On the Design of Passive RFID Tags with RF-energy Harvesting

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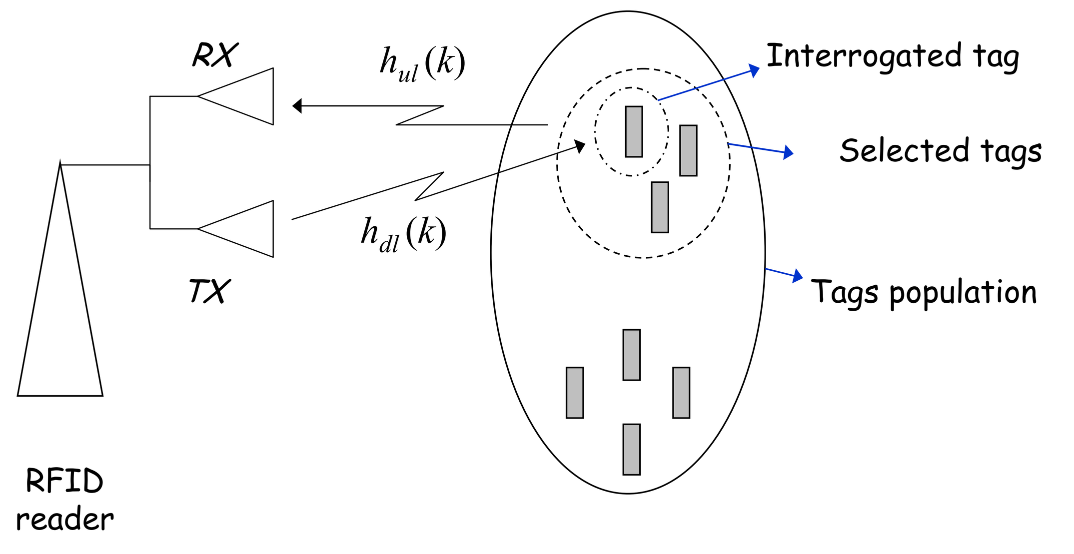
Far-Field Passive RFID Systems

Far-field Passive RFID system characteristics:

- ✓ A bidirectional communication, exploiting the far-field component of the electromagnetic field, is established through one (or more) *RFID reader* and many *RFID tags* in the reader range.
- ✓ Passive RFID tags do not have an onboard source of energy.
- ✓ An RFID reader can transmit a continuous wave (CW) whose RF energy is used:

1. To activate passive tag circuitries.
2. To enable backscatter modulation performed by the tags.



Main limitations of a "traditional" passive RFID tags are:

- ✓ *Tag sensitivity:* Tags must receive enough energy to activate their circuitry.
- ✓ *Reader sensitivity:* The reader must receive enough energy from the backscatter signal to be able to reliably demodulate.
- ✓ Overall, both sensitivities above limit the *read range*, which is the distance at which the tag can be reliably read from the reader.

Improving Passive Tag Performance

Observations:

1. In a RFID system with several tags communicating with a reader, each tag experiences long period of inactivity while other tags transmit.
2. The RFID reader, keeps transmitting a CW to communicate with other tags.
3. Tags may be provided with energy storage devices such as batteries or ultracapacitors (initially uncharged).

⬇ **Idea 1**

RF-Energy harvesting during period of inactivity

4. To improve reader sensitivity, tags may be provided with a power amplifier (PA) which is fed by the RF-charged battery. The PA may be then used by the tags to amplify the backscatter signal when they are required to transmit.

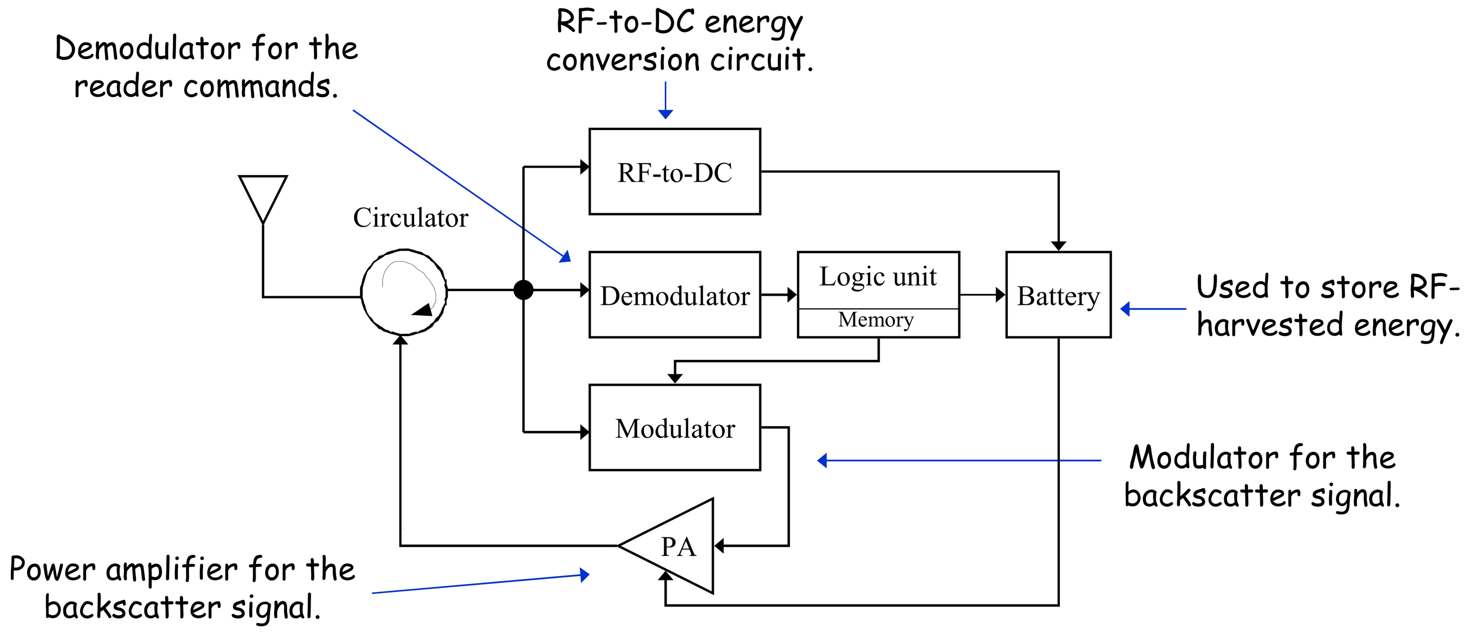
⬇ **Idea 2**

Opportunistic amplification of the backscatter signal

⬇ **New class of tags**

Amplified Backscattering through Energy Harvesting (ABEH) tags

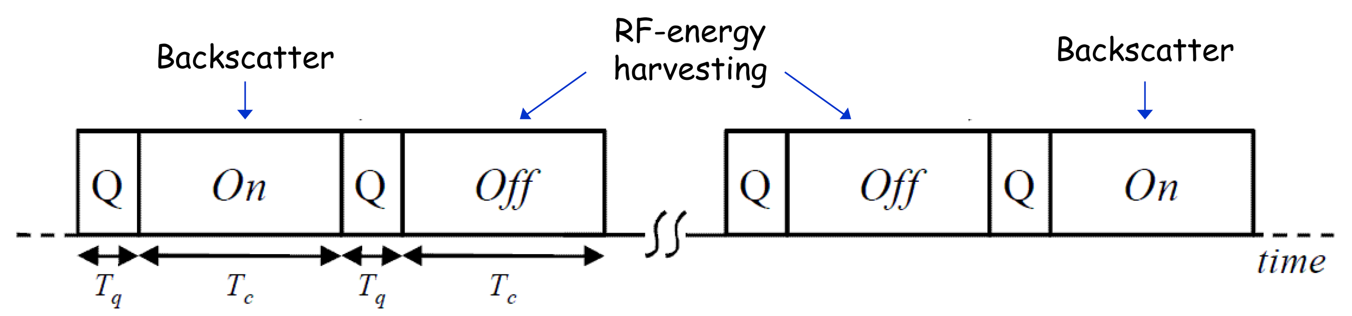
Block Diagram of the ABEH Tag



System Model

We focus on the performance of ABEH tags with respect to standard passive tags, considering RFID systems limited by the reader sensitivity. We assume that:

- ✓ RFID readers with 2 antennas, one for TX and one for RX (*Bistatic reader*).
- ✓ Time slotted transmissions, where each *time-slots*, of duration T [s], is composed by two parts:
  1. ***Query* commands**, of duration T_q, transmitted by the reader to request information at the tags.
  2. **CW transmission**, of duration T_c, emitted by the reader to allow tags to perform **backscatter modulation.**
- ✓ The communications reader-tag (*downlink*) and tag-reader (*uplink*) are subject to block Rayleigh fading independent on each other (justified by bistatic reader assumption [Kim et al. '03]), and also independent and identically distributed (iid) over the slots.
- ✓ A tag is interrogated by each query with probability p independently from the past and future queries, and on the presence of the other users (no tag collisions):
  - ✓ **Off time-slots**, which occur with probability $q=1-p$, where the tag under investigation is not interrogated.
  - ✓ **On time slots**, which occur with probability p, where the tag under investigation is interrogated and needs to perform backscatter modulation.



We also neglect possible demodulation errors of the query commands at the tag (which can be included in the definition of p), and consider $T_q << T_c \approx T$.

Energy Harvesting and Backscatter SNR

The signal received at the tag[1], during time slot k, can be expressed as:

$$y(t;k) = \sqrt{L}h_{dl}(k)x(t-\vartheta_k) + w(t;k)$$

The received energy (random variable) is:

$$E(k) = \eta_{DC}\|y(t;k)\|^2 \hat{=} \eta_{DC}\int_{kT}^{(k+1)T}|y(t;k)|^2 dt \cong \eta_{DC} L E_0 |h_{dl}(k)|^2$$

Off time-slots (energy harvesting)

- The battery is quantized and represented through N_δ discrete energy levels of size δ_E.
- The evolution of the battery can be analyzed through a Markov chain (MC).
- The probability of recharging the battery from energy level n to l, is denoted by β_{nl}, and depends on the PDF of the received energy $E(k)$.

On time-slots (backscatter modulation)

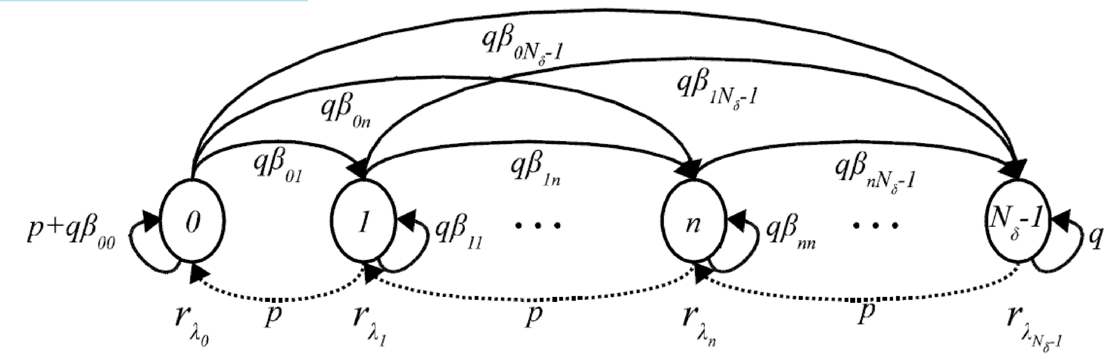
We are interested in the SNR at the RFID reader when a tag performs backscatter modulation. The SNR can be shown to be:

$$\gamma(E_b(k);k) = \frac{L^2 E_0 |h_{ul}(k)|^2 |h_{dl}(k)|^2}{E_n}\eta_{mod} + \frac{L|h_{ul}(k)|^2 E_b(k)}{E_n}\eta_{amp}$$

[1] L is the path loss, $h_{dl}(k)$ ($h_{ul}(k)$) is the downlink (uplink) channel coefficient, $x(t)$ is the CW emitted by the reader with energy per slot E_0, θ_k is a random phase term, $w(t)$ is additive noise, $E_b(k)$ is the energy draw from the battery in time slot k, E_n is the energy of the additive at the reader noise, η_{DC}, η_{amp}, η_{mod} are the efficiencies of the RF-to-DC converter, PA and of the backscatter modulation process respectively.

Markov Decision Process Approach

State of the battery modeled with a finite state MC ➡ Optimal amount of energy drawn from the battery (**policy**) for amplification obtained through: ➡ **Markov Decision Process**



Instantaneous reward if the tag draws an energy $\lambda\delta_E$ from battery to amplify the backscatter signal:

$$r_\lambda = \Pr[\gamma(\lambda\delta_E;k) \geq \gamma_{th}]$$

➡
- ✓ γ_{th} SNR threshold
- ✓ λ policy
- ✓ δ_E quantum of energy

We can restrict attention without loss of optimality to stationary policies[2] and aim at maximizing the long term average reward, which can be expressed in term of the expected gain per slot.

Definition 1: A stationary policy $\boldsymbol{\lambda}=[\lambda_0, ..., \lambda_{N_\delta-1}]^T$ dictates the number $\lambda_n \in \{0,..., n\}$ of energy levels δ_E drawn from the battery by the tag when $S(k)=n$, used to feed the PA.

Definition 2: The expected gain per slot for the stationary policy $\boldsymbol{\lambda}$ is defined as:

$$g^{\boldsymbol{\lambda}} = \sum_{n=0}^{N_\delta-1}\pi_n^{\boldsymbol{\lambda}} r_{\lambda_n} = \left(\boldsymbol{\pi}^{\boldsymbol{\lambda}}\right)^T \mathbf{r}^{\boldsymbol{\lambda}}$$

where $\boldsymbol{\pi}^{\boldsymbol{\lambda}} = [\pi_0^{\boldsymbol{\lambda}}, ..., \pi_{N_\delta-1}^{\boldsymbol{\lambda}}]$ and $\mathbf{r}^{\boldsymbol{\lambda}} = [r_{\lambda_0}, ..., r_{\lambda_{N_\delta-1}}]$ are the steady state distribution and the reward vector for a given policy.

Definition 3: The optimal stationary policy $\boldsymbol{\lambda}^*=[\lambda^*_0, ..., \lambda^*_{N_\delta-1}]^T$ is defined as the stationary policy that maximizes the expected gain per slot:

$$g^{\boldsymbol{\lambda}^*} \geq g^{\boldsymbol{\lambda}}, \quad \forall \boldsymbol{\lambda}$$

[2] Under mild conditions on the policies, all the MCs obtained with different policies are time-homogeneous and unichain [Derman '70].

Howard Policy Improvement Algorithm

We resort to the Howard Policy Improvement algorithm to find the optimal stationary policy. It is based on the following system of equations:

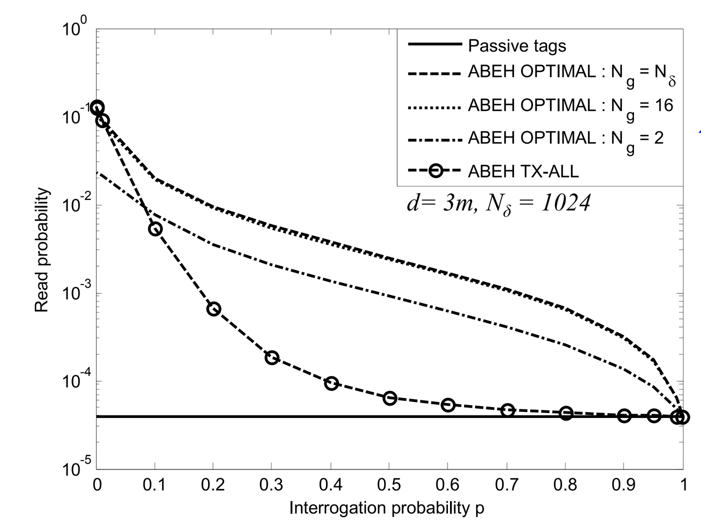
$$\mathbf{w}^{\boldsymbol{\lambda}} + g^{\boldsymbol{\lambda}}\mathbf{e} = \mathbf{r}^{\boldsymbol{\lambda}} + \mathbf{P}^{\boldsymbol{\lambda}}\mathbf{w}^{\boldsymbol{\lambda}}$$

$w^{\boldsymbol{\lambda}} = [0, w_1^{\boldsymbol{\lambda}}, ..., w_{N_\delta-1}^{\boldsymbol{\lambda}}]$ is the relative gain vector of having the MC starting in a certain state w.r.t. state 0 (no energy in the battery), $\mathbf{P}^{\boldsymbol{\lambda}}$ is the transition matrix of the MC above and **e** is all 1's vector.

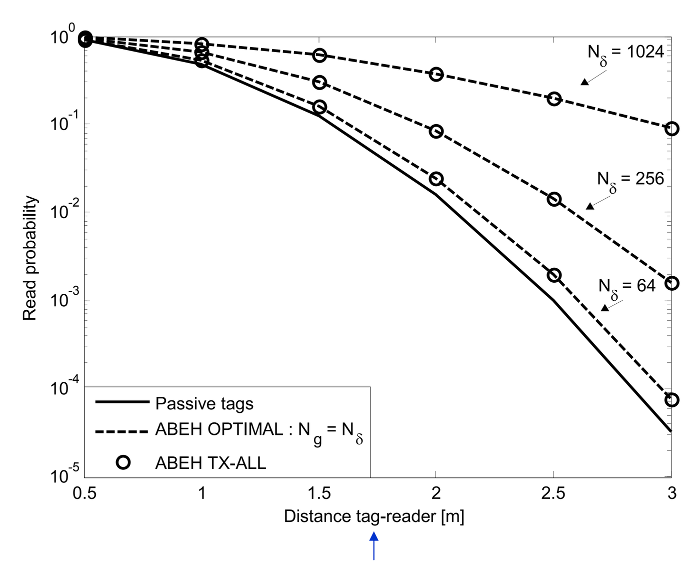
Algorithm

1. Choose an arbitrary policy $\boldsymbol{\lambda}=[\lambda_0, ..., \lambda_{N_\delta-1}]^T$;
2. Calculate $w^{\boldsymbol{\lambda}}$ from the system above;
3. If $r^{\boldsymbol{\lambda}}+\mathbf{P}^{\boldsymbol{\lambda}}w^{\boldsymbol{\lambda}} \geq r^{\boldsymbol{\theta}}+P^{\boldsymbol{\theta}}w^{\boldsymbol{\lambda}}$ for all $\boldsymbol{\theta}=[\theta_0, ..., \theta_{N_\delta-1}]^T$, then $\boldsymbol{\lambda}$ is optimal (N_δ inequalities to satisfy);
4. Otherwise, find a $\boldsymbol{\theta}$ such that at least one of the above inequalities is not satisfied;
5. Update $\boldsymbol{\lambda}=\boldsymbol{\theta}$ and iterate with the new policy step 2 through 5.

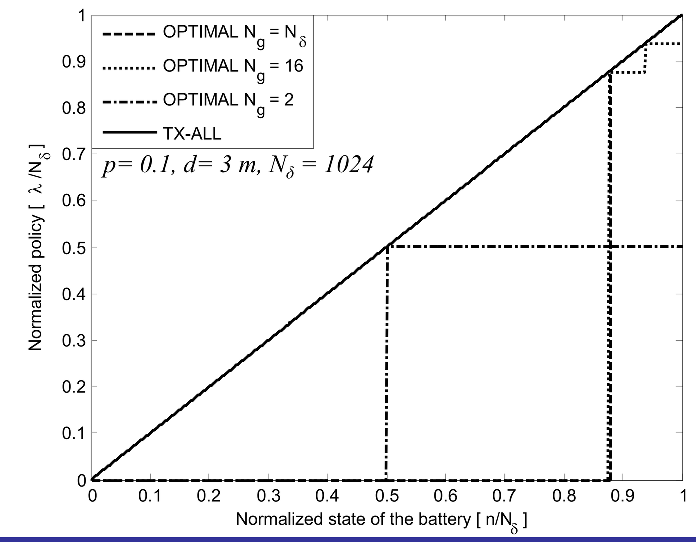
Numerical Results



Average reward of ABEH tags with optimum and transmit-all policies (i.e., the ABEH tag always draws all the energy in the battery) and passive tags versus the interrogation probability p for different policy complexities N_g (N_δ/N_g contiguous states are grouped together and are given the same policy).



Average read range of ABEH tags and passive tags versus the reader-tag distance for different battery sizes.



Normalized policies λ/N_δ versus normalized battery states n/N_δ

System parameters common to all simulations are:

E_0=33dBm, δ_E=3x10^{-6} J, T=1 s, E_n/T=-100dBm, $\eta_{DC}=\eta_{amp}$=0.4, η_{mod}=0.5.