Article Identifier
DOI: 10.22032/dbt.58932
URN: urn:nbn:de:gbv:ilm1-2023isc-063:5

OUTAGE MINIMIZATION OF ENERGY-HARVESTING WIRELESS SENSOR NETWORK SUPPORTED BY UAV

Maša Milošević[1], Aleksandra Cvetković[1], Nevena Tomić[2], Emina Petrović[1]

[1]Faculty of Mechanical Engineering, University of Niš, A. Medvedeva 14, 18000 Niš, Serbia
[2]Faculty of Technology in Leskovac, University of Niš, Bulevar Oslobodjenja 124, 16000 Leskovac, Serbia

ABSTRACT

Due to their adaptability, mobility, and capacity to offer an ideal channel, unmanned aerial vehicles (UAVs) have become a potential option for wireless power transfer and data collection in wireless sensor networks (WSNs). This paper examines energy-constrained WSNs, where data transfer to the data center is facilitated by UAV and sensors rely on radio frequency (RF) energy obtained by a Power Beacon (PB). However, due to energy limitations, sensors can only send data using the harvested energy. We consider a WSN in which the nodes are randomly distributed within a circular area, with the PB placed at the center of the WSN. To evaluate the system performance, we consider the dynamic nature of the wireless channel, which includes factors such as signal reflection, scattering, and diffraction. Through numerical analysis and simulations, the main aim is to identify the optimal system parameters that minimize the outage probability. This analysis provides valuable insights for designing more effective and reliable energy-harvesting WSNs with UAV as data collector. By leveraging UAV in WSNs, system performance can be improved, ensuring data transmission to destination nodes placed at a large distance from the WSN.

Index Terms - energy harvesting, wireless sensor network, power beacon, unmanned aerial vehicles.

1. INTRODUCTION

Wireless sensor networks (WSNs) are utilized in various applications where remote monitoring, data collection, and environmental sensing are required [1]. They consist of small, autonomous sensor nodes deployed in a target area to gather data and transmit it to a Data Center (DC). These sensor nodes are typically equipped with sensing capabilities, data processing units, and wireless communication modules. One of the critical challenges in WSNs is the limited lifespan of the sensor nodes due to their reliance on battery power. To address this issue, energy harvesting techniques are employed to supply power to the sensor nodes. Energy harvesting allows the nodes to gather energy from the environment, such as solar radiation, thermal gradients, vibrations, or Radio Frequency (RF) electromagnetic signals [2]. The use of energy harvesting in WSNs not only prolongs the network's lifetime but also reduces maintenance costs and enables deployment in remote or inaccessible areas. One significant advantage of RF energy harvesting in WSNs is the ability to simultaneously transfer both information and energy, known as simultaneous wireless information and power transfer (SWIPT). This allows the sensor nodes to harvest energy from the environment while receiving data or instructions from the base station or other network nodes. SWIPT enables a more efficient and sustainable operation of the network by reducing reliance on traditional power sources and enabling continuous data transmission. The integration of alternative energy sources and SWIPT capabilities in WSNs offers numerous advantages. It enhances the sustainability of the network by reducing the need for frequent battery replacements or recharging [3]. In papers [4] and [5] quality-of-service (QoS) in energy-harvesting WSN is investigated. In [4], a new algorithm is proposed for generating energy-efficient schedules for wireless networks with energy harvesting. The algorithm demonstrates low complexity and optimality, leading to improved QoS and larger effective transmit regions compared to existing alternatives. Paper [5] discusses techniques for ensuring QoS in energy-harvesting WSN and the design of EH-powered transmitters. Papers [6-8] focus on the integration of wireless power transfer (WPT) technologies into networks. These studies investigate various aspects, including techniques for wireless rechargeable sensor networks. In [6], the challenges of energy replenishment and consumption in WSNs are addressed, while optimal charging strategies to maximize lifetime considering energy transfer efficiency and data transmission reliability are presented in [7]. Optimal time allocation for SWIPT systems, aiming to optimize system performance by balancing information transmission and energy harvesting, is discussed in [8]. The utilization of SWIPT in hierarchical WSNs is investigated in [9]. The study explores the application of a power beacon (PB) that can provide energy to sensor nodes and also serve as a power source for access points in cellular networks, as demonstrated in [10].

The past decade has witnessed significant advancements in unmanned aerial vehicle (UAV) technology, opening up possibilities for various applications such as inspections [11], agriculture [12], surveillance [13] and damage assessment, among others. Furthermore, the use of UAVs has gained considerable attention due to their ability to provide optimal channels for wireless power transfer and data collection. In [14] and [15], authors discuss the concept of WPT and data collection using UAVs, presenting an overview of the challenges and opportunities in this area. In the context of UAV-assisted IoT coverage in disasters, Wang et al. [16] propose a transceiver design and multihop device-to-device (D2D) communication scheme for UAVs, investigating the communication coverage and connectivity aspects of UAVs in disaster scenarios. Bithas et al. [17] study the channel modeling for UAV-to-ground nodes, considering various fading and shadowing effects. The outage performance of UAV-assisted relaying systems with RF energy harvesting is analyzed in [18]. The authors investigate the outage probability of UAV-based relaying systems employing RF energy harvesting techniques. Sharma et al. [19] studied the outage probability of UAVs in hybrid satellite-terrestrial networks, deriving the system performance under different environmental parameters. The wireless battery recharging from UAV in WSN under lognormal-Nakagami-*m* fading channels is investigated in [20]. Tran et al. [21] focus on UAV relay-assisted emergency communications in IoT networks, addressing resource allocation and trajectory optimization to maximize the number of IoT devices covered. Singh et al. [22] analyze the outage probability and throughput performance of UAV-assisted rate-splitting multiple access systems.

The security aspect of UAV IoT communication systems against randomly located eavesdroppers is analyzed in [23]. Lei et al. investigate various techniques to safeguard UAV IoT communication systems, considering different propagation environments and security threats. In the paper [24], authors discuss the employment of UAVs for analyzing and mitigating disaster risks in industrial sites, highlighting the potential benefits and challenges associated with the deployment of UAVs in various scenarios. A survey on machine learning techniques for UAV-based communications is provided in [25]. The authors consider various machine learning approaches and their applications in UAV communication systems, exploring the potential of machine learning techniques in enhancing the performance and efficiency of UAV-based communications.

In this paper, we analyze an energy-constrained WSN with the PB utilized for supplying energy to sensors. Sensors harvest RF energy from the PB and further transmit data to the UAV. Energy harvesting and data transmission is performed using the Time-Switching (TS) protocol. The UAV is employed to collect sensor data and forward it to the DC. We assume that the sensor nodes are uniformly randomly positioned within a circle of a certain radius. Assuming the random position of sensors, the analytical expression for the system outage probability is derived and numerical results are presented. The numerical results are validated through simulation. The objective of this study is to provide valuable insights into the design and performance of UAV-assisted energy-constrained WSN systems with randomly located sensors.

2. SYSTEM AND CHANNEL MODEL

The system configuration examined in this study consists of a PB, sensors without a conventional power supply, a UAV, and a DC, as shown in Fig. 1. The PB supplies energy to the sensors, which have limited battery power. The sensors utilize the harvested energy to transmit data to the UAV. The sensors are randomly positioned within an area with a radius R. The UAV acts as data collector, aiming to relay the collected information to the DC.

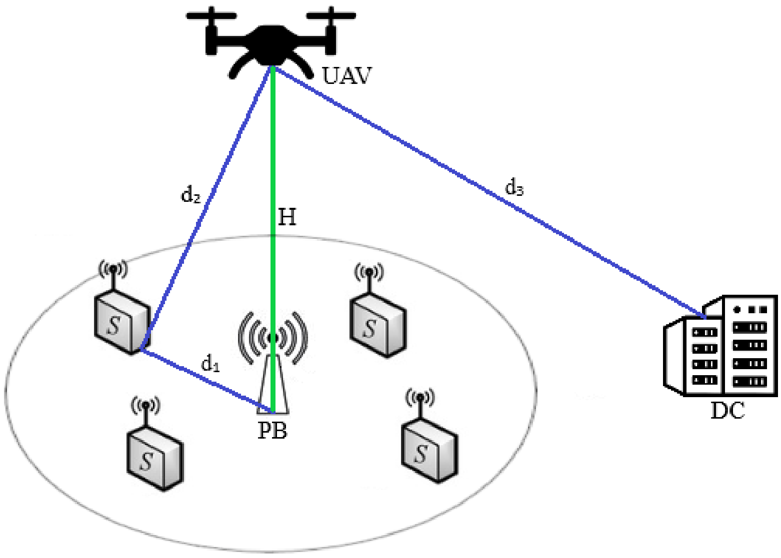

Figure 1. System model with UAV based data collector

The PB is strategically positioned to cover a specific area with a radius of R. The sensor locations are uniformly distributed on the surface of a circle, and the distance d_1 between the PB and sensors is a random variable. Additionally, considering the height H at which the UAV flies, the distance between the sensors and the UAV can be determined using $d_2 = \sqrt{d_1^2 + H^2}$, resulting in another random variable due to its relationship with d_1. The distance between the UAV and the DC is denoted as d_3.

The sensors harvest RF energy transmitted from the PB based on the TS protocol. Within a time frame of duration T, the sensors harvest RF energy from the PB during the first part αT, where $0 \leq \alpha < 1$. The remaining time $(1 - \alpha)$T is allocated for signal transmission. The transmission interval is divided equally into two parts, $(1 - \alpha)T/2$, for the S-UAV and UAV-DC transmissions, as presented in Fig. 2.

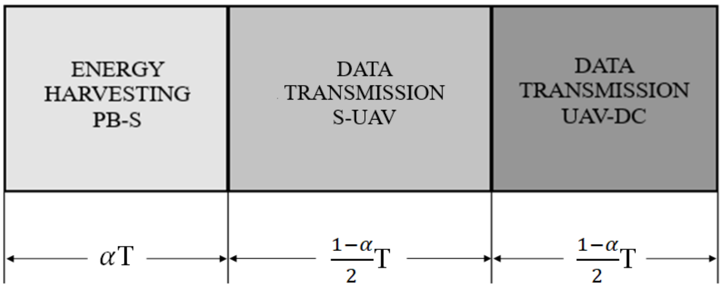

Figure 2. EH and information transmission intervals within time frame T

The total harvested energy from PB at the sensor during the time interval αT is given by

$$E_H = \eta \frac{P_B \gamma_1}{d_1^{\delta_1}} \alpha T \ , \tag{1}$$

where P_B represents the transmit power of the beacon, γ_1 denotes the channel power gain between the P_B and the sensor, and η ($0 < \eta < 1$) represents the energy conversion efficiency. The parameter δ_1 represents the path loss exponent at the distance d_1.

As all the harvested energy is used for information transmission to the UAV, the power is expressed as

$$P_S = \frac{E_H}{(1\text{-}\alpha)T} = \frac{\eta\alpha}{(1\text{-}\alpha)} \frac{P_B}{d_1^{\delta_1}} \gamma_1 . \tag{2}$$

The sensor transmits the signal s with the power P_S and the received signal at the UAV has the form

$$y_{UAV} = \sqrt{\frac{P_S}{d_2^{\delta_2}}} h_2 s + n_2 , \tag{3}$$

where n_2 is an Additive White Gaussian Noise (AWGN) with the power σ_2^2, h_2 denotes the fading envelope over the S-UAV link and δ_2 represents the path loss exponent at the distance d_2.

The received signal-to-noise ratio (SNR) at the UAV can be express as

$$\gamma_{UAV} = \frac{P_S}{d_2^{\delta_2} \sigma_2^2} \gamma_2 , \tag{4}$$

where γ_2 represents the channel power gain of the S-UAV link, $\gamma_2 = |h_2|^2$.

Further, combining eq. (4) with eq. (2), the received SNR at the UAV can be represented as

$$\gamma_{UAV} = \frac{\eta\alpha}{\left(1-\alpha\right)} \frac{P_B}{d_1^{\delta_1} d_2^{\delta_2} \sigma_2^2} \gamma_1 \gamma_2 . \tag{5}$$

The UAV functions as a DF relay, decoding and re-encoding the signal before forwarding it to the DC with a transmit power P_{UAV}. Consequently, the received signal at the DC is given by

$$y_D = \sqrt{\frac{P_{UAV}}{d_3^{\delta_3}}} h_3 s + n_3 , \tag{6}$$

where δ_3 represents the path loss exponent at the distance d_3.

Therefore, the instantaneous SNR at the destination (DC) takes the form

$$\gamma_D = \frac{P_{UAV}}{d_3^{\delta_3} \delta_3^2} \gamma_3 . \tag{7}$$

In order to describe the propagation environment in the WSN and between the UAV and the ground nodes (S and DC), the channel envelopes are modeled by Nakagami-*m* distribution. This distribution provides an excellent fit for various environmental scenarios. The corresponding channel gains γ_i, i=1, 2, 3 are considered to be subject to the Gamma distribution with the probability density function (PDF) given by

$$p_{\gamma_i}\left(\gamma\right) = \frac{m_i^{m_i}}{\bar{\gamma}_i^{m_i} \Gamma\left(m_i\right)} \gamma^{m_i-1} \exp\left(-\frac{m_i \gamma}{\bar{\gamma}_i}\right), i=1, 2, 3, \tag{8}$$

where $\Gamma(\cdot)$ denotes gamma function [26, eq. (8.310.1)], $\bar{\gamma}_i = \mathrm{E}\{\gamma_i\}$, i=1, 2, 3 and m_i, i=1, 2, 3 represents the fading parameter for the corresponding link.

3. OUTAGE PERFORMANCE ANALYSIS

The outage probability is an important system performance measure. In the considered system, where the UAV decodes and forwards collected data to the destination (DC), an outage occurs if the received SNR at the UAV or DC falls below a predetermined threshold, γ_{th}, which is determined by the required user's QoS [27].

The conditional outage probability regarding to distance d_1 is defined as

$$P_{out}\left(\gamma_{th} \left| d_1\right.\right) = \Pr\left(\gamma_{UAV} \le \gamma_{th} \left| d_1\right.\right) + \Pr\left(\gamma_D \le \gamma_{th}\right) - \Pr\left(\gamma_{UAV} \le \gamma_{th} \left| d_1\right.\right) \Pr\left(\gamma_D \le \gamma_{th}\right), \tag{9}$$

where $\Pr\{\cdot\}$ denotes the corresponding probability.

The expression in (9) can be rewritten as

$$P_{out}\left(\gamma_{th} \left| d_1\right.\right) = F_{UAV}\left(\gamma_{th} \left| d_1\right.\right) + F_D\left(\gamma_{th}\right) - F_{UAV}\left(\gamma_{th} \left| d_1\right.\right) F_D\left(\gamma_{th}\right), \tag{10}$$

where $F_{UAV}\left(\gamma_{th}\left|d_1\right.\right)$ denotes cumulative density function (CDF) conditional to d_1 and $F_D\left(\gamma_{th}\right)$ is CDF obtained using [27] and [28] is

$$F_D\left(\gamma_{th}\right)=1-\frac{\Gamma\left(m_3,\frac{m_3 d_3^{\delta_3}\sigma_3^2\gamma_{th}}{\bar{\gamma}_3 P_{UAV}}\right)}{\Gamma\left(m_3\right)}, \tag{11}$$

where $\Gamma(\cdot,\cdot)$ denotes incomplete gamma function [26, eq. (8.350.2)].

For the observed system and a certain fixed position of the S, the PDF of the current SNR at the UAV, defined by (5), can be calculated by combining equations [28, eqs. (7-46) and (5-7)] and using [26, eq. (3.471.9)]. The PDF represents the generalized K distribution [29] and can be expressed in the following form

$$\begin{aligned} p_{UAV}\left(\gamma\left|d_1\right.\right)=&\frac{2}{\Gamma\left(m_1\right)\Gamma\left(m_2\right)}\left(\frac{\left(1-\alpha\right)m_1 m_2 d_1^{\delta_1}\left(d_1^2+H^2\right)^{\delta_2}\sigma^2}{\bar{\gamma}_1\bar{\gamma}_2\eta\alpha P_B}\right)^{\frac{m_1+m_2}{2}}\gamma^{\frac{m_1+m_2}{2}-1}\\ &\times K_{-m_1+m_2}\left(2\sqrt{\frac{\left(1-\alpha\right)m_1 m_2 d_1^{\delta_1}\left(d_1^2+H^2\right)^{\delta_2}\sigma^2\gamma}{\bar{\gamma}_1\bar{\gamma}_2\eta\alpha P_B}}\right), \end{aligned} \tag{12}$$

where $K_\beta\left(\times\right)$ is the *β-th* order modified Bessel function of the second kind [26, eq.(8.432.3)]. Assuming that the WSN area represents a circle with a radius R and the PB is positioned at the origin of the circle, the PB-S distance d_1 is uniformly distributed according to the distribution [19] presented in

$$p_r\left(d_1\right)=\frac{2}{R^2}d_1. \tag{13}$$

The corresponding CDF can be determined as shown in

$$F_{UAV}\left(\gamma_{th}\left|d_1\right.\right)=\frac{1}{\Gamma\left(m_1\right)\Gamma\left(m_2\right)}G_{1,3}^{2,1}\left(\frac{\left(1-\alpha\right)m_1 m_2 d_1^{\delta_1}\left(d_1^2+H^2\right)^{\delta_2}\sigma^2\gamma_{th}}{\bar{\gamma}_1\bar{\gamma}_2\eta\alpha P_B}\left|\begin{matrix}1\\ m_2,m_1,0\end{matrix}\right.\right)^{\frac{m_1+m_2}{2}}. \tag{14}$$

By averaging the previous equation over the variable d_1 using the distribution provided in (13), it is obtained:

$$F_{UAV}\left(\gamma_{th}\right)=\int_0^R\frac{2d_1}{R^2}F_{UAV}\left(\gamma_{th}\left|d_1\right.\right)dd_1. \tag{15}$$

The integral in the previous expression cannot be solved in the exact closed-form due to the involvement of the special functions and the finite integration limits.

Finally, the total outage probability can be obtained by

$$P_{out}\left(\gamma_{th}\right)=F_{UAV}\left(\gamma_{th}\right)+F_{D}\left(\gamma_{th}\right)-F_{UAV}\left(\gamma_{th}\right)F_{D}\left(\gamma_{th}\right), \tag{16}$$

where $F_D\left(\gamma_{th}\right)$ and $F_{UAV}\left(\gamma_{th}\right)$ are defined by (12) and (15), respectively.

4. NUMERICAL AND SIMULATION RESULTS

Impact of the system and channel parameters on outage probability is examined in this Section. Numerically obtained results based on derived expressions are confirmed with the results obtained by an independent simulation method. Simulation results are obtained by generating 10^8 samples of the signal envelope. The outage probability is determined by averaging over successive channel realizations. The parameters used for numerical and simulation results are P_B=30dBmW, m_1=2, m_2=3.5, m_3=5, δ_1=2.1, δ_2=δ_3=2, η=0.9, σ^2=10^{-5}mW, unless otherwise indicated in the figures.

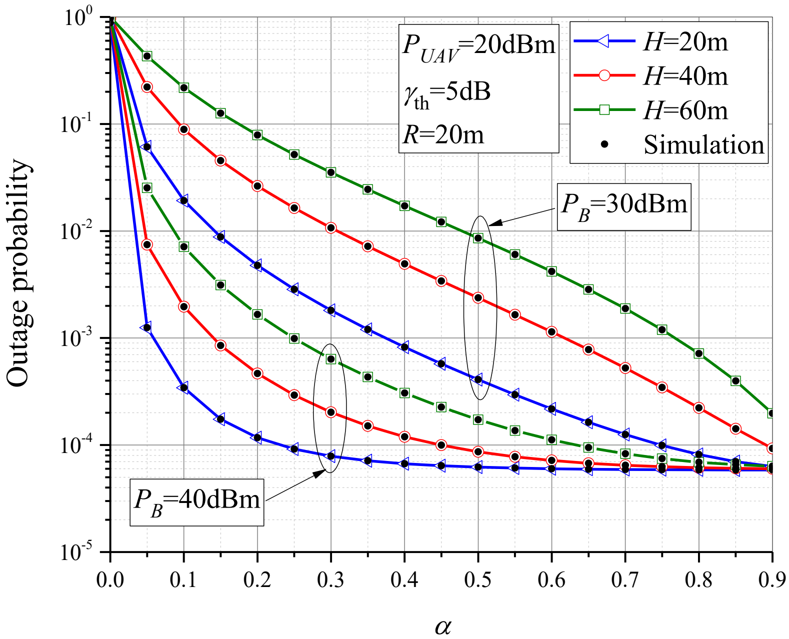

Figure 3. The outage probability dependence on the time switching parameter α for different values of H and P_B

The dependence of outage probability on the energy harvesting ratio α for different values of UAV altitude and output power of PB is presented in Fig. 3. for PB-DC horizontal distance L of 500m. The outage probability decreases when the transmit power of PB increases. The increase of α leads to higher sensor output power, but for P_B=40dBm, it can be observed that the increase of α does not lead to better system performance. Above certain values of α, the outage floor appears, and further energy harvesting does not significantly affect outage performances. The floor value only depends on the parameters of the UAV-DC link.

The impact of system parameters of the UAV-DC link (UAV transmit power, P_{UAV}, and horizontal PB-DC distance, L) is investigated in Fig 4. The outage probability values in the function of P_{UAV} for different values of horizontal PB-DC distance and various energy harvesting ratios are presented. For low values of P_{UAV}, outage is determined by the UAV-DC link, and the distance of the UAV-DC has an influence on outage probability values, i.e., increasing the UAV-DC distance, thus increasing the path loss, leads to an increase in the probability of system failure. For high values of P_{UAV}, the system performance depends on the S-UAV link, and up to the certain value of P_{UAV}, the outage floor appears, and the further increase of P_{UAV} does not significantly affects outage performance. The outage floor is determined by the S-UAV link, and it depends on time switching parameter α.

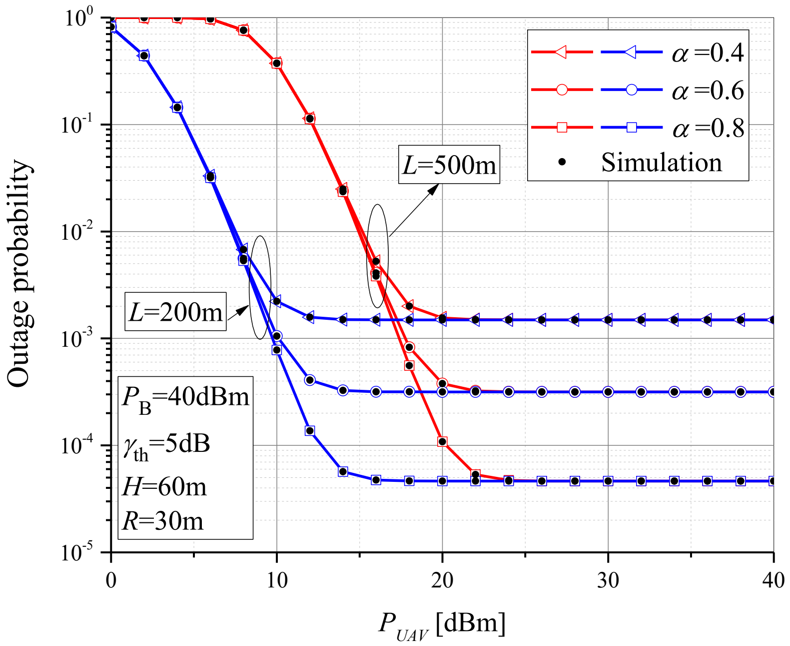

Figure 4. The outage probability dependence on P_{UAV} for different values of α and PB-DC horizontal distance L

The contour plot of outage probability for P_B=P_{UAV}=30dBm, R=30m and PB-DC horizontal distance L=800m is presented in Fig. 5. The influence of UAV altitude and time switching parameter α on system failure is obtained. The results indicate that in order to obtain the outage probability smaller than 10^{-3} time switching parameter must be above 0.6. The altitude of the UAV data collector above 40m demands charging time above 0.8T to achieve an outage probability smaller than 10^{-3}.

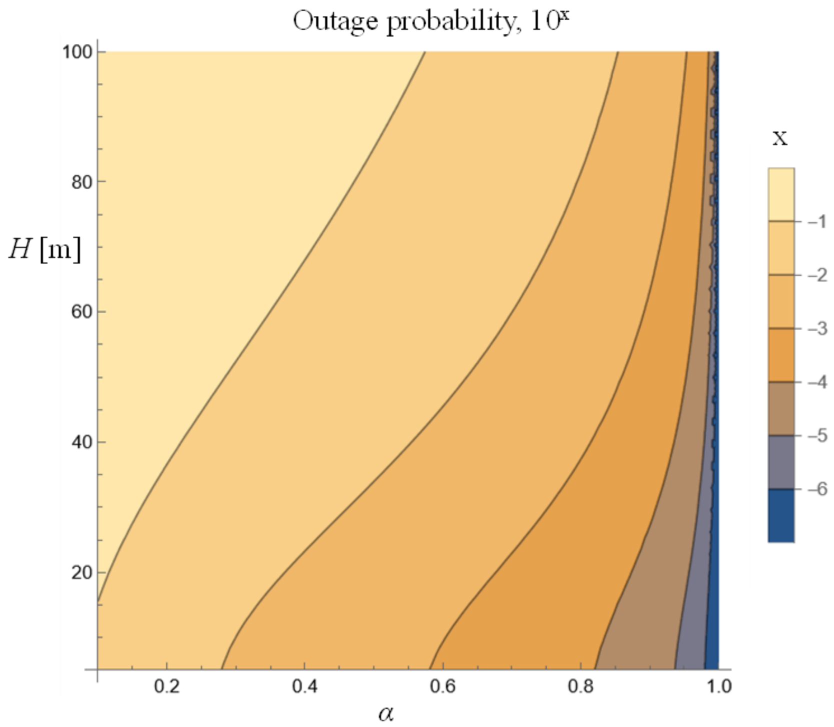

Figure 5. The outage probability dependence on the UAV height H and time switching parameter α

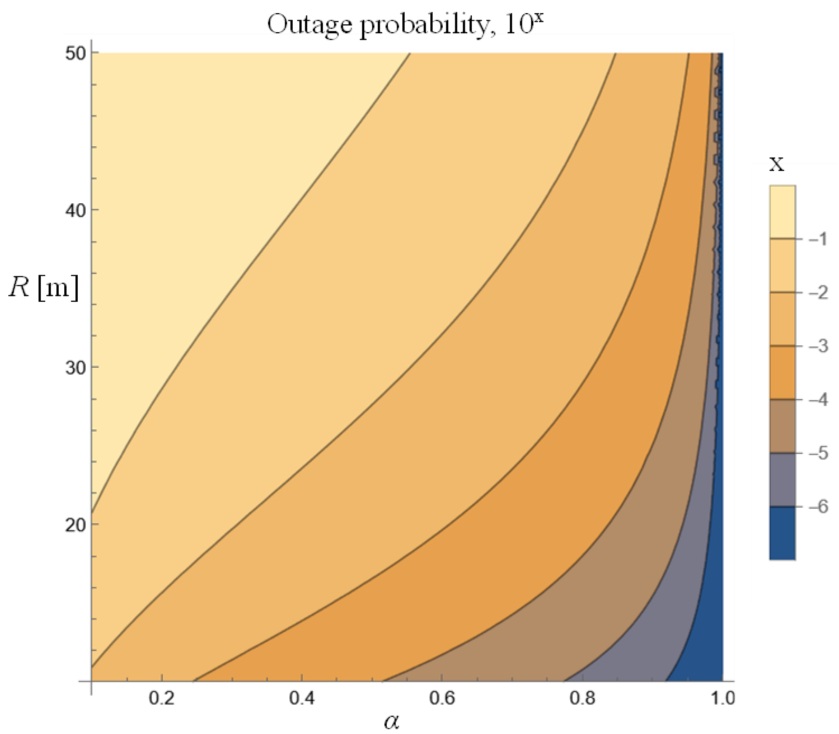

Figure 6. The outage probability dependence on the radius R and time switching parameter α

In Fig. 6 the dependence of the outage probability on the time switching parameter α and the size *R* of the circular area where the sensor is randomly positioned, is presented. For *R*>30m, to achieve an outage probability smaller than 10^{-2}, the time of battery charging should be above

60% of the frame duration. If the sensor is uniformly distributed within the circular shaped area of a larger radius, it will be more often located at the positions farther from the PB, resulting in the higher propagation losses and smaller amount of collected power. The raise of α leads to an increase in the sensor transmit power and a decrease in outage probability. It also leads to a decrease of the time interval dedicated for information transmission. That fact is important for other performance metrics, like capacity and achievable throughput. By reducing time for information transmission, capacity and throughput are reduced.

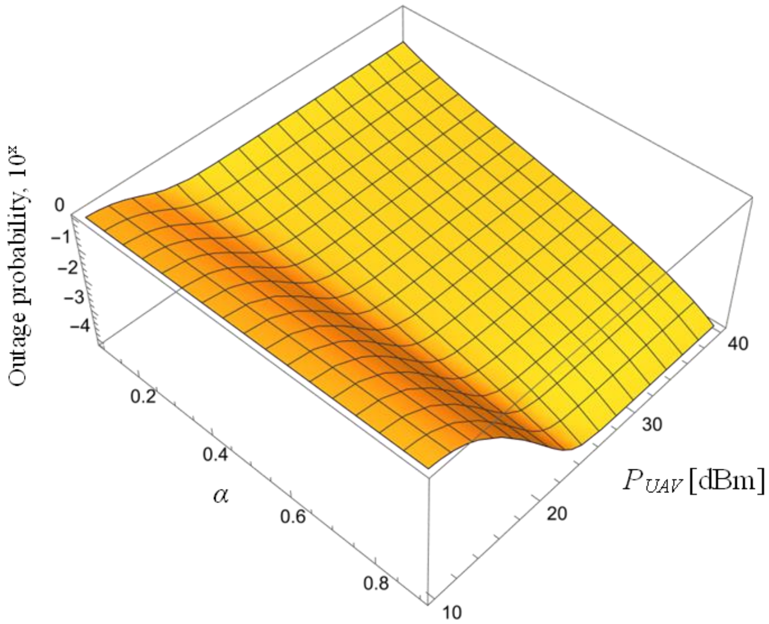

Figure 7. Outage probability dependence on the PUAV and time switching parameter α

In Fig. 7, a 3D plot of outage probability as a function of UAV output power and time switching parameter α is presented. The results are obtained for P_B= 30dBm, H=50m, R=20m and PB-DC horizontal distance L=800m. It can be seen that there are optimal values of α and P_{UAV} that lead to a certain outage probability. Increasing the transmission power of the UAV above a certain value as well as increasing sensor charging time does not always lead to an improvement in performance.

5. CONCLUSION

In this study, we investigated the performance of an energy-constrained WSN supported by UAVs for data collection. Our focus was on the scenario where sensors are randomly positioned and collect RF energy from a PB to transmit data to the UAV using harvested power. The UAV further transfers the collected data to the DC. We derived analytical expressions to evaluate the outage performance, considering the randomness of the sensor positions within a certain radius and the dynamic nature of the wireless channel. The numerical results obtained based on analytical expressions were validated using an independent simulation method. We investigated the impact of system and channel parameters on system performance, such as energy harvesting time-switching ratio, WSN area size, UAV height, and distance between sensors and PB. The system parameters that lead to the optimal outage probability values and enhance the reliability of the system are determined. We identified the system parameters that optimize the outage probability and enhance the reliability of the system. The results obtained from this study provide valuable guidelines for designing WSN systems with UAVs for data acquisition in various applications.

ACKNOWLEDGEMENT

This research was financially supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia (Contract No. 451-03-47/2023-01/200109).

REFERENCES

[1] M. Majid, S. Habib, A.R. Javed, M. Rizwan, G. Srivastava, T.R. Gadekallu, and J.C. Lin, "Applications of Wireless Sensor Networks and Internet of Things Frameworks in the Industry Revolution 4.0: A Systematic Literature Review," Sensors. 22(6):2087, 2022.
[2] X. Tang, X. Wang, R. Cattley, F. Gu, and A.D. Ball, "Energy Harvesting Technologies for Achieving Self-Powered Wireless Sensor Networks in Machine Condition Monitoring: A Review," Sensors, vol. 18, no. 12, article 4113, 2018.
[3] H. Azarhava and J. Musevi Niya, "Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks," IEEE Transactions on Wireless Communications, vol. 9, no. 7, pp. 1000-1003, July 2020.
[4] X. Chen, W. Ni, X. Wang, and Y. Sun, "Provisioning quality of-service to energy harvesting wireless communications," IEEE Communications Magazine, vol. 53, no. 4, pp. 102-109, 2015.
[5] X. Chen, W. Ni, X. Wang, and Y. Sun, "Optimal quality-of service scheduling for energy-harvesting powered wireless communications," IEEE Transactions on Wireless Communications, vol. 15, no. 5, pp. 3269-3280, May 2016.
[6] S. He, J. Chen, F. Jiang, D.K. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," IEEE Transactions on Mobile Computing, vol. 12, no. 10, pp. 1931-1942, Oct. 2013.
[7] L. Fu, P. Cheng, Y. Gu, J. Chen, and T. He, "Optimal charging in wireless rechargeable sensor networks," IEEE Transactions on Vehicular Technology, vol. 65, no. 1, pp. 278-291, Jan. 2016.
[8] F. Zhao, L. Wei, and H. Chen, "Optimal time allocation for wireless information and power transfer in wireless powered communication systems," IEEE Transactions on Vehicular Technology, vol. 65, no. 3, pp. 1830-1835, March 2016.
[9] Y. Liu, K. Xiong, Y. Lu, Q. Ni, P. Fan and K. B. Letaief, "UAV-Aided Wireless Power Transfer and Data Collection in Rician Fading," Wireless Communications and Mobile Computing, vol. 39, no. 10, pp. 3097-3113, Oct. 2021.
[10] H.-H. Choi and J.-R. Lee, "Energy-Neutral Operation Based on Simultaneous Wireless Information and Power Transfer for Wireless Powered Sensor Networks," Energies, vol. 12, no. 20, article 3823, 2019.
[11] C.B. Le and N.D. Nguyen, "Enabling Power Beacons and Wireless Power Transfers for Non-Orthogonal Multiple Access Networks," Journal of Telecommunications and Information Technology, vol. 3, pp. 1, Sept. 2021.
[12] J. Cui, M. Liu, Z. Zhang, S. Yang, and J. Ning, "Robust UAV thermal infrared remote sensing images stitching via overlap-prior-based global similarity prior model," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 270–282, 2021.
[13] H.C. Oliveira, V.C. Guizilini, I.P. Nunes, and J.R. Souza, "Failure detection in row crops from UAV images using morphological operators," IEEE Geoscience and Remote Sensing Letters, vol. 15, no. 7, pp. 991–995, July 2018.
[14] Y. Jin, Z. Qian, and W. Yang, "UAV cluster-based video surveillance system optimization in heterogeneous communication of smart cities," IEEE Access, vol. 8, pp. 55654–55664, 2020.

[15] K. Li, W. Ni, L. Duan, M. Abolhasan and J. Niu, "Wireless Power Transfer and Data Collection in Wireless Sensor Networks," IEEE Transactions on Vehicular Technology, vol. 67, no. 3, pp. 2686-2697, March 2018.
[16] C. Wang, S. Guo and Y. Yang, "Energy-efficient mobile data collection in energy-harvesting wireless sensor networks," 20th IEEE International Conference on Parallel and Distributed Systems (ICPADS), pp. 55-62, Hsinchu, Taiwan, 2014.
[17] P. S. Bithas, V. Nikolaidis, A. G. Kanatas and G. K. Karagiannidis, "UAV-to-Ground Communications: Channel Modeling and UAV Selection," IEEE Transactions on Communications, vol. 68, no. 8, pp. 5135-5144, Aug. 2020.
[18] L. Yang, J. Chen, M. O. Hasna and H. -C. Yang, "Outage Performance of UAV-Assisted Relaying Systems With RF Energy Harvesting," IEEE Communications Letters, vol. 22, no. 12, pp. 2471-2474, Dec. 2018.
[19] P. K. Sharma, D. Deepthi and D. I. Kim, "Outage Probability of 3-D Mobile UAV Relaying for Hybrid Satellite-Terrestrial Networks," IEEE Communications Letters, vol. 24, no. 2, pp. 418-422, Feb. 2020.
[20] N.P. Le, L.C. Tran, X. Huang, E. Dutkiewicz, C. Ritz, S.L. Phung, A. Bouzerdoum, D. Franklin, and L. Hanzo, "Energy-Harvesting Aided Unmanned Aerial Vehicles for Reliable Ground User Localization and Communications Under Lognormal-Nakagami- m Fading Channels," IEEE Transactions on Vehicular Technology, vol. 70, no. 2, pp. 1632-1647, 2021.
[21] D. -H. Tran, V. -D. Nguyen, S. Chatzinotas, T. X. Vu and B. Ottersten, "UAV Relay-Assisted Emergency Communications in IoT Networks: Resource Allocation and Trajectory Optimization," IEEE Transactions on Wireless Communications, vol. 21, no. 3, pp. 1621-1637, March 2022.
[22] S. K. Singh, K. Agrawal, K. Singh and C. -P. Li, "Outage Probability and Throughput Analysis of UAV-Assisted Rate-Splitting Multiple Access," IEEE Wireless Communications Letters, vol. 10, no. 11, pp. 2528-2532, Nov. 2021.
[23] H. Lei, D. Wang, K.-H. Park, I. S. Ansari, J. Jiang, G. Pan, and M.-S. Alouini, "Safeguarding UAV IoT Communication Systems Against Randomly Located Eavesdroppers," IEEE Internet of Things Journal, vol. 7, no. 2, pp. 1230-1244, Feb. 2020.
[24] G. Aiello, F. Hopps, D. Santisi and M. Venticinque, "The Employment of Unmanned Aerial Vehicles for Analyzing and Mitigating Disaster Risks in Industrial Sites," in IEEE Transactions on Engineering Management, vol. 67, no. 3, pp. 519-530, Aug. 2020.
[25] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A Survey on Machine-Learning Techniques for UAV-Based Communications," Sensors, vol. 19, no. 23, article 5170, 2019.
[26] I. S. Gradshteyn and I. M. Ryzhik, Table of Integrals, Series, and Products, 8th ed., Elsevier/Academic Press, London, UK, 2014.
[27] A. Goldsmith, Wireless Communications, Cambridge University Press, Cambridge, UK, 2005.
[28] A. Papoulis, Probability, Random Variables, and Stochastic Processes, McGraw-Hill, New York, USA, 1991.
[29] G. K. Karagiannidis, N. C. Sagias, and P. T. Mathiopoulos, "N∗Nakagami: A Novel Stochastic Model for Cascaded Fading Channels," IEEE Trans. Commun., vol. 55, pp. 1453-1458, 2007.

CONTACTS

Maša Milošević — email: masa.milosevic@masfak.ni.ac.rs
ORCID: https://orcid.org/0000-0002-5399-2870

Prof. Dr. Aleksandra Cvetković — email: aleksandra.cvetkovic@masfak.ni.ac.rs
ORCID: https://orcid.org/0000-0003-3737-7656

