16

Cyber-Physical Real-Time Monitoring and Control: A Case Study of Bioenergy Production

Amin Mirkouei
University of Idaho

CONTENTS

16.1 Cyber-Physical Systems 309
16.1.1 Data Analytics and Energy Prediction 310
16.1.2 Cyber-Physical Real Monitoring and Control 312
16.2 Biomass-Based Energy Production 314
16.2.1 Existing Infrastructures of Bioenergy Production 316
16.2.2 Future Directions of Bioenergy Production 317
16.3 Conclusion 319
References 319

16.1 Cyber-Physical Systems

Our world is constantly changing and becoming progressively complex. The fourth industrial revolution, termed Industry 4.0, integrates mechanical inventions with cyber-enabled tools to control the processes and becomes increasingly capable of advancing the production processes and manufacturing systems (Monostori et al. 2016; Hansen and Mirkouei 2018). The motivation behind the Industry 4.0 lies in addressing energy consumption in the various sectors (e.g., industrial, commercial, and transportation), as well as inherent system failures and constraints of the existing methods in machine monitoring and data-driven process planning (Lee 2008). The most critical gaps in evaluating energy cyber-physical systems (CPSs) are due to the limited access to raw data, inadequate data extraction modules, and lack of standardized post-processing techniques to identify why an operation failed or productivity was lost (U.S. DOE 2013; Ford 2014; Roco 2016). Therefore, new advancements in automation, sensing, communication, and data collection can bridge the gaps and provide ground-breaking opportunities for future research and growth (Popovic, Kezunovic, and Krstajic 2015; Tariq et al. 2014; Clarens and Peters 2016; Han, Huang, and Ansari 2013; Zodrow et al. 2017). This section highlights the challenges of introducing CPS in manufacturing, as well as creates opportunities to provide a tangible source of data that other researchers may use to develop and validate smart-manufacturing technologies.

16.1.1 Data Analytics and Energy Prediction

Advanced data analytics collect data from various entities, analyze them based on the history of data, and make a decentralized decision after understanding the patterns and developing the prediction models. Based on the disparate nature of technologies and inherent complexity associated with cyber-physical infrastructure, it is not surprising that few works have been done to integrate CPS with existing manufacturing processes. Mainly, the intersection of energy production and CPS requires additional investigation to advance the developed computational methods, using machine learning (ML) and artificial intelligence (AI) techniques (Jha et al. 2017; Black et al. 2016). For example, support vector machine (SVM) for massive datasets with various data types can be applied as data-driven techniques to work side by side with humans (Shang, Huang, and You 2017; Connelly et al. 2016). Thus, conducting such evaluations requires an integrated performance measurement method, analytical models, metrics, and computational tools for decision support.

In evaluating production processes, many requirements enter into decision-making, such as different resources, throughput, and process conditions. Data analytics consist of two primary modules: (i) data extraction agent and (ii) knowledge extraction agent, presented in Figure 16.1. The data extraction agent retrieves raw data, such as process parameters, from target operations and performs post-processing to develop meaningful training databases without requiring any insights of the outputs. The collected data needs to be correctly contextualized and classified to identify those parameters that possibly affect the results, such as yields and product quality (Bhinge et al. 2017).

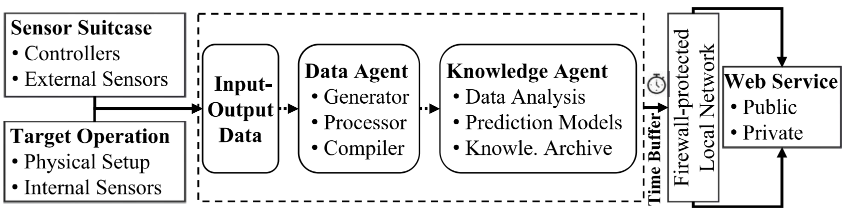

FIGURE 16.1
Data analytic components.

The raw data can be categorized into three groups—direct, indirect, and simulated data (Figure 16.2)—with the assistance of R, an open-source language and environment for statistical computing and graphics (Ihaka and Gentleman 1996). The knowledge extraction agent investigates the processed data and finds the patterns between inputs and outputs after each experiment, using the artificial neural network (ANN) and SVM. The learning algorithms analyze training datasets to predict the outputs from given inputs and develop hypothesis functions to predict future values (Mirkouei and Haapala 2014). For the production processes, several parameters can be continuously updated and affect real-time prediction models with new measurement data. The developed models can find optimal process parameters to improve energy systems.

A robust, accurate energy prediction model can be developed, utilizing generated training datasets from a set of numerous scenarios, data-driven algorithms, such as the SVM with the assistance of Python, an open-source, high-level programming language (Van Rossum 2007). The use of data-driven energy prediction algorithms is more accessible and feasible to implement than traditional practices. Previously, only empirical estimates from physics-based modeling, using physical laws, were available to account for predicting energy consumption (Bhinge et al. 2017). The response outputs achieved from real-time optical monitoring and in-line analysis can be used to develop correlations between energy consumption and various parameters of each operation (Mirkouei, Silwal, and Ramiscal 2017).

The concept of process monitoring and controlling can be extended to any parameters that affect energy consumption. Energy prediction modeling includes three major steps (Figure 16.3):

1. Understand energy consumption patterns across the energy systems.
2. Determine different operational strategies and the effects on energy consumption.
3. Derive the most effective process and energy-efficient strategy.

Rational improvements will be accomplished by effective process configurations and the trade-off between quality and yield, using computational prediction models along with real scenarios. Next section discusses coupling

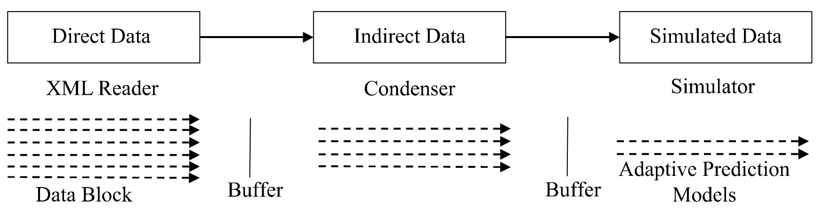

FIGURE 16.2
Data processing architecture.

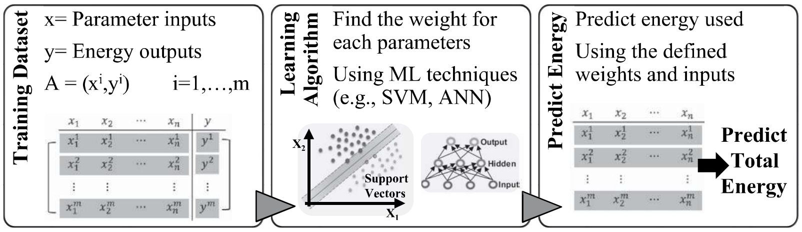

FIGURE 16.3
Energy prediction architecture.

mechanical inventions with cyber-enabled tools to (i) understand and visualize interactions between multi-scale processes and (ii) control the operations and become increasingly capable of advancing the production processes to an extent not done previously.

16.1.2 Cyber-Physical Real Monitoring and Control

In today's manufacturing economy, decision makers are looking for real-time data and information to evaluate the key parameters, gain insights, and make the best decision, while ensuring their resources are properly utilized and operated. Monitoring the reaction mechanisms and detailed kinetics, quality and yield relations, and prediction of energy consumption enables the operation process toward desired productivity and yield rates, using generated data. Real-time monitoring and analysis provide novel insights about the correlation of the necessary parameters and measurements (Hutchinson and Lee 2017).

During the past three decades, engineers have developed tools and methods for controlling the physical processes, and simultaneously, computer scientists have developed realistic methods for cyber systems (Liu et al. 2017). However, there is a considerable gap between the cyber and physical worlds, where information and real materials are transformed and exchanged. The CPS, as the fourth major industrial revolution after first three revolutions (i.e., mechanization, electrification, and automation), embraces physical components and advanced cyber-based technologies (e.g., high computation power, remote operations, interoperability standards, and communication protocols) to locally control systems and analytics (Monostori et al. 2016), as well as optimize operation performance metrics, such as accuracy, security, and reliability (Shang, Huang, and You 2017; Lee 2015). The CPS have significantly changed and exhibited more flexibility by utilizing the recent innovations. For instance, advanced CPS utilize low-cost, small-size transistors that offer more flexibility and availability of electromechanical sensors to improve performance measurement in semiconductor manufacturing industry (Gao et al. 2015; Teti et al. 2010; Lee, Bagheri, and Kao 2015). Figure 16.4 depicts simple CPS architecture, each part striving to maximize its own inherent objectives (Monostori et al. 2016).

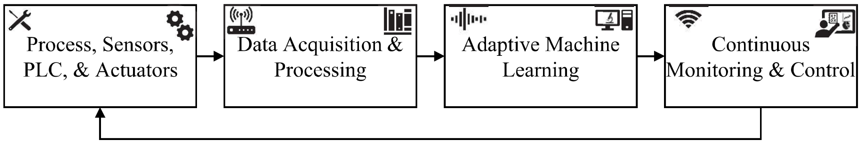

FIGURE 16.4
Cyber-Physical System (CPS) architecture.

The training datasets developed earlier will use standard training algorithms, such as back propagation to expand predictive models. The models will consist of inputs that are expected to be varied in real-world conditions, outputs that will include results from energy production and consumption, and product throughput. Real-time process evaluations with advanced statistical, data-driven techniques capture valid process-level parameters, as well as investigate interrelationships at multi-commodity levels.

Sensing, real-time extraction and visualization of data, fast transform analysis, and cloud-based backend computing facilitate production developments and assessments in many niche applications, as well as promote process efficiency, clean energy solutions, and cross-cutting benefits (Hussain et al. 2014; Sztipanovits et al. 2014; Lu et al. 2015; Lee et al. 2012). Decision makers in different levels (i.e., operational, tactical, and strategic) will benefit from integrated resources and operations, as well as adaptive methods. The implications of CPS will be in various realms affecting STEM (science, technology, engineering, and mathematics) disciplines, such as intelligent cyber-infrastructure, advanced networking technology, and smart manufacturing (Pal and Vaidyanathan 2015; Manic et al. 2016; Mirkouei, Bhinge, et al. 2016; Wang et al. 2017; Zodrow et al. 2017).

CPS address lack of data and practical methods, along with associated deficiencies across the systems through investigating several parameters (e.g., reaction temperatures and catalyst quantities) and variables (e.g., carbon efficiency, production yield, and product quality) under real-world conditions to extend dimensions of CPS and data-driven decision-making. Table 16.1 links research questions, hypotheses, and tasks to shed light on components and support a solution-oriented project.

The need for further investigation is increasing not only in the creation of the conceptual platform but in empirical work for specific applications that can advance monitoring of the operations and increase technical growth. Growing CPS initiatives promote sustainability and resilience of design and manufacturing through integrated cyber-physical data-enabled decision-making, which is still in nascent stages, but growing steadily with improvements in sensing technologies, interoperability standards, and data-influenced decision-making. Technology breakthroughs are essential in addressing production challenges, such as process efficiency and productivity.

TABLE 16.1

Overview of Research Questions Linked to Hypotheses and Research Tasks

Research Question	Hypothesis	Task
What are the baseline, status quo interactions between operation parameters and production process entities? What are the potential approaches and tools?	Existing intricacies are not well understood; elucidation of the effects of parameters is critical to maximizing effective management of pervasive data and extracted information to meeting market needs.	Real-time process monitoring, including optical monitoring, inline analysis, and scenario analysis.
How can the integrated technologies and cyber-physical infrastructure be configured to become increasingly capable of advancing the production processes?	Deficiency in transforming current production to the next generation is not being met; particular attention should be placed on intelligent decision approaches due to disparate nature of technologies and inherent complexity associated with the cyber-physical infrastructure.	Data-driven decision-making, including data analytics, adaptive prediction modeling, and multi-layer cyber-physical infrastructures.
How can the interactions of technologies and stakeholders' needs be modified to boost resilience and sustainability benefits across energy systems?	Approaches developed in prior work have not been integrated to date to transform existing technologies to next generation; understanding the complex compounds and commercial viability of technologies provide a base of knowledge to scale up production and enhance sustainability benefits.	Sustainability assessment, including techno-economic analysis, life cycle assessment, and social analysis.

16.2 Biomass-Based Energy Production

According to the U.S. Energy Information Administration (EIA), an average of 7.8 million barrels of crude oil per day were imported into the United States in 2015 that represents a value of about $400 million per day (U.S. EIA 2017). Renewable sources have been suggested as part of a comprehensive strategy to cut the use of fossil oil in half by 2030, in addition to phasing out the use of coal (Union of Concerned Scientists 2012). Figure 16.5 demonstrates that biomass-based energy currently comprises the most substantial portion (47%) of renewables in the United States (U.S. DOE Energy Information Administration 2016); thus, more efficient process-based solutions can result in promoting bioenergy production. Since biomass is a critical renewable resource that can address national priorities, such as support energy security, mitigate global warming, and create domestic jobs (Sadasivam 2015), special attention should be placed on biomass-based energy production.

Energy sources from biomass, as a meaningful environmental solution, are being developed as a substitute for conventional energy sources (Agblevor et al. 2016; Heavers et al. 2013). However, bioenergy sources are unreliable

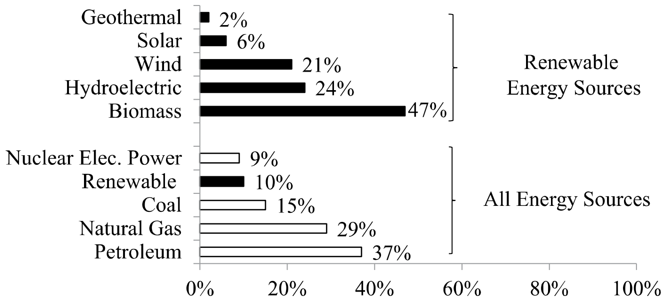

FIGURE 16.5
Total U.S. energy consumption percentage in 2016.

due to uncertain efficiency, compatibility, and profitability (Onarheim, Solantausta, and Lehto 2015). The U.S. Department of Energy (DOE) defines biomass as a renewable energy resource derived from natural materials (e.g., forest resources, energy crops, algae, agricultural residues, and animal manure) that is convertible into bioenergy (Heavers et al. 2013; Mirkouei and Kardel 2017). Biomass represents a promising renewable resource due to its abundance and low price; however, according to the U.S. EIA, over 45% of biomass feedstocks are underutilized due to immature production (conversion) technologies (U.S. EIA 2014). Earlier studies focused on evaluating biomass resources, in-depth production, and cost analyses to address upstream and downstream challenges, particularly fostering ethanol production (Cundiff, Dias, and Sherali 1997; Solantausta et al. 1992; Czernik 1994; Bridgwater and Bridge 1991). Later research focused primarily on "green" and sustainable bioenergy supply chain design and evaluated cellulosic biofuels and biodiesel (Mobini, Sowlati, and Sokhansanj 2011; You and Wang 2011; Mirkouei and Haapala 2015). Recent studies established foundational concepts in biofuels use and commercialization of new technologies by integrating various disciplines, such as algae and advanced feedstocks, strategic analysis, and cross-cutting sustainability (U.S. DOE 2016a,b; Mirkouei et al. 2016b,c; Shang, Huang, and You 2017).

Bioenergy 4.0 applies the concept of Industry 4.0 to address existing challenges (e.g., production yield, product quality, and commercialization) in the bioenergy industry and results in cost-competitive operations with low resource and processing energy required. Bioenergy 4.0 can address the limitations of current conversion process practices in bioenergy production. This section discusses the existing challenges in the traditional bioenergy production pathways with respect to the state of technology, as well as future directions for bioenergy production, coupling cyber-based data-driven decision-making with physical-based control and improvement of the operations. Finally, a cyber-physical real-time monitoring and control platform is proposed for bioenergy production from biomass feedstocks.

16.2.1 Existing Infrastructures of Bioenergy Production

Over the past 50 years, the need for more reliable, efficient, and productive production process arises in the industrial sector to address major challenges regarding high energy consumption (Helu, Hedberg, and Barnard Feeney 2017; Vogl, Weiss, and Helu 2016; Wolfe et al. 2016). Biomass-based energy conversion process challenges are associated with feedstock types, process configurations, and resources used to balance yield and product quality (Dutta et al. 2015). Carbon efficiency (the key to the commercial viability), deoxygenation (reduce oxygen content), and hydrogenation (increase hydrogen content) are three primary parameters in advancing the bioenergy conversion process (Dutta et al. 2015).

Most strategies for large-scale production of advanced biofuels focus on biochemical technology platforms, using terrestrial biomass (U.S. DOE 2016b). Lignocellulosic biomass, such as forest biomass, is an intricate matrix of polymers, e.g., cellulose, hemicellulose, starch, and lignin (U.S. DOE 2016a). Most biochemical conversion processes are, therefore, designed for a specific, limited range of feedstocks to maximize process efficiency. Biochemical technologies are not suitable for distributed production due to high capital cost and feedstock specificities as previously reported (Mirkouei et al. 2017a; Lin et al. 2016; Muth et al. 2014). In contrast, thermochemical technologies, such as pyrolysis and hydrothermal liquefaction, can be designed to be feedstock agnostic and are amenable to distributed processing, such as mobile or portable biorefinery (Mirkouei et al. 2016c; Brown, Rowe, and Wild 2013; Mirkouei et al. 2017b).

Pyrolysis is a thermochemical decomposition at 400°C–650°C temperature in the absence of oxygen, which can be grouped in two main categories: slow pyrolysis and fast pyrolysis; it differs in residence time, temperature, and heating rate (Bridgwater and Peacocke 2000; U.S. DOE 2013). Currently, fast pyrolysis is commonly used to produce bio-oil (a liquid similar to crude petroleum, with much higher oxygen and water content) and biochar (a valuable soil amendment similar to charcoal), using a wide range of algae and terrestrial feedstocks (Mirkouei et al. 2017a). The focus of this study is on fast pyrolysis because of high liquid (bio-oil) yield achieved with heating rate >1,000°C/s, resident time <2 s, and temperature 400°C–650°C. Prior studies reported that the catalytic fast pyrolysis (CFP) produces high-quality bio-oil, which needs less deoxygenation; however, the yields have been reduced (Agblevor et al. 2016; Onarheim, Solantausta, and Lehto 2015; Heavers et al. 2013; Bridgwater 2012; Black et al. 2016; Choi et al. 2016; Vasalos et al. 2016). Further details about reactors, processes, and intermediate or final products are given by Gamliel, Wilcox, and Valla (2017), Bridgwater (2012), and Badger et al. (2010).

Bio-oil varies due to complex feedstock composition and pyrolysis reactions (e.g., mixed of depolymerization, fragmentation, re-polymerization, and dehydration), which are not entirely understood. Bio-oil consists of several compounds (e.g., furan, hydroxyaldehydes, carboxylic acids, hydroxyketones, anhydrosugars, and phenolic) and has several issues (e.g., oxygen content, corrosion, viscosity, and storage characteristic) due to high oxygen-to-carbon (O/C) ratio and low hydrogen-to-carbon (H/C) ratio that indicate the quality of liquid product (Isahak et al. 2012; Evans et al. 2006). Bio-oil produced from biomass pyrolysis can potentially be used in fueling heaters, furnaces, and boilers, as well as industrial turbines, stationary dual-fuel diesel engines, and eventually upgrading to transport fuels and chemicals (Kersten and Garcia-Perez 2013; Mirkouei et al. 2017a).

CFP is touted to be one of the most promising pathways among existing, nascent thermochemical conversion technologies for cheap, local, nonfood, lignocellulosic feedstocks (Heavers et al. 2013; Pruski et al. 2016; Dickerson and Soria 2013). The presence of catalysts (e.g., Red mud, HZSM-5, $ZnCl_2$, Pt/Hbeta, and Al/MCM-41) can influence the desired modifications before the initial condensation (Agblevor et al. 2016; Pruski et al. 2016). Recent research reports transportation fuels (biofuels) and chemicals from biomass, using catalytic pyrolysis, benefit from the advantage of multifunctional catalysts, which affect various cracking and reforming reactions, and produce high-quality bio-oil by reducing viscosity, increasing H/C ratio of the final products (Agblevor et al. 2016). Current studies center on promoting catalyst effectiveness and longevity, which can address many challenges, such as liquid yield (Pruski et al. 2016). Based on the disparate nature of conversion processes and inherent complexity associated with CPS structure, it is not surprising that little work has been done to integrate CPS with existing bioenergy processes. Specifically, the intersection of CFP and CPS requires further investigation and will be covered in the section 16.2.2.

16.2.2 Future Directions of Bioenergy Production

This section centers on increasing the intelligence in biomass-based energy production process through real-time process evaluations and data-driven decision-making in order to advance bioenergy production and maximize energy consumption reduction. Additionally, a cyber-physical bioenergy production platform is proposed for CFP conversion technology, particularly bio-oil production from biomass feedstocks, such as invasive plant species. The proposed platform includes quantitative methods (e.g., ML and AI techniques) and qualitative methods (e.g., classification analysis and decision support systems), as well as a set of intelligent tools (e.g., wireless sensors and cloud-based services) for advanced data analytics to support Bioenergy 4.0 toward more efficient operations. The platform is able to examine and improve the process-level operations with CPS architecture by coupling data-driven decision-making with Internet of Things that can result in extensive sharing of information and feedback from each conversion process entity to decision makers.

Integrating cyber infrastructures and physical components of current bioenergy conversion technologies is a critical challenge to move toward Bioenergy 4.0. Bioenergy CPS decisions are influenced by dynamic business environments and suboptimal system-level solutions, which must be mitigated to accommodate industrial revolution in bioenergy production. Understanding the impact of cyber-based communication networks on physical systems aims to promote system reliability, process efficiency, and sustainability benefits (Jha et al. 2017; Baheti and Gill 2011; Graham, Baliga, and Kumar 2009; Gupta, Mukherjee, and Venkatasubramanian 2013).

Up to this time, most of the efforts have been built upon the physical-based models (Morgan et al. 2017; Woods et al. 2015), and there is an essential need in cyber-based models to construct a market-responsive conversion concept, which can produce high-value, cost-competitive products (Kezunovic et al. 2013; Gupta et al. 2011). Bioenergy production will soon be engulfed by the new advances of CPS and data-driven decision-making, which includes real-time data analytics, proactive analysis to detect problems, and predictive modeling to solve problems before happening, such as process failures or lost productivity. Thus, efficient data-driven decision-making will play a major role in the future growth of bioenergy industry (Ford 2014; Shekhar et al. 2017).

The systemic intricacies are not well understood; gaining understanding is critical not only to maximizing production efficiency and profitability but to increase the intelligence in bioenergy production through proactive analysis and predictive modeling to solve the problems before they impact the process. Advanced data-driven techniques help to capture valid process-level parameters and create data inventory, as well as improve profitability and net returns for all stakeholders by reducing the materials and processing energy used.

The cyber-physical real-time monitoring and control platform presented in Figure 16.6 is a test bed comprised of interrelated and external players who must synthesize a wealth of disparate information to make complex decisions, particularly in promoting the process efficiency and production yield. This platform relies on the latest developments in computer and data science, and manufacturing science and technology (e.g., information and

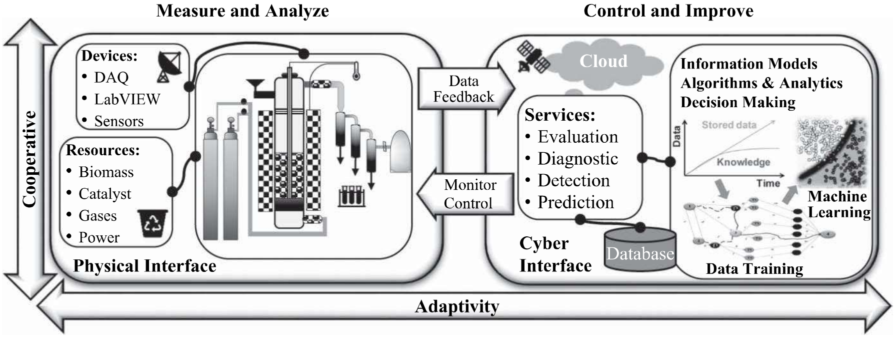

FIGURE 16.6
Cyber-physical real-time monitoring and control platform for Catalytic Fast Pyrolysis (CFP).

communication technologies), which leads to significant advantages concerning the amount of time, material, and processing energy required to generate the same amount of data by many orders of magnitude.

16.3 Conclusion

This chapter discusses the deficiency of existing bioenergy production pathways and the critical limitation of earlier studies, as well as the benefits of cyber-physical infrastructure in addressing the existing biomass-to-bioenergy supply chain challenges (e.g., market-responsive bioproducts). A scalable, multi-layer cyber-physical control and improvement platform is essential for detailed analyses (e.g., advanced data analytics and adaptive predictive analytics) and defining relationships among process parameters and variables, such as input rates of catalyst, catalyst type, and residence time. Dynamic, real-world scenarios generate a large dataset, including multiple process parameters and output variables, by creating several experiments out of each scenario. Several decision objectives, various alternatives, and pick a preferred alternative are applied, using historical and collected data to establish multiple decision criteria and to weight each criterion. Later, decision objectives are evaluated, using established criteria. These analyses provide required inputs (e.g., mass and energy calculations, size and equipment costs, cash flow, and rate of return) using various tools to evaluate productivity, capital expenditures, investment factors, and the bottlenecks of process configurations. The proposed platform herein is expected to improve the overall process performance, productivity, and flexibility through (i) diagnostic and prognostic assessment via data analytics and data-driven algorithms; (ii) resource management, quality control, and predictive maintenance; and (iii) investigating trade-offs among various factors, such as feedstock type versus yields, process conditions versus operating cost, or energy consumption versus size of pyrolysis systems. Ultimately, modernizing current bioenergy conversion pathways through adaptive cyber-physical controllers can enhance sustainability benefits across biomass-to-bioenergy supply chains at multi-spatiotemporal scales.

References

Agblevor, F.A., D.C. Elliott, D.M. Santosa, M.V. Olarte, S.D. Burton, M. Swita, S.H. Beis, K. Christian, and B. Sargent. 2016. Red mud catalytic pyrolysis of pinyon juniper and single-stage hydrotreatment of oils. *Energy & Fuels* 30, no. 10: 7947–7958.

Badger, P., S. Badger, M. Puettmann, P. Steele, and J. Cooper. 2010. Techno-economic analysis: Preliminary assessment of pyrolysis oil production costs and material energy balance associated with a transportable fast pyrolysis system. *BioResources* 6, no. 1: 34–47.

Baheti, R., and H. Gill. 2011. Cyber-physical systems. *The Impact of Control Technology* 12: 161–166.

Bhinge, R., J. Park, K.H. Law, D.A. Dornfeld, M. Helu, and S. Rachuri. 2017. Toward a generalized energy prediction model for machine tools. *Journal of Manufacturing Science and Engineering* 139, no. 4: 041013.

Black, B.A., W.E. Michener, K.J. Ramirez, M.J. Biddy, B.C. Knott, M.W. Jarvis, J. Olstad, O.D. Mante, D.C. Dayton, and G.T. Beckham. 2016. Aqueous stream characterization from biomass fast pyrolysis and catalytic fast pyrolysis. *ACS Sustainable Chemistry & Engineering* 4, no. 12: 6815–6827.

Bridgwater, A.V. 2012. Review of fast pyrolysis of biomass and product upgrading. *Biomass and Bioenergy* 38: 68–94.

Bridgwater, A.V., and S.A. Bridge. 1991. A review of biomass pyrolysis and pyrolysis technologies. In Bridgwater, A.V. and Grassi, G. (eds.) *Biomass Pyrolysis Liquids Upgrading and Utilization*, pp. 11–92. Springer, Dordrecht, Netherlands.

Bridgwater, A.V., and G.V.C. Peacocke. 2000. Fast pyrolysis processes for biomass. *Renewable and Sustainable Energy Reviews* 4, no. 1: 1–73.

Brown, D., A. Rowe, and P. Wild. 2013. A techno-economic analysis of using mobile distributed pyrolysis facilities to deliver a forest residue resource. *Bioresource Technology* 150: 367–376.

Choi, J.-S., Zacher, A. H., Wang, H., Olarte, M. V., Armstrong, B. L., Meyer III, H. M., … Schwartz, V. (2016). Molybdenum carbides, active and in situ regenerable catalysts in hydroprocessing of fast pyrolysis bio-oil. *Energy & Fuels* 30(6), 5016–5026.

Clarens, A.F., and C.A. Peters. 2016. Mitigating climate change at the carbon water nexus: A call to action for the environmental engineering community. *Environmental Engineering Science* 33, no. 10 (October 1): 719–724.

Connelly, E.B., J.H. Lambert, F. Asce, and F. Sra. 2016. Resilience Analytics in Systems Engineering with Application to Aviation Biofuels. In *2016 Annual IEEE Systems Conference (SysCon)*, Orlando, FL, 1–6.

Cundiff, J.S., N. Dias, and H.D. Sherali. 1997. A linear programming approach for designing a herbaceous biomass delivery system. *Bioresource Technology* 59, no. 1 (January): 47–55.

Czernik, S. 1994. Storage of biomass pyrolysis oils. In Proceedings of Specialist Workshop on Biomass Pyrolysis Oil Properties and Combustion, Estes Park, CO, 26–28.

Dickerson, T., and J. Soria. 2013. Catalytic fast pyrolysis: A review. *Energies* 6, no. 1: 514–538.

Dutta, A., A. Sahir, E. Tan, D. Humbird, L.J. Snowden-Swan, P. Meyer, J. Ross, D. Sexton, R. Yap, and J.L. Lukas. 2015. Process Design and Economics for the Conversion of Lignocellulosic Biomass to Hydrocarbon Fuels. Thermochemical Research Pathways with In Situ and Ex Situ Upgrading of Fast Pyrolysis Vapors. (National Renewable Energy Laboratory (NREL), Golden, CO.

Evans, R.J., S. Czernik, R. French, and J. Marda. 2006. Distributed Bio-Oil Reforming. DOE Hydrogen Program FY 2006 Annual Progress Report, Washington, DC.

Ford, S.M. 2014. *Advanced Cyber-Physical Systems for National Priorities (+$7.5 Million)*. National Institute of Standards and Technology, Gaithersburg, MD.

Gamliel, D.P., L. Wilcox, and J.A. Valla. 2017. The effects of catalyst properties on the conversion of biomass via catalytic fast hydropyrolysis. *Energy & Fuels* 31, no. 1: 679–687.

Gao, R., L. Wang, R. Teti, D. Dornfeld, S. Kumara, M. Mori, and M. Helu. 2015. Cloud-enabled prognosis for manufacturing. *CIRP Annals-Manufacturing Technology* 64, no. 2: 749–772.

Graham, S., G. Baliga, and P.R. Kumar. 2009. Abstractions, architecture, mechanisms, and a middleware for networked control. *IEEE Transactions on Automatic Control* 54, no. 7 (July): 1490–1503.

Gupta, S.K.S., T. Mukherjee, and K.K. Venkatasubramanian. 2013. *Body Area Networks: Safety, Security, and Sustainability*. Cambridge University Press, Cambridge.

Gupta, S.K., T. Mukherjee, G. Varsamopoulos, and A. Banerjee. 2011. Research directions in energy-sustainable cyber–physical systems. *Sustainable Computing: Informatics and Systems* 1, no. 1: 57–74.

Han, T., X. Huang, and N. Ansari. 2013. Energy agile packet scheduling to leverage green energy for next generation cellular networks. In *2013 IEEE International Conference on Communications (ICC)*, Budapest, Hungary, 3650–3654.

Hansen, S., and A. Mirkouei. 2018. Past infrastructures and future machine intelligence (MI) for biofuel production: A review and MI-based framework. In *ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference,* Vol. DETC2018–86150, Quebec City, Quebec, August 26–29.

Heavers, A.D., M.J. Watson, A. Steele, and J. Simpson. 2013. Platinum group metal catalysts for the development of new processes to biorenewables. *Platinum Metals Rev* 57, no. 4: 322.

Helu, M., T. Hedberg, and A. Barnard Feeney. 2017. Reference architecture to integrate heterogeneous manufacturing systems for the digital thread. *CIRP Journal of Manufacturing Science and Technology* 19 (May 22): 191–195.

Hussain, A., T. Faber, R. Braden, T. Benzel, T. Yardley, J. Jones, D.M. Nicol, et al. 2014. Enabling collaborative research for security and resiliency of energy cyber physical systems. In *Distributed Computing in Sensor Systems (DCOSS), 2014 IEEE International Conference On,* Marine Del Rey, CA. IEEE, 358–360.

Hutchinson, C.P., and Y.J. Lee. 2017. Evaluation of primary reaction pathways in thin-film pyrolysis of glucose using 13C labeling and real-time monitoring. *ACS Sustainable Chemistry & Engineering* 5, no. 10 (October 2): 8796–8803.

Ihaka, R., and R. Gentleman. 1996. R: A language for data analysis and graphics. *Journal of Computational and Graphical Statistics* 5, no. 3: 299–314.

Isahak, W.N.R.W., M.W. Hisham, M.A. Yarmo, and T.Y. Hin. 2012. A review on bio-oil production from biomass by using pyrolysis method. *Renewable and Sustainable Energy Reviews* 16, no. 8: 5910–5923.

Jha, S.K., J. Bilalovic, A. Jha, N. Patel, and H. Zhang. 2017. Renewable energy: Present research and future scope of artificial intelligence. *Renewable and Sustainable Energy Reviews* 77: 297–317.

Kersten, S., and M. Garcia-Perez. 2013. Recent developments in fast pyrolysis of ligno-cellulosic materials. *Current Opinion in Biotechnology* 24, no. 3: 414–420.

Kezunovic, M., A.M. Annaswamy, I. Dobson, S. Grijalva, D. Kirschen, J. Mitra, and L. Xie. 2013. Energy cyber-physical systems: Research challenges and opportunities. In *NSF Workshop on Energy Cyber Physical Systems,* Arlington, VA.

Lee, E.A. 2008. Cyber physical systems: Design challenges. In *Object Oriented Real-Time Distributed Computing (ISORC), 2008 11th IEEE International Symposium*, Orlando, FL. IEEE, 363–369.

Lee, E.A. 2015. The past, present and future of cyber-physical systems: A focus on models. *Sensors* 15, no. 3: 4837–4869.

Lee, J., B. Bagheri, and H.-A. Kao. 2015. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters* 3: 18–23.

Lee, I., O. Sokolsky, S. Chen, J. Hatcliff, E. Jee, B. Kim, A. King, et al. 2012. Challenges and research directions in medical cyber–physical systems. *Proceedings of the IEEE* 100, no. 1: 75–90.

Lin, T., L.F. Rodríguez, S. Davis, M. Khanna, Y. Shastri, T. Grift, S. Long, and K.C. Ting. 2016. Biomass feedstock preprocessing and long-distance transportation logistics. *GCB Bioenergy* 8, no. 1 (January 1): 160–170.

Liu, Y., Y. Peng, B. Wang, S. Yao, and Z. Liu. 2017. Review on cyber-physical systems. *IEEE/CAA Journal of Automatica Sinica* 4, no. 1: 27–40.

Lu, C., J. Cao, D. Corman, C. Julien, L. Sha, and F. Zambonelli. 2015. Cyber-physical systems and pervasive computing: Overlap or divergent? (PerCom Panel). In *Pervasive Computing and Communications (PerCom), 2015 IEEE International Conference*, Kyoto, Japan. IEEE, 187–188.

Manic, M., D. Wijayasekara, K. Amarasinghe, and J.J. Rodriguez-Andina. 2016. Building energy management systems: The age of intelligent and adaptive buildings. *IEEE Industrial Electronics Magazine* 10, no. 1: 25–39.

Mirkouei, A., R. Bhinge, C. McCoy, K.R. Haapala, and D.A. Dornfeld. 2016a. A pedagogical module framework to improve scaffolded active learning in manufacturing engineering education. *Procedia Manufacturing* 5: 1128–1142.

Mirkouei, A., and K. Haapala. 2014. Integration of machine learning and mathematical programming methods into the biomass feedstock supplier selection process. In *Proceedings of 24th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM)*, San Antonio, TX, May, 20–23.

Mirkouei, A., and K.R. Haapala. 2015. A network model to optimize upstream and midstream biomass-to-bioenergy supply chain costs. In *ASME 2015 International Manufacturing Science and Engineering Conference (MSEC), MSEC2015–9355*, Charlotte, NC, June 8–12.

Mirkouei, A., K.R. Haapala, J. Sessions, and G.S. Murthy. 2016b. Evolutionary optimization of bioenergy supply chain cost with uncertain forest biomass quality and availability. In *Proceedings of the IIE-ISERC*, Anaheim, CA, May 21–24.

Mirkouei, A., K.R. Haapala, J. Sessions, and G.S. Murthy. 2017a. A review and future directions in techno-economic modeling and optimization of upstream forest biomass to bio-oil supply chains. *Renewable and Sustainable Energy Reviews* 67: 15–35.

Mirkouei, A., K.R. Haapala, J. Sessions, and G.S. Murthy. 2017b. A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. *Applied Energy* 206 (November 15): 1088–1101.

Mirkouei, A., and K. Kardel. 2017. Enhance sustainability benefits through scaling-up bioenergy production from terrestrial and algae feedstocks. In *Proceedings of the 2017 ASME IDETC/CIE: 22nd Design for Manufacturing and the Life Cycle Conference*, Cleveland, OH, August 6–9.

Mirkouei, A., P. Mirzaie, K.R. Haapala, J. Sessions, and G.S. Murthy. 2016c. Reducing the cost and environmental impact of integrated fixed and mobile bio-oil refinery supply chains. *Journal of Cleaner Production* 113 (February 1): 495–507.

Mirkouei, A., B. Silwal, and L. Ramiscal. 2017. Enhancing Economic and Environmental Sustainability Benefits Across the Design and Manufacturing of Medical Devices: A Case Study of Ankle Foot Orthosis. In *Proceedings of the 2017 ASME IDETC/CIE: 22nd Design for Manufacturing and the Life Cycle Conference*, Cleveland, OH, August 6–9.

Mobini, M., T. Sowlati, and S. Sokhansanj. 2011. Forest biomass supply logistics for a power plant using the discrete-event simulation approach. *Applied Energy* 88, no. 4 (April): 1241–1250.

Monostori, L., B. Kádár, T. Bauernhansl, S. Kondoh, S. Kumara, G. Reinhart, O. Sauer, G. Schuh, W. Sihn, and K. Ueda. 2016. Cyber-physical systems in manufacturing. *CIRP Annals—Manufacturing Technology* 65, no. 2: 621–641.

Morgan, H.M., Q. Bu, J. Liang, Y. Liu, H. Mao, A. Shi, H. Lei, and R. Ruan. 2017. A review of catalytic microwave pyrolysis of lignocellulosic biomass for value-added fuel and chemicals. *Bioresource Technology* 230 (April 1): 112–121.

Muth, D.J., M.H. Langholtz, E.C.D. Tan, J.J. Jacobson, A. Schwab, M.M. Wu, A. Argo, et al. 2014. Investigation of thermochemical biorefinery sizing and environmental sustainability impacts for conventional supply system and distributed preprocessing supply system designs. *Biofuels, Bioproducts and Biorefining* 8, no. 4: 545–567.

Onarheim, K., Y. Solantausta, and J. Lehto. 2015. Process simulation development of fast pyrolysis of wood using aspen plus. *Energy & Fuels* 29, no. 1 (January 15): 205–217.

Pal, P., and P.P. Vaidyanathan. 2015. Pushing the limits of sparse support recovery using correlation information. *IEEE Transactions on Signal Processing* 63, no. 3: 711–726.

Popovic, T., M. Kezunovic, and B. Krstajic. 2015. Implementation requirements for automated fault data analytics in power systems. *International Transactions on Electrical Energy Systems* 25, no. 4 (April 1): 731–752.

Pruski, M., A.D. Sadow, I.I. Slowing, C.L. Marshall, P. Stair, J. Rodriguez, A. Harris, G.A. Somorjai, J. Biener, C. Matranga, C. Wang, J.A. Schaidle, G.T. Beckham, D.A. Ruddy, T. Deutsch, S.M. Alia, C. Narula, S. Overbury, T. Toops, R. Morris Bullock, C.H.F. Peden, Y. Wang, M.D. Allendorf, J. Nørskov, and T. Bligaard. 2016. Virtual special issue on catalysis at the US department of energy's national laboratories. *ACS Catalysis* 6(5): 3227–3235. doi:10.1021/acscatal.6b00823.

Roco, M.C. 2016. Principles and methods that facilitate convergence. In *Handbook of Science and Technology Convergence*, Bainbridge, W.S., and Roco, M.C. (Eds.) 17–41. Springer International Publishing, Switzerland.

Sadasivam, N. 2015. Economy Would Gain Two Million New Jobs in Low-Carbon Transition.

Shang, C., X. Huang, and F. You. 2017. Data-driven robust optimization based on kernel learning. *Computers & Chemical Engineering* 106: 464–479.

Shekhar, S., J. Colletti, F. Muñoz-Arriola, L. Ramaswamy, C. Krintz, L. Varshney, and D. Richardson. 2017. Intelligent Infrastructure for Smart Agriculture: An Integrated Food, Energy and Water System (May 4).

Solantausta, Y., D. Beckman, A.V. Bridgwater, J.P. Diebold, and D.C. Elliott. 1992. Assessment of liquefaction and pyrolysis systems. *Biomass and Bioenergy* 2, no. 1: 279–297.

Sztipanovits, J., T. Bapty, S. Neema, L. Howard, and E. Jackson. 2014. OpenMETA: A model-and component-based design tool chain for cyber-physical systems. In *From Programs to Systems. The Systems Perspective in Computing. Lecture Notes in Computer Science*, vol 8415, Bensalem, S., Lakhneck, Y., Legay, A. (Eds) 235–248. Springer, Berlin, Heidelberg.

Tariq, M.U., B.P. Swenson, A.P. Narasimhan, S. Grijalva, G.F. Riley, and M. Wolf. 2014. Cyber-physical co-simulation of smart grid applications using Ns-3. In *Proceedings of the 2014 Workshop on Ns-3*, 8, Atlanta, GA. ACM.

Teti, R., K. Jemielniak, G. O'Donnell, and D. Dornfeld. 2010. Advanced monitoring of machining operations. *CIRP Annals-Manufacturing Technology* 59, no. 2: 717–739.

Union of Concerned Scientists. 2012. The Promise of Biomass Clean Power and Fuel—If Handled Right.

U.S. DOE. 2013. In-Situ Catalytic Fast Pyrolysis Technology Pathway.

U.S. DOE. 2016a. 2016 Billion-Ton Report | Department of Energy.

U.S. DOE. 2016b. *Bioenergy Technologies Office—Multi-Year Program Plan*. DOE/EE-1385. U.S. Department of Energy, Bioenergy Technologies Office, Washington, DC.

U.S. DOE Energy Information Administration. 2016. Monthly Energy Review, August 2016.

U.S. EIA. 2014. *Annual Energy Outlook 2014 with Projections to 2040*, Energy Information Administration, United States Department of Energy, Washington, DC.

U.S. EIA. 2017. Total Crude Oil and Products Imports from All Countries. www.eia.gov/.

Van Rossum, G. 2007. Python programming language. In *USENIX Annual Technical Conference*, Santa Clara, CA, June 17–22.

Vasalos, I. A., Lappas, A. A., Kopalidou, E. P., & Kalogiannis, K. G. (2016). Biomass catalytic pyrolysis: Process design and economic analysis. *Wiley Interdisciplinary Reviews: Energy and Environment* 5(3): 370–383. doi:10.1002/wene.192.

Vogl, G.W., B.A. Weiss, and M. Helu. 2016. A review of diagnostic and prognostic capabilities and best practices for manufacturing. *Journal of Intelligent Manufacturing*: 1–17.

Wang, H., Y. Gao, S. Hu, S. Wang, R. Mancuso, M. Kim, P. Wu, L. Su, L. Sha, and T. Abdelzaher. 2017. On exploiting structured human interactions to enhance sensing accuracy in cyber-physical systems. *ACM Transactions on Cyber-Physical System*. 1, no. 3 (July): 16: 1–16:19.

Wolfe, M.L., K.C. Ting, N. Scott, A. Sharpley, J.W. Jones, and L. Verma. 2016. Engineering solutions for food-energy-water systems: It is more than engineering. *Journal of Environmental Studies and Sciences* 6, no. 1 (March 1): 172–182.

Woods, E.M., M. Qiao, P. Myren, R.D. Cortright, and J. Kania. 2015. Production of Chemicals and Fuels from Biomass. Google Patents.

You, F., and B. Wang. 2011. Life cycle optimization of biomass-to-liquid supply chains with distributed–centralized processing networks. *Industrial & Engineering Chemistry Research* 50, no. 17: 10102–10127.

Zodrow, K.R., Q. Li, R.M. Buono, W. Chen, G. Daigger, L. Duenas-Osorio, M. Elimelech, et al. 2017. Advanced materials, technologies, and complex systems analyses: Emerging opportunities to enhance urban water security. *Environmental Science & Technology* 51, no. 18 (July 25): 10274–10281.