

Traffic Control and Energy Harvesting in High Altitude Platforms: A Semi-Markov Process Approach

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Abstract—This study uses a cooperative communication approach to propose a radio frequency (RF) energy harvesting (EH) policy for relay nodes in space-air-ground networks. The proposed policy is employed in three-layer networks: low Earth orbit (LEO) satellites, high-altitude platforms (HAP), and user devices on the ground. This type of aerial communication network is adopted in most Internet of Things (IoT) networks. The analysis is carried out by constructing traffic and energy harvesting models. The traffic model is analyzed using the semi-Markov process due to the non-exponential behavior of some state transitions. A discrete-time Markov chain (DTMC) is used to analyze the energy harvesting model. The novel traffic model investigates the network's practical lifetime, the average delay of source/relay packets, and throughput. The energy harvesting model is used to compute the average harvested energy of the HAP in closed form. Finally, through numerical illustrations, the impact on performance measures is shown by conducting a sensitivity analysis.

Index Terms—Cooperative communication, 6G, high altitude platform, internet of things, satellite-aerial-terrestrial network, RF energy harvesting, semi-Markov process, and traffic model.

I. INTRODUCTION

Space-air-terrestrial (SAT) networks provide ubiquitous access to the Internet of Things (IoT) and mobile users through the sixth generation (6G). A high-altitude platform (HAP) and low Earth orbit (LEO) satellite can be used to accomplish this objective, which not only improves system performance but also provides coverage for mobile and IoT users in areas where ground base stations cannot. QoS (quality of service) and traffic control are critical objectives of SAT networks. The continuous operation of HAP is equally important for maintaining satisfactory QoS for users. Therefore, power/energy provisioning for HAPs is an important area that should be addressed.

The aforementioned challenges are addressed by offering diverse network designs and analyzing them through various modeling techniques. This aerial communications research aims to tackle these issues from a stochastic modeling standpoint. Regarding the first issue of traffic control, we consider a model of the SAT network that applies to a wide range of IoT networks. As for the second issue, we propose a novel energy harvesting model for HAP. In this approach, HAP extracts energy from the radio frequency signals emitted by ground IoT devices. The proposed model has the potential to extend

the lifespan of these devices and enhance QoS metrics such as packet delay and transmission probability.

A. State of the Art

Researchers have initiated a focused study on network modeling using satellites, HAPs, and IoT users (see, [1], [2]). A key obstacle in IoT networks is the efficient transmission and reception of data. In this context, energy management for longer network operations without compromising QoS is a crucial and challenging issue. The cooperation of HAPs as relay nodes between satellites and IoT users ensures the QoS requirements in IoT networks. In [3], the authors explored how HAPs and satellites can collaborate to build a space-air-ground IoT network. In [4], the author evaluated the performance of HAP-LEO networks in a broader context by modeling the uneven distribution of satellites using a non-homogeneous Poisson point process.

Several studies have emphasized that one major impediment to utilizing HAPs to improve current wireless networks is the limited on-board energy and flight time (see [5], [6]). According to Alam et al. [7], the batteries in a HAP have a lifespan of less than an hour. This lifespan is further shortened when energy is used for signal processing, payload operations, and communication. As a result, HAP systems typically rely on power sources that transfer energy via thin cables or ropes, such as solar panels, lithium-ion batteries, or ground-based energy sources.

In IoT networks, energy harvesting (EH) technology may be the most effective means of extending HAPs' battery life and improving energy efficiency. HAPs can harvest energy from multiple resources, such as solar panels, radio frequency (RF) signals, and ground-based energy sources. The proposed study focuses on RF-EH technology for HAPs and introduces a novel stochastic model for analysis. For large-scale networks, network coding-based cooperative communications have been studied in [8], where only the relays harvest RF energy. The authors of [9] proposed a relay policy to harvest energy for IoT networks.

B. Motivation & Contribution

The proposed network model comprises three essential components: LEO satellites, HAPs, and IoT devices. This

model holds significant potential for integration into various IoT networks. However, it faces several challenges, including traffic control, maximizing throughput, and meeting QoS requirements for IoT devices. Ensuring QoS necessitates addressing the power and energy provisioning for HAPs, which is particularly challenging given their prolonged presence in Earth's stratosphere. To tackle this issue, this study employs RF-EH technology for HAPs. A novel stochastic model is developed and thoroughly analyzed to address these challenges. This paper offers valuable insights into the potential advantages of integrating the proposed RF-EH-based policy with a cooperative communication approach within the SAT network.

The primary contributions of this study are as follows:

- 1) A stochastic model has been crafted to scrutinize the traffic dynamics within this multi-layer architecture. Within this model, certain transition states exhibit behaviour that deviates from exponential distributions. Consequently, we employ the methodology of semi-Markov processes (SMP) to comprehensively analyze this traffic model. Through this model, we derive crucial performance metrics, including transmission probabilities, throughput, and average packet delay.
- 2) A pioneering discrete-time Markov chain (DTMC) model has been formulated to evaluate the RF-EH technology deployed in HAP. Through analysis of this model, key performance metrics such as the average harvested energy and total energy consumption are derived.
- 3) The proposed study provides sensitivity analysis for both the stochastic models to describe the behaviour of performance measures. The impact of the transmission probability of HAP on the average energy harvesting of HAP is evaluated through the proposed DTMC EH model.

C. Paper Organization

The proposed study is divided into the following sections. Section II consists of the network topology, traffic model and energy harvesting model. The potential stochastic model for traffic control is described in Section III, followed by key performance indicators. The analysis of the energy harvesting model is presented in Section IV along with the model's performance measures. Section V provides in-depth presentations of important performance measures with respect to the several parameters of the system. Finally, Section VI concludes with suggestions for further research.

II. SYSTEM DESCRIPTION

A. Network Topology

We employ a simple model to assess the efficacy of a HAP relay in enhancing uplink UE-LEO communication. This model involves a single HAP positioned at the origin on the x-y ground plane, elevated to a fixed height of h_H km, and a single LEO satellite also positioned at the origin but elevated to a higher fixed height of h_L km, where $h_H < h_L$. Both the HAP and LEO feature circular coverage areas on the ground

plane, with their centers aligned at the origin. All uplink UEs are situated on the ground plane within the coverage area of the HAP. There are two types of UEs: one type (UE_1) uses the HAP as a relay, while the second type (UE_2) consists of higher-powered users communicating directly with the LEO satellite. Figure 1 depicts the system architecture of the HAP-LEO system, which has been modeled using the stochastic process.

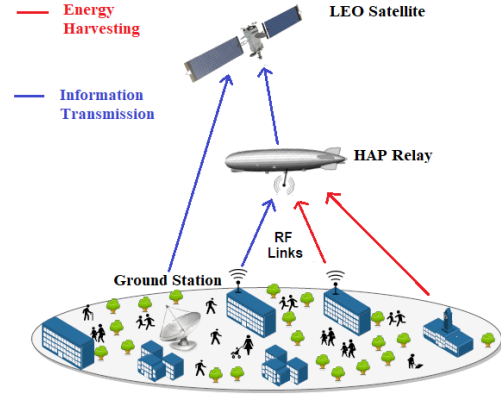


Fig. 1: System architecture of HAP-LEO system

B. Traffic Control Model

For the traffic control model, it has been considered that there are two queues for UE_1 and UE_2 at HAP and LEO, respectively. To reduce the complexity of the proposed model, it has been assumed that queue 1 can contain a maximum K number of UE_1 's and queue 2 consists of a maximum M number of UE_2 's. The service of UE_1 will be completed in two phases; in phase 1, it will receive the service from the HAP; in phase 2, it will receive service from LEO. After completing the service from LEO, the UE_1 will exit the system. At the same time, the LEO will directly complete the service of UE_2 . Table I provides concrete information about the states of the system.

C. Energy Harvesting Model

HAP is a radio frequency-energy harvesting (RF-EH) device. It can transmit the packet and harvest energy also using RF waves. It is considered that HAP will harvest a constant amount of energy denoted as E_{eh} and will be called one unit of energy hereafter. Furthermore, it is assumed that each transmission consumes a constant amount of energy (k) indicated by E_c . Let the initial value and maximum value of HAP energy be E_0 and E_{max} . In terms of energy units, such energies are $e_0 = E_0/E_{eh}$ and $e_{max} = E_{max}/E_{eh}$, respectively.

In this model, it is assumed that e_0 is the system's initial state. From this state, there are four possible transitions;

- HAP transmits only packets,
- HAP transmits packets and harvests energy both,
- HAP only harvests energy,
- HAP neither transmits the packets nor harvests energy.

States	Functionalities
Idle state	The system remains idle until packets arrive.
Active state of HAP & LEO on the arrival of UE_1	a) when HAP is providing the service to incoming UE_1 packets b) when LEO is providing the service to those UE_1 packets which HAP has served in phase 1.
Active state of LEO on the arrival of UE_2	LEO is providing the service to UE_2 packets

TABLE I: Description of states of traffic control model

TABLE II: Notations and their description

Notation	Description
λ_1, λ_2	Arrival of UE_1 , and UE_2 , respectively.
μ_H, μ_L	Service of UE_1 from HAP and LEO, respectively.
μ_2	Service of UE_2 from LEO

III. SMP MODEL FOR TRAFFIC CONTROL

This section consists of the steady-state analysis of the proposed model. Let $\{X(t), t \in T\}$ denote the state process of the system where $X(t)$ is the state of the system at time t . Here, each system state corresponds to the time instances, e.g., $X = \{(0,0) \cap (i^H, j) \cap (i^L, j); 1 \leq i^H \leq K, 1 \leq i^L \leq K, 1 \leq j \leq M\}$ corresponds to $T = \{t_0, t_1, t_2, \dots\}$.

The sojourn times for the service processes of the packets follow general distributions where the Markov property is satisfied at time epochs T . Therefore, the semi-Markov process (SMP) is the apt representation of the underlying stochastic process. The state space for the defined stochastic process is given as

$$\Omega = \{(0,0) \cap (i^H, j) \cap (i^L, j); 1 \leq i^H, i^L \leq K, 1 \leq j \leq M\}.$$

Table II provides the notations and their description used in the proposed traffic model. Table III denotes the distributions of sojourn times for the semi-Markov model. Figure 2 represents the state transition diagram of the proposed traffic model. The finite capacity of the system defines its stability. Hence, the steady-state probabilities of the SMP exist and are unique. The two-stage method is used to compute the steady-state probabilities.

The cumulative distribution function (CDF) for the transition from state m to n of the state space is defined as $F_{m,n}$. The non-zero elements of the kernel matrix are computed as follows.

$$\begin{aligned} K_{(0,0),(1^H,0)}(t) &= \int_0^t (1 - F_{(0,0),(0,1)}(x)) dF_{(0,0),(1^H,0)}(x), \\ &= \frac{\lambda_1}{\lambda_1 + \lambda_2} (1 - e^{-(\lambda_1 + \lambda_2)t}) \end{aligned} \quad (1)$$

Similarly, following Equation (1), the other entries are computed and are given in Table IV.

A. Steady-State Analysis

The matrix $K(\infty)$ with entries $K_{m,n}(\infty)$ gives the one step transition probabilities for the model where $K_{m,n}(\infty) =$

TABLE III: Distributions of sojourn times in semi-Markov model for general distributions

CDF	General Distribution	Mean
$F_{(i^H,j),(i^L,j)}(t)$	Deterministic	$\frac{1}{\mu_H}$
$F_{(i^L,j),((i-1)^L,j)}(t)$	Deterministic	$\frac{1}{\mu_L}$
$F_{(i^H,j),(i^H,j-1)}(t)$	Deterministic	$\frac{1}{\mu_2}$
$F_{(i^H,j),((i+1)^H,j)}(t)$	Exponential	λ_1
$F_{(i^H,j),(i^H,j+1)}(t)$	Exponential	λ_2

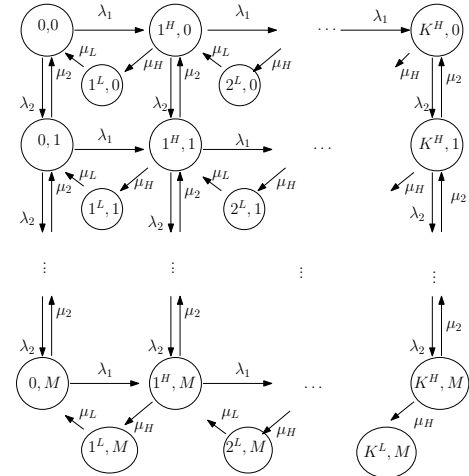


Fig. 2: State transition diagram of traffic model

$\lim_{t \rightarrow \infty} K_{m,n}(t)$, where $m, n \in \Omega$. The steady-state probabilities of embedded Markov chain (v_i) are obtained by solving Equation (2)

$$v = vK(\infty), \quad \sum_{i \in \Omega} v_i = 1, \quad (2)$$

where, $v = (v_1, v_2, \dots, v_i)$; $i \in \Omega$ is the steady-state probability vector. The steady-state probability of state i , for the SMP model is given by Equation (3)

$$\pi(i, j) = \frac{v_i h_i}{\sum_{l \in \Omega} v_l h_l}, \quad i, j \in \Omega, \quad (3)$$

where h_i is the mean sojourn time spent by the process in each state i .

By relaxing the assumption of non-exponential distribution, the proposed model will be converted into a continuous time Markov chain (CTMC) model. We have also presented a comparison of results with both the models in the numerical

TABLE IV: Kernel matrix entries

$K_{(0,0),(0,1)}(t)$	$\frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)t})$	$K_{(i^H,0),((i+1)^H,0)}(t)$	$\begin{cases} \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_H}), & t \geq \frac{1}{\mu_H} \\ \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)t}), & t < \frac{1}{\mu_H} \end{cases}$
$K_{(i^H,0),(i^H,1)}(t)$	$\begin{cases} \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_H}), & t \geq \frac{1}{\mu_H} \\ \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)t}), & t < \frac{1}{\mu_H} \end{cases}$	$K_{(i^H,0),(i^L,0)}(t)$	$\begin{cases} e^{-(\lambda_1+\lambda_2)/\mu_H}, & t \geq \frac{1}{\mu_H} \\ 0, & t < \frac{1}{\mu_H} \end{cases}$
$K_{(K^H,0),(K^L,0)}(t)$	$\begin{cases} e^{-\lambda_2/\mu_H}, & t \geq \frac{1}{\mu_H} \\ 0, & t < \frac{1}{\mu_H} \end{cases}$	$K_{(K^H,0),(K^H,1)}(t)$	$\begin{cases} 1 - e^{-\lambda_2/\mu_H}, & t \geq \frac{1}{\mu_H} \\ 1 - e^{-\lambda_2 t}, & t < \frac{1}{\mu_H} \end{cases}$
$K_{(i^L,j),((i-1)^H,j)}(t)$	$\begin{cases} 1, & t \geq \frac{1}{\mu_L} \\ 0, & t < \frac{1}{\mu_L} \end{cases}$	$K_{(i,j),(i,j-1)}(t)$	$\begin{cases} e^{-(\lambda_1+\lambda_2)/\mu_2}, & t \geq \frac{1}{\mu_2} \\ 0, & t < \frac{1}{\mu_2} \end{cases}$
$K_{(i,j),(i,j+1)}(t)$	$\begin{cases} \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_2}), & t \geq \frac{1}{\mu_2} \\ \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)t}), & t < \frac{1}{\mu_2} \end{cases}$	$K_{(i,j),((i+1)^H,j)}(t)$	$\begin{cases} \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_2}), & t \geq \frac{1}{\mu_2} \\ \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)t}), & t < \frac{1}{\mu_2} \end{cases}$
$K_{(i^H,j),(i^H,j-1)}(t)$	$\begin{cases} e^{-(\lambda_1+\lambda_2)/\mu_2}, & t \geq \frac{1}{\mu_H} > \frac{1}{\mu_2} \\ e^{-(\lambda_1+\lambda_2)/\mu_H}, & t \geq \frac{1}{\mu_2} > \frac{1}{\mu_H} \\ 0, & \text{otherwise} \end{cases}$	$K_{(i^H,j),((i+1)^H,j)}(t)$	$\begin{cases} \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_H}), & t \geq \frac{1}{\mu_2} > \frac{1}{\mu_H} \\ \frac{\lambda_1}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_2}), & t \geq \frac{1}{\mu_H} > \frac{1}{\mu_2} \\ 0, & \text{otherwise} \end{cases}$
$K_{(i^H,j),(i^H,j+1)}(t)$	$\begin{cases} \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_H}), & t \geq \frac{1}{\mu_2} > \frac{1}{\mu_H} \\ \frac{\lambda_2}{\lambda_1+\lambda_2}(1 - e^{-(\lambda_1+\lambda_2)/\mu_2}), & t \geq \frac{1}{\mu_H} > \frac{1}{\mu_2} \\ 0, & \text{otherwise} \end{cases}$	$K_{(0,M),(1^H,M)}(t)$	$\begin{cases} 1 - e^{-\lambda_1/\mu_2}, & t \geq \frac{1}{\mu_2} \\ 1 - e^{-\lambda_1 t}, & t < \frac{1}{\mu_2} \end{cases}$
$K_{(0,M),(0,M-1)}(t)$	$\begin{cases} e^{-\lambda_1/\mu_2}, & t \geq \frac{1}{\mu_2} \\ 0, & t < \frac{1}{\mu_2} \end{cases}$	$K_{(i^H,M),(i^H,M-1)}(t)$	$\begin{cases} (1 - e^{-\lambda_1/\mu_2}), & t \geq \frac{1}{\mu_2} > \frac{1}{\mu_H} \\ (1 - e^{-\lambda_1/\mu_2}), & t \geq \frac{1}{\mu_H} > \frac{1}{\mu_2} \\ 0, & \text{otherwise} \end{cases}$

illustration.

B. Performance Measures

This section provides the performance indicators related to the network traffic model in the expression form.

- Transmission probability of HAP

$$p^t = \sum_{i^H=1}^K \sum_{j=0}^M \pi(i^H, j). \quad (4)$$

- Throughput of the system

$$\begin{aligned} \text{TP} = & \left[\sum_{i^H=1}^K \sum_{j=0}^M \pi(i^H, j) + \sum_{i^L=1}^K \sum_{j=0}^M \pi(i^L, j) \right. \\ & \left. + \sum_{j=1}^M \pi(0, j) \right] \mu. \end{aligned} \quad (5)$$

- Average packet delay at HAP and LEO queues

$$D_s = \frac{\sum_{i=1}^K \sum_{j=0}^M i \pi(i^H, j)}{\lambda_1} + \frac{\sum_{i^H=1}^K \sum_{j=0}^M j \pi(i^H, j)}{\lambda_2}.$$

- Total energy consumption

$$\begin{aligned} E_{cons} = & E_{idle} \pi(0, 0) + E_{hap} \sum_{i^H=1}^K \sum_{j=0}^M \pi(i^H, j) \\ & + E_{Leo} \left(\sum_{i^L=1}^K \sum_{j=0}^M \pi(i^L, j) + \sum_{j=1}^M \pi(0, j) \right). \end{aligned} \quad (6)$$

Here, E_{idle} , E_{hap} , E_{Leo} is the amount of energy consumed by the system in an idle state, energy consumed by HAP and LEO, respectively.

IV. DTMC FOR MODELLING EH PROCESS

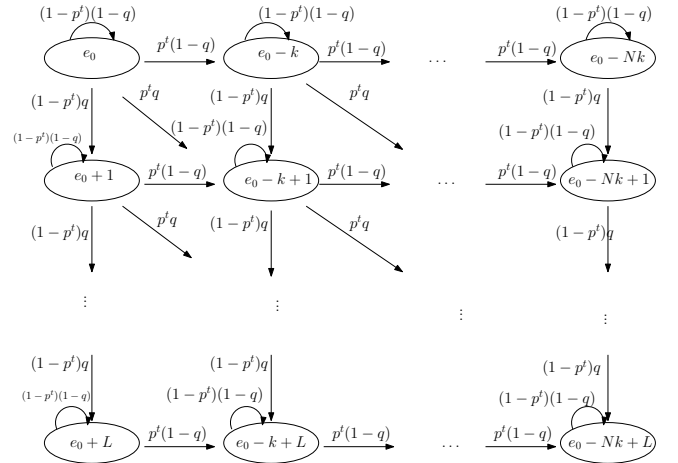


Fig. 3: State transition diagram of RF-EH model for HAP

Figure 3 denotes the state transition diagram of the proposed DTMC for the RF-EH model. Based on these assumptions, the state transition diagram of the proposed scenario has been constructed using the discrete-time Markov chain model. Here, the probability of transmission of packets is p^t , computed from the traffic model. The probability of energy harvesting is assumed as q . Therefore, HAP will only transmit the packet with probability $p^t(1-q)$; HAP will harvest the energy with probability $(1-p^t)q$, HAP will transmit and harvest energy

both with probability $p^t q$ and in case of neither transmission nor energy harvesting, the probability is $(1 - p^t)(1 - q)$. Each packet transmission will consume k unit of energy, and one unit of energy will be harvested every time.

Let the process $\{Y_n, n = 0, 1, 2, \dots\}$ denote the normalized source energy state at the beginning of n th time slot. Assume the p^t is the HAP transmission computed from the traffic model. The transition probabilities for the proposed energy harvesting model are given below. The notation for this model is defined as follows:

- $\overline{0, N-1} = 0, 1, 2, \dots, N-1$.
- P = probability measure.
- $p_{i,j}$ = transition probability from state i to state j .

$$p_{e_0 - ik + j, e_0 - (i+1)k + j} = P\{Y_{n+1} = e_0 - (i+1)k + j \mid Y_n = e_0 - ik + j\} = p^t(1 - q); i = \overline{0, N-1}, j = \overline{0, L} \quad (7)$$

$$p_{e_0 - ik + j, e_0 - ik + j} = P\{Y_{n+1} = e_0 - ik + j \mid Y_n = e_0 - ik + j\} = (1 - p^t)(1 - q); i = \overline{0, N-1}, j = \overline{0, L} \quad (8)$$

$$p_{e_0 - ik + j, e_0 - (i+1)k + (j+1)} = P\{Y_{n+1} = e_0 - (i+1)k + j + 1 \mid Y_n = e_0 - ik + j\} = p^t q; i = \overline{0, N-1}, j = \overline{0, L} \quad (9)$$

$$p_{e_0 - ik + j, e_0 - ik + (j+1)} = P\{Y_{n+1} = e_0 - ik + (j+1) \mid Y_n = e_0 - ik + j\} = (1 - p^t)q; i = \overline{0, N-1}, j = \overline{0, L}. \quad (10)$$

Based on these transition probabilities, the one-step transition probability matrix P can be obtained and solved following the methodology of DTMC. The steady-state probabilities u_i of the proposed model are computed using $uP = u$, where P is the square transition probability matrix of order $(N+1)(L+1)$ and u is the transition probability vector of order $1 \times (N+1)(L+1)$.

A. Performance Measures

In this section, the expression for average harvested energy level of HAP at the beginning of the n th time slot is given as follows

$$E_{harv} = e_0 - np^t k + np^t q. \quad (11)$$

V. NUMERICAL ILLUSTRATION

This section provides a sensitivity analysis of the performance measures concerning the system parameters. Estimation of the parameters is out of the scope this study, therefore, the values of some of the parameters have been taken from [6]. Table V denotes the values of parameters considered for the numerical illustration.

TABLE V: Default values of parameters [6]

Parameters	λ_1, λ_2	μ_H, μ_L, μ_2	$M = K$
Possible values	$0.5 - 3/ms$	$0.5 - 3/ms$	100

The behaviour of the transmission probability of HAP (p^t) with regard to μ_H and λ_1 is shown in Figures 4 and 5. p^t increases with respect to λ_1 due to more arrival of packets and increases if the service rate is increased. The behaviour of delay (D_s) with regard to K and λ_1 is shown in Figures 6 and 7. The average packet latency will increase relative to λ_1 .

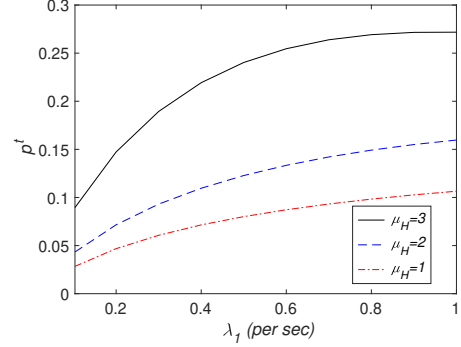


Fig. 4: Transmission probability versus arrival and service rates of UE_1

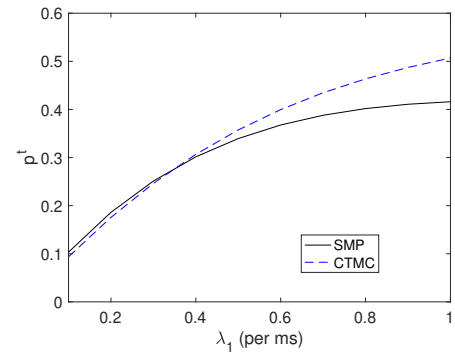


Fig. 5: Transmission probability versus arrival rate of UE_1 with SMP and CTMC case

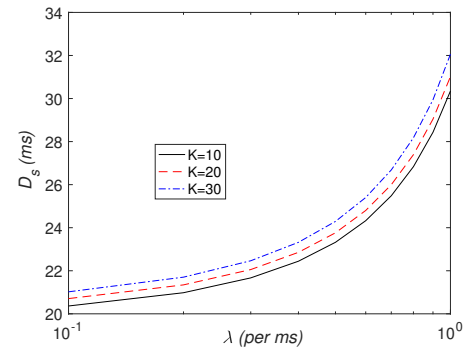


Fig. 6: Delay versus arrival rate

The behavior of throughput (TP) in relation to μ and λ is depicted in Figure 8. Due to more packets in the system, a greater parameter λ value corresponds to an increased TP . It

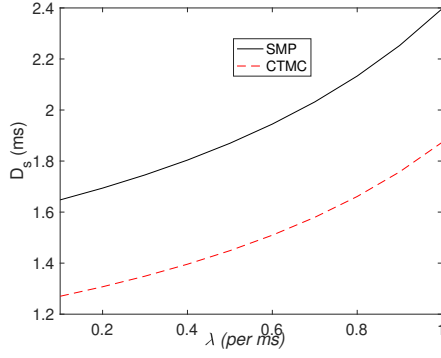


Fig. 7: Delay versus arrival for SMP and CTMC cases

is also observed that TP rises as μ increases, indicating that more packets are served and hence, higher throughput.

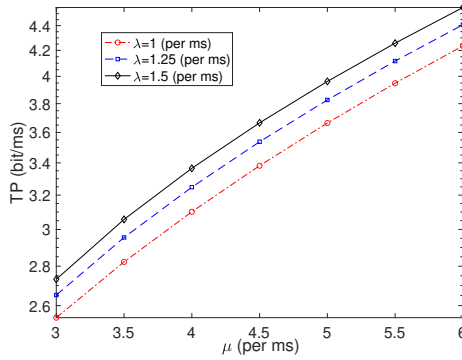


Fig. 8: Throughput versus service rate

The trade-off between energy consumption (E_{cons}) and energy harvesting (E_{harv}) is shown in Figure 9. When the parameter λ is increased, the number of packets in the system rises, leading to an increase in E_{cons} and, consequently, higher energy consumption. Similarly, when μ increases, E_{cons} also rises, indicating that the system operates for a longer period and consumes more energy as a result. This is due to the fact that the HAP remains operational, prioritizing service delivery to incoming packets over energy harvesting. Conversely, as μ increases, E_{harv} decreases, as there is a higher likelihood that the HAP is in an active state, with some of its functions dedicated to providing services.

VI. CONCLUSIONS & FUTURE DIRECTIONS

This study introduces a cooperative SAT communication network with an RF-EH policy for HAP. The proposed stochastic model is specifically designed for deployment across three layers: LEO, HAP, and user devices on the ground. The analysis includes the construction of both traffic and energy harvesting models. The traffic model is analyzed using a SMP to account for the non-exponential behavior observed in certain state transitions, while the energy harvesting model is examined using a DTMC. The traffic model evaluates critical metrics such as network practical lifetime, average

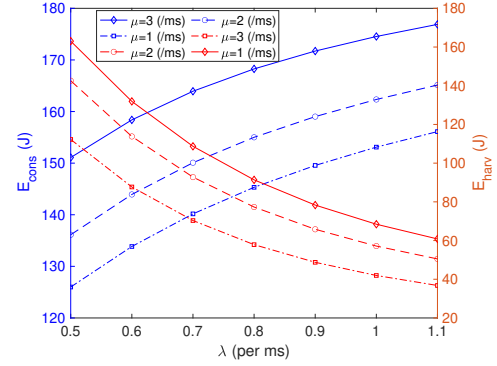


Fig. 9: Trade-off between energy consumption and average harvested energy

delay of source/relay packets, and throughput. Meanwhile, the energy harvesting model computes the average harvested energy for HAP. A comprehensive numerical illustration is provided to demonstrate the impact of these performance measures through sensitivity analysis.

VII. ACKNOWLEDGEMENT

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