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APPLICATION OF ARTIFICIAL INTELLIGENCE IN OPTIMIZING UAV RELAY OPERATION TO EXTEND WIRELESS COMMUNICATION RANGE

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ABSTRACT

This paper presents an artificial intelligence based approach for optimizing the operation of unmanned aerial vehicles (UAVs) used as relay nodes to extend wireless communication range. Instead of selecting the relay only from instantaneous signal-to-noise ratio (SNR), the proposed method evaluates each candidate UAV through a composite score that considers normalized SNR, SNR variation trend, residual energy, relay switching delay, and a hysteresis preference for the current relay. A MATLAB simulation model is developed for a ground station-aircraft communication scenario supported by multiple UAV relays. The results show that the proposed method improves link availability and reduces unnecessary relay switching compared with a conventional threshold-based selection method. The approach is suitable for dynamic radio communication environments where channel quality and UAV resources change continuously over time.

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INTRODUCTION

Wireless communication range extension and stable link maintenance are important requirements in modern aerial and ground communication systems. In practical operating conditions, the received signal quality decreases as the distance between the transmitter and the receiver increases. This degradation is caused by free-space path loss, shadowing, fading, antenna orientation, terrain blockage, and the limitation of line-of-sight propagation. When an aircraft operates beyond the direct coverage of a ground station, a relay platform can be used to maintain the communication link and improve the operational radius of the system. Unmanned aerial vehicles have attracted considerable attention as flexible airborne relay nodes because they can be rapidly deployed, repositioned, and operated at different altitudes. Compared with fixed relay towers or ground repeaters, UAV relays offer better adaptability to mission geometry and can provide temporary coverage in areas where communication infrastructure is unavailable or damaged. A UAV relay can also improve line-of-sight conditions by flying at a suitable altitude, thereby reducing obstruction and improving received signal quality. However, the use of UAVs as relay nodes introduces a dynamic relay selection problem. The channel quality associated with each UAV varies over time due to UAV motion, aircraft motion, multipath fading, and energy limitations. A simple selection method normally chooses the UAV with the highest instantaneous SNR. Although this method is easy to implement, it may lead to frequent relay switching when the SNR values of several UAVs fluctuate around similar levels. Excessive switching increases the risk of temporary link interruption, consumes additional control resources, and reduces the stability of the communication system. To overcome these limitations, this paper proposes an AI-oriented decision method based on a composite evaluation function. The proposed method does not rely only on instantaneous SNR. It also considers the trend of SNR variation, the residual energy of each UAV, the delay caused by relay switching, and a hysteresis term that prioritizes maintaining the current relay when the improvement offered by a new relay is not significant. The objective is to obtain a balance between communication quality and relay stability. The main contributions of this study are the formulation of a practical UAV relay selection model, the development of an AI-based scoring algorithm, and the comparison between the proposed method and a conventional SNR-threshold method using MATLAB simulation.

METHODOLOGY

The research methodology consists of four main stages. First, a wireless communication scenario is formulated using a ground station, an aircraft, and multiple UAV relay candidates. Second, the quality of each two-hop communication path is represented through time-varying SNR values. Third, a composite AI-based score is

constructed from normalized SNR, SNR trend, residual UAV energy, and relay persistence. Finally, MATLAB simulation is used to compare the conventional relay selection method and the proposed method in terms of link availability and number of relay switches. The system model considered in this paper is shown in Fig. 1. A ground station G communicates with an aircraft A through one of n UAV relay nodes. At each decision instant, only one UAV is selected as the active relay. The communication process is represented by the two-hop path G → UAV_i → A. The use of multiple UAVs increases the probability that at least one relay can provide a reliable path when the direct communication range is insufficient.

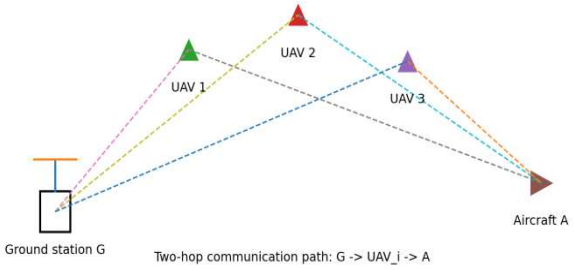


Fig. 1. UAV relay model for extending wireless communication range

The proposed algorithm evaluates the communication quality of each relay candidate at every sampling instant. Unlike a purely threshold-based method, the proposed decision process includes both instantaneous and predictive information. The predictive information is represented by the SNR trend, which indicates whether the link quality of a UAV is improving or degrading. In addition, energy awareness is included because a UAV with high SNR but low remaining energy may not be a suitable long-term relay. The relay switching delay is also considered because each relay change may produce a short communication interruption.

SYSTEM MODEL AND PROPOSED ALGORITHM

Let SNR_i(t) denote the signal-to-noise ratio of the communication path through the i-th UAV at time t. To maintain a reliable communication link, the SNR must be greater than or equal to a predefined minimum threshold. In this study, the minimum acceptable value is selected as SNR_min = 10 dB, which is used as the basic link availability criterion.

The binary link state can be expressed as follows:

$$Link(t) = \begin{cases} 1, & if\ SNR_{selected}(t) \geq SNR_{min} \\ 0, & otherwise \end{cases} \quad (1)$$

When relay switching occurs, the communication link may be interrupted for a short switching interval t_sw. This effect is included in the simulation because relay switching is not instantaneous in practical systems. During the switching interval, the link state is assigned to zero:

$$Link(t : t + t_{sw}) = 0 \quad (2)$$

In the conventional method, the relay UAV is selected only by maximizing the instantaneous SNR value:

$$U(t) = \arg\max_i SNR_i(t) \quad (3)$$

This rule can provide good instantaneous signal quality, but it does not consider whether the selected UAV will remain suitable in the next decision period. Therefore, the relay may switch repeatedly between UAVs when their SNR values are close. To improve relay stability, the proposed AI-based method calculates a composite score for each UAV:

$$Score_i(t) = \omega_1 \bar{SNR}_i(t) + \omega_2 Trend_i(t) + \omega_3 E_i(t) \quad (4)$$

In (4), SNRbar_i(t) is the normalized SNR value of the i-th UAV, Trend_i(t) represents the variation tendency of the SNR, E_i(t) is the residual energy level of the UAV, and ω_1, ω_2, and ω_3 are weighting coefficients. The SNR trend is calculated as:

$$Trend_i(t) = SNR_i(t+1) - SNR_i(t) \quad (5)$$

A positive trend indicates that the link quality is improving, while a negative trend indicates that the link is degrading. This term helps the selection algorithm avoid UAVs whose SNR is currently high but rapidly decreasing. Since the score combines different quantities, normalization is required to ensure that each component contributes within a comparable numerical range.

To reduce unnecessary relay switching, a hysteresis preference is added to the score of the currently selected relay:

$$Score_{current}(t) = Score_{current}(t) + \Delta \quad (6)$$

The parameter Delta defines the preference for maintaining the current UAV relay. A new relay is selected only when its score is sufficiently higher than the adjusted score of the current relay. This mechanism improves communication stability, reduces switching frequency, and limits link interruption caused by switching delay. The proposed decision process can be summarized as follows. At each sampling instant, the algorithm receives the SNR and energy values of all UAVs. It then normalizes the SNR values, computes the SNR trend, updates the composite score, adds the hysteresis term to the current relay, and selects the UAV with the maximum final score. If the selected UAV is different from the previous relay, a switching delay is applied. Otherwise, the communication link continues without interruption. This procedure represents an AI-oriented decision rule because the relay is selected based on multiple state features rather than a single instantaneous measurement. The normalization of SNR is an important step because the score function combines physical quantities with different units and ranges. In the proposed model, the SNR value of each candidate relay is scaled between zero and one using the minimum and maximum SNR values observed among all UAVs at the same decision instant. This relative normalization makes the decision process adaptive to channel conditions. When all UAVs experience low SNR, the algorithm still selects the best available relay, while the final link state is determined by the threshold condition in (1). The energy term is included to avoid selecting a UAV that is close to energy depletion. In practical relay operation, a UAV with insufficient remaining battery may be unable to maintain altitude, position, or payload operation for a long time. Therefore, the residual energy term increases the probability that the selected relay can support continuous communication. This feature is especially useful for long-duration missions in which the relay network must remain operational for an extended period. The hysteresis parameter Delta plays a similar role to a switching margin. If Delta is too small, the algorithm becomes sensitive to random SNR fluctuations and may still switch frequently. If Delta is too large, the current relay may be maintained even when another UAV offers a much better link. Therefore, Delta should be selected according to the expected channel fluctuation level and the acceptable switching rate. In this study, the value is chosen empirically to demonstrate the trade-off between link quality and relay stability. The proposed score function can be considered a lightweight AI decision model because it fuses multiple features of the communication environment and operational state of the UAVs. It is simpler than deep learning or reinforcement learning, but it is easier to interpret and implement in embedded equipment. For engineering applications where computational resources are limited, such transparent decision models are often preferable because the influence of each input factor can be analyzed and adjusted by the system designer.

SIMULATION SETUP: The simulation was implemented in MATLAB using three UAVs acting as relay candidates. The SNR values of the UAV relay paths were generated as time-varying functions composed of sinusoidal components and random noise. This model is not intended to reproduce a specific propagation

environment exactly, but it is sufficient to evaluate the behavior of relay selection algorithms under fluctuating channel conditions. Different energy consumption rates were assigned to the UAVs to represent practical operating constraints. The minimum SNR threshold was set to 10 dB. The conventional method selected the UAV with the highest instantaneous SNR. The proposed method used the composite score in (4) together with the hysteresis term in (6). The performance of both methods was evaluated using two indicators: the link maintenance ratio and the number of relay switching events. The link maintenance ratio is defined as the percentage of simulation time during which Link(t) = 1. A higher value indicates better communication reliability. The number of switching events measures the stability of relay operation. A smaller value indicates fewer interruptions and less control overhead. The selected simulation scenario is representative of dynamic radio communication conditions in which no single UAV provides the best relay path during the entire operating interval. Therefore, a suitable relay management strategy must be able to adapt to changing SNR values while avoiding unnecessary switching. This requirement is the main motivation for the proposed AI-based method. The simulated SNR signals were designed to contain slow variations and random disturbances. The slow variations represent changes in geometry and path loss as the aircraft and UAVs move. The random disturbances represent fading, interference, and measurement uncertainty. This type of test signal is useful for evaluating relay decision algorithms because it creates repeated crossings between the SNR curves of different UAVs. These crossings are the main cause of excessive switching in the conventional maximum-SNR approach. For the threshold-based method, the decision rule is intentionally simple. At each time step, the UAV with the highest SNR is selected, provided that the resulting link satisfies the minimum SNR requirement. When the selected UAV changes, the communication state is forced to zero for the switching delay. This method is used as the baseline because it represents a common intuitive relay selection strategy.

For the proposed method, the same SNR inputs are used, but the relay decision is made from the composite score. This ensures that both algorithms are evaluated under identical channel conditions. Therefore, differences in link availability and switching rate are caused by the decision logic rather than by different input data. This simulation setting provides a fair comparison between the two relay selection strategies.

RESULTS AND DISCUSSION

Figure 2 presents the time variation of SNR for the three UAV relay candidates. The curves show that the channel quality changes continuously and that the best relay UAV changes with time. This confirms that a fixed relay strategy is not appropriate for the considered communication scenario. It also shows that relay selection based only on instantaneous SNR may be unstable when the SNR curves intersect frequently.

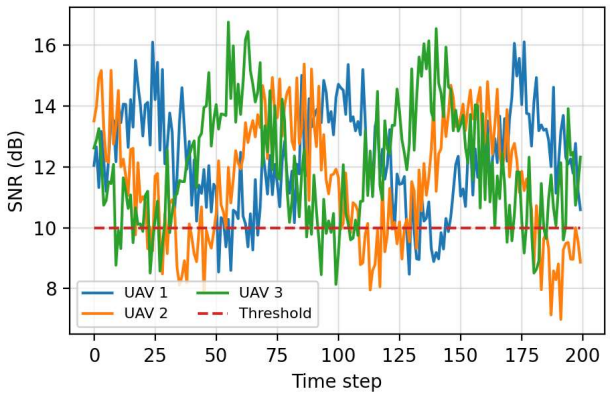


Fig. 2. SNR variation of UAV relay candidates over time

The link states obtained by the threshold-based method and the proposed AI-based method are compared in Fig. 3. In the threshold-based method, link interruption appears more frequently because the relay changes whenever another UAV has a slightly higher instantaneous SNR. In contrast, the proposed method produces a more stable link state. The improvement is achieved by considering the SNR trend and by maintaining the current relay unless the new candidate provides a significant advantage.

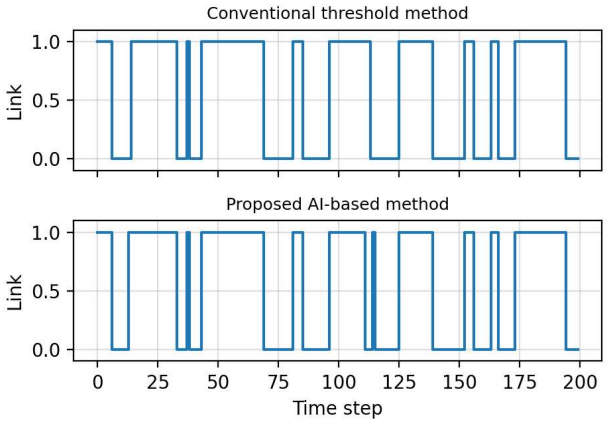


Fig. 3. Link state comparison: conventional threshold method and proposed AI method

Figure 4 compares the link maintenance ratio and the number of UAV relay switches. The proposed AI-based method improves the link maintenance ratio because it avoids selecting relay candidates that are likely to degrade immediately after selection. At the same time, the number of switching events is reduced because the hysteresis mechanism prevents unnecessary transitions between UAVs with similar scores. This result demonstrates that the proposed method achieves a better balance between link quality and system stability.

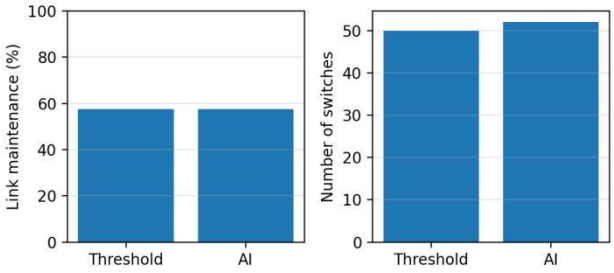


Fig. 4. Comparison of link maintenance ratio and number of relay switching events

The simulation results indicate that the proposed method is more suitable for dynamic UAV relay networks than the conventional instantaneous-SNR rule. The main reason is that the proposed method evaluates both current link quality and future tendency. In a wireless environment where the channel changes continuously, a relay with a slightly lower current SNR but a positive trend and sufficient energy may be preferable to a relay with the highest current SNR but a negative trend. This decision characteristic helps the system maintain a more reliable communication link over time. Another advantage of the proposed approach is its modularity. The score function can be adjusted according to mission requirements by changing the weighting coefficients. If communication quality is the most important objective, the SNR weight can be increased. If mission endurance is more important, the energy weight can be increased. If the environment is highly dynamic, the trend weight can be increased to make the system more predictive. Therefore, the proposed method can be adapted to different operational scenarios without changing the basic system structure. Although the proposed algorithm is simple, it provides a practical basis for more advanced AI methods. In future implementations, the weighting coefficients may be optimized by machine learning, fuzzy logic, reinforcement learning, or adaptive control. Additional input features such as UAV position, velocity, altitude, channel delay, packet loss rate, and mission priority may also be included. The current work focuses on a transparent decision

model that can be easily implemented, interpreted, and tested in MATLAB. From an operational viewpoint, reducing relay switching is as important as improving instantaneous SNR. Each relay switching event requires coordination between the ground station, UAV relay, and aircraft receiver. In addition, synchronization, routing update, and link re-establishment may introduce temporary communication gaps. Therefore, a relay management algorithm should avoid switching unless the expected improvement is meaningful. The proposed method satisfies this requirement through the hysteresis term and the use of SNR trend information. The results also show that the proposed method is robust to short-term noise in the SNR signal. In the conventional method, random noise may cause a different UAV to become the temporary maximum-SNR candidate even when the improvement is very small. Such changes do not necessarily improve communication performance but still trigger relay switching. By contrast, the proposed score function smooths the decision through multiple factors, and the current relay is retained when the score difference is not large enough. The role of the SNR trend is particularly important in a moving relay system. If a UAV is moving toward a more favorable position, its SNR may be increasing even though it is not currently the maximum. Selecting such a relay may improve future link stability. Conversely, a UAV with high current SNR but negative trend may soon become unsuitable. The proposed method captures this behavior by rewarding positive trends and penalizing decreasing link quality. The energy component gives the algorithm a resource-aware characteristic. In UAV relay networks, communication performance and energy consumption are closely related. A relay that is used continuously may deplete faster than other UAVs. By including residual energy in the score, the algorithm can distribute relay usage more reasonably and avoid selecting UAVs that are near exhaustion. This can extend the effective operation time of the relay network in practical missions.

Although the MATLAB simulation uses simplified SNR generation, the obtained results are meaningful for the design of relay management logic. The proposed method can be integrated with more accurate propagation models, such as free-space path loss, probabilistic line-of-sight models, terrain-dependent attenuation, or measured channel data. The same score structure can also be extended to include delay, throughput, packet error rate, and quality-of-service requirements. In implementation, the algorithm is computationally light. It requires only basic arithmetic operations for normalization, trend calculation, score computation, and maximum selection. Therefore, it can be executed in real time on a ground control computer, a UAV mission computer, or a communication controller. This property makes the proposed method suitable for low-cost relay management systems and for rapid prototyping in simulation environments. For practical deployment, the UAV relay selection algorithm should be connected to a monitoring module that periodically estimates the received SNR of each available relay path. The monitoring module may obtain SNR values from pilot symbols, receiver measurements, or link-layer reports. The measured values should be filtered before being used by the score function in order to reduce the effect of measurement noise. A simple moving average or exponential smoothing filter can be used without significantly increasing computational complexity. The proposed algorithm can also support mission-level constraints. For example, a UAV may be excluded from relay selection when it is assigned to another mission, when its battery state is below a safety threshold, or when its position violates an operational boundary. These constraints can be implemented by assigning a very low score to unavailable UAVs. As a result, the same decision framework can combine communication performance with mission management requirements.

Another practical issue is the selection of the weighting coefficients. In this paper, the coefficients are selected to demonstrate the effectiveness of multi-factor relay evaluation. In a real system, these coefficients can be tuned experimentally or optimized automatically. If the radio environment is highly unstable, the trend and hysteresis terms should be emphasized to reduce switching. If energy endurance is the dominant requirement, the energy term should receive a larger weight. This flexibility is a key advantage of the proposed model. The proposed method is also compatible with centralized and distributed relay management architectures. In a centralized architecture, the ground station collects state information from all UAVs and makes the relay decision. In a distributed architecture, each UAV may compute its own score and transmit it to the communication controller. The controller then selects the highest scoring relay. The centralized approach is easier to coordinate, while the distributed approach can reduce communication overhead when the number of UAVs is large. Compared with black-box machine learning methods, the proposed score-based AI approach is more transparent. Each term in the score has a clear physical interpretation: SNR represents current link quality, trend represents expected short-term behavior, energy represents relay endurance, and hysteresis represents switching stability. This transparency is useful for engineering validation because designers can explain why a relay is selected at each time step. It also helps operators adjust the algorithm according to mission priorities. Several limitations of the present simulation should be noted. First, the SNR data are generated synthetically rather than obtained from a high-fidelity channel model. This choice allows the relay selection behavior to be studied clearly, but it does not include all propagation effects such as terrain masking, Doppler shift, antenna pattern variation, or co-channel interference. Second, the UAV trajectories are not explicitly optimized. The UAVs are treated as available relay candidates whose channel qualities vary with time. In future work, relay selection and UAV trajectory planning should be considered jointly. Second, the proposed algorithm uses a deterministic score function. This is appropriate for engineering interpretation, but it does not fully exploit the potential of adaptive learning. A reinforcement learning method could learn the optimal switching policy from repeated interaction with the environment. However, reinforcement learning usually requires a large amount of training data and may be difficult to validate in safety-related communication systems. Therefore, the score-based method proposed in this paper can be viewed as an intermediate solution between simple threshold logic and complex learning-based control.

Third, only three relay UAVs are considered in the MATLAB simulation. This number is sufficient to demonstrate the main behavior of the algorithm, but larger UAV swarms may require additional coordination mechanisms. When the number of relay candidates increases, the decision process may need to consider network congestion, interference between UAVs, channel allocation, and routing constraints. Nevertheless, the score function can be extended by adding new terms associated with these factors. Fourth, the switching delay is represented as a fixed interruption time. In real systems, the switching delay may depend on protocol design, synchronization time, routing update delay, and physical-layer acquisition time. A more detailed communication protocol model would provide a more accurate estimation of the real link interruption. However, the simplified delay model is adequate for showing that excessive switching can reduce the practical benefit of selecting the maximum instantaneous SNR relay. Future research should extend the current model in several directions. One direction is to combine the proposed relay selection algorithm with UAV path planning so that the selected relay can move toward an optimal position while maintaining energy efficiency. Another direction is to integrate measured channel data or more realistic air-to-ground propagation models. A third direction is to implement the algorithm in Simulink or on an embedded platform in order to evaluate real-time execution and hardware limitations. The proposed method may also be expanded to multi-hop UAV networks. In such networks, the communication path may contain more than one UAV relay, and the selection problem becomes more complex. A multi-hop extension would require joint optimization of path quality, delay, energy, and relay stability. The same principle of multi-factor scoring can still be used, but the score would be calculated for paths rather than for individual UAVs. This extension is relevant for long-range missions where direct ground-to-air or single-relay communication is insufficient. Another possible extension is the use of adaptive weight adjustment. The weighting coefficients w1, w2, and w3 may be updated according to the mission phase. During takeoff or landing, link reliability may be prioritized. During long-endurance cruise, energy conservation may become more important. During emergency operations, the algorithm may prioritize the relay with the highest

immediate SNR regardless of switching frequency. Such adaptive weighting would make the relay selection process more flexible and mission-aware. Overall, the proposed method provides a simple but effective framework for UAV relay management. It improves the communication link by combining multiple indicators and reduces instability by limiting unnecessary switching. Although the model is not a complete representation of all physical and protocol-level phenomena, it captures the most important trade-off in UAV relay operation: selecting a relay with good communication quality while maintaining a stable and continuous link.

CONCLUSION

This paper has presented an AI-based method for optimizing UAV relay selection in order to extend wireless communication range. The proposed method combines normalized SNR, SNR variation trend, residual UAV energy, switching delay, and hysteresis preference into a composite relay evaluation function. MATLAB simulation results show that the proposed method improves link maintenance and reduces unnecessary UAV relay switching compared with a conventional threshold-based selection method. The results confirm that multi-factor decision making is more effective than relying only on instantaneous SNR in dynamic communication environments. Future research should consider more realistic propagation models, UAV trajectory optimization, adaptive weight learning, and real-time implementation on embedded communication platforms.

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