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Internet of Things, Ad Hoc and Sensor Networks Technical Committee Newsletter (**IoT-AHSN TCN**)

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PREFACE

The IEEE ComSoc Ad Hoc and Sensor Networks Technical Committee (IoT-AHSN TC) sponsors papers, discussions, and standards on all aspects of IoT, ad hoc and sensor networks. It provides a forum for members to exchange ideas, techniques, and applications, and share experience among researchers. Its areas of interest include systems and algorithmic aspects of sensor and ad hoc networks, networking protocols and architecture, embedded systems, middle-ware and information management, novel applications, flow control and admission control algorithms, network security, reliability, and management. In an attempt to make all the TC members as well as the IoT-AHSN worldwide community aware of what is going on within our main areas of concerns, this newsletter had been set up. The newsletter aims at inviting the authors of successful research projects and experts from all around the world with large vision about IoT-AHSN-related research activities to share their experience and knowledge by contributing in short news. So, the eleventh issue of the IoT-AHSN TC Newsletter features one high quality news item gently provided by Samira Chouikhi, Leila Merghem-Boulahia and Moez Esseghir (Université de Technologie de Troyes, France). We thank them as well as all the previous contributors for their effort to make this newsletter successful towards fulfilling its objectives.

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NEWS RELATED TO AHSN TC

SOLOTEC Project: Multi-Level Intelligent Solution for Electricity Management in Smart Grid

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Abstract
The ever-increasing demand for electrical energy is a major challenge for any country around the world. Unfortunately, traditional electricity networks that were set up over the last decade are encumbered and unable to satisfy the future energy needs of a digital economy. Further, in order to reduce the impact of climate change on the environment, there is a need to integrate clean and renewable energy. Thus, these electrical installations become smarter, more reliable and more robust, in order to take into account these new changes without any loss in terms of stability and efficiency, leading to the emergence of the Smart Grid. However, the migration to the Smart Grid requires the development of new techniques and strategies to obtain a network that makes optimal use of the features and services offered by the integrated technologies. In this context, SOLOTEC project aims to develop an interdisciplinary, multi-level solution for electricity demand management based on hierarchical management of data collected by downstream sensors/actuators and integrating high-level data that represent the user's profile and preferences. In this newsletter, we present the different solutions and approaches proposed to achieve the goals of the project. Artificial Intelligence techniques such as multi-agent systems (MAS), game theory and machine learning are used are used in particular to allow the decision-making autonomy.

1. Introduction

Smart Grid (Xi 2012) is an electrical network that integrates Information and Communication Technologies (ICT) to optimally manage the resources and enhance the provided services. The combination of different technologies enables the coordination between different actors in the processes of generating, distributing, transmitting and consuming electricity (suppliers, consumers, equipment, etc.). Smart Grid may be divided into three major systems: a smart infrastructure system, a smart management system and a smart protection system. The smart infrastructure is the basic infrastructure for energy, information and communication that supports a bidirectional flow of electricity and information, i.e. electricity may be fed into the network by the consumers. This infrastructure may, in turn, be divided into three sub-systems: energy system (generation, distribution and consumption of energy), information system (collecting information, surveillance, monitoring, and management) and communication system (transmission of information between systems, devices and applications). The intelligent management system provides services and advanced features for monitoring and management. As new applications are developed and new management services are supported by smart infrastructure, the network continues to become smarter and smarter. The management system may set many goals related to improving energy efficiency, balancing supply and demand, controlling emissions, reducing operating costs and maximizing utility. Finally, the smart protection system provides an advanced analysis of the network's reliability, protection against breakdowns and of the security services and privacy protection. This system makes it possible to develop mechanisms to respond to threats to cybersecurity and protect privacy.

The development of Smart Grids relies not only on the advances in technologies and energy equipment, but also on the improvement of automated monitoring, analysis and sophisticated control services. These services are distributed and localized. Energy demand management is considered as one of the most challenging services offered by the modern Smart Grid. Demand management services are generally classified into two categories: Demand-Response services (DR) and Demand-Side Management (DSM). DR services offer reactive solutions that encourage consumers to dynamically adjust their demand in the short-term following signals provided by the system (pricing change, congestion, emergency condition, etc.). These techniques are typically used to reduce demand around peak hours or to avoid system failures. DSM services are generally based on proactive methods aiming to improve the energy efficiency of consumers. In literature, the terms DS and DSM are often used interchangeably or considered synonymous, however they represent completely different methods that can be used at the same time. DSM systems are designed to identify the optimal energy demand scheduling for a single residential consumer or for a community of consumers. This scheduling may have several goals: minimizing electricity bills, minimizing the consumer discomfort, maximizing the consumption of locally-produced energy, maximizing the use of renewable energy, smoothening consumption profiles etc. The optimization may be based on a single objective or multiple objectives simultaneously (multi-objective optimization).

The rest of the paper is organized as follows. Section 2 overviews some of the most interesting researches in demand management topic. Section 3 is dedicated to the SOLOTEC project with its goals and achieved results. Finally, Section 4 concludes the paper.

2. Demand Management: An Overview

In literature, researches have chosen different techniques and methods to solve the demand scheduling problem. Among them, three techniques have been proven to be relevant for demand management: game theory, multi-agent systems and machine learning. Electricity consumption scheduling approaches often use these three techniques simultaneously to combine their advantages. Game theory is one of the most widely used techniques to develop approaches consumer demand scheduling. This technique can express the interactions between users and the competition/cooperation between them to better manage their consumption. In (Soliman and Leon-Garcia 2014), the authors proposed an approach based on a non-cooperative game to describe the competition between users in order to find the optimal demand scheduling that minimizes the consumption costs. Energy storage units are also used to reduce the demand during peak hours. Consumers can thus charge the batteries outside these hours to use or sell this energy later. However, if more users follow this technique, a new consumption peak may be produced. To solve this problem, the authors introduced a Stackelberg game between the consumers and the supplier in which the latter can act on the price of electricity in order to regulate the demand. The major disadvantage of this approach is that the users must share information on their hourly requests, which limits the practical implementation of this solution and raises the question of protecting consumers' privacy. The authors of (Atzeni et al. 2013b) introduced a non-cooperative game to represent the problem of managing demand in Smart Grid with conventional (passive) consumers as well as consumers with storage units and/or distributed energy sources (active consumers). The proposed approach aims to determine the optimal strategies for energy storage and production in order to optimize demand. The strategy of each active consumer depends on three parameters: their appliances, the strategies of other consumers, and the total consumption of passive users. The authors have shown that the Nash equilibrium can be achieved based on proximal decomposition. Ibars et al. (2010) proposed a solution based on a network congestion game to guarantee that the local solution of each selfish consumer is the solution of the global optimization problem. The authors monitored energy demand during peak hours through a dynamic pricing strategy. In (Mohsenian-Rad et al. 2010), the authors used game theory to formalize a demand planning game between consumers. They proposed an autonomous and distributed management system using the communication infrastructure integrated in the microgrid. Dehghanpour and Nehrir (2017) modeled the problem of demand management as a negotiation game between different entities with different objectives. They applied a Distributed Gradient Algorithm (DGA) to solve this problem in real time. In (Ininahazwe et al. 2018), the authors proposed an autonomous distributive solution for demand-side management based on a Bayesian game. In this game, the schedulable loads of each consumer are modeled as a game with three players where one user plays against the storage unit and an opponent representing all the other users.

Multi-agent systems (MAS) are a set of autonomous intelligent entities (agents) having the ability to perceive aspects of their environment and, in many cases, to act on the environment to change it. Agents can have different degrees of intelligence depending on their roles in the MAS architecture. They can communicate with each other to exchange information or, in more complex cases, negotiate or cooperate to achieve the same objective. In the context of smart grids, MAS technology can be applied in a wide range of applications. Demand management is an essential service for smart grids, where Multi-Agent Systems have demonstrated what they can contribute and their performance. An

MAS is capable of making intelligent decisions without human intervention, which makes demand management systems autonomous, flexible, scalable and fault tolerant. Consequently, many researchers have opted for MAS to develop high-performing DSM approaches. In (Anvari-Moghaddam et al. 2017), an ontology-oriented multi-agent energy management system was proposed for optimal monitoring and control of buildings and houses in a microgrid integrating renewable resources and controllable loads. Different agents, ranging from those with a simple reflex to those integrating complex learning, were designed and implemented to achieve the optimal operating strategy. The proposed agent-based approach solves the demand management problem using cooperation and communication between decision-making agents.

Machine learning focuses on the design and development of algorithms that enable control systems to predict the behavior of microgrid components from empirical data such as sensor data. O'Neill et al. (2010) used an online learning application to implicitly assess the impact of future energy prices and consumer decisions on long-term energy costs, and thus schedule the use of residential electrical appliances and devices. Fang et al. (2011) used online machine learning to analyze strategies for using renewable energy resources in an isolated microgrid. More specifically, the consumer tries to decide which source, among several, should be used in order to maximize his profit. Although the profile of renewable energy production is not known in advance, the authors have shown that there is a relatively small difference between the profit obtained using the optimal renewable energy source and that obtained by following their strategy. Sheiki et al. (2016) proposed an automatic energy management system based on a reinforcement learning algorithm. They modeled the interaction between the electricity and natural gas networks. Their goal was to motivate residential consumers to participate in demand management programs and reduce their consumption of electricity and natural gas during peak hours.

In (Kofins et al. 2018), the authors introduced a cooperative MAS for energy monitoring and management in an autonomous micro grid. This system learns to control the components of the micro grid through a learning method by distributive and collaborative reinforcement in a continuous action-state space. The authors proposed the use of fuzzy Q-learning methods for agents representing the components of the microgrid to act as independent learners who share their states in order to coordinate their behaviors. The results showed the effectiveness of individual agents in controlling the components, as well as the effectiveness of the MAS in guaranteeing the supply of electricity and increasing the reliability of the micro grid.

3. SOLOTEC Project

This project focuses on the proposal of a fully interdisciplinary, multi-level approach for energy demand management based on hierarchical management of data collected by downstream sensors/actuators and integrating high-level data that represent the user's profile and preferences. The originality of this project consists in: i) the consideration and processing of data at the source, ii) the hierarchical integration of decision-making autonomy within the equipment, and iii) the taking into account of each consumer preferences and the overall gain obtained by all consumers when managing energy demand.

3.1. Project Goals

The main objective of the SOLOTEC project is to manage energy demand with an aim to reduce the residential energy consumption by implementing an embedded decision-making system. This system uses sensors and actuators that can collect and manage states and consumption instantly and automatically or make suggestions to the user, in order to achieve the reduction of energy demand. In addition, the project aims to demonstrate the correlation between local balances and the overall balance within a building or a neighborhood. This clearly proves the relevance of certain concepts such as the sharing of needs taking into account the general interest of users. Consumption management approaches incorporate high-level data (data representing consumer behavior and collected directly from him) in addition to the data collected and processed by the equipment.

3.2. Energy Management

As a first step, a distributed approach for electricity demand scheduling based on an incentive energy price was proposed (Chouikhi et al. 18a). In the proposed solution, the consumers of the same building interact in order to aggregate their demands before sending them to the energy supplier. The supplier, thus, sees these consumers as a single consumer. In addition, the price of energy depends on the total demand, which encourages users to cooperate. The scheduling problem is modeled as a multi-objective optimization problem with three objectives: i) minimizing the total cost of consumption; ii) reducing demand during peak hours; iii) maximizing the consumption of renewable energy. An MAS is introduced where a smart agent is defined for each consumer and each building. A cooperative game is performed between consumer agents to schedule energy consumption with minimal information exchange in order to protect the privacy of users. However, the energy is assumed to be sufficient to meet all the demands, which does not reflect reality. Thus, this solution was extended and a utility function, which represents the satisfaction of each consumer based on the availability of energy and the priorities of the consuming applications, was added (Chouikhi et al. 2018b). Moreover, the new proposal integrates a network of wireless sensors/actuators for managing and monitoring the consumption of certain devices. This network optimizes the energy consumption by making it possible to stop/ start these devices automatically based on several factors (e.g., the temperature or the presence of the user in the apartment). In addition, a mechanism that insulates the microgrid and protects it from any disturbance in the main electrical network was proposed.

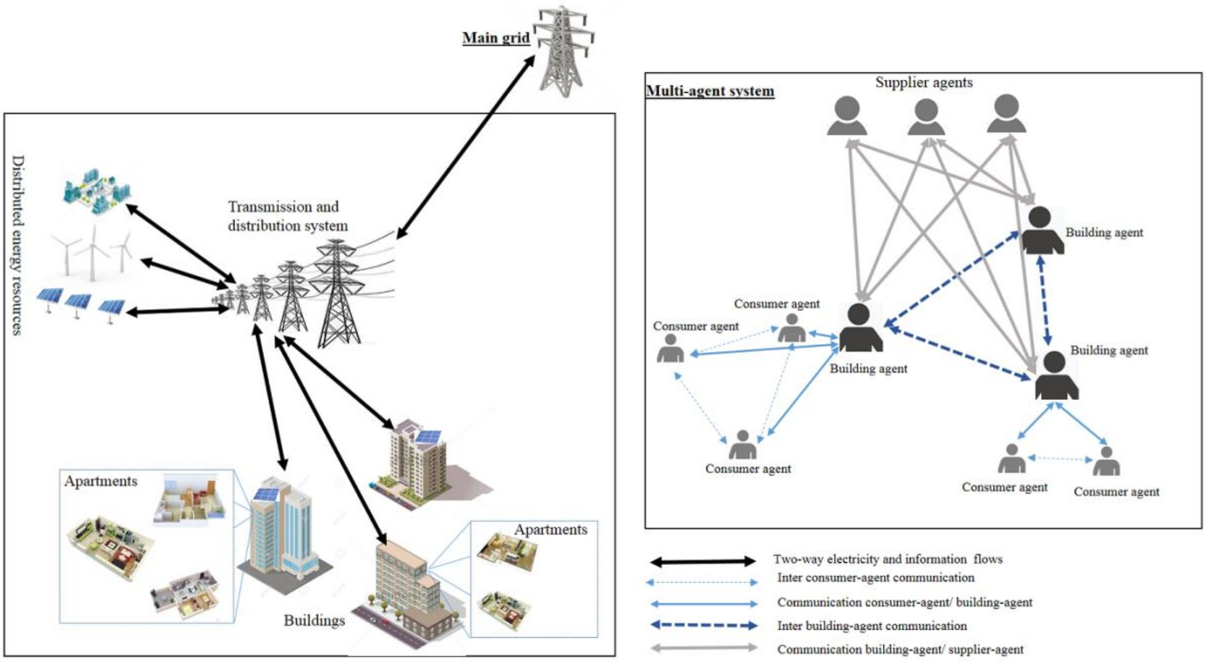

Fig.1 System architecture and correspondent multi-agent system

As a second step, a multi-scale solution based on multi-agent negotiation game, to better manage energy costs and consumption, was developed (Chouikhi et al. 2019a). The proposed approach tries to find a compromise to satisfy each consumer while taking into account total consumption and available resources (especially renewable energy resources). The negotiation game makes it possible to optimize energy bills by exploiting the diversity of producers and suppliers with different pricing strategies whilst respecting consumer preferences. In addition, the adoption of multi-scale decision-making has allowed to minimize the information exchanged between the various players in the electrical system and thus protect confidential consumer data.

With the apparition of cloud computing, the solving of complex problems is delegated to the cloud servers that have high capacity in terms of CPU, memory, storage space, etc. Thus, several smart grid applications use cloud computing services to improve their efficiency such as devices' handling, tasks' scheduling, and energy management. Unfortunately, the long distance between the consumers and the cloud servers as well as the huge amount of data generated by the consumers' connected appliances might represent serious issues for latency. Luckily, fog computing is proposed as an interesting technology to mitigate this problem since it displaces the data treatment closer to the end users. It complements the cloud computing rather than substituting it. In smart grid and smart cities domains, fog computing offers several interesting services to the end users. Hence, a quasi-distributed cooperative game was proposed to execute energy consumption scheduling at fog level (Chouikhi et al. 2019b).

Given the importance that intelligent storage systems can play in the energy context, multi-agent negotiation algorithms were proposed to reduce consumers' energy bills and limit access to conventional energy for better use of renewable energy. MAS are used to minimize consumer bills by optimizing the charge and discharge of the smart energy storage system (Klaimi et al. 2015a, 2015b, 2016). In this solution, the entities in the system (producer, consumer, storage system) are represented by agents who communicate with each other. The proposed scheme integrated renewable resources and tried to solve their intermittency problem. However, these solutions do not take into account energy losses during transport. Then, an extension is proposed in order to minimize losses due to transmission lines (Klaimi et al. 2018). The new approach presented algorithms for negotiation and cooperation between agents in order to maximize each entity's gain and balance the supply and demand of energy.

3.3. Anomaly Detection

The anomaly detection mechanism aims to improve the energy efficiency and detect abnormal behavior (Chahla et al. 2019). In particular, machine learning techniques are used to identify days when consumption patterns are abnormal, in order to avoid taking them into account when constructing models representing normal user behavior. The K-means algorithm is used to learn the different scenarios representing the energy consumption behavior of each user, as well as the LSTM (Long Short Term Memory) algorithm to predict the energy consumption of the next hour. The identification of outliers not only has the advantage of detecting abnormal events such as electrical theft or defective equipment, but it can also serve as an indicator for residents to help them change their consumption habits and warn them of device failures. The proposed model is evaluated using actual energy consumption data collected from Pecanstreand in United States.

3.4. Acceptability Investigation

Since the project focuses on optimizing energy consumption on the consumer side, it is essential to study the user reaction regarding the proposals made in the project since its success depends not only on the user's acceptability to integrate the specific technological aspects, but also on the contradiction of the decisions taken by the proposed system with its habits. Hence, as a part of the study of consumer behavior and acceptability of the approach, a qualitative survey of a number of consumers is conducted to determine how users perceive and use the proposed devices, identify the factors of resistance and appropriation and define them from the data collected (socio-economic data and capacities for behavioral change). Interesting recommendations are issued in order to enable the integration of social aspects into the deployment of the tools at the different study levels and thus obtain the sociotechnical feasibility of the proposed solutions.

3.5. SOLOTEC Demonstrator

The results obtained by the solutions proposed in SOLOTEC project are tested and validated through demonstrators and prototypes. The first prototype was developed by AUBELEC (Troyes, France) to control and manage the energy consumption in the company offices. The second demonstrator is located in one of the buildings in University of Technology of Troyes UTT (France). Radio valves, thermostats and sensors are installed in the offices to control the Heating, Ventilation and Air-Conditioning system (HVAC) through a graphic interface as shown in Fig.2.

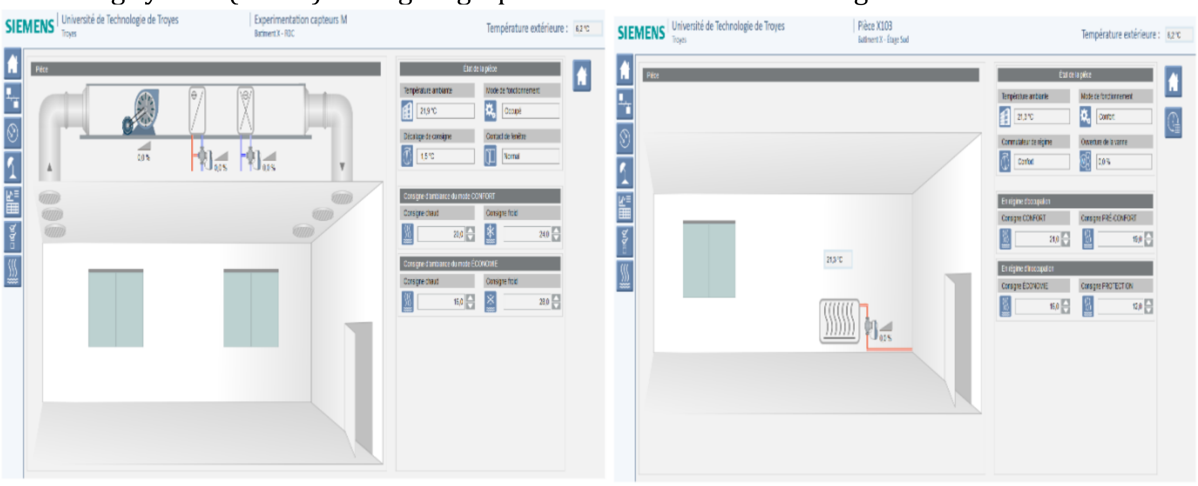

Fig.2 Graphic interface for HVAC management system

4. Conclusion

Migrating towards a smart grid allows information and communication technologies to be integrated into electrical networks in order to better manage resources and improve the services provided. This new environment offers better management of the production, distribution and consumption of energy. However, new challenges arise and must be resolved. Researchers are therefore increasingly interested in the design and development of mechanisms and approaches that make it possible to take advantage of the features offered. In this context, SOLOTEC focused on the development of interdisciplinary, multi-level solution for energy demand management based on hierarchical management of data. The aim of the solution is to implement a distributed embedded decision-making system for control and management of consumers' electricity demand not only in to reduce their bills or conserve energy, but also to improve the electrical network efficiency. Different solutions and approaches for energy and data management were proposed as a part of the project. The proposals opt mainly three techniques of Artificial Intelligence, namely: game theory, multi-agent systems and machine learning.

References

1. Anvari-Moghaddam, A., Rahimi-Kian, A., Mirian, M.S., Guerrero, J.M. (2017). A multi-agent based energy management solution for integrated buildings and microgrid system. Applied Energy, 203, 41–56.
2. Atzeni, I., Ordonez, L.G., Scutari, G., Palomar, D.P., Fonollosa, J.R. (2013a). Noncooperative and Cooperative Optimization of Distributed Energy Generation and Storage in the Demand-Side of the Smart Grid. IEEE Transactions on Signal Processing, 61(11), 2454–2472.
3. Atzeni, I., Ordonez, L.G., Scutari, G., Palomar, D.P., Fonollosa, J.R. (2013b). Demand-Side Management via Distributed Energy Generation and Storage Optimization. IEEE Transactions on Smart Grid, 4(12), 866–876.
4. Chahla, C., Snoussi, H., Merghem-Boulahia, L., and Esseghir, M. (2019). A Novel Approach for Anomaly Detection in Power Consumption Data, ICPRAM-8th International Conference on Pattern Recognition Applications and Methods, Prague, Czech Republic.
5. Chouikhi, S., Merghem-Boulahia, L., Esseghir, M. (2018a). Energy Demand Scheduling Based on Game Theory for Microgrids. IEEE International Conference on Communications (ICC). IEEE, Kansas City.
6. Chouikhi, S., Merghem-Boulahia, L., Esseghir, M. (2018b). Multi-Level Energy Consumption Optimization for Smart Buildings. IEEE Global Communications Conference (Globecom). IEEE, Abu Dhabi.
7. Chouikhi, S., Merghem-Boulahia, L., Esseghir M., and Snoussi ,H. (2019a). A Game-Theoretic Multi-Level Electricity Demand Management for Smart Buildings, IEEE Transactions on Smart Grids, pp. 6768- 6781.
8. Chouikhi, S., Merghem-Boulahia, L., Esseghir, M. (2019b). A Fog Computing Architecture for Energy Demand Scheduling in Smart Grid. International Wireless Communication and Mobile Computing (IWCMC), Morocco.
9. Dehghanpour, K., Nehrir, H. (2017). Real-Time Multiobjective Microgrid Power Management Using Distributed Optimization in an Agent-Based Bargaining Framework. IEEE Transactions on Smart Grid, 6(9), 6318–6327.
10. Fang, X., Yang, D., Xue, G. (2011). Online strategizing distributed renewable energy resource access in islanded microgrids. IEEE Global Telecommunications Conference (GLOBECOM). IEEE, Houston.
11. Ibars, C., Navarro, M., Giupponi, L. (2010). Distributed Demand Management in Smart Grid with a Congestion Game. IEEE International Conference on Smart Grid Communications (SmartGridComm). IEEE, Gaithersburg.
12. Ininahazwe, H., Muriithi, C.M., Kamau, S. (2018). Optimal demand-side management for smart micro grid with storage. Journal of Power and Energy Enginee-ring, 6(12), 38–58.
13. Klaimi, J., Merghem-Boulahia, L., Rahim-Amoud, R., Jrad, A. (2015a). An energy management approach for smart-grids using intelligent storage systems. International conference on digital information and communication technology and its applications (DICTAP). IEE, Beyrout.
14. Klaimi, J., Rahim-Amoud, R., Merghem-Boulahia, L., Jrad, A. (2015b). An agent-based approach for energy management in smart-grids. Highlights of practical applications of agents, multi-agent systems, and sustainability – The PAAMS collection, Bajo, J. et al. (dir.). Springer, Berlin, 225–236.
15. Klaimi, J., Rahim-Amoud, R., Merghem-Boulahia, L., Jrad, A., Esseghir, M. (2016). An intelligent storage-based energy management approach for smart grids. International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). IEEE, New York.

16. Klaimi, J., Rahim-Amoud, R., Merghem-Boulahia, L., Jrad, A. (2018). A novel loss-based energy management approach for smart grids using multi-agent systems and intelligent storage systems. Sustainable Cities and Society, 39, 344–357.
17. Kofins, P., Dounis, A., Vouros, G. (2018). Fuzzy Q-Learning for multi-agent decentralized energy management in microgrids. Applied Energy, 219, 53–67.
18. Mohsenian-Rad, A.H., Wong, V.W., Jatskevich, J., Schober, R., Leon-Garcia, A. (2010). Autonomous demand-side management based on game theoretic energy consumption scheduling for the future smart grid. IEEE Transactions on Smart Grid, 1(13), 320–331.
19. O'Neill, D., Levorato, M., Goldsmith, A., Mitra, U. (2010). Residential Demand Response Using Reinforcement Learning. IEEE International Conference on Smart Grid Communications. IEEE, Gaithersburg.
20. Sheikhi, A., Rayati, M., Ranjbar, A.M. (2016). Demand side management for a residential customer in multi-energy systems. Sustainable Cities and Society, 22, 63–77.
21. Soliman, H.M., Leon-Garcia, A. (2014). Game-Theoretic Demand-Side Management with Storage Devices for the Future Smart Grid. IEEE Transactions on Smart Grid, 5(13), 1475–1485.
22. Xi, F., Satyajayant, M., Guoliang, X., Dejun, Y. (2012). Smart Grid – The New and Improved Power Grid: A Survey. IEEE Communications Surveys & Tutorials, 14, 944–980.