Cognitive Internet of Things: A Unified Perspective (Invited Paper)

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Abstract. In this article, we present a unified perspective on the cognitive internet of things (CIoT). It is noted that the CIoT design is the convergence of energy harvesting, cognitive spectrum access and mobile cloud computing technologies. We unify these distinct technologies into a CIoT architecture which provides a flexible, dynamic, scalable and robust network design road-map for a large scale IoT deployment. A general statistical framework is developed and new metrices are introduced so that the design space of the CIoT can be quantitatively explored in the future. A brief overview of both the energy and spectral performances of the CIoT network is presented and its possible future extensions are highlighted.

Keywords: Internet-of-things · Cognitive radios · Cloud · Energy harvesting · Shared spectrum · Underlay · Interference

1 Introduction

The term 'internet-of-things' (IoT) was coined by Kevin Ashton in 1999. The central idea was to empower everyday objects with internet connectivity thus enabling pervasive and autonomous communication. The foundation of IoT is based on Weiser's [1] vision of profound software/hardware technologies that weave themselves into fabric of everyday life such that they become indistinguishable. The functionality and modalities of these technologies is distributed across a variety of interconnected objects. The inter-connectivity of these objects is pivotal as the collective intelligence of the IoT network emerges from simple object level interactions. In turn, such a collective intelligence can be credited with driving significant innovations in the context of various applications under the umbrella of smart homes and cities.

R. Giaffreda et al. (Eds.): IoT360 2014, Part II, LNICST 151, pp. 201–210, 2015.
DOI: 10.1007/978-3-319-19743-2_30

1.1 The IoT Grand Challenge

A recent survey from EiU [2] indicated that around 75 % of businesses are either actively considering or employing IoT enabled solutions. It is projected that around 500 billion [3] so-called 'smart things' will become part of our day-to-day activities by 2020. Consequently, the IoT faces the challenge of becoming heavy on 'things' while struggling on the connectivity frontier.

A quick glance at the frequency allocation charts provided by the regulatory bodies reveals that most of the prime spectrum is already assigned and the margin for accommodating the emerging wireless applications such as IoT is low. Consequently, it seems natural to think of the spectrum scarcity as a real challenge posed due to the high utilization of the Hertzian medium. However, a reality check on the usage patterns of the available spectral resources reveals that in a nutshell the spectrum scarcity is nothing but artificial. Spectrum occupancy measurements [4,5] have revealed that these licensed bands are highly under-utilized across space and time. From 13 % to 87 % of the radio spectrum remains unused across spatio-temporal domains. This sporadic utilization of scarce electromagnetic spectrum creates an artificial scarcity which in turn poses the inter-connectivity challenge for IoT. Regulatory bodies such as the FCC (in the USA) and Ofcom (in the UK) have already noticed that such under-utilization of the spectrum can be avoided by more flexible and dynamic spectrum access (DSA) mechanisms [6]. Radio spectrum is a multidimensional entity, i.e., frequency is not the only parameter/dimension which characterizes the spectral opportunity. Space, time, transmission power, polarization, medium access and interference all combinely shape the radio environment. The dynamic spectrum access (DSA) mechanism employs one or more of these parameters to break the shackles of rigidity imposed by the command and control mechanism. Cognitive radios (CRs) are envisioned to be the key enablers for provisioning DSA. CRs are based on opportunistic exploitation of radio spectrum across one or more dimensions. Nevertheless, while the CR platform renders itself as a promising solution for improving connectivity, its suitability in context of IoT is limited due to two main reasons:

1. High cost: CRs employ sophisticated hardware to derive operational environment awareness and so naturally the radio platforms costs are higher as compared to dumb radio terminals. For IoT solutions, the radio platforms will be embedded inside objects requiring both additional cost and form factors. Thus the radio platforms should be as simple as possible, ideally comprising of a single chip on which a radio transceiver is integrated with the micro-controller unit (MCU). Manufacturers such as Texas Instrument, Nordic Semi-conductor, Maxim, CSR ,etc., are already providing such simple solutions.
2. Energy consumption and life-time: CR terminals often pay the cost of opportunism in terms of their higher energy consumption. More specifically, the operational environment awareness is driven from the inference process which consumes more energy as compared to simple radio platforms. For the wireless access applications, energy consumption is not considered as a design

constraint due to supply of power from the grid. Nevertheless, for IoT based applications energy-consumption is of the utmost important. As discussed earlier, the radio platform is part of variety of objects, most of them having no/limited access to the power running on coin cells, etc. In this context, the cost of opportunism may be incurred in terms of the reduced operational life-time of these objects.

While object life-time is a critical aspect of design, the issue of so called 'green design' is further brought into play due to a predicted high volume of smart things. Specifically, as predicted in a recent report by Ericsson [3], the CO_2 emissions due to increased number of internet connected devices will increase from 800 Mtonnes to 1200 Mtonnes by 2020. In terms of net emissions, ICT will continue to maintain its 2 % contribution to the global carbon foot-print. Nevertheless, according to the Intergovernmental Panel on Climate Change (IPCC) current emission trends are far from sustainable, requiring exponential reduction to meet a 2°C rise in global temperature. In a recent survey by Cable News Network (CNN) it was estimated that a 2°C rise in global temperature will result in a 100 billion US dollar expense rise for addressing various challenges due to climate change. In summary, like all other sectors ICT should exponentially reduce energy consumption to operate in a eco-friendly manner. Thus in summary, for deployment of 500 billion IoT devices a clean slate design is necessary to address both energy and spectral efficiency issues.

1.2 Design Attributes and Proposed Architecture

The grand challenges posed in the context of the cognitive IoT (CIoT) can be easily translated into design attributes/constraints. To summarize, the radio platform employed in CIoT devices should be: (i) simple yet agile; (ii) spectrally efficient and (iii) low power with a minituarized form factor. To satisfy these design attributes, the definition of cognition in context of the IoT must be revisited. In particular, not only spectral agility is of a prime importance but power consumption awareness should also be embedded into the cognitive engine. We advocate that the cognitive engine must be equipped with a potential to harvest energy from ambient sources and in some cases from the objects themselves. For instance, consider smart door locks installed in modern houses. The radio transceivers on these locks can be powered using solar panels harvesting indoor ambient light from both natural and synthetic sources. Moreover, these locks can also harvest power from the mechanical motion of door itself. As smart objects have a very low-duty cycled traffic harvested energy provides a significant potential for designing self-sustainable so called 'zero-energy consumption' CIoT networks.

In this paper, we propose a cloud enabled CIoT platform as depicted in Fig. 1 to address the aforementioned challenges. From an object oriented programming approach it is well known that an object can be adequately described by its attributes and functionalites. These functionalites and attributes can be linked to external stimuli characterizing events. The behavior of the object in response to

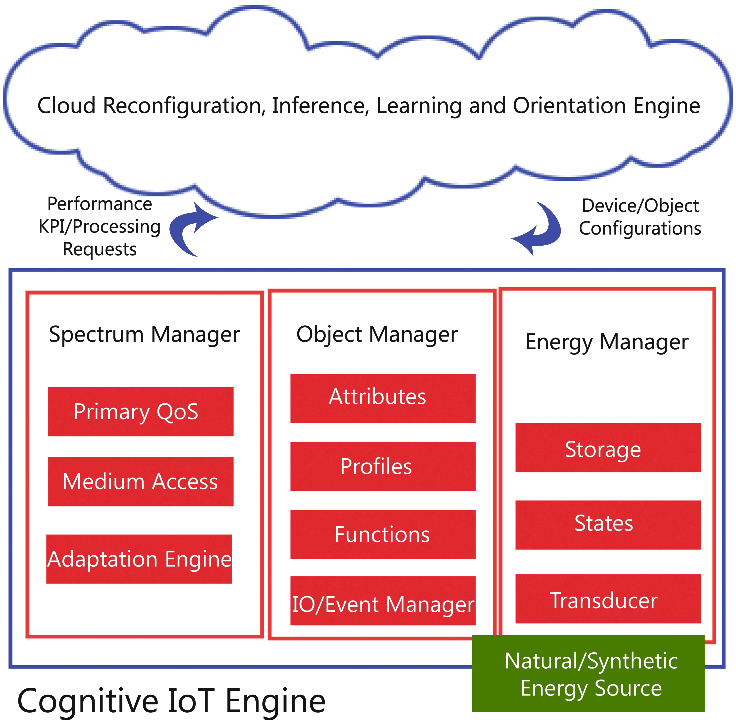

Fig. 1. Proposed architecture for cognitive IoT networks

an external stimulus is defined by the device profile. External and internal stimului may trigger interrupts which should be handled in accordance with device profile and current state. We propose that this object related functionality should be implemented in the so called 'object manager' which forms the central part of CIoT engine. The object engine coordinates with both the energy and spectrum managers to provide context awareness and indicate required quality-of-service or quality-of-information constraints. The object management life cycle can be simplified as most of the inference can be moved up to the centralized cloud processor. Thus objects can be made simpler by implementing basic look-up tables which map events, stimulus, attributes and functionality. Notice that the cloud based architecture provides flexibility of re-configuring the object management engine on the fly.

Spectrum and energy management engines are responsible for maximizing the spectral and energy efficiencies of a CIoT network. We advocate the use of a cognitive underlay based spectrum access which requires only transmit power/medium access probability adaptation at the CIoT platforms [7]. The intrinsic advantage of the proposed spectrum access is that its implementation is simple and does not require additional sophisticated hardware. Based on the dynamics of the primary network, the cloud re-configuration engine can re-configure access probabilities and transmit power to guarantee that the QoS of the legacy network is not violated. Thus, implementing a robust co-existence framework between the primary users and the CIoT devices. The practical implementation of such a spectrum access would require a simple look up table at each device, i.e. CIoT platforms do not lose either their cost-effectiveness or the form factor through the implementation of the proposed cognitive access strategy. A general framework for performance characterization of these engines is introduced in a subsequent discussion.

2 Energy Outage Probability in Harvesting Empowered CIoT

In order to maintain generality, in this article, we do not restrict our analytical models to a particular scenario. We will present a general framework for performance characterization of the CIoT networks which can be employed to study various specific use-cases.

Harvesting energy from natural (solar, wind, vibration, etc.) and synthesized (microwave power transfer) sources is envisioned as a key enabler for realizing green wireless networks. In this context, the energy management engine plays a central role. Energy harvested from the ambient sources such as natural and man-made light, temperature gradients, vibrations and mechanical motions results in an energy field which possesses the following form

$$I_H\left(t,\boldsymbol{x}\right)=I_D\left(t,\boldsymbol{x}\right)+I_R\left(t,\boldsymbol{x}\right) \quad {}^{Watts}/\mathrm{m}^2, \tag{1}$$

where I_D is the deterministic power density and I_R captures random fluctuations in ambient power field due to the environment. In general, the power arrival process at a transducer has both spatial and temporal dynamics. For instance, the power arriving at a indoor solar panel is a function of its latitude, longitude, zenith angle, hour angle and the day number [8]. Transducers are not ideal in converting the ambient energy into output power. Generally, the input-output relationship of the transducer is non-linear. Thus the output load is often matched to provide a maximum energy transfer. In general, the power output of a transducer can be represented as

$$P_{out}\left(t,\boldsymbol{x}\right)=f_T(I_D\left(t,\boldsymbol{x}\right)+I_R\left(t,\boldsymbol{x}\right)) \;\; \text{Watts}. \tag{2}$$

where $f_T(.)$ is the non-linear transducer response. For instance, for the PV panel the output current can be expressed in terms of the ambient solar irradiance I_H (see eq. (1)) as follows [8]

$$I_{PV}=I_{sc}\left[1-\kappa_3\left\{\exp\left(\frac{V_{PV}}{\kappa_4 V_{oc}}\right)-1\right\}\right], \tag{3}$$

where $\kappa_3=\left(1-\frac{I_{MPP}}{I_{sc}}\right)\exp\left(\frac{V_{MPP}}{\kappa_4 V_{oc}}\right)$ and $\kappa_4=\left(\frac{V_{MPP}}{V_{oc}}-1\right)/\ln\left(1-\frac{I_{MPP}}{I_{sc}}\right)$ which depends on the module parameters: (i) short circuit current I_{sc}; (ii) open circuit voltage V_{oc}; (iii) maximum power point voltage V_{MPP} and (iv) maximum power point current I_{MPP}. These parameters can be expressed as a function of the ambient temperature and global horizontal irradiance as

$$I_{sc} = I_{scs} \times \frac{I_H}{I_S} \times [1 + \varsigma_1 (T - T_s)], \tag{4}$$

$$V_{oc} = V_{ocs} + \varsigma_2 (T - T_s), \tag{5}$$

$$I_{MPP} = I_{MPPS} \times \frac{I_H}{I_S} \times [1 + \varsigma_1 (T - T_s)], \tag{6}$$

$$V_{MPP} = V_{MPPS} + \varsigma_2 (T - T_s), \tag{7}$$

where I_{scs}, V_{ocs}, I_{MPPS},V_{MPPS} are defined at standard conditions, i.e., $I_S = 100\,{}^{\mathrm{mW}}/_{\mathrm{cm}^2}$ for outdoor/$I_S = 100\,{}^{\mu\mathrm{W}}/_{\mathrm{cm}^2}$ for indoor and $T_s = 25°\mathrm{C}$ with ς_1 and ς_2 being the current and the voltage coefficients. These parameters are generally provided in the data sheet of a PV module. From Eq. (3), the output power of the PV panel can be computed as a function of the voltage as $P_{out} = I_{PV} V_{PV}$. Most of the modern day panels are equipped with maximum power point tracking algorithms[1]. The maximum output power can be extracted by adjusting the cell load resistance. The maximum extracted power is denoted by P_{out}^{max} and is computed by maximizing P_{PV} with respect to output voltage.

The short-fall of the energy for a certain desired power P_{req} can be measured in terms of the 'energy outage probability' as

$$\begin{aligned} \epsilon_{out}^{\{e\}}(t, \boldsymbol{x}) &= \mathbb{P}\{P_{out} < P_{req}\} = \mathbb{P}\left\{I_R < f_T^{-1}(P_{req}) - I_D\right\}, \\ &= \mathcal{F}_{I_R}\left(f_T^{-1}(P_{req}) - I_D(t, \boldsymbol{x})\right), \end{aligned} \tag{8}$$

where $\mathcal{F}_{I_R}(.)$ is the cumulative density function of I_R the random component of the ambient energy field for a certain time t and location $\boldsymbol{x}$. Generally, $f_T^{-1}(a)$ is a monotonically decreasing function with respect to a and thus ϵ_{out} is increasing function of P_{req}, i.e. with an increase in required power for a fixed time instance and a spatial location the energy outage probability also increases towards unity. The dynamics of the energy harvester and thus the management engine of a CIoT platform can be completely characterized in terms of energy outage probability.

3 Spectral Access Outage Probability in CIoT

Consider a large scale CIoT network co-existing with the primary network. The spatial distribution of both primary and CIoT nodes is captured by two independent *homogenous Poisson point processes* (HPPPs) $\Pi_p(\lambda_p)$ and $\Pi_c(\lambda_c)$ respectively[2]. Further assume that CIoT nodes employ a random access strategy similar to the slotted ALOHA MAC protocol to schedule their transmissions over

[1] Sometimes implemented at inverter level rather than panel level .

[2] The HPPP assumption is reasonable in the context of CIoT as the objects are deployed by the user and are spatially distributed across the entire city.

a shared medium. More specifically, at an arbitrary time instant both the primary and the secondary devices can be classified into two distinct groups, i.e., nodes which are granted with the medium access and those whose transmissions are deferred. If p_i denotes the medium access probability (MAP) for an arbitrary user $\boldsymbol{x} \in \Pi_i$[3], then the set of active users under slotted ALOHA MAC also forms a HPPP:

$$\Pi_i^{\{TX\}} = \{ \boldsymbol{x} \in \Pi_i : \mathbb{1}(\boldsymbol{x}) = 1\} \text{ with density } \lambda_i p_i, \quad \text{where } i \in \{c, p\}. \tag{9}$$

where $\mathbb{1}(\boldsymbol{x})$ denotes a Bernoulli random variable and is independent of Π_i. The received SIR of a typical primary user can be characterized as

$$\begin{aligned} \text{SIR} = \Gamma_p &= \frac{h_p l(r_p)}{\sum_{i \in \Pi_p^{\{TX\}} \setminus \{\boldsymbol{x}\}} h_i l\left(\|\boldsymbol{x}_i\|\right) + \sum_{j \in \Pi_c^{\{TX\}}} \eta g_j l\left(\|\boldsymbol{x}_j\|\right)}, \\ = \Gamma_p &= \frac{h_p l(r_p)}{I_p + \eta I_c} = \frac{h_p l(r_p)}{I_{tot}}, \end{aligned} \tag{10}$$

where $h_p, h_i, g_j \sim \mathcal{E}(1)$ random variables capturing the effect of Rayleigh fading, $l(r) = r^{-\alpha}$ is the path-loss function with $\alpha \geq 2$ being the environment dependent exponent, $\eta = \frac{P_c}{P_p}$ is the transmit power ratios of the CIoT and primary networks and r_p is the distance between primary transmitter and receiver.

The primary user's QoS constraint can be expressed in terms of the desired SIR threshold $\gamma_{th}^{\{p\}}$ and an outage probability threshold

$$\mathbb{P}_{out}^{\{p\}}\left(P_c, p_c\right) = \Pr\left\{\Gamma_p \leq \gamma_{th}^{\{p\}}\right\} \leq \rho_{out}^{\{p\}}. \tag{11}$$

Notice that the primary user's outage probability is coupled with the aggregate interference generated by the CIoT network. Consequently, secondary access is limited subject to the constraint in Eq. (11). It can be easily shown that the maximum permissible MAP for the CIoT devices can be characterized as

$$p_c = \frac{f_{MAP}\left(\lambda_p, \lambda_c, \rho_{out}^{\{p\}}, \gamma_{th}^{\{p\}}\right)}{P_c^{2/\alpha}}, \tag{12}$$

where $f_{MAP}(.)$ depends on the primary networking parameters, the propagation characteristics of the co-located networks and the required QoS requirements. For an ad-hoc network $f_{MAP}(.)$ is characterized in [7] which can be easily extended to the cellular primary network. Generally, $f_{MAP}(.)$ decreases with an increase in the QoS requirement and/or the density of the primary transmitters. It decreases with an increase in a CIoT transmit power and increases with a decrease in the CIoT transmitter density. The spectral outage probability is the event that the

[3] With a slight abuse of notation, $\boldsymbol{x} \in \mathbb{R}^2$ is employed to refer to the node's location as well as the node itself.

CIoT transmitter is in a spectrum limited regime, i.e., it has had to defer its transmission for the current slot. Thus

$$\epsilon_{out}^{\{s\}} = 1 - \frac{f_{MAP}\left(\lambda_p, \lambda_c, \rho_{out}^{\{p\}}, \gamma_{th}^{\{p\}}\right)}{P_c^{2/\alpha}}. \tag{13}$$

Consequently, the relationship between spectral and energy outages can be characterized as follows

$$\epsilon_{out}^{\{e\}} = \mathcal{F}_{I_R}\left(f_T^{-1}\left(\left(\frac{f_{MAP}\left(\lambda_p, \lambda_c, \rho_{out}^{\{p\}}, \gamma_{th}^{\{p\}}\right)}{1-\epsilon_{out}^{\{s\}}}\right)^{\frac{\alpha}{2}}\right) - I_D\left(t, \boldsymbol{x}\right)\right). \tag{14}$$

For the case of indoor solar energy harvesting, the formulation can be simplified using Eq. (3) as

$$\epsilon_{out}^{\{e\}} = \mathcal{F}_{I_R}\left(\Theta\left(\frac{1}{1-\epsilon_{out}^{\{s\}}}\right)^{\frac{\alpha}{2}}\right), \tag{15}$$

where $f(x) = \Theta(g(x))$ implies that $c_1 g(x) \leq f(x) \leq c_2 g(x)$ following the Landua notation. From [9], we have that

$$\epsilon_{out}^{\{e\}} = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{\left(1-\epsilon_{out}^{\{s\}}\right)^{-\alpha/2}}{2}\right)\right]. \tag{16}$$

This provides us with the spectral-energy outage operating curve (SE-OPC) for CIoT networks. The SE-OPC serves as a guideline to decide whether a CIoT network is operating in energy limited regime or the spectrum limited regime. The exact shape of the curve is coupled with the operating parameters of the harvester and the network. However, in this study we are only interested in the scaling behavior and thus do not consider the specific values.

4 Discussion and Future Directions

Figure 2 illustrates the SE-OPC for CIoT networks for the considered reference scenario of an indoor solar panel. It is clear that both the energy and spectral outage probability are positively coupled with each other. Specifically, both the spectral and the energy outages are increasing functions of the CIoT platform transmit power, i.e., a high transmit power for CIoT radio will result in:

1. vanishing transmission opportunities due to interference protection implemented by the cloud controller to guarantee the primary user's QoS requirement;
2. requiring an amount of energy for transmissions which cannot be fulfilled by the harvester.

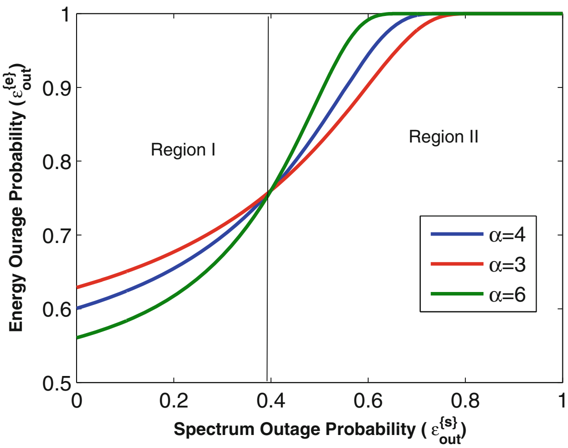

Fig. 2. SE-OPC for CIoT network for varying path-loss exponents (see Eq. (16)).

This leads to the conclusion that adopting a low transmit power will reduce both the energy and the spectrum outage probabilities. However, the low transmit power employed by a CIoT platform may not be able to guarantee the required QoS or QoI at each CIoT node. Consequently, the transmit power must be optimized by considering all three factors, i.e., energy and spectral outages and CIoTs throughput. Due to space limitations, the optimization of transmit power is deferred for the journal version of this article.

From the energy outage perspective, there exist two distinct regions. These regions mainly demonstrate the impact of an increase in the path-loss exponent. An increase in the path-loss exponent results in: (i) signal power reduction; (ii) rapid attenuation for co-channel interference. Thus intuitively these two regions demonstrate the power limited vs. interference limited operation.

5 Conclusion

In this article, we provided a unified architecture for the cognitive internet-of-things (CIoT) framework. We advocated that the definition of cognition must be extended to incorporate IoT specific design challenges. We solicited a cloud based cognitive underlay spectrum access for the IoT radio platforms. Furthermore, energy harvesting is proposed to attain so called self-sustainable network design. We introduce a novel statistical framework to characterize the energy and spectral outages in CIoT networks. The relationship between energy and spectral outages was explored for a reference scenario of indoor solar energy harvesting. It was shown that both outages are positively coupled as they are governed by the same underlying parameter, i.e., transmit power. It was shown that there exists tradeoff between minimizing the outages and maximizing the QoS and thus optimal transmit power must be adopted to maximize network level performance.

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