Aggregation Points Planning for Smart Grid Communications: Wired and Wireless Cases

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***Abstract*—Aggregation Point (AP) plays a vital role in smart grid, which forwards data stream between the client terminals and the control center in smart grid communication system. In this paper, we investigate two representative AP planning models: wired and wireless, and develop efficient algorithms to address the formulated AP planning problems in a cost-efficient way. For the wired case, a 5-approximation algorithm is proposed to minimize the total capital expenditure with the consideration of the installation cost of each AP in the neighborhood area networks (NANs) and the connecting cost between the AP and the home area network (HANs) served by it. For the wireless media-based networking scenario, an $O(\log W)$-approximation algorithm is presented to minimize the total deployment cost of the opening APs under their coverage constraints, where W is the maximum capacity among these APs. Numerical results show that our proposed approximation algorithms have great advantages compared to other heuristic methods.**

I. Introduction

Smart grid employs an intelligent network infrastructure to improve the efficiency, reliability and safety of a power grid with smooth integration of renewable and alternative energy sources, and is taken as an important form of the Internet of Things(IoTs) [1, 2]. A smart grid not only delivers electricity from suppliers to consumers, but also uses a two-way flow of data communications to exchange information between users and suppliers to provide various services, such as demand response, load management and real-time pricing broadcasting [3]. As a result, smart grid communication plays an important role for the implementation of a smart grid, which involves power system, telecommunications, smart devices, information technology, and automatic control.

As an evolution of modern power grid, the smart grid is an interconnected network which generally employs a three-layer infrastructure as shown in Fig.1: home area network (HAN), neighborhood area network (NAN) and wide area network (WAN) [4]. HANs always distribute randomly in the service area, while WANs usually locate in the network operation centers of the electricity companies. As for NANs, each of them serves multiple HANs by deploying an aggregation point (AP) to receive information from those HANs. The demand response information from a variety of smart meters is collected by the HAN and sent to the control center of the WAN via the AP. The other way of data flow is to send the control information from the control center to the smart meters for the purpose of load management and price broadcasting, where the AP also works as a relay for the information exchanging between the HAN and the WAN. The APs are the core infrastructure for data transmission and should be planned carefully to meet the requirements of scalability and reliability of the smart grid.

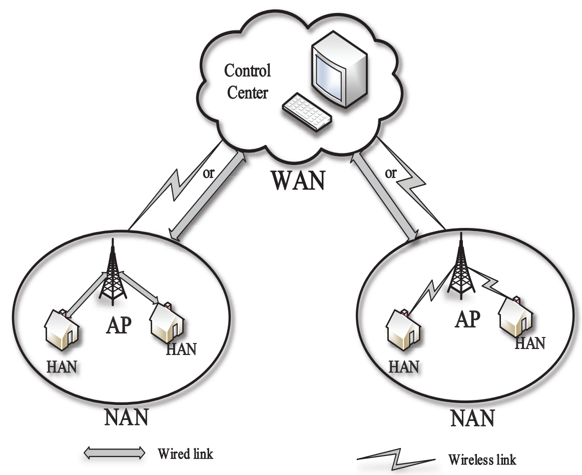

Fig. 1. The architecture of smart grid communication.

Different access technologies can be adopted for the communication between the APs and the HANs. Wired technologies mainly include fiber optic communications and power line communications (PLCs). The former can provide high speed data transmission, as well as good security guarantee [5]. The latter is a promising technology since there usually exists a mature infrastructure in a power grid for smart grid communications [6]. Compared to the wired technologies, wireless communications have the following benefits: low installation cost, rapid deployment and seamless coverage [7]. Since the installation of the APs is always costly, as well as the link cost between an AP and the HANs served by it, the APs should be planned in a cost-efficient way to reduce the capital expenditure of the smart grid [8].

In this paper, we investigate how to plan the APs to minimize the total deployment cost of the smart grid. For the wired case, our network model leads to a facility localization problem [9]. The wireless case falls into a class of set cover problem [10, 11]. We propose efficient approximation

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algorithms to address the formulated optimization tasks. The rest of this paper is organized as follows. In Section II, we give the network models with different communication technologies and formulate the optimization tasks. In Section III, we introduce two approximation algorithms to address the optimization problems. Numerical results and discussions are given in Section IV. In Section V, we conclude this paper and point out future researches.

II. System Models and Problems Formulation

A. Wired Case

Consider an area served by a smart grid communication system. Optical fiber cable is used to connect the APs to the HANs. Denote $\mathcal{N} = \{1, 2, \ldots, N\}$ as a set of candidate sites where APs can be installed and $\mathcal{M} = \{1, 2, \ldots, M\}$ is the set of HANs. Each AP $n \in \mathcal{N}$ requires an installation cost of c_n and equips with a capacity of w_n. Each HAN $m \in \mathcal{M}$ requests a traffic demand d_m. When an AP is selected for opening, optical fibers should be installed between the AP and the HANs covered by this AP. The cost of connecting the HAN m with the AP n is u_{nm}, which is related to their distance c_{nm}, that is, $u_{nm} = \phi(c_{nm})$. In this paper, we assume that the connection cost u_{nm} is linear to the distance c_{nm} between the AP n and the HAN m.

Define x_n as an index variable which indicates that the AP n is selected or not,

$$x_n = \begin{cases} 1 & \text{if AP } n \text{ is selected,} \\ 0 & \text{otherwise.} \end{cases}$$

Let z_{nm} be an index variable to show the HAN m is assigned to the AP n or not,

$$z_{nm} = \begin{cases} 1 & \text{if HAN } m \text{ is assigned to AP } n, \\ 0 & \text{otherwise.} \end{cases}$$

Our planning objective is to select a subset from the candidate sites to install the APs to serve all HANs in smart grid with the minimum cost that consists of the expenditures of the APs and the fiber optic cable cost between the HANs and the APs. Mathematically, the optimization problem can be written as follows:

$$\begin{aligned} \min_{x_n, z_{nm}} \; & \sum_{n\in\mathcal{N}} c_n x_n + \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} u_{nm} z_{nm} \\ s.t. \quad & C_1 : \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} d_m z_{nm} \geq \sum_{m\in\mathcal{M}} d_m, \\ & C_2 : \sum_{m\in\mathcal{M}} d_m z_{nm} \leq w_n x_n, \forall n \in \mathcal{N}, \\ & C_3 : x_n \geq z_{nm}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \\ & C_4 : \sum_{n\in\mathcal{N}} z_{nm} = 1, \forall m \in \mathcal{M}, \\ & C_5 : x_n \in \{0,1\}, \forall n \in \mathcal{N}, \\ & C_6 : z_{nm} \in \{0,1\}, \forall n \in \mathcal{N}, m \in \mathcal{M}. \end{aligned} \tag{1}$$

C_1 ensures that the total traffic demand of the HANs should be satisfied. C_2 means that the sum traffic demand provided by an AP cannot exceed its capacity. C_3 means that a HAN can be covered by an AP that has been selected to open. C_4 ensures a HAN can be covered by only one AP. It is easy to verify that Eq.(1) defines an integer programming problem. More specifically, it is equivalent to a facility location problem.

As an alternative of wired connection scenario, PLC can be used to provide links between APs and HANs. The difference between the PLC and the fiber optic cable is that there is no deployment cost between an AP and the HANs served by it. Thus the APs planning problem for the PLC case is as follows:

$$\begin{aligned} \min_{x_n, z_{nm}} \; & \sum_{n\in\mathcal{N}} c_n x_n \\ s.t. \quad & C_1 : \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} d_m z_{nm} \geq \sum_{m\in\mathcal{M}} d_m, \\ & C_2 : \sum_{m\in\mathcal{M}} z_{nm} \leq w_n x_n, \forall n \in \mathcal{N}, \\ & C_3 : x_n \geq z_{nm}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \\ & C_4 : \sum_{n\in\mathcal{N}} z_{nm} \geq 1, \forall m \in \mathcal{M}, \\ & C_5 : x_n \in \{0,1\}, \forall n \in \mathcal{N}, \\ & C_6 : z_{nm} \in \{0,1\}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}. \end{aligned} \tag{2}$$

Intuitively, (2) can be seen as a special case of (1), where $u_{nm} = 0$.

B. Wireless Case

For a smart grid that adopts wireless transmission to exchange data between APs and HANs, there are remarkable differences compared to the wired case: First, a wireless AP has a limited coverage because of channel fading existing in wireless environment. That is to say, only the HANs that fall into the coverage of an AP can be served by the AP; Second, once a HAN is within the coverage of an AP, there is no connection cost between the HAN and the AP, so it is reasonable to serve a HAN by multiple APs that can cover it. Denote the set of the HANs in the coverage of the AP n as S_n, and y_{nm} is the fraction of the traffic demand required by the HAN m that is supplied by the AP n, the planning problem of the wireless scenario can be formulated as follows,

$$\begin{aligned} \min_{x_n, y_{nm}} \; & \sum_{n\in\mathcal{N}} c_n x_n \\ s.t. \quad & C_1 : \sum_{n\in\mathcal{N}} d_m y_{nm} \geq d_m, \forall m \in \mathcal{M}, \\ & C_2 : \sum_{m\in\mathcal{M}} d_m y_{nm} \leq w_n x_n, \forall n \in \mathcal{N}, \\ & C_3 : 0 \leq y_{nm} \leq 1, \forall n \in \mathcal{N}, m \in S_n, \\ & C_4 : y_{nm} = 0, \forall n \in \mathcal{N}, m \notin S_n, \\ & C_5 : x_n \in \{0,1\}, \forall n \in \mathcal{N}. \end{aligned} \tag{3}$$

C_1 ensures that the traffic demand of each HAN should be satisfied. Notice that this constraint is equivalent to that of the C_1 in (1). C_2 is the capacity constraint of APs. C_3 and C_4 are the coverage constraints. (3) is also a linear integer programming problem. However, it falls into the class of set cover problems, which is different from the facility location problem that can characterize the wired case shown in (1).

III. Proposed Algorithms

A. 5-Approximation Algorithm for Wired Case

First, we relax the primal conditions and achieve the dual program of the primal problem at first. The relaxation form of (1) can be written as follows:

$$\begin{aligned}
&\min_{x_n, z_{nm}} \sum_{n\in\mathcal{N}} c_n x_n + \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} u_{nm} z_{nm} \\
s.t.\quad & C_1 : \sum_{n\in\mathcal{N}} w_n z_{nm} \geq d_m, \forall m \in \mathcal{M}, \\
& C_2 : \sum_{m\in\mathcal{M}} z_{nm} \leq w_n x_n, \forall n \in \mathcal{N}, \\
& C_3 : x_n \geq z_{nm}, \forall n \in \mathcal{N}, m \in \mathcal{M}, \\
& C_4 : \sum_{n\in\mathcal{N}} z_{nm} \geq 1, \forall m \in \mathcal{M}, \\
& C_5 : x_n \leq 1, \forall n \in \mathcal{N}, \\
& C_6 : z_{nm} \leq 1, \forall n \in \mathcal{N}, m \in \mathcal{M}.
\end{aligned} \tag{4}$$

(4) is the linear programming relaxation of (1), where the last set of integrality constraints C_5 and C_6 are relaxed to allow the variables x_n and z_{nm} to take rational values between 0 and 1. The dual form of (4) is as follows:

$$\begin{aligned}
&\max_{\alpha_m, \beta_{nm}, \gamma_n, \delta_n} \sum_{m\in\mathcal{M}} \alpha_m \\
s.t.\quad & C_1 : \alpha_m \leq u_{nm} + \beta_{nm} + d_m \gamma_n, \forall n \in \mathcal{N}, m \in \mathcal{M}, \\
& C_2 : \sum_{m\in\mathcal{M}} \beta_{nm} \leq c_n + \delta_n - w_n \gamma_n, \forall n \in \mathcal{N}, \\
& C_3 : \alpha_m, \beta_{nm}, \gamma_n, \delta_n \geq 0, \forall n \in \mathcal{N}, m \in \mathcal{M}.
\end{aligned} \tag{5}$$

$\alpha_m, \beta_{nm}, \gamma_n, \delta_n$ are dual variables. Intuitively, we can think of α_m as the total cost of HAN m including the connecting cost and part of deployment cost of AP which is connecting HAN m.

A special case of the proposed formulation, where there is only one HAN, plays an important role for designing our proposed approximation algorithm for (1). Assume that only the HAN $k \in \mathcal{M}$ exists, the special problem can be described as follows:

$$\begin{aligned}
&\min_{v_n, g_n} \sum_n c_n v_n + \sum_n c_n^{'} g_n \\
s.t.\quad & C_1 : \sum_{n\in L_k} g_n \geq D_k, \\
& C_2 : g_n \leq w_n v_n, \forall n \in L_k, \\
& C_3 : v_n \leq 1, \forall n \in L_k, \\
& C_4 : v_n, g_n \geq 0, \forall n \in L_k,
\end{aligned} \tag{6}$$

where L_k is the set of APs that fractionally serve the HAN k. D_k is the total traffic demand served by these APs, and $c_n^{'}$ is the cost of connecting the HAN k with the AP n. v_n indicates if the AP n is open or not, and g_n is the traffic demand assigned to the AP n. We can set $\widehat{v}_n = \frac{g_n}{w_n}$ and obtain a feasible solution of no greater cost. A greedy algorithm for the special single HAN problem is shown in Table I, by which an optimal solution to (6) can be obtained.

TABLE I
Greedy algorithm for single HAN problem

Algorithm: Greedy Algorithm

Initialize $g_n = v_n = 0$;
for n in increasing order of $(\frac{c_n}{w_n} + c_n^{'})$;
  while $D_k \neq 0$
    $g_n = \min(w_n, D_k)$;
    $v_n = \frac{g_n}{w_n}$;
    $D_k = D_k - g_n$;
  end while
end for
return (g, v)

TABLE II
The proposed algorithm for APs planning problem

Step 1: Clustering

Clustering:
while $S \neq \varnothing$ **do**
  for m in increasing order of α_m
    $B_m = \{n \in F_m : n \notin \bigcup_{k\in C} N_k, c_{nm} \leq \min_{k\in C} c_{nk}\}$;
    $S = S \setminus m$;
    while $B_m \neq \varnothing$
      $k = m$;
      $N_k = B_m$;
      $C = C \cup \{k\}$;
    end while
  end for
end while
$U = F - \bigcup_{k\in C} N_k$;
for $n \in U$ **do**
  if $k = \arg\min_{k\in C} c_{nk}$
    $N_k = N_k \cup \{n\}$;
  end if
end for

Denote $F = \{n : x_n > 0\}$ as the set of APs and $F_m = \{n : n \in F, z_{nm} > 0\}$ as the set of APs in F that fractionally serve the HAN m, respectively. Our proposed approximation algorithm is divided into two step: clustering and rounding.

Step 1, Clustering. We partition the APs with $x_n > 0$ into clusters, each of which will be centered around a HAN. We call this as a cluster center. Denote the cluster centered around the HAN k as N_k. The cluster N_k consists of the HAN k, the set of APs assigned to it, and the fractional demands served by these APs.

Let C be the set of current cluster centers which is initially empty and S be the set of all HANs that could be chosen as cluster centers which is initially $\mathcal{M}$. For each HAN $m \notin C$, B_m represents the set of unclustered APs that are closer to it than to any other clustered center. To find all cluster centers, $m \in \mathcal{M}$ is ordered in increasing of α_m and the cluster N_k can be formed by B_m. The procedure of clustering is described in Table II.

Step 2, Rounding. In this step, we will decide which AP will be fully opened in each cluster. For each cluster obtained

TABLE III
THE PROPOSED ALGORITHM FOR APS PLANNING PROBLEM

Step 2: Rounding
Rounding:
for each N_k
$L_k = \{n \in N_k : x_n < 1\}$;
$D_k = \sum_{n \in L_k} \sum_m z_{nm}$;
find $(g_n^{(k)}, v_n^{(k)})$ by greedy algorithm in Table III and calculate the value O_k^*;
end for
for each N_k
while $0 < v_n^k < 1$
$x_n = 1$;
end while
end for

in the first step, it can be seen as the single HAN problem. Therefore, the cluster N_k can obtained by the greedy algorithm in Table II. Then we have $L_k = \{n \in N_k : x_n < 1\}$ and $D_k = \sum_{n \in L_k} \sum_m d_m z_{nm}$, where the tuple of $(g_n^{(k)}, v_n^{(k)})$ is an optimal solution produced by the greedy algorithm. While $0 < v_n^{(k)} < 1$, all APs are fully opened in L_k, i.e., $x_n = 1$ for $n \in L_k$. Piecing together the solutions for all clusters, x_n's are assigned by $\{0, 1\}$. Once all APs have been located, each HAN is assigned to the closest AP around it. The procedure of rounding is described in Table III. Basically, our proposed method is an approximation algorithm. We do not give the proof in detail of the approximation ratio because of room limitation. Interested readers can find the similar proof in [9].

B. $O(\log W)$-Approximation Algorithm for wireless case

The wireless case falls into a class of set cover problem which is also NP-hard. In this paper, we develop an $O(\log W)$-approximation algorithm to solve this case. (7) is the linear programming relaxation of (3), in which the last set of integrality constraints C_5 is relaxed to allow the variables x_n to take rational values between 0 and 1.

$$\begin{aligned} &\min \sum_{n \in \mathcal{N}} c_n x_n \\ s.t. \quad &C_1 : \sum_{n \in \mathcal{N}} y_{nm} \geq d_m, \forall m \in \mathcal{M} \\ &C_2 : \sum_{m \in \mathcal{M}} y_{nm} \leq w_n x_n, \forall n \in \mathcal{N} \\ &C_3 : 0 \leq y_{nm} \leq 1, \forall n \in \mathcal{N}, \forall m \in S_n \\ &C_4 : y_{nm} = 0, \forall n \in \mathcal{N}, \forall m \notin S_n \\ &C_5 : 0 \leq x_n \leq 1, \forall n \in \mathcal{N}. \end{aligned} \tag{7}$$

Let $f(N)$ be the maximum traffic demand supplied by a given set of APs $N \subset \mathcal{N}$. Denote $S_n \subseteq \mathcal{M}$ as a set of HANs which can be served by AP n. We can calculate the $f(N)$ by solving the following linear program problem:

TABLE IV
THE PROPOSED ALGORITHM OF WIRELESS CASE

Algorithm: The $O(\log W)$-Approximation Algorithm
Set $N_l \leftarrow \emptyset$, $l = 0$;
while $f(N_l) < \sum_{m \in \mathcal{M}} d_m$ **do**
$l = l + 1$,
for all $n \in \mathcal{N} \setminus N'_{l-1}$ **do**
find n that maximizes $\frac{F_{N_l}(n)}{c(n)}$;
$N_l \leftarrow N_l \cup \{n\}$;
end for
end while
return N_l.

$$\begin{aligned} &\max_{y_{nm}} \sum_{m \in \mathcal{M}} \sum_{n \in N} y_{nm} \\ s.t. \quad &C_1 : \sum_{n \in N} y_{nm} \leq d_m, \forall m \in \mathcal{M}, \\ &C_2 : \sum_{m \in \mathcal{M}} y_{nm} \leq w_n, \forall n \in N, \\ &C_3 : 0 \leq y_{nm} \leq 1, \forall n \in N, \forall m \in S_n, \\ &C_4 : y_{nm} = 0, \forall n \in N, \forall m \notin S_n. \end{aligned} \tag{8}$$

Denote $c(N)$ as the total cost for such a deployment. For $n \in \mathcal{N}$, define

$$F_N(n) = f(N \cup \{n\}) - f(N) \tag{9}$$

the proposed approximation algorithm (Algorithm 2) is described in Table V.

Lemma 4.1. *The minimize cost Algorithm achieves an approximation of $O(\log W)$, where $W = \max_{n \in \mathcal{N}} w_n$.*

Proof: Let OPT_2 be a set of APs that comprise an optimal solution. $N_l^{'}$ is the solution at the end of iteration l of algorithm 2. For each iteration l and $n \in OPT_2 \setminus N_l^{'}$, we define a value $a_l(n)$, so that it is possible to cover all the HANs using the APs in $OPT_2 \cup N_l^{'}$ with the capacities $a_l(n)$ for $n \in OPT_2 \setminus N_l^{'}$ and w_n for $n \in N_l^{'}$.

There exists a solution **(x, y)** of Eq.(3) such that the APs in $N_l^{'}$ satisfy a total demand of $f(N_l^{'})$ and each AP $n \in OPT_2 \setminus N_l^{'}$ satisfies at most $a_{l-1}(n)$ demand units. For each $n \in OPT_2 \setminus N_l^{'}$, $a_l(n) = \sum_{m \in \mathcal{M}} w_n y_{nm}$. We charge each $n \in OPT_2 \setminus N_l^{'}$ with $\frac{c_{n_l}}{F_{N'_{l-1}}(n_l)} \cdot (a_{l-1}(n) - a_l(n))$.

Consider a AP $n \in OPT_2$. If $n \in N^{'}$, let L denote the iteration in which it was added to the solution. For $l < L$, it follows from the definition of $a_{l-1}(n)$ that $F_{N'_{l-1}}(n) \geq a_{l-1}(n)$. By the greediness of algorithm in Table IV it holds that:

$$\frac{c(n_l)}{F_{N'_{l-1}}(n_l)} \leq \frac{c(n)}{F_{N'_{l-1}}(n)} \leq \frac{c(n)}{a_{l-1}(n)}, \tag{10}$$

and the total cost charged upon n is

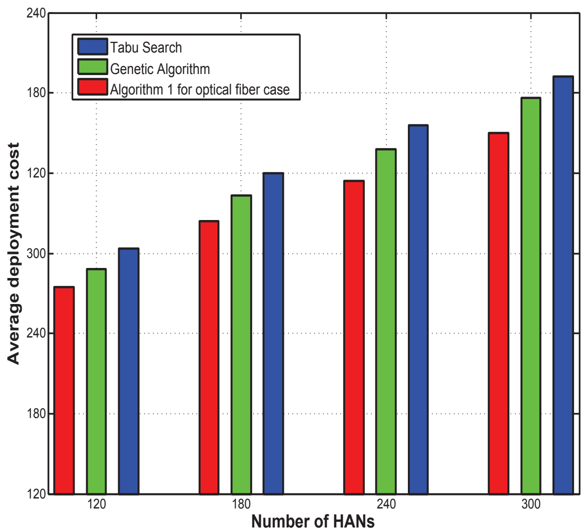

Fig. 2. Average deployment cost for the fiber optic case as the number of HANs M changes. $N = 60$, $c_n = 9.3, \forall n \in \mathcal{N}$, $u_{nm} = 0.001 c_{nm}, \forall n \in \mathcal{N}, m \in \mathcal{M}$.

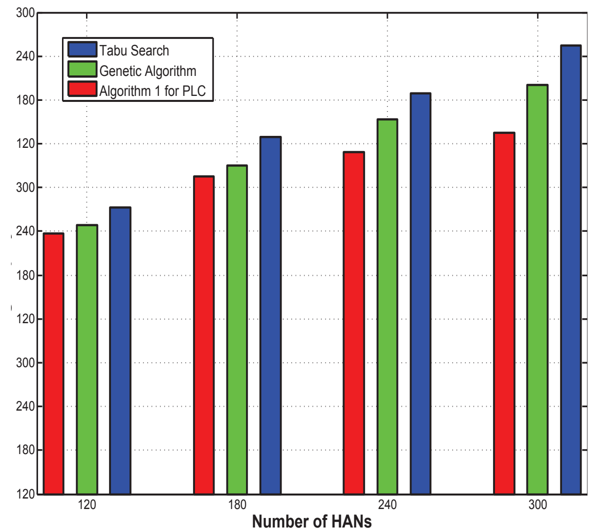

Fig. 3. Average deployment cost for the PLC case as the number of HANs M changes. $N = 60$, $c_n = 9.3, \forall n \in \mathcal{N}$, $u_{nm} = 0, \forall n \in \mathcal{N}, m \in \mathcal{M}$.

$$
\begin{aligned}
&\sum_{l=1}^{L} \frac{c(n_l)}{F_{N'_{l-1}}(n_l)} \cdot (a_{l-1}(n) - a_l(n)) \\
&\le c(n) \sum_{l=1}^{L} \frac{(a_{l-1}(n) - a_l(n))}{a_{l-1}(n)} \\
&= c(n) \cdot H(a_0(n)) \\
&= c(n) \cdot O(\log a_0(n)) \\
&= c(n) \cdot O(\log w_n),
\end{aligned}
\tag{11}
$$

where $a_0(n) = \sum_{m \in \mathcal{M}} w_n y_{nm}$ and $H(r)$ is the rth harmonic number. ∎

IV. Numerical Results and Discussions

We compare the performance of our proposed approximation algorithms with other classic heuristic methods that can be employed to address NP-hard problems with reasonable complexity: genetic algorithm [12, 13] and tabu search [10, 14]. We will find that our proposals outperform other algorithms in all discussed instances.

Consider a $3km \times 3km$ area served by a smart grid communication system, where all HANs and candidate sites for installing the APs locate randomly in it. The number of candidate sites to install APs is 60. For the candidate site n, its capacity w_n is distribute uniformly within $(600, 900)$. For the HAN m, its traffic demand d_m is distribute uniformly within $(20, 30)$. Without loss of generality, we assume the installation costs of all APs are equal for both the wired and the wireless cases.

Fig.2 and Fig.3 show the average costs of deploying APs by using fiber optic cable and PLC, respectively, as the number of HANs changes. The cost of the AP n is set to $c_n = 9.3$ and the connection cost of the AP n and the HAN m is $u_{nm} = 0.001 c_{nm}$, where c_{nm} is the distance between the HAN and the AP. As can be seen from the figures, our proposed 5-approximation algorithm (Algorithm 1) outperforms the genetic algorithm and the tabu search notably. For the fiber optic scenario, the total cost of our proposal is about 20% lower than that of the tabu search, which is also the case for the PLC scenario as shown in Fig.3.

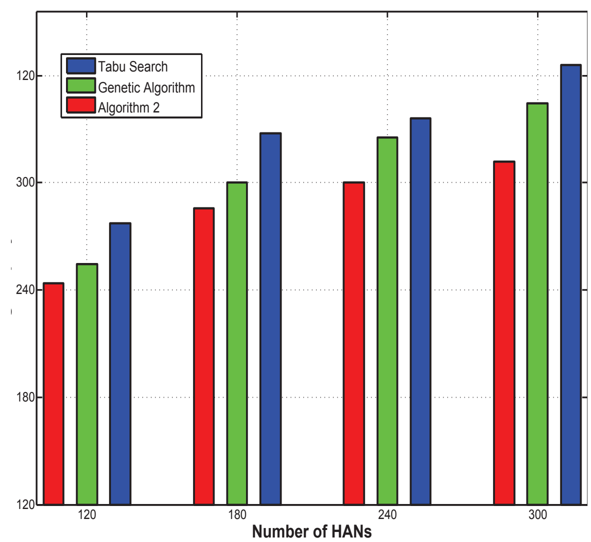

Fig. 4. Average deployment cost for wireless case M changes. $N = 60$, $c_n = 9.3, \forall n \in \mathcal{N}$.

Fig.4 shows the performance differences between our proposed $O(logW)$-approximation algorithm for the wireless scenario and other two methods: genetic algorithm and tabu search. The coverage radio of wireless APs are $250m$. Again, we can see that our proposal algorithm (Algorithm 2) has at least 15% performance gain compared to other two methods. Especially, when the number of HANs increases, the perfor-

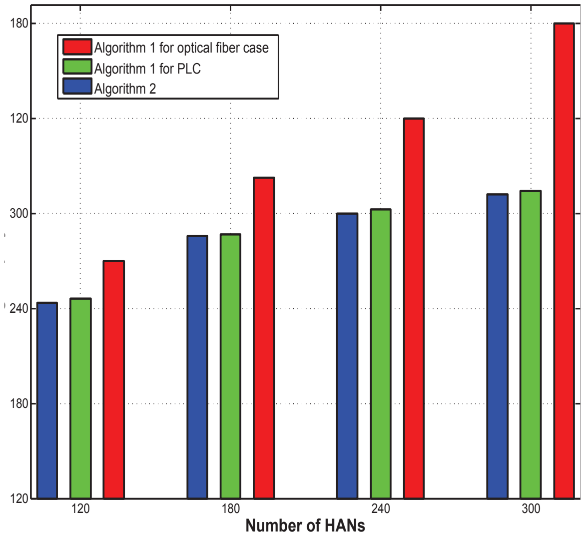

Fig. 5. Comparison of wired cases and wireless case.

mance gap between our proposed algorithm and the others becomes larger.

From Fig.2-4 we can see that the proposed algorithms can produce better solutions to the formulated problems in all discussed scenarios as compared with other heuristic methods. Recall that the approximation algorithms have the worst case performance guarantees. It is difficult even impossible for the other heuristic methods to provide such an guarantee so we can conclude conservatively that our proposal is promising for applications in smart grid with requirements of scalability and reliability.

Finally, we compare the total cost of the wired scenario and the wireless one. The cost of an AP is set to 9.3 for both of the scenarios. The number of candidate sites for installing APs is 60. The coverage radius of a wireless AP is $250m$. From Fig.5 we can see that the cost of employing fiber optic cable is much higher than the other cases: the wireless transmission and wired transmission with PLC. The reason is obvious: there exist additional connection cost between a HAN and the AP that serves it for the fiber optic cable scenario. It can also be observed that the difference between the PLC and the wireless is slight. Both of them require no connection cost between a HAN and the serving AP. Specially, when the number of HANs increases, the deployment cost of the fiber optic cable increases sharply as seen in Fig.5. It is cost-effective to adopt wireless technology or PLC if they are available and the required data rate is not high. However, the fiber optic cable is preferred for the high data rate requirement case. Furthermore, the coverage radius of a wireless AP is also implicitly related to the total deployment cost of APs with wireless technology, which should be considered further for a practical smart grid.

V. CONCLUSION

In this paper, we studied the minimum cost APs planning, which plays an important role for the deployment of a smart grid. We have consider the wired and wireless access technologies separately, resulting different problem formulations. Both of them are NP-hard. We introduce a 5-approximation algorithm for the wired case and an $O(\log W)$-approximation algorithm for the wireless case, respectively. Besides the worst case performance guarantees of the proposed algorithms, we also give comparisons of the proposed algorithms with other representative heuristic methods. Numerical results show the proposed algorithms perform better than the others. Some insights can also be found from the analysis and numerical results. In future work, hybrid networking model should be investigated, e.g., a smart grid may employ wired technology for parts of the service area and wireless technology for the others, depending on the data rate requirement, as well as the installation and connection cost.

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