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***Abstract*—Wireless sensor networks (WSNs) have the potential for realization economical automation systems in a smart grid where the different type of sensors mote can be used to monitor a wide range of the smart grid environment's parameters. Energy restriction of wireless sensor nodes and consequently lifetime of the network is a real challenge in WSNs applications like the smart grid. The WSN lifetime can be formulated as an optimization problem. In this paper, the alternating direction method of multipliers (ADMM) algorithm is used to implement a novel distributed iterative algorithm for the problem of extending the sensor network lifetime. The proposed algorithm has some striking feature that including use of local information, low overhead of message passing, low computational complexity, fast convergence, and reduced energy consumption. The experiment results related to the convergence and number of iterations required to achieve the stopping criterion presented. As well as, the results of proposed algorithm compared with the subgradient methods. In comparison, the proposed ADMM-based algorithm outperforms the other methods.**

Keywords-wireless sensor network; smart grid; energy efficiency; ADMM

I. INTRODUCTION

A Smart Grid is an electricity network that can combine various components connected to it – generators, transmitters, distributors, and consumers– in an intelligent way in order to provide efficient, reliable, economical energy services [1].

In fact, smart grid is a hybrid technology that integrates information technology (IT) and traditional power grid. The application of intelligent and advanced digital technology into the existing electrical power network results in the innovation of smart grid. Smart grid can provide a variety of predictive information that it can be useful for operational management and energy saving schemes.

Wireless sensor networks (WSN) have considerable abilities in order to use in smart grid. So, it is adopted by electric utilities and suppliers for energy management applications, substation automation, and monitoring, and wireless automatic meter reading (WAMR) system etc. [1]. As mentioned, WSNs can use for monitoring and securing the transmission and distribution sector. Also, WSNs have potentials that can help consumers to have clear insight into their consumption.

Home area networks (HANs) can be implemented by wire- less sensor networks. As mentioned, WAMR systems are one of the applications WSN for smart grid. These systems can dynamically specify the amount of electricity that users consumed over a given period. Additionally, WAMR remotely operated and control household appliances, HVAC, light, and other devices of the users.

Furthermore, some operations in electric power system and also automation in the substation can be performed with help of WSNs. In this application, different types of sensors could be installed in order to check situation in the transmission systems and real-time power consumption in the system [2]. Wireless sensor networks have a great potential for remote monitoring various factor in the substations such as circuit currents, power usage, and station apparatus.

Power generation is another sector in a smart grid net- work that can be benefit from WSNs. There are a number of complicated units in a power generation plant such as generation units, actuators, fuel tanks, and so on. Because of this complexity, the conventional monitoring system is not efficient and reliable when raising a problem in the plant. Simultaneously, WSNs by offer several robust and effective wireless solutions can help the utilities to solve this problem. There a couple of parameters that ought to be monitor in a power plan, namely temperature, electrical voltage, electrical current, frequency. Implementation a wired monitoring system in this environment is quite tricky, because you need extra electrical equipment to supply energy to the equipment and transmitting data. By contrast, implementations of wireless systems on some units such as high transmission line are risky, due to the constant noise and conflict in WSNs.

However, WSNs pose challenges like security, integrity and availability to smart grid. In addition, using of wireless sensor networks cause concerns such as attack on the network, routing in WSNs and issues associated with wireless sensor networks limitations, for instance, energy, memory and processing unit. Wireless sensor networks are more vulnerable than wired net- works. Hence, attackers can execute attacks to smart grid net- work to achieve specific information [3]. Energy issue is one of the most important concerns in wireless sensors network because there is a direct relation between the network lifetime and sensors energy. Also, design the energy-aware wireless sensor network is the primary objective of researchers in this field. Overall, sensors mote have a restricted energy source. Therefore, a number of studies have been conducted into this issue. Accordingly, in this paper we proposed distributed iterative algorithm based on alternating direction method of multipliers (ADMM) in order to increase lifetime of sensors and consequently longevity of the applications of WSNs in smart grid.

II. Related Work

That limited energy of sensors node is a big challenge in applications associated with WSNs, especially in challenging environments like smart grid that there are noise, heat, interference, and multipath effects can causes the energy wasting. So, a number of works are published in these years that focused on energy optimization on wireless sensor networks. Brooke et al. in [4] proposed communication network architecture for the electrical network to tackle the aforementioned problem. An energy-aware optimal data aggregation for communication in smart grid such as smart meters, aggregators, and cellular base stations is proposed in [5] .In [6], an energy-aware routing protocol is proposed. In this method, the nodes that have a predefined energy threshold participate in the routing. Packet size optimization is a positive approach to increase the lifetime of the network. Kurt et al. [7] a innovative Mixed Integer Programming (MIP) and a model for link layer have introduced to optimize transmission power in WSNs. In [8] Idrees et al. proposed a protocol that it named distributed lifetime coverage optimization protocol (DiLCO), in order to achieve a trade-off between the coverage of an area and the lifetime of a wireless sensor network. The authors in [9] put forward a novel distributed algorithm for mobile data gathering in WSN by means of anchor data gathering scheme. The alternating direction method of multipliers (ADMM) is a powerful algorithm, especially for distributed convex optimization [14]. Liang et al. [10] was considered resource allocation in wireless network virtualization. They also developed a distributed virtual resource allocation algorithm based on the ADMM. In [11], a distributed version of ADMM- named D- ADMM- provided to tackle separable optimization problems in interconnected nodes or agents as a network.

III. Problem Formulation

In this study, we modelled a WSN as a directed graph $G = (S, D)$, where S and D are sets of vertices which demonstrate the sensor nodes (including sink node with index 0), and edges representing bi-directional wireless links, respectively. Each sensor node i, which is denoted by S_i, $i = 1 : length(S)$, has an initial energy e_i and generates the data traffic at a constant deterministic rate g_i bit per second. Also, let us introduce a cost function $E : D \rightarrow \mathbb{R}^+$ on the set D, where E_{ij} indicates the required amount of power to send a composite bit-stream at rate r_{ij} (bps) from S_i to S_j if and only if $d_{ij} \in D$:

$$C_{ij} = \alpha + \beta d_{ij}^2 \tag{1}$$

$$E_{ij} = C_{ij} r_{ij} \tag{2}$$

where the non-negative constant term α depends on the electronics energy which is measured in joule/bit [6]. We also assume the free space transmission model and use amplifier energy as βd_{ij}^2 measured in joule/bit/m^2. Also, d_{ij} is the Euclidean distance between S_i and S_j. In the following, we initially define the network lifetime T and then we address the problem of maximizing the network lifetime through a distributed optimization approach.

Definition1: The network lifetime T is defined as the time duration since the launch of network operation till the first sensor node drains its entire battery.

By defining the lifetime of each node S_i as $\tau_i = \frac{e_i}{\sum_{j \in \mathcal{N}_i}(\alpha + \beta d_{ij}^2) r_{ij}}$, the maximum of network lifetime will be obtained equal to $T = \min_{\forall i \in S}(\tau_i)$. Therefore, the main problem is how to determine the optimal data flow rates r_{ij} among sensor nodes with respect to the fixed location of the sink and satisfying the following constraints:

$$\sum_{j \in \mathcal{N}_i} (r_{ij} - r_{ji}) = g_i \tag{3}$$

$$T \sum_{j \in \mathcal{N}_i} (\alpha + \beta d_{ij}^2) r_{ij} \leq ei \tag{4}$$

The first constraint states that the sum of total incoming flow rates plus self-generated data rate g_i must be equal to the sum of total outgoing flow rates to other nodes, r_{ij}, including sink. For consistency reasons, we define the $g_0 = -\sum_{i=1:N} g_i$. Through the second constraint, the total required transmission energy cannot exceed its initial energye_i. Therefore, the mathematical optimization model to obtain the optimal data rates is presented as follows:

$$\begin{aligned} & \quad maximize\ T \\ s.t.& \\ & \quad Contraint\ (3)\ and\ (4) \\ & \quad Var: T > 0, r_{ij} > 0 \end{aligned} \tag{5}$$

We note that the definition of network lifetime, and the mathematical model (5) have been used in some of the previous studies [16]. However, our main contribution is to solve the model (5) using the distributed ADMM method.

IV. Proposed Method

Our main motivation of proposing a distributed algorithm based on ADMM [14] is that each sensor node i computes its transmission data rate while all nodes converge to an identical maximum network lifetime in a reasonable time. Further, message complexity or the number of transmitted messages among nodes to converge to the global value is one of the main issues that must be taken into account. To design a distributed ADMM-based algorithm for mathematical model (5), firstly, we convert the nonlinear model (5) into a linear programming model by introducing $q = 1/T$. Thus, we have:

$$\begin{aligned} & \quad minimize\quad q \\ s.t.& \\ & \quad Contraint\ (3)\ and\ (4) \\ & \quad Var: q > 0, r_{ij} > 0 \end{aligned} \tag{6}$$

To simplify the development of our distributed ADMM-based model, we inspire the proposed algorithm in [15], and divide the neighbors of S_i into two sets: predecessors and successors of S_i denoted by $\mathbb{P}(i)$ and $\mathbb{S}(i)$. If $i < j$ and $d_{ij} \in D$, then $S_i \in \mathbb{P}_j$ and $S_j \in \mathbb{S}_i$; and if $i > j$ and $d_{ij} \in D$, then $S_j \in \mathbb{P}_i$ and $S_i \in \mathbb{S}_j$. In addition, casting the inequality constraint (4) to equality requires us to introduce some auxiliary variables for facilitating use of ADMM method.

Let q_i be the global network lifetime obtained in S_i. To convert the inequality constraint (4) to an equality constraint, we need to define positive variable z_i as a difference between the lifetime of S_i and the network lifetime q_i. Thus, the constraint (II) can be written in equality form as follows:

$$\sum_{j\in\mathcal{N}_i}(\alpha+\beta d_{ij}^2)r_{ij} = (q_i - z_i)e_i, \forall i \in S \quad (7)$$

where $\forall i,j,\ q_i - q_j = 0$. Since each node i should determine r_{ij} in distributed manner, we define A_{ij} equal to the difference between r_{ij} and r_{ji}; and substitute the first constraint in (5) with

$$r_{ij} - r_{ji} = A_{ij}, \forall i \in S, j \in \mathcal{N}_i \quad (8)$$

$$\sum_{j\in\mathcal{N}_i} A_{ij} = g_i, \forall i \in S \quad (9)$$

Finally, we consider the following convex model with equality constraints to propose a distributed ADMM-based model:

$$\begin{aligned} &minimize \quad \sum_{i\in S} q_i \quad (10)\\ &s.t.\\ &\text{Constraints (7)-(9)}\\ &q_i - q_j = 0, \forall i,j \in S\\ &Var: r_{ij}, q_i, z_i, and\ A_{ij} \geq 0 \end{aligned}$$

Now, the proposed model (10) has potential to be solved in distributed way. Considering the augmented Lagrangian function of (10) for node i is as follows:

$$\begin{aligned} L_\rho^{(i)}(r,q,z,A,\lambda,\mu,\gamma,\varphi) &= q_i\\ &+\lambda_{ij}(r_{ij} - r_{ji} - A_{ij}) + \tfrac{\rho}{2}\left\|r_{ij} - r_{ji} - A_{ij}\right\|_2^2\\ &+\mu_i\left(\sum_{j\in\mathcal{N}_i} A_{ij} - g_i\right) + \tfrac{\rho}{2}\left\|\sum_{j\in\mathcal{N}_i} A_{ij} - g_i\right\|_2^2\\ &+\gamma_i\left(\sum_{j\in\mathcal{N}_i}(\alpha+\beta d_{ij}^2)r_{ij} - (q_i - z_i)e_i\right) + \tfrac{\rho}{2}\left\|\sum_{j\in\mathcal{N}_i}(\alpha + \beta d_{ij}^2)r_{ij} - (q_i - z_i)e_i\right\|_2^2\\ &+\varphi_{ij}(q_i - q_j) + \tfrac{\rho}{2}\left\|q_i - q_j\right\|_2^2 \quad (11) \end{aligned}$$

each node i must compute r_{ij}^k, q_i^k, z_i^k, and A_{ij}^k at iteration k in a sequential order as follows:

$$r_{ij}^{(k)} = argmin\Big(\tfrac{\rho}{2}\left\|r_{ij} - if\left(i<j, r_{ji}^{(k-1)}, r_{ji}^{(k)}\right) - A_{ij}^{(k-1)} + \tfrac{1}{\beta}\lambda_{ij}^{(k-1)}\right\|^2 + \tfrac{\rho}{2}\left\|if\left(i<j, r_{ji}^{(k-1)}, r_{ji}^{(k)}\right) - r_{ij} - if\left(i<j, A_{ji}^{(k-1)}, A_{ji}^{(k)}\right) + \tfrac{1}{\beta}\lambda_{ji}^{(k-1)}\right\|^2 + \tfrac{\rho}{2}\left\|e_{ij}r_{ij} + \sum_{l\in\mathcal{N}_i, l\neq j} e_{il}\overline{r}_{il} - (q_i^{(k-1)} - z_i^{(k-1)})B + \tfrac{1}{\beta}\gamma_i^{(k-1)}\right\|^2\Big) \quad (12)$$

Where $if(a<b,c,d)$ is interpreted as if $(a<b)$ then c else d.

$$q_i^{(k)} = argmin\left(q_i + \tfrac{\beta}{2}\left\|\sum_{j\in\mathcal{N}_i} e_{ij}r_{ij}^{(k)} - \left(q_i - z_i^{(k-1)}\right)B + \tfrac{1}{\beta}\gamma_i^{(k-1)}\right\|^2 + \tfrac{\beta}{2}\sum_{j\in\mathcal{N}_i}\left\|q_i - if\left(i<j, q_j^{(k-1)}, q_j^{(k)}\right) + \tfrac{1}{\beta}\varphi_{ij}^{(k-1)}\right\|^2\right) \quad (13)$$

$$z_i^{(k)} = argmin\Big(z_i + \frac{\beta}{2}\left\|\sum_{j\in\mathcal{N}_i} e_{ij}r_{ij}^{(k)} - \left(q_i^{(k)} - z_i\right)B + \frac{1}{\beta}\gamma_i^{(k-1)}\right\|^2\Big) \quad (14)$$

$$A_{ij}^{(k)} = argmin\Big(\frac{\beta}{2}\left\|r_{ij}^{(k)} - \left(i<j: r_{ji}^{(k)}; r_{ji}^{(k)}\right) - A_{ij} + \frac{1}{\beta}\lambda_{ij}^{(k-1)}\right\|^2 + \frac{\beta}{2}\left\|A_{ij} + \sum_{l\in\mathcal{N}_i, l\neq j} A_{il}^{(last\ k)} - S_i + \frac{1}{\beta}\mu_i^{(k-1)}\right\|^2\Big) \quad (15)$$

Moreover, the associated variables: λ_{ij}^k, μ_i^k, γ_i^k, and φ_{ij}^k must be updated at iteration k:

$$\forall j \in \mathcal{N}_i: if\ i>j \ :\ \lambda_{ij}^{(k)} = \lambda_{ij}^{(k-1)} + \beta\left(r_{ij}^{(k)} - r_{ji}^{(k)} - A_{ij}^{(k)}\right) \quad (16)$$

$$\forall j \in \mathcal{N}_i: if\ i>j \ :\ \varphi_{ij}^{(k)} = \varphi_{ij}^{(k-1)} + \beta\left(q_i^{(k)} - q_j^{(k)}\right) \quad (17)$$

$$\gamma_i^{(k)} = \gamma_i^{(k-1)} + \beta\Big(\sum_{j\in\mathcal{N}_i} e_{ij}r_{ij}^{(k)} - \left(q_i^{(k)} - z_i^{(k)}\right)B\Big) \quad (18)$$

$$\mu_i^{(k)} = \mu_i^{(k-1)} + \beta\Big(\sum_{j\in\mathcal{N}_i} A_{ij}^{(k)} - S_i\Big) \quad (19)$$

V. PERFORMANCE EVALUATION

In this section, numerical results are provided to show performance of the proposed ADMM algorithm and compare it to the subgradient based approach [12], [13], and [16]. We used random topologies of N =10, N =15, N=20 and N =40 over a square of side 100 units, where all the available links are shown with blue lines. Our simulations are written in MATLAB and are run on a computer with Intel core i7 2.5 GHz CPU and 8GB memory.

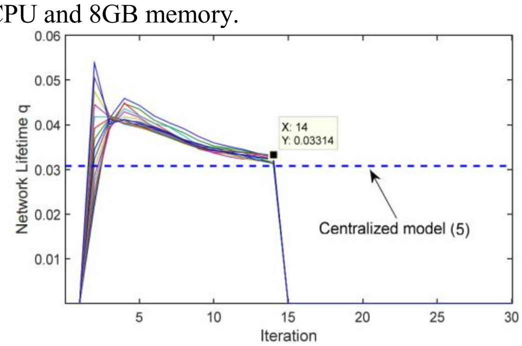

Figure 1. Convergence to global solution.

In Figure 1, the horizontal axis represents the number of iterations and the vertical axis represents q or the question solution (N = 15). The blue dotted line represents the solution in the central state and the rest of the curves represent the solutions in the distributed state. As can be seen, the ADMM-based algorithm could converge to the global optimal solution at 14 iterations. The low number of the iterations has a remarkable influence on reducing the energy consumption and increasing the sensor nodes lifetime.

To compare the results of the proposed ADMM-based method, in this part, the model (10) is stimulated using the subgradient method [16]. In Figure 2, the horizontal axis represents the number of iterations and the vertical axis represents the lifetime. As shown in this Figure, the number of the required iterations to achieve the global solution in the subgradient method is 1,330 which is very high compared to the ADMM-based method (Figure 1) and considerably increases the energy consumption and reduces the lifetime of the sensor nodes. As a result, the convergence speed of the proposed ADMM-based method is much more than the sub-gradient method.

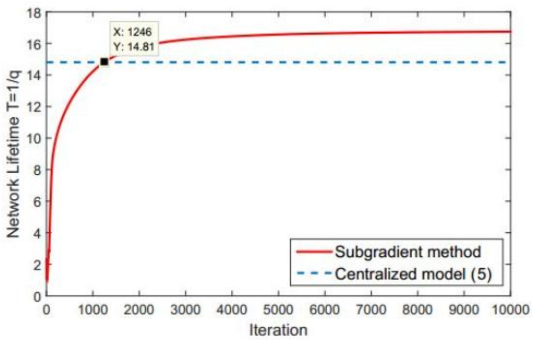

Figure 2. Convergence to global solution in subgradient method at iteration 1,245.

VI. CONCLUSIONS

In the past few years, WSNs have the potential for realization economical automation systems in smart grid. The energy efficiency in WSNs have become a major challenge in both academia and industry. That is because; each sensor node has a limited energy supply. Therefore, network energy optimization and lifetime maximization are serious problems in WSNs to explore. Due to the nature of this problem, there has been wide attention to distributed optimization approaches. One of these distributed approaches is Alternating Direction Method of Multipliers (ADMM) which has demonstrated a great empirical performance on several distributed applications. However, this method has not been used so far in order to maximize the WSN lifetime. Due to the limited energy consumption in sensor nodes and low computational complexity of the ADMM, the applications of this method in WSNs have had impressive results. Therefore, in this paper, we presented a distributed iterative algorithm based on the ADMM to increase the WSN lifetime by determining the high-accurate transmission rates from sensor nodes to the fixed sink node. In fact, in this approach, the problem decomposed into locally solvable per-node sub-problems which require a small amount of local information exchange. Extensive numerical results illustrated how significantly faster the proposed algorithm can converge to the near-optimal solution comparing to commonly used subgradient-based methods. As future work directions, there are several challenges which are worth to explore. One of these challenges is applying the distributed ADMM optimization in other WSN applications, like WSNs with a mobile sink to collect data from source nodes. In addition, different parameters such as packet loss, node/link failures, delay, etc. can be considered as constraints to enhance the optimization problem. As the last direction, proposing an asynchronous ADMM-based algorithm for WSN lifetime maximization is an interesting problem to discover.

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