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RESEARCH ARTICLE

Recursive Perceptron Long Short Term Memory for Wireless Data Transmission in Unmanned Aerial Vehicles

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Abstract – In Wireless Sensor Networks, diverse nodes are associated with each other for monitoring definite circumstances. So, sensors are considerably utilized in distinct real-time utilizations namely remote operated unmanned vehicle, atmospheric surveillance, disaster management, and so on. Transmitting data from a remote operated unmanned vehicle to server via Long Term Evolution (LTE) with the harmony of Bluetooth Low Energy (BLE) relaying remains the core of significant data transmission in wireless networks. The utilization of Unmanned Aerial Vehicles (UAVs) for wireless networks is swiftly heightening as the driving force of new applications due to their distinctive resources for improving coverage and energy efficiency of wireless network UAVs act as base stations. In other condition, data-driven Deep Learning-assisted (DL) strategies using multilayer perceptron are acquiring an increasing interest for not utilizing huge frequency of generated data, however ensuring network procedure in an optimal manner and hence providing QoS requirements of wireless networks. But, UAVs is resource-constrained devices specifically in power resources and data transmission. With traditional DL scheme being cloud-centric necessitate UAVs' data are stored in centralized server, therefore generating huge communication overhead and thus result in network bandwidth and energy inefficiency of UAV devices. To address these issues in this work, a Fully Recursive Long Short Term Memory (FR-LSTM) for improving data transmission rates and quality of service in wireless networks is proposed. Initially, Deep Learning-based model was designed in Long Term Evolution (LTE) Dominant Influencing Criterions (DIC) estimation. The applications of power resources and bandwidth allocation (PRBA) in self-organizing LTE small cell network, therefore minimizing RMSE and average end-to-end delay involved in transmission. Next, a Fully Recursive Perceptron Network (FRPC) and LSTM model was utilized and applied for DIC to resolve the UAV position which reduces overall system performance and user throughput. Hence, for classification regression tasks, when is there no LTE signal, data can be transmitted to another device through BLE (Bluetooth Low Energy), therefore ensuring throughput and ensuring minimum latency. The effectiveness of FR-LSTM is yet to be validated using four kinds of evaluation metrics with diverse number of nodes, namely, RMSE, throughput, average end-to-end delay, and latency.

Index Terms – Wireless Sensor Network, Long Term Evolution, Long Short Term Memory, Dominant Influencing Criterion, Root Mean Square Error, Power Resources and Bandwidth Allocation.

1. INTRODUCTION

Long Term Evolution identification necessitates Medium Access Control (MAC) scheduler entity in bestows full proof QoS in downlink and uplink direction. However, LTE-MAC usually takes into consideration only single impediment like, radio resource availability, user throughput and channel conditions so on. However, in reality not taking into consideration all the constraints in a synchronous manner would affect the QoS requirements.

A multilayer perceptron neural network was proposed in [1] based on UAV localization was proposed with the objective of enhancing the localization accuracy. Here, the UAV height plays the dominant role on accuracy aspect, the flying height was initially optimized and followed by which the localization was said to be performed. Moreover, nonlinear MLP model with nonlinear activation functions was employed that in turn serves enhanced as localizing node in WSNs by UAV, therefore not only improving localization accuracy but also minimizing the deployment cost. However, MLP-based

RESEARCH ARTICLE

localization for Unknown Nodes (UN) localization in UAV aided WSN is resource-constrained devices specifically in power resources and data transmission.

A Multi Objective QoS aware LTE-A Downlink-MAC Scheduler (MOQDS) method was proposed in [2] that provided a two level QoS and fairness analysis. Here, the scheduling were said to be performed at various levels by means of each level provides own objective with respect to numerous operational restrictions. Each transmission time gap, the method utilized multi-objective optimization for the purpose of obtaining correct users' based on the utilization for converged LTE QoS requirements. With this average reduction in packet drop was said to be ensured along with the improved cell throughput. However with multi objective multi constraint being cloud-centric due to cloud-based radio access networks for LTE necessitates UAVs' data to be stored in a centralized server, therefore generating huge communication overhead and thus result in network bandwidth and energy inefficiency of UAV devices.

In this article, novel data transmission method was designed from unmanned vehicle to the server via LTE, called, Fully Recursive Long Short Term Memory (FR-LSTM) which will simultaneously address QoS and data transmission in wireless network. The contributions are given below.

1.1. Contribution

- A new Fully Recursive Long Short Term Memory (FR-LSTM) method is developed and it can effectively perform data transmission for UAVs via LTE and BLE into a unified representation. The spatial and temporal factors that influence data traffic generation are Deep Influencing Learning-based LTE and Fully Recursive Perceptron-based Long Short Term Memory.
- To capture the optimal vehicle when network coverage is available, a Deep Influencing Learning-based LTE algorithm is put forward to obtain data matrix split into different grids based on frequency and bandwidth. Then, a successive Dominant Influencing Criterions (DIC) strategy is proposed to capture the deviations and covariance of each vehicle.
- The Fully Recursive Perceptron-based Long Short Term Memory is also explored to fully utilize the mapping from an input sequence to output sequence, updating the weight and bias by employing Fully Recursive Perceptron, thus further analyzing UAV positioning performance.

1.2. Motivation

Many researchers have been carried out for data transmission. But the consumption of energy is higher.

- Data transmission rate was found to be too low.
- Security aspects were not analyzed.
- Large number of overhead.
- Bandwidth and energy is inefficient.
- Performance analysis was not carried out.
- Small amount of latency and signaling overhead.

This motivates to introduce the Fully Recursive Long Short Term Memory (FR-LSTM) method.

1.3. Scope

The scope of wireless data transmission is used to reduce the time consumption while communication between sender and receiver. In addition transmission overhead needs to be reduced during data communication.

The rest of the articles are organized as follows. Section 2 describes overview of significant data transmission for UAV in wireless networks. Section 3 explains Fully Recursive Long Short Term Memory (FR-LSTM) method and analysis. Section 4 illustrates UAV positioning and data transmission metrics to estimate FR-LSTM method. Section 5 explains simulation parameters and discusses in detail by comparing it with state-of-the-art methods. Section 6 concludes the present work.

2. RELATED WORKS

Over of the past few years, Unmanned Aerial Vehicle (UAV) is being considered as the future device for distinct application solutions and also has been accessible for practical development. This is due to the reason that with the advanced sensor implementations, autopilot missions are said to be implemented for different applications. In [3], secured UAV-assisted heterogeneous network environment was proposed to ensure secure continuous connectivity. Challenges and several open problems and issues accordingly concerning use of UAV based on Federated Deep Learning (FDL) was investigated in [4]. An elaborate study was conducted in [5] to minimize 5G deployment cost within small and medium-sized enterprises.

The utilization of UAVs as wireless communication manifestos for easing communication has received great level of significance in the recent years. Vehicles that bestow such prerequisites are essential in dreadful circumstances for assisting rescue squads for reducing fatalities and keep away from supplement destruction in the concerned area. Line of sight and non-line of sight were discussed in [6] detail for healthcare applications. However, the data transmission rate was found to be too low. To improve the data transmission rate, massive random access of devices was performed in [7] using double queue model.

Taking into consideration the rising requirements of maritime digital data services, there arise a requirement to design

RESEARCH ARTICLE

maritime communications assisting high-speed data rates and improved communication exposure. A long term development for maritime was designed in [8] therefore improving communication coverage in an extensive manner. Performance modeling and analysis of LTE system to access unlicensed spectrum was designed in [9]. However, security aspects were not analyzed. To address this issue, a non-repudiation key hint transmission between devices was proposed in [10], therefore contributing to protected data sharing in D2D communication.

Long Term Evolution (LTE) in unlicensed spectrum band (LTE-U) is presented that used 5 Giga Hertz for 3rd Generation Partnership Project (3GPP) in the cellular networks. However, performance analysis was not carried out. In [11] with the weighted area spectral efficiency, the transmission duration was said to be improved enhancing the transmission duration also. On the other hand, wavelet transforms were employed in [12] to significantly minimizing the error involved. However, issues were related to over load remained unaddressed. To address this issue, current standardized solutions were analyzed for group-based communication in [13].

A novel vertical handover scheme was proposed in [14] on the basis of a multi-criteria prediction decision. With this, accuracy percentage involved in vertical handover was said to be improved significantly. Yet another heuristic method integrating radio and transport resources was investigated in [15] with the objective of reducing the total cost involved in handover. Yet another enhanced handover mechanism employing mobility prediction was proposed in [16] to not only improve the network throughput but also to reduce the retransmission gradually.

However, the above said techniques may cause a small amount of latency and signaling overhead. To address this issue, a user application based commercial access point selection method was proposed in [17], therefore minimizing the association latency and achieving higher throughput. Certain insights and methods for LTE using Orthogonal Frequency Division Multiplexing was investigated in [18] therefore improving robustness and reliability to certain extent. A historical perspective involving evolution and impact of Wi-Fi was investigated in [19]. Yet another performance evaluation model for vehicular networking concerning LTE towards minimization of delay was proposed in [20]. A joint resource allocation problem based on cognitive radio (CR) techniques was developed in [21] for user equipment with multi-homing capabilities. The long-term dynamical evolution and orbital lifetime of low-inclination GTOs are introduced in [22] based on the Semi-analytic Tool for End of Life Analysis software (STELA) with the solar radiation pressure (SRP) and Earth's shadow taken into account. A measurement-based neural-network-based root-mean-square (RMS) delay spread model was designed in [23] for ubiquitous indoor IoTs scenarios. The Long Short-Term Memory (LSTM) Neural Network model was developed in [24] to predict irrigation prescriptions. The cloud radio access network (C-RAN) architecture is proposed in [25] to fully meet the requirements of 5G mobile networks.

Previous proposal have made extensive contributions to the deployment of UAV and data transmission. Although with high resource constraint the QoS is said to be compromised. For this reason, this study supplements previous research studies by proposing new method, Fully Recursive Long Short Term Memory (FR-LSTM) and its elaborate description is provided in the forthcoming sections.

3. FULLY RECURSIVE LONG SHORT TERM MEMORY (FR-LSTM) METHOD

In this section, the proposed Fully Recursive Long Short Term Memory (FR-LSTM) method is introduced.

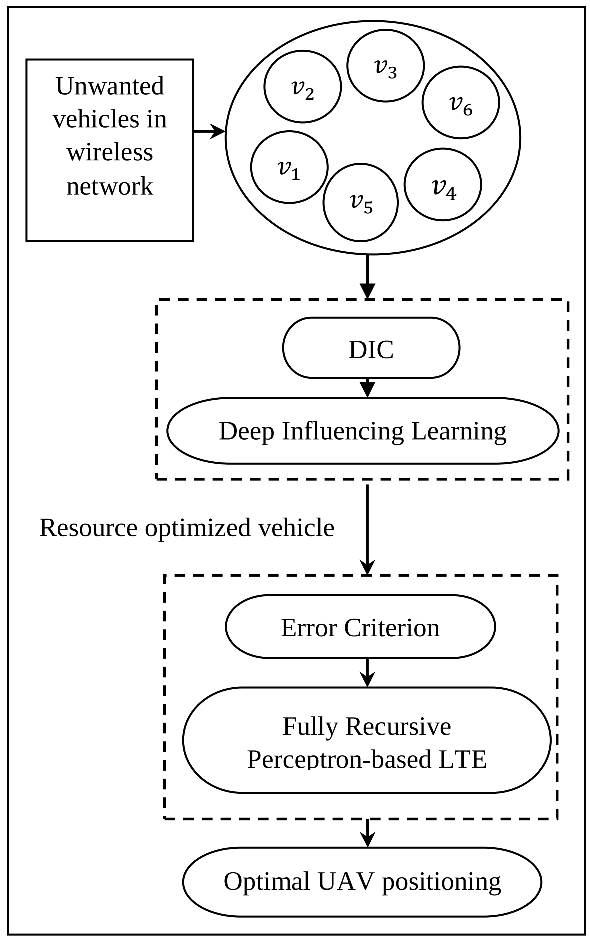

Figure 1 Block Diagram of Fully Recursive Long Short Term Memory (FR-LSTM) Method

In Figure 1, a broad interpretation on the main body of FR-LSTM is given first. To identify the optimal vehicle for data forwarding to the server through LTE, the Deep Influencing Learning-based LTE algorithm is designed. With this both the error in obtaining optimal vehicle is reduced with minimum end-to-end delay in transmission. Then, a Fully Recursive Perceptron-based LTE strategy is put forward to enhance throughput with minimum delay in data transmission.

3.1. System Model

In this section, the information flow and power configuration from transmitter '$T_i(UAV)$' denoted as 'BS' to the receiver '$R_i(Users)$' denoted as 'U' is presented. It comprises network environment by '$three\ BS$' as base station 'BS' and 'nUs' represented by '$U_1, U_2, \ldots, U_n$' that are served by the deployed 'BS'. On the basis of the system model structure, all 'BS' communicate with each other and are positioned at different locations. Let us consider a graph '$G(BS, E)$', where 'BS' represents the set of UAVs, also the positions cannot be changed and 'E' represents the set of links between users 'U_i' and 'U_j'. Moreover, a link '$L(BS_i, BS_j)$' is said to exist between any two base stations 'BSs' if and only if they lie within the transmission range of each other, '$L(BS_i, BS_j) > Dis(PBS_i, PBS_j) \leq T_i$', where '$T_i$' refers to the transmission range and 'PBS_i, PBS_j' denote the positions of two base stations 'BS_i', 'BS_j' respectively. In addition each '$BS\ u \in U$' provides communication service to set of users, '$S(U)$' where each user receives signals from single base station 'BS'.

3.2. Deep Influencing Learning-based LTE

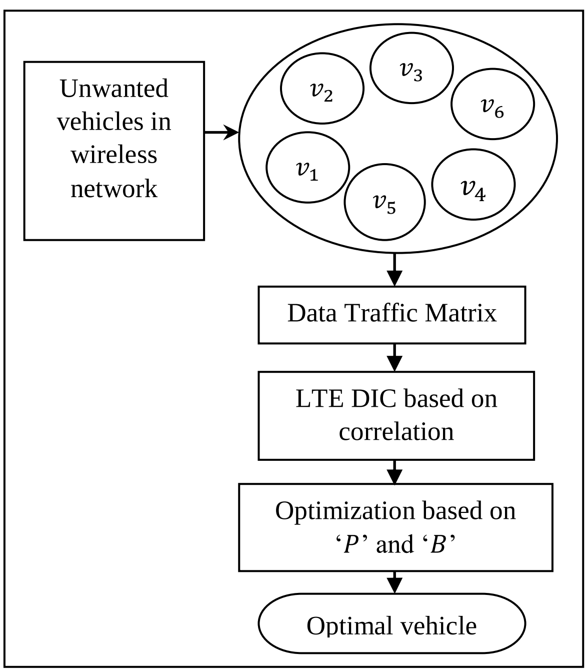

Figure 2 Block Diagram of Deep Influencing Learning-based LTE Model

While transmitting data from a remote operated unmanned vehicle to server via Long Term Evolution (LTE) with the coexistence of BLE Relaying resource-constrained device nature in terms of power and bandwidth, a strict delay is introduced, therefore causing error also. To address this issue in this section, first, a Deep Learning-based model for Long Term Evolution (LTE) Dominant Influencing Criterions (DIC) estimation is presented. This application is analyzed to the use case of power resources and bandwidth allocation (PRBA) for self-organizing LTE small cell network, therefore reducing RMSE and average end-to-end delay involved in transmission. Figure 2 shows the block diagram of Deep Influencing Learning-based LTE model.

In figure 2, let us consider a sequence of data points for each unmanned vehicle '$V = v_1, v_2, \ldots, v_n$' and '$V_{P,B}$' represents the data traffic matrix taking into consideration both the power 'P' and bandwidth 'B'. Then, then at 'tth' time interval with the service 'S' representing the power and bandwidth, the data traffic matrix is mathematically expressed as given below.

$$V_{S,t} = \begin{bmatrix} v_{S,t}^{(1,1)} & v_{S,t}^{(1,2)} & \ldots & v_{S,t}^{(1,n)} \\ v_{S,t}^{(2,1)} & v_{S,t}^{(2,2)} & \ldots & v_{S,t}^{(2,n)} \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ v_{S,t}^{(m,1)} & v_{S,t}^{(m,2)} & \ldots & v_{S,t}^{(m,n)} \end{bmatrix} \quad (1)$$

From equation (1), the data traffic matrix for each vehicle with power and bandwidth, '$V_{S,t}$' is derived based on its corresponding service 'S' including power 'P' and bandwidth 'B' at time 't' with coordinates '(m, n)' respectively. If the receiver '$R_i(Users)$' has LTE signal and upon availability of the network coverage, the correlation coefficient is mathematically expressed as given below.

$$R_k = \frac{\sum_{t=1}^{T-k}\left[\left(v_t^{(m,n)} - v^{(m,n)}\right)\right]\left[v_{t+k}^{(m,n)} - v^{(m,n)}\right]}{\sum_{t=1}^{T}\left[\left(v_t^{(m,n)} - v_t^{(m,n)}\right)\right]^2} \quad (2)$$

From equation (2), '$v^{(m,n)}$' represent the mean value of the vehicles services (i.e., based on power and bandwidth) over time domain 't'. However, in case of uneven distribution or upon non-existence of LTE signal, then, Dominant Influencing Criterions (DIC) employing the Pearson Spatial Correlation (PSC) is measured to permit data transmission via Bluetooth Low Energy (BLE). Finally, upon detecting the LTE signal transfer can be made. The probability estimation using is mathematically expressed as given below.

$$\rho = \frac{\text{cov}\left[v^{(m,n)} - v^{(m,n)}\right]}{\sigma v^{(m,n)} \sigma v^{(m,n)}} \quad (3)$$

RESEARCH ARTICLE

From equation (3), the estimation of DIC is measured based on the PSC 'ρ' employing the covariance operator for the respectively unmanned vehicle 'COV', standard deviation of the corresponding vehicles 'σ', actual coordinates '(m, n)' and referral coordinates '(m', n')' respectively. Finally, the power and bandwidth optimized vehicle for data forwarding is obtained as given below.

$$v^{opt} = OV = argmax\ \rho^{(m,n)} \tag{4}$$

From equation (4), the optimal vehicle for data forwarding 'v^{opt}' is selected using the argmax function '$argmax$' relative to the DIC employing PSC '$\rho^{(m,n)}$' respectively. The pseudo code representation of Deep Influencing Learning-based LTE for optimal unmanned serving vehicle for data forwarding is given below.

Input: Unmanned vehicles '$V = v_1, v_2, \dots, v_n$'

Output: Optimal vehicle '$OV = ov_1, ov_2, \dots, ov_n$'

1: Initialize power 'P', bandwidth 'B', time 't'

2: Begin

3: For each unmanned vehicles '$V = v_1, v_2, \dots, v_n$'

4: Obtain the data traffic matrix using (1)

5: Estimate correlation coefficient upon availability of the network coverage using (2)

6: Evaluate Dominant Influencing Criterions (DIC) using (3)

7: Return (power and bandwidth optimized vehicle for data forwarding)

8: End for

9: End

Algorithm 1 Deep Influencing Learning-based LTE

In algorithm 1, Deep Influencing Learning-based LTE objective remains in obtaining the power and bandwidth optimized vehicle for data forwarding. First, data traffic matrix is generated based on two resources, power and bandwidth. Next, correlation coefficient is estimated for the available network so that the RMSE involved in selecting the optimal vehicle is minimized. Finally, optimal vehicle is arrived at based on the DIC, therefore reducing the end-to-end delay involved in transmission.

3.3. Fully Recursive Perceptron-based Long Short Term Memory

In wireless system, the performance and throughput estimation for UAV system heavily based on data traffic load and offered resource (i.e., power and bandwidth) to support that load. To address this issue in this section, with the obtained resource optimized unmanned vehicle, a Fully Recursive Perceptron Network (FRPC) and LSTM model is designed. FRPC with LSTM is applied to DIC to determine UAV position that in turn maximizes overall system performance and throughput. Figure 3 shows the block diagram of Fully Recursive Perceptron-based Long Short Term Memory model.

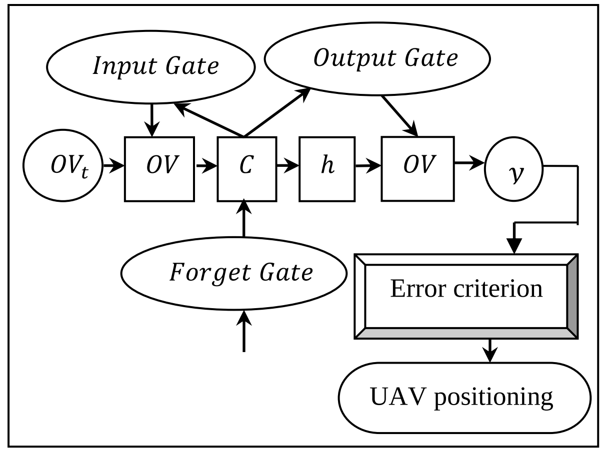

Figure 3 Block Diagram of Fully Recursive Perceptron-based Long Short Term Memory Model

In figure 3, let us utilize the LSTM to model LTSE temporal dependency and to estimate UAV positioning. Here, LSTM network evaluates the mapping from an input sequence, '$OV = (ov_1, ov_2, \dots, ov_n)$' to an output sequence, '$Y = (y_1, y_2, \dots, y_t)$' by estimating the network unit activations employing the equations given below in an iterative manner.

$$i_t = \sigma\ (W_{iov} OV_t + W_{im} M_{t-1} + W_{ic} C_{t-1} + b_i) \tag{5}$$

$$f_t = \sigma\left(W_{fov} OV_t + W_{fm} M_{t-1} + W_{ic} C_{t-1} + b_f\right) \tag{6}$$

$$c_t = f_t\ \odot c_{t-1} + i_t \odot g\ (W_{cov} OV_t + W_{cm} M_{t-1} + b_c) \tag{7}$$

$$o_t = \sigma\ (W_{oov} OV_t + W_{om} M_{t-1} + W_{oc} C_t + b_o) \tag{8}$$

$$y_t = \left(W_{ym} M_t + b_y\right) \tag{9}$$

From equations (5) to (9), 'i_t', 'f_t', 'o_t' denotes the input gate (i.e., input sequences representing the optimal vehicles), forget gate and output, 'c' and 'm' represents the activation vectors for each cell (i.e., for each input sequence) of memory block, weight matrices 'W' bias vectors 'b' are employed to construct associations among input layer, output layer, and memory block based on data traffic load and the available resource. Here, '$\odot$' denotes the scalar product of two vectors i.e., forget vector and cell state with '$\sigma(.)$' representing the standard logistics sigmoid function, and '$g(.)$' and '$h(.)$' corresponds to the cell input and cell output activation

RESEARCH ARTICLE

functions. The Fully Recursive Perceptron-based Long Short Term Memory gate are the integration of input the forget gates, and preceding hidden state 'h' is associated to the reset gate, whereas in the conventional LSTM, the memory content to be utilized in the network is supervised by the output gate at time 't'. Followed by which an instantaneous error criterion is formulated as given below.

$$EC = \frac{1}{2}(e^T e) \tag{10}$$

From equation (10), the error criterion 'EC' is measured on the basis of the output error as '$(e_i = ao_i - eo_i)$', with 'ao_i' representing the actual output and 'eo_i' denoting the estimated output respectively. Next, with the aid of Fully Recursive Perceptron Network (FRPC), the weight and bias factors are evaluated to determine the position of a UAV and this is mathematically expressed as given below.

$$W_{ij}^{new} = W_{ij}^{old} - \eta \frac{\partial J}{\partial W_{ij}} \tag{11}$$

$$\frac{\partial J}{\partial b_i} = \sum_{i=1}^{n} e_i \frac{\partial y_i}{\partial b_i} = \sum_{i=1}^{n} e_i \frac{\partial W_{ij} i_j}{\partial b_i} \tag{12}$$

$$\frac{\partial J}{\partial b_i} = \sum_{i=1}^{n} e_i \sum_{i=1}^{n} W_{ij} \frac{\partial i_j}{\partial b_i} \tag{13}$$

From equations (12) and (13), the position of UAV is estimated on the weight 'W_{ij}' and bias factor 'b_i' respectively. The pseudo code representation of Fully Recursive Perceptron-based Long Short Term Memory for UAV positioning is given below.

In algorithm 2, Fully Recursive Perceptron-based LSTM objective here remains in obtaining the positioning of UAV with maximum throughput and minimum latency. To achieve this objective, first, the network unit activations for each unmanned vehicles and input sequences are measured via Fully Recursive Perceptron-based Long Short Term Memory gate. This model possesses the advantage of connecting the hidden gate directly to the input, whereas in the conventional LSTM model it is connected via the output gate.

Input: Unmanned vehicles '$V = v_1, v_2, \ldots, v_n$'

Output: UAV positioning with minimum latency and maximum throughput

1: Initialize input sequence, '$OV = (ov_1, ov_2, \ldots, ov_n)$', weight matrices '$W$' and bias vectors '$b$'

2: Begin

3: For each Unmanned vehicles '$V = v_1, v_2, \ldots, v_n$' input sequence, '$OV$'

4: Estimate input gate, forget gate, cell state and output gate using (5), (6), (7) and (8)

5: Estimate output sequence using (9)

6: Estimate weight using (10)

7: Evaluate bias using (11) and (12)

8: Return UAV positioning

9: End for

10: End

Algorithm 2 Fully Recursive Perceptron-based Long Short Term Memory

With this the throughput involved in UAV positioning is said to be improved. Next, with the aid of Fully Recursive Perceptron employed in evaluating the weight and bias get rid of obtaining amount of hidden layers and neurons (i.e., layer power and bandwidth optimized vehicle), therefore reducing the latency.

4. EXPERIMENTAL SETUP

The experimental settings of proposed Fully Recursive Long Short Term Memory (FR-LSTM) method are implemented in NS-2 simulator. The FR-LSTM method is simulated in a network area of size 1500m * 1500m for conducting simulation using 500 different nodes or unmanned vehicles. The simulation parameters utilized in our work are shown in Table 1.

Simulation Parameter	Value
Network area	1500m * 1500m
Number of unmanned vehicles	50, 100, 150, 200, 250, 300, 350, 400, 450, 500
Vehicle distribution	Uniform random
Initial energy in each unmanned vehicle	2J
Control packet size	48bytes
Data packet size	100bytes
Simulation time	100s
Pause time	10s
Mobility model	Random Way Point
Transmission range	300m
Number of runs	10

Table 1 Simulation Parameters

5. SIMULATION PARAMETERS AND DISCUSSION

The simulation of proposed FR-LSTM method for 500 different unmanned vehicles for measuring the proposed performance is presented in this section. The performance of FR-LSTM method is measured in error, end-to-end delay,

RESEARCH ARTICLE

throughput and latency. The result of FR-LSTM method is compared with existing multilayer perceptron neural network [1] and MOQDS [2] methods.

5.1. Performance Measure of End-to-End Delay

Remote operated unmanned vehicle is an end-to-end delay incurred in identifying optimal vehicle. This is mathematically expressed as given below.

$$E2ED = \sum_{i=1}^{n} V_i * Time\ [v^{opt}] \quad (14)$$

From equation (14), the end-to-end delay '$E2ED$' is calculated on the basis of number of unmanned vehicles involved in simulation 'V_i' and the time consumed in obtaining optimal vehicles '$Time\ [v^{opt}]$' across a network for source to destinations. It is measured in milliseconds (ms). The impact of end-to-end delay on data delivery performance is shown in Table 2.

Number of Unmanned Vehicles	Average End-to-End Delay		
	FR-LSTM	Multilayer Perceptron Neural Network	MOQDS
50	1.25	2	2.25
100	1.95	2.25	3.05
150	2.15	2.4	3.25
200	2.55	2.95	3.55
250	2.6	3.15	3.85
300	2.95	3.45	4.35
350	3.15	3.95	4.95
400	3.55	4.25	5
450	3.75	4.45	5.15
500	3.95	4.85	5.35

Table 2 Impact of Average End-to-End Delay Using FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

From table 2, the end-to-end delay performance for FR-LSTM, multilayer perceptron neural network and MOQDS methods. Taking performance in end-to-end delay as an example, proposed FR-LSTM method brings about 37.5% and 44.44% improvements when compared to [1] and [2] for 50 number of unmanned vehicles into consideration.

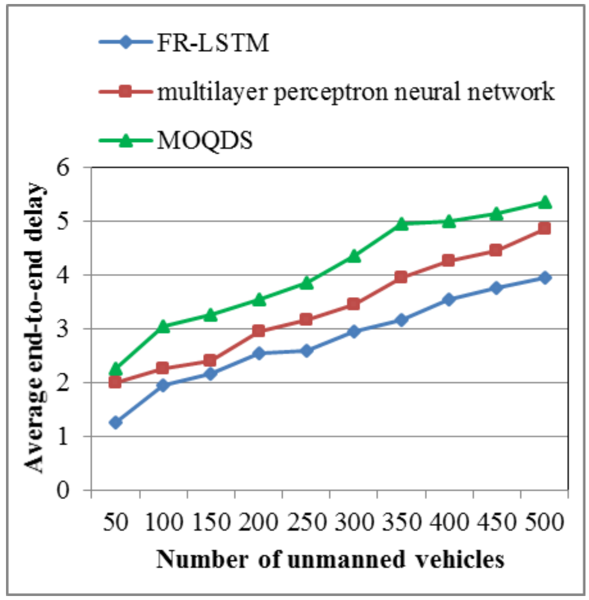

Figure 4 Average End-to-End Delay Comparisons for FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

Figure 4 illustrates the end-to-end delay of proposed FR-LSTM method and existing multilayer perceptron neural network [1] and MOQDS [2] depended on the number of iterations. Variation was identified in end-to-end delay estimation when dissimilar numbers of epochs were employed. The figure demonstrates the calculated results of FR-LSTM, multilayer perceptron neural network [1] and MOQDS [2] and can be used to accurately measure the delay incurred for optimal vehicle identification in the UAV coverage. From the figure it is inferred that the proposed system can minimize the end-to-end delay with increasing number of unmanned vehicles enhance capability and reliability of UAVs. Besides, proposed FR-LSTM method can correctly measures user end-to-end delay even when the vehicles are moved. The reason behind the improvement is due to the estimation of Dominant Influencing Criterions based on power and bandwidth. Only on the basis of this DIC, the optimal vehicles are identified. Hence, the end-to-end delay using the FR-LSTM method is said to be reduced by 18% compared to [1] and 33% compared to [2].

5.2. Performance Measure of Root Mean Square Error

The second parameter of importance is the root mean square error. This is utilized in measuring the differences among predicted values and experimental values. In our work, it refers to the differences between predicted optimal vehicle and the observed optimal value. In order to aggregate magnitudes of errors, RMSE serves has different vehicles in single measure of predictive power. This is mathematically expressed as given below.

RESEARCH ARTICLE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(PV-OV)^2}{n}} \quad (15)$$

From equation (15), the root mean square error '$RMSE$' is measured based on the predicted vehicle 'PV' and the observed vehicle 'OV' respectively. It is measured in percentage (%).The RMSE on data delivery performance is summarized in Table 3.

Number of Unmanned Vehicles	Root Mean Square Error		
	FR-LSTM	Multilayer Perceptron Neural Network	MOQDS
50	0.4	1.6	3.6
100	0.45	1.75	3.85
150	0.55	1.9	4.15
200	0.8	2.05	4.45
250	0.92	2.25	4.65
300	1.15	2.4	4.8
350	1.35	2.55	4.85
400	1.55	2.7	4.9
450	1.85	2.85	4.92
500	2.05	3.05	5

Table 3 Impact of Root Mean Square Error Using FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

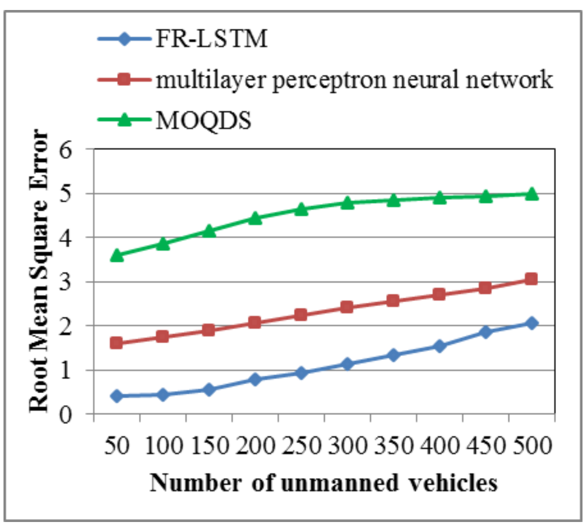

Figure 5 Root Mean Square Error Comparisons for FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

From table 3 the RMSE performance for all the three methods. Taking the performance in RMSE as an example, proposed FR-LSTM method brings about 55% and 76% improvements when compared to [1] and [2] for 50 number of unmanned vehicles.

From Figure 5, the RMSE with number of unmanned vehicles placed at different positions under diverse conditions. In figure 5, increasing number of unmanned vehicles to be placed in the network for transmitted data from an unmanned vehicle to the server via LTE also increases the RMSE. However, 2ith '50' number of unmanned vehicles considered for simulation, actual optimal vehicle being '35' and the observed optimal vehicle being '37', the error was found to be '-2' using FR-LSTM, and the observed optimal vehicles being '39', the error was found to be '-4' using [1] and observed optimal vehicles being '41, the error was found to be '-6' 'using [2], the RMSE was found to be 0.4, 1.6 and 3.6 respectively. The proposed method is simply adapts and efficient transmissions. The reason behind improvement was the incorporation of Deep Influencing Learning-based LTE algorithm. By applying this algorithm, initially, data traffic matrix was generated on the basis of power and bandwidth. Followed by which the correlation coefficient was evaluated for the available network. With this, the RMSE involved in selecting the optimal vehicle using FR-LSTM was said to be minimized by 56% compared to [1] and 76% compared to [2].

5.3. Performance Measure of Throughput

The third parameter for significant data transmission using unmanned vehicles is the throughput rate. It is defined as the amount of information delivered in a specific period of time using the optimal vehicles.

$$TP = \frac{DP_{rec}}{DP_{sent}} \quad (16)$$

From equation (16), the throughput rate 'TP' is calculated on the data packets successfully received 'DP_{rec}' using the unmanned vehicles and data packets sent 'DPT_{sent}'. It is measured in percentage (%).The impact of throughput on data delivery performance is summarized in Table 4.

Number Of Unmanned Vehicles	Throughput (%)		
	FR-LSTM	Multilayer Perceptron Neural Network	MOQDS
50	88	84	80
100	86.25	83.15	79.65
150	86.16	83	79.25

200	86	82.85	79
250	85.85	82.65	78.85
300	85.65	82.35	78.55
350	85.35	82	78.25
400	84.15	81.45	77
450	84	80.85	76.35
500	82.15	79.55	76

Table 4 Impact of Throughput Using FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

From Table 4 the throughput performance for all the three methods. Taking the performance in terms of throughput as the performance metric as an example, the proposed FR-LSTM method brings about 4% and 9% improvements when compared to [1] and [2] for 50 unmanned vehicles.

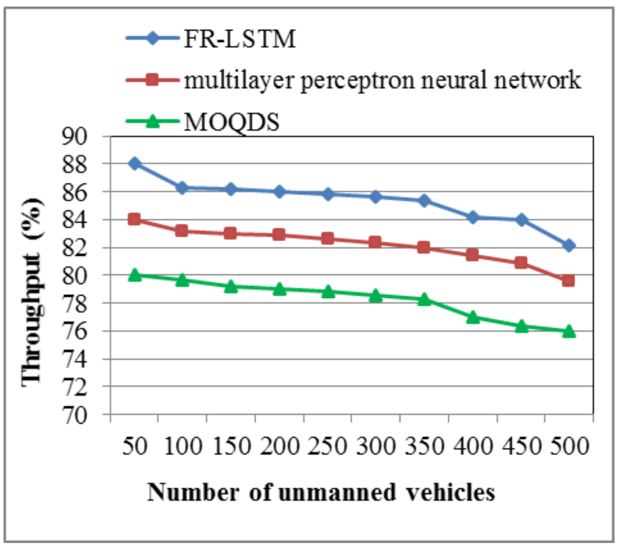

Figure 6 Throughput Comparisons for FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

From Figure 6, the throughput with the number of unmanned vehicles based on the three different methods, FR-LSTM, multilayer perceptron neural network [1] and MOQDS [2]. In figure 6, the throughput minimized with enhanced number of unmanned vehicles or simulation conducted. The training accuracy converged rapidly to lower values of 86.25%, 83.15% and 79.65% for 100 unmanned vehicles from 88%, 84% and 80%.

The RMSE on validation set matches the training set and influence of input unmanned vehicles on number of iterations during training of optimal vehicle identification reduced when number of iterations improved. Though, proposed method denotes potential of precisely calculating throughput values since the application of Fully Recursive Perceptron Network (FRPC) and LST) model. With application of this model, UAV positioning is obtained by estimating the network unit activations accordingly to Fully Recursive Perceptron. Therefore the throughput rate using FR-LSTM method is said to be improved by 4% compared to [1] and 9% compared to [2] respectively.

5.4. Performance Measure of Latency

Finally, the metrics considered for simulation is latency. The latency in our work refers to the difference in time between the simulation and the response time. This is mathematically expressed as given below.

$$L = [Sim_t - Res_t] \qquad (17)$$

From equation (17), latency 'L' is measured on the basis of the simulation time 'Sim_t' and the response time 'Res_t'. It is measured in milliseconds (ms). The impact of latency on data delivery performance is summarized in Table 5.

Number of Unmanned Vehicles	Latency		
	FR-LSTM	Multilayer Perceptron Neural Network	MOQDS
50	3	4	5
100	4.5	5	6.3
150	4.95	6.25	6.55
200	5.35	6.85	7
250	5.85	7	7.65
300	7	7.45	8
350	7.35	7.65	8.35
400	7.85	8.85	10.35
450	9	11.35	12.15
500	10.25	13	14.55

Table 5 Impact of Latency Using FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

From table 5 the latency performance for all the three methods. Taking the performance in terms of latency as an example, the proposed FR-LSTM method brings about 16% and 24% improvements when compared to [1] and [2] for 50 number of unmanned vehicles.

RESEARCH ARTICLE

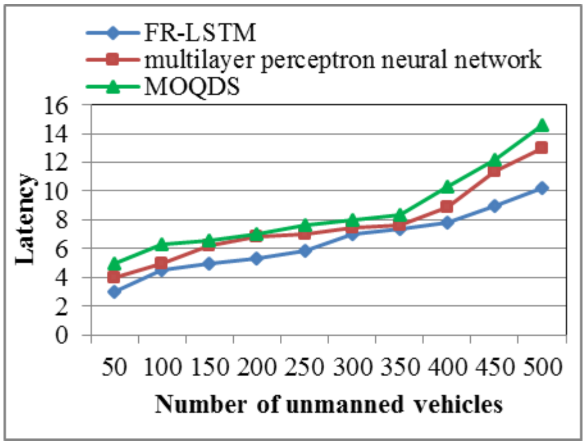

Figure 7 Latency Comparisons for FR-LSTM, Multilayer Perceptron Neural Network [1] and MOQDS [2]

Finally from Figure 7, the latency comparisons made for three different methods, FR-LSTM, multilayer perceptron neural network [1] and MOQDS [2] respectively. From the above figure it is illustrative that the rate of latency is directly proportional to the unmanned vehicles involved in the simulation. In other words, increasing the unmanned vehicles causes an increase in mapping input sequence to output sequence this in turn increases the latency rate also. However, with '50' unmanned vehicles considered for simulation, the simulation time being '$20ms$' and response time being '$15ms$' using FR-LSTM, response time being '$16ms$' using [1] and response time being '$15ms$' using [2], the latency was observed to be 3ms, 4ms and 5ms respectively. From this result it is inferred that the latency is said to be reduced using FR-LSTM upon comparison with [1] and [2]. The reason behind the improvement is due to the application of Fully Recursive Perceptron-based Long Short Term Memory algorithm. By applying this algorithm, for each unmanned vehicles and input sequences are obtained using Fully Recursive Perceptron-based Long Short Term Memory gate, where the hidden gate is said to be directly connected to the input. With this the latency involved in data transmission is said to be minimized using FR-LSTM method by 16% compared to [1] and 24% compared to [2].

6. CONCLUSION

In this paper, the Fully Recursive Long Short Term Memory (FR-LSTM) method was presented for solving the problem of UAV positioning to reduce the latency and maximize throughput. We used Dominant Influencing Criterions (DIC) for performing learning-based LTE and select the optimal vehicles for training and testing phases. Depend on network unit activations and instantaneous error criterion, proposed system was evaluated by Fully Recursive Perceptron. The proposed FR-LSTM method is compared with state-of-the-art methods to data transmission from remote unmanned vehicle. The proposed method was found to have a better throughput with respect to the data transmission method. In addition, the proposed FR-LSTM method have lower end-to-end delay and latency, the error distributions in every set of testing points are small and limited. In each development, the proposed method of RMSE complexities was reduced compared with other state-of-the-art methods. Thus, FR-LSTM method gives state-of-the-art method on data transmission from a remote operated unmanned vehicle, therefore facilitating BLE transmission. In future data transmission can be performed by new artificial Intelligence method in order to improve the throughput, end-to-end delay, root mean square error, latency.

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