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# Energy-Efficient UAV-to-User Scheduling to Maximize Throughput in Wireless Networks

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**ABSTRACT** The unmanned aerial vehicle (UAV) communication is a potential technology to meet the excessive next-generation cellular users' demand due to its reliable connectivity and cost-effective deployment. However, UAV communications have to be energy efficient so that it can save energy. Thus, the UAV flies sufficiently long enough time to serve the ground users with limited on-board energy. In this paper, we investigate an energy-efficient UAV communication via designing the UAV trajectory path. We consider throughput and the UAV propulsion energy consumption jointly. We assume that the UAV flies at a fixed altitude such that it can avoid tall obstacles. A binary decision variable is assigned to schedule UAV-to-user communication. First, we derive the UAV-to-user channel model based on the line of sight and non-line of sight communication links and jointly optimize the trajectory, transmit power, and the speed of UAV; and UAV-to-user scheduling to maximize throughput. Then, we apply the UAV propulsion energy consumption, which is a function of the UAV trajectory and speed. Finally, we formulate the UAV energy-efficiency maximization problem, which is defined as the total bits of information sent to the ground users by consuming the UAV energy for a given UAV flight duration. The formulated energy-efficiency maximization problem is non-convex, fractional, and mixed-integer non-linear programming in nature. We propose an efficient algorithm based on successive convex approximation and classical Dinkelbach method to achieve the optimal solution of energy-efficient UAV. We present simulation results to validate the efficacy of our proposed algorithms. The results show a significant performance improvement compared to the benchmark methods.

**INDEX TERMS** UAV, throughput, UAV propulsion energy, energy-efficiency, UAV-user scheduling.

## I. INTRODUCTION

Recently, the unmanned aerial vehicles (UAVs) communication has attracted substantial attention by fifth-generation (5G) and beyond wireless networks researchers due to its salient features to support convenient connectivity with enhanced spectral efficiency [1]. The UAV provides on-demand, cost-effective deployment, on-board communication, and the flexible system reconfiguration compared to the base stations (BSs) on the ground [2]–[4]. In particular, it can support better communication links between air and ground terminals due to less signal blockage and shadowing effects.

The specific system reconfiguration provides flexible and reliable connections between the UAV and its users with reduced power consumption. The BS can be excessively crowded nowadays while serving the exploding traffic demands. Moreover, the BS may malfunction anytime. Thus, there arises a burning issue to serve the users in the event of too congested traffic, the BS hardware limitation, etc. Fortunately, the UAV potentially overcomes this issue owing to its cost-effective and energy-efficient features. Moreover, the UAVs offer a better line of sight (LOS) communication links by significantly shortening the UAV to user distance. UAV communication has many potential applications, which can be categorized as follows:

1) The UAV works as the aerial BS o support the ground users [5]–[7]. In any case, the UAV also provides

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reliable connectivity with low latency. In this scenario, the UAV flies while it has a quasi-stationary position on the air. This kind of UAV communication can apply in many areas, such as recovering the natural disaster, remote areas, etc.

2) The UAV can also work as a relay to support the distance/remote users [8], [9]. The UAV relay can be mobile/static and is a great choice to support smart cities in the next-generation wireless networks.
3) UAV communication can be used to send/receive real-time information [10]. This also suitable for the periodic sensing applications such that the UAV can fly over the sensors. This leads to potential network lifetime enhancement.

When the UAV serves like the terrestrial wireless communication infrastructure, it can enlarge the next generation wireless capacity due to its reliable uplink and downlink communication, mobility, swift deployment, and on-demand service, etc. Moreover, the UAV deployment as an aerial BS can also compensate signal blockage due to its LOS channel advantages. Furthermore, the UAV deployment can limit the higher transmit power compared to the BS on the ground because the UAV can easily adjust its mobility and altitude based on the user's location. These features eventually provide a solution of the energy-efficient UAV deployment to serve the users on the ground in the event of the malfunctioning of the BS on the ground [5], [11].

Though the UAV has many potential features, it still has the challenge of energy-efficient UAV deployment due to its limited on-board energy. Thus, our primary motivation is to design the energy-efficient UAV communication when the BS has the hardware limitation. It is essential to maximize the amount of information per unit UAV energy consumption during the UAV flight time to achieve optimal energy efficiency. This is because of the fixed weight and size of UAV, which may limit the overall system performance. Thus, designing energy-efficient UAV communication is more challenging than energy-efficient terrestrial BS communication infrastructure. Unfortunately, the UAV has limited power resources on-board due to its wight, flight time, etc. However, the UAV is required sending the maximum amount of information with these limited resources to attain the quality of service (QoS).

Energy-efficient UAV wireless communication has been an active research topic lately. There are many examples of simplified models for UAV-assisted networks in the literature [12]–[26]. For example, the UAV is not designed to support the distant users on the ground because of its limited energy supplies [14] unless the UAV works as the relay. However, the UAV moves on-demand basis, which is a good fit for nearby users. Throughput optimization using multiple antennae [15] and system throughput maximization using the UAV [16] were studied based on trajectory optimization. However, the energy-efficient UAV deployment is not considered in these works. The authors in [17] investigated the energy-efficiency approach by considering a simple channel model. An energy-efficient UAV communication by optimizing the trajectory is investigated in [18]. Furthermore, the authors in [18] considered the fixed UAV altitude to optimize energy-efficiency for various trajectory designs. The authors proposed an efficient algorithm to design the energy-efficient UAV communication considering the single user and simple channel model. Though they proved the improved performance for the single user, they did not consider the decision binary variable to schedule the UAV-to-user in the event of BS malfunctioning.

The authors in [19] proposed the UAV-enabled mobile edge computing, where the offloading is performed via trajectory design, and throughput maximization for UAV fixed altitude is studied. Authors in [20] proposed the resource allocation algorithm to design multicarrier solar-powered UAV networks, which serves ground users. On the other hand, an algorithm is proposed to design the UAV trajectory, considering energy-efficient UAV communication in [21]. They also aimed to secure the wireless network via UAV. In [22], the authors studied the underlaid D2D communications. They also investigate the spectrum sharing with UAV-assisted wireless networks. The UAV implementation can substitute the traditional BS of the cellular networks due to its innovative method with flexible, robust, and low latency wireless communication [23].

The authors in [24] studied the energy-efficient machine-to-machine communication system, where they assumed the fixed UAV flying speed. A novel scheme is proposed in [25], where the users and the UAV share the same frequency, and there is no user-to-user communication. In their system, the total number of orthogonal channels is higher than the total number of users, and the received signal to interference and noise ratio (SINR) is higher than the minimum SINR level. The author in [26] investigated the average worst-case secrecy rate considering a simple channel model in the presence of the unknown adversaries. However, energy-efficient UAV communication is not studied in the proposed system model in [26]. None of [15]–[18], [24]–[26] considers the decision variable for the UAV-to-users scheduling and LOS/NLOS based channel model in their investigations.

In this paper, we maximize the system throughput and energy-efficiency of the UAV via optimizing the UAV trajectory optimization by considering the air-to-ground channel based on LOS and non-line of sight (NLOS), and the UAV propulsion energy consumption. We consider orthogonal frequency-division multiple access (OFDMA) in the proposed system. Table 1 describes the mathematical symbol used in the paper. The main contributions of our paper are described as follows:

- We formulate the channel model based on both LOS and NLOS communications links. We use LOS and NLOS based channel model to formulate throughput maximization problem via designing the UAV trajectory while multiple users are present on the ground. The binary decision variable indicates the connectivity of the UAV-to-user. However, the formulated

**TABLE 1.** List of mathematical symbols used in the paper.

| Parameter | Description |
|---|---|
| $v_u$ | UAV speed |
| $c_u$ | Throughput |
| $c_l$ | Speed of light |
| T | UAV flight time |
| $(x, y)$ | Location of UAV |
| $\delta^{ee}_{uav}$ | Energy efficiency |
| $f_c$ | Carrier frequency |
| $\alpha$ | Path loss exponent |
| $h^c_u$ | Average channel gain |
| $g$ | Gravitational constant |
| $v_{max}$ | Maximum UAV speed |
| $b_u$ | UAV-to-user scheduling |
| $p^u_{LoS}$ | Probability of LOS link |
| $(x_u, y_u)$ | Static location of user, $u$ |
| $p^u_{NLoS}$ | Probability of NLOS link |
| $v_{nv}$ | Newly introduced variable |
| $\mathcal{U}$ | Set of users on the ground |
| $f_u$ | Approximated channel model |
| $p_u$ | UAV transmit power to user $u$ |
| $\Phi$ and $\psi$ | Environment dependent constants |
| $a$, $b$ | UAV weight dependent constants |
| $PL^u_{LoS}$ | Path loss model for the LOS link |
| $PL^u_{NLoS}$ | Path loss model for the NLOS link |
| $\rho$ | Each equal time slots with slot size |
| $\sigma^2$ | Power of the AWGN at the receiver |
| $N$ | Number of equal and static time slot |
| $e_u$ | UAV propulsion energy consumption |
| $r_u$ | Distance between the UAV and user, $u$ |
| $p^{max}_u$ | Maximum UAV transmit power to user, $u$ |
| $\delta_1$ | Excessive path loss coefficient for LOS |
| $\delta_2$ | Excessive path loss coefficient for NLOS |
| $f^{opt}_{u,max}$ | Upper limit of approximated channel gain |

problem is non-convex and mixed-integer non-linear problems (MINLP) problems. We tackle to throughput maximization problem by using the successive convex approximation (SCA) [27]. *cvx* solver, *mosek* can address MINLP.

- We investigate the UAV propulsion energy consumption, which is a function of UAV trajectory and speed. The UAV energy-efficiency problem is formulated via jointly optimizing the UAV trajectory radius, UAV transmit power, UAV-users scheduling, and UAV mobility. However, the formulated problem is non-convex, fractional, and MINLP.
- To reduce the complexity of the formulated energy-efficiency optimization problem, we perform the approximation of the formulated problem. The optimization problem is solved effectively by our proposed efficient algorithm based on SCA, which tackles the conconvexity. Moreover, the Dinkelbach method deals with the fractional problem. Moreover, *cvx* solver, *mosek*, can tackle MINLP.
- Finally, we present the improved performance of the proposed algorithm via the simulation results by using the optimal parameter configuration for the UAV trajectory, the UAV height, decision variable, and UAV mobility.

The rest of the sections of the paper are organized as follows: We present the system model in Section II. In Section III, the throughput maximization problem is formulated and solved. The UAV optimal energy-efficiency maximization problem is analyzed in Section IV. We propose two efficient algorithms, which solve throughput and energy-efficiency maximization in Section V. Finally, the proposed schemes are validated via simulation results in Section VI. We conclude in Section VII.

*Notations:* Lower case boldface letter, italic letters, $\log_2(.)$, $\| \, . \, \|$, [.], $(.')$, $(.)_i$, $(.)_{i+1}$,and $\tan(.)^{-1}$ denote vectors, scalars, logarithm with base 2, norm, function of time, transpose of vector, $i$ iteration, $(i+1)$ iteration, and inverse tangent function, respectively.

## II. SYSTEM MODEL AND KEY DEFINITIONS

Nowadays, the base stations (BSs) are too congested with next-generation users, which may prevent users from attaining the required quality of service (QoS). As an alternative, the unmanned aerial vehicles (UAVs) can support excessive users, especially when the BS has the hardware limitation or the malfunctioning. In that case, the UAV can also serve as a terrestrial wireless network infrastructure [28].

### A. SYSTEM MODEL

In Fig. 1, we consider a wireless communication system in a geographical area, containing a UAV, and a set of multiple users $\mathcal{U}$ on the ground, where $\mathcal{U} = \{1, 2, 3, \ldots, U\}$ and $U$ is the total number of users. The UAV is dedicated to supporting a $\mathcal{U}$ set of users. In our investigation, the UAV dynamically moves to serve the users. The UAV flight duration to serve the users on the ground is $0 \leq t \leq T$.

The locations of the users are entirely known to the UAV, which is used for designing the trajectory. The location of the static user $u$ on the ground is denoted as $(x_u, y_u)$. We investigate the LOS and NLOS communication links based channel model, which has negligible shadowing and multipath effect. Thus, we leave these issues as our future work. We consider the time varying location of the UAV is $(x(t), y(t))$.

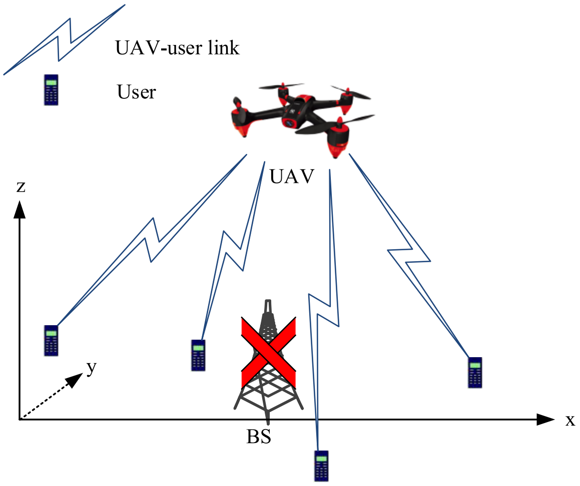

**FIGURE 1.** **The UAV flies over the users on the ground. A binary decision variable schedules UAV-to-user communication in the event of the BS malfunctioning or hardware limitation, etc. Thus, the UAV works as terrestrial wireless network infrastructure.**

The distance between the UAV and user $u$ is:

$$r_u(t) = \sqrt{(x(t)-x_u)^2 + (y(t)-y_u)^2 + h}. \tag{1}$$

where $h$ is the UAV fixed altitude. In particular, $r_u$ can balance throughput maximization and eventfully results in the energy-efficient UAV.

### B. THE UAV-TO-USER SCHEDULING

Binary decision variable, $b_u(t)$, is used as an indication of the connectivity between the user $u$ and the UAV. If $b_u(t)$ is 1, the user $u$ is supported by the UAV. If $b_u(t)$ equals 0, then otherwise. We can express as follows:

$$b_u(t) = \begin{cases} 1, & \text{the user } u \text{ supported by the UAV,} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

### C. CHANNEL MODELING

The channel between the UAV and the users consists of both LOS and NLOS paths. Firstly, the probability of existing a LOS link [29] between UAV and user $u$ is:

$$p^u_{LoS}(t) = \frac{1}{1+\psi \exp\left[\Phi\left(\frac{180}{\pi}\tan^{-1}\frac{h}{r_u(t)}\right)-\psi\right]}, \tag{3}$$

where $\Phi$ and $\psi$ are constant values depending on the environment such as urban, and suburban. The probability of NLOS between the UAV and user $u$ is:

$$p^u_{NLoS}(t) = 1 - p^u_{LoS}(t). \tag{4}$$

The increment of $r_u(t)$ results in the decrements of $p^u_{LoS}(t)$ in (3) and the increment of $p^u_{NLoS}(t)$ in (4). However, the path loss model for the LOS link between the UAV and the user $u$ is [4]:

$$PL^u_{LoS}(t) = \delta_1\left[\frac{4\pi f_c h}{c_l}\right]^\alpha p^u_{LoS}(t), \tag{5}$$

where $\delta_1$ is the excessive path loss coefficient for LOS links, which is an environment constant depending on the area type, such as urban, suburban, etc. Moreover, $f_c$ is the carrier frequency, $\alpha$ is the path loss exponent, and $c_l$ is the speed of light. The path loss model for the NLOS links between the UAV and the user $u$ is:

$$PL^u_{NLoS}(t)=\delta_2\left[\frac{4\pi f_c h}{c_l}\right]^\alpha p^u_{NLoS}(t), \tag{6}$$

where $\delta_2$ is the excessive path loss coefficient for NLOS links, which is also the environment constant depending on the area type. However, it is impossible to determine the path loss type experienced by the UAV and the user $u$ by only knowing $r_u$ if it is LOS or NLOS paths. Thus, to find the path loss model, we determine an average path loss model for these two types.

### D. THROUGHPUT

Now, we achieve the average path loss using (3) - (6). Thus, the average path loss between the UAV and the user $u$ is:

$$PL^u_{avg}(t)=\left[\frac{4\pi f_c h}{c_l}\right]^\alpha (\delta_1 p^u_{LoS}(t) + \delta_2 p^u_{NLoS}(t)). \tag{7}$$

The average channel gain for the user $u$ is the inverse of (7) [4, Eq. (3)]. The channel gain is expressed as follows:

$$h^c_u(t) = \frac{1}{PL^u_{ag}(t)}, \tag{8}$$

where $h^c_u(t)$ represents the channel gain based on LOS and NLOS communication links. We apply the Shannon capacity to define the throughput for user, $u$ during the UAV flight time $0 \leq t \leq T$ as follows:

$$c_u(t) = b_u(t)\log_2\left(1+\frac{p_u(t)h^c_u(t)}{\sigma^2}\right), \tag{9}$$

where $p_u$ is the UAV to user $u$ transmit power and $\sigma^2$ defines the additive white Gaussian noise (AWGN) power at the receiver. (9) also considers the UAV-to-user $u$ scheduling while calculating the channel gain.

### E. UAV PROPULSION ENERGY CONSUMPTION

The amount of energy consumed by UAV is propulsion energy consumption, which has a significant impact on system performance. Energy consumption due to the signal processing energy, radiation, and circuitry energy consumption of the UAV has a negligible impact on the overall system performance. If UAV is flying with fixed wings with no abnormalities, such as no engine abnormality to generate a backward thrust against forwarding speed, then the required total propulsion energy consumption is a function of $r_u$ during $0 \leq t \leq T$ period. Moreover, for energy-efficient trajectory design, UAV velocity and energy consumption should have an optimal trade-off, which can be obtained by designing the UAV trajectory. Thus, UAV energy consumption [18] due to user $u$ for a circular trajectory path can be expressed as follows:

$$e_u(t) = \left(a\|v_u(t)\|^3 + \frac{b}{\| v_u(t) \|} + \frac{b \; \| v_u(t) \|^3}{r_u(t)^2 g^2}\right), \tag{10}$$

where $a$ and $b$ are both UAV weight dependent constants. Furthermore, $v_u$ is the velocity, while flying over the user $u$. $g$ is gravitational constant, while $r_u$ is the distance between the UAV and the user $u$.

### *F. ENERGY-EFFICIENCY*

We maximize the UAV energy-efficiency by jointly optimizing throughput and energy consumption. First we formulate the UAV energy-efficiency problem, $\delta_{uav}^{ee}$. Thus, energy-efficiency for the total number of users during the UAV flight time is formulated by combining (9) and (10) as:

$$\delta_{uav}^{ee}(t) = \frac{\sum_{u=1}^{U} \sum_{t=1}^{T} c_u(t)}{\sum_{u=1}^{U} \sum_{t=1}^{T} e_u(t)}. \tag{11}$$

## III. THROUGHPUT MAXIMIZATION

### *A. PROBLEM FORMULATION*

We now formulate throughput maximization problem under the constraints of the UAV trajectory, binary variable, transmit power, and velocity. This maximization problem is:

$$\mathbf{P_1}: \max_{x(t),y(t),b_u(t),p_u(t)} \frac{1}{UT} \sum_{u=1}^{U} \sum_{t=1}^{T} c_u(t) \tag{12a}$$

$$\text{s.t. } 0 \leq p_u(t) \leq p_u^{max}, \quad \forall t, \tag{12b}$$

$$r_u(0) = r_u(T), \tag{12c}$$

$$\sum_{u=1}^{U} b_u(t) \leq 1, \quad \forall t, \tag{12d}$$

$$(x(t+1)-x(t))^2 + (y(t+1)-y(t))^2 \leq v_u^2, \tag{12e}$$

$$b_u(t) \in \{1, 0\}. \tag{12f}$$

where (12b) defines the UAV transmit power control limit during $0 \leq t \leq T$ period. $p_u^{max}$ is the maximum UAV transmit power to user $u$. In (12c), the UAV returns to its initial location, where $r_u(0)$ is initial and $r_u(T)$ is final locations of the UAV. Moreover, $b_u(t)$ allows user $u$ to be served by the UAV. The UAV and user $u$ association, scheduled by $b_u(t)$, is described in (12f). We define (12d) as follows. Recall that a binary variable $b_u(t) \in \{1, 0\}$ schedules the UAV and user $u$ communication, which is shown in (2). Here, if $b_u(t)$ is 1, then the UAV is connected to support the user $u$. Thus, (12d) defines the UAV and $\mathcal{U}$ set of users connectivity. The mobility constraint of the UAV is defined in (12e).

However, it is readily observed that $\mathbf{P_1}$ is not a convex problem with fractional objection function. Thus, $\mathbf{P_1}$ cannot be solved directly due to *1) continuous function,* $r_u(t)$, *2) continuous UAV flight time*, and *3) MINLP nature*. Hence, we approximate $\mathbf{P_1}$ to the new problem to solve it optimally. The transformation of problem $\mathbf{P_1}$ is presented in the next subsection.

### *B. PROBLEM TRANSFORMATION*

The transformation of the $\mathbf{P_1}$ is performed in several steps, resulting in the final approach as convex. To make this process transparent and understandable, we summarize these essential steps as follows. Firstly, the transformation of $\mathbf{P_1} \longrightarrow \mathbf{P_2}$ is performed, where we employ the discrete space representation, i.e. replacing $t$ by $n$. Secondly, the transformation of $\mathbf{P_2} \longrightarrow \mathbf{P_3}$ is developed. We add the auxiliary variable to the objective function. However, the transformed problem $\mathbf{P_3}$ is still a non-convex problem due to its one of the newly added constraint. Therefore, we approximate (12) to make them convex. We then propose an algorithm based on SCA to solve the problem $\mathbf{P_1}$ optimally.

#### 1) TRANSFORMATION OF $\mathbf{P}_1$ to $\mathbf{P}_2$

The problem $\mathbf{P_1}$ can be rewritten as follows:

$$\max_{x[n],y[n],b_u[n],p_u[n],v_u[n]} \frac{1}{UN} \sum_{u=1}^{U} \sum_{t=1}^{T} c_u[n], \tag{13a}$$

$$\text{s.t. } 0 \leq p_u[n] \leq p_u^{max}, \quad \forall n, \tag{13b}$$

$$r_u[0] = r_u[N], \tag{13c}$$

$$\sum_{u=1}^{U} b_u[n] \leq 1, \quad \forall n, \tag{13d}$$

$$(x[n+1]-x[n])^2 + (y[n+1]-y[n])^2 \leq (v_u \rho)^2, \quad \forall n, \tag{13e}$$

$$b_u[n] \in \{1, 0\}. \tag{13f}$$

where

$$c_u[n] = b_u[n] \log_2 \left(1 + \frac{p_u[n] h_u^c[n]}{\sigma^2}\right). \tag{14}$$

We explain the detailed approximation in (13), as follows: we divide the UAV flight time period $T$ into $N$ equal and static number of time slots with a slot size $\rho = \frac{T}{N}$ and $n = 1, 2, 3, \ldots N$. The time slots are represented by $N$ vector sequences for designing the trajectory of the UAV. Furthermore, $(x, y)$, $v_u$, and $b_u$ can be approximated for the each time interval, $\rho$. Thus, (13b) - (13f) can be expressed as the equivalent expressions to (12b) - (12f). The binary variable in (13f) is described as the continuous variables [30]. Thus, it can be expressed as follows:

$$0 \leq b_u[n] \leq 1, \quad \forall n, \forall U. \tag{15}$$

The relaxation of binary variable $b_u[n]$ results that the objective function serves as a upper bound for (16), Moreover, (13e) is the UAV mobility constraint. The new optimization problem is reformulated as $\mathbf{P_2}$:

$$\mathbf{P_2}: \max_{x[n],y[n],b_u[n],p_u[n],v_u[n]} \frac{1}{UT} \sum_{u=1}^{U} \sum_{n=1}^{N} c_u[n],$$

$$\text{s.t. } (13b) - (13e), \ (15). \tag{16a}$$

#### 2) TRANSFORMATION OF $\mathbf{P}_2$ to $\mathbf{P}_3$

$\mathbf{P_2}$ is not convex due to its objective function. We approximate the objective function of (16a) to a convex function by introducing a new variable. Throughput based on Shannon capacity is defined in (14). Thus, we approximate the channel gain, $h_u^c[n]$, into $f_u[n]$ for user $u$.The throughput with the new variable is appeared as follows:

$$c_n^u[n] = b_u[n] \log_2 \left(1 + f_u[n]\right) - \log_2(\sigma^2). \tag{17}$$

where (17) is equivalent to (14).

*Proof:* The proof is given in Appendix VII. ☐

Now, $f_u[n]$ can be expressed as follows:

$$f_u[n] \triangleq \frac{1}{W r_u[n]} \left( \frac{1}{\delta_1 p_{LoS}^u[n] + \delta_2 p_{NLoS}^u[n]} \right), \tag{18}$$

where $W = \frac{c}{4\pi f_c}$. New variable, $f_u[n]$ can be replaced with $r_u[n]$ in (13b), which is the UAV transmit power control. Therefore, we have the new upper limit $f_{u,max}^{opt}[n]$ can be defined as follows:

$$f_u[n] \triangleq \frac{1}{W r_{max}} \left( \frac{1}{\delta_1 p_{LoS}^u[n] + \delta_2 p_{NLoS}^u[n]} \right). \tag{19}$$

It is seen that (19) is a concave-surrogate function. We make a further explanation of the concave surrogate $f_u^m[n]$ for $f_u^{opt}[n]$ in Theorem 1.

*Theorem 1:* At $i^{th}$ iteration, the concave surrogate $f_u^m[n]$ for $f_u^{opt}[n]$ is:

$$f_u^m[n] = \left[ X_A[n] + X_B[n] + \frac{p_{LoS_i}^u[n]}{{p_{NLoS_i}^u}^2[n]} \right] \leq f_u^{opt}[n], \tag{20}$$

where

$$X_A[n] = \frac{2\delta_2^2 - \delta_1^5 {p_{LoS_i}^u}^2[n] {p_{LoS_{i+1}}^u}^3[n]}{\delta_2^2 \delta_1^4 {p_{NLoS_{i+1}}^u}^2[n] {p_{LoS_i}^u}^2[n] {p_{LoS_{i+1}}^u}^2[n]}, \tag{21}$$

$$X_B[n] = \frac{k_n^i}{\delta_1^4 {p_{LoS_{i+1}}^u}^2[n] {p_{NLoS_{i+1}}^u}^2[n] \left( p_{LoS_i}^u[n] + p_{NLoS_i}^u[n]^2 \right)}. \tag{22}$$

$k_n^i$ is defined as follows:

$$-2 - \delta_1^4 {p_{LoS_{i+1}}^u}^2[n] {p_{NLoS_{i+1}}^u}^2[n] (3 p_{LoS_i}^u[n] + p_{NLoS_i}^u[n]).$$

Finally, the problem $\mathbf{P}_2$ is transformed to $\mathbf{P}_3$ with newly added optimizing variables and constraints as follows:

$$\mathbf{P_3}: \max_{\substack{x[n], y[n], f_u[n] \\ v_u[n], p_u[n], b_u[n]}} \frac{1}{UT} \sum_{u=1}^{U} \sum_{n=1}^{N} c_u^n[n], \tag{23a}$$

$$\text{s.t. } 0 \leq f_u[n] \leq f_{u,max}^{opt}[n], \quad n = 1, 2, 3, \ldots N,$$
$$(13b) - (13e), \ (15). \tag{23b}$$

The constraint in (23b) is proved to be convex due to the newly added variable. Thus, (23) is a convex problem and ready to solve using the standard optimization toolbox [31].

## IV. UAV OPTIMAL ENERGY EFFICIENCY

### A. PROBLEM FORMULATION

We now formulate the energy-efficiency maximization problem. We use the optimal throughput maximization problem solution from Section III. However, we still need the UAV propulsion energy consumption from (10) and is continuous in nature. We replace the continuous-time series into the discrete state-space representation. The UAV energy efficient maximization problem is:

$$\mathbf{P_4}: \max_{\substack{x[n], y[n], f_u^{opt}[n] \\ v_u[n], p_u[n], b_u[n]}} \sum_{u=1}^{U} \sum_{n=1}^{N} \left( \frac{c_u^n[n]}{e_u[n]} \right), \tag{24a}$$

$$\text{s.t. } v_{min} \leq v_u[n] \leq v_{max}, \quad \forall n,$$
$$(13b) - (13e), \ (15), \ (23b). \tag{24b}$$

where

$$e_u[n] = \left( a \parallel v_u[n] \parallel^3 + \frac{b}{\parallel v_u[n] \parallel} + \frac{b \parallel v_u[n] \parallel^3}{r_u[n]^2 g^2} \right). \tag{25}$$

where (24b) defines the limit of $v_u$ in $0 \leq t \leq T$ period, where $v_{min}$ and $v_{max}$ are the minimum and maximum UAV velocity, respectively. $\mathbf{P_4}$ is not a convex problem due to its fractional objection function. Thus, $\mathbf{P_4}$ cannot be solved directly due to *1) intractable fractional energy-efficiency problem*, and *2) MINLP nature*. Hence, we approximate $\mathbf{P_4}$ to the new problem to solve it optimally. The transformation of problem $\mathbf{P_4}$ is presented in the next subsection.

### B. PROBLEM TRANSFORMATION

The transformation of the $\mathbf{P_4}$ is also performed in several steps, resulting in the final approach as convex. The transformation of $\mathbf{P_4} \longrightarrow \mathbf{P_5}$ is developed by adding the UAV trajectory variable to the denominator. By doing so, these can couple with other trajectory variables. Hence, it transforms the denominator as a convex function. Finally, the transformation of $\mathbf{P_5} \longrightarrow \mathbf{P_6}$ is derived, where the Dinkelbach method is applied with a numerical constant, which is iteratively updated. We propose an efficient algorithm based on SCA and Dinkelbach to solve the problem $\mathbf{P_4}$ optimally.

#### 1) TRANSFORMATION OF $\mathbf{P_4}$ to $\mathbf{P_5}$

Due to the non-convexity of the objective function, we add a new variable, $v_{nv}$, to the denominator [11] in (25). Hence, optimizing the new variable, $v_{nv}$, meaning that we jointly optimize the trajectory variable, $v_u$, and $r_u$. We rewrite the UAV propulsion energy consumption in (25) as follows:

$$e_u^n[n] = \left( a \|v_{nv}[n]\|^3 + \frac{b \|v_{nv}[n]\|^3}{g^2 r_u[n]^2} + \frac{b}{v_u[n]} \right). \tag{26}$$

The problem $\mathbf{P}_4$ is transformed to $\mathbf{P}_5$ with newly added optimizing variables and constraints as follows:

$$\mathbf{P_5}: \max_{\substack{x[n], y[n], f_u^{opt}[n] \\ v_u[n], p_u[n], b_u[n], v_{nv}[n]}} \sum_{u=1}^{U} \sum_{n=1}^{N} \frac{c_u^n[n]}{e_u^n[n]}, \tag{27a}$$

$$\text{s.t. } \| v_u[n] \| \leq v_{max}, \quad n=1,2,3,\dots N, \qquad (27b)$$

$$v_{nv}[n]^2 \leq \| v[n] \|^2, \quad n=1,2,3,\dots N,$$

$$(13b)-(13e),\ (15),\ (23b). \qquad (27c)$$

The constraints in (27b) is proved to be convex due to the added variable. However, we still have the non-convex constraint (27c) due to its non-linearity. Therefore, we make an approximation to reformulate (27c) to make it convex. Our approximation is expressed as:

$$\| v_{nv}[n] \| \leq \left( - \| v_{i+1}[n] \|^2 + 4 v_i v_{i+1}[n] \right), \qquad (28)$$

where (28) is defined as follows. Firstly, $\|v_{nv}[n]\|$ is convex. Moreover, $\|v_{i+1}[n]\|$ is differential function w.r.t. $\|v_i[n]\|$, for any local point $v_i[n]$ obtained at $i$-th iteration [11], which is approximated from (27c). Thus, newly added variable $v_{nv}[n]$ in (26) makes the problem $\mathbf{P_5}$ optimally solvable by using the SCA method. However, we also need to tackle the fractional problem in order to get the optimal solution of the optimization problem, which is discussed in the following subsection.

#### 2) TRANSFORMATION OF $\mathbf{P}_5$ to $\mathbf{P}_6$

To solve the problem $\mathbf{P}_5$, we would apply the Dinkelbach method to a fractional problem and then formulate the $\mathbf{P_6}$ with the new objective function. We briefly explain the Dinkelbach method in the following (interested readers can find more information in [32], [33]). Here, $f(r) = \frac{P(r)}{Q(r)}$ is described as $f(r) = P(r) - \lambda Q(r)$ under all convex constraints [12], where $\lambda$ is a constant. This value is iteratively updated by $\lambda_{j+1} = \frac{P_{r_j}}{Q_{r_j}}$, where $j$ is the iterative index. This process guarantees the convergence, and hence, the locally optimal solution is achieved. Hence, $\mathbf{P_5}$ can be approximated as $\mathbf{P_6}$, where the objective function and all constraints are convex as follows:

$$\mathbf{P_6}: \max_{\substack{x_{i+1}[n], y_{i+1}[n], v_{i+1}[n], \\ f^{opt}_{u,i+1}[n], v_{nv}[n], b_u[n], p_u[n]}} \sum_{u=1}^{U} \sum_{n=1}^{N} \left( c^n_u[n] - \lambda_i e^n_u[n] \right),$$

$$\text{s.t. } (13b)-(13e),\ (15),\ (23b),\ (27b),\ (28). \qquad (29a)$$

where $\lambda_i$ is a new numerical value that can be iteratively updated as $\sum_{u=1}^{U} \sum_{n=1}^{N} \left( \frac{c^n_u[n]}{e^n_u[n]} \right)$. $\mathbf{P_6}$ is a convex problem and is ready to solve using the standard optimization toolbox.

## V. PROPOSED ALGORITHMS

### A. THROUGHPUT MAXIMIZATION ALGORITHM

The efficient algorithm based on the SCA method can solve the problem $\mathbf{P_3}$ optimally, which is summarized in Algorithm 1. Moreover, there is a binary variable of $b_u[n]$, which makes the problem MINLP. The *cvx* solver *mosek* in the algorithm can help to solve the problem efficiently. The proposed algorithm to maximize throughput is summarized in Algorithm 1.

**Algorithm 1** Solution of Throughput i.e., $\mathbf{P_1}$

```
Inputting : $\sigma^2$, $\Phi$, $\psi$, and $f_c$.
Initializing : iterative number $i = 1$, $r_u[n]$, $p_u[n]$, $b_u[n]$, and $v_n[n]$
Optimization :
repeat 1
    Calculate $f_u[n]$, $f^{opt}_{u,max}[n]$, $p^u_{LoS}[n]$, and $p^u_{NLoS}[n]$
    Update $i \longleftarrow i+1$
until convergence
repeat 2
    Solve $\mathbf{P_3}$ using cvx and cvx solver mosek
    Update $i \longleftarrow i+1$
until convergence
```

Algorithm 1 has complexity, which is polynomial in the worst case [34]. This is because Algorithm 1 solves the convex optimization problem at each iteration. Moreover, achieving the UAV optimal trajectory is found offline before the UAV dispatch at the ground control station. This also has a high computational capability.

**Algorithm 2** Solution of Energy-Efficiency i.e., $\mathbf{P_4}$

```
Inputting : $\sigma^2$, $a$, $b$, $g$, $\Phi$, $\psi$, and $f_c$.
Initializing : iterative number $i = 1$, $r_u[n]$, $p_u[n]$, $b_u[n]$, and $v_n[n]$
Optimization :
repeat 1
    Calculate $f_u[n]$, $f^{opt}_{u,max}[n]$, $v_{nv}[n]$, $p^u_{LoS}[n]$, and $p^u_{NLoS}[n]$
    Update $i \longleftarrow i+1$
until convergence
repeat 2
    Solve $\mathbf{P_6}$ for given $c^n_u[n]$, $e^n_u[n]$, and iteratively updated $\lambda_m$, using cvx and cvx solver mosek
    Update $i \longleftarrow i+1$
until convergence
```

### B. ENERGY-EFFICIENCY MAXIMIZATION ALGORITHM

The efficient algorithm, based on SCA and Dinkelbach methods, can solve the UAV energy-efficiency maximization problem optimally, which is summarized in Algorithm 2. The classical Dinkelbach method tackles the fractional problem. The *cvx* solver *mosek* in the algorithm can help to solve the problem efficiently. The proposed algorithm to maximize the UAV energy efficiency is summarized in Algorithm 2.

Algorithm 2 also has complexity polynomial in the worst case as Algorithm 2 solves the convex optimization problem at each iteration.

## VI. SIMULATION RESULTS

We present simulation results in this section to show the improved performance of the proposed scheme. We compare

**TABLE 2.** List of parameters used in the simulation results.

| Parameter | Value |
|---|---|
| Speed of light | $1.1 \times 10^9$ km/h |
| UAV flight time | 180 s |
| Carrier frequency | 1 GHz |
| UAV flight altitude | 100 m |
| UAV minimum flying speed | 50 km/h |
| UAV maximum flying speed | 100 km/h |
| Number of users on the ground | 6 |
| UAV weighted depended constant, $a$ | 0.001 |
| UAV weighted depended constant, $b$ | 2250 |
| UAV environment depended constant, $\Phi$ | 4.88 |
| UAV environment depended constant, $\psi$ | 0.43 |
| Excessive path loss coefficient for LOS links, $\delta_1$ | 0.01 |
| Excessive path loss coefficient for NLOS links, $\delta_2$ | 21 |

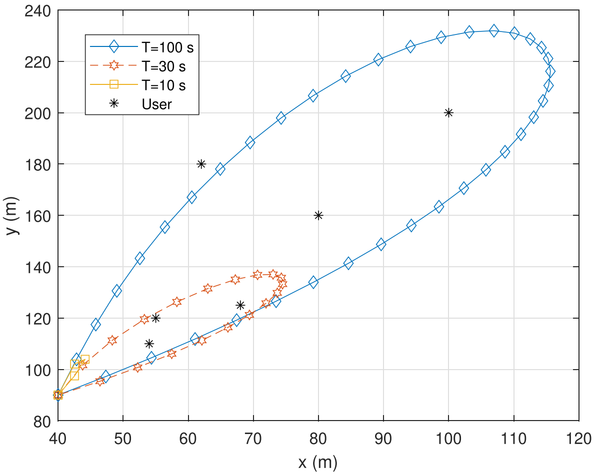

**FIGURE 2.** The UAV trajectory design.

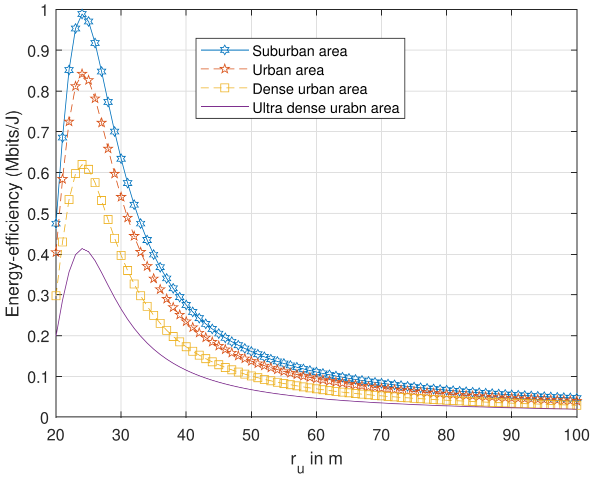

**FIGURE 3.** Only one environment dependent maximum point of $\delta_{uav}^{ee}$.

the proposed scheme with a static system and an unconstrained approach. The static scheme is defined as the objective function is maximized after achieving the optimal UAV fixed trajectory radius. We evaluate the system model performance for a suburban environment. The list of parameters used in the simulation is presented in Table 2.

Fig. 2 shows the UAV trajectory design for the given UAV fight time. The UAV has a different hovering path for different UAV flight time. When the UAV flight time is higher, the hovering path is larger. Thus, for higher UAV flight time, it can support more users on the ground. Fig. 2 also shows the location of the users while the UAV is hovering. We consider the random distribution of the users in our proposed model. From Fig. 2, it is seen that the ground users reside under/nearby the UAV hovering trajectory path. Even for shorter UAV flight time, many of the ground users also reside under the UAV hovering path. Due to the closeness of the users to the UAV hovering path, we achieve the improved performance of both throughput and energy-efficiency maximization problem. The UAV trajectory path both for shorter and higher UAV flight time proves the supremacy of the proposed algorithms.

We study the impact of the UAV-to-user, $u$ distance, i.e., $r_u$ on the proposed $\delta_{uav}^{ee}$ performance in Fig. 3. To do so, we determine $p_{LoS}^{u}$, $p_{NLoS}^{u}$, and UAV energy consumption. In various environments, it can be readily found that proposed $\delta_{uav}^{ee}$ has a maximum global value in each area. Fig. 3 clearly shows the maximum point of $\delta_{uav}^{ee}$ in various areas such as the suburban, urban, dense urban, and ultra-dense metropolitan area. We obtain the best performance in the suburban area,

**TABLE 3.** Performance comparison for energy-efficient UAV algorithms.

| | Average speed $(m/s)$ | Average acceleration $(m/s^2)$ | Average power $(Watt)$ |
|---|---|---|---|
| Algorithm 2 | 25.01 | 2.95 | 110.44 |
| Energy-efficiency [19] | 25.67 | 3.24 | 116.02 |

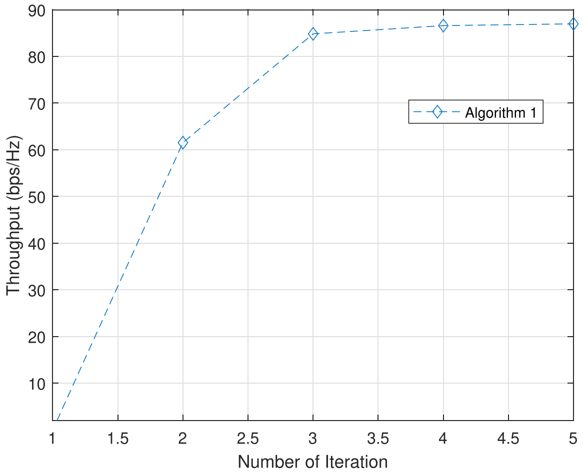

**FIGURE 4.** Convergence of algorithm 1.

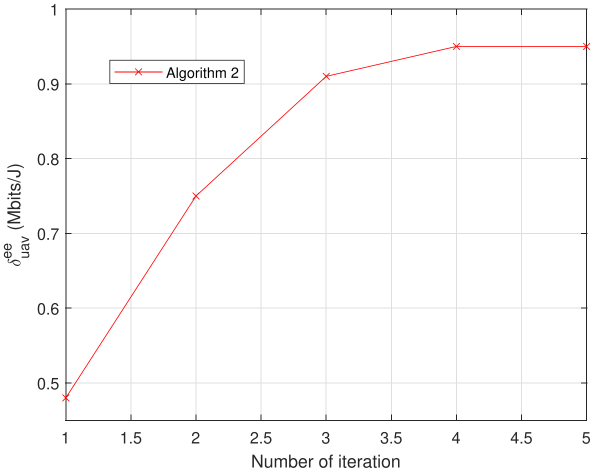

**FIGURE 5.** Convergence of algorithm 2.

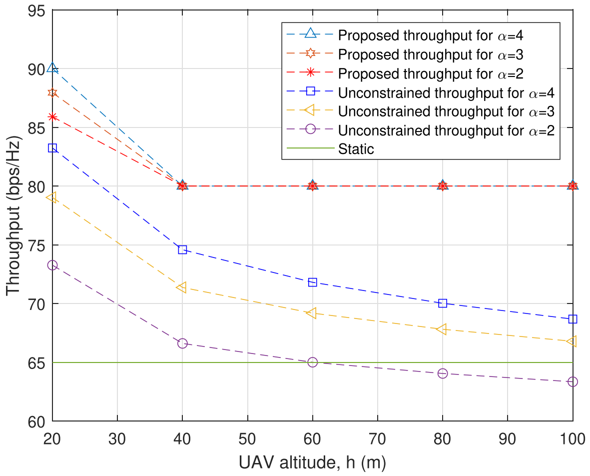

**FIGURE 6.** Throughput versus time.

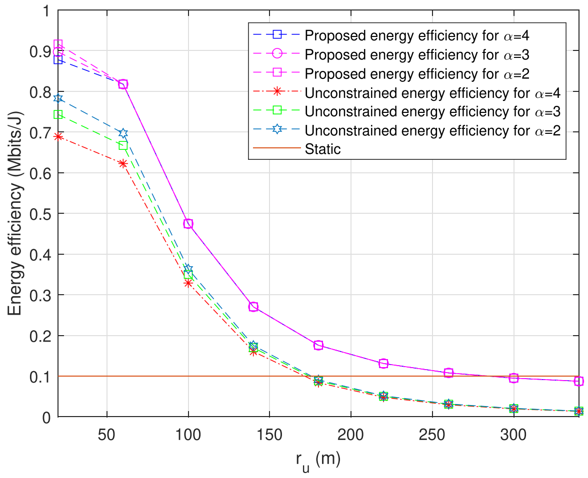

**FIGURE 7.** Energy-efficiency maximization versus the UAV-user distance.

as shown in Fig. 3. So, from now, we only consider this area for the remaining results. We show the optimizing variables and compared it with [18] in Table 3.

We also present the convergence of Algorithm 1 and Algorithm 2 in Fig. 4 and Fig. 5, respectively. Both Algorithm 1 and Algorithm 2 are proved to be efficient due to their fast convergence.

Throughput vs. time is shown in Fig. 6. As LOS and NLOS communication links are both considered to design the channel model, various values of path loss exponent $\alpha = 2, 3, 4$ have been studied to analyze the best performance. We investigate the improved performance of throughput maximization based on Algorithm 1 compared to other schemes. Our proposed throughput maximization illustrates the significant improvement for $\alpha = 2, 3, 4$. Our proposed throughput almost maintains a constant and higher value though there is the initial drop up to 10% of our proposed throughput from $\alpha = 4$ to $\alpha = 2$. That observation proves the superiority of our proposed throughput and compares it with the unconstraint and static throughput.

We compare the performance between energy-efficiency maximization, static energy-efficiency, and unconstraint energy-efficiency problem in Fig. 7. For $\alpha = 4$, there is a significant improvement in energy-efficiency for our proposed energy-efficient Algorithm 2 compared to the benchmark methods. When $r_u = 150$ m or more substantial, both our proposed $\delta^{ee}_{uav}$ and unconstraint energy-efficiency problem are investigated as impractical due to their low performance. On the other hand, the static scheme has low performance due to the optimal static location of the UAV. The UAV is not expected to cover larger areas when the UAV altitude is too high. though Thus, proposed energy-efficient UAV is proved useful for the 5G and beyond wireless networks.

## VII. CONCLUSION

The UAV provides a better communication link based on LOS and NLOS, which guarantees a better QoS. In this paper, an energy-efficient UAV serves the users via jointly optimizing the UAV trajectory path, the UAV to users scheduling, the UAV transmit power, and the UAV mobility. We design the UAV-user channel model based on LOS and NLOS communication links. A binary variable is introduced to schedule the connectivity between UAV to the user. Before formulating the energy-efficient problem formulation, we develop a throughput maximization problem and propose an efficient algorithm to solve it optimally. We also formulate an energy-efficiency maximization problem via optimizing throughput and UAV propulsion energy. We also formulate the UAV propulsion energy expression. We derive the energy-efficient maximization problem. The problem is investigated as a non-convex fractional, and MINLP problem. We propose an efficient algorithm based on SCA and Dinkelbach method, non-convexity, fractional, and MINLP problems are tackled by SCA, Dinkelbach, and *cvx* solver *mosek*, respectively. Simulation results prove the supremacy of the algorithm in terms of the energy-efficiency and throughput maximization. We claim our proposed model is an excellent fit to design the energy-efficient UAV communication in 5G and beyond wireless technology due to the consideration of the feasible channel model and the UAV trajectory design.

## APPENDIX

## PROOF

Consider a function of $r$ [25], [33] as

$$\top_A(r) \triangleq \frac{1}{x}, \tag{30}$$

where $x = \| r \|^2 + y$. $x > 0$ and $y > 0$ are constant.

We can write the following expression

$$\triangle \top_B(r \mid r_i) \triangleq g_1 + g_2, \tag{31}$$

where

$$g_1 = \frac{\| r \|^2 - \|r_i\|^2 + 2r' r_i}{y^2} \tag{32}$$

$$g_2 = \frac{x + 2 \| r \|^2 - 2r' r_i}{x^2}. \tag{33}$$

For $r_i$, $\top_B(r)$ needs to satisfy the following conditions

$$\triangle \top_A(r_i) = \triangle \top_B(r \mid r_i), \tag{34}$$

$$\top_A(r_i) \geq \top_B(r \mid r_i). \tag{35}$$

Also, it can be written as a gradient of $\triangle \top_A(r)$ and $\triangle \top_B(r \mid r_i)$ w.r.t. $r$

$$\top_A(r) = \frac{2r}{x^2}, \tag{36}$$

and

$$\top_B(r \mid r_i) = \frac{2(r_i - r)}{y^2} - \frac{2r_i}{x^2}. \tag{37}$$

Now, (36) and (37) become the same at $r = r_i$. The second surrogate condition is satisfied by (31).

Thus, the proof is complete.

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