Optimum Trajectory Planning for Robotic Data Ferries in Delay Tolerant Wireless Sensor Networks

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***Abstract*—We consider the issue of energy efficient data collection in the context of a mobile robot-aided delay tolerant wireless sensor network (DTSN). The latter is composed of static nodes (SNs), a fusion center (FC) and a mobile robot (MR), which acts as a data ferry in order to reduce energy consumption at the SNs, thereby increasing their lifetime. The considered wireless channel model accounts for both path loss and shadowing. We propose a method to optimise the trajectory of the MR so as to minimise the overall energy consumption of the DTSN, while controlling the latency of the end-to-end transmission and maintaining the number of bits in the SNs' buffers bounded. Simulation results show the effectiveness of the proposed solution in reducing the energy consumption of the DTSN.**

***Index Terms*—Wireless sensor network, energy efficiency, mobile robot, delay tolerant networks**

I. Introduction

Wireless sensor networks (WSNs), together with the Internet of Things (IoT) [1], are considered as one of the most important emerging digital technologies. Their deployment in the last 10 years has been witnessed in several sectors such as health-care, building infrastructure, agriculture, environment monitoring and military applications [3]–[8], [20]. Recently, there has been an increasing interest in the exploitation of mobility and MRs to improve the performance of WSNs, e.g. routing in [9], energy balancing in [10], and improving security in [11]. MRs can also be used as data ferries to collect data from sensor networks [19], [20], [12]. This is a suitable solution to reduce the energy consumption of the WSN when the sensing nodes are located far from the FC, and the sensors are powered by batteries. In this paper, we consider this scenario and propose a method to optimise the trajectory of the MR under a number of practical constraints.

We consider a delay tolerant sensor network (DTSN) composed of a fusion center (FC), a mobile robot (MR), operating as a data ferry, and a number of spatially distributed static sensor nodes (SSNs), among which only K can communicate with the MR; the remaining SSNs could be served by other MRs, or else the set of the K SSNs that communicate with the MR could be operating as cluster heads within the WSN gathering data from the other SSNs and then forwarding it to the MR. We consider a realistic communication channel experiencing shadowing. We propose a new adaptive algorithm to optimise the trajectory of the MR in order to extend the life-time of the DTSN. Note that the lifetime of the DTSN depends on both the energy consumptions of the SSNs and of the MR. To the authors' knowledge, this is the first time that the trajectory of a data ferry is optimised in this context while accounting for the shadowing in the wireless channels. We also determine the maximum capacity of this system by determining the conditions under which the stability of the WSN is maintained.

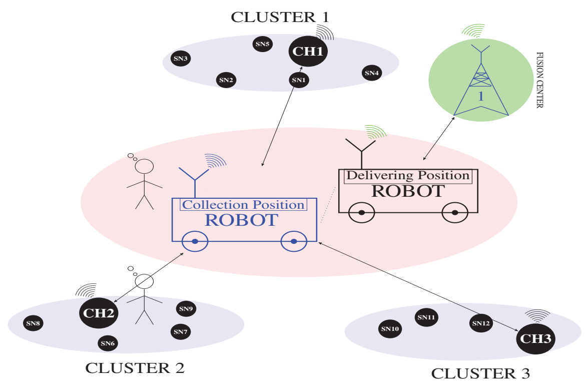

Fig. 1. Schematic communication architecture of the studied MR-aided DTSN, in the case where the SSN communicating with the MR are cluster heads.

II. System Model

The position of the k^{th} SSNs that can communicate with the MR is denoted by $\mathbf{p}_k$, with $k = 1, 2 \cdots, K$; we denote the geometrical center of all these K SSNs as $\bar{\mathbf{p}}$; the positions of the FC and the MR are denoted by $\mathbf{p}_0$ and $\mathbf{p}(t)$ respectively. For mathematical simplicity, we will use a single integrator model for the MR and so its position is related to the control signal $\mathbf{u}$ by $\mathbf{p}(t) = \mathbf{p}(0) + \int_0^t \mathbf{u}(\tau)\mathrm{d}\tau$ where $\|\mathbf{u}(\tau)\| \leq u_{max}$. Also, for mathematical simplicity, we consider that the electrical energy consumed by the MR motors from time instant t_1 up to time instant t_2 is given by:

$$E(t_1, t_2) = \mathcal{K}_m \int_{t_1}^{t_2} \|\mathbf{u}(\tau)\|^2 \mathrm{d}\tau \qquad (1)$$

where $\mathcal{K}_m$ is a constant proportional to the MR's mass. We note that the results derived in this paper can be easily extended to consider more elaborated models (i.e., including the

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MR's dynamic model and the resulting energy consumption model, as in [14]).

A. Communication Network Model

The wireless channels related to the SSN-to-MR and MR-to-FC links are assumed to be both time and frequency invariant, and consist of both path loss and shadowing. In this work, we assume that the small-scale fading has been already compensated for by one of the existing compensation techniques [13], [14]. Thus, the received signal ($y_k(t)$) at the MR from the k^{th} SSN can be expressed as:

$$y_k(t) = \left(\frac{s(\mathbf{p}_k, \mathbf{p}(t))}{\|\mathbf{p}_k - \mathbf{p}(t)\|_2^{\alpha/2}} \right) x_k(t) + n(t) \qquad (2)$$

where α is the pathloss exponent, $n(t) \sim \mathcal{CN}(0, \sigma_n^2)$ is the additive white Gaussian noise (AWGN), $s(\mathbf{p}_k, \mathbf{p}(t))$ is the shadowing term which follows a lognormal distribution. Hence, $s_{dB}(\mathbf{p}_k, \mathbf{p}(t)) = 10 \log (s(\mathbf{p}_k, \mathbf{p}(t)))$ is Gaussian distributed with spatial correlation function [15]:

$$\mathbb{E}\left[s_{dB}(\mathbf{o}, \mathbf{p}) s_{dB}(\mathbf{o}, \mathbf{q})\right] = \beta \exp\left(\frac{-\|\mathbf{p} - \mathbf{q}\|_2}{\gamma} \right) \qquad (3)$$

where $\mathbf{o}, \mathbf{p}, \mathbf{q} \in \mathbb{R}^2$ are any points within the operation region; β is the variance of the shadowing term (in dBs) and γ is the $decorrelation$ distance.

With regard to the modulation technique, we assume a single-carrier M-PSK with symbol duration T_s. Power control mechanism is used so that a reference power P_{ref} at the receiver is ensured. So, during the data transmission, the transmit power of the k^{th} SSN ($P_k^{tx}(t)$) can be expressed as [1]:

$$P_k^{tx}(t) = \left(\frac{\|\mathbf{p}_k - \mathbf{p}(t)\|_2^{\alpha}}{s^2(\mathbf{p}_k, \mathbf{p}(t))} \right) P_{ref}. \qquad (4)$$

Next, we consider the network management and elaborate on the data transmission scheme.

III. Problem description and MR operation

As stated before, we consider a DTSN which is composed of a FC and a number of SSNs, K of which can communicate with the MR. These SSNs gather data at a constant bit rate r and store it into a buffer of limited size L. [2] When the buffer of the k^{th} SSN is full, then all the new data gathered by this SSN will be discarded until space in the the buffer is liberated via the transmission of the existing data to the MR.

To further ensure the reliability of the network, the data stored in a SSN's buffer is transmitted to the MR using the Transmission Control Protocol (TCP)[3]. We also assume that the distances $\{\|\mathbf{p}_0 - \mathbf{p}_k\|_2\}_{k=1}^K$ are large enough so that direct communication from the SSNs to the FC would quickly deplete their batteries. To increase the lifetime of the SSNs, the MR is used as a data ferry to forward all the data from the SSNs.

[1]The transmit power of the MR when transmitting to the FC is given by (4) with $k = 0$.

[2]Note that the SSNs are battery operated and have limited resources onboard, in terms of both memory and signal processing capabilities.

[3]The same transmission protocol is used for data transmission by the MR to the FC.

A. MR Operation

The MR's operation is divided into four different cyclic phases (to be described next) and the period to complete all these phases (starting at the first phase) is referred to as an *epoch*. The duration of the j^{th} *epoch* is denoted by T_j. Now, during the j^{th} *epoch*, the four MR's cyclic phases can be described as follows in **Algorithm1** :

Algorithm1 : MR's Data Ferry Operation

POSITIONING PHASE FOR COLLECTION- (time instant t_1^j to t_2^j):
In this first phase, the MR moves in a straight line from the initial point $\mathbf{q}_d^{j-1}$ to the *collection point* $\mathbf{q}_c^j$ with a constant speed v^j;

COLLECTION PHASE- (time instant t_2^j to t_3^j):
During this phase, located at the optimum *collection point* ($\mathbf{q}_c^j$) (detailed in Section IV), the MR is now tasked to collect the data from all the K SSNs. The k^{th} SSN transmits to the MR $b_{j,k}$ bits of information stored within its buffer by means of TCP packets. If an error is detected during the packet reception, then the corresponding packet is re-transmitted until successfully received. Upon successfully receiving all the packets sent by the k^{th} SSN, the MR is then tasked to collect the next SSN's (i.e., the $(k+1)^{th}$ SN) data and the above process is repeated $\forall K$ SSNs.

POSITIONING PHASE FOR DELIVERING- (time instant t_3^j to t_4^j):
During this phase, the MR moves in a straight line from $\mathbf{q}_c^j$ to the optimum *delivering point* $\mathbf{q}_d^j$ (detailed in Section IV) with a constant speed v^j;

DELIVERING PHASE- (time instant t_4^j to t_1^{j+1}):
In this phase, located at the optimum *delivering point* $\mathbf{q}_d^j$, the MR transmits all the data received from the SSNs to the FC using the TCP protocol. Upon transmitting all the data to the FC, the MR proceeds to execute the *positioning phase*;

Directly considering the limited size of the SSNs' buffers significantly complicates the DTSN analysis and optimization. Therefore, for simplicity and tractability, we assume the buffers' size to be infinite during the analysis and the optimisation of the DTSN. Then, after the optimisation procedure, the designer could select the proper size L of the buffer by analysing the behaviour of the buffer.

So, the number of bits in the k^{th} SSN's buffer during the *collection phase* of the j^{th} epoch before and after the transmission are denoted by $b_k^-(j)$ and $b_k^+(j)$ respectively:

$$\begin{aligned} b_k^-(j) &= b_k^+(j-1) + r\tau_{j,k}^- \\ b_k^+(j) &= b_k^-(j) + r\tau_{j,k} - b_{j,k} \end{aligned} \qquad (5)$$

where $\tau_{j,k}$ is the duration of the k^{th} SSN transmission process during the j^{th} epoch; $\tau_{j,k}^-$ is the time elapsed from the end of the k^{th} SSN transmission process during the $(j-1)^{th}$ epoch until the beginning of its transmission process during the j^{th} epoch; $b_{j,k}$ is the total number of information bits $successfully$ transmitted to the MR during the j^{th} epoch by all SSNs. Next, we discuss the TCP packet composition.

B. TCP Packet Composition

Each packet contains a header of h bits containing the relevant information for the MR's operation. The total number of bits in the payload is denoted by G. The number of TCP packets transmitted (without taking into account re-transmissions) by the k^{th} CH to the MR during the j^{th} epoch is $N^P_{j,k} = \lceil b_{j,k}/G \rceil$. The payload of the first $N^P_{j,k} - 1$ packets consists of G bits of information while the payload of the last packet consists of $b_{j,k} - G(N^P_{j,k} - 1)$ bits of information and *filler* bits (if necessary) to complete the G bits of payload for that packet.

The MR processes the received packets and is capable of discarding the *filler* bits [4]. Hence the number of packets that the MR will transmit to the FC is $N^P_{j,0} = \lceil \frac{\sum_{k=1}^{K} b_{j,k}}{G} \rceil$.

For simplicity, we assume that $\frac{G+h}{\log_2(M)} \in \mathbb{N}$ where $\log_2(M)$ is the number of bits transmitted per symbol when using the M-PSK modulation. Therefore, the transmission duration of a single TCP packet is $T_P = N_s T_s$ where $N_s = (G+h)/\log_2(M)$ is the number of symbols per packet. Regarding the ACK messages (for simplicity) we will neglect their duration and assume that they are always received without errors.

The probability of receiving an error free packet can be easily shown to be:

$$\mathrm{P_{efp}} = (1 - \mathrm{P}_s)^{N_s} \tag{6}$$

where P_s is the symbol error probability, and for the M-PSK modulation we have [16] $\mathrm{P}_s \approx 2\mathrm{Q}\left(\sqrt{\frac{2P_{ref}}{\sigma_n^2}} \sin\left(\frac{\pi}{M}\right)\right)$.

It is worth pointing out that various transmission strategies for the k^{th} SSN (i.e., $b_{j,k}$) are possible in general. In this paper, due to limited space, we only consider $b_{j,k} = b_k^-(j)$ (i.e., transmit the full content of the buffer).

Before considering the optimization of the DTSN in the next section, we would like to note that it can be demonstrated [5] that a *necessary condition* for the buffers' stability (i.e., $b_k^-(j) < +\infty \;\; \forall j$) is:

$$Z \triangleq \frac{2K(G+h)T_s r}{G \log_2(M) P_{efp}} < 1. \tag{7}$$

We will elaborate more on this in the simulation results section. Next we consider the DTSN optimisation.

IV. DTSN OPTIMISATION

As stated before, during the optimisation process, we will consider infinite size buffers. Also, during the optimisation process, we will replace the shadowing term $s(\mathbf{p}_k, \mathbf{p}(t))$ with its predicted value denoted $\tilde{s}(\mathbf{p}_k, \mathbf{p}(t))$ which can be calculated by the MR using the same technique used in [18].

Before formulating the optimisation problem, we derive the expected value of the energy consumed by the MR and the k^{th} SSN during the j^{th} epoch. Note that the number of times a TCP packet has to be transmitted before being received without errors is a discrete random variable with a geometrical probability mass function with a mean equal to $1/P_{\mathrm{efp}}$. [6] Considering (1), (4), and (6), it can be easily shown that the average energy consumption by the MR during the j^{th} epoch is:

$$\begin{aligned} \mathbb{E}[E_0(j)] &= E(t_1^j, t_2^j) + E(t_3^j, t_4^j) + \mathbb{E}\left[\int_{t_4^j}^{t_1^{j+1}} P_0^{tx}(t)\mathrm{d}t\right] \\ &= \mathcal{K}_m \left(\|\mathbf{q}_c^j - \mathbf{q}_d^{j-1}\| + \|\mathbf{q}_d^j - \mathbf{q}_c^j\|\right) v^j \\ &+ \left(\frac{\|\mathbf{p}_0 - \mathbf{q}_d^j\|_2^\alpha P_{ref}}{\tilde{s}^2(\mathbf{p}_0, \mathbf{q}_d^j)}\right) \left\lceil \frac{\sum_{k=1}^K b_k^-(j)}{G} \right\rceil \frac{T_P}{\mathrm{P_{efp}}} \end{aligned} \tag{8}$$

where the first two terms correspond to the energy consumed in motion during the *"positioning phase for collection"* and *"positioning phase for delivering"* while the third term is the energy spent by the MR during the *"delivering phase"*.

Following a similar approach, it can be shown that the energy spent by the k^{th} SSN during the j^{th} epoch is:

$$\begin{aligned} \mathbb{E}[E_k(j)] &= P_k^{tx}(t)\tau_{j,k}, \\ &= \left(\frac{\|\mathbf{p}_k - \mathbf{q}_c^j\|_2^\alpha P_{ref}}{\tilde{s}^2(\mathbf{p}_k, \mathbf{q}_c^j)}\right) \left\lceil \frac{b_k^-(j)}{G} \right\rceil \frac{T_P}{\mathrm{P_{efp}}}. \end{aligned} \tag{9}$$

Finally, the expected duration T_j of the j^{th} epoch can be shown to be:

$$\begin{aligned} \mathbb{E}[T_j] &= \frac{\|\mathbf{q}_d^{j-1} - \mathbf{q}_c^j\|}{v^j} + \sum_{k=1}^K \left\lceil \frac{b_k^-(j)}{G} \right\rceil \frac{T_P}{\mathrm{P_{efp}}} \\ &+ \frac{\|\mathbf{q}_d^j - \mathbf{q}_c^j\|}{v^j} + \left\lceil \frac{\sum_{k=1}^K b_k^-(j)}{G} \right\rceil \frac{T_P}{\mathrm{P_{efp}}} \end{aligned} \tag{10}$$

In this work, the DTSN optimisation problem is formulated such that the overall DTSN energy consumption is minimised. Note that the optimisation of the DTSN parameters used during the j^{th} epoch is performed at the end of the $(j-1)^{th}$ epoch. So, the optimisation problem is formulated as follows:

$$\begin{aligned} &\min_{P_{ref}, \mathbf{q}_c^j, \mathbf{q}_d^j, v^j} \; (1-\theta)\mathbb{E}\left[E_0(j)\right] + \frac{\theta}{K}\sum_{k=1}^K \mathbb{E}\left[E_k(j)\right] + g_j(\lambda) \\ &\text{s.t.} \\ &g_j(\lambda) = \exp\left(\tfrac{\lambda(\mathbb{E}[T_j] - \bar{T})}{\bar{T}}\right), \mathbf{p}(t_1^j) = \mathbf{q}_d^{j-1}, \mathbf{q}_d^j \in \mathcal{C}(\{\bar{\mathbf{p}}, \mathbf{p}_0\}) \\ &b_1^-(j) = b_1, \quad b_k^-(j) = b_k + r\textstyle\sum_{n=1}^k \tau_{j,n}, \; k = 2, \cdots, K \\ &v^j \le u_{max}, \quad P_{ref} \le P_{MAX}, \; Z < 1. \end{aligned} \tag{11}$$

where θ (a design parameter) determines the importance of minimising both the mean energy consumption of the SSNs and the energy consumption of the MR; θ can be chosen by taking into consideration both the capacity of the SSNs' and MR's batteries as well as taking into account how easy or difficult it is to recharge the MR's battery in the considered

[4]The MR has knowledge about the location of the *filler* (redundant) bits used to complete the frame.

[5]The necessary condition can be obtained by deriving the first order difference equation describing the behaviour of $b_k^-(j)$ and then analysing its pole so that the zero-input response is stable. Due to lack of space, we are unable to provide in this paper further demonstration details.

[6]Note that P_{efp} depends on P_{ref} (see (6) and paragraph below).

scenario; $\mathcal{C}(\mathcal{S})$ is the convex hull of the points contained in the set $\mathcal{S}$; $\{b_k\}_{k=1}^{K}$ are the numbers of bits in the buffers of the SSNs at time instant t_1^j when the optimisation problem is solved; and P_{MAX} is the maximum value of the reference power. The constraint $Z < 1$ ensures the stability of the buffer as mentioned in (7); more details about this are in the simulation results section.

The cost function (11) is the convex combination of the mean of the expected SSNs' energy consumption and the MR's energy consumption plus a penalisation term $g_j(\lambda)$ (λ being a large positive number). This term penalises the cost function significantly if $\mathbb{E}[T_j] > \bar{T}$, where $\bar{T}$ is the intended time limit for each epoch[7]. The higher (lower) the value of θ, the shorter (longer) the epochs will be. As a consequence, a lower (higher) $b_k^-(j+1)$ implies a lower (higher) SSNs buffer size L.

To effectively solve (11), we first consider the optimisation with respect to P_{ref} for a constant $g_j(\lambda)$[8]. This yields a suboptimum solution but reduces the computational load considerably. Thus, we have that:

$$P_{ref}^* = \min\left[\max\left(P_Z, P_0\right), P_{MAX}\right] \tag{12}$$

where P_Z is the minimum value of P_{ref} that satisfies $Z < 1$ (see (7)), and P_0 is the value of P_{ref} that solves:

$$\frac{\partial}{\partial P_{ref}}\left\{\frac{P_{ref}}{\left(1-2\mathrm{Q}\left(\sqrt{\frac{2P_{ref}}{\sigma_n^2}}\sin\left(\frac{\pi}{M}\right)\right)\right)^{N_s}}\right\} = 0. \tag{13}$$

Equation (13) is the derivative of the cost function in (11) for $\mathrm{P}_s \approx 2\mathrm{Q}\left(\sqrt{\frac{2P_{ref}}{\sigma_n^2}}\sin\left(\frac{\pi}{M}\right)\right)$ in (6) as stated before. This equation can be easily solved numerically.

Finally, we optimize (11) with respect to $\mathbf{q}_d^j$ and $\mathbf{q}_c^j$ (for P_{ref}^*) using simulated annealing (SA) algorithm [17] by initiating the optimisation with the parameters obtained during the previous epoch (i.e., $(j-1)^{th}$). It can be shown that the MR's optimum speed is a quadratic function which is parametrised by q_d^j and q_c^j. [9]

V. Simulations

In this section, we evaluate numerically the performance of our proposed solution. We simulate a DTSN composed of M SSNs equally divided into $K = 4$ clusters with arbitrary SSN geometry, where the distances of the MR-SSNs and MR-FC links are assumed to be known. We consider a pathloss coefficient $\alpha = 2$, a 16-PSK modulation scheme, and a symbol duration of $T_s = 100\mu$s. The SSNs position are $\mathbf{p}_1 = [5\gamma\ 0]^{\mathrm{T}}$, $\mathbf{p}_2 = [-5\gamma\ 0]^{\mathrm{T}}$, $\mathbf{p}_3 = [0\ 5\gamma]^{\mathrm{T}}$, $\mathbf{p}_4 = [0\ \ -5\gamma]^{\mathrm{T}}$ and FC position $\mathbf{p}_0 = [60\gamma\ 0]^{\mathrm{T}}$. We set $\gamma = 1.4$ m; $\beta = 2$ dB; $u_{max} = 3$ m/s and $\mathcal{K}_m = 2 \cdot 10^{-6}$; $P_{MAX} = 150$ nW, $\sigma_n^2 = 0.7071$ nW. For the TCP packet, we set $h = 160$ bits and $G = 600$ bits. For the SSNs, we have that $r = 2$ kb/s and $\bar{T} = 900$ s.

[7]The exponential form of the penalization term $g_j(\lambda)$ allows to significantly penalize the cost function even if $\mathbb{E}[T_j]$ is just slightly greater than $\bar{T}$.

[8]$g_j(\lambda)$ being constant implies P_{ref} is independent of $\mathbf{q}_c^j$, $\mathbf{q}_d^j$, and v^j.

[9]Due to lack of space, we are unable to provide further details.

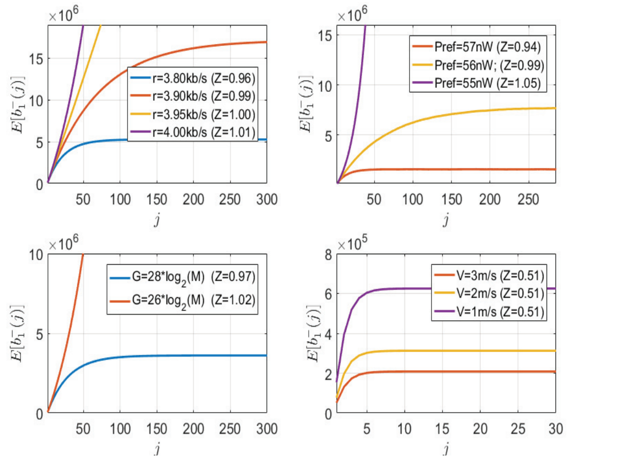

Fig. 2. $\mathbb{E}[b_1^-(j)]$ under different parameter configurations and values of the pole Z.

We would like to first verify by means of simulations that equation (7) is indeed a necessary condition for the buffer stability. In Fig. 2, we plot $\mathbb{E}[b_1^-(j)]$ for different values of Z (see (7)). [10] To get insight into the problem, we vary only a single parameter at a time while maintaining the other parameters constant during all epochs.

From Fig. 2, we observe that indeed when $Z \geq 1$, the system's buffer becomes unstable (i.e., $\lim_{j\to+\infty}\mathbb{E}[b_1^-(j)] = +\infty$). Also, for smaller values of Z, shorter duration of the transient state as well as lower values of $\mathbb{E}[b_1^-(j)]$ during the steady state are observed. Note that in practice, the design parameter (Z) can be used to estimate the number of SSNs that can be served by the MR while the stability is maintained. We also note that Z is independent of the MR's velocity, (see (7)). Hence, the MR's velocity does not affect the buffer's stability but only its steady state value (see Fig. 2). Clearly, this implies that the MR can move slow enough without affecting the system stability but this will results in a larger latency and higher number of bits ($\mathbb{E}[b_1^-(j)]$) in the buffer.

In Fig. 3, we consider four different scenarios: i) $\theta = 2/3$ and full knowledge of the shadowing maps $\{s(\mathbf{p}_k, \mathbf{p}(t))\}_{k=0}^{K}$; ii) $\theta = 2/3$ but considering a generic shadowing predictor modelled as $\tilde{s}_{dB}(\mathbf{p}_k, \mathbf{p}(t)) = s(\mathbf{p}_k, \mathbf{p}(t)) + w_k(\mathbf{p}(t))$ where $w_k(\mathbf{p}(t)) \sim \mathcal{N}(0, 0.01)$ is a spatial Gaussian random process with the same spatial correlation as that of the shadowing and represents a mildly noisy predictor; iii) same parameters as configuration ii) but with $\theta = 1$; iv) no optimization and $\mathbf{q}_c^j = \bar{\mathbf{p}}$, $\mathbf{q}_d^j = \mathbf{p}_0 - [5\gamma,\ 0]^{\mathrm{T}}$, $v = u_{max}$ and $P_{ref} = P_{MAX}$.

In Fig. 3 we observe that the energy consumption of the optimised DTSN (i.e., configuration i)) is significantly lower for both the MR and the SSNs. This shows that the proposed technique enables significant reduction of the overall energy consumption. Also, for all of the optimised scenarios, $\mathbb{E}[T_j] < \bar{T}$. Clearly, the penalisation term $g_j(\lambda)$ in (11) does enable an epoch duration limit to $\bar{T}$.[11] It is also interesting to note in

[10]$\{\mathbb{E}[b_k^-(j)]\}_{k=2}^{K}$ provide us with the same information.

[11]As long as there is a feasible set of parameter values that can satisfy such constraint.

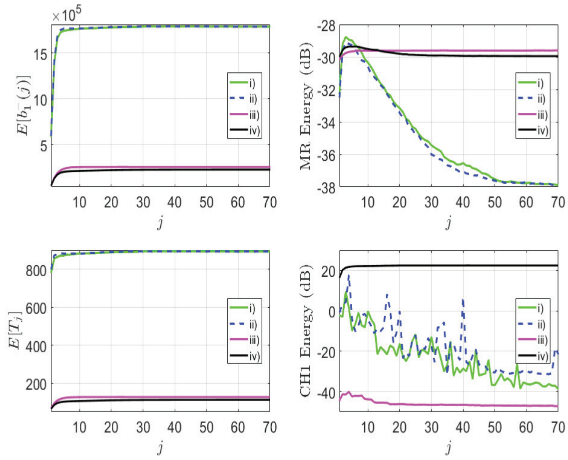

Fig. 3. Expected number of bits in the buffer prior to transmission $\mathbb{E}[b_1^-(j)]$, expected epoch duration $\mathbb{E}[T_j]$, and energy consumption for CH 1 and for the MR for different configurations.

Fig. 3 that even after $\mathbb{E}[b_1^-(j)]$ has reached the steady state, the energy consumption for both the MR and the SSN 1 are still on a transient state. This is due to the random nature of the SA algorithm. [12] Due to lack of space, we are unable to provide further insight into this behaviour but future work will analyse this in more detail.

Now, configuration i) provides an upper bound on the system's performance since it considers full knowledge of the shadowing maps while configuration ii) considers a mildly noisy predictor for the shadowing. Clearly, there is only a small degradation (among these two) in terms of the SSNs energy consumption. Finally, configuration iii) considers $\theta = 1$ such that the SSNs' only minimisation is considered (without taking into account the MR's energy consumption). As expected, the SSNs' energy consumption is significantly reduced with respect to configurations i) and ii). However, the MR's energy consumption is significantly increased. As a result, values of θ close to one do not reduce the overall DTSN network (i.e., SSNs and MR).

VI. Conclusions

In this paper, we have considered a delay tolerant sensor network (DTSN) which relies on data ferrying using a mobile robot. We have proposed an efficient solution to improve the DTSN operational lifetime by reducing the network overall energy consumption through the optimisation of the MR's trajectory. We have also derived the DTSN stability condition and insight into the problem have been provided. Simulation results show that the proposed solution (provided that the stability condition is met) can effectively reduce the SSNs energy consumption. Future work will investigate the case where the DSTN is assisted by multiple MRs.

[12]This optimisation algorithm partially uses a random search and the probability of finding the optimum value tends to one as the number of interactions tends to infinity. As a result, a finite number of iterations indicates inability of the SA algorithm to reach the optimum.

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