

Peak Demand Reduction Through Demand Control: A Mathematical Analysis

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Abstract—The utilization of information and communication technologies in power systems is a vital tool for the transformation of the entire infrastructure, from generation, distribution, to electricity consumption, into an intelligent, reliable and energy-efficient *smart grid*. The concept of Demand Response (DR) includes all the activities that target the alteration of the electricity consumers' demand profile, which will benefit not only themselves, but also the power grid. In this paper, we propose new and more effective DR-based power-demand control scenarios that target the peak demand reduction in a smart grid infrastructure. The proposed scenarios and corresponding analytical models are applied to a residential area, where each residence is equipped with a specific number of appliances with diverse power demands. Moreover, the proposed scenarios take into account the fact that some appliances are able to contribute to the peak demand reduction more effectively, compared to other, by incorporating different power thresholds per appliance for the activation of the power control mechanisms. The accuracy of the proposed models is verified through simulation and found to be quite satisfactory.

Keywords—demand response; power demand scheduling; smart grid; performance evaluation.

I. INTRODUCTION

Demand Response commonly refers to programs that target to motivate energy consumers to change their electric usage habits in response to changes in electricity prices or incentive payments, in order to achieve low electricity usage in peak demand periods or when grid reliability is jeopardized [1]. The application of a DR program is mainly based on a *smart* and *intelligent* power generation and supply system, by embedding bi-directional communication and information architectures with power grids [2]. However, the success of a DR program lies not only on these intelligent technologies, but mainly on implementing an effective design of the DR-based mechanism that will improve the efficiency, reliability, and safety of the grid, as well as it will be beneficial for the consumers.

The efficiency of a DR program is highly affected by the adaptation of power demands to time pricing or incentives offered to consumers in order to motivate them to change their electric use behaviors. This customer-enabled power consumption management is mainly achieved by either postponing power requests or compressing power demands during high demand periods. The first method is known as a “task scheduling” mechanism [3], and various models that are based on the activation of consumers' loads in specific time periods have been presented in the literature, e.g. in [4]–[6].

Alternatively, the objective of the “energy scheduling” methods is to reduce the power consumption of specific loads, in order to reduce the total power consumption during peak-demand hours [3]. A combination of the two mechanisms has been also studied in [7]–[9], where a task-scheduling mechanism is applied to appliances that consume power in adjustable time-slots, while an energy-management mechanism is considered for appliances that have flexible power demands.

In [10], we have proposed various power demand control scenarios that target to schedule the demand requests of consumers in order to decrease the peak demand. All scenarios are applied to a residential area and assume that each residence is equipped with a specific number of appliances. Each appliance is defined by its power demand, its operational time and an arrival procedure of demand requests to a Central Load Controller (CLC). The *default scenario* is initially introduced, in order to define the upper bound of the peak demand, since this scenario does not consider any scheduling mechanism. The Compressed Demand Scenario (CDS) considers that a number of appliances are able to compress their demands when the total power consumption exceeds multiple predefined power thresholds. The Delay Request Scenario (DRS) considers that the power requests of some appliances can be delayed in buffers for a specific time period, by considering similar power thresholds as in the CDS case, in order to decrease the total power consumption. Finally, the Postponement Request Scenario (PRS) considers only two power thresholds; when the total power consumption exceeds the higher threshold, power requests are delayed not for a specific time period (as in the DRS case), but until the total power consumption drops below the lower threshold. All scenarios assume that power requests arrive according to a Poisson process (infinite number of appliances). The consideration of finite number of appliances has been used in the analysis presented in [11], in order to determine the peak demand under the four demand control scenarios. Furthermore, in [12] we have proposed similar scheduling scenarios and corresponding analytical models that take into account the appliance's feature to alternate between ON and OFF states.

In this paper, we revisit the power demand scheduling scenarios proposed in [10], and we propose new and more realistic scenarios and corresponding analytical models for the calculation of the peak demand in a residential area. Precisely, in [10] we proposed analytical models for different power demand control scenarios, under the assumption that the scheduling mechanism is activated for all appliances when the

total power consumption exceeds predefined power thresholds, which are common for all appliances. However, the later assumption results in an uneven number of appliances of different types that contributes to the total peak demand reduction. For example, if the distribution-network operator requires a reduction of 40 kWh of the total demand within an hour, then this reduction could be achieved by the deactivation of 10 water heaters with nominal power of 4 kW, or of 400 refrigerators with nominal power of 0.1 kW. Therefore, a more realistic approach would be to consider different power thresholds per appliance, which will be defined so that the scheduling mechanism is activated at lower thresholds for appliances with high nominal power, while low power consumption appliances will contribute at higher total power consumption levels. Therefore, under the proposed approach the desired peak demand reduction is achieved in a nondiscriminatory fashion regarding the appliances' types, so that each residence can equally contribute to the demand control program. Furthermore, the application of multiple power thresholds reduces the effect of a significant power-request delay or power demand reduction, which may decrease the consumers' comfort, especially for specific appliances that consumers disfavor to schedule their operation. The proposed demand control scenarios are named the Extended Demand Request Scenario (EDRS) and the Extended Compressed Demand Scenario (ECDS). These two scenarios are applied to task and energy scheduling appliances, respectively, and can be jointly used for the peak demand calculation in cases where both types of scheduling appliances are considered, together with appliances that cannot endure delays of power compressions. The validation of the proposed analytical models is achieved through the comparison of analytical results from the proposed models with results from simulation; the accuracy of the proposed models found to be quite satisfactory.

The rest of the paper is organized as follows. In Section II we firstly introduce the baseline scenario, where no scheduling procedure occurs, in order to define the upper bound of the peak demand in the residential area under study. In Section II we also present the proposed scheduling scenarios with the corresponding analytical models. Section III is the evaluation section, where analytical and simulation results are compared and discussed. We conclude our paper in Section IV.

II. THE PROPOSED DEMAND CONTROL MODEL

This section provides the modeling principles of the smart grid infrastructure under study, while we also present the default scenario, in order to determine the upper bound of the peak demand. Moreover, this section presents the proposed demand control models that target the peak demand reduction through the alternation of the users' energy consumption habits.

A. The Default Scenario

We consider a residential area where each residence is equipped with an Energy Consumption Controller (ECC), which is connected to up to M appliances. The ECC is also connected to the CLC through a Local Area Network (LAN). Furthermore, each residence is connected to the power line

coming from the energy source.

Each appliance requires a specific amount of power for its proper operation; for appliance m ($m=1, \dots, M$) the power demand is denoted as p_m power units (p.u.). The maximum number of p.u. that the distribution network can support in the residential area under study is denoted as P . Each appliance sends its power requests to the ECC, which in turn reports these requirements to the CLC by using the control channel of the LAN. Under the default scenario, the CLC activates all requests immediately; therefore, no power request scheduling occurs. A type- m appliance starts its operation upon the activation of a power request from the CLC. The operational times of type- m appliances are considered to follow a general distribution with mean d_m^{-1} . Furthermore, the power-requests' arrival process from type- m appliances is considered to follow a Poisson distribution with mean λ_m . The latter assumption has been widely considered in several research schemes [12]-[15]. By considering the abovementioned assumptions, we are able to derive the distribution of p.u. in use, through the following recursive formula:

$$jq(j) = \sum_{m=1}^M (\lambda_m \cdot d_m^{-1}) p_m q(i - p_m), \quad j = 1, \dots, P \quad (1)$$

Eq. (1) provides the distribution of the probabilities $q(j)$ that j p.u. are in use in the residential area ([10]). A comparable recursive formula has been proposed in [16] for the distribution of the occupied bandwidth in multi-rate communication networks, which also assumes Poisson arrivals and generally distributed service times.

Due to the finite nature of P (the maximum number of p.u. that the area can support), there is a probability that after the acceptance of a power request, the total number of p.u. exceeds P . This probability can be calculated from (1) as the sum of the probabilities of all states that results the total number of p.u. in use to exceed P :

$$B_m = \sum_{j=P-p_m+1}^P \frac{q(j)}{Q} \quad (2)$$

where $Q = \sum_{j=0}^P q(j)$. Equation (2) can be used in order to determine the minimum value of P so that the values of B_m for a request with the highest demand in p.u. will not exceed a predefined maximum value e . Therefore, since all power requests should be accepted, by considering a small value for e (e.g. $e=10^{-6}$), we can use (1) and (2) in order to derive the minimum value of the peak demand P .

B. The Extended Delay Request Scenario

The Extended Delay Request (EDRS) scenario is applied to appliances that are able either to postpone their power requests. These *task scheduling* appliances are prompted that their power requests will be delayed in buffers that are installed in the CLC, when the total power consumption exceeds predefined power thresholds. In this case, power requests are delayed in buffers; we consider that M buffers are installed in the CLC, one for each type of appliances. In this manner, when the total power consumption exceeds a power threshold, new power demands are not accepted for a specific

time period and therefore the total power consumption is not increased. At the same time, a number of already accepted requests are terminated during the same time period (since a number of appliances terminate their operation), which result in the reduction of the total power consumption is reduced.

The delay of power requests causes the reduction of the final arrival rate of requests. This is due to the increase of the inter-arrival time, as a result of the delay in the buffer. More precisely, we consider that for type- m there are T_m predefined power thresholds, named $P_{m,1}, P_{m,2}, \dots, P_{m,T}$, with $P_{m,1} < P_{m,2} < \dots < P_{m,T}$. Therefore, by assuming different power threshold for each type of appliance, the CLC is able to distribute the power-consumption reduction more evenly to the different appliances' types. We assume that when the current power consumption is $P_{m,t-1} \leq j < P_{m,t}$ the delay that a power request of type- m appliances suffers is denoted as $\delta_{m,t}$. The values of $\delta_{m,t}$ increase with the increment of the power consumption so that $\delta_{m,1} < \delta_{m,2} < \dots < \delta_{m,T}$, while they are chosen based on the ability of an appliance to tolerate delays. For example, dishwashers can tolerate an operation delay, while a home entertainment set cannot. For appliances that belong to the latter case, the values of the parameters $\delta_{m,t}$ are equal to zero, i.e. no buffers are reserved for these types of appliances.

The activation of the power-request delay procedure should be followed by incentives offered to consumers, in order to approve the appliance operation delay. These incentives should be in the form of lower electricity prices for consumers that agree to participate in the program, while they should be adjusted based on the total power consumption, in order to motivate more consumers to postpone the activation of their appliances during peak demand periods. These incentives are mentioned in the message sent by the CLC to the consumers, which in turn respond with their decision to postpone the activation of their appliance (or not). We consider that the probability that a consumer will agree to postponed the request of a type- m appliance, when the current power consumption is $P_{m,t-1} \leq j < P_{m,t}$, is $w_{m,t}$, while the probability that the consumer will refuse to participate in the program is $1-w_{m,t}$. These probabilities are a function of the current power threshold; by considering that the offered incentives are more attractive when the total power consumption is high, more consumers will agree to compress their demands.

Evidently, the delay that a power request suffers will affect the final arrival procedure of accepted power requests. In order to define the resulted arrival rate of power requests when the total p.u. in use exceeds a power threshold, we first define the inter-arrival time of the power requests of type- m appliances. This time is equal to the inter-arrival time $1/\lambda_m$ of requests that arrive at the buffer plus the delay $\delta_{m,t}$ that these request suffer at the buffers, for $P_{m,t-1} \leq j < P_{m,t}$. By reversing the resulting sum, we find the rate $\Lambda_{m,t}$ for type- m appliance that power requests egress the buffer:

$$\Lambda_{m,t} = \frac{v_m}{1 + v_m \delta_m} \quad (3)$$

As mentioned above, consumers have the capability to select whether they agree to postpone their power requests. By considering the probabilities $w_{m,t}$ that a consumer agrees to postpone the activation of a type- m appliance, then two groups of the same appliance type should be considered; the first group comprises of appliances that will postpone their requests, while the second group will refuse to participate in the scheduling program. However, there are some types of appliances that are not able to delay the activation of their operation. To this end, the proposed analysis considers $2M$ appliances' types: the first group comprises of appliances that agree to postpone their requests, together with half of appliances that are not able to delay their demands, while the second group consists of appliances that refuse to participate in the scheduling program, together with the other half of appliances that are unable to delay their operation activation. Therefore, the power requests' arrival rate $R_m(j)$ of the m' -th type of appliance ($m'=1, \dots, 2M$) is denoted as:

$$R_{m'}(j) = \begin{cases} \frac{\lambda_m}{2} & \text{if } \gamma_{m'}=0, m' \in 2M, j \in P \\ w_{m',t} \frac{\lambda_m \delta_{m,t}}{\lambda_m + \delta_{m,t}} & \text{if } \gamma_{m'}=1, m' \leq M, (j - p_{m',t}) \in [P_{m',t-1}, P_{m',t}) \\ \lambda_m (1 - w_{m',t}) & \text{if } \gamma_{m'}=1, m' > M, (j - p_{m',t}) \in [P_{m',t-1}, P_{m',t}) \end{cases} \quad (4)$$

where the parameter $\gamma_{m'}$ is used in order to express the appliances' ability to postpone its activation; $\gamma_{m'}=0$ for "non-scheduling" appliances, while $\gamma_{m'}=1$ for "scheduling" appliances. Therefore, since each "scheduling" ($\gamma_{m'}=0$) appliances belong to two groups in the set $[1, 2M]$, their final arrival rate is $\lambda_m/2$ ($m=1, \dots, M$). On the other hand, the final inter-arrival time of the $w_{m,t}$ percentage of the "scheduling" appliances will be reduced by a factor $\Lambda_{m,t}$, while the inter-arrival time of the remaining $(1-w_{m,t})$ percentage will remain unchanged. Note that $\lambda_m = \lambda_{m'}$ and $w_{m',t} = w_{m,t}$ for $m' \leq M$.

The probabilities distribution $q(j)$ of the p.u. in use can be calculated by using the following recursive formula:

$$jq(j) = \sum_{m'=1}^{2M} R_{m'}(j) d_{m'}^{-1} c_{m'}(j) p_{m'} q(j - p_{m'}) + \quad (5)$$

$$\sum_{m'=1}^{2M} \sum_{t=1}^{T_{m'}} R_{m'}(j) d_{m',t}^{-1} c_{m',t}(j) p_{m',t} q(j - p_{m',t}), \quad j = 1, \dots, P,$$

where

$$c_{m'}(j) = \begin{cases} 1 & \text{if } (1 \leq j - p_{m'} < P_0 \text{ and } \gamma_{m'} = 1) \\ & \text{or if } (1 \leq j < P \text{ and } \gamma_{m'} = 1 \text{ and } m' > M) \\ & \text{or if } (1 \leq j < P \text{ and } \gamma_{m'} = 0) \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$c_{m',t}(j) = \begin{cases} 1 & \text{if } (P_{m',t-1} \leq j < P_{m',t} \text{ and } \gamma_{m'} = 1 \text{ and } m' \leq M) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

The proof of (5) is based on the procedure described in [10] for the proof of the recursive formula for the DRS.

However, the assumption of different power thresholds per appliance results in different margins that each local balance equation is defined. Precisely, the local balance equation for type m' appliances when the current power consumption is $P_{m',t-1} \leq j - p_{m'} < P_{m',t}$ is:

$$\begin{aligned} q(j - p_{m'}) R_{m'}(j) &= q(j) y_{m',t}(j) d_{m'}^{-1} \Leftrightarrow \\ q(j - p_{m'}) \frac{R_{m'}(j)}{d_{m'}} p_{m'} &= q(j) y_{m',t}(j) p_{m'} \end{aligned} \quad (8)$$

By applying (8) to all $T_{m'}$ power thresholds and to all $2M$ appliances types, we derive the following equation:

$$\sum_{m'=1}^{2M} \sum_{t=1}^{T_{m'}} q(j - p_{m'}) \frac{R_{m'}(j)}{d_{m'}} p_{m'} = q(j) \sum_{m'=1}^{2M} \sum_{t=1}^{T_{m'}} y_{m',t}(j) p_{m'} \quad (9)$$

The total number of p.u. in use in any state ($0 \leq j \leq P$) is equal to the sum of products of the mean number $y_{m',t}(j)$ of type- m' appliances by their demand $p_{m',t}$, for all power thresholds and all types of appliances:

$$j = \sum_{m'=1}^{2M} \sum_{t=1}^{T_{m'}} y_{m',t}(j) p_{m'} \quad (10)$$

Therefore, in order for (9) to be equal to (5), we have to assume that the mean number of $y_{m',0}(j) \cong 0$ for $j \leq P_{m',0} - p_{m'}$ and that $y_{m',t}(j) \cong 0$ for $j > P_{0,t} - p_{m',t}$. The first assumption is expressed by the function $c_m(t)$, while the second assumption is expressed by the functions $c_{m',t}(j)$. It should be noted that the concept of multiple threshold per different appliance was initially introduced in a communication network that supports multiple bandwidth thresholds per service-class [17]. However, the model in [17] does not consider that a percentage of end-users may refuse to participate in the program (i.e. to compress their bandwidth requirements), as in the case of our proposed model.

The probability that the total power consumption will exceed P upon the arrival of a power demand from a type- m appliance can be calculated by (2), where $q(j)$ is given by (5). Equations (2) and (5)-(7) can be used in order to determine the minimum value of P (peak demand), so that the outage probability will not exceed a predefined value e .

C. The Extended Compressed Demand Scenario

We now proceed with the analysis for the energy scheduling appliances under the Extended Compressed Demand (ECDS) scenario. As in the case of EDRS, the ECDS considers T_m predefined power thresholds for type- m appliances. Under the ECDS and upon the arrival of a power request from a type- m appliance, if the total power consumption is less than the first power threshold $P_{m,0}$, then the power request is accepted with its nominal power requirement p_m . However, when the total power consumption j is $P_{m,t-1} \leq j < P_{m,t}$, then consumers are informed that type- m appliances will begin their operation with a compressed power demand $p_{m,t}$ and extended operational time $d_{m,t}^{-1}$, with $p_m > p_{m,1} > \dots > p_{m,T}$ and $d_m^{-1} < d_{m,1}^{-1} < \dots < d_{m,T}^{-1}$. The values of

the parameters $p_{m,t}$ and $d_{m,t}^{-1}$ should be selected in such a way so that energy consumption reduction is achieved, i.e. $(d_{m,t-1}^{-1} \times p_{m,t-1}) > (d_{m,t}^{-1} \times p_{m,t})$.

As in the case of EDRS, in ECDS the consumers are informed by the CLC for the activation of the scheduling procedure and they respond with their decision regarding their participation in the peak demand reduction program. In order to increase the participation rate, the distribution network should offer incentives to the consumers, e.g. lower electricity rates to the consumers who agree to compress their demands. Therefore, the analysis for ECDS considers that a percentage $w_{m,t}$ will agree to participate in the program, while a percentage $(1-w_{m,t})$ of consumers will refuse to compress their demands. This procedure is activated only for appliances that are able to compress their demands; appliances that are incapable of compressing their demand (e.g. computers or entertainment sets) will operate at their nominal power, regardless of the total power consumption.

The fact that a percentage of consumers agree to participate in the scheduling program, while others refuse to compress their demands, affects the final power-request arrival procedure at the CLC. Therefore, as in the case of the EDRS, we also consider $2M$ types of appliances under the ECDS. By following a similar procedure that is used for the derivation of (4), we define the final arrival rate for type- m' appliances ($m'=1, \dots, 2M$) under the ECDS:

$$R_{m'}(j) = \begin{cases} \frac{\lambda_m}{2} & \text{if } \gamma_{m'}=0, m' \in 2M, j \in P \\ \frac{\lambda_m}{2} & \text{if } \gamma_{m'}=1, m' \in 2M, j \leq P_0 \\ S_m w_{m',t} & \text{if } \gamma_{m'}=1, m' \leq M, (j - p_{m',t}) \in [P_{m',t-1}, P_{m',t}) \\ S_m (1 - w_{m',t}) & \text{if } \gamma_{m'}=1, m' > M, (j - p_{m',t}) \in [P_{m',t-1}, P_{m',t}) \end{cases} \quad (11)$$

where $\gamma_{m'}=0$ is used to express appliances that are not able to compress their demands, while $\gamma_{m'}=1$ refers to appliances that are able to participate in the scheduling program. It should be noted that due to the assumption of $2M$ appliances, the parameters that refer to the "new" set ($m' \in 2M$) are defined based on the corresponding parameters of the original set ($m \in M$) of appliances: $p_{m'} = p_{m'+M} = p_m$ and $p_{m',t} = p_{m,t}$ for $m' \leq M$, $p_{m',t} = p_m$ for $m' > M$ (due to the fact that power demands from the second group of appliances are not compressed), $d_{m',t}^{-1} = d_{m,t}^{-1}$ for $m' \leq M$, and $d_{m',t}^{-1} = d_m^{-1}$ for $m' > M$.

The probabilities distribution $q(j)$ of the p.u. in use can be calculated by using the following recursive formula:

$$\begin{aligned} jq(j) &= \sum_{m'=1}^{2M} R_{m'}(j) d_{m'}^{-1} b_{m'}(j) p_{m'} q(j - p_{m'}) + \\ &\sum_{m'=1}^{2M} \sum_{t=1}^{T_{m'}} R_{m'}(j) d_{m',t}^{-1} b_{m',t}(j) p_{m',t} q(j - p_{m',t}), \quad j = 1, \dots, P, \end{aligned} \quad (12)$$

where

$$b_{m'}(j) = \begin{cases} 1 & \text{if } (1 \leq j - p_{m'} < P_0 \text{ and } \gamma_{m'} = 1) \\ & \text{or if } (1 \leq j < P \text{ and } \gamma_{m'} = 1 \text{ and } m' > M) \\ & \text{or if } (1 \leq j < P \text{ and } \gamma_{m'} = 0) \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

$$b_{m',t}(j) = \begin{cases} 1 & \text{if } (P_{m',t-1} \leq j < P_{m',t} \text{ and } \gamma_{m'} = 1 \text{ and } m' \leq M) \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

For the proof of (12) we follow a similar procedure that is used for the derivation of (5). As in the case of EDRS, the functions $b_{m'}(j)$ and $b_{m',t}(j)$ are used in order to activate (11) when a power request from type- m' appliance is able to compress its demand.

The outage probability $B_{m'}$ for requests that arrive from appliances that are not able to compress their demand can be calculated by using (2), while the outage probability $B_{m',t}$ for appliances that are able to compress their demands is calculated by using the following formula:

$$B_{m',t} = \sum_{j=P-p_{m',t}+1}^P \frac{q(j)}{Q} \quad (12)$$

As in the case of the default scenario and the EDRS, the proposed analysis can be used for the determination of the minimum value of P so that the outage probability will not exceed a predefined value e . However, under ECDS both values of $B_{m'}$ and $B_{m',t}$ should be considered for the peak demand determination.

III. EVALUATION AND DISCUSSION

In this section, we evaluate the proposed analytical models by comparing analytical and simulation results. To this end, we consider a residential area where each residence is equipped with $M=10$ appliances: (1) a water heater, (2) a dishwasher, (3) an electric stove, (4) a refrigerator, (5) a laundry pair, (6) an air condition, (7) lightning, (8) an electric vehicle, (9) a home office set, and (10) an entertainment set. The power demands of each one of these appliances are: $(p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}) = (40, 10, 20, 6, 15, 25, 4, 100, 5, 7)$ p.u.. These values are selected by considering the typical power consumption of these appliances [18], and by assuming that 1 p.u. = 100 Watt. Furthermore, we consider that the laundry pair, the water heater and the air-condition are energy scheduling appliances, the electric stove, the dishwasher and the electric vehicle are task scheduling appliances, while the home office set, the refrigerator the entertainment set and lighting are not participating in any scheduling scheme (i.e. their demands are not postponed nor compressed). By using this categorization, we consider that the task scheduling devices together with the entertainment set and lighting are considered for the EDRS model, while the energy scheduling appliances together with the home-office set and the refrigerator are applied to the ECDS model.

The accuracy of the proposed analysis is evaluated through the comparison of analytical and simulation results. The latter results are obtained as mean values of 8 runs with 95% confidence interval. The simulation results presented in the

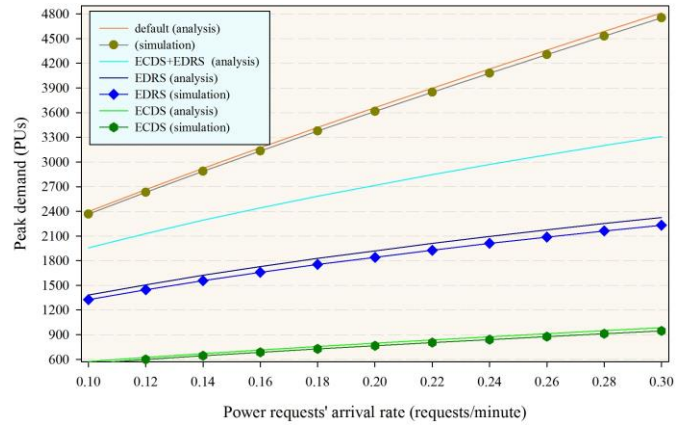


Fig. 1. Analytical and simulation peak demand results versus the power requests' arrival rate for the combined EDRS-ECDS scenario.

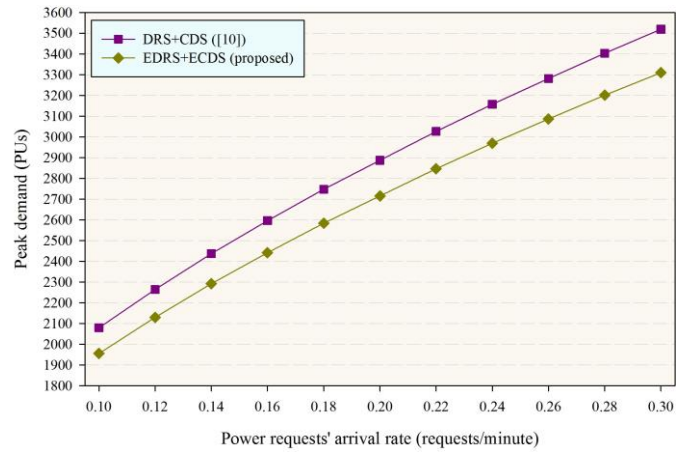


Fig. 2. Comparison of the proposed EDRS and ECDS models with the DRS and CDS models of [10].

following pictures are based only on the mean values of the 8 simulation runs, since the reliability ranges are found to be very small. In Fig. 1 we present analytical and simulation results for the peak demand versus the power requests' arrival rate, which, for presentation purposes, is assumed to be the same for all appliances' types. In Fig. 1 we also present analytical results for the baseline scenario, in order to highlight the peak demand reduction when the proposed demand control mechanisms are applied. Two thresholds are assumed for each appliance, while their values are expressed as a function of their power demands: for the higher load (electric vehicle) the two thresholds are set to 50% and 65% of P , for the water heater to 52% and 67%, for the air-condition to 54% and 69%, for the electric stove to 56% and 71%, for the laundry pair to 58% and 73%, while for the dishwasher the thresholds are set to 65% and 80% of P . When the current power consumption exceeds the first threshold, power requests are delayed for 4 min., while this delay is increased to 8 min. when the current power consumption exceeds the second power threshold. Also, consumers are prompted to reduce their power demands by 15% and expand their operational time by 15% when the current power consumption exceeds the first power threshold, while these values are both changed to 25%, when power

consumption exceeds the second threshold. Furthermore, we assume that 60% of the consumers of all appliances agree to participate in the scheduling program when the total power consumption exceeds the first threshold, while this percentage is increased to 70% for the second power threshold. The peak demand results are calculated so that the outage probability for all appliances does not exceed $\epsilon=10^{-5}$. The comparison of analytical and simulation results presented in Fig. 1 shows that the accuracy of the proposed analysis is quite satisfactory. Moreover, under the proposed scheduling mechanisms the peak demand is reduced by 25.38% in average; this fact proves the necessity of a well-designed DR mechanism when the reduction of the total power consumption is of vital importance during high demand periods.

In Fig. 2 we compare analytical results from the combined scenario of the EDRS and ECDS models, with corresponding results from the combined scenario of DRS and CDS of [10]. In order to provide a fair comparison, the values of all parameters are the same for the two combined cases, while for the DRS and CDS of [10] we assume that the two thresholds are equal to 60% and 75%, respectively, which is equal to the mean values of the power thresholds assumed for the proposed models. The results of Fig. 2 prove the superiority of the proposed models compared to the models [10], since the average peak demand reduction achieved by the proposed models is 5.95%, compared to the models of [10]. Therefore, by considering diverse power thresholds for all appliances and carefully selecting these thresholds so that the scheduling procedure is activated in lower consumption levels for heavy loads compared to smaller loads, we can achieve higher peak demand reductions.

IV. CONCLUSION

In this paper, we revisit the power demand control scenarios of [10], in order to provide a more realistic approach for the demand scheduling procedures that target the peak demand reduction. The proposed analysis considers that the scheduling mechanism is activated when the total power consumption exceeds predefined power thresholds, which are different for each appliance type. In this way, the peak demand reduction is achieved fairly, since each residence can equally contribute to the demand control program. Furthermore, the evaluation of the proposed scenarios indicates the satisfactory accuracy of the proposed analysis. The study of the results of the proposed analytical models show that a significant reduction of the peak demand can be achieved by scheduling the appliances' operation, while this reduction is highly affected by the selection of the parameters' values of the system under study.

ACKNOWLEDGEMENT

This work has been funded by the FP7-PEOPLE-2013-IAPP-COMANDER project (Contract No. 612257).

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