Blockchain-based Energy Trading among UAVs and Base Stations for Net-Zero

Ferheen Ayaz, Maziar Nekovee[†] and Nagham Saeed[*]
Department of Computer Science, City St. George's, University of London, UK
[†]6G Lab, School of Engineering and Informatics, University of Sussex, UK
[*]School of Computing and Engineering, University of West London, UK
ferheen.ayaz@city.ac.uk, m.nekovee@sussex.ac.uk, nagham.saeed@uwl.ac.uk

***Abstract*—The recent development in Internet-of-Things (IoT) networks utilizing Unmanned Aerial Vehicles (UAVs) have greatly enhanced system analysis and management. For example, an energy management system can exploit UAVs to intelligently predict output from renewable resources and estimate grid supply. However, UAVs are battery-operated and need to be charged regularly. It has become crucial to maintain supply and achieve net-zero with negligible emissions for high energy demanding IoT networks, such as those incorporating UAVs. A promising solution is to utilize backup batteries of cellular base stations (BSs) which often remain idle when grid supply is consistent. A P2P energy exchange between a BS seller and UAV buyer is possible in exchange of some incentives. However, BS operators may become selfish and not share their energy. Also, they can behave maliciously by selling energy at unreasonably high prices or sharing false information about the original source of energy. This paper proposes an energy trading system between 5G BSs and UAVs. A Reinforcement Learning (RL) algorithm is used by UAVs to select BS which maximizes incentives for both BSs and UAVs. Blockchain security increase energy exchange by 0.26 kWh and 4.9 kWh in presence of malicious and selfish BS seller respectively.**

***Index Terms*—Base station, UAV, energy, blockchain.**

I. Introduction

The Internet of Things (IoT) is rapidly transforming various sectors by connecting devices and enabling them to communicate and share data. This interconnectivity and heterogeneity facilitate smarter and more efficient operations. However, the proliferation of IoT devices also leads to a significant increase in energy demand and security requirements. Each connected device, sensor, and network component requires power to operate, adding to the overall energy consumption. IoT devices face challenges stemming from the heterogeneity in energy requirements and processing capabilities, which can lead to potential limitations in communication and the implementation of security solutions [1]. Meanwhile, environmental sustainability has become a significant focus for the Information and Communications Technology (ICT) industries. One of the environmental goals of recent IoT systems is achieving net-zero, i.e., maintaining energy demand and supply balance with negligible emissions [2].

An essential step towards net-zero goal is utilizing renewable energy resources. However, energy output from a renewable source often fluctuates. With rising energy demands of IoT systems, it has become challenging to rely on renewable sources alone for achieving net-zero. To address this issue, peer-to-peer (P2P) energy exchange among distributed consumers and sources is rapidly evolving. In a P2P exchange, the consumer, for example an Electric Vehicle (EV), can also become energy provider by trading surplus energy in its battery in exchange of some incentives [3]. This concept of prosumerism has been highly effective in reducing the burden on grid and maintaining demand-supply balance. Recently, the potential for cellular Base Stations (BSs) as prosumers has been studied [4]. The BSs are equipped with backup batteries to provide energy in case of a power disruption or incident. However, these backup batteries often remain unused and underutilized and may become resourceful to meet the energy demands of other users, such as, IoT devices.

One of the noteworthy devices in recent IoT networks is Unmanned Aerial Vehicle (UAV). Their features such as ease of mobility, small weight and aerial outreach make them highly suitable for moving in various physical environments and dynamically adjusting in diverse and heterogeneous networks [5]. They can also enable ambient intelligence for energy management and trading systems by monitoring weather parameters and predicting wind and solar energy outputs. However, they are equipped with small batteries and require efficient energy consumption and charging techniques [6]. Due to mobile nature of UAVs, they can travel to any energy-offering prosumer for a P2P energy exchange.

It is worthwhile mentioning here that the distributed control of energy trading in prosumerism comes with its own challenges including security, scalability and automation. Blockchain effectively addresses these challenges and results in a reliable P2P energy exchange [7]. Also,

Ferheen Ayaz was with University of Sussex, UK when this research work was done.

various intelligent optimization algorithms, such as Reinforcement Learning (RL) are used to manage energy exchange by matching the best traders to achieve net-zero and maximize utilities [8]. Considering the energy requirements of a UAV and sharing capabilities of a BS, this paper proposes an incentivized energy exchange from 5G BS to UAV which is secured by blockchain to provide protection from malicious or selfish behaviour of 5G BS operators. The UAVs employ RL to find the most appropriate BS for energy exchange.

A. Related Works

The capability of BS to provide energy is studied in [9]. Also, a model for bidirectional energy exchange between a BS and a solar-powered grid is outlined in [10]. A bidirectional energy exchange among BSs, EVs and grid optimized by quantum algorithm is presented in [4]. Furthermore, existing literature extensively studies energy consumption of UAVs [6]. A distributed energy trading framework for UAVs and charging stations is proposed in [11]. However, the capability of BSs to fulfill demands of UAVs is not yet explored.

Meanwhile, the utilization of blockchain for secure energy trading is extensively studied in literature. In [2], P2P energy exchange among EVs and other prosumers is presented where blockchain maintains the tamper-proof record original energy source. In [7], smart contract of blockchain enhances customizability and reliability in residential energy management systems. Federated RL supported by blockchain is used to optimize P2P energy trading among EVs and other prosumers in [8]. However, blockchain can also be used to address issues related to adversarial behavior of prosumers, such as, acting maliciously to maximize profit or being uncooperative or selfish by not sharing the energy with other devices.

B. Contributions and Organization

The main contributions of the paper are as follows

- We conceptualize an incentivized P2P energy exchange from BS to UAV.
- We formulate an RL algorithm for UAVs to select the most appropriate BS for energy trade.
- We propose blockchain to secure energy trade against adversarial behavior of BS.

The rest of the paper is organized as follows. Section II defines system model. Section III analyzes incentives maximization and describes RL optimization algorithm. Performance evaluation and conclusion are presented in Section IV and V respectively.

II. System Modeling

A. System Architecture

Consider a 5G network where $\mathcal{I} = \{1, 2, ..., I\}$ UAVs, $\mathcal{J} = \{1, 2, ..., J\}$ BSs and $\mathcal{M} = \{1, 2, ..., M\}$ microgrids producing energy from renewable resources are randomly distributed within a finite two-dimensional area. UAVs are equipped with sensors to predict weather parameters including temperature, wind speed and solar radiance to predict energy output from microgrids and energy consumption of BSs through machine learning (ML) algorithms defined in [3] and [12] respectively. BSs and their backup batteries are powered by main grid, as shown in Fig 1. UAVs charge their batteries either from microgrid or from backup batteries of BSs through wireless charging [13]. Each energy exchange of BS and UAV is recorded in the blockchain automatically through smart contract. The record consists of cryptographic identities of buyer and seller, and original source, price and amount of energy transferred. Each prosumer has its own copy of blockchain which is regularly updated. All UAVs are granted access to view blocks related to energy transactions of BSs, so they can extract information about the available energy in the backup batteries.

B. Adversary Model

The 5G BS operators who earn profit by selling energy may perform an adversarial action. We consider the following adversarial threats

a) Malicious: A malicious BS may acquire energy from a less clean or non-renewable source with low sustainability ranking and share a false energy source with the UAV or sets a very high selling price to gain large profit.

b) Selfish: A selfish BS does not sell its energy despite having sufficient available capacity.

C. Utility Model

The utility of UAV i if it buys energy from a BS j instead of a microgrid m is

$$\begin{aligned} U_i =& \frac{\alpha_1}{SoC_i} log(1 + E^x_{i,j} + S_{E^x}) + \alpha_2(p_m - p_j)E^x_{i,j} \\ &+ \alpha_3(E^t_{i,m} - E^t_{i,j}) - \sigma E^x_{i,j}, \end{aligned} \tag{1}$$

where S_{E^x} is the sustainability ranking of the energy acquired [2], SOC_i is the state of charge of UAV i, $E^x_{i,j}$ is the energy exchanged from BS j to UAV i, p_m and p_j are the prices at which energy is sold by microgrid m and BS j respectively, $E^t_{i,m}$ and $E^t_{i,j}$ are the energy consumed by UAV in traveling to a microgrid m and BS j respectively, σ is the battery degradation cost and α_n represents the adjustment coefficients. $E^t = TP^t$, where T is the travel time and P^t is the propulsion power consumption for a rotary-wing UAV with speed v defined as [14]

$$P^t = P_0\Big(1+\frac{3v^2}{v_r^2}\Big)+P_i\left(\sqrt{1+\frac{v^4}{4v_0^4}}-\frac{v^2}{2v_0^2}\right)^{\frac{1}{2}}+\frac{1}{2}\eta\tau\phi A v^3, \tag{2}$$

where P_0 and P_i are the blade profile power and induced power in hovering respectively, v_r is the speed of rotor

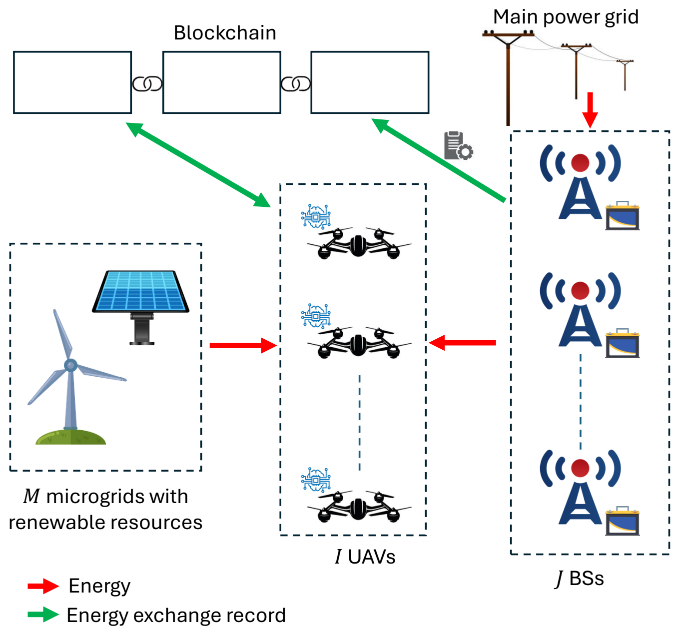

Fig. 1: System Model.

blade, v_0 is the mean rotor velocity induced in hover, η is the air density, τ is the rotor solidity, ϕ is the drag ratio and A is the rotor disc area. Assuming uniform speed of UAV, $T = d/v$, where d is the distance between UAV i and the energy seller n, defined as

$$d = \sqrt{(X_n - X_i)^2 + (Y_n - Y_i)^2 + Z_i^2}, \tag{3}$$

where X, Y and Z are location coordinates.

The utility of a BS j is

$$U_j = p_j E^x_{i,j} - Cost(E^x_{i,j}), \tag{4}$$

where $Cost(E^x_{i,j})$ is the cost at which $E^x_{i,j}$ was originally acquired and is defined as $Cost(E^x_{i,j}) = a(E^x_{i,j})^2 + bE^x_{i,j}$.

III. The Proposed Optimization Solution

A. Utility Maximization

To obtain the maximum utilities of both UAVs and BSs, we formulate a two stage Stackelberg game [15]. At first stage, a BS j announces its available energy E^x and price p_j. At second stage, UAV i determines optimal $E^{x^*}_{i,j}$ resulting in maximum utility.

Definition 1: Assume that $E^{x^*}_{i,j}$ is the optimal amount of energy for an optimal price p^*_j then

$$U_i(E^{x^*}_{i,j}, p^*_j) \geq U_i(E^x_{i,j}, p^*_j), \tag{5}$$

$$U_j(E^{x^*}_{i,j}, p^*_j) \geq U_j(E^x_{i,j}, p^*_j). \tag{6}$$

Theorem 1: The Stackelberg equilibrium point of the utility model exists which results in maximum U^*_i and U^*_j.

Proof: The first order and second order derivatives of (1) are

$$\frac{\partial U_i}{\partial E^x_{i,j}} = \frac{\alpha_1}{SoC_i E^x_{i,j}} + \alpha_2 p_m - p_j - \sigma, \tag{7}$$

and

$$\frac{\partial^2 U_i}{\partial (E^x_{i,j})^2} = \frac{-\alpha_1}{SoC_i (E^x_{i,j})^2}. \tag{8}$$

The second order derivative is negative and a strictly concave function proving the existence of Nash equilibrium. Also, the first order and second order derivatives of (4) are

$$\frac{\partial U_j}{\partial E^x_{i,j}} = p_j - 2aE^x_{i,j}, \tag{9}$$

and

$$\frac{\partial^2 U_j}{\partial (E^x_{i,j})^2} = -2a. \tag{10}$$

The second order derivative is negative and a strictly concave function proving the existence of Nash equilibrium. Therefore, the Stackelberg game equilibrium resulting in maximum U^*_i and U^*_j exists when

$$\frac{\alpha_1}{SoC_i E^x_{i,j}} + \alpha_2 p_m - p_j - \sigma = p_j - 2aE^x_{i,j}. \quad \square \tag{11}$$

Algorithm 1 Blockchain based RL Solution.

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1: procedure RL BASED MDP.
2:     Obtain E^x_{i,j}, S_{E^x}, Cost(E^x_{i,j}) ∀j ∈ 𝒥 and verify blockchain record.
3:     Obtain p_j ∀j ∈ 𝒥 from BS.
4:     For any stage t, determine s_i(t).
5:     while j ≤ J do
6:         For every state s(t) compute U_i + U_j.
7:     end while
8:     Select optimum BS j* with maximum U_i + U_j meeting C1 to C5.
9:     return j* for every UAV i.
10: end procedure
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B. RL Algorithm

The proposed RL solution, as shown in Algorithm 1, optimizes the problem to find optimal $E^x_{i,j}$ and select the most appropriate BS for a UAV by Markov Decision Process (MDP). The optimization problem and MDP are defined as follows.

1) Optimization Problem Formulation: Each UAV i optimizes the following problem

P1:

$$
\begin{aligned}
\max_{j,\, E^x_{i,j}} \quad & U_i + U_j \\
\text{s.t.} \quad & \text{C1: } U_i > 0, \\
& \text{C2: } U_j > 0, \\
& \text{C3: } p_j - Cost(E^x_{i,j}) \leq \bar{p}, \\
& \text{C4: } S_{E^x} \geq \underline{S}, \\
& \text{C5: } \sum_{i=1}^{I} E^x_{i,j} \leq \underline{E^x},
\end{aligned}
\tag{12}
$$

where constraint C1 and C2 guarantee the positive utilities of UAV and BS respectively, C3 and C4 set the upper and lower bound to the profit and sustainability factor of the energy and C5 ensures a minimum amount of energy that a BS must keep to power itself in emergency situations even after selling a portion to one or more UAVs. The blockchain record contains immutable values of $Cost(E^x_{i,j})$ and S_{E^x} to prevent cheating by adversarial BSs.

2) Markov Decision Process (MDP): The MDP is represented by the following parameters.

a) State Space: Any UAV i is viewed as an agent in the system, and its state is a combination of its speed $v(t)$, $E^x_{i,j}(t)$ and $T_j(t)$ at time t, where $T_j(t)$ represents the traveling time from UAV to a BS j at time t. Let s_i be the state of UAV defined as

$$s_i(t) = (v(t), E^x_{i,j}(t), T_j(t)) \tag{13}$$

TABLE I: Simulation Parameters

Parameter	**Value**	**Parameter**	**Value**
I	[10, 30]	J	10
α_1	0.1	α_2	0.002
α_3	0.1	σ	0.501
a	0.1	b	0.096
η	1.225 kg/m^2	τ	0.05
ϕ	0.6	A	0.503
v_0	4.03 m/s	v_r	120 m/s
v	30 m/s	z_i	100 m
P_0	79.86 W	P_i	88.63 W
$\bar{p}$	0.5	$\underline{E^x}$	5 kWh

b) Action Space: The action set $\mathcal{A} = \{1, 2, ..., J\}$ represents the set of possible actions. The action that an agent takes is to select a BS j out of J BSs.

c) Reward Function: The reward function is the objective function of problem P1, which is the sum of utilities of UAV and BS. The gain of the reward is determined by the actions of agent. It is possible that a BS j results in the maximum reward for more than one UAV. In this case, a BS may decide number of buyers for itself according to its available capacity and constraints.

C. Complexity

According to the two stage Stackelberg game, the complexity of first stage is $\mathcal{O}(J)$. For second stage, line 5 of Algorithm 1 shows complexity of $\mathcal{O}(J)$. Therefore, the overall computational complexity of the solution is $\mathcal{O}(J^2)$. The complexity of the solution rises with the increase in number of BSs. However, it can be limited if a UAV considers only a range of BSs in a restricted or pre-defined area instead of all available and connected BSs.

IV. Performance Evaluation

We analyze the performance of the proposed solution using Python. Table I lists the simulation parameters which align with other related research [14]. Two renewable resources of wind and solar energy each are considered with sustainability rankings defined in [2]. The energy consumption of BSs is extracted at a random time from open-source dataset provided in [16]. The SoC of UAV is assumed as random variable following normal distribution with mean and variance of 0.5. The battery capacities of BS and UAV are 30 kWh and 2.59 kWh respectively. The results are averaged over 100 simulations with each simulation running for one hour.

Fig. 2 illustrates Definition 1 and Theorem 1. It shows the Nash equilibrium points of U_i and U_j both lying at the Stackelberg equilibrium point depicting $E^{x^*}_{i,j}$. A UAV i can earn positive U_i even when the price offered by a BS is higher than a microgrid price when it has to travel less to reach a nearby BS than a microgrid resulting in less energy consumption while traveling. Installing a microgrid with renewable energy output requires additional infrastructure cost, whereas, the installation of BSs is now increased due to 5G rollout. A higher number of BSs is already expected

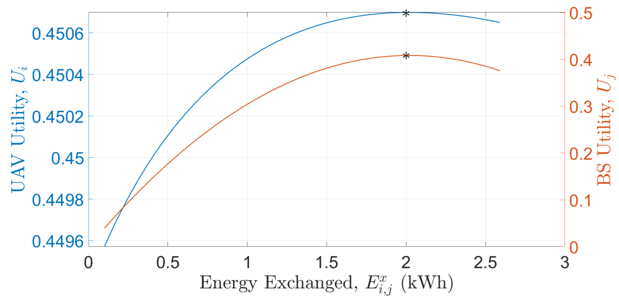

Fig. 2: Utilities of UAV and BS.

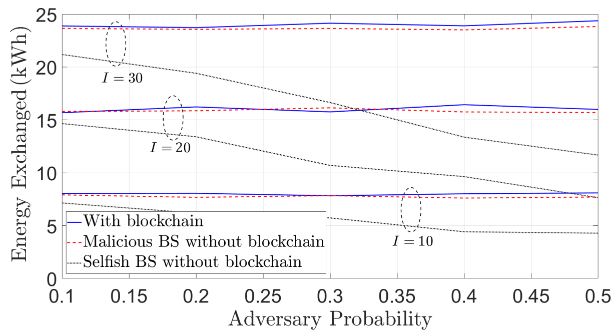

Fig. 3: Total energy exchanged from BSs to UAVs.

with their primary purpose of providing connectivity. Therefore, the installed 5G BSs can also contribute to net-zero without any additional cost.

Fig. 3 shows the total amount of energy sold by BSs to UAVs in presence of varying percentage of adversary. Adversarial BSs are assumed to be present uniformly with a random probability. The blockchain has an immutable record of all energy transactions by BSs. Therefore, UAVs are able to evaluate the available surplus energy and profit margin for each BS. Without blockchain, the malicious BSs may significantly increase their profit resulting in low or negative U_i. A UAV does not complete energy exchange if $U_i \leq 0$, as identified in C1. Also, the energy exchange does not take place if BSs become selfish and choose not to share their energy. However, the use of blockchain enforces positive cooperation. The increase in energy exchange by blockchain is 0.26 kWh and 4.9 kWh as compared to no blockchain in presence of malicious and selfish BSs respectively.

Fig. 4 shows the number of exchanges taken place in each simulation. Similar to total energy exchange shown in Fig. 3, the number of exchanges increase with the number of UAVs. With use of blockchain, the number of exchanges are independent of the probability of adversary. Malicious probability also has no direct impact on the number of exchanges. This is because a high selling price may also result in $U_i > 0$ if a BS is located nearby. However, selfish BSs significantly affect the amount of energy and number of exchanges.

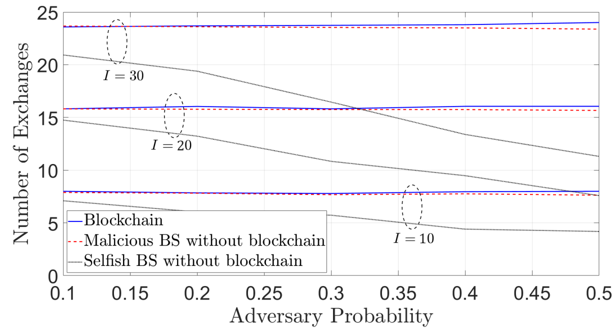

Fig. 4: Number of exchanges.

V. Conclusion

This paper proposes cellular BSs as the energy sellers in P2P distributed energy exchange. Their potential to power UAVs through their available capacity in backup batteries is studied. An RL algorithm is proposed through which UAVs find the most suitable BS for charging their batteries on the basis of sum of utilities UAVs and BSs. Furthermore, the security aspect of energy exchange is also studied by considering two types of adversaries: malicious and selfish. Blockchain is presented as a solution to smoothly run the algorithm despite the presence of adversaries. Simulation results show 0.26 kWh and 4.9 kWh increase in energy exchange by blockchain in presence of malicious and selfish BSs respectively, compared with the same algorithm executed without blockchain.

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