Information Theoretical Optimization Gains in Energy Adaptive Data Gathering and Relaying in Cognitive Radio Sensor Networks

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***Abstract*—Cognitive radio (CR) technology helps mitigate wireless resource scarcity problem by dynamically changing frequency spectrum, power and modulation type. Opportunistic spectrum access increases the network capability and quality. Recently, CR applied to wireless sensor networks (WSNs) generated the paradigm of cognitive radio sensor networks (CRSNs) overcoming the challenges posed by event-driven traffic demands of WSNs. To realize advantages of CRSN, spectrum and power allocation, and routing must be jointly considered to maximize the information capacity, resource utilization and the lifetime. In this paper, power and rate adaptation problem is analyzed for a multi-hop CRSN in an information theoretical (IT) capacity maximization framework combined with energy adaptive (EA) mechanisms and utilization of sensor data information correlations (ICs). CRSN characteristics, i.e., fast data aggregation, bursty traffic and node failures, are considered. The capacity optimization problem is defined analytically and practical local schemes are presented showing the superiority of objective functions utilizing ICs and EA mechanisms in terms of the resulting maximum information rate at sink, i.e., R_{max}, lifetime, and energy utilization. Furthermore, dependence of performance on total bandwidth and various relay energy distributions is explored observing the logarithmic dependence of R_{max} on total bandwidth.**

***Index Terms*—Cognitive wireless sensor network, adaptive power control, information capacity.**

I. Introduction

THE ELECTROMAGNETIC radio spectrum usage is regulated under strict licensing terms resulting in significant inefficiency in spectrum utilization by the licensed primary users (PU) [1]. Dynamic and opportunistic spectrum access (OSA) as an efficient utilization mechanism allows the secondary users (SU) use the best available channel [1], [2]. To this end, cognitive radio (CR) is proposed for effective utilization of unused bands opportunistically [3] making it possible for SUs and PUs operate in the same region by adapting the operating conditions of SUs in a manner not to disturb the normal communication standards of PUs. Cognitive radio networks (CRNs) are capable of spectrum sensing of PU and SU activity with intelligent adaptation mechanisms.

Recently, wireless sensor network (WSN) imposing strict cost limitations on sensors has been introduced with the advantages of using nodes with CR capability, i.e. cognitive radio sensor network (CRSN). It increases the reliability of the channel used under bursty traffic, utilizes WSN in crowded spectrum bands without license, uses adaptive power and bandwidth allocation resulting in lifetime maximization and makes heterogeneous WSN constructions possible [2].

An analytical information theoretical (IT) optimization framework combining routing, OSA, power and rate control is significantly important in order to best utilize the resources, e.g., increasing lifetime and throughput, and to solve the challenges of CRSNs, e.g., energy constraints, spectrum mobility, time-varying conditions, multi-hop communications sharing licensed and unlicensed bands, power control, demand for low-cost and power-efficient nodes [2], [4], [5].

There is a limited amount of work on optimizing resources of CRSNs. Spectrum utilization and energy efficiency [6], lifetime and power consumption [7], [8], [10] are optimized. The channel assignment and management are analyzed in terms of energy consumption and network lifetime in [9], [11]. However, IT capacity optimization and the fundamental characteristics of CRSNs, e.g., multi-hop routing, fast data aggregation and bursty traffic, are not so far considered.

Although CRSN is a new field to be analyzed for optimizations, CRNs have a significant amount of work concentrating on performance optimization [4], [12]–[21]. On the other hand, there are studies analyzing the IT limits of CRNs [22], [23]. However, various aspects like multi-hop routing, information correlations (ICs), spectrum allocation and scheduling, power control and characteristics of CRSN are not considered in a combined IT optimization framework.

Despite the availability of few works optimizing CRSNs, their characteristics are not considered in an IT point of view and combined with optimization framework. To the best of our knowledge, this is the first attempt incorporating the basic CRSN characteristics in a capacity maximization (CMax) framework defined by using local realtime objective functions (OFs) via an adaptive power and bandwidth control with energy adaptive (EA) mechanisms balancing the energy consumption and IC utilization preventing to transmit correlated data. CRSN basics are taken into account in a realistic networking scenario with Gaussian sensor data sources. Three

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different OFs, i.e., EA, utilizing IC and the one with neither of them are devised and compared. Simulation study solves the problem within a Branch and Bound (BB) framework. Various performance metrics, i.e., R_{max}, node lifetime and the energy utilization, are defined to compare OFs. The results show the superiority of EA mechanisms and IC utilization especially in networks with unequal node energies. Besides that, the dependence of the metrics on total bandwidth is simulated, e.g., the logarithmic dependence of R_{max} on total bandwidth.

The remainder of the paper is organized as the following. In Section II, related work on spectrum and power allocation on CRNs and CRSNs are explored. In Section III, the CRSN system model is defined. Then, in Section IV, Cmax problem is defined theoretically and various optimization frameworks are defined. After the framework is defined, in Section V, a simulation study is performed for varying total bandwidth and the optimization methods are compared. Finally, in Section VI, the conclusions are given and future works are pointed out.

II. Related Work

To the best of our knowledge, there is no IT optimization study about CRSNs although some works optimize the utilization of only a limited set of network resources. In [6], the number of spectrum handoffs is reduced. Spectrum utilization and energy efficiency are improved in a multi-objective optimization with a modified game theory solution. Although spectrum allocation and transmission power are optimized, multi-hop routing, ICs and the fundamental features of CRSN, e.g., fast data aggregation, node failures and bursty data traffic, are not considered.

Power consumption is reduced by optimizing modulation constellation size [7], through the minimization of energy per bit over the subcarriers [8] and optimization for application-oriented source sensing, e.g., collecting information of temperature, sound, etc., and ambient-oriented channel sensing in [10]. Although lifetime and power consumption are optimized, IT metrics and multi-hop CRSN characteristics are not addressed in these works.

Channel assignment with residual energy balancing in a cluster-based CRSN is accomplished in [9] with random pairing, greedy search and optimization-based approaches. Adaptive channel management scheme decreasing the energy consumption, providing PU protection and optimizing operation mode selection is presented for CRSN in [11]. However, IT capacity optimization, multi-hop routing, fast data aggregation and bursty data traffic are not addressed.

There are significantly more studies on optimization of CRNs. Spectrum allocation and power control are optimized maximizing capacity for a CR link in [12] and the sum-rate of CRs in single-hop ad hoc CRNs in [18]. Spectrum utilization is maximized for downlink transmission in [20] and the system throughput is maximized in [4]. However, in none of these works, multi-hop routing, IT considerations and CRSN characteristics are discussed. Power control and channel selection in [16] and total capacity in [21] are optimized with cognitive water-filling algorithm. However, multi-hop routing of WSN, ICs and EA mechanisms are not considered.

Joint power and rate control is analyzed in [17] with a game theoretical approach and in [19] with ergodic capacity optimization. Although power control is used in these works, spectrum allocation, scheduling and routing are not addressed within a WSN framework. Spectrum sharing is achieved in [13] with a mixed-integer non-linear program (MINLP) optimization for a set of user sessions. CRN is assumed to include multi-hop, multi-path routing, and multiple channels. However, power control and IT capacity analysis are not given.

In [14], [15], a cross-layer power control, scheduling and routing problem of MINLP type are solved by BB algorithm for minimizing the required resources and the interference in a software defined radio (SDR) wireless network. Although multi-hop routing, power control and spectrum allocation are considered, IT considerations, ICs and CRSN characteristics are not considered.

Network information theoretical considerations for CRNs are discussed in [22], [23]. The fundamental IT limits of CRs, the effects of side informations obtained by SU, i.e., spectral gaps, knowledge of the PU interference, channel gain, coding, on IT capacity are analyzed. Scaling laws for homogeneous and heterogeneous networks are discussed in terms of the throughput emphasizing node distributions, communication and routing protocols. However, an IT optimization Cmax framework of CRSNs and CRs with multi-hop topology, power and rate control are not given and the fundamental features of CRSN are not mentioned at all.

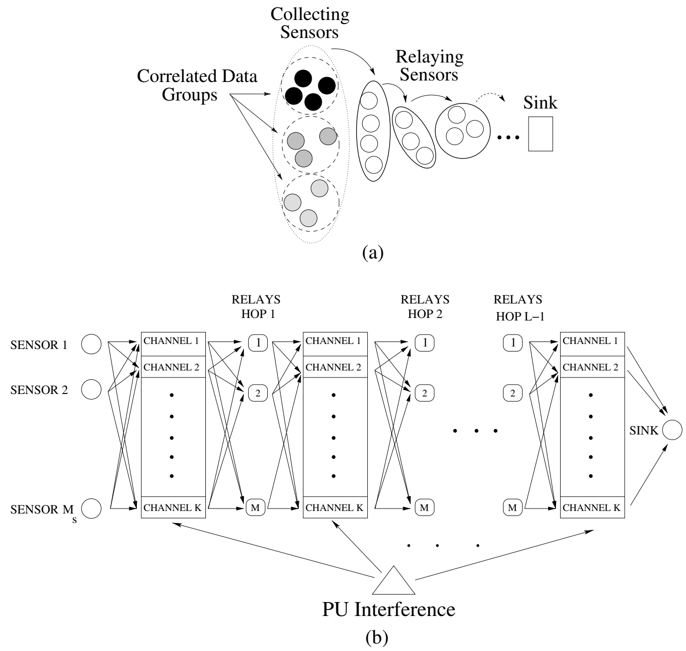

Fig. 1. (a) Networking topology of general dense multi-hop relay CRSN with data collecting and relaying sensors and (b) its simplified topology with PU interference and equal distance layers of node groups.

III. System Model

Multi-hop relaying in WSNs increases network lifetime with smaller hop distances and lower transmission power [24]. In this article, multi-hop topology is examined with multiple sensors collecting possibly different kinds of information, and forwarding them to a sink node via relaying sensors currently not collecting data. In Table I, global constants and variables of the network model are explained and in Fig. 1(a) and (b), networking topology and its simplified version are shown.

As shown in Fig. 1(a), the network is assumed to consist of two main groups of sensors, i.e., data collecting sensors and relaying sensors grouped with respect to the distance to the source and sink to simplify routing where the distance between neighboring groups is assumed to be approximately equal leading to symmetric hop levels and making it easier to compare the performance improvements due to utilization of ICs and EA mechanisms. A more general network makes the situation complicated to observe the isolated advantages of the discussed optimizations. Besides that, a dense network topology can be assumed, e.g., it can be grouped in such node groups easily by simplifying the routing task.

The network has M_s data collecting sensors, $L-1$ hop count between them and the sink, and at most M relaying sensors at each multi-hop level denoted with r. Nodes are indexed with (r, m) where m is the relay id number in that hop level. $r = 1$ denotes the data collecting sensors and $r \in [2, L]$ denotes relaying sensors where $r = L$ denotes relays neighboring to the sink. The subscripts S, R and D denote the hop levels $r = 1$, $r \in [2, L-1]$ and $r = L$, respectively.

Sensor data is received and transmitted in time slots of width T_s denoted by t^+ where t is the slot start time. In simulations, sink data is observed until a fixed final time t_f but sensors collect data until t_f for continuous traffic and until several seconds before t_f for bursty traffic.

W_{Tot}, i.e., the total available bandwidth at a single hop level which can be allocated by PU and SU, is divided into K intervals of size W_{ch}, i.e., $K = W_{Tot} / W_{ch}$. PU allocates channels in a probabilistic scheme depending on r, t^+ and channel k denoted by the probabilities $P_R^{PU}(r, k, t^+)$ and $P_S^{PU}(k, t^+)$ for the channels of nodes at $r \in [2, L]$ and between $r = 1$ and $r = 2$, respectively. The remaining spectrum after PU allocation, i.e., $W_{SU}^R(r, t)$ for $r \in [2, L-1]$, $W_{SU}^S(t)$ for $r = 1$ and $W_{SU}^D(t)$ for $r = L$, is used by SUs freely without constraining it to discrete channels such that any fractional value can be used. A relay node is assumed to be capable of receiving data at multiple bands from multiple transmitters, but transmitting only to a single next hop node. In this article, we do not consider Gaussian multiple access channel (MAC) with interference, feedback information or any joint transmission allowing cooperation in capacity calculations. The nodes are simple enough and send data independently. After the sensors are queried by the sink, the data should reach the sink at most in V_s slots, i.e., time-to-live (TTL) count, otherwise, the data becomes obsolete. The relays forward the data in a rush manner without complicated collaboration scenarios as a realistic case for low-energy nodes with limited knowledge. However, the channel state information is available and channel sharing is accomplished in a time slot.

Relays are assumed to have finite initial energies of $E_{r,m}$ where $E_{r,m}^*(t)$ denotes the remaining energy at time t. Data collecting sensors are assumed to be capable of continuously collecting and the energy for collecting is not taken into account. Despite the importance of their energy levels, it is assumed that there is a large number of sensors continuously feeding data to multi-hop CRSN and task of data collection of the failed nodes is assigned to nearby sensors. Therefore, it becomes possible to observe the advantages of EA scheme and utilization of IC in multi-hop CRSN for continuous and bursty data traffic while concentrating on data carrying. The failure of data collection is left as a future work for a more general framework. In a time slot, a transmission power P (Watts) bounded with P_{max} consumes the energy $P \times T_s$. Node failure due to finite relay lifetime is a fundamental WSN constraint and included in optimization architecture.

TABLE I
THE GLOBAL CONSTANTS AND DEFINITIONS FOR CRSN MODEL

Parameter	**Meaning**
M_s, M, L	Number of sensors, relays at a hop level and number of hop levels
T_s, t_f	Time slot interval and final duration for sink data aggregation (seconds)
D_s, σ_s^2	Distortion and the variance of the continuous random variable for the sample of sensor s
$H(X_{s,j})$	Number of bits sent per time slot for the random variable $X_{s,j}$
V_s	TTL (seconds) for sensor s data
G_i	Sensors $s \in G_i$ have the same data types, e.g., temperature, $i \in [1, N_g]$
$E_{r,m}$, $E_{r,m}^*(t)$	Initial and remaining energy (Joule) at t, $r \in S_3$, $m \in [1, M]$
B_s, $B_{r,m}$	Buffer size in bits for sensor s and relay (r, m), $r \in S_3$, $m \in [1, M]$
$P_S^{PU}(k, t^+)$, $P_R^{PU}(r, k, t^+)$	PU channel allocation probability at $r = 1$ and $r \in S_3$, channel k, at t^+
$\sigma_S(t^+)$, $\sigma_R(r, t^+)$, $\sigma_D(t^+)$	Noise spectral density (Watts/Hz) at $r = 1$, $r \in S_1$ and $r = L$ at t^+
$W_{SU}^S(t)$, $W_{SU}^R(r, t)$, $W_{SU}^D(t)$	Available bandwidth at $r = 1$, $r \in S_1$ and $r = L$ at t^+
W_{Tot}, W_{ch}, K	Total available bandwidth to PU and SU at a hop level, single channel bandwidth and number of channels
P_{max}	Maximum transmission power
S_1, S_2, S_3	$[2, L-1]$, $[3, L-1]$, $[2, L]$

The noise spectral density throughout the network is given by $\sigma_R(r, t^+)$, $\sigma_S(t^+)$ and $\sigma_D(t^+)$ for $r \in [2, L-1]$, $r = 1$ and $r = L$, respectively. The channel is assumed to be of type bandwidth-constrained additive white Gaussian noise (AWGN). Communication protocols and physical layer aspects including channel gains and received power levels are not analyzed in order to isolate the problem of utilization of ICs and EA mechanisms. Then, the basic expression, i.e., $C = W \log(1 + P / (N W))$, is used to compute the rate C (bits/sec) of AWGN channel with bandwidth $W\,(Hz)$ and noise power spectral density of $N\,(Watts/Hz)$ in a time slot.

The random variable for samples collected by sensor s at time j is denoted by $X_{s,j}$ with information size of $H(X_{s,j})$. For Gaussian multi-variate distributed sensor data, $\sigma_s^2 = E\{X_{s,j}^2\}$ is the variance of $X_{s,j}$ and D_s is the distortion for the sample for the description of the quantized data within a specific distortion constraint. Data collecting sensor s and relay (r, m) have finite buffer sizes of B_s and $B_{r,m}$ (bits), respectively. The sensors form N_g groups such that only the ones in a group G_i for $i \in [1, N_g]$ have the same type of correlated data, i.e., temperature, image, etc. Next, Cmax problem is defined in a general optimization framework.

IV. Capacity Maximization Problem

In this article, OF is based on maximizing the local information rates at hop levels at each time slot. Furthermore, some *linear utility functions*, i.e., $g_{S,R,D}(.)$, are defined utilizing the knowledge of the remaining energies to achieve *energy adaptation* and ICs are used to prevent the transmission of correlated data. Local IT gains at hop levels indirectly increase the data collected at the sink where the optimization of a level is independent from others. Nodes at a level exchange messages to find an optimum scheme by virtue of a node with more resources. Although the algorithms compute slowly due to NP hardness, sub-optimal gain for sink data obtained from local hop level optimizations utilizing EA mechanism and ICs is the main purpose of the article. The global optimization for sink is not considered since it is impractical, complex and uses all the knowledge until t_f for all hop levels.

Firstly, energy adaptive OF, i.e., EAOF, is defined by using utility functions, and then problem constraints are given. Unity utility functions result in a non-adaptive scheme, i.e., NEAOF. Then, ICOF utilizing ICs is defined. Sensors collect data of multi-variate space-time Gaussian random processes. The constraints presented for EAOF are valid for other OFs.

A. Information theoretical objective function with linear utility functions

The definitions used are described in Table I where $m,\, n \in [1, M]$, $s \in [1, M_s]$, $t \in [1, t_f]$, $j \in [1, t]$ and $r \in S_1$ whenever they are not explicitly stated. The subscript (s, j) or j denotes data of sensor s collected at time j. Furthermore, m, s and n denote transmitting relay, sensor, and receiver node, respectively, in indicators and denote indices of the owner node for buffer, bandwidth and power variables. The indicators I_j^S, $I_{s,j}^D$, and $I_{s,j}^R$ denote the transmission of the specific sample (s, j). I^S, I^R and I^D denote the existence of data transmission. $I_{s,j}^{B,R}$ and $I_j^{B,S}$ show whether sample (s, j) resides at the buffer. Then, EAOF is defined as the following,

$$\textbf{max} \sum_{n=1}^{M}\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j})\, g_S(s,\, n,\, t)\, I_j^S(s,n,t^+) \tag{1}$$

$$\textbf{max} \sum_{m=1}^{M}\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j})\, g_D(m,\, t)\, I_{s,j}^D(m,t^+) \tag{2}$$

$$\textbf{max} \sum_{m,n=1}^{M}\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j})\, g_R(r,m,n,t)\, I_{s,j}^R(r,m,n,t^+) \tag{3}$$

for sensors, the relays at $r = L$ and $r \in S_1$ levels, respectively, **w.r.t.** $I_{s,j}^R$, I_j^S, $I_{s,j}^D$, I^R, I^S and I^D, bandwidth and power variables, i.e., W^R, W^S, W^D, P^R, P^S and P^D. (1), (2) and (3) define local OFs at $r = 1$, $r = L$ and $r \in S_1$, respectively, where each level optimizes its transmission independently. These OFs do not utilize any IC. If $g_{S,R,D}(.)$ functions are set to 1, OFs include neither energy adaptation nor utilization of IC. Next, the constraints are defined.

Buffer inequalities bounding with the buffer size are

$$\sum_{j=1}^{t} H(X_{s,j})\, I_j^{B,S}(s,t) \quad\leq\quad B_s \tag{4}$$

$$\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j})\, I_{s,j}^{B,R}(r,m,t) \quad\leq\quad B_{r,m},\; r \in S_3 \tag{5}$$

Flow inequalities bounding with available capacity are

$$\sum_{n=1}^{M}\sum_{j=1}^{t} H(X_{s,j})\, I_j^S(s,n,t^+) \leq C^S(s,t^+,\sigma_S) \tag{6}$$

$$\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j}) I_{s,j}^D(m,t^+) \leq C^D(m,t^+,\sigma_D) \tag{7}$$

$$\sum_{n=1}^{M}\sum_{s=1}^{M_s}\sum_{j=1}^{t} H(X_{s,j}) I_{s,j}^R(r,m,n,t^+) \leq C^R(r,m,t^+,\sigma_R) \tag{8}$$

where the capacities are found by inserting P^*, W^* and σ_* with $*$ denoting S, D or R into the basic capacity expression C. Routing inequalities are

$$\sum_{n=1}^{M} I^S(s,n,t^+) \,\leq\, 1; \qquad \sum_{n=1}^{M} I^R(r,m,n,t^+) \,\leq\, 1 \tag{9}$$

$$I_j^S(s,n,t^+) \quad\leq\quad I^S(s,n,t^+) \tag{10}$$

$$I_{s,j}^R(r,m,n,t^+) \quad\leq\quad I^R(r,m,n,t^+) \tag{11}$$

$$\sum_{n=1}^{M} I_{s,j}^D(m,t^+) \quad\leq\quad I_{s,j}^{B,R}(L,m,t) \tag{12}$$

$$\sum_{n=1}^{M} I_j^S(s,n,t^+) \quad\leq\quad I_j^{B,S}(s,t) \tag{13}$$

$$\sum_{n=1}^{M} I_{s,j}^R(r,m,n,t^+) \quad\leq\quad I_{s,j}^{B,R}(r,m,t) \tag{14}$$

where (9) constrains the next node selection to only a single node, (10 - 14) permit the transmission only if the next node is chosen in routing and the data resides in the buffer. At the same time, power inequalities bounding the total consumed energy are

$$\sum_{t=1}^{t_f} T_s\, P^D(m,t^+) \,\leq\, E_{L,m}; \quad \sum_{t=1}^{t_f} T_s\, P^S(s,t^+) \,\leq\, E_s; \tag{15}$$

$$\sum_{t=1}^{t_f} T_s\, P^R(r,m,t^+) \,\leq\, E_{r,m} \tag{16}$$

where $0 \leq P^{S,R,D}(.) \leq P_{max}$. Bandwidth inequalities bound $W^{S,R,D}(.) \geq 0$ with the following

$$\sum_{s=1}^{M_s} W^S(s,t^+) \,\leq\, W_{SU}^S(t); \; \sum_{m=1}^{M} W^D(m,t^+) \,\leq\, W_{SU}^D(t) \tag{17}$$

$$\sum_{m=1}^{M} W^R(r,m,t^+) \,\leq\, W_{SU}^R(r,t) \tag{18}$$

Buffer flow equalities for conservation of flow are

$$I_{s,j}^{B,R}(r,m,t+1) = I_{s,j}^{B,R}(r,m,t) + \sum_{q=1}^{M} I_{s,j}^{R}(r-1,q,m,t^+) - \sum_{n=1}^{M} I_{s,j}^{R}(r,m,n,t^+) \quad (19)$$

$$I_{s,j}^{B,R}(2,m,t+1) = I_{s,j}^{B,R}(2,m,t) + \sum_{s=1}^{M} I_{j}^{S}(s,m,t^+) - \sum_{n=1}^{M} I_{s,j}^{R}(2,m,n,t^+) \quad (20)$$

$$I_{s,j}^{B,R}(L,m,t+1) = I_{s,j}^{B,R}(L,m,t) + \sum_{q=1}^{M} I_{s,j}^{R}(L-1,q,m,t^+) - I_{s,j}^{D}(m,t^+) \quad (21)$$

$$I_{j}^{B,S}(s,t+1) = I_{j}^{B,S}(s,t) - \sum_{n=1}^{M} I_{j}^{S}(s,n,t^+) \quad (22)$$

where ($r \in S_2$). Finally, all indicators, i.e., $I(.)$, are either 0 or 1. Since OF and the constraints consist of both integer and continuous valued parameters, i.e., power and bandwidth, and they are of nonlinear type, the optimization problem defined in this article is a MINLP problem [25]. The convexity of the defined objective functions and the constraints are discussed in subsection IV-C. Next, OF utilizing ICs is given.

B. Information theoretical objective function utilizing sensor data correlation

OF utilizing ICs is similar to NEAOF but the total information entropy is used. The data is assumed to form a multivariate jointly Gaussian distribution with correlated data in time and space. Let us define the information rate of a set of samples, i.e., $G = 1, 2, ..., n$, taken from the jointly Gaussian random field with a sampling rate r_S (Hz) as [26],

$$R_G = r_S \left(h_X - 0.5 \log_2 \left((2\pi e)^n \prod_{i=1}^{n} D_i \right) \right) \quad (23)$$

where $h_X = h(X_1, X_2, ..., X_n) = 0.5 \log_2 \left((2\pi e)^n \mid K_G^X \mid \right)$ is the joint differential entropy of the continuous variables, $\mid K_G^X \mid$ is the determinant of the $n \times n$ correlation matrix K_G^X of the samples with the elements $K_G^X(i,j) = E\{X_i X_j\}$ and D_i is the distortion for the sample i such that quantized samples describe the data within specific distortion constraints.

Define the set $C \equiv (s_1, j_1), (s_2, j_2), ..., (s_n, j_n)$ representing the samples $X_{s,j}$, $(s,j) \in C$ to be transmitted and $Y_i \equiv X_{s_i,j_i}$. Defining $\sigma_i^2 = E\{X_i^2\}$ as the variance and $\rho_{i,j} = E\{X_i X_j\} / (\sigma_i \sigma_j)$ as the correlation coefficient for the samples $X_{s,j}$, $\rho_{i,j}$ is assumed to depend exponentially on the spatial distance and sampling time difference between samples, i.e., $\rho_{k,l} = e^{-\alpha_{k,l}^T (j_k - j_l)} e^{-\alpha_{k,l}^S (Pos(s_k) - Pos(s_l))}$ where $\alpha_{k,l}^T$ and $\alpha_{k,l}^S$ are time and space decay parameters, respectively, for the samples k, l. $Pos(s_i)$ denotes the physical coordinate of a sensor s_i assuming the sensors are located in one dimension (1D) where 2D extension is straightforward.

An OF design considering both the correlation and fractional values of integer variables in a relaxed IP problem is explored by modifying (23). The resulting OF should give the correct information rate whenever all the indicator variables are integer and should converge to reasonable results utilizing IC as much as possible. After experimenting various objective functions with the generic information rate for Gaussian random fields, ICOF can be defined as,

$$\textbf{max} \quad \frac{r_S}{2} \log_2 \left(\frac{\mid K_C^{B_1} \otimes B_2 \mid}{D_{dist}} \right) \quad (24)$$

where $K_C = K_G^Y$ is the correlation matrix of data, $K_C^{B_1}$ represents the element wise exponent of K_C by the matrix B_1, the operator $\otimes$ represents element wise product, $B_1 = B_S \otimes ((1 - I_n)\, c_1 + I_n)$, $B_2 = B_S \otimes (1 - I_n)\, c_1 + I_n$, I_n is the identity matrix of size n, $B_S = A \otimes \left(A^T \otimes (1 - I_n) + I_n \right)$ and A is formed by replication of the column vector a_y by n, i.e., $A = [a_y\, a_y \ldots a_y]$. a_y including the total data corresponding to each sample $(s,j) \in C$ is $\sum_{m,\, n=1}^{M} I_{s_i,j_i}^{R}(r,m,n,t^+)$ $g_R(r,\, m,\, n,\, t)$ for $r \in S_1$, $\sum_{n=1}^{M} I_{j_i}^{S}(s_i,n,t^+)$ $g_S(s,\, n,\, t)$ for $r = 1$ and $\sum_{m=1}^{M} I_{s_i,j_i}^{D}(m,t^+)$ $g_D(m,\, t)$ for $r = L$. D_{dist} is found by using the distortions D_i and the total data for the sample $(s,j) \in C$ as $D_{dist} = \prod_{i=1}^{n} D_i^{\chi}$ where χ equals to $\sum_{m,\, n_l=1}^{M} I_{s_i,j_i}^{R}(r,m,n_l,t^+)$ for $r \in S_1$, $\sum_{n_l=1}^{M} I_{j_i}^{S}(s_i,n_l,t^+)$ for $r = 1$ and $\sum_{m=1}^{M} I_{s_i,j_i}^{D}(m,t^+)$ for $r = L$.

The constant c_1 is used to decrease the effect of the off-diagonal terms such that $\mid K_C^{B_1} \otimes B_2 \mid$ is positive and operates in the convex regime. c_1 is initialized to 1 and decreased adaptively. Assuming $g_{S,R,D}(.)$ functions are set to 1, OF convergence is experimented in simulations. For the diagonal terms, $a_y(i)$ is used as the exponent of the cross correlation, and for the off-diagonal terms, $a_y(i)\, a_y(j)$ both multiplies the cross correlation and at the same time appears as exponent. When the indicator for a sample is 0, or correspondingly $a_y(i)$ is 0, the corresponding diagonal value becomes 1 due to the exponent, and the other values on that column and row become 0 and the cross-correlation diminishes. When it is equal to 1, the diagonal term becomes the variance for that sample, and the other values in the corresponding row and column are not affected by that sample value. If all $a_y(i)$ are either 0 or 1, (24) correctly calculates the information rate as defined in (23). Defined OF gives the same value with NEAOF under no correlation. For the denominator in (24), similar rules apply, i.e., when $a_y(i)$ of the sample is 0 it has no effect as an exponent on D_i and when it is equal to 1, it gives the distortion D_i. Furthermore, the convexity of the objective function in (24) is discussed in the next section, i.e., subsection IV-C.

In simulations utilizing ICs but not EA methods, (24) is used while setting $g_{S,R,D}(.)$ functions to 1. However, (24) is defined with EA functions to reflect the fact that in a future work both utilization of ICs and EA methods can be combined. In this article, these are separately simulated and analyzed. Next, BB algorithm is presented where OFs in (1-3) and (24) are solved.

Algorithm 1: Branch and Bound Sub-optimal Algorithm

for all $t = 1$ to t_f **and** $r = L$ to 1 **do**
  Initialize $Incumbent$ to $-\infty$, B_{Up}, Cnt_{Opt}, Cnt_{NLP} to 0
  Initialize $NBuff$ to $\{\emptyset\}$, solve the first NLP with x_0
  if The solution x is feasible **then**
    Update $B_{Up} = f_{obj}(x)$ and $NBuff = NBuff \bigcup x$
  end if
  while $Cnt_{Opt} \leq N_f$ AND $Cnt_{NLP} \leq N_s$ AND $NBuff \neq \{\emptyset\}$ AND $|B_{Up} - Incumbent| \,/\, B_{Up} \geq p_U$ **do**
    Solve NLP subproblems in $NBuff$, increase Cnt_{NLP}, update B_{Up}
    Delete x_i from $NBuff$ where $f_{obj}(x_i) \,/\, Incumbent - 1 < p_U$
    Order nodes in buffer w.r.t. either descending order for $f_{obj}(x_i)$ or depth
    Choose the last node in the buffer, i.e., x_{node}, and delete from $NBuff$
    if x_{node} is feasible **then**
      if $f_{obj}(x_{node}) - Incumbent \geq p_f \times Incumbent$ **then**
        Update $Incumbent = f_{obj}(x_{node})$
      end if
      if $|f_{obj}(x_{node}) - Incumbent| < p_f \times Incumbent$ **then**
        $Cnt_{Opt} = Cnt_{Opt} + 1$
      end if
    else
      Solve NLP problem for the node, $Cnt_{NLP} = Cnt_{NLP} + 1$
      if Branching is possible w.r.t. routing **then**
        Branch w.r.t. $I^R(r, m, n, t^+)$, $I^S(s, n, t^+)$ and $I^D(m, t^+)$
        $NBuff = NBuff \bigcup M$ new nodes
      else {Branching w.r.t transmission}
        Branch w.r.t. $I^R_{s,j}(r, m, n, t^+)$, $I^S_j(s, n, t^+)$ and $I^D_{s,j}(m, t^+)$
        $NBuff = NBuff \bigcup 2$ new nodes
      end if
    end if
  end while
end for

C. Branch and Bound Sub-optimal Algorithm

Sub-optimal algorithms are obtained with BB solutions significantly reducing search space for MINLP problems with a subset [25]. Relaxation of the problem with branches of 0-1 integer variables results in nonlinear programming (NLP) subproblems solved with MATLAB *fmincon* optimization function using a sequential quadratic programming (SQP) method.

The constraints in (4 - 22) and OFs in (1 - 3) either include convex linear combinations of the variables or expressions of the form $-W\log(1 + P\,/\,(N_0 W))$ which is a convex function [4]. For ICOF in (24), the convexity depends on the expression $-\log_2\left(|\,K_C^{B_1} \otimes B_2\,|\right)$ which is a convex function if the matrix $K_C^{B_1} \otimes B_2$ is positive semidefinite (PSD) [27]. It is not guaranteed to be PSD as observed in simulations and c_1 is inserted to make it PSD and to obtain a feasible solution. Therefore, for ICOF, the obtained solutions of NLP subproblems are sub-optimal.

In this article, the aim is to observe the advantages of the utilization of ICs and EA mechanisms for CRSNs. Therefore, the optimum usage of BB, i.e., the computational complexity is as high as of exhaustive search in the worst case [28], or finding better algorithms suitable to the nature of the problem is left as a future work. The obtained sub-optimal solutions give a lower bound to the optimization gains. A faster but less accurate solution is achieved by using a percentage ratio, i.e., p_U, for the proximity of the value of the best feasible solution obtained, i.e., *incumbent*, to the upper bound. Another method is counting the feasible values close enough within a percentage of p_f, i.e., Cnt_{Opt}, and counting the number of solved NLP subproblems, i.e., Cnt_{NLP}. These counts are checked for the thresholds N_f and N_s, respectively.

BB Algorithm is summarized in Algorithm-1. It runs until t_f starting from the last hop level and progressing backwards. Incumbent value is initialized with a depth-first search [25]. The next node selection in the buffer after forming branches is achieved by ordering the nodes with respect to either depth-first (the deepest branch first) or best-first search (the maximum objective function value first). Since the networking topology includes symmetric branches in terms of routing the data to possibly equal energy next nodes or different packets resulting in the same data rate, the whole tree is not tracked and the deepest nodes are given priority.

The algorithm starts by finding an initial solution x_0 satisfying the constraints by using heuristic methods such as randomly assigning routing and data transmissions. The ancestor nodes whose NLP solution is in the p_U percentage of incumbent value are discarded to increase the speed. The buffer holding the NLP subproblem nodes is denoted by $NBuff$. The branching operation is of either related to selection of the next relay level, i.e., routing, or related to data transmission boolean, i.e., whether the data in the buffer will be transmitted. For each node (except at $r = L$), M branches are formed corresponding to different routing decisions. Then, the transmission variables are set to either 0 or 1 resulting in 2 branches per variable. The algorithm stops if the count of the feasible solutions and solved NLP subproblems exceed their thresholds, or $NBuff$ is emptied or the best feasible solution obtained is in a percentage p_U of the bound B_{Up}. Next, OF performances are compared in simulation study.

TABLE II
THE GLOBAL VALUES USED IN NUMERICAL SIMULATIONS.

Parameter	Value
M_s, M, L	3, 3, 4
T_s, t_f	1, 70 (sec)
D_s, σ_s^2	0.005, 9
$H(X_{s,j})$, r_S	11895 bits, 2200 Hz
$\alpha^T_{k,l}$, $\alpha^S_{k,l}$	0.1
V_s	$L + 1$
B_s, $B_{r,m}$	$3\,H(X_{1,1})$, i.e., 3 samples
$P_R^{PU}(r, k, t^+)$, $P_S^{PU}(k, t^+)$	0.5
$\sigma_R(r, t^+)$, $\sigma_D(t^+)$, $\sigma_S(t^+)$	10^{-12} (Watts/Hz)
W_{Tot}	9, 18, 27, 36, 45, 54 kHz
W_{ch}	3 kHz
P_{max}	3×10^{-8} Watts
p_U, p_f	0.1
N_f, N_s	20, 150

V. Numerical Simulation Results

In this section, performance vs. the total bandwidth is analyzed for relays having equal energy with continuous data traffic and for relays with unequal initial energies and bursty traffic. EAOF, NEAOF and ICOF are compared in terms of R_{max}, node lifetime and energy utilization.

The values of the simulation parameters are given in Table-II. The network consists of 3 sensors and nodes at each hop level, i.e., $M = M_s = 3$ with $L = 4$. The first 2 sensors form a group with the assumption that they are located on a line at the spatial positions 1, 1.05 (a.u.). The network size

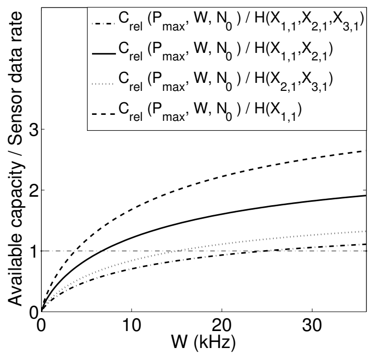

Fig. 2. Ratio of available capacity for relays to the size of the data collected from 3 sensors at time $j = 1$ with relays operating at full power, i.e., P_{max}.

is chosen as small-scale due to computational complexity as discussed in subsection IV-C. For large-scale networks, e.g., in a large physical area effected through a particular event, the correlated information size becomes greater making the utilization of IC more important. Furthermore, as L increases, energy utilization becomes more important to make the data reach the sink with limited node energy. Therefore, advantages of EA mechanisms and utilization of ICs will be observed more clearly in large-scale networks left as a future work.

Two different kinds of PU-SU interference schemes, i.e., PU_1 and PU_2, are considered where the probability that PU allocates channel k (divided into discrete intervals of W_{ch}, e.g., 3 kHz) at the position corresponding to the sensors at hop level r at time t is set to 0.5, i.e., $P_S^{PU}(k, t^+) = P_R^{PU}(r, k, t^+) = 0.5$. The remaining spectrum is used by sensors freely. PU_1 assumes PU activity is the same at each hop level such that PU effects the network globally. As a result, the total bandwidth available to sensors at different hop levels is the same, i.e., $W_{SU}^R(r,t) = W_{SU}^S(t) = W_{SU}^D(t)$. PU_2 assumes that PU activity is location dependent, e.g., sensor network with a wide area coverage, and the available bandwidth is different at each hop level. Much more MC simulations are performed for PU_2 due to increased variation compared with PU_1. For PU_1 and PU_2, 30 and 80 MC simulations are performed, respectively. Besides that, W_{Tot} is varied between 9-54 kHz enough to transmit the packets of 3 sensors as shown in Fig. 2. The change of $P_{R,S}^{PU}(.)$ is not simulated since the diverse change of W_{Tot} results in the same effect for SUs.

$\alpha_{k,l}^T$ and $\alpha_{k,l}^S$ are set to 0.1 such that in an approximately 7 arbitrary units of spatial distance and 7 seconds time difference, the correlation coefficient drops to half value. The buffers hold 3 samples, i.e., $3 \times H(X_{s,j})$. V_s is set to $L+1$ such that a packet waiting more than 2 seconds is dropped as a realistic assumption for fast data gathering.

In the first simulation, the amounts of energies for 3 relays in a level are equal, i.e., symmetric case, as $E_1 \equiv [6.6\ 6.6\ 6.6] \times P_{max} \times T_s$, and for the second simulation, i.e., asymmetric case, $E_2 \equiv [3\ 7\ 10] \times P_{max} \times T_s$ results in the same total level energy with E_1. Simple EA utility functions are defined as $g_R(r,m,n,t) = \left(E_{r,m}^*(t) + E_{r+1,n}^*(t)\right) / P_{max}$, $r \in S_1$, $g_S(s,n,t) = E_{2,n}^*(t) / P_{max}$ and $g_D(m,t) = E_{L,m}^*(t) / P_{max}$ where the node selects data from and to the nodes with higher energies such that sum of the remaining energies of transmitting and/or receiving nodes multiplies OF value.

In a dynamic CRSN with limited energy, the important metrics are delay, reliability, and energy consumption [29]. The reliability is modeled as the capability of the sink to detect events with a small time delay. Reliability is measured by adjusting TTL to a very low value such that only the packets sent to the sink in a rush manner live. Therefore, by observing the total amount of correlated information, i.e., $I_c(t_f)$, a reliability measure is achieved. R_{max} is defined as the maximum rate of $I_c(t_f)$, i.e., $R_{max} \equiv \max(I_c(t) / t)$. In using ICOF, the sink accumulates the correlated samples if enough time is given and the effect of sending highly uncorrelated data could vanish. In this case, only R_{max} gives high performance difference among OFs. The energy efficiency is reflected in node lifetime, i.e., LT_n, where one node gets out of energy and energy utilization, i.e., EU_n, which is the ratio of the consumed energy until t_f to total initial energy in relays [30]. Next, channel capacity vs. input power is analyzed.

A. Channel capacity vs. input power

IT parameters, i.e., D_s, σ_s, $H(X_{s,j})$ and r_S, are assigned by experimenting with P_{max}, W_{Tot} and $\sigma_R(r,t^+)$, $\sigma_D(t^+)$ and $\sigma_S(t^+)$. It is desired that with P_{max} and W_{Tot}, and noise spectral density N_0, it should be possible to transmit the total data received from 3 sensors at time j, e.g., $j = 1$, i.e., $C(P_{max}, W, N_0) \geq H(X_{1,1}, X_{2,1}, X_{3,1})$. The relation between data and available capacity for P_{max}, i.e., $C_{rel}(P_{max}, W, N_0)$, is seen in Fig. 2 for settings in Table-II.

Information rates of each sensor are assumed to be equal, i.e., $H(X_{s,j})$ is the same for all s and j. P_{max} is chosen such that the maximum signal to noise ratio (SNR) for bandwidth W_{ch} is 10 dB, i.e., $SNR_{max} = P_{max} / (W_{ch} N_0) = 10$ where $N_0 = \sigma_R(r,t^+) = \sigma_D(t^+) = \sigma_S(t^+)$. Next, the performance for varying bandwidths is simulated for the case of nodes having equal energies under continuous data traffic and then for the asymmetric case under bursty traffic.

B. Network performance for symmetric energy distribution with continuous data traffic

In this part, the network performance under continuous data traffic is analyzed for symmetric node energy levels, i.e., E_1, with PU model of PU_1. In plots, R_{max} is normalized by $H(X_{1,1}, X_{2,1}, X_{3,1})$. It is shown that EAOF with intelligent energy consumption and ICOF utilizing IC give better performances than NEAOF for R_{max} as observed in Fig. 3(a). However, the comparison between EAOF and ICOF is questionable since they are not directly comparable and more theoretical and simulation analyses are necessary to compare the gains obtained with energy adaptation and IC utilization. In this work, 2 different kinds of comparisons are considered, i.e., EA vs. non-EA and utilizing IC vs. not utilizing. OF design combining IC utilization and EA mechanisms is necessary for further performance improvement and left as a future work. For all OFs, the increase in R_{max} with W_{Tot} is due to the

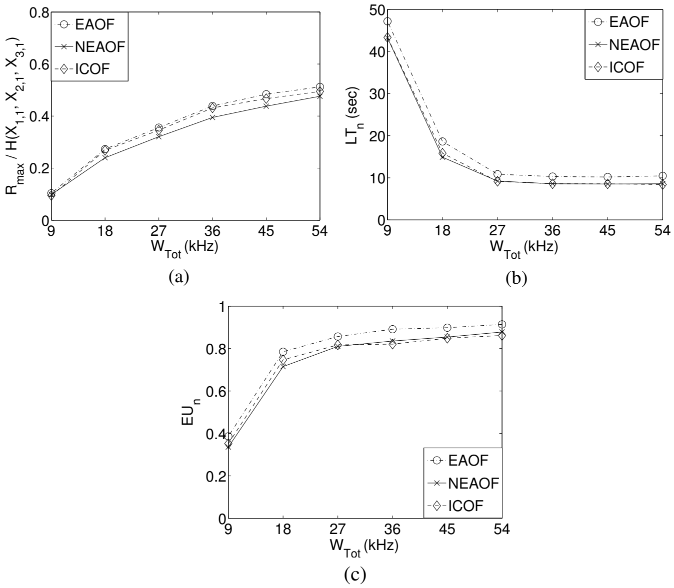

Fig. 3. OF performances at energy level E_1 under continuous data traffic for (a) R_{max} vs. W_{Tot}, (b) LT_n vs. W_{Tot} and (c) EU_n vs. W_{Tot}.

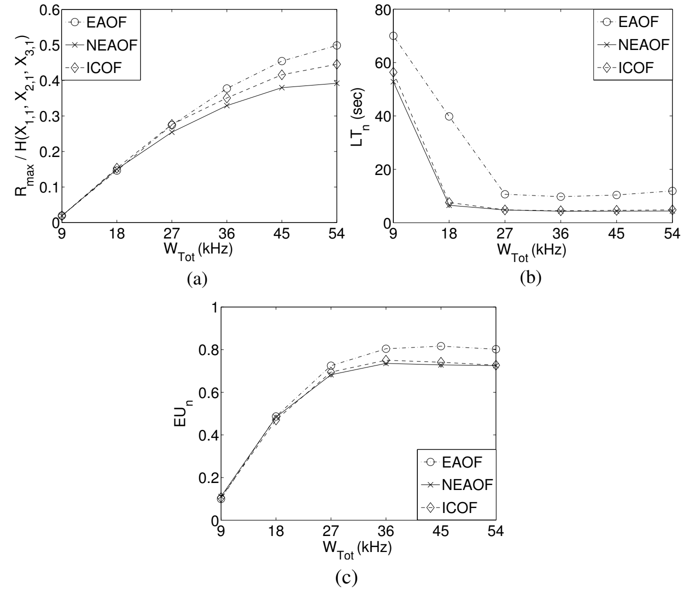

Fig. 4. OF performances at energy level E_2 under bursty data traffic for (a) R_{max} vs. W_{Tot}, (b) LT_n vs. W_{Tot} and (c) EU_n vs. W_{Tot}.

increasing capacity for nodes as shown in Fig. 3(a). On the other hand, the saturation observed for R_{max} upon an increase in W_{Tot} resembles the capacity vs. bandwidth for a single link similar to Fig. 2 and it is concluded that R_{max} has a roughly logarithmic bandwidth dependence like the single channel capacity expression.

In terms of LT_n, EA case has slightly better performance than the other two OFs due to more balanced use of nodes as shown in Fig. 3(b). However, since initial node energies are equal, the increase is slightly. LT_n decreases and saturates as W_{Tot} is increased since as W_{Tot} is increased, the capacity increases and the probability to send data is increased bringing the node depletion earlier under a continuous data traffic. LT_n performance firstly decreases with increase in W_{Tot} since as the available bandwidth becomes larger, the nodes reach the capability to send data and to consume energy. After a higher level of increase in W_{Tot}, the nodes transmit data more probably and the expected difference due to decrease in the consumed power is not observed in saturated behavior because of the combined effect of fast depletion of nodes under a continuous data traffic and the small initial node energies letting transmission of only a couple of packets preventing to observe the effect of decrease in the power consumption.

EA case has a superior performance in terms of EU_n as shown in Fig. 3(c) due to more intelligent utilization of the nodes without cutting off the connection between relay levels. In a non-adaptive scheme, the nodes are chosen randomly, and less number of nodes are able to transmit decreasing the possible pathways between hops due to node failures. As W_{Tot} is increased, EU_n increases and saturates due to the increase in the capability and probability to send data.

C. Network performance for asymmetric energy distribution with bursty data traffic

In event-driven WSN, the data traffic can have a bursty character [2]. The simulations are performed by collecting data for small interval of 10 seconds, PU allocation type of PU_2 and relay energy level of type E_2 with asymmetric distribution.

In Figs. 4(a), (b) and (c), the comparison of OFs are shown in terms of R_{max}, LT_n and EU_n, respectively.

Observations, comparisons and conclusions similar to the symmetric case can be derived more clearly. The logarithmic behavior of R_{max} is better observed. Furthermore, EAOF has better EU_n and a significantly better LT_n performance due to the asymmetric energy distribution such that without EA scheme the nodes with lower energies are exhausted in a short time. Besides that, EA performance of LT_n in saturation becomes slightly better as W_{Tot} is further increased as shown in Fig. 4(b) due to the combined effect of decreased power consumption with increased bandwidth levels, smaller traffic compared with continuous case and the intelligent energy consumption. In bursty traffic, since it is less probable for a node to operate with P_{max} to send randomly encountered data, the advantage of smaller power consumption due to higher bandwidth combined with intelligent energy consumption is observed in LT_n performance. In NEAOF case, the nodes are randomly used and this advantage is not clearly observable.

VI. Conclusions

In this paper, an optimization framework is introduced for a multi-hop CRSN topology maximizing the information capacity sent to the sink combining CRSN characteristics with EA mechanisms, power-bandwidth control and IC utilization. The general Cmax problem is defined analytically and then local realtime OFs are presented. Simulation study is given for a simple CRSN with Gaussian sensor data sources and the optimization methods are compared in terms of R_{max}, node lifetime and energy utilization of the network. Characteristic behaviors of these metrics for varying total bandwidth are derived emphasizing the logarithmic dependence of R_{max} on total bandwidth. It is concluded that EA mechanism performs better compared with the non-adaptive mechanism while its superiority is better observed in a realistic sensor network with asymmetric energy distributed nodes and bursty traffic. Furthermore, the optimization mechanism using IC among the sensor data performs better compared with the one not utilizing. It is concluded that a theoretical design of a convex OF mixing the EA mechanism and IC utilization with possibly superior performance is left as a future work.

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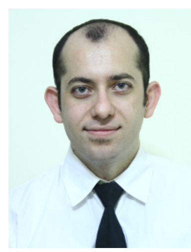

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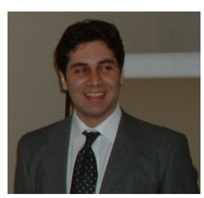

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