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Joint Optimization of Electricity and Communication Cost for Meter Data Collection in Smart Grid

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ABSTRACT Smart grid is recently proposed as an enhancement for the next generation power grid. To achieve efficient status monitoring, control, and billing, a large number of smart meters are deployed and they would produce a huge amount of data. To efficiently collect them imposes a great challenge on the communication networks. In this paper, we study the efficient meter data collection problem by exploring the secondary spectrum market in cellular networks. The electricity power reserved by sending meter data via leased secondary channels would be charged at a lower price. With the objective of reducing the overall cost of both power and communication, we formulate a problem called cost minimization for meter data collection (CMM) that is to find optimal solution of channel selection and transmission scheduling. The CMM problem under a linear power pricing model is formulated as a mixed integer linear programming problem and is then solved by a branch-and-bound algorithm. Under a nonlinear power pricing model, we formulate it as a nonconvex mixed integer nonlinear programming problem and propose an optimal algorithm by integrating the sequential parametric convex approximation method into the branch-and-bound framework. Extensive simulation results show that our proposal can significantly reduce the overall cost.

INDEX TERMS Smart grid, meter data collection, spectrum, optimization.

I. INTRODUCTION

Smart grid is regarded as the next generation power grid with a glorious future. In contrast to traditional power grid with a tree-like hierarchical structure, it uses two-way flows of electricity and information to create a widely distributed automated energy delivery system. In smart grid, the Advanced Metering Infrastructure (AMI) [1], [2] is one of the most critical components to achieve efficient status monitoring, control and pricing by deploying a large number of smart meters in homes, buildings and factories. Such smart meters would produce a huge amount of data that should be efficiently collected, imposing a great challenge on communication networks. Due to security and cost issues [3], [4] of current wired communication technologies, wireless technologies have been considered more appropriate to be used in smart grid because of its flexibility, large-coverage and low-cost [5]–[8].

In this paper, we study the efficient meter data collection problem by exploring the secondary spectrum market in cellular networks [9]–[13]. Although the spectrum has become a scarce resource because of booming growth of various wireless applications, measurement results show that spectrum is under-utilized in many places [14]. Such an observation motivates the design of a secondary spectrum market, where new services, such as meter data collection in smart grid, can access licensed channels with appropriate payment when they are unused by their owner. Compared with other opportunistic channel access schemes, such as cognitive radio, the secondary spectrum market based on contracts can provide stable communication service and easy cost management.

All existing work on secondary spectrum market studies problems from the perspective of communication networks only. When it is applied in meter data collection for power pricing problem studied in this paper, the interaction between power and communication networks should be taken into consideration. The power pricing model proposed in recent literature [15], [16] show that the power price is a decreasing function of the amount of collected meter data attached with power reservation information. Less power cost is incurred if more meter data are collected. However, it requires more channels or larger channel capacity, leading to a higher communication cost. On the other hand, reducing communication cost by leasing less channel resources may cause meter data may loss due to congestion, such that the power cost will be increased. This tradeoff motivates us to design an efficient meter data collection scheme to minimize the total cost. To the best of our knowledge, we are the first to study the benefit of leasing secondary channels for meter data collection by jointly considering the power and communication cost. The main contributions of this paper are summarized as follows.

- First, we consider meter data collection based on a two-stage power pricing model, under which power is supplied with a lower price if it is reserved in advance. Thus, if more meter data with the power reservation information are collected, less power payment will be produced, but at a higher leasing fee for more communication channels. With the objective of reducing the total cost, we propose a problem called CMM (Cost Minimization for Meter data collection) that is to find the optimal scheme for channel selection and transmission scheduling scheme.
- Second, we analyze the hardness of the CMM problem by proving its NP-hardness. Specifically, we reduce the well-known knapsack problem to a special case of the CMM problem with a linear power price function, i.e., the power price linearly increases as the growth of power supply.
- We solve the CMM problems under both linear and nonlinear power pricing models. The former is formulated as a mixed integer linear programming (MILP) problem and solved by a branch-and-bound algorithm. To deal with the latter, we formulate it as a nonconvex mixed integer nonlinear programming (MINLP) problem and propose an optimal algorithm by integrating the SPCA (Sequential Parametric Convex Approximation) method into our branch-and-bound framework.
- Finally, extensive simulations are conducted to evaluate the proposed algorithms. The experimental results show that our proposal can significantly reduce the power and communication cost.

The rest of this paper is organized as follows. Section II reviews the related work. Section III presents the network model and pricing model. The hardness of the CMM problem is analyzed in Section IV. Section V presents optimal algorithms for the CMM problem under both linear and nonlinear power pricing model. Simulation results are given in Section VI. Finally, Section VII concludes this paper.

II. RELATED WORK

Smart metering is the most important mechanism used in smart grid for obtaining information from end users' devices and applications. A Zigbee Advance Metering Infrastructure (ZAMI) is proposed in [17] for automatic meter data collection and energy auditing and management. In the ZAMI, the system operates with multiple channels and frequency hopping and coexists with potential interferers. Garlapati et al. [18] have proposed a Hybrid Spread Spectrum (HSS) based advanced smart metering infrastructure that reduces the overhead and latency in data transfer when compared to the use of 3G/4G technologies for smart meter data collection. Matheson et al. [19] have developed a software system called the metering data management (MDM) using the web service technology to support meter data collection, validation, estimation, versioning and publishing at Bonneville Power Administration. One of its key features is the validation and estimation of the meter data based on statistical models. The application of cooperative transmission for the meter data collection in smart grid is introduced in [16]. To analyze the relay transmission strategy of the community, the noncooperative game model is formulated, and the Nash equilibrium is considered as the solution.

Recently, many efforts have been made to use CR (cognitive radio) in smart grid [20], [21]. Sreesha et al. [22] have proposed a multi-layered approach to provide energy and spectrum efficient designs of cognitive radio based wireless sensor networks at the smart grid utility. Their design provides a reliable and low-latency routing support for large-scale cognitive smart grid networks. Qiu et al. [23] have built a real-time CR network testbed, which can help tie together CRs in the next-generation smart grid network. Later, Qiu et al. [24] have systematically investigated the idea of applying CR to smart grid on system architecture, algorithms, and hardware testbed, and proposed a microgrid testbed supporting both power flow and information flow. Furthermore, the concept of independent component analysis in combination with the robust principal component analysis technique is employed to recover data from the simultaneous smart wireless transmissions in the presence of strong wideband interference. Yu et al. [25] have proposed an unprecedented cognitive radio based communications architecture for the smart grid, which is mainly motivated by the explosive data volume, diverse data traffic, and need for QoS support.

III. SYSTEM MODEL

In this section, we first introduce the network model for meter data collection, and then present the pricing models of both power and spectrum.

A. NETWORK MODEL

In this paper, we consider a typical three-layer wireless network model for meter data collection in smart grid as shown in Fig. 1.

Home area network (HAN): The lowest layer is HAN that connects home appliances with smart meters to support demand response, home energy management, load management, and smart metering. Short-range or local area wireless technologies, such as ZigBee, Bluetooth, and WiFi, can be used for HAN [26], [27].

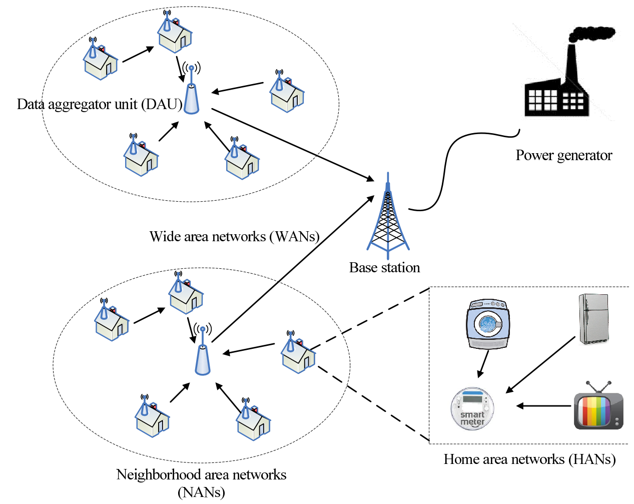


FIGURE 1. **Network model.**

Neighborhood area network (NAN): Multiple homes form a community that is served by a data aggregator unit (DAU), which collects meter data from HAN gateways via NAN in a single- or multiple-hop manner.

Wide area network (WAN): WAN is at the top layer and forwards the collected meter data at DAUs to a remote power management system (PMS). Long-distance communication technologies, e.g., 3G or satellite, should be used in WAN for coverage consideration [28], [29]. In contrast to HAN and NAN that can be easily constructed using dedicated hardware with low cost, WAN needs the support of high-end communication technologies that are shared by multiple services. Thus, the communication cost cannot be neglected in WAN.

Under this model, we exploit the secondary spectrum market in cellular networks for meter data collection. Specifically, we consider a WAN that consists of a base station and a set of n DAUs $S = \{s_1, s_2, \ldots, s_n\}$. There are a set of secondary channels $B = \{b_1, b_2, \ldots, b_m\}$ available in the network, which can be rented by DAUs. Due to geographical differences, the set of accessible channels at $s_i \in S$, which is denoted by $B(s_i)$, may be different at each DAU. We let c_{ij} denote capacity of the wireless link from DAU s_i to the base station under channel b_j. Each DAU is equipped multiple antennas such that it can work on multiple channels simultaneously. Each channel can accommodate multiple DAUs as long as the sum of their transmission rate does not exceed the channel capacity.

B. PRICING MODEL

The two-stage power pricing model [15], [16] has received an increasing attention because it provides incentives for efficient electricity use. In such model, power supply is charged in a period-by-period manner, where each period may last several hours or days according to the strategy adopted by PMS. In the first stage, users reserve power supply from power generators before each period. For this purpose, each DAU s_i collects an amount of R_i meter data, including a total power demand D_i, from its community. The collected data at DAUs should be forwarded to PMS within time T over leased cellular channels, whose capacity, unfortunately, may not be always enough to support R_i data transmission due to limited channel resource and communication cost consideration. As a result, packets at DAU s_i are uniformly abandoned such that only a portion of data is successfully delivered to PMS, leading to only $d_i \leq D_i$ power demand successfully received by PMS in the first stage.

In the second stage, the reserved power of each community is supplied with a lower price. If the reserved power is not enough, additional power will be bought at a higher price. To describe this power pricing model, we define two functions $f_r(x)$ and $f_a(x)$, $f_r(x) \leq f_a(x)$, such that their derivatives characterize the pricing rate of electricity use in reserved and exceeding portion, respectively. Letting $g(d_i, x)$ be the power price to community s_i with actual power demand x while only d_i received by PMS, we therefore have:

$$\frac{\partial g(d_i, x)}{\partial x} = \begin{cases} f_r'(x), & x \leq d_i, \\ f_a'(x), & \text{otherwise.} \end{cases}$$

After solving this differential equation, we obtain the power price with demand D_i as:

$$g(d_i, D_i) = f_a(D_i) - \big(f_a(d_i) - f_r(d_i)\big). \tag{1}$$

Two typical forms of function f_a/f_r have been described by a linear [16] and a nonlinear model [30]–[32]. The former requires payment linearly proportional to the power usage, i.e., each unit of power is charged with the same price. The latter discourage excessive electricity use by applying a nonlinear, e.g., exponential, pricing model. It has recently been adopted by many electricity companies as a measure to reduce power usage.

Without loss of generality, we consider $f_a(x) = \alpha f_r(x)$, $\alpha > 1$ in our model. In the following, $f_r(x)$ and $f_a(x)$ in both linear and nonlinear forms will be studied.

- *Linear power price function*: As shown in Fig. 2, $f_r(x)$ is given as $f_r(x) = p^e x$ in a linear form [16], where p^e is unit price for reserved power. After substituting it into (1), $g(d_i, D_i)$ can be expressed as:

$$g(d_i, D_i) = p^e d_i + \alpha p^e (D_i - d_i), \tag{2}$$

  where the two terms in right-hand represent the payment of reserved power d_i and additional portion $D_i - d_i$, respectively.
- *Nonlinear power price function*: In addition to the simple linear pricing model, functions $f_r(x)$ is often modelled in nonlinear forms [30]–[32], i.e., $f_r(x) = e^{\lambda x} - 1$, $\lambda \geq 1$ as shown in Fig. 3. According to (1), the power price function $g(d_i, D_i)$ can be expressed as:

$$g(d_i, D_i) = \alpha(e^{\lambda D_i} - 1) - (\alpha - 1)(e^{\lambda d_i} - 1). \tag{3}$$

In addition to power cost, communication cost A is incurred by leasing wireless channels connecting DAUs and

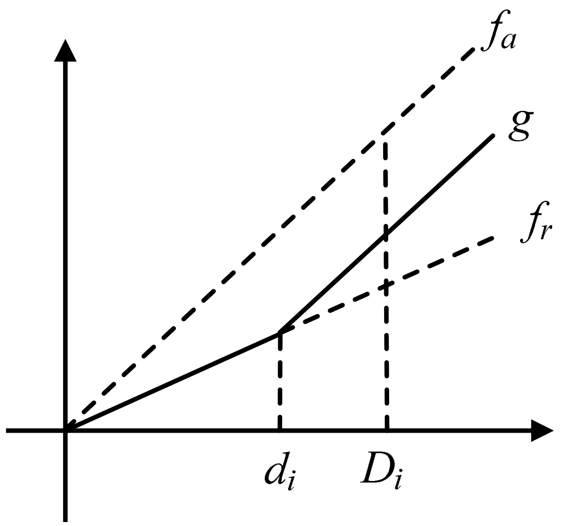


FIGURE 2. Linear power pricing model.

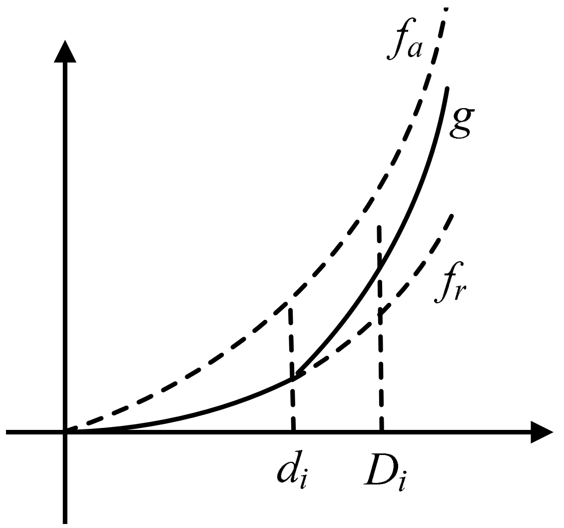


FIGURE 3. Nonlinear power pricing model.

remote PMS. Let p_j^c be the payment of using channel b_j during time T. Note that a channel is the minimum trade unit in spectrum market considered in our model, i.e., once DAUs decide to rent a channel b_j, they should pay p_j^c even if this channel is not fully utilized.

The total cost M in time T is calculated by summing power and communication cost, i.e.,

$$M = \sum_i g(d_i, D_i) + A. \tag{4}$$

We observe from (2) and (3) that lower power cost can be achieved if more power reservation data are forwarded to PMS, however, more channels required for such data lead to higher communication cost. Even for forwarding a fixed amount of data, the challenge of channel selection to minimize communication cost still exists.

In this paper, the total cost minimization problem in meter data collection, which is also referred to as CMM, can be defined as follows. *Given a WAN consisting a base station, a set of DAUs, and several available channels, the CMM problem is to select a set of channels and find a transmission scheduling of DAUs on these channels to minimize total cost M.*

IV. HARDNESS ANALYSIS

In this section, we prove the CMM problem NP-hard.

Theorem 1: The CMM problem is NP-hard.

Proof: In order to prove an optimization problem NP-hard, we need to show the NP-completeness of its decision form, which is formalized as follows.

The CMM_D problem

INSTANCE: Given a WAN consisting a base station, a set of n DAUs S, and a set of available channels B, a price function $g(d_i, D_i)$, a constant $\mathcal{M}$.

QUESTION: Is there a channel purchase scheme and a transmission scheduling such that the total cost $M \leq \mathcal{M}$?

It is easy to see that the CMM_D problem is in NP class as the objective function associated with a given channel purchase scheme and a transmission scheduling can be evaluated in a polynomial time. The remaining proof is done by reducing the well-known knapsack problem with identical price-per-pound to the CMM_D problem.

The knapsack problem

INSTANCE: Given a set of items $\Phi = \{\phi_1, \phi_2, \ldots, \phi_m\}$, where item $\phi_j \in \Phi$ has value v_j and size w_j, a knapsack capacity W, and a constant V.

QUESTION: Is there a subset $\Phi' \subseteq \Phi$ such that $\sum_{\phi_j \in \Phi'} w_j \leq W$ and $\sum_{\phi_j \in \Phi'} v_j \geq V$?

We now describe the reduction from the knapsack problem to an instance of the CMM_D problem. We consider a linear power pricing functions $g(d_i, D_i)$ shown in (2) in our proof. The process of instance construction is shown as follows.

- *Step 1*: for each item ϕ_j in Φ, we create a channel b_j with price $p_j^c = w_j$, which can be accessed by all DAUs with identical channel capacity $c_{ij} = \bar{c}_j = v_j$, $1 \leq i \leq n$;
- *Step 2*: the sum of power demand from all communities is V, i.e., $\sum_{1 \leq i \leq n} D_i = V$;
- *Step 3*: we let $\mathcal{M} = p^e V + W$;
- *Step 4*: set the value of α to a large number such that the power cost will exceed $\mathcal{M}$ if demands are not fully delivered to PMS.

In the following, we only need to show that the knapsack problem has a solution if and only if the resulting instance of CMM_D problem has a channel selection and a transmission scheduling that satisfy total cost constraint. First, we suppose that there exists a subset $\Phi' \subseteq \Phi$ such that $\sum_{\phi_j \in \Phi'} w_j \leq W$ and $\sum_{\phi_j \in \Phi'} v_j \geq V$. The corresponding solution of CMM_D problem is a subset $B' \subseteq B$ such that the total cost is calculate by:

$$
\begin{aligned}
M &= \sum_{1 \le i \le n} g(d_i, D_i) + A \\
&= \sum_{1 \le i \le n} [p^e d_i + \alpha p^e (D_i - d_i)] + \sum_{b_j \in B'} p_j^c \\
&= \alpha p^e \sum_{1 \le i \le n} D_i + (1-\alpha) p^e \sum_{1 \le i \le n} d_i + \sum_{b_j \in B'} p_j^c \\
&\le \alpha p^e \sum_{1 \le i \le n} D_i + (1-\alpha) p^e \sum_{b_j \in B'} \bar{c}_j + \sum_{b_j \in B'} p_j^c \\
&= \alpha p^e V + (1-\alpha) p^e \sum_{\phi_j \in \Phi'} v_j + \sum_{b_j \in B'} p_j^c \\
&\le \alpha p^e V + (1-\alpha) p^e V + W \\
&= p^e V + W.
\end{aligned}
$$

Then, we suppose that the CMM_D problem has a solution $B' \subseteq B$ such that $M \le \mathcal{M}$. Due to the large α, all demand should be delivered to PMS. Thus, in the corresponding solution Φ', we have:

$$\sum_{\phi_j \in \Phi'} v_j = \sum_{b_j \in B'} \bar{c}_j = \sum_{1 \le i \le n} D_i \ge V. \tag{5}$$

On the other hand, the communication cost should be no greater than W, which lead to:

$$\sum_{\phi_j \in \Phi'} w_j = \sum_{b_j \in B'} p_j^c \le W. \tag{6}$$

Thus, the CMM_D problem in decision form is NP-completeness and its original optimization problem CMM is NP-hard. ■

V. SOLVING THE CMM PROBLEM

In this section, we solve the CMM problem under both linear and nonlinear power pricing models.

A. LINEAR POWER PRICING MODEL

We define a variable y_j for channel selection, i.e.,

$$y_j = \begin{cases} 1, & \text{if channel } b_j \text{ is selected,} \\ 0, & \text{otherwise.} \end{cases}$$

Since each DAU is allowed to transmit on multiple channels, we define x_{ij} to denote the time fraction of DAU s_i working on channel b_j. By letting g_i denote the power cost of DAU s_i, the CMM problem using linear power price function can be formulated as:

$$
\begin{aligned}
&\min \sum_{1 \le i \le n} g_i + A, \quad \textit{subject to} \\
&0 \le \sum_{1 \le i \le n} x_{ij} \le y_j \quad \forall 1 \le j \le m, && (7) \\
&x_{ij} = 0 \quad \forall 1 \le i \le n, b_j \notin B(s_i), && (8) \\
&d_i \le \frac{TD_i}{R_i} \sum_{1 \le j \le m} x_{ij} c_{ij} \quad \forall 1 \le i \le n, && (9) \\
&d_i \le D_i \quad \forall 1 \le i \le n, && (10) \\
&g_i \ge p^e d_i + \alpha p^e (D_i - d_i) \quad \forall 1 \le i \le n, && (11) \\
&A \ge \sum_{1 \le j \le m} y_j p_j^b. && (12)
\end{aligned}
$$

Multiple DAUs working on a common channel should share this channel according to time division, which leads to constraint (7). The power demand delivered by any DAU s_i is determined by transmission rate and can not exceed D_i, represented by constraints (9) and (10), respectively. Constraints (11) and (12) represent the power and communication cost, respectively.

The formulated CMM problem is in a form of mixed integer linear programming (MILP) that can be solved by a branch-and-bound algorithm shown in Algorithm 1. We use $\mathcal{P}$ to denote a problem set with an upper bound U and a lower bound L of the optimal solution that are tightest found

Algorithm 1 Solving the CMM problem

```
P = {P_0}, U = ∞;
set l_{P_0} as the optimal solution of the relaxed problem P_0;
while P ≠ ∅ do
    select a problem P ∈ P with the minimum l_P and let L = l_P;
    set u_P as the solution of P using rounding;
    if u_P < U then
        u* = u_P, U = u_P;
        if L ≥ (1 − ε)U then
            return the (1 − ε)-optimal solution u*;
        else
            remove all problems P' ∈ P with l_P ≥ (1 − ε)U;
        end if
    end if
    select the maximum unfixed variable y_j from the results of the relaxed problem P and remove P from P;
    construct a problem P_1 with y_j = 1 and solve it to obtain l_{P_1}.
    if l_{P_1} < (1 − ε)U, then put P_1 into P; end if
    construct a problem P_2 with y_j = 0 and solve it to obtain l_{P_2}.
    if l_{P_2} < (1 − ε)U, then put P_2 into P; end if
end while
return the (1 − ε)-optimal solution u*;
```

so far. Initially, $\mathcal{P}$ only includes the original problem, denoted by P_0. For any $P \in \mathcal{P}$, the corresponding relaxed problem can be easily solved and the optimal solution serves as an lower bound, denoted as l_P, of the solution to the original problem. Then, the algorithm proceeds iteratively as follows. In each round, we find a problem $P \in \mathcal{P}$ with minimum l_P and then set $L = l_P$. While any feasible solution of P can serve as an upper bound, the one obtained using rounding under the satisfaction of all constraints is used and denoted by u_P. The smallest upper bound U is updated from line 6–13. If the performance gap between L and U is less than a predefined small number ϵ, a $(1-\epsilon)$-optimal solution u^* is returned. Otherwise, we find the maximum unfixed variable y_j from the results and create two subproblems P_1 and P_2 by fixing y_j to 1 and 0, respectively. If the results of relaxed P_1 and P_2 are less than $(1-\epsilon)U$, they are put into the problem set $\mathcal{P}$.

B. NONLINEAR POWER PRICING MODEL

Similar with the formulation under linear power pricing model, we also define $y_j (1 \le j \le m)$ and $x_{ij} (1 \le i \le n, 1 \le j \le m)$ for channel selection and transmission scheduling, respectively, such that the CMM problem under nonlinear power pricing model can be formulated as:

$$\min \sum_{1 \le i \le n} g_i + A, \qquad \textit{subject to}$$

$$\ln\left(\frac{g_i - \alpha(e^{\lambda D_i} - 1)}{1-\alpha} + 1\right) \le \lambda d_i \qquad \forall 1 \le i \le n, \quad (13)$$

$$(7) - (10), \text{ and } (12).$$

We observe that above formulation is a nonconvex mixed integer nonlinear programming (MINLP), which is difficult to be solved, due to constraint (13), whose left side is denoted by $H_i(g_i)$. To deal with this challenge, we explore the SPCA (Sequential Parametric Convex Approximation) method [33] whose basic idea is to iteratively solve the resulting linear programming (LP) problem by replacing original nonconvex constraints with linear ones until a converged solution is achieved. At each iteration, a new linear constraint is constructed such that the corresponding line is tangent to the curve defined by the nonconvex constraint at the point, which is a solution obtained in the previous iteration. By applying the SPCA technique, the relaxed CMM problem (*i.e.*, all integer variables are relaxed to real ones), denoted as CMM_R, can be quickly solved. Specifically, in the k-th iteration, we replace nonconvex constraint (13) by

$$\frac{z(g_i - \bar{g}_i^{(k-1)})}{z\bar{g}_i^{(k-1)} - Q_i} + \ln(z\bar{g}_i^{(k-1)} - Q_i) \le \lambda d_i, \qquad (14)$$

where $z = \frac{1}{1-\alpha}$ and $Q_i = z\alpha(e^{\lambda D_i} - 1) - 1$.

We denote the left side of (14) as $h_i^{(k)}(g_i)$, in which $\bar{g}_i^{(k-1)}$ denotes the optimal solution of variable g_i obtained in the $(k-1)$-th iteration. As shown in Fig. 4, after solving the corresponding linear programming in the k-th iteration, we construct a new linear constraint $h_i^{(k+1)}(g_i)$ to approximate (14)

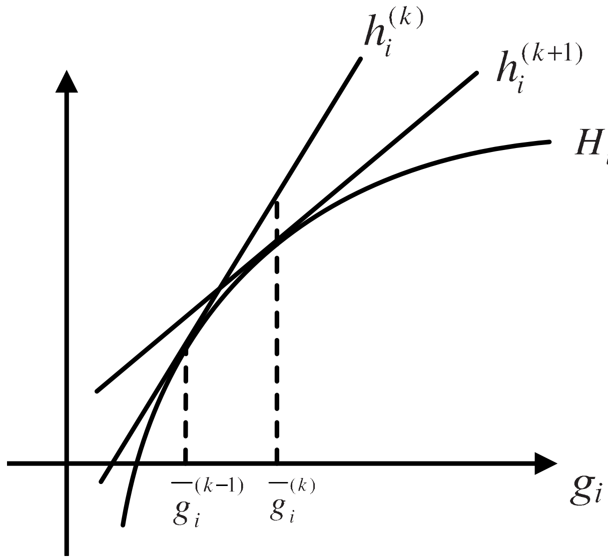


FIGURE 4. Illustration of the SPCA method.

in the next iteration. The algorithm to solve the CMM_R problem is formally described in Algorithm 2, in which CMM_R(k) and $\Delta^{(k)}$ are the problem formulation and its optimal solution in the k-th iteration, respectively. Since the initial value of $\bar{g}_i^{(0)}$ can be set as an arbitrary positive number, we set $\bar{g}_i^{(0)} = e^{\lambda D_i} - 1$.

Algorithm 2 Solving the CMM_R problem

1: $k = 0, \Delta = -\infty, \Delta^{(0)} = 0, \bar{g}_i^{(0)} = e^{\lambda D_i} - 1 (1 \le i \le n)$
2: **while** $|\Delta^{(k)} - \Delta| > \xi$ **do**
3: $\quad \Delta = \Delta^{(k)}$,
4: $\quad k = k + 1$
5: $\quad$ obtain $\Delta^{(k)}$ as well as $\bar{g}_i^{(k)} (1 \le i \le n)$ by solving the following LP problem with relaxed variables:

$$CMM\_R(k): \qquad \min \textstyle\sum_{1 \le i \le n} g_i + g^c$$
$$\text{s.t.} \qquad (7) - (10), (12) \text{ and } (14).$$

6: **end while**

In the following theorem, we show that the solution obtained by Algorithm 2 satisfies the Karush–Kuhn–Tucker (KKT) conditions, i.e., the first-order necessary conditions for a solution in nonlinear programming to be optimal [34].

Theorem 2: The solution of the CMM_R problem obtained by Algorithm 2 satisfies the Karush–Kuhn–Tucker (KKT) conditions.

Proof: For any feasible point $(\bar{g}_i^{(k-1)}, h^{(k-1)}(\bar{g}_i^{(k-1)}))$, we update the linear constraint for the CMM_R formulation in Algorithm 2. As guaranteed by the analysis in [33], the conclusion is achieved when the nonlinear function, which is denoted by $H_i(g_i)$, and its approximated linear function $h_i^{(k)}(g_i)$ have the same values at $g_i = \bar{g}_i^{(k-1)}$ for the original and their first-order differential functions, respectively.

These can be verified by:

$$h_i^{(k)}(\bar{g}_i^{(k-1)}) = H_i(\bar{g}_i^{(k-1)}) = \ln(z\bar{g}_i^{(k-1)} - Q_i),$$
$$\nabla h_i^{(k)}(\bar{g}_i^{m-1}) = \nabla H_i(\bar{g}_i^{m-1}) = \frac{z}{z\bar{g}_i^{(k-1)} - Q_i}.$$

■

Note the KKT conditions are satisfied only for the relaxed problem, referred to as CMM_R here, not for the MINLP problem. Although Algorithm 2 returns a solution satisfying the KKT conditions, we find out that it is always the global optimal solution empirically through extensive numerical experiments.

In order to solve the original CMM problem, we integrate Algorithm 2 into the branch-and-bound framework shown in Algorithm 1 by solving each relaxed problem in problem set $\mathcal{P}$ using Algorithm 2.

To apply our proposal in practice, we first need to collect the information from both network and power systems, such as available channels and power price model. Then, the proposed algorithm is executed in a centralized manner. After obtaining optimization results, we negotiate with the network service provider to lease the selected channels such that the transmission scheduling can be applied in these channels to achieve the minimum total cost.

VI. PERFORMANCE EVALUATION

In this section, we conduct extensive simulations to evaluate the performance of the proposed algorithm. Simulation setup is first introduced and then the results under different network parameters are presented.

A. SIMULATION SETTINGS

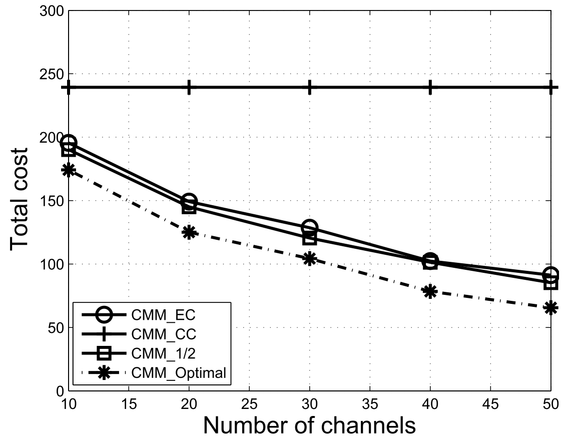
In our simulation setting, the total power demand of each community is distributed within range [1, 5] according to random uniform distribution. The power price p^e is set to \$1. The capacity of each channel is specified as a uniform distribution in the range [1,5]. Since there is no existing algorithms for the CMM problem that is first investigated in our paper, we propose three heuristic algorithms in the following to compare against our proposal that is denoted as CMM_optimal.

- CMM_EC: all meter data are transfered to PMS regardless of how many channels are used.
- CMM_CC: it does not forward any data such that the communication cost is zero.
- CMM_1/2: it sends half of the meter data to the PMS.

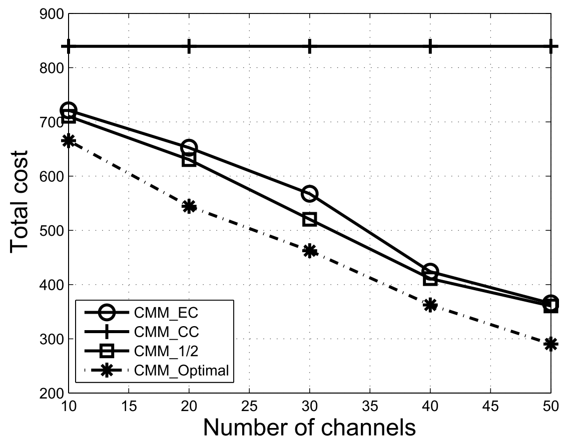
Our proposed optimal algorithm is referred to CMM_optimal. Note the all results in the following are obtained by averaging 50 random network instances.

B. SIMULATION RESULTS

We first investigate the effect of number of channels on the total cost. The values of α and λ are set to 2 and 50, respectively. The channel price is a Gaussian distribution with mean 3 and variance 0.5. When the number of DAU is 30, as shown in Fig. 5, the total cost of CMM_optimal, CMM_1/2 and CMM_EC decreases as the number of channels grows from 10 to 50 under both linear and nonlinear power pricing models. For example, the total cost of CMM_optimal is 184.3 in 10-channel networks under linear power pricing models, and when channel number increases to 50, this number decreases to 75.5, by about 60%. Similar observation are made for the nonlinear power pricing model. That is because more channels provide more chances for DAUs to select cheap channels with higher capacity. The performance of CMM_CC shows horizontal lines under both models since it does not affected by the number of channels in the network.



(a)



(b)

FIGURE 5. The total cost versus different number of channels. (a) Linear power pricing model. (b) Nonlinear power pricing model.

We then evaluate the total cost under different number of DAUs by fixing the number of channels to 30. As shown in Fig. 6(a), the total cost of all schemes grows as the number of DAUs increases since more DAUs bring more power demands. For example, the total cost of CMM_CC is 59.1 when there are 10 DAUs. The corresponding performance of CMM_EC and CMM_optimal is only its 65% and 59%, respectively. When the number of DAUs grows

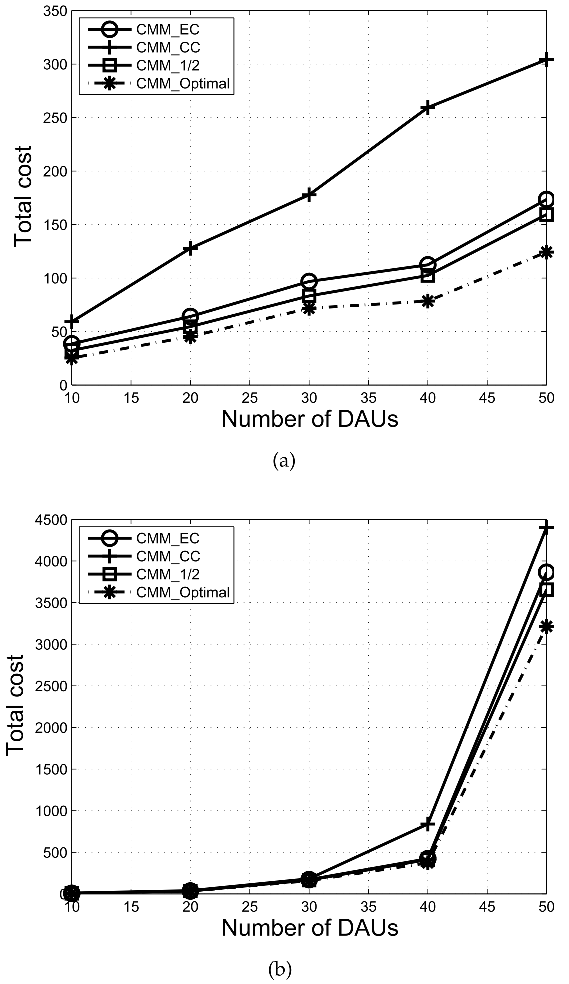


FIGURE 6. The total cost versus different number of DAUs. (a) Linear power pricing model. (b) Nonlinear power pricing model.

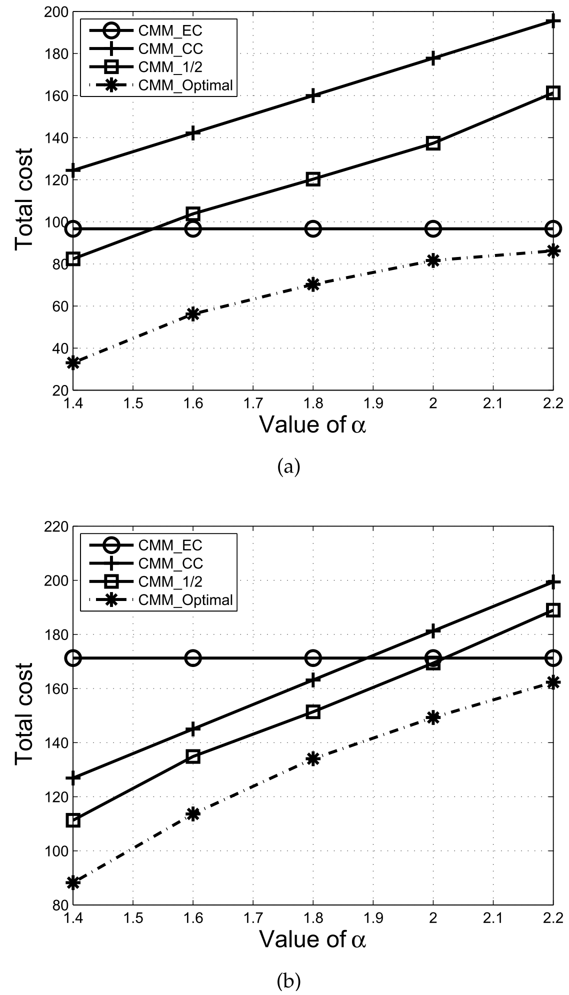


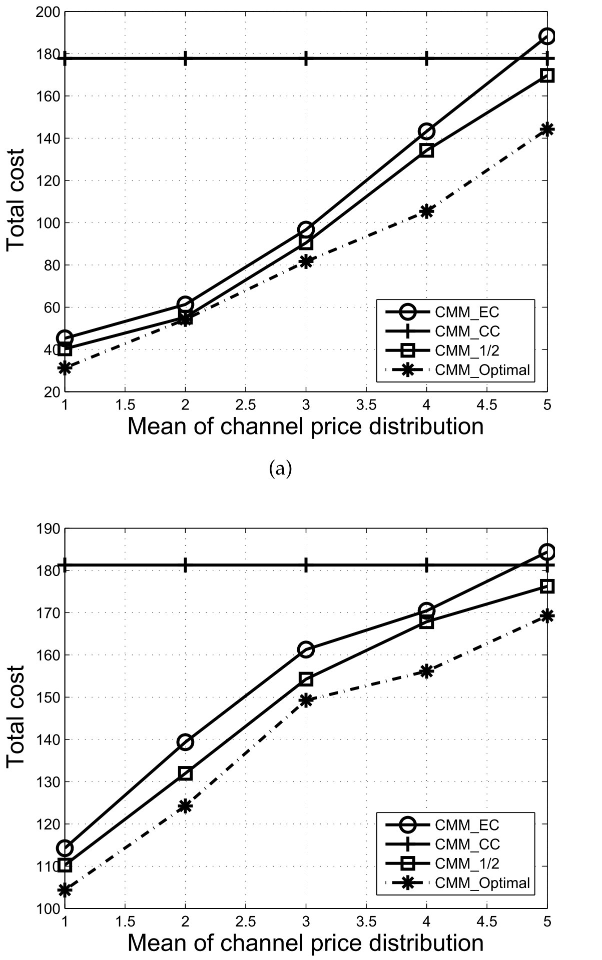
FIGURE 7. The total cost versus different value of α. (a) Linear power pricing model. (b) Nonlinear power pricing model.

to 50, the performance of CMM_EC, CMM_optimal, and CMM_CC is 4.5, 3.8, and 5.1 times of that under 10-DAU networks, respectively. We have similar observations under nonlinear power pricing model and the cost growth is sharper because of the exponential power price function.

The influence of α to the total cost is investigated by changing its value from 1.4 to 2.2. The results under 30 DAUs and 30 channels are shown in Fig. 7. In both Fig. 7(a) and 7(b), the performance of CMM_EC shows as horizontal lines because it forwards all meter data to PMS such that its power price is determined only by p^e. The total cost of CMM_CC increases linearly to α under both models since all power is charged with αp^e per unit. We notice that while the total cost of CMM_optimal shows as an increasing function of α as well, the growth rate decreases under larger α. That is because our algorithm will forward more data to PMS under larger α such that the power cost will be reduced. For example, the total cost of CMM_optimal is 33.1 and 88.2 under $\alpha = 1.4$, and exhibit a growth of 266% and 184% when α increases to 2.2, as shown in Fig. 7(a) and 7(b), respectively.

Finally, we study the effect of channel price on the total cost by changing its mean value from 1 to 5. As shown in Fig. 8, the total cost of CMM_EC, CMM_1/2 and CMM_optimal increases as the mean value grows under both linear and nonlinear power pricing models. For example, in Fig. 8, their total cost is 45.3 and 31.2, respectively, when mean value is 1. When we set the mean value to 5, their total cost increases to 188.2 and 144.3, respectively. Moreover, the performance gap between CMM_EC and CMM_optimal becomes larger as the growth of mean value. Since CMM_CC does not forward any meter data, it has no communication cost such that its performance shows as a horizontal line under different channel prices.

To evaluate the performance of the SPCA method, we show the distribution of iterations in Fig. 9. When the error bound ξ is set to 0.1, the number of iterations is no greater than 12 over 90% executions. As we reduce the value of ξ to 0.01, this percentage decreases to 55%, but there are about 90% executions can achieve this bound within 16 iterations.



(a)

(b)

FIGURE 8. The total cost versus different mean of channel price distribution. (a) Linear power pricing model. (b) Nonlinear power pricing model.

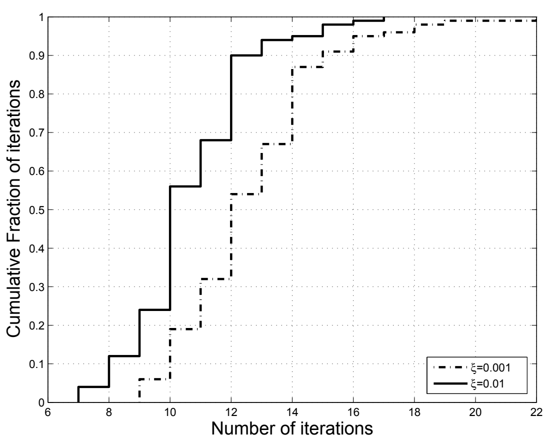


FIGURE 9. The distribution of iterations of SPCA method.

VII. CONCLUSION

In this paper, we investigate the efficient meter data collection problem in smart grid by exploring the secondary spectrum market in cellular networks. With the objective of reducing the total cost, we propose a problem called CMM (Cost Minimization for Meter data collection) that is to find the optimal scheme for channel selection and transmission scheduling scheme. This problem is formulated based on a three-layer network model and a two-stage pricing model, and is proved to be NP-hard. Under linear power pricing model, it is formulated as a mixed integer linear programming problem and solved by a branch-and-bound algorithm. Under nonlinear power pricing model, we formulate it as a nonlinear mixed integer programming (MINLP) problem and propose an optimal algorithm by integrating SPCA method in our branch-and-bound framework. Finally, simulation results show that the proposed algorithm can significantly reduce the overall cost.

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