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Power Allocation for a Self-Sustainable Power Substation Monitoring System Using Wireless Transfer of Energy

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ABSTRACT Internet of Things (IoT) can provide an on-line monitoring system for power substations and therefore offer a much more reliable maintenance strategy for power devices. However, energizing the monitoring sensors in a power substation and around High Voltage (HV) devices is difficult and costly. It is possible to reduce the installation costs significantly if the monitoring sensors can be self-sustainable. In this work, we study an autonomous Wireless Sensor Network(WSN), based on energy harvesting and wireless transfer of energy. In order to optimize the performance of this system, we propose and analyze two power allocation techniques, aiming to energize the monitoring sensors wirelessly. This paper concludes that by optimizing the parameters of the system, a self-sustainable WSN in a power substation can be successfully deployed.

INDEX TERMS Energy harvesting, wireless transfer of energy (WTE), internet of things (IoT).

I. INTRODUCTION

THE Internet of Things (IoT) paradigm promises that, in the nearfuture, everything that would benefit from being connected will be connected, creating a massive and continuously growing network. Power substation monitoring system is one of the interesting applications of IoT. Enabling an on-line monitoring system would increase the efficiency and accuracy of power substations and help prevent disastrous incidents due to critical equipment failure. One of the important challenges preventing the implementation of such IoT systems in a power substation area is the provision of energy to all nodes in the network: the numerous devices in IoT systems, including tiny monitoring sensors, would make it virtually impossible to wire them all to a stable source of energy; batteries also would eventually run out of energy and therefore woudl nto represent a long-term solution. One interesting approach for energizing IoT systems is Wireless Transfer of Energy (WTE), which has obtained an increasing amount of interest in the recent years. WTE eliminates the problem of wiring IoT devices and allows to recharge their batteries wirelessly.

Finding the best WTE technology to energize an IoT system depends on a variety of factors such as the environment where the network is deployed. *Inductive coupling*, *Magnetic resonance coupling* and *Electro Magnetic* (EM) radiation are the three main technologies for WTE. Inductive Coupling is only effective over very short ranges (tens of centimeters) [1]; Magnetic Resonance Coupling can transfer energy over a couple of meters [2], [3], and WTE using Electromagnetic (EM) radiation can be used for very long ranges of transmission (up to tens of kilometers) [2], [4]. Inductive coupling is used widely in the near-field Radio Frequency Identification (RFID), such as ID cards. Another common use for inductive coupling is in short range charging of many devices such as tooth brushes, mobile phones and medical implants [5]. Magnetic resonance coupling was introduced in 2007, followed up by the establishment of WiTricity, the license holder of the technology. The main focus of this technology is to cut the last cord and to allow devices to be charged wirelessly, over medium distances. There is a wide range of applications for this technology, including

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wireless recharging of consumer's devices, LED lighting, medical devices, electric vehicles and wireless sensor networks [6]–[8]. Using EM radiation for wireless transfer of energy was first exhibited by William C. Brown in 1960 [4]. In order to enable WTE using electromagnetic radiation, power is first converted to Radio Frequency (RF) signals using a microwave generator. The generated signal is then transmitted through free space by radiating electromagnetic beams to the target. Finally, at the receiver, the received signal is converted back to power using a device called rectifying antenna or *rectenna* [9]. This device converts RF signals to a DC voltage using a diode-based circuit. Several designs have been proposed for rectennas to make them suitable for different systems and frequencies [10]. Typically, more than one rectenna is necessary for reliable device operation [11]. Increasing the Power Conversation Efficiency (PCE) of a rectenna is one of the major design challenges. PCE depends on a variety of factors, such as the signal's frequency, the input power and the designed circuit [12], [13]. In [14] a PCE of 64% is achieved for a mean available incident power of 4 dBm at 2.4 GHz. EM radiation has many applications, mostly for long range transmissions. One benefit of this technology is that the energy receivers can be very small and are able to maintain RF to DC conversion efficiency over a wide range of operating conditions [7]. Therefore, using EM technology is a good choice for charging nodes in a WSN [7], in which wireless nodes may be situated at a distance from any relaible power source.

In this paper we combine WTE using RF signals and energy harvesting, in order to create a fully autonomous WSN. Due to the strong alternating electric field around High Voltage (HV) devices, scavenging energy in a substation environment is a practical option. Energy harvesting from the alternating electric fields has been widely studied in the literature and different designs have been proposed to improve the performance of the energy harvester [15]–[24]. In this paper, by placing the energy harvester close to HV devices, we would allow the harvester to scavenge more energy. The harvested energy can later on be distributed amongst sensors that are located further away by radiating RF signals towards them. This system model was first studied in [25] and [26] as a hierarchical energy harvesting model to enable an autonomous WSN, with a focus on the single sensor scenario. In this paper however, we are considering a multiple sensors scenario, where more than one sensor needs to be energized wirelessly. We are assuming that sensors are competing for access over a shared channel using a CSMA protocol. This setup adds more complexity to the system as compared to its initial description [26], but also makes the system model more practical, due to the fact that in practice a monitoring system almost always consists of many monitoring devices. In this work, we propose two power allocation methods to energize the monitoring sensors wirelessly, and to communicate between the nodes. The probability of a failed transmission is referred to as the *outage probability*; it is used as a figure of merit to evaluate the performance of our system. The proposed methods would allow us to assign a sub-optimal and an optimal transmission power to the nodes, in order to minimize the outage probability. We analyze the performance of these methods through analytical and simulation results.

The rest of this paper is organized as follows. Section II is a discussion of the details of our system model. In Section III we analyze the considered CSMA protocol. Section IV studies the evolution of energy for the sensors. Our proposed power allocation schemes are presented in Section V, followed by a study of power optimization in Section VI. Simulation analysis are presented in Section VII. Finally, we end this paper with a summary and conclusion in Section VIII.

II. SYSTEM MODEL

A. ENERGY HARVESTING AND DISTRIBUTION MODEL

In this system model, we are considering three sets of nodes, namely, a *base node*, *power nodes* and *sensors*. The base node is connected to a stable source of energy and is the final destination for the data transmitted by sensors. In a power substation area, a base node can be the monitoring room in the vicinity of the substation yard that is the site of deployment of the WSN. Power nodes are placed close to HV terminals and sensors are mounted where they are needed to carry out their sensing tasks. A power node continuously harvests energy from the alternating electric field around HV devices. Furthermore, a power node distributes a portion of the harvested energy amongst multiple surrounding sensors by radiating RF signals towards them, through what we call *energy signals*. The remaining portion of the power harvested at the power node is used by the power node to transmit collected data back to the base node. We are assuming that sensors are not connected to a stable source of energy. Therefore, all the required energy for the sensors is received from the power node. Sensors transmit their data to the power node and the power node relays the data back to the base node. In this paper a signal that is used for transmitting data is referred to as a *data signal*. Figure 1 summarizes the energy harvesting and distribution model considered in this paper.

Because a power node is placed in the close proximity of the HV terminals, it is able to harvest a considerable amount of energy. The ratio, $0 < r < 1$, in which the energy harvested at the power node is divided between transmitting data to the base node and energizing the sensors, is a critical factor for optimizing the performance of the system.

The figure of merit that is used in this work to evaluate our system is the *outage probability*. Namely, the probability that the received data signal at the power node or base node is less than a certain threshold. Therefore, the outage probability can be written as:

$$\mathbb{P}_{out} = \mathbb{P}\left\{\mathbf{SNR}_{sp} < \Omega_{sp} \cup \mathbf{SNR}_{pb} < \Omega_{pb}\right\}, \tag{1}$$

where $\mathbf{SNR}_{sp}$ and $\mathbf{SNR}_{pb}$ are the signal to noise ratio at the power node (when a data signal is sent from the sensor to the power node) and at the base (when a data signal is sent from the power node to the base node) respectively. The acceptable thresholds for the signal to noise ratios are denoted by

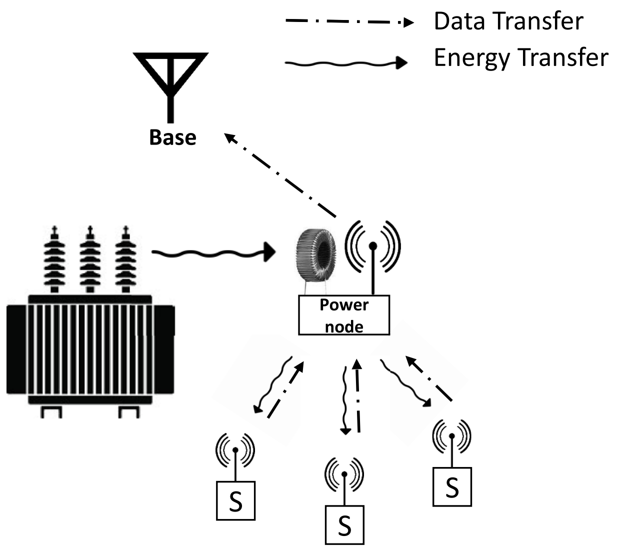

FIGURE 1. Energy harvesting and distribution model.

Ω_{sp} and Ω_{pb}. Both $\mathbf{SNR}_{sp}$ and $\mathbf{SNR}_{pb}$ are in boldface to represent the fact that they are random variables. In case a node (sensor or power node) does not have enough energy to initiate a scheduled transmission, this tansmission would be counted as a failed transmission and would contribute to the outage probability.

In order to minimize the outage probability, the following set of powers need to be optimized:

- The data signal transmission power, $\mathbf{P}_{s_i}$, from sensors to the power node, for $i = 1, \ldots, M$, where M is the number of sensors.
- The energy signal transmission power, P_{ps_i}, from power node to the i-th sensor.
- The data signal transmission power, P_{pb}, from power node to the base.

In the above formulation, sensors transmit to the power node at different transmission powers. As it will be explained in the next section, the transmission power from sensors to the power node can be a random variable and therefore it is denoted in boldface. The power node assigns different transmission powers for energizing each sensor, but uses one single transmission power for transmitting the received data from all sensors back to the base node.

B. SIGNAL PROPAGATION MODEL

We assume that all the channels are Rayleigh distributed with unit expected value. Therefore, the power of the channel fading is exponential with unit variance. We use the Friis equation to model the electromagnetic wave propagation. Therefore, when a data signal is transmitted from sensor s_i to the power node, the SNR at the power node is:

$$\mathbf{SNR}_{s_ip} = \frac{\mathbf{P}_{s_i} G_{sp} \mathbf{h}_{s_ip} d_{s_ip}^{-\alpha} (4\pi f/c)^{-\alpha}}{P_N}, \qquad (2)$$

where $\mathbf{P}_{s_i}$ is the transmission power for the sensor s_i and G_{sp} is the antenna gain for the sensor's transmitter. Note that since we are considering a homogeneous network of sensors, all the sensor nodes are sharing a same value for the antenna gain. The power of the channel fading is shown by $\mathbf{h}_{s_ip}$. In (2), $\mathbf{P}_{s_i}$, $\mathbf{SNR}_{s_ip}$ and $\mathbf{h}_{s_ip}$ are in boldface to represent a random variable. The term d_{s_ip} is the distance between the sensor s_i and the power node. The transmission frequency is denoted by f, c is the speed of light, α is the propagation-loss exponent and P_N is the noise power.

Similarly, when a power node transmits to the base, the received SNR at the base node is:

$$\mathbf{SNR}_{pb} = \frac{P_{pb} G_{pb} \mathbf{h}_{pb} d_{pb}^{-\alpha} (4\pi f/c)^{-\alpha}}{P_N}, \qquad (3)$$

where P_{pb} is the transmission power used by the power node to transmit a data signal to the base, G_{pb} is the antenna gain for the power node's transmitter and d_{pb} is the distance between the power node and the base.

C. CHANNEL ACCESS SCHEME

In this work, we consider M active sensor nodes using a CSMA scheme over a slotted shared channel to communicate with the power node. Each node starts the transmission process by first listening to the channel. If the sensor finds the channel free, at the beginning of the next time slot, it would transmit with a probability of p. It is implied that after each transmission, there would be one time slot of silence in the channel (all the sensors are listening). We assume each transmission would occupy N time slots. On the other hand, if the channel is busy, the sensor node continues listening to the channel until it is free and then would transmit with a probability of p. We assume that when a collision happens the packet would be lost and it would contribute to the outage probability. Moreover, if a node does not have enough energy to transmit a signal, the packet would be dropped and it would be counted as a failed transmission. In this work we are assuming that sensors always have data to transmit. In other words, when the channel is free and a sensor has enough energy, a sensor node would always initiate a transmission with a probability of p.

A received data signal from the sensors at the power node would be relayed to the base immediately. Therefore, the transmission period from the power node to the base is not fixed. On the other hand, the energy signals from the power node to sensors is transmitted periodically and on a regular basis. We assume that energy signals are transmitted from the power node every unit of time. In order to improve the efficiency of the system, directed antennas are used to aim at each sensor. Since there are M sensors around the power node, the frequency at which a sensor receives an energy signal would be proportional to $1/M$.

III. ANALYSIS OF CARRIER SENSE MULTIPLE ACCESS PROTOCOL

In this section we analyze the considered CSMA protocol. To this end, we notice that when a sensor finishes a transmission, from the beginning of the next time slot until one

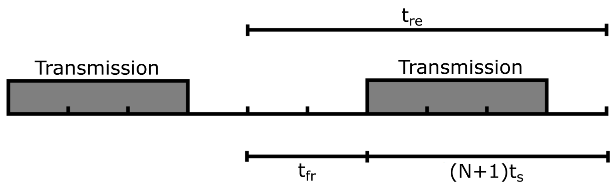

FIGURE 2. **The reset cycle for a sensor node.**

time slot after the end of the next transmission is a reoccurring period. We call this interval *reset cycle*. Fig. 2 illustrates this time interval for one sensor. Each transmission may end up being successful or collides with another node's transmission. The idle time between two consecutive transmissions is either as a result of a node listening to the channel or if it is not transmitting with a probability of $1-p$ or simply because a node does not have sufficient energy to transmit.

The length of a reset cycle is a random variable. If we represent this time with $\mathbf{t_{re}}$, then we have:

$$\mathbf{t_{re}} = \mathbf{t_{fr}} + (N+1)t_s \tag{4}$$

where t_s is the duration of a slot in our slotted CSMA scheme, $\mathbf{t_{fr}}$ is a random variable representing the free time between two successive transmissions and N is the fixed value for the packet length. Both $\mathbf{t_{re}}$ and $\mathbf{t_{fr}}$ are in bold format to represent random variables.

When the channel is free for transmission, a sensor transmits with a probability of p. Therefore, the average number of free time slots during which a node waits before transmission is:

$$\sum_{i=0}^{\infty} ip(1-p)^i = \frac{1}{p} - 1 \tag{5}$$

We also note that from the perspective of one sensor, when the channel is available, with probability $(1-p)^{M-1}$ none of the other $M-1$ sensors would transmit and with a probability of $(1-(1-p)^{M-1})$ at least one other sensor would transmit. In the case that at least one other sensor transmits, the channel would be occupied for the next $N+1$ time slots. Therefore, the average waiting time for a sensor to transmit can be written as:

$$\bar{\mathbf{t}}_{fr} = (\frac{1-p}{p})\left((N+1)(1-(1-p)^{M-1}) + (1-p)^{M-1}\right) t_s \tag{6}$$

therefore:

$$\bar{\mathbf{t}}_{re} = (\frac{1-p}{p})\left((N+1)(1-(1-p)^{M-1}) + (1-p)^{M-1}\right) t_s + (N+1)t_s \tag{7}$$

Furthermore, when a node transmits, a collision occurs if at least one more node transmits during the same time slot. Therefore the collision probability would be:

$$p_{col} = 1-(1-p)^{M-1} \tag{8}$$

The outage probability for this system can be written as:

$$\begin{aligned}\mathbb{P}^{s_i}_{out} &= (\mathbb{P}^{s_i}_{out}|\text{collision})p_{col} + (\mathbb{P}^{s_i}_{out}|\text{no collision})(1-p_{col}) \\ &= p_{col} + (\mathbb{P}^{s_i}_{out}|\text{no collision})(1-p_{col}) \\ &= p_{col} + (\mathbb{P}\left\{\mathbf{SNR}_{pb} < \Omega_{pb}|\mathbf{SNR}_{s_ip} \geq \Omega_{sp}\right\} \\ &\quad \times \mathbb{P}\left\{\mathbf{SNR}_{s_ip} \geq \Omega_{sp}\right\} + \mathbb{P}\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\})(1-p_{col})\end{aligned} \tag{9}$$

where the outage probability when there is a collision is one and the terms Ω_{pb} and Ω_{sp} are the threshold for the tolerable SNR at the base node and the power node respectively.

IV. EVOLUTION OF THE ENERGY OF SENSORS

As it was explained in Section II-B, the transmission channels are assumed to be Rayleigh distributed with unit expected value. Therefore, when a signal is transmitted from the power node to sensor s_i, the received power can be determined using Friis equation as follows:

$$\boldsymbol{\lambda}_{s_i} = P_{ps_i} G_{ps} G_s \mathbf{h}_{ps_i} d_{s_ip}^{-\alpha} (4\pi f/c)^{-\alpha}, \tag{10}$$

where $\mathbf{h}_{ps_i}$ is the power of the fading channel between the power node and sensor s_i. Both $\boldsymbol{\lambda}_{s_i}$ and $\mathbf{h}_{ps_i}$ are written in boldface to represent a random variable. P_{ps_i} is the energy signal transmission power, G_{ps} is the antenna gain from the power node to the sensor, G_s is the receiver gain at the sensor and d_{s_ip} is the distance between the power node and sensor s_i. In this paper we assume that the duration of all the transmissions between different nodes is fixed and equal to t_d units of time. In other words, every T_{ps}, the power node would release an energy equal to $P_{ps_i}t_d$, aiming towards s_i and the power that is received at the sensor would be computed using (10). Since the power of the channel fading is assumed to be exponential with unit variance, the average received power at the sensor would be:

$$\bar{\boldsymbol{\lambda}}_{s_i} = P_{ps_i} G_{ps} G_s d_{s_ip}^{-\alpha} (4\pi f/c)^{-\alpha}. \tag{11}$$

As it was described in Section III, the sensor transmits data to the power node every $\mathbf{t_{re}}$. Therefore, each transmission is initiated after reception of many energy signals. As a result, and based on the law of large numbers, the harvested energy by each sensor before initiating a transmission can be approximated as:

$$\mathbf{E}^{s_i}_h \approx \bar{\boldsymbol{\lambda}}_{s_i} \left\lfloor \frac{\mathbf{t_{re}}}{T_{ps}} \right\rfloor t_d \tag{12}$$

where $\bar{\boldsymbol{\lambda}}_{s_i}$ is the average received power to sensor s_i, T_{ps} is the period at which power node energizes each sensor and t_d is the duration for each transmission from the power node to sensors. The term $\lfloor \mathbf{t_{re}}/T_{ps} \rfloor$ indicates how many energy signals are received by sensor s_i before the next data transmission to the power node. As the ratio of $\lfloor \mathbf{t_{re}}/T_{ps} \rfloor$ increases, a sensor receives more energy signals before initiating the next transmission and therefore the approximation becomes more accurate.

V. POWER ALLOCATION TECHNIQUES

In this section we propose two techniques to allocate powers to the nodes in the considered CSMA scenario. Both of these techniques guarantee that, every time a node needs to transmit, it has already stored enough energy to initiate the transmission.

A. DATA SIGNAL POWER ALLOCATION

1) FIXED POWER ALLOCATION

In this method, we assign a fixed power to each of the nodes. The transmission powers are set at the beginning and cannot be changed later. The challenge however is that, as it is indicated by (12), the energy harvested by a sensor varies from one reset cycle to another. From Fig. 2 however, we notice that each reset cycle always ends with a transmission block followed by a time slot of listening to the channel. Since the transmitters and receivers at the power node and sensors work independently, we can assume that a sensor has harvested energy over at least $(N+1)t_s$ units of time. Therefore, the following conservative power assignment can be considered for the sensors:

$$P_{s_i} = \bar{\boldsymbol{\lambda}}_{s_i} \left\lfloor \frac{(N+1)t_s}{T_{ps}} \right\rfloor. \tag{13}$$

By comparing (13) and (12) it can be observed that since $\mathbf{t_{re}} \geq (N+1)t_s$, therefore (13) gives a very conservative power assignment to each sensor, compared to the energy that is harvested by the node.

Similarly, the length of the transmission period from the power node to the base is also a random variable. However, the highest frequency at which a power node would be transmitting data to the base node would happen if sensors transmit every $(N+1)t_s$ units of time. Therefore, considering that we have M sensors, the power node would have needed to relay the data back to the base every $(N+1)t_s/M$ units of time. As it was explained in Section II-A, for an energy dividing ratio of r, $(1-r)$ portion of the harvested energy at the power node would be used for communicating with the base. Therefore, the following conservative power assignment to the power node can be considered:

$$P_{pb}t_d = \lambda_p(N+1)t_s(1-r)/M, \tag{14}$$

where λ_p is the harvested power by the power node and is assumed to be time invariant.

In order to compute the outage probability, using (2) we have:

$$\begin{aligned} &\mathbb{P}\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\} \\ &\quad = \mathbb{P}\left\{\frac{P_{s_i}G_{sp}\mathbf{h}_{s_ip}d_{s_ip}^{-\alpha}(4\pi f/c)^{-\alpha}}{P_N} < \Omega_{sp}\right\} \\ &\quad = 1 - \mathbb{P}\left\{\mathbf{h}_{s_ip} \geq \frac{P_N\Omega_{sp}d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{P_{s_i}G_{sp}}\right\} \\ &\quad = 1 - \exp(-\frac{P_N\Omega_{sp}d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{P_{s_i}G_{sp}}) \end{aligned} \tag{15}$$

where the last line of (15) derives from the fact that channels are assumed to be Rayleigh distributed with unit variance, and therefore the power of the channel fading is exponentially distributed with unit variance.

Similarly, using (3), for the link from the power node to the base we have:

$$\begin{aligned} &\mathbb{P}\left\{\mathbf{SNR}_{pb} < \Omega_{pb} | \mathbf{SNR}_{s_ip} \geq \Omega_{sp}\right\} \\ &\quad = \mathbb{P}\left\{\mathbf{SNR}_{pb} < \Omega_{pb}\right\} \\ &\quad = \mathbb{P}\left\{\frac{P_{pb}G_{pb}\mathbf{h}_{pb}d_{pb}^{-\alpha}(4\pi f/c)^{-\alpha}}{P_N} < \Omega_{pb}\right\} \\ &\quad = 1 - \exp(-\frac{P_N\Omega_{pb}d_{pb}^{\alpha}(4\pi f/c)^{\alpha}}{P_{pb}G_{pb}}) \end{aligned} \tag{16}$$

Finally, using (9) we have:

$$\begin{aligned} \mathbb{P}_{out}^{s_i} = p_{col} + \Bigg(1 - \exp(-\frac{P_N\Omega_{sp}(4\pi f/c)^{\alpha}d_{s_ip}^{\alpha}}{P_{s_i}G_{sp}}) \\ \times \exp(-\frac{P_N\Omega_{pb}(4\pi f/c)^{\alpha}d_{pb}^{\alpha}}{P_{pb}G_{pb}})\Bigg)(1-p_{col}), \end{aligned} \tag{17}$$

where p_{col} is determined using (8).

The fixed power allocation method that was described in this section is a sub-optimal method for assigning power to the nodes. This is due to the fact that regardless of how much power is harvested by a node, we are always assigning a fixed value to the transmission powers.

2) DYNAMIC POWER ALLOCATION

Our dynamic power allocation method assigns the maximum amount of transmission power to each node, based on how much energy they have scavenged over the past reset cycle. The duration of the reset cycle determines the amount of the harvested energy at each cycle. Since the duration of the reset cycle is a random variable, at the beginning of each cycle, the transmission power also needs to be readjusted. Consequently we have:

$$\begin{cases} \mathbf{P}_{pb}t_d = \lambda_p\mathbf{T}_{pb}(1-r) \\ \mathbf{P}_{s_i}t_d = \mathbf{E}_h^{s_i} \end{cases} \tag{18}$$

where $\mathbf{T}_{pb}$ is the transmission period from the power node to the base, λ_p is the harvested power by the power node, r is the energy dividing ratio and $\mathbf{E}_h^{s_i}$ is the harvested energy by the sensor s_i and can be approximated using (12). In (18), $\mathbf{P}_{pb}$, $\mathbf{T}_{pb}$, $\mathbf{P}_{s_i}$ and $\mathbf{E}_h^{s_i}$ are in bold format to represent random variables.

In order to find the outage probability for this system, similar to the fixed power allocation method and for the sensor s_i we have:

$$\begin{aligned} &\mathbb{P}\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\} \\ &\quad = \mathbb{P}\left\{\frac{\mathbf{P}_{s_i}G_{sp}\mathbf{h}_{s_ip}d_{s_ip}^{-\alpha}(4\pi f/c)^{-\alpha}}{P_N} < \Omega_{sp}\right\} \\ &\quad = 1 - \mathbb{P}\left\{\mathbf{h}_{s_ip} \geq \frac{P_N\Omega_{sp}d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{\mathbf{P}_{s_i}G_{sp}}\right\}. \end{aligned} \tag{19}$$

Since we are assuming that all the channels are Rayleigh distributed with unit mean value, the power of the channel fading is exponential with unit variance. Therefore, we can continue:

$$\mathbb{P}\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\} = 1 - \mathbb{E}\left(\exp(-\frac{P_N \Omega_{sp} d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{\mathbf{P}_{s_i} G_{sp}})\right). \tag{20}$$

In order to proceed, from (18) and (12) we have:

$$\mathbf{P}_{s_i} \approx \bar{\boldsymbol{\lambda}}_{s_i} \left\lfloor \frac{\mathbf{t_{re}}}{T_{ps}} \right\rfloor \tag{21}$$

where $\mathbf{t_{re}}$ is the random variable representing the length of a reset cycle. The probability distribution function of $\mathbf{t_{re}}$ however is not very easy to work with and is a function of the packet length and the number of the neighboring sensors. We however note that for random variables $\mathbf{X}$ and $\mathbf{Y}$, if $\mathbf{Y} = g(\mathbf{X})$, then the expected value of $\mathbf{Y}$ can be estimated as [27, p.150]:

$$\mathbb{E}(\mathbf{Y}) \simeq g(\mathbb{E}(\mathbf{X})) + g''(\mathbb{E}(\mathbf{X}))\frac{\sigma^2}{2} + \cdots + g^{(n)}(\mathbb{E}(\mathbf{X}))\frac{\mu_n}{n!} \tag{22}$$

where g'' is the second and $g^{(n)}$ is the n-th derivative of the function $g(\cdot)$. The term σ^2 is the variance and $\mu_n = \mathbb{E}(|\mathbf{X} - \mathbb{E}(\mathbf{X})|^n)$ is the n-th central moment of the random variable $\mathbf{X}$. In order to develop more insightful analytical results, in this paper we will only use the first term of this estimate. The effect of this approximation will be discussed in the simulation results section.

By using the above approximation with $\mathbf{X} = \mathbf{P}_{s_i}$ and equations (20) and (21) we have:

$$\begin{aligned}\mathbb{P}&\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\} \\ &\approx 1 - \exp(-\frac{P_N \Omega_{sp} d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{\mathbb{E}(\mathbf{P}_{s_i}) G_{sp}}) \\ &= 1 - \exp(-\frac{P_N \Omega_{sp} d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{\bar{\boldsymbol{\lambda}}_{s_i} \left\lfloor \frac{\bar{\mathbf{t}}_{re}}{T_{ps}} \right\rfloor G_{sp}}).\end{aligned} \tag{23}$$

where $\bar{\mathbf{t}}_{re}$ is determined using (7). A similar analysis can be conducted for the power node. We should however note that since a power node always relays the received information to the base immediately, the average transmission period assigned to each transmission needs to be divided by the number of sensors. Therefore we have:

$$\bar{\mathbf{P}}_{pb} t_d = \frac{\bar{\mathbf{t}}_{re}}{M} \lambda_p (1 - r) \tag{24}$$

where M is the number of the sensors. With a similar process we have:

$$\begin{aligned}\mathbb{P}&\left\{\mathbf{SNR}_{pb} < \Omega_{pb} | \mathbf{SNR}_{s_ip} \geq \Omega_{sp}\right\} \\ &= \mathbb{P}\left\{\frac{\mathbf{P}_{pb} G_{pb} \mathbf{h}_{pb} d_{pb}^{-\alpha}(4\pi f/c)^{-\alpha}}{P_N} < \Omega_{pb}\right\} \\ &= 1 - \mathbb{E}\left(\exp(-\frac{P_N \Omega_{pb} d_{pb}^{\alpha}(4\pi f/c)^{\alpha}}{\mathbf{P}_{pb} G_{pb}})\right). \\ &\approx 1 - \exp(-\frac{P_N \Omega_{pb} d_{pb}^{\alpha}(4\pi f/c)^{\alpha}}{\bar{\mathbf{P}}_{pb} G_{pb}}).\end{aligned} \tag{25}$$

Finally, using (9) we have:

$$\begin{aligned}\mathbb{P}_{out}^{s_i} \approx p_{col} + \Bigg(1 - \exp(-\frac{P_N \Omega_{pb} d_{pb}^{\alpha}(4\pi f/c)^{\alpha}}{\bar{\mathbf{P}}_{pb} G_{pb}}) \\ \times \exp(-\frac{P_N \Omega_{sp} d_{s_ip}^{\alpha}(4\pi f/c)^{\alpha}}{\bar{\boldsymbol{\lambda}}_{s_i} \left\lfloor \frac{\bar{\mathbf{t}}_{re}}{T_{ps}} \right\rfloor G_{sp}})\Bigg)(1 - p_{col})\end{aligned} \tag{26}$$

where p_{col} is the collision probability and is determined by (8).

In dynamic power allocation all the harvested power is used for transmission and at the same time the assigned transmission power never exceeds the harvested power.

The performance of any system comprised of multiple levels of transmission powers, from which a node can pick its transmission power at the beginning of each cycle, will be placed somewhere between fixed and dynamic power allocations. Therefore, comparing these two power allocation schemes can be insightful.

B. ENERGY SIGNAL POWER ALLOCATION

The transmission power for the energy signals from the power node to sensors would vary depending on how far each sensor is located with respect to the power node. In order to optimize the transmission powers we define the vector $\vec{P}_{ps} = (P_{ps_1}, \ldots, P_{ps_M})$, where P_{ps_i} is the transmission power from the power node to the i-th sensor. By replacing (11) in (21) and (12), and using equations (15) and (23) we have:

$$\mathbb{P}\left\{\mathbf{SNR}_{s_ip} < \Omega_{sp}\right\} \approx 1 - \exp(-\frac{C d_{s_ip}^{2\alpha}}{P_{ps_i}}). \tag{27}$$

where for the fixed power allocation technique $C = \frac{P_N \Omega_{sp}(4\pi f/c)^{2\alpha}}{\lfloor (N+1)t_s/T_{ps} \rfloor G_{ps} G_s G_{sp}}$ and for the dynamic power allocation technique $C = \frac{P_N \Omega_{sp}(4\pi f/c)^{2\alpha}}{\lfloor \bar{\mathbf{t}}_{re}/T_{ps} \rfloor G_{ps} G_s G_{sp}}$. The distance between the sensor s_i and the power node is denoted by d_{s_ip}.

In order to optimize the vector $\vec{P}_{ps}$, we form the following function:

$$f(\vec{P}_{ps}) = \sum_{i=1}^{M} 1 - \exp(-\frac{C d_{s_ip}^{2\alpha}}{P_{ps_i}}) \tag{28}$$

Minimizing (28) would assure that we have the least number of total outage events over all the M links to the power node. On the other hand, we know that the summation of all the powers on the vector $\vec{P}_{ps}$ should not be exceeding the portion of the harvested power assigned to energizing the sensors. As a result we have:

$$\sum_{i=1}^{M} P_{ps_i} = r\lambda_p \frac{T_{ps}}{t_d}, \tag{29}$$

where λ_p is the harvested power at the power node. The energy dividing ratio r determines the portion of the harvested power that is used for energizing the sensors. The transmission period from the power node to sensors is T_{ps}, and t_d is the length of each energy signal.

Regardless of the value for the energy dividing ratio r, minimizing (28) would adjust how much of the harvested power should be assigned to each sensor. Equation (28) can be minimized using Lagrange multiplier method, by applying the constraint $g(\vec{P}_{ps}) = \sum_{i=1}^{M} P_{ps_i} - r\lambda_p \frac{T_{ps}}{t_d} = 0$ from (29). Therefore we would have:

$$\mathcal{L}(\vec{P}_{ps}, \mu) = \sum_{i=1}^{M} 1 - \exp(-\frac{Cd_{s_ip}^{2\alpha}}{P_{ps_i}}) - \mu\left(\sum_{i=1}^{M} P_{ps_i} - r\lambda_p \frac{T_{ps}}{t_d}\right) \tag{30}$$

where μ is the Lagrange multiplier. Taking the derivative of (30) with respect to $\vec{P}_{ps}$ and μ, results in the following set of equations to be solved for the optimum $\vec{P}_{ps}$:

$$\begin{cases} \frac{Cd_{s_1p}^{2\alpha}}{P_{ps_1}^2} \exp(-\frac{Cd_{s_1p}^{2\alpha}}{P_{ps_1}}) - \mu = 0 \\ \vdots \\ \sum_{i=1}^{M} P_{ps_i} - r\lambda_p \frac{T_{ps}}{t_d} = 0 \end{cases} \tag{31}$$

A close approximate solution to (31) is found by assuming that for the optimum value of $\vec{P}_{ps}$, the exponential terms are very close to one. An intuitive reasoning for this assumption is that, according to (27), $1-\exp(-\frac{Cd_{s_ip}^{2\alpha}}{P_{ps_i}})$ is the outage probability for the link from the sensor to the power node. Therefore, for the outage probability to be small, the exponential term has to be very close to one. This assumption can also be supported by observing that for $x > K$, $\exp(-K/x)$ converges to one very quickly. In our setup and for typical values of C and d_{s_ip}, K would be around 10^{-13}. Therefore, as long as P_{ps_i} is not in the same order of the number as K, the exponential term remains close to one. Using this approximation we will have:

$$P_{ps_i} \approx \frac{d_{s_ip}}{\sum_{i=1}^{M} d_{s_ip}} r\lambda_p T_{ps}/t_d \tag{32}$$

Equation (32) implies that a higher power should be assigned for energizing sensors that are located further from the power node. Of course, when all the sensors are located at an equal distance from the power node, each one of them takes $1/M$ of the harvested power.

VI. OPTIMUM ENERGY DIVIDING RATIO

By replacing (32) in (11), we observe that $\overline{\boldsymbol{\lambda}}_{s_i}$ can be written as a function of r. Consequently, using (13) for the fixed power allocation and by replacing (12) in (18) for the dynamic power allocation, transmission power from the sensors to the power node can be written as a function of r. On the other hand, using (14) and (18), the transmission powers from the power node to the base also can be written as a function of r. By replacing these expressions in (17) for the fixed power allocation and in (26) for the dynamic power allocation, the outage probability can be written as a function of r. The optimum value of r would minimize the outage probability. Therefore, by taking the derivative of the outage probability with respect to r, the optimum energy dividing ratio can be obtained. After taking the derivative, similar to (31), we assume that the exponential terms are very close to one. Then, the optimum value for r, both for the fixed and dynamic power allocation methods can be approximated as:

$$r_{opt} \approx \frac{1}{1 + \sqrt{\frac{\Omega_{pb}}{\Omega_{sp}} \cdot \frac{G_{sp}G_{ps}G_s}{G_{pb}} \cdot (4\pi f/c)^{-\alpha} \cdot \frac{M^2 d_{pb}^{\alpha}}{(\sum_{i=1}^{M} d_{s_ip}^{\alpha})^2}}} \tag{33}$$

The optimum transmission powers are obtained by replacing r_{opt} in (13), (14) and (32).

VII. SIMULATION RESULTS

In order to verify our analysis and evaluate the performance of the system, computer simulations using MATLAB were conducted and are presented in this section. Our analysis does not require for the sensors to be located at an equal distance from the power node. However, in order to have a better comparison, for all the following simulations we assume all the sensors are 4m away from the power node. The distance between the power node and the base is $d_{pb} = 10$m. Phe power conversion efficiency for sensors is assumed to be 60%; in other words, sixty percent of the received power from the power node can be collected at the sensors. The acceptable SNR threshold at the receivers are assumed to be $\Omega_{sp} = \Omega_{pb} = 10$. The transmission period at which the power node energizes the sensor is $T_{ps} = 1$s. To reduce the transmission loss, directed antennas are used. All the transmission gains are assumed to be $G_{ps} = G_{sp} = G_{pb} = 8$. The receiver's gain is $G_s = 2$. Similar to the previous sections, the harvested power at the power node is assumed to be $\lambda_p = 0.04$W. The number of neighboring sensors is $M = 10$ and the packet length is assumed to be $N = 10$. The transmission frequency is $f = 915$MHz, the transmission length is $t_d = 1$s and in our slotted CSMA method $t_s = 1$s. The power of the channel fading is generated randomly from and exponential distribution with unit variance. When the channel is free, a sensor transmits with a probability of p. If more than one sensor transmit at the same time, a collision occurs and the transmissions is not be successful. When there is no collision, if the signal to noise ratio, both from the sensor to the power node and from the power node to the base, is not less than a set threshold, the transmission is counted as successful. At the end, the outage probability is the ratio between the number of successful transmissions and the total number of transmission attempts.

Fig. 3 and Fig. 4 show the evolution of energy for one sensor, under the fixed and dynamic power allocation schemes, respectively. The transmission probability is assumed to be $p = 0.1$. As it can be observed, in the fixed power allocation,

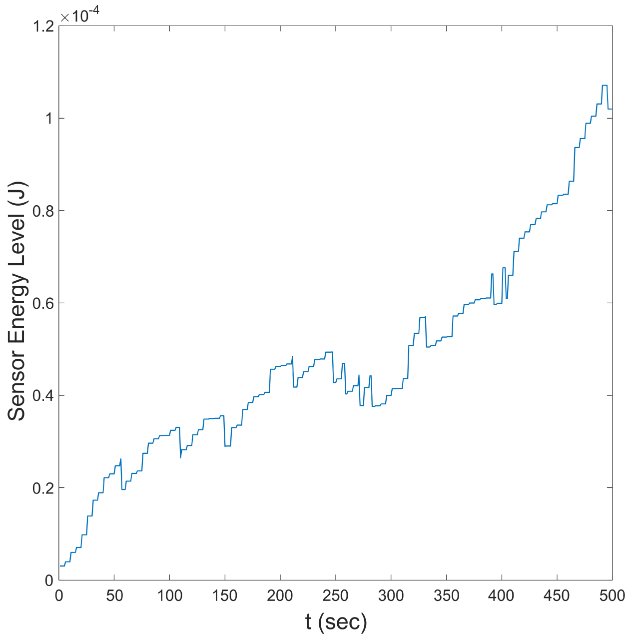

FIGURE 3. The evolution of energy for one sensor, under the fixed power allocation scheme.

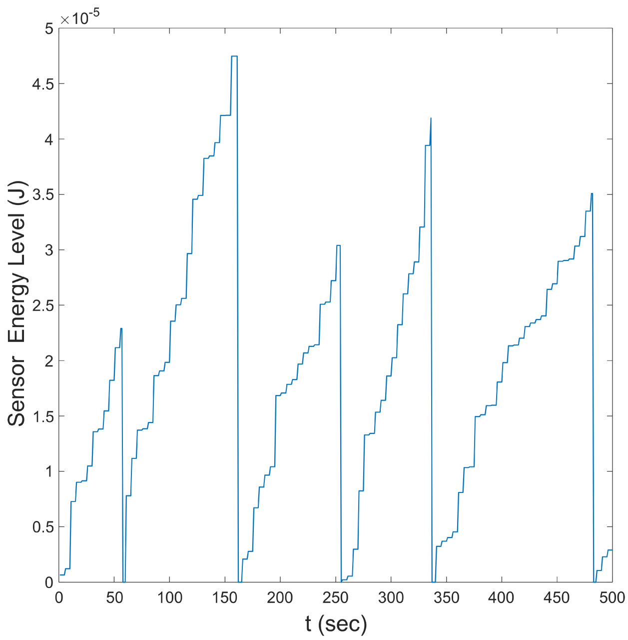

FIGURE 4. The evolution of energy for one sensor, under the dynamic power allocation scheme.

the energy level in a sensor on average would be increasing over time. That is due to the fact that in this scheme, over a reset cycle, the consumed energy is always less than or equal to the collected energy. As a result, in practice, the harvested energy will eventually be limited by the storage capacity of the sensor's battery. In the dynamic power allocation however, over one reset cycle, the consumed energy is always equal to the collected energy.

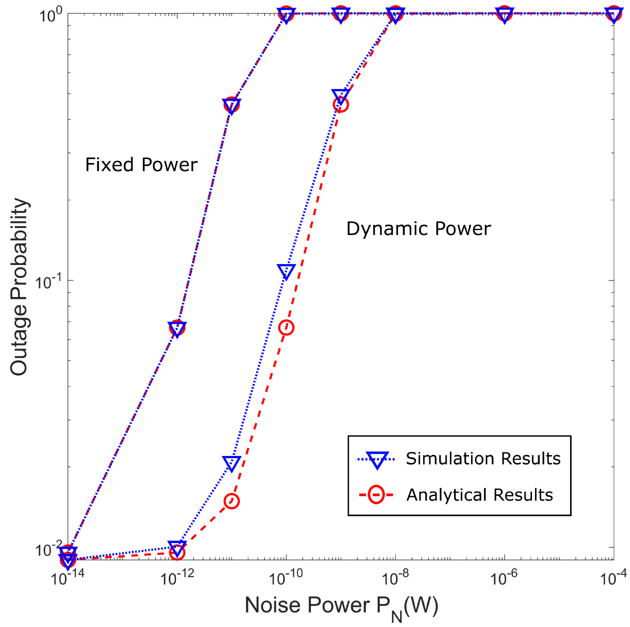

FIGURE 5. Outage probability versus noise power for CSMA based multiple sensors scenario.

In Fig. 5 the performance of the two power allocation techniques are compared for different noise powers. The transmission probability for each node is assumed to be $p = 0.001$. From equations (7) and (8), the average reset time and the collision probability for this setup would be $\bar{\mathbf{t}}_{re} = 18$ min and $p_{col} = 0.009$. As it can be observed in Fig. 5, dynamic power allocation can provide better performance compared to fixed power allocation technique. For very low values of noise power however, even a lower transmission power can provide enough SNR and therefore both techniques provide the same level of outage probability. Similarly, for very high values of noise power, regardless of the assigned transmission power, a successful transmission cannot be accomplished. Therefore, both techniques would approach one hundred percent of outage probability. We should also notice that the simulation and analytical results for the CSMA technique are not completely matched, due to the fact that (26) is an approximation of the outage probability.

Fig. 6 compares the outage probability for the fixed and dynamic power allocation techniques, versus different transmission probabilities. The noise power is assumed to be $P_N = 10^{-13}$W. It can be observed that by decreasing the transmission probability, dynamic power allocation outperforms fixed power allocation significantly. That is due to the fact that when the transmission probability p decreases the reset time from (7) increases. Dynamic power allocation takes advantage of this time in order to assign a higher value of power to each node but fixed power allocation would assign the same value of power to nodes regardless. We should also note that after a point both techniques approach their best possible performance and the corresponding outage probability remains unchanged with respect to p. The reason is that, for very small values of p, the collision probability approaches

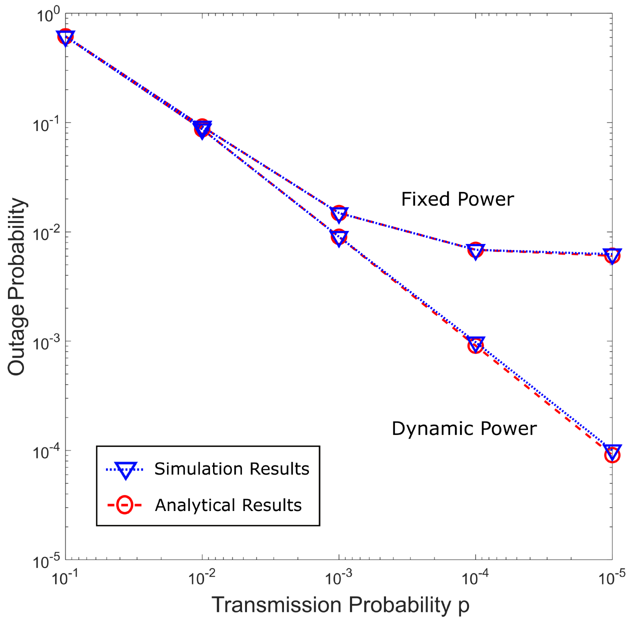

FIGURE 6. **Outage probability versus sensor's transmission probability p for CSMA multiple sensors scenario.**

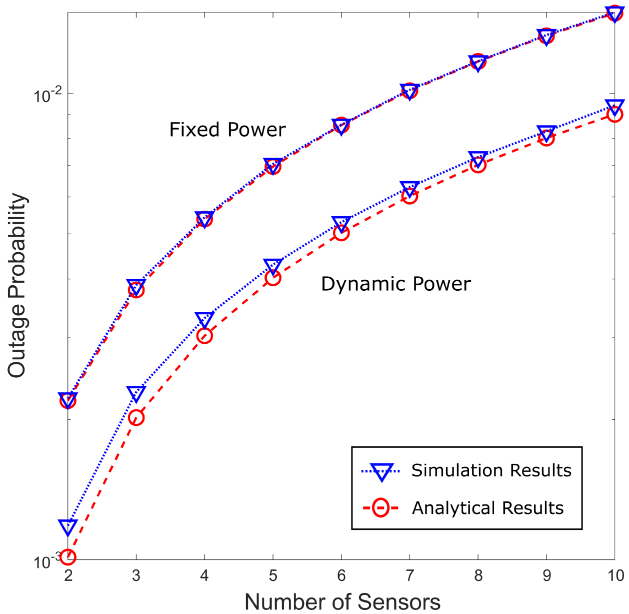

FIGURE 7. **Outage probability versus the number of surrounding sensors for CSMA multiple sensors scenario.**

zero and the transmission powers are more than enough already to deliver enough SNR at the receiver. Therefore, reducing p more than that would not change the outcome.

Fig. 7 depicts the outage probability for different number of surrounding sensors. In this picture we are assuming $p = 0.001$ and the noise power $P_N = 10^{-13}W$. As it can be expected increasing the number of sensors would increase the outage probability. For CSMA channel access however, the effect of increasing the surrounding sensors is twofold. Firstly, the harvested energy needs to be divided amongst more sensors. Secondly, increasing the number of sensors would increase the collision probability. We should note that the main source of contribution to the outage probability is because of the collision amongst neighboring sensors and not due to the limited amount of energy available.

VIII. SUMMARY AND CONCLUSION

In this work, a self-sustainable WSN, consisting of multiple sensors supported by a power node was studied. Two power allocation techniques were proposed. In the first technique a fixed power is assigned to each node. This technique was discussed as a suboptimal power allocation technique which has a lower performance in exchange for a simpler implementation. In the second technique, the assigned powers could be adjusted dynamically in order to give the maximum possible power to each node. Our considered WSN can potentially be implemented in a substation environment or close to HV power lines to enable an on-line monitoring system. The results of this paper suggest that even though wireless transfer of energy can be wasteful, by setting the involved parameters on close to optimum values, a self-sustainable WSN in a power substation can be accomplished.

REFERENCES

[1] R. Want, "An introduction to RFID technology," *IEEE Pervasive Comput.*, vol. 5, no. 1, pp. 25–33, Jan. 2006.
[2] K. Huang and V. K. N. Lau, "Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 902–912, Feb. 2014.
[3] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljačić, "Wireless power transfer via strongly coupled magnetic resonances," *Science*, vol. 317, no. 5834, pp. 83–86, Jul. 2007.
[4] W. C. Brown, "The history of power transmission by radio waves," *IEEE Trans. Microw. Theory Techn.*, vol. 32, no. 9, pp. 1230–1242, Sep. 1984.
[5] L. Xie, Y. Shi, Y. T. Hou, and W. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Commun. Mag.*, vol. 20, no. 4, pp. 140–145, Aug. 2013.
[6] X. Mou, O. Groling, and H. Sun, "Energy-efficient and adaptive design for wireless power transfer in electric vehicles," *IEEE Trans. Ind. Electron.*, vol. 64, no. 9, pp. 7250–7260, Sep. 2017.
[7] S. D. Barman, A. W. Reza, N. Kumar, M. E. Karim, and A. B. Munir, "Wireless powering by magnetic resonant coupling: Recent trends in wireless power transfer system and its applications," *Renew. Sustain. Energy Rev.*, vol. 51, pp. 1525–1552, Nov. 2015.
[8] M. Kesler, *Highly Resonant Wireless Power Transfer: Safe, Efficient, and Over Distance*. Watertown, MA, USA: WiTricity, 2013.
[9] R. Mehrotra, *Cut the Cord: Wireless Power Transfer, its Applications, and its Limits*. [Online]. Available: http://www.cse.wustl.edu/~jain/cse574-14/ftp/power.pdf
[10] I. Krikidis, "Simultaneous information and energy transfer in large-scale networks with/without relaying," *IEEE Trans. Commun.*, vol. 62, no. 3, pp. 900–912, Mar. 2014.
[11] U. Olgun, C. C. Chen, and J. L. Volakis, "Investigation of rectenna array configurations for enhanced RF power harvesting," *IEEE Antennas Wireless Propag. Lett.*, vol. 10, pp. 262–265, 2011.
[12] V. Palazzi, J. Hester, J. Bito, F. Alimenti, C. Kalialakis, A. Collado, P. Mezzanotte, A. Georgiadis, L. Roselli, and M. M. Tentzeris, "A novel ultra-lightweight multiband rectenna on paper for RF energy harvesting in the next generation LTE bands," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 1, pp. 366–379, Jan. 2018.
[13] H. J. Visser, S. Keyrouz, and A. B. Smolders, "Optimized rectenna design," *Wireless Power Transmiss. Sustain. Electron.*, vol. 48, no. 3, pp. 44–50, Mar. 2015.
[14] R. Ibrahim, D. Voyer, M. E. Zoghbi, J. Huillery, A. Bréard, C. Vollaire, B. Allard, and Y. Zaatar, "Novel design for a rectenna to collect pulse waves at 2.4 GHz," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 1, pp. 357–365, Jan. 2018.

[15] S. Sudevalayam and P. Kulkarni, "Energy harvesting sensor nodes: Survey and implications," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 3, pp. 443–461, Sep. 2011.

[16] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embedded Comput. Syst.*, vol. 6, no. 4, p. 32, Sep. 2007.

[17] M. Zhu, M. D. Judd, and P. J. Moore, "Energy harvesting in substations for powering autonomous sensors," in *Proc. Int. Conf. Sensor Technol. Appl.*, Jun. 2009, pp. 246–251.

[18] O. Cetinkaya and O. B. Akan, "Electric-field energy harvesting in wireless networks," *IEEE Wireless Commun.*, vol. 24, no. 2, pp. 34–41, Apr. 2017.

[19] C. Keun-Su, S.-M. Kang, K.-J. Park, S.-H. Shin, and H.-S. Kim, "Electric field energy harvesting powered wireless sensors for smart grid," *J. Electr. Eng. Technol.*, vol. 7, no. 1, pp. 75–80, 2012.

[20] F. Guo, H. Hayat, and J. Wang, "Energy harvesting devices for high voltage transmission line monitoring," in *Proc. IEEE Power Energy Soc. General Meeting*, Jul. 2011, pp. 1–8.

[21] H. Zangl, T. Bretterklieber, and G. Brasseur, "A feasibility study on autonomous online condition monitoring of high-voltage overhead power lines," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 5, pp. 1789–1796, May 2009.

[22] M. J. Moser, T. Bretterklieber, H. Zangl, and G. Brasseur, "Strong and weak electric field interfering: Capacitive icing detection and capacitive energy harvesting on a 220-kV high-voltage overhead power line," *IEEE Trans. Ind. Electron.*, vol. 58, no. 7, pp. 2597–2604, Dec. 2011.

[23] N. M. Roscoe and M. D. Judd, "Harvesting energy from magnetic fields to power condition monitoring sensors," *IEEE Sensors J.*, vol. 13, no. 6, pp. 2263–2270, Jun. 2013.

[24] S. Yuan, Y. Huang, J. Zhou, Q. Xu, C. Song, and P. Thompson, "Magnetic field energy harvesting under overhead power lines," *IEEE Trans. Power Electron.*, vol. 30, no. 11, pp. 6191–6202, Nov. 2015.

[25] M. Hajikhani and F. Labeau, "Deploying autonomous sensors in a substation area using energy harvesting and wireless transfer of energy," in *Proc. IEEE Int. Conf. Commun. Syst.*, Dec. 2016, pp. 1–6.

[26] M. Hajikhani, F. Labeau, and B. L. Agba, "An autonomous wireless sensor network in a substation area using wireless transfer of energy," *IEEE Access*, vol. 6, pp. 62352–62360, 2018.

[27] A. Papoulis and S. U. Pillai, *Probability, Random Variables and Stochastic Processes*, 4th ed. New York, NY, USA: McGraw-Hill, 2002.

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