Enhancing Operational Performance and Productivity Benefits by Implementing Smart Manufacturing Technologies in Breweries

Sachin Nimbalkar, Oak Ridge National Laboratory
Sarang Supekar, Argonne National Laboratory
Will Meadows, Mississippi State University
Thomas Wenning, Oak Ridge National Laboratory
Wei Guo, Oak Ridge National Laboratory
Joseph Cresko, U.S. Department of Energy

ABSTRACT

This paper uses case studies to demonstrate the potential of smart manufacturing (SM) and Internet of Things (IoT) technologies to enhance operational performance and productivity in industry. The analysis highlights benefits like cost reduction, production flexibility, shorter product times-to-market, energy/water efficiency and environmental impact reduction, and increased productivity. To illustrate the effectiveness of SM and IoT approaches, the authors sought out manufacturers currently implementing or seeking to implement SM & IoT technologies. The authors identified beer brewing (NAICS Code —312120) as a rapidly expanding industry whose members appear eager to implement SM technologies to optimize production lines by revealing bottlenecks and identifying performance-reducing nodes. The paper presents two case studies based on SM and IoT technologies in breweries. It briefly describes a systematic framework introduced elsewhere by the authors and uses it to assess the energy productivity and competitiveness of SM applications in breweries. The paper addresses questions concerning the information and communications technology infrastructure needed to build smart breweries, and how corporations simplify the installation and deployment of SM and IoT components.

Smart Manufacturing and Internet of Things

Smart manufacturing (SM) has attracted the attention of both manufacturers and government organizations worldwide in the past decade (Tao et al. 2018). SM encompasses advanced sensing, instrumentation, monitoring, controls, and process optimization technologies and practices that merge information and communication technologies (including data management and data analytics) with the manufacturing environment for real-time management of costs, resource use, and productivity across a manufacturing facility or supply chain. SM and the Internet of Things (IoT) can provide benefits such as cost reduction, production flexibility, shorter product times-to-market, improved energy/water/material efficiency, enhanced safety, and increased productivity. This paper focuses on energy productivity, defined as the ratio of the economic value of the output to the energy input.

As SM spans a wide variety of advanced technologies and improves exponentially over time, a single definition is inadequate to describe its full capabilities and advantages. Schmidt et al. (2015) simply define SM as the use of smart products/machines in digital and physical manufacturing processes. Chris Evans of Mitsubishi Electric (Mitsubishi Electric 2016) defines "smartness" in manufacturing as the use of transformed information gathered as data during manufacturing processes to make better decisions that enhance productivity and efficacy while reducing waste, energy consumption, and production lead time. Another definition, used by

Sudarsan Rachuri of the US Department of Energy Advanced Manufacturing Office, is the use of effective, secure human-system platforms to improve decision making and the overall productivity and efficiency of manufacturing across a networked enterprise.

Because SM technologies provide substantial benefits, government agencies and their associated research laboratories invest in their advancement and widespread adoption. For instance, the US National Institute of Standards and Technology, in a comprehensive report devoted to SM (Gallaher et al. 2016), forecasts that it will result in $57.4 billion in annual savings related to material, energy, and labor. (The report also notes that although there are numerous benefits to implementing SM, it often requires large capital investments.)

Lasi et al. (2014) provide a historical evolution of SM and summarize reasons why it is often referred to as the fourth industrial revolution (Industry 4.0). The method of handling and the significance of data collected during manufacturing processes indicate the maturity level of an industry. Tao et al. (2018) categorize data handling in four industrial ages: (1) handicraft age, (2) machine age, (3) information age, and (4) big data age. Throughout these ages, the importance and the amounts of data have increased significantly. In the early manufacturing ages, few data were gathered, and they were not processed to improve the overall system. The information usually did not get past the machine level and did not reach decision makers. However, in the current manufacturing era, the information obtained from one operation is not only directed to decision-makers but also virtually and physically shared with other machines/systems to automate decision-making. This level of automation has been made possible by the IoT, defined as a combination of cloud computing, big data, machine-to-machine communication, and real-time analysis of data from interconnected sensor devices (Chen et al. 2014).

Ang et al. (2017) summarize the enabling technologies of SM as intelligent robots, automated simulations, IoT, cloud computing, additive manufacturing, augmented reality, and big data analytics. More specifically, Tao et al. (2018) refer to robotic arms and cutting, polishing, slicing, cleaning, and viscose machines as examples of SM technologies. For the purposes of the discussion in this paper, any technology used to generate useful information or allow the transfer of the information in manufacturing environments with the goal of using it to improve performance and deliver economic and environmental benefits can be considered an SM technology.

SM and IoT Technologies in the Brewing Industry

To illustrate the effectiveness of SM/IoT programs in industry, we sought out manufacturers currently implementing these technologies or seeking to implement projects involving them. The authors identified *brewing* (NAICS–312120) as a rapidly expanding industry that seems eager to implement SM and IoT. In 2018, US beer distributors shipped about 190 million barrels of beer (Alcohol and Tobacco Tax and Trade Bureau 2019), and US vendors sells more than $118 billion in beer and malt-based beverages to US consumers each year (Beer Institute 2018). In 2018, 82% of all beer sold in the United States was domestically produced and 18% was imported from more than 100 different countries around the world (National Beer Wholesalers Association 2019). The authors interviewed representatives of several US breweries, including Deschutes Breweries, Full Sail Brewing, Hexagon Brewing Co., and Blackberry Farm Brewery, who are interested in adopting SM and IoT technologies. These companies seek to automate and optimize their production lines while revealing production bottlenecks and performance-reducing nodes.

Overview of the Brewing Process

Brewing has been called as much a science as an art form. Therefore, brewing is a great candidate enterprise to benefit from SM and IoT. Brewing is an inherently batch process. Beer-making starts with the raw materials: malted barley, unmalted grain, hops, water, and yeast (Galitsky et al. 2003). The grain is first cracked in a mill to allow the extraction of sugar and starch, known as "wort," from the grain. Then, it is transferred to a vessel known as a "mash tun" where water is added to form a thick soup, the "mash." The mash is heated to 160–180°F (71–82°C) to extract the maximum amount of wort without introducing other undesired flavors to the batch. It is then transferred to a vessel called a "lauter tun" where the wort is separated from the mash. In some cases, they use the modern mash filter systems to separate the wort from the mash (O'Rourke 2003). The solid, spent grains settle on a screen and the wort is drained, leaving the grains behind. Afterward, the filtered wort is transferred to another vessel where it is boiled for 1–1.5 hours to sterilize the wort, coagulate proteins, and separate other unwanted substances from the solution (Galitsky et al. 2003).

During the wort boiling process, hops are added according to a specific schedule to achieve the desired bitterness and aroma in the batch. After the boiling process is completed, the precipitated solids and added hops are removed. This is commonly done using a process called "whirlpooling," in which the centrifugal force of circulating the wort around the brew kettle causes heavier solids to gather at the bottom of the conical base. Following the whirlpooling process, the wort is rapidly cooled, causing additional unwanted proteins to coagulate and settle out of the solution. This process is necessary to create a habitable environment for yeast, which is added in the fermentation stage. Upon cooling, the filtered wort is transferred to a fermentation vessel where the yeast is added. Over the course of several days, the yeast consumes the sugars contained in the wort, producing alcohol, CO_2, and heat. The beer produced is then filtered one last time to remove the yeast, pasteurized (optional), and packaged (Endress+Hauser 2018).

SM and IoT Advances in Brewing

Brewers worldwide are taking on new systems and processes related to SM. The core aim of using these technologies in breweries is to connect the entire brewing process over a digital network—from conceptualization and design to production to customer delivery. Modern breweries should be able to obtain relevant information from this network in real time at every stage of the production and sales process. In other words, modern breweries use a computing and communication core to monitor, coordinate, control, and integrate physical and engineered systems. Interactions between humans and systems create dynamic networks that can, for example, be used to improve cost structures and resource utilization. The following are ways breweries could use SM/IoT solutions to transform their operations up and down the value chain to drive efficiency, productivity, and quality in their facilities (Morfas 2017):

- Create real-time visibility to enable data-driven decision-making
- Improve workforce productivity
- Monitor assets in operation and predictive maintenance
- Increase product safety
- Manage recipe variation
- Reduce the cost of quality testing

There are several points at which the brewing process can be improved with smart technologies and data analytics. For example, Hexagon Brewing faced the problem of a lack of precision or certainty in each batch size before the start of the packaging step. Hexagon staff said there was an 10% loss in the brewing process, due to unknown causes, that could possibly be reduced if they had more information. The uncertainty regarding the losses made it difficult to adjust production volumes to meet customer demand. This problem could be easily resolved by using flow meters positioned between several stages of the brewing process: meters placed between the mash tun and lauter tun, the lauter tun and the wort kettle, and the wort kettle and fermentation vessels could help track batch amounts during all production stages. By tracking the batch volumes between processes, the staff could identify the losses at each stage and better predict how much input was necessary to meet demand.

Another SM technology implementation example is temperature control and automation of the boiling process. The boiling schedule is crucial for obtaining a proper taste and aroma in the beer. Several microbreweries, including Hexagon, manually control the boiling and hops addition processes. Using SM and process automation, these manufacturers could ensure the desired taste and quality consistently (Rockwell Automation 2019a). Note, however, that simply using flow meters and pressure and temperature sensors in the brewing process to collect process data does not make the manufacturing process "smart." It is the proper use of large quantities of process data to improve or optimize production, often in real time and integrated with upstream and downstream processes, that makes the process and/or supply chain smart. For instance, Hexagon had around 40 sensors and actuators installed that displayed real-time process information and recorded or analyzed the underlying data; however, the setup could not resolve their production issues and would not qualify as a smart system.

New Belgium Brewery had installed a new bottling line in 2007 that ran 24 hours per day, 7 days a week, and thought another expensive new line was needed to accommodate its continued growth. However, the company instead leveraged IoT and data to improve operational efficiency (Automation World 2018). New Belgium staff compared the bottling line capacity of 150,000 cases/week with its theoretical line capacity of 294,000 cases per week, based on a production capacity of 700 bottles/min under 24/7 operation. They found there was considerable room for improvement in the line capacity (Automation World 2018). As a possible solution, the company chose a manufacturing execution system (MES) to deliver the information it needed. The MES recognized and recorded line operation factors, exposed factors that took down the line and their causes, and provided a graphical user interface that allowed operators to add input for the downtime context. Collectively, the changes made based on application of the MES data helped the company understand the real capacity of its bottling line. The staff were able to measure intentional and unintentional downtimes and thus understand and work on specific issues impacting the line operation and production capacity (Automation World 2018).

In addition to the methods discussed in these examples, various other SM and IoT interventions could be used in the brewing industry. Figure 1 and Table 1 contain examples of smart technologies, IoT, and data analytics in breweries, along with their potential impacts on energy and productivity and other benefits.

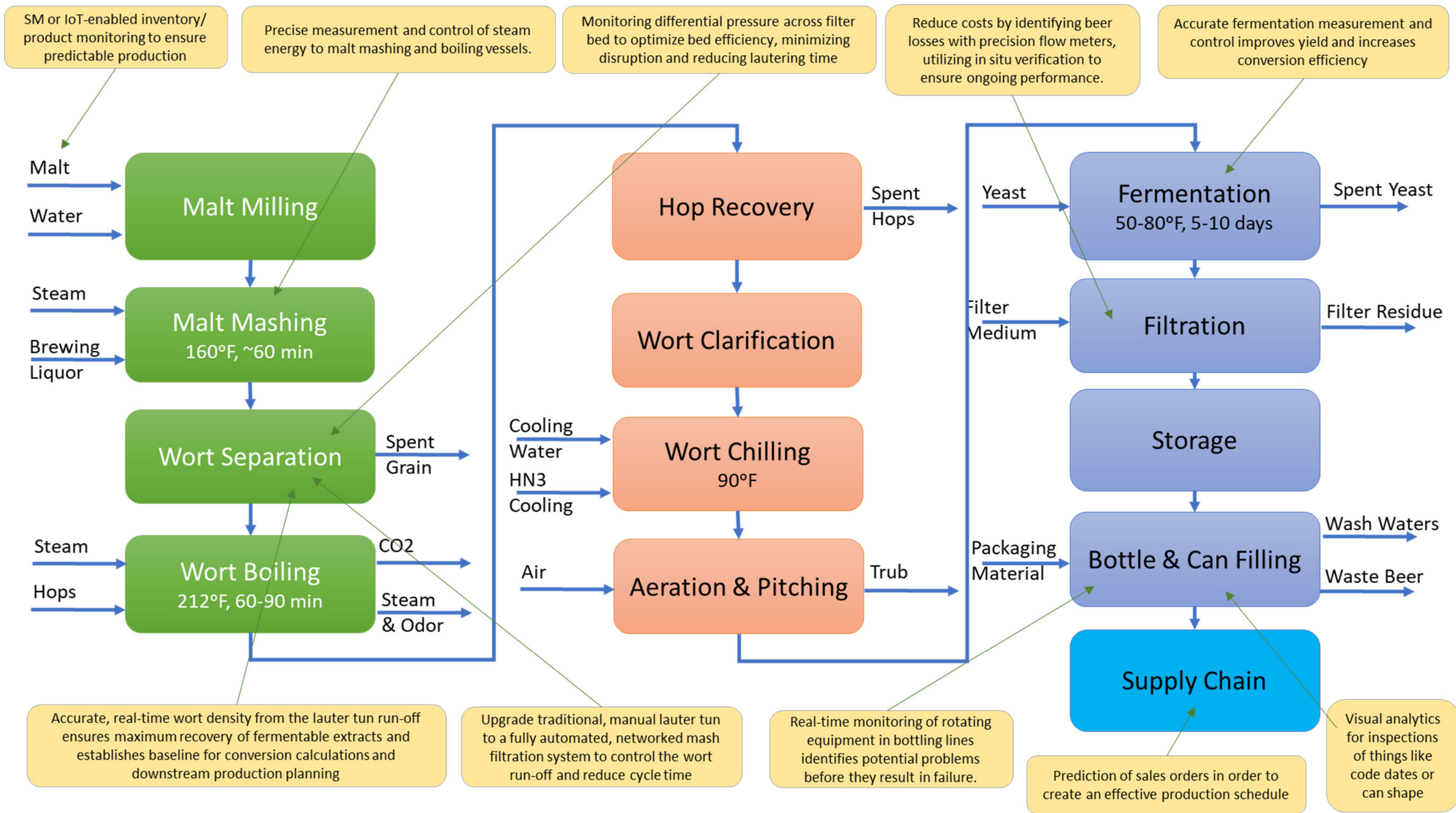

Figure 1 | Overview of the brewing process and its material flows. SM and IoT strategies with potential applications in the brewing process are shown in yellow boxes.

Table 1 | SM and IoT strategies for breweries and their potential impacts and benefits.

No.	SM/IoT Strategy	Process Step	Impact/Benefits
1	SM or IoT-enabled inventory/product monitoring to ensure predictable production	Raw material inventory and preparation	Increased revenue and reduced waste (Angeles 2016)
2	Precise measurement and control of steam energy to malt mashing and boiling vessels	Malt mashing and boiling	Reduced energy use
3	Accurate, real-time wort density from the lauter tun runoff to ensure maximum recovery of fermentable extracts and establish a baseline for conversion calculations and downstream production planning	Wort separation	Increased throughput
4	Monitoring of differential pressure across the filter bed to optimize bed efficiency, minimizing disruption and reducing lautering time	Wort separation	Increased throughput and reduced cycle time
5	Upgrade of the traditional, manual lauter tun to a fully automated, networked mash filtration system	Wort separation	Increased brewing capacity, reduced cycle time, and decreased water use (Rockwell Automation, 2019a)
6	Accurate fermentation measurement and control to improve yield and increase conversion efficiency	Fermentation	Increased throughput.
7	Cost reduction by identifying beer losses with precision flow meters, using in situ verification to ensure ongoing performance	Filtration	Waste reduction and increased revenue
8	Real-time monitoring of rotating equipment in bottling lines to identify potential problems before they result in failure	Bottle and can filling	Reduced downtime and increased throughput
9	Visual analytics for inspection of parameters like code dates or can shape	Bottle and can filling	Reduced lead-time and increased revenue
10	Prediction of sales orders to create an effective production schedule	Supply chain	Reduced inventory and reduced waste

Quantifying Energy and Productivity Benefits of SM and IoT Technologies

To facilitate decision-making regarding whether SM interventions create significant value and improve energy productivity in breweries, we used an analysis framework proposed by Supekar et al. (2019). The framework proposes that key performance indicators (KPIs) should define the specifications of the cyber-physical system (CPS) and define the analysis system boundaries (Figure 2a). The cyber-physical system (CPS) is a physically aware engineered system that has tightly collaborating “cyber” components (those that can compute, communicate, and control) with the physical world (e.g. boiler system, chiller system, process equipment, etc.), providing a wide range of control and optimization strategies. (Yao, 2017) The cost-effectiveness of various SM and IoT interventions from an energy standpoint to improve a given set of KPIs is then measured using a metric called "cost of conserved energy" (CCE).

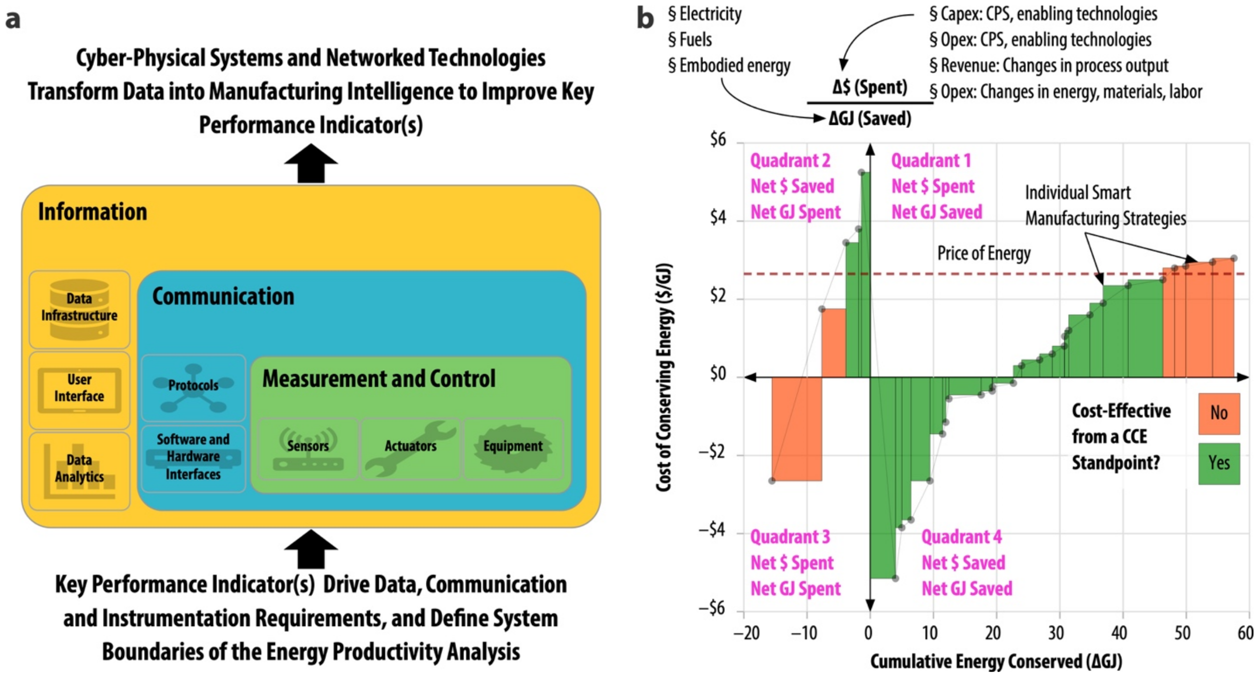

Figure 2 | **a.** Key performance indicators (KPIs) determine the target metrics to be measured and define the system boundaries within which to quantify the energy productivity impacts of a smart intervention. Specifications of cyber-physical systems within the SM system are thus also driven by chosen KPIs. **b.** The cost-effectiveness of various SM interventions or strategies aimed at improving specified KPIs is measured using the cost of conserved energy (CCE) metric. Figure obtained from Supekar et al. (2019).

CCE, which is given by Eq. (1), is defined as the ratio of the incremental costs resulting from an intervention to the incremental energy saved as a result of the intervention. In developing the CCE metric for use in the analysis of SM systems, Supekar et al. (2019) build on prior work by Worrell et al. (2003) to include cases where energy may be spent instead of being saved, but the additional energy creates enough value to justify its use. When several SM or IoT interventions can be implemented, the CCE for each can be estimated and the relative merits of each one assessed using a chart such as the one depicted using dummy data in in Figure 2b. If an intervention leads to net energy savings relative to the case without the intervention—i.e., the denominator in Eq. (1) is positive—the intervention is considered viable from an energy standpoint if the CCE is less than the price of primary energy. When an intervention leads to a net energy expenditure—the denominator in Eq. (1) is negative— the intervention is considered viable if the CCE is greater than the price of primary energy, because the value created by a unit of energy is greater than its cost. Note that the energy use term in Eq. (1)includes the energy use of the CPSs within the factory and any upstream/downstream energy uses resulting from the CPS, such as large data servers. Additional details of the CCE metric and the systematic analysis framework can be found in Supekar et al. (2019).

$$CCE = \frac{\Delta\$_{spent}/year}{\Delta GJ_{saved}/year} = \frac{(\Delta C + \Delta OM - \Delta R)/year}{\Delta E/year} \quad (1)$$

ΔC - the capital cost which is annualized over the expected lifetime of the SM or IoT project using an appropriate discount rate. The capital cost includes the cost of sensors, information and communications (ICT) components, computers, data storage and processing cost, labor, etc.

ΔOM - the operation and maintenance (O&M) costs which include variable costs and fixed costs of the SM/IoT system and enabling technologies when applicable.

ΔR - any increases in revenue. For example – increase in revenue due to increased productivity or reduction in cycle time, or product recovery, etc.

ΔE - the energy term which represents the direct energy use within the system boundaries, the life cycle energy use associated with the direct energy use including indirect upstream energy use, or the direct, indirect, and embodied energy use in energy and material flows within the system. As with costs, the direct and indirect energy use terms include energy associated with SM/IoT and enabling technologies.

In the following case studies, the KPI-based SM framework and the CCE metric are used to quantify the energy and productivity benefits of SM and IoT technologies in breweries. Because of space constraints, we focus on only two of the several SM and IoT interventions described in Figure 1 and Table 1. Note that the CCE would likely be just one of many cost-effectiveness metrics that a manufacturer would use, along with other metrics such as payback, to decide the viability of an SM intervention.

Case Study 1: Data-Driven Fermentation Measurement and Control for Yield Improvement and Higher Feedstock Conversion Efficiency

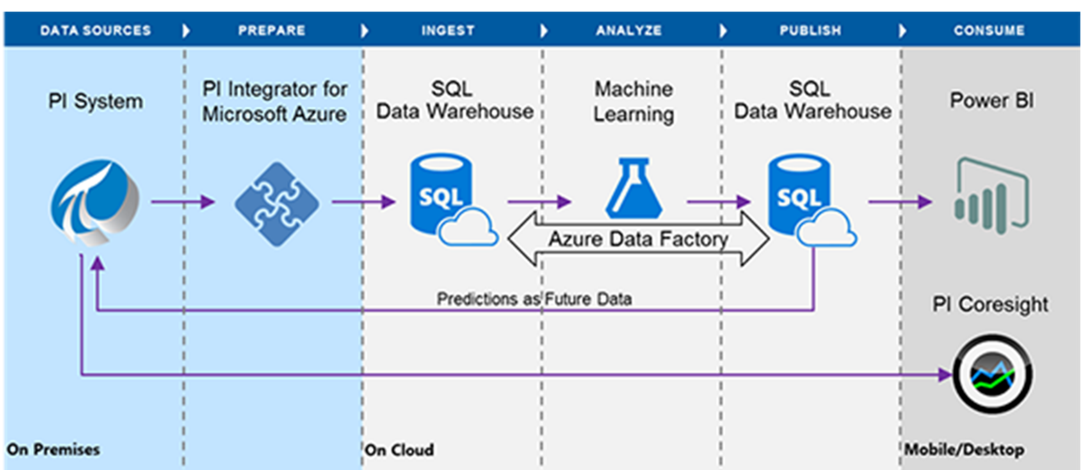

Figure 3 | IoT architecture used by Deschutes Brewing to collect and analyze process data and develop process control to increase throughput and curtail waste. Image obtained from OSIsoft (2017).

A detailed version of this case study is provided in Supekar et al. (2019) (the other work published by the primary authors). Herein we provide a brief overview and summary key findings of the energy productivity analysis of this particular SM intervention. Deschutes Brewery in Bend, OR, produces different types of beers to maintain customer interest. The fermentation process for each of these beers is different, and the different processes are known to create major process bottlenecks. At Deschutes, regular manual readings of the apparent degree of fermentation using a hydrometer, and other process parameters such as temperature, are gathered and analyzed to determine when to move a particular beer from one phase to the next. In 2016, Deschutes joined the OSIsoft and Microsoft Red Carpet Incubation Program (RCIP) to use OSIsoft's PI System data and machine learning to predict when a beer transitions from one stage to another. The goal was to minimize the need for manual readings (see Figure 3). The SM strategy was to conduct predictive analytics on the apparent degree of fermentation data collected, using hydrometers to monitor and appropriately control the process parameters in real-time. This approach was expected to reduce the fermentation time and reduce taste/aroma quality issues emerging from improper fermentation. The analytics would predict the next step in fermentation accurately without the need to monitor specific gravity in real time. Since the goal of this SM intervention was to reduce cycle time and waste, the KPI of choice for the energy productivity analysis was the hectoliters (HL) of beer production per year (throughput).

Using process estimates provided by Deschutes staff, we analyzed whether the proposed SM intervention would be cost-effective from an energy standpoint. We examined direct energy use in the form of natural gas for process heating and steam generation, and electricity use in the production process (upstream impacts of natural gas and electricity production were excluded). This particular SM intervention was expected to increase the process throughput by 4% (roughly 1200 HL/year). Using production energy use values for craft brewing from Kubule et al. (2016) and incremental capital and operating costs of the SM intervention from Alexander (2018), and assuming the average price of craft beer at about $450/HL (The Nielsen Company 2017) and the price of primary energy (natural gas) as $3.3/MMBtu, we calculated the CCE for this SM intervention. The CCE is shown in Figure 4 as a function of the variable operation and maintenance cost and the CPS energy use, both of which were unknown parameters in the analysis. Since the SM intervention increases product output, which leads to an increase in the annual energy use (energy use per unit remains unchanged), the SM intervention would be cost-effective if the CCE is greater than the price of energy – that is if the value created by a unit of additional energy used is more than the cost of that unit of energy (Quadrant 2 in Figure 2b). Under a reasonable assumption of $350/HL for the variable O&M cost, Figure 4 shows that if the CPS energy use is less than about 5.7 GWh/year (intersection of the energy price plane with the CCE surface at VOM = $350/HL), the CCE for this SM intervention would be favorable and the SM intervention would be cost-effective from an energy standpoint. This CPS energy budget of 5.7 GWh is three orders of magnitude higher than the roughly 5 MWh/year energy use associated with cloud computing and the content service calculated based on power consumption rates described by Baliga et al. (2011). Additional details supporting these calculations can be found in Supekar et al. (2019).

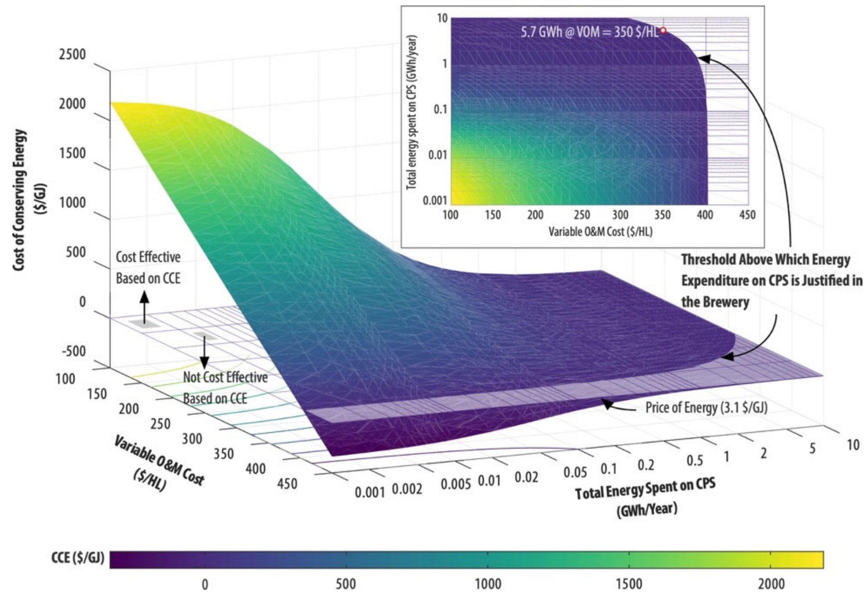

Figure 4 | Cost of conserved energy (CCE) for SM intervention involving the use of sensor data and cloud-based analytics to reduce fermentation time as a function of the variables of operations and maintenance cost and CPS energy use, both of which had uncertain or unavailable data. The color of the surface represents CCE (lighter is better). Figure adapted from Supekar et al. (2019).

Case Study 2: Replacement of Traditional Manual Lauter Tun by a Fully Automated and Networked Mash Filtration System

Full Sail Brewery, like the vast majority of craft brewers, uses a lauter tun, a manual brewing vessel, to filter the slushy mash of water and crushed grain that contains the sugars fermented to produce beer. The lauter tun system requires continuous, manual data testing and reporting. In addition to the beer, the spent grain—a byproduct of the process—is sold by the company as livestock feed. The spent grain was analyzed and found to have an 82% moisture content; thus, valuable mash liquid was being wasted with the byproduct. In addition, the cost of transporting this water-laden spent grain was high. Full Sail was losing money on the byproduct transaction, essentially paying farmers to take the spent grain (Rockwell Automation 2019b).

To address this issue, Full Sail considered upgrading its traditional manual lautering process to a fully automated and networked mash filtration system. The goal was to upgrade its processes to improve product quality and increase filtration efficiency, capacity, and throughput, which in our analysis framework would serve as the KPIs of interest. The company also wanted to minimize operator dependency by implementing SM technology. Note that, in some cases, an automated mash filtration system could decrease flexibility with regard to the batch size, recipe type, and specific gravity range for the wort. Although mash filtering companies are working on overcoming this limitation of automated systems, their flexibility remains limited compared with a typical lauter tun. This may be a concern, especially for craft breweries (O'Rourke 2003).

The new mash filtration system that Full Sail implemented leverages the PlantPAx Process Automation System from Rockwell Automation, which incorporated role-appropriate, real-time KPIs (i.e., manufacturing intelligence) that Full Sail can use to improve operations. The system allows Full Sail to configure sequences directly into an Allen-Bradley ControlLogix controller through FactoryTalk View Human Machine Interface software. To gain insight into the new system, the IoT contractor implemented a manufacturing intelligence strategy based on the

FactoryTalk protocol and software. Through an Ethernet/IP network, FactoryTalk Historian software identifies and gathers data tags directly from the control system for real-time, granular production data. With more than 60 steps in the filtration process, the mash filter produces copious amounts of data. The mash filter and software can pull up to 250 data tags.

Within the limits of the mash filter system, multiple parameters can be optimized using the smart system. The following are some parameters that can be optimized before the filtration steps:

- Water-to-grist ratio: This is the volume of strike water divided by the mass of the grist. A weaker malt solution might be faster to filter and might yield better efficiency, but it could also decrease the mash thickness, which would impact the quality and flavor of the beer.
- Mash profile: Changing the mash profile could break down more sugars and proteins and increase the rate or the extract. However, since malt is hammer-milled for a mash filter, the mash profile should have less effect. A lower mashing time with a mash filter is one of its benefits.
- Number of cycles: Mash filters go through cycles of squeezing out liquid, adding water and then squeezing out liquid again. Usually there are just two cycles, although with smart automation one could add more cycles to get more wort from the grain.
- Temperature of the water: Using different water temperatures for this squeezing process could help adjust the extraction yield.
- The pressure/speed of the squeeze-outs: Faster or slower squeezing and higher or lower maximum pressure would also affect process speed and efficiency of the filtering process (removing more moisture from the spent grains). Note that a faster process speed would be less efficient.
- The process of graining out and cleaning: One of the biggest disadvantages of using a traditional mash filter is the necessity to go through each individual plate at the end of a brew, knock all the spent grain from it, and spray it down to clean it. Smart automation in this process could save considerable time, effort, and water and potentially chemicals.

The FactoryTalk VantagePoint software is used to aggregate the data into predetermined dashboards. The dashboards provide role-appropriate, real-time key performance indicators to improve operation. Real-time data are now retrievable over variable time spans, helping to achieve optimum functionality of the system and catch discrepancies or problems that may have occurred during a batch. With the PlantPAx system, brewing capacity is estimated to increase by 25% and the time for each brew cycle can be cut by almost half. Full Sail's annual brewing capacity in 2010 was estimated to be about 228,130 HL/year. Since the contribution of the "smart" component of this automation is unknown and uncertain, we parameterized the throughput improvement from the data-driven part of this intervention in our CCE calculations. We varied throughput (productivity) improvement value from 0% to 5% and quantified its impact on the CCE using equation 1. We used a similar approach to show sensitivity of CCE values to energy used by the cyber-physical system (CPS).

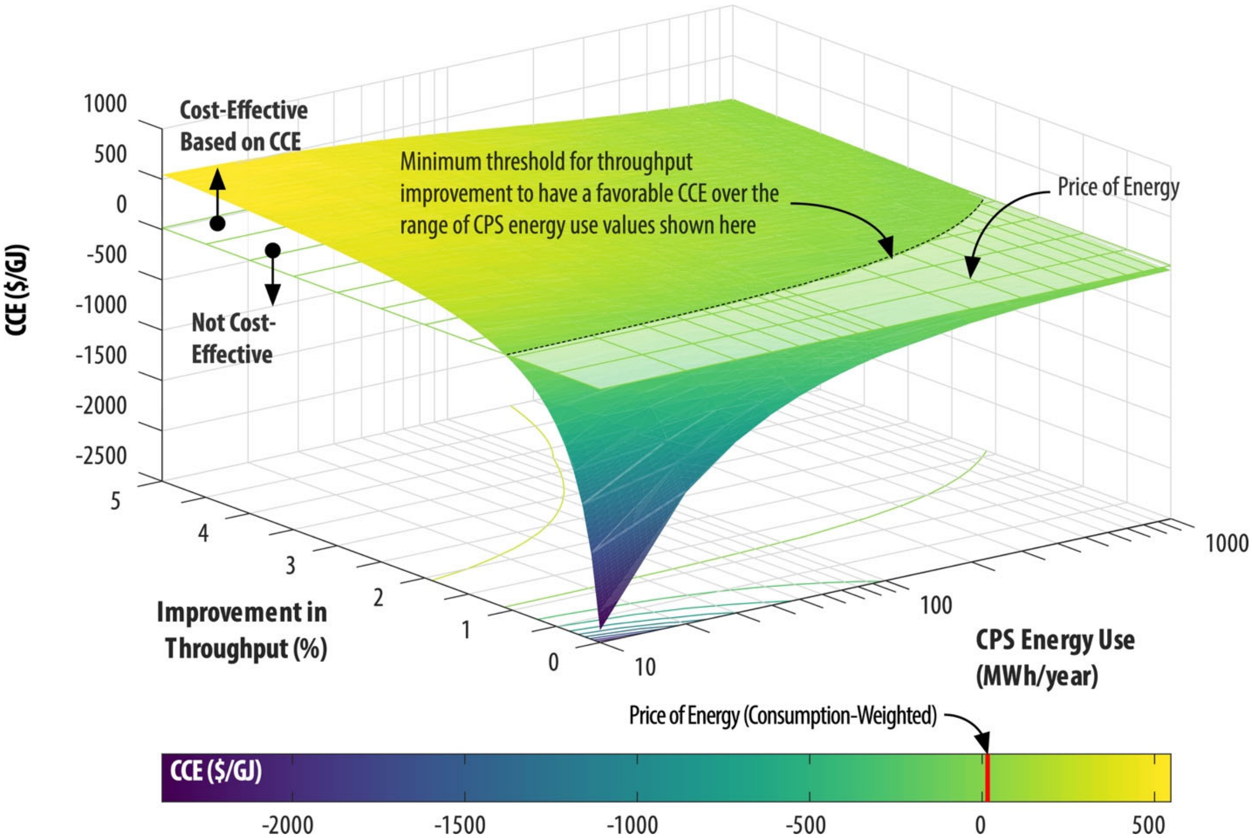

Figure 5 | Cost of conserving energy (CCE) for the SM intervention involving data-driven mash filtration system monitoring and predictive control, expressed as a function of the expected throughput improvement that could be attributed to the SM intervention and the energy use of the cyberphysical system.

Full Sail reported an investment of approximately $1 million in the new system and expected a full ROI in 3 years. The savings were anticipated to come from reduced raw material and spent grain hauling costs alone. The use of remote support was expected to save about $60,000 by reducing the need for site visits. Manual dispensing and automated dispensing were both reduced from two-person to one-person operations, resulting in an estimated annual cost savings of $150,000. Furthermore, the software would eliminate more than 50,000 manual transactions that were previously entered in the enterprise resource planning system. Based on reported capital investment and expected cost savings, increased throughput, and the aforementioned assumptions, along with beer production energy use values from Kubule et al. (2016), we calculated the CCE for this SM intervention as a function of the improvement in throughput and CPS energy use. Note that a nuanced and detailed process modeling effort would be needed to fully characterize the changes in the costs, energy use, and productivity of the new smart process. However, data availability for such modeling remains a challenge, and we develop rough estimates here for the CCE based on a set of assumptions.

Since this SM intervention would increase throughput (no expected reductions in energy intensity per unit of beer produced), together with the energy use associated with CPS, this smart manufacturing intervention would increase the overall energy use in the production facility (Quadrants 2 and 3 in Figure 2b). Thus, from a CCE standpoint, this SM intervention would be cost-effective if the CCE is greater than the price of a new unit of energy – that is, if the value created by this additional energy expenditure is greater than the cost of that energy expenditure.

Figure 5 plots the CCE surface as a function of the unknown parameters – CPS energy use and the expected improvement in throughput from the SM intervention – and is interpreted using the same approach as Figure 4. Thus, a favorable CCE can be realized over the range of CPS energy use values shown in Figure 5 as long as the throughput improvement that can be ascribed to the SM intervention (as opposed to other aspects of the automated system that are not necessarily data-driven and smart) is greater than values indicated by the dotted line that marks the intersection of the CCE surface with the energy price plane. For a CPS energy use value of 10 MWh/year (double the amount based on Baliga et al. (2011) used in the previous case study) and using the same variable O&M production cost of 350 $/HL used in the previous case study, this minimum throughput improvement threshold attributable to the IoT part of the process improvement is about 1.1%. This amounts to roughly 2,280 HL/year of the 57,030 HL/year of increase in beer production anticipated by Full Sail after the switch to the automated and networked mash filtration system. Although data were unavailable for the fraction of throughput improvements attributable to the automation and networked parts of this new system, we project that the networked part of the SM intervention is quite likely to meet the 1.1%-point CCE favorability threshold.

Conclusions

SM and IoT technologies can improve energy efficiency and productivity and reduce energy costs in process-supporting energy systems. Many breweries are already taking advantage of the increasing capabilities of technologies such as energy management systems, advanced metering and sub-metering solutions, data analytics, and internet-connected sensors. The authors analyzed two case studies from the brewery industry to demonstrate the potential of SM and IoT technologies to enhance operational performance and improve the energy productivity in this industry. The analysis found that despite the nontrivial amount of energy the smart CPS and its associated upstream/downstream processes are expected to use, the SM interventions analyzed in the case studies are likely to result in a net improvement in energy productivity, provided the resulting throughput improvements are about 5% for a craft brewery of a typical size. The paper also summarizes the systematic framework for assessing energy productivity and competitiveness of SM/IoT applications in breweries.

Acknowledgments

The submitted manuscript was prepared by Oak Ridge National Laboratory, which is managed by UT-Battelle LLC for the US Department of Energy under contract DE-AC05-00OR22725.The authors gratefully acknowledge the support of the US Department of Energy's Advanced Manufacturing Office. The authors also thank William Morrow (Lawrence Berkeley National Laboratory), Alberta Carpenter (National Renewable Energy Laboratory), Eric Masanet (Northwestern University), Diane Graziano (Argonne National Laboratory), and Matthew Riddle (Argonne National Laboratory) who reviewed a draft of this paper and provided valuable comments. The authors also thank Deschutes Breweries, Full Sail Brewing, Hexagon Brewing Co., and Blackberry Farm Brewery for their input to the brewery case studies.

References

Alcohol and Tobacco Tax and Trade Bureau. 2019. "Number of Brewers by Production Size - CY 2018." Cincinnati, OH: U.S. Department of Treasury. https://www.ttb.gov/statistics/production_size/2018_brew_prod_size_ttb_gov.pdf.

Alexander, T. 2018. "Research Case Study on Deschutes Brewery - Predictive Analytics (Personal Communication)."

Ang, J.H., Goh, C., Saldivar, A.A.F., and Li, Y. 2017. "Energy-Efficient Through-Life Smart Design, Manufacturing and Operation of Ships in an Industry 4.0 Environment." *Energies* 10 (5) (May): 610. doi:10/gbjqzj.

Angeles, R. 2016. "Internet of Things (IOT)-Enabled Product Monitoring: Insights from Socio-Technical Systems Theory, Affordances Theory, and Structurational Model of Technology." In *Proceedings of the 2016 Annual Conference of the Decision Sciences Institute*. Austin, TX. 35.

Automation World. 2018. "New Belgium Brewery Leverages Data to Improve Operational Efficiency | Automation World," September 11. https://www.automationworld.com/article/new-belgium-brewery-leverages-data-improve-operational-efficiency.

Baliga, J., Ayre, R.W.A., Hinton, K., and Tucker, R.S. 2011. "Green Cloud Computing: Balancing Energy in Processing, Storage, and Transport." *Proceedings of the IEEE* 99 (1) (January): 149–67. doi:10.1109/JPROC.2010.2060451.

Beer Institute. 2018. "Annual Report 2017-2018." *Beer Institute*. http://www.beerinstitute.org/wp-content/uploads/2018/12/Beer-Institute-Annual-Report-2018.pdf.

Chen, M., Wan, J., Gonzalez, S., Liao, X., and Leung, V.C.M. 2014. "A Survey of Recent Developments in Home M2M Networks." *IEEE Communications Surveys Tutorials* 16 (1): 98–114. doi:10/gf227t.

Endress+Hauser. 2018. "Instrumentation in the Brewing Industry – Automating the Art of Brewing." Greenwood, IN. https://portal.endress.com/wa001/dla/5000581/3669/000/00/SO00008B24EN_US%20Brewing.pdf.

Galitsky, C., Martin, N., Worrell, E., and Lehman, B. 2003. "Energy Efficiency Improvement and Cost Saving Opportunities for Breweries." LBNL-50934. Berkeley, CA. https://www.osti.gov/servlets/purl/819468-BCeVpF/native/.

Gallaher, M.P., Oliver, Z.T., Rieth, K.T., and O'Connor, A.C. 2016. "Economic Analysis of Technology Infrastructure Needs for Advanced Manufacturing: Smart Manufacturing." NIST GCR 16-007. National Institute of Standards and Technology. doi:10.6028/NIST.GCR.16-007. https://nvlpubs.nist.gov/nistpubs/gcr/2016/NIST.GCR.16-007.pdf.

Kubule, A., Zogla, L., Ikaunieks, J., and Rosa, M. 2016. "Highlights on Energy Efficiency Improvements: A Case of a Small Brewery." *Journal of Cleaner Production* 138 (December): 275–86. doi:10/f9b55t.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., and Hoffmann, M. 2014. "Industry 4.0." *Bus Inf Syst Eng* 6 (4) (August 1): 239–42. doi:10/gfx8dd.

Mitsubishi Electric. 2016. "Factory Automation." *EMEA - Factory Automation*. https://eu3a.mitsubishielectric.com/sps2016.

Morfas, D. 2017. “4 IIoT Use Cases That Show Real Business Impacts for Manufacturing.” *PLEX Manufacturing Blog*. https://www.plex.com/blogs/industrial-internet-of-things-use-cases-for-manufacturing.html.

National Beer Wholesalers Association. 2019. “Industry Fast Facts.” *NBWA: America’s Beer Distributors*. https://www.nbwa.org/resources/industry-fast-facts.

O’Rourke, T. 2003. “Mash Separation Systems.” *The BREWER International*, February. http://www.ibdlearningzone.org.uk/article/show/pdf/502/.

OSIsoft. 2017. “Deschutes: Better Data for Better Beer.” San Leandro, CA. https://www.osisoft.com/uploadedFiles/Dynamic_Content/Media_Resources/Case_Studies/cb-Deschutes-lt-en.pdf.

Rockwell Automation. 2019a. “Brewery Automation – Brewery Production and Packaging Automation and Control Systems.” *RockwellAutomation.Com*. https://www.rockwellautomation.com/en_NA/industries/food-beverage/overview.page?pagetitle=Brewery-Production-and-Packaging-Automation-and-Control-Systems&docid=595530911dade69fa72f08c263ea1f89.

———. 2019b. “Full Sail Brewing Taps Manufacturing Intelligence to Enhance Process.” *RockwellAutomation.Com*. https://www.rockwellautomation.com/global/news/case-studies/detail.page?pagetitle=Craft-Brewing-Manufacturing-Intelligence-Process-%7C-Case-Study&content_type=casestudy&docid=1c133ca1ae6b0948db847491bf4999c1.

Schmidt, R., Möhring, M., Härting, R.-C., Reichstein, C., Neumaier, P., and Jozinović, P. 2015. “Industry 4.0 - Potentials for Creating Smart Products: Empirical Research Results.” In Abramowicz, W. ed. *Business Information Systems*. Lecture Notes in Business Information Processing. Springer International Publishing. 16–27.

Supekar, S.D., Graziano, D.J., Riddle, M.E., Nimbalkar, S.U., Das, S., Shehabi, A., and Cresko, J. 2019. “A Framework for Quantifying Energy and Productivity Benefits of Smart Manufacturing Technologies.” *Procedia CIRP* 80 (2019): 699–704. doi:10.1016/j.procir.2019.01.095.

Tao, F., Qi, Q., Liu, A., and Kusiak, A. 2018. “Data-Driven Smart Manufacturing.” *Journal of Manufacturing Systems* 48 (July): 157–69. doi:10.1016/j.jmsy.2018.01.006.

The Nielsen Company. 2017. “The State of the U.S. Beer Market.” New York, NY. https://www.nielsen.com/us/en/insights/reports/2017/the-state-of-the-us-beer-market.html.

Worrell, E., Laitner, J.A., Ruth, M., and Finman, H. 2003. “Productivity Benefits of Industrial Energy Efficiency Measures.” *Energy* 28 (11) (September): 1081–98. doi:10.1016/S0360-5442(03)00091-4.

Yao, Xifan, et al. "Smart manufacturing based on cyber-physical systems and beyond." *Journal of Intelligent Manufacturing* (2017): 1-13.