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Energy-efficient resource allocation for aerial-assisted internet of things networks using deep reinforcement learning

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ABSTRACT

Networks based on the internet of things (IoT) face many challenges, including the battery power limitation and the transmission sensors range. Also, a new technology mode is needed to spread the IoT platform, reduce delay, optimize costs, optimize power consumption, and spread heterogeneous connections. One of the most important candidates for answering these challenges is using an unmanned aerial vehicle as an aerial base station (ABS) with the ability to fly. This research aims to present a new scenario which will answer the question of whether ABSs can solve the challenges in the IoT. Also, the number of ABSs, the average ABSs height, the total power transmitted by users and the modulation order have been compared in three ABSs modes fixed location, direct vision model, and integrated model. Since in the integrated model, ABSs can be placed at lower altitudes compared to the direct vision model, the total users' transmitted power is reduced. Therefore, the integrated model, which is a completely innovative and new model, is superior to the direct vision model.

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1. INTRODUCTION

The need for dependable, scalable, and energy-efficient wireless communication networks has grown due to the internet of things (IoT) explosive expansion. Unmanned aerial vehicles (UAVs) and other aerial platforms offer IoT devices in distant and infrastructure-constrained places flexible communication assistance. Aerial-assisted IoT networks increase connectivity between dispersed devices, decrease communication latency, and expand network coverage. However, the limited energy resources of IoT devices and aerial platforms pose serious obstacles to effective network functioning [1]. Optimizing transmission power, bandwidth usage, communication scheduling, and energy consumption all depend heavily on resource allocation. Conventional methods of allocating resources frequently have difficulty adapting. The need for energy-efficient resource allocation has grown due to the IoT rapid expansion, and deep reinforcement learning and aerial platforms present viable ways to optimize network resources, lower energy consumption, and enhance overall communication performance.

IoT technology enables a network of interconnected objects that intelligently exchange information with each other or central systems. It drives advancements in 5th generation (5G) and big data technologies [2]. Aerial base stations (ABSs), supported by the affordability and miniaturization of UAVs, are essential for expanding IoT networks by reducing delays, optimizing costs and power, and supporting diverse connections [3]. UAVs, used in various industries such as traffic control, weather monitoring, and rescue operations, face challenges like optimal three-dimensional (3D) positioning, path management, and radio resource allocation in wireless networks [4]. Their mobility and adaptability make ABSs ideal for IoT applications, overcoming limitations of low-power IoT devices by dynamically updating their locations to relay data over larger ranges [5]. The article reviews IoT resource allocation, proposes ABS-based solutions, evaluates results, and concludes with future research directions.

2. RELATED WORK

This article proposes a comprehensive scenario for utilizing ABSs in IoT-based wireless networks. It optimizes radio resource allocation, user assignment, and the 3D positioning of ABSs simultaneously to minimize total user power consumption and enhance network performance. The innovations of the proposed scenario are: allocation of radio resources, allocation of users, and 3D positioning of ABSs together [5]. The key advantage of ABSs over traditional ones is their ability to update their location. If resource or user allocation is handled independently of their positioning, this advantage is lost. Furthermore, solely focusing on 3D positioning results in suboptimal radio resource allocation, hindering optimal network performance [6]. To achieve a practical and effective solution, radio resource allocation and 3D positioning must be integrated.

However, according to the reviewed articles, no research has yet addressed this combined approach. Analysis of two direct and combined vision channel models and their comparison for the presented algorithms: the proposed scenario introduces two models for ABSs: the direct vision model, where stations maintain direct line-of-sight with users, and the integrated model, where stations connect with users both directly and indirectly [7]. The comparison aims to evaluate performance differences. When power consumption is not a significant constraint, ABSs can operate at higher altitudes, ensuring direct vision with all users. However, under strict power limitations, the integrated model is preferred. Despite their potential, no prior research has explored these models according to the reviewed literature. Using the order of different modulations and comparing them from different opinions: in the proposed scenario, by using different modulation orders and comparing them, this work is looking for the best possible mode for the IoT-based network [8].

According to the review of the related articles, no work has been done in this field. Converting complex non-convex problems into convex problems with approximate methods: in the proposed scenario, the issues that are raised have a complex and non-convex form [9]. These problems cannot be solved, by using the approximate solution methods of geometric programming (GP), semi-definite relaxation (SDR), and alternative algorithm; this work converts them into sub-problems with appropriate complexity and solve them. Obtaining the computational complexity and proving the convergence of the presented algorithms: as stated in the previous part, by using approximate methods, this works approximate problems with a very high level of complexity to problems with a suitable level of complexity, and finally, also checks the computational complexity of each of the new problems [10]. Also prove the convergence of the final solution of the proposed method.

3. PROPOSED MODEL

This model focuses on the uplink in IoT networks, involving multiple ABSs and IoT users. Given the battery limitations of IoT devices, the primary objective is to minimize users' power consumption. To achieve this, the model optimizes the 3D positioning of ABSs, user allocation to base stations, subcarrier allocation, and modulation order allocation. The system model is illustrated in Table 1. The goal is to reduce the total power consumption of IoT users. Figure 1 present the proposed model working section with different parameters.

One of the most important advantages that ABSs have over other base stations is the ability to create a direct vision with the user. The probability of direct visibility between the ABSs j and the IoT user i is shown as (1) to (3) [11].

$$Pr_{LoS,ij} = \frac{1}{1+\alpha exp(-\beta(\frac{180}{\pi}\theta_{ij}-\alpha))} \quad (1)$$

Where θ_{ij} parameter is the elevation angle. The elevation angle can be expressed as (2).

$$\theta_{ij} = \frac{180}{\pi} \times sin^{-1}\left(\frac{h_j}{d_{ij}}\right), \quad \forall i,j \tag{2}$$

Also, d_{ij} is the distance between user i and the ABS j, which is displayed as (3).

$$d_{ij} = \sqrt{(x_j - N_i)^2 + (y_j - J_i)^2 + h_j^2}, \quad \forall i,j \tag{3}$$

The path loss between the user and the ABS in the direct and indirect vision modes is given in (4) and (5) [12].

$$L_{LOS,ij} = 10n\ log\ log\ (\frac{4\pi f_c d_{ij}}{c}) + N_{LoS}, \quad \forall i,j \tag{4}$$

In this model, use m-ary phase shift keying (MPSK) modulation. The bit error rate in this type of modulation is in the form of (5) [13].

$$BER_{imj} = \frac{2}{m+1} Q \sqrt{\frac{2P_{imj}^{receive}}{N_{ij}N_0}} \frac{\pi}{2^{m+1}} \tag{5}$$

The parameters inside the expressions are mentioned in the parameter definition Table 1 [14].

Table 1. Definition of the parameters used in the presented system model

Definition	Parameter
IoT user counter	i
Aerial station counter	J
Modulation order counter	m
Subcarrier counter	l
Two-dimensional location of the *i*-th IoT user	$(x^i; y^i)$
Elevation angle of the *j*-th aerial base station from the *i*-th user	θ_{ij}
Probability of direct vision between user *i* and aerial base station *j*	$Pr_{LoS,ij}$
The direct vision probability threshold	ε
A binary variable of subcarrier allocation and user allocation	$p^l imj$
Threshold of sending rate for *i*-th user	T_i
The distance between the *i*-th user and the *j*-th aerial base station	d_{ij}
Route loss power index	n
Average path loss for direct vision	$L_{LoS,ij}$
Average additional power loss for direct vision	ξ_{LOS}
Speed of light	c
Carrier frequency	$\int_i^N n\ C$
The symbol rate sent from the *i*-th IoT	r_{ij}
The transmission power of the *i*-th IoT user to the j-th aerial base station with the modulation order m	$p_{imj}^{transmit}$
The bit rate sent from the *i*-th IoT user to the *j*-th aerial base station with the m-modulation order	r_{imj}
Noise power spectrum density	N0

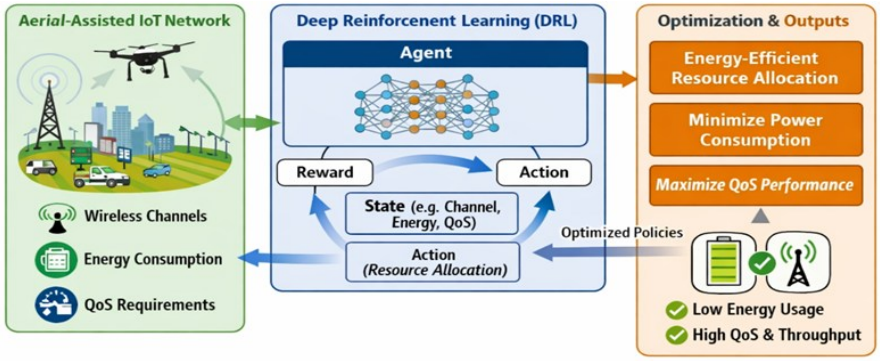

Figure 1. The proposed system model architecture

3.1. Direct vision scenario optimization problem

In this scenario, it is considered that all aerial stations have direct visual communication with users. As a result, there is only direct visual communication and the average path loss is equal to the path loss in direct vision mode. The relationship between the user-transmitted power and the ABS received power is in the form of (6).

$$P_{imj}^{transmit} = P_{imj}^{receive} \times 10^{\frac{L_{LOS,ij}}{10}} \tag{6}$$

Considering the path loss power index equal to 2, the lowest transmitted power of the IoT user is written as (7) considering the desired bit error rate [15].

$$P_{imj}^{transmit} = A_m . r_{imj} . d_{ij}^2 \tag{7}$$

Where r_{imj} is the bit rate sent by the user to the aerial station, which is done under modulation of order m. The transmitted bit rate is written as (8). This equation guarantees that the sending rate of each user is greater than one threshold.

$$r_{imj} = N_{ij}(m+1) \tag{8}$$

This is only a function of the modulation order and can be displayed as (9) [16]. This equation indicates that a maximum of one ABS can be connected to a specific user.

$$A_m = (Q^{-1}(\frac{1}{2}\delta(m+1)) \times \frac{1}{sinsin\left(\frac{\pi}{2^{m+1}}\right)})^2 \times \frac{1}{(m+1)} \times \frac{1}{2} N_0 \times \left(\frac{4\pi f_c}{c}\right)^2 \times 10^{\frac{n_{LOS}}{10}} \tag{9}$$

In the direct vision model, the necessary condition for connecting the user to the ABS is that the probability of direct vision is greater than a threshold. In other words, $Pr_{LOS(\theta_{ij})} \geq \varepsilon$ must be established that is equivalent to $\theta_{ij} \geq pr_{los}^{-1}(\varepsilon)$ which leads to (10) by simplifying the relations a little [17]. This equation guarantees that for a specific user, a specific ABS, and a subcarrier, only one modulation order is used guarantees that a subcarrier is used only once. In (10) also guarantees that there is a direct vision [18].

$$d_{ij} \leq \frac{h_j}{sinsin\left(Pr_{LoS}^{-1}(\varepsilon)\right)} \ , \ \forall i,j \tag{10}$$

3.2. The optimization problem of the integrated scenario of direct and indirect vision

In this scenario, ABSs can communicate with some users with direct vision and with some users with indirect vision. Therefore, in times when we are faced with the limitation of the number and height of ABSs, this integrated model can be desirable. The relationship between the received power of the ABSs and the transmitted power of the IoT a user is in the form of (11).

$$P_{imj}^{transmit} = P_{imj}^{receive} \times 10^{\frac{n_{(x_j,y_j,h_j)}}{10}} \tag{11}$$

The minimum power sent by the user to reach the desired bit error rate is given by (12).

$$P_{imj}^{transmit} = B_m \times r_{imj} \times d_{ij}^2 \times 10^{\frac{Pr_{LOS,ij}(n_{LOS} - j_{NLOS})}{10}} \tag{12}$$

Where B_m is a function of the modulation order. B_m is in the form of (13) [19].

$$B_m = (Q^{-1}(\frac{1}{2}\delta(m+1)) \times \frac{1}{sinsin\left(\frac{\pi}{2^{m+1}}\right)})^2 \times \frac{1}{(m+1)} \times \frac{1}{2} N_0 \times \left(\frac{4\pi f_c}{c}\right)^2 \times 10^{\frac{n_{NLOS}}{10}} \tag{13}$$

Finally, the optimization problem in integrated model is in the form of (13) taking into account (8) to (13) [20].

3.3. Solving the optimization problem

The direct and combined vision scenarios involve non-convex, mixed-integer non-linear programming (MINLP), and non-deterministic polynomial-time (NP)-hard problems. So, the main problems

are divided into continuous and discrete sub-problems, solved using methods like SDR, GP, and the alternative method [21]. The alternative method simplifies high-dimensional problems by iteratively solving sub-problems, with solutions feeding into the next until convergence. This approach provides near-optimal results. For the direct vision scenario, the main problem is split into two sub-problems: continuous (3D positioning of ABSs) and discrete (radio resource and user allocation) [22].

3.3.1. Solving the sub-problem of 3D positioning of aerial base stations

The sub-problem of 3D positioning of ABSs can be represented in quadratic constraint quadratic programming (QCQP) form as (14), considering the limitation of (15).

$$st.p_{imj}^{l} d_{ij} \leq \frac{h_j}{sin sin\left(pr_{los}^{-1}(\varepsilon)\right)}, \quad \forall i,j \in, \forall m,l \tag{14}$$

Where $\Omega = \{(i,j)|p_{imj}^{l} \in p_{0\forall m,l}\}$ and ρ_0 is the initial matrix to start the iterative algorithm. By placing (14) in (15) and (16), the mentioned sub-problem is in the form of (17) [23].

$$\begin{aligned} &\min_{x,y,h} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{l=1}^{L} A_m r_{imj} p_{imj}^{l} \left((x_j - \hat{x}_i)^2 + (y_{i-}\hat{y})^2 + h_j^2\right) \\ &st.p_{imj}^{l} (x_j - \hat{x}_i)^2 + p_{imj}^{l} + p_{imj}^{l} h_j^2 \left(1 - \frac{1}{sin^2\left(pr_{los}^{-1}(\varepsilon)\right)}\right) \leq 0 \end{aligned} \tag{15}$$

$$\Lambda_j = \left[-2LM \sum_i^n r\, \vartheta_{ij} \hat{x}_i \quad -2LM \sum_i^n p\, \vartheta_{ij} \hat{y}_i \quad 0\right]_{l\times 3} \tag{16}$$

$$Q_i = \left[\Theta_{il} \ldots \Theta_{ij}\right]_{3J\times l}^{T} \tag{17}$$

Considering that the W_i matrix is not semi-definite positive, the sub-problem of 3D positioning of ABSs in the direct vision model is a non-convex QCQP problem. To convert this problem into a convex QCQP form, the SDR method is used. First, the problem from an inhomogeneous form to a homogeneous form is converted. By considering (18) to (21), the homogeneous form of the problem can be expressed as (22) [24].

$$\Theta_{ij} = \left[-2LM \sum_i^n p\, \vartheta_{ij} \hat{x}_i \quad -2LM \sum_i^n r\, \vartheta_{ij} \hat{y}_i \quad 0\right]_{l\times 3} \tag{18}$$

$$\hat{r}_0 = LMJ \sum_i^n p\, \gamma_i (\hat{x}_i^2 + \hat{y}_i^2) \tag{19}$$

$$\gamma_j = \sum_i^n p \sum_j^n r \sum_l^m p\, A_m r_{imj} \tag{20}$$

$$\hat{r}_i = LMJ(\hat{x}_i^2 + \hat{y}_i^2)\gamma_i \tag{21}$$

$$\frac{1}{2}[V^T \quad a][W_i\ Q_i\ Q_i^T\ 0\ ][V^T \quad a]^T + \hat{r}_0 \tag{22}$$

The above homogeneous problem can be written as (22), and considering (23) to (24). Where rank (U) indicates the order of the matrix U. In the next step, this study have to convert the non-convex homogeneous problem into a convex problem. For this purpose, omit (25), which makes the problem non-convex. As a result, the approximate convex problem will be represented as (26) and considering (27) to (28) [25].

$$s.t.\frac{1}{2}[V^T \quad a][W_i\ Q_i\ Q_i^T\ 0\ ][V^T \quad a]^T + \hat{r}_i \tag{23}$$

$$\frac{1}{2}[V^T \quad a][0\ 0\ 0\ 1\ ][V^T\ a]^T = 1 \tag{24}$$

$$\frac{1}{2} tr(T_0 U) + \hat{r}_0 \tag{25}$$

$$\frac{1}{2} tr(T_i U) + \hat{r}_i \leq 0 \tag{26}$$

$$U \geq 0 \tag{27}$$

$$tr(HU) = 1 \tag{28}$$

In (29) to (32), express the radio resource and user allocation subproblem as a binary linear optimization problem, which this study in this section. Discrete optimization software can handle the problem with minimal computer complexity since it contains binary choice variables and linear restrictions [26]. The goal is to efficiently distribute radio resources while meeting network and user constraints. Additionally, the allocation mechanism seeks to enhance overall network performance and reduce resource waste. By facilitating efficient resource use in aerial-assisted IoT networks, this optimization also promotes energy-efficient communication.

$$\sum_i^n p \sum_m^n r \sum_l^n m \, A_m r_{imj} p_{imj}^l \geq \tau_i, \forall i \tag{29}$$

$$p_{imj}^l + p_{im'j}^{l'} \leq 1, \forall i, j \neq j', m, l \tag{30}$$

$$p_{imj}^l + p_{im'j}^l \leq 1, \forall i, j, m \neq m' \tag{31}$$

$$\sum_{m=1}^M r \sum_{i=1}^I p \sum_{j=1}^n r \, p_{imj}^l = 1, \ \forall l \tag{32}$$

The problem is in linear binary form and can be solved directly using MOSEK software, a branch of CVX. For the integrated model, the optimization problem is also divided into continuous and discrete sub-problems. The final solution is achieved using the alternative algorithm. The continuous sub-problem involves the 3D positioning of ABSs and is treated as an unconstrained optimization problem according to (32) [27]. To solve this complex problem, this work uses the GP method. Using the GP method, in (33) becomes (34) [28].

$$\frac{1}{2} x_j \tag{33}$$

$$\frac{1}{2} y_j \tag{34}$$

In (35) originates from inequality $\frac{d_{ij}}{h_j} \leq f_{0,ij}$. The approximation process in the GP method [29] is described in (35) to (37). Finally, the final problem becomes the GP form as (38) [30].

$$(\frac{1}{f_{0,ij}}) \approx \mu_3 f_{0,ij}^{\omega_2} \tag{35}$$

$$exp(\frac{180}{\pi} \beta \mu_2 f_{0,ij}^{\omega_2}) \approx (1 + \frac{\frac{180}{\pi} \beta \mu_2 f_{0,ij}^{\omega_2}}{\psi})^{\psi} \tag{36}$$

$$10^{\eta \mu_3 f_{1,ij}^{\psi - \omega_3}} \approx (1 + \frac{\eta \mu_3 f_{1,ij}^{\psi - \omega_3} log_e^{10}}{\phi})^{\phi} \tag{37}$$

$$f_{1,ij}^{\psi} + \alpha \, exp \, exp \, (\alpha \beta) \approx \mu_3 f_{1,ij}^{\omega_3} \tag{38}$$

Next, this problem, which is in the form of geometric planning, can be solved with CVX software [31].

3.3.2. Solving the general problem by the alternative algorithm

Like the direct vision model, in this model, after finding the answers to the sub-problems will reach the final solution by applying the alternating algorithm [32]. First step: select an initial ρ from the feasible set from the range of the domain. Second step: find X^*, Y^*, h^* from the sub-problem of 3D positioning of ABSs. Third step: calculate (39) to (49). Fourth step: repeat the loop until the difference between (43) and (44) is greater than the threshold σ [33].

$$\sum_{j=1}^J j \sum_{m=1}^M m \sum_{i=1}^I r \sum_{l=1}^L b \, B_m r_{imj} \rho_{imj}^l (t_{0,ij}^2 + t_{1,ij}^2 + h_j^2) \times f_{2,ij}^{\phi} \tag{39}$$

$$\frac{1}{2} x_j (\hat{x}_i)^{-\frac{1}{2}} t_{0,ij}^{-\frac{1}{2}} = 1, \forall i, j \in \Omega \tag{40}$$

$$\frac{1}{2} y_j (\hat{y}_i)^{-\frac{1}{2}} t_{1,ij}^{-\frac{1}{2}} = 1, \forall i,j \in \Omega \quad (41)$$

$$f_{0,ij}^{-2} t_{0,ij}^{2} h_j^{-2} + f_{0,ij}^{-2} t_{1,ij}^{2} h_j^{-2} + f_{0,ij}^{-2} \leq 1, \quad \forall i,j \in \Omega \quad (42)$$

$$f_{1,ij}^{-1} + \frac{180}{\pi} \beta \mu_2 f_{0,ij}^{\omega_2} \psi^{-1} f_{1,ij}^{-1} \leq 1, \quad \forall i,j \in \Omega \quad (43)$$

$$f_{2,ij}^{-1} + \frac{\eta \mu_3 f_{1,ij}^{\psi-\omega_3} log_e^{10}}{\phi} f_{2,ij}^{-1} \leq 1, \quad \forall i,j \in \Omega \quad (44)$$

3.4. Alternative method convergence

This section examines the convergence of the alternating method to reach the final solution. By considering subcarrier allocation and P^T user allocation in the T stage and 3D positioning calculation in the $T+1$ stage, this work will have [34].

$$OBJ(P^T, X^{T+1}, Y^{T+1}, h^{T+1}) \leq OBJ(P^T, X^T, Y^T, h^T) \quad (45)$$

In (46) originates from the fact that SDR and GP methods were used to solve the sub-problem of 3D positioning, and these types of methods are standard. Also, standard approximations (such as Taylor expansion) were used so that there would be no problem for the feasible set, and as a result, the objective function will be improved in each iteration [35]. OBJ is the objective function of the optimization problem. Since the objective function in the proposed optimization problem is a minimization type, (46) shows that the worst solution is obtained with X^T, Y^T, and h^T variables. Similarly, considering a fixed location for ABSs P^T, X^{T+1}, Y^{T+1}, h^{T+1} and performing subcarrier and user assignment in stage $T+1$, this work will have [36].

$$OBJ(P^{T+1}, X^{T+1}, Y^{T+1}, h^{T+1}) \leq OBJ(P^T, X^{T+1}, Y^{T+1}, h^{T+1}) \quad (46)$$

As mentioned, to solve the radio resource allocation subproblem (discrete problem), this work used MOSEK software, which is based on CVX software. As a result, the solution is improved in each iteration step. According to (45) and (46), it can be seen that after each interval, the objective function either does not change or decreases. Therefore, for a limited range of channel gain and location range, the final solution converges to some extent and this solution can be accepted as the local optimal solution [37].

3.5. Computational complexity

In this section calculates the computational complexity of the direct vision model and the integrated model. Each of the models includes discrete and continuous subproblems. In the sub-problem of 3D positioning of ABSs of the direct vision model, this work used the SDR solution method. Therefore, the complexity of the mentioned subproblem will be in the form of (47) [38].

$$max\{3J+1, I+1\}^3 + (3J+1)^{0.5} \, log \, log \, (n) \quad (47)$$

Where $\hat{\mu}$ indicates the accuracy of the solution in the interior point method. In terms of computational complexity, the SDR method is a very suitable method for solving QCQP problems. The computational complexity of the user and subcarrier assignment problem in the direct vision model, which is a discrete problem, is in the form of (48) [39].

$$\frac{log(\frac{4IMJL+I+L}{\hat{t}\hat{\mu}})}{log(\hat{\xi})} \quad (48)$$

Where $\hat{\mu}$, $\hat{\xi}$, and $\hat{t}$ and are, respectively the solution accuracy, the stopping condition threshold, and the initial point for approximation in the interior point method. In the continuous sub-problem of the integrated model in which 3D positioning of ABSs is performed, the geometric planning solution method is used. So, the computational complexity in this sub-problem is in the form of (49) [40].

$$\frac{log(\frac{5IJ}{\hat{t}\hat{\mu}})}{log(\hat{\xi})} \quad (49)$$

Due to the same structure of the discrete sub-problem in each model. The computational complexity of the discrete sub-problem in the integrated model. Table 2 summarizes the computational complexity of each sub-problem [41].

Table 2. The computational complexity of different methods

Model	Subproblem	Computational Complexity
Direct vision model	Three-dimensional positioning	$max\{3J+1, I+1\}^3 + (3J+1)^{0.5}\ log\ log\ (n)$
	Radio resources and user allocation	$\frac{log\left(\frac{4IMJL+I+L}{\hat{t}\hat{\mu}}\right)}{log(\hat{\xi})}$
Integrated model	Three-dimensional positioning	$\frac{log\left(\frac{5IJ}{\hat{t}\hat{\mu}}\right)}{log(\hat{\xi})}$
	Radio resources and user allocation	$\frac{log\left(\frac{4IMJL+I+L}{\hat{t}\hat{\mu}}\right)}{log(\hat{\xi})}$

4. RESULTS AND DISCUSSION

Users are located in an area of 1 km × 1 km in an urban environment with medium to high density. Figure 2 shows which users are supported by each ABSs and where they are located to minimize the total power sent by users. In Figure 2, the number of ABSs is 5 and the number of IoTs users is 80. Each ABS can assign a maximum of 25 users due to the limitation of radio resources. Therefore, the maximum size of the IoTs users' category is 25. The users' location affects the number of users in each category as well as the desired ABS location [42].

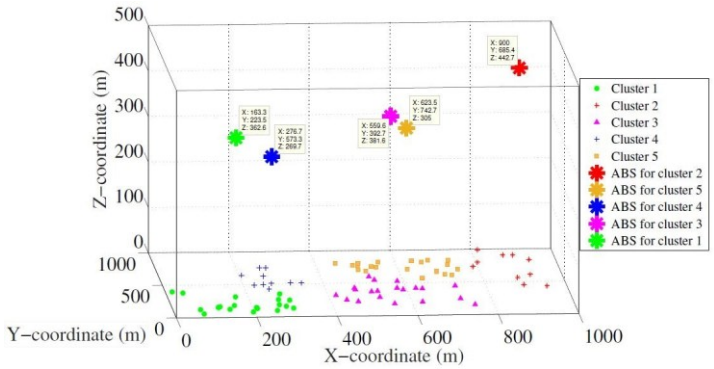

Figure 2. 3D positioning of ABSs and user allocation in direct vision model

Figure 3 examines the effect of varying the number of users and the size of the user area on the objective function. It finds that as the number of users and the area size increase, total power consumption rises. Smaller user numbers and area sizes improve the solution's performance. However, since the network model focuses on IoT, the number of users and area size should still be practical for wireless networks. Figure 4 compares urban environments with and without tall buildings in terms of ABS height. In areas with tall buildings, base stations need higher altitudes to maintain direct visibility to users, resulting in a higher average height than in regular urban environment Figure 4. 2D positioning of ABSs and user allocation in direct vision model. Figures 5 and 6 present the overall transmit power used by the proposed model and other baseline models using different base stations and a different number of nodes in different environments [43].

The minimum and maximum size of the user group is 10 and 20, respectively. Figure 7 shows the 3D placement of ABSs to minimize the total power sent by users. The higher the desired ABS height, the more users it will be able to support in direct vision. In Figure 8, as the number of ABSs increases, their average height decreases, and the overlap of their coverage areas increases. To optimize this, ABS should be placed at lower heights. In the integrated model, ABS can communicate with both dense user groups via direct vision and dispersed users through indirect vision, allowing for expanded coverage and further reduction in placement height.

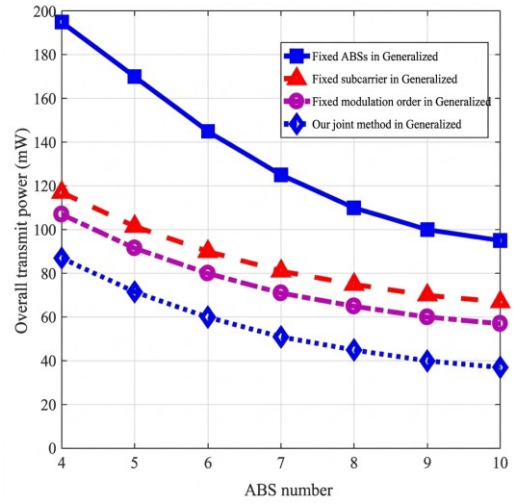

Figure 3. Comparison of the proposed with others model

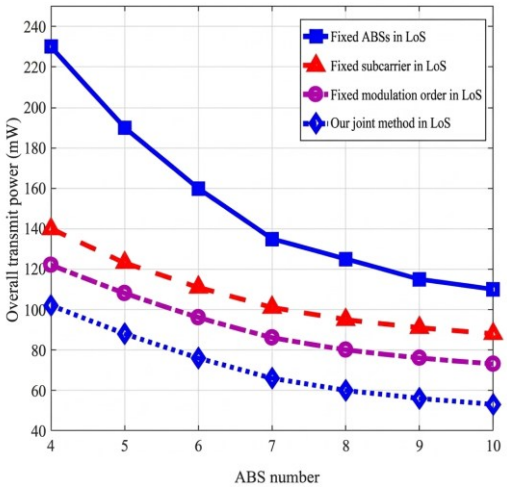

Figure 4. Proposed result compares with others model

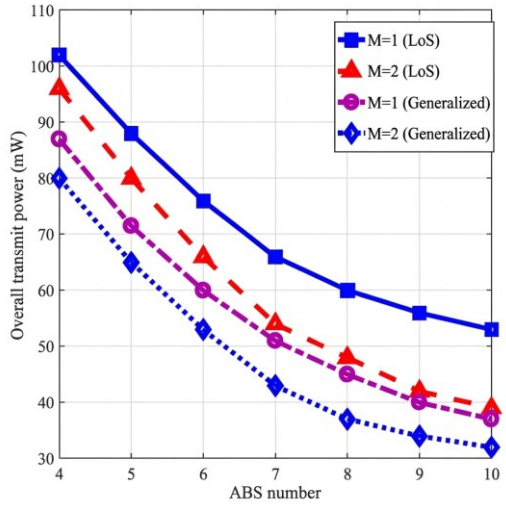

Figure 5. Comparison of transmit power with other models

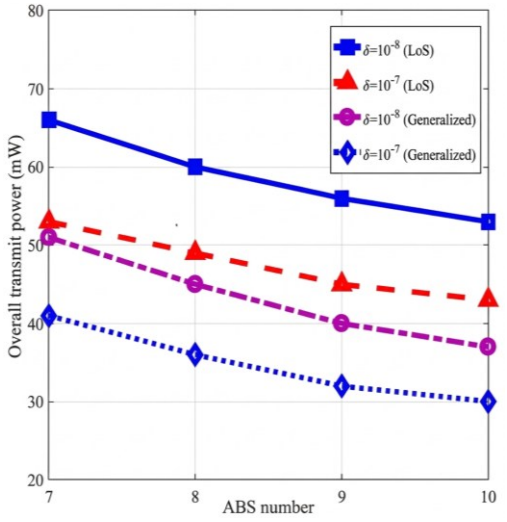

Figure 6. Comparison of transmit power with other models with different range

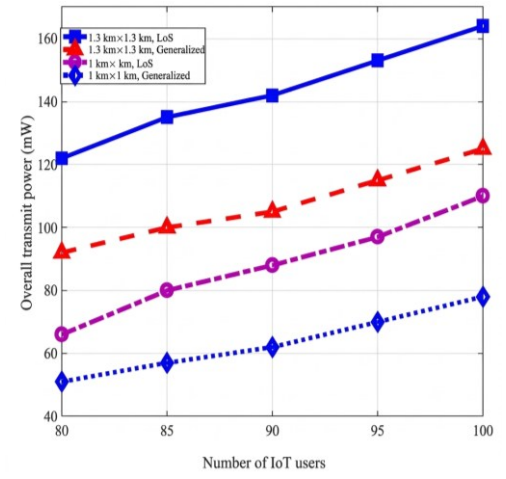

Figure 7. Comparison of transmits power of proposed model with baseline model

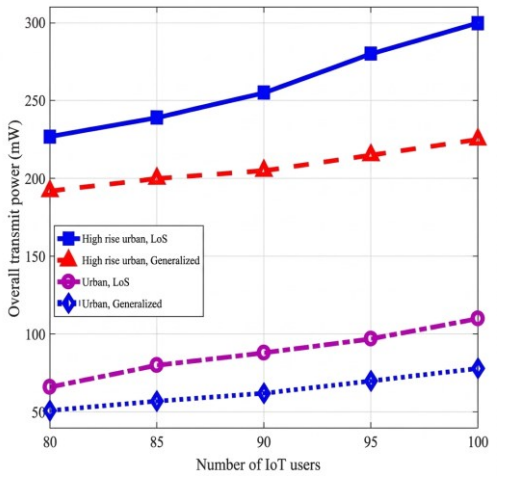

Figure 8. Comparison of transmits power of proposed model with baseline model with different range

Figure 7 compares the total transmitted power of users in different models. The direct vision model is compared with a fixed 3D location model of ABSs, where base stations are set at a height of 550 meters, and users are assigned to the nearest base station. As the number of ABSs increases, the maximum size of each user category decreases. The direct vision model shows lower total power consumption compared to the other models. Figure 7 compares the total transmitted power of users in the proposed integrated model with a fixed 3D location model of ABSs. In the integrated model, the reduced height of base stations results in lower transmitted power for all users compared to the direct vision model [44].

Overall, the integrated model shows lower total power consumption than the other models. Figure 8 shows how the transmitted power of users relates to the number of ABSs, comparing the integrated and direct vision models based on modulation order. It highlights that using different modulation orders is crucial for minimizing the total power sent by users. Figure 8 investigates the impact of different bit error rates on the objective function in both models. It shows that higher bit error rates reduce total power consumption. When the number of ABSs exceeds a certain threshold, the integrated model benefits from using a higher error rate, making it more economical than the direct vision model for power reduction, assuming the bit error rate is acceptable.

5. CONCLUSION

This research explores the use of ABSs in IoT networks, focusing on their potential to improve network performance. By employing millimeter waves, ABSs can utilize less crowded spectrums, reducing interference. The integration of multiple-input multiple-output (MIMO) technology with ABSs enhances network output and helps reduce the number of required base stations due to the mobility of ABSs. Given the high number and diversity of IoT devices, ABSs are proposed as dynamic providers of heterogeneous services, with adaptable pricing models. The study introduces an innovative integrated model, placing ABSs at lower altitudes to reduce user power consumption, outperforming the direct vision model. Additionally, the use of different modulation levels increases network efficiency. The model optimizes user allocation, radio resource management, and ABS positioning, improving IoT network performance, particularly in terms of power consumption.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest between the authors.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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