Optimal Node Allocation in Multiservice WSNs Based on Correlated Strategy

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***Abstract*—A distributed game theoretic framework based on correlated strategies is proposed to maximize the lifetime of dense homogeneous multiservice wireless sensor networks (MS-WSNs), that support multiple services continually and ubiquitously over the WSN deployment. The MS-WSN operation is dealt with as a game played by the multimode nodes. A correlated strategies approach is proposed to lead the MS-WSN close to its theoretical optimal state with respect to the network lifetime. The computationally efficient correlated strategy proposed to implement service selection by the multimode WSN nodes is distributed, based solely on local information exchange. Indicative simulation results concerning the application of the proposed scheme on top of *k*-hop clustering reveal that the proposed correlated strategies based framework leads the MS-WSN operation close to its theoretical optimal at no significant exchange of overhead messages.**

***Index Terms*—Wireless sensor networks, lifetime maximization, game theory, correlated strategies, multiservice, multimodal, clustering.**

I. Introduction

THE OPERATION of Multi-Service Wireless Sensor Networks (MS-WSN) is defined over sets of diverse node activities that arise as a result of multiple sensing capabilities. A WSN *service* or *application* employs a subset of the nodes sensing capabilities to deliver relevant information to the WSN operator. Such sensing capabilities/services are usually related to temperature and/or humidity sensing, movement sensing, fire detection, landslide detection etc. [1], [2]. Often, the sensed phenomena exhibit spatio-temporal correlation, that is, the measurements performed by neighboring WSN nodes are correlated in either space or time. In this context and in the attempt to save energy, neighboring nodes may be allocated to sensing different services as, in this case, only a subset of their sensors will be activated. The nodes allocated to support a specific service form *service clusters*. In this paper, the various service clusters are assumed disjoint, i.e. a node can only serve a single service at a time. In this context, a specific sensing target is specified for every WSN service. Depending on the multiple WSN services supported, the MS-WSN operation is characterized by severe energy consumption heterogeneity, necessitating the deployment of WSNs capable of responding to the high energy consumption.

Node clustering in WSNs refers to the procedure of grouping cooperative nodes to maximize their energy efficiency. The majority of the clustering schemes proposed so far in the literature consider only single-service WSNs. Among the first distributed clustering schemes attempting dynamic WSN optimization is *LEACH* [3]. LEACH selects stochastically WSN nodes as *cluster heads* (CHs) that collect data from other nodes and forward it to the WSN sink, thus implementing hierarchical clustering. In [4], *TASC*, an adaptive WSN clustering scheme, is proposed based on balanced spatial clustering. Although TASC makes use of spatial clustering, it uses a priori acquired information and does not exploit effectively the inherent spatial correlation of the sensed physical phenomena. [5] introduces a *k*-hop clustering method that forms connected clusters of predefined size. A similar method is discussed in [6]. *k*-hop clustering leads to the formation of clusters comprising nodes that are at most *k*-hops away from their CHs. CHs are also employed in [7], where data aggregation based on clustering is examined, with a focus on reliability and coverage. CHs and relay nodes have been also employed to form energy-efficient clusters on the basis of a distance-based algorithm that ensures uniform energy dissipation across the whole WSN deployment [8]. Spatio-temporal clustering is discussed in [9] where an adaptive scheme for hybrid clustering is presented according to which the nodes operate based on the perceived spatio-temporal behavior of the target phenomenon and not on measured data. Depending on the characteristics of the target phenomenon, the use of multiple levels of data aggregation/compression that depend on the characteristics of the target phenomenon is proposed in [10], where a hierarchical clustering scheme is presented. Coalitional game theory is combined with the notion of the *bargaining set* in [11] in order to form clusters of cooperating nodes that collectively increase the WSN lifetime. However, the case of multiple services is not examined. A review of the most recent non-typical hierarchical clustering schemes can be found in [12].

Recently, heterogeneous WSN architectures are explored in the attempt to address the increasing demand for ubiquitous, multimodal operation [13]. A LEACH variant is proposed in [14] that deals with node heterogeneity by properly taking into account the energy reserves of the WSN nodes, whereas [15] presents a multi-modal WSN paradigm for environmental monitoring. [16] demonstrates the application of multi-modal

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WSNs in the framework of critical infrastructure protection, whereas [17] presents a hierarchical multi-modal WSN architecture that aims at securing critical infrastructures. In [18], a distributed clustering method for heterogeneous WSNs is proposed based on coalitional game theory. In [19], the clustering scheme proposed in [18], is investigated in the attempt to address multiple services assuming that the nodes are capable of joining as many clusters as the number of WSN services. A scheme that clusters cooperative nodes employing non-cooperative game theory is proposed in [20], in the attempt to achieve energy efficient task allocation in heterogeneous WSNs. [20] employs CHs that coordinate the operation of ordinary nodes from a task-oriented perspective. Although the results of this work seem to match multi-modal WSN operation, the approach is based on serving time-limited tasks in the context of a single service. Finally, in [21], *EDIT*, an algorithm managing the trade-off between energy consumption and delay is presented that aims at supporting WSN applications characterized by different delay specifications. However, the focus of [21] is mainly on proper CH selection for delay-critical applications, rather than on guaranteeing ubiquitous MS-WSN coverage.

This work proposes a service clustering scheme of low complexity that maximizes the MS-WSN lifetime by appropriately forming service clusters based on correlated strategies. Homogeneous MS-WSNs are assumed comprising nodes equally capable of serving any of the available services. Proper MS-WSN operation requires that all the services are supported, continually and ubiquitously, over the MS-WSN deployment area. Since MS-WSN lifetime maximization is inseparably related to the prolongation of the ubiquitous coverage of all the services without exception, optimal node allocation to service clusters is necessary. To acquire an additional benefit from service clustering, the MS-WSN nodes exchange information about the energy profile of all the services supported and autonomously choose to serve the service that maximizes their expected lifetime under a max-min criterion. The contribution of the proposed service clustering scheme is twofold: (i) the correlated strategies approach proposed to model the nodes behavior in homogeneous MS-WSNs leads to lifetime maximization and the proposed node allocation scheme is both distributed, as the nodes operation requires only the local exchange of a small number of overhead messages, and adaptive to changes in either the number or the energy profile of the multiple services supported. The proposed scheme can be applied on top of any single-service node clustering, aggregation, or task allocation scheme.

The rest of the paper is organized as follows. In Section II, the theoretical equilibrium MS-WSN state is determined as the optimal nodes allocation to the various services in the framework of maximizing the duration of ubiquitous service coverage. Section III analyzes the proposed game theoretic approach based on correlated strategies, whereas Section IV presents the relevant implementation scheme. The simulations carried out to validate the proposed scheme and explore its various aspects are presented in Section V. Finally, Section VI concludes the paper.

II. Theoretical Considerations

The MS-WSN lifetime is defined as the time period during which all the services without exception are ubiquitously served by the MS-WSN. This definition conforms with the common definition of WSN lifetime as the time until the first WSN node runs out of energy resources and directs the relevant design toward maximizing the minimum expected lifetime of all services [22]. To determine the optimal node clustering, the following design targets should be accomplished:

T.1 Guarantee ubiquitous coverage of all the services.
T.2 Maximize the MS-WSN lifetime.
T.3 Guarantee fair support of all the services.

As to the first target, this work considers the MS-WSN lifetime inseparably associated to the necessity for ubiquitous service coverage. On the other hand, both lifetime maximization and inter-service fairness necessitate the symmetric support of all the MS-WSN services, in the sense that, at the MS-WSN steady state, equal service duration should be imposed on all the services supported. Since fairness and efficiency cannot be simultaneously optimized, the relevant trade-off should be appropriately managed.

A. Value Analysis Under Single-Service Clustering

Let us assume a WSN where $\mathcal{N} = \{n_1, n_2, \ldots, n_N\}$ is the set of the WSN nodes serving a single WSN service, say s_j. The *single-service value* of a node, hereafter referred to as node value, represents the prolongation of its lifetime due to its clustered behavior. Let $v(n_i, s_j)$ be the function assigning value to cooperating WSN nodes. Evidently, $v(n_i, s_j)$ depends on (i) the particular clustering scheme applied to cluster the WSN nodes and (ii) the characteristics of the target phenomenon. To comply with the design targets already mentioned, v should depend only on the service served and not on the specific nodes serving it [18]; consequently, at steady state:

$$v(n_i, s_j) = v(s_j), \forall n_i \in \mathcal{N} \tag{1}$$

An indicative node clustering approach adopting the above principle is k-hop clustering, outlined in Appendix A.

B. Value Analysis Under Multiservice Clustering

Let us consider a dense[1] homogeneous MS-WSN where any node belonging to $\mathcal{N}$ is capable of serving any service belonging to the set of available services $\mathcal{S} = \{s_1, s_2, \ldots, s_S\}$. The energy characteristics of service s_j are represented by the triade $[E_j^s, T_j, f_j]$, where E_j^s is the energy required to perform a sensing task related to the target phenomenon of s_j, T_j is the average duration of a single reporting of sensed data and f_j is the reporting frequency of s_j defined as the number of messages reported per reporting cycle. For simplicity, let us assume that (i) the MS-WSN is sufficiently dense so that the mean distance between 1-hop neighbors may be considered constant and

[1] A WSN is dense when its nodes can acknowledge the presence of a sufficient number (of the order of several tens) of nodes within their transmission range [23].

the energy consumed per message transmission is proportional to the message size [24]. Then, assuming that the transmission duration T_j is constant, it is easily deduced that the average energy consumed per message trasmission, E_j^t, is also constant [25]. Note that T_j depends on the message length of the reportings related to the target phenomenon of s_j whereas f_j depends on the temporal correlation and the QoS level specified for s_j; hence, T_j and f_j are not related. Practically, though E_j^s and E_j^t depend solely on the respective sensed phenomenon, f_j may vary to address multiple QoS levels, if necessary. Taking the preceding arguments into account, the energy per reporting cycle e_j consumed by a node to properly serve s_j is given from

$$e_j = \left(E_j^s + E_j^t\right) \cdot f_j \tag{2}$$

Hence, the total number of reporting cycles, γ_j, that a node can perform when it serves service s_j is given from

$$\gamma_j = \frac{E_o}{e_j} = \frac{1}{f_j} \cdot \frac{E_o}{E_j^s + E_j^t} \tag{3}$$

where E_o is the initial nodes energy. Hereafter, as γ_j determines the energy profile of service s_j, it will be used as the respective metric.

Consider an MS-WSN where $\mathcal{C}$ is the set of all possible service clusters. In particular, $\boldsymbol{C}(s_j)$ denotes the set of clusters comprising the nodes that serve service s_j. The information exchange procedure between a node n_i and the rest of the nodes is denoted by $\phi(n_i, \boldsymbol{n}_{-i})$[2]. In addition to the direction of information exchange, $\phi(n_i, \boldsymbol{n}_{-i})$ also incorporates the type of exchanged information. Moreover, $\mathfrak{I}(n_i)$ denotes the *information neighborhood* of n_i, namely the set of nodes with which node n_i can exchange information, either directly or indirectly. Depending on the implementation of $\phi(n_i, \boldsymbol{n}_{-i})$, $\mathfrak{I}(n_i)$ may contain more nodes than the 1-hop neighborhood of n_i, $\boldsymbol{NG}(n_i)$, i.e. $\mathfrak{I}(n_i) \supseteq \boldsymbol{NG}(n_i)$. $\mathfrak{I}(n_i)$ reflects the knowledge that node n_i has acquired about the MS-WSN.

Proper MS-WSN operation requires that all services are continually supported over the whole WSN deployment area[3]. Otherwise, the overall network utility is nullified as the MS-WSN fails to ubiquitously accomplish its multi-task operation. Hence, the multi-service node payoff must explicitly take into account the necessity for ubiquitously serving all the services. In this respect, to their *own knowledge*[4], the nodes should be aware of whether all the services are ubiquitously served. The necessity for ubiquitous/universal coverage of all the WSN services is taken into account via the ubiquitous/universal coverage indicator (UC indicator):

$$c(n_i, s_j) = \begin{cases} 1 & \text{if } \exists n_m : n_m \in \mathfrak{I}(n_i) \text{ s.t. } n_m \in \boldsymbol{C}(s_j), \\ & \boldsymbol{C}(s_j) \in \mathcal{C},\ |\boldsymbol{C}(s_j)| \geq 1 \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

[2]Hereafter, the subscript $-i$ will denote the set $\mathcal{X} \setminus \{x_i\}$, i.e. $\boldsymbol{x}_{-i} = \mathcal{X} \setminus \{x_i\}$.

[3]Certain services may be available only in a specific segment of the MS-WSN deployment area. The necessary modification of the ongoing analysis is easy to make and will not be given in this work.

[4]The knowledge of a node quantifies how a node perceives its environment via information exchange with its neighbors.

where $|\bullet|$ denotes the size of a cluster.

The above UC indicator definition reflects that n_i considers s_j unserved if neither n_i nor any of its neighbors serve s_j. In this context and to its own knowledge, node n_i considers service s_j *annihilated* if $c(n_i, s_j) = 0$. Taking into account the utility nullification of an MS-WSN when even one of its services is not served ubiquitously, the value of a node that temporarily annihilates a service should be zero.

Considering the above and assuming that the proposed scheme is applied on top of a single-service clustering scheme, the *multi-service* payoff (hereafter referred to simply as payoff) $\pi(n_i, s_j)$ of node n_i belonging to a service cluster serving s_j is expressed as

$$\pi(n_i, s_j) = \gamma_j \cdot v(s_j) \cdot c(n_i, s_j) \tag{5}$$

Equation (5) implies that, in addition to the single-service node value $v(s_j)$, the payoff of node n_i participating in a service cluster supporting service s_j takes also into account (i) the energy profile of this service and (ii) the UC indicator of this service as perceived by n_i. In this context, the payoff of MS-WSN nodes communicating via $\phi(n_i, \boldsymbol{n}_{-i})$ is directly related to the lifetime prolongation accomplished due to their cooperative/clustered behavior as opposed to being non-cooperative and expresses the maximum number of reportings that they can perform.

The ubiquitous service coverage perceived by the MS-WSN nodes is based only on the local knowledge represented by the UC indicator. Consequently, the nodes information neighborhoods should be sufficiently large to guarantee ubiquitous service coverage, hence necessitating the deployment of sufficiently dense MS-WSNs [26]. Hereafter, the terms neighborhood and neighbors will be used to denote an information neighborhood and its members, respectively.

C. Optimal Nodes Allocation

Consider an MS-WSN comprising N nodes and S services where the nodes destined to serving s_j are allocated to service clusters $\boldsymbol{C}(s_j)$. If a_j is the proportion of the MS-WSN nodes allocated to $\boldsymbol{C}(s_j)$, then $|\boldsymbol{C}(s_j)| = \alpha_j \cdot N$, $j = 1, 2, \ldots, S$ with $\sum_{j=1}^{S} a_j = 1$. Evidently, $N = \sum_{s_j \in \mathcal{S}} |\boldsymbol{C}(s_j)|$. The maximum service duration of any service cluster $\boldsymbol{C}(s_j)$ is given from

$$\begin{aligned} T(s_j) &= \sum_{n_i \in \boldsymbol{C}(s_j)} \pi(n_i, s_j) = \gamma_j \cdot v(s_j) \cdot \sum_{n_i \in \boldsymbol{C}(s_j)} c(n_i, s_j) \\ &= \gamma_j \cdot v(s_j) \cdot \langle s_j \rangle \end{aligned} \tag{6}$$

where $\langle s_j \rangle = |\boldsymbol{C}(s_j)|$ denotes the number of nodes that serve service s_j. In deriving the right hand of (6), the UC indicator is taken equal to 1. To conform with the requirement that, at the MS-WSN steady state, equal service duration should be imposed on all the services supported, the optimal nodes allocation to the S services supported by an MS-WSN is determined by solving for α_j the following set of $\binom{S}{2} + 1$ equations

$$T(s_i) = T(s_j), \quad \forall s_i, s_j \in \mathcal{S}, s_i \neq s_j \tag{7}$$

which is equivalent to the set of equations

$$\gamma_i \cdot v(s_i) \cdot \alpha_i = \gamma_j \cdot v(s_j) \cdot \alpha_j, \quad \forall s_i, s_j \in \mathcal{S}, s_i \neq s_j \tag{8}$$

$$\sum_{j=1}^{S} \alpha_j = 1 \tag{9}$$

Equations (8) and (9) determine the theoretical optimal nodes allocation to the S available services of the MS-WSN.

D. Dynamic MS-WSN Operation

Assume that, at a time instance t_0, an MS-WSN has reached the steady state where its nodes are optimally allocated to $m - 1 < S$ services, namely services $s_1, s_2, \ldots, s_{m-1}$, as imposed by (8) and (9) when applied for $m - 1$ services. Suppose that, at a later time instance t_1, the support of a new service, say $s_m, m \leq S$, is initiated. Then, $\phi(n_i, \boldsymbol{n}_{-i})$ should ensure that the MS-WSN nodes:

1) become aware of the initiation of s_m and of its energy profile metric γ_m.
2) perform the minimum state changes to form the new service clusters that constitute the new steady state.

In this course, the nodes are re-allocated to the services each time supported by the MS-WSN so that nodes leave service clusters serving less energy demanding services to join service clusters serving more energy demanding services. In any case, to guarantee ubiquitous coverage of all the services, the nodes re-allocation should conform with (8) and (9).

III. The Proposed Distributed Game Theoretic Approach

Next, a distributed game theoretic approach is proposed to implement the theoretical optimal MS-WSN nodes distribution which is defined by (8) and (9).

A. Correlated Equilibrium

A critical notion related to game theory is the *equilibrium* [27] which is generally defined as the strategy profile that is optimal for all players, i.e. no player will get a better payoff if it deviates from its behavior at equilibrium. As numerous stability criteria exist and various optimization targets may be set, many types of equilibria have been proposed, the *Nash Equilibrium* (NE) being the most frequently considered. Formally, a strategy profile (i.e. a set of strategies followed by the game participants) $\boldsymbol{G}^* = \left\{G_1^* \times \ldots \times G_{|\mathcal{N}|}^*\right\}$ is a NE if no unilateral deviation from $\boldsymbol{G}^*$ is to the benefit of any player [28], i.e.

$$\pi(G_i^*, \boldsymbol{G}_{-i}^*) \geq \pi(G_i', \boldsymbol{G}_{-i}^*), \quad \forall G_i' \neq G_i^*, \ \forall n_i \in \mathcal{N} \tag{10}$$

where G_i^* is the strategy followed by n_i at NE and G_i' is any other strategy that player n_i may choose.

Stability in multi-player games cannot always be determined nor guaranteed. Moreover, the existence of a NE requires the validity of several conditions that may be too stringent. In the MS-WSN under consideration, neither players rationality nor full game knowledge can be guaranteed on a per node basis since the number of messages that can be exchanged by the MS-WSN nodes is usually limited.

The *Correlated Equilibrium* (CE) can effectively cope with the lack of full knowledge in a game. Being closer to the mixed strategies concept, the correlated strategies are defined as probability distributions over the players actions space. In this work, the players (nodes) actions space consists of the S services supported by the MS-WSN belonging to $\Omega = \{s_1 \times s_2 \times \ldots \times s_S\}$ [29]. A correlated strategy $\boldsymbol{p}^* = \{\boldsymbol{p}_1^* \times \boldsymbol{p}_2^* \times \ldots \times \boldsymbol{p}_S^*\}$ is a CE if the *expected* payoff when the players follow $\boldsymbol{p}^*$ is at least as much as the payoff that the players expect when deviating from $\boldsymbol{p}^*$, that is $\forall n_i \in \mathcal{N}, s_j \in \mathcal{S}$

$$\sum_{\boldsymbol{p}_j^*(n_i) \in \boldsymbol{p}^*} \boldsymbol{p}_j^*(n_i) \cdot \pi(n_i, s_j) \geq \sum_{\boldsymbol{p}_j(n_i) \notin \boldsymbol{p}^*} \boldsymbol{p}_j(n_i) \cdot \pi(n_i, s_j) \tag{11}$$

where $p_j(n_i)$ denotes the probability that player n_i chooses service s_j and $\pi(n_i, s_j)$ is the corresponding expected payoff. In contrast to the NE where the game players simultaneously choose which action to perform, the CE makes use of a signaling (information exchange) mechanism informing the players about events that may affect their decisions, i.e. the players strategies are correlated. To apply CE theory in energy constrained homogeneous MS-WSNs, the nodes choose which service to serve based on the knowledge about their neighborhood acquired via the signaling mechanism.

B. The Proposed Correlated Strategies Based Framework

The proposed correlated strategies approach aims at ensuring that the nodes optimize their active participation in the MS-WSN by autonomously choosing which service to serve. In this distributed framework, to optimize the nodes allocation to the services supported by an MS-WSN, the proposed game is defined as a triade $\langle \mathcal{N}, \mathcal{G}, \pi \rangle$, where $\mathcal{N}$ is the set of WSN nodes, $\mathcal{G}$ is the set of correlated strategies and π is the payoff function of the game. An action is defined as a service choice made by a node. To select its strategy, a node must determine the respective payoff which should satisfy the following requirements:

- R.1 As the proposed scheme aims at maximizing the MS-WSN lifetime, the payoff should reflect the expected energy benefit when a node selects a strategy.
- R.2 To reduce energy consumption and also to effectively adapt to service changes, the information exchange required per node for payoff evaluation should be minimum but sufficient to ensure fast convergence to the CE.

As the nodes can acquire only local information about the MS-WSN and do not have a clear knowledge about the nodes allocation over the whole the MS-WSN deployment, the exact nodes payoff is not known since (5) cannot be directly applied. Instead, the nodes have to determine their multi-service payoffs based on their estimation of how the nodes in their neighborhoods are allocated to the services supported by the MS-WSN. Hence, the expected multi-service payoff of node n_i serving service s_j in the framework of the proposed scheme should be determined from

$$\widehat{\pi}\left(n_i, s_j\right) = \gamma_j \cdot \widehat{v}\left(n_i, s_j\right) \cdot c\left(n_i, s_j\right) \tag{12}$$

where $\widehat{v}(n_i, s_j)$ is the estimation made by n_i of the value it will get when serving s_j. Equation (12) constitutes a modified version of (5) that takes into account that the nodes payoffs can only be estimated based on local information.

C. Optimal Nodes Allocation in Multiservice WSNs

To proceed with the formulation of the proposed scheme, consider a dense MS-WSN characterized by a constant mean node *degree*[5] $\overline{d}$. To manage how the nodes decide which service to serve, a correlated strategies approach is proposed that leads to a CE. In the framework of maximizing the MS-WSN lifetime, a node allocation game is formulated. The two-service WSN node allocation game is analyzed first, followed by its generalization to the multi-service case.

Consider a node $n_i \in \mathcal{N}$ in a two-service WSN where $\gamma_1 > \gamma_2$. Since the order of how the services are initiated does not affect the steady state of the MS-WSN operation, it may be assumed that, initially, n_i serves s_1. Then, assume that, at $t = t_0$, n_i must decide whether it should switch to s_2; also, let p denote the probability that n_i continues to serve s_1 and $1 - p$ the probability that n_i switches to serve s_2. The CE probability distribution is determined by equating the expected payoffs of n_i:

$$p \cdot \widehat{\pi}(n_i, s_1) = (1 - p) \cdot \widehat{\pi}(n_i, s_2) \tag{13}$$

Substituting the expected payoffs determined from (12) yields

$$p = \frac{\gamma_2 \cdot \widehat{v}(n_i, s_2) \cdot c(n_i, s_2)}{\gamma_1 \cdot \widehat{v}(n_i, s_1) \cdot c(n_i, s_1) + \gamma_2 \cdot \widehat{v}(n_i, s_2) \cdot c(n_i, s_2)} \tag{14}$$

The estimations $\widehat{v}(n_i, s_1)$ and $\widehat{v}(n_i, s_2)$ are made by n_i based on information acquired from its neighbors employing $\phi(n_i, \boldsymbol{n}_{-i})$. By correlating the estimations of $\widehat{v}(n_i, s_1)$ and $\widehat{v}(n_i, s_2)$, (14) forces the nodes to act to the benefit of the two-service WSN as a whole.

To generalize the preceding two-service WSN analysis, let $p(n_i, s_j)$ denote the probability that node n_i chooses to serve service s_j. As in the two-service case, the application of the payoff equating method $\forall n_i \in \mathcal{N}, s_j \in \mathcal{S}$ yields

$$p(n_i, s_j) \cdot \widehat{\pi}(n_i, s_j) = \left(1 - p(n_i, s_j)\right) \cdot \widehat{\pi}(n_i, \boldsymbol{s}_{-j}) \tag{15}$$

where $p(n_i, s_j)$ is the probability that n_i selects s_j at CE and $\widehat{\pi}(n_i, \boldsymbol{s_{-j}})$ denotes the average payoff that node n_i expects when it serves any service other than s_j. By recursively processing (15), $p(n_i, s_j), \forall n_i \in \mathcal{N}, s_j \in \mathcal{S}$ is determined from

$$p(n_i, s_j) = \frac{\prod\limits_{\substack{m=1\\ m\neq j}}^{S} \gamma_m \cdot \widehat{v}(n_i, s_m) \cdot c(n_i, s_m)}{\sum\limits_{k=1}^{S} \prod\limits_{\substack{m=1\\ m\neq k}}^{S} \gamma_m \cdot \widehat{v}(n_i, s_m) \cdot c(n_i, s_m)} \tag{16}$$

[5]The degree of a node is defined as the number of its 1-hop neighbors.

Equation (16) shows that, in order to maximize the MS-WSN lifetime, the multi-mode WSN nodes tend to serve under-served services. A careful examination of (16) also shows that due to the UC indicator, the probability that node n_i chooses a temporarily annihilated service s_j becomes equal to 1, to guarantee the ubiquitous coverage of all the services.

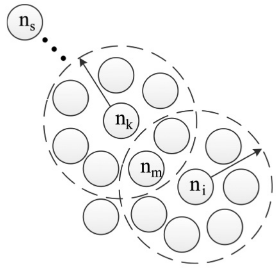
By equating the expected payoffs of a node as it is done in (15), the number of possible network states is significantly reduced because the nodes are not certain as to which service to serve. Moreover, the exchange of information that correlates the nodes strategic decisions reduces further the number of possible network states and leads to efficient CE calculation from both a computational and an energy consumption point of view. Finally, since for optimal service selection the nodes acquire the necessary information only from nodes in their neighborhood, the MS-WSN scalability is straightforward since the nodes behavior is solely dependent on local information acquired from a small number of the WSN nodes.

The equilibrium determined via Eq. (16) is a CE because no node can acquire a higher payoff if it deviates from the CE by adopting a different strategy. In fact, following the definition of CE given by Eq. (11) and assuming that a node adopts a strategy different from the one imposed by the CE, say the strategy of always selecting to serve the least energy-demanding service, its neighboring nodes may change their own service selections in the attempt to guarantee ubiquitous coverage of all the services. Hence, any better payoff expected from the node deviating from the CE is not guaranteed, as the other nodes may change their own service selections. Moreover, according to [30], (i) all games have at least one CE and (ii) (mixed) NE are also CE, that is, the set of correlated strategies is an extension of the set of mixed strategies. Taking into consideration that Eq. (16) is based on equating the expected payoffs of the players choosing their strategic actions (as it is done when determining mixed strategies), it is deduced that (16) determines a CE.

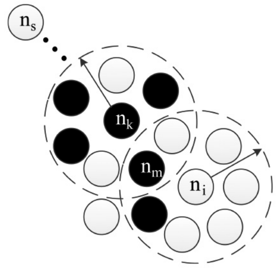
IV. The Proposed Scheme for MS-WSNs

Having analyzed the theoretical aspects of the proposed correlated strategies approach, the implementation of the relevant MS-WSN optimal operation will be presented. The proposed scheme is performed in three phases, namely the neighborhood detection, the optimization and the steady state phase. The last two phases are re-initiated whenever a change occurs either in the number or in the characteristics of the services supported by the MS-WSN.

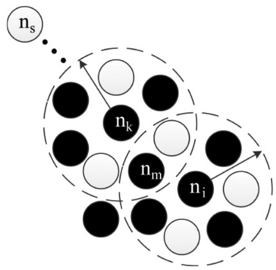
During the neighborhood detection phase, the nodes exchange messages in order to detect their information neighborhood. Upon completion of the first phase, the WSN operation enters the optimization phase, where the nodes perform a series of wait-optimize-transmit (WOT) operations. During the WOT operations, a node waits for a random period of time before deciding which service to serve following the proposed correlated strategies approach determined by (16). When a node selects a new service, it broadcasts a message to inform its neighbors; otherwise, the WOT operation ceases until a service change might be necessary. An indicative example of the



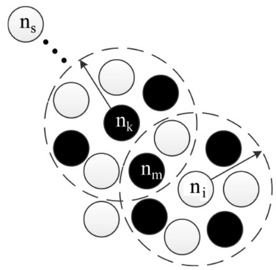
(a) Initial WSN deployment. Only s_1 is served.



(b) The first nodes acknowledging s_2 are more likely to choose serving it.



(c) The nodes temporarily prefer to serve s_2 as, to their own knowledge, they underestimate its support over the MS-WSN deployment.



(d) The nodes reconsider their initial choices, finally leading the WSN operation to its equilibrium.

Fig. 1. Schematic representation of the optimization phase of the proposed WSN multi-service operation. White circles represent nodes serving s_1 whereas black circles represent nodes serving s_2. The dashed circles indicate the neighborhoods of nodes n_k and n_i.

proposed correlated strategies based node allocation scheme is depicted in Fig.1.

The waiting period before a node decides which service to serve must allow for the collection of sufficient information in order to: (i) estimate as accurately as possible how the nodes in its neighborhood are allocated to the WSN services initiated up to that instant and (ii) perform as few service changes as possible in the attempt to avoid unnecessary messaging. As temporal service state variations aggravate the service selection procedure, since the estimated values $\widehat{v}(n_i, s_m)$ employed in (16) vary rapidly. In fact, the nodes acquire better knowledge of the service states in their neighborhood if they wait for long. Consequently, long waiting periods alleviate the effect of temporal variations, thus leading to a more accurate application of (16) which, in turn, results in significant energy saving. On the other hand, long waiting periods delay the completion of service clustering. The preceding trade-off affects significantly the overall MS-WSN performance, necessitating a compromise between the energy efficiency and speed of convergence to the theoretical CE, on the one hand, and the delay of the clustering operation, on the other.

In the proposed MS-WSN framework, the waiting period of node n_i is taken into account as a random variable uniformly distributed in $(1, 2 \cdot |\boldsymbol{NG}(n_i)|)$ with mean value proportional to the size of its $1 - hop$ neighborhood. Considering that, though the nodes can directly communicate only with their $1 - hop$ neighbors, the nodes also disseminate information regarding their information neighborhood, the probabilistic waiting period must, on average, provide sufficient time to acquire the information necessary for proper application of (16).

Another critical point of the optimization procedure is how to define its completion. Since the theoretical optimal nodes distribution is not known to the nodes, the completion of the optimization phase cannot be based on the difference between the actual nodes allocation, implemented applying (16), and the optimal nodes allocation, as determined applying (8) and (9). Also, the probability distribution given from (16), determining the actual service selection performed by the nodes, may not be sufficiently close to the theoretical optimal. Service state switches made by a single node affect the current CE probabilities and may lead to unceasing service state changes, known as *ping-pong effect*, which delays the clustering procedure and, at the same time, causes excessive overhead message exchange. The proposed scheme detects a ping-pong syndrome if a service state change sequence $s_j \to s_i \to s_j, \forall s_i, s_j \in \mathcal{S}, i \neq j$ is acknowledged. In this case, the nodes *lock* to service s_j, avoiding any further service switching unless a change in the MS-WSN operation occurs.

A. Case Study: The Proposed Scheme Combined With k-Hop Clustering

In this subsection, the proposed correlated strategy based scheme is examined in the framework of k-hop clustering, outlined in Appendix A. According to k-hop clustering and referring to Appendix A,

$$\widehat{v}(n_i, s_j) = d(n_i, s_j) \cdot k_j^2, \forall s_j \in \mathcal{S} \tag{17}$$

where $d(n_i, s_j)$ is the number of neighbors of node n_i that serve s_j.

Equation (17) implies that the expected payoff acquired applying k-hop clustering depends on (i) the node density and the k-value characterizing each service. Ignoring k-hop clustering specifics as to the selection of CH nodes, the expected payoff of node n_i when it serves s_j in the framework of multi-service operation on top of k-hop clustering is given from

$$\widehat{\pi}(n_i, s_j) = \gamma_j \cdot d(n_i, s_j) \cdot k_j^2 \cdot c(n_i, s_j) \tag{18}$$

Accordingly, the proposed service clustering scheme performed on top of k-hop clustering is based on the selection probabilities, $\forall n_i \in \mathcal{N}, s_j \in \mathcal{S}$:

$$p(n_i, s_j) = \frac{\prod\limits_{\substack{m=1 \\ m \neq j}}^{S} \gamma_m \cdot d(n_i, s_m) \cdot k_m^2 \cdot c(n_i, s_m)}{\sum\limits_{k=1}^{S} \prod\limits_{\substack{m=1 \\ m \neq k}}^{S} \gamma_m \cdot d(n_i, s_m) \cdot k_m^2 \cdot c(n_i, s_m)} \tag{19}$$

Equation (19) confirms that the nodes should be aware of: (i) how their neighbors are allocated to the various WSN services –as determined by $d(n_i, s_m) \cdot k_m^2$–, (ii) the energy profile of each service –as determined by γ_m and (iii) whether all the services are ubiquitously supported over the MS-WSN

TABLE I
THEORETICAL OPTIMAL NODE ALLOCATION TO THE WSN SERVICES

WSN state (in timeslots)		Service s_1	s_2	s_3
Phase 1	[0, 300)	100%	-	-
Phase 2	[300, 600)	28.57%	71.43%	-
Phase 3	[600,)	19.35%	48.39%	32.26%

deployment –as determined by $c(n_i, s_m)$. Applying (8) and (9) to the S services of an MS-WSN, the theoretical optimal node allocation in the framework of k-hop clustering is determined from

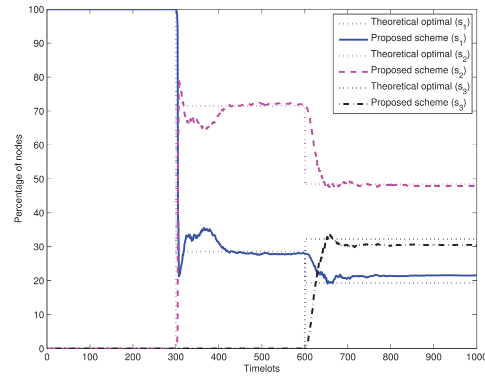
$$\alpha_j = \frac{\prod_{\substack{m=1 \\ m \neq j}}^{S} k_m \cdot \sqrt{\gamma_m}}{\sum_{k=1}^{S} \prod_{\substack{m=1 \\ m \neq k}}^{S} k_m \cdot \sqrt{\gamma_m}}, \forall s_j \in \mathcal{S} \tag{20}$$

V. SIMULATION RESULTS AND DISCUSSION

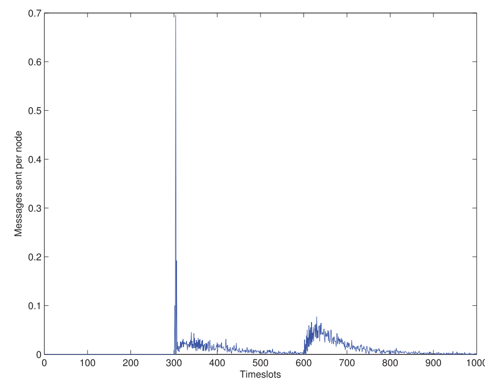
The simulation results concerning the performance of the proposed correlated strategies based scheme have been obtained based on a hypothetical WSN consisting of $N = |\mathcal{N}| = 1000$ nodes of fixed transmission range $T_r = 8\ m$, randomly deployed in an $L \times L$ square area, $L = 100\ m$. This setup probabilistically assures full WSN connectivity since the mean node degree, $\bar{d} = (N/L^2) \cdot \pi \cdot T_r^2 \approx 20$ exceeds 6, corresponding to a dense WSN [31]. The hypothetical MS-WSN under consideration supports three services, namely $\mathcal{S} = \{s_1, s_2, s_3\}$, with indicative energy profile metrics given from $\mathcal{G} = \{\gamma_1, \gamma_2, \gamma_3\} = \{10000, 40000, 10000\}$. The underlying clustering scheme adopted to maximize the MS-WSN lifetime is the k-hop clustering adapted to MS-WSNs. The respective k-values that define the clustering profile of each service are given from $\mathcal{K} = \{k_1, k_2, k_3\} = \{5, 1, 3\}$.

The WSN deployment is completed in three phases. During the first phase lasting until timeslot 299, service s_1 is the only service supported. At timeslots $t_2 = 300$ and $t_3 = 600$, services s_2 and s_3 are successively initiated and announced to the WSN nodes. For each phase, the successive theoretical optimal nodes allocation to the three WSN services are determined applying (20) and are tabulated in Table I.

The nodes allocation to the supported services following the proposed scheme is depicted in Fig. 2. Specifically, Fig. 2(a) shows how the nodes are re-allocated each time a new service is initiated. The proposed scheme converges fast to the theoretical optimal nodes allocation, exhibiting a maximum deviation of the order of 2% which is negligible. Also, the equilibrium and, consequently, the steady state are each time reached very fast. The efficiency of the proposed scheme with regard to the number of messages exchanged by the nodes is examined in Fig. 2(b), where the number of overhead messages per node is plotted against the time elapsed from the WSN deployment; the average number of messages exchanged per node in order to adapt to the initiation of a new WSN service is equal to 8.77.



(a) Percentage of nodes allocated to the various services.

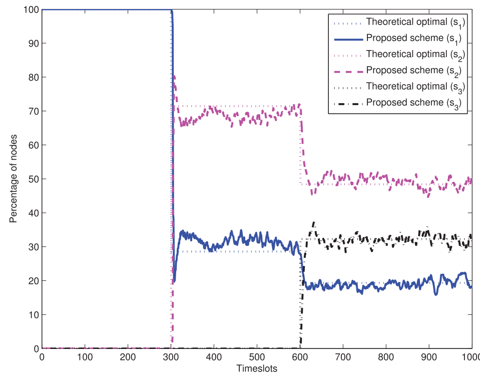


(b) Number of overhead messages sent per node.

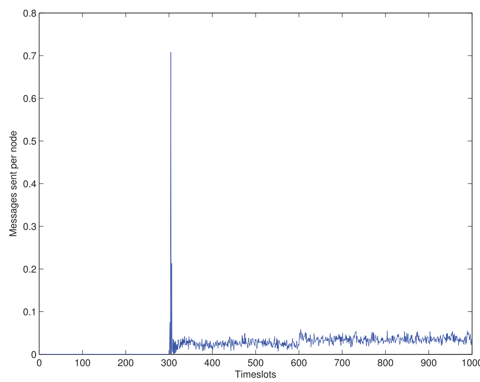
Fig. 2. Proper application of the proposed scheme (sufficient waiting period – ping-pong suppression)

The WSN behavior when the ping-pong effect is not properly suppressed is depicted in Fig. 3. Though the ping-pong effect does not prevent convergence to the optimal nodes allocation, it does not guarantee system stability since a number of nodes tend to unceasingly switch between services, thus causing severe energy consumption. Though it renders the MS-WSN operation unstable, the ping-pong effect implicitly allows the system to adapt to MS-WSN changes. Fig. 3(b) shows that the respective number of overhead messages required by the MS-WSN to stabilize increases unceasingly due to the uncontrollable node switching between services, when no ping-pong suppression is done, reaching an average of 22.4 messages per node in the first 1000 timeslots.

On the other hand, underestimating the time required by the nodes to schedule an efficient WOT operation leads to non optimal successive equilibria. In this case, though the MS-WSN reaches the CE states very shortly after the successive initiation of new WSN services, a short WOT fails to lead the MS-WSN sufficiently close to its optimal state of operation. Also, as the nodes detect the ping-pong effect earlier, the message exchanging period is reduced. However, the message exchange frequency becomes higher, leading to a slight increase in the average number of overhead messages exchanged per node. Plots depicting either the nodes allocation to the various services or the number of overhead messages per node when the waiting period of the nodes is not sufficient, are not given for reasons of space.

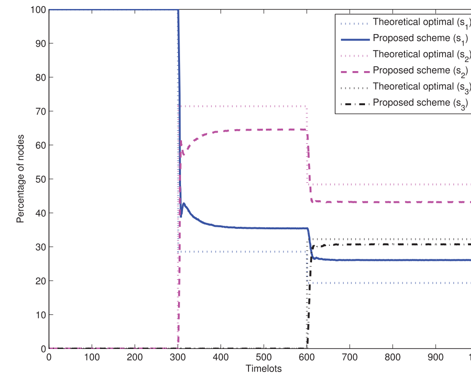


(a) Percentage of nodes allocated to the various services.

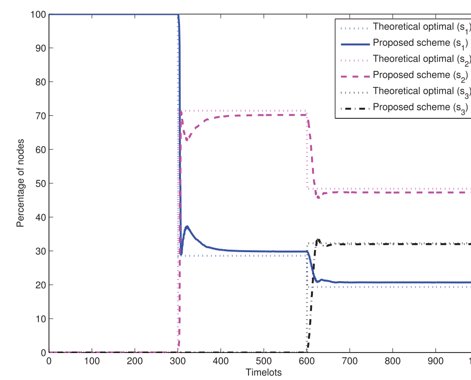


(b) Number of overhead messages sent per node.

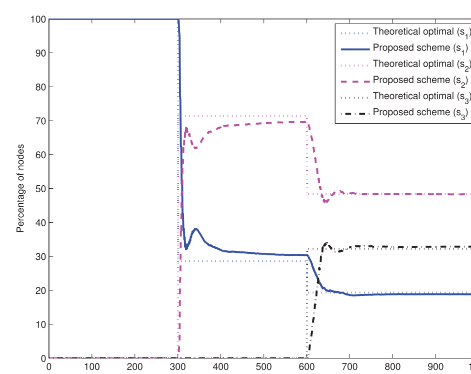
Fig. 3. Sufficient waiting period – No ping-pong suppression.



(a) $\bar{d} = 5$.



(b) $\bar{d} = 10$.



(c) $\bar{d} = 20$.

Fig. 4. Scheme performance examined with regard to the mean WSN node degree ($\bar{d}$).

Next, the dependence of the convergence speed to the theoretical optimal nodes distribution is examined in Fig. 4. The average behavior after 50 simulations is plotted. As deduced from Fig. 4(a), when the MS-WSN is not sufficiently dense, its adaptation capability is limited since the inefficient estimation of the number of neighbors reduces the nodes capability of accurately estimating the benefits expected from clustering. Hence, the nodes cannot properly determine their correlated strategy. As the node degree increases, so does the knowledge of how the nodes in every neighborhood are allocated to the multiple services supported. Figs. 4(b)–4(c) reveal that, as the node density increases, the nodes allocation to the services supported comes closer to the theoretical optimal nodes allocation. The relevant convergence time is slightly increased since, as the nodes schedule their optimization process after waiting for a random period proportional to the node degree, higher node degree values delay the convergence.

The number of exchanged messages depends on the execution of the three phases implemented by the proposed scheme. The nodes exchange messages in order to (i) detect their neighborhood, (ii) inform their neighbors about changes in the number or characteristics of the services supported by the MS-WSN and (iii) inform their neighbors about changes regarding the service they serve. Neighborhood detection requires the transmission of a single message. The number of messages transmitted by the nodes to inform about service changes is equal to the expected number of service changes. Finally, as the number of service changes allowed in the framework of mitigating the ping-pong effect is limited, the relevant number of messages exchanged is also limited. Hence, the message overhead complexity is $O(1)$. How the node density affects the number of overhead messages exchanged in the framework of the proposed scheme is depicted in Fig. 5. It is readily observed that the average number of messages necessary for convergence to the steady state phase slightly decreases with the mean node degree. However, as deduced from the simulations plotted in Fig. 4, convergence is not severely affected by $\bar{d}$ for $\bar{d} > 10$.

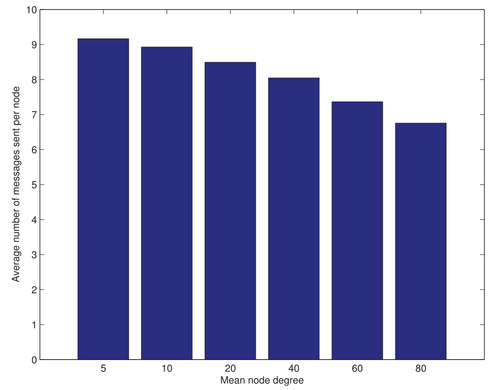


Fig. 5. Scheme performance with regard to the total number of messages sent per node

Hence, the expected reduction in the number of overhead messages is not critical to warrant the deployment of very dense MS-WSNs.

VI. Conclusion

A correlated strategies based distributed scheme optimizing nodes allocation in multi-service WSNs has been proposed. The theoretical optimal nodes allocation to the services supported by the MS-WSN has been determined in the framework of (i) guaranteeing continual service coverage over the whole MS-WSN deployment and (ii) maximizing the MS-WSN lifetime. The proposed, computationally efficient, correlated strategy regulating service selection by the multi-mode WSN nodes is based solely on local exchange of information. The convergence of the proposed scheme to the theoretical optimal and its efficiency with regard to the overhead traffic created are verified and explored via indicative simulations in the framework of k-hop clustering.

Appendix A
Introduction to k-Hop Clustering

k-hop clustering is based on sets of cluster head (CH) nodes that cluster the nodes in their area [6] following the simple rule that every node should be at most k hops away from exactly one CH. By definition, k-hop clustering schemes create equally sized clusters with an average cluster population equal to $d \cdot k_j^2$ nodes, where d is the mean node degree and k_j is the k-value of service s_j. When clustered, the nodes send their measurements to their CH in a round-robin mode, their reporting frequency being inversely proportional to their degree. Hence, the expected lifetime prolongation under k-hop clustering is proportional to the node degree. Therefore, the expected value of node n_i when it serves service s_j in the framework of k-hop clustering is given by (17) of the main text.

References

[1] D. Puccinelli and M. Haenggi, "Wireless sensor networks: Applications and challenges of ubiquitous sensing," *IEEE Circuits Syst. Mag.*, vol. 5, no. 3, pp. 19–31, Sep. 2005.

[2] J. Steffan, L. Fiege, M. Cilia, and A. Buchmann, "Towards multi-purpose wireless sensor networks," in *Proc. Syst. Commun.*, Aug. 2005, pp. 336–341.

[3] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660–670, Oct. 2002.

[4] R. Virrankoski and A. Savvides, "TASC: Topology adaptive spatial clustering for sensor networks," in *Proc. IEEE Int. Conf. Mobile Adhoc Sens. Syst. Conf.*, Nov. 2005, pp. 605–614.

[5] J. Wu and J. Cao, "Connected k-hop clustering in ad hoc networks," in *Proc. Int. Conf. Parallel Process. (ICPP'05)*, 2005, pp. 373–380.

[6] M. Youssef, A. Youssef, and M. Younis, "Overlapping multihop clustering for wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 20, no. 12, pp. 1844–1856, Dec. 2009.

[7] R. Velmani and B. Kaarthick, "An efficient cluster-tree based data collection scheme for large mobile wireless sensor networks," *IEEE Sensors J.*, vol. 15, no. 4, pp. 2377–2390, Apr. 2015.

[8] M. Tarhani, Y. Kavian, and S. Siavoshi, "SEECH: Scalable energy efficient clustering hierarchy protocol in wireless sensor networks," *IEEE Sensors J.*, vol. 14, no. 11, pp. 3944–3954, Nov. 2014.

[9] A. Ali, A. Khelil, N. Suri, and M. Mahmudimanesh, "Adaptive hybrid compression for wireless sensor networks," *ACM Trans. Sens. Netw.*, vol. 11, no. 4, pp. 53:1–53:36, May 2015.

[10] X. Xu, R. Ansari, A. Khokhar, and A. V. Vasilakos, "Hierarchical data aggregation using compressive sensing (HDACS) in WSNS," *ACM Trans. Sens. Netw.*, vol. 11, no. 3, pp. 45:1–45:25, Feb. 2015.

[11] K. Yue, J. Zhang, J. Li, T. Wu, and W. Liu, "A theoretic approach for prolonging lifetime of wireless sensor networks based on the coalition game model," *Int. J. Distrib. Sens. Netw.*, vol. 2014, pp. 1–14, 2014.

[12] X. Liu, "Atypical hierarchical routing protocols for wireless sensor networks: A review," *IEEE Sensors J.*, vol. 15, no. 10, pp. 5372–5383, Oct. 2015.

[13] A. MeenaKowshalya and A. Sukanya, "Clustering algorithms for heterogeneous wireless sensor networks - A brief survey," *Int. J. Ad Hoc Sens. Ubiq. Comput. (IJASUC)*, vol. 2, no. 3, pp. 57–69, Sep. 2011.

[14] L. Qing, Q. Zhu, and M. Wang, "Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor networks," *Comput. Commun.*, vol. 29, no. 12, pp. 2230–2237, Aug. 2006.

[15] C. E. Lopes, F. D. Linhares, M. M. Santos, and L. B. Ruiz, "A multi-tier, multimodal wireless sensor network for environmental monitoring," in *Proc. 4th Int. Conf. Ubiq. Intell. Comput. (UIC'07)*, 2007, pp. 589–598.

[16] L. Buttyan, D. Gessner, A. Hessler, and P. Langendoerfer, "Application of wireless sensor networks in critical infrastructure protection: Challenges and design options [security and privacy in emerging wireless networks]," *IEEE Wireless Commun.*, vol. 17, no. 5, pp. 44–49, Oct. 2010.

[17] H. Karvonen, J. Suhonen, J. Petäjäjärvi, M. Hämäläinen, M. Hännikäinen, and A. Pouttu, "Hierarchical architecture for multi-technology wireless sensor networks for critical infrastructure protection," *Wireless Pers. Commun.*, vol. 76, no. 2, pp. 209–229, 2014.

[18] A. C. Voulkidis, M. P. Anastasopoulos, and P. G. Cottis, "Energy efficiency in wireless sensor networks: A game-theoretic approach based on coalition formation," *ACM Trans. Sens. Netw.*, vol. 9, no. 4, pp. 43:1–43:27, Jul. 2013.

[19] A. Voulkidis, S. Livieratos, and P. Cottis, "Spatially correlated multi-modal wireless sensor networks: A coalitional game theoretic approach," in *Proc. 3rd Int. Conf. Auton. Intell. Syst. (AIS'12)*, 2012, pp. 1–9.

[20] V. Pilloni, P. Navaratnam, S. Vural, L. Atzori, and R. Tafazolli, "TAN: A distributed algorithm for dynamic task assignment in WSNS," *IEEE Sensors J.*, vol. 14, no. 4, pp. 1266–1279, Apr. 2014.

[21] A. Thakkar and K. Kotecha, "Cluster head election for energy and delay constraint applications of wireless sensor network," *IEEE Sensors J.*, vol. 14, no. 8, pp. 2658–2664, Aug. 2014.

[22] Y. Chen and Q. Zhao, "On the lifetime of wireless sensor networks," *IEEE Commun. Lett.*, vol. 9, no. 11, pp. 976–978, Nov. 2005.

[23] M. P. Johnson, D. Sariöz, A. Bar-Noy, T. Brown, D. Verma, and C. W. Wu, "More is more: The benefits of denser sensor deployment," *ACM Trans. Sen. Netw.*, vol. 8, no. 3, pp. 22:1–22:19, Aug. 2012.

[24] C. Haas, J. Wilke, and V. Stöhr, "Realistic simulation of energy consumption in wireless sensor networks," in *Proc. 9th Eur. Conf. Wireless Sens. Netw. (EWSN'12)*, 2012, pp. 82–97.

[25] A. Tiwari, P. Ballal, and F. L. Lewis, "Energy-efficient wireless sensor network design and implementation for condition-based maintenance," *ACM Trans. Sen. Netw.*, vol. 3, no. 1, pp. 1:1–1:23, Mar. 2007.

[26] R. Machado, W. Zhang, G. Wang, and S. Tekinay, "Coverage properties of clustered wireless sensor networks," *ACM Trans. Sen. Netw.*, vol. 7, no. 2, pp. 13:1–13:21, Sep. 2010.

[27] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. Cambridge, MA, USA: MIT Press, Jul. 1994.
[28] R. B. Myerson, *Game Theory: Analysis of Conflict*. Cambridge, MA, USA: Harvard Univ. Press, Sep. 1997.
[29] R. J. Aumann, "Correlated equilibrium as an expression of Bayesian rationality," *Econometrica*, vol. 55, no. 1, pp. 1–18, Jan. 1987.
[30] C. H. Papadimitriou and T. Roughgarden, "Computing correlated equilibria in multi-player games," *J. ACM*, vol. 55, no. 3, pp. 14:1–14:29, Aug. 2008.
[31] A. Savvides, C.-C. Han, and M. B. Strivastava, "Dynamic fine-grained localization in ad-hoc networks of sensors," in *Proc. 7th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom'01)*, 2001, pp. 166–179.

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