Adaptive Energy Consumption Scheduling for Connected Microgrids Under Demand Uncertainty

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***Abstract*—Energy consumption scheduling to achieve low-power generation cost and a low peak-to-average ratio is a critical component in distributed power networks. Implementing such a component requires the knowledge of the whole power demand throughout the network. However, due to the diversity of power demands, this requirement is not always satisfied in practical scenarios. To address this inconsistency, this paper addresses energy consumption scheduling in a distribution network with connected microgrids consisting of a local area with a determined demand and neighboring areas with an uncertain demand. The total cost and peak-to-average ratio minimizations are formulated as a multiobjective optimization problem. In addition to a deterministic optimal solution, an adaptive scheduling approach is provided with *online* stochastic iterations to capture the randomness of the uncertain demand over time. Numerical results demonstrate the effectiveness of the proposed adaptive scheduling schemes in the following results obtained from optimal solutions.**

***Index Terms*—Adaptive optimization, energy consumption scheduling, microgrid, power grid, uncertain power demand.**

I. Introduction

REPORTS ON energy consumption reveal the increasing demand for electrical energy worldwide [1]. This increase, along with growing environmental concerns, motivates the idea of establishing new power systems with flexible and intelligent programs of demand-side management. These programs run by utility companies aim to provide consumers with reliable and cost-efficient energy and, at the same time, make efficient use of the generation and transmission infrastructure. While many of these programs are still under investigation, a number of practical applications already exist in many countries across the world [2]. Demand side can be managed by either reducing or shifting the consumption of energy. While the former can be efficient to some extent, the latter proposes shifting of high-load household consumptions to offpeak hours in order to reduce peak-to-average ratio (PAR) [3]. The high PAR might lead to degradation of power quality, voltage problems, and even potential damage to utility and consumer equipment.

With the advancement of smart-metering technologies [4] and increasing interest in power distribution networks with two-way communications capability [5], load management has been appeared in the form of energy consumption scheduling (ECS) [6]. In the ECS, the power consumption time-of-connected units is optimally scheduled so that some interesting measures, such as generation cost and PAR, can be optimized efficiently. This results in reducing the risk of getting into a condition that may lead to a blackout. As an incentive that subscribers follow ECS decisions, intelligent pricing schemes in the form of lower utility charges should be provided. Consequently, customers will be encouraged to shift their heavy loads to off-peak hours. These issues motivate the design of ECS with the aim of minimizing power generation cost and PAR.

Traditionally, demand-management programs use direct load control, where portions of the system load are under the direct operational control of utility companies [7], [8]. With the emerging real-time pricing schemes [9], consumers would be able to schedule their own demand following incentives provided by the utility. In a grid of appliances, given predetermined daily total demand of each appliance, the works in [10] and [11] propose real-time load scheduling schemes based on a multiobjective linear problem of cost and waiting time minimization. Utility-based power scheduling, to enhance the customer experience and satisfaction degree of the scheduled power, has been investigated in [12] and [13]. In particular, the work in [12] presents power allocation as a social welfare maximization problem.

With known prior information on the daily demand of all connected consumers, power scheduling has been modeled as a game between consumers in a grid toward cost minimization in [14] and [15]. Under the assumption that the utility charges consumers proportional to their demands, these works propose incentive-based energy scheduling games with near optimal performance. Power scheduling with uncertainty in renewable energy sources, but with given probability distribution, has been handled using particle swarm optimization in [16]. Power dispatching with a nonconvex cost function has also been tackled with an improved particle swarm optimization in [17] and incremental consensus algorithm in [18]. The Markov chain has been employed in [19] to design power scheduling policies in a grid with random demand request arrivals but with known statistical characteristics.

The proposed ECS schemes in the literature mainly perform network-wide load management with the assumption of the knowledge of the whole network demand *a priori* or at least with known statistical characteristics. In other words, a network operator should be aware of the whole network demand in some way. Due to the diversity of power customers ranging from household to industrial domains with uncertain

Manuscript received July 24, 2012; revised November 22, 2012, January 14, 2013, and March 14, 2013; accepted April 05, 2013. Date of publication April 30, 2013; date of current version June 20, 2013. Paper no. TPWRD-00779-2012.

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Digital Object Identifier 10.1109/TPWRD.2013.2257877

demands, however, this case is not *mostly* valid. Alternatively, an operator who is aware of demand in a local area, not other neighboring areas, might be interested in ECS within this area. The fact that aggregate power generation cost depends on the network-wide demand necessities considering the impact of uncertain demands in the design of the ECS.

To investigate the mentioned difficulty, in this paper, we consider a distribution network connecting to a local area (LA) consisting of several microgrids with known demand in average and other neighbor areas (NAs) with uncertain demands. The network operator performs ECS of demand in the LA considering NAs demand as a random variable. This ECS is formulated with two stochastic optimization problems–one with the objective of the network-wide power generation cost minimization and the other with the objective of PAR minimization. While these two objectives are correlated in some extent, optimizing one does not necessarily imply the optimality of the other.

These objectives are compared using optimal, adaptive, and uniform scheduling schemes in terms of generation cost and PAR. In the optimal one, the optimal solution of two underlying problems is achieved with the assumption of the knowledge of NAs demand in advance. Without this assumption for practical purposes, we propose an adaptive scheme with *online* stochastic iterations to capture the randomness of uncertain demands over the time horizon continually. Finally, in uniform scheduling, the demand of MGs in LA is uniformly distributed over the time horizon regardless of NAs demand.

The paper is organized as follows. Background and modeling is described in Section II. The cost and PAR minimization formulations along with their solutions are presented in Sections III and IV, respectively. Numerical results are given in Section V and the paper concludes in Section VI.

II. Background and Modeling

A. Distribution Network With Connected Microgrids

A microgrid (MG) is an interconnection of domestic loads and low-voltage distributed energy sources, such as microturbines, wind turbines, PVs, and storage devices. The domestic load can be divided into sensitive/critical and nonsensitive/noncritical loads via separate feeders. For the feeders with sensitive loads, the local power supply, such as diesel generators or energy capacitor systems with enough energy saving capacity, are needed to avoid interruptions of electrical supply. Each unit's feeder has a circuit breaker and a power-flow controller commanded by the central controller.

A simplified architecture of a distribution network organized by a distribution company (Disco_1) is shown in Fig. 1. This network consists of N-connected microgrids in a LA, and NAs which may belong to another company (Disco_i). The microsources and storage devices use power-electronic circuits to connect to the MG. The MG can be connected to the network by a point of common coupling (PCC) via a static switch. This switch is capable of islanding the MG for maintenance purposes or when faults or a contingency occur. Each MG can operate in autonomous (isolated from the main grid) and grid-connected modes. The performance measure in autonomous mode is the reliability of stand-alone operation. However, in grid-connected

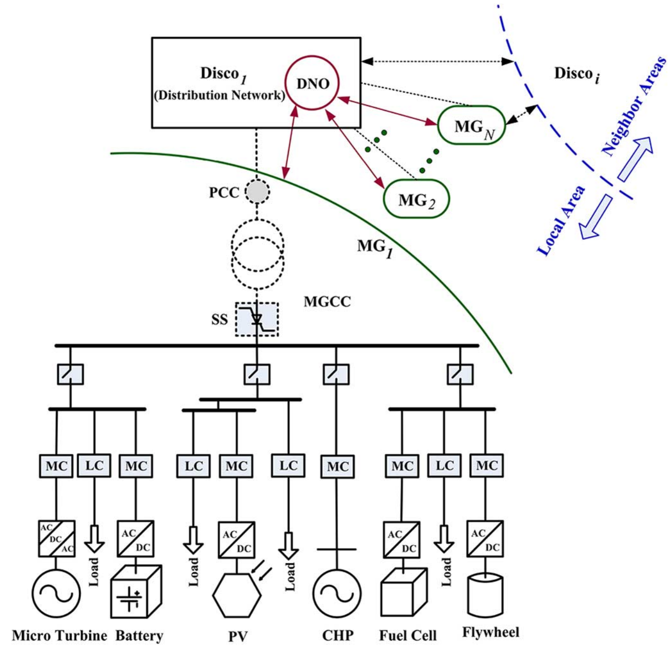

Fig. 1. Local and neighbor areas in a distribution network.

mode, the demand load supplement is guaranteed all of the time by the grid as a result of power sharing.

An MG central controller (MGCC) interfaces between an MG and the distribution network (main grid). This controller facilitates a high-level management of the MG operation by means of technical and economical functions. The microsource controllers (MCs) control the microsources and the energy storage systems. Finally, the controllable loads are controlled by load controllers (LCs). For increasing reliability in the overall power network, the MG systems must be able to have proper performance in the connected mode. In this mode, the main grid is responsible for controlling and maintaining the power network in a desirable condition [20]–[22].

B. Distribution Network Operator (DNO)

The DNO deals with some overall responsibilities for the distribution network (Disco) and the connected MGs, such as interchange power between the main grid and the MGs. This unit, which is located in the application layer of the distribution-management system (DMS), is acting in an economical-based energy management between the main grid and the neighboring MGs. It is similar to the existing supervisors for power exchanges and economic dispatch in a conventional multiarea power system [2], [23]. To meet the aforementioned global objectives, wide-area monitoring and estimation are needed for many parameters and indices including fuel and storage conditions, commercial power cost,and demand charge tariffs, MG reliability, real/reactive power components (power factor), predicted weather, system constraints, and load pattern.

As shown in Fig. 1, DNO interfaces the main grid (Disco_1) with the connected MGs (in the LA) as well as other neighboring grids (in NAs which may be covered by another Disco). DNO also supervises the power-flow control and market operation. This operator controls power flow from the main grid to the MGs to be maintained close to the scheduled values.

In the mentioned network, identifying the optimal consumption/generation schedule to minimize production costs and to balance the demand and supply, as well as online assessment of security and reliability are the responsibilities of the DNO unit. The DNO, together with the MGCCs, supervise the MGs' market activities, such as buying and selling active and reactive power to the grid and possible network congestions for transferring energy from a distribution network to the MGs in the local area and other neighboring areas.

The mentioned global task for an interconnected power network should be implemented through the cooperation of its various grids, on the basis of communication and collection of information about distributed energy systems and control commands [24]. Due to the high diversity of generation and loads, an interconnected network exhibits high nonlinearities, changing dynamics, and uncertainties that may require advanced control and optimization strategies, such as the used methodology in this paper. This paper focuses on the optimal/adaptive ECS problem as an important objective of the DNO for the connected MGs in a distributed electric network.

C. System Model

A network as shown in Fig. 1 is considered. This network, owned by a Disco, is connected to a set $\mathcal{N} \triangleq \{n : n = 1, \ldots, N\}$ of MGs operating in LA and other MGs working as NAs, which may belong to a different Disco. It is assumed that all MGs operate in the grid-connected mode. The DNO performs ECS for MGs in the LA during a time horizon $\mathcal{T} \triangleq \{t : t = 1, \ldots, T\}$. The aim of ECS is to optimally manage and to shift the LA demand to reduce power generation cost and PAR within the power network. The demand of each MG_n in LA during this interval is assumed to be a known value E_n in average. However, the demand by MGs in NAs is assumed to be an unknown value, denoted by γ.

Let p_n^t be the power provided to MG_n in LA during time slot t. The objective of ECS is to determine a power set $\mathbf{P} \triangleq \{p_n^t\}_{n\in\mathcal{N}}^{t\in\mathcal{T}}$ to optimize a target performance measure and, at the same time, to provide each MG_n with a determined demand E_n in average. Since the generation cost in the distribution network depends on LA and NAs demands, the uncertainty of γ should be taken into account in the determination of $\mathbf{P}$. Moreover, these powers have strict minimum and maximum power levels. This imposes a constraint that each p_n^t must be within p_n^{min} and p_n^{max}, minimum and maximum power levels, respectively. In the mentioned network, the objective of DNO by implementing ECS could be either to minimize power generation cost or to minimize PAR. These objectives are discussed in subsequent sections.

III. Cost Minimization Formulation

The pricing of electricity can be used as a mechanism to encourage customers to follow a specified load scheduling. Various pricing schemes have been proposed by economists and regulatory agencies such as flat pricing, critical-peak pricing, time-of-use pricing, and real-time pricing. These schemes have been also used in communications and transportation networks [25]. Among them, real-time pricing is motivated to be used in the next generation power systems concerning its environmental and economical gains [26], [27]. Accordingly, in the present paper, an energy scheduling approach based on real-time generation cost is proposed, which can be used to establish a real-time pricing scheme.

Let $p^t = \sum_{n=1}^{N} p_n^t + \gamma(t)$ be the total amount of power generated at time t to be delivered to LA and NAs. The power generation cost at this time can be denoted as a differentiable and convex function of p^t, denoted by $C(p^t)$. Accordingly, minimizing the average generation cost during the time horizon $\mathcal{T}$ is formulated as

$$\min_{\mathbf{P}} \frac{1}{T}\sum_{t=1}^{T} C\left(\sum_{n=1}^{N} p_n^t + \gamma(t)\right) \tag{1}$$

$$\text{s.t.} \quad \frac{1}{T}\sum_{t=1}^{T} p_n^t \geq E_n \qquad \forall n \in \mathcal{N} \tag{2a}$$

$$p_n^{\min} \leq p_n^t \leq p_n^{\max} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \tag{2b}$$

Constraints (2a) satisfy the required average demands by MGs in LA. Constraints (2b) restrict the power levels within some upper and lower bounds. This problem is convex and can be solved using convex optimization techniques such as interior point method (IPM) [28]. This requires the knowledge of $\gamma(t)$ for all t in the beginning of the time horizon $\mathcal{T}$. However, this assumption is not valid in practice as the DNO is not aware of NAs demand *a priori* (i.e., in the beginning of the horizon). Alternatively, we consider γ as an uncertain parameter in the form of a random variable varying over the time, but without any assumption on its probability density function (PDF). With this assumption, (1) and (2) can be rewritten as

$$\min_{\mathbf{P}} \mathbb{E}_\gamma \left[C\left(\sum_{n=1}^{N} p_n + \gamma\right)\right] \tag{3}$$

$$\text{s.t.} \quad \mathbb{E}_\gamma[p_n] \geq E_n \qquad \forall n \in \mathcal{N} \tag{4a}$$

$$p_n^{\min} \leq p_n \leq p_n^{\max} \qquad \forall n \in \mathcal{N} \tag{4b}$$

where $\mathbb{E}_\gamma$ denotes the expectation with respect to γ. The aforementioned problem is also convex. However, we are interested in solving this problem progressively over time, when γ is realized at each time instant t.

The challenge in the solution of problem (3) and (4) is due to the expectations that couple the scheduling over time. The solution would be straightforward if one decouples the demand constraints over time. This motivates the incorporation of (4a) into the objective function and forms a Lagrangian function as

$$L(\mathbf{P}, \Lambda) = \mathbb{E}_\gamma \left[C\left(\sum_{n=0}^{N} p_n + \gamma\right)\right] - \sum_{n=1}^{N} \lambda_n \left(\mathbb{E}_\gamma[p_n] - E_n\right) \tag{5}$$

and the corresponding dual function as

$$D(\Lambda) = \inf_{\mathbf{P}} \{L(\mathbf{P}, \Lambda) : (4\text{b})\} \tag{6}$$

where $\Lambda = \{\lambda_n \geq 0\}_{n\in\mathcal{N}}$ is the set of Lagrange multipliers and inf represents infimum operation. The dual function provides a lower bound on the optimal solution of (3) and (4). The best lower bound is surely achieved by the corresponding dual problem as

$$\max_{\Lambda \geq 0} D(\Lambda). \tag{7}$$

Prior to solving this problem in the dual domain, we first need to evaluate $D(\Lambda)$. $L(\mathbf{P}, \Lambda)$ can be rewritten as

$$L(\mathbf{P}, \Lambda) = \mathbb{E}_\gamma \left[C\left(\sum_{n=1}^{N} p_n + \gamma \right) - \sum_{n=1}^{N} \lambda_n p_n \right] + \sum_{n=1}^{N} \lambda_n E_n. \tag{8}$$

Therefore, to evaluate $D(\Lambda)$ in (6), we solve

$$\min_{\mathbf{P}} \mathbb{E}_\gamma \left[C\left(\sum_{n=1}^{N} p_n + \gamma \right) - \sum_{n=1}^{N} \lambda_n p_n \right] \tag{9}$$

$$\text{s.t.} \quad p_n^{\min} \leq p_n \leq p_n^{\max} \quad \forall n \in \mathcal{N}. \tag{10}$$

For each value of γ, this problem is convex and can be solved using IPM [28] to obtain the optimal values $\{p_n^*(\gamma)\}_{n\in\mathcal{N}}$.

Having obtained $\{p_n^*(\gamma)\}_{n\in\mathcal{N}}$, the dual problem in (7) can be solved using the subgradient method [29]. Beginning with an initial $\lambda_n(0)$, given $\lambda_n(t)$ at time t, the optimal values $\{{p_n^t}^*(\gamma)\}_{n\in\mathcal{N}}$ can be obtained from (9), (10). Based on our experience, we usually choose $\lambda_n(0)$'s values such that the solution of the problem with relaxed constraints using these initial multipliers lies within the feasible region of decision variables, rather than the margin of feasible region. We then update the Lagrange multiplier as

$$\lambda_n(t+1) = \lambda_n(t) + \alpha \left(E_n - \mathbb{E}_\gamma \left[{p_n^t}^*(\gamma) \right] \right)^+ \tag{11}$$

where $E_n - \mathbb{E}_\gamma[{p_n^t}^*(\gamma)]$ is the subgradient of $D(\Lambda)$ with respect to λ_n, α is a step size, and $(x)^+ \triangleq \max(x, 0)$.

The gradient iteration (11) is efficient to find the optimal scheduling. A key knowledge we need in (11) is the PDF of γ, only with which the expected value $\mathbb{E}_\gamma$ can be evaluated. The assumption of a known PDF of γ may be reasonable for theoretic studies. However, the importance of practical energy scheduling schemes motivate the optimal strategy by *learning* NAs demand on the fly. Interestingly, a stochastic gradient iteration can be developed to solve (7) without the PDF of γ *a priori*. To this end, we consider dropping $\mathbb{E}_\gamma$ from (11) to devise online iterations for *adaptive* decisions, based on per slot realization $\gamma(t)$, as

$$\hat{\lambda}_n(t+1) = \hat{\lambda}_n(t) + \alpha \left(E_n - {p_n^t}^*(\gamma(t)) \right)^+ \tag{12}$$

where hats are to emphasize that these iterations are stochastic estimates of those in (11). Provided that the random NAs demand process is stationary and ergodic, the stochastic gradient iteration (12) and the ensemble gradient iterations (11) consist of a pair of primary and averaged systems [30]. The convergence of such a stochastic gradient iteration can be established statistically, provided that α is small enough [31]. The above described solution can be summarized as an adaptive cost-aware ECS (ACA-ECS) scheme in Algorithm 1.

Algorithm 1 ACA-ECS scheme

1: Initialization: $t = 0$ and $\hat{\lambda}_n(0) = \lambda_{\text{init}}\ \forall n \in \mathcal{N}$.
2: **while** $t \leq T$ **do**
3: Generate a new NAs demand $\gamma(t)$.
4: Determine optimal $\{p_n^*(\gamma(t))\}_{n\in\mathcal{N}}$ from problem (9), (10).
5: Update $\hat{\lambda}_n(t)$ using (12) for all $n \in \mathcal{N}$.
6: $t = t + 1$.
7: **end while**

IV. PAR Minimization Formulation

In order to minimize PAR of the total instantaneous power delivered to LA and NAs during the time period $\mathcal{T}$, a minmax formulation is proposed with the objective of minimizing the peak of this power. The objective is expressed as

$$\min_{\mathbf{P}} \max_{t\in\mathcal{T}} \sum_{n=1}^{N} p_n^t + \gamma(t). \tag{13}$$

Due to the unavailability of $\gamma(t)$ *a priori*, this objective, along with the already mentioned constraints in Section III, can be translated into the problem

$$\min_{\mathbf{P}} s \tag{14}$$

$$\text{s.t.} \quad s \geq \sum_{n=1}^{N} p_n + \gamma \tag{15a}$$

$$\mathbb{E}_\gamma[p_n] \geq E_n \qquad \forall n \in \mathcal{N} \tag{15b}$$

$$p_n^{\min} \leq p_n \leq p_n^{\max} \qquad \forall n \in \mathcal{N} \tag{15c}$$

where s is an auxiliary variable. The solution is mostly similar to that of the cost minimization. The Lagrangian can be formed as

$$L(\mathbf{P}, \mu) = s - \sum_{n=1}^{N} \mu_n \left(\mathbb{E}_\gamma[p_n] - E_n \right) \tag{16}$$

and dual function as

$$D(\mu) = \inf_{\mathbf{P}} \{ L(\mathbf{P}, \mu) : (15\text{a}), (15\text{c}) \} \tag{17}$$

where $\mu = \{\mu_n \geq 0\}_{n\in\mathcal{N}}$ is the set of Lagrange multipliers. To evaluate $D(\mu)$, the following minimization problem should be solved:

$$\min_{\mathbf{P}} s - \sum_{n=1}^{N} \mu_n \mathbb{E}_\gamma[p_n] \tag{18}$$

$$\text{s.t.} \quad (15\text{a}), (15\text{c}). \tag{19}$$

Similar to the online learning iteration in Section III, the stochastic estimation of each μ_n (i.e., $\hat{\mu}_n$) can be learned over the time using

$$\hat{\mu}_n(t+1) = \hat{\mu}_n(t) + \alpha \left(E_n - {p_n^t}^*(\gamma(t)) \right)^+. \tag{20}$$

By these iterations, problem (18) and (19) at each iteration t can be rewritten as

$$\min_{\mathbf{P}} s - \sum_{n=1}^{N} \hat{\mu}_n(t) p_n^t \tag{21}$$

$$\text{s.t.} \quad s \geq \sum_{n=1}^{N} p_n^t + \gamma(t) \qquad \forall t \in \mathcal{T} \tag{22a}$$

$$p_n^{\min} \leq p_n^t \leq p_n^{\max} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}. \tag{22b}$$

Constraint (22a) can be expressed as $s = s' + \sum_{n=1}^{N} p_n^t + \gamma(t)$, where $s' \geq 0$ is an auxiliary variable. Substituting s with s' in (21), (22), we obtain

$$\min_{\mathbf{P}} s' + \sum_{n=1}^{N} (1 - \hat{\mu}_n(t))\, p_n^t \tag{23}$$

$$\text{s.t.} \quad p_n^{\min} \leq p_n^t \leq p_n^{\max} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{24a}$$

$$s' \geq 0. \tag{24b}$$

The solution for this problem is trivially achieved when $s' = 0$ and each term $(1 - \hat{\mu}_n(t))p_n^t$ is minimized for $p_n^{\min} \leq p_n^t \leq p_n^{\max}$. The latter is absolutely dependent on the sign of $(1 - \hat{\mu}_n(t))$. Doing so, it is concluded that $p_n^t = p_n^{\min}$ if $\hat{\mu}_n(t) < 1$, $p_n^t = p_n^{\max}$ if $\hat{\mu}_n(t) > 1$, and $p_n^t = (p_n^{\max} + p_n^{\min})/2$ as a midpoint between these two extremes if $\hat{\mu}_n(t) = 1$. This solution results in an adaptive PAR-aware ECS (PAR-ECS) scheme in Algorithm 2.

Algorithm 2 PAR-ECS scheme

Initialization: $t = 0$ and $\hat{\mu}_n(0) = \mu_{\text{init}}\ \forall n \in \mathcal{N}$.
while $t \leq T$ **do**
  Generate a new NAs demand $\gamma(t)$.
  for $n \in \mathcal{N}$ **do**
    if $\hat{\mu}_n(t) < 1$ **then**
      $p_n^t = p_n^{\min}$
    else if $\hat{\mu}_n(t) > 1$ **then**
      $p_n^t = p_n^{\max}$
    else
      $p_n^t = p_n^{\min} + p_n^{\max}/2$
    end if
    Update $\hat{\mu}_n(t)$ using (20) for all $n \in \mathcal{N}$.
  end for
  $t = t + 1$.
end while

V. Performance Evaluation

A distribution network is considered in connection with a LA consisting of $N = 10$ MGs and an NA. The ECS located in the DNO schedules energy consumption of MGs in LA during a time horizon of length 6 h. The scheduling is updated every 1 min (i.e., $T = 360$). Average demands of MGs in LA are $E = [1/T, 2/T, \ldots, n/T, \ldots, N/T]$, where n/T is the average demand of MG_n in kilowatt-hours per unit of time [i.e., E_n in constraints (2a) and (15b)]. Minimum and maximum power levels are $p^{min} = [0, 1, \ldots, 9]$ and $p^{max} = [5, 6, \ldots, 14]$, respectively. The power generation cost is considered to be quadratic function [i.e., $C(.) = (.)^2$ in (1) and (2)], even though the proposed solutions are valid for any convex cost function. The performance of the proposed algorithms are evaluated in the following subsections.

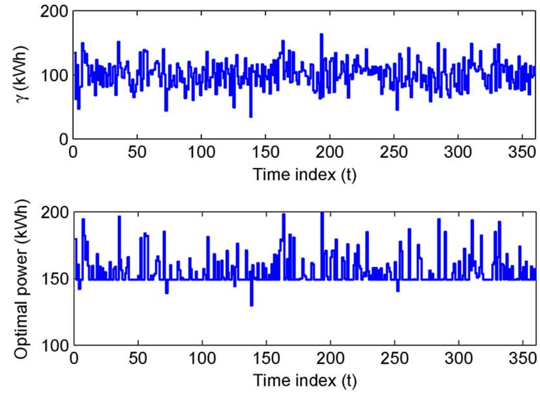

Fig. 2. Generated NAs demand and the system-wide optimal demand.

A. Cost Formulation

First, we are interested in evaluating the impact of the proposed ACA-ECS scheme in Algorithm 1 on the time-domain curvature of the total grid demand in the presence of an *unknown* NAs demand. We are also interested in comparing this curve with that of the optimal solution in (1) and (2), albeit when NAs demand is *known* in the beginning of the time horizon $\mathcal{T}$. Toward this end, NAs demand during this horizon is required to be generated in some way. Here, we assume that this demand is a normal random variable with a mean of 100-kWh per unit of time and standard deviation σ (i.e., $\gamma \sim \mathcal{N}(100, \sigma)$). Given these values, the optimal solution of the cost minimization problem in (1) and (2) is obtained using IPM, once in the beginning of the time horizon. In fact, it is a *deterministic* solution when the knowledge of NAs demand is fully available. It is noteworthy that the ACA-ECS scheme still makes scheduling decisions per time instant and at each instant only uses the corresponding NAs demand value. A typical realization of $T = 0$ 36 samples of NAs demand with $\sigma = 20$ kWh and the corresponding optimal total demand p^t in (1) and (2) are shown in Fig. 2. As observed, the optimal solution schedules LA demand such that the system-wide total demand becomes smooth suitable for cost minimization. In fact, scheduling the LA demand provides a diversity for the ECS to mitigate the stochastic nature of NAs demand. Total demand using the ACA-ECS scheme and the corresponding Lagrange multipliers in (12) are also shown in Fig. 3. Intuitively, after some initial time slots, the behavior of the total demand curve approximately converges to that of the optimal solution in Fig. 2. This observation is completely

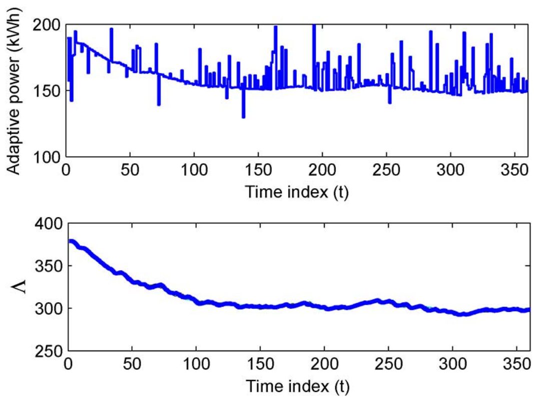

Fig. 3. Adaptive system-wide demand and Lagrange multipliers.

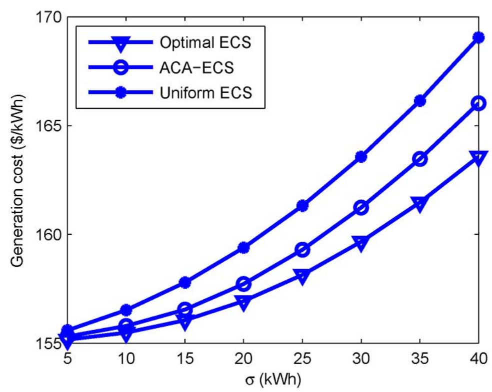

Fig. 4. Generation cost per kilowatt-hour in cost formulation.

in accordance with the convergence of Lagrange multipliers of (12) in Fig. 3.

Performance measures of the ACA-ECS and the optimal ECS schemes, such as generation cost per kilowatt-hour and PAR, versus the randomness of the NAs demand could be interesting as follows. As another scheduling scheme, the results of uniform ECS scheme are also included. In this scheme, the demand of each MG_n in LA is *uniformly* distributed over the whole time horizon, independent of the NAs demand (i.e., $p_n^t = E_n \forall n \in \mathcal{N}, t \in \mathcal{T}$). This can also be considered as a deterministic solution. Cost and PAR performances versus the standard deviation of γ (i.e., σ) are shown in Figs. 4 and 5, respectively. For each instance of σ, similar to the time-domain performance, we first generate a data set with $T = 360$ samples of the distribution $\mathcal{N}(100, \sigma)$, as partially shown in Table I. This set is used to obtain the optimal ECS solution once in the beginning of the time horizon as well as to provide the ACA-ECS scheme with instantaneous realized NAs demand. As shown in the first part of Fig. 2, there is a typical generated data set with $\sigma = 20$ kWh.

As a common observation in Figs. 4 and 5, performance measures are getting worse as σ increases. In the case of cost measure, this is due to the fact that the considered squared cost function results in higher cost per kilowatt-hour for high demand values in comparison with low demand values. The results in PAR are based on the fact that the averages of both LA and NAs demands are made constant when σ increases. Considering PAR as a fractional term of the peak demand over the average demand, it is reasonable to conclude that PAR increases as σ

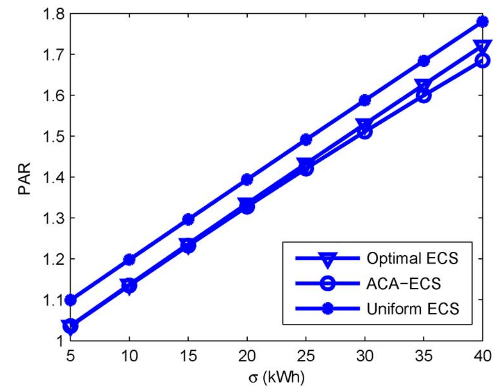

Fig. 5. PAR in cost formulation.

increases. Moreover, in Fig. 4, with an increase in σ, the performance gap between the compared ECS schemes and the optimal one increases. In case of ACA-ECS, this is due to the fact that the stochastic estimator (12) would be far from optimality with the increase in the randomness of $\gamma(t)$. In case of uniform ECS, the degradation effect of high randomness would be more severe since this scheme does not take care of NAs demand in the scheduling decisions.

Furthermore, in Fig. 4 and Fig. 5, the generation cost and PAR performances of the ACA-ECS scheme outperform those of uniform ECS. This is reasonably expected as ACA-ECS takes advantage of the diversity in NAs demand to smooth the total demand and therefore achieves a better performance. In the comparison between ACA–ECS and the optimal solution, it is observed that the optimal solution achieves lower cost. This is due to the fact that this solution fully takes into account the knowledge of NAs demand at the beginning of the time horizon for the scheduling of LA demand. However, ACA-ECS makes a scheduling decision adaptively per a time unit, when the demand of NAs is available in that unit. Remarkably, the PAR of ACA–ECS is comparable to that of the optimal solution. This implies that the optimality of generation cost does not necessarily imply the optimality of PAR too. This observation motivates the performance evaluation of PAR formulation in the following.

B. PAR Formulation

In order to evaluate the efficiency of PAR formulation, the generation cost per kWh and PAR performances of this formulation are illustrated in Figs. 6 and 7, respectively. Similar to the cost formulation in Section V-A, the results of the optimal solution in PAR formulation (optimal PAR) and uniform scheduling (uniform PAR) scheme are also included. Since the scheduling of the uniform strategy is independent of the objective function, the achieved results are the same in both cost and PAR formulations. We take advantage of this equality and take uniform strategy curves as references for comparison between these formulations.

Comparing Figs. 4 and 6, it is observed that uniform scheduling was the worst in the former, whereas it is the best in the latter. Considering the results of uniform scheduling as reference in both figures, we conclude that cost minimization formulation is more cost efficient in comparison with PAR formula-

TABLE I
NAs DEMAND FOR SIMULATION

σ (kWh)	γ (kWh)													
	1	2	3	4	...	181	182	183	184	...	357	358	359	360
5	108.6	90.5	103.8	86.7	...	99.6	99.3	96.2	98.5	...	99.0	99.7	103.0	100.3
10	95.0	100.9	81.7	90.5	...	85.3	109.4	109.9	101.0	...	87.1	100.9	106.7	95.1
15	115.1	93.3	114.3	108.8	...	84.7	76.1	98.8	76.5	...	80.3	118.9	81.3	118.2
20	96.6	117.1	126.0	93.8	...	102.3	92.6	88.9	80.3	...	98.4	59.6	123.7	126.9
25	67.8	93.2	115.4	121.7	...	72.7	115.0	78.5	104.8	...	49.0	64.7	91.4	111.7
30	118.2	100.5	105.0	118.4	...	128.5	140.5	113.8	151.7	...	78.2	114.8	75.1	110.8
35	125.9	130.7	16.7	121.5	...	127.5	85.5	87.0	87.7	...	90.0	93.6	78.3	89.3
40	136.9	65.1	128.4	82.07	...	116.7	112.5	75.01	116.5	...	139.2	87.1	82.3	126.6

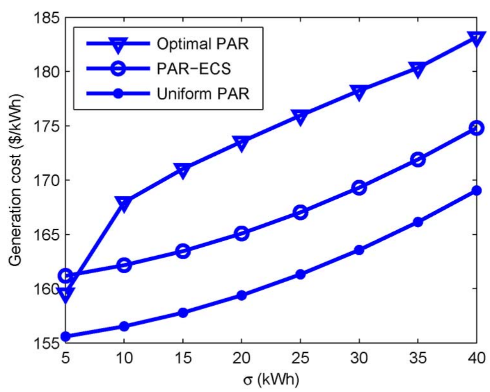

Fig. 6. Generation cost per kilowatt-hour in the PAR formulation.

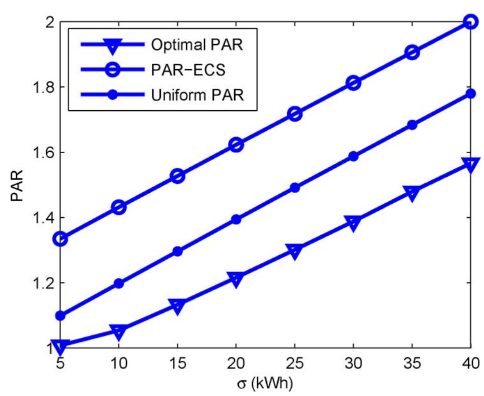

Fig. 7. PAR in PAR formulation.

tion. In terms of PAR, the optimal solution in the PAR formulation achieves the lowest PAR. This is reasonably expected since this solution takes NAs demand into account *a priori*. In comparison with the uniform strategy, the PAR of PAR-ECS scheme is high. This is due to oscillations between min and max power levels in PAR-ECS scheme in Algorithm 2. More important, this implies that PAR performance of our proposed adaptive approach in cost minimization formulation even outperforms its equivalent one in the PAR minimization formulation. This observation along with the lower generation cost in cost formulation demonstrates that our proposed adaptive approach achieves more *efficient* results with this formulation compared with PAR one. Also the proposed adaptive approach is a trade off between the optimal (full NAs demand) and uniform (no NAs demand) schemes in terms of generation cost and PAR minimization.

C. Comparison With Game Theory

One interesting proposed approach for power scheduling in the literature is game theory [14], [15]. Customized to our work, in this approach, each MG in LA autonomously updates its own strategy (demand), given strategies (demands) by other MGs. In this section, the performance of our proposed adaptive approach is investigated in comparison with the game-theoretic approach. Without loss of generality, the cost minimization formulation (i.e. ACA–ECS algorithm) is considered even though the comparison is also valid for PAR minimization formulation.

To apply the game-theoretic approach to solve (1) and (2), we first need to make it clear if this approach assumes either known or unknown NAs demand. Either case results in a different solution. In the case of known demand *a priori*, the game-theoretic approach takes this knowledge into account to obtain the solution immediately in the beginning of the time horizon $\mathcal{T}$. As shown in [14] and [15], the performance in this case is that of the optimal solution, due to the convexity of problem (1) and (2). In other words, the game-theoretic performance translates to the optimal solution, shown in the appeared figures.

Under the assumption that NAs demand is unknown in advance, the game-theoretic approach has to make scheduling decisions per time instant, once NAs demand value is realized. In other words, this approach decouples problem (1) and (2) over time. Suppose that MG_n wishes to determine p_n^t at time instant t in the presence of NAs demand $\gamma(t)$ and given demands by other MGs in LA (i.e., $p^t_{n' \in \mathcal{N}, n' \mathcal{N} \neq n}$). Revising problem (1) and (2) with this setup, it is equivalent to

$$\min_{p_n^t} C\left(p_n^t + A\right) \tag{25}$$

$$\text{s.t.} \quad p_n^t \geq E_n \tag{26a}$$

$$p_n^{\min} \leq p_n^t \leq p_n^{\max} \tag{26b}$$

where $A \triangleq \sum_{n' \neq n} p_{n'}^t + \gamma(t)$ takes a constant value. The trivial solution of this problem, assuming $E_n \geq p_n^{\min}$, is always $p_n^t = E_n$. In other words, the performance of the game-theoretic approach in this case is that of the uniform scheduling in the appearing figures. Numerically from Fig. 4, the generation cost of game theory in the case of known NAs demand is 86% of that in the case of unknown NAs demand. Similarly, the PAR of known NAs demand is 87% of that in unknown NAs demand, derived from Fig. 7.

In summary, the game-theoretic approach outperforms the proposed adaptive one if the knowledge of NAs demand is fully taken into account in the beginning of the time horizon. On the other hand, our adaptive approach achieves better performance.

VI. Conclusion

The unpredictable demand throughout a distribution network avoids global and optimal energy consumption scheduling. Alternatively, we resort to local and suboptimal scheduling schemes that adaptively perform energy scheduling. In this paper, a stochastic model of scheduling in a local area of a network with the objective of cost minimization and peak-to-average ratio minimization has been presented. In both cases, it is shown that optimal scheduling can be followed by an online iteration that captures the randomness of neighbor grids demand adaptively. This approach makes decisions progressively over time. Indeed, the proposed adaptive schemes can provide an estimation of the optimal solution. Through simulations, we concluded that the general performance of cost minimization formulation outperforms the peak-to-average ratio minimization formulation with an underlying adaptive approach.

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