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Demand Management and Wireless Sensor Networks in the Smart Grid

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1. Introduction

The operation principles and the components of the electrical power grid are recently undergoing a major renovation. This renovation has been triggered by several factors. First, the grid recently showed signs of resilience problems. For instance, at the beginning of 2000s, California and Eastern interconnection of the U.S. experienced two major blackouts which have caused large financial losses. The second factor to trigger the renovation of the grid is that in a near future, the imbalance between the growing demand and the diminishing fossil fuels, aging equipments, and lack of communications are foreseen to worsen the condition of the power grids. Growing demand is a result of growing population, as well as nations' becoming more dependent on electricity based services. The third factor that triggers the renovation, is the inefficiency of the existing grid. In (Lightner et al., 2010), the authors present that in the U.S. only, 50% of the generation capacity is used 100% of the time, annually, while over 90% capacity is only required for 5% of the time where the figures are similar for other countries. Moreover, more than half of the produced energy is wasted due to generation and transmission related inefficiencies (Lui et al., 2010). This means that the operation of the power grid is rather inefficient. In addition to those resilience and efficiency related problems, high amount of Green House Gases (GHG) emitted during the process of electricity generation need to be reduced as the Kyoto protocol is pressing the governments to reduce their emissions. The renovation targets to increase the penetration level of renewable energy resources, hence reduce the GHG emissions. Finally, the power grids are not well protected for malicious attacks and acts of terrorism. Physical components of the grid are easy to reach from outside and they can be compromised unless they are monitored well.
To address the above mentioned problems, the U.S., Canada, the E.U. and China have recently initiated the smart grid implementations. Smart grid aims to integrate the opportunities that have become available with the advances in Information and Communications Technology (ICT) to the grid technologies in order to modernize the operation and the components of the grid (Massoud-Amin & Wollenberg, 2005). The basic building blocks of the smart grid can be listed as; the assets, sensors used to monitor those assets, the control logic that realizes the desired operational status and finally communication among those blocks (Santacana et al., 2010). These layers are presented in Fig. 1.
The priorities of the governments in the implementation of the smart grid may be different. For instance, the U.S. focuses on energy-independence and security while the E.U. is more

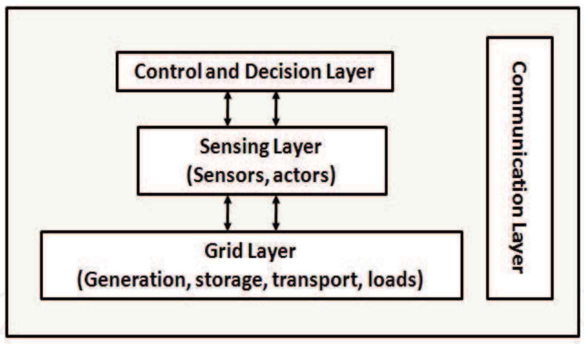

Fig. 1. Building blocks of the smart grid.

concerned about environmental issues and integrating renewable resources. On the other hand, China targets efficient transmission and delivery of electricity. The objectives that are set forward for smart grid implementation can be summarized as:

- Integrating renewable energy sources
- Enabling two-way flow of information and electricity
- Self-healing
- Being environment-friendly
- Enabling distributed energy storage
- Having efficient demand management
- Being secure
- Integrating Plug-in Hybrid Electric Vehicles (PHEV)
- Being future proof

An illustration of a city with smart grid is presented in Fig. 2. The illustration shows distributed renewable energy generation and storage, consumer energy management, integration of PHEVs, and communication between the utility and the parts of the grid.

Among the objectives of the smart grid, demand management will play a key role in increasing the efficiency of the grid (Medina et al., 2010). In the smart grid, demand management extends beyond controlling the loads on the demand-side. Controlling demand side load is known as Demand Response (DR), and it is already implemented in the traditional power grid for large-scale consumers although it is not fully automated yet. DR directly aims to control the load of the commercial and the industrial consumers during peak hours. Peak hours refer to the time of day when the consumption exceeds the capacity of the base power generation plants that are build to accommodate the base load. When the amount of load exceed the capacity of base power plants, they are accommodated by the peaker power plants. Commercial and industrial consumers can have a high impact on the overall load depending on their scale. Briefly, DR refers to those consumers' decreasing their demand following utility instructions and it is generally handled by the utility or an aggregator company. The subscribed consumers are notified by phone calls, for example, to turn off or to change the set point of their HVAC systems for a certain amount of time to reduce the load. In smart grid, Automated Demand Response (ADR) is being considered. In ADR programs, utilities send signals to buildings and industrial control systems to take a pre-programmed

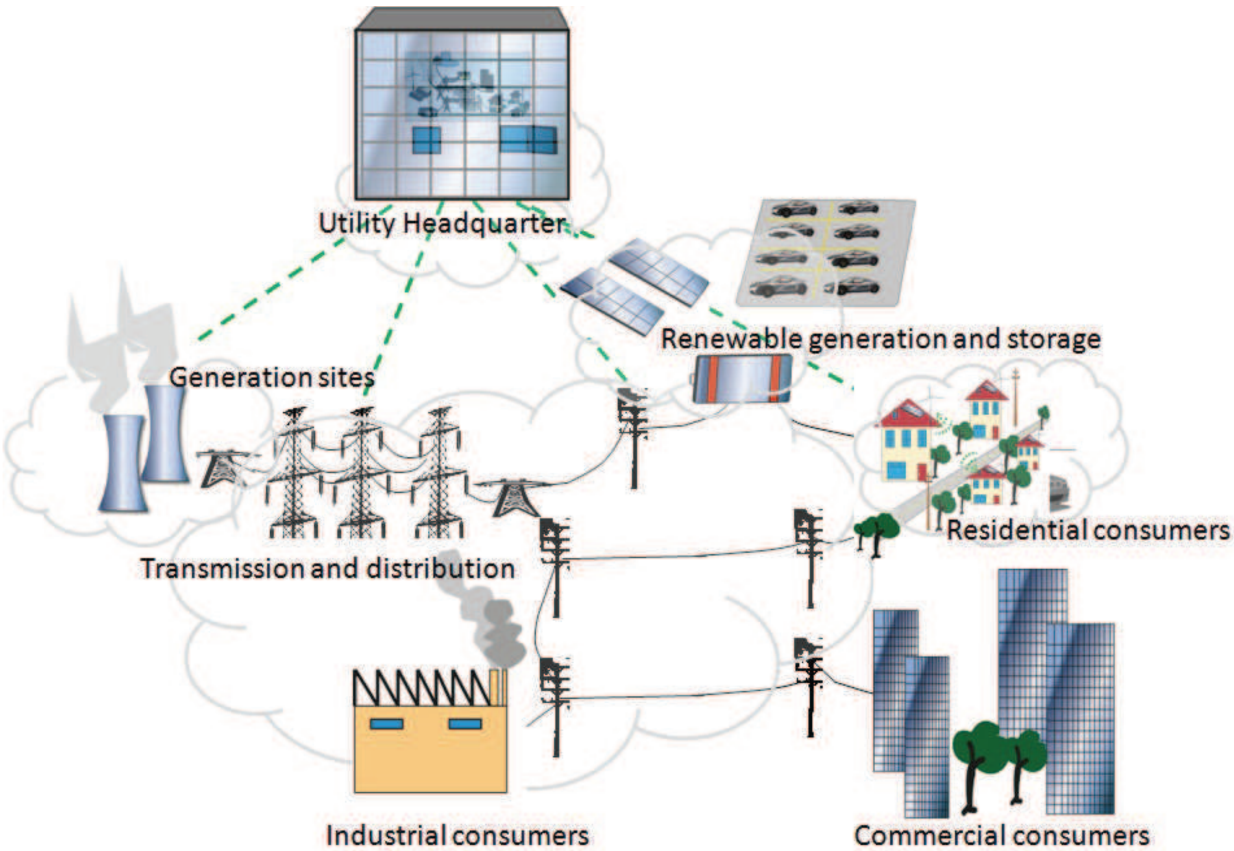

Fig. 2. Illustration of the smart grid with communications.

action based on the specific signal. Recently, OpenADR standard has been developed by the Lawrence Berkeley National Laboratory and the standard is being used in California (Piette et al, 2009). Another well-known data communication standard for Building Automation and Control network is the BACnet. BACnet has been initially developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and later adopted by ANSI (Newman, 2010).

The traditional grid does not employ DR for residential consumers although demand-side management has been discussed since late 1990s (Newborough & Augood, 1999). Previously residential consumers used electricity without feedback about its availability and price (Ilic et al., 2010). In the smart grid, by the use of smart meters, consumers will have information about their consumption without waiting for their monthly or bi-monthly bills.

The smart grid provides vast opportunities in the DR field. The DR solutions target both peak load reduction and consumer expense reduction. Furthermore, in the smart grid, DR is extended to demand management since the consumers are also able to generate energy. Energy generation at the demand-side requires intelligent control and coordination algorithms. In addition to those, widespread adoption of the PHEVs will impose tight operation constraints for the power grids. PHEVs will be charged from the grid and their energy consumption rating may be as high as a households' daily consumption. The PHEV loads are anticipated to multiply the demand for electricity. For those reasons, demand management will become even more significant in the following years (Shao et a., 2010).

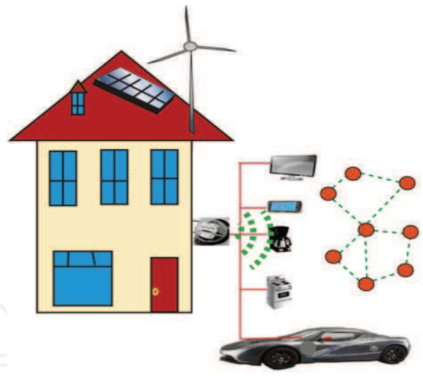

Fig. 3. Smart home with energy generation, WSN and a PHEV.

In the following sections, we will introduce the recent demand management schemes. One of the promising demand management techniques is employing Wireless Sensor Networks (WSNs) in demand management. A WSN is a group of small, low-cost devices that are able to sense some phenomena in their surroundings, perform limited processing on the data and transmit the data to a sink node by communicating with their peers using the wireless medium. The advances in the Micro-Electro-Mechanical Systems (MEMS) have made WSN technology feasible in the recent years, and WSNs find applications in diverse fields. Environmental monitoring and surveillance applications are the pioneering fields to utilize WSNs however following those successful applications, WSNs are today used in tele-health, intelligent transportation, disaster recovery and structure monitoring fields (Chong & Kumar, 2003). WSNs also provide vast opportunities for the smart grid (Erol-Kantarci & Mouftah, 2011a). Especially WSNs can have a large number of applications in demand management in the smart grid since they are able to provide pervasive communications and control capabilities at low cost. Furthermore, they can provide applications that comply with consumers' choices where leaving the consumer as the decision maker is stated as one of the desired properties of the smart grid demand management applications (Lui et al., 2010).
Briefly, there are a large number of opportunities that will become available with the new smart grid technologies however the implementation of the smart grid has several challenges. Regulations and standardization is one of the major challenges. Currently, various governmental agencies, alliances, committees and groups are working to provide standards so that smart grid implementations are effective, interoperable and future-proof. Security is another significant challenge since the grid is becoming digitized, integrating with the Internet, and generally using open media for data transfer. Smart grid may be vulnerable to physical and cyber attacks if security is not handled properly (Metke & Ekl, 2010). Furthermore, successful market penetration of demand management systems is important for the smart grid to achieve its goals. Last but not least, the load on the grid is expected to increase as PHEVs are plugged-in for charging. Unbalanced and uncoordinated charging may cause failures and the smart grid calls for novel coordinated PHEV charging mechanisms (Erol-Kantarci & Mouftah, 2011c). Moreover, as renewable resources become dominant and PHEVs are used as storage devices the intermittency of supply will require rethinking of the traditional planning, scheduling and dispatch practices of the grid operators (Rahimi & Ipakchi, 2010).

In the following sections, we first give a broad perspective on the possible utilization of WSNs in the smart grid. Then, we focus on demand management and introduce the recent demand management techniques which we group under communication-based, incentive-based, real-time and optimization-based demand management techniques. Demand management using WSNs falls under communication-based techniques and they are explained in detail in Section 3.1.

2. Smart grid and Wireless Sensor Networks

In this section, we will briefly summarize the literature on the use of WSNs in the power grid in order give a complete picture of the state of the art. The electrical power grid is a large network that can be partitioned into three main conceptual segments as energy generation, power transmission and electricity distribution, and consumption segments. In the smart grid, the traditional radial organization and this partitioning will change since the electricity will be also produced and used within a distribution system forming a microgrid.

In this section, we follow the organization of the traditional grid for the sake of increasing the understandability of the text. We start with electricity generation sites, continue with power transmission and electricity distribution and finally reach to consumption which is the last mile of the electricity delivery services. WSNs have broad range of applications in all of those segments.

2.1 WSNs for generation facilities

In the traditional power grid, energy generation facilities are generally monitored with wired sensors which are limited in amount and located only at a few critical places. This is due to the high cost of installation and maintenance of those sensors. WSNs offer low-cost sensors that can communicate via wireless links hence have flexible deployment opportunities. In fact, the utilization of WSNs becomes even more essential with the increasing number of renewable energy sites in the energy generation cycle. These renewable energy generation facilities can be in remote areas, and operate in harsh environments where fault-tolerance of WSNs makes them an ideal candidate for such applications. Furthermore, the output of the renewable energy resources is closely related with the ambient conditions such as wind velocity for wind power generation and cloudiness for solar panels. These varying ambient conditions cause intermittent power generation which makes renewable resources hard to integrate to the power grid. For instance, at high wind speeds, to avoid damage to the blades and gears inside the hub of the wind turbine, the turbines are shut off. This causes a steep reduction of output that has to be balanced with other resources (Ipakchi & Albuyeh, 2009). Prediction of such events will give opportunities for preparedness and fast restoration capabilities by the help of backup generators. This emphasizes the importance of ambient data collection. For those reasons, WSNs can offer solutions for renewable energy generation sites, such as solar (PV) farms or wind farms. Furthermore, wireless sensor and actor networks can take part in increasing the efficiency of the equipments.

In (Shen et al., 2008), the authors address the challenge of varying wind power output by employing prediction where WSNs are used to collect and communicate the wind speed prediction data to a central location. WSNs can also be used for condition monitoring of the wind turbines. Wind turbines are expensive equipments which may experience break downs in time due to wear. Early detection of malfunctioning components may increase the lifetime of the wind tribunes and reduce the time spared for maintenance which increases the efficiency of production. In (Al-Anbagi et al., 2011), the authors utilize WSNs for monitoring the condition of the bearings within the gearboxes where accelerometers are used to monitor wind turbine vibration. WSNs are used to provide early detection for bearing failures or other related problems. The authors address the issue of delay-sensitive data transmission in WSNs for a wind turbine by modifying the Medium Access Control (MAC) protocol of IEEE 802.15.4 standard in order to provide service differentiation for critical and non-critical data, and reduce the end-to-end delay for critical data.

A WSN-based energy evaluation and planning system for industrial plants have been introduced in (Lu et al., 2010). The authors have discussed the feasibility of using WSNs and the benefits of replacing the conventional wired sensor with WSNs. A similar WSN-based system can also be used for condition monitoring of power plants. Low-cost, ease of deployment, fault-tolerance, flexibility are among the advantages of the WSN-based systems.

2.2 WSNs for transmission and distribution assets

Transmission system consists of towers, overhead power lines, underground power lines, etc., that are responsible for transportation of electricity from the generation sites to the distribution system. In the traditional power grid, the voltage is stepped up in order to reduce the losses at the transportation, and then, it is step down at the distribution system. Distribution system consists of substations, transformers and wiring to the end-users. In the transmission and distribution segment, an equipment failure or breakdown may cause blackouts or it may even pose danger for public health. Moreover, these assets can be easily reached from outside, therefore they can be a target of terrorism. WSNs, once again, provide promising solutions for monitoring and securing the transmission and distribution segment.

In (Leon et al., 2007), the authors utilize WSNs for detection of mechanical failures in the transmission segment components such as conductor failure, tower collapses, hot spots, extreme mechanical conditions, etc. WSNs provide a complete physical and electrical picture of the power system in real time and ease diagnosing faults. Moreover, power grid operators are provided with appropriate control suggestions in order to reduce the down time of the system. The authors employ a two-level hierarchy where short-range sensor nodes collect data from a component and deliver the collected data to a gateway. This gateway is called as Local Data and Communications Processor (LDCP). The LDPC has the ability to aggregate the data from the sensors, besides it has a longer-range radio which it uses to reach the other LDPCs that are several hundreds of meters away. The mechanical status of the transmission system is processed and delivered to the substation by the LDPCs. This hierarchical deployment increases the scalability of the WSN which emerges as a necessity when the large geographical coverage of the transmission system is considered.

The use of an IEEE 802.15.4 based WSN in the substations has been discussed in (Ullo et al, 2010) and data link performance has been evaluated. The communication services provided by WSNs have been shown to be useful for automation and remote metering applications. Similarly in (Lim et al., 2010), the authors utilize WSNs in transmission and distribution system for power quality measurements. The authors proposed a data forwarding scheme between pole transformers and the substation using multi-hop WSNs. Power quality measurements include harmonics, voltage sags, swells, unbalanced voltage, etc. These measurements are communicated using the IEEE 802.15.4 standard.

Further potential applications of sensor networks in the power delivery system have been defined in (Yang et al., 2007) as:

- Temperature, sag and dynamic capacity measurements from overhead conductors
- Recloser, capacitor, and sectionalizer integrity monitoring
- Temperature and capacity measurements from underground cables
- Faulted circuit indication
- Padmount and underground network transformers
- Monitoring wildlife and vegetation contact
- Monitoring underground network components, e.g. transformers, switches, vaults, etc.

2.3 WSNs for demand-side applications

In the traditional power grid, power grid operators do not have services for the demand-side except the DR programs for large-scale consumers. However, in the smart grid, by using the smart meters and the utility Advanced Metering Infrastructure (AMI), it will be possible to communicate with the consumers. A smart meter and AMI interconnection using Zigbee has been considered in (Luan et al., 2009). Furthermore, energy generation at the consumer premises will be also available. In fact, energy generation by solar panels and wind turbines are already possible, even the locally generated energy can be sold to the grid operators. However, Distributed Generation (DG) is not fully implemented. DG refers to a subsystem that can intentionally island. There are several reasons why this has not been implemented yet. Power quality problems may occur in an islanded system, safety of power personnel may be endangered due to unintentionally energized lines and there might be synchronization problems. In this context, utilization of WSNs can provide efficient monitoring and control capabilities to increase the reliability of the DGs (Sood et al., 2009). WSN applications in the demand-side will be discussed in detail in Section 3.1.

3. Demand management in the smart grid

In the smart grid, it will be possible to communicate with the consumers for the purposes of monitoring and controlling their power consumption without disturbing their business or comfort. This will bring easier administration capabilities for the utilities. On the other hand, consumers will require more advanced home automation tools which can be implemented by using advanced sensor technologies. For instance, consumers may need to adapt their consumption according to the dynamically varying electricity prices which necessitates home automation tools. In the smart grid, time-differentiated billing schemes will be employed. For instance, very soon Time of Use (TOU) will be activated by most of the utilities in North America. TOU rates will be applied to the metering operations by the help of smart meters and the AMI.

TOU is a natural result of consumer activity. Consumer demands have seasonal, weekly and daily patterns. For instance, during overnight hours consumer activity decreases, or heating loads increase during cold days, or similarly cooling loads increase during hot days. The daily load pattern of a typical household on a winter weekday is illustrated in Fig. 4. Morning and evening peaks are visible from this plot. In Fig. 5, we present the accumulated loads of a large

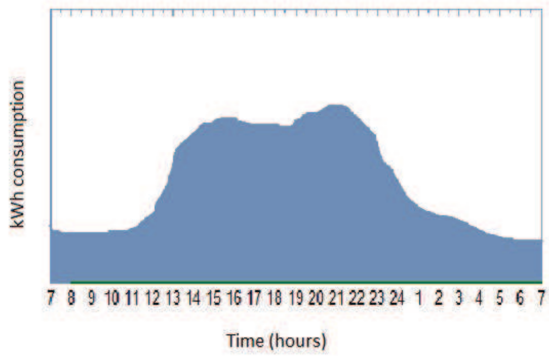

Fig. 4. Illustration of the daily load profile for a winter weekday.

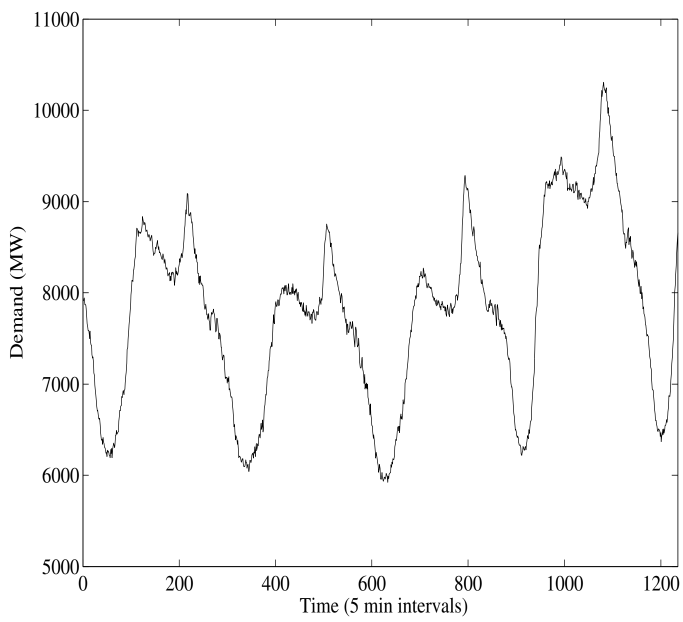

Fig. 5. Electricity load on the grid for four days in winter.

number of consumers collected by the Australian Independent System Operator (AISO). As seen from the figure the peaks become more significant as they are accumulated (Erol-Kantarci & Mouftah, 2010d). The hours of high consumer activity, i.e. high load durations, is called on-peak periods, while moderate and low load durations are called mid-peak and off-peak periods, respectively.

In TOU tariff, electricity is more expensive during peak hours because utilities handle peak load by bringing peaker plants online. Peaker plants have high maintenance costs and they use expensive fossil fuels. They burn coal, natural gas, or diesel which they have shorter response times. On the other hand, those fuels are fossil based and they incur higher CO_2 emissions (Erol-Kantarci &Mouftah, 2010b). They are also expensive fuels, therefore, the generation cost increases during peak hours. To compensate for these costs utilities apply block rates, i.e. TOU. Block rates are different than the conventional flat billing. The price of electricity is fixed during a block of consecutive hours, then it changes for another block of hours. The reason for varying rates are as follows. The length of the block of hours and

	Period	Time	Rate
Winter Weekdays	On-Peak	7:00am to 11:00am	9.3 cent/kWh
	Mid-Peak	11:00am to 5:00pm	8.0 cent/kWh
	On-Peak	5:00pm to 9:00pm	9.3 cent/kWh
	Off-Peak	9:00pm to 7:00am	4.4 cent/kWh
Summer Weekdays	Mid-Peak	7:00am to 11:00am	8.0 cent/kWh
	On-Peak	11:00am to 5:00pm	9.3 cent/kWh
	Mid-Peak	5:00pm to 9:00pm	8.0 cent/kWh
	Off-Peak	9:00pm to 7:00am	4.4 cent/kWh
Weekends	Off-peak	All day	4.4 cent/kWh

Table 1. TOU rates of an Ontario utility as of 2011.

the price for each block is determined by the utilities based on the consumption pattern and the raw market price of electricity. Electricity consumption during peak periods have higher price than consumption during off-peak periods as explained above. Furthermore, higher prices are employed to discourage consumers to use electricity during peak hours, and hence, avoid dangerous grid conditions. The rate chart of an Ontario-based utility is given in Table 1 (online:Hydro Ottawa, 2011) as an example of TOU rates. Note that, TOU hours and rates may vary from one utility to another based on the local load pattern and cost. For instance, cold weather conditions in northern countries increase heating demand throughout the winters whereas, southern countries may have less heating demand during the same period of the year.

In fact, residential demand control has been previously developed for the smart homes. Smart homes employ energy saving applications that can turn the lights off depending on the occupancy of the rooms, or dim the lights off based on outside light intensity and shutter positions, or adjust the thermostat based on the outside temperature and sensor measurements. etc. These type of comfort-focused energy management applications date back to 1990s (Brumitt et al., 2000; Lesser et al., 1999). However, smart home implementations have been rare. Today most of the residential premises do not have such energy management systems. Furthermore, smart home related techniques do not involve communication and coordination with the power grid. The smart grid introduces a number of opportunities for the home energy management and enables, communication-based, incentive-based, real-time demand management and optimization-based techniques which will be described in the following sections. Furthermore, smart grid and WSNs can enable consumers to have more control over their consumption. We will describe a WSN-based home energy management system in the following sections, as well.

3.1 Communication-based demand management

In this section, we introduce four communication-based demand management schemes, which are in-Home Energy Management, iPower, Energy Management Using Sensor Web Services and Whirlpool smart device network.

3.1.1 in-Home Energy Management (iHEM)

In (Erol-Kantarci & Mouftah, 2011b), the authors have used WSNs and smart appliances for residential demand management. This residential demand management scheme is called

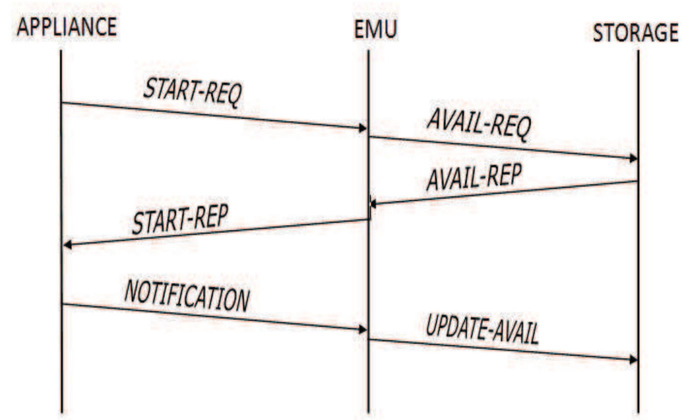

Fig. 6. Message flow for iHEM.

in-Home Energy Management (iHEM). iHEM employs a central Energy Management Unit (EMU) and appliances with communication capability. EMU and appliances communicate via wireless links where their packets are relayed by a WSN. iHEM is based on the appliance coordination scheme that was proposed in (Erol-Kantarci &Mouftah, 2010a;c). It attempts to shift consumer demands at times when electricity usage is less expensive according to the local TOU tariff.

The message flow of the iHEM application is given in Fig. 6. According to iHEM, when a consumer turns on an appliance, the appliance generates a START-REQ packet and sends it to EMU. EMU communicates with the smart meter regularly to receive the price updates of the TOU tariff applied by the grid operator. The authors assume that the smart home is also able to produce energy by solar panels or small wind turbines. Therefore, upon receiving a START-REQ packet, EMU communicates with the storage units of the local energy generators and retrieves the amount of the available energy by sending an AVAIL-REQ packet. Upon reception of AVAIL-REQ, the storage unit replies with an AVAIL-REP packet where the amount of available energy is sent to the EMU. After receiving the AVAIL-REP packet, EMU determines the convenient starting time of the appliance by using Algorithm 1. EMU computes the waiting time as the difference between the suggested and requested start time, and sends the waiting time in the START-REP packet to the appliance. The consumer decides whether to start the appliance right away or wait until the assigned timeslot depending on the waiting time. The decision of the consumer is sent back to the EMU with a NOTIFICATION packet. Afterwards, EMU sends an UPDATE-AVAIL packet to the storage unit to update the amount of available energy (unallocated) on the unit after receiving the consumer decision. This handshake protocol among the appliance and the EMU, ensures that EMU does not force an automated start time. We avoid this approach to increase the comfort of the consumers and to provide more flexibility. Furthermore, energy is allocated on the storage units as per request. Therefore, when the smart home exports electricity (sells), the amount of unallocated, hence available energy will be known.

The format of the iHEM packets are given in the figures below. START-REQ packet format is shown in Fig. 7. The first field of the packet is the Appliance ID. The sequence number field denotes the sequence number of the request generated by the appliance since the appliance may be turned on several times in one day. Start time is the timestamp given when the

Octets: 4	1	4	1
Appliance ID	Seq. No	Start Time	Duration

Fig. 7. START-REQ packet format.

Octets: 4	1	1
Storage ID	Seq. No	Code

Fig. 8. AVAIL-REQ packet format.

Octets: 4	1	2	4
Storage ID	Seq. No	Required Energy Estimate	Stop Time

Fig. 9. UPDATE-AVAIL packet format.

consumer turns on the appliance. The duration field denotes the length of the appliance cycle. Each appliance has different cycle lengths. A cycle could be a washing cycle for a washer or the time required for the coffee maker to make the desired amount of coffee. This duration depends on the consumer preferences, i.e. the selected appliance program. The AVAIL-REQ packet format is given in Fig. 8. The storage ID field is the ID of the storage unit that is attached to the local energy generation unit. When the house is equipped with multiple energy generation devices such as solar panels and small wind tribunes, the amount of energy stored in their local storage units may have to be interrogated separately. The packet sequence number is used for the same purpose as described previously. Code field carries the controller command code. In iHEM, this field is used for inquiring the amount of available energy, hence it is a static value. However, other applications may also use this code field, e.g. to send a command to the storage unit to dispatch energy to the grid. Other code combinations have been reserved for future use. NOTIFICATION packet has the same format as the START-REQ packet. The start-time field of the NOTIFICATION packet denotes the negotiated running time of the appliance, i.e., it could be either the time when the appliance is turned on, or the start time suggested by the EMU. This information is required to allocate energy on the local storage unit when it is used as the energy source. As we mentioned before, since it is further possible to sell excess energy to the grid operators, the amount of energy that needs to be reserved for the appliances that will run with the local energy has to be known ahead. The format of the UPDATE-AVAIL packet is given in Fig. 9. Storage ID and the code fields are explained above. The required energy estimate field, is the power consumed by the appliance multiplied by the duration of a cycle. Stop time denotes the time when the appliance is scheduled to finish its cycle.

The algorithm of scheduling (Algorithm 1) works as follows. EMU first checks whether locally generated power is adequate for accommodating the demand. If this is the case, the appliance starts operating, otherwise the algorithm checks if the demand has arrived at a peak hour, based on the requested start time, St_i. If the demand corresponds to a peak hour, it is either shifted to off-peak hours or mid-peak hours as long as the waiting time does not exceed D_{max}, i.e. maximum delay. The computed delay, d_i is returned to the consumer as the waiting time. D_{max} parameter limits the delay, hence it guarantees a maximum delay for the

Algorithm 1 | Scheduling at the EMU

```
{D_max: maximum allowable delay}
{d_i: delay of appliance i}
{St_i: requested start time of appliance i}
if (stored energy available = TRUE) then
   StartImmediately()
else
   if (St_i is in peak) then
      d_i ← ShiftToOffPeak()
      if (d_i > D_max) then
         d_i ← ShiftToMidPeak()
         if (d_i > D_max) then
            StartImmediately()
         else
            StartDelayed()
         end if
      else
         StartDelayed()
      end if
   else
      if (St_i is in mid-peak) then
         d_i ← ShiftToOffPeak()
         if (d_i > D_max) then
            StartImmediately()
         else
            StartDelayed()
         end if
      else
         StartImmediately()
      end if
   end if
end if
```

consumers, and at the same time it prevents the requests to pile up at certain off-peak periods. $StartImmediately()$ and $StartDelayed()$ functions determine the scheduled time of operation. iHEM uses a WSN to relay the packets shown in Fig. 6. The same WSN may also be responsible for other smart home applications such as inhabitant health monitoring since installing a WSN for the sole purpose of iHEM would increase cost. The WSN uses the Zigbee protocol. In (Erol-Kantarci & Mouftah, 2011b), the authors show the impact of these underlying smart home applications on the performance of the WSN. They also demonstrate the savings achieved by the iHEM application. iHEM is shown to be able to reduce consumer expenses, appliance loads during peak hours and carbon emissions related with electricity usage during peak periods.

3.1.2 iPower

Intelligent and Personalized energy conservation system by wireless sensor networks (iPower) implements an energy conservation application for multi-dwelling homes and offices by using the context-awareness of WSNs (Yeh et al., 2009). iPower is similar to the energy management applications in the smart homes. It includes a WSN with sensor nodes and a gateway node, in addition to a control server, power-line control devices and user identification devices. Sensor nodes are deployed in each room and they monitor the rooms with light, sound and temperature sensors. When a sensor node detects that a measurement exceeds a certain threshold, it generates an event. Sensor nodes form a multi-hop WSN and they send their measurements to the gateway when an event occurs. The gateway node is able to communicate with the sensor nodes via wireless communications and it is also connected to the intelligent control server of the building. iPower uses Zigbee for WSN communication and X10 for power-line communications. Intelligent control server performs energy conservation actions based on sensor inputs and user profiles. The action of the server can be turning off an appliance or adjusting the electric appliances in a room according to the profiles of the users who are present in the room. Server requests are delivered to the appliances through their power-line controllers.

3.1.3 Energy management using sensor web services

Web services can invoke remote methods on other devices without the knowledge of the internal implementation details and enable machine-to-machine communications (Groba & Clarke, 2010). In (Asad et al., 2011), the authors consider a smart home that contains smart appliances with sensor modules that enable each appliance to join the WSN and communicate with its peers. The authors present three energy management applications that use sensor web services. The basic application enables users to learn the energy consumption of their appliances while they are away from home. The current drawn by each appliance is monitored by the sensors on board and this information is made available through a home gateway to the users. Users can access the gateway from their mobile devices using web services. Second application of (Asad et al., 2011) is a load shedding application for the utilities. Load shedding is applied to HVAC systems only during peak hours and when the load on the grid is critical. In addition to monitoring and load shedding applications, the third application focuses on a case when the energy generated and stored is either sold to the grid or consumed at home. The application enables the storage units to be controlled by the remote users.

3.1.4 Whirlpool Smart Device Network (WSDN)

Whirlpool Smart Device Network (WSDN) aims to provide simple smart grid participation options for the end-users (Lui et al., 2010). WSDN is based on machine-to-machine communications and it aims to minimize consumer interaction. WSDN consists of three networking domains which are the HAN, the Internet, and the smart meter network. WSDN utilizes several wired and wireless physical layer technologies together, e.g. Zigbee, Wi-Fi, Broadband Internet, Power Line Carrier (PLC). The Wi-Fi connects the smart appliances and forms the HAN. The ZigBee and the PLC connects the smart meters and the broadband Internet connects consumers to the Internet. Above the physical layer, there are the TCP and the IP layers. On top of those, Open Communication Protocol stack is placed which includes Extensible Markup Language (XML), Simple Authentication and Security Layer (SASL), Transport Layer Security (TLS), Extensible Messaging and Presence Protocol (XMPP) protocols. WSDN application is aimed to be easily downloadable from a smart phone. The WSDN also handles user authentication since security is a major concern for such a network.

Moreover, utilities are able to use WSDN and perform load shedding during critical peaks. All of the consumer or utility generated transactions are handled by the Whirlpool-Integrated Service Environment (WISE). Security objectives of WISE has been summarized as:

- Availability: the smart grid system is protected from denial-of-service attacks and always available
- Privacy: consumers have control over their own personal data
- Confidentiality: information is not disclosed unless authorized
- Integrity: data sent between the appliance and utility is not modified

3.2 Incentive-based demand management

In (Mohsenian-Rad et al., 2010a;b), the authors deploy an Energy Consumption Scheduling (ECS) mechanism for a local neighborhood. The ECS is assumed to be implemented in each smart meter. The smart meters communicate and interact in order to find an optimum consumption schedule for each subscriber in the neighborhood. ECS relies on a distributed algorithm. The objective of ECS is to reduce consumer expenses and reduce peak-to-average ratio in the load curve. ECS is an incentive-based scheme as the consumers are given incentives based on pricing which varies according to a game theoretic approach. The ECS does not reduce the overall consumption of the appliances, instead it shifts consumer demands to off-peak hours. This naturally reduces peak-to-average ratio since ECS basically does peak shaving and valley filling. Within a time horizon of $T = 24$ hours, the daily energy consumption of each consumer, $c \in C$, is formulated as:

$$\sum_{a \in A_c} E^t_{c,a} \qquad t \in T \tag{1}$$

where $E^t_{c,a}$ is the hourly consumption of the appliances, a, in the appliance set of the c^{th} consumer, A_c, (i.e. $a \in A_c$). When complete knowledge of the consumer demands are available and a central controller schedules the demands, it is possible to schedule demands by minimizing the $E^t_{c,a}$ of all A_c appliances that belongs to all C consumers during T hours. This can be formulated as:

$$minimize \sum_{t=1}^{T} \beta_t \sum_{c \in C} \sum_{a \in A_c} E^t_{c,a} \qquad t \in H \tag{2}$$

where β denotes the cost function. The incentives are given regarding the billing of consumers. In the game theoretic approach, consumers select their consumption to minimize their payments to the utility. It has been shown in (Mohsenian-Rad et al., 2010b) that for increasing and strictly convex β, Nash equilibrium of the energy consumption game exists and is unique.

3.3 Real-time demand management

In (Mohsenian-Rad & Leon-Garcia, 2010), the authors propose the Residential Load Control (RLC) scheme considering a power grid that employs real-time pricing. According to real time pricing, the price of the electricity follows the raw market price of the electricity. The market price of electricity is generally determined by the regional independent system operator. The independent system operator arranges a settlement for the electricity prices of the next-day or

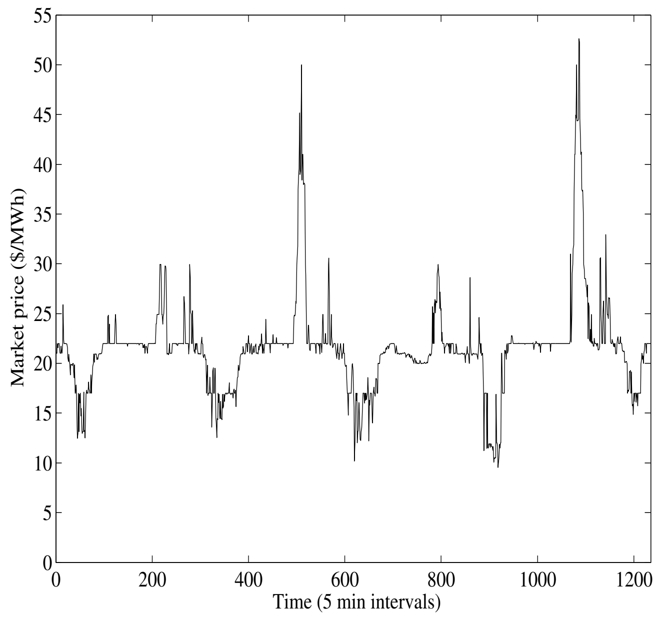

Fig. 10. Electricity price data from an ISO on four days.

next-hour, based on the load forecasts, supplier bids and importer bids. A typical price data is shown in Fig. 10 (Erol-Kantarci & Mouftah, 2010d).
(Mohsenian-Rad & Leon-Garcia, 2010) proposes an automated load control scheme that aims to minimize the consumer expenses as well as the waiting times of the delayed demands. The scheduling scheme is augmented with a price predictor in order to attain the prices of several hours ahead. This is necessary if the grid operator only announces the prices for the next one or two hours. In fact, load and price forecasting is widely studied in the literature. Load forecasts are essential for dispatchers, who are the commercial or governmental bodies responsible for dispatching electricity to the grid. Load forecasting provides tools for operation and planning of a dispatcher where decisions such as purchasing or generating power, bringing peaker plants online, load switching and infrastructure development can be made (Gross & Galiana, 1987). Electricity market regulators and dispatchers rely on forecasting tools that provide short, medium and long-term forecasts.
Short-term load forecasts cover hourly or daily forecasts where medium-term forecasts span a time interval from a week to a year and long-term forecasts cover several years. Forecasting techniques may differ according to this range. For short-term forecasting, the similar day approach searches the historical database of days to find a similar day with properties such as weather, day of the week, etc. (Feinberg & Genethliou, 2006). Regression is another widely used statistical technique for load forecasting. Regression methods aim to model the relationship of load and environmental factors, e.g. temperature (Charytoniuk et al., 1998). Time series methods try to fit a model to data. Previous studies have employed a wide variety of time series methods such as Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Moving Average with eXogenous variables (ARMAX) and Autoregressive Integrated Moving Average with eXogenous variables (ARIMAX) methods. Neural networks, expert systems, support

vector machines and fuzzy logic are among the recent forecasting techniques. The techniques proposed for load forecasting can be used for price forecasting, as well.
In (Mohsenian-Rad & Leon-Garcia, 2010), the authors use a simple AR process that uses the price values of previous two days and the same day of the last week. This is due to the weekly pattern of the consumption data.

3.4 Optimization-based demand management

In this section, we introduce two optimization-based demand management schemes, which are Decision-support Tool (DsT) and Domestic Optimization and Control techniques.

3.4.1 Decision-support Tool (DsT) for the smart home

In (Pedrasa et al., 2010), the authors propose a Decision-support Tool (DsT) for the smart homes. The DsT aims to help the household in making intelligent decisions when operating their appliances. The authors focus on appliances that have high energy consumption, e.g. PHEV, space heater, water heater and pool pump. The authors define an aggregate, must-have services such as lighting, cooking, refrigeration,etc., which exists beside the loads of space heating, water heating and pool pumping services and PHEV charging loads. The energy consumption properties such as duration, battery capacity, maximum charging rating are assumed to be determined by the consumer. In the initial phase of DsT, consumers assign values to those desired energy services. Moreover, DsT assumes the availability of generation via solar panels and the peak output of the PV is also set at the initial phase. Then, consumption is optimized by scheduling the available distributed generation, energy storage and controllable end-use loads which are called as distributed energy resources (DER). The scheduling algorithm attempts to maximize the net benefits for the consumer which is equal to the total energy service benefits minus the cost of energy. The cost of energy is based on a TOU tariff with critical pricing during several hours of a day. The must-run services are delivered regardless of cost and the other services are restricted to run only during defined hours. For instance, the pool pump is not allowed to work overnight due to noise issues.
The scheduling of the DER is formulated and solved via the particle swarm optimization (PSO) heuristic. PSO is a population-based optimization technique that enables to attain near-optimal schedules within manageable computation times.
In (Pedrasa et al., 2010), the communication among the DER and consumers has not been considered. However the authors emphasize the significance of coordinated scheduling using a centralized decision-maker that controls the operation of all the various DERs. The benefits of having a decision-maker that can access the dynamic prices of electricity as well as weather forecasts through the Internet, and that can communicate with the sensors have also been discussed in (Pedrasa et al., 2010).
In Table 2, we give a comparison of the presented demand management techniques that have similar objectives, i.e. iHEM, RLC, DsT and ECS.

3.4.2 Domestic optimization and control

In (Moldernik et al., 2009; 2010), the authors propose using domestic optimization and control scheme to achieve the following goals:

- optimize efficiency of power plants
- increase penetration of renewable resources

	Method	Pricing	Comm.	Coverage	Monthly cost reduction	Peak load reduction
iHEM (Erol-Kantarci & Mouftah, 2011b)	Interactive demand shifting	TOU	Yes	local	30%	40%
RLC (Mohsenian-Rad & Leon-Garcia, 2010)	Automated load control with LP-based optimization	Real-time pricing	No	local	10%-25%	22%
DsT * (Pedrasa et al., 2010)	Particle swarm optimization	TOU and Critical Peak Pricing (CPP)	No	local	16%-25%	N/A
ECS (Mohsenian-Rad et al., 2010a)	Game theoretic pricing and scheduling	Proportional to daily load and generation cost	No	neighbor-hood	37%	38%

* Using TOU tariff, no PHEV and no critical peak pricing scenario.

Table 2. Comparison of iHEM, RLC, DsT and ECS.

- optimize grid efficiency

Domestic optimization is based on predicting the demand and the day-ahead prices and optimize the resources accordingly. The authors use a neural network-based prediction approach to predict the next-day heat demand. The schedule of the Micro combined heat and power (micro-CHP) device is determined based on this prediction. CHP, also known as cogeneration, provides ability to simultaneously produce heat and electricity. Electricity is generated as a by-product of heating.

The neural network is trained such that a set of given inputs produce the desired outputs. In (Moldernik et al., 2010), the output of the neural network predictor is the heat demand per hour. The factors affecting the heat demand is assumed to be the behavior of the residents, the weather, and the characteristics of the house which are given as inputs to the prediction model. The data are derived from historical demand and consumer behavior databases.

Following the prediction step, planning of the runs of the microCHP is established. Thus, the times when the microCHP is switched on is planned. This planning is based on local decisions. However, a group of houses is considered to act as a virtual power plant where in the global planning phase, global production is optimized via iterative distributed dynamic programming. In the next step, the authors schedule the appliances in a single house based on the global planning decisions. Local appliances are controlled to optimize electricity import/export of home.

3.5 Summary and discussions

In this book chapter, we grouped the demand management schemes proposed for the smart grid under four categories as:

- Communication-based demand management
- Incentive-based demand management
- Real-time demand management
- Optimization-based demand management

Communication-based techniques have been studied in (Asad et al., 2011; Erol-Kantarci &Mouftah, 2010c; Erol-Kantarci & Mouftah, 2011b; Lui et al., 2010; Yeh et al., 2009). Demand management schemes that employ WSNs have been presented under communication-based techniques, as well. Communication-based techniques provide flexible solutions that can compromise between reducing the energy consumption of the consumers and accommodating their preferences.

Incentive-based techniques have been studied in (Mohsenian-Rad et al., 2010a;b). These schemes try to shift the consumer demands to off-peak hours, and in the meanwhile they provide incentives to the consumers by configuring the prices based on a game theoretic approach. Incentive-based schemes can shape consumer behavior according to the needs of the smart grid.

Real-time demand management has been studied in (Mohsenian-Rad & Leon-Garcia, 2010). In real-time demand management, scheduling makes use of the real-time price of the electricity. Based on the varying prices an automated load control scheme chooses the appliance schedules with the objective of minimizing the consumer expenses, as well as the waiting times of the delayed demands. Those schemes are suitable for the grids where the operators apply real-time pricing tariffs.

Optimization-based demand management has been studied in (Moldernik et al., 2009; 2010; Pedrasa et al., 2010). Optimization-based demand management assumes that the consumer demands are known ahead or at least they can be predicted. Local generation capacity of a house or group of houses is scheduled based the predicted demand profile. Optimization-based schemes may increase the efficiency of the demand management programs significantly.

4. Conclusion

Growing demand for energy, diminishing fossil fuels, desire to integrate renewable energy resources, efforts to reduce Green House Gases (GHG) emissions and resilience issues in the electrical power grid, have led to a common consensus on the necessity for renovating the power grid. The key to this renovation is the integration of the advances in the Information and Communication Technologies (ICTs) to the power grid. The new grid empowered by ICT is called smart grid.

Smart grid can employ ICT in almost every stage from generation to consumption, i.e. electricity generation, transport, delivery and consumption. ICT can increase the efficiency of the generation facilities, transmission and distribution assets and consumption at the demand-side. In this chapter, we reviewed the demand management schemes for the smart grid with a focus on the potential uses of Wireless Sensor Networks (WSN) in the building blocks of the smart grid. We first discussed the use of WSNs at the electricity generation sites. We, then, continued with power transmission and electricity distribution, and finally reached to demand-side which is the last mile of the delivery services. WSNs provide promising solutions for efficient integration of intermittent renewable energy resources, low-cost monitoring of traditional power plants and high-resolution monitoring of utility transport assets. Furthermore, WSNs offer vast variety of applications in the field of consumer demand management.

The ultimate aim of those demand management schemes is to schedule the appliance cycles so that the use of electricity from the grid during peak hours is reduced which consequently reduces the need for the power from the peaker plants and reduces the carbon footprint of the household. In addition, consumer expenses will be reduced as peak hour usage results in higher expenses. Moreover, the use of locally generated power is aimed to be maximized.

Demand management for the smart grid is still in its infancy. The demand management techniques introduced in this chapter have been recently proposed, and they need to be improved as the technology advances. For instance, consumer-in-the-loop or predicted demands can be mitigated by employing learning techniques from the Artificial Intelligence (AI) field. This would increase the consumer comfort and pervasiveness of the demand management applications. Furthermore, those schemes mostly consider conventional appliances, but in a close future, smart appliances will be commercially available. In this case, demand management schemes may be extended to allow sub-cycle scheduling. The availability of such appliances will enrich the opportunities that become available with the demand management applications of the smart grids.

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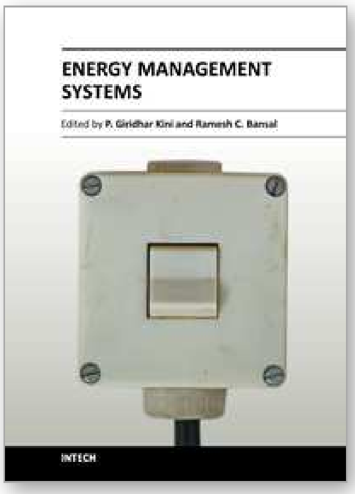

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This book comprises of 13 chapters and is written by experts from industries, and academics from countries such as USA, Canada, Germany, India, Australia, Spain, Italy, Japan, Slovenia, Malaysia, Mexico, etc. This book covers many important aspects of energy management, forecasting, optimization methods and their applications in selected industrial, residential, generation system. This book also captures important aspects of smart grid and photovoltaic system. Some of the key features of books are as follows: Energy management methodology in industrial plant with a case study; Online energy system optimization modelling; Energy optimization case study; Energy demand analysis and forecast; Energy management in intelligent buildings; PV array energy yield case study of Slovenia;Optimal design of cooling water systems; Supercapacitor design methodology for transportation; Locomotive tractive energy resources management; Smart grid and dynamic power management.