Interest-aware Energy Collection & Resource Management in Machine to Machine Communications

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Abstract— The emerging paradigm of Machine to Machine (M2M)-driven Internet of Things (IoT), where physical objects are not disconnected from the virtual world but aim at collectively provide contextual services, calls for enhanced and more energy-efficient resource management approaches. In this paper, the problem is addressed through a joint interest, physical and energy-aware clustering and resource management framework, capitalizing on the wireless powered communication (WPC) technique. Within the proposed framework the numerous M2M devices initially form different clusters based on the low complexity Chinese Restaurant Process (CRP), properly adapted to account for interest, physical and energy related factors. Following that, a cluster-head is selected among the members of each cluster. The proposed approach enables the devices of a cluster with the support of the cluster-head to harvest and store energy in a stable manner through Radio Frequency (RF) signals adopting the WPC paradigm, thus prolonging the operation of the overall M2M network. Each M2M device is associated with a generic utility function, which appropriately represents its degree of satisfaction in relation to the consumed transmission power. Based on the distributed nature of the M2M network, a maximization problem of each device's utility function is formulated as a non-cooperative game and its unique Nash equilibrium point is determined, in terms of devices' optimal transmission powers. Considering the devices' equilibrium transmission powers, the optimal charging transmission powers of the cluster-heads are derived. The performance of the proposed approach is evaluated via modeling and simulation and under various topologies and scenarios, and its operational efficiency and effectiveness is demonstrated.

Keywords— Internet of Things (IoT); Machine-to-Machine (M2M) communication; Wireless Powered Communication Networks (WPCN); Clustering; Power Management.

I. Introduction

Wireless communication systems and networks have grown explosively in recent past due to the increasing popularity of devices like smart phones, tablets with powerful multimedia capabilities and applications, sensors, actuators, vehicles, human-wearables, etc. The Wireless World Research Forum envisions in 2020 seven trillion wireless devices will be serving seven billion people [1]. According to CISCO prediction [2], the monthly global mobile data traffic will be *49* exabytes by 2021, and the annual mobile data traffic will exceed half a zettabyte. Key part of the evolving wireless communication environment is the Internet of Things (IoT), which presents an emerging topic of great technical, social and economic significance. Projections for the impact of IoT on the Internet and economy are impressive. Recent statistics anticipate as many as *100* billion connected IoT devices and a global economic impact of more than *$11* trillion by 2025 [3]. The emerging paradigm of Machine to Machine (M2M)-driven IoT will differ fundamentally from that in the classic internet that focused on human to human communication. M2M communications will feature orders of magnitude more nodes, most of which will be extremely low-power or self-powered devices.

A. Related Work

Among the key concerns related to the IoT applications is the prolongation of the mobile M2M devices' battery life, towards guaranteeing the operation of the IoT system for a longer time period. Therefore, in the vast majority of the IoT applications, the energy efficient communication and the stable energy supply to them have become among the primary objectives in resource allocation. The latter becomes even more critical due to the growing proliferation of M2M devices, which are often deployed in areas where frequent human access or battery replacement is not always feasible [4].

Aiming at improving the energy efficient communication among the M2M devices, and in parallel overcoming the wireless access congestion problem, the joint clustering of devices and resource management arises as a promising solution. Various M2M devices clustering methods have been proposed in the recent literature based on different criteria, such as M2M devices' achievable signal to interference plus noise ratio [5], transmission delay [6], etc. The induced hierarchy for management and control via the clustering methods provide an immediate and intuitive benefit [24] – [26]. Furthermore, the concept of data priority has been adopted towards devising energy efficient and congestion mitigated clustering algorithms thus improving the energy efficient transmission of the M2M devices for the IoT applications. The authors in [7] propose a data-centric clustering algorithm of the M2M devices in a resource constrained M2M network by prioritizing the quality of the overall data transmitted by the individual devices. Following the concept of data priority, a healthcare IoT application is studied in [8], where the criterion of health-based priority of the transmitted data is utilized towards performing M2M devices' clustering. In [9] the problem of energy-efficient clustering is studied by jointly considering cluster formation, transmission scheduling and power control while the problem of energy efficient transmissions of M2M devices has been studied in [10] considering an existing clustering in the M2M network. More specifically, the authors allow the cluster-head to coordinate the congestion within the existing cluster via assigning weights to the M2M devices based on various criteria, such as data priority, energy availability, and M2M devices' mobility. In [11], a primitive joint interest, energy and physical-aware framework for coalitions' formation among the wireless IoT devices and an energy-efficient resource allocation in M2M communication networks is introduced. Despite the promising results obtained, the main drawback of this approach is that it only emphasizes on the energy efficient communication among the devices, while their available energy/battery is fixed and they are not capable of harvesting additional energy from the RF signals.

In parallel of devising clustering algorithms to improve the energy efficiency, the stable energy supply to the M2M devices is of great importance to prolong their battery life, as well as the operational life of the overall IoT network. Towards this direction, the Wireless Powered Communication (WPC) technique has emerged as a promising alternative to the conventional battery-powered operation and/or the energy harvesting technique based on natural energy sources such as solar or wind. The M2M devices participating in an IoT application, whether battery-free or not, can benefit by adopting the WPC technique, due to the fact that they can harvest and store energy in a stable manner from the Radio Frequency (RF) signals via dedicated neighbor devices, e.g., cluster-heads, during the wireless energy transfer (WET) phase. Then, the saved energy can be further exploited via adopting energy efficient transmission techniques, as the one discussed before, and transmit their information signals to the cluster-head or evolved NB (eNB) during the wireless information transmission (WIT) phase [12]. Several research works have been proposed in the literature dealing with the energy utilization efficiency via adopting the wireless powered communication technique and devising intelligent resource management frameworks. In [13], a joint time allocation and power control framework is proposed towards maximizing network's energy efficiency under different conditions, such as the initial battery energy of each mobile device and the minimum system throughput constraints. The maximization problem of the uplink sum-rate network's performance is studied in [14], while adopting the WPC technique and via jointly determining the optimal energy and time resource allocation for the multiple mobile devices. This work has been extended in [15] considering additional constraints, such as infinite or finite capacity energy storage. Furthermore, the problem of joint subcarrier scheduling and power allocation via jointly adopting the orthogonal frequency division multiplexing

(OFDM) and WPC techniques has been studied in [16] towards maximizing system's sum-rate. Also, the problem of energy-efficient resource management in a distributed manner has been thoroughly studied in the literature, considering either single control parameter (e.g., power control) [17]-[19] or multiple control parameters (e.g., power and rate control) [20] considering complex networking paradigms [21].

Though the aforementioned: (a) clustering approaches for supporting energy efficient communication among M2M devices and (b) resource management efforts, while adopting the WPC technique, present significant results towards improving the overall system's energy efficiency and M2M devices' battery saving, their main drawbacks are:

a. Their joint effect in prolonging M2M devices' battery life has not been studied and exploited yet and
b. Their main goal is to optimize system's welfare, thus they cannot be properly adapted to device-centric paradigms, where the goal of the devices is to optimize device's perceived satisfaction from the allocated resources.

Last but not least, it should be noted that as the IoT represents a vision in which the Internet extends into the real world embracing everyday objects, physical items are no longer disconnected from the virtual world and aim at collectively provide contextual services. Therefore the Internet of Things comprises a digital overlay of information over the physical world, where objects and locations, along with device purpose and interest become interrelated. This paper aims at exactly dealing with these challenging issues and filling the corresponding gap in the literature.

B. Paper Contribution

Specifically, to overcome the aforementioned drawbacks, in this paper, it is the first time in the literature to the best of our knowledge that a joint interest and energy-aware devices' clustering methodology and a resource management framework adopting wireless powered communication (WPC) technique in M2M communication networks for supporting IoT applications is proposed. The basic contributions and differences of our proposed approach and framework in this paper are summarized as follows.

1. A joint interest, physical and energy-aware cluster formation mechanism is proposed based on the Chinese Restaurant Process (CRP) [15] in order to create clusters among the numerous M2M devices. In a nutshell, the fundamental novelties of the proposed cluster formation mechanism are:
   (a) the overall combined communication interest among the M2M devices is determined based on three factors, i.e., interest of interaction among the M2M devices regarding the examined IoT application, physical proximity and energy availability, while the vast majority of the literature considers only the two latter factors in order to create clusters among the devices and

(b) the adoption of the CRP admission control policy towards creating the clusters, which consists of closed formulas with low implementation complexity and therefore presents a realistic solution.

2. The use of WPC technique in M2M networks enables the devices in each cluster to harvest energy from the RF signals of the cluster-head. The fundamental benefits of incorporating the WPC technique in M2M networks are: (a) the elimination of the need for frequent manual replacement and recharging, (b) higher throughput, (c) prolongation of devices' lifetime and (d) low network operating cost. Moreover, instead of and in contrast to adopting an energy harvesting technique, where the devices opportunistically harvest renewable energy from sources which are not dedicated to power them, e.g., solar or wind power, the WPC technique enables us to provide stable energy supply from the cluster-head under different physical conditions and service requirements.
3. We introduce a holistic approach of utility-based transmission power allocation for the devices of each cluster, and charging transmission power control for the cluster-heads, meeting their QoS prerequisites, while being able of supporting multiple IoT applications. Each M2M device, i.e., cluster-heads and devices, is associated with an appropriately designed utility function representing its degree of satisfaction with respect to the power consumption and the fulfillment of its QoS demands. The form of the considered utility function is a generic one, so as to efficiently capture devices' QoS prerequisites for multiple IoT applications.
4. Based on the non-cooperative nature of the M2M network, a maximization problem of each device's utility function is formulated and confronted as a non-cooperative game. Towards confronting the non-cooperative power management game, we follow an approach based on the quasi-concavity of the device's utility functions in order to conclude to a unique Nash equilibrium point. Based on the Nash equilibrium transmission powers of the devices, the necessary and sufficient power supply to them by the cluster-heads is determined, thus the optimal charging transmission powers of the cluster-heads are derived.
5. The proposed framework enables the realization of autonomic device-centric management. The joint interest and energy-aware devices' clustering and the resource management via adopting the WPC technique in M2M communication networks supports M2M devices' self-* properties, e.g., self-configuring, self-optimization, self-adaptation, etc. and these self-managing properties enable the devices themselves to conclude to their optimal strategies.
6. Detailed numerical results are provided that demonstrate the performance and operational effectiveness and efficiency of the proposed framework, along with its flexibility and adaptability under various scenarios.

C. Outline

The outline of the paper is as follows. Section II elaborates on the details of the adopted system model. In Section III.A, the interest and energy-aware devices' cluster formation mechanism is introduced via adopting an admission control policy based on the Chinese Restaurant Process. In Section III.B, the cluster-head selection process is presented based on the concept of closeness centrality and devices' energy availability. In Section IV, the energy efficient resource allocation problem is formulated and solved in a distributed manner towards determining devices' optimal transmission powers and cluster-heads optimal charging transmission powers. The performance of the proposed approach is evaluated in detail through modeling and simulation in Section V. finally, Section VI concludes the paper.

II. System Model

We consider the uplink of an LTE/LTE-Advanced Machine-to-Machine (M2M) communication type network consisting of an evolved NB (eNB) and multiple LTE based M2M devices (e.g., actuators, sensors). Within the IoT era and its corresponding smart applications, the majority of M2M communications traffic is in the uplink direction, due to the periodic transmission of sensing and/or measurement data to a central controller for further exploitation. The set of energy-collecting M2M devices is denoted by M, where $M = \{1,...,m,...,|M|\}$. Sensors are typically used to collect data as per their functionality and send the same to the central application controller through the eNB. Considering sensors' data collection, two types of communication are possible: (a) eNB-M2M communication, i.e., each device communicates through the eNB and (b) direct M2M communication, i.e., direct communication among energy-collecting M2M devices. In this paper, owing to its energy-efficiency superiority [4], we focus on direct M2M communication, while proposing an interest and energy-aware cluster formation mechanism. The data from the M2M devices are collected to a selected cluster-head, which further forwards the aggregated and processed information to the eNB. M2M devices are organized in $|C|$ clusters, where $C = \{1,...,c,...,|C|\}$ denotes the corresponding set of clusters. The idea of clustering M2M devices based on sophisticated criteria stems from the need of manageability and scalability of the extremely crowded M2M networks. Through the proposed cluster formation (see Section III) and energy-collection and resource allocation mechanisms (see Section IV), each M2M device is associated with a cluster-head for communication to and from the eNB. The cluster-head is appropriately selected among the set of M2M devices, i.e., $ch_c \in M$, where $c \in C$, and is in charge of more functionalities and responsibilities compared to the rest of M2M devices, e.g., perform traffic aggregation or data compression before relay. Each M2M device m belongs exclusively to a cluster c with cluster-head ch_c . The number of the devices belonging to the cluster c with cluster-head ch_c is denoted by $|M_c|$, while their corresponding set is $M_c = \{1,...,|M_c|\}$.

III. INTEREST AND ENERGY-AWARE MACHINES CLUSTERING

In this section, we describe an admission control policy based on Chinese Restaurant Process (CRP) in order to create clusters among numerous M2M devices. Suppose that we have a collection of entities – in our case the M2M devices – and we want to cluster them into groups. In Chinese Restaurant metaphor, each group corresponds to a table and each entity to a customer entering the Chinese Restaurant. The Chinese Restaurant is assumed to have countably infinitely many tables, labelled *1, 2, ...* In our case, the tables correspond to the clusters. The customers walk in and sit down at some table. The customers are assumed to prefer sitting at popular tables, however there is always a non-zero probability that a new customer will sit at a currently unoccupied table. The tables are chosen according to the following random process: (a) the first customer always chooses the first table and (b) the m^{th} customer chooses an occupied table with probability $\frac{c}{m-1+a}$ (where c is the number of customers already sitting at that table) and the first unoccupied table with probability $\frac{a}{m-1+a}$, where a is called the "concentration parameter" of the CRP, indicating the willingness of each customer to stay alone and create a new cluster.

In the following analysis, the concept of CRP is adopted towards clustering M2M devices into groups. However, in order to make the clustering results more practical, we will extend CRP towards considering several M2M related factors, including interest of M2M devices to communicate with each other, physical proximity, as well as their energy availability.

A. CLUSTER FORMATION

The CRP approach can correlate interest similarity and physical proximity among M2M devices to group them into clusters. The proposed Interest and Physical-aware CRP (IP-CRP) approach will exploit the interest based and distance based graphs to form the clusters in an intelligent manner. Moreover, the energy availability of the M2M devices will be further exploited to select the cluster-head ch_c of each cluster $c, c \in C$, as it will be explained in subsection III.B.

Based on the system model introduced in Section II, let us define the interest based graph $G^I = \{v, \varepsilon^I\}$ and the physical based graph $G^P = \{v, \varepsilon^P\}$, where the set of M2M devices v represents the vertex set and the edges $\varepsilon^I = \left\{\varepsilon^I_{m,m'}, \forall m, m' \in v\right\}$ and $\varepsilon^P = \left\{\varepsilon^P_{m,m'}, \forall m, m' \in v\right\}$ are the edges set representing the first one the level of interest – denoted by $p\left(m,m'\right)$ - for communication among m,m', where $\varepsilon^I_{m,m'} = p\left(m,m'\right), p\left(m,m'\right) \in [0,1]$ and the second one the normalized (as explained later) distance weights $\varepsilon^P_{m,m'} = d\left(m,m'\right)$, $d\left(m,m'\right) \in [0,1]$, respectively. The probability of M2M device m to select device m' as its partner to form a cluster can be calculated as follows:

$$P\left(m,m'\right) = \begin{cases} \dfrac{f\left(IDD\left(m,m'\right)\right)}{\sum\limits_{m \neq m'} f\left(IDD\left(m,m'\right)\right) + a}, m \neq m' \\ \dfrac{a}{\sum\limits_{m \neq m'} f\left(IDD\left(m,m'\right)\right) + a}, m = m' \end{cases} \tag{1}$$

where a is the parameter of IP-CRP showing the willingness of each M2M device to stay alone and create a new cluster, as explained before. The function $f\left(IDD\left(m,m'\right)\right)$ is the interest and distance based function defined as:

$$f\left(IDD\left(m,m'\right)\right) = w_1 \frac{1}{ID\left(m,m'\right)} + w_2 D\left(m,m'\right) \tag{2}$$

where w_1 and w_2 are weights showing the importance of interest and distance factor in M2M devices' decision influence for clustering, respectively. It is noted that $w_1 + w_2 = 1$. Furthermore, the factor $IDD\left(m,m'\right)$ shows the M2M devices' decision relation with respect to both individual influential factors, i.e., the interest distance $ID\left(m,m'\right)$ and the physical proximity $D\left(m,m'\right)$. The interest distance $ID\left(m,m'\right)$ between the M2M devices is formulated in order to evaluate the effect of their mutual interest to communicate and exchange information. Thus, we calculate the interest distance based on the level of interest $p\left(m,m'\right)$ as:

$$ID\left(m,m'\right) = -\log_2\left(p\left(m,m'\right)\right) \tag{3}$$

where as explained before $p\left(m,m'\right) \in [0,1]$ is the level of interest between M2M devices m and m'. Note that larger value of $p\left(m,m'\right)$ concludes to smaller $ID\left(m,m'\right)$, which is interpreted as follows: the shorter the interest distance between two M2M devices is, the larger the probability of willingness to communicate with each other, thus larger is their intention to belong to the same cluster. The above formulation stems from the observation that the M2M devices have different interests to interact with each other in order to achieve a common goal. For example, in a smart home application there are included several M2M devices, e.g., smart thermostats, connected lights, smart fridge sensors, smart door lock sensors, etc. The smart thermostats and the sensors measuring the temperature have greater interest to communicate with each other, form a coalition and transmit their data to the coalition-head, which further transmits all the collected data to the eNB for further exploitation and decision making. The same holds true for the set of sensors participating in the smart lighting system or smart fridge application and so on and so forth.

In addition, the physical proximity or physical distance function $D(m,m')$ is defined as:

$$D(m,m') = -\log_2\left(d(m,m')\right) \tag{4}$$

where $d(m,m')$ is the normalized (with reference to the maximum distance) physical distance among M2M devices m and m' such that $d(m,m') \in [0,1]$.

Based on equation (1), we can calculate the probabilities of M2M device m to select other devices in order to form a cluster. Thus, M2M device m determines the probability of joining cluster c with the set of M2M devices M_c as follows:

$$P_c(m) = \sum_{m' \in M_c} \frac{f\left(IDD(m,m')\right)}{\sum_{m \neq m'} f\left(IDD(m,m')\right) + a} \tag{5}$$

Following this methodology both the physical and interest distance among the M2M devices are jointly taken into consideration for the cluster formation mechanism. It is noted that by jointly considering the interest and physical distance to form the clusters, our proposed IP-CRP methodology can boost the benefits from both the interest-based and physical-based information of the M2M devices. Specifically, in the proposed IP-CRP scheme, M2M devices belonging to the same cluster have high interest to exchange information while they are in relevantly close physical proximity, thus the system performance can be enhanced in terms of both decreased energy-consumption and increased system throughput by involving IP-CRP M2M devices clustering.

B. CLUSTER-HEAD SELECTION

Given the cluster formation as presented in the previous section, the next step is to appropriately select the cluster-head of each cluster, among its members. The cluster-head is selected based on multiple factors: (a) interest ties among M2M devices, (b) physical proximity and (c) energy availability. Recalling the aforementioned interest based graph G^I and physical based graph G^P, we introduce the interest and physical-based graph $G^{IP} = \{\nu, \varepsilon^{IP}\}$, where $\nu = M_c$ denotes the set of M2M devices belonging to the same cluster c and ε^{IP} denotes the edge among the two M2M devices. The weight of each edge is a composite distance that consists of the interest distance and the physical distance of the potentially connected M2M devices and is defined as follows:

$$w(m,m') = w_I \frac{ID(m,m')}{ID_0} + w_D \frac{D_0}{D(m,m')} \tag{6}$$

where w_I, w_D are the corresponding weights for different indexes, i.e., interest and distance, respectively. The parameters ID_0, D_0 are assumed to be the maximum values of the corresponding indexes of M2M devices belonging to the same cluster.

Towards selecting the cluster-head ch_c of cluster *c*, we propose the concept of closeness centrality considering the factors of interest and physical distance (CC-IP). Given the graph G^{IP}, the metric $CC-IP(m)$ for each M2M device *m* is formulated as follows:

$$CC-IP(m) = \sum_{\substack{m \in M_c \\ m \neq m'}} \left[\frac{sp(m,m')}{|M_c|-1} \right]^{-1} \tag{7}$$

where $sp(m,m')$ is the overall cost/weight as presented in equation (7) of the shortest path between M2M devices *m* and *m′*. The final score of each device, which is the one that defines which one M2M device we choose as a cluster-head is calculated as follows.

$$score(m) = w_{CC} CC - IP(m) + w_E \frac{E_0}{E(m)} \tag{8}$$

where E_o is the maximum value of the available energy values of the devices and w_{CC}, w_E are the weights of closeness centrality and energy availability, respectively. The M2M device with the largest value of $score(m)$ is selected as the cluster-head ch_c of the cluster c, $c \in C$, i.e., $ch_c = \arg\max_{m \in M_c} \{score(m)\}$. Based on equation (8), we observe that the cluster-head ch_c has increased available energy, it is closest to the rest of the M2M devices organized in the same cluster c and its neighbor devices have high interest to communicate with it.

IV. Energy Collection and Resource Management

As mentioned before, energy-efficient uplink transmission power and long-lasting system lifetime are among the major concerns of various IoT applications adopting M2M communication. In this section, we formulate the process of energy collection of M2M devices, as well as the problem of resource management, which is solved in a distributed manner. The "harvest and then transmit" protocol is considered, adopting the WPC technique, where the M2M devices in each cluster harvest energy from the broadcasted RF signals by the cluster-head (downlink communication) during the wireless energy transfer (WET) phase and then transmit their information signals (uplink communication) during the wireless information transmission

(WIT) phase. The energy collection and resource management approach proposed in this paper aims at determining the optimal transmission power of each M2M device towards fulfilling its QoS prerequisites and maximizing its perceived satisfaction from its operation within the M2M network, as well as the optimal charging transmission power of each cluster-head in order to guarantee the smooth operation of the overall system.

The thermal noise components and the M2M devices' control signals can be regarded together as an Additive White Gaussian Noise (AWGN) process, with constant power spectral density I_0. Therefore, the overall sensed interference by an M2M device $m, m \in M$ can be formulated as follows:

$$I_m = \sum_{m \neq m'} G_{m,m'} P_{m'} + I_0 \tag{9}$$

where $P_{m'}$ is the transmission power of the M2M device $m', m' \in M, m \neq m'$ and $G_{m,m'}$ is the channel gain from the transmitter m' to the receiver m. We assume that each M2M device is aware of its location (i.e., its coordinates) and the eNB can send via a broadcast message the locations and the uplink transmission powers of all connected M2M devices. From this information, each M2M device can calculate in a distributed manner its sensed interference, as described in equation (9). The corresponding received signal-to-interference-plus-noise-ratio (SINR) γ_m of M2M device $m, m \in M$, at its corresponding cluster-head ch_c belonging to cluster c, $c \in C$ is given by:

$$\gamma_m = \frac{G_{m,ch_c} P_m}{I_{ch}} \tag{10}$$

where I_{ch} is the sensed interference of the cluster-head as defined in equation (9).

Furthermore, each M2M device $m, m \in M$ adopts a utility function towards expressing its QoS prerequisites, which are differentiated per type of IoT application that the M2M device participates. The adopted utility function is a continuous, $C^{(n)}$ differentiable function with respect to M2M device's transmission power P_m and is given as follows:

$$U_m\left(P_m, \boldsymbol{P_{-m}}\right) = \frac{W \cdot f_m\left(\gamma_m\right)}{P_m} \tag{11}$$

where W is the system's bandwidth and $f_m\left(\gamma_m\right)$ is M2M device's efficiency function representing the successful transmission probability of M2M device m belonging to cluster c to its cluster-head ch_c. The efficiency function $f_m\left(\gamma_m\right)$ is a continuous, differentiable and increasing function of γ_m and has a sigmoidal shape such that there exists γ_m^{target} below which $f_m\left(\gamma_m\right)$ is convex and above which $f_m\left(\gamma_m\right)$ is concave. For presentation purposes and without loss of generality, we adopt $f_m\left(\gamma_m\right) = \left(1 - e^{-A\gamma_m}\right)^M$, where A, M are real valued parameters controlling the slope of the sigmoidal-like function. It is noted that for different IoT application differentiated γ_m^{target} are requested by the M2M devices. These differentiated M2M devices' QoS prerequisites can be captured by the adopted efficiency function via the control parameters *A* and *M*.

The cluster-head ch_c, as it was determined in the previous section (based on equation (8)), has better energy availability compared to the rest of the M2M devices in the same cluster c, $c \in C$. We consider that the latter collect energy from the cluster-head ch_c for time τ_1, while they transmit their data for time τ_2 and $\tau_1 + \tau_2 = t$, where t is the duration of each timeslot. Let us assume that the timeslot is split as $\tau_1 = \tau \cdot t$ and $\tau_2 = (1-\tau) \cdot t$, where τ is the control parameter of energy collection. The received energy of M2M device m belonging to cluster c by the cluster-head ch_c is

$$E_m^{rec} = n\tau_1 P_{ch_c} G_{ch_c,m} \tag{12}$$

where $n \in (0,1]$ is the energy conversion efficiency factor, depending on the type of the receivers. The average uplink transmission power of the m^{th} M2M device during τ_2 is :

$$P_m = \frac{E_m^{rec}}{\tau_2} = \frac{n\tau_1 P_{ch_c} G_{ch_c,m}}{\tau_2} = \frac{n\tau P_{ch_c} G_{ch_c,m}}{1-\tau} \tag{13}$$

The goal of each M2M device is to maximize its utility, as it has been introduced in equation (11), via selecting an appropriate strategy of the uplink transmission power. Therefore, for each M2M device the following distributed utility maximization problem is formulated:

$$\begin{aligned} &\max_{P_m \in A_m} U_m\left(P_m, \boldsymbol{P_{-m}}\right) \\ &s.t.\ \ 0 < P_m \le P_m^{Max} \end{aligned} \tag{14}$$

where $A_m = \left(0, P_m^{Max}\right]$ is the strategy space of the m^{th} M2M device, P_m^{Max} is its maximum available power and $\boldsymbol{P_{-m}}$ is the uplink transmission power vector of all the M2M devices except for the m^{th} device.

The above presented distributed utility maximization problem is confronted as a non-cooperative game $G = \left[M, \{A_m\}, \{U_m\}\right]$. The solution of the non-cooperative game *G* should determine the optimal equilibrium for the system, concluded by the individual decisions of each M2M device, given the decisions made by the rest of the devices. A Nash equilibrium point of the game $G = \left[M, \{A_m\}, \{U_m\}\right]$ is a vector of M2M devices' uplink transmission powers $\boldsymbol{P}^* = \left[P_1^*, ..., P_m^*, ..., P_{|M|}^*\right]^T \in A = A_1 \times ... \times A_m \times ... \times A_{|M|}$, where the superscript *T* denoted the transpose operation of a vector. The Nash equilibrium point of the game *G* can be defined as follows:

Definition 1: A power vector $\boldsymbol{P}^* = \left[P_1^*,...,P_m^*,...,P_{|M|}^*\right]^T$ in the strategy set $A = A_1 \times ... \times A_m \times ... \times A_{|M|}$ is a Nash equilibrium of the game $G = \left[M, \{A_m\}, \{U_m\}\right]$ if for every M2M device *m* the following condition holds true:

$$U_m\left(P_m^*, \boldsymbol{P_{-m}}\right) \geq U_m\left(P_m, \boldsymbol{P_{-m}}\right)$$

for all $P_m \in A_m$.

Towards showing the existence of the Nash equilibrium point, we study the properties of M2M device's utility function.

Theorem 1: The non-cooperative power control game $G = \left[M, \{A_m\}, \{U_m\}\right]$ has a unique Nash equilibrium point $\boldsymbol{P}^* = \left[P_1^*,...,P_m^*,...,P_{|M|}^*\right]^T$, where

$$P_m^* = \min\left\{\frac{\gamma_m^* I_m}{WG_{m,ch_c}}, P_m^{Max}\right\} \tag{15}$$

for all $m, m \in M$, where γ_m^* is the unique positive solution of the equation $\frac{\partial f_m(\gamma_m)}{\partial \gamma_m}\gamma_m - f_m(\gamma_m) = 0$

The proof of the above theorem can be concluded following similar steps as in [22], [23F].

The interpretation of the Nash equilibrium point, as determined by equation (15) is that no M2M device has the incentive to change its strategy, due to the fact that it cannot unilaterally improve its personal utility by making any change to its own strategy, given the strategies of the rest of the M2M devices. Moreover, it is concluded that the existence of the Nash equilibrium point guarantees a stable outcome of the non-cooperative game $G = \left[M, \{A_m\}, \{U_m\}\right]$.

Given the optimal uplink transmission power of each M2M device $m, m \in M$, as determined in equation (15), we determine the optimal charging transmission power P_{ch_c} of the cluster-head ch_c to its M2M devices belonging to the same cluster *c*, as follows:

$$P_{ch_c}^* = \min\left\{\max_{m \in M_c}\left\{\min\left\{\frac{\gamma_m^* I_m}{WG_{m,ch_c}}, P_m^{Max}\right\}, P_{ch_c}^{Max}\right\}\right\} \tag{16}$$

It should be noted that in case that a user during the WIT phase does not exhaust all of the energy harvested during the corresponding WET phase of the timeslot under consideration, he could store any excessive energy in a rechargeable built-in battery (if exists), in order to be available for use in future transmissions or for performing other processing tasks. In this paper, however we do not consider this feature and assume that if some energy is not fully exploited in current timeslot it is not accounted for transmissions in future timeslots, but could be used for performing other functions if desired. The consideration of this feature in turn would influence the value of the maximum available uplink transmission power of M2M device m, as the stored energy should be properly reflected in the calculation.

Table 1: Parameters / Notation

M, C	Set of M2M devices, clusters
$\|M\|$, $\|C\|$	Number of M2M devices, clusters
ch_c	Cluster-head of cluster c
M_c ($\|M_c\|$)	Set (number) of M2M devices belonging to cluster c
$p(m,m')$ ($d(m,m')$)	Communication interest (physical distance) among m, m' devices
$ID(m,m')$ ($D(m,m')$)	Interest (physical) distance function among m, m' devices
ID_0, D_0	Maximum values of $ID(.)$, $D(.)$
γ_m	Signal-to-interference-plus-noise-ratio
W	System's bandwidth
$f_m(.)$	Efficiency function
P_m	M2M device's transmission power
$G_{m,m'}$	Channel gain from the transmitter m' to the receiver m

V. NUMERICAL RESULTS

In this section, we provide some numerical results evaluating the operational features and performance of the proposed clustering methodology and resource management framework adopting the WPC technique in M2M communication networks. Initially, we focus on the operation performance achievements of the proposed framework, in terms of power consumption during the wireless energy transfer (WET) and information transmission (WIT) phase. The above detailed study is performed via considering different implementation scenarios, in terms of devices' interest and physical ties among them, as well as topologies and network sizes. Then, we provide a comparative evaluation of the proposed approach against other conventional approaches that are merely based on either interest or distance, with respect to the achievements in devices' power savings.

In the following, initially we consider an M2M network consisting of $|M|=50$ M2M devices randomly distributed in a square coverage area $500m\times500m$ and an eNB residing outside of the square. Parameter a of the clustering methodology, which shows the willingness of each M2M device to stay alone and create a new cluster, is assumed to be $a = 2$. The weights w_1 and w_2 showing the importance of interest and distance factor in M2M devices' decision influence for clustering are $w_1 = 0.5$ and $w_2 = 0.5$. The weights w_I and w_D for the different indices, i.e., interest and distance, considered in the overall weight of each edge ε^{IP} are $w_I = 0.5$ and $w_D = 0.5$ while the weights w_{CC} and w_E showing the importance of the closeness centrality and energy availability, respectively, in order to select the cluster-head are $w_{CC} = 0.5$ and $w_E = 0.5$. The thermal background noise is $I_o = 5 \cdot 10^{-15}$, the system bandwidth is $W = 10^6 Hz$, the energy conversion efficiency factor is $n = 0.6$ and the timeslot is $\tau = 0.4$, while the timeslot duration is $t = 0.5 m\sec$.

Towards providing realistic and representative results, we examine three different simulation scenarios as follows:

A. Random scenario: The level of interest between two devices distributed in the examined topology i.e., $p(m, m')$, is randomly assigned.

B. Best-case scenario: The devices which are close to each other have high interest to communicate, as well as the devices which are far from each other have small communication interest among them.

C. Worst-case scenario: The devices which are close to each other have small communication interest, while the devices that are placed far from each other have high communication interest.

Based on the aforementioned examined scenarios, we examine a wide range of possible real-life communication scenarios and IoT applications.

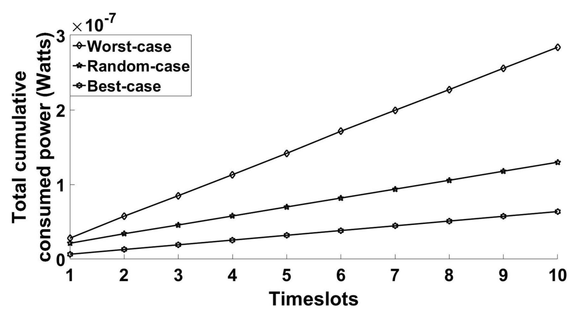

Fig. 1 Total cumulative consumed power during the WIT phase as function of time (slots).

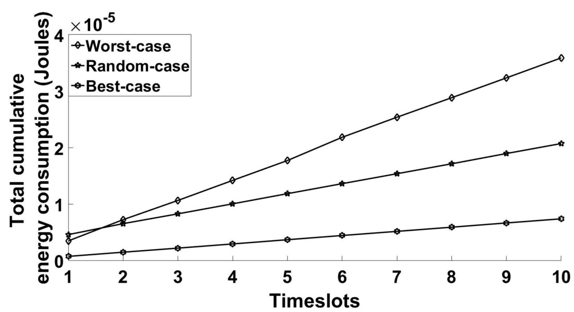

Fig. 2 Total cumulative energy consumption during the WIT and WET phase as function of time (slots).

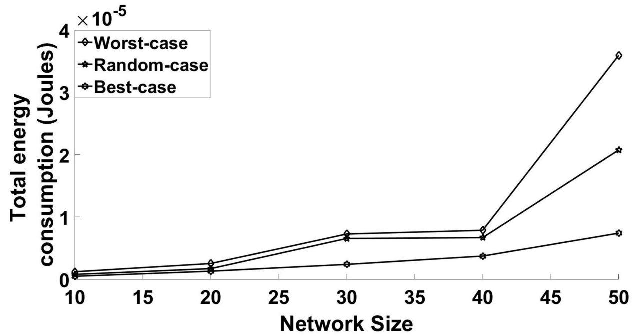

Fig. 3 Total energy consumption as a function of network size.

First, we study the power consumption of the devices during the WIT phase, i.e., information transmission from the devices of each cluster to their corresponding cluster-head and from the cluster-head to the eNB. Fig. 1 represents the total cumulative consumed power as a function of the time in the examined M2M network in order the M2M devices to report their information to their corresponding cluster-head and the cluster-head to the eNB, under the examined scenarios, i.e., random, best-case and worst-case scenario. The results reveal that the best-case scenario achieves improved power savings, due to the fact that the M2M devices with high communication interest reside close to each other, thus their communication channel conditions are improved, and therefore their necessary power consumption during the WIT phase is low. On the other hand, considering the worst-case scenario, the exact opposite behavior with respect to the power consumption is observed. More specifically, the M2M devices spend a lot of power to communicate with each other, due to the fact that the devices which have high interest of communication reside far from each other, thus they experience deteriorated channel conditions. An average state of the wireless IoT environment with respect to the power consumption for information transmission is observed in the random scenario. Specifically, in the random scenario, the M2M devices with high communication interest reside in an average distance among each other, thus their corresponding total power consumption lies in between the best and the worst-case scenario.

Fig. 2 illustrates the total cumulative energy consumption of all the devices (i.e. $|M| = 50$) in the examined M2M network, during both the WET and WIT phases, as the time evolves, i.e., for *10* consecutive timeslots. Specifically, the presented total energy consumption consists of the following components: (a) the consumed energy of the cluster-heads to report the collected information to the eNB (WIT phase) and (b) the charging consumed energy of the cluster-head to charge the M2M devices residing in each cluster (WET phase). It is noted that based on the conditions of forming the clusters, i.e, best, worst and random case scenario, the corresponding overall consumed energy is influenced. More specifically, the results reveal that in the case where the M2M devices in the same cluster lie far from each other, i.e., worst-case scenario, the cluster-head consumes increased energy in order to charge them, due to the devices' deteriorated channel conditions, while the exact opposite holds true for the best-case scenario, where the M2M devices reside closer to their corresponding cluster-head. In the random case scenario, the M2M devices have an average distance from their corresponding cluster-head, thus the corresponding overall consumed energy lies in between the worst and the best-case scenario.

Fig. 3 presents the overall energy consumption, as presented in Fig. 2, at the *10*th timeslot, as a function of the network size, i.e., for topologies ranging from *10* to *50* M2M devices. The illustrated results show the scalability behavior of our proposed framework as the number of devices in the M2M network increases. Also, the overall consumed energy for the three examined scenarios follow the same trend, as discussed in Fig. 1 and Fig. 2. It should be highlighted that the low values of the total energy consumption, i.e., order of magnitude of μJ for a medium density IoT network and the total energy consumption's slow increase with respect to the number of devices support the scalability of the proposed interest-aware energy collection and resource management framework in M2M communications.

Below we perform a comparative study towards illustrating the benefits in power savings of jointly considering the interest and physical ties among the M2M devices during the cluster formation process. More specifically, we compare the following three different methodologies for clustering formation.

A. IP-approach. The proposed clustering formation process as it has been proposed in this paper, where the weight of each edge in the M2M devices' graph considers both the interest and the physical ties among the devices.

B. I-approach. The clustering methodology considers only the interest ties among the M2M devices in order to create the clusters.

C. P-approach. The clusters are created via considering only the physical ties among the M2M devices.

Towards comparing the above presented scenarios in a fair manner, we propose two indicative normalized Interest-based Aggregation Factors (IAF) for each cluster, as follows:

$$IAF_1 = |M_c| - \sum_{\substack{m \in M_c \\ m \neq ch_c}} p(m, ch_c) \tag{17}$$

and

$$IAF_2 = sqrt\left\{ |M_c|\left(|M_c| - 1\right) - \sum_{\substack{m, m' \in M_c \\ m \neq m'}} p(m, m') \right\} \tag{18}$$

The physical meaning of the IAF_1 and IAF_2 is explained below. The IAF_1 quantifies the interest of the M2M devices belonging to the same cluster to communicate with their corresponding cluster-head.

Specifically, the second term of the IAF_1 represents the cumulative communication interest of the $|M_c|$ devices in cluster c with their corresponding cluster-head ch_c. The maximum value of $\sum\limits_{\substack{m\in M_c \\ m\neq ch_c}} p\left(m,ch_c\right)$ is $|M_c|$.

Thus, a small IAF_1 value corresponds to the successful cluster-head selection within the cluster, due to the fact that the $|M_c|$ devices belonging to cluster c have high communication interest with their cluster-head ch_c. Following the same philosophy, the IAF_2 quantifies the homogeneity of all the M2M devices in the same cluster, by taking into account in a pair-wise manner the corresponding interests between all pairs of the devices of the cluster, i.e., $\sum\limits_{\substack{m,m'\in M_c \\ m\neq m'}} p\left(m,m'\right)$. A small IAF_2 value shows that the cluster is homogeneous, i.e., the M2M devices have high interest to communicate with each other. As a result, when the devices create clusters based only on their physical proximity, P-approach, they do not have high interest to communicate with each other and with the cluster-head, thus their overall interest expressed is low and therefore the corresponding aggregation factors obtain high values. The opposite observations hold true for the I-approach. The aforementioned drawbacks are faced via considering both physical and interest ties among the devices towards creating the clusters communities, i.e., IP-approach. Implicitly both these factors express different degrees of aggregation that can be achieved at the cluster-head – due to the commonalities and/or homogeneity that the devices of a cluster present – which in turn can be translated to the transmission of reduced information from the cluster-head to the eNB. As a consequence, and in order to quantify the importance of the clustering approaches as expressed through these factors, in the following we examine the total cumulative transmission power during the WIT phase considering the potential aggregation that can be achieved due to the efficient clustering.

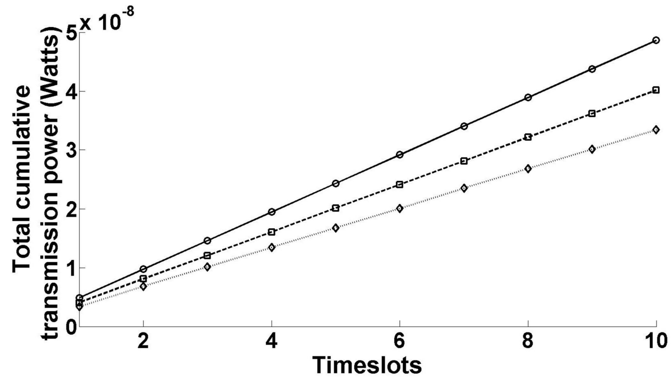

Fig. 4 Total cumulative transmission power during the WIT considering IAF_1 as function of time (slots).

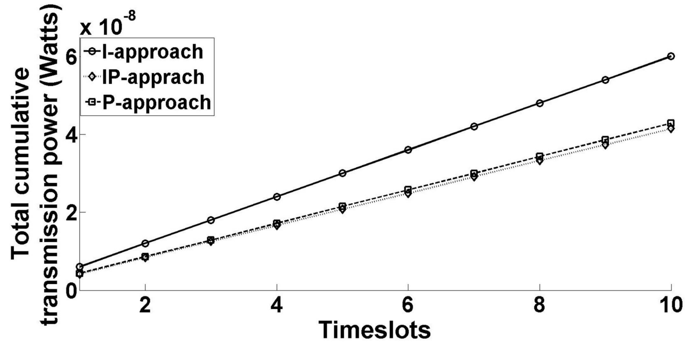

Fig. 5 Total cumulative transmission power during the WIT considering IAF_2 as a function of time (slots).

Specifically, in Fig. 4 and Fig. 5, we present the combined outcome of the total cumulative transmission power during the WIT phase, considering the IAF_1 and IAF_2, respectively, as time evolves (indicatively for 10 consecutive time slots), considering the three examined approaches, i.e., IP, P and I-approach, for an M2M network consisting of $|M| = 40$ devices, following the random scenario described above. The comparison of the three different clustering approaches reveals the pure benefits in power savings, while considering jointly the interest and physical ties among the M2M devices in order to form the clusters. It is noted that especially in the P-approach the M2M devices will create clusters based on their physical proximity and their good channel conditions without however having high interest to communicate with each other (i.e., large values of IAF_1 and IAF_2). The main drawback of the P-approach is that the cluster-head will mainly act as a relay reporting to the eNB the collected information from the M2M devices in the same cluster for further exploitation. Therefore, in the P-approach the cluster-head have to perform multiple transmission and/or consume high power in order to report the collected data to the eNB. On the other hand, the main drawback of the I-approach is that the M2M devices belonging to the same cluster may present large distances among them, thus they consume increased transmission power to send their data to the cluster-head. The cluster-head needs fewer transmissions to send the processed data to the eNB (i.e., small values for IAF_1 and IAF_2) due to the fact that the M2M devices have high communication interest. Finally, the combined benefits of simultaneously considering the physical and interest ties among the M2M devices is achieved by the IP-approach, which results in decreased total cumulative power consumption, as shown in Fig. 4 and Fig. 5. Finally, Fig. 6 and Fig. 7 presents the power consumption during the WIT phase at the *10^th^* timeslot of the evolving system operation, as a function of the network size, i.e., for topologies ranging from *10* to *40* M2M devices, where similar observation can be concluded.

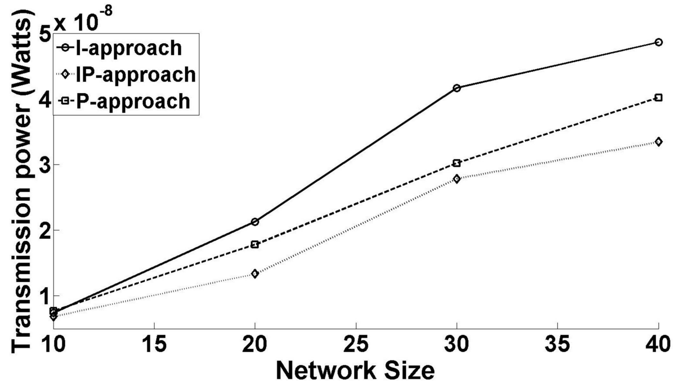

Fig. 6 Transmission power during the WIT phase considering IAF_1 as function of network size.

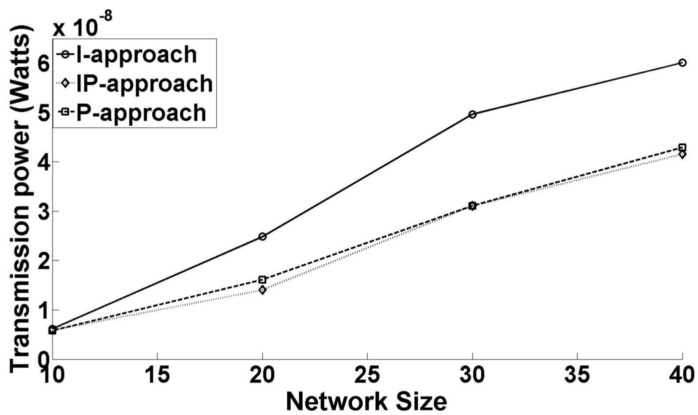

Fig. 7 Transmission power during the WIT phase considering IAF_2 as a function of network size.

VI. CONCLUSIONS

In this paper, we introduce the concept of joint consideration of interest, physical and energy related properties in the clustering and resource management processes in M2M communication networks supporting various IoT applications. Initially, a joint interest, physical and energy-aware cluster formation mechanism is proposed based on the low-complexity Chinese Restaurant Process in order to create clusters among the M2M devices and select the cluster-head, while WPC technique is adopted, where the cluster-heads that are characterized by improved energy-availability as a result of their election process, charge the M2M devices belonging to their cluster during the WET phase. Each M2M device is associated with a generic utility function representing its Quality of Service prerequisites. A holistic utility-based transmission power allocation approach is introduced, formulating the power control problem as a distributed non-cooperative game among the devices. The existence and uniqueness of a Nash equilibrium point is shown, determining devices' transmission powers during the WIT phase. Based on the equilibrium transmission powers of the M2M devices, the necessary and sufficient charging transmission powers of the cluster-heads are determined. The operational efficiency and efficacy of the proposed framework is evaluated through modeling and simulation under various topologies and scenarios that illustrate and reveal its benefits. It should be noted that the proposed approach facilitates the creation of a more flexible and general framework, where the control intelligence and the decision-making process lie at the M2M device, thus enabling the realization of mobile node's self-optimization and self-adaptation functionalities. Therefore, the proposed framework can be applied in realistic IoT applications, towards enabling and supporting the battery-life extension of the M2M devices via realizing an efficient clustering methodology among them and adopting the WPC technique. Furthermore, the proposed approach can be easily adopted in the emerging multi-purpose sensor devices, where communication and clustering among the various devices is determined based on proximity, need of measurement which could vary dynamically in time and space, and interest/objective of the measurement.

Part of our current and future work contains the implementation and testing of the proposed framework in a realistic testbed environment, where multiple M2M devices participating in different IoT applications with different corresponding interest ties can be included. Finally, the concept of M2M devices' mobility, both in terms of absolute velocity values as well as moving direction, is of great interest and practical importance to be included in the weight of each edge in the M2M devices' relation graph towards creating devices' clusters and improving cluster stability.

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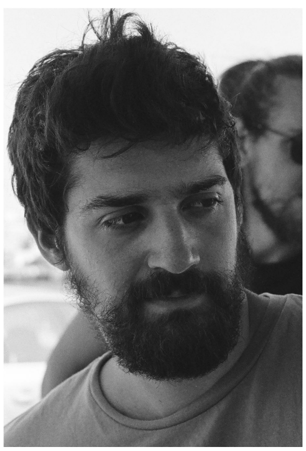

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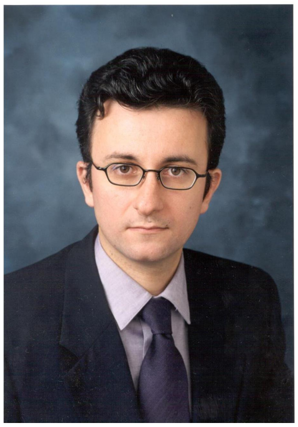

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