Leveraging Predictability for Global Optimization of IoT Networks

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***Abstract*—We consider IoT networks where nodes are able to move to change the network topology and improve area coverage and network performance. We focus on the problem of global optimization where the nodes make use of the predictability of circumstances that affect network operations, such as the communication and sensing ranges, to anticipate future actions that need to be taken so that the correct operation of the network continues to be guaranteed with a minimum global cost. We provide a Mixed Integer Quadratic Program (MIQP)-based solution that minimizes the overall energy consumed over the entire deployment period while maintaining network connectivity and full area coverage. Results show that significant performance enhancement can be obtained when taking predictability into account compared to the case where nodes make decisions based only on their current observations.**

I. Introduction

In many typical IoT applications, nodes are deployed over a geographical area to perform sensing and transmit the collected data to a local or remote entity in charge of decision-making. The viability of these applications is heavily dependent on minimizing energy consumption and ensuring both area coverage and network connectivity. In the literature, a lot of research efforts focused on static networks where optimal node locations and configurations are calculated prior to deployment (e.g. [1], [2]). Extensive research also targeted mobile networks where nodes, initially deployed arbitrarily, seek to find better locations in response to changing operational circumstances such as to continue ensuring coverage of a moving phenomenon [2], [3]. Many techniques have been proposed to allow nodes to move from an initial to a target deployment with various objectives such as maximizing coverage, maintaining connectivity, or minimizing energy consumption by reducing the distance traveled by nodes. Most of these techniques have concentrated on maintaining coverage while reducing energy consumption and have been inspired by various mathematical techniques (e.g. virtual force mechanics, geometric computation, fuzzy logic, bio-inspired metaheuristics). As such they did not focus on providing solutions that jointly optimize energy consumption, connectivity, and coverage, during and after redeployment. Recently, a Mixed Integer Linear Programming (MILP) formulation has been proposed to provide solutions that jointly optimize node placement and movements, as well as their activity scheduling [1]. Although the mathematical formulation presented in [1] leads to an optimal solution, it is limited to static networks where only collector nodes are mobile.

More generally, all of the aforementioned solutions have mainly been designed to find an optimal solution to move nodes from an initial situation to another one usually considered final. This is the best that can be done when future circumstances that affect the operations of the network cannot be known in advance. However, when these circumstances can be predicted, a better solution can be obtained by optimizing all nodes movements throughout the intermediary situations between the initial and the final situation. Among those predictable circumstances that affect network operations, there are those related to weather changes such as temperature and humidity which mainly affect the operations of the nodes electronic circuitry [4]. It has been shown in [5] that temperature variations significantly affect the global network connectivity and coverage in a predictable way. As the predictability of weather conditions has significantly improved over time [6], it is becoming plausible to take them into account in the design of optimal solutions with a very high accuracy. Moreover, in addition to omitting predictability in general, traditional solutions did not provide an inclusive global framework based on mathematical modeling that incorporates network connectivity in the design of jointly optimized energy consumption and coverage.

To deal with the deficiency of the existing literature in this area and leverage the predictability of the conditions affecting the network operations, particularly connectivity and coverage, we provide in this paper a mathematical formulation based on a MIQP which seeks to find the optimal initial placement and trajectories of nodes over a time interval where circumstances affecting coverage and connectivity can be predicted. Our

solution finds the optimal number of nodes and the actions they need to take to ensure that the global performance of the network remains optimal during its entire lifetime by taking the future circumstances into account as they can be predicted. Simulation results on some representative data taken from the literature have shown that significant energy savings will be achieved by taking into account predictability in the optimization framework.

The remainder of the paper is organized as follows. In Section II, we discuss the related work. In Section III, we formulate the problem statement. In Section IV, we model the problem as a Mixed Integer Quadratic Program. In Section V, we present an evaluation of the proposed MIQP model. We conclude the paper and we provide some future directions in Section VI.

II. Related Work

Strategies for preserving the optimal operation of mobile sensor networks developed in the literature can be found in the following survey papers [7], [8]. Many of these strategies have been proposed based on the relation between the communication and sensing ranges [9] and had various objectives such as coverage maximization [2], and lifetime maximization [1], [10], [11]. For instance, the authors in [1] have proposed a Mixed Integer Linear Programming (MILP) formulation to maximize the network lifetime by considering optimal node deployment, activity scheduling, data routes, etc., and proposed two heuristics for the solution of their MILP formulation. Unfortunately, this solution and other similar propositions assume that once the network is deployed, the circumstances governing the performance of communication and sensing will remain unchanged and thus the network continues to operate optimally.

In a more realistic setting, the communication and sensing performance are dynamic and sometimes can be predictable. Therefore, the solutions found prior to deployment will unlikely continue to provide global optimal performance, particularly where the sensed phenomenon is dynamic and moves over time [3]. In this case, nodes need to move individually or collectively to continue to ensure coverage while maintaining connectivity and optimizing their operations in relation to energy, reliability, and delay [12].

Other mathematical techniques have been proposed such as the one presented in [13] in which the authors propose a virtual force algorithm (VFA) to maximize the coverage of the network, using attractive and repulsive forces. The purpose is to maintain a constant distant between every pair of nodes and thus guarantee a uniform distribution of nodes over the deployment area. Although VFA are proven to converge, the time needed before the algorithm converges may be considerable. Enhancements to this algorithm have been proposed: in [14] to accelerate convergence of the algorithm, in [15] to preserve connectivity in the network in addition to coverage, and in [16] to maximize the lifetime of the network by considering the residual energy in nodes before their relocation. However, and these approaches do not take into account the predictability of future conditions that effects coverage and connectivity and thus would not result in global optimal performance.

Geometric computation-based approaches have also been used in [17], [18], [19], [20] to preserve coverage by discovering existing coverage holes (holes are discovered by Voroni diagrams) and determine the target position where nodes will be relocated. In [17], the authors define three movement-assisted protocols based on Voronoi diagram in an attempt to reach a uniform distribution of nodes in the covered area. Although this algorithm and its variants [18], [19], [20] maximize the overall coverage, they are greedy and thus are not optimal. Moreover, they neither focus on energy savings, nor do they take into account the future circumstances that influence on the topology of the network.

Other approaches using fuzzy logic systems to control the node movements, such as those presented in [21], [22], [23], [24] are efficient in providing rapid deployment, where oscillation and unnecessary movements are efficiently avoided and fast deployment is achieved. Unfortunately, like other existing approaches in the literature, they do not take into account the predictability of the circumstances affecting the network operation.

Meta-heuristic approaches have also been used to solve the problem of network lifetime maximization. Various techniques such as evolutionary algorithms, simulated annealing, particle swarm optimization, and graph cellular automata have been used [25], [26], [27]. However, most of the existing efforts focused on minimizing the node mobility according to the currently observed circumstances and overlooked the fact that conditions affecting the operation of the network, such communication and sensing ranges, could be predicted, and thus resulted in suboptimal solutions.

Therefore, to cope with the deficiency of the literature on taking advantage of the predictability of certain circumstances affection the operation of the network, we propose an optimization model for globally optimal performance.

III. Problem Statement and Assumptions

We consider an IoT network composed of N nodes deployed over a rectangular area. We assume that all nodes are identical and that the deployment area is homogeneous. In such conditions, all nodes have similar sensing and communication ranges, r_t and R_t, respectively, that are both dependent on time t. We consider that a deployment is good if (i) the network is connected, i.e. there is a path between any two nodes, and (ii) that every point in the deployment area is covered by

at least K nodes, i.e. any point in the deployment area is within the sensing range of at least K nodes. We assume that nodes are free to move and can travel to any point in the deployment area. We also assume that nodes can be in one of two modes: On and Off. In the Off mode, nodes cannot contribute to sensing and communication operations and thus the amount of energy consumed in this mode is considered negligible. We consider solving the following problems: (i) at each time t, what is the optimal deployment and activity scheduling of nodes, i.e. where nodes should be placed and which ones should be in the On mode? and (ii) which nodes should move and where they need to go? Both (i) and (ii) should result in minimum energy consumption while both connectivity and coverage should be preserved, over the entire duration of network operation.

We consider that the deployment area is represented by a square grid where C and V are the sets of all square centers and vertices. We consider that a node can only be positioned at the center of a square. Clearly when the square area becomes too small, we approach the continuous case. We assume that there is a central entity, called the Collector, that is able to collect nodes positions and instruct them on the action to take: move or switch to Off or On modes. Nodes execute the instructions at the beginning of each time slot and keep the same configuration until the next instruction at the beginning of the next slot. We assume that the deployment area is obstacle-free. Thus nodes travel according a direct line to reach their destinations. The distance traveled by nodes is used to calculate the energy consumed during the movements.

IV. Problem Formulation as a MIQP

A. Decision Variables

We define the following binary decision variables x_{ip}^t and e_p^t. Let x_{ip}^t express the presence of a node at a given point of the monitored area. We have:

$$x_{ip}^t = \begin{cases} 1 & \text{if node } i \text{ is located at center } p \in C \text{ at time } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Let e_p^t denote the node status, i.e. whether the node located at center p is On or Off. We have:

$$e_p^t = \begin{cases} 1 & \text{if a node is at center } p \in C \text{ and it is On at time } t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Definition (2) might not seem intuitive at first glance, however it has the property of avoiding quadratic constraints. A more straightforward modeling would use a different decision variable e_i^t to denote whether a node is On at time t or not. However, as the latter leads to quadratic constraints and thus increases the execution time dramatically, we choose to use the first definition, i.e., the one described in (2).

B. Objective Function

The energy consumed during the time interval $[t, t+1]$ is composed of three parts: the energy spent in communication (EC^t), sensing (ES^t), and movement (EM^t). The energy consumed in communication (EC^t) depends on traffic and the underlying access method used. Without loss of generality, we assume in our model a simple traffic model where each node rebroadcasts each packet it receives once. In this case, every node sends exactly one packet and receives as many packets as the number of its neighbors. We also assume an access method where energy is consumed in transmission and reception. Outside these operations, the node is assumed to be in sleep mode to save energy. We use the P_{tx}, P_{rx}, and P_{slp} to refer to the power consumed in transmission, reception, and sleep modes, respectively. The energy consumed by a node that is in On mode and located at position p during time interval $[t, t+1]$ is given by the following expression:

$$\text{EC}_p^t = m(P_{\text{tx}}T_{\text{tx}} + \eta_p^t P_{\text{rx}}T_{\text{rx}} + P_{\text{slp}}T_{\text{slp}}) \tag{3}$$

where m is the number of messages generated during interval $[t, t+1]$ and η_p^t is the number of neighbors of the node located at center p at time t. We have:

$$\eta_p^t = \sum_{q \in C} b_{pq}^t * e_q^t \qquad p \in C; t \in T \tag{4}$$

where b_{pq}^t is defined as follows:

$$b_{pq}^t = \begin{cases} 1 & \text{if } d_{pq} \leq R_t \qquad \text{where } p, q \in C; t \in T \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where d is the euclidean distance between points p and q.

The energy ES_p^t consumed in sensing during interval $[t, t+1]$ is given by the following equation:

$$\text{ES}_p^t = T_{\text{sens}}P_{\text{sens}} \tag{6}$$

where T_{sens} and P_{sens} are the sensing duration and the power consumed in sensing, respectively.

The energy EM_i^t consumed by the movement of node i at time t is related to the distance d_{pq} between the previous position p of the node, i.e. at time $t-1$, and its current position q at time t, x_{ip}^{t-1}, as well as the moving force F_{mov} consumed in the movement. We have:

$$\text{EM}_i^t = F_{\text{mov}} \sum_{p \in C} \sum_{q \in C} d_{pq} * x_{ip}^{t-1} * x_{iq}^t \quad i \in N; p, q \in C; t \in T \tag{7}$$

Our goal is to minimize the total energy consumption, i.e., the sum of the amounts of energy consumed in communication, sensing, and movement by all nodes over the entire operation duration T. Therefore, the objective function $\mathcal{F}$ expressing the

energy consumption that needs to be minimized is expressed as follows:

$$\mathcal{F} = \sum_{t\in T}\sum_{p\in C} e_p^t * \mathrm{EC}_p^t + \sum_{t\in T}\sum_{p\in C} e_p^t * \mathrm{ES}_p^t + \sum_{\substack{t\in T\\ t\neq 0}}\sum_{i\in N} \mathrm{EM}_i^t \quad (8)$$

C. Deployment and On/Off Constraints

We define the following constraints in relation with the node deployment and the On/Off scheduling:

$$\sum_{p\in C} x_{ip}^t = 1 \qquad i\in N; t\in T \quad (9)$$

$$\sum_{i\in N} x_{ip}^t \leq 1 \qquad p\in C; t\in T \quad (10)$$

$$e_p^t \leq \sum_{i\in N} x_{ip}^t \qquad p\in C; t\in T \quad (11)$$

Constraint (9) guarantees that a node is placed at exactly one location at each time slot. Constraint (10) guarantees that at most one node can be placed at a given location at each time slot. Constraint (11) ensures that absent nodes are Off. Both x_{ip}^t and e_p^t are binary, thus the following additional constraints are defined:

$$x_{ip}^t \in \{0,1\} \quad (12)$$

$$e_p^t \in \{0,1\} \quad (13)$$

D. Coverage Constraints

With the square grid chosen in our model, it is sufficient to guarantee that each square vertex is covered to ensure that the entire area is covered. This is due to the fact that the length of each square side is always smaller than smallest range, between communication and sensing, at any given time, i.e. the square side should be smaller than $\min(R_t, r_t)$. To reduce the number of points resulting to the discretization we consider that the square side is equal to $\min(R_t, r_t)$. The entire area coverage is guaranteed if the following constraint is satisfied.

$$\sum_{p\in C} a_{pv}^t e_p^t \geq K \qquad v\in V; t\in T \quad (14)$$

where a_{pv} is defined as:

$$a_{pv}^t = \begin{cases} 1 & \text{if } d_{pv} \leq r_t \\ 0 & \text{otherwise} \end{cases} \qquad \text{where } p\in C;\ v\in V;\ t\in T \quad (15)$$

K is the number of nodes covering vertex v. In what follows, we assume that it is sufficient to have each point covered by at least one node; therefore, we take K equal to 1.

E. Connectivity constraints

We formulate the connectivity constraint as a network flow problem. We define the decision variables f_{pq} as the flow quantity transmitted from a node potentially located at center p to another node potentially located at q ($p, q \in C$). We assume that each node generates a flow unit in the network and verify if these units can be recovered by the Collector. The following constraints ensure that the deployed nodes and the Collector form a connected network. The flow conservation model that ensure that the network is connected is modelled by the following constraints.

$$\sum_{\substack{p\in C\\ p\neq q}} f_{pq}^t + e_q^t = \sum_{\substack{r\in C\\ r\neq q}} f_{qr}^t \quad q\in C\setminus\{s\}; t\in T \quad (16)$$

$$f_{pq}^t \leq N * b_{pq}^t e_p^t \qquad p,q\in C; t\in T \quad (17)$$

$$\sum_{\substack{p\in C\\ c\neq s}} f_{ps}^t = \sum_{p\in C} e_p^t \qquad t\in T \quad (18)$$

$$f_{pq}^t \geq 0 \quad (19)$$

Constraint (16) expresses the condition of flow conservation at each position. More specifically, if an active node is located at point q, it injects one more packet. Constraint (17) ensures that no packets goes out from center p to center q if: (i) the distance between p and q is greater than the communication radius, or (ii) no active node is located in p or in q. Constraint (18) ensures that injected units can be recovered by the Collector. Constraint (19) ensures that decision variables f_{pq}^t are positive.

F. Global MIQP Model

Our general optimization model can be written as follows:

minimize: (8)

subject to:

(9), (10), (11), (12), (13), (14), (16), (17), (18), and (19)

V. Evaluation

To evaluate the gain obtained where conditions that affect the operation of the deployed network can be predicted, we compare the performance of our solution with a baseline solution that does not take into account the predictability of these conditions. We consider measuring the energy consumption in both solutions where both connectivity and coverage are maintained. We use IBM CPLEX [28] to solve our MIQP model.

In the first set of simulations, we use 9 nodes in a square area of 80x80m^2. We model the predictability of sensing and communication ranges by time series which vary according to the plots shown in Fig. 1 (top subplot). For energy consuming operations, we use the following values: 72mW, 72mW, 3μW, 3μW, 3Newton for P_{tx}, P_{rx}, P_{slp}, P_{sens}, and F_{mov}, respectively. We consider that the exchanged messages are generated at

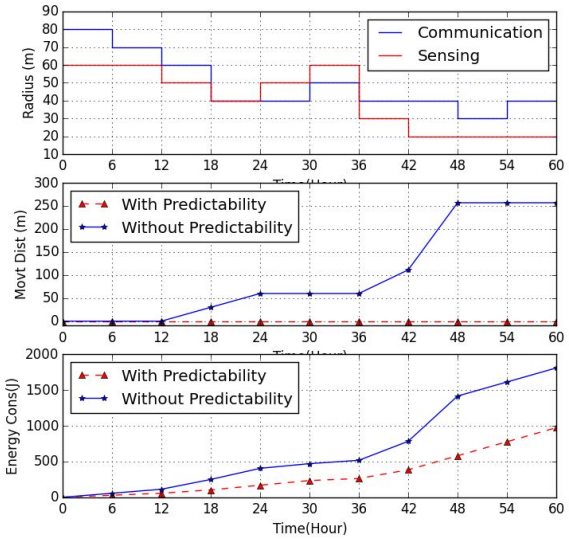

Fig. 1. Energy consumption and distance traveled by nodes in both cases: with and without predictability.

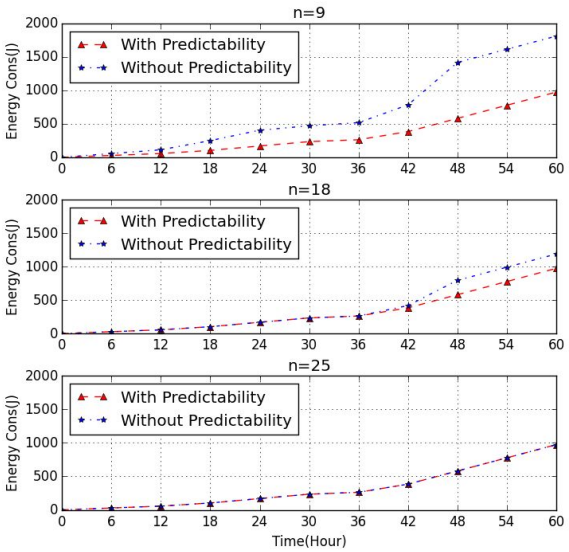

Fig. 2. Impact of the number of nodes on energy consumption in both cases: with and without predictability.

a rate that the transmission of messages occupies 3% of the time slot. Under such configuration, node movement generally consumes much more energy than communication.

In Fig. 1 (middle subplot), we plot the total distance traveled by all nodes in the case of the baseline solution and compare it with our solution. In both cases, nodes run

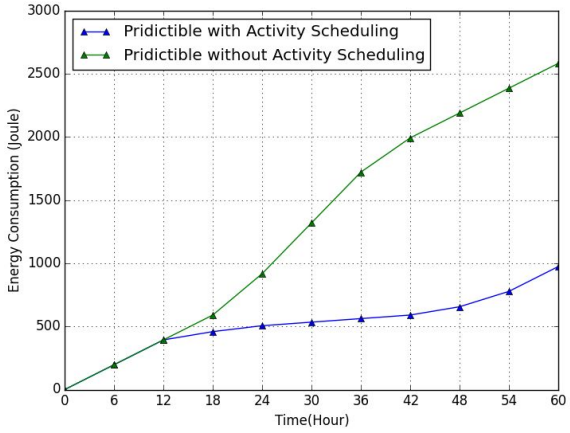

Fig. 3. Impact of Nodes Number on Energy Consumption in the Predictive and No Predictive Models

a scheduling technique according the On/Off strategy and are able to move to any other location if it is deemed to reduce global energy consumption. In the baseline solution, nodes do not take advantage of the predictability of the circumstances affecting the operation of the network. Therefore, their goal is to minimize energy consumption during the time interval $[t, t+1]$ taking into account the previous setting. In the case of our solution, nodes leverage the predictability of the settings and aim at minimizing the total energy consumption during the entire time during which the circumstances can be predicted, i.e. in $[0, T]$. Fig. 1 (middle subplot) shows that in the baseline solution, nodes perform location change each time interval with the aim to keep the network at the lowest energy consumption. However, as shown in Fig. 1 (bottom subplot) this does not turn out to be always globally optimal over time. The reason is that, as nodes do not know the future variations of the circumstances under which the network operate, they will perform local optimization. However, our solution shows that it is better that nodes do not move because the benefit obtained with such movement will be suppressed by subsequent settings and nodes might need to move back again. In our solution, we show that making use of the predictability information allows nodes to take the optimal decision on movement and scheduling at any given time that will be globally optimal in the future as well. We also show that our solution achieves a significant gain compared to the baseline solutions and thus the advantage of taking into account the predictability of circumstances affecting the network.

In Fig. 2, we show the energy consumption of both the baseline solution and ours under the variability of the number of nodes. We show that predictability consideration achieves higher energy gains when the number of nodes deployed initially is small. However, if the number of nodes deployed

initially is large, to the extent where there is a node in every square center, both methods achieve the same amount of energy consumption. In such setting, the solution obtained with the baseline solution does not involve node mobility but only scheduling, which explains the same amounts of energy consumption obtained in both methods.

To assess the benefit of activity scheduling to the global solution, we plot in Fig. 3 the amount of energy consumption over time in cases where nodes switch between On and Off modes and the case where nodes are constantly in On mode. We remind that in On mode, nodes use an ideal access method, so idle listening is minimized. The Off mode mainly allows nodes to save energy that would have been spent in sensing otherwise.

VI. Conclusion

We have proposed a Mixed Integer Quadratic Program that allows minimizing global energy consumption in IoT networks while maintaining both connectivity and coverage. We have shown that taking into account the predictability of the circumstances affecting the operations of the network, such as the communication and sensing ranges, results in significant energy savings because it allows nodes to take optimal decisions on movement and activity scheduling based on future conditions rather than current observations only. In a future work, we plan to extend the provided initial solution and formulation by designing specific heuristics to deal with the complexity of the addressed problem, as well as providing a distributed solution for the predictability-based optimality problem.

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