Dedicated RF Power Transfer for Wirelessly - Powered Wearable Medical Sensors

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Abstract—We investigate the possibility of wirelessly charging autonomous wearable sensors for patient health-monitoring through dedicated power transfer from Power Beacons (PB). We propose a novel strategy for transmitting energy beams towards patients, where sensors emit a charging request based on a battery lower threshold and receive energy till the battery reaches an upper threshold. These energy beams are steered towards the patient’s smartphone rather than towards the sensor, relieving the need for tracking the PB-sensor channel at only negligible performance loss. Furthermore, as PBs cannot serve all requiring sensors simultaneously, we compare different scheduling algorithms, jointly with the battery thresholds and the energy beam width. For the examined configurations, results show that the energy outage probability is slightly affected by the scheduling policy, and most of the energy is harvested from non-intended beams. We show that the strategy for energy-beam transmission should be adjusted to the sensor location on the human body and the patient’s velocity for better performance. Finally, proposing new strategies minimizing the waiting duration can be used as a guideline to reduce the energy outage.

Index Terms—E-health networks, medical sensors, energy harvesting, far-field power transfer, energy beams, scheduling

I. INTRODUCTION

Wearable Wireless Sensors (WSs) are paving the way for a revolution of health-care and medicine by facilitating early detection and treatment of diseases, supporting independent aging to the elderly and reducing hospitalization [1]. Health and motion information is monitored in real-time by autonomous medical sensor devices, wearable or implantable, and forwarded to off-site health-care providers for processing, diagnosis and concrete-action triggering (e.g. automatic drug delivery or medical emergency care response). Significant research has been carried out on ultra low-power circuitry and dedicated communications protocols to overcome the energy constraint at sensors, but the sensor efficiency and lifetime highly depend on their power supply as well. Human battery control, recharging or replacement cannot achieve the reliability required for such critical service or may be hardly feasible, especially for implanted sensors. In addition, the miniaturization of medicals sensors has spurred the design of energy harvesting autonomous sensors equipped with compact low-capacity batteries or running without batteries [2].

Energy can be efficiently harvested from solar irradiation [3], mechanical motion or thermo-electric sources [4]. Yet, such conventional sources are essentially opportunistic and intermittent. The power availability highly fluctuates, is neither predictable nor controllable [5], and hardly suits indoor and low-mobility environments. Recently, the concept of Radio-Frequency (RF) charging, or wireless far-field power transfer, has emerged to take advantage of the broadcast nature of wireless communications (e.g. WiFi hotspots). Such energy-harvesting receivers can be easily and cheaply integrated into limited-size sensors, already equipped with antennas [6].

As the energy harvested from the ambient RF electromagnetic radiation is conditioned by the data traffic and the time of day, it can be temporally insufficient to run sensors [7]. The network can then be provided with specialized stations named power beacons (PBs), which generate RF signals for the sole purpose of wireless charging [6–9]. This so-called dedicated power transfer renders harvesting stable and controllable in its transmit power, time-frequency resource allocation, and waveform. As the use of omni-directional antennas provides no antenna gain, limits the power coverage, i.e. the maximal PB-patient distance permitting wireless charging, and raises serious health concerns due to excessive electromagnetic exposure [7, 10], directional antennas should be considered instead.

However, the use of directional antennas raises the issue of energy-beam shaping, steering, and scheduling [7]. While this has been largely investigated for data communication, little has been proposed for power transfer despite its unique constraints. First, energy receivers operate with a much higher sensitivity threshold than data receivers and the harvested energy significantly fluctuates due to shadowing or user mobility. Second, the coverage of PBs is much shorter and generally non-overlapping, implying that sensors may experience potentially long non-charging periods. Research on wireless powering has mostly targeted circuitry design and simultaneous information and power transfer ([8] and ref. therein), but the choice of the strategy to transmit energy beams has been primarily addressed only in [10] for cellular networks. Yet, the considered assumptions do not apply to battery-limited sensors.

Contribution: We address dedicated power transfer for autonomous and wearable medical sensors in indoor environments, e.g. hospitals, identify the potential issues of such harvesting solution and investigate their impact. To do so, we propose a novel strategy for wireless charging based on two battery thresholds for charging request and ending, and where
the energy beams are steered towards the patient’s smartphone rather than directly to the sensors, to avoid the need for tracking the PB-sensor channel. We then analyze the joint impact of the channel attenuation, the patient’s mobility and the human body intrinsic motion on the probability of energy outage, for several beam widths and scheduling policies.

Paper organization: Section II describes the network model and main assumptions for energy harvesting at sensors. Section III describes the considered strategy for charging request, beam steering and scheduling. Performance metrics are presented in Section IV and simulation results in Section V. Section VI summarizes main results and concludes this paper.

II. System Model and Main Assumptions

This section describes the considered network and channel models, together with the assumptions for the energy consumption and harvesting at WSs.

A. Network model for medical monitoring

We assume that the WSs are connected via a short-range wireless technology, such as Bluetooth, to the patient’s smartphone (SP), which is itself connected to the core network via a base station, a femtocell or a Wi-Fi access point and acts as a bridge between the patient and the health-care provider.

1) Distribution of PBs and patients: We consider a network provided with PBs, which radiate RF signals towards patients and their sensors for the sole purpose of energy harvesting. These PBs can be collocated, for instance, with existing hot spots or small-cell base stations (BS). We assume that PBs have a fixed height $H_B$ and are distributed as indoor BSs, i.e. uniformly in the two-dimensional plane, following a homogeneous Poisson point process (PPP) $\Phi_B$ with intensity $\lambda_B$.

The patients are distributed on the plane according to a homogeneous PPP $\Phi_P$ of intensity $\lambda_P$, independent from the PPP describing the PBs location. Each is equipped with a smartphone, typically located around the belt, at height $H_P$.

2) Assumptions for patients’ motion: For each particular realization of the number and position of PBs and patients, the patients start moving according to a fractal Brownian motion, as in [7], with Hurst parameter $H$ and speed $\nu$. The Hurst parameter describes the smoothness of the resulting motion by accounting for the correlation between the patient’s directional changes. In particular, taking $H = 0.85$ ensures high positive correlation of each step and better fits to human behavior.

3) Assumption for human-body WSs: In our scenario, the sensor’s motion is assumed to result from both the patient’s walking in the hospital (large-scale motion) and the human body dynamics (small-scale motion), e.g. rising the foot to walk. At a given instant, a sensor is positioned at $(x_s, y_s, z_s)$:

\[ x_s = x + \delta_x; \quad y_s = x + \delta_y; \quad z_s = H_s + \delta_z \]  

(1)

with $(x, y)$ being the current patient’s location on the plane and $H_s$ the sensor’s height when the patient is not moving. $\delta_x$, $\delta_y$ and $\delta_z$ account for the human body intrinsic motion and

\[ \delta_x = \frac{x_s - x}{\lambda \nu}; \quad \delta_y = \frac{y_s - y}{\lambda \nu}; \quad \delta_z = \frac{z_s - H}{\lambda \nu} \]  

are uniformly distributed in $[-\Delta x/2, \Delta x/2], [-\Delta y/2, \Delta y/2]$ and $[-\Delta z/2, \Delta z/2]$, respectively, as depicted in Figure 1.

A sensor can be placed on different parts of the patient’s body\(^2\), e.g. feet or chest, but a sensor worn on the patient’s ankle has a much higher motion amplitude than one worn on the chest, such that the received energy potentially fluctuates a lot depending on the sensor’s location on the human body.

We consider four categories of sensors:

- **Type A**: far from the patient’s belt, with low motion amplitude, e.g. sensors located on the head,
- **Type B**: close to the patient’s belt, with low motion amplitude, e.g. sensors worn on the chest,
- **Type C**: close to the patient’s belt, with high motion amplitude, e.g. sensors worn on the arm,
- **Type D**: far from patient’s belt, with high motion amplitude, e.g. sensors on the ankle.

B. Channel model for wireless charging

As a first approach to dedicated RF energy harvesting, we consider out-of-band wireless energy transfer, i.e. energy transfer and data transmission operate on a separate frequency and energy can be scavenged at any time slot, independently of the sensors duty cycle. We assume that wireless charging is operated at the 915MHz ISM band, which is suggested in [7] as one of the most efficient frequency bands for energy transfer. The channel attenuation at instant $t$ is given by [12]:

\[ PL(r)\ [dB] = 20\log_{10}\left(\frac{4\pi}{\lambda}\right) + 10\alpha\log_{10}(r) + X_\sigma^t[dB], \]  

(2)

where $r$ is the PB-patient distance, $\alpha$ the path-loss exponent, $\lambda$ the wavelength, and $20\log_{10}\left(\frac{4\pi}{\lambda}\right)$ is the spreading loss of the electromagnetic signal due to propagation through the medium. $X_\sigma^t[dB]$ is a zero-mean normally distributed random variable with standard deviation $\sigma$ that models the shadowing attenuation. As the patient moves, its shadowing value $X_\sigma^t$ at a given time instant is expected to be correlated with the one at previous instant, denoted by $X_\sigma^t$. The smaller the distance $d$ covered between these two instants is, the higher the correlation is expected to be. To model such a distance-
based dependency, we assume that the shadowing correlation reduces exponentially with the covered distance as in [13]:

$$X'(d)\ [dB] = \rho^{\frac{d}{\lambda d_{ant}}} X_0^0[\text{dB}] + \sqrt{1-\rho^2(d)}Z[\text{dB}],$$  

(3)  

where $Z[\text{dB}]$ is a normal variable with zero mean and standard deviation equal to $\sigma[\text{dB}]$ and $\rho^{\frac{d}{\lambda d_{ant}}}$ is the correlation coefficient at a distance $d$ from the initial patient location, given the reference distance $d_{ref}$.

C. Model for the wearable sensor

Medical sensors generally operate on a duty cycle mode. We consider the time-slotted model depicted in Fig. 2, where each slot has a duration of $T_0$. Data sensing and transmission is performed periodically (but without synchronization between patients), once every $n_{duty}$ slots, and for a period of $n_{on}$ slots. The rest of the time ($n_{off} = n_{duty} - n_{on}$), sensors are in idle mode. We consider a large duty cycle ratio $\frac{n_{on}}{n_{ant}}$ of 100ms/5s, as in [14], and assume the same model for energy consumption at each sensor, i.e. $P_{on}T_0$ during an activity period and $P_{off}T_0$ during an idle period, to account for battery leakage and other circuitry imperfections. We denote $P_{duty} = n_{on}P_{on} + n_{off}P_{off}$.

We assume in this work that the sensors battery has capacity $L_{max}$ and can run for a maximum of a few duty cycles without the need of being charged. Furthermore, each sensor is equipped with an omni-directional antenna for wireless charging, also called rectifying antenna or rectenna, with unitary gain, i.e. $G_{Rx} = 1$, for any signal angle of arrival. Finally, the RF-DC conversion efficiency factor is denoted by $\eta_{Rx}$ and the minimal power detectable by the rectenna, namely the sensitivity threshold, is denoted by $P_{Rx}^{(\text{min})}$.

III. ASSUMPTIONS AND STRATEGY FOR ENERGY BEAMS TRANSMISSION AND SCHEDULING

This Section focuses on the assumptions for the energy beam steering and scheduling at the PB side. Such an issue encompasses (i) the antenna pattern radiation, (ii) the beam direction, (iii) the decision for a sensor to request charging, (iv) the scheduling decision at a PB, i.e. the selection of the sensor to be served, and (v) the PB release after charging.

A. Assumption for the antenna radiation pattern

PBs are equipped with planar array antennas, which provide directional beams with a high-power main lobe and low-power side lobes. Considering squared $N\times N$ array antennas and ignoring mutual coupling effects, the radiation pattern has rotational symmetry with respect to the main beam axis and the normalized gain with uniform illumination is given by [15]:

$$G_{Tx}(N, \theta) = \left( \frac{\sin \left( N\pi \frac{\cos \theta}{\lambda} \right)}{N\sin \left( \pi \frac{\cos \theta}{\lambda} \right)} \right)^2, \ \theta \in [0, \pi]$$  

(4)  

where $\theta$ is the signal arrival angle and $d_{ant}$ is the distance between antenna elements. Generally, $\frac{\lambda}{\lambda_{ant}}$ is equal to $\frac{1}{4}$. The beam width can be adjusted by varying the number $N$ of array elements involved in the power transfer. In addition, we assume that PBs can only radiate one signal beam at a time. Following regulation on the 915MHz band (FCC 15.247), the maximum value $P_{Tx}G_{Tx}$ permitted for such antenna is equal to 36dBm for ($N \leq 4$) and 33dBm for $N = 6$, since the directional gain exceeds 6dBi in this case.

B. Assumption for energy beam steering

Steering the energy beam directly towards the patient’s sensor requires acquisition of accurate channel state information at the transmitters. However, this implies significant signaling overhead and most wearable sensors operate with low transmit power such that estimating the PB-WS channel is hardly feasible in practice. On the contrary, the PB-SP channel can be easily tracked as for data transmission. We thus propose that PBs steer energy beams in the direction of the patient’s smartphone. Energy is hence received at sensors with a beam alignment error $\theta_e$, as illustrated in Figure 1. Since energy beams are not aligned with WSs by definition, perfect beam alignment with the smartphone is not required and less signaling is needed for channel estimation.

C. Battery-based strategy for WS request and PB release

The battery level at sensors is fluctuating over time, depending on the consumed and harvested energies. As illustrated in Figure 2, a sensor sends a request for wireless charging when its battery level reaches a given threshold $L_-$, to notify a critical energy state. Such a request is forwarded to PBs via the smartphone. Once scheduled, energy is transferred from the PB to the selected sensor till its battery reaches a second threshold $L_+$ or till the patient goes out of range for wireless charging. The PB is then released and can serve another sensor in critical energy state. Adjusting the two thresholds $L_-$ and $L_+$ allows controlling the probability of energy outage, but also the system fairness by adapting the time during which a PB is held for a single patient’s service. The larger the difference $L_+ - L_-$ is, the longer the charging duration is.

D. Investigated energy beam schedulers

Assuming that there are $N_{PB}$ PBs available at a given instant and $N_P > N_{PB}$ patients requesting power transfer, a maximum of $N_{PB}$ patients can be served, raising the issue of scheduling decision. The following schedulers are considered:

- Random scheduling ($R$): Each PB randomly selects the patient to be served among patients requesting charging and within its power coverage.

Fig. 2: Time model for energy consumption and harvesting.
- Opportunistic scheduling ($O$): Each PB selects the patient with the best PB-SP channel realization. The ratio of the received power over the transmitted power is maximized but such a scheduler exhibits some major issues in low-mobility environments since a nearby patient will always be given preference (near-far effect).
- Mobility-based scheduling ($M$): Each PB selects the patient with the highest velocity. This allows to counteract the detrimental impact of non-overlapping PB coverage since a patient with high mobility may suffer long out-of-coverage periods without charging possibility.
- Battery-based scheduling ($B$): Each PB selects the patient with the lowest sensor battery level. To do so, the battery level is broadcast to PBs besides the charging request.

No PB coordination is assumed in this work, such that a patient can be potentially scheduled by more than one PB. However, such an event has a low probability of occurrence since the PB-coverage areas generally do not overlap.

IV. HARVESTED ENERGY AND PERFORMANCE METRIC

In this section, we present the main performance metrics considered for the performance analysis.

A. Amount of harvested energy

Given the channel model described in subsection II-B, the power received at a given time slot from power beacon $k$ at a sensor on patient $j$ is given by

$$P_{kj}[dB] = P_{Tx}[dB] + G_{Rk}[dB] + G_{Tx}[dB] - PL(r_{kj})[dB]. \quad (5)$$

In addition, energy can be harvested from a beam that is intentionally sent to sensor $j$ by a PB, but also from beams intended to another nearby sensor if the beam width is sufficiently large. The total amount of energy harvested by sensor $j$ is equal to:

$$P_j = \begin{cases} 
0 & \text{if } \eta_{Rs} \sum_k P_{kj} < P_{Rx}^{(min)} \\
L_{max} & \text{if } L_{max} \leq \eta_{Rs} \sum_k P_{kj} \\
\eta_{Rs} \sum_k P_{kj} & \text{otherwise}
\end{cases} \quad (6)$$

Transferring energy through a wider energy beam allows charging several sensors at the same time, but in return less directivity gain is provided and the PB coverage is reduced.

B. Performance metrics

As the transferred RF signal is not decoded, performance metrics such as the SINR or the achieved rate are meaningless for wireless charging and we consider the probability of energy outage $P_{out}$ as main metric. An outage is declared at a sensor if its battery level $l$ is below $P_{an}T_0$ at any time slot$^3$. For a sensor of type $X$,

$$P_{out}^{(X)} = \mathbb{P}_{\theta_1, \varphi_1, \varphi_0} \left[ l < P_{an}T_0 \right] \quad (7)$$

where $P_{out}^{(X)}$ is averaged over time (accounting for the patient’s motion) and over the PBs and patients initial locations.

$^3$The outage level is set to $P_{an}T_0$ both when the sensor is in activity and idle mode. This is due to the fact that the battery cannot remain arbitrarily low even during an idle period as it may prevent the sensor to wake up for a new duty cycle or request charging.

| $P_{an} / T_0$ | $P_{Rx}^{(min)} / \eta_{Rs}$ | $P_{an} / P_{eff}$ | $\sigma / \Delta_{xy}$ | $\lambda_{B} / \lambda_{P}$ | $\alpha / \rho$ |
|----------------|-----------------------------|---------------------|-----------------------|--------------------------|-----------------|
| 4min / 25ms    | -10dBm / 0.7                | 5 / 0.1mW           | 5.2 dB / 5m           | 0.003 / 0.025           | 2.5 / 0.7       |

TABLE I: Simulation parameters

V. SIMULATION RESULTS

In this section, we simulate the presented strategies and highlight the parameters which affect performance the most.

A. Simulation settings

For performance analysis, we use Monte-Carlo simulations. Each simulation trial consists in generating the PPPs modeling the PBs and patients location in a finite window. For each trial, the motion of sensors is simulated over a four-minute period, with a change every five seconds for large-scale motion and every second for small-scale motion, as described in Sections II-A2 and II-A3 respectively. This four-minute period is further divided in time slots as described in Section II-C. At each slot, the battery level is updated depending on the sensor duty cycle and the harvested energy. A wireless charging request is sent if necessary and available PBs perform scheduling decision. At the end of each time slot, PBs are released if the sensor of the selected patient has reached $L_+$ or if the patient goes out of range for wireless charging. Performance is computed by averaging over 10,000 such trials and evaluated for a single patient, called the typical patient, as allowed by the Slivnyak’s theorem for PPP networks.

For each simulation set, the typical patient is provided with a sensor of a given type $X \in \{A, B, C, D\}$ and is moving with a fixed velocity $\nu_0$ (0.5m/s or 2m/s, e.g. by using an electric wheelchair). On the contrary, the other patients are equipped with one sensor uniformly taken from type A, B, C or D, and are moving at a random velocity, taken in the range $[0, 1]$m/s (slowly moving environment) or $[0, 3]$m/s (fast moving environment). Four scenarios are considered: (i) the typical patient and other patients are walking slowly (referred as $\mathcal{E}_1$), (ii) the typical patient is walking slowly, but other patients are moving faster ($\mathcal{E}_2$), (iii) the typical patient is moving fast while other patient are walking slowly ($\mathcal{E}_3$), (iv) all patients are moving fast ($\mathcal{E}_4$). The rest of the simulation parameters are given in Table I. Finally, the two following strategies are considered as benchmark schemes: (i) the power beacons are equipped with omni-directional antennas, i.e. $\lambda = 1$, continuously radiating a RF signal, independently from the battery thresholds, and (ii) the PB-WS channel can be estimated such that the energy beams are received without alignment error, i.e. $\theta_e = 0$.

B. On the impact of the energy beam scheduler

In Figure 3, we plot the probability of energy outage $P_{out}^{(B)}$ of the typical patient as a function of the battery upper threshold $L_+$. The patient’s sensor is located on the chest (type B), but
the performance trends are similar for other sensor types. For each value of \( N \in \{2, 4, 6\} \) and each simulation environment in \( \{E_1, E_2, E_3, E_4\} \), we analyze the performance achieved by the four schedulers described in Section III-D. Simulations show that the choice of the scheduler has a negligible impact on the outage probability, for all considered beam widths and battery thresholds. For clarity purposes, only the case \( N = 6 \) / \( E_4 \) has been plotted in Figure 3.

Such a result is in contrast to the conclusions in [10], where a significant improvement is achieved by opportunistic scheduling. The performance analysis in [10] is related to the amount of received power, suggesting infinite-capacity battery, and is averaged with respect to the spatial dimension only, i.e. the initial position of the users in the network. Nevertheless, the time dimension, i.e. the fluctuations of the battery level and the users motion, has to be considered for sensors with limited battery capacity, as assumed in this work. For the rest of this section, we plot the performance achieved by the opportunistic scheduler only, without loss of generality.

C. Impact of the energy beam width and transmit power

Next, as shown in Figure 3, the beam directionality, given by the number of antenna elements \( N_e \), noticeably affects the outage probability in a non-monotonic way and suggests a trade-off linking the power coverage and the ability to harvest energy from non-intended beams. To highlight this trade-off, we plot in Figure 4 the average ratio \( \gamma \) of the energy received from intended beams (i.e. the patient is effectively scheduled) over the harvested-energy amount, as given in Eq. (6).

For the omni-directional case \(^4\) and \( N=2 \), the power coverage does not exceed 8 to 10 meters, but allows nearby patients to harvest energy from the same beam. As shown in Fig. 4, 70 to 80% of the received energy is harvested from unintended beams. Decreasing the beam width by setting \( N \) to 4 significantly reduces the power outage and increases the power coverage. More energy is harvested thanks to high directivity gain at the transmit antenna, while the beam is still wide enough to harvest energy from unintended beams. Yet, further reducing the beam width (\( N=6 \)) degrades performance since (i) the FCC regulation imposes to decrease the transmit power from 36dBm to 33dBm, (ii) due to high directivity, less energy is harvested from unintended beams and \( \gamma \) is doubled by comparison with the case \( N=4 \), as observed in Fig. 4.

Remark: The two cases \( N=2 \) and \( N=6 \) show similar performance in terms of outage probability. Given that such performance is achieved with \( N=6 \) using less transmit power at the PB, we only plot this case in the following sections.

D. Impact on the sensor location on the body

We move into analyzing the impact of the sensor location, i.e. its type. Figure 5 depicts the energy outage probability obtained for each sensor type for both \( N=4 \) and \( N=6 \), in environment \( E_4 \). First, steering the beam towards the smartphone (\( \theta_e > 0 \)) rather than towards the sensor (\( \theta_e = 0 \)) has a negligible impact for \( N=4 \) and reduces the outage probability by 2% at most for \( N=6 \), given that the beam is narrower. Such result validates the proposed strategy for beam steering, which does not require tracking the PB-sensor channel.

Second, the outage probability is significantly increased for sensors located on the ankle (type D), for both cases \( \theta_e = 0 \) and \( \theta_e > 0 \). Such sensors experience high motion amplitude and the angle of arrival of non-intended beams is generally large since beams are always steered towards the nearby patients’ smartphone for \( \theta_e > 0 \) or have a low probability to be steered towards a nearby patient’s ankle for \( \theta_e = 0 \). As also confirmed by Figure 4, most of the received energy is harvested from intended beams. Such a result should not be neglected for designing efficient harvesting sensors.

E. Impact of the patients’ velocity and battery thresholds

We tackle the issue of the patients’ velocity by comparing the performance achieved by the proposed strategies regarding the environments \( E_1 \), \( E_2 \), \( E_3 \) and \( E_4 \) as described in section V-A. As observed in Figure 3, high-mobility patients (\( E_3 \) / \( E_4 \)) exhibit a lower outage probability compared to the slow ones (\( E_1 \) / \( E_2 \)), regardless of the velocity of other patients.

First, a slowly moving patient is slightly affected by the battery thresholds, especially for the case \( N=4 \), and performance mostly depends on the patient’s initial location. In fact, the patient may stay for a notable amount of time with strong or weak channel conditions, due to distance or shadowing.

\(^4\)For fair comparison in Figure 3, the omni-directional case has been plotting for both \( P_{\text{Tx}}=36\text{dBm} \), as for \( N=2 \) and 4, and \( 33\text{dBm} \), as for \( N=6 \).
By increasing the upper threshold $L_+$ performance is significantly affected by the battery thresholds. and non-charging periods by moving around PBs. The per-

channel diversity, although they alternate between charging

On the contrary, high-mobility patients benefit from additional

waiting duration refers to the average time duration be-

which the battery level continues to decrease.

We further investigate the impact of the battery threshold by considering the waiting duration and the charging duration. We define the charging duration as the average time duration

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which the battery is released, i.e. the average time necessary to

charging periods. Similarly, increasing the lower threshold $L_-$ allows to anticipate potentially long waiting periods during

which the battery level continues to decrease.

We further investigate the impact of the battery threshold by considering the waiting duration and the charging duration. We define the charging duration as the average time duration between the instant a patient is scheduled and the instant the serving PB is released, i.e. the average time necessary to charge the battery from its current level up to $L_+$. Similarly, the waiting duration refers to the average time duration between the instant a request is sent and the instant the patient is effectively scheduled. While simulations show that the average charging duration increases almost linearly with the difference $L_+ - L_-$. and does not allow to differentiate the simulated configurations, the average waiting duration appears closely related to the outage probability. As depicted in Figure 6, the lowest outage probability is obtained for configurations with reduced waiting duration. This suggests that minimizing the waiting duration should be considered as a guideline to reduce outage probability and may open new perspectives for further research on energy-harvesting wearable sensors.

VI. Conclusion

This work has examined the feasibility of dedicated wireless power transfer for autonomous medical sensors worn by patients inside a hospital and has highlighted the configuration parameters which allow to reduce the probability of energy outage. The main outcomes from the simulation results are the following: (i) the scheduling policy slightly impacts the system performance, (ii) steering beams towards the smartphone of the patients and not their sensors does not noticeably degrade performance, (iii) since most of the energy is harvested from non-intended beams, a trade-off exists between the transmit antenna gain, the power coverage and the beam width, (iv) the configuration for energy beam transmission should be adjusted based on the location of the sensor on the body, (v) the decision for charging request and ending (battery thresholds) should be adapted to the patient’s velocity, and slowly moving patients are subject to a higher energy outage, (vi) proposing new strategies that minimize the waiting duration can be used as a guideline for the reduction of the energy outage.

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