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Differential Game for Resource Allocation in Energy Harvesting Wireless Sensor Networks

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Abstract—In this paper, we consider power control and data scheduling in an Energy Harvesting (EH) multi-hop Wireless Sensor Network (WSN) using Differential Game (DG) framework. The network consists of M sensor nodes aiming to send their data to a sink node. Each sensor node has a battery of limited capacity to save the harvested energy and a buffer of limited size to store both the sensed and relayed data from neighboring nodes. Each sensor node can exchange information within its neighborhood using single-hop transmission. Our goal is to develop a distributed algorithm that adaptively changes the transmitted data and power according to the traffic load and available energy such that the sensed data are received at the sink node. DG framework is proposed to efficiently utilize the available harvested energy and balance the buffer of all sensor nodes. The solution is obtained based on the open-loop receding horizon Nash equilibrium. Simulation results demonstrate the merits of the proposed solution.

Index Terms—Wireless sensor network, energy harvesting, differential game, open-loop Nash equilibrium, receding horizon.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are autonomous networks of distributed sensor nodes that are capable of wirelessly communicating with each other in a multi-hop fashion. Recently, there is a tremendous increase in the deployment of WSNs for different applications such as home automation, healthcare, surveillance, transportation, smart cities and many more. Low cost and self organizing WSN has been identified as one of the major technologies for future wireless communication systems such as the internet-of-things (IoT), green 5G and beyond 5G networks. The formulation of such complex networks necessitates extensive cooperation among wireless sensor nodes, i.e., the sensor node needs to help in forwarding the data of neighboring nodes in addition to its sensed data. This will increase the energy demand of a sensor node. Therefore, it may not be possible to use standard battery powered nodes, especially for sensor nodes deployed in inaccessible locations [1], [2].

Energy-harvesting (EH) techniques have the potential to overcome the battery size constraints in WSNs and

enable green communications. Examples of energy that can be harvested include solar energy, piezoelectric energy, thermal energy and radio frequency energy. Using conventional transmitter is subject to a power constraint or sum energy constraint, whereas using environmental energy source is subject to causality constraints in addition to other constraints, i.e., in every time-slot, each transmitter is constrained to use at most the amount of energy currently available [3].

Various aspects of EH-WSNs are discussed in [4]–[10]. Efficient utilization of the available energy is one of the main challenges in EH-WSNs [7], [11]. In the literature, several resource allocation problems for EH sources are considered aiming to achieve different objectives such as throughput maximization, reward maximization and outage minimization as in [1], [12]–[15].

Distributed and semi-centralized resource allocation algorithms are easier to implement and can play an important role in large scale WSNs. Differential-game (DG) theory is a promising framework for distributed resource allocation (control) problems¹ in dynamic systems. In this sense, a DG through a connected graph is proposed aiming at an online dynamic and distributed control for the operation of EH-WSN, where each sensor node is allowed to select a utility (cost) function and then can control its own actions [16]. The proposed DG is solved using the open loop Receding Horizon Nash Control (RHNC) approach. DG framework has been used to solve several problems in different domains such as leader follower network formulation [17] and urban drainage systems control [18], but to the authors best of knowledge, this is the first time that the DG-RHNC approach is applied for the online operation of EH-WSNs².

The remainder of this paper is organized as follows. In Section II, the system model of EH-WSNs is introduced. In Section III, the problem formulation and DG framework are presented. Numerical results are presented and

¹Resource allocation problems and control problems are used interchangeably throughout this paper.

²Preliminary results of this work appeared in ICC 2018 [19].

Fig. 1: System model of an EH-WSN: the small circles represent sensor nodes, green rectangles represent data buffers, gray rectangles represent energy batteries and the dashed circle represents the neighboring set of $\mathcal{N}_4$.

discussed in Section IV. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL

The system under consideration is schematically shown in Fig. 1. The sender (source) node S_i for $i = 1, \dots, M$ is aiming to transmit data to the sink node S_{M+1} using multi-hop communications. The source node S_i communicates with its neighboring set denoted as $\mathcal{N}_i$ using a single-hop transmission. The set $\mathcal{N}_i$ consists of one-hop neighbors of node S_i which are allowed to serve as the next-hop. The channel gain $h^{(i,j)}$ between node S_i and node S_j is assumed to be constant throughout the transmission period. Reciprocal channel gains are assumed using Time Division Duplex (TDD), i.e., $h^{(i,j)} = h^{(j,i)}$.

We assume, orthogonal access to the medium where only non-interfering links can transmit simultaneously. Orthogonal access to the medium is nearly optimal when interference is strong [20]. The connectivity graph of the wireless multihop network is used to identify the feasible schedules. The finite set of all possible independent sets of links (i.e., links that do not interfere with each other) is first identified. A feasible schedule is then used for network communications, similar approach is adopted in the literature as in [21]. The structure of a static multi-hop WSN can be captured by a graph [22]. A vertex of the graph corresponds to a sensor node and the edges of the graph capture the dependence of the interconnections. A directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ consists of a set of vertices $\mathcal{V} = \{\nu_1, \dots, \nu_{M+1}\}$, indexed by the sensor nodes in the network and the sink node, and a

set of edges $\mathcal{E} = \{(\nu_i, \nu_j) \in \mathcal{V} \times \mathcal{V}\}$, containing ordered pairs of distinct vertices. Assuming the graph has no loops, i.e., $(\nu_i, \nu_j) \in \mathcal{E}$, implies $\nu_i \neq \nu_j$. A graph is connected if for any vertices $\nu_i \in \mathcal{V}$ and $\nu_j \in \mathcal{V}$, there exists a path of edges in $\mathcal{E}$ from ν_i to ν_j . To transmit data in WSNs, the graph connectivity is necessary [23]. The incidence matrix $\mathcal{D}$ of a directed graph $\mathcal{G}$ is a matrix with entries belong to $\{0, -1, +1\}$. For the matrix $\mathcal{D}$, the rows are indexed by the vertices of $\mathcal{V}$ and the columns are indexed by the edges of $\mathcal{E}$. The (i, j) entry of $\mathcal{D}$ is equal to 1 if the vertex i is the head of the edge j , -1 if the vertex i is the tail of the edge j and 0, otherwise. The edges of the WSN are oriented in the direction of the sink node and represent the flow of information. Let $\mathcal{N}_i = \{\nu_j \in \mathcal{V} | (\nu_i, \nu_j) \in \mathcal{E}\}$ be the neighborhood set of sensor node S_i .

An edge-weighted graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \omega)$ is a graph in which the edge (ν_i, ν_j) is assigned a weight $\omega_{ij} \geq 0$. The weight vector associated with $\mathcal{E}$ is defined as ω . The Laplacian matrix $\mathcal{L}$ is used to characterize an edge-weighted graph defined as [17]: $\mathcal{L} = \mathcal{D}\Omega\mathcal{D}^T$, where $\Omega = \text{diag}(\omega)$ is a diagonal weight matrix with dimension $|\mathcal{E}|$. The Laplacian is a symmetric and positive definite matrix.

The transmission of the investigated EH-WSN is organized in time-slots of duration T and it transmits for K time-slots. We assume that the solar energy is harvested and stored without any energy loss in the battery. For sensor node S_i for $i = 1, \dots, M$, the energy level $E_{k+1}^{(i)}$ of the battery at time-slot $k+1$ evolves as:

$$E_{k+1}^{(i)} = (E_k^{(i)} - T \sum_{j \in \mathcal{N}_i} l_k^{(i,j)} P_k^{(i,j)})^+ + H_k^{(i)}, \quad (1)$$

where $(x)^+ = \max(x, 0)$, $l_k^{(i,j)} \geq 0$ and $P_k^{(i,j)} \geq 0$ denote the time-fraction and the power level at time-slot k , respectively, which are used to transmit $r_k^{(i,j)}$ bits from sensor node S_i to sensor node S_j , and $H_k^{(i)}$ denotes the harvested energy during time-slot k . We assume that the energy is consumed in transmission only; the energy consumed by the internal circuits for sensing and processing is negligible compared to the transmitted power. This assumption is adopted in many papers such as [12], [21]. The data buffer of sensor node S_i at time-slot $k+1$ evolves as:

$$C_{k+1}^{(i)} = (C_k^{(i)} - \sum_{j \in \mathcal{N}_i} r_k^{(i,j)})^+ + \sum_{j \in \mathcal{N}_i} r_k^{(j,i)} + d_k^{(i)}, \quad (2)$$

where $C_k^{(i)}$ is the buffer capacity of node S_i at time-slot k in bits, and $d_k^{(i)}$ denotes the data sensed by source node S_i during time-slot k . The data buffer at the sink node S_{M+1} evolves as:

$$C_{k+1}^{(M+1)} = C_k^{(M+1)} + \sum_{j \in \mathcal{N}_{M+1}} r_k^{(j,M+1)} + d_k^{(M+1)}. \quad (3)$$

The transmitted data $r_k^{(i,j)}$ from sensor node S_i to a neighboring node S_j at time-slot k are constrained by the channel capacity of the link as:

$$0 \leq r_k^{(i,j)} \leq TW l_k^{(i,j)} \log_2 \left(1 + \frac{|h^{(i,j)}|^2 P_k^{(i,j)}}{N_0} \right), \quad (4)$$

where W is the channel bandwidth and N_0 is the noise power at the receiver node. Half-duplex and TDD transmission scheme is assumed at each sensor node, this constraint can be expressed as:

$$0 \leq \sum_{j \in \mathcal{N}_i} l_k^{(i,j)} + \sum_{j \in \mathcal{N}_i} l_k^{(j,i)} \leq 1, \quad (5)$$

where $l_k^{(j,i)} \geq 0$ is the time-fraction of time-slot k used for receiving $r_k^{(j,i)}$ bits from sensor node S_j . The storage energy constraint of the battery of sensor node S_i is expressed as:

$$0 \leq E_k^{(i)} \leq E_{\max}^{(i)}, \quad (6)$$

and the data buffer capacity constraint at sensor node S_i for $i = 1, \dots, M+1$ and $k = 0, \dots, K$ can be expressed as:

$$0 \leq C_k^{(i)} \leq C_{\max}^{(i)}. \quad (7)$$

The sink buffer is assumed to have a very large capacity compared to the buffer of source node S_i , i.e., $C_{\max}^{(M+1)} \gg C_{\max}^{(i)}$.

The vector notation is introduced to simplify the paper presentation as follows: Let $\mathbf{C}_k = [C_k^{(1)}, \dots, C_k^{(M+1)}]^T$ and $\mathbf{E}_k = [E_k^{(1)}, \dots, E_k^{(M)}]^T$ denote the buffer and battery state vectors of all sensor nodes at time-slot k , respectively. Sensor node S_i control vector is defined as $\mathbf{u}_k^{(i)} = [e_k^{(i)T}, \mathbf{r}_k^{(i)T}, \mathbf{l}_k^{(i)T}]^T$, where the control vector of the energy, data and time allocation are defined as $e_k^{(i)} = [e_k^{(i,j)}]_{\{\forall j \in \mathcal{N}_i\}}$ with $e_k^{(i,j)} = l_k^{(i,j)} P_k^{(i,j)}$, $\mathbf{r}_k^{(i)} = [r_k^{(i,j)}]_{\{\forall j \in \mathcal{N}_i\}}$, and $\mathbf{l}_k^{(i)} = [l_k^{(i,j)}]_{\{\forall j \in \mathcal{N}_i\}}$, respectively.

III. PROBLEM FORMULATION

The operation of EH-WSNs is mainly affected by the power allocation and data scheduling at all sensor nodes in the network. The resource allocation problem in EH-WSNs has many properties that differentiate it from resource allocation problems in conventional WSNs. Theoretically, EH sensor node has unlimited source of energy, but its energy can not be used before being harvested and the amount of harvested energy is not known in advance and may vary from one spacial position to another and from one time to another, whereas conventional sensor node has a limited source of energy, EH spacial and time variations, and causality constraints are not applicable [3].

Developing resource allocation algorithm for power control and data scheduling in EH-WSNs plays a key

role in the operation of such networks. Furthermore, distributed algorithms for dynamical systems are practical and have the potential to enhance the network scalability and reduce the communication overheads [10]. DGs have been successfully selected to solve many distributed control problems such as robots formulation as [17] and urban drainage systems control [18]. In this sense, a distributed resource allocation algorithm for the operation of EH-WSNs is proposed based on a DG formulation.

The proposed EH-WSN DG is defined as: $DG = \{S_i, \mathcal{J}^{(i)}(\cdot), \mathbf{u}^{(i)}\}_{i=1, \dots, M}$, where sensor node S_i seeks to minimize its utility (cost) function $\mathcal{J}^{(i)}(\mathbf{C}, \mathbf{e}^{(i)})$ with respect to the admissible strategies $\mathbf{u}^{(i)} = [\mathbf{u}_0^{(i)T}, \dots, \mathbf{u}_{K-1}^{(i)T}]^T$ defined as:

$$\mathcal{J}^{(i)}(\mathbf{C}, \mathbf{e}^{(i)}) = \sum_{k=0}^K \tilde{\mathbf{C}}_k^T \mathbf{Q}_k \tilde{\mathbf{C}}_k + \sum_{k=0}^{K-1} \mathbf{e}_k^{(i)T} \mathbf{R}_k^{(i)} \mathbf{e}_k^{(i)}, \quad (8)$$

where $\mathbf{C} = [\mathbf{C}_0^T, \dots, \mathbf{C}_K^T]^T$, $\mathbf{e}^{(i)} = [\mathbf{e}_0^{(i)T}, \dots, \mathbf{e}_{K-1}^{(i)T}]^T$. The normalized buffer state vector at time-slot k defined as $\tilde{\mathbf{C}}_k = [\frac{C_k^{(1)}}{C_{\max}^{(1)}}, \dots, \frac{C_k^{(M+1)}}{C_{\max}^{(M+1)}}]^T$ is used to model buffers of different capacities. The quadratic cost function is selected because of its nice mathematical properties; minimizing the cost function can drive the buffer state to the origin state, while using minimum amount of energy, i.e., emptying the data buffer using a minimum amount of energy. The weighting matrices of the state and the controller vectors are defined as $\mathbf{Q}_k \geq 0$ and $\mathbf{R}_k^{(i)} > 0$. The buffer state vector weighting matrix is chosen to be the Laplacian matrix $\mathbf{Q}_k = \mathcal{D} \Omega_k \mathcal{D}^T$. Large values of $\mathbf{Q}_k$ in comparison to $\mathbf{R}_k^{(i)}$ drives the state vector to the origin quickly at the expense of large control action. Penalizing the control action through large values of $\mathbf{R}_k^{(i)}$ relative to $\mathbf{Q}_k$ is the way to reduce the control action and slow down the rate at which the state approaches the origin.

Using game theory framework, Nash Equilibrium (NE) is used as the optimal solution. NE is a set of strategies where no player can improve its payoff by changing its own strategy while others keep theirs fixed [16], [24]. NE of the EH-WSN DG is a set of admissible strategies, where $\mathbf{u}^{(i)*}$ is the best response for sensor node S_i . A set of controllers $\{\mathbf{u}^{*(1)}, \dots, \mathbf{u}^{*(i)}, \dots, \mathbf{u}^{*(M)}\}$ is a NE for the EH-WSN DG, if for all admissible strategies $(\mathbf{u}^{(1)}, \dots, \mathbf{u}^{(i)}, \dots, \mathbf{u}^{(M)})$, the following inequalities hold:

$$\begin{aligned} & \mathcal{J}^{(i)}(\mathbf{u}^{*(1)}, \dots, \mathbf{u}^{*(i)}, \dots, \mathbf{u}^{*(M)}) \\ & \leq \mathcal{J}^{(i)}(\mathbf{u}^{*(1)}, \dots, \mathbf{u}^{(i)}, \dots, \mathbf{u}^{*(M)}), \forall i \in \{1, \dots, M\}. \end{aligned} \quad (9)$$

In DGs, two types of information structures are commonly used to find the NE; open-loop and state feedback information structures. In open-loop information

Fig. 2: The RHC concept.

structure, all players make their decisions based on the initial state vector, each player computes its open-loop equilibrium at the beginning of the game and commit to follow that equilibrium during the whole period. The open-loop NE is obtained by simultaneous minimization of the cost functions, where each player minimizes its cost function given the initial state vector. In state feedback information structure, the players make their decisions based on a state feedback information at each stage of the game. The state feedback NE is analytically and computationally difficult to obtain [16].

Receding-horizon-control (RHC) is a multi-variable control framework used to provide reliable controllers for nonlinear models with constraints. The aim of RHC is to determine an online optimal control sequence that minimizes the cost function of reaching a target state for a given horizon assuming knowledge of the system model and the current (initial) state [25]. Fig. 2 shows the RHC algorithm, which can be explained as follows: Consider a starting time-slot s and a horizon extending to N time-slots into the future, with $N \leq K$. First, the buffer and battery states are estimated/measured at time-slot s . Second, the optimal control values of the energy, time allocation and transmitted data of the system are obtained for all time slots $\{s, \dots, s+N-1\}$ by solving an optimization problem. The control actions at time-slot s are then applied to the system. The starting time is shifted to time-slot $s+1$, and the same procedure is repeated again.

Practically, an open-loop NE for a horizon of length N for the DG can be found and then the receding-horizon-Nash-control (RHNC) can be used to simulate the state feedback NE [17]. The idea of RHNC is an extension of the RHC such that instead of solving a control problem to find the controller, a DG game is solved to find the controller. At each RH episode (i.e., N time-slots starting from time slot s), each player finds its open loop NE for a horizon of length N , but it does not commit to follow that equilibrium during the whole period, it only uses it

to control one time step. The procedure then is repeated again after receding (shifting) the horizon.

The harvested and sensed data are stochastic processes and unknown in future time slots. A conservative approach is to exclude them from the dynamics of the DG and capture their effects by updating the battery and buffer states after each sensor node applies its first control vector. Therefore, the harvested energy and sensed data profiles at the current time slot are stored and then utilized in the next RH (planning) game.

The utility (cost) function of sensor node S_i fitting the DG-RHNC for a horizon of length $N \leq K$, and starting at time slot s , for $s = 1, \dots, K$ is expressed as³:

$$\mathcal{J}_s^{(i)}(C, e^{(i)}) = \sum_{k=s}^{s+N} \tilde{C}_k^T Q_k \tilde{C}_k + \sum_{k=s}^{s+N-1} e_k^{(i)T} R_k^{(i)} e_k^{(i)}. \quad (10)$$

The EH-WSN DG for $\{S_i\}_{1,\dots,M}$ is formulated as:

$$\min_{r, l, e, C, E} \mathcal{J}_s^{(i)}(C, e^{(i)}), \quad (11a)$$

subject to:

$$\text{given } E_s \text{ \& } C_s, \quad (11b)$$

$$(4), (5), (6), \text{ \& } (7) \quad (11c)$$

$$E_{t+1}^{(m)} = E_t^{(m)} - T \sum_{j \in \mathcal{N}_m} e_t^{(m,j)}, t = s, \dots, s+N-1, \quad (11d)$$

$$C_{t+1}^{(m)} = C_t^{(m)} - \sum_{j \in \mathcal{N}_m} r_t^{(m,j)} + \sum_{j \in \mathcal{N}_m} r_t^{(j,m)}, \quad (11e)$$

$$T \sum_{k=0}^s \sum_{j \in \mathcal{N}_m} e_k^{(m,j)} \leq E_0^{(m)} + \sum_{k=0}^{s-1} H_k^{(m)}, \quad (11f)$$

$$\sum_{k=0}^s \sum_{j \in \mathcal{N}_m} r_k^{(m,j)} \leq C_0^{(m)} + \sum_{k=0}^{s-1} \sum_{j \in \mathcal{N}_m} r_k^{(j,m)} + \sum_{k=0}^{s-1} d_k^{(m)}, \quad (11g)$$

Since the harvested energy and sensed data at time slots $s, \dots, s+N-1$ are unknown to sensor node m , they are not included in the system dynamics in (11d)-(11e) and treated as disturbances. Constraints (11f) & (11g) are energy and data causality constraints need to be satisfied only at the first time-slot (i.e., time-slot s), since the harvested energy and sensed data are unknown in future time-slots. $E_0^{(m)}$ denotes the initially stored energy in the battery of sensor node S_m , and $C_0^{(m)}$ denotes the

³From now on C , $u^{(i)}$ and $e^{(i)}$ are re-defined as $C = [C_s^T, \dots, C_{s+N}^T]^T$, $u^{(i)} = [u_s^{(i)T}, \dots, u_{s+N-1}^{(i)T}]^T$, and $e^{(i)} = [e_s^{(i)T}, \dots, e_{s+N-1}^{(i)T}]^T$, respectively.

initially stored data in the buffer of sensor node S_m . At time-slot s , the measured (or estimated) battery and buffer states of all sensor nodes are given as E_s and C_s , respectively.

The existence of the open-loop NE for EH-WSN DG (11) can be proved based on Theorem 4.2 in [16]. The cost function $\mathcal{J}_s^{(i)}(\cdot)$ is continuous in all its arguments and strictly convex in $e^{(i)}$, and $u^{(i)}$ is a closed bounded convex subset. Only for few DGs, the solution (NE) can be obtained analytically as discussed in [16]. For example, the analytical solution (open loop NE) for continuous-time non-constrained quadratic-linear programming DG is obtained in [18] & [17]. Note that the open loop NE existence can be proved for the EH-WSN DG formulated without including the stochastic harvested energy and sensed data processes. The investigation of the open loop NE with stochastic harvested energy and sensed data processes is out the scope of this paper. The unknown stochastic harvested energy and sensed data profiles are captured by the RH framework, where the harvested energy and sensed data are measured at the beginning or/end of each time-slot and used to update the buffer and battery states.

Differential games with constraints are in general difficult to solve (i.e., finding the open-loop NE numerically). Fortunately, there is a class of dynamic games, named differential potential games (DPGs) that can be solved through related multivariate optimal control problem. The benefit of DPG is that solving a single optimal control problem is generally simpler than solving a set of coupled multi-objective optimization problems (the DG) [26], [27].

The EH-WSN DG given in (11) is a potential game, since the utility (cost) function $\mathcal{J}_s^{(i)}(\cdot)$ of each sensor node is expressed as the sum of a term (first summation) that is common to all sensor nodes plus another term (second summation) that depends on its own action [26]. The potential function (common objective) associated with the EH-WSN DG is given as:

$$\mathcal{P}_s = \sum_{k=s}^{s+N} \tilde{C}_k^T Q_k \tilde{C}_k + \sum_{j=1}^M \sum_{k=s}^{s+N-1} e_k^{(j)T} R_k^{(j)} e_k^{(j)}. \quad (12)$$

The open loop NE of the EH-WSN DG $\{S_i, \mathcal{J}_s^{(i)}(\cdot), u^{(i)}\}_{i=1, \dots, M}$ can be obtained by minimizing the potential function $\mathcal{P}_s$ and satisfying the dynamics/constraints in (11b)-(11g). Since, the potential function $\mathcal{P}_s$ with the given dynamics/constraints is a convex optimization problem several algorithms can be used to find its solution. Utilizing the neighborhood information (the graph structure), the open loop NE can then be obtained in a distributed manner, where each sensor node solves iteratively an optimization problem given the actions of neighboring nodes in the previous

iteration. Several algorithms were developed in the literature, for more algorithmic details see [28].

Obtaining the open loop NE using a distributed iterative algorithm is desirable in many control applications. However, for the EH-WSN DG using distributed iterative algorithms are challenging for the following reasons: First, an open loop NE needs to be computed for each planning game, and only the control vector at the first time slot is applied. Second, information exchange (i.e., the control vectors) needs to be carried on after each iteration, which entails communication overheads and energy consumptions which may not be ignored. Third, the iterative algorithm needs to converge before the RH is shifted, otherwise a suboptimal solution (action) will be applied.

In EH-WSN it is more desirable to find optimal solution (or a suboptimal solution) that avoids any iterative procedure and as well as avoids information exchange after each iteration. Non-iterative schemes for solving control problems are usually conservative due to the fact that local control actions are based on restricted/worst-case assumptions regarding neighboring subsystems [28]. In this sense, we develop a distributed non-iterative algorithm at each sensor node based on the following assumptions: 1) Sensor node S_i knows its own dynamics but not the dynamics of other sensor nodes. 2) Sensor node S_i knows its neighborhood set $\mathcal{N}_i$, and the initial buffer states of neighboring sensor nodes. 3) Sensor node S_i exchanges within its neighborhood the buffer state only once for each RH game.

The utility function of sensor node S_i based on the above assumption is expressed as:

$$\tilde{\mathcal{J}}_s^{(i)}(C, e^{(i)}) = \sum_{k=s}^{s+N} \tilde{C}_k^T Q_k^{(i)} \tilde{C}_k + \sum_{k=s}^{s+N-1} e_k^{(i)T} R_k^{(i)} e_k^{(i)}. \quad (13)$$

where the weighting matrix of the buffer state $Q_k^{(i)} \geq 0$ is chosen to be the Laplacian matrix $Q_k^{(i)} = \mathcal{D} \Omega_k^{(i)} \mathcal{D}^T$ with $\Omega_k^{(i)} = \text{diag}(\omega_k^{(i)})$, where each element in the vector $\omega_k^{(i)}$ represents the edge worth with respect to sensor node S_i . An edge that is not connected to node S_i has zero weight.

The control problem of sensor node S_i for a horizon of length N (i.e., $k = s, \dots, s+N$) is then expressed as:

$$\min_{u^{(i)}} \tilde{\mathcal{J}}_s^{(i)}(C, e^{(i)}), \quad (14a)$$

$$\text{s.t. Given } E_s^{(i)}, C_s^{(i)}, C_s^{(j)}, \forall j \in \mathcal{N}_i \quad (14b)$$

$$E_{t+1}^{(i)} = E_t^{(i)} - T \sum_{j \in \mathcal{N}_i} e_k^{(i,j)}, \quad t = s, \dots, s+N-1, \quad (14c)$$

$$C_{t+1}^{(i)} = C_t^{(i)} - \sum_{j \in \mathcal{N}_i} r_t^{(i,j)}, \quad t = s, \dots, s + N - 1, \quad (14d)$$

$$C_{t+1}^{(j)} = C_t^{(j)} + r_t^{(i,j)}, \quad \forall j \in \mathcal{N}_i, \quad t = s, \dots, s + N - 1, \quad (14e)$$

$$T \sum_{k=0}^s \sum_{j \in \mathcal{N}_i} e_k^{(i,j)} \leq E_0^{(i)} + \sum_{k=0}^{s-1} H_k^{(i)}, \quad (14f)$$

$$\sum_{k=0}^s \sum_{j \in \mathcal{N}_i} r_k^{(i,j)} \leq C_0^{(i)} + \sum_{k=0}^{s-1} \sum_{j \in \mathcal{N}_i} r_k^{(j,i)} + \sum_{k=0}^{s-1} d_k^{(i)}, \quad (14g)$$

$$(4), (5), (6), \text{ \& } (7). \quad (14h)$$

The received data from the neighborhood at time slots $s, \dots, s + N - 1$ are unknown to the sensor node, hence, they are excluded in the system dynamics (14d)-(14e) and treated as disturbances. In this approach, dynamic coupling is taken into account as disturbance. The RH framework handles not only the effect of unknown harvested energy and sensed data in future time slots but also the effect of the coupled dynamics.

Since (14) is a convex optimization problem (i.e., quadratic-linear programming with convex constraints), it can be solved using different numerical techniques such as the interior point method. In problem (14) no need for an iterative algorithm with information exchange to find the open loop NE, each sensor node solves a decoupled optimization problem given the initial states.

After each sensor node applies its control vector obtained from solving (14) at time-slot s , the buffer and the battery states are measured at each sensor node, the measured buffer state is shared within the set of neighboring sensor nodes, and the procedure is repeated again. The EH-WSNs distributed RH approach is illustrated in Algorithm 1.

The greatest part of energy is spent by the peripherals, especially by the radio module and a lot of power-saving mechanisms exploit the energy consumption reduction of the RF module as in [29]. In [30], the energy cost of the processing circuitry is taken into account in an energy harvested broadband communication channel, where the processing cost is considered constant for each active channel use. The same approach can be applied to our problem, i.e., a constant energy cost which can be subtracted from the energy level at each-time slot for processing (finding the open-loop NE). Applying this approach will not change or affect the type of the problem or the solution approach, the dynamics and the constraints can be modified to take into account the processing cost. The size of the harvesting panel may need to be adjusted to account for the extra processing energy cost. In [31], the problem of power management of wireless sensor network is addressed using a RHC

Algorithm 1 Online Operation of Sensor Node S_i

- 1: **Given** the network parameters: $T, W, N_0, N, \mathcal{N}_i, Q_k^{(i)}, R_k^{(i)}, C_{\max}^{(i)}, E_{\max}^{(i)}, h^{(i,j)}, C_{\max}^{(j)}$ and $E_{\max}^{(j)}$.
 - 2: **Initialize** $s = 0$,
 - 3: **while** Stopping criterion is not satisfied **do**
 - 4: Sensor node S_i **measures** the states $E_s^{(i)}$ and $C_s^{(i)}$.
 - 5: Sensor node S_i **transmits** the state $C_s^{(i)}$ to sensor node $S_j, \forall j \in \mathcal{N}_i$.
 - 6: Sensor node S_i **receives** the state $C_s^{(j)}$ from sensor node $S_j, \forall j \in \mathcal{N}_i$.
 - 7: Sensor node S_i **solves** (14).
 - 8: Sensor node S_i **applies** the control $e_s^{(i)}, r_s^{(i)}$ and $l_s^{(i)}$.
 - 9: **Update** $s = s + 1$.
 - 10: **end while**
-

framework and the proposed solution was implemented using a low cost testbed. The objective function is formulated as mixed integer constrained quadratic programming, which is more complex than solving (14) (i.e., constrained quadratic programming problem) as in our paper. Therefore, following the same lines, we believe that the proposed algorithm can be implemented in low-cost testbeds with limited memory and computational capabilities.

IV. SIMULATION RESULTS AND DISCUSSION

The system parameters are based on the IEEE 802.15 standard as in [32]. The EH-WSN under investigation consists of 6 sensor nodes as shown in Fig. 3. Sensor nodes $\{S_1, \dots, S_5\}$ are aiming to transmit their data to the sink node S_6 . The channel coefficients $h_k^{(i,j)}$ are modeled as zero mean complex Gaussian with variance $h^{(i,j)} \sim \mathcal{CN}(0, \frac{\kappa}{d_{i,j}^\alpha})$, where $d_{i,j}$ is the separating distance between any two sensor nodes S_i and S_j , $\alpha = 4$ is the propagation loss factor and $\kappa = 0.01$ is the propagation gain. The xy -coordinates (x_i, y_i) in meters of sensor node S_i for $i = 1, \dots, 6$ are as $(x_1, y_1) = (10, 30)$, $(x_2, y_2) = (0, 20)$, $(x_3, y_3) = (20, 20)$, $(x_4, y_4) = (10, 10)$, $(x_5, y_5) = (30, 10)$ and $(x_6, y_6) = (20, 0)$.

The incidence matrix $\mathcal{D}$ of the EH-WSN in Fig. 3 is obtained as:

$$\mathcal{D} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & -1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & -1 & -1 \end{bmatrix}.$$

We assume time-independent weighting matrices, i.e., $Q_k^{(i)} = Q^{(i)}$ and $R_k^{(i)} = R^{(i)}$. We assume the weighting

Fig. 3: The investigated scenario: EH sensor nodes $\{S_1, \dots, S_5\}$ are aiming to transmit their data to the sink node S_6 .

vectors $\omega^{(i)}$ for $i = 1, \dots, 5$, are:

$$\omega^{(1)} = [1, 1, \mathbf{0}_{1 \times 5}], \quad \omega^{(2)} = [1, 0, 1, \mathbf{0}_{1 \times 4}], \quad \omega^{(3)} = [0, 1, 0, 1, 1, 0, 0], \\ \omega^{(4)} = [0, 0, 1, 1, 0, 1, 0], \quad \text{and} \quad \omega^{(5)} = [\mathbf{0}_{1 \times 4}, 1, 0, 1],$$

where $\mathbf{0}_{n \times m}$ is the all zeros matrix of size $n \times m$. The weighting matrices $\mathbf{R}^{(1)} = \mathbf{R}^{(2)} = \mathbf{R}^{(5)} = \mathbf{I}_2$, and $\mathbf{R}^{(3)} = \mathbf{R}^{(4)} = \mathbf{I}^{(3)}$, where $\mathbf{I}_n$ is the $n \times n$ identity matrix.

The harvested energy of sensor node S_i in time-slot k is computed as $H_k^{(i)} = TA\eta\mathcal{I}$, where A is the solar panel area, η is the conversion efficiency, which typically ranges between 15% and 20%. The solar irradiance is $\mathcal{I}$ modeled as a Gaussian random variable generated using a four-state-Hidden-Markov model with parameters specified in Table II in [33]. The area of the solar panel is 1 cm^2 and the conversion efficiency is assumed $\eta = 20\%$. The sensed data $d_k^{(i)}$ of sensor node S_i for $i = 1, \dots, M$ in time-slot k are modeled as Poisson random variables with an arrival packet rate $\lambda = 0.6$ packets/s and packet size of 200 bits. The energy and data arrivals of all sensor nodes are independent identically distributed [34].

The maximum buffer capacity is $C_{\max}^{(i)} = 100$ kbits for $i = 1, \dots, 5$ and $C_{\max}^{(6)} = 1$ Mbits. The maximum battery capacity is $E_{\max}^{(i)} = 10$ Joules for $i = 1, \dots, 5$. The transmission bandwidth $W = 100$ KHz, the time-slot duration $T = 1$ ms, and the noise power $N_0 = -70$ dBm.

In this paper, we compare the solution of DG-RHNC in (11) (coupled dynamics) and (14) (decoupled dynamics) with the offline approach. The offline resource allocation problem is formulated assuming that all future data and energy arrivals of all sensor nodes are known non-causally and presented in Appendix A. We consider two scenarios: In Scenario 1, we aim to show how the proposed DG-RHNC is used to transmit the sensed data to the sink node. In this sense, only sensor node S_1 has data to transmit. Whereas, in Scenario 2, we aim to show

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
$C_k^{(1)} (14)$	100	33.3	33.3	20.7	20.7	14.6	14.6	10.6	10.6	7.9	7.7	5.6	5.6	4.0	4.0	S_1
$C_k^{(2)} (14)$	0	33.3	17.1	20.7	13.7	14.6	10.6	10.6	7.3	7.7	5.3	5.6	3.8	4.0	2.8	S_2
$C_k^{(3)} (14)$	0	37.1	24.1	16.6	11.4	7.9	5.4	3.7	2.6	1.8	1.2	0.8	0.6	0.4	0.3	S_3
$C_k^{(4)} (14)$	0	0	27.0	6.3	16.2	5.2	11.4	3.9	8.3	2.8	6.0	2.0	4.3	1.5	3.2	S_4
$C_k^{(5)} (14)$	0	0	10.9	1.1	9.2	0.9	6.8	0.6	5.0	0.5	3.6	0.3	2.6	0.2	1.9	S_5
$C_k^{(6)} (14)$	0	0	0	30.6	30.6	50.0	50.0	63.7	63.7	73.7	73.7	80.9	80.9	86.1	89.9	S_6

Fig. 4: Scenario 1: The buffer value of DG-RHNC in (11) and (14) for S_i , $i = 1, \dots, 6$ at each time-slot k .

Fig. 5: Scenario 1; the buffer state using the DG-RHNC in (11), (14) and offline approaches for S_i , $i = 1, \dots, 6$ as a function of the time-slot k .

how the proposed DG-RHNC is used to balance the data buffers and the battery states of all sensor nodes. Hence, sensor nodes S_i for $i = 1, \dots, 5$, are all assumed to have data to transmit.

Figs. 5 & 6 show the buffer and the battery state vectors for the proposed DG-RHNC in (11), (14) and offline approaches for scenario 1, where one data packet arrived at sensor node S_1 at $k = 1$. For this scenario the receding horizon length $N = 5$, and $K = 15$ time-slots are assumed. The values of the buffer state for DG-RHNC in (11) and (14) are tabulated in Fig. 4. Examples, $C_1^{(i)} = 100$ bits as shown in row 1 and column 1 of sub-table 1, $C_{15}^{(i)} = 4$ bits using (14) as shown in row 1 and column 15 of sub-table 1.

The solutions of the DG-RHNC in (11) and (14) and

Fig. 6: Scenario 1; the battery state using the DG-RHNC in (11), (14) and offline approaches for S_i , $i = 1, \dots, 5$ as a function of the time-slot k .

TABLE I: The NSEs of the DG-RHNC in (14) compared to (11).

N	ϵ_C^2	ϵ_E^2	ϵ_J^2
10	6.8×10^{-2}	2.2×10^{-5}	2.8×10^{-2}
5	7.0×10^{-2}	4.2×10^{-5}	2.9×10^{-2}
3	7.1×10^{-2}	7.5×10^{-5}	3.2×10^{-2}

the offline approaches were obtained using CVX MATLAB toolbox (i.e., interior-point-method) [35]. Clearly, the proposed DG-RHNC in (11) and (14) successfully achieve the desired objective of transmitting the data of sensor node S_1 to the sink node S_6 . It is noticed that an oscillatory behavior of the buffer state may appear using the proposed (14), this is due to lack of cooperation between sensor nodes. The actions of the other sensor nodes, the harvested energy and the sensed data in the future time slots are assumed disturbances. Whereas, in (11) only the harvested energy and sensed data in the future time slots are assumed disturbances. The proposed DG-RHNC in (11) and (14) have the same trend as the offline approach of transmitting the data of sensor node S_1 to the sink node S_6 .

To evaluate the performance of the proposed DG-RHNC in (14) compared to (11), the normalized-squared-error (NSE) of the buffer state vector ϵ_C^2 , the battery state vector ϵ_E^2 and the cost function ϵ_J^2 are used. The NSEs are defined as $\epsilon_C^2 = \frac{\|C_{(14)} - C_{(11)}\|_2^2}{\|C_{(11)}\|_2^2}$, $\epsilon_E^2 = \frac{\|E_{(14)} - E_{(11)}\|_2^2}{\|E_{(11)}\|_2^2}$ and $\epsilon_J^2 = \frac{|\mathcal{J}_{(14)} - \mathcal{J}_{(11)}^*|^2}{|\mathcal{J}_{(11)}^*|^2}$, where $C_{(11)}$, $E_{(11)}$ and $\mathcal{J}_{(11)}^*$ are the buffer state vector, the battery state vector, and the cost function using the DG-RHNC in (11), respectively, and $C_{(14)}$, $E_{(14)}$ and $\mathcal{J}_{(14)}^*$ are the buffer state vector, the battery state vector, and the cost

Fig. 7: The harvest energy is modeled using a Markov model as in [33].

Fig. 8: The sensed data are modeled as Poisson random variables as in [34].

function using the DG-RHNC in (14), respectively.

The NSEs are shown in Table I. Clearly, the small values of the NSEs, demonstrate that the proposed decoupled approach in (14) can be used successfully for the operation of EH-WSNs. The NSEs performance, show that a short horizon length can be used with marginal increase in the NSEs.

Figs. 7 & 8 show the harvested energy and sensed data of Scenario 2. The battery and buffer states of the DG-RHNC in (11), (14) and offline approaches for $N = 5$ and $K = 100$ are shown in Figs. 9 & 10, respectively. $K = 100$ is selected as the length of the time horizon in EH-WSNs as in [32], [36]. Clearly, the proposed DG-RHNC in (11) and (14) have the same trend of transmitting the sensed data and saving the harvested energy. The proposed DG-RHNC in (14) can be used to balance the buffer and the stored energy of all sensor

Fig. 9: Scenario 2; the buffer state using the DG-RHNC in (11) and (14) and the offline for S_i , $i = 1, \dots, 6$ as a function of time-slot k .

Fig. 10: Scenario 2; the battery state using the DG-RHNC in (11) and (14) and the offline for S_i , $i = 1, \dots, 5$ as a function of time-slot k .

nodes, i.e. the buffer and the battery states of sensor nodes $S_1, \dots, S_5$ at $k = 100$ are almost the same.

V. CONCLUSION

In this paper, we propose an online power control and data scheduling algorithm for EH-WSNs based on DG-RHNC. The cost function is formulated as a finite-time-constrained-linear-quadratic-programming aiming to balance the buffer states of all sensor nodes and minimize the amount of energy used for data transmission. The open loop RH Nash equilibrium is used as a solution to the proposed EH-WSN DG. The effect of the receding horizon length on the NSE of the buffer and battery states is investigated. The NSEs of the buffer and the battery states, and the NSE of the cost function were used

to compare the performance of the proposed decoupled dynamic approach with the coupled dynamic approach.

APPENDIX

The offline resource allocation problem is formulated assuming that all future data and energy arrivals of all sensor nodes are known non-causally to a central unit before transmission. The objective (cost) of the resource allocation problem is formulated aiming to make a balance between using the harvested energy and emptying of the data buffers as:

$$\mathcal{J}(C, e) = \sum_{k=0}^K \tilde{C}_k^T Q_k \tilde{C}_k + \sum_{k=0}^{K-1} \sum_{i=1}^M e_k^{(i)T} R_k^{(i)} e_k^{(i)}, \quad (15)$$

where $C = [C_0^T, \dots, C_K^T]^T$ is the buffer state vector of all sensor nodes, $C_k = [C_k^{(1)}, \dots, C_k^{(M+1)}]^T$ is the buffer state vector of all sensor nodes at time-slot k , $e = [e_0^{(1)T}, \dots, e_{K-1}^{(1)T}, \dots, e_0^{(M)T}, \dots, e_{K-1}^{(M)T}]^T$ is the energy control vector of all sensor nodes and $e_k^{(i)} = [e_k^{(i,j)}]_{\forall j \in \mathcal{N}_i}$ is the energy control vector of sensor node S_i at time-slot k with $e_k^{(i,j)} = l_k^{(i,j)} P_k^{(i,j)}$. The offline resource allocation problem is formulated taking into consideration the limited capacity battery and buffer at each sensor node as:

$$\min_{r, l, e, C, E} \mathcal{J}(C, e), \quad (16a)$$

subject to:

$$\text{given } E_0 \text{ \& } C_0, \quad (16b)$$

$$(1)-(7), \text{ for } k = 0, \dots, K-1, \text{ \& } i = 1, \dots, M, \quad (16c)$$

where the transmitted data control vector r is defined as $r = [r_0^{(1)T}, \dots, r_{K-1}^{(1)T}, \dots, r_0^{(M)T}, \dots, r_{K-1}^{(M)T}]^T$. the time allocation control vector l is defined as $l = [l_0^{(1)T}, \dots, l_{K-1}^{(1)T}, \dots, l_0^{(M)T}, \dots, l_{K-1}^{(M)T}]^T$, with $l_k^{(i)} = [l_k^{(i,j)}]_{\forall j \in \mathcal{N}_i}$, and the battery state vector E is defined as $E = [E_0^{(1)}, \dots, E_K^{(1)}, \dots, E_0^{(M)}, \dots, E_K^{(M)}]^T$, with the initial energy state vector defined as $E_0 = [E_0^{(1)}, \dots, E_0^{(M)}]^T$. Similarly, the initial data state vector is defined as $C_0 = [C_0^{(1)}, \dots, C_0^{(M+1)}]^T$. Problem (16) is a convex optimization problem, since the objective function is a quadratic function and the constraints are convex.

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