PROCESS SYSTEMS OPPORTUNITIES IN POWER GENERATION, STORAGE AND DISTRIBUTION

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Abstract

This paper presents an overview of the current process systems opportunities in power generation, storage and distribution. It puts in perspective how process systems engineering (PSE) has contributed to the area and explores the current technical problems that PSE can contribute to. Fuel cells, solar cells, wind turbines, flow batteries and rechargeable batteries as well as their interactions with the smart grid are considered. PSE has contributed and will contribute to the design and optimal operation of the individual power generators and power grids, through mathematical modeling, control and optimization.

Keywords

Power generation, power storage, power distribution, fuel cells, wind turbines, rechargeable batteries, smart grids

1. Introduction

The increasing cost of generating power from fossil fuels and increasing public awareness about the negative environmental impacts of using fossil fuels for power generation have made power generation from renewable sources, such as solar radiation, tides, wind, geothermal and biomass, more attractive. Furthermore, the cost of power generation from renewable sources is decreasing quickly. For example, excluding tax credits and other incentives the price paid for wind based electricity in 2006 was 5 to 8.5 cents/kWh (Wiser and Bolinger, 2008). However, units generating power from renewable sources are located at disperse locations, and renewable sources are intermittent. The disperse nature and intermittency of renewable sources place major burdens on the transmission grid and have generated significant interest in "Smart Grid" technology. This paper deals with the smart grid challenge as well as the current challenges in power generation (from renewable sources) and storage. It also highlights some potential opportunities for the PSE community.

1.1. The Power Grid and Renewable Source Impacts

A large-scale electric power system is a rather complicated interconnection of many systems. At one end there are generation units that convert available energy sources (either fossil, nuclear or renewable) into electric energy. This generated power must then be transported to load centers via high voltage AC transmission lines. The received energy is then delivered to individual customers via a distribution network. During operation, one of the highest priorities is the availability of high quality power to all consumers at all times. Such reliability is difficult to achieve, because of two challenges:

(a) Consumer demand is continually changing and cannot be controlled by the power provider, and
(b) With current storage technology, electric energy is virtually impossible to store in large quantities.

Consequently, a provider must track consumer demand to send dispatch commands to the generators. Furthermore, these dispatch commands must be aware of the power flow limitations imposed by the transmission and distribution network. Failure to implement a suitable dispatch policy will result in poor power quality (erratic voltage levels) and in the worst case in power outages. The poor power quality is addressed by the implementation of a power management strategy, which considers small fluctuations in power demand over small time-scales (seconds to minutes). Fundamental to power management is the concept of spinning reserves. The idea is that a generator can quickly increase or decrease power output within a reasonably sized window of power conditions. Power outage can be prevented by energy management, which considers large demand changes over large time-scales. Fundamental to energy management is the fairly predictable nature of consumer demand. The basic idea is that generation facilities can schedule to provide power within specific time periods.

While an overall power balance, between consumers and generators, is necessary for reliable operation, constraints imposed by the transmission network must also be considered. One constraint is the capacity limit of each transmission line. Additionally, there are capacity constraints imposed by adjacent lines. The effect of the second constraint is made more complicated (but in some ways more manageable) by the AC nature of most transmission systems. As such, determination of the actual flow of power through a network requires solution of a set of nonlinear balance equations. These load flow relations are an integral part of the power and energy management policies described previously. On the scale of years and decades, consumer demand for power will increase. As such, power producers must identify expansion plans with regard to generation units as well as the transmission network.

As renewable sources, such as wind and solar, are introduced to the system, additional burden will be placed on the transmission network. Renewable sources tend to be located dispersedly at great distances from load centers and will likely require significant expansion of the transmission hardware (Lindenberg et al., 2008). In addition, renewable sources are inherently intermittent and non-dispatchable. With capacity factors of 30 to 40%, power output from renewable sources will vary from zero to three times the average. Short term variations in power output (due to wind gusts and small clouds) are also expected. It is further noted that the power production gaps created by renewable sources must be made up by the remaining dispatchable sources. Another important change in the power industry is the introduction of deregulation. Under this scenario, power generators and transmission lines are owned and operated by entities independent of the electric utility, and must compete to provide services at the lowest cost. This additional level of operational complexity has created significant activity, as researchers scramble to develop new analysis and design methods to address the market based system.

1.2. Organization of this Paper

We begin with an overview grid level power system modeling, control and optimization, and illustrate parallels between these techniques and those of the PSE community. Section 3 highlights challenges in the power generation, with a focus on renewable sources, their impact on the grid as well as the dispatchability of other generators. Section 4 discusses storage technologies and their role in grid operation and planning.

There are several other approaches to renewable-based grid challenges that are not discussed in this paper, but are noteworthy. One is the use of High Voltage DC (HVDC) transmission lines, which are more efficient than AC lines and provide a mechanism for direct manipulation of power flow (Flourentzou et al., 2009). Another approach is the use of Flexible AC Transmission Systems (FACTS), for greater utilization of existing grid hardware by allowing power flow control in AC lines (Ford et al., 2008). A third approach is conversion to fuel-based energy carriers. The most common is hydrogen, although many other liquid fuels are being considered (Ogden, 1999; Momirlan and Veziroglu, 2002; Simbeck and Chang, 2002; Steinfeld, 2005). Many are also looking to encourage consumer participation through the introduction of real time pricing. The largest impact of real time pricing is expected to be with regard to industrial and large commercial consumers. In large commercial buildings, the energy used by Heating Ventilation and Air Conditioning (HVAC) is close to 30% of total usage (Conti et al., 2009). Utilization of active and passive Thermal Energy Storage (TES), to shift HVAC power consumption to periods of low demand will reduce the burden placed on energy management policies (Henze et al., 2004; Oldewurtel et al., 2010; Qin et al., 2012; Mendoza-Serrano and Chmielewski, 2012). In the industrial sector, opportunities to improve energy and power management are both possible. For example, the cost of energy intensive operations can be reduced by moving to a period of low power demand (Roos and Lane, 1998; Kirschen, 2003; Karwan and Keblis, 2007; Baumrucker and Biegler, 2010). In the case of power management, the idea is to relinquish control of power usage to the power provider, who will use this manipulation to improve power quality of the network. As one would expect, premium revenue can be received for fairly small modifications in plant operation (Parvania and Fotuhi-Firuzabad, 2010; Nguyen et al., 2011).

2. Power System Operation and Planning

Fundamental to power system operation and planning is the notion of load flow analysis (Grainger and Stevenson, 1994). The objective of load flow analysis is to determine appropriate manipulations to balance power between generators and consumers. At the core of these calculations is a nodal analysis. If the phaser voltage at each bus k is denoted as $E_k=U_ke^{j\theta k}$ and collected into a vector $E = [E_1\ E_2\ ...\ E_N]^T$, then the current in (or out) of bus k from an external source (or sink) is $I_k=Y_kE$, where Y_k is the admittance vector containing characteristics of the transmission lines attached to bus k. The phaser power in (or out) of bus k is $S_k=E_k\ I_k^*$ (where I_k^* is the complex conjugate of I_k), which is usually expressed in complex rather than phaser form: $S_k=P_k +jQ_k$. The real component, P_k, represents active (or actual) power into bus k, while the imaginary, Q_k, represents reactive power. Though reactive power is not directly related to mechanical power put into the generator, it is central to regulating system voltage. In sum, each bus of the network is governed by the following complex valued relation: $P_k +jQ_k = E_k\ Y_k^*E^*$. In addition, each bus contains four variables, P_k, Q_k, U_k and θ_k (other combinations of four variables could have been selected, but these four are the usual convention). Thus, to completely specify the network, two of these variables should be specified for each bus. In general, buses that are providing power to consumers (load buses) have P_k and Q_k specified by the load condition and one would like to determine if voltage magnitude constraints are satisfied. If the bus is connected to a generator, then in most cases P_k, is specified (by the mechanical power input) and U_k is regulated to a specific value. In this case, one should determine if the voltage angle and reactive power needed to satisfy network conditions are feasible for the generator. To account for line losses, which are functions of the power flows, at least one generator must have its real power unspecified. Such a bus is usually denoted as a slack bus. In addition, one of the slack busses must have its voltage angle specified and will serve are the reference bus for the whole network. If the load flow setup defines a single bus as the slack bus, then the network will be completely specified and all variables can be calculated. If more than one slack bus is defined, then the system will be under-specified, since P_k, Q_k and θ_k will all be unspecified for the non-reference slack buses. Such a scenario will give additional freedom in determining which generator will make up for line losses and changes in power demand.

2.1. Power Management

In general, power management will occur at two time-scales. At small time-scales (on the order of seconds), an understanding of load flow properties is needed, but explicit load flow calculations are not performed. Specifically, there is a strong coupling between real power and voltage angle as well as between reactive power and voltage magnitude. Such relations provide a basis for feedback control at the small time-scales; that is, if real power demands increase, then the generators will sense this change by a small decrease voltage angle, and compensate by slightly increasing mechanical power to the generator. Similarly, a drop in voltage magnitude can be compensated by increasing reactive power. Publications on voltage and frequency control include (Weedy and Cory, 1998; Marwali et al., 2004; Blaabjerg et al., 2006; Kim et al., 2008; Venkat et al., 2008; Hovgaard et al., 2011). In Kim et al. (2006), a power-control strategy of a grid-connected hybrid generation system with versatile power transfer was presented. Their hybrid system was a combination of photovoltaic (PV) array, wind turbine, and battery storage via a common dc bus.

At larger time-scales (on the order of minutes) the system operator performs explicit load flow calculations. These form the basis of higher level controllers within the operational hierarchy. The load flow relations are used to define an Optimal Power Flow (OPF) problem, where the objective function is usually a combination of generation costs, transmission losses and reactive power reserves. The operator may also add a set of security constraints to meet the so called N-1 criterion. These guarantee that suitable operation will be possible if one of the generating units drops out of service (operation with N-1 units). While nonlinearity of the OPF problem suggests the possibility of multiple local optima, this issue is usually of little concern, since at the time-scale of interest only small perturbations are imposed at each time step and the primary objective is feasibility rather than optimality. This is reflected by the solution procedures usually employed, which are gradient based and use the current condition as the initial condition for the solver. The computational cost of OPF problems is in general significant, especially in the context of the time constraints required. Specifically, it is not uncommon to find systems with hundreds or thousands of buses and sample times on the order of seconds. More details on OPF can be found in (Bacher, 1993; Glavitsch, 1993; Ilic and Zaborszky, 2000; Zhang and Li, 2010).

An alternative to the OPF approach is to exploit the time-scale differences in the various performance objectives to construct a control system hierarchy. Under this scenario, a hierarchical (multi-layer) control system is used. Primary controllers regulate frequency by manipulating active power, secondary controllers regulate voltage within a region by manipulating reactive power, and tertiary controllers regulate voltage between regions (Ilic and Liu, 1996).

Another important issue is the estimation of system conditions (Grainger and Stevenson, 1994; Abur and Exposito, 2004). The mathematical structure of the power flow estimation problem is similar to the static nonlinear data reconciliation problem frequently encountered in the process industries. Owing to the large size of a power system, the problem of cost effective sensor network design is also an important issue, where the methods in Bagajewicz (2000) may be applicable.

2.2. Energy Management

In contrast to power management (with the objective of regulating instantaneous power), energy management has the objective of ensuring power is available during longer time intervals (i.e., sufficient energy is available). Integral to energy management is the prediction of future power demand, either day-ahead or hour-ahead. These predictions are then used to identify commitments from the generating units. If all generating units are operated by a single entity, and thus can be dispatched at will, then the Unit Commitment Problem (UCP) is rather straightforward to construct. In this case, the objective is similar to OPF problem, but more focused on economics. In addition, a UCP includes unit start-up and shut-down decisions (integer variables) as well as ramp rate constraints. In general, slowly responding units (nuclear and coal) are active in the day-ahead schedule, while fast responding units (gas turbine and hydro-electric) are active in hour-ahead scheduling. In both cases, additional constraints are used to ensure sufficient levels of spinning reserve are on hand to implement the power management policy. Sample publications on UCP are (Grainger and Stevenson, 1994; Sheble and Fahd, 1994; Ilic and Zaborszky, 2000; Richter, 2007; Marcovecchio et al., 2011; Zamarripa et al., 2011). To address the intermittency of renewable sources, many are working to augment user demand predictors to include prediction of generation from renewable sources, which can be directly incorporated into existing UCP formulations. However, an expectation of additional error in these predictions has motivated uncertainty-based formulations (Takriti et al., 1996; Carpentier et al., 1996; Nowak and Romish, 2000; Ozturk et al., 2004; Constantinescu et al., 2011).

Under a deregulated scenario (i.e., all generating units are not operated by the same entity), the question of unit commitment becomes much more interesting. In this case, an Independent System Operator (ISO) will hold auctions for day-ahead and hour-ahead commitments (Philipson and Willis, 1999; Lo and Yuen, 2001). As expected, a significant body of literature has been developed for the analysis and prediction of unit commitment characteristics under deregulation (Ilic and Liu, 1996; Takriti et al., 2000; Arroyo and Conejo, 2000; Ilic and Zaborszky; 2000; Shahidehpour et al., 2002; Richter, 2007; Li et al., 2007).

2.3. Expansion Planning

The power and energy management problems just discussed assume that a fixed set of hardware is available. However, to address the challenge of meeting future power demands, one must consider the question of where and when new generating units and transmission lines should be installed. In the power literature, this problem is usually denoted as the Transmission Expansion Planning (TEP) problem (Villasana et al., 1985; Khator and Leung, 1997; Romero et al., 2002; Lee et al, 2006). A central challenge in TEP is disparity in time scales; that is, the predicted performance depends on large time-scale decisions (where and when to upgrade) as well as small time-scale variables (how do postulated upgrades impact unit commitments). The TEP problem is also burdened by the sheer size of existing networks, where problems containing 10,000 or more buses are common. To address the computational challenge, numerous model approximations and optimization algorithms have been proposed (Latorre et al., 2003). Of particular note are the efforts aimed at dealing with the additional uncertainty created by renewable sources (Yang and Wen, 2005; Billinton and Wangdee, 2007; Yu et al., 2009; Xiao et al., 2011) as well as those addressing market deregulation (Roh et al., 2007; de la Torre et al., 2008; Motamedi et al., 2010).

2.4. PSE Opportunities

We see three PSE opportunity areas in power distribution systems. The first is in the area of power management control using the hierarchical approach of Ilic and Liu (1996). This philosophy greatly parallels the hierarchical control structures used in chemical plants and seems to be underutilized by the power industry. The second is in the area of state estimation. Recent advances in information technology have made available new techniques to measure voltage angle differences between buses separated by great distance. While these methods have created much excitement within the power industry, the resulting estimation problem is very similar to the nonlinear data reconciliation problems frequently solved in the chemical industry. The third PSE opportunity is with respect to the TEP problem, which is likely the most challenging optimization problem facing the power community, especially if one considers the time-dependent and *N-1* variations of the problem. It seems that the computational strides in mixed integer and nonlinear programming made by the PSE community could be brought to bear on the important problem.

3. Power Generation

In the context of grid coordination, power sources can be classified in terms of their dispatchability (Kalich, 2011). At the lowest level is nuclear, which cannot be shut-down and in most cases has limited ability to change power output (see Na et al. (2005) for the exception). As such, nuclear power is not considered an asset to power or energy management and may even be a detriment when total demand decreases below the nuclear base-load. The opposite extreme is natural-gas-based sources. The simple cycle variety or Combustion Turbine (CT) is characterized has having fast start-up and shut-down capabilities (on the order of 15min), but limited power output flexibility once started. As such CTs contribute mostly to hour-ahead aspects of energy management (Due to their high fuel costs, CT are usually the last units schedule in day-ahead planning.) The combined cycle variety (CCCT) is more efficient than CT and has greater power output flexibility. However, CCCTs are much slower in start-up and shut-down (on the order of several hours). As such, CCCTs contribute mostly to the regulation aspects of power management and day-ahead aspects of energy management. While many coal plants were designed for based load operation, they do have output flexibility and can be shut-down. However, start-up is slow (one the order of several hours, depending on the start state of warm or cold). Output flexibility is also quite slow on a percent of nameplate basis, but due to their large size coal plants can provide substantial flexibility on an absolute basis. As such, coal plants commonly play a significant role in both power and energy management. Hydroelectric power has significant power output flexibility, and if geographically available will likely play a large role in both power and energy management. However, limitations with respect to reservoir levels must be carefully observed.

In the context of grid management, most renewable sources are classified as anti-dispatchable. That is, in contrast to a non-dispatchable source (i.e., no change in power output), anti-dispatchable sources do change power output levels, but the grid operator usually has no (or very little) influence over these changes. Thus, a renewable source is more appropriately classified as a disturbance, in the sense that it puts additional burden on both power and energy management objectives. However, this uncertainty in renewable power output does not mean a lack of predictability. Similar to power demand forecasting, significant efforts are being made to develop highly accurate forecasts of renewable power output (Zavala et al., 2009; Wu and Hong, 2007), and will provide an important piece to the energy management challenge.

Solar and wind energy systems are attractive power generating sources due to their availability and topological advantages, especially for local power generations in remote areas. Especially since the oil crises of early 1970s, they have become increasingly significant and cost-effective, leading to extensive studies on the utilization of solar and wind energies as alternative sources of energy. However, solar and wind energy systems have two disadvantages: (a) their power production dependence on unpredictable weather and climatic conditions, and (b) mismatch between the availability of solar and wind energies and the consumer power demand.

3.1. Wind Sourced Generation

In the United States, the cumulative 17 GW of wind capacity installed by the end of 2007 is able to supply roughly 1.2% of the nation's electricity consumption (DOE, 2008b). To meet 20% of the demand of electricity in 2030, U.S. wind power capacity has to reach more than 300 GW (DOE, 2008a). This is 17 times larger than today's total installed wind capacity.

There have been a number of papers on modeling the time characteristics of wind power. For example, Petru and Thiringer (2002) studied wind turbines to develop a mathematical model suitable for use in power grid simulations. The model accounted for aerodynamic conversion, drive train, and generator representation. The model was validated using field measurements from a stall-regulated fixed-speed wind turbine.

Because of the stochastic nature of wind velocity (Van der Hoven, 1957), wind energy conversion systems cannot be operated efficiently without the use of an optimal control system; automatic control is a very useful tool to ensure high efficiency and reliability of wind power conversion systems.

For wind power systems, solving a global dynamic multi-objective optimization with performance indices including energy conversion efficiency, mechanical reliability, and quality of the energy has been proposed (Munteanu et al., 2009). Control techniques, such as PI control, maximum power point strategies and gain-scheduling techniques, sliding-mode techniques, feedback linearization control and robust control, have been applied, assessed and compared in (Munteanu et al., 2009). Bhowmik et al. (1999) used a brushless doubly fed machine to develop a variable-speed wind power generator. The controller used a wind-speed-estimation-based maximum power point tracker and a heuristic-model-based maximum efficiency point tracker to optimize the power output of the system. Their strategy is applicable to all doubly fed configurations such as conventional wound-rotor induction machines. Regardless of wind turbine technology, the replacement of conventional generation with wind will result in higher rates of change of system frequency. The magnitude of the frequency excursion following a loss of generation may also increase. Power management or modification of wind turbine inertial response characteristics is needed to facilitate increased levels of wind generation, especially in small isolated power systems. Lalor et al. (2005) studied the impact of increasing wind penetration on frequency control on the Ireland electricity system. Song et al. (2000) investigated variable speed control of wind turbines using nonlinear and adaptive algorithms, which was shown to be able to achieve smooth and asymptotic rotor speed tracking. Hansen et al. (2006) studied the control of a wind farm consisting of doubly fed induction generators. They used a multi-level (cascade) control system to regulate the wind farm power production to the reference power ordered by the system operators. The master controller controls the power production of the whole farm by sending out reference power signals to each individual wind turbine, while the slave controller ensures that the reference power signal send by the central control level is achieved. Spie et al. (1995) used an adaptive maximum power point tracking strategy to implement an efficiency maximization loop in parallel with the regular maximum tip speed ratio tracker, without the measurement of mechanical quantities. The overall power output of the generation system was increased with a minimal increase in controller cost.

3.2. Solar Sourced Generation

Solar energy systems are also attractive power generating sources due to their availability and topological advantages, especially for local power generations in remote areas. However, a stand-alone solar energy system cannot provide a continuous power supply due to seasonal and periodical variations (Zhou et al., 2010).

Mathematical models of solar cells can predict the performance of the cells, the IV curve and the cells efficiency, provide a better understanding of the physics behind the photo-conversion processes, and can be used in the design and optimal operation of the cells. Generally, mathematical models can be developed on the basis of two different viewpoints, detailed level and system level. Hence, a photovoltaic system can be modeled to describe the cell characteristics, module characteristics, orientation and geometric characteristics, array-level characteristics, power conditioning unit level characteristics, plant-level characteristics, operations and maintenance characteristics and so on (Smith and Reiter, 1984).

Currently the silicon-based solar cell is the dominant commercialized photovoltaic technology. However, the new emerging technology relying on nanocrystalline materials and conducting polymer films has gained substantial momentum due to its lower cost and higher flexibility (Grätzel, 2001). Although modeling of the solid state solar cell has been extensively investigated and comprehensive models are available for this technology (Smith and Reiter, 1984; Liu and Dougal, 2002; Alam and Alouani, 2010), the new generation of solar cell still needs to be studied as the physical phenomena occurring in the cell can be substantially different. Examples are dye sensitized and bulk heterojunction solar cells with inclusion of electrochemical processes and exciton-charge recombination (Grätzel, 2009; Hwang et al., 2009). In summary, a solar cell system model can be developed by accounting for phenomena such as photovoltaic, electro-thermal and direct heating and cooling processes (Liu and Dougal, 2002). Different approaches including equivalent circuit modeling and continuum modeling have been introduced as an effective way to predict the cell system behavior (Anta et al., 2006; Ferber and Luther, 2001; Ferber et al., 1998; Kern et al., 2002). Because of the nonlinear dependence of the current-voltage characteristics of the cells on temperature and irradiance level, the models are highly nonlinear (Brunton et al., 2009).

For any type of solar cells, high efficiency is the key factor toward the large scale applications (Pelanchon and Mialhe, 1990). In this respect, optimization studies are indispensible. Simulation studies should be performed to obtain the optimal design parameters at different irradiances. The decision variables are those characteristics of solar cell design which can be manipulated to achieve the optimization goal depending on the type of the solar cell (Girardini and Jacobsen, 1991). As an example in the case of silicon solar cells, major design parameters involve rear point contact area coverage, substrate doping concentration, and cell thickness (Huang and Moroz, 2011). Another important feature to consider in optimization studies is the sensitivity of efficiency to variations in the cell design parameters (Girardini and Jacobsen, 1991).

To optimize solar array performance under varying environmental conditions and load disturbances, a maximum power point tracker should be employed to deal with the nonlinear and time-varying nature of the systems (Solodovnik et al., 2004). Consequently, the operating current and voltage at which the power output of a cell is maximum, varies with the environmental conditions. A switching power converter is usually implemented to accomplish this task (Brunton et al., 2009). The maximum power output can be achieved by employing an appropriate duty ratio at the converter control input (Solodovnik et al., 2004). The controller should be able to track the time-varying maximum power reference point and to reject static load disturbances while the system should be asymptotically stable. For maximum power point tracking, the solar cell array current can be estimated using a state observer (Kim et al., 2006). Linear observers may not perform well due to the existence of nonlinearities, unknown parameter variations, uncertainties and unmeasured disturbances.

3.3. Fuel Cells

A fuel cell is an energy conversion device that produces electricity directly from the chemical potential energy of a fuel. Fuel cells are classified on the basis of the electrolyte used in the system. The type of the electrolyte of a cell also determines the operating temperature of the fuel cell. The most common commercially available fuel cells today are polyelectrolyte membrane fuel cells (PEMFCs), solid oxide fuel cells (SOFCs), phosphoric acid fuel cells (PAFCs), and molten carbonate fuel cells (MCFCs). Commercial fuel cell systems are comprised of a fuel cell stack and the so-called balance-of-plant (BOP). The balance of plant pre-processes and provides suitable fuel to the stack's anode and pre-heats air and provides it to the cathode. The primary components of a fuel cell are an ion conducting electrolyte, an anode, and a cathode. In this section, for brevity only PEMFCs and SOFCs are considered. As the electrolyte of a SOFC can be oxygen ion conducting, proton conducting or both, we also limit our focus to the SOFCs in which the electrolyte conducts oxygen ions only.

Materials for an oxygen-ion-conducting SOFC are generally yttria-stabilized zirconia (YSZ) for the electrolyte, strontium-doped lanthanum manganite (LSM) for the cathode, nickel/YSZ for the anode, and doped lanthanum chromite or high-temperature metals for the interconnect (Bavarian et al., 2010). A SOFC usually operates at a temperature range of 700 to 1000°C. At these high operating temperatures, oxygen anions migrate through the electrolyte. When a fuel gas containing hydrogen flows over the anode, negatively charged oxygen ions move across the electrolyte to oxidize the fuel. The oxygen is supplied, usually from air, at the cathode. Electrons generated at the anode move through an external load to the cathode, completing the circuit and supplying electric power. These fuel cells have a generating efficiency up to about 60 percent. A desired application of SOFCs is in large, stationary power plants. Their high operation temperatures allows for "co-generation"; that is, using waste heat to generate steam for a variety of applications such as space heating, industrial processing, and steam turbines to make more electricity.

Polyelectrolyte membrane (PEM) fuel cells have a polymer electrolyte in the form of a permeable sheet. This membrane is thin and light, and it typically operates at low temperatures (about 80^oC). A PEMFC has a membrane-electrode assembly (MEA) that includes a polymer electrolyte membrane that conducts protons. Typically a perfluorosulfonic acid ionomer membrane, such as Nafion® (introduced by DuPont), is used. The MEA is positioned between flow channels that supply the reactants to the MEA at both the anode and cathode sides. Hydrogen atoms lose their electrons (become ionized) at the anode, and the (positively charged) protons diffuse through one side of the porous membrane and move towards the cathode. The electrons are transported from the anode to the cathode through an external circuit (load) and provide electric power. At the cathode the electrons, protons and oxygen from the air react and form water. Efficiency for a PEMFC is typically 35 to 45% (Hoogers, 2003). A PEMFC requires an external fuel processing system to convert fuels such as methanol or gasoline to hydrogen.

The type and the level of details included in a mathematical model depend on what the application of the model is. For real-time applications, the model equations should be solvable in real-time. This requirement at the present time limits drastically the set of models that can be used. In fuel cell modeling the art is not to include every complexity but to include enough details to predict the variables of interest accurately enough. Accounting for every complexity in fuel cell modeling leads to the development of very complex, multi-time-scale, multi-dimensional models, which may be hard to solve even with the present computers and numerical methods. An extensive list of papers on modeling the fuel cells can be found in the two recent review papers (Bavarian et al., 2010; Hajimolana et at., 2011).

Fuel cells are inherently multi-time-scale systems. The multi-time-scale nature is a consequence of the involvement of processes with significantly different response times (Zenith and Skogestad, 2009). Electronic components of a fuel cell have the fastest responses, while the thermal processes in a fuel cell usually have the slowest responses. The existence of the significantly different time constants, e.g., from 1 ms to 10,000 s, in a fuel cell makes the governing dynamic equations very stiff. However, it allows one to simplify the model systematically based on the time scale of interest (Bavarian et al., 2010).

A SOFC or a PEMFC can have one (stable), three (two stable and one unstable) or five (three stable and two unstable) steady states depending on the operation conditions (Bavarian e at., 2010). The problem of steady state multiplicity including hot spots in SOFCs and wet spots in PEMFCs should be considered critical in the operation of the cells. In SOFCs, steady-state multiplicity is cause by the positive feedback between oxygen ion migration and heat production (Mangold et al., 2006), and in PEMFCs by the positive feedback between proton migration and water production (Moxley et al., 2003). While there have been many theoretical stability studies, there have a few attempts to validate the theoretical results experimentally. An interesting study is to operate a fuel cell at an unstable steady state in real time (experimentally). An evaluation of the advantages and disadvantages of operating a fuel cell at each (unstable or stable) steady state is needed.

Optimization is conducted to obtain optimal operating conditions and design specifications of fuel cell systems, especially when these systems are integrated with fuel processing systems and/or are used together with other power generating and storage systems. The design of fuel cells is a challenging task due to several physical phenomena that should be optimized simultaneously to achieve proper fuel cell operation. Fuel cell design is a multi-objective, multi-variable problem. To design fuel cells by computational design, a mathematical formulation of the design problem needs to be developed. The problem is then solved using a numerical optimization method and a fuel cell model. In the past decade, the fuel cell community has paid more attention to the computational design of fuel cells.

In a recent review paper, Secanell et al. (2011) have discussed the strengths, limitations, advantages, and disadvantages of optimization formulations and numerical optimization algorithms in the design of fuel cell and fuel cell systems. They highlighted the importance of developing numerical optimization formulations for the design of fuel cell and fuel cell systems. They also provided a discussion on the state-of-the-art in fuel cell optimization and suggested future research directions in the area of fuel cell and fuel cell systems design.

Kim and Peng (2007) formulated a combined power management/design optimization problem for the performance optimization of a fuel cell hybrid vehicle. This included subsystem-scaling models to predict the characteristics of components of different sizes. A parameterizable and near-optimal controller was used for power management optimization. Simulation results demonstrated that combined optimization can efficiently provide excellent fuel economy. Song et al. (2004) conducted one- and two-parameter numerical optimization analyses of the cathode catalyst layer of a PEM fuel cell with the objective of optimizing the current density of the catalyst layer at a given electrode potential. Catalyst design parameters, such as Nafion content, platinum loading, catalyst layer thickness and porosity, were considered. Numerical analysis showed the existence of a global, optimal solution for each one-parameter optimization.

The control problem in a fuel cell system is a multi-objective one. A fuel cell system should be controlled effectively to ensure (a) the system supply of required power in the presence of rapid variations in the external loads, (b) high efficiency of the system, and (c) long life of the system, among others. Fuel cell heat and water management, fuel and air supply and distribution, electric drive, and main and auxiliary power management have been studied to improve the performance and durability of fuel cells. Another control problem in fuel cells is the phenomenon of oxygen/fuel starvation, which may occur when there is a sudden large increase is the load power. In this case, the partial pressure of oxygen/fuel decreases significantly, accompanied by a rapid decrease in cell voltage, which in turn shortens the life of the fuel cell stack (Pukrushpan et al., 2004). The need for control strategies that can regulate optimally the fuel cell operating conditions is recognized in the literature (Varigonda and Kamat, 2006). There have been many studies focused on controller design for both SOFCs and PEMFCs. A detailed review of many papers on this topic can be found in (Bavarian et al., 2010).

The maximum power output drawn from a fuel cell system depends on the fuel feed composition and flow rate (fuel utilization), heat removal (radiator), active area of MEA, air flow rate, air humidity (for PEMFCs), and feed temperature, among others. One objective in fuel cell control is to maintain optimal temperature, membrane hydration (in case of PEMFCs), and partial pressures of the reactants across the electrolyte to avoid degradation as the current drawn by the load varies (Pukrushpan et al., 2004). Water and thermal management, and prevention of fuel and air starvation, which can permanently damage the stack during load transients, should be treated carefully (Varigonda and Kamat, 2006; Pukrushpan et al., 2005). Control of BOP components in fuel cell systems is also of critical importance. As an example, the temperature of a reforming catalyst of a natural gas fuel processor system must be maintained at a certain level. There is a trade-off between the catalyst damage prevention and the methane reaction rate. High temperature will permanently damage the partial oxidation catalyst bed, while low catalyst temperature slows down the CH_4 reaction rate and may lead to carbon deposition. Control objectives and priorities for a fuel cell can be different depending on the type of the fuel cell. While CO poisoning of the fuel cell catalyst is another hurdle that should be considered in PEMFCs with an integrated fuel processor, SOFCs have no such CO poisoning problem (Varigonda and Kamat, 2006). Optimal start-up, operation and shutdown of the stack and system components are important in both SOFCs and PEMFCs. When a fuel cell operates within an electrical grid, the fuel cell control system should also act in coordination with other control systems in the grid.

Previous control studies of fuel cells indicate that a multi-level (multi-layer) control structure should be used for fuel cells (Ahmed and Chmielewski, 2011; Lauzze and Chmielewski, 2006). Pure feedback and combined feedback and feedforward loops should be used in inner loops. Ratio control for ensuring adequate supply of fuel and air is also needed. The outer loop should have an optimization-based supervisory controller to ensure high overall efficiency of the fuel cell stack and the BOP. PI controllers for the inner feedback loops have been shown to be adequate (Bavarian et al., 2010).

Only a very limited number of variables and parameters can be measured in a typical fuel cell. Temperature is usually measured at a few points inside the cell stack as well as at the fuel reformer, and gas compositions are either not measured or measured rarely. Information on variables that are not measured can be obtained using an observer/estimator (Soroush, 1998). The central part of an observer is a process model. A few studies have focused on observer design in fuel cells. One of the obstacles in achieving reliable and efficient control for fuel cells is the inadequacy of existing hydrogen partial pressure sensors. Most of hydrogen sensors suffer from slow response times, low accuracy, and high cost (Arcak et al., 2004; Jardine, 2000). To overcome these problems, one approach is to estimate hydrogen partial pressure using an observer. Arcak et al. (2004) designed an adaptive observer for hydrogen partial pressure estimation in a PEMFC. Das and Mukherjee (2007) designed an observer for estimation of species concentrations in an SOFC with a reformer. Lin and Hong (2005) presented a sliding-mode state observer to estimate the unmeasurable gas temperatures inside a SOFC from measurements such as that of gas pressure. Jin-Woo and Keyhani (2007) presented an asymptotic observer to estimate the load current from measured line-to-line load voltage.

3.4. PSE Opportunities

In the area of wind generation, it seems that the application of hierarchical control methods to turbine operation will yield improvements in conversion efficiency, grid coordination and reductions in equipment fatigue. While others have begun this effort, the hierarchical control experience of the PSE community will likely shed new light. In the area of solar thermal generation, the methods of dynamic optimization, which are typically applied to chemical plants, will likely be of great utility. In solar cells, novel modeling and optimization in fabrication will likely yield meaningful efficiency gains. In the area of fuel cells, balance of plant optimization is a fertile but challenging opportunity, due to a non-obvious set of design objectives and the severe nonlinearity of the process.

4. Energy Storage

Energy Storage Systems (ESSs) can be categorized into those designed for power and energy management. Power management technologies include rechargeable batteries, flywheels and flow batteries and, capacitors. We discuss rechargeable batteries and flow batteries herein. Energy management technologies include pumped hydro storage, compressed air energy storage and thermal energy storage, all of which are discussed herein.

4.1. Rechargeable Batteries

A battery includes one or more electrochemical cells. Each cell has an electrolyte, a positive electrode (anode), and a negative electrode (cathode). Reversible electrochemical reactions play the central role in the power storage and release processes in a rechargeable battery. During discharge, electrochemical reactions occur at the two electrodes generating a flow of electrons through an external circuit. Once an external voltage is applied across the electrodes, the reactions are reversed (battery is recharged). Batteries have several advantages for electrical energy storage applications. They respond very rapidly to load changes and can accept co-generated and/or third-party power. Furthermore, the batteries usually have very low standby losses and high energy efficiency (60–95%). Their short lead time, ability to withstand sitting and modularity are of great importance (Chen et al., 2009). However, because of factors such as small power capacity, low energy densities, high maintenance costs, a short cycle life and a limited discharge capability, large-scale utility battery storage has been rare until quite recently. Batteries that are currently being used and/or have potential for utility-scale energy storage applications include nickel cadmium, sodium sulphur, sodium nickel chloride, lead acid, and lithium ion (Chen et al., 2009).

At the present time, lithium-ion (Li-ion) batteries are considered as the most promising battery system for hybrid electric vehicles, plug-in hybrid electric vehicles and electric vehicles applications. However, a battery management system that can guarantee safe and reliable operation is lacking. A better understanding of aging and other performance degrading mechanisms in the batteries will facilitate the development of the management system.

Generally, there are different classes of models from nonlinear and coupled PDEs to simple linear ODEs. The first principles give wide varieties of models depending on different hypotheses, which depend on the utilization (input) of the battery. A decade ago, research in this area was more focused on developing chemical models (Ong and Newman, 1991), and control researchers worked more with electrical models extended by simple chemical properties. Since then, many have worked on reducing electrochemical models to make them useable in real time, leading to some good results (Smith and Rahn, 2008; Forman et al., 2011; Cai and White, 2008; Smith et al., 2007). Chaturvedi et al. (2010) also presented a compact model that can be used to study the Li-ion battery. Their simple approximate model is commonly known as the single particle model**.** Research continues in this field in order to take into account more phenomena, such as thermal effects.

Researchers are currently faced with two problems: (1) very little variation of the battery open voltage with the state of charge, which complicates the estimation of the charge from the voltage, and (2) the necessity to know the level of ageing of a battery. To address these two problems, attempts have been made to reduce first-principles models while keeping all effects necessary for the estimation and to develop a suitable estimation method. One can start with Newman 1D model (4 nonlinear PDEs) with some chemical assumptions and without taking into account the thermal effects yet considering the double capacitance layer (Ong and Newman, 1991). This model is valid above 50 Hz. To account for electrochemical processes, Buttler-Volmer equation is used. The dependence of concentration on electrolyte ionic conductivity is accounted for. The developed model represents the system well, but the hurdle is parameter estimation and input-excitation identification. So, one needs to reduce the model with some physical, chemical or mathematical assumptions linked to the inputs. To achieve this goal, different approaches are available, based on the assumption of uniform density (Smith and Rahn, 2008), quasi-linearization and Pade approximation (Forman et al., 2011), proper orthogonal decomposition (Cai and White, 2008), finite element method (Smith et al., 2007), and reformulation of the problem (Chaturvedi et al., 2010). There is a need to obtain an accurate reduced-order ODE model to accurately estimate physical parameters linked to battery ageing. Another interesting problem is the development of optimal charging policies that minimize ageing in a battery (maximize the life of the battery).

4.2. Flow Batteries

Flow batteries store electricity in a form of chemical energy known as electrolytes. While electrolytes flow through the cell, electricity is produced via electrochemical reaction. Electrolytes are regenerated and stored externally in tanks. Various electrolytes such as vanadium redox (VRB), zinc bromine (ZnBr), and polysulfide bromide (PSB) can be used in flow batteries. The storage period of flow batteries ranges from seconds to hours. Typical cycle efficiency is about 75 to 85% with a rating of 30 kW to 15MW (Chen et al., 2009) and a maximum storage capacity of 120 MWh.

The total capital cost of flow batteries in the range of 8 to 10 MW and 2 to 4 hours of storage is 1,400 to 4,700 $/kW) (EUC SETIS, 2011). The life-cycle time of flow batteries is about 10 to 15 years (EUC SETIS, 2011). The time-response of flow batteries from zero to full power is of the order of seconds (less if the electrolyte is primed). The reported energy storage capacity and power accessible domain of flow batteries facilities are roughly between 100 kWh to 500 MWh and 50 kW to 50 MW, respectively.

4.3. Pumped Hydro Storage

Pumped Hydro Storage (PHS) consists of two water reservoirs at different elevations. Surplus electricity is used to pump water from the low elevation reservoir to the high elevation reservoir (converting the electric energy to potential energy). As water flows back to the lower reservoir, a turbine is used to recover the stored energy. Storage capacity is dependent on elevation and reservoir size. PHS is characterized as a mature technology with large storage capacity, a long storage period, high cycle efficiency and relatively low capital cost per unit of energy. Typical cycle efficiency is about 70 to 85%, with power flow ranging from 100 MW to 3000 MW (Chen et al., 2009). The main drawback of PHS is that geological conditions limit the placement of such facilities. Currently, there are over 200 units and 100 gigawatt (GW) of PHS in operation worldwide (Chen et al., 2009).

The total capital cost of hydro-pumped storage facilities strongly depends on the site and whether an existing dam infrastructure is used. The total capital cost for nominal capacities between 200 MW to 500 MW is 1,400 to 5,150 $/kW (EUC SETIS, 2011). Energy and power accessible ranges of hydro-pumped storage facilities have been reported to be between 5 MWh to 50 GWh and 1 MW to 5 GW, respectively. Their time-response from zero to full power is in the order of several minutes. The expected life of a hydro-pumped storage is 50 to 60 years (EUC SETIS, 2011).

4.4. Compressed Air Energy Storage

Compressed Air Energy Storage (CAES) consists of a reservoir and a set of gas turbines. Surplus electricity is used to drive compressors to compress air (typically to 40-80 bar) which is then stored in an underground reservoir or storage tank. To recover the stored energy, the compressed air is released from the reservoir and used in a gas turbine (where its usual air compression stage is bypassed). Characteristics of CAES are that it can be operated efficiently during partial load conditions, and can switch quickly between generation and compression modes. Also, CAES is based on commercially available technology with a relatively long storage period, high efficiency and relatively low capital cost. Typical cycle efficiency of CAES is about 70 to 90%. Typical rating of CAES is about 50 to 300 MW with a storage capacity ranging from 580 MWh to 2860 MWh (Chen et al., 2009). Unfortunately, CAES is limited to favorable geologic conditions.

Because of the requirement for a geological cavern, the capital cost of CAESs is also site specific. The capital cost is in the range of 570 to 1650 $/kW for a plant with a nominal capacity of about 300 MW (EUC SETIS, 2011). For small-scale, above ground CAES with capacities between 10 to 50 MWe, the total capital cost is in the range of 1050 to 3750 $/kW (EUC SETIS, 2011). The expected life of CAES technologies is about 25 to 30 years (EUC SETIS, 2011). The time-response from cold conditions to maximum capacity is of the order of several minutes (EUC SETIS, 2011).

4.5. Thermal Energy Storage

Thermal Energy Storage (TES) works by heating or refrigerating specific materials (Chen et al., 2009). The High Temperature TES (HTTES) options currently in use and under development include molten salt storage, room temperature ionic liquid, concrete storage and phase change materials. Aquiferous Low TES (ALTES) utilizes a refrigeration cycle to ice water during off-peak hours and then later use to meet cooling needs during peak hours. ALTES is particularly suitable for large commercial buildings. Cryogenic TES (CES) is a new electricity storage system (Ordonez, 2000). Cryogen (e.g. liquid nitrogen or liquid air) is generated by off-peak electricity. During peak hours, heat from the surrounding environment boils the cryogen to drive a cryogenic heat engine and generate electricity. CES could have a relatively high energy density (100 to 200 Wh/kg), low capital cost per unit energy, and a relatively long storage period (Chen et al., 2009). However, CES has relatively low cycle efficiency (40 to 50%) according to current energy consumption for air liquefaction (Chen et al., 2009).

4.6. PSE Opportunities

In the area of batteries (both rechargeable and flow) the PSE opportunity is in estimation; that is, estimation of battery state of charge and aging (material degradation). The opportunity stems from highly nonlinear, spatially distributed models required to accurately describe batteries. The opportunity with regard to energy management type storage is to apply the methods of dynamic optimization and incorporate these storage units into the TEP problems discussed in Section 2.3.

5. Concluding Remarks

This paper presented an overview of the current systems engineering opportunities in power generation, storage and distribution. Major power generation and storage systems as well as power management strategies were reviewed, and open systems engineering problems in each category were pointed to. It is concluded that the process systems engineering can contribute significantly to the design and optimal operation of power generation and smart grid systems. Standing out are optimization and optimal control, which will be needed increasingly, as the costs of power generation will rise and more dispersed renewable energy sources will be commissioned.

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