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A queueing-inventory model for energy-constrained UAV base stations in non-terrestrial networks

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Abstract. Unmanned aerial vehicle base stations are envisioned as key enablers of sixth-generation non-terrestrial networks, offering on-demand aerial coverage for remote areas, mass events, and emergency scenarios; however, their operational continuity is fundamentally limited by finite onboard battery capacity, a constraint that existing analytical models address inadequately by either ignoring energy dynamics or treating battery charge as a static parameter. The purpose of this study is to develop an analytical framework that jointly captures stochastic user service and discrete battery dynamics under a controlled recharging discipline. We propose a queueing-inventory model in which the unmanned aerial vehicle base station is represented as a loss system with a discrete energy resource and a threshold-based recharging policy; users arrive according to a Poisson process, service times are exponentially distributed, each served connection consumes one energy unit, and recharging is triggered when the battery level reaches a critical threshold. The system is formulated as a two-dimensional continuous-time Markov chain, and explicit expressions are obtained for the mean number of active users, the mean battery reserve, and the user blocking probability. Numerical experiments across three operational scenarios — remote area monitoring, mass event coverage, and emergency response — reveal that the threshold parameter governs a fundamental trade-off between user throughput and recharging overhead, providing a tractable tool for selecting unmanned aerial vehicle specifications at the design stage of sixth-generation communication systems.

Key words and phrases: queueing-inventory system, loss queueing system, unmanned aerial vehicle base station, non-terrestrial network, threshold-based recharging, discrete energy resource, continuous-time Markov chain, blocking probability, sixth-generation networks

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1. Introduction

Non-terrestrial networks are recognized as a critical component of next-generation communication infrastructure, enabling the integration of space-borne and airborne platforms into terrestrial networks to provide ubiquitous connectivity [1]. Within this framework, unmanned aerial vehicles (UAVs) have emerged as key elements due to their mobility, deployment flexibility, low-altitude operation providing line-of-sight connectivity, and relatively low operational costs [2]. However, line-of-sight availability is not guaranteed in dense urban environments, where ground and rooftop-mounted obstacles introduce non-trivial blockage effects that must be accounted for in deployment planning [3]. The transition to sixth-generation (6G) networks necessitates a fundamental change of perspective on non-terrestrial architectures, positioning UAV-based platforms as indispensable components of the future communication landscape [4]. Indeed, UAVs are now recognized alongside terahertz communication and intelligent reconfigurable surfaces as key enabling technologies for 6G wireless networks [5]. The integration of UAVs with 6G networks unlocks new possibilities for applications ranging from real-time environmental monitoring and cargo delivery to emergency communications and secure relay services [6].

Despite these promising prospects, UAV adoption faces a fundamental challenge: limited energy autonomy. The operational continuity of UAVs is strictly constrained by the finite capacity of their onboard batteries. Flight times of modern UAVs typically range from 10 to 60 minutes due to size, weight, and power limitations [7]. Simply increasing battery capacity creates a paradoxical effect — larger batteries increase weight, requiring more energy for lift and potentially degrading aerodynamic performance [8]. When serving as mobile radio access nodes, additional payload equipment further increases energy consumption, reducing operational time. In remote deployment scenarios lacking ground infrastructure, UAVs must travel significant distances between service areas and recharging stations before battery depletion [9].

These constraints necessitate analytical frameworks that capture the stochastic interaction between user traffic, energy consumption, and recharging discipline. Existing queueing models for UAV networks typically abstract away energy constraints or treat battery charge as a static parameter, failing to capture the dynamic interplay between stochastic service and battery replenishment. Conversely, energy consumption models for UAVs lack the stochastic service perspective necessary for quality-of-service analysis in 6G scenarios. While substantial research has addressed each stream independently, as reviewed in Section 2, their synthesis remains underexplored.

To address this gap, we adopt the formalism of queueing-inventory systems, which provides a unified mathematical framework for jointly modeling service processes and resource replenishment [10]. The UAV battery charge is treated as a discrete resource consumed by stochastic user connections and replenished exclusively through controlled charging from a ground station. The main contributions of our study are as follows:

- We propose a queueing-inventory model for a UAV base station that jointly captures stochastic user arrivals and discrete battery dynamics under a threshold-based recharging policy.
- We formulate the system as a two-dimensional continuous-time Markov chain and derive explicit expressions for three key performance indicators: the mean number of active users, the mean battery reserve, and the user blocking probability.
- We conduct a numerical study across three representative operational scenarios — remote area monitoring, mass event coverage, and emergency response — and quantify the fundamental trade-off between user throughput and recharging overhead governed by the critical threshold parameter.

The remainder of this paper is organized as follows. Section 2 provides a concise review of related work on UAV energy modeling and queueing theory applications. Section 3 describes the system model, including the network scenario, user arrival process, and energy management policy. Section 4 presents the analytical model, where we define the state space, transition rates, and global balance equations, and derive key performance measures. Section 5 contains the numerical results and discussion for three representative operational scenarios. The final section concludes the paper and provides an outlook for further investigations.

2. Related work

This section reviews three streams of related work directly relevant to the proposed model: UAV energy modeling, queueing-theoretic analysis of UAV networks, and queueing-inventory frameworks for resource-constrained systems.

Energy constraints remain a primary operational limitation for UAV systems. Beyond the fundamental size, weight, and power trade-offs [7], propulsion efficiency varies significantly with flight parameters, and payload configuration substantially impacts overall consumption patterns [8]. Empirical models based on battery discharge experiments have established quantitative relationships between flight characteristics and energy consumption rates [11], while generalized propulsion models capture the nonlinear effects of velocity and acceleration on energy usage [8]. Energy-aware path planning has been shown to extend operational time by 15–30% compared to baseline approaches, though gains depend heavily on environmental conditions [9]. Radio-frequency energy harvesting techniques have also been explored as a means of sustaining UAV operations [12], yet such solutions remain limited by low power density and environmental variability. Trajectory optimization combining metaheuristic and reinforcement learning methods has demonstrated adaptive energy management under dynamic conditions [13]. More recently, privacy-preserving federated learning frameworks have been applied to UAV path optimization, enabling autonomous data-driven route planning without centralized data sharing [14]. Diffusion approximation has been applied to model stochastic energy changes in harvesting batteries [15], offering a complementary perspective to the discrete-state approach adopted in the present work.

Queueing-theoretic approaches have been employed to analyze UAV network performance under stochastic traffic conditions. The interaction between signal interference and queue dynamics in unlicensed spectrum has been studied, yielding models for distributed transmission control that account for both channel conditions and buffer states [16, 17]. Digital twin architectures integrated with queueing analysis have shown potential for real-time performance optimization [18]. For multi-UAV systems, Markov models capturing controlled degradation strategies in swarm delivery scenarios have been developed [19], virtual coordinate-based intra-swarm routing protocols have been proposed for GPS-denied environments [20], and deep reinforcement learning has been applied to dynamic resource allocation under quality-of-service constraints [21]. Cognitive communication frameworks with optimized downlink power control have also been investigated [22]. Joint resource allocation and path planning in mobile edge computing scenarios have been examined to minimize latency and energy expenditure simultaneously [23]. While these works address various aspects of UAV network performance, they do not incorporate discrete energy inventory dynamics into the queueing model.

The queueing-inventory framework simultaneously captures service processes and resource dynamics, making it a natural fit for systems in which service capacity depends on a replenishable resource. A comprehensive survey of inventory systems with positive service time established the theoretical foundations for this class of models [10]. The applicability of the framework to energy-constrained systems has been demonstrated through analysis of queues with controlled

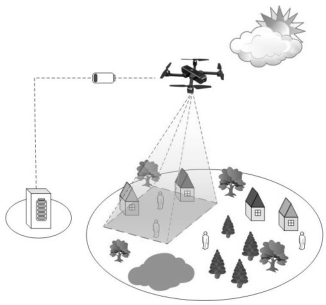

Figure 1. Schematic representation of the UAV base station system

replenishment under general input processes [24]. Queueing-inventory systems under catastrophic inventory depletion and various replenishment policies have been investigated [25], illustrating the versatility of inventory-based models for capturing complex resource dynamics.

Despite this body of work, no existing model jointly addresses stochastic user traffic and discrete battery dynamics under a threshold-driven recharging policy in a UAV base station context. This gap motivates the queueing-inventory formulation proposed in the present paper.

3. System model

The system under consideration is a UAV-mounted base station deployed in environments with limited or absent ground infrastructure, such as remote areas, mass public events, or emergency response zones. The UAV provides wireless connectivity to users in its coverage area while operating autonomously on battery power. The system comprises three main components: a rechargeable battery that supplies energy for user service, a transceiver unit that handles incoming user connections, and a controller that governs system operation by monitoring both the battery level and the number of active connections. The transceiver unit can handle up to N user connections simultaneously, reflecting the radio resource limitations of the UAV. The battery has a finite capacity divided into K identical energy slots, where each slot represents the energy required to serve one user connection to completion. The critical threshold s ($0 \leqslant s < K$) defines the minimum battery level at which the UAV must cease serving users and initiate recharging. A schematic representation of the system architecture is shown in Figure 1.

Users arrive at the coverage area and request connection to the base station according to a Poisson process with intensity λ. If the number of active connections is less than N and the battery level is above the threshold s, the arriving user is accepted and service begins immediately; otherwise the user is blocked and lost. The system thus operates as a loss system without waiting. Each completed connection consumes exactly one energy slot, causing the battery level to decrease by one unit upon service completion. Service times are independent and exponentially distributed with rate μ.

The controller continuously monitors the battery level. When the charge drops to the critical threshold s, the UAV ceases to accept new users, suspends all ongoing connections, and proceeds to the recharging station, which is assumed to be always available. The recharging process restores the battery from level s back to the maximum capacity K, with recharging time exponentially distributed with rate ν. The UAV remains completely unavailable for user service during the entire recharging cycle and resumes normal operation only after the battery reaches level K. The notation used throughout this paper is summarized in Table 1.

Table 1

Main notation

Parameter	Description
N	Maximum number of simultaneous user connections
K	Maximum battery capacity (energy slots)
s	Critical battery threshold ($0 \leqslant s < K$)
λ	User arrival rate (Poisson process intensity)
μ	Per-connection service rate (exponential service time)
ν	Battery replenishment rate (exponential recharging time)
n	Current number of active connections
k	Current battery level (energy slots)

4. Queueing-inventory model

The state of the system at time t is described by a two-dimensional stochastic process $\{\tilde{n}(t), \tilde{k}(t)\}$, where $\tilde{n}(t)$ is the number of active user connections ($0 \leqslant \tilde{n}(t) \leqslant N$) and $\tilde{k}(t)$ is the current battery level ($s \leqslant \tilde{k}(t) \leqslant K$). The system operates in two modes: the serving mode, in which the UAV accepts user connections with battery level above the threshold s, and the recharging mode, in which the UAV is at the charging station with battery level s and no connections are served. The state space is accordingly defined as:

$$\mathcal{X} = \{(n, s) : 0 \leqslant n \leqslant N-1\} \cup \{(n, k) : 0 \leqslant n \leqslant N, s < k \leqslant K\}.$$

States with $k < s$ are unreachable, since the battery never drops below the recharging threshold. The state (N, s) is also unreachable: the battery reaches level s only upon a service completion, which simultaneously frees one connection slot, so the system transitions to $(N-1, s)$ rather than (N, s). Consequently, all recharging states satisfy $0 \leqslant n \leqslant N-1$. A schematic representation of the model is shown in Figure 2.

The system dynamics are governed by three types of transitions, as illustrated in the transition intensity diagram (Figure 3):

- User arrival: from state (n, k) to $(n+1, k)$ at rate λ, when $n < N$ and $k > s$.
- Service completion: from state (n, k) to $(n-1, k-1)$ at rate $n\mu$, when $n > 0$ and $k > s$. If the resulting battery level equals s, the system enters recharging state $(n-1, s)$.
- Recharging completion: from state (n, s) to (n, K) at rate ν, for $0 \leqslant n \leqslant N-1$.

The nonzero elements of the transition intensity matrix Q are:

$$\begin{aligned}
&Q[(n,s),\ (n,K)] = \nu, \quad 0 \leqslant n \leqslant N-1,\\
&Q[(n,k),\ (n+1,k)] = \lambda, \quad 0 \leqslant n \leqslant N-1, s+1 \leqslant k \leqslant K,\\
&Q[(n,k),\ (n-1,k-1)] = n\mu, \quad 1 \leqslant n \leqslant N, s+1 \leqslant k \leqslant K.
\end{aligned}$$

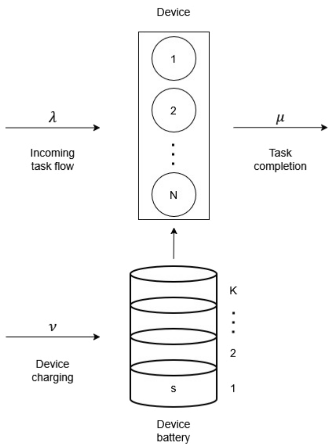

Figure 2. Queueing-inventory model

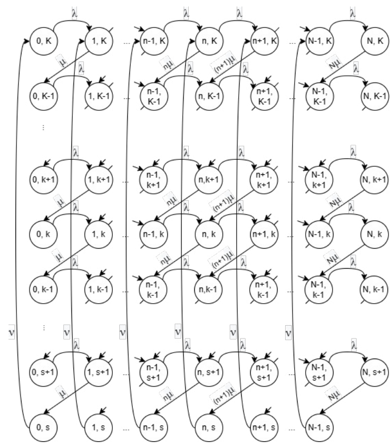

Figure 3. Transition intensity diagram

Let $\pi(n,k) = \lim_{t\to\infty} \mathrm{P}\{\tilde{n}(t) = n, \tilde{k}(t) = k\}$ denote the stationary probability of state (n,k). The global balance equations are:

$$\nu\pi(0,s) = \mu\pi(1,s+1),$$
$$\nu\pi(n,s) = (n+1)\mu\pi(n+1,s+1), \quad n = 1,\dots,N-1,$$
$$\lambda\pi(0,k) = \mu\pi(1,k+1), \quad k = s+1,\dots,K-1,$$
$$(\lambda + n\mu)\pi(n,k) = \lambda\pi(n-1,k) + (n+1)\mu\pi(n+1,k+1), \quad n = 1,\dots,N-1, k = s+1,\dots,K-1,$$
$$N\mu\pi(N,k) = \lambda\pi(N-1,k), \quad k = s+1,\dots,K,$$
$$\lambda\pi(0,K) = \nu\pi(0,s),$$
$$(\lambda + n\mu)\pi(n,K) = \nu\pi(n,s) + \lambda\pi(n-1,K), \quad n = 1,\dots,N-1,$$

supplemented by the normalization condition $\sum_{(n,k)\in\mathcal{X}} \pi(n,k) = 1$. The stationary distribution is obtained numerically by solving this linear system.

Based on the stationary distribution, three key performance metrics are defined. The mean number of active connections is:

$$L = \sum_{n=0}^{N} \sum_{k=s+1}^{K} n\pi(n,k) + \sum_{n=0}^{N-1} n\pi(n,s).$$

The mean battery reserve is:

$$Y_{\text{avg}} = \sum_{n=0}^{N} \sum_{k=s+1}^{K} k\pi(n,k) + \sum_{n=0}^{N-1} s\pi(n,s).$$

The user blocking probability accounts for two sources of blocking — energy depletion and capacity saturation:

$$P_{\text{block}} = \underbrace{\sum_{n=0}^{N-1} \pi(n,s)}_{\text{energy blocking}} + \underbrace{\sum_{k=s+1}^{K} \pi(N,k)}_{\text{capacity blocking}}.$$

These performance metrics are evaluated numerically in Section 5 for varying system parameters N, K, s, λ, μ, and ν.

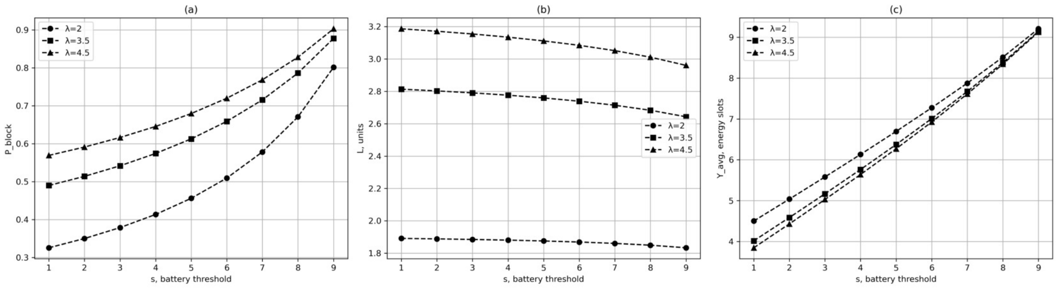

Figure 4. Performance metrics as functions of critical battery threshold s for varying arrival intensities λ: (a) user blocking probability P_{block}, (b) mean number of active connections L, (c) mean battery reserve Y_{avg}

5. Numerical results

Having obtained the stationary distribution $\pi(n, k)$ for all states $(n, k) \in \mathcal{X}$, we evaluate the three performance indicators introduced in Section 4: the mean number of active connections L, the mean battery reserve Y_{avg}, and the user blocking probability P_{block}. The numerical analysis proceeds in two stages. First, we examine the sensitivity of all three metrics to the critical threshold s for varying arrival intensities. Second, we evaluate system behavior across three representative operational scenarios that reflect distinct real-world deployment conditions.

Figure 4 illustrates the dependence of P_{block}, L, and Y_{avg} on the critical threshold s for three values of the arrival intensity ($\lambda = 2,\ 3.5,\ 4.5$). The blocking probability increases monotonically with both s and λ: higher values of s trigger recharging cycles more frequently, reducing the time the station is available for user service, and this effect is amplified under heavier traffic. The mean number of active connections remains relatively stable at low λ but decreases slightly as s increases at higher loads, reflecting the growing fraction of time spent in the recharging mode. The mean battery reserve Y_{avg} grows nearly linearly with s across all arrival intensities, confirming that it is primarily determined by the threshold rather than by traffic load. Collectively, these results demonstrate that s governs a fundamental trade-off: conservative thresholds preserve battery reserves and reduce the risk of energy depletion, while aggressive thresholds sustain higher throughput at the cost of increased blocking.

To evaluate system performance under realistic deployment conditions, we consider three scenarios summarized in Table 2, each characterized by distinct traffic intensity, radio resource capacity, battery capacity, and recharging rate. The ratio K/N reflects the energy-to-capacity balance, while the product $K \times \nu$ characterizes the overall energy throughput of the recharging infrastructure.

In the remote area scenario, the UAV operates under severe resource constraints: a very small number of simultaneous connections ($N = 2$–3), a modest battery ($K = 5$–6), and extremely slow based recharging ($\nu = 0.05$–0.10). Because the system spends most of its time in the recharging mode, the blocking probability is the highest among all three scenarios and remains nearly constant at approximately 0.97 as λ increases, while both the mean number of active connections and the mean battery reserve stay at very low levels. In the mass event scenario, the system has substantially more radio resources ($N = 12$–20), a larger battery ($K = 25$–35), and moderate recharging capability ($\nu = 0.30$–0.60). The blocking probability grows from approximately 0.40 to 0.72 as λ increases, reflecting progressive capacity saturation under heavy traffic, while the mean battery reserve decreases steadily due to continuous high-rate energy consumption. In the rescue and emergency scenario, all system parameters are scaled to their maximum values ($N = 20$–30, $K = 40$–60,

Table 2

System parameters for three operational scenarios

Scenario	λ	N	K	K/N	ν	$K \times \nu$
(A) Remote area	0.5–1	2–3	5–6	2.0–2.5	0.05–0.10	0.3–0.5
(B) Mass events	10–30	12–20	25–35	1.5–2.0	0.30–0.60	10–15
(C) Rescue and emergency	15–25	20–30	40–60	1.3–1.7	0.80–1.20	35–60

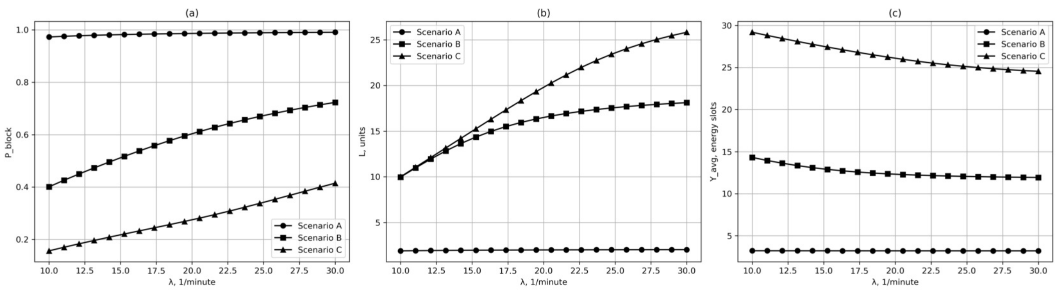

Figure 5. Performance metrics as functions of arrival intensity λ for three operational scenarios: (a) user blocking probability P_{block}, (b) mean number of active connections L, (c) mean battery reserve Y_{avg}

ν = 0.80–1.20) to maximize availability. This generous provisioning yields the lowest blocking probability among the three scenarios, rising from approximately 0.15 to 0.40, and supports the highest mean number of active connections. However, the mean battery reserve exhibits the steepest decline, underscoring the intense energy demand imposed by sustained high-throughput operation.

Figure 5 presents P_{block}, L, and Y_{avg} as functions of λ for each scenario. The results confirm the qualitative distinctions described above and reveal how the interplay between traffic load, battery capacity, and replenishment rate shapes system performance across deployment contexts. The remote area scenario exhibits the highest blocking probability due to its severely limited resources and slow recharging, while the rescue and emergency scenario achieves the lowest blocking probability owing to its maximized capacity and rapid recharging infrastructure.

6. Conclusion

This paper proposed a queueing-inventory model for a UAV base station with a discrete energy resource and a threshold-based recharging policy. The system was formulated as a two-dimensional continuous-time Markov chain, yielding explicit expressions for the mean number of active connections, the mean battery reserve, and the blocking probability. Numerical analysis across three scenarios — remote area monitoring, mass event coverage, and emergency response — confirmed that the threshold parameter s governs a fundamental trade-off between user throughput and recharging overhead, providing a tractable tool for UAV specification selection at the design stage of 6G systems. Future work includes incorporating flight trajectory energy costs, multi-UAV cooperation with handover mechanisms, and heterogeneous traffic models such as batch arrivals or non-exponential service times.

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Система массового обслуживания с запасами для беспилотных базовых станций с ограниченным энергоресурсом в неназемных сетях

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Аннотация. Беспилотные базовые станции рассматриваются как ключевые элементы неназемных сетей шестого поколения, обеспечивающие мобильное покрытие в удалённых районах, при массовых мероприятиях и в чрезвычайных ситуациях; вместе с тем их операционная непрерывность принципиально ограничена конечной емкостью бортового аккумулятора — ограничение, которое существующие аналитические модели либо игнорируют, либо учитывают лишь статически. Целью исследования является разработка аналитической модели, совместно описывающей стохастическое обслуживание пользователей и дискретную динамику заряда батареи в условиях политики подзарядки. Предлагается система массового обслуживания с запасами, в которой беспилотная базовая станция представлена как система с потерями, дискретным энергетическим ресурсом и пороговой политикой подзарядки; пользователи поступают согласно пуассоновскому процессу, времена обслуживания экспоненциальны, каждое соединение потребляет одну единицу заряда, а подзарядка инициируется при достижении критического порога. Система формализована как двумерный марковский случайный процесс; получены выражения для среднего числа активных пользователей, среднего уровня заряда батареи и вероятности блокировки. Численный анализ трёх сценариев — удаленная территория, массовое мероприятие и аварийное реагирование — показывает, что параметр порога определяет компромисс между пропускной способностью и накладными расходами на подзарядку, предоставляя инструмент для выбора характеристик беспилотных станций.

Ключевые слова: система массового обслуживания с запасами, система с потерями, беспилотная базовая станция, неназемная сеть, пороговая политика подзарядки, дискретный ресурс энергии, марковский случайный процесс, вероятность блокировки, сети шестого поколения