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Joint Energy-Efficient Cooperative Spectrum Sensing and Power Allocation in Cognitive Machine-to-Machine Communications

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Abstract—In battery-powered Cognitive Machine-to-Machine Communications (CM2M), the energy consumption, opportunistic data access capacity and interference to the licensed system need to be optimized simultaneously. We consider this as joint cooperative spectrum sensing and power allocation, and model this as a constraint multiobjective optimization problem of three objectives. Our model helps to find a Pareto optimal variable set of sensing duration, detection threshold and transmission power for each individual sensor in cooperative spectrum sensing. The evaluation of our model shows that energy consumption, opportunistic data capacity and interference are optimized simultaneously while keeping the total cooperative spectrum sensing error lower than a predefined threshold. Pareto optimal results show that better energy efficiency [bits/joule] makes lower harmful interference to the primary system.

Index Terms—Cognitive Machine-to-Machine, Multiobjective optimization, Joint Optimization, Energy-Efficient Cooperative Spectrum Sensing, Power Allocation.

I. INTRODUCTION

Wireless networks have become more and more intensively used and accessed by wireless devices such as mobile phones, tablets, and by almost all types of so called Internet-of-Thing devices and Machine-to-Machine for ubiquitous access. In addition, high demand for wireless services from all types of connected devices significantly increases energy consumption in wireless communication, especially energy consumption for radio signal receiving, processing and transmitting. So, improving spectrum utilization by accurately sensing available unused radio spectrum using cognitive radio network [1] as well as minimizing energy consumptions for spectrum sensing are critical for the next generation of energy-efficient wireless communication networking.

This paper is motivated by the emerging technology for cognitive machine-to-machine (CM2M) where battery-powered cognitive machines coexist with primary users and opportunistically utilize the primary spectrum by mean of cooperative spectrum sensing [2], [3]. Opportunistic spectrum access improves the spectrum utilization to avoid the potential shortage of spectrum used for M2M communications when machines are massively deployed in high numbers [4], [5].

From the energy consumption point of view for CM2M, it is important to minimize the total energy used for spectrum sensing and opportunistic data transmission when the primary spectrum is detected as available. In addition, the CM2M network expects to maximize its opportunistic data capacity in order to better utilize the detected primary spectrum band, while in the mean time minimizing any potential interference caused to the primary system due to miss detection. It turns out that for better energy and spectrum utilization efficiency, CM2M needs to consider those three mentioned optimization problems at the same time.

In this paper, we model this concern using constraint multi-objective optimization for joint cooperative spectrum sensing and power allocation, where Pareto front optimality can be effectively found. Since, each machine has different signal-to-noise ratio as well as different radio channel condition, a Pareto optimal set of three variables such as sensing duration, detection threshold and transmission power is found for each individual cognitive machine. In our model, the energy consumption, opportunistic data capacity and interference energy are optimized simultaneously while keeping total cooperative spectrum sensing error lower than a predefined threshold. Our simulation results of the Pareto optimal front show that a better strategy for the energy efficiency [bits/joule], which is defined as the opportunistic data access capacity divided by the total energy consumption for sensing and transmitting, results in lower harmful interference energy.

There has been some earlier work on multiobjective optimization for spectrum sensing in cognitive radio networks. Dang et al. studied in [6] two interesting minimization problems for throughput and interference in multi-channel cognitive radio using non-constraint multiobjective optimization. However, energy consumption and cooperative spectrum sensing results are not discussed, and their model does not take into account throughput from miss detection or channel fading. The authors in [7] formulated multiobjective optimization for objective functions as energy consumption, false alarm and detection probabilities. However, their energy consump-

tion model assumes that the spectrum sensing energy and transmission energy are known. Data rate and interference optimization due to spectrum sensing are not considered. In [8], the authors minimize missed detection probability and to maximize secondary network throughput using multiobjective optimization. However, energy consumption and interference optimization problems are not studied.

The rest of the paper is organized as follows. Section II illustrates the system model and formulates the three optimization problems. Next, the proposed constraint multiobjective optimization problem is formulated in Section III. Numerical simulations are presented in Section IV to explore the Pareto front optimal solutions and validate the multiobjective optimization framework. Conclusions are stated in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a CM2M network where its cognitive machines will need to sense the primary spectrum before accessing for data transmission. Hence without loss of generality, we assume each cognitive machine (CM) implements a Media Access Control (MAC) scheme as shown in Fig. 1. Each MAC frame duration T consists of a spectrum sensing slot τ_s and an opportunistic access T_a slot for data transmission when the primary system is detected as idle [4], [9]. The cognitive gateway [10] synchronizes the cognitive machines to implement cooperative spectrum sensing, then decides the machines to access or not the primary spectrum band.

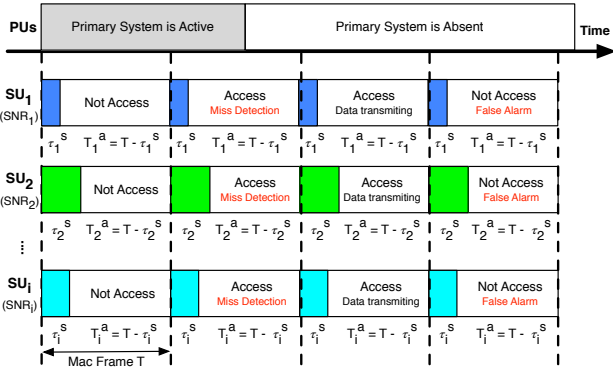


Fig. 1. CM2M access scheme with cooperative sensing.

In this cooperative spectrum sensing and opportunistic access model, the MAC duration T is assumed to be fixed. However, each $CM_i, i \in [1, 2, \dots, N_s]$ in a cooperative sensing group of N_s cognitive machines will sense the primary band during its own sensing period τ_i^s , which is not necessary to be the same as of the other machines. The fact is that the signal-to-noise ratio ($\gamma_i \equiv SNR_i$) detected by each machine is different from each other due to different geographical location and radio condition, hence different CM_i should implement different sensing duration τ_i^s as well as different energy detection threshold λ_i in order to satisfy a given spectrum detection accuracy requirement.

A. Energy Detection for Spectrum Sensing under NonFading and Rayleigh Fading Channel

The energy detection scheme [11], [12], [13] is chosen thanks to its key advantages on simplicity to implement and

that it can be applied to detect not only known, deterministic but also unknown and random signals since it does not require prior information about the primary signal.

For the input signal $y(t)$ with bandwidth $B = 2W(Hz)$, over the observation time T , the energy detector evaluates the false alarm probability p^{fa} and the detection probability p^d by comparing the test statistics V with a given threshold λ :

$$\begin{aligned} p^{fa} &= Prob\{V > \lambda | H_0\} \\ p^d &= Prob\{V > \lambda | H_1\} \end{aligned} \quad (1)$$

where, H_0 and H_1 are the hypotheses corresponding to “no signal transmitted” (noise waveform alone) and “signal transmitted” (actual signal plus noise), respectively. The test statistics $V = \frac{1}{N_{02}} \int_0^T y^2(t) dt$, and N_{02} denotes the two-sided noise power spectral density. The expressions of p^d and p^{fa} under nonfading then can be derived as:

$$\begin{cases} p^{fa} = \frac{\Gamma(m, \frac{\lambda}{2\sigma^2})}{\Gamma(m)} \\ p^d = Q_m \left(\sqrt{\frac{2m\gamma}{\sigma^2}}, \sqrt{\frac{\lambda}{\sigma^2}} \right) \end{cases} \quad (2)$$

where σ^2 is the noise variance of the zero-mean additive white Gaussian noise and the positive integer $m = TW$ denotes the time-bandwidth product. $Q_m(a, b)$ is the generalized Marcum Q -function given by $Q_m(a, b) = \int_b^\infty \frac{x^u}{a^{u-1}} e^{-\frac{a^2+x^2}{2}} I_{u-1}(ax) dx$ with $I_{u-1}(ax)$ representing the modified Bessel function of the $(u-1)$ th order. $\Gamma(a)$ is the gamma function given by $\Gamma(a) = \int_0^\infty e^{-x} x^{a-1} dx$, and $\Gamma(a, b)$ is the incomplete gamma function given by $\Gamma(a, b) = \int_b^\infty e^{-x} x^{a-1} dx$ [14].

In a strong Rayleigh fading environment, the signal amplitude follows a Rayleigh distribution, and the SNR γ follows an exponential probability distribution given by $f_{\bar{\gamma}}(\gamma) = \frac{1}{\bar{\gamma}} \exp(-\frac{\gamma}{\bar{\gamma}})$. Hence, the detection probability p^d can be estimated by averaging (3) over the SNR fading distribution, while the false alarm probability derived in (2) is unchanged.

$$\begin{aligned} p_{Ray}^d &= \frac{\Gamma(m-1, \frac{\lambda}{2\sigma^2})}{\Gamma(m-1)} + e^{-\frac{\lambda}{2(\sigma^2+m\bar{\gamma})}} \times \left(\frac{\sigma^2 + m\bar{\gamma}}{m\bar{\gamma}} \right)^{m-1} \\ &\times \left[1 - \frac{\Gamma(m-1, \frac{\lambda m\bar{\gamma}}{2\sigma^2(\sigma^2+m\bar{\gamma})})}{\Gamma(m-1)} \right] \end{aligned} \quad (4)$$

The detail proofs of equations (2), (3), and (4) are given in our technical report [15].

B. Cooperative Spectrum Sensing

When a group of N_s cognitive machines implements cooperative spectrum sensing, each CM_i makes a binary decision on whether the primary system is present or not. This decision is then forwarded to the cognitive gateway [10] via the common control channel. The cognitive gateway makes decision on whether the primary system is active or idle, using the

following ‘‘K-out-of-N’’ voting rule [16], [17] to derive the cooperative miss detection and false alarm probabilities:

$$Q^{md} = 1 - \sum_{i=K}^{N_s} \binom{N_s}{i} (p_i^d)^i (1 - p_i^d)^{N_s-i} \quad (5)$$

$$Q^{fa} = \sum_{i=K}^{N_s} \binom{N_s}{i} (p_i^{fa})^i (1 - p_i^{fa})^{N_s-i}$$

where $\binom{N_s}{i} = \frac{N_s!}{i!(N_s-i)!}$. The individual probabilities p_i^d and p_i^{fa} represent the local detection and false alarm probabilities of CM_i , respectively. $K = 1$ and $K = N_s$ are the special cases of the OR rule and AND rule, respectively [16].

C. Minimizing Total Energy Consumption

When the cooperative sensing result determines that the primary system is absent, the cognitive machines can start data transmission on the primary band, and each CM_i 's access period is $T_i^a = T - \tau_i^s$. If we denote the transmit power allocated for CM_i as P_i^t during T_i^a , then we can model the total energy consumed by machine i during T when applying its individual sensing strategy $x_i \equiv (\tau_i^s, \lambda_i, P_i^t)$ as:

$$\delta E_i(\tau_i^s, \lambda_i, P_i^t) = \mathcal{E}_i^s \tau_i^s + P_i^t (T - \tau_i^s) (1 - p_i^{fa} + p_i^{md}) \quad (6)$$

where $\mathcal{E}_i^s = \mathcal{E}^s$ denotes the sensing energy consumption per time unit, which is assumed to be constant and the same for all sensing machines without loss of generality. Eq. (6) takes into account not only the energy consumed for spectrum sensing, but also the opportunistic transmission energy when the primary system is detected as idle with $(1 - p_i^{fa})$ probability and when the primary system is actually busy but detected with miss detection probability $p_i^{md} = 1 - p_i^d$.

The total energy consumed by the cooperative group is then derived as:

$$E_T = \sum_{i=1}^{N_s} \delta E_i(\tau_i^s, \lambda_i, P_i^t) = \sum_{i=1}^{N_s} \left[\delta E_i^s \tau_i^s + P_i^t (T - \tau_i^s) (1 - p_i^{fa} + p_i^{md}) \right] \quad (7)$$

Thus, we can formulate the constraint minimization problem for the total energy consumption for cooperative spectrum sensing and opportunistic access of the CM2M as:

$$\text{Minimize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} E_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \quad (8)$$

subject to:

$$Q^{md} + Q^{fa} \leq \epsilon \quad (9)$$

where $X \equiv (\mathcal{T}^s, \Lambda, \mathcal{P}^t)$ represents the multi dimensional decision (variable) vectors as $\mathcal{T} = \{\tau_i^s\}_{i=1}^{N_s}$, $\Lambda = \{\lambda_i\}_{i=1}^{N_s}$, and $\mathcal{P}^t = \{P_i^t\}_{i=1}^{N_s}$. The cooperative miss detection and false alarm probabilities are defined in (5) as Q^{md} and Q^{fa} , respectively. ϵ is a given constant as a threshold for the maximum total cooperative spectrum sensing error ($Q^{md} + Q^{fa}$).

D. Maximizing Opportunistic Data Capacity

In addition, by opportunistically accessing the primary band during T_i^a with the allocated transmit power P_i^t under the local spectrum detection result (p_i^{md}, p_i^{fa}) , a cognitive machine i can transmit the following opportunistic data capacity [bits]:

$$\delta d_i = \left(T_i^a (1 - p_i^{fa}) B \log_2 \left[1 + \frac{|H_{ii}|^2 P_i^t}{N_i^o + \sum_{j \neq i}^{N_s} |H_{ji}|^2 P_j^t} \right] \right) + \left(T_i^a p_i^{md} B \log_2 \left[1 + \frac{|H_{ii}|^2 P_i^t}{N_i^o + \sum_{j \neq i}^{N_s} |H_{ji}|^2 P_j^t + \sum_r^{N_p} |H_{ri}|^2 P_{PU_r}^t} \right] \right) \quad (10)$$

where B is the primary spectrum bandwidth, H_{ji} is the channel gain for the link from CM_j to CM_i and N_i^o defines the additive white Gaussian noise power at CM_i when accessing the primary spectrum. H_{ri} is the channel gain for the link from primary user PU_r to CM_i , and $P_{PU_r}^t$ is the transmit power of the primary user PU_r . P_i^t and P_j^t are the allocated transmit power of the CM_i and CM_j , respectively. In this equation, $B \log_2 \left[1 + \frac{|H_{ii}|^2 P_i^t}{N_i^o + \sum_{j \neq i}^{N_s} |H_{ji}|^2 P_j^t} \right]$ represents the well-known Shannon channel capacity [bits/s] [18].

Hence, the total data capacity [bits] the cognitive machines can opportunistically access on the primary spectrum is:

$$D_T = \sum_{i=1}^{N_s} \left(T_i^a (1 - p_i^{fa}) B \log_2 \left[1 + \frac{|H_{ii}|^2 P_i^t}{N_i^o + \sum_{j \neq i}^{N_s} |H_{ji}|^2 P_j^t} \right] \right) + \sum_{i=1}^{N_s} \left(T_i^a p_i^{md} B \log_2 \left[1 + \frac{|H_{ii}|^2 P_i^t}{N_i^o + \sum_{j \neq i}^{N_s} |H_{ji}|^2 P_j^t + \sum_r^{N_p} |H_{ri}|^2 P_{PU_r}^t} \right] \right) \quad (11)$$

In this paper, we are interested in maximizing the opportunistic data access capacity of the CM2M formulated in Eq. (11) as a constraint optimization problem to find the optimal sensing strategy and optimal transmit power of each individual CM in the cooperative sensing group as follows:

$$\text{Maximize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} D_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \quad (12)$$

subject to:

$$Q^{md} + Q^{fa} \leq \epsilon \quad (13)$$

The constraint optimization (12) indicates some trade off in finding the optimal solution vector $(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$. First, by shortening each CM_i sensing period τ_i^s , the individual false alarm probability p_i^{fa} could increase, which would increase D_T also. However, a shorter τ_i^s may harm the detection accuracy constraint (13), since a short sensing period may produce higher miss detection Q^{md} . Second, every individual CM_i wants to increase its own δd_i by increasing its transmission power P_i^t . However, the higher the transmission power from the machines, the higher the generated intra-frequency interference. A higher interference would lower the Shannon

channel capacity for each CM_i , which causes lower data capacity δd_i when accessing the primary spectrum band.

E. Minimizing Interference Energy to Primary System

With miss detection from spectrum sensing when the primary system is actually active, the cognitive machines transmission cause harmful interference to the primary system. The higher the transmit power the more the interference. In addition, the longer the access period, the more signal energy transmitted by the CM2M, resulting in more harmful interference energy¹. When the primary system is active, the cognitive machines have to limit not only their transmission power but also their harmful access duration. Hence, we model the harmful interference energy transmitted by a CM_i when it applies a sensing and transmit power strategy $x_i \equiv (\tau_i^s, \lambda_i, P_i^t)$ that results in miss detection probability p_i^{md} and illegally accessing the primary spectrum during $T_i^a = T - \tau_i^s$, when the primary system is actually present:

$$I_i^e(\tau_i^s, \lambda_i, P_i^t) = P_i^t T_i^a p_i^{md} = P_i^t (T - \tau_i^s) p_i^{md} \quad (14)$$

Thus, due to miss detection, the total harmful interference energy generated by the group of N_s cooperative cognitive machines during a MAC frame T is derived as:

$$I_T^e = \sum_{i=1}^{N_s} \left[P_i^t (T - \tau_i^s) p_i^{md} \right] \quad (15)$$

Finally, we formulate the following constraint minimization problem for the total harmful interference energy (15) as:

$$\text{Minimize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} I_T^e(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \quad (16)$$

subject to:

$$Q^{md} + Q^{fa} \leq \epsilon \quad (17)$$

III. THREE OBJECTIVE OPTIMIZATION FOR JOINT SPECTRUM SENSING AND POWER ALLOCATION IN CM2M

We recall the three separate optimization problems formulated in (8), (12), and (16) as:

$$(\hat{\mathcal{T}}^s, \hat{\Lambda}, \hat{\mathcal{P}}^t) \triangleq \begin{cases} \text{Minimize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} & E_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \\ \text{Maximize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} & D_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \\ \text{Minimize:}_{\mathcal{T}^s, \Lambda, \mathcal{P}^t} & I_T^e(\mathcal{T}^s, \Lambda, \mathcal{P}^t) \\ \text{subject to:} & \\ & Q^{md} + Q^{fa} \leq \epsilon \end{cases}$$

We observe that these objective functions represent a conflict of interest. For example, minimizing energy consumption $E_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$ requires a shorter sensing duration vector \mathcal{T}^s and a lower transmission power allocation \mathcal{P}^t . However, a shorter \mathcal{T}^s could result in lower spectrum detection quality, which would increase the interference energy $I_T^e(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$ toward the primary system. Moreover, a lower \mathcal{P}^t for the sake of a lower energy consumption would lower the opportunistic data capacity $D_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$ to utilize the primary spectrum.

¹Signal energy over period T of the signal $y(t)$ is $E_y = \int_0^T y^2(t) dt$ [11]

In addition, maximizing $D_T(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$ by increasing the opportunistic access duration and increasing the transmit power allocation \mathcal{P}^t would significantly increase the interference energy $I_T^e(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$, especially when the CM2M cannot find the good sensing strategy vector $(\mathcal{T}^s, \Lambda, \mathcal{P}^t)$, which could result in not being able to detect the visibility of the primary system due to a bad detection probability outcome.

Hence, in this paper we formulate such conflicts in multiple optimization objectives in the context of the well-known multiobjective optimization [19], [20] to optimized the proposed objective functions simultaneously. Multiobjective optimization helps to find a number of Pareto optimal solutions, which will reflect the conflicts between different objective functions. Pareto optimal solutions would give the acceptable outcomes of all objective functions to the decision maker.

Thus, we formulate the three separate optimization problems as a constraint multiobjective minimization as follows:

$$\text{Minimize:}_{X \in \mathcal{S}} F(X) = (E_T(X), -D_T(X), I_T^e(X)) \quad (18)$$

subject to:

$$Q^{md} + Q^{fa} - \epsilon \leq 0 \quad (19)$$

The objective vectors $(E_T(X), -D_T(X), I_T^e(X))^T$ are considered as optimal if none of their components can be improved without deterioration of at least one of the other components. Then, the corresponding decision vectors is referred to as Pareto optimal [21], [20].

In this paper, we apply the popular multiobjective generic algorithm NSGA-II [19], in which Deb et al. developed a nondominated sorting-based evolutionary multiobjective algorithm. NSGA-II produces a fast nominated sorting with $\mathcal{O}(MN^2)$ computational complexity, where M and N are the number of objectives and the population size, respectively. According to [22], evolutionary optimization (EO) algorithms use a population based approach where multiple solutions participate in an iteration in order to produce a new population of better solutions for the next iteration. In addition, EO methodologies are direct search procedures, where an EO procedure does not usually use gradient information in its search procedure. This makes EO a popular approach in solving practical optimization problems [22].

IV. PERFORMANCE EVALUATION

This section presents numerical simulations to validate the proposed multiobjective optimization framework. We implement our simulations in Matlab using the multiobjective optimization package NGPM v1.4 [23], which implements the popular multiobjective genetic NSGA-II algorithm [19].

In our simulations, the primary LTE devices and the cognitive machines are randomly deployed in a cellular cell $[1000m \times 1000m]$, where the LTE primary base station is located in the center. Equations (2) and (4) are used to estimate the false alarm and detection probabilities in Rayleigh fading, respectively. The OR rule is used for cooperative sensing data

fusion. The path loss model 3GPP TR 36.942 [24] is used to evaluate channel gains and signal-to-noise ratios:

$$L_b(dB) = 40(1 - 4 \times 10^{-3} h_B) \log_{10}(d) - 18 \log_{10}(h_B) + 21 \log_{10}(f_c) + 80; \quad (20)$$

where d (km) is the distance between the transmitting base station and the receiver, h_B (m) is the height of the transmit base station, and f_c (MHz) is the central frequency.

Table I lists the parameter settings used for our simulations. Each cognitive machine is assumed to consume the same amount of energy per time unit as $\mathcal{E}^s = 50$ (mW) due to its baseband processing unit. The MAC frame duration is assumed to be the same as for LTE, i.e. $T = 10$ ms.

TABLE I

System Model Settings	Value
LTE central frequency f_c	1800 (MHz)
LTE frequency bandwidth $B = 2W$	20 (MHz)
Radio propagation	3GPP TR 36.942 [24]
Primary LTE BS transmit power	30 (dBm) (1W) [24]
Primary LTE devices transmit power	23 (dBm) (0.1995W) [24]
Primary LTE BS antenna height h_B	30 (m)
Noise figure	10 (dB)
Shadow fading standard deviation	9 (dB)
CM2M noise variance σ^2	2 (dB)
CM2M noise uncertainty	0.1 (dB)
Number of primary LTE devices	$N_p = 10$
Number of cognitive machines	N_s
Optimization Settings	Value
Pareto population size	100
Max generation	200
Number of objectives	3
Number of constraints	1
Number of variables	$N_s \times 3$
Spectrum sensing variable	$\{\tau_i^s\}_{i=1}^{N_s} \leq 5ms$
Detection threshold variable	$\{\lambda_i\}_{i=1}^{N_s} \in [0dB, 300dB]$
Power allocation variable	$\{P_i^t\}_{i=1}^{N_s} \in [50mW, 100mW]$ [5]

Fig.2 illustrates a 3D plot of the Pareto front found after 200 generations in comparison with the solutions found after just four generations. The obtained Pareto front indicates again also that the formulated three objectives, total energy consumption, opportunistic data capacity, and interference to the primary system are indeed conflicting.

Fig. 3 illustrates the Pareto front solutions found for the maximum data capacity and the minimum total energy consumption objectives, with regard to different number of cooperative cognitive machines. The figure also demonstrates the conflict between the two objectives as described before. The result confirms the fact that the more cognitive machines are participating in the cooperative sensing, the higher is the total energy consumption. As a consequence, the whole group gains higher opportunistic data capacity.

However, and more importantly, it also indicates that the energy efficiency [bits/joule] could reach to a maximum point where spending more for both sensing and opportunistic transmission does not help the CM2M gaining more opportunistic data access capacity. To illustrate this in another point of view, we take the comparison between Energy Efficiency [bits/joule] = $\frac{D_T(\hat{T}^s, \hat{\Lambda}, \hat{P}^t)}{E_T(\hat{T}^s, \hat{\Lambda}, \hat{P}^t)}$ and the average energy consumption $\frac{E_T(\hat{T}^s, \hat{\Lambda}, \hat{P}^t)}{N_s}$ as shown in Fig. 4. This result gives

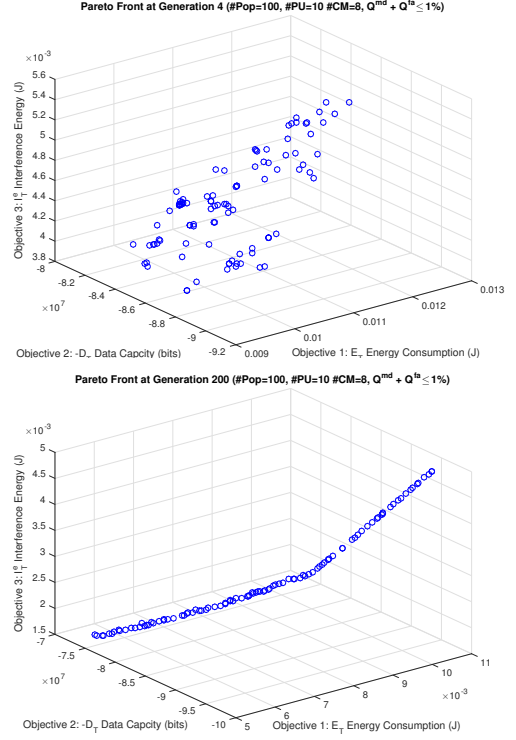


Fig. 2. Pareto front found after 4 and 200 generation.

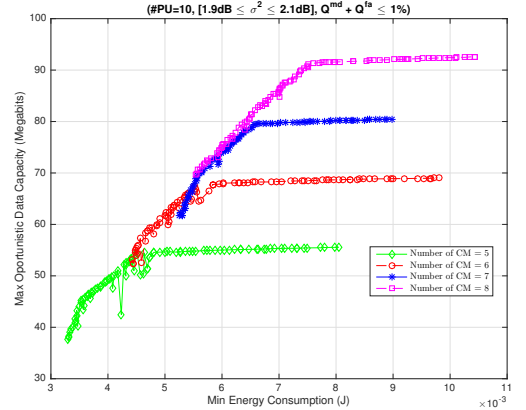


Fig. 3. Maximum data capacity vs. minimum energy consumption.

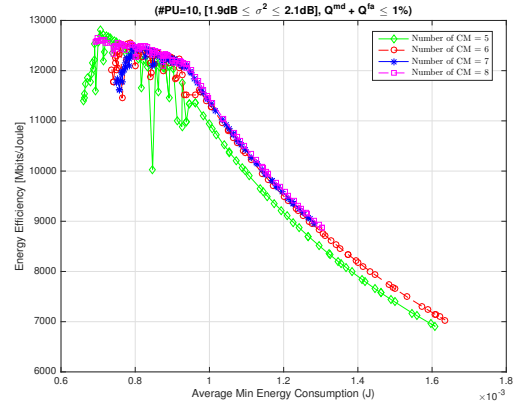


Fig. 4. Maximum data capacity vs. average energy consumption.

a hint for decision makers in finding the best optimal point among the Pareto optimal solutions that gains the highest energy efficiency [bits/joule] with the smaller total energy consumption.

In addition, we can validate the harmful interference due to miss detection with regard to the energy efficiency of the optimized Pareto solution as illustrated in Fig. 5. The results indicate the practical point that the better the sensing and access strategy, the higher the opportunistic data access capacity, the lower the energy consumption (hence the higher energy efficiency), and the lower the harmful interference.

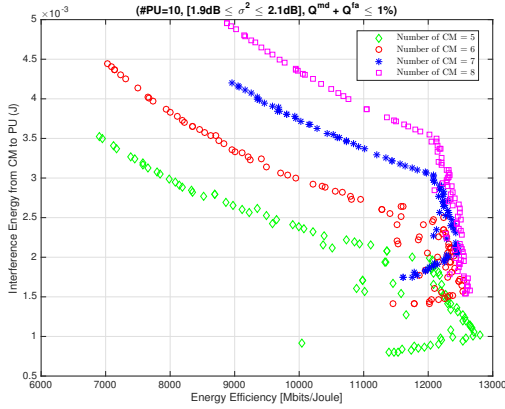


Fig. 5. Harmful interference vs. energy efficiency[Mbits/joule].

Finally, Fig. 6 validates that for all the populations in the found optimal Pareto front that the total cooperative spectrum sensing error $Q^{md} + Q^{fa}$ is always smaller than the predefined threshold $\epsilon = 0.01$, thanks to the constraint (19) defined in the proposed multiobjective optimization.

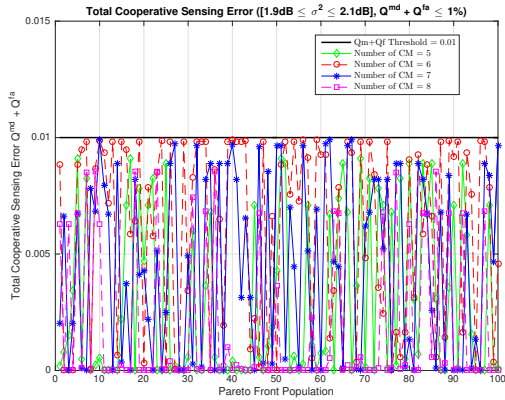


Fig. 6. Total cooperative spectrum sensing error $Q^{md} + Q^{fa}$.

V. CONCLUSION

In this paper, we optimized simultaneously the energy consumption, opportunistic data capacity and interference, while keeping the total cooperative spectrum sensing error lower than a predefined threshold. The Pareto optimal solutions show that the risk of high harmful interference energy caused by miss detection can be reduced through a good strategy for energy efficiency [bits/joule].

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