Efficient Energy Management for the Internet of Things in Smart Cities

Waleed Ejaz, Muhammad Naeem, Adnan Shahid, Alagan Anpalagan ...+1 more authors

Institutions: Ryerson University, COMSATS Institute of Information Technology, Ghent University, Korea University

Published on: 01 Jan 2017 - IEEE Communications Magazine (IEEE)

Topics: Smart city, Smart system, Efficient energy use and Energy management

Efficient Energy Management for the Internet of Things in Smart Cities

Waleed Ejaz, Muhammad Naeem, Adnan Shahid, Alagan Anpalagan, and Minho Jo

The authors present a brief overview of energy management and challenges in smart cities. They then provide a unifying framework for energy-efficient optimization and scheduling of IoT-based smart cities. They also discuss the energy harvesting in smart cities, which is a promising solution for extending the lifetime of low power devices and its related challenges.

ABSTRACT

The drastic increase in urbanization over the past few years requires sustainable, efficient, and smart solutions for transportation, governance, environment, quality of life, and so on. The Internet of Things offers many sophisticated and ubiquitous applications for smart cities. The energy demand of IoT applications is increased, while IoT devices continue to grow in both numbers and requirements. Therefore, smart city solutions must have the ability to efficiently utilize energy and handle the associated challenges. Energy management is considered as a key paradigm for the realization of complex energy systems in smart cities. In this article, we present a brief overview of energy management and challenges in smart cities. We then provide a unifying framework for energy-efficient optimization and scheduling of IoT-based smart cities. We also discuss the energy harvesting in smart cities, which is a promising solution for extending the lifetime of low-power devices and its related challenges. We detail two case studies. The first one targets energy-efficient scheduling in smart homes, and the second covers wireless power transfer for IoT devices in smart cities. Simulation results for the case studies demonstrate the tremendous impact of energy-efficient scheduling optimization and wireless power transfer on the performance of IoT in smart cities.

INTRODUCTION

Smart city solutions use communication and networking technologies for dealing with the problems precipitated by urbanization and growing population. The Internet of Things (IoT) is a key enabler for smart cities, in which sensing devices and actuators are major components along with communication and network devices. The sensing devices are used for real-time detection and monitoring of city operations in various scenarios. It is projected that in the near future, common industrial, personal, office, and household devices, machines, and objects will hold the ability to sense, communicate, and process information ubiquitously [1]. However, it is challenging to design a fully optimized framework due to the interconnected nature of smart cities with different technologies. Further, smart city solutions have to be energy-efficient from both the users' and environment's points of view.

These challenges have forced network designers to consider a wide range of scenarios in different conditions for IoT-enabled smart cities. Thus, efficient deployment of sensors and an optimized operational framework that can adapt to the conditions is necessary for IoT-enabled smart cities. In other words, smart city solutions have to be energy-efficient, cost-efficient, reliable, secure, and so on. For example, IoT devices should operate in a self-sufficient way without compromising quality of service (QoS) in order to enhance the performance with uninterrupted network operations [2]. Therefore, the energy efficiency and life span of IoT devices are key to next generation smart city solutions.

We classify the energy management in smart cities into two main types: energy-efficient solutions and energy harvesting operations. This classification along with a few examples of research topics are shown in Fig. 1. Energy-efficient solutions for IoT-enabled smart cities include a wide range of topics such as lightweight protocols, scheduling optimization, predictive models for energy consumption, a cloud-based approach, low-power transceivers, and a cognitive management framework [3–5]. Energy harvesting allows IoT devices to harvest energy from ambient sources and/or dedicated RF sources. The aim of energy harvesting is to increase the lifetime of IoT devices. The research topics included within both types of energy harvesting are energy harvesting receiver design, energy arrival rate, placement of a minimum number of dedicated energy sources, scheduling of dedicated energy sources, and multi-path energy routing [2, 6].

Both academia and industry are focusing on energy management in smart cities. The IEEE in partnership with the International Telecommunication Union (ITU) has a smart cities community with the aim to provide assistance to municipalities for the transition to smart cities. Fujitsu suggested an approach to energy management for companies and has introduced an energy management system for smart buildings as cloud service [7]. In addition, companies such as IBM, Cisco, Honeywell, Intel, and Schneider Electric are involved in various energy-efficient solutions for smart cities. There have been various projects on energy-efficient smart cities sponsored by the Seventh Framework Programme (FP7) for research of the European Commission in the past

Digital Object Identifier: 10.1109/MCOM.2017.1600218CM

Waleed Ejaz and Alagan Anpalagan are with Ryerson University; Muhammad Naeem is with the COMSATS Institute of Information Technology and Ryerson University; Adnan Shahid is with Ghent University; Minho Jo (corresponding author) is with Korea University.

0163-6804/17/$25.00 © 2017 IEEE

few years. For example, the main objectives of the "Reliable, Resilient, and Secure IoT for Smart City Applications" project are to develop, evaluate, and test a framework of IoT-enabled smart city applications in which smart objects can operate energy-efficiently [8]. The "ALMANAC: Reliable Smart Secure Internet of Things for Smart Cities" project focuses on IoT-enabled green and sustainable smart solutions [9]. Likewise, energy-saving solutions are developed for smart cities under the projects "Planning for Energy Efficient Cities (PLEEC)" and "NiCE — Networking Intelligent Cities for Energy Efficiency."

In this article, we consider energy management for IoT in smart cities. An illustration of smart cities with the focus on smart homes is shown in Fig. 2. Our contributions can be summarized as follows:

- We provide an optimization framework for research in IoT-enabled smart cities. We present the objectives, problem type, and solution approaches for energy management.
- We cover energy-efficient solutions for IoT-enabled smart cities. A case study is presented to show the performance gains achieved by scheduling optimization in smart home networks.
- Next, we devote a section to energy harvesting for IoT-enabled smart city applications. A case study is provided to investigate the performance gains achieved by the scheduling of dedicated energy sources.
- Finally, the conclusions are drawn, and we provide future research directions for energy management in IoT-enabled smart cities.

Energy Management and Challenges for Smart City Applications

An urgent need for energy management has emerged all over the globe due to a continuous increase in consumption demands. Global warming and air pollution are serious threats to future generations. This is caused by the emission of fumes with volume increased with the increase in energy demand. On the other hand, according to the statistics provided by Cisco, there will be more than 50 billion IoT devices connected to the Internet by 2020 [10]. This explosion in devices will pose serious energy consumption concerns; thus, it is imperative to manage energy for IoT devices so that the concept of smart cities can be better realized in a sustained manner. Following are a few examples where we can reduce energy consumption by effective management.

Home Appliances: Home appliances are the major sources of energy consumption. Demand management is a key for customizing energy use by managing the lighting, cooling, and heating systems within residential units. On the other hand, the intelligent operation of activities can also facilitate the optimized management and operation of energy.

Education and Healthcare: Considering the importance of educational and healthcare services, it is difficult to dematerialize them. However, it is possible to demobilize services for the reduction of energy consumption; for example, exploiting remote healthcare by visualizing sensors and mobile phones, and distance education

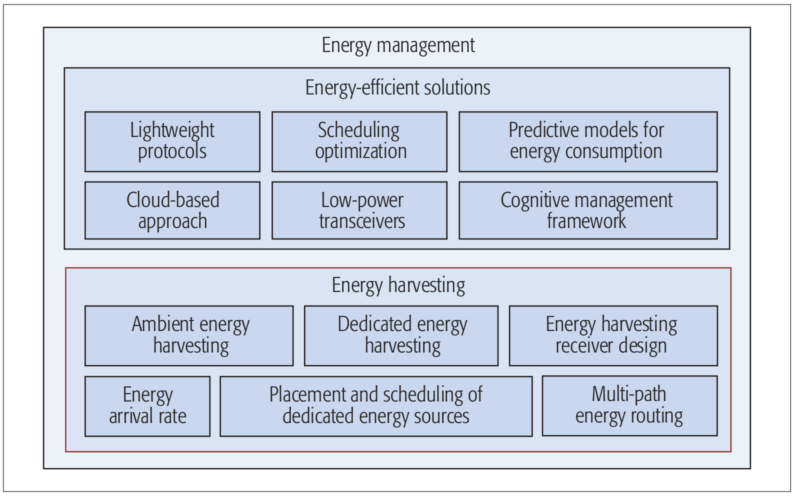

Figure 1. Classification of energy management for IoT in smart cities.

can create a significant reduction in energy consumption.

Transportation: The energy use for transportation includes public transport, daily commuting to work in personal vehicles, leisure travel, and so on. In addition to the energy consumed by public transport and personal vehicles, they are also a major cause of pollution in cities. IoT-enabled solutions can be employed for energy management, such as traffic management, congestion control, and smart parking. This can significantly reduce energy consumption as well as CO_2 emission.

Food Industry: Energy consumption in the food industry is not only related to the storage, purchase, and preparation of food; it also includes diners moving into restaurants in search of food. IoT-enabled solutions can be used here for making optimized choices in terms of food availability. On the other hand, the transportation of the food can also be optimized by incorporating intelligent means of transportation.

IoT devices are generally battery operated and have limited storage space. Concerning these fundamental limitations of sensors, it is difficult to realize the IoT solutions with prolonged network life. In order to efficiently utilize the limited sensor resources, an optimized energy-efficient framework is of paramount importance. It will not only reduce energy consumption, but also maintain the minimum QoS for the concerned applications.

A typical optimization framework for IoT-enabled smart cities is given in Fig. 3. This framework provides details of the objectives, problem types, and corresponding optimization techniques for energy management. For example, an optimization problem for minimizing the cost of electricity usage is presented in [11]. The authors developed an optimization-based residential energy management scheme for energy management of appliances. The authors in [12] presented an optimization framework for smart home scheduling of various appliances and assignment of energy resources. This results in a mixed integer combinatorial problem which is transformed into a standard convex programming problem. The goal of this study is to minimize cost and user dissatisfaction. In [13], the authors presented an energy-centered and QoS-aware services selec-

With the increase in IoT applications for smart cities, energy-efficient solutions are also evolving for low-power devices. There are some energy-efficient solutions that can either reduce energy consumption or optimize resource utilization.

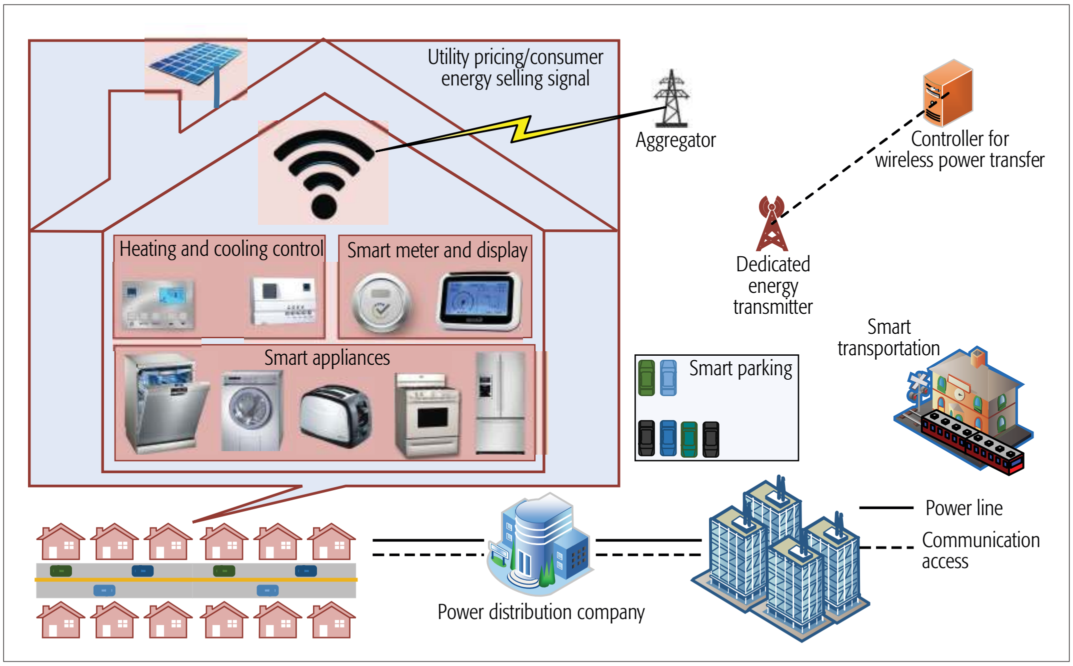

Figure 2. An illustration of smart cities focused on smart homes.

tion algorithm for IoT environments. The objective is to minimize energy consumption while satisfying QoS requirements. Similarly, the objectives shown in Fig. 3 can be considered, and the framework can be used as a guideline to solve the optimization problems.

Energy-Efficient Solutions for Smart Cities

With the increase in IoT applications for smart cities, energy-efficient solutions are also evolving for low-power devices. There are some energy-efficient solutions that can either reduce energy consumption or optimize resource utilization. Following are some main research trends for energy-efficient solutions of IoT-enabled smart cities.

Lightweight Protocols: Lightweight means that a protocol causes less overhead. IoT-enabled smart cities have to use various protocols for communication. There are several existing protocols in the literature such as Message Queue Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), Extensible Messaging and Presence Protocol (XMPP), Advanced Message Queue Protocol (AMQP), 6lowPAN, and Universal Plug and Play (UPnP) IoT. MQTT and CoAP are the most popular protocols. MQTT is a lightweight protocol that collects data from IoT devices and transmits to the servers. CoAP is designed for constrained devices and networks for web transfer (See [14] for IoT protocols). Each of these protocols is designed for specific scenarios and applications in which it performs well. In addition, protocol conversion is an important building block for IoT, which may require that the IoT devices be from different manufacturers or using different protocols.

Scheduling Optimization: Scheduling optimization for IoT-enabled smart cities refers to the optimization of resources with the aim of minimizing energy consumption and subsequently reducing electricity usage. In this regard, demand-side management (DSM) is of prime importance; it refers to the manipulation of residential electricity usage by altering the system load shape and consequently reducing the cost. Broadly speaking, DSM comprises two main tasks: load shifting and energy conservation, where load shifting refers to the transfer of customers' load from high-peak to low-peak levels. By adopting this, electricity can be conserved and provide room for other customers.

Predictive Models for Energy Consumption: Predictive models for energy consumption in IoT-enabled smart cities are indeed of vital importance. They refer to the wide range of applications in smart cities, including predictive models for traffic and travel, predictive models for controlling temperature and humidity, and so on. Various prediction models such as neural networks and Markov decision processes can be incorporated here. Exploiting the predictive models will not only reduce the significant energy consumption but also lead to many societal benefits.

Cloud-Based Approach: Cloud computing has reshaped the computing and storage services, which can be used to provide energy-efficient solutions for IoT-enabled smart cities. More precisely, the cloud-based approach helps in managing the massive data center flexibility and in a more energy-efficient manner.

Low-Power Transceivers: Since the IoT devices in smart city applications operate on limited batteries, a low-power design architecture or operation framework is of superior importance for addressing the energy management in IoT-enabled smart cities. Mostly, the existing application protocols for IoT devices are not in accordance with the energy efficiency perspective. More specifically, the radio duty cycle for IoT devices is an important factor in energy efficiency, and researchers are exploring methods of reducing the radio duty cycle of IoT devices and subsequently to achieve the energy-efficient architecture.

Cognitive Management Framework: IoT

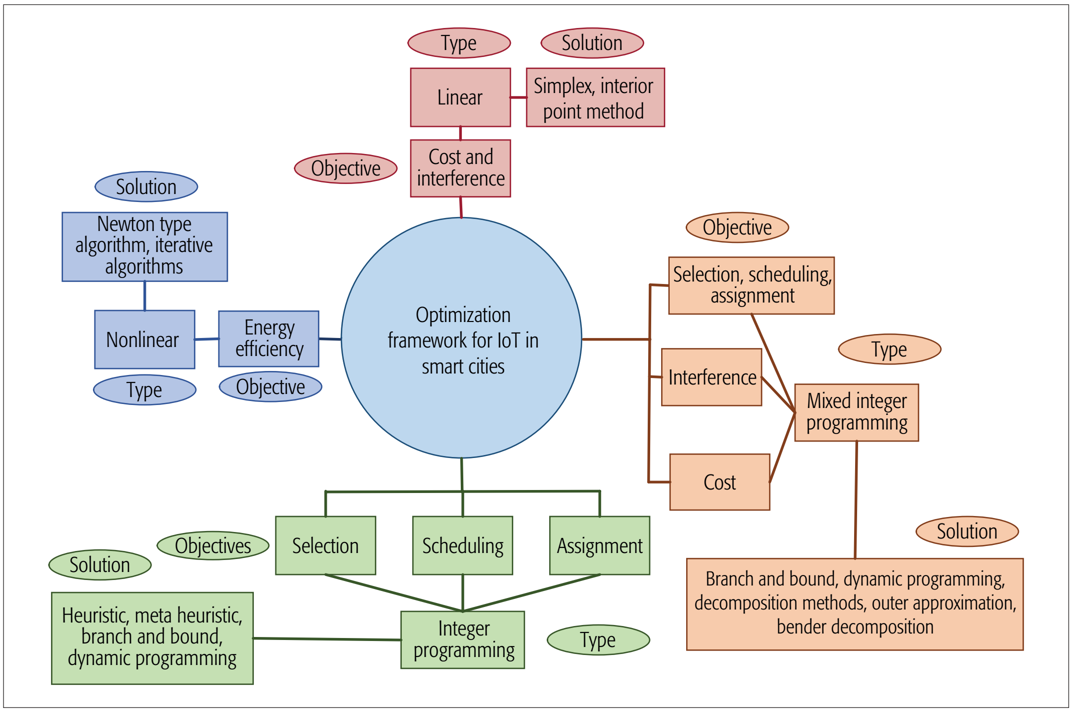

Figure 3. A typical optimization framework for IoT in smart cities.

To reduce electricity bills, smart home networks offer better life style, customized day to day schedule, and so on. The smart grid has provided the ability to keep the electricity demand in line with the supply during the peak time of usage. This is called demand-side management.

devices are heterogeneous in nature, and the associated services are unreliable. Therefore, it is important to investigate a cognitive management framework that adopts intelligence and cognitive approaches throughout the IoT-enabled smart cities. The framework should include reasoning and learning in order to improve decisions for IoT networks. A context-aware cognitive management framework was presented in [4], which made decisions regarding IoT devices (when, why, and how to connect) according to the contextual background.

Case Study on Smart Home Networks

Smart home networks enable home owners to use energy efficiently by scheduling and managing appliances. In addition, to reduce electricity bills, smart home networks offer better lifestyles, customized day-to-day schedules, and so on. The smart grid has provided the ability to keep the electricity demand in line with the supply during the peak time of usage. This is called demand-side management. DSM reduces the electricity cost by altering/shifting the system load [5]. Generally, DSM is responsible for the demand response program and load shifting. In the demand response program, a customer's load can be reduced in peak hours by shifting it to off-peak hours. This helps to provide more electricity at less cost.

Home appliances are becoming smart with added features of connectivity that enable consumers to take advantage of the demand response program. The electric utility can contact consumers to reduce/shift their electricity consumption in return for certain monetary benefits. In smart home networks, appliance load can further be categorized into manageable and unmanageable loads. Here, we focus on the energy management of manageable appliance load in smart homes since it has high energy consumption and predictability in operations. The manageable load is further divided into shiftable load (e.g., washing machine, dishwasher), interruptable load (e.g., water heater and refrigerator), and weather-based load (e.g., heating and cooling). An illustration of the smart home network model for appliance scheduling is given in Fig. 2.

We consider a smart home network in which N_A is the set of load types, A_n is the set of appliances in the nth load type, and A is the set that is a union of all appliances. We define T, C^t, and P^t_{na} as number of time slots in a day, tariff/cost in dollars in time slot t, and P^t_{na} power of the nth load type's ath appliance in time slot t, respectively. We formulate a problem for scheduling of smart home appliances while considering the tariffs and peak load. The overall objective is to schedule the appliances in such a way that total cost is minimum, that is, minimize the $x^t_{na} C_t P^t_{na}$ for whole set of N_A, A for all T time slots, where x^t_{na} is a binary variable with value 1 when the nth load type's ath appliance in time slot t is on; otherwise, 0. We consider practical constraints on time occupancy and time consecutiveness that need to be satisfied for realistic execution of appliance scheduling. The constraints ensure that each appliance should not occupy more time slots than required, and the time slots for shiftable loads are consecutive. The optimization problem here is integer programming; such problems are generally NP-hard and require very efficient algorithms. We solved the optimization problem using an efficient heuristic algorithm.

Performance Analysis

For illustration purposes, we consider only four types of appliances: washing machine, dryer, dishwasher, and electric vehicle. Figure 4a shows the tariff, and slot time for appliances with (thick slots) and without DSM (thin slots). It is considered that a dryer cannot be activated before a washing machine. It is evident that with DSM the appliances are activated when the tariff is low. However, without DSM, there is no scheduling for appliances, and they can be activated at any time. For instance, all the appliances are scheduled at the time when the tariff is low with DSM. In contrast, only the dryer is activated when the tariff is low in the absence of DSM. Similarly, Fig. 4b shows that the total load is less in the case of optimum energy management when the tariff is high. It is important to notice that at some times the total load for both optimum energy management and no energy management is the same. This is because there is no shiftable load at this time.

Energy Harvesting in Smart Cities

Energy harvesting is considered as a potential solution to increase the lifetime of IoT devices in smart cities. Energy harvesting can generally be classified into two categories:

- In ambient energy harvesting, IoT devices harvest energy from ambient sources such as wind, RF signals in the environment, vibration, and solar. However, harvesting from ambient sources depends on their availability, which is not always guaranteed.
- In dedicated energy harvesting, the energy sources are intentionally deployed in the surroundings of IoT devices.

The amount of energy harvested by each IoT device depends on the sensitivity of harvesting circuits, the distance between an IoT device and an energy source, the environment, and so on. Thus, the success of energy harvesting for IoT devices in smart cities has to face several challenges, which are discussed below.

Energy Harvesting Receiver Design: The harvesting circuit design is the primary issue in RF-based energy harvesting. The sensitivity required for the harvesting circuit is higher than for traditional receivers, which can result in fluctuations in energy transfer due to the environment and mobility (energy source and IoT devices). Therefore, efficient and reliable harvesting circuit design is required to maximize the harvested energy. In addition, RF-to-DC conversion is the fundamental ingredient of RF energy harvesting. Hence, circuit designers should enhance the efficiency of RF-to-DC conversion using advanced technologies.

Energy Arrival Rate: The level of uncertainty of the energy arrival rate is higher in energy harvesting from ambient sources than in dedicated energy harvesting. This is because the former uses renewable energy sources, whereas the latter uses dedicated energy sources the location of which is set by network designers based on the harvesting requirements of IoT devices. Accurate and detailed modeling of the energy arrival rate is indispensable in order to analyze the performance of energy harvesting systems in smart cities.

Placement of a Minimum Number of Dedicated Energy Sources: IoT devices that are spatially distant from energy sources can result in uneven energy harvesting. This can result in energy depletion of devices that are far from dedicated energy sources and thus reduce the lifetime of the network. We can ot do much in the case of ambient energy sources; however, optimal placement and number of dedicated energy sources are crucial issues in dedicated energy harvesting.

Scheduling of Energy Transmitters: Energy consumed by dedicated energy sources can be reduced by introducing task-based energy harvesting, where energy transmitters can be scheduled for RF power transfer based on the harvesting requirements of IoT devices. This requires a certain level of coverage and sufficient time to harvest. Therefore, scheduling of energy transmitters with guaranteed coverage and duration is vital for the energy efficiency of dedicated energy harvesting.

Multi-Path Energy Routing: Multi-path energy routing collects the scattered RF energy from different sources with the help of RF energy routers. Then these energy routers can transfer energy via an alternative path to IoT devices. Multi-path energy routing is based on the idea of multihop energy transfer in which relay nodes are deployed near IoT devices. This will help to reduce path loss between the relay node and the IoT devices, and also improve the RF-to-DC conversion efficiency.

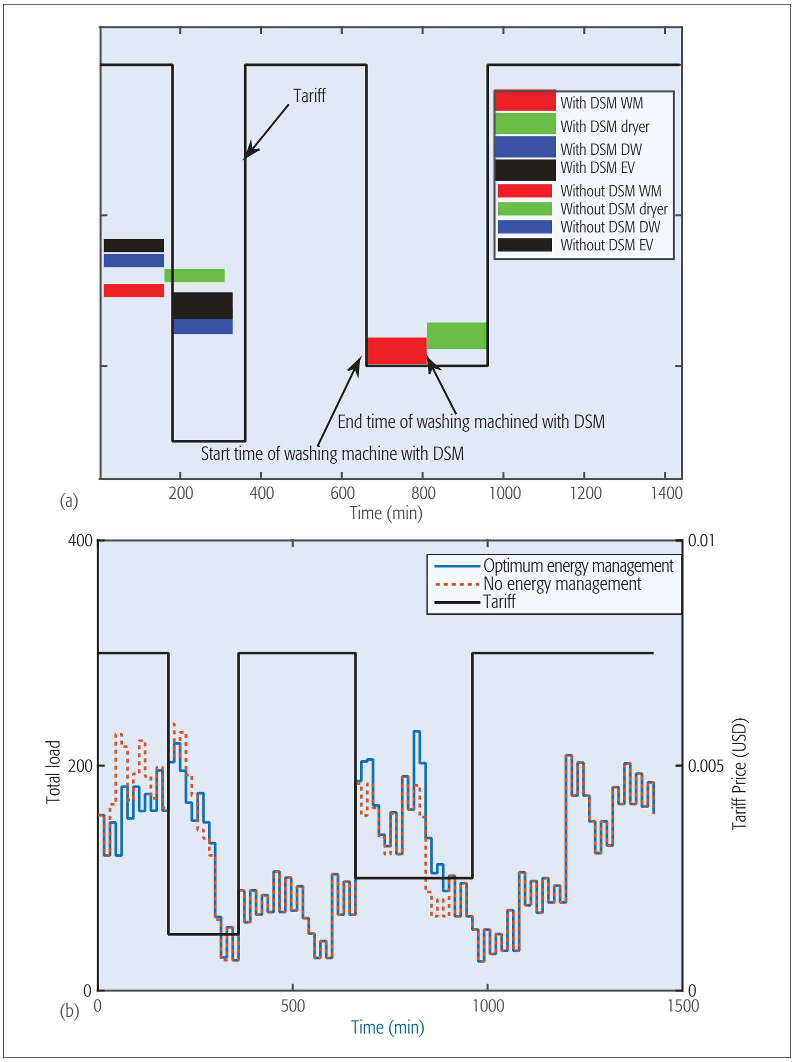

Figure 4. Load pattern: a) appliances starting and ending times with and without DSM; b) load pattern of appliances while minimizing total electricity cost and tariff.

Case Study: Scheduling of Energy Sources in Dedicated Energy Harvesting for IoT devices

We consider a network in smart cities with dedicated RF energy transmitters that consists of N_I IoT devices (each device is equipped with a harvesting circuit) and N_E energy transmitters, as shown in Fig. 5. It is assumed that energy transmitters have continuous power supply, and they can satisfy the requirements of all IoT devices in the area. The IoT devices can request power transfer from a harvesting controller, which is considered as task k. The harvesting controller is considered as a cloudlet controller, which is a centralized resource pool with information about the location of IoT devices and energy transmitters. The controller can assign multiple tasks from K (K is a set of tasks) to the energy transmitters. The transmit power of the eth energy transmitter is denoted by P_e. The energy transmitter e can transfer power to a task $k \in K$ if the requesting IoT device is in the harvesting range of e. The harvesting range is denoted by ϕ_{et}, which is 1 if task k is in the harvesting range of e and 0 otherwise. Let the energy consumption of the eth energy transmitter in active mode be $\xi_{e,A}$ and in sleep mode $\xi_{e,S}$.

We propose a scheduling scheme for energy transmitters in dedicated energy harvesting for IoT devices, as shown in Fig. 5. IoT devices request power transfer from the controller by sending a request if their residual energy is less than a preset threshold ξ_{Th}. The threshold is set while considering that the node has sufficient energy for critical operations. The request packet contains the requesting node's ID, the controller's ID, and energy harvesting requirements. Here, we adopt the RF-medium access control (RF-MAC) protocol proposed in [15]. A sensor node with residual energy less than a preset threshold can send RFP for instant charging through an access priority mechanism (for details about this mechanism, see [15]), which ensures that the node with residual energy $\leq \xi_{Th}$ gets channel access before data transmission by other sensor nodes. The nodes that have data to transmit are forced to freeze their backoff timers as data transmission is not possible at this time. The controller receives this packet and processes it to activate the energy transmitter(s). The harvesting controller receives this request for task k and calculates ϕ_{et} for all energy transmitters. An energy transmitter can be activated for harvesting the target IoT device(s) if and only if task k is within the harvesting range of e, that is, $\phi_{et} = 1$; and task k is scheduled/activated on e. We define a binary variable ψ_e, which is 1 if the energy transmitter e is scheduled/activated and 0 otherwise.

The objective here is to activate the minimum number of energy transmitters to minimize the energy consumed by dedicated energy transmitters, that is, $\psi_e\xi_{e,A} + (1 - \psi_e)\xi_{e,S}$. This is subject to constraints on coverage ϕ_{et}, duration of energy harvesting δ_e, and target harvesting energy $\overline{E_C}$. One way to get an optimal solution is to enumerate over all possible combinations of ψ_e, which is computationally expensive and unrealistic for a large number of energy transmitters and tasks. Therefore, we consider a branch and bound algorithm for the scheduling of dedicated RF energy sources. Once the activation of energy sources is optimized at the controller, a grant for a power transfer packet is sent to the energy transmitters that are selected for RF power transfer. Finally, the energy source(s) send the acknowledgment packet to the IoT device(s) that requested the power transfer. This packet has the information of the central frequency of the energy transmitter and the duration of energy charging.

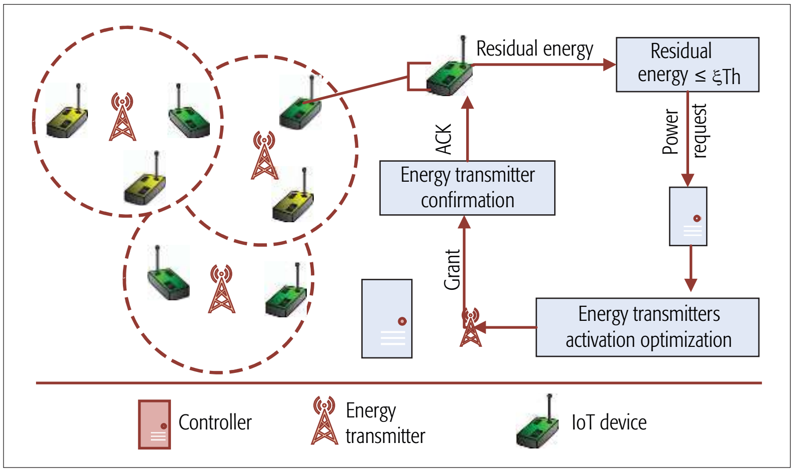

Figure 5. A mechanism for scheduling of energy transmitters.

Performance Analysis: We evaluate the performance of energy-efficient scheduling of energy transmitters. We consider omnidirectional energy transmitters that radiate waves with power 46 dBm. The proposed schemes can be modified to use with directional energy transmitters to overcome path losses, which can certainly help to improve the charging efficiency. The transmit and receive energy for IoT devices are considered from MICA2 specifications. We consider $N_I = 200$ IoT devices, which are randomly distributed in a rectangular field of 100 m × 100 m.

Figures 6a and 6b illustrate the impact of a number of tasks and energy transmitters on energy consumption, respectively, for an energy-efficient scheduling scheme (branch and bound, exhaustive search, and a traditional wireless sensor network [WSN]). Figure 6a shows that the energy consumption is increased slowly with the increase in the number of tasks in an energy-efficient scheduling scheme (for a given number of energy transmitters, i.e., $N_E = 10$ and 20). This is because energy transmitters are activated based on the number of tasks and their location instead of a total number of energy transmitters. We may need a different number of active energy transmitters if requesting devices are far from or close to each other. The energy consumption in traditional WSNs is constant regardless of the number of tasks, that is, all the energy transmitters are activated all the time. Thus, the energy consumption is doubled when $N_E = 20$ compared to the case when $N_E = 10$. The energy consumption in the proposed scheme is reduced at the cost of overhead and delay due to the exchange of packets among IoT devices, controller, and energy transmitters. From Fig. 6b, it can be noted that the energy consumption for efficient scheduling schemes is not much affected by the increase on energy transmitters N_E for a given number of tasks ($K = 5$ and $K = 15$). We consider a small network size for which the probability that tasks are spatially nearby is high. Thus, for different numbers of tasks, we may need to activate the same number of energy transmitters based on their location. Therefore, curves are superimposed. In contrast, traditional

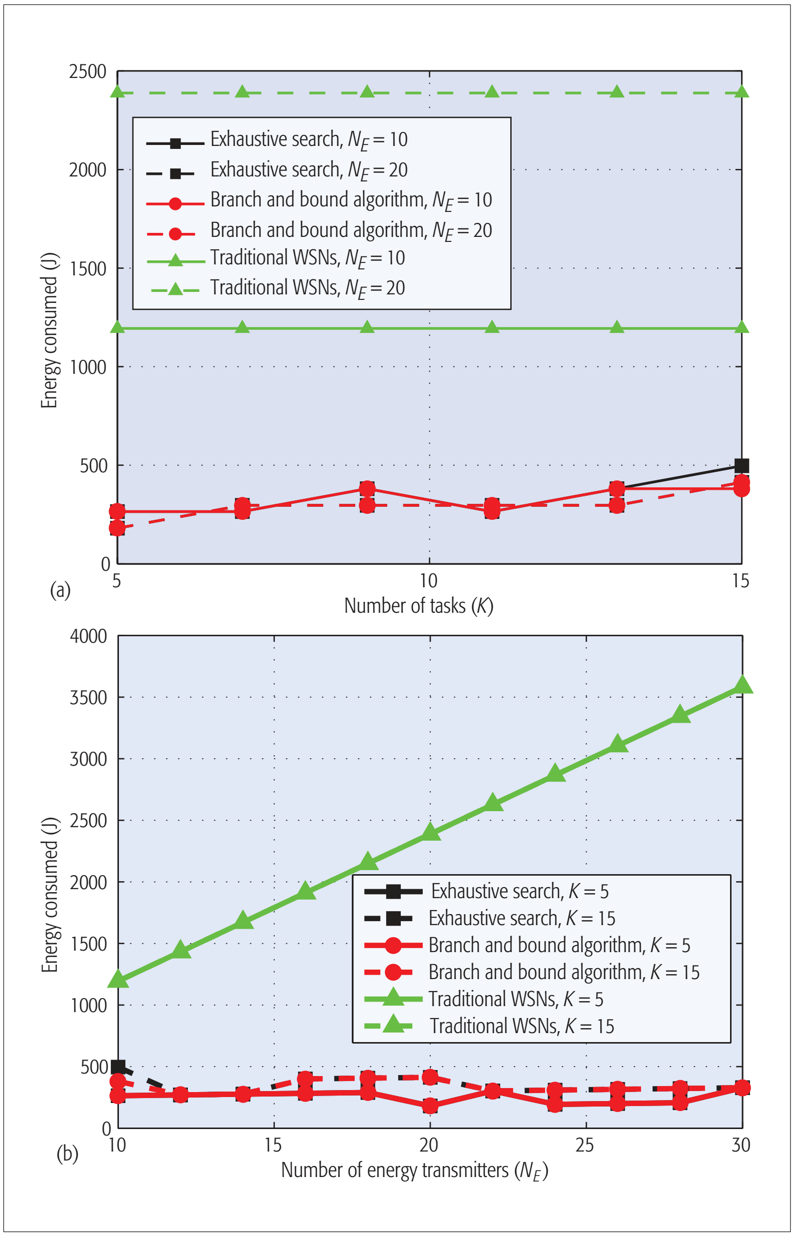

Figure 6. Impact of: a) number of tasks K on energy consumption; b) energy transmitters (N_E) on energy consumption for different numbers of tasks K for different numbers of energy transmitters (N_E).

WSNs in IoT-enabled smart cities activate all the energy transmitters regardless of the number of tasks, which results in a linear increase in energy consumption. Moreover, results of the branch and bound algorithm are very similar to exhaustive search with less complexity.

Conclusions and Future Work

Energy management in smart cities is an indispensable challenge to address due to rapid urbanization. In this article, we first present an overview of energy management in smart cities, and then present a unifying framework for IoT in smart cities. Energy management has been classified into two levels: energy-efficient solutions and energy harvesting operations. We cover various directions to investigate energy-efficient solutions and energy harvesting for IoT devices in smart cities. Furthermore, two case studies have been presented to illustrate the significance of energy management. The first case study presents appliance scheduling optimization in smart home networks where the objective is to reduce the electricity cost. The second case study covers efficient scheduling of dedicated energy sources for IoT devices in smart cities. Simulation results are presented to show the advantage of energy management in IoT for smart cities. Possible future directions for energy management in smart cities are:

- Energy-efficient mechanisms for software-defined IoT solutions, which can provide scalable and context-aware data and services.
- Directional energy transmission from dedicated energy sources for wireless power transfer.
- Energy efficiency and complexity of security protocols are crucial aspects for their practical implementation in IoT; thus, it is important to investigate robust security protocols for energy constraint IoT devices.
- Fog computing can lead to energy saving for most of the IoT applications; therefore, it is important to study energy consumption of fog devices for IoT applications.

Acknowledgment

This research was supported by the Korea-China Joint Research Center Program (2016K1A3A1A20006024) through the National Research Foundation (NRF), South Korea.

References

[1] A. El-Mougy *et al.*, "Reconfigurable Wireless Networks," *Proc. IEEE*, vol. 103, no. 7, July 2015, pp. 1125–58.
[2] P. Kamalinejad *et al.*, "Wireless Energy Harvesting for the Internet of Things," *IEEE Commun. Mag.*, vol. 53, no. 6, June 2015, pp. 102–08.
[3] W. Ejaz *et al.*, "Energy and Throughput Efficient Cooperative Spectrum Sensing in Cognitive Radio Sensor Networks," *Trans. Emerging Telecommun. Technologies*, vol. 26, no. 7, July 2015, pp. 1019–30.
[4] P. Vlacheas *et al.*, "Enabling Smart Cities through a Cognitive Management Framework for the Internet of Things," *IEEE Commun. Mag.*, vol. 51, no. 6, June 2013, pp. 102–11.
[5] F. Qayyum *et al.*, "Appliance Scheduling Optimization in Smart Home Networks," *IEEE Access*, vol. 3, Nov. 2015, pp. 2176–90.
[6] D. Mishra *et al.*, "Smart RF Energy Harvesting Communications: Challenges and Opportunities," *IEEE Commun. Mag.*, vol. 53, no. 4, Apr. 2015, pp. 70–78.
[7] T. Ozawa *et al.*, "Smart Cities and Energy Management," *Fujistu Scientific and Technical J.*, vol. 50, no. 2, Apr. 2015, pp. 49–57.
[8] H. C. Pohls *et al.*, "RERUM: Building a Reliable IoT upon Privacy-and Security-Enabled Smart Objects," *IEEE Wireless Commun. Networking Conf. Wksps.*, Istanbul, Turkey, Apr. 2014, pp. 122–27.
[9] D. Bonino *et al.*, "ALMANAC: Internet of Things for Smart Cities," *Proc. Int'l. Conf. Future Internet of Things and Cloud*, Rome, Italy, Aug. 2015, pp. 309–16.
[10] D. Evans, "The Internet of Things: How the Next Evolution of Internet Is Changing Everything," Cisco tech. rep., Apr. 2011.
[11] M. Erol-Kantarci and H. T. Mouftah, "Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid," *IEEE Trans. Smart Grid*, vol. 2, no. 2, June 2011, pp. 314–25.
[12] K. M. Tsui and S.-C. Chan, "Demand Response Optimization for Smart Home Scheduling under Real-Time Pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, Dec. 2012, pp. 1812–21.
[13] M. E. Khanouche *et al.*, "Energy-Centered and QoS-Aware Services Selection for Internet of Things," *IEEE Trans. Automation Science Eng.*, vol. 13, no. 3, July 2016, pp. 1256–69.
[14] A. Al-Fuqaha *et al.*, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *IEEE Commun. Surveys & Tutorials*, vol. 17, no. 4, Nov. 2015, pp. 2347–76.

[15] M. Y. Naderi, P. Nintanavongsa, and K. R. Chowdhury, "RF-MAC: A Medium Access Control Protocol for Re-Chargeable Sensor Networks Powered by Wireless Energy Harvesting," *IEEE Trans. Wireless Commun.*, vol. 13, no. 7, July 2014, pp. 3926–37.

Biographies

Waleed Ejaz [S'12, M'14, SM'16] (waleed.ejaz@ieee.org) is a senior research associate in the Department of Electrical and Computer Engineering, Ryerson University, Toronto, Canada. Prior to this, he was a postdoctoral fellow at Queen's University, Kingston, Canada. He received his Ph.D. degree in information and communication engineering from Sejong University, Republic of Korea in 2014. He earned his M.Sc. and B.Sc. degrees in computer engineering from the National University of Sciences & Technology, Islamabad, Pakista,n and the University of Engineering & Technology, Taxila, Pakistan, respectively. His current research interests include IoT, energy harvesting, 5G cellular networks, and mobile cloud computing.

Muhammad Naeem [SM'16] (muhammadnaeem@gmail.com) received his B.S. (2000) and M.S. (2005) degrees in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan. He received his Ph.D. degree (2011) from Simon Fraser University, British Columbia, Canada. From 2012 to 2013, he was a postdoctoral research associate with WINCORE Lab at Ryerson University. Since August 2013, he has been an assistant professor with the Department of Electrical Engineering, COMSATS Institute of IT, Wah Campus, Pakistan, and a research associate with WINCORE Lab. His research interests include optimization of wireless communication systems, non-convex optimization, resource allocation in cognitive radio networks, and approximation algorithms for mixed integer programming in communication systems.

Adnan Shahid (adnan.shahid@intec.ugent.be) received his B.Eng. and M.Eng. degrees in computer engineering with communication specialization from the University of Engineering and Technology in 2006 and 2010, respectively, and his Ph.D degree in information and communication engineering from Sejong University, South Korea, in 2015. He is currently working as a postdoctoral researcher at iMinds/IBCN, Department of Information Technology, University of Ghent, Belgium. From September 2015 to June 2016, he was with the Department of Computer Engineering, Taif University, Saudi Arabia. From March 2015 to August 2015, he worked as a postdoctoral researcher at Yonsei University, South Korea. He was also the recipient of the prestigious BK 21 plus Postdoc program at Yonsei University. His research interests include device-to-device communication, self-organizing networks, small cells networks, cross-layer optimization, and integration of WiFi and small cells.

Alagan Anpalagan [SM] (alagan@ee.ryerson.ca) received his B.A.Sc. M.A.Sc., and Ph.D. degrees in electrical engineering from the University of Toronto, Canada. He joined the Department of Electrical and Computer Engineering at Ryerson University in 2001 and was promoted to full professor in 2010. He served the department as graduate program director (2004–2009) and interim electrical engineering program director (2009–2010). During his sabbatical (2010–2011), he was a visiting professor at the Asian Institute of Technology and a visiting researcher at Kyoto University. His industrial experience includes working at Bell Mobility, Nortel Networks, and IBM Canada. He directs a research group working on radio resource management and radio access and networking within the WINCORE Lab. His current research interests include cognitive radio resource allocation and management, wireless cross-layer design and optimization, cooperative communication, M2M communication, small cell networks, energy harvesting, and green communications technologies. He serves as an Associate Editor for *IEEE Communications Surveys & Tutorials* (2012–) and *Springer Wireless Personal Communications* (2009–), and a past Editor for *IEEE Communications Letters* (2010–2013) and the *EURASIP Journal of Wireless Communications and Networking* (2004–2009). He also served as Guest Editor for two *EURASIP* Special Issues on Radio Resource Management in 3G+ Systems (2006) and Fairness in Radio Resource Management for Wireless Networks (2008), and a *MONET* Special Issue on Green Cognitive and Cooperative Communication and Networking (2012). He co-authored or edited three books:: *Design and Deployment of Small Cell Networks* (Cambridge University Press, 2014), *Routing in Opportunistic Networks* (Springer, 2013), and *Handbook on Green Information and Communication Systems* (Academic Press, 2012). He is a registered Professional Engineer in the Province of Ontario, Canada.

Minho Jo [SM'16] (minhojo@korea.ac.kr) is a professor in the Department of Computer and Information Science, Korea University, Sejong Metropolitan City. He received his Ph.D. in industrial and systems engineering from Lehigh University in 1994 and his B.A. in industrial engineering from Chosun University, South Korea, in 1984. He was one of the founding members and Founding Captain of the IT Team, LCD Division, Samsung Electronics. He has extensive experience in wireless communications and software development in industry for more than 15 years. He is Founding Editor-in-Chief of *KSII Transactions on Internet and Information Systems*. He served as an Editor of *IEEE Network*. He is now an Editor of *IEEE Wireless Communications* and an Associate Editor of the *IEEE Internet of Things Journal*. He is an Associate Editor of *Security and Communication Networks* and *Wireless Communications and Mobile Computing*. He was Vice President of the Institute of Electronics and Information Engineers and is now Vice President of the Korean Society for Internet Information. His current research interests include IoT, LET-Unlicensed, cognitive radio, mobile cloud computing, network security, heterogeneous networks in 5G, wireless energy harvesting, AI in IoT, optimization in wireless communications, and massive MIMO.