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Implementation Of Long Short-Term Memory (LSTM) For Routing Optimization In Ad Hoc Networks (FANETS)

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ABSTRACT

Flying Ad Hoc Network (FANET) is a mobile wireless network formed by multiple Unmanned Aerial Vehicles (UAVs) with highly dynamic topology. This rapid topology change makes routing more complex than in conventional Mobile Ad Hoc Networks, since UAV movement can continuously affect link quality, disconnection probability, and packet delivery delay. This study applies Long Short-Term Memory (LSTM) to optimize FANET routing using time-series network metrics, including signal-to-noise ratio, delay, throughput, energy, packet loss rate, jitter, and bandwidth utilization. The LSTM model learns temporal relationships among network conditions, enabling next-hop selection to consider not only current link status but also its evolution over time. The proposed method is evaluated against AODV, OLSR, and the Stochastic Probability Algorithm (SPA) using Packet Delivery Ratio (PDR) and end-to-end delay under different numbers of UAVs and UAV speeds. Results show that LSTM consistently achieves the highest PDR across all scenarios. For UAV number variation, LSTM improves PDR from 0.166 to 0.380, outperforming AODV, OLSR, and SPA. For UAV speed variation, LSTM maintains PDR between 0.89 and 0.73, remaining superior to the comparison methods. In addition, LSTM produces the lowest delay, ranging from 0.60 to 0.70 s for UAV number variation and 0.35 to 0.61 s for UAV speed variation. These results demonstrate that LSTM effectively captures the temporal dynamics of FANET and is suitable for adaptive routing support.

1. INTRODUCTION

Flying Ad Hoc Network (FANET) is an ad hoc network formed by several UAVs that communicate with each other without full dependence on fixed infrastructure[1]. UAVs are implemented in military operations, agriculture, disaster monitoring, traffic, logistics, aerial photography, mapping[2], and communication networks such as FANET because they can move quickly, flexibly, and reach areas that are difficult to access. In this network, each UAV can function as a source node, destination node, as well as a relay node that forwards packets to other UAVs[3]. Its working mechanism begins when a node observes the neighbors around it, measures link quality and then selects the multi-hop path considered most feasible for sending packets to the destination. Different from static networks, FANET operates in three-dimensional space so that changes in position, speed, and flight direction will directly affect network topology[4]. As a result, the routing process must be carried out adaptively, quickly, and be able to respond to channel condition changes in near real time. If the route decision is delayed, packets can be sent through a link that has already weakened or even disconnected, thereby reducing Packet Delivery Ratio (PDR) and increasing delay.

Figure 1 shows the packet delivery process in FANET from the source to the destination through several alternative paths. The source cannot always send directly to the destination because of radio range limitations, so the packet must pass through intermediate UAVs[5]. In the illustration, several candidate paths are available, such as Path 1, Path 2, and Path 3, with different numbers of hops and different link

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conditions. In practice, path selection is not sufficient if it is based only on the smallest number of hops, because a short path is not necessarily stable[6]. A path with more hops but stronger and more stable links can produce better PDR and lower retransmission. Therefore, FANET routing is essentially a dynamic decision-making problem[7] that must consider link stability, channel quality, node mobility, and the possibility of topology changes in the next time slot.

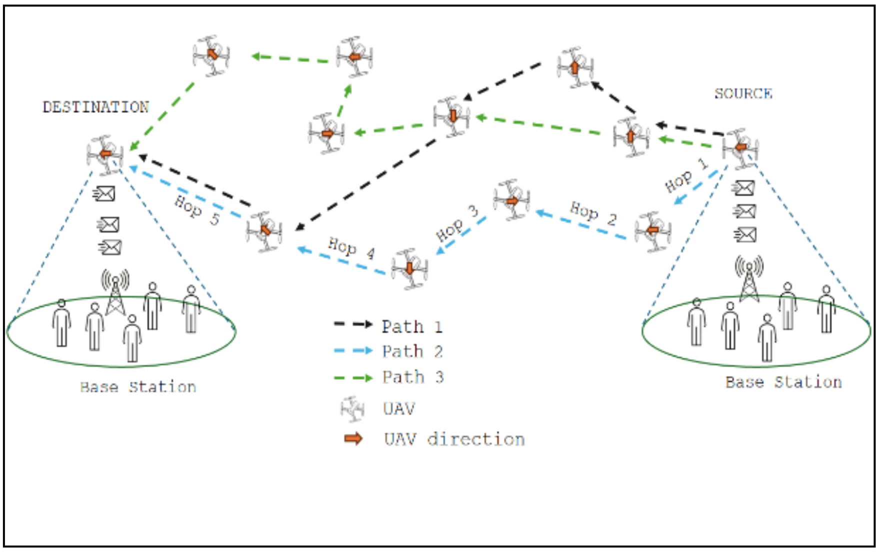

Figure 1. Packet delivery process in FANET

The main constraints of FANET lie in very high mobility[8], frequent link disconnection, and channel quality variation that is difficult to predict. When UAV speed increases, the distance between nodes changes more rapidly, so the routing table built by conventional protocols can quickly become outdated[9]. AODV is indeed flexible because it is reactive[10], but it still often experiences route discovery overhead when a link breaks. OLSR can maintain topology information through periodic updates[11], but the control burden can increase under high-mobility conditions. SPA uses probabilistic principles to select routes[12], but its accuracy is strongly determined by the quality of link success probability estimation. Other challenges are the limited energy of UAVs, changing packet queues, inter-channel interference, as well as the need to balance throughput, delay, and delivery reliability simultaneously.

In addition, the data traffic characteristics in FANET are also highly fluctuating. Telemetry packets, images, videos, and control data can arrive in unpredictable patterns that cause queue conditions at UAVs to change rapidly from one interval to the next. Therefore, a good routing decision must observe the sequence of metric changes, not merely a single value. A temporal learning-based approach becomes relevant because it can connect past conditions, current conditions, and future condition tendencies. This is the reason LSTM is selected in this study, because its memory structure allows the model to retain information that is important for route prediction, while discarding old information that is no longer relevant to current network dynamics.

The novelty of this study lies in the use of LSTM[13] as a route-quality prediction mechanism based on time series for FANET routing. Rather than only evaluating an instantaneous snapshot of current network conditions, LSTM processes a sequence of observations from several time intervals so that it can recognize patterns of link quality change before a routing decision is taken. With this approach, the system not only responds to instantaneous conditions, but also utilizes short-term and long-term memory to avoid paths that tend to deteriorate. The proposed implementation arranges the network metrics of each link into a sequential input vector, processes it inside the LSTM, and then produces a route-quality score used to select the best next hop. The contribution of this study is the availability of a concrete input-process-output scheme for integrating deep learning into FANET routing, together with a direct comparison with AODV, OLSR, and SPA in two main mobility scenarios.

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2. METHOD

The implementation of LSTM in this study is designed as a route-quality prediction module that operates on top of the FANET routing process. Each UAV periodically collects link-condition data to its nearest neighbors, and then the data are formed into a time sequence before being sent to the LSTM model. The main system inputs are the network metrics that are most relevant to packet delivery success, namely signal-to-noise ratio (SNR), local delay, throughput, residual node energy, packet loss rate (PLR), jitter, and bandwidth utilization. These parameters are common measures for assessing how a network performs[14]. Thus, at each time t, a feature vector is obtained that represents the quality of a candidate next hop. A set of vectors from several previous times forms an observation window that is used to predict route feasibility at the next time. The model output is not merely a good-or-bad label, but a route-quality score that can be used to rank all candidate paths adaptively.

Concretely, the implementation flow consists of three stages. The input stage begins when the source UAV or relay reads network conditions from active neighbors and arranges them into a standardized numerical vector. The process stage is carried out by feeding the vector sequence into the LSTM unit so that temporal relationships among metrics can be learned. The output stage produces a prediction value that is interpreted as path quality or next-hop priority. This mechanism is important because changes in delay, energy, and channel quality are not purely random, where there are often patterns of degradation or improvement that can be captured from the history of several time slots. In other words, LSTM allows routing decisions to be made based on the tendency of network dynamics, not merely based on a single instantaneous measurement.

Figure 2 shows the basic working mechanism of LSTM. Information from the previous time is stored in the cell state and hidden state. The forget gate selects the part of the old memory that needs to be retained, the input gate determines the new information that deserves to be written into memory, while the candidate state carries the representation of candidate new information resulting from nonlinear transformation. After that, the output gate determines which part of the latest cell state is forwarded as the hidden state. In the FANET context, the cell state can be understood as memory regarding the tendency of link stability, for example whether a neighbor over several intervals tends to experience decreasing SNR, increasing delay, or rapid energy depletion. The hidden state then becomes a compact representation that is ready to be used to predict routing quality at the next step.

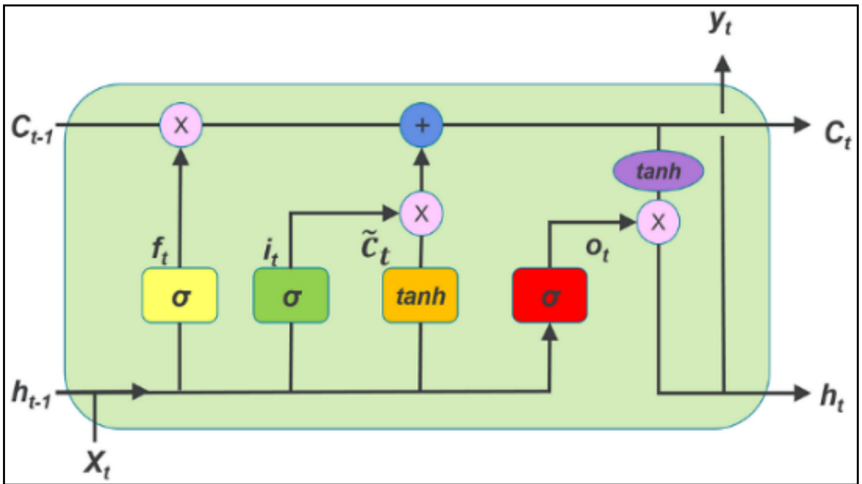

Figure 2. LSTM working mechanism

Table 1 summarizes the LSTM-based FANET routing flow in three stages: input, process, and output. UAVs collect network metrics, convert them into feature vectors, and arrange them as time sequences. The LSTM processes these sequences to predict route quality, then the sender ranks candidate next hops and selects the best path adaptively.

Table 1. Input-process-output flow of LSTM implementation in FANET routing

Stage	Implementation	Output
Input	Each UAV reads SNR, delay, throughput, residual energy, PLR, jitter, and bandwidth utilization from candidate neighbors at each time slot.	Feature vector x_t for each candidate link.
Process	Feature vectors are arranged into a time sequence, normalized, and then processed by LSTM to capture temporal patterns of link-quality change.	Hidden-state representation h_t and route-quality prediction score.
Output	The sender node ranks all candidate next hops based on the prediction score and selects the path with the best value that still satisfies connectivity requirements.	Adaptive routing decision and best next-hop selection.

The following are the core equations used to implement LSTM in FANET.

$$x_t = [SNR_t, D_t, PLR_t, J_t, BU_t]^T \quad (1)$$

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (2)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (4)$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (5)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t * \tanh(c_t) \quad (7)$$

$$\hat{y}_t = W_y h_t + b_y \quad (8)$$

In these equations, W and b are the weights and biases learned during training, σ is the sigmoid function, $\tanh$ is the hyperbolic function, and $*$ denotes element-wise multiplication. The value $\hat{y}_t$ is used as a route-quality prediction score to evaluate each candidate next hop.

For these equations to become truly operational in FANET routing, each candidate neighbor is treated as an evaluation object having its own condition sequence. Suppose UAV i has several neighbors j, then each link $i \rightarrow j$ is formed into its own input sequence. After the model produces score $\hat{y}_t$ for each candidate, the sender node selects the next hop with the highest score as long as it still satisfies the basic connectivity requirements. This strategy provides two advantages. First, the decision becomes more anticipatory because the model has observed historical patterns. Second, route changes do not need to wait for total link failure, because path quality that begins to decline can be detected earlier from the sequence pattern.

To test the effectiveness of the proposed method, LSTM performance is compared with three other approaches, namely AODV, OLSR, and Stochastic Probability Algorithm (SPA). AODV represents a reactive protocol, OLSR represents a proactive approach, while SPA represents probability-based route selection. Evaluation is carried out in two main scenarios: variation in the number of UAVs of 10, 20, 30, 40, and 50 nodes, and variation in UAV speed of 20, 25, 30, 35, and 40 m/s. The two evaluation metrics analyzed are Packet Delivery Ratio (PDR) and end-to-end delay. PDR is used to observe the packet delivery success rate, while delay shows how quickly data reach the destination. With this test design, the advantages of LSTM can be observed both under increasing node-density conditions and under increasingly aggressive mobility conditions.

Table 2 presents the comparison methods used to evaluate the proposed routing model. LSTM is positioned as the proposed method because it applies a predictive time-series approach with temporal memory, allowing routing decisions to consider historical network behavior. AODV is included as a reactive baseline since it builds routes only when needed, making it useful for observing route-discovery response to link changes. OLSR represents a proactive baseline because it maintains topology information through periodic updates, which helps examine control overhead under high mobility. SPA is used as a probabilistic baseline, where route selection depends on link success probability, enabling comparison of prediction accuracy.

Table 2. Comparison methods in the evaluation

Method	Main characteristic	Role in evaluation
LSTM	Predictive time-series-based approach with temporal memory.	Proposed method for routing optimization.
AODV	Reactive routing protocol that establishes routes when needed.	Baseline to observe route-discovery response to link dynamics.
OLSR	Proactive routing protocol with periodic topology updates.	Baseline to observe the impact of control overhead under high mobility.
SPA	Route selection based on link success probability.	Probabilistic baseline to compare route prediction accuracy.

3. RESULTS AND DISCUSSION

Figure 3 shows the comparison of PDR with respect to the number of UAVs. In general, all methods show an increasing trend when the number of UAVs increases from 10 to 50 nodes. This increase is logical because more UAVs mean more alternative relay paths are available, so the probability that the source finds a route to the destination also increases. However, LSTM still provides the highest PDR values at all test points, namely 0.166, 0.282, 0.334, 0.363, and 0.380. These values consistently remain above AODV, which reaches 0.137 to 0.357, OLSR at 0.102 to 0.340, and SPA at 0.050 to 0.316. These results indicate that the use of network-condition history makes LSTM better in selecting paths that are truly feasible for packet delivery.

From an operational point of view, the superiority of LSTM in Figure 3 indicates that an increase in network density does not necessarily automatically produce optimal routing decisions if the algorithm is not able to filter candidate paths correctly. When the number of UAVs increases, the number of possible next hops also increases and the complexity of decision-making increases. LSTM is able to transform this complexity into an advantage because the model can distinguish links that tend to be stable from links that only appear good momentarily. Compared with conventional methods that depend more on route updates or static probability estimation, LSTM utilizes temporal relationships among observations so that packets are more often sent through paths with a higher probability of success. Thus, Figure 3 confirms that sequence learning is suitable for routing in FANET topology that is rich in path alternatives.

Figure 4 shows the comparison of PDR with respect to UAV speed. All methods experience a performance decline when speed increases from 20 m/s to 40 m/s, because higher mobility accelerates topology changes and increases the possibility of link breakage during the delivery process. Even so, LSTM still maintains the best performance with PDR values of 0.89, 0.83, 0.80, 0.75, and 0.73. As a comparison, AODV produces 0.85 to 0.65, OLSR 0.79 to 0.63, and SPA 0.75 to 0.58. This difference shows that LSTM is more resistant to network-quality degradation caused by speed, especially under the heaviest condition when UAVs move at 40 m/s.

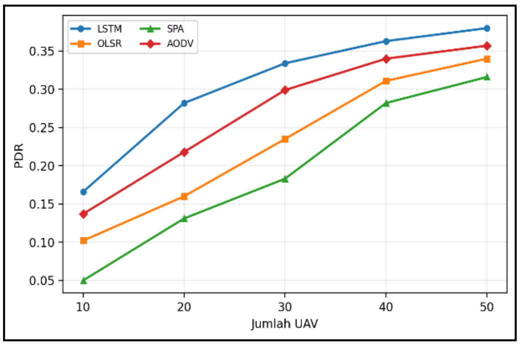

Figure 3. PDR comparison based on number of UAVs

This superiority can be explained by the ability of LSTM to capture patterns of link-quality change before the link truly fails. At high speed, the distance between nodes and communication orientation change very rapidly, so protocols that only react after the route is broken will always lag behind by one step. LSTM works more predictively, where if in the last several intervals a neighbor shows a pattern of decreasing SNR, increasing delay, or increasing PLR, the model can reduce the route score earlier and direct packets to another, safer path. It is this predictive character that makes LSTM PDR remain the highest at all speed levels. In other words, Figure 4 confirms that temporal memory is an important component for maintaining routing reliability in highly dynamic FANET.

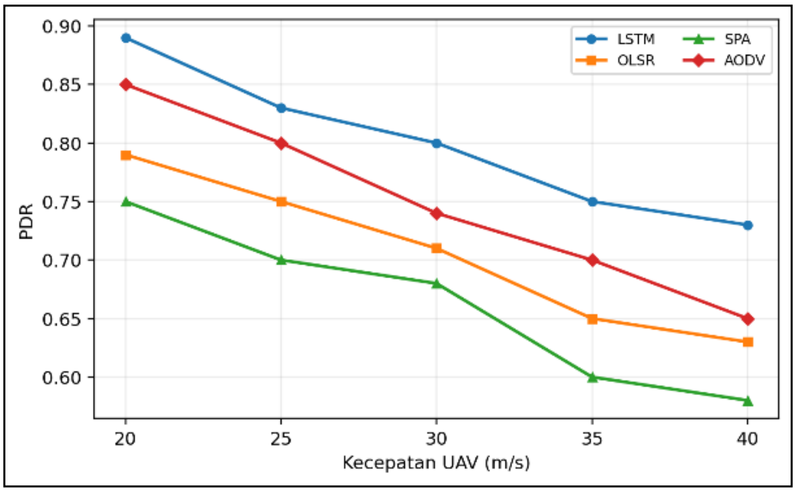

Figure 4. PDR comparison based on UAV speed

Figure 5 shows end-to-end delay with respect to the number of UAVs. Different from PDR, which is expected to increase, delay instead increases in all methods as the number of UAVs grows, because the increase in nodes enlarges traffic, queues, and the possibility of longer multi-hop forwarding processes. However, LSTM again shows the best results with delays of 0.60, 0.63, 0.66, 0.67, and 0.70 s. These values are lower than AODV at 0.61 to 0.73 s, OLSR at 0.65 to 0.80 s, and SPA at 0.68 to 0.90 s. Thus, although the network becomes increasingly dense, LSTM is still able to keep packet travel time lower than the other methods.

Analytically, lower delay indicates that LSTM not only succeeds in delivering more packets but also directs packets through more efficient paths. When route selection is performed on more stable links, the need for retransmission, route repair, and delays due to route switching can be reduced. This effect is very important in FANET because unstable topology often causes packets to wait for new route establishment. LSTM reduces this phenomenon by selecting next hops that have better stability prospects based on observation history. The results in Figure 5 show that predictive intelligence not only affects reliability, but also directly contributes to system latency, which is highly crucial for UAV-based monitoring, search, and tactical communication applications.

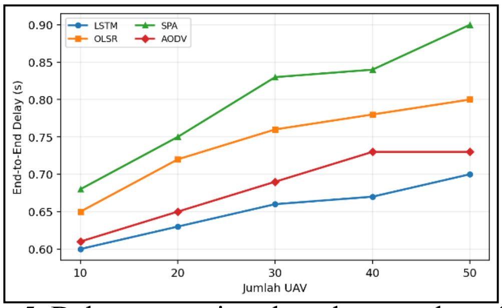

Figure 5. Delay comparison based on number of UAVs

Figure 6 shows delay with respect to UAV speed, and the results show a stronger impact of mobility. All methods experience increasing delay as speed rises from 20 m/s to 40 m/s. LSTM still records the lowest delays, namely 0.35, 0.44, 0.49, 0.56, and 0.61 s. In contrast, OLSR is at 0.49 to 0.71 s, AODV is at 0.56 to 0.78 s, and SPA is at 0.60 to 0.80 s. From these data, it can be seen that the gap between LSTM and the comparison methods becomes even more pronounced when speed increases, which means that the adaptation capability of LSTM becomes increasingly valuable in more dynamic environments.

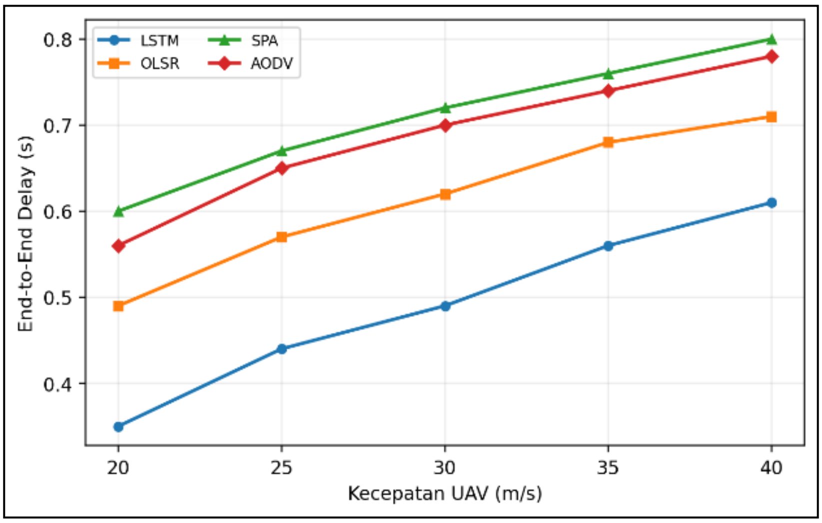

Figure 6. Delay comparison based on UAV speed

The interpretation of Figure 6 is that high mobility not only affects delivery success, but also increases waiting time due to frequent route switching, packet buffering, and link-break recovery. LSTM is able to suppress this effect because routing decisions are made based on temporal patterns that have been learned, not merely based on current link status. When a candidate path shows a deteriorating trend, the model can lower the priority of that path before failure occurs, so that the forwarding process continues on a more stable trajectory. Therefore, the combination of results in Figures 3 to 6 provides a consistent conclusion: LSTM excels both in reliability metrics and in delay metrics, and this superiority becomes increasingly important when FANET complexity increases because of additional nodes or higher UAV speed.

Table 3 shows a summary of UAV performance using the LSTM method compared with other methods. The PDR value of LSTM is 11% higher than AODV, 25% higher than OLSR, and 37% higher than SPA. Meanwhile, the delay in LSTM is 4% lower than AODV, 12% lower than OLSR, and 18% lower than SPA.

Table 3. Summary of method comparison

Method	Average PDR	Average Delay
LSTM	0.305	0.652
OLSR	0.229	0.742
AODV	0.270	0.682
SPA	0.192	0.800

4. CONCLUSION

The implementation of LSTM is proven to improve the quality of routing decisions in FANET because it is able to utilize the history of network metrics as the basis for route-quality prediction.

Compared with AODV, OLSR, and SPA, this method produces the highest average Packet Delivery Ratio of 0.305 in scenarios of both variation in the number of UAVs and variation in UAV speed, while at the same time maintaining the lowest average end-to-end delay of 0.652. In the node-variation scenario, LSTM shows that network density can be transformed into an advantage when next-hop selection is carried out predictively. In the speed-variation scenario, LSTM remains stable even though topology changes rapidly, so links with the potential to fail can be avoided earlier. Overall, this study confirms that LSTM is feasible to be used as the core of adaptive routing optimization in FANET. Future development can be directed toward adding energy metrics, throughput, or time-weighting mechanisms so that the model becomes more responsive to extreme network dynamics in the future.

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