CHEMICAL ENGINEERING TRANSACTIONS

VOL. 76, 2019

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Petar S. Varbanov, Timothy G. Walmsley, Jiří J. Klemeš, Panos Seferlis

ISBN 978-88-95608-73-0; **ISSN** 2283-9216

DOI: 10.3303/CET1976153

Incentive-based Energy Management Strategies for Smart-grids based on an Internet of Things (IoT) Connectivity Framework

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Smart-grids create a new paradigm in energy distribution, transmission and consumption and their operations domain aim to balance the demand with the production in a flexible and cost-efficient manner. Energy providers can use Demand Response (DR) to control electricity load during peak hours and can have the ability to shift energy demand from one time period to another to achieve smooth consumption patterns. This work presents the development of an incentive based Demand Response (DR) method. The preferences and behaviour of each residential user are modelled using an Internet of Things (IoT) reference architecture, while the DR actions are derived by the solution of a dynamic optimization problem. The overall energy management is performed by a local aggregator system and relies on this optimization-based approach with priorities that are dynamically updated based on the status of each consumer. A simulation scenario is presented that demonstrates how a DR program can affect the consumer's behaviour in an optimal manner. The aggregator managed one of the appliances (Air Condition) of the participants to reduce the necessary amount of power. As a result, the power reduction was on average 23 % while the demand for reduction was 20 %, which is a clear indication that the applied actions by the aggregator fulfilled the energy provider's request. The key result is the customer empowerment which is achieved by the reduction of the cost of electricity while maintaining the desired level of comfort. On the other hand, DR provides energy operators and utilities additional operational and enhancement of their resource capacity.

1. Introduction

The increasing demand for power, the fluctuation in fuel prices and the need for security of energy supply have led to an ongoing transition to a new paradigm for the electricity grid, the smart grid that consists of smart and multi-source power nodes along with active consumers that play an emerging role. Smart grid operations target to bring a balance between the energy production and demand (Al Haj Hassan et al., 2015). Demand Side Management (DSM) is one of the methods that contribute to this balancing as it can modify the consumer's load and reduce the total cost of energy for the participants (Gelazanskas et al., 2014). DSM methods are based on two key options: Demand Response (DR) method and methods that aim to energy savings based on equipment upgrade, such as LED lighting or more energy efficient appliances. DR includes any demand-side activity that aims to modify end user's energy consumption patterns during specific time periods that can improve the energy efficiency and optimize the use of electricity (Hu et al., 2018). DR has proven to be a distributed energy resource of great potential for electrical systems operation (Roldán-Blay et al., 2019) when appropriate information is provided to the end users to help them improve their benefits. Also the integration of energy and information technology has facilitated the development of aggregators and end-users with enhanced interaction capabilities and when combined with standardized models (Liu et al., 2019) there is a significant increase in the DR benefits. The use of appropriate models provides the operator insights about the effect of DR actions and economic

Paper Received: 11/05/2019; Revised: 21/06/2019; Accepted: 07/07/2019
Please cite this article as: Ziogou C., Papadopoulou S., Voutetakis S., 2019, Incentive-based Energy Management Strategies for Smart-grids based on an Internet of Things (IoT) Connectivity Framework, Chemical Engineering Transactions, 76, 913-918 DOI:10.3303/CET1976153

aspects of the system along with effects of the price elasticity of demand (Aalami et al., 2019) and the benefits for the end user.
Overall residential appliances can be classified into two groups, the critical and the non-critical. The non-critical have high potential to participate in the DR events and earn rewards. The non-critical appliances are managed by the community aggregator, which is responsible to change the status of the non-critical appliances in response to the specific DR events by the utility. At this context interconnectivity and interoperability are very important requirements for the development of integrated DR management systems. In general, the information exchange among the involved stakeholders at smart grids, constitute a significant aspect of their operation. The main challenge is to minimize the inconvenience for the end user (Paudyal and Ni, 2019) and to encourage them to participate to DR programs and concurrently satisfy the required demand reduction. The information to be exchanged concerns on the one hand the energy providing company and other generation or distribution entities and on the other the consumers and the local aggregator. The adoption of an Internet of Things (IoT) model for the data formulation and representation can contribute significantly to the seamless communication and status awareness of the participants' situation. A flexible and expandable strategy for exchanging energy-related information among the smart grid entities is a topic of research the past few years. To this end, this work presents an IoT-based framework to facilitate the development of a DR management system for residential users. Additionally, we developed an optimization based framework to derive a systematic and optimum way of managing the residential appliances during DR events and to optimally coordinate the timing of household energy consumption at the local level. The main contribution and novelty of this work is the synergy between a flexible DR method with an IoT-based connectivity framework and the development and testing of a dynamic optimization scheme which determines the DR actions for the involved participants.

2. Demand Response (DR) method

The management of the residential appliances can be approached by two DR methods. The price-based DR (PbDR) and the incentive based DR (IbDR). In general, DR methods aim at optimizing the usage of the appliances of each participating household while ensuring that the requested energy reduction is satisfied. Although both approaches have various benefits, in this work we selected the IbDR in order to show how the engagement of the participants can increase the effectiveness of DR programs using incentives. The objective of IbDR methods is to create an active dynamic cooperation between energy providers and consumers to reduce electricity demand during peak hours. The incentives that are given to the consumers are quantified in rewards based on their behaviour and preferences. The participation to DR is translated into reduced price or even in some cases free electric power (specific kWh) that they consume. During the day, the energy provider (utility) sends Demand Response Events (DRE) that are consist of a time duration (t_{DR}) in minutes and the power to be reduced (P_{DR}) in kW.

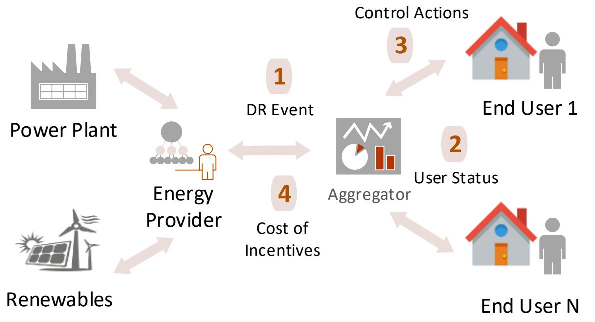

Figure 1: Information flow when the aggregator receives a DR request

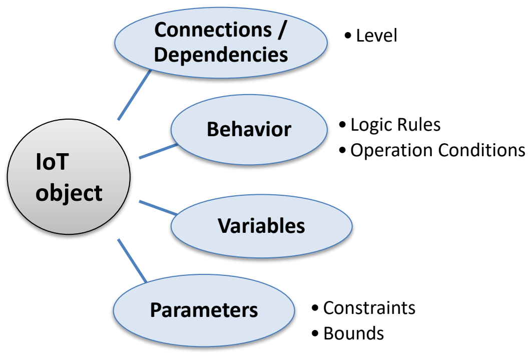

Figure 2: IoT Object – Main structure elements

The load management is handled by an aggregator (Figure 1) which is responsible for the coordinated communication with the energy grid operators, energy providers and the consumers. The aggregator receives notifications about DR requests (DR_R) to be applied to the local grid and informs the energy provider about the cost of the rewards that the consumers are entitled due to their participation in the DR program. Finally, based on predefined preferences of each consumer, the aggregator modifies selected non-critical loads to achieve the desired result, which is a combination of cost and consumer comfort.

3. Internet of Things (IoT) reference model

At an IoT ecosystem, data is generated by multiple types of devices, processed in different ways, transmitted to different locations, and acted upon by applications. The IoT ecosystem is a set of elements that constitute a wider infrastructure that enables the implementation of advanced services through the interconnection of (physical and virtual) things using existing and interoperable information technologies (Atzori et al., 2010). Based on this approach, we aim to develop a framework that takes into account existing architectures and can transform their various levels of operation and communication into an IoT-compliant architecture. The implementation of such an approach can provide a better insight into the management of physical systems and their interconnection. The use of an IoT-based architecture facilitates the design and development of extensible, flexible and easy-to-maintain systems for the field of operations of smart grids (Bassi et al., 2013). In that context, the information exchange between the aggregator and the consumers is represented by an IoT reference model to provide a homogeneous and generalized way of interconnection. Each consumer is an IoT node. The proposed modelling is not technically limited to the implementation of a particular network and it can be used for a wide range of applications, besides the DR method. Each node (consumer) on a network can be represented as an IoT object - Figure 2 (Ziogou et al., 2016).

Overall an energy network consists of consumers with different preferences and energy consumption needs. The aggregator should be able to cope with this variety and concurrently satisfy the DR request by the energy provider. The interconnection of the individual nodes and the topology is made in such a way that it can be adjusted to any network. In this work the systematic consideration of the functional and energy parameters that can be altered at each interconnected node, is modeled in order to achieve the dynamically changing goals as defined by the energy utility (Ziogou et al., 2017). Each consumer has a set of appliances that can be managed in case of demand reduction request (such as: Air condition - AC, Water Heater - WH, Dish Washer - DW, Clothes Dryer Washing and Dryer - CD). Also, each consumer defines a set of desired limits for the room temperature and the hot water, along with the desired priorities for the order in which the appliances will be affected. The description of the nodes consists of:

- The structure that specifies the connection of the individual nodes with the aggregator.
- The components, which define the structural and operational parameters and variables along with the relationships between the parameters.
- The limits that define the range of actions for each node.
- The behaviour, which includes the concept of whether the status of an appliance or a preference is activated or not.

Overall the part of the network which is handled by the aggregator can be represented as a system and is defined as a set $Sys = \{Un_1, Un_2, ..., Un_n\}$ consisting of individual units, the nodes. One unit is defined as the set $Un_i = \{St_i, Mt_i, \delta_i\}$ where *St* is the set of the static parameters and *Mt* is a set of the time-varying parameters. The activation of the various states and appliance status is associated with logical variables (δ_i). More specifically, the components of each node-consumer which are available to the aggregator are:

- The set of constant parameters $St_{const} = \{Eff, L_R, P_{App,RATED}\}$, where *Eff* is the effect that the usage of a specific appliance has to the room or water temperature, L_R is the loss coefficient which is defined for the room and the boiler for each consumer and $P_{app,RATED}$ is the nominal power consumption of each non-critical load.
- The set of static parameters that can be modified by the consumer $St_{\mathrm{mod}} = \{T_{0,\mathrm{k}}, T_{high,\mathrm{k}}, T_{low,\mathrm{k}}\}, \mathrm{k} = [\mathrm{AC}, \mathrm{WH}]$ which are related to the initial temperature, the maximum and minimum desired limit that define the comfort zone for AC and the water heater of each consumer.
- The set of variables for each node $Mt = \{T_{R,\mathrm{k}}, T_{amb}, P_{crit}, P_{non-crit}, P_{w/oDR}\}, \mathrm{k} = [\mathrm{AC}, \mathrm{WH}]$, where T_R is the room temperature, T_{amb} is the ambient temperature, P_{crit} is the power of the critical loads, $P_{non\text{-}crit}$ is the power of the manageable appliances and $P_{w/oDR}$ is the estimated power consumption in case the DR is not applied of each consumer.
- The logical variables (Boolean) that are related to the static parameters and are modified dynamically during a DR event: δ_{App}, δ_{DR}, δ_{com}, which are the status of the appliances, their activation/deactivation due to DR event and the consumer preference for willingness to compromise or not.

According to the above approach, the consumer preferences which participate to the DR program can be represented and the aggregator can flexibly adapt to the number of connected consumers. The next step is to define the indices that are affected by the DR events for each consumer.

4. Comfort Index (CI) and Incentive Index (InI)

The implementation of the IbDR method requires the calculation of consumer incentives and comfort indicators. The level of incentives is the combination of consumer preferences and comfort index, calculated dynamically during the day and depends on how the appliances are modified due to the DR event. More specifically, the calculation of the incentive (*In*) for each time interval (*t*) is calculated according to:

$$In_{i,t} = \left(P_{w/oDR,i,t} - \left(P_{crit,i,t} + P_{non-crit,i,t}\right)\right) In_{L,i,t}\text{ , } i=[1..N_{res}] \quad (1)$$

$$P_{non-crit,i,t} = \sum_j P_{App,RATED,i,j}\delta_{App,i,j,t}\delta_{DR,i,j,t},\ j = [\mathrm{AirC, WH, DW, CD}]\text{ , } i=[1..N_{res}] \quad (2)$$

$$In_{L,i,t} = \begin{cases} L_1, CPI_{i,t} > CI_{nom,i} \\ L_2, \left(CPI_{i,t} \le CI_{nom,i}\right)\delta_{com} \\ L_3, \left(CPI_{i,t} \le CI_{nom,i}\right)!\delta_{com} \end{cases} \quad (3)$$

$$CPI_{i,t} = \sum^{k} w_{CI,\mathrm{k}} CI_k + w_{CIapp,\mathrm{i}} \sum^{j} \delta_{App,i,j,t}, k = [AirC, WH], j = [AirC, WH, DW, CD], i = [1..N_{res}] \quad (4)$$

$$CI_k = \left| \frac{2T_{R,k} - T_{high,k} - T_{low,k}}{T_{low,k} - T_{high,k}} \right|, k = [\mathrm{AirC, WH}] \quad (5)$$

$$T_{R,k} = T_{0,k} - L_{R,k}(T_{0,k} - T_{amb,k}) - Eff_k P_{App,RATED,k}\delta_{App,k}, k = [\mathrm{AirC, WH}] \quad (6)$$

Where N_{res} is the number of consumers connected to the aggregator, *CPI* is the overall comfort index, *CI* and CI_{nom} are the comfort index per appliance and the standard comfort index per consumer, and w_{CIk} and w_{CIapp}, are the weights of each appliance to the overall comfort index and the weight that the weight related to the total number of activated appliances. Eq.(1-6) are part of the behaviour analysis of each node and constitute the basic component of the IoT object. After the modelling of the consumer behaviour, the optimization of the DR actions by the aggregator is necessary in order to ensure that both the energy provider and the consumers are satisfied by their engagement in the DR program.

5. Optimum operation using a DR method

The aggregator implements a power management strategy (PMS) by solving an optimization problem, that combines the requirements for reducing the cost of energy consumption and improving the reliable operation of the network. Also, the optimization results to the reduction of energy demand during peak hours or when the energy provider requests it. For this purpose, the optimization problem has two objectives: a) to reduce the reward costs for the energy provider and b) to maintain consumer's comfort at specific levels:

$$\begin{aligned} &J = \min\left\{ w_{In} \sum_i^{Nres} In_{i,t} + w_{CPI} \sum_i^{Nres} \Delta CPI_{i,t} \right\} \\ &s.t.: \left(P_{tot,i,t} - \left(P_{crit,i,t} + \sum_j P_{App,RATED,i,j}\delta_{App,i,j,t}\delta_{DR,i,j,t} \right) \right) > P_{DR}, j = [\mathrm{AirC, WH, DW, CD}] \end{aligned} \quad (7)$$

Where P_{DR} is the power to be reduced over a DR event and w_{In}, w_{CPI} are the weights of the incentives and the weight of the modification of the comfort index. The above optimization problem is solved when a DR event is received.

6. Results and discussion

To investigate the operation of the IbDR method, a small scale simulation scenario was developed, that consists of an aggregator with 5 consumers that all have the same appliances. The time interval that the consumer exchanges data with the aggregator is set at 15 min. There are three levels (L1, L2, L3) of the incentive index (In_L). In order to avoid the quantification of the rewards on the base of a specific price, which can vary between countries, energy providers within a country etc., the equivalent rewards are expressed in kilowatt hours. The three levels of rewards are 1 kWh, 2 kWh and 3 kWh. Whenever a consumer participates in the IbDR program, will be rewarded accordingly. To increase the fairness for the participation of the consumers, their history is considered (DR_{hist}). In case two consumers have the same performance index the priority is given to the one that has lower participation history. The DR_{hist} affects the weights in the objective function (7). The average consumption of the 5 participants is 35.7 kW. The critical loads consumption has a variation of +/-15 % during the day and ranges from 1.1 kW to 1.8 kW. The appliances CD and DW operate twice a day for 2 hours at a time. The priority column refers to the appliance that will be affected after the aggregator has already modified the status of the AC and WH or in case that these two appliances do not operated during the DR event. The characteristics of consumers are shown in Table 1.

Table 1: Consumer choices participating in the IbDR program

#N	$T_{range,AC}$ (ºC)	P_{crit} (kW)	P_{AirC}, P_{WH}, P_{DW}, P_{CD} (kW)	$P_{App, Rated}$ (kW)	Priority	DR_{hist}
1	22-24	1.1	1.8, 3.1, 2.5, 3.7	10.4	CD	9
2	21-23	1.3	1.3, 4.0, 1.8, 4.1	10.2	-	7
3	20-24	1.0	1.2, 3.5, 2.0, 3.0	9.7	DW	3
4	20-22.5	1.5	1.5, 3.8, 2.0, 3.5	10.8	CD	5
5	19-22	1.1	1.3, 3.9, 2.2, 3.0	10.4	DW	21

In order to evaluate the operation of the IbDR program and the effect on consumer's comfort, the results from a DR event are presented. The aggregator receives a request to reduce 20 % of power consumption for one hour that corresponds to 5.6 kW. The optimization problem is solved and considers the status (activated or not) of the appliances and the preferences of the consumers. Figure 3 shows how consumption is reduced when consumers participate in the IbDR program compared to the power request without it.

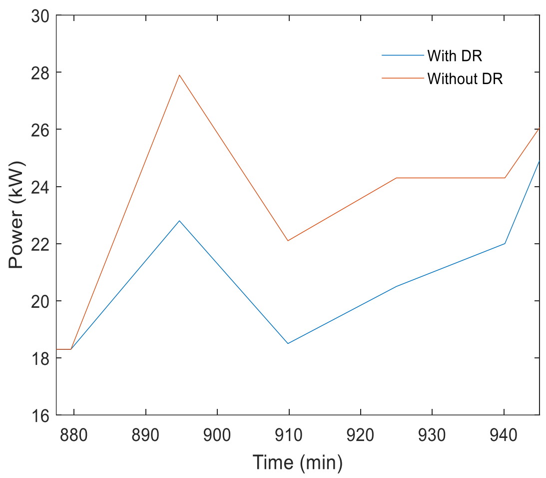

Figure 3: Total power consumption with and without participation in the IbDR program for the 5 consumers

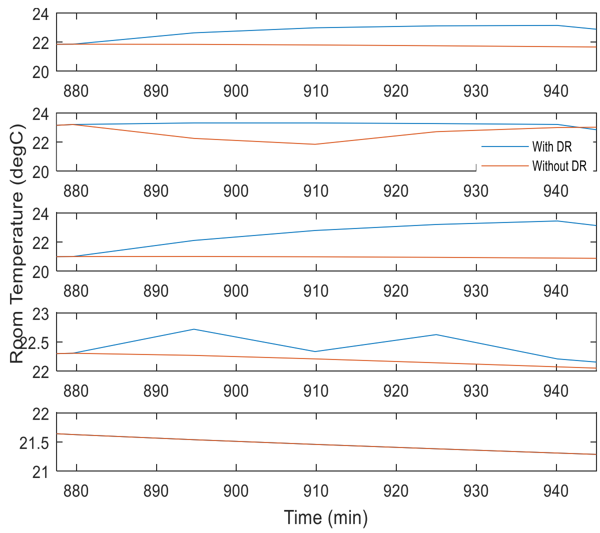

Figure 4: Room temperature modification with and without participation in the IbDR program (from top to bottom: Consumer 1-5)

In this case, the aggregator manages the AC of the participants to reduce the necessary amount of power as shown in Table 2 during the DR event. Table 2 shows the overall comfort, the levels of incentives that were given to consumers and the cost of reward. Fig. 5 shows how the room temperature is affected accordingly.

Table 2: DR result request for 20 % power reduction

#N	Comfort (%)	Incentive Level	Reward Cost (kWh)	Affected Appliance
1	100	L1	4	AC
2	100	L1	4	AC
3	100	L1	4	AC
4	75	L1,L2	5	AC
5	100	L1	4	-

Each node remains within the comfort zones selected, except for the 4th which is out of the maximum comfort zone for 15 min and is rewarded with L2 for this effect. Overall consumers 1-4 have participated, while the consumer 5 although willing to contribute, did not have to be activated as the reduction was covered by the others. Consumer 5 had the largest number of DR participation (DR_{hist}), which results to the lowest weight in the optimization problem. Nevertheless, the consumer 5 was also rewarded just by its participation to the IbDR program. The reward was at the lowest level (L1). Overall, the power reduction was on average 23 % while the demand for reduction was 20 %, which is a clear indication that the applied actions by the aggregator fulfilled the energy provider's request.

7. Conclusions

An optimization based IbDR method has been developed that allows the local aggregator to make the appropriate decisions during DR events that are initiated by the energy provider. The representation of consumer's time-varying behaviour was performed by a platform independent IoT reference model where the static and dynamic characteristics of the residential appliances were included. Furthermore, the necessary actions are derived by the solution of a centralized dynamic optimisation problem. The developments of this work were verified by a simulation scenario. The main objective to response to the specific demand for power consumption reduction and at the same time to maintain the comfort of the consumer was achieved. The key findings of this work shows that the implementation of IbDR-type programs can increase the potential for power savings during peak hours whereas the implementation of dynamic optimization scheme can significantly improve the usage of available smart-grid resources.

Acknowledgments

Research supported by EU funded HORIZON2020 project inteGRIDy - integrated Smart GRID Cross-Functional Solutions for Optimized Synergetic Energy Distribution, Utilization & Storage Technologies, H2020 Grant Agreement Number: 731268.

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