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Proximate Relay Propagated Deep Learning for Power Efficient Data Transmission in Wireless Networks

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Abstract

The swift uptake and the advancing demand of wireless services cause unparalleled requirements on wireless networking environment. Upcoming wireless networks have to sustain accelerating wireless traffic volumes with higher data rate and wide range of network coverage to increase user experience. Accelerating higher data rate for unmanned vehicle node can be performed using long term evolution. However, in wireless networks, it is not possible for unmanned vehicle node to be connected directly to LTE all the time. Also, as substantial fragment of energy is utilized during data transmission, methods are required to minimize power consumption. To address these issues in this work, an immense investigation between power saving methods and QoS support, called, power-efficient proximate linear regression and relay-propagated deep learning (PPLR-RDL) framework is designed for improving data transmission rates and quality of service in wireless networks. The efficiency of PPLR-RDL framework is estimated in terms of average end-to-end delay, energy consumption, packet delivery ratio and latency and compared with the existing methods.

***Key Words*:** Long Term Evolution, Deep Learning, Nearest Neighbour, Relay Propagation

1. Introduction

In recent years, machine-to-machine (M2M) network is a dominating technology which does not requires any human interaction. IoT becomes a prominent network today which connects millions of machines to communicate and control each other. This technology can be used for daily aspects of our lives, especially in the areas of emergency response. There is also no defined infrastructure for facilitating the M2M and a two-way interface for communication between these M2M via LTE and BLE is proposed in this work. LTE has the capability to manage fast-moving nodes and can support multi-cast and broadcasting. The increasing demand for high data rate, speed and quality of service was also a reason for LTE usage. The LTE is supposed to address the coverage extension to mobile users especially in hotspot areas. An alternate solution to cater the need for direct communication between mobile devices and thereby extending the direct transmission between a device to device is developed. For this, a cheapest and an efficient technology i.e. BLE for covering a shorter distance communication considering the line of sight transmission in case of wireless sensor networks is used.

With the ever growing requirements and expectations of wireless networks, users have been forcing manufacturers and network operators in charge of providing applications with quality of service (QoS) guarantees. On the other hand, as a large proportion of energy is consumed during data transmission, the most customary method is to minimize power consumption so that the node lifetime is improved and hence the overall user quality. In this regard, a QoS-constrained medium access probability (QoS-constrained MAP) [1] scheme focused on maximization of network throughput. This was achieved by optimizing the MAPs of all users under quality-of-

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service constraints in wireless networks.

Multi objective QoS aware LTE-A downlink-MAC scheduler (MOQDS) [2] algorithm was investigated that satisfied two level QoS and fairness requirements of long term evaluation. Min-max principle was used in the MOQDS algorithm to reduce cell drop rate and packet drop rate. Despite minimization observed in the cell and packet drop rate, the amount of data packet transmitted over wireless network in a given amount of time was not addressed.

This work seeks to maximize the quality of service in terms of average end-to-end delay, data loss and bandwidth in addition to power utilization by learning proximate vehicle for power efficient data transmission in wireless networks. A novel power-efficient proximate vehicle identification model is developed to establish connection, considering the RSSI values of individual vehicles. Based on the proposed model, each unmanned source vehicle will be able to compute their proximate vehicles by estimating the distance and position. A QoS-constrained relay propagation technique is established to minimize average end-to-end delay, energy consumption and latency by taking into account three levels of features, vehicle flow demand vector as well as application-specific traffic conditions. Simulations have been conducted to measure the performance of both power-efficient Proximate Positional Linear Regression and Relay Propagation Deep Learning algorithm.

2. Related Works

Future generation wireless networks combine several heterogeneous technologies. In [3], a novel fuzzy-analytic hierarchy process (AHP) based network selection was investigated with the objective of addressing several qualities of services that conventional method failed to address. Yet another content aware packet scheduling was designed in [4] based on temporal complexity to improve packet delay performance.

One of the foremost problems faced while transmitting video in wireless networks is the network bandwidth. The conventional model of bandwidth estimation is not found to be correct. This is because of arrival of ping packet, bandwidth and so on. In [5], an adaptive playback buffer management scheme was presented to support live video streaming. Another problem of interest found in wireless network is beamforming. To maximize the energy consumption under users' QoS, path-following computational procedures were designed in [6]. However, if the access nodes were deployed densely, the quality of service was said to be compromised. Therefore, full-duplex access nodes [7] were utilized to address quality of service under minimum data rate for each user.

The outburst in the diversity and frequency of video services makes two important performances, bandwidth and latency more desperate to the user. However, with desperate communication ranges, data transmission was said to be compromised. To address this issue, in [8], minimum connected dominating set was applied using greedy approximation algorithm.

Yet another allocation method based on joint power and sub channel was introduced in [9]. This method used time sharing concept to maximize total system energy efficiency. Multi agent reinforcement learning technique was investigated in [10] where power and channel were utilized to identify the neighbour node. As a result, significant network lifetime was said to be improved through greedy-based resource allocation mechanism. Besides, another optimization framework was designed in [11] using threshold based on cost and resource availability. Based on the above said issues, in this paper, the quality of service has been improved by learning data packet transmissions in wireless networks using power-efficient proximate positional linear regression technique for data packet forwarding. In addition, a relay-propagated deep learning technique is also introduced for power efficient data packet transmission. Finally, a detailed analysis to demonstrate the power and quality of service in terms of average end-to-end delay, data loss and bandwidth through LTE with the coexistence of BLE relaying is also provided.

3. Power-efficient Proximate Linear Regression and Relay-propagated Deep Learning Framework

In wireless network, several unmanned vehicles communicate with each other and forward data packets to the destination. In 3GPP Release 14, C-V2X is defined as the LTE and considered to activate more than few modes. 3GPP Release 14 works in two ways: device-to-device (V2V or V2I) and device-to-network (V2N). In LTE Release 14, it comprised latency reduction, improvement for machine-type communication, process in unlicensed spectrum, massive multi-antenna systems, broadcasting, positioning and support for intelligent transportation systems. Proximate unmanned vehicle recognition is considered to be one of the most critical tasks because improper recognition of proximate vehicle disturbs the network performance.

The architecture of the wireless networks with the transmission range is shown in Figure 1.

Figure 1 shows the architecture of wireless network which is centrally coordinated (infrastructure mode). All devices are connected to wireless network i.e. Internet through the access point (AP) within the transmission range. Wireless APs are connected to internet. Here the mobiles, laptops, unnamed vehicles are considered as a devices. In general, communication is classified as a two types such as device to device (D2D) and the device to internet (D2I). These two types of communication is shown in above Figure 1. Device-to-device (D2D) communication is defined as direct communication between the devices without using access point. Device to internet (D2I) communication is a communication between the devices to internet through the access point.

3.1 Problem Definition

Due to the deployment of unmanned vehicles in an uncontrolled or harsh environment, it is common for the unmanned vehicles to become faulty and unreliable. An area coverage problem is detected or tracked via sensors. In recent years, the coverage and connectivity issues in sensor networks have received large attention in the research community. Throughout simulation, different transmission probabilities change the strength of the interference but not the distribution of the aggregate interference.

LTE supports exclusively the packet switched domain which ensures that it is suited to support both for high capacity and a constant high QoS for the network users. However, LTE suffers for latency while handling high data rates and also the mobile terminal power efficiency is decreases. As LTE utilizes only packet switched domain, it requires high-level security and mobility. Due to these issues in LTE, an additional requirement of BLE is introduced in this work. Though BLE is a short-distance cable replacement technology, it operates on lower power consumption and the modules also costs lower.

This paper proposes a framework for transmitting data from an unmanned vehicle to the server through long term evolution with the coexistence of bluetooth low energy (BLE) relaying. The framework is called as Power-efficient Proximate Linear Regression and Relay-propagated Deep Learning (PPLR-RDL). Figure 2 shows the block diagram of PPLR-RDL framework.

As illustrated in the Figure 2, each unmanned vehicle in the network learns the environment using proximate positional linear regression technique and identifies proximate unmanned vehicles that possess more power and hence acts as a serving vehicle, for packet forwarding and therefore minimizing the power. In order to improve the learning capacity of vehicle, the relay-propagation deep learning technique is employed. In this technique, data packet transmission is performed when IP address of the destination is identified or the signal is detected through long-term evolution. On the other hand, upon unsuccessful identification of IP address, a relay of intermediate devices connected to a pivotal vehicle is used. Later, the data packets are said to be transferred through pivotal vehicle to LTE when the LTE signal is deducted.

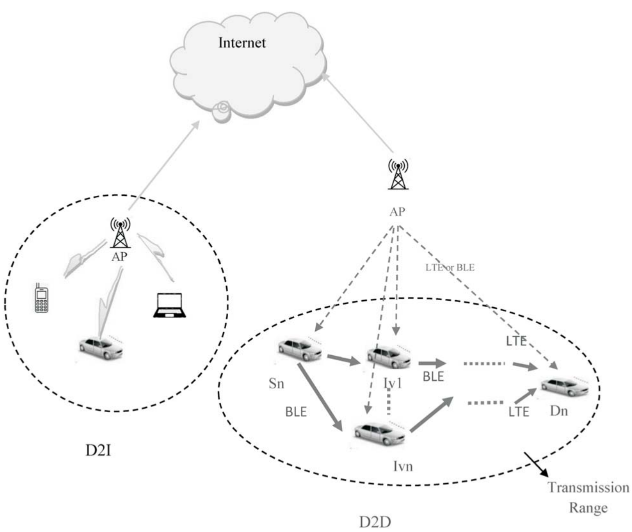

Figure 1. Architecture of Wireless Networks.

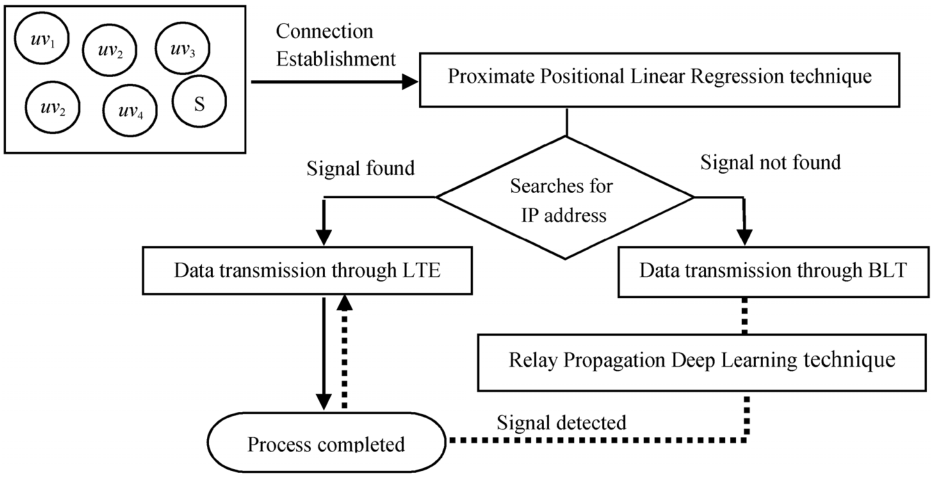

Figure 2. Block diagram of PPLR-RDL framework.

3.2 Proximate Positional Linear Regression Technique

In this work, a proximate positional linear regression technique is applied to communicate with the environment and take actions based on the distance and position. In the proposed framework, an integrated wireless networks with two-tier 'N_n', where '$n \in (u, i)$' [5] that corresponds to the technologies providing universal and intermittent coverage are considered. Whenever an unmanned source vehicle has to forward data, it first searches for IP address by establishing connection through environment learning.

The proposed proximate positional linear regression algorithm gives a method to identify the proximate vehicles possessing higher power from the unmanned source vehicle to the destination. Here, the power consumption rate is measured to identify the consumption of power to execute the task and this is measured in terms of watt. It is given as below.

$$PC = [watts_{req} * H_{con} * Op_{time}] \tag{1}$$

From the above equation (1), 'PC', denotes the power consumption formulated using the product of watts required '$watts_{req}$' for each unmanned vehicle to perform the task of connection establishment, number of hours consumed by the vehicle for connection establishment 'H_{con}' and the operating time 'Op_{time}' respectively.

Let us assume pairs '$\{(P_1, Q_1), (P_2, Q_2), \ldots, (P_n, Q_n)\}$', where '$Q_i$' corresponds to the class labels of 'P_i', where 'P_i' corresponds to the set of unmanned vehicles in the wireless network. Then, the position estimation of each vehicle in the wireless networks along with the distance measurement is made. The mathematical formulation for the position estimation is then performed as given

$$y = \{y_j \mid j \in R_y\} \tag{2}$$

From the above equation (2), 'y', represent the list of RSSI values from access point 'AP_j' with the set of APs in the range of 'R_y' and the number of vehicles measured from 'AP_j' corresponds to the length of the list 'y_j'.

Access points are used for extending the wireless coverage of a LTE or BLE networks in the relay of transmitting the information. Access point itself provides signal to the corresponding vehicle. These signal strength is measured as received signal strength indicator (RSSI). The RSSI value is measured as Transmit Power + Antenna Gain - Path Loss.

Let us further assume that 'y' includes only the sample unmanned vehicles in wireless network. Let the list be given as below.

$$L_m = \{Pos_1, Pos_2, \ldots, Pos_m\} \tag{3}$$

From the above equation (3), 'L_m', corresponds to the list of positions coordinates corresponding the list of 'm' unmanned vehicles. Then, the average position of the unmanned vehicles is evaluated on the basis of Euclidean distance. It is mathematically formulated as given below.

$$Dis = \left(PC\left[\sqrt{\left(uv_1 - Iv_1\right)^2 + \left(uv_2 - Iv_2\right)^2} \right] \right) \tag{4}$$

From the above equation (4), the distance factor '*Dis*', between the unmanned source vehicles 'uv_1, uv_2' and intermediate vehicles 'Iv_1, Iv_2' is measured. Followed by which the vehicle possessing higher power is considered.

The identification of proximate unmanned vehicles 'P_{uv}' is evaluated by means of RSSI values. It is mathematically formulated as given below.

$$P_{uv} = Min[RSSI\{uv_1, uv, \ldots, uv_m\}] \quad (5)$$

Finally, from the above value, whether the identified unmanned vehicle in the network is either the proximate vehicle '*PV*' or not proximate vehicle '*NPV*' based on the '*RSSI*' is obtained and through which data packet forwarding is performed.

The pseudo code representation of proximate positional linear regression algorithm is given Algorithm 1.

As given in the Algorithm 1, for each unmanned source vehicle within range 'R_y', the objective lies in identifying the high power proximate vehicles through learning process. Finally, connection is said to be established with proximate unmanned vehicles, hence acting as an unmanned serving vehicle for data forwarding.

3.3 Relay Propagation Deep Learning Technique

In order to improve the learning capacity of unmanned vehicle node, Relay Propagation Deep Learning technique is employed. As several vehicles are connected between the source and receiver, relay of intermediate vehicles are used to transmit data between the source and receiver. Also, as any number of vehicles enters into the network at different time intervals, the relay is said to be propagated. Therefore, to this relay propagated vehicles, deep learning technique is applied when there is no LTE signal, causing the data to be sent through BLE. Figure 3 shows the block diagram of relay propagation model.

Input: range 'R_y', Access Point 'AP_j', unmanned vehicles '$uv = uv_1, uv_2, \ldots, uv_m$', Actions '$\{PV, NPV\}$'
Output: Proximate Unmanned Vehicles '$PUV = puv_1, puv_2, \ldots, puv_m$'
1: **Begin** 2: **For** each unmanned vehicles '*uv*' within range 'R_y' 3: Measure power consumption using equation (1) 4: Obtain the list of position of '*y*' unmanned vehicles using equation (3) 5: Measure distance using equation (4) 6: Measure proximate unmanned vehicle using equation (5) 7: **End for** 8: **End**

Algorithm 1. Proximate positional linear regression algorithm.

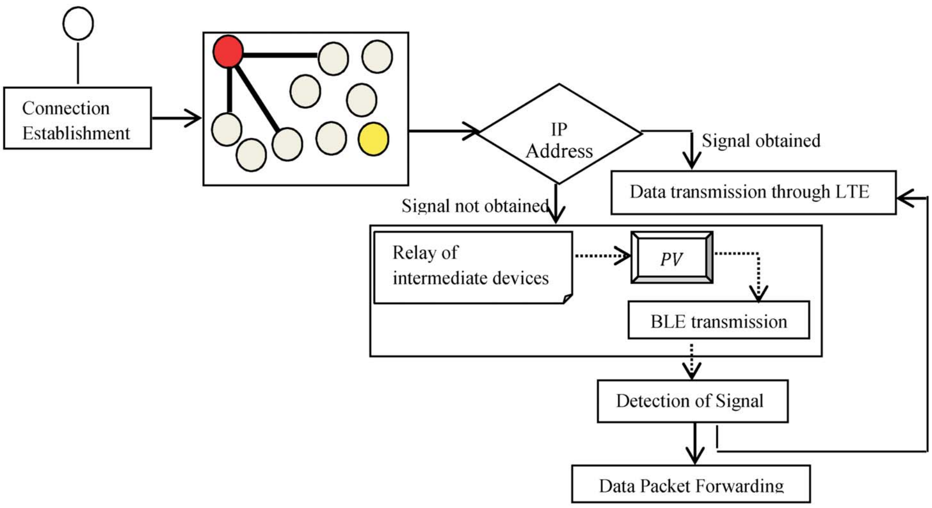

Figure 3. Block diagram of relay propagation model.

As illustrated in the Figure 3, upon connection establishment, the unmanned source vehicle searches for the IP address for destination. Upon successful detection of signal or IP address, data transmission is performed through LTE. When signal is not found, RDL technique uses bluetooth low energy to facilitate transmission. Here, series of intermediate unmanned vehicles are connected at a fixed point to facilitate BLE transmission. Later upon detection of LTE signal by the pivotal vehicle, data transmission is said to take place through LTE. This repeated learning of series of intermediate devices employed to each layer of network using relay propagation model therefore ensures minimum end-to-end delay with improved packet delivery ratio. To improve the learning rate of each vehicle, the proposed work utilizes relay propagation deep learning (RPDL) technique to discover the associations.

The entire wireless network is logically split into several layers. It starts from identified series of vehicles to the destined vehicle to which the data packet has to be sent. The technique then constructs on this hierarchically to identify what association of intermediate vehicles and pivotal vehicle we can find. After successive hierarchical identification of complex concepts, it then determines which of the features are accountable for identifying the pivotal vehicle. The pseudo code representation of relay propagation deep learning algorithm is given in Algorithm 2.

In order to apply the relay propagation deep learning algorithm to our pivotal vehicle evaluation problem, initially, the work starts with the definition of input and output layers. The pivotal vehicle flow information is expressed as a pivotal vehicle flow demand vector 'pv_v' forms the input layer and is mathematically defined as given below.

$$pv_v = \begin{cases} D, \text{if } \ n = s \\ -D, \text{if } \ n = d \\ 0, \, otherwise \end{cases} \tag{7}$$

From the above equation (7), 'pv_v' corresponds to each entry in the wireless network with '$N * 1$'. In each layer, a pivotal vehicle 'PV' is identified based on the learned 'LR' value. The identified pivotal vehicle possessing maximum power acts as the pivotal vehicle 'PV' and is mathematically formulated as

$$PV = \sum_{i=1}^{n} Max[\rho(pv_i)] \tag{8}$$

From the above equation (8), 'PV', represents the pivotal vehicle with '$\rho(pv_i)$', representing the power of 'i' intermediate vehicles. Besides, only from this identified pivotal vehicle, facilitate bluetooth low energy transmission. Later data packet transmission upon detection of LTE signal and hence, improving the bandwidth with minimum data loss.

Relay propagation deep learning employed is based on 'LR' learning. The vehicle having the highest 'LR' learning with higher power 'ρ' is selected as the pivotal vehicle. The vehicles in the network then make use of this two values 'LR' and power value 'ρ' to facilitate BLE transmission. Hence, when detected with LTE signal, data packet transmission is facilitated.

4. Performance Evaluations & Discussions

To evaluate the performance of the proposed work, PPLR-RDL framework is implemented in NS-2 simulator. Simulation parameters are shown in Table 1. The simulation of PPLR-RDL framework for several instances with respect to varied number of nodes and data packet for evaluating proposed performance is presented in this

Input: Proximate Unmanned Vehicles '$PUV = puv_1, puv_2, \ldots, puv_m$', learning rate '$LR$', power '$\rho$'
Output: Pivotal vehicle 'PV'
1: **Begin** 2: **For** each proximate unmanned vehicles identified 'PUV' with learning rate 'LR' 3: Obtain the input layer using the equation (7) 4: Identify the pivotal vehicle 'PV' using equation (8) 5: **End for** 6: **End**

Algorithm 2. Relay propagation deep learning algorithm.

Table 1. Simulation parameters

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

section. The performance of PPLR-RDL framework is measured in terms of average end-to-end delay, latency, data packet delivery.

Figure 4 illustrates the average end-to-end delay comparison. The average end-to-end delay for data packet transmission is said to be improved using PPLR-RDL framework by 32% compared to QoS-constrained MAP [1] and 51% compared to MOQDS [2]. Figure 5 illustrates the performance result of total energy consumption. The proposed PPLR-RDL framework minimizes the energy consumption for proximate vehicle identification by 32% and 43% when compared to existing QoS-constrained MAP [1] and MOQDS [2] respectively. Figure 6 illustrates the impact of packet delivery ratio. The packet delivery ratio using PPLR-RDL framework is said to be improved by 15% and 32% compared to QoS-constrained MAP [1] and MOQDS [2]. Figure 7 illustrates the latency measure. Latency rate is said to be reduced using PPLR-RDL framework by 20% compared to [1] and 34% compared to [2].

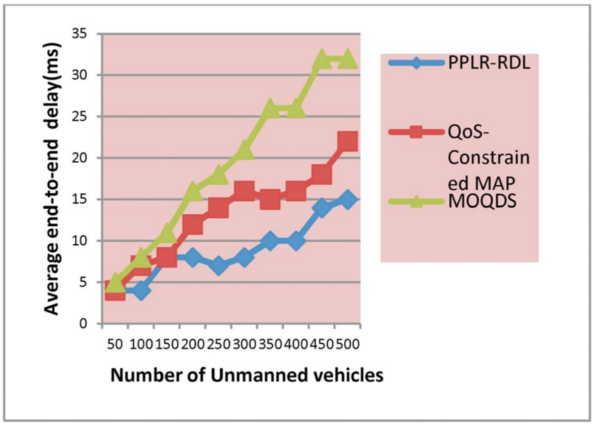

Figure 4. Measure of average end-to-end delay.

5. Conclusion

The key objective of PPLR-RDL framework is to ensure power and address quality of service during data transmission. In proximate positional linear regression technique, proximate unmanned vehicles for connection establishment are performed with vehicles possessing higher power. After the connection establishment, upon detection of IP address, data transmission is performed

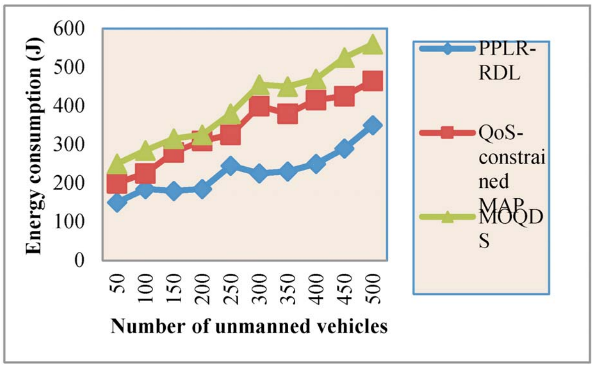

Figure 5. Measure of energy consumption.

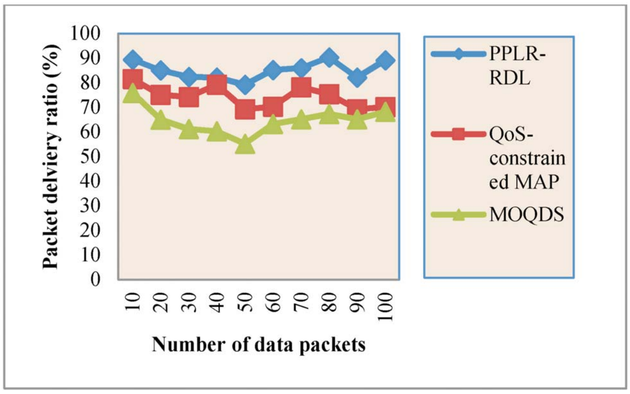

Figure 6. Measure of packet delivery ratio.

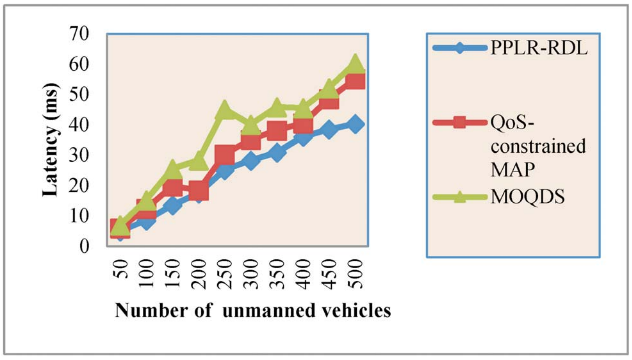

Figure 7. Measure of latency.

through LTE signal or else pivotal vehicle identification is performed to facilitate BLE transmission. The PPLR-RDL framework reduces the energy consumption during data transmission by efficient identification of proximate vehicles. The efficiency of PPLR-RDL framework is estimated in terms of average end-to-end delay, energy consumption, packet delivery ratio and latency and compared with state-of-the-art works. The simulation results expose that PPLR-RDL framework presents better performance with an enhancement of packet delivery ratio and minimization of energy consumption when compared to the state-of-the-art works.

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