Chapman Kolmogorov and Deep Recurrent Network Based Seamless Mobility for IOT Data Transmission in Wireless Network

Somashekhara Reddy
Jain University
Thrimoorthy N
Presidency University
Kadiravan G (kadiravanphd@gmail.com)
Koneru Lakshmaiah Education Foundation
Thurai Pandian M
Vellore Institute of Technology

Research Article

Keywords: Seamless mobility, Chapman Kolmogorov, Deep recurrent network, Poisson Taylor, Optimum Beacon, Route discovery, Data transmission

Posted Date: November 13th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3533874/v1

Additional Declarations: No competing interests reported.

Chapman Kolmogorov and Deep Recurrent Network Based Seamless Mobility for IOT Data Transmission in Wireless Network

Somashekhara Reddy, D[1], Thrimoorthy, N[2], Kadiravan, G[3*], Thurai Pandian M[4]

[1]Dept. of computer Science and Engineering, Jain University, Bangalore, India.

[2]Assistant professor, School of Information Science, Presidency University, Bangalore, India.

[3*]Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.

[4]School of computer Science and Engineering, Vellore Institute of Technology, Vellore, India.

Corresponding author (s). E-mail (s): kadiravanphd@gmail.com;
Contributing authors: r.somashekar@jainuniversity.ac.in; murthysvpm@gmail.com;
thuraipandian.m@vit.ac.in;

Abstract

Next-generation wireless networks will be designed via all-IP-based network framework that ensures seamless mobility and universal access to Internet via wireless networks. Also over the past few years, wireless network has gained its popularity due to its exorbitant volume and reasonable access cost. Despite its familiarity owing to the constraint in WLAN coverage, handover between nodes may cause elevated amount of handover failures. Seamless mobility is an empirical framework that seizes prevailing circumstances of what user or node is doing, with the objective that the users inclined services are said to be optimized. To develop a smart decision-making mechanism for seamless mobility and reducing energy consumption, deep learning-enabled reconfigurable wireless network solutions are required. In this work, a new method called, Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) IoT data transmission in wireless network is introduced to validate handoffs in pragmatic frameworks. First, with the raw data obtained from IoT device network logs, Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery algorithm is designed with the objective of ensuring seamless mobility in an energy efficient manner. Second, Deep Recurrent Network-based Data Transmission is proposed that with the aid of concurrent utilization of the numerous paths initiates numerous subflow associations covering disjoint routes and transmits via the subflows, therefore ensuring greater amount of throughput. Simulation of CK-DRN achieves

Direction of Arrival (DOA) and ID oriented Socket Layer (IoSL) in terms of delay, energy saving, and throughput.

Keywords: Seamless mobility, Chapman Kolmogorov, Deep recurrent network, Poisson Taylor, Optimum Beacon, Route discovery, Data transmission

1 Introduction

5G networks are established through several countries for ensuring framework to numerous transpiring technologies. Also, by the development of 5G progress, sheer growth during the amount of associated devices with various network infrastructures which also denote high radio link frequent handovers. However, the delay performance was not sufficient by using present transport layer. With the objective of ensuring agile as well as moderate latency service, it is crucial for enhancing the delay performance at transport layer for ensuring seamless management via high rate of mobility as well as vertical handovers.

With DOA is time varying, prevailing method for evaluating DOA employing MUSIC as well as ESPRIT are not highly significance owing to the reason that the eigenvalue decomposition are found to be time consuming process. Moreover, the DOA estimation algorithms of SNR are found to be lesser. In [1], a novel DOA tracking algorithm was proposed with the purpose of minimizing computational complexity for ensuring seamless connectivity. Experimental assessment ensured minimal time upon comparison with traditional DOA estimation methods. Also the novel DOA tracking algorithm was found to be unaffected by SNR.

With increasing dynamics of network conditions during mobility, the prevailing transport layer was not found to be sufficient with progressing lower layers to address network dynamics during mobility. Owing to differences in continual interference within lesser layers as a consequence of handovers compromises degradation in transport layer. IoSL was proposed in [2] that maintained unique identifier between transport layers for ensuring seamless connectivity. As a result Quality-of-Service (QoS) was said to be improved with better user experience, therefore minimizing latency and improved throughput.

5G network bestows framework to upcoming technologies. It is paving path for contemplated autonomous production being the pivotal necessitates in achieving end-to-end connectivity. However, present transport layer was not found to be well-resourced using progressing lesser layers for dispensing network during mobility. Network circumstances as well as persistent interference within minimal layers owing to handovers results in degradation as far as transport layer is concerned. Also, the end-to-end delay (E2E) was not reduced.

To minimize the E2E delay, four-layer architecture was proposed in [3] with the aid of 5G New Radio (NR) for ensuring throughput and latency for different values. The seamless connectivity issues being solved with high throughput; however, the congestion factor was not considered. To address on this aspect, a buffer loss estimation mechanism to handle congestion by employing queue equilibrium equation was designed in [4]. Yet another method utilizing stream controlled transmission protocol was presented in [5] that in turn not only improved performance and reliability but also minimized delay.

Wireless networks were advancing for bestow better data rates, with boost in frequency of mobile users. In this environment, 5G is a mechanism for providing mobile users by better coverage as well as enhances network. In such a situation, a mobile user was identifying more than one interface to perform a handover. Here, seamless mobility in heterogeneous networks plays as a major role in IoT.

RElay and MObility model is employed to enhance IoT with the objective of ensuring improved QoS to exchange data among IoT in [6]. An elaborate overview of mobility management taking into consideration the upcoming 5G architectures was proposed in [7]. Moreover, specific mechanisms of vertical handover were expressed taking into consideration the architectural transform manipulated using Software defined Networking. However, delivery of services depends on connectivity. To address on this issue, seamless connectivity between devices was proposed in [8] for sustaining minimum power and cost. But, it failed to measure the throughput.

1.1 Motivation

The current transport layer's goal necessitates several constraints in order to meet the accessibility needs of future technologies.. In this various network infrastructure, the current mobile devices are prepared by using multiple wireless interfaces that enhance the handover situations. But, the current transport layer was not aid IP mobility with default. In addition, variations in the radio level involve the transport layer protocol performance with service continuity and bandwidth employment. The next part goes over the issues, trends, and future demands that prompted us to go ahead with the idea we had. The main motive of the proposed CK-DRN IoT data transmission is a higher throughput and lesser energy consumption for seamless congestion and handoffs in wireless network.

1.2 Novelty and contributions of the work

IoT-based seamless mobility scheme is taken into consideration congestion and guarantee service continuity. The contribution of our work is explained below:

- To propose a method called Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) IoT data transmission to handle congestion and seamless handoffs in wireless network.
- The novelty of Second Order Taylor Series is applied to a Chapman Kolmogorov Poisson Optimum Beacon (POB) function for identifying the route via optimal beacon. By applying Poisson Optimum Beacon Second Order Taylor Series, energy saving efficiency is said to be ensured through handoffs. In this way, the delay is said to be minimized for seamless mobility in an energy efficient manner.
- The Data Transmission model uses the innovation of Deep Recurrent Network to consider data packet order number (DPON), subflow order number (SON), and data packet order mapping (DPOR) separately in three hidden layers. In addition, seamless handover employs the activation function to attain service continuity even during handover. With this, throughput involved in IoT-based data transmission in wireless network is said to be enhanced.

Experimental analysis of CK-DRN method ensures IoT data transmission in energy efficient and minimum delay manner. Then, the throughput illustrates CK-DRN was compared to the most advanced procedures.

1.3 Organization of the paper

The article is summarized by: Section 2 provides brief description of IoT-based data transmission, seamless mobility and connectivity techniques. Section 3 explains Chapman Kolmogorov as well as Deep Recurrent Network-based (CK-DRN) IoT data transmission in wireless network. Section 4 describes the experimental setup with a detailed discussion in Section 5 comparing CK-DRN method using conventional techniques. Section 6 provides the conclusion of paper.

2 Related works

Evolution in next-generation mechanisms has opened the gateway for Internet of Things (IoT) owing to the reason that the IoT establishes a communication network between numerous physical devices that are connected with various other sensors. However, mobility between devices degrades network efficiency and performance owing to hand off. As a result, a seamless secure anonymous authentication method was designed in [9] with the objective of establishing a secured session in cloud-based mobile computing.

In [10], a novel proactive mobility support algorithm was designed with the objective of predicting handoff event with minimum delay and energy conservation. Yet another traffic congestion control mechanism was designed in [11] employing deep neural network. Seamless service of users is utilizing distributed IP mobility management was proposed in [12].

Seamless handover between networks of same and different types have to be performed in a significant manner. A vertical handover mechanism for appropriate network selected was designed in [13]. The method was split into two parts, first, RSS were obtained and second the network selection was done by taking into consideration both the cost and energy during handover. With this both delay and communication cost were reduced.

In [14], a seamless method was proposed. Here, initially, Multi-Criterion based Deep Packet Inspection technique was designed with objective of network traffic classification and next, a Partially Connected Network Topology was employed for effective routing. However, issues related to congestion were not focused. In [15], congestion prediction was made by utilizing machine learning algorithm. Yet another eHMP with the objective of proving the users with seamless connectivity was proposed in [16].

Trend-based analysis of traffic was made in [17] for measuring abrupt changes and predominant trends in IoT networks. Yet another smart traffic monitoring for seamless mobility with the objective of minimizing the time as well as enhance bandwidth was designed in [18]. A method to consider the delay involved during handover using delay gradient was proposed in [19]. With this delay gradient function, packet sending rates were said to be improved. A seamless public transportation services in metropolitan area were designed in [20]. In [34], the author done optimizing the data rate with a Bayesian Regularised Neural Network technique, the packet dependability is improved, making the network more dependable and sustainable. The optimization process is divided into three stages: network layout, data rate forecasting, and dependability assessment. In [35] Levenberg Marquardt Artificial Neural Network (LM-ANN) self-organise Network model is adopted for bandwidth, spreading factor, and its most important parameter such as power for data transmission

An elaborative survey on managing seamless mobility in 5G networks was investigated in [21]. To model seamless mobility in heterogeneous network, optimization mechanism employing regressive dragonfly and deep neural learning utilizing shift invariant model was proposed in [22]. With this the throughput rate was said to be improved. However, better quality of service was not ensured. To address on this aspect, a probabilities model for seamless handover was designed in [23] that with the aid of optimal cell selection process ensured better communication quality. Yet another ensemble of bagging and perceptron classifier for handling seamless mobility was presented in [24]. However, with the increase in the traffic, mobility management issue was also hard to be achieved. In [25], a light gradient boost classifier was employed that with the aid of tree-based model not only ensured seamless data delivery but also guaranteed minimum delay.

Security threats against WSN and IoT were analyzed in [26] to handle the security problems. Mobility-aware seamless handover method basis of the multipath transmission control protocol (MPTCP), metaheuristic clustering protocol, node localization with intrusion detection, and energy efficient protocols was developed in [27, 31–33] to deal with managing users' access and mobility concerns. But, the energy consumption was not considered. A generalized RACH-less handover scheme was discussed in [28] for minimizing the handover latency. The mobility support approach was introduced in [29] with a lower hand-off delay as well as higher Packet Delivery Ratio. However, the node energy and network congestion were not estimated. An improvized vertical handover decision method was developed in [30] for accurate and precise handover decisions by combining the multicriteria. But the delay during the handover was not reduced.

Table 1 Tabulation of literature survey

Author name	Technique	Advantage	Disadvantage
Balamurugan et al. [1]	Novel DOA tracking algorithm	Computational complexity was reduced	The prevailing transport layer was not enough
Arunachalam et al. [2]	ID oriented Socket Layer (IoSL)	Latency was decreased and throughput was enhanced	The transport layer was not considered
Lalita Mishra et al. [3]	Four layer architecture	Latency was diminished	Congestion factor was not focused
Verma et al. [4]	Buffer loss estimation mechanism	The packet loss rate was reduced	Energy consumption was not measured

Chen et al. [5]	Stream controlled transmission protocol	Network congestion was decreased	Throughput was not increased
Simiscuka et al. [6]	RElay and MObility Scheme for improved IoT communication performance	Communication performance was enhanced	Delay was not minimized
Akkari et al. [7]	Mobility management Solutions for 5g Networks	Delay was lower	Delivery of services depends on connectivity
Celic and Magjarevic [8]	Seamless connectivity between devices	Maintain low power, low cost	Throughput was not considered
Deebak et al. [9]	Seamless secure anonymous authentication method	Secured service connection rate was achieved	Energy based trade-off model was not minimized
Srinidhi et al. [10]	New proactive mobility support algorithm	Delay and energy conservation were minimized	Throughput was not increased

The current IP put mostly relies on TCP to guarantee end-to-end communication along with other features such as reliability, low and congestion control. Several congestion control alternatives were proposed in order to maximise the use of available bandwidth. Nevertheless, these techniques operate flawlessly in many network settings; yet they describe the current condition of the network and its congestion imprecisely. But, energy consumption, throughput, and delay parameters are not enough and lead to unnecessary packet data transmission. In order to overcome the issue, a novel method for seamless mobility called Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) is proposed to ensure data transmission between devices in wireless networks. The subsequent chapters offer an extensive overview of the CK-DRN strategy.

3 Methodology

From WSN, Robust mobility may make a mess of a prevailing link between two communicating nodes. Owing to the reason that several MAC incapable of modifying strong node mobility, node regularly selects to carry on with data communication until prevailing link is completed, followed by which search is said to be made for relay node for establishing finer association. But, situation would result in transmission latency. To handle this issue, a proposed Deep Recurrent Network-assisted mobility-aware seamless handoff model is developed. The work flow of proposed method is designed with the combination of Seamless Mobility-based Chapman Kolmogorov Poisson Taylor Optimum Beacon Route Discovery and Deep Recurrent Network-based Data Transmission and it is explained in Sections 3.1 and 3.2.

The model ensures handoff with an additional genuine and authentic link as perpetuating communication atop present association, where present association is interrupted upon successful set up of new link. To show the advantage of handoff, data transmission of nodes or ceaseless speed, Chapman Kolmogorov Poisson Optimum Beacon (POB) functionality is designed with a novel Second Order Taylor Series as handoff initiation signal, predicts subsequent node positioning with a Deep Recurrent Network, formulates a mobility-aware seamless handoff module on top of the POB functionality, and compares loss, E2E delay, throughput, and energy efficiency. Figure 1 shows the structure of Chapman Kolmogorov Poisson Beacon and Deep Recurrent Network-based Seamless Mobility.

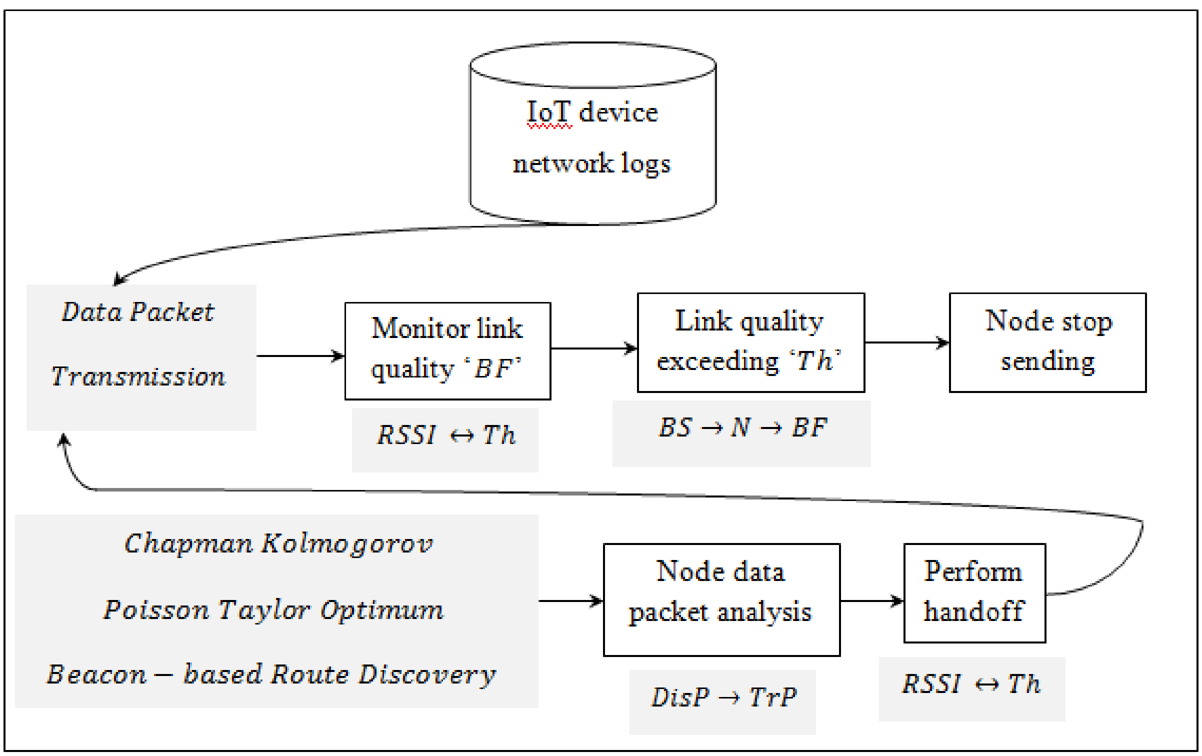

Fig. 1 Structure of Chapman Kolmogorov Poisson Beacon and deep recurrent network-based seamless mobility.

As shown in the above figure, the proposed Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) method the node works in two phases, namely, data packet transmission, and route discovery. As far as data packet transmission is concerned, nodes ceaselessly monitor link quality via beacon frame "BF" by comparing RSSI to the threshold "Th". Beacon frame "BF" consists of the network information (i.e., the thirteen features mentioned in Table 1) required by a node prior to the transmission of data packet.

With the link quality exceeding the threshold value, the base station "BS" notifies the node, as well as the node, stops sending the data packets. On other hand, the node begins Discovery Phase by sending Discovery Packets "$DisP$" to request neighboring nodes to respond using Transmission Packets "TrP". Next, node analyses received Transmission Packets "TrP", as well as RSSI values over neighboring nodes are better than threshold 'Th," it achieves handoff procedure and resumes transmission of data, or else, the transforming Discovery Packets "$DisP$" packets.

3.1 Seamless mobility-based Chapman Kolmogorov Poisson Taylor optimum Beacon route discovery

Route discovery models extend node localization in time by means of localization and predictions. Better error in node results in an erroneous calculation of link quality. The proposed Seamless Mobility-based Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery offloads perform Bayesian filter by modeling Hidden Markov Model (HMM).

In our work, the novel HMM represents a graphical statistical model that correlates unobservable states (i.e., frame, eth, ip, and TCP actual positioning) with respect to previous states (i.e., frame, eth, ip, and TCP node previous positioning) and the node noisy observations (on the basis of the RSSI resultant values). Within the model, the novel Bayesian filter-based HMM holds that at every state "$k - th$" at the time the route discovery on the preceding state "$(k-1) - th$".

Moreover, data packet format has also certain influence on the seamless handoff process that can be specifically addressed via previous node notifications. This we call it as Route Projection Data Packet represented as "DP_{RP}". It is vital to stop the previous node from sending data packets immediately after switching to a new node otherwise two nodes will forward data packets, therefore causing error or congestion. To solve this problem, in our work, the Seamless Mobility-based Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery model is designed to handle seamless mobility via congestion control. Figure 2 shows the structure of

Seamless Mobility-based Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery model.

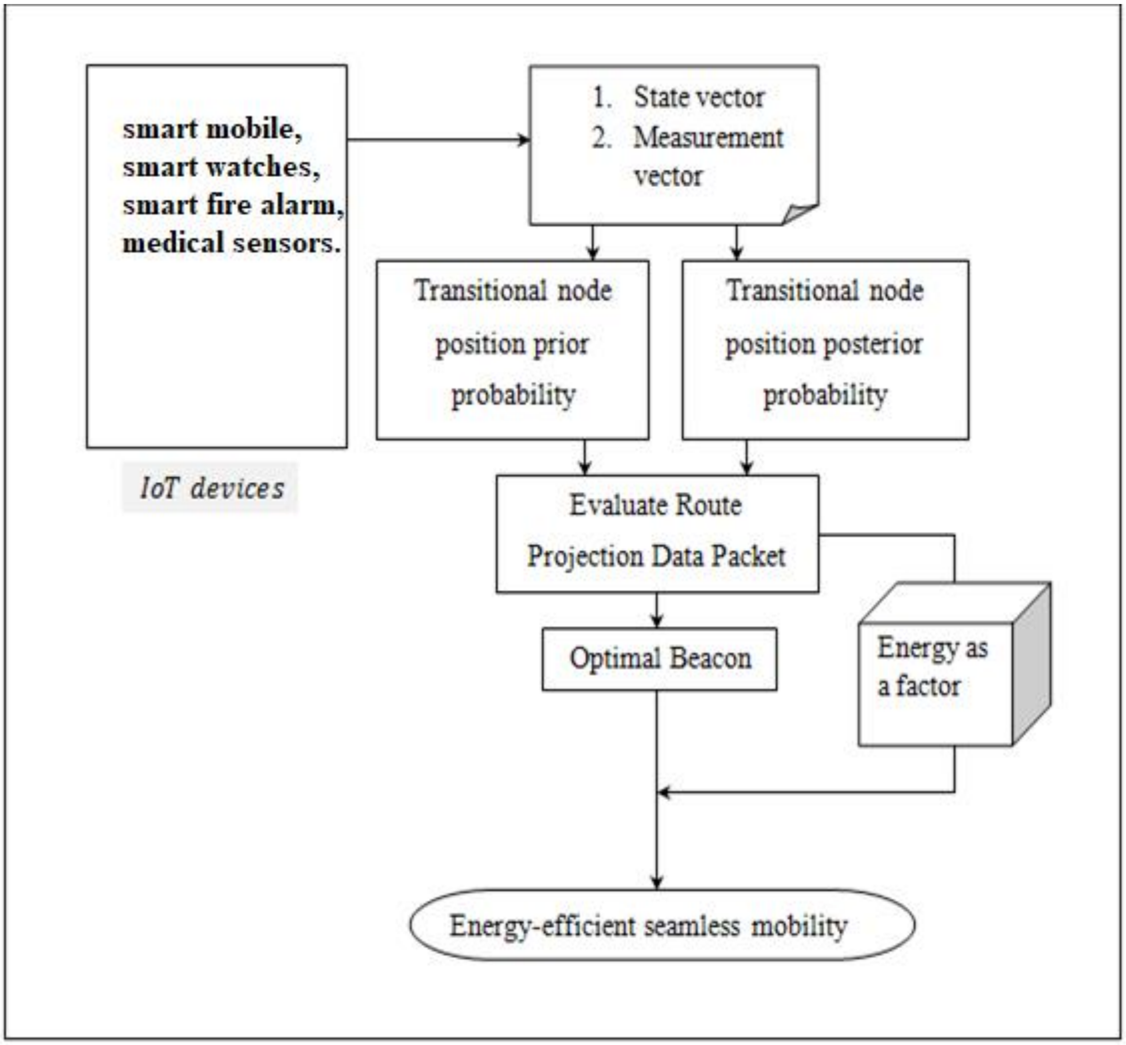

Fig. 2 Structure of seamless mobility-based Chapman Kolmogorov Poisson Taylor optimum Beacon-based route discovery model.

As shown in Figure 2, with numerous IoT devices such as smart mobile, smart watches, smart fire alarm, and medical sensors data packets are captured for seamless mobility. Let us consider the state vector as well as the measurement vector by "$k-th$" time instance to be "$p_k = [p\ q\ v_p\ v_q]^T$" as well as "$q_k = [p'\ q'\ v_p'\ v_q']^T$," respectively, with "$p$" and "$q$" denoting the IoT device network logs. Then, for each node "N" given with the node frame number, frame time, frame length, and so on acquired from the IoT device network logs dataset, the transitional node position probabilities (i.e., based on a frame number) are formulated employing the Chapman

Kolmogorov equation. Then, the transitional node position prior probability for the current time slot "$T_1: k-1$" is mathematically formulated as given below.

$$Prob(p_k|T_1: k-1) = \int Prob(p_k|p_{k-1}) Prob(p_{k-1}|T_1: k-1) dp_{k-1} \qquad (1)$$

In a similar manner, the transitional node position posterior probability for current time slot "$T_1: k$" is mathematically stated as given below.

$$Prob(p_k|T_1: k) = \frac{Prob(T_k|p_k) Prob(p_k|T_{1:k-1})}{Prob(T_k|T_{T:k-1})} \quad (2)$$

After obtaining the prior and posterior probability of both current and previous time slots, the Route Projection Data Packet to handle seamless mobility (i.e., roam around distinct networks without any interference or disturbance) in case of huge number of data packets to be transmitted between end points. Then, by employing Route Projection Data Packet represented as "DP_{RP}." denotes link to node "q" and data packet is misplaced if "$RSSI(q)[t] < Th$". Therefore, data packet loss probability is estimated to arrive at route projection. It is mathematically stated as given below.

$$DP_{Loss}[t] = Prob\ \{RSSI(p)[t] < Th\} * Prob\ (DP_{RP} < t) + Prob\ \{RSSI(q)[t] < Th\} * Prob\ (DP_{RP} < t) \qquad (3)$$

From the above equation (3), data packet loss probability "$DP_{Loss}[t]$" at time instance "t" is measured, based on the probability distribution of Route Projection Data Packet "$Prob\ (DP_{RP} < t)$". This is formulated by employing probability distribution integral function "$\int_0^t Prob\ (DP_{RP=\theta}) d\theta$" mathematically stated as given below.

$$Prob\ (DP_{RP} < t) = \int_0^t Prob\ (DP_{RP=\theta}) d\theta \quad (4)$$

Upon successful estimation of the priori and posterior probability for the respective route projection, optimal beacon frame has to be evaluated. In our work, optimal beacon rate is measured by employing Second Order Taylor Poisson Optimum Beacon Series as handoff initiation signal. Hence, seamless handoff is ensured even in case of two or more simultaneous data packet transmissions.

In this way, by obtaining the optimum beacon energy consumption in the network is reduced. Hence, upon the occurrence of two or more simultaneous data packet transmissions congestion is said to happen, therefore wasting the energy consumed during beacon transmission. Moreover, energy consumed by the sender node while waiting for beacon frame "$E(W)$" and data packet transmission "$E(Tr)$" are also said to be wasted. Hence, the total energy waste due to congestion is mathematically stated as given below.

$$E_{Con}\,(t) = E(BF) + [E(W) + E(Tr)] * \sum fun(\lambda, i) \qquad (5)$$

From the above equation (5), the energy consumed or wasted due to congestion "E_{Con} " at time 't' is obtained based on the energy consumed in transmitting beacon frame "$E(B)$," energy consumed in waiting for "$E(W)$" for obtaining subsequent beacon frame and the energy consumed in transmitting data packets "$E(Tr)$," respectively, with a Poisson arrival rate or "λ" and "i" transmissions.

$$E_{BF}^{fun}(\lambda) = \lambda \left[\frac{(1+e)E(BF)-(1-e)[E(W)+E(Tr)\,]}{e}\right] + \left[\frac{E(W)+E(Tr)+E(BF)(fun-\lambda)^2}{2e\lambda}\right] \quad (6)$$

From the above equation (6), Poisson Optimum Beacon Second Order Taylor Series "$E_{BF}^{fun}(\lambda)$" is evaluated. Second Order Taylor Series data packet loss is minimized as handoff initiation signal and seamless mobility is said to be ensured even in case of two or more simultaneous data packet transmissions. Hence, energy efficiency is enhanced to a greater extent. The pseudo code representation of Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery for seamless mobility is given below.

Algorithm 1: Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery

Input: Dataset 'DS', Features '$F = F_1, F_2, \ldots, F_n$', Node '$N = N_1, N_2, \ldots, N_n$', node identifier '$NId$'

Output: Energy-efficient Seamless Mobility

Step 1: **Initialize** DisP, TrP, Th

Step 2: **Begin**

Step 3: **For** each 'DS' with 'F' and 'NId'

Step 4: Measure transitional node position prior probability for the current time slot '$Prob(p_k|T_1: k-1)$'

Step 5: Measure transitional node position posterior probability for current time slot '$Prob(p_k|T_1: k)$'

Step 6: Measure data packet loss probability '$DP_{Loss}[t]$'

Step 7: Evaluate probability of obtaining Route Projection Data Packet '$Prob\ (DP_{RP} < t)$'

Step 8: Formulate Poisson Optimum Beacon frame '$E_{Con}\ (t)$'

Step 9: Evaluate Poisson Optimum Beacon Second Order Taylor Series '$E_{BF}^{fun}(\lambda)$'

Step 10: **End for**

Step 11: **End**

As given in the above Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery algorithm, with the objective of ensuring seamless mobility and congestion control in an energy-efficient manner. At first, transitional node position prior and posterior probabilities are measured. Second, to ensure seamless mobility across a heterogeneous network, the data packet loss probability is minimized by measuring Route Projection. Finally, Poisson Optimum Beacon Second Order Taylor Series for each node is evaluated. This Second Order Taylor Series function minimizes the amount of handoffs achieved as well as conserves consumption of energy.

3.2 Deep recurrent network-based data transmission

From wireless network, the signaling process is employed to Deep Recurrent Network-based Data Transmission with seamless handover execution. As far as TCP/IP sessions are considered (i.e., from iot-device-network-logs dataset), numerous paths or routes are said to exist for data packet transmission. Concurrent utilization of the numerous paths for single TCP/IP session results with a higher throughput. The proposed Deep Recurrent Network-based Data Transmission with seamless handover execution model initiates numerous subflow associations covering disjoint routes and transmits via the subflows.

In the frame organization, to retain the data packets originating from numerous routes in order, the Deep Recurrent Network-based Data Transmission with a seamless handover execution model is utilized. It arranges the DPON, SON, and DPOR. Here, DPOR denotes the mapping from SON to DPON. DPON represents the order of all data packets, whereas the SON refers to the data packet order in an analogous subflow. The structure of Deep Recurrent Network-based Data Transmission with seamless handover execution model is shown in figure.

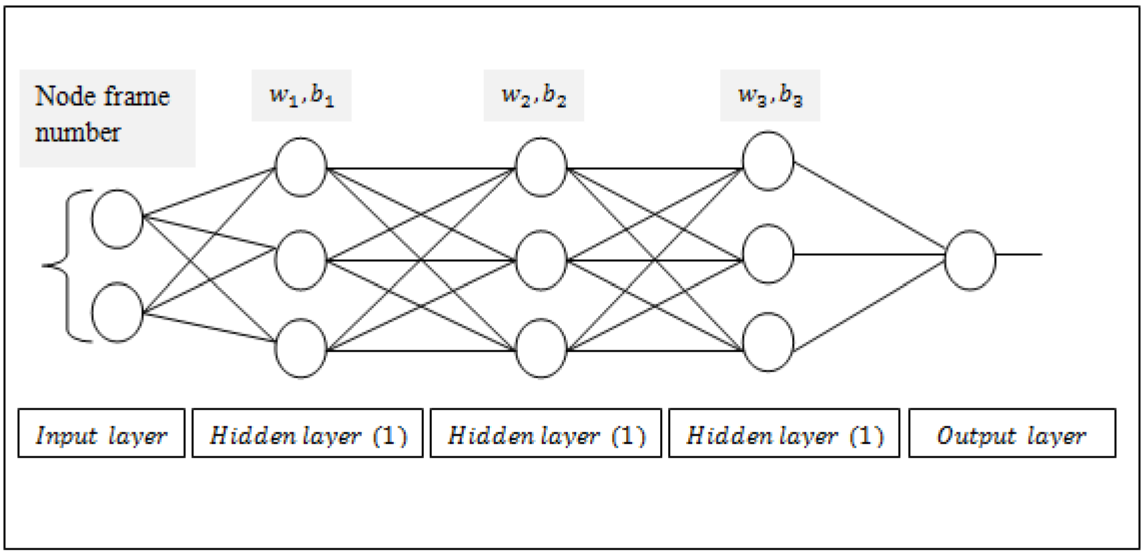

Fig. 3 Structure of deep recurrent network-based data transmission.

As shown in Figure 3, the deep here represents the utilization of a deeper network by one input layer, three hidden layers, and one output layer, respectively. From figure, the deep here represents the utilization of deeper network. Input layer here comprises of unique frame number. The first hidden layer includes DPON, second hidden layer includes SON, whereas the third hidden layer includes the DPOR.

With three distinct hidden layers employed three different weights and bias are employed for each hidden layer (i.e., "(w_1, b_1)" for "$hidden\ layer - 1,$" "(w_2, b_2)" for "$hidden\ layer - 2$" and "(w_3, b_3)" for "$hidden\ layer - 3,$" respectively. Finally, the output layer forms the seamless mobile data transmission in wireless network. To start with the input layer is modeled via the frame number as given below.

$$IL = \sum_{i=1}^{n} FN_i \qquad (7)$$

From the above equation (7), the input layer “IL” consists of distinct frame numbers “FN_i” network logs lists. Initially, the current state of the corresponding frame via frame number “FN” is mathematically formulated as given below.

$$H_t = f(H_{t-1}, FN_t) \quad (8)$$

From the above equation (8), the current state “H_t” via frame number “FN" (i.e., input state) is obtained based on the previous state results “H_{t-1}”. Second, the activation function for the hidden layers is mathematically stated as given below.

$$H_t = \tanh(W_{HH}H_{t-1} + W_{FNH}FN_t) \quad (9)$$

From the above equation (9), the activation function results “H_t” are obtained by employing the weight at recurrent neuron “$W_{HH}H_{t-1}$” and the weight at input neuron “$W_{FNH}FN_t$,” respectively. Finally, the resultant outputs (i.e., either transmission or no transmission) are obtained as given below.

$$Out_t = W_{HOut}H_t \qquad (10)$$

On the basis of the results obtained from the output layer “Out_t,” either data transmission or no transmission is said to be performed. With this, numerous sub-flows construction, seamless mobility based data transmission with higher throughput is achieved. The pseudo code representation of Deep Recurrent Network-based Data Transmission is given below.

Algorithm 2 Deep Recurrent Network-based Data Transmission

Input: Dataset 'DS', Features '$F = F_1, F_2, \ldots, F_n$', Node '$N = N_1, N_2, \ldots, N_n$', node identifier '$NId$'

Output: Throughput efficient seamless mobility

Step 1: **Initialize** (w_1, b_1)', '(w_2, b_2)' and '(w_3, b_3)'

Step 2: **Begin**

Step 3: **For** each 'DS' with 'F' and 'NId'

//Input layer

Step 4: For each frame number 'FN'

Step 5: Acquire the data 'IL'

Step 6: End for

//Hidden layer

Step 7: Obtain current state of the corresponding frame 'H_t'

Step 8: Apply activation function for hidden layers

Step 9: Obtain results in the output layer 'Out_t'

//Output layer

Step 10: **If** '$Out_t > 0.5$ and $Out_t < 1$'

Step 11: Perform data transmission

Step 12: **End if**

Step 13: **If** '$Out_t > 0$ and $Out_t \leq 0.5$'

Step 14: Do not perform data transmission

Step 15: **End if**

Step 16: **End for**

Step 17: **End**

As given in the above Deep Recurrent Network-based Data Transmission, the advantage is that it concurrently utilizes numerous sub-flows via distinct routes between nodes. Here, the Deep Recurrent Network-based Data Transmission model split the flow of traffic of a single session into numerous sub-flows. At the same time, for each sub-flow's data packet communication, Deep Recurrent Network-based Data Transmission model signify one sub-session. On the other hand, received data packets over distinct sub-flows were reconstructed within single flow to DPON. From concurrent utilization of numerous sub-flows, Deep Recurrent Network-based Data

Transmission model make entire utilization of the network resources, thus resulting in higher throughputs.

4 Experimental setup

In this part, extensive studies are carried out to demonstrate the effectiveness of the Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) IoT data transmission in wireless network for seamless mobility in Python. The experiment data called IoT Device Network Logs are available online over https://www.kaggle.com/datasets/speedwall10/iot-device-network-logs. It comprises preprocessed dataset to network-based intrusion detection system within IoT devices. Ultrasonic sensor using Arduino as well as NodeMCU were utilized for examining network as well as acquire network. It was also employed for sending data packets to the server via wifi. Table 2 lists the details of IoT device network logs dataset.

Table 2 Details of IoT device network logs dataset

S. No	Features	Description
1	Frame.time	Frame time
2	Frame.len	Length of frame
3	Frame.number	Frame number
4	eth.src	Source of eth
5	eth.dst	Destination of eth
6	ip.src	Source of IP
7	ip.dst	Destination of IP
8	ip.proto	IP protocol
9	ip.len	IP length
10	TCP.len	Length of TCP
11	TCP.srcport	Source port of TCP
12	TCP.dstport	Destination port of TCP
13	Value	Corresponding value
14	Normality	Normality value

First, we evaluate the energy consumption and delay of CK-DRN. Then, compared with existing Direction of Arrival tracking (DOA tracking) [1] and ID oriented Socket Layer (IoSL) [2], our method outperforms it a lot in energy savings and end-to-end delay. From the experiments, the significant enhancement is due to the less complicated mathematical operations in each stage of deep learning. Second, we estimated the throughput rate to ensure the efficiency of the method. In the experiments, the data are stored on a computer.

5 Result and discussion

Simulation of CK-DRN and the existing Direction Of Arrival tracking (DOA tracking) [1] and ID oriented Socket Layer (IoSL) [2] are compared with certain parameters such as energy consumption, delay, and throughput using to distinct numbers of samples. The performance of proposed as well as existing technique is explained below.

5.1 Comparison of proposed and existing methods

The results of the proposed CK-DRN method and existing DOA tracking [1] IoSL [2] methods are compared via graphical representations, considering energy consumption, end-to-end delay, and throughput parameters. Tables 2–4 provide the comparison of 5G with existing IoT and wireless technologies. We compared the technology in terms of energy consumption (how much energy is taken to data transmission), end-to-end delay (how much time is taken to data send), and throughput (data packets are transmitted per unit time), which are essential components in IoT and wireless technologies. Here, data are stored on a computer with an Intel(R) Core(TM) i5-7200 CPU @2.50GHz and 8.00GB of RAM, to compare with IoT and wireless technologies.

5.2 Comparative analysis of energy consumption for proposed and existing methods

It refers to number of energy utilized for IoT data transmission with seamless mobility in wireless network. In other words, it is the total amount of energy consumed to provide data transmission to the devices. Energy conservation in turn therefore results in more effective mechanisms hence minimizing the number of handoffs ensuring seamless mobility. The following calculation is used to calculate how much energy is used. $EC = \sum_{i=1}^{n} S_i * EC\ (HO)$ (11)

From the above equation (11), energy consumption "EC" is measured based on the samples involved (i.e., frame numbers provided as input during simulation) "S_i" and the energy consumed during handoffs "$EC\ (HO)$". It is measured in terms of joules "J". This experiment compares our proposed CK-DRN method with the existing DOA tracking [1] and IoSL [2] based methods given in the literature. The comparison is based on energy consumption. Table 3 compares our technique's results to those of various earlier seamless connectivity-based data transfer systems.

Table 3 Energy consumption using CK-DRN, DOA tracking [1] and IOSL [2]

Samples	Energy consumption (J)		
	CK-DRN	DOA tracking	IoSL
500	25	35	40
1000	27	38	45
1500	31	42	50
2000	35	45	55
2500	38	52	58
3000	42	58	65
3500	45	65	71
4000	50	70	82
4500	55	73	95
5000	60	78	102

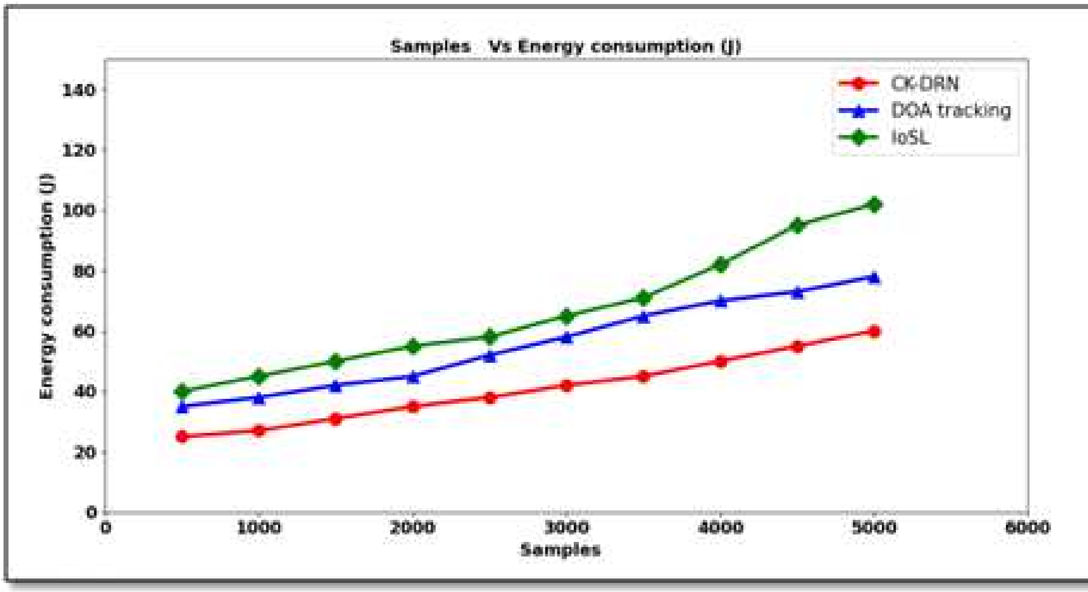

Fig. 4 Graphical representation of energy consumption

Figure 4 given explains energy consumed while performing the IoT data communication with seamless connectivity between nodes in wireless network. From the above figure, the energy consumption is found to be directly proportional to the number of sample frames of inputs acquired from IoT device network logs dataset. In other words, increasing the number of samples of frames acquired from the nodes causes an increase in the frequency of frame to be analyzed and this results in an increase in the energy consumption and vice versa. But, simulations conducted with 500 frames saw 25J of energy consumption using CK-DRN, 35J using [1] and 40J using [2], respectively. The energy spent while preprocessing for data analysis utilising the CK-DRN approach was shown to be considerably lower than that spent by current techniques. This is because of the enhancement of Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery algorithm. By applying this algorithm, first transitional node position prior and posterior probabilities are measured by modeling the state space as a Hidden Markov Model (HMM). Next, route projection across heterogeneous network was measured via data packet loss probability. Finally, for each frame, optimum beacon was arrived at based on the second-order Taylor series. It was managed in reducing the number of handoffs performed, therefore not only ensuring seamless mobility but also minimizing the energy consumption using CK-DRN by 27% and 38% compared with [1] and [2].

5.3 Comparative analysis of end-to-end delay for proposed and existing methods

It is discussed to measure the performance of proposed method. While performing IoT data transmissions with seamless mobility, a significant amount of delay is said to take place during the handover operation. It refers to the time consumed for a node in wireless network for transferring data packets to intended node. It is mathematically formulated as given below.

$$Delay_{EE} = \sum_{i=1}^{n} S_i * \{[t_{act}] - [t_{ex}]\} \quad (12)$$

From the above equation (12), the end to end delay "$Delay_{EE}$" is measured by taking into evaluation, the actual arrival time "$[t_{act}]$" and the expected arrival time "$[t_{ex}]$," respectively, for the corresponding numbers of samples "S_i". It is measured in terms of milliseconds (ms). This experiment compares our proposed CK-DRN method with the existing DOA tracking [1] IoSL [2] methods given in the literature. The comparison is based on delay. Table 4 compares the results of our technology to earlier seamless connectivity-based data transfer solutions.

Table 4 Tabulation for end-to-end delay using CK-DRN, DOA tracking [1] and IoSL [2]

Samples	End-to-end delay (ms)		
	CK-DRN	DOA tracking	IoSL
500	175	215	260
1000	215	285	340
1500	245	315	380
2000	280	355	410
2500	315	390	485
3000	335	435	525
3500	355	480	590
4000	415	525	635
4500	435	585	680
5000	485	635	725

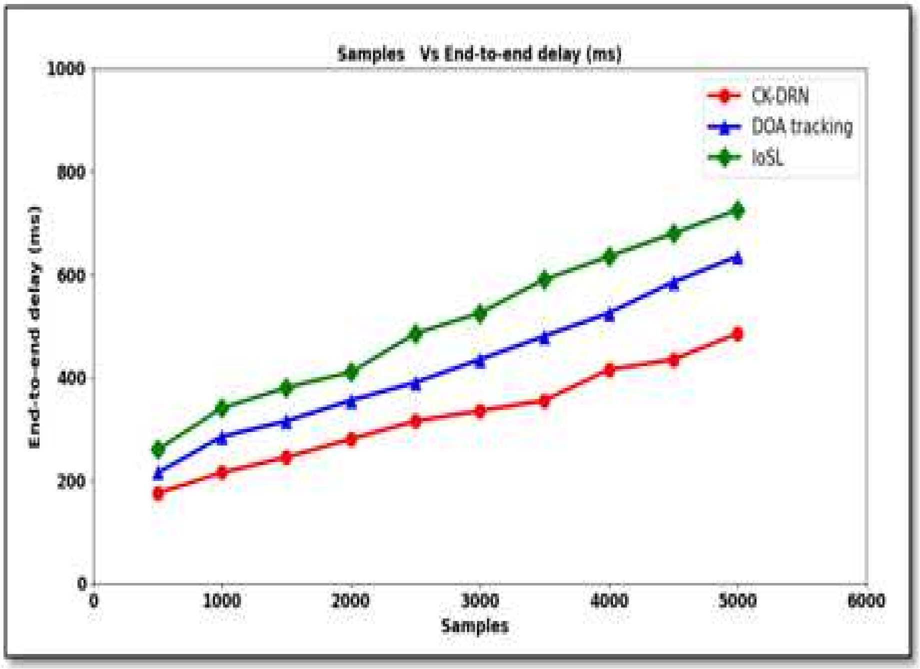

Fig. 5 Graphical representation of end-to-end delay

Figure 5 illustrates delay analysis using 5000 sample frames obtained from IoT device network logs associated with the modelling process for 10 separate simulation runs done within various conditions. From the above figure, a linear increase is found in the end-to-end delay by applying all the three methods. In simple terms, raising the number of samples improves the amount of network traffic in a wireless connection, leading to the end-to-end delay or the period required in transmitting information among the nodes, consequently raising the delay. Nevertheless, calculations for 500 vehicles utilising the recommended CK-DRN technique revealed 175 ms, 215 ms, and 260 ms, correspondingly. As a result, the end-to-end delay based on the suggested CK-DRN approach has been determined to be shorter than [1] and [2]. The reason behind the minimization of end-to-end delay using CK-DRN was due to the application of Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery algorithm. By applying this algorithm, the transitional node position prior and posterior probabilities were measured between state vector and measurement vector. On the basis of the results further proceedings were made. With this the actual arrival time was comparatively less owing to the consideration of timely reports from neighboring nodes that in turn minimized the end-to-end delay using CK-DRN method by 22% and 35% compared to [1] [2].

5.4 Comparative analysis of throughput for proposed and existing methods

It is defined as the amount of messages or data packets effectively send per unit time. It is controlled by available bandwidth, available signal-to-noise ratio. It is calculated with number of data send among multiple locations through certain period of time.

$$T = (Frames * Bits\ carried)/time \qquad (13)$$

From the above equation (13), throughput "T" is measured on the basis of the frames involved in the simulation and the actual bits carried by the network. Then, the throughput is measured as given below for the three methods. It is measured in terms of megabytes per seconds (Mbps). Finally, the experiment compares the proposed CK-DRN method over the existing DOA tracking [1] and IoSL-based methods given in the literature. The comparison is based on throughput. Table 5 compares the results of our technology to earlier seamless connectivity-based data transfer solutions.

Table 5 Tabulation for throughput using CK-DRN, DOA tracking [1] and IoSL [2]

Samples	Throughput (Mbps)		
	CK-DRN	DOA tracking	IoSL
500	4.16	2.91	1.66
1000	4.85	3.15	1.85
1500	5.25	3.85	2.35
2000	5.85	4.35	2.85
2500	6.15	4.95	3.45
3000	6.85	5.25	4.55
3500	7.35	5.85	5.35
4000	7.95	6.15	5.35
4500	8.25	6.85	6
5000	9.35	7	6.35

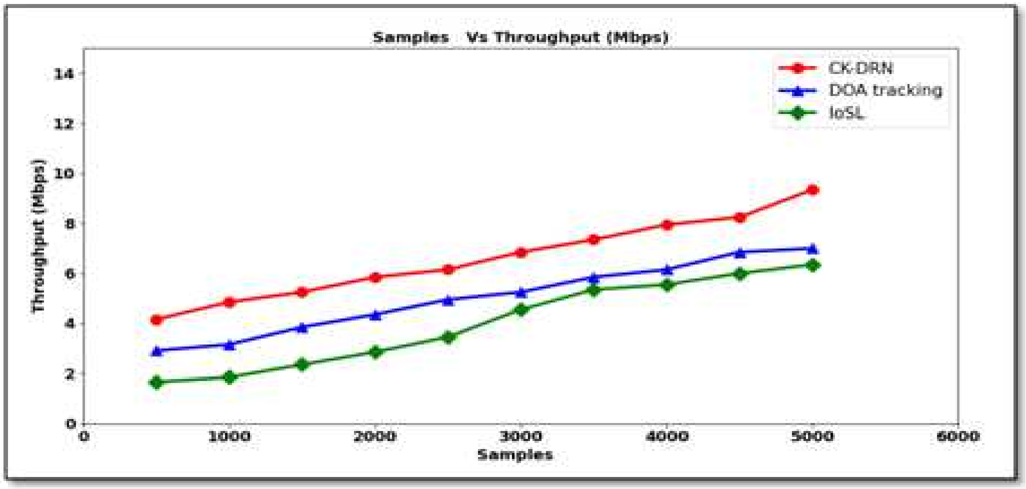

Fig. 6 Graphical representation of throughput

Lastly, consider Figure 6 depicts a visual representation of performance on the y axis using 5000 separate frame data generated for 10 different simulations to acquire the findings. With large propagation productivity, the entire network renders wireless communication highly challenging since the volume of handover grows with the equivalent speed. As consequence, there is a considerable chance of data transmission failure. In our work by employing a Deep Recurrent Network-based Data Transmission along with the concurrent utilization of numerous subflows via distinct routes between nodes, a three hidden layer model is designed to mitigate the handover issue in traditional wireless network systems. The proposed CK-DRN method employing Deep Recurrent Network alleviates interruption time associated with the conventional handover process, via three different factors, DPON, SON, and the DPOR, therefore ensuring seamless mobility. As a result, the throughput using CK-DRN is enhanced as 33% and 84% compared to [1] and [2].

6 Discussion

This study compares and discusses the proposed CK-DRN method with the existing DOA tracking [1] IoSL [2] using IoT Device Network Logs based on various factors, such as energy consumption, end-to-end delay, and throughput. In the simulation, ten different results are obtained for each method based on the input counts 500, 1000, … 5000. The "500" samples are considered to conduct the experiments for the existing and proposed method. The comparison results indicate that the proposed CK-DRN method provided a better performance of higher throughput by 29%, lesser energy consumption by 33%, and delay by 14% than compared to the existing [1] and [2] with aid of the IoT Device Network Logs.

7 Conclusion

Seamless mobility refers to the ability of a node to change its point of connection to an Internet Protocol (IP)-based network without interruption or error in the existing connections or disruption during communication. With increased network traffic, maintaining continuous network access to information at all times is a difficult issue. In this work, a novel method called, Chapman Kolmogorov and Deep Recurrent Network-based (CK-DRN) IoT data transmission in wireless network, is proposed. The CK-DRN method ensures seamless mobility even in case of congestion by means of two different phases, Chapman Kolmogorov Poisson Taylor Optimum Beacon-based Route Discovery and Deep Recurrent Network-based Data Transmission. Extensive simulation results were provided to demonstrate that the proposal can enhance or boost the performance of IoT-based data transmission in wireless network. Simulation of CK-DRN was analyzed with various performance metrics such as delay, energy consumption, as well as throughput compared with conventional techniques. Numerical results of CK-DRN outperform conventional techniques and yield lower delay by 14% and consumption of energy by 33% ensuring a better throughput rate of 29% for seamless mobility-based IoT data transmission in a wireless network. In the future, the proposed method is further extended to measure the data delivery rate and packet loss rate by using a novel deep neural network and optimization method.

Declarations

Ethical Approval:

Not Applicable

Funding:

Not Applicable

Availability of data and materials:

Not Applicable

References

[1] Balamurugan, N. M., Mohan, S., Adimoolam, M., John, A., Thippa Reddy G., & Wang, A. (2022). DOA tracking for seamless connectivity in beamformed IoT-based drones. *Computer Standards & Interfaces*. Elsevier, [Direction Of Arrival tracking (DOA tracking)].

[2] Arunachalam, K., Gantha, S. S., Jaiswal, S., Pallan, J. M., Song, S., & Nigam, A. (2022). A session-based cross-layer approach for seamless connectivity in next-generation mobile networks. *IEEE Access*, [ID oriented Socket Layer (IoSL)].

[3] Mishra, L., Vikash, & Varma, S. (2021). Seamless Health Monitoring Using 5G NR for Internet of Medical Things. *Wireless Personal Communications*, Springer.

[4] Verma, H., Chauhan, N., Chand, N., & Awasthi, L. K. (2022). Buffer-loss estimation to address congestion in 6LoWPAN based resource-restricted 'Internet of Healthcare Things' network. *Computer Communications*, Elsevier.

[5] Chen, J.-M., Chu, C.-H., Hsiao-KuangWu, E., Tsai, M.-F., & Wang, J.-R. (2011). Improving SCTP performance by Jitter-based congestion control over wired-wireless networks. *EURASIP Journal on Wireless Communications and Networking*.

[6] Simiscuka, A. A., & Muntean, G.-M. (2021). REMOS-IoT-A relay and mobility scheme for improved IoT communication performance. *IEEE Access*.

[7] Akkari, N., & Dimitriou, N. (2020). Mobility management solutions for 5G networks: architecture and services. *Computer Networks*, Elsevier.

[8] Celic, L., & Magjarevic, R. (2020). Seamless connectivity architecture and methods for IoT and wearable devices. *Journal for Control, Measurement, Electronics, Computing and Communications*.

[9] Deebak, B. D., Al-Turjman, F., & Mostarda, L. (2020). Seamless secure anonymous authentication for cloud-based mobile edge computing. *Computers and Electrical Engineering*. Elsevier.

[10] Srinidhi, N., Raghavendra, S., Shreyas, J., Kiran Kumar, A., & Tengli, N. S. (2021). Establishing self-healing and seamless connectivity among IoT networks using Kalman filter. *Natural Volatiles and Essential Soils*.

[11] Siddiqui, S. Y., Ahmad, I., Khan, M. A., Khan, B. S., Ali, M. N., Naseer, I., Parveen, K., & Usama, H. M. (2021). AIoT enabled traffic congestion control system using deep neural network. *Endorsed Transactions on Scalable Information Systems*.

[12] Im, J., Astillo, P. V., & You, I. (2020). DMM-SEP: secure and efficient protocol for distributed mobility management based on 5G networks. *IEEE Access*.

[13] Ahmad, A., Paul, A., Rathore, M. M., & Rho, S. (2015). Power aware mobility management of M2M for IoT communications. *Mobile Information Systems*.

[14] Begovic, M., Causevic, S., Memic, B., & Haskovic, A. (2020). AI-aided traffic differentiated QoS routing and dynamic offloading in distributed fragmentation optimized SDN-IoT. *International Journal of Engineering Research and Technology*, *13*(8), ISSN 0974-3154.

[15] Majumdar, S., Subhani, M. M., Roullier, B., Anjum, A., & Zhu, R. (2021). Congestion prediction for smart sustainable cities using IoT and machine learning approaches. *Sustainable Cities and Society*.

[16] Yap, K.-L., Chong, Y.-W., & Liu, W. (2020). Enhanced handover mechanism using mobility prediction in wireless networks. *PLOS ONE*, https://doi.org/10.1371/journal.pone.0227982.

[17] Shahraki, A., Taherkordi, A., & Haugen, Ø. (2021). TONTA: trend-based online network traffic analysis in ad-hoc IoT networks. *Computer Networks*, Elsevier.

[18] Dhingra, S., Madda, R. B., Patan, R., Jiao, P., Barri, K., & Alavi, A. H. (2020). Internet of things-based fog and cloud computing technology for smart traffic monitoring. *Internet of Things*, Elsevier.

[19] Rathod, V., Jeppu, N., Sastry, S., Singala, S., & Tahiliani, M. P. (2019). CoCoA++: delay gradient based congestion control for Internet of Things. *Future Generation Computer Systems*, Elsevier.

[20] Chavhan, S., Gupta, D., Chandana, B. N., Khanna, A., & Rodrigues,J. J. P. C. (2019). IoT-based context-aware intelligent public transport system in a metropolitan area. *IEEE Internet of Things Journal*.

[21] Reddy, S., & Venkatarama, S. (2018). A comprehensive survey on seamless mobility management in 5G communications. *International Journal of Future Generation Communication and Networking*.

[22] Somashekhara Reddy, D. (2020). Support vector regressive dragonfly optimized shift invariant deep neural learning based handover for seamless data delivery in heterogeneous network. *International Journal of Computer Networks and Applications (IJCNA)*.

[23] Somashekhara Reddy, D. (2019). Probabilistic model for optimal cell selection for seamless handover in LTE/LTE-A networks. *Indian Journal of Public Health Research & Development*.

[24] Somashekhara Reddy, C. D. (2020). Bagging ensembled perceptron classifier for seamless mobility system in heterogeneous network. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*.

[25] Somashekhara Reddy, D. (2020). Generalized light gradient boost classifier for traffic aware seamless mobility management in heterogeneous network. *Indian Journal of Computer Science and Engineering (IJCSE)*.

[26] Lata, S., Mehfuz, S., & Urooj, S. (2021). Secure and reliable WSN for internet of things: challenges and enabling technologies. *IEEE Access*.

[27] Tong, H., Wang, T., Zhu, Y., Liu, X., Wang, S., & Yin, C. (2021). Mobility-aware seamless handover with MPTCP in software-defined HetNets. *IEEE Access*.

[28] Choi, J.-H., & Shin, D.-J. (2019). Generalized RACH-less handover for seamless mobility in 5G and beyond mobile networks. *IEEE Access*.

[29] Vaezian, A., & Darmani, Y. (2022). MSE-RPL: mobility support enhancement in RPL for IoT mobile applications. *IEEE Access*.

[30] Abdullah, R. M., Abualkishik, A. Z., Alwan, A. A. (2018). Improved handover decision algorithm using multiple criteria. *Procedia Computer Science*, Elsevier.

[31] Kadiravan, G., Sujatha, P., Asvany, T., Punithavathi, R., Elhoseny, M., Pustokhina, I.V., Pustokhin, D. A., & Shankar, K. (2021).Metaheuristic clustering protocol for healthcare data collection in mobile wireless multimedia sensor networks. *Computers, Materials & Continua*, *66*(3), 3215–3231.

[32] Punithavathi, R., Thanga Selvi, R., Latha, R., Kadiravan, G., Srikanth, V., & Shukla, N. K. (2022). Robust node localization with intrusion detection for wireless sensor networks. *Intelligent Automation and Soft Computing*, *33*(1), 143–156.

[33] Kadiravan, G., Sujatha, P., & Amudhavel, J. (2017). A state of art approaches on energy efficient routing protocols in mobile wireless sensor networks. *IIOAB J*, *8*(2), 234–238.

[34] Pundir, M., Sandhu, J. K., Gupta, D., Gadekallu, T. R., Juneja, A., Gulzar, Y., & Nauman, A. (2023). Data rate aware reliable transmission mechanism in wireless sensor networks using Bayesian regularized neural network approach. *Physical Communication*, *59*, 102115.

[35] Hakim, G. P. N., Habaebi, M. H., Elsheikh, E. A. A., Suliman, F. M., Islam, M. R., Yusoff, S. H. B., Adesta, E. Y. T, & Anzum, R. (2023). Levenberg Marquardt artificial neural network model for self-organising networks implementation in wireless sensor network. *IET Wireless Sensor Systems*.