges to the passenger experience (e.g., comfort, convenience, dispatching, traffic flow) also increase dramatically with taller buildings.

Automated Destination Dispatching

Tall buildings and their operators must accommodate the need to efficiently move large numbers of people. With megatall buildings, passengers' experience must be considered from the moment they enter the building, traverse the lobby, and approach the elevator system.

The potentially competing experiences of seamless elevator use and robust security must be balanced via access control. Effective integration of these aspects is demonstrated at 7 World Trade Center, where the presentation of credentials at lobby turnstiles automatically calls the elevator within milliseconds as passengers walk the 45 meters to board the elevator.

Elevator travel in very tall buildings can be enhanced by faster, smoother rides, but the demands on the propulsion system require that the journey be broken into two or more partial trips. Thus a passenger wishing to go to the 100th floor might board an elevator in the lobby, exit into a "sky lobby" at the 50th floor, and board a different elevator to complete the trip to the 100th floor. One or more of these momentary pauses can delay arrival at the destination floor and increase confusion for the passenger.

Destination dispatching systems were introduced at the turn of the 21st century largely to increase building efficiency and improve traffic flow. They have mathematical advantages over traditional up/down dispatching in taller buildings. Because the passenger enters the final destination ("floor 72") on the building landing, rather than entering first an "up" call and then "floor 72" in the elevator cab, the dispatching algorithms can intelligently group passengers, route them to the appropriate car, and improve the building's dispatching efficiency.

In addition, the elevator of the not-too-distant future will be able to automatically recognize individuals, call the elevator, and adapt to where they are going in the building from day to day and hour by hour.

Double-Deck and Multiple Elevators

Megatall building lobbies and their layout must accommodate both the natural flow of people and the desired outcomes of the architects and elevator designers. Double-deck elevators⁴ appeared in 1931, enabling the transport of significantly more people in a single elevator shaft (Figure 5). Double-deck and super-double-deck elevators (where two cars travel together but can move up to 2 meters independently to accommodate floor height differences) may be used to move larger populations throughout buildings, but they can also be used to segment populations and ferry people to different locations in the building.

The introduction of multiple cars in elevator hoistways provides a dramatic change to the experience of riding an elevator, mandating changes to how elevators communicate with individuals who become more like the passengers of vertical trains.

Evacuation

Evacuation and egress of megatall buildings is of special concern. Historical practice for evacuating any building mandates the use of stairwells for safe evacuation. With increasingly tall buildings and the need to move larger numbers of people, the use of elevators for evacuation is preferable to stairs or refuge spaces. Newer versions of the International Building Code (IBC) provide incentives for using elevators in an occupant evacuation operation for any building over 420 feet tall (128 meters or roughly 38 floors; NEII 2016).

CONCLUSION

The Internet of Things, advances in connectivity, ubiquitous smartphones, and other new digital technologies offer enormous opportunities for interpersonal communication and improvements in myriad dimensions of urban life, including people's vertical movement in increasingly towering structures for living and working.

Megatall buildings amplify the challenges in all aspects of elevator design for both technology and passenger experience. The goal of vertical transportation systems in megatall buildings should be to provide a natural interaction with the building ecosystem for a safe, efficient, convenient, and personalized passenger experience, balancing advances in elevator and building performance to provide a delightful ride every time.

⁴ Two elevator cars attached to the same frame move together, the bottom car serving odd-numbered floors and the upper car even-numbered floors.

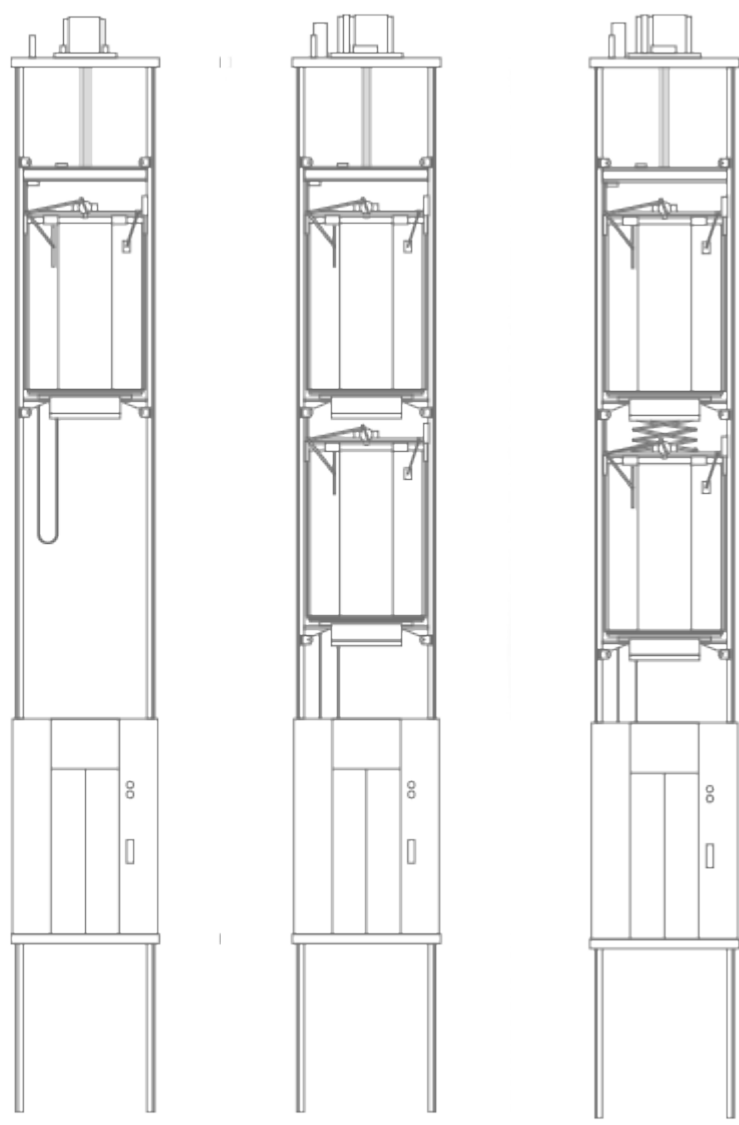


FIGURE 5 (Left) Most elevators are a single-deck configuration: one car serves all the floors for a given hoistway. (Center) High-rise buildings that require efficient flow of large numbers of people may use a double-deck car: two linked elevator cars move together, the top one stopping at the even-numbered floors and the lower one at the odd-numbered floors. (Right) Super-double-deck cars accommodate buildings with different floor heights (e.g., an entrance lobby with a higher ceiling) and heavy passenger traffic: the two cars travel together but can move up to 2 meters independently via a pantograph scissor-like device between them. Courtesy Otis Elevator Company.

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Supertall Timber: Functional Natural Materials for High-Rise Structures

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Wood and wood products have been used as building materials since before recorded history, but the full potential of timber and other plants as building materials has not yet been realized.

Engineered timber materials, among them cross-laminated timber (CLT) and laminated veneer lumber (LVL), have enabled architects and engineers to design and build larger and larger timber buildings. The tallest is Brock Commons, a 55-meter, 18-story student dormitory completed in 2016 at the University of British Columbia. Before that, the tallest was Treet (“tree” in Norwegian), a 53-meter, 14-story condominium completed in 2015 in Bergen, Norway (Figure 1). Brock Commons has two concrete cores, while Treet is a fully timber structure, so each may be the tallest of its type (Foster et al. 2016).

The scale of these contemporary buildings is significant, as the first metal-framed skyscraper, William Le Baron Jenney’s Home Insurance Building in Chicago, was 55 meters tall when completed in 1891, and 1931 saw the completion of the Empire State Building in New York City, at 381 meters.

Innovation in natural materials, design, and construction may allow a similar increase in the height of timber skyscrapers. And the use of natural materials instead of steel and concrete in taller and larger buildings can reduce carbon emissions. Furthermore, CLT construction requires only about 30 m³ for an apartment for two people. Using wood from only 30 percent of Europe’s managed forests with current practices, the entire population of Europe could be housed in perpetuity, even assuming the entire housing stock was renewed every 50 years (Ramage et al. 2017a).



FIGURE 1 Treet, a 14-story apartment building in Bergen, Norway, rises 52.8 meters and is made of cross-laminated and glued laminated timber.

BACKGROUND

Timber has exceptional properties for building, many of which have been overlooked in the construction of ever-taller buildings in the past century. Advances in biological knowledge, engineering of plant-based materials, and interest in renewable construction are converging to create new possibilities for materials and allow for larger, taller, and more natural engineered wood buildings (Green 2012; Ramage et al. 2017a).¹

There is also competition in the building industry to construct the tallest timber tower. Height increases are currently incremental, but through a combination of theoretical design and physical testing, the viability of timber buildings can be demonstrated at much greater heights than previously possible (Ramage et al. 2017b).

By pushing the limits of theoretical designs into the realm of the supertall²—and sometimes beyond that which is feasible using current materials and construction technologies—our research sets out the requirements for the next generation of engineered plant-based materials. Research and the design and construction of contemporary large-scale timber buildings together further the architectural and structural engineering knowledge necessary to make tall timber buildings a reality.

Materials science has advanced the industrial production of steel and reinforced concrete since the mid-19th century. The materials science of natural materials is less well understood, but the use of biofuels has helped drive fundamental research on the makeup of plant cells and their constituent parts.

Improved information about how to break down plants into useful components can also enhance understanding of their underlying properties. As an example, the model plant *Arabidopsis thaliana*, whose genome is well defined and editable, is essentially the mouse of plant science. Through biochemistry, it can be grown with lignin-depleted cells for studies of the role of lignin in giving plant cells their characteristic properties. In *Arabidopsis*, lignin appears to help control the way cells move past each other as they are pulled apart in tensile tests.

With better knowledge of how the elements of cell walls contribute to the properties of plants and forest products, it may be possible to breed or genetically engineer plants with specific functional properties that are more favorable to construction.

CURRENT DEVELOPMENTS AND APPLICATIONS

Novel properties in trees may give rise to a new class of natural materials, but engineered timber products on the market are already giving designers around the

¹ Also see the 2013 technical report of the SOM Timber Tower Research Project, available at http://www.som.com/ideas/research/timber_tower_research_project.

² Supertall buildings are 300–600 meters. For reference, the original 110-floor World Trade Towers in New York were just over 540 meters, and the Sears Tower in Chicago is 442 meters.

world opportunities to innovate with large-scale construction. CLT can be used much like slabs of concrete in walls and floors, and glue-laminated timber and LVL can substitute for steel or concrete columns and beams. All can be used with existing modes of construction.

But there are limitations. For example, platform construction with CLT is limited by the perpendicular-to-grain crushing of panels at floor junctions, a phenomenon that is difficult to overcome above 10 stories or so. And although the axial strength of some hardwood LVL in compression and tension is sufficient to engineer very large buildings, the ability to transfer tensile loads that can be carried by the full section from one element of timber to another remains to be determined.

Our supertall timber project, in which we have designed wooden skyscrapers (Figure 2), shows the viability of commercial and residential buildings at a new scale in timber, using components and materials that are commercially available



FIGURE 2 Maquette of River Beech Tower proposed for Chicago. The 80-story residential skyscraper is a design collaboration of Perkins+Will, Thornton Thomasetti, and Cambridge University Centre for Natural Material Innovation.

today. Our design and research demonstrate the architectural, engineering, and economic possibilities that stem from thinking about traditional materials in new ways.

OTHER PLANTS

A variety of plants may add to the materials available. Bamboo has excellent properties in tension and compression, and is among the world's fastest growing plants—it can be harvested every few years. In addition, a number of processing methods exist to turn the raw product into an engineered material (Sharma et al. 2015), and more are being developed. Engineered bamboo looks like wood and is crafted with woodworking equipment. It behaves differently as a structural material (Reynolds et al. 2016), so new engineering codes are necessary.

Other crops, such as flax and hemp, are being used to make structural composites for automotive and industrial design and at the same time engineered to deliver improved properties. All of these crops are available at a scale necessary for construction.

ADVANTAGES

Construction with timber has many advantages, not least for the environment.

- Timber is the only major building material that can be grown, and the sustainable harvest of lumber is vast—crop-planted forests around the world are expanding.
- Timber is five times lighter than concrete, so to construct an equivalent volume of building, only one timber truckload is needed, as compared to five concrete mixers.
- No formwork needs to be brought to site (and removed) and no reinforcing steel is necessary. The steel in timber connections is negligible. We roughly redesigned the Treet building in reinforced concrete for comparison and discovered that it would have five times as much steel in it as the timber building.
- The savings multiplier on construction truck traffic can be as high as eight.³ These savings have implications for today's crowded metropolises: smaller foundations, or indeed no new ones, as the existing foundation for a demolished 10-story concrete building can hold a timber building three to four times as tall, with quieter construction and smaller cranes.
- Contemporary timber buildings are largely prefabricated for component assembly, meaning they are quick to erect accurately on site and tend

³ Personal communication February 2, 2017, with Ralph Austin of Seagate Structures, which has built a number of large-scale timber buildings in Vancouver.

to be naturally draft-proof and efficient, saving time and energy and improving overall quality.

CONCLUSION

As manufacturers, architects, engineers, and contractors learn to expand what they can do with large-scale engineered timber, a new architecture of 21st century timber will arise, drawing on a rich tradition of centuries of wooden construction while reaching higher to embrace the full potential of innovation and construction with natural materials.

ACKNOWLEDGMENT

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Applications of Insights from Biology and Mathematics to the Design of Material Structures

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For the past 12 years, Jenny Sabin Studio and the Sabin Lab (based at Cornell University's College of Architecture, Art, and Planning) have engaged in work at the forefront of a new direction for 21st century architectural research practice—one that investigates the intersections of architecture and science, and applies insights and theories from biology and computation to the design of material structures that are adaptive, interactive, and resilient.¹

This paper describes multidirectional and multidisciplinary investigations shaping the future trajectories of these material innovations and technologies for architecture. The work aims to advance materials research and digital fabrication across disciplines to effect pragmatic change in the economical, ecological, and cultural production of contemporary architecture.

BACKGROUND

Buildings account for nearly 40 percent of CO₂ emissions in the United States, with the remainder primarily from the industrial and transportation sectors.² Most contemporary sustainable approaches to reduce these emissions offer technological solutions through sanctioned rating systems such as LEED, a rating system launched by the US Green Building Council for both new construction and renovations of existing buildings. While these measures adequately address

Portions of this paper have been adapted from Sabin (2015).

¹ See Sabin and Jones (2017), a book on design research across disciplines through the lens of LabStudio, cofounded by Sabin, an architectural designer, and Jones, a molecular and cell biologist.

² See "Benefits of Green Building," <https://www.usgbc.org/articles/green-building-facts>.

resource consumption in buildings, they do not address the systemic ecology of the built environment over the long term.

What are ways to rethink conceptual approaches to sustainability in architecture? What design research models are available to address these questions and thus shape future innovations and applications in architecture?

RECENT PIONEERING RESEARCH

Forward-thinking research in building materials includes that of Matthias Kohler's group at ETH Zürich.³ In the group's work with industrial robots Kohler coined the term *digital materiality*, which enables real-time feedback with material constraints through robotic digital fabrication processes. His more recently coined term, *computational contextualism*, refers to how sensors operate to integrate environmental feedback in a robust design process for the built environment.

Ronald Rael and Virginia San Fratello of Emerging Objects (www.emergin-gobjects.com) claim that all materials start as powder or end in dust. Their 3D-printed work integrates bits of data and particles of light to transform this dust into nonstandard objects and products for future building blocks, challenging the status quo of rapid prototyping by designing the material itself.

Researchers such as Rob Shepherd and Maria Paz Gutierrez explore architecture applications in programmable matter and materials science. Shepherd's work on actuators, sensors, displays, and additive manufacturing protocols for soft wearable robots underscores the importance of iterative complex feedback between material and mechanical design in the development of these techniques and wearables.

In parallel, the work of the BIOMS group (Bio Input onto Material Systems), directed by Gutierrez at the University of California, Berkeley, takes direct inspiration from skins found in nature. Repurposing the textile as an important architectural element, the BIOMS multifunctional membrane features an integrative sensor and actuator system that not only is designed to answer to many functions through what Gutierrez calls the "synergistic optimization of heat, light, and humidity transfer" but also is a closed loop system.⁴ It therefore does not require energy input through mechanical actuators, sensors, and a mainframe.

And through select research projects at the Institute for Computational Design and Construction at the University of Stuttgart, Achim Menges argues that technological innovation across multiple disciplines suggests that design computation is no longer limited to the binary world of the digital, but is now interfacing with

³ As discussed at the Matter Design Computation Symposium: The Art of Building from Nano to Macro, Cornell AAP Preston Thomas Memorial Lecture Series, March 10–11, 2017.

⁴ As stated in an unpublished text, "Multifunctional Building Membrane: Self-Active Cells, Not Blocks," M.P. Gutierrez (BIOMS director/lead) with L.P. Lee (BioPoets director), the UC Berkeley BIOMS team (C. Irby, K. Sobolski, P. Hernandez, D. Campbell, P. Suen), and B. Kim (BioPoets team).

the complex realm of the physical. How is this innovative and forward-thinking work leveraged and funded?

FEDERAL SUPPORT FOR INNOVATION

In 2010 the National Science Foundation (NSF), under the Emerging Frontiers for Research Innovation (EFRI) Science in Energy and Environmental Design (SEED) umbrella, solicited proposals for transdisciplinary research teams to engage the problem of sustainability in terms of building energy use and its impacts on the built environment.

In an unprecedented occurrence, applicant teams were to include architects and, importantly, AIA licensure was not required. This opened up opportunities for both licensed architects and architectural designers engaged in practice and core academic design research to apply with collaborative teams across academia, practice, and industry. Successful project proposals required a radical departure from traditional research and design models in architecture and science, with a move toward hybrid, transdisciplinary concepts and new models for collaboration.

DRAWING ON NATURE TO INFORM ARCHITECTURE

In the Sabin Lab we ask: How might architecture address issues of ecology and sustainability so that buildings behave more like organisms in their built environments? We are interested in studying the human body for design models that give rise to new ways of thinking about adaptation, change, and performance in architecture.

Our expertise and interests focus on the study of natural and artificial ecology and design, especially in the realm of nonlinear biological systems and programmable materials that use minimum energy with maximum effect. Seminal points of reference for the work include matrix biology, materials science, bioengineering, and mathematics through the filter of crafts-based media such as textiles and ceramics, with advanced digital fabrication protocols including robotic fabrication and 3D printing.

Our collaborative work looks to nature, specifically cellular biology, for an analogous deep organicity of interrelated parts, material components, and building ecology. Generative design techniques emerge with direct references to natural systems such as cellular networking behavior and models of structural color found in the wings of the blue *Morpho* butterfly or the feathers of hummingbirds. We do not simply mimic these exquisite systems and structures, but instead focus on modeling and simulating behavior and processes through custom tools and methods that translate flexibility, adaptation, growth, and complexity into applied architectural prototypes and adaptive materials systems. Our work offers novel possibilities for redefining architecture in terms of ecological design and digital fabrication.

RESEARCH TO CREATE ADAPTIVE BUILDING SKINS

Since the start in fall 2010 of our NSF SEED project, Energy Minimization via Multi-Scalar Architectures: From Cell Contractility to Sensing Materials to Adaptive Building Skins, my colleague Andrew Lucia and I (as co-PI) have led a team of architects, graduate architecture students, and researchers in the investigation of biologically informed design. We use the visualization of complex datasets, digital fabrication, and the production of experimental material systems for prototype speculations of adaptive building skins, designated eSkin, at the macrobuilding scale (Figure 1). The full team, led by principal investigator Shu Yang, is engaged in rigorous scientific research at the core of ecological building materials and design.

The work described here is a subset of ongoing transdisciplinary research spanning cell biology, materials science, electrical and systems engineering, and architecture. The eSkin project applies these disciplines to the design and engineering of responsive materials and sensors (Sabin et al. 2014), operating on a multiyear research plan in three phases:

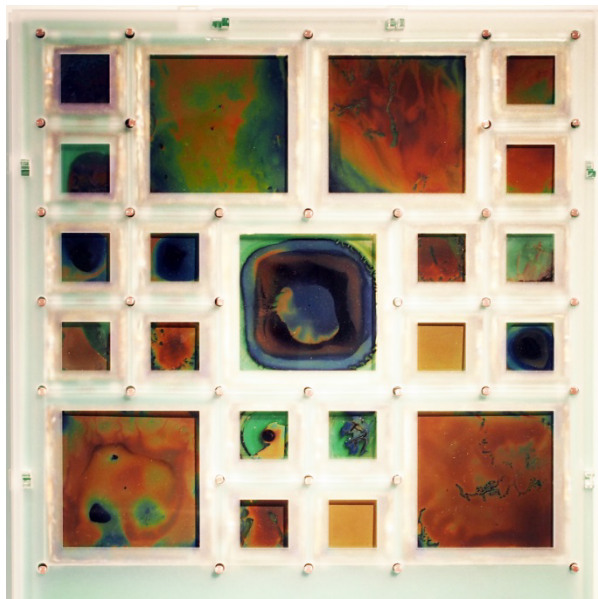


FIGURE 1 eSkin interactive prototype. Indium tin oxide (ITO)-treated glass cells with voltage-controlled nanoparticle solution, housed on a custom-built PCB substrate and controlled locally via ambient sensing nodes. © Sabin Design Lab, Cornell University; Shu Yang Group, University of Pennsylvania; Jan Van der Spiegel and Nader Engheta, University of Pennsylvania.

1. production of catalogues of visualization and simulation tools to discover new behaviors in geometry and matter;
2. exploration of the material and ecological potentials of these tools using experimental structures and material systems created through digital fabrication; and
3. generation of scientifically based, design-oriented applications in contemporary architecture practice for adaptive building skins and material assemblies.

The goal of the eSkin project is to explore materiality from nano to macro scales based on an understanding of nonlinear, dynamic human cell behaviors on geometrically defined substrates. To achieve this, human smooth muscle cells are plated on polymer substrates at a micro scale. Sensors and imagers are being designed and engineered to capture material and environmental changes based on manipulations by the cells, such as changes in color, transparency, polarity, and pattern (Lee et al. 2014; Li et al. 2012).

In recent eSkin prototypes, the team is exploring dynamic switching between opaque, transparent, and highly colorful components assembled in a single full-scale prototypical building façade unit (Figure 1). Specifically, the team is working with structural color, where physical structures in the form of particles interact with light to produce a particular color.

Silica colloidal nanoparticles dispersed in an organic medium (solvent) are sandwiched between two transparent conductively treated indium tin oxide (ITO) pieces of glass, housed in an assembly of three laser-cut plexiglass frames. The light reflected from the ordered structure (depending on the particle size, distance, and reflective index contrast between the silica nanoparticles and the organic medium) is of a specific wavelength.

When a voltage is applied to the particulate solution, the surface charge of the particles is altered, changing both the distance between the particles and the color. At each intersection between the color cells, a sensor based on shifts in light intensity levels actuates voltage change between the adjacent color cells. Thus when a finger, hand, or figure passes by a sensor, a detected shift in light intensity triggers a small voltage shift across the ITO component, reorganizing the distribution of particles in the solution, ultimately affecting the reflected appearance of color from the nanoparticle solution (Sabin et al. 2014; Sabin and Jones 2017).

The relevance of this particular prototype and the eSkin project to megatall buildings is primarily in building façade design. For example, in many glass-clad megatall buildings, a glazing treatment known as ceramic frit patterning is used to minimize solar heat gain and energy loss without obstructing the occupants' view. These treatments are effective but permanently static.

We envision and have demonstrated a strategy for dynamic and adaptive building skin treatments that behave similarly to a standard frit pattern, but change throughout the day and night and in response to extreme shifts in climate and local

environment. We propose to integrate eSkin in either existing building façade construction to enhance energy saving or in new megatall building façade design.

CONCLUSION

Through the eSkin project, insights into how cells can modify their immediate extracellular microenvironment are investigated and applied to the design and engineering of highly aesthetic passive materials, sensors, and imagers that will be integrated in responsive building skins. Such skins will enable buildings to adapt to external changes in temperature and internal solar heat gains to better regulate energy consumption and loss.

Our project addresses energy minimization at multiple scales of architecture by working toward challenging goals such as those put forward by the US DOE.⁵ We hope that our interdisciplinary work will not only redefine research and design through collaboration but also address social, environmental, and technological dimensions that ultimately enhance building design and the built environment.

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⁵ See <https://www.energy.gov/eere/buildings/commercial-buildings-integration-0>.

APPENDIXES

Contributors

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Mariana Bertoni is an assistant professor of electrical, computer, and energy engineering at Arizona State University. Her research focuses on defect engineering of materials for energy conversion and the underlying physical mechanisms that govern degradation, charge transport, and collection. She specializes in advanced correlative characterization using X-ray probes and multidimensional image analysis.

Rajan Bhattacharyya is a senior research engineer at HRL Laboratories, where his work focuses on how humans process information and interact with the environment with the goal of developing smarter autonomous systems, enhancing human performance, and creating novel processing systems. His research involves the development of large-scale, neuro-biologically and behaviorally validated neural and cognitive models, experimental work measuring neural activity (EEG, fMRI), and neuro-inspired algorithms for resilient autonomous systems, dexterous robots, and threat warning applications.

Bouchra Bouqata is a senior analytics product manager and senior scientist at GE Renewable Energy and GE Global Research. She leads programs in large-scale,

automated-intelligent Big Data advanced analytics; the industrial Internet; prognostics and health management; remote and online monitoring; and diagnostics.

Jordan Boyd-Graber is an associate professor of computer science at the University of Maryland, where he studies human-in-the-loop machine learning applied to natural language. His research focuses on making machine learning more useful, more interpretable, and able to learn and interact from humans. Applications include having machines that can sift through decades of documents; discover when individuals lie, reframe, or change the topic in a conversation; and compete against humans in games that are based in natural language.

Robert Braun is dean of engineering and applied science at the University of Colorado Boulder. His research focuses on planetary entry systems, hypersonics, landing systems design, and multidisciplinary optimization.

Emma Brunskill is an assistant professor of computer science at Carnegie Mellon University. Her work focuses on reinforcement learning, machine learning, sequential decisionmaking, and human-in-the-loop systems to create automated artificial intelligence agents that help people reach their goals.

Jose Carmena is a professor of electrical engineering and computer sciences at the University of California, Berkeley. His research program in neural engineering and systems neuroscience aims to understand the neural basis of sensorimotor learning and control and to build the science and engineering base that will allow the creation of reliable neuroprosthetic systems for the severely disabled.

Katherine Dykes is a senior engineer at the National Renewable Energy Laboratory, where she leads a group that seeks to integrate wind turbine, plant engineering, and cost models to enable full-system analysis and to apply a variety of advanced analysis methods to the study of wind plant system performance and cost.

Azita Emami is the Andrew and Peggy Cherng Professor of Electrical Engineering and Medical Engineering at the California Institute of Technology. Her research is in integrated circuits and systems, high-speed communication systems, silicon photonics, and wearable and implantable devices for neural recording, stimulation, sensing, and drug delivery.

Maria-Paz Gutierrez is an associate professor of architecture at the University of California, Berkeley, where she focuses on exploring the biophysical and cultural implications of functional natural materials and agricultural waste through multi-scale additive manufacturing. She founded BIOMS, an interdisciplinary research initiative that brings together architecture and science to integrate principles of design and biophysics from the nanoscale to the building scale.

Xue Han is an assistant professor of biomedical engineering at Boston University, where she leads a neuroengineering lab that focuses on developing radical new genetic, molecular, and optical neurotechnologies and application protocols for understanding disease mechanisms with the goal of designing next-generation neurotechnologies to treat neurological and psychiatric disorders.

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Konrad Kording is a Penn Integrates Knowledge Professor of Bioengineering at the University of Pennsylvania. His group uses data science to understand brain function, improve personalized medicine, collaborate with clinicians to diagnose diseases based on mobile phone data, and understand the careers of professors through the analysis of large datasets to test new models and better understand complex problems in bioengineering, neuroscience, and beyond.

Ellis Meng is a professor and department chair of biomedical engineering at the University of Southern California. Her research interests include microelectromechanical systems (MEMS), microsensors and actuators, micromachining and microfabrication, microfluidics, polymer MEMS, flexible devices, implantable devices, medical MEMS, wireless power and data telemetry for implants, and neural engineering.

Jeremy Munday is an associate professor of electrical and computer engineering at the University of Maryland, where his focus is on demonstrating new technologies based on novel physics and engineering. His research interests range from solar energy, optics, and plasmonics to quantum electrodynamic phenomena (such as the Casimir effect), solar sails, and novel energy conversion processes.

Stephen Nichols is associate director of the passenger experience segment at the Otis Elevator Company. His team works at the intersection of human experience and people-centered-design with vertical transportation technology and the building ecosystem. Products and concepts focus on digital interaction, human interface, and intuitive behavior with work spanning the disciplines of engineering, marketing, and information technology.

David Parekh is the corporate vice president of research and the director of the United Technologies Research Center (UTRC), providing global leadership for United Technologies Corporation's (UTC) central research organization. In this role, he develops technology strategies in anticipation of future trends and

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Michael Ramage is an architectural engineer and senior lecturer of architecture at the University of Cambridge. His research focuses on developing low-energy structural materials and systems in masonry, better housing in the developing world, and large-scale, high-rise buildings in engineered timber and bamboo through natural material innovation.

Jenny Sabin is the Arthur L. and Isabel B. Wiesenberger Associate Professor of Architecture at Cornell University, where she investigates the intersections of architecture and science and applies insights and theories from biology, emerging technologies, and mathematics to the design of material structures for application at the building scale. She is principal of Jenny Sabin Studio, an experimental architectural design studio based in Ithaca and director of the Sabin Lab at Cornell AAP (Architecture, Art, and Planning), a trans-disciplinary design research lab with specialization in computational design, data visualization, and digital fabrication.

Suchi Saria is an assistant professor of computer science at Johns Hopkins University. Her research spans machine learning, computational statistics, and their applications to domains where one has to draw inferences from observing a complex, real-world system evolve over time. Her focus is on Bayesian and probabilistic graphical modeling approaches to address challenges associated with modeling and prediction in real-world temporal systems.

Maryam Shanechi is an assistant professor and the Viterbi Early Career Chair of Electrical Engineering at the University of Southern California. She works at the interface of control, machine-learning, and neuroscience to develop neuro-technologies that improve the quality of care for millions of patients, including the development of brain-machine interfaces to restore movement in paralyzed patients, to automatically control unconsciousness under anesthesia, and to treat neuropsychiatric disorders through brain stimulation.

Marija Trcka is a technology sourcing specialist at United Technologies, where she disseminates cutting-edge research into industrial practice that facilitates fast and impactful energy retrofits in existing buildings, making a significant impact on worldwide carbon emissions. Her software tool seamlessly analyzes advanced building technologies and provides building managers with decision support metrics based on complex techno-economic analysis.

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