Chapter 1
Smart Grid for the Smart City

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Abstract

Modern cities are embracing cutting-edge technologies to improve the services they offer to the citizens from traffic control to the reduction of greenhouse gases and energy provisioning. In this chapter, we look at the energy sector advocating how Information and Communication Technologies (ICT) and signal processing techniques can be integrated into next generation power grids for an increased effectiveness in terms of: electrical stability, distribution, improved communication security, energy production and utilization. In particular, we deliberate about the use of these techniques within new demand response paradigms, where communities of prosumers (e.g., households, generating part of their electricity consumption) contribute to the satisfaction of the energy demand through load balancing and peak shaving. Our discussion also covers the use of big data analytics for demand response and serious games as a tool to promote energy-efficient behaviors from end users.

1.1 Introduction

Modern cities are becoming more and more dependent on the reliability and efficiency of the electrical distribution infrastructure. In the past few years, a great effort has been devoted to the creation of an integrated infrastructure that combines a resilient power distribution system, the presence of distributed generation devices based on renewables (as, for example, photovoltaic panels and wind turbines), a reliable and secure communication system, and real-time energy pricing policies. The resulting infrastructure is called *smart grid* and constitutes the backbone of the *smart city*. As noted in [23], "The *smart city* is all about how the city "organism" works together as an integrated whole and survives when put under extreme conditions" and, moreover: "the energy infrastructure is arguably the single most important feature in any city. If unavailable for a significant enough period of time, all other functions will eventually cease". Hence, developing and implementing a fully functional *smart grid* infrastructure is a priority for future *smart cities*.

In order to implement a *smart grid*, at least the following three technical domains must cooperate, namely: *i)* power electronics, *ii)* information and communication technology (ICT), and *iii)* economics.

From a power electronics standpoint, the diffusion of distributed energy resources (DERs) poses a number of interesting challenges that the future power distribution grid must face to evolve into a smart power distribution grid. On the one hand, the presence of grid connected DERs (i.e., DC power generators connected to the main power distribution system through grid-tie inverters or capacitor banks) must be carefully handled to maintain acceptable electrical power quality. In particular, voltage sags (overvoltages) due to the switch off (on) of groups of DERs must be avoided. Moreover, harmonic distortion must be minimized, since it is one of the major factors degrading the overall power quality [17]. On the other hand, if the presence of grid tie DERs is fully accepted and embraced, these devices can be exploited to ameliorate the overall power grid performance and to provide ancillary services.

The coordination of DERs relies on three basic tiles: *i)* measurement devices (i.e., synchrophasors measuring real time voltages and currents) distributed across the power distribution system, *ii)* a communication infrastructure that allows sharing the collected data between the active agents in the grid (i.e., the DERs and the utility), and *iii)* suitable algorithms that use the electrical measurements to automatically coordinate the DERs' actions in order to enhance the grid performance. The synergy between power electronics and IT solutions supported by a communication infrastructure constitutes the basement of a *smart grid*.

Once the *smart grid* basement has been set up, the catalyst that will boost the cooperation between the grid agents lies in economics. Guaranteeing economic advantages to those agents that contribute to the electrical grid efficiency is, indeed, a key factor to turn the *smart grid* concept into reality, i.e., to make this profitable for customers and utilities.

The aim of this chapter is to present the main electrical, IT and economic open challenges to the *smart grid* and to discuss some of the solutions that have been proposed in the scientific literature. Finally, some real-world examples of *smart grids* will be considered and the adopted solutions will be analyzed.

The rest of this chapter is organized as follows: in Section 1.2, we introduce the electrical background, the communication scenario, and we formally describe the considered power grids. In Section 1.3, we discuss open issues related to the electrical optimization of smart grids, identifying some promising solutions from the literature. In Section 1.4, we highlight some key points to spur the adoption of smart grid technologies and their widespread diffusion. In Section 1.5 we elaborate on state-of-the-art gaming approaches to promote electrically efficient behaviors by power grid customers. In Section 1.6, we focus on data mining techniques, whereas in Section 1.7 we discuss relevant real-world deployments, and the benefits that are obtained by them. In Section 1.8 we present our concluding remarks.

1.2 Notation

In this section, the electrical scenario and the notation that will be used throughout the chapter are introduced.

1.2.1 Notions of electrical distribution

In order to define the electrical scenario that is considered in this chapter, a brief description of the traditional power production and transmission system is needed. Moreover, the main differences between the U.S. and European systems are introduced. The reader already familiar with these subjects may skip to the next section.

The traditional power distribution system has a well established hierarchical structure. Electrical power is produced in dedicated power plants that can be based on several energy sources (i.e., thermal power plants, nuclear reactors, biomass, gas turbines and water turbines are the most common sources of energy). The power generator uses the mechanical energy obtained by these sources to operate a rotor that produces three sinusoidal currents oscillating at the same frequency (called *utility frequency*, 50 Hz in Europe and 60 Hz in the U.S.A.) but with a 120 degrees phase shift between each other. These currents are called 3-phase current. The 3-phase voltage at the power generator is then raised to a transmission level which depends on the length of the transmission lines and is aimed at reducing the distribution power losses. The produced power flows through high voltage transmission lines until it reaches transmission or local distribution substations where step down transformers reduce the voltage. Distribution substations connect the high voltage transmission lines to the medium voltage distribution systems. From there, distribution lines carry medium voltage power to medium to low voltage transformers where the voltage is reduced to 110 V_{rms} in the U.S.A. or 230 V_{rms} in Europe[1] and is used to feed houses, small businesses and so on.

In the past few years, many end users started installing small power generation devices based on renewables in their properties. At first, the locally generated power was used directly by the generator's owner to feed relatively small home appliances off-the-grid. As this technology started spreading, main power suppliers started buying the generated power which was converted into AC current by inverters. At this point, the power flow was not unidirectional anymore.

Bidirectional flows open new new opportunities as energy is generated in a distributed fashion by the end users and can be utilized to compensate for high peaks in the demand, etc., but it also leads to important challenges as this bidirectional flow model, if not properly handled, can lead to grid instability.

[1] rms stands for root mean square and equals the peak value divided by $\sqrt{2}$.

1.2.2 Electrical Details

In this chapter, single phase low voltage (i.e., 110 V_{rms}/230 V_{rms}) power grids are considered. These networks result from the extraction of one of the phase wires and the neutral from the three-phase low voltage distribution grid and provide electrical power to small neighborhoods. The considered grids are connected to the main distribution grid through a special node called the point of common coupling (PCC) which, if needed, can be equipped with intelligent control algorithms and can act as a coordinator for the grid end users. The reason for this choice lies in the fact that along main power transmission paths solutions for monitoring and guaranteeing voltage - and, in turn, power quality - are already in place by means of capacitor banks, transformers, circuit breakers and so on [17]. In the considered grid scenarios, instead, the coordinated cooperation between end users equipped with small power generation devices can greatly ameliorate the overall power quality of the area and result in economic advantage for the community (by reducing the power distribution losses) as well [9]. It is the authors' opinion that these are the grids in which the deployment of the *smart grid* technology will have a greater impact.

End users of the considered power grids can be divided into two main categories: *i) consumers*, and *ii) prosumers* (end users that are at the same time energy producers and consumers).

Comsumers do not own any kind of power generation device, hence they completely depend on the power grid for feeding their electrical appliances. These users will be called *loads* in the rest of the chapter. Loads are usually classified based on their behavior. In particular, there are 1) constant impedance loads, 2) constant power loads, and 3) constant current loads. Constant impedance loads exhibit a constant impedance with respect to voltage variations, hence when variations occur to the supplied voltage, the absorbed current will vary as well resulting in a variable power demand. Examples of constant impedance loads are incandescent light bulbs and water heaters. Constant power loads have the characteristic of absorbing a constant power despite voltage variations, i.e., the current they need varies inversely with respect to the applied voltage. Examples of constant power loads are motor drives for which the torque changes inversely with the rotation speed. Finally, constant current loads absorb a constant current despite voltage variations, hence their impedance must vary. Constant current loads are quite rare and can be found in only few applications as, for example, magnetic ballasts (which, by the way, are being replaced by the most efficient electronic ballasts whose characteristics resemble more those of a constant power load) and airport runways lighting. It is worth noting that loads rarely exactly fall into one of the above categories. The most common scenario is that where loads are a mixture of the three categories. The characteristics of this mixture strongly depend on the type of activity of the end user associated with the load (i.e., household, small business, industrial, ...) and on the season. For example residential loads during summer usually are 70% constant power and 30% constant impedance [54].

Prosumers are end users equipped with power generators. The power generation can come from renewables (i.e., mostly wind and solar energy) or, for example, from bidirectional electric vehicle (EV) chargers. In the latter case, the energy source is the EV battery. All these sources generate DC current that is fed to an inverter which, in turn, delivers AC power to the user. Initially, generators based on renewables were only used to fullfil the owners' power demand. The diffusion of grid-tie inverters[2], however, allowed the owners to start selling the produced energy to the utility. As powerline communication has been developed, signaling from the utility to the end users began to turn the grid into a *smart* entity. By means of grid-tie inverters, *prosumers* can inject some of their excess energy (if any) into the grid. This energy can either be bought by the utility or, where a control infrastructure is in place, be used to provide ancillary services improving the overall performance of the grid. In this chapter, *prosumers* are modeled as AC current generators with adjustable current phase connected in parallel to a load which will be called the "associated load".

The coordination of *prosumers* and (if possible) loads by means of a communication infrastructure and intelligent control strategies is a much advocated scenario, since it can relieve the main utility from some of its workload and at the same time greatly ameliorate the quality of the delivered power, especially during peak hours. This condition appears even more important if we consider the fact that the biggest source of greenhouse gas emissions are the electricity production plants [1].

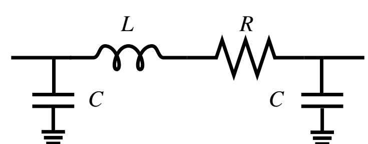

Fig. 1.1 *Π* line section example.

The distribution lines are the last piece of the considered grids. Usually, transmission and distribution lines are theoretically modeled as π-sections [24] whose characteristic impedances vary with respect to their position in the grid, i.e., their distance from the PCC. A π-section example is shown in Fig. 1.1. The *RL* series represent the actual path of the current, while the capacitors represent the intrinsic shunt capacitance of the two conductors. For short transmission lines (i.e., shorter than 80 km) the shunt capacitance becomes so small that can be neglected [52], and, hence, these lines can be represented as *RL* series. Due to the inductive and capacitive components, the impedance of the distribution lines vary according to the utility frequency. As the distance from the PCC grows, so does the impedance of the distribution lines. This is due to the face that thinner (thus cheaper) cables are used as the delivered current decrease, hence the lines connecting the end users to the grid are the ones with the greatest resistive characteristic, while the line connecting the PCC to the grid is the one with the smallest one.

[2] Grid-tie inverters are devices that allow to interface with the main distribution line and inject the generated power directly into the grid.

1.2.3 Communication Infrastructure

The cooperation between the *prosumers*, the loads and the utility is a key feature for the *smart grid*. Such a cooperation is however possible only if a communication infrastructure supports the operations of the grid agents. The requirements for the communication infrastructure greatly vary depending on the control algorithms that are to be supported. For this reason, there is no single "one-fit-all" technology which meets all the *smart grid* requirements. For example, some algorithms require that local data (i.e., real time currents and voltages) be frequently sent to a central control unit, which then dispatches the control actions to the end users [8]. Other algorithms are fully distributed and require that only few agents, within the same area, communicate among themselves sharing local measurements and estimating the impedances of the lines connecting them [6, 49]. In the first case, a wireless-based solution (for example, exploiting cellular networks) might be the right choice since it allows the central control unit to act as a base station, broadcasting the control actions to the local users. In large and distributed networks, instead, powerline communication (PLC) based solutions might be the ones to go for. Note that the PLC technology besides enabling communication over distribution lines, can also be utilized for the estimation of their impedance. Moreover, the PLC network topology is the same as that of the electrical grid which utilizes it. Hence, as a side product, PLC can also be exploited to get topology estimates, which may then be a valuable information to certain smart grid algorithms [21, 55].

1.2.4 Formal Grid Representation

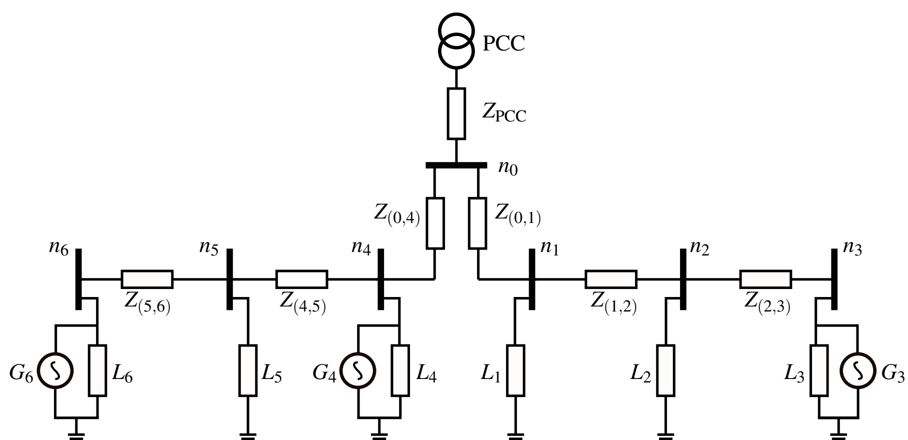

Fig. 1.2 Grid example.

In this section, the mathematical notation used in the rest of this chapter is introduced. Let the *smart grid* agents (i.e., the end users and the PCC) be represented by the set $\mathscr{N}$ in (1.1),

$$\mathscr{N} = \{n_0, \ldots, n_N\} \subseteq \mathbb{N}\,. \tag{1.1}$$

End users will be called nodes from now on. Moreover, let n_0 be the PCC.

The distribution grid is represented as a graph $(\mathscr{N}, \mathscr{E})$, where the node set $\mathscr{N}$ contains the vertexes and $\mathscr{E}$ is the set of arcs connecting pairs of vertexes, representing the distribution lines. Each arc (i, j) is weighted by the quantity $Z_{(i,j)} \in \mathscr{Z} \subseteq \mathbb{C}$ representing the impedance associated with the distribution line (i, j) at the utility frequency. Equations (1.2) and (1.3) represent the *load* and *prosumer* sets, $\mathscr{L}$ and $\mathscr{G}$ respectively.

$$\mathscr{L} \subseteq \mathscr{N}\,, \tag{1.2}$$

$$\mathscr{G} \subseteq \mathscr{N}\,. \tag{1.3}$$

Loads and *prosumers* (which from now on will be called distributed generators, DGs) are subsets of the node set. Each load is identified by $L_i,\ i \in \{1, \ldots, N\}$ where i identifies the index of the node n_i to which L_i refers to. Similarly, DGs are identified by $G_j,\ j \in \{1, \ldots, N\}$. The PCC is considered as a special DG, hence it is always true that $n_0 \in \mathscr{G}$. $\mathscr{L}$ and $\mathscr{G}$ are disjoint set. Moreover, let $L, G \leq N$ be the cardinalities of $\mathscr{L}$ and $\mathscr{G}$, respectively. In this representation, nodes can be considered as buses from a power systems point of view, hence the two terms will be used interchangeably in this chapter. As said before, loads can be classified into three main categories (i.e., constant power, constant impedance and constant current). If needed, the load type will be specified by $L_i^{(k)},\ k \in \{1, 2, 3\}$, where $k = 1$ identifies a constant power load, $k = 2$ identifies a constant impedance load and $k = 3$ identifies a constant current load.

In order to provide a full electrical description of each network element, four quantities are associated to each node, load, and DG. These quantities are the current ($I \in \mathbb{C}$), the voltage ($V \in \mathbb{C}$) , the active ($P \in \mathbb{R}$) and the reactive ($Q \in \mathbb{R}$) power, as shown in (1.4).

$$\begin{cases} V_{n_i}, I_{n_i}, P_{n_i}, Q_{n_i} & \forall\ i \in \mathscr{N} \\ V_{L_i}, I_{L_i}, P_{L_i}, Q_{L_i} & \forall\ L_i \in \mathscr{L} \\ V_{G_i}, I_{G_i}, P_{G_i}, Q_{G_i} & \forall\ G_i \in \mathscr{G} \\ V_{Z_{(i,j)}}, I_{Z_{(i,j)}}, P_{Z_{(i,j)}}, Q_{Z_{(i,j)}} & \forall\ (i, j) \in \mathscr{E} \end{cases} \tag{1.4}$$

Fig. 1.2 shows a power grid example. End users are connected to the distribution lines (identified by $Z_{(i,j)}$) through the nodes (also called buses) $n_1, \ldots, n_6$. Consumers are represented electrical loads, namely L_1, L_2, and L_5. Prosumers are represented through the parallel connection of an electrical load and a generator, namely (L_3, G_3), (L_4, G_4), and (L_6, G_6). Node n_0 represents the connection point between the PCC and the distribution grid.

1.3 Electrical Grid: Open Problems and Solutions

As stated in [17], the quality of the power delivered by the electric utilities has become one of the main concerns for the end users and the energy provider. This is due to a number of reasons, the main ones being that *i)* loads have become more sensitive to power quality variations, *ii)* there is a worldwide quest for increasing the efficiency of the distribution system, and *iii)* end users are more aware of what happens in the distribution grid, and hence they pay more attention to the quality of the power being delivered. The *smart grid*, thanks to the interconnection of measurement units (i.e., synchrophasors), DGs, and control algorithms, may have a great impact on the improvement of the quality of the power delivered to the end users. An important goal, which can be reached through the interconnection and the subsequent control of the aforementioned DG devices is the reactive power management. In this section, two main topics that heavily affect the power quality and that can be alleviated through an intelligent reactive power management are investigated, namely, *i)* voltage stability, and *ii)* distribution power loss reduction.

1.3.1 Voltage Stability

According to the IEEE/CIGRE definition:

"the term voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition. It depends on the ability to maintain/restore equilibrium between load demand and load supply from the power system. Instability that may result occurs in the form of a progressive fall or rise of voltages of some buses. A possible outcome of voltage instability is loss of load in an area, or tripping of transmission lines and other elements by their protections leading to cascading outages that in turn may lead to loss of synchronism of some generators".

With regards to voltage stability, DGs can have a positive impact by stabilizing the voltages in the portions of the grid where they operate. The ability of a power system to maintain the grid voltage levels stable and within the operating limits under different load conditions is measured through the so-called voltage stability margins. One of the most common voltage stability margin is the Saddle Node Bifurcation (SNB). This voltage margin is based on the difference between the active power actually delivered measured at a bus of the grid and the active power corresponding to the SNB point of the bus Power-Voltage curve. Fig. 1.3 shows an example of the voltage stability margin. It can be noticed that as the active power delivered by the considered bus grows (which is identified by P_{op} and corresponds to an increase of the load in the considered portion of the grid), the voltage at the same point gradually decreases. As the maximum deliverable active power (P_{max}) is met, the voltage suddenly drops and the delivered active power starts decreasing as well. This condition may lead to a *voltage collapse* and, consequently, to blackouts. When adequately coordinated/placed/sized, by injecting power in the grid, DGs can

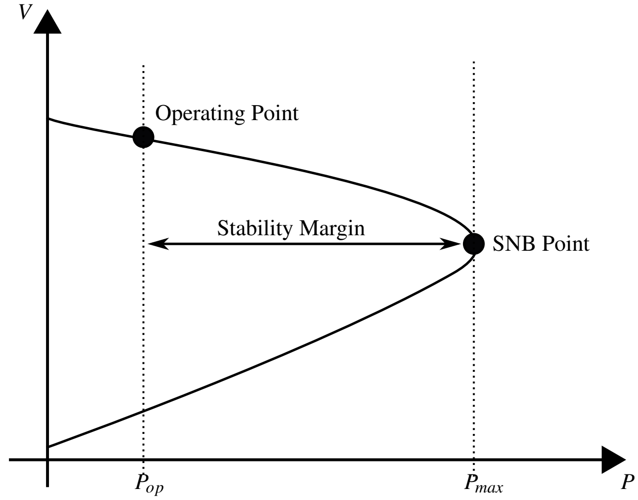

Fig. 1.3 Saddle Node Bifurcation voltage stability margin example.

reduce the power P delivered at the bus, hence a voltage rise happens and the stability margin increases. In [3], for example, the impact of DGs on the voltage stability in power grids is analyzed. In that paper, the authors show that when the power demand in the grid increases DGs do not cause voltage stability issues when operating in acceptable voltage conditions. Moreover, in [34] it is shown that, when the amount of power injected by the DGs is controlled, their distributed generation can enhance the overall system performance in terms of steady state voltage profile and voltage stability. As expected, this enhancement becomes more pronounced as the number of DGs in the grid grows. Given these encouraging results, great effort has been devoted to studying the placement of DGs, their dimensioning, and control policies to provide voltage stability in distribution grids.

In [29], the impact of reactive power management on the voltage stability of the grid is evaluated. Moreover, a heuristic management algorithm is proposed. In this work, the DGs are used to inject a controlled amount of reactive power in the grid in order to minimize the voltage fluctuations measured at the buses. To determine the optimal amount of reactive power that each DG has to inject, an optimization problem is formulated. In (1.5) the objective function of the proposed optimization problem is shown. This function measures the weighted sum (by means of the parameters $\omega_1, \omega_2 \in \mathbb{R}^+$) of the total voltage deviation with respect to the specified voltage V_i^{spec} that each node should achieve and the total reactive power injected by the DGs. The voltage deviation has to be minimized, while the reactive power has to be maximized to relieve the main supplier from some of the reactive power demand. The constraints for this optimization problem depend on the physical limitations of the devices installed in the grid.

$$U = \omega_1 \sum_{i=1}^{N} |V_{n_i}^{spec} - V_{n_i}| + \sqrt[3]{|V_{n_i}^{spec} - V_{n_i}|} + \omega_2 \sum_{i \in \mathscr{G}} Q_{n_i} \,. \tag{1.5}$$

To maximize Eq. (1.5), the authors use a centralized approach requiring little communication. The voltage at each bus, together with the injected reactive power must be sent to a central controller which, in turn, uses a genetic optimization approach. The resulting optimal reactive power that each DG has to inject is then dispatched. Quantitative results demonstrate the effectiveness of controlled power injection (i.e., injection of reactive power by the DGs) in ameliorating the voltage stability margin of all the buses of the considered power grid [29].

Another important aspect is the placement and sizing of DGs. Some of them are installed directly by the end users and, in turn, their size and placement cannot be controlled by the utility operator (actually, these facts can be influenced by incentives that are beyond the scope of this chapter). In future *smart grids*, it is expected that the utility operators will install smart power production units based on renewables acting as DGs. Hence, the problem of finding optimal positions and sizing for these DGs is well founded. Several approaches to accomplish this task have been proposed so far. In this chapter, two of them are briefly discussed. It is worth recalling that placement and sizing of DGs are not dynamic procedures. They require knowledge of the grid topology and its load distribution. Moreover, the computation of the optimal parameters is once for all (offline) when DGs are installed. In [40], the authors used the voltage stability margin proposed in [48], which differs from the SNB presented above. This margin, referred to here as *SI*, turns out to be useful when placing and sizing DGs, as it requires to solve the power flow equations of the grid only once, considering pairs of buses connected by one distribution line. In (1.6), the computation of *SI* for a generic bus j connected to a bus i is shown.

$$SI(n_j) = 2V_{n_i}^2 V_{n_j}^2 - V_{n_j}^4 - 2V_{n_j}^2 (P_{n_j} R_{(i,j)} + Q_{n_j} X_{(i,j)}) - |Z_{(i,j)}|^2 (P_{n_j}^2 + Q_{n_j}^2) \,. \tag{1.6}$$

Solving the power flow equations allows to know the voltages of all the nodes and the currents of all the branches. Hence, the quantities P_{n_j} and Q_{n_j} can be easily calculated $\forall n_j \in \mathscr{N}$. The bus with the lowest *SI* is the most prone to voltage collapse, and hence is the best candidate for the placement of a DG. The sizing of DGs highly depends on the grid load conditions and in [40] is determined heuristically. This method results in a considerably increased stability margin for all the considered scenarios, although, if no attention is paid to the reduction of power losses, these may actually increase as a result of placing the DGs.

In [2], the stochastic nature of the power production from DGs based on renewables and of the power demand from the loads are considered and a mixed integer nonlinear maximization problem is formulated. Firstly, a statistical analysis of the power production (i.e., solar irradiance and wind speed) and load power demand is performed based on a data set spanning over three years. The result of this analysis is a 24 h average day for each one of the four seasons (hence, 96 possible combinations) for power production and demand. DGs and loads are then represented according to this model. Let $Pr[\xi]$ be the probability of the output power and load demand $\xi \in \{1,\ldots,\Xi\}$, where Ξ is the number of possible combinations. Moreover, let V_P^{DG} and $V_P^{\mathrm{No\ DG}}$ be the voltage profiles of the grid with and without DGs, respectively. The utility function is defined as in (1.7),

$$U = \frac{\sum_{\xi=1}^{\Xi} \frac{V_P^{\mathrm{DG}}}{V_P^{\mathrm{No\ DG}}} Pr[\xi]}{96}, \tag{1.7}$$

which is subject to several constraints representing the physical limitations of the power grid (i.e., voltage limits, devices capacities, etc.) and the maximum number of available DGs. Simulation results show that solutions exist (i.e., placement and sizing of the DGs) for which the stability margin is greatly improved. These results are also confirmed by [40].

An interesting point of [2] is the probabilistic approach to the modeling of the power production of DGs and the power demand of the loads. This approach allows for the simulation of many dynamic power systems using random data generators, whose probability distributions are based on real-world data, see, e.g., [8, 36]. It is the authors' opinion that this approach is of high value for the development of future *smart grids*. Using algorithmic techniques to synthetically generate a large number of distribution grids [39] allows studying the impact of new solutions on a large number of scenarios without the burden of collecting new data for each, see [10]. Moreover, being able to generate the electrical grid parameters, according to randomly generated data (whose probability distributions are based on real world data sets) may have a great impact on the quantitative assessment of new control schemes.

1.3.2 Power Distribution Loss Reduction

Power distribution losses are the result of current flowing through the distribution lines. Considering a distribution line with equivalent impedance Z and a current I flowing through it, the dissipated power is $P = I^2R$ due to Joule's effect. When delivering power to the end users, distribution losses have many downsides for the costumers and the energy producer. From the costumers' point of view, the main downside is that the dissipated power must be paid even though it is not consumed. From the producer's point of view, power dissipation shortens the life of distribution lines because of the heat generated by the Joule's effect. Moreover, the losses force the generators to produce more power, hence having higher working regimes. In distribution systems, line impedances can be changed only by actually replacing the distribution lines, and this solution is economically impractical. Hence, the only viable way to reduce power distribution losses is to reduce the amount of current flowing through the distribution lines. Since the dissipated power is proportional to the square of the current flowing through the lines, even a small reduction of the current can result in a substantial improvement on the efficiency of the power delivery process. To this end, three approaches are possible: *i)* move the power supply closer to the power's destination, hence reducing the path length the current travels to supply the loads, *ii)* reduce the amount of current flowing through the line, and *iii)* a mixture of *i)* and *ii)*. These three methods can be implemented exploiting the DGs operating in a grid-connected way. The first mentioned way requires that the DGs inject a certain amount of current based on the total amount of power needed in the area where it is economically convenient for them to operate. Operating in this way, the path the current travels before reaching its destination is shortened and hence also the power distribution losses are reduced. The second way is based on the fact that the cosine of the phase shift between voltage and current (called power factor) equals the ratio between the active and the apparent powers (i.e., the power that is actually used by the load and the delivered power, respectively). The power factor is formally expressed through (1.8):

$$\cos\phi = \frac{P}{S}\,. \tag{1.8}$$

A first result coming from (1.8) is that achieving a unitary power factor (i.e., $\phi = 0$) assures that all the delivered power can actually be converted into work. Moreover, from (1.8), and recalling that $S = VI$, (1.9) holds,

$$P = S\cos\phi = VI\cos\phi\,. \tag{1.9}$$

(1.9) tells that, in order to reduce the current flowing through the distribution lines while keeping the voltage fixed, the power factor must be raised as close as possible to 1. Recalling that the apparent power S results from $S^2 = P^2 + Q^2$, it holds that a unitary power factor means that no reactive power flows through the lines. This condition is not acceptable, since many loads (for example electric motors and, in general, every load that has inductive or capacitive components) need a certain amount of reactive power. Once again, DGs can be coordinated to supply small areas with the correct amount of reactive power, hence moving the apparent power delivered by the main supplier as close as possible to the active power that is actually needed. The third way is the most effective, yet far looking, approach. We can implement this by having the DGs 1) to locally supply a fraction of the active power required by the end users and, at the same time, 2) to allow their cooperation to keep the power factor (as seen by the main power supplier) as close as possible to 1, by selectively injecting reactive power into the grid. Through this approach, power distribution losses can be drastically reduced. In the following, three methods exploiting the cooperation between DGs to reduce the power distribution losses are presented and discussed. In [51] and [50] the authors propose a lightweight control scheme for reactive power control solely based on local measurements. In [50], a local control scheme for reactive power injection is introduced. Considering a DG G_i with an associated load L_i, the proposed scheme compensates for the needed reactive power Q_{L_i} by injecting Q_{G_i}, as defined in (1.10),

$$Q_{G_i} = \min(Q_{G_i}^{max}, Q_{L_i})\,, \tag{1.10}$$

where $Q_{G_i}^{max}$ is the maximum reactive power that the DG's inverter can generate. In [51], voltage control is taken into account as well. Considering a node n_i connected to a node n_j through line $Z_{(i,j)}$, in order to reduce the voltage variation at node n_i, the power combined power flow $R_{(i,j)}P_{(i,j)} + X_{(i,j)}Q_{(i,j)}$ must be minimized. To do so, (1.11) must hold,

$$Q_{G_i} = \min\left(Q_{G_i}^{max}, Q_{L_i} + (P_{L_i} - P_{G_i})\frac{R_{(i,j)}}{X_{(i,j)}}\right). \tag{1.11}$$

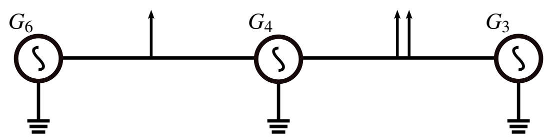

Fig. 1.4 Grid example.

To reduce the power distribution losses, while minimizing voltage variation, the authors combine (1.10) and (1.11) through a weighted sum. Their results show that even these simple schemes can have a great impact on the reduction of power distribution losses. More refined schemes fully exploiting a communication infrastructure to achieve cooperation between end-users have been proposed. For example, in [49] a fully distributed power loss minimization algorithm where DGs are coordinated through a token ring control approach is proposed. Considering Fig. 1.4, the voltage $V_{G_i}^*$ that G_i should reach in order to operate in the best condition with regards to the power loss minimization task is given by (1.12),

$$V_{G_i}^* = \frac{\sum_{k \in \mathscr{C}_k} \frac{R_{(i,k)}}{Z_{(i,k)}^2} V_{G_k}}{\sum_{k \in \mathscr{C}_k} \frac{R_{(i,k)}}{Z_{(i,k)}^2}}. \tag{1.12}$$

By sharing their actual voltage with their neighbors and estimating the impedance of distribution lines, DGs are in the position of evaluating the optimal voltages they should achieve. These voltages are then reached through iterative current injections, as dictated by (1.13) and (1.14),

$$Re(\Delta I_{G_i}) = \frac{R_i^{eq}(Re(V_{G_i}^*) - V_{G_i}) + X_i^{eq} Im(V_{G_i}^*)}{Z_i^{eq2}}, \tag{1.13}$$

$$Im(\Delta I_{G_i}) = \frac{-X_i^{eq}(Re(V_{G_i}^*) - V_{G_i}) + R_i^{eq} Im(V_{G_i}^*)}{Z_i^{eq2}}, \tag{1.14}$$

where Z_i^{eq} is the equivalent Thevenin impedance seen from node n_i, and V_{G_i} is assumed to be real. The results proposed in this work show that by coordinating the end-users equipped with DGs, the power distribution losses can be further reduced with respect to the previous two cases (i.e., where the DGs are operated independently, with no coordination).

Many other distributed algorithms for the reduction of power distribution losses through the coordinated operation of DGs have been proposed. It is beyond the scope of this chapter to analyze and discuss all of them in details. If interested, the reader can further check [5,7], as these represent two technically sound approaches.

1.4 Pricing: Open Problems and Solutions

Economics is expected to play a major role in the *smart grid* infrastructure. A noticeable effort has been devoted to developing efficient demand response algorithms that the energy provider can utilize to shape the end-users energy demand. Moreover, new electricity market models and energy pricing strategies tailored to enforce and promote the cooperation between the *prosumers* and the utility to boost the grid stability and efficiency are emerging. Agents implementing demand response algorithms usually exploit a communication infrastructure to dispatch real time energy price information. The price is used by end users to determine whether some appliances should be utilized or not. Some form of reward (as for example economic benefits) might also be implemented in the demand response algorithms to incentivize the end users towards adopting a good behavior. Market models and pricing strategies that enforce the cooperation among *prosumers* are paramount elements for the techniques introduced in the previous section to work. As a matter of fact, end users that decide to install energy production plants based on renewables have to face non negligible initial investments and maintenance costs. In order for these users to cooperate to the whole grid's benefit, some form of economic incentive must be put in place to reward cooperative behaviors. Although very appealing, these aims are still under debate and a widely accepted solution is yet to come, as stated in [16].

1.4.1 Demand Response

As noticed in [43], many benefits may come from embracing the demand response paradigm. These benefits range from savings on the electricity bills for the end users involved (and also by end users that are not involved, as a consequence of reduced wholesale market prices), increased reliability and stability of the grid (and, hence, increased customer satisfaction), enhanced market performance, an increased number of choices for electricity costs management, and increased system security. The implementation of demand response algorithms requires the presence of control and measurement devices as, for example, communication devices and synchrophasors. These devices are also much needed for implementing the electrical optimization techniques discussed in the previous section, hence it becomes clear that the role of ICT, in terms of hardware and control software, and the utilization of the data they allow to collect and share are key enablers for the *smart grid* infrastructure.

Examples of demand response schemes can be found in [18, 19, 35, 42]. All these schemes set up mathematical optimization problems to determine the best demand response policy according to the system condition and the to desired outcome. Possible desirable outcomes are the economic benefit of the end users with respect to the case where no demand response is in place, diminished production cost for the energy producer, diminished peak workload for the energy producer, and combinations of the previous ones. The results presented in the mentioned papers lead to the conclusion that demand response is effective in achieving the desired goals.

1.4.2 Electricity Markets

The development of new electricity market models that account for the presence of DGs and that incentivize the end users, not only to install DGs (hence to become *prosumers*) but also to cooperate to the efficiency of the power grid as a whole is currently an open issue. Work has been done in defining new mathematical frameworks that model a multi-utility electricity market (i.e., a market in which multiple energy providers compete in selling their energy to a specific group of end users). For example, in [47] a model allowing for the forecast of electricity prices in a multi utility scenario has been developed. In this work, the authors notice that electricity markets differ from other markets (as, for example, the oil market) and hence they develop a price forecasting model different from the standard day ahead prediction. The model proposed in [47], however, does not account for the presence of small generation units (i.e., DGs) willing to sell small, yet potentially crucial for the grid's efficiency, amounts of energy to the utility or directly to other end users. In [11, 26, 31] market models integrating the presence of distributed energy resources are introduced. However, no strategy for the energy trading between end-users is devised, which is nowadays a much advocated scenario, see, for example, [28] and also the European project "Peer to Peer Smart Energy Distribution Networks (P2P-SmartTest)".

1.5 Serious Games

Several researches have been conducted on the use of gamification as a tool to promote a wise use of energy in households or work places.

In [44], aspects of gamification were applied to motivate users to adopt and develop proactive behaviors in an intelligent environment scenario. The authors use indicators (extracted from sensor readings) to assess the energy efficiency of different rooms in a building. This information is then processed through a reasoning (context-based) engine that builds recommendations, in order to promote energy virtuous behavioural changes. To promote competition among users, with the general objective of improving energy sustainability indicators, the authors exploit gamification elements such as: game points, levels, achievements, and leaderboards. Their results demonstrate that gamification helps stimulate the competitiveness among users, resulting in a desire to achieve the global objective with more determination and proactively. Other works like [32, 46] exploit a cooperative game among coworkers in order to achieve energy savings in their workplace. [46] focuses on the design requirements of a pervasive game and indicates three main points: unobtrusiveness, cooperation, and privacy. The game the authors came up with just sends feedback to the users about their performance, without requiring an active participation. The game sets goals and quests in order to get points. Results shows that the cooperative aspect of the game was the main driving force for the success of the experiment. In [32], a rather large contractor enterprise (over 300 employees in five locations) was involved in a collaborative game. Teams were organized by work units so that employees were on a team with the coworkers they worked with most regularly. A website was set up, where user could claim points, submitting actions, sharing photos and stories. Over the course of a six-month game there were small monthly cash prizes for individuals in the lead to keep the users involvement high. In the context of households' energy consumption, [12] identifies raising collective awareness as the key aspect to enable behavioural changes and motivate people in making sustainable decisions about energy consumption. The authors state that feedback systems and social connectivity constitute the essential elements to motivate the participation of players and their engagement, the same conclusions were drawn in [15]. They design of a mobile service based on social mediated interaction through a game design, investigating competitive and a cooperative approaches, concluding that if no other involvement strategies (i.e., monetary rewards) are given, players tend to prefer the competitive aspect. The authors of [25] developed a game with a stimulating user interface for the definition and management of flexibilities in the use of home appliances, embedding a scoring system and social competition aspects to promote participation. However, the study just evaluates the learnability and the ease of use of the developed framework, without investigating the long-term user engagement.

A recent paper [27] provides a comprehensive discussion of gamification approaches, analyzing their effectiveness in terms of O1) motivational affordances, O2) psycological outcomes and O3) behavioral outcomes. The final conclusions are that gamification does seem to work but with some caveats. Methodological limitations were in fact identified in previous studies such as: small sample sizes (e.g., twenty users), the lack of validated psychometric measures, some experiments lacked control groups, many experiments only present descriptive statistics, the timeframes for the trials were in most cases very short, no single study used multilevel measures jointly considering O1, O2 and O3. Hence, although gamification has received a great deal of attention lately, and is often perceived as a modern and effective way of engaging users, most has still to be understood. At the same time, we lack well established theoretical and validation frameworks, it is not clear whether successes were in some cases due to the fact that the experiments/projects have addressed a population segment with certain qualities and so on.

1.6 Big Data Analytics

New technologies are starting to permeate through the power grid, encompassing energy generation, transmission and distribution. Renewable energy sources such as wind, sun and geothermal are being widely adopted, not only by power utilities but also by end users (e.g., through solar panels or small wind turbines). Phasor Measurement Units (PMUs) are being used over long-distance transmission networks for detection and prevention of failures and, at the same time, smart metering technology is being massively installed at end user's premises to monitor, in realtime, the energy consumption of households. A great deal of communication technologies is also required to permit the communication between end users (e.g., local energy systems in households) and the electrical utility.

All of this entails a massive amount of information that is being gathered and of control signals that are being distributed to the customers according to the *demand response* paradigm. Control actions are devoted to adjusting the energy consumption from the customers so as to match the energy supply with the demand. Note that this is especially important in the presence of renewables, as these often have an erratic behavior which does not necessarily follow the actual load (the energy request). It is thus clear that modern smart grids are progressively becoming *Cyber-Physical Systems (CPS)*, where communication technologies, machine learning and adaptation are key elements.

Various experimental initiatives involving data mining are flourishing worldwide. Among many, we cite the Los Angeles Smart Grid Project [45], which is sponsored by the US Department of Energy. This initiative was launched in 2010 and is set to transform the Los Angeles municipal utility into a Smart Grid. Its main goals are: *i)* install smart meters to thousands of customer premises, *ii)* implement and experiment with demand response mechanisms, *iii)* develop scalable machine-learning algorithms trained over large amounts of data to *forecast the demand* at intervals of 15 minutes (for single buildings and aggregate structures) within a few hours or the next day. The *demand response* control loop roughly entails the following steps:

1. Monitor and send data from households to aggregators and from here to the utility servers (utilizing a cloud-based infrastructure).
2. Ingest, store, share and visualize the data.
3. Forecast power demand and renewable energy income from the distributed sources.
4. Decide the best *demand response* strategy based on: 1) current demand, 2) predicted demand, 3) current generation capacity, 4) predicted generation capacity from renewables.

Reliable forecast algorithms are key to a successful application of this control strategy and we believe that the problem of forecasting demand and energy resources is still open. Various algorithms are emerging such as [4, 22, 30]. In [30], the authors propose a new evolutionary kernel regression technique assessing its performance with real power consumption data. This is a non-parametric approach based on a Kernel-based estimator from Nadaraya and Watson [37, 53]. The authors of [4] propose a data mining approach to predict the peak load of a consumer. To that end, they use support vector regression with online learning. [22] proposes and compares other approaches exploiting Artificial Neural Networks (ANN) and Support Vector Machines (SVMs). Their solutions can forecast electricity demand for individual households with good accuracy. Besides the prediction of demand, as pointed out in [22], the identification of sources of energy consumption within buildings is another key issue for the automated planning of energy schedules. This leads to the appliance recognition problem [33,41], which is another form of data mining, whose value is more localized and inherent to the energy management within the building.

Besides forecasting, other relevant application of data mining techniques lie in the detection of events in large Smart Grids. In [38], the authors use data from Phasor Measurement Units (PMUs) to detect line events in a wide-area power grid. In their paper, they show that machine learning (decision trees with various feature types) can be effectively used to perform line-event detection with performance very close to that attained by a domain expert's hand-built classification rule (when applied to a signal located near a fault). Along similar lines, [13] focuses on Dynamic Vulnerability Assessment (DVA) for self-healing and adaptive reconfiguration of the Smart Grid based on time series analysis. Specifically, the authors apply some data mining techniques to time series (Multichannel Singular Spectrum Analysis, MSSA, and Principal Component Analysis, PCA) as well as SVMs to find hidden patterns in electric signals, which then allow for an effective classification of the system vulnerability status.

As a last example of data mining, we cite [14], where the authors deal with the detection of attacks in network and system management tools for power systems. They analyze a flood attack and a buffer overflow attack causing Denial of Service (DoS) using a testbed-driven, experimental approach. Using a real setup, they perform a careful selection of *attack attributes*, testing how these can be used in combination with a large number of classifiers (e.g., Bayes, neural networks, SVMs, rule-based classifiers, decision trees, etc.) for a total of 64 data mining algorithms. Results are very good, indicating that quite a few algorithms, if properly trained, are able to deliver detection rates higher than 99%.

Overall, we believe that data mining will be one of the most important processing blocks of future Smart Grids. Processes such as the realtime detection of activities, forecasting energy demand and generation, but also tracking the presence of users within buildings (e.g., for automated heating, ventilation, and air conditioning) are unavoidable technologies for an effective implementation of demand response algorithms, the adaptation of the distribution network, the prediction of major faults and their prevention.

1.7 Application Examples

Currently, smart grids are being developed all around the world, including Australia, Canada, China, Europe, India, Japan and the U.S. For a full list of ongoing projects, please refer to [20]. Here, for the sake of brevity, three projects are discussed. The projects considered in this section are, namely, the "Pecan Street Project Inc.", the "Duke Energy West Carolinas Modernization Project", and the "Model City Mannheim Project".

The Pecan Street Project Inc. started in 2009 and was concluded in February 2015. Its aims were to develop and implement an Internet of Energy infrastructure in Austin, Texas (U.S.A.). Home energy monitoring systems, a smart meter research network, energy management gateways, distributed generation, electric vehicles with Level 2 charge systems and smart thermostats are the elements that constituted its smart grid, which counts 1000 residential users (i.e., homes) and 25 commercial users (i.e., small businesses). A consistent part of the end users is equipped with distributed generation devices (i.e., rooftop PV panels) and electric vehicles. The integration of the aforementioned technologies into the power grid allows the users to monitor their energy consumption in real-time at the device level, to control the electricity usage of the appliances and to sell the excess energy back to the grid. The use of level-2 chargers allows utilizing the electric vehicles as additional distributed generators, hence enhancing the energy storage capability and self sufficiency of the end users. Advanced data acquisition and management structures that transform big energy data into useful information are being developed in the scope of this project. The results published in May, 2014, stress the fact that the participation of the end users to the project has been enthusiastic. The possibility of interacting with the grid by acquiring data on consumes and smartly tuning the use of electricity - from the end users perspective - resulted in an increased awareness, satisfaction and economic benefits as well. The final project report states: "[...] By moving towards decentralized energy production and management, utilities can build greater resilience into the grid, reduce the need for costly upgrades to centralized grid infrastructure and offer more services to residents that increase the value they receive from their utility while creating opportunities for new product markets that will generate economic development and local innovation".

The Duke Energy West Carolinas Modernization Project started in May, 2015. It is aimed at providing the end users with reliable and affordable green energy. The current expected investment amounts to 1.1 billion dollars and the project completion is expected in 2019. Expected achievements include: *i)* the modernization and expansion of transmission lines and substations, *ii)* the dismission of the Asheville 376 MW coal power plant and its replacement with a new combined natural gas and solar energy power plant, *iii)* the removal of the coal ash and the ash basin closure. The achievement of these goals is expected to meet the increased power demand (which is expected to grow by more than 15% in the next decade), while preserving the environment from the production of greenhouse gases and reducing the water usage by as much as 97% by 2020. The new production system, moreover, is expected to reduce the production of nitrous oxide, sulfure dioxide and carbon dioxide.

The Model City Mannheim Project is aimed at integrating the different areas of which a smart grid is made of, namely, electronics, ICT and economics, in order to create an Internet of energy. This project is based on an intelligent power network working as a market place where power supply and demand interact. An intelligent controller, called “energy butler” and installed at the end users, optimizes the power usage in terms of energy and economic efficiency. This control is a key element in the Mannheim project and allows a full interaction between the end users and the power grid. By embracing this system, the end users have a chance of reducing their environmental impact and of experiencing a different kind of power grid usage model. This system is based on the efficient and fast interaction of all the components in the distribution network. The Mannheim project is based on IP-based communication on a broadband powerline communication infrastructure that exploits the existing electricity grid. The project results have shown that the total power consumption dropped by a considerable amount. Moreover, the end users behavior changed thanks to the real time energy monitoring, made possible by the energy butler, leading to considerable economic benefits. This project, from the initial 200 end users involved, nowadays involves 1500 end users and is claimed to be scalable and applicable all around the world.

1.8 Conclusions

In this chapter we have elaborated on the usefulness of smart grid technology for smart cities. Our discussion started from electrical optimization schemes aimed at increasing the quality of power, reducing power losses and preventing failures or blackouts. We thus delved into the description of market policies, gamification strategies and data mining, by summarizing the scope and the results of some successful deployments. As expected, smart grids are proven to be of great value for future cities, are expected to provide economical benefits for all the actors involved, while also benefiting the environment through a reduction of CO2 emissions (as testified by nearly all technical studies and experimental trials).

Techniques such as power injection, load balancing and demand response seem to be a well studied ground, featuring a variety of centralized and distributed solutions. What instead deserves further investigation is the use of gamification approaches, which looks at an embryonic stage. Although it has potential, its actual effectiveness is still unknown for real installations and a sound and methodical evaluation practice is still to be found.

Data mining is as another very much needed and lively field of research, which is becoming increasingly important and is found less explored than electrical optimization algorithms. Especially, its integration within forecasting techniques, demand response, failure detection / prevention and communication security are still very much open to future developments.

References

1. United States Climate Action Report 2014. First Biennial Report of the United States of America. U.S. Department of State (2014)
2. Al Abri, R.S., El-Saadany, E.F., Atwa, Y.M.: Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. IEEE Transactions on Power Systems **28**(1), 326–334 (2013). DOI 10.1109/TPWRS.2012.2200049
3. Araujo, F.B., Prada, R.B.: Distributed generation: Voltage stability analysis. In: Proc. IEEE Conference on PowerTech (POWERTECH). Grenoble, FR. (2013)
4. Aung, Z., Toukhy, M., Williams, J.R., Sanchez, A., Herrero, S.: Towards Accurate Electricity Load Forecasting in Smart Grids. In: Proc. International Conference on Advances in Databases, Knowledge and Data Applications. Saint Gilles, Reunion Island (2012)
5. Bolognani, S., Carli, R., Cavraro, G., Zampieri, S.: Distributed reactive power feedback control for voltage regulation and loss minimization. IEEE Trans. Automatic Control **60**(4), 966–981 (2015). DOI 10.1109/TAC.2014.2363931
6. Bolognani, S., Zampieri, S.: Distributed control for optimal reactive power compensation in smart microgrids. In: Proc. 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC). Orlando, FL, U.S. (2011)
7. Bolognani, S., Zampieri, S.: A distributed control strategy for reactive power compensation in smart microgrids. IEEE Trans. Automatic Control **58**(11), 2818–2833 (2013). DOI 10.1109/TAC.2013.2270317
8. Bonetto, R., Caldognetto, T., Buso, S., Rossi, M., Tomasin, S., Tenti, P.: Lightweight energy management of islanded operated microgrids for prosumer communities. In: Proc. IEEE International Conference on Industrial Technology (ICIT). Seville, ES. (2015)
9. Bonetto, R., Rossi, M., Tomasin, S., Zorzi, M.: On the interplay of distributed power loss reduction and communication in low voltage microgrids. IEEE Transactions on Industrial Informatics **12**(1), 322–337 (2016). DOI 10.1109/TII.2015.2509251
10. Bonetto, R., Tomasin, S., Rossi, M.: When order matters: Communication scheduling for current injection control in micro grids. In: Innovative Smart Grid Technologies Conference (ISGT), 2015 IEEE Power Energy Society. Washington D.C., U.S. (2015)
11. Cardell, J.B., Chin Yen Tee: Distributed energy resources in electricity markets: The price droop mechanism. In: Proc. IEEE Conference on Communication, Control, and Computing, pp. 58–65. Allerton, IL, U.S. (2010)
12. Castri, R., De Luca, V., Lobsiger-Kgi, E., Moser, C., Carabias, V.: Favouring behavioural change of households energy consumption through social media and cooperative play. In: Proc. Behave Energy Conference. Oxford, UK (2014)
13. Cepeda, J.C., Colomé, D.G., Castrillón, N.J.: Dynamic Vulnerability Assessment due to Transient Instability based on Data MiningAnalysis for Smart Grid Applications. In: IEEE PES Conference on Innovative Smart Grid Technologies (ISGT Latin America). Medellín, Colombia (2011)
14. Choi, K., Chen, X., Li, S., Kim, M., Chae, K., Na, J.: Intrusion Detection of NSM Based DoS Attacks Using Data Mining in Smart Grid. MDPI Energies **5**(10), 4091–4109 (2012)
15. Darby, S.: The effectiveness of feedback on energy. Oxford: Environmental Change Institute (2006)
16. De Martini, P., Wierman, A., Meyn, S., Bitar, E.: Integrated Distributed Energy Resource Pricing and Control. In: CIGRE Grid of The Future Symposium. Kansas City, MO, U.S. (2012)
17. Dugan, R.C., McGranaghan, M.F., Santoso, S., Beaty, H.W.: Electrical Power Systems Quality, Third Edition. McGraw-Hill Education (2012)
18. Duy Thanh Nguyen, Negnevitsky, M., de Groot, M.: Pool-based demand response exchange: Concept and modeling. In: Proc. IEEE Power and Energy Society General Meeting. San Diego, CA, U.S. (2011)

19. Duy Thanh Nguyen, Negnevitsky, M., de Groot, M.: Market-based demand response scheduling in a deregulated environment. IEEE Trans. Smart Grid **4**(4), 1948–1956 (2013)
20. EIA: Smart Grid Legislative and Regulatory Policies and Case Studies (2011)
21. Erseghe, T., Tomasin, S., Vigato, A.: Topology estimation for smart micro grids via powerline communications. IEEE Transactions on Signal Processing **61**(13), 3368–3377 (2013). DOI 10.1109/TSP.2013.2259826
22. Gajowniczeka, K., Ząbkowskia, T.: Short term electricity forecasting using individual smart meter data. In: Proc. International Conference on Knowledge-Based and Intelligent Information and Engineering Systems. Gdynia, Poland (2014)
23. Geisler, K.: The Relationship Between Smart Grids and Smart Cities. IEEE Smart Grid Newsletter Compendium (2013)
24. Glover, J., Sarma, M., Overbye, T.: Power System Analysis and Design, Fifth Edition. Cengage Learning (2012)
25. Gnauk, B., Dannecker, L., Hahmann, M.: Favouring behavioural change of households energy consumption through social media and cooperative play. In: Proc. Joint EDBT/ICDT Workshops, pp. 103–110. Berlin, DE (2012)
26. Guobin Xu, Moulema, P., Wei Yu: Integrating distributed energy resources in smart grid: Modeling and analysis. In: Proc. IEEE Energytech, pp. 1–5. Cleveland, OH, U.S. (2013)
27. Hamari, J., Koivisto, J., Sarsa, H.: Does Gamification Work? – A Literature Review of Empirical Studies on Gamification. In: Proc. IEEE Hawaii International Conference on System Sciences (HICSS). Waikoloa, HI, US (2014)
28. Heinberg, R.: Powerdown: Options and Actions for a Post-Carbon World. New Society Publishers, Nanaimo, BC, CA (2004)
29. Kazari, H., Abbaspour-Tehrani Fard, A., Dobakhshari, A.S., Ranjbar, A.M.: Voltage stability improvement through centralized reactive power management on the smart grid. In: Proc. IEEE Conference on Innovative Smart Grid Technologies (ISGT). Washington D.C., U.S. (2012)
30. Kramer, O., Satzger, B., Lässig, J.: Hybrid Artificial Intelligence Systems, chap. Power Prediction in Smart Grids with Evolutionary Local Kernel Regression. Lecture Notes in Artificial Intelligence. Springer (2010)
31. Kumar, J., Jayantilal, A.: Models of distributed energy resources markets in distribution grid operations. In: Proc. IEEE Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), pp. 1–6. Manchester, UK (2011)
32. Kuntz, K., Shukla, R., Bensch, I.: How many points for that? a game-based approach to environmental sustainability. In: Proc. ACEEE Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA, U.S. (2012)
33. Laia, Y.X., Laib, C.F., Huanga, Y.M., Chaob, H.C.: Multi-appliance recognition system with hybrid SVM/GMM classifier in ubiquitous smart home. Elsevier Information Sciences **230**(1), 39–55 (2013)
34. Londero, R.R., Affonso, C.M., Nunes, M.V.A.: Impact of distributed generation in steady state, voltage and transient stability; real case. In: Proc. IEEE Conference on PowerTech (POWERTECH). Bucharest, RO. (2009)
35. Ma, K., Hu, G., Spanos, C.J.: A cooperative demand response scheme using punishment mechanism and application to industrial refrigerated warehouses. IEEE Trans. Industrial Informatics **PP**(99) (2015). DOI 10.1109/TII.2015.2431219
36. Miozzo, M., Zordan, D., Paolo Dini, P., Rossi, M.: SolarStat: Modeling Photovoltaic Sources through Stochastic Markov Processes. In: Proc. IEEE ENERGYCON. Dubrovnik, Croatia (2014)
37. Nadaraya, E.A.: On Estimating Regression. Theory of Probability and Its Applications **9**(1), 141–142 (1964)
38. Nguyen, D., Barella, R., Wallace, S.A., Zhao, X., Liangt, X.: Smart Grid Line Event Classification Using Supervised Learning Over PMU Data Streams. In: Proc. IEEE Green Computing Conference and Sustainable Computing Conference (IGSC). Las Vegas, NV, US (2015)

39. Pagani, G.A., Aiello, M.: Power Grid Network Evolutions for Local Energy Trading. arXiv:1201.0962 [physics.soc-ph] (2012)
40. Parizad, A., Khazali, A., Kalantar, M.: Optimal placement of distributed generation with sensitivity factors considering voltage stability and losses indices. In: Proc. IEEE Iranian Conference on Electrical Engineering (ICEE). Isfahan, IR. (2010)
41. Ruzzelli, A., Nicolas, C., Schoofs, A., O?Hare, G.: Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor. In: Proc. EEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON). Boston, MA, US (2007)
42. Safdarian, A., Fotuhi-Firuzabad, M., Lehtonen, M.: A distributed algorithm for managing residential demand response in smart grids. IEEE Trans. Industrial Informatics **10**(4), 2385–2393 (2014)
43. Siano, P.: Demand response and smart gridsa survey. Renewable and Sustainable Energy Reviews **30**(C), 461–478 (2014)
44. Silva, F., Analide, C., Rosa, L., Felgueiras, G., Pimenta, C.: Gamification, social networks and sustainable environments. International Journal of Interactive Multimedia and Artificial Intelligence **2**(4), 52–59 (2013)
45. Simmhan, Y., Aman, S., Kumbhare, A., Liu, R., Zhou, S.S.Q., Prasanna, V.: Cloud-Based Software Platform for Big Data Analytics in Smart Grids. Computing in Science & Engineering **15**(4), 38–47 (2013)
46. Simon, J., Jahn, M., Al-Akkad, A.: Saving energy at work: the design of a pervasive game for office spaces. In: Proc. ACM Conference on Mobile and Ubiquitous Multimedia (MUM ’12). Ulm, DE (2012)
47. Skantze, P., Ilic, M., Chapman, J.: Stochastic modeling of electric power prices in a multi-market environment. In: Proc. IEEE Power Engineering Society Winter Meeting, vol. 2, pp. 1109–1114 vol.2. Singapore, SG (2000)
48. Stott, B., Alsac, O.: Fast decoupled load flow. IEEE Transactions on Power Apparatus and Systems **PAS-93**(3), 859–869 (1974). DOI 10.1109/TPAS.1974.293985
49. Tenti, P., Costabeber, A., Mattavelli, P., Trombetti, D.: Distribution loss minimization by token ring control of power electronic interfaces in residential microgrids. IEEE Trans. Industrial Electronics **59**(10), 3817–3826 (2012). DOI 10.1109/TIE.2011.2161653
50. Turitsyn, K., Sŭlc, P., Backhaus, S., Chertkov, M.: Distributed control of reactive power flow in a radial distribution circuit with high photovoltaic penetration. In: Proc. IEEE Power and Energy Society General Meeting. Minneapolis, MN, U.S. (2010)
51. Turitsyn, K., Sŭlc, P., Backhaus, S., Chertkov, M.: Local control of reactive power by distributed photovoltaic generators. In: Proc. IEEE International Conference on Smart Grid Communications (SmartGridComm). Gaithersburg, MD, U.S. (2010)
52. U.A. Bakshi, M.B.: Electrical Power Transmission And Distribution. Technical Publications (2007)
53. Watson, G.S.: Smooth Regression Analysis. Sankhyā: The Indian Journal of Statistics, Series A **26**(4), 359–372 (1964)
54. Willis, H.L.: Power Distribution Planning Reference Book, Second Edition. Power Engineering (Willis). CRC Press (2004)
55. Zhang, C., Zhu, X., Huang, Y., Liu, G.: High-resolution and low-complexity dynamic topology estimation for plc networks assisted by impulsive noise source detection. IET Communications **10**(4), 443–451 (2016). DOI 10.1049/iet-com.2015.0454