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Proactive resource allocation in Mobile Networks: A Predictive Guard Channel Scheme using Long Short-Term Memory

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Abstract
The escalating demand for mobile data services necessitates efficient resource management in cellular networks. Traditional reactive resource allocation schemes often suffer from delays and inefficiencies due to the dynamic nature of user mobility and traffic patterns. This paper proposed a proactive resource allocation scheme utilizing a predictive guard channel mechanism powered by Long Short-Term Memory (LSTM) networks. The proposed scheme anticipated future resource demands based on historical traffic and mobility data, enabling the dynamic adjustment of guard channel sizes to mitigate handoff failures and improve Quality of Service (QoS). We presented the system architecture, mathematical model, and algorithmic flow, followed by a performance evaluation comparing our LSTM-based scheme with a conventional guard channel scheme. Simulation results showed that the new call blocking probabilities for Static Guard Channel Scheme ranged from 2 to 7.5 while that of Predictive Guard Channel Scheme ranged from 1.0 to 7.0. Also, the handoff call blocking probabilities for Static Guard Channel Scheme ranged from 1 to 11.9 while that of Predictive Guard Channel Scheme ranged from 0.5 to 5.0 which shows that the Predictive Guard Channel Scheme significantly reduces new call blocking probability and handoff drop probability, and improves resource utilization, making it a promising solution for future mobile networks.

Keywords: Long Short-Term Memory, Guard channel, Proactive resource allocation, Handoff Drop Probability, New Call Blocking Probability

1. Introduction

The huge increase in the number of mobile devices and the coming into existence of data-intensive applications are responsible for placing considerable pressure on the cellular networks' capacity and efficiency. Ensuring preferable QoS and continuous connectivity become a great task particularly in situations where there is significant user mobility and inconsistent traffic loads (Alomari *et al.*, 2023). The procedure of handing off an ongoing call to another base station in mobile network, termed handoff, is a complicated process. Sometimes, rapid handoffs in thickly populated areas or busy hours engenders failures in handoff if there are not enough resources in the target cell to accept the incoming connection (Gupta *et al.*, 2022). High dropping of calls, lower throughput and user dissatisfaction are part of the outcomes of handoff failures.

To solve these problems, different resource allocation schemes were built. Guard channel (GC) schemes are a common approach where a small portion of the total available channels in each cell is reserved exclusively for handoff calls (Jana *et al.* 2020). While effective in reducing handoff drop probability, static guard channel allocation can lead to inefficient resource utilization, as reserved channels may remain idle when handoff demand is low. Conversely, a shortage of guard channels during high handoff demand can still result in numerous handoff failures. This highlights the need for a more dynamic and intelligent approach to guard channel management.

Engaging Long Short-Term Memory (LSTM) neural networks, we developed a unique proactive resource allocation scheme that can adaptively regulate the size of guard channels and project future handoff requests. Owing to their capacity to learn long-term dependencies in sequential data, LSTMs are appropriate for time-series prediction operations (Hochreiter & Schmidhuber, 1997). Our scheme proactively allocated resources, thereby reducing handoff failure while enhancing spectrum utilization, by predicting the volume of incoming handoff requests.

2. Literature Review

Resource allocation in mobile networks has been a subject of extensive research, with numerous studies focusing on optimizing various aspects like throughput, latency, and fairness. Early work on guard channel schemes primarily focused on static allocation strategies. These schemes, while simple to implement, often struggled to adapt to the dynamic nature of mobile traffic (Olwal *et al.*, 2019). To improve efficiency, researchers began exploring dynamic guard channel allocation. For instance, some schemes dynamically adjust guard channel sizes based on instantaneous traffic load or channel occupancy, but these reactive approaches can still suffer from delays in adapting to rapid changes in network conditions (Chen *et al.*, 2022).

With the advent of machine learning, predictive approaches have gained traction. Kim *et al.*, 2020 explored the use of basic neural networks for traffic prediction in mobile networks to inform resource allocation. But these old models found it difficult to cope with the complex temporal dependencies built in network traffic data. In recent studies, deep learning techniques for enhancing network efficiency was emphasized. For instance, (Liu *et al.*, 2023) suggested a reinforcement learning-based strategy to adaptively slice resources in 5G networks, while (Zhao *et al.*, 2023) examined the significance of Graph Neural Networks (GNNs) in apportioning resources in highly-dense networks.

Specifically, for handoff management, several predictive approaches have emerged. Kumar & Suganthi,(2021) proposed using a Markov chain model to predict user mobility and allocate resources proactively. However, Markov chains can be limited in capturing complex, non-linear patterns in user behaviour. The application of recurrent neural networks (RNNs) and their variants like LSTMs for time-series prediction in mobile networks has shown significant promise. (Hasa *et al.*, 2023) demonstrated the effectiveness of LSTMs in predicting call arrival rates in cellular networks for dynamic channel allocation. Similarly, (Zhang *et al.*, 2023) used LSTMs to forecast user demand in vehicular ad-hoc networks (VANETs) to optimize resource provisioning. These studies highlight the superior ability of LSTMs to handle the temporal dynamics of network traffic, making them an ideal candidate for predicting handoff demand and informing proactive guard channel allocation. Building on these advancements, this work aims to specifically integrate LSTM-based handoff prediction into a dynamic guard channel scheme to achieve enhanced performance.

3. Methodology

This paper proposed a proactive resource allocation scheme for mobile network using a predictive guard channel mechanism. The system utilizes Long Short-Term Memory (LSTM) networks within each base station (BS) to predict future handoff demands. This prediction module dynamically adjusts the size of guard channels (reserved for handoffs) in the channel pool. Historical traffic and mobility data are used for training, while a real-time network monitor provides current network parameters. An LSTM model is trained on historical data (handoff rates, traffic load, user mobility) to forecast the number of incoming handoff requests for a future time window (e.g. 5 minutes). LSTMs are chosen for their ability to learn long-term dependencies in time-series data.

Based on the LSTM's prediction, the number of guard channels (GGC) is dynamically increased if the predicted handoff demand exceeds a predefined threshold. If the predicted demand is below the threshold, the number of guard channels is decreased, freeing up channels for new call attempts. This adjustment operates within defined maximum and minimum guard channel limits.

The handoff requests are given priority. They first attempt to use an available guard channel. If none are available, they try to use a regular traffic channel. If neither is available, the handoff fails. The new call requests only use available regular traffic channels. If no traffic channels are free, the new call is blocked.

3.1. System Architecture

The system architecture for the predictive guard channel scheme is depicted in figure 1

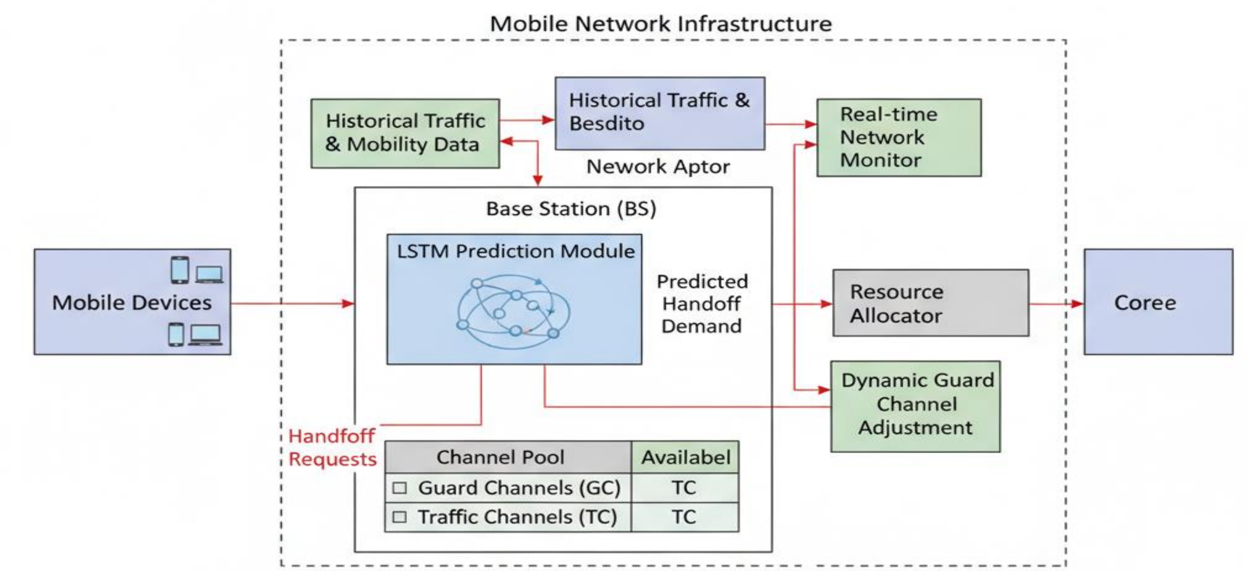

Figure 1: System Architecture

The core components include:

Mobile Devices: Produce handoff requests when users traverse among cells.

Base Station (BS): Each BS has:

(a) LSTM Prediction Module: This is trained on historical traffic and mobility data. It forecasts the volume of incoming handoff requests for subsequent time frame.

(b) Channel Pool: It has Traffic Channels (TC) and Guard Channels (GC).

(c) Resource Allocator: Allocates free channels (TC or GC) to new calls and handoff requests.

(d) Dynamic Guard Channel Adjustment: Adaptively adjusts the number of guard channels in the channel pool according to the forecasted handoff requests from the LSTM module.

Historical Traffic and Mobility Data: This is a database responsible for keeping past network traffic patterns, user movement, handoff rates, and channel occupancy. It is important for training the LSTM model.

Real-time Network Monitor: Always collects current network parameters such as channel utilization, number of active users, and active handoff requests. This data can be incorporated into the LSTM for online learning or fine-tuning.

3.2 Algorithm

Algorithm: Proactive Guard Channel (PGC) Scheme

Input:

Historical Traffic and Mobility Data (H_data)

Real-Time Network State (N_state): current traffic load, channel availability, active handoff requests

Trained LSTM Model (LSTM_model) for handoff prediction

Prediction Horizon (k)

Guard Channel Threshold (th)

Guard Channel Adjustment Step (ΔC_GC)

Minimum Guard Channels (C_GC, min)

Maximum Guard Channels (C_GC, max)

Output:

Successful Handoffs

Minimized Handoffs Drops

Optimized Resource utilization

Initialization:

1) Initialize LSTM_model by training on H_data

2) Set initial number of Guard Channels (C_GC) within C_GC, min and C_GC, max

3) Set initial number of Traffic Channels (C_TC)

Loop (continuously in real-time):

1) Collect current network state:

N_state = Monitor current channel utilization, active users, handoff requests

2) Predict Handoff Demand:

Predicted_Handoff_Demand = LSTM_model.predict (N_state, horizon = k)

3) Dynamically adjust guard channels:

If Predicted_Handoff_Demand > t

C_GC = min (C_GC + ΔC_GC, C_GC, max)

Else If Predicted_Handoff_Demand <= th

C_GC = max (C_GC - ΔC_GC, C_GC, min)

Update C_TC based on C_GC and total channels

4) Handoff Request Arrives:

If C_GC > 0 (Guard Channel Available)

Allocate a guard channel

C_GC = C_GC-1

Handoff Successful

Else (No guard channel available)

Attempt Traffic Channel Allocation:

If C_TC > 0 (Traffic channel available)

Allocate a traffic channel

C_TC = C_TC -1

Handoff successful

Else (No traffic channel available)

Handoff failed (handoff drop)

5) Update Network State:

Record successful/failed handoffs, channel occupancy for failure H_data and LSTM_model updates

6) Repeat from step 1

3.3 Flowchart

The operational flowchart of the predictive guard channel scheme is illustrated in figure 2.

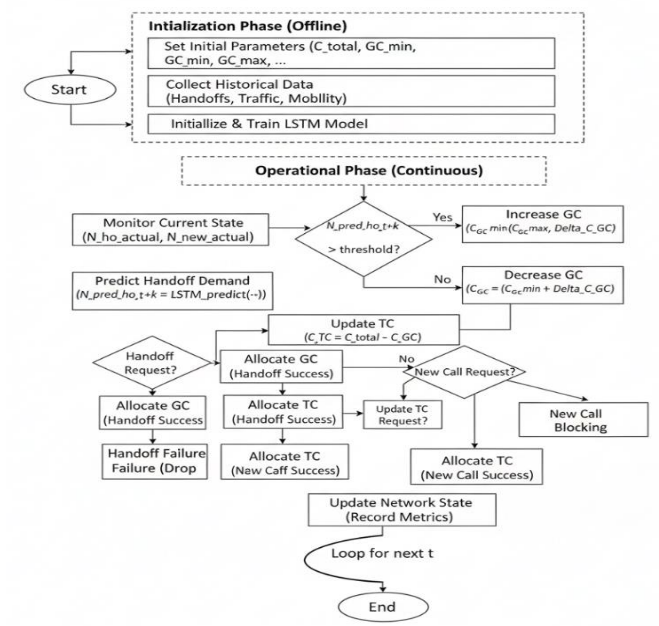

Figure 2: System Flowchart

3.4 System Model

Key parameters and notations used in the model are:

N: Total number of available channels in a cell.
$C_{GC}(t)$: Number of guard channels at time t.
$C_{TC}(t)$: Number of traffic channels at time t
$C_{GC}, \min$: Minimum number of guard channels (can be 0)
$C_{GC}, \max$: Maximum number of guard channels
$\lambda_{new}(t)$: Arrival rate of new calls at time t. (Assumed Poisson distributed)
$\lambda_{ho\_actual}(t)$: Actual arrival rate of handoff request at time t. (Assumed Poisson distributed)
$\lambda_{ho\_pred}(t)$: Predicted arrival rate of handoff request at time t, generated by the LSTM model
μ: Service rate for both new calls and handoff calls. (Assumed exponentially distributed)
ht : Handoff prediction threshold
$P_{drop}(t)$: Handoff drop probability at time t.
$P_{block}(t)$: New call blocking probability at time t.
$S(t)$: Current network state vector at time t, which can include channel occupancy, current handoff rate, etc
k: Prediction horizon for the LSTM model (e.g. 5 minutes)

Relationship between Channel Types
The total number of channels N is fixed

$$N = C_{GC}(t) + C_{TC}(t) \tag{1}$$

(2) LSTM Prediction Model
The core of the proactive scheme is the LSTM prediction module. Let $X(t)$ be the input sequence to the LSTM model at time t. This sequence typically consists of historical network data.

$$\left.\begin{aligned} &\lambda(t) = \{\lambda_{ho\_actual}(t-1), \lambda_{ho\_actual}(t-2)\ldots \\ &..\lambda_{ho\_actual}(t-L_h), S(t-1), S(t-2), \ldots\} \end{aligned}\right\} \tag{2}$$

where L_h is the look-back window for historical handoff rates, and $S(t-i)$ represents historical network state features.

The LSTM model learns a function f_{LSTM} that maps historical data to a future handoff prediction:

$$\lambda_{ho\_pred}(t+k) = f_{LSTM}(X(t)) \tag{3}$$

where $\lambda_{ho\_pred}(t+k)$ is the predicted number of handoff requests for the next time window k.
(3) Dynamic Guard Channel Adjustment Mechanism:
Based on the predicted handoff demand, the number of guard channels $C_{GC}(t)$ is dynamically adjusted. Let $\Delta C_{GC}(t)$ be the increment/decrement step for guard channels.
At time t, after obtaining:

$$\lambda_{ho\_pred}(t+k) \tag{4}$$

If

$$\lambda_{ho\_pred}(t+k) > ht \tag{5}$$

$$C_{GC}(t+k) = \min(C_{GC}(t) + \Delta C_{GC}, C_{GC,} \max) \tag{6}$$

If

$$\lambda_{ho\_pred}(t+k) \le ht \tag{7}$$

$$C_{GC}(t+k) = \max(C_{GC}(t) - \Delta C_{GC}, C_{GC,} \min) \tag{8}$$

(4) Handoff and New Call Admission Control:
When a request arrives (either a new call or a handoff request):
Handoff Request Admission:
(1) If $C_{GC}(t) > 0$: The handoff request is admitted using a guard channel.

$$C_{GC}(t) \leftarrow C_{GC}(t) - 1 \tag{9}$$

(2) Else if $C_{TC}(t) > 0$: The handoff request is admitted using a traffic channel.

$$C_{TC}(t) \leftarrow C_{TC}(t) - 1 \tag{10}$$

(3) Else: The handoff request is dropped

New Call Request Admission:
(1) If $C_{TC}(t) > 0$: The new call request is admitted using a traffic channel.

$$C_{TC}(t) \leftarrow C_{TC}(t) - 1 \tag{11}$$

(2) Else: The new call request is blocked

(5) Performance Metrics
Handoff Drop Probability (P_{drop}):

P_{drop} = Number of dropped handoff requests

Total number of handoff requests (12)

New Call Blocking Probability (P_{block}):

$$P_{block} = \frac{\text{Number of blocked new call requests}}{\text{Total number of new call requests}} \quad (13)$$

(6) State Representation for Simulation (Example using a state-space model for channel occupancy)

Let $N_c(t)$ be the number of currently occupied channels (traffic + guard)
Let $N_{ho}(t)$ be the number of active handoff calls
Let $N_{new}(t)$ be the number of active new calls
At any given time t, the number of available channels for new calls is $C_{TC}(t)$
The number of available channels for handoffs is:

$$C_{GC}(t) + C_{TC}(t) = N \quad (14)$$

Channel Allocation Probability (Conceptual, for an M/M/N/N+M type system where M represents new calls and N represents handoff calls):
Let P_j be the probability of having j channels occupied.
For new call blocking, a new call is blocked if all $C_{TC}(t)$ channels are occupied by other new calls or handoff calls that have already utilized all $C_{GC}(t)$ channels and overflowed into $C_{TC}(t)$
A handoff call is dropped if all N channels are occupied.
The above model provides a framework for simulating and analyzing the proposed guard channel scheme. The LSTM's role is crucial in providing the intelligent prediction $\lambda_{ho\_pred}(t+k)$, which directly informs the dynamic adjustment of $C_{GC}(t)$, thereby optimizing P_{drop} and P_{block}

4. Result and Discussion

As shown in Figure 3, the Predictive Guard Channel (PGC) scheme consistently outperforms the Static Guard Channel (SGC) scheme in terms of handoff drop probability. At lower handoff arrival rates, both schemes exhibit relatively low drop probabilities. However, as the handoff arrival rate increases, the SGC scheme's performance degrades significantly, reaching nearly 12% drop probability at 20 handoffs/min. Contrariwise, the PGC scheme initiatively modify guard channel allocation based on LSTM forecasts and keeps a drastically lower handoff drop probability, showing its capability to adjust to rising demand and circumvent failures. This reduction is important for keeping user satisfaction and QoS, particularly in congested network situations.

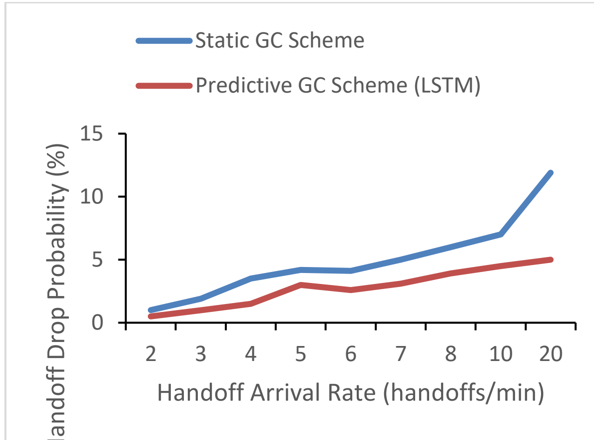

Figure 3: Handoff Drop Probability versus Handoff Arrival Rate

Figure 4 illustrates the new call blocking probability for both schemes. While guard channel schemes inherently prioritize handoff calls over new calls, the dynamic nature of the PGC scheme allows for a more efficient balance. The PGC scheme shows a slightly lower new call blocking probability compared to the SGC scheme, especially at higher handoff arrival rates. This is because when predicted handoff demand is low, the PGC scheme can reduce the number of guard channels, thereby increasing the availability of traffic channels for new call attempts. This demonstrates that the predictive approach not only improves handoff success but also optimizes overall resource utilization without excessively penalizing new call attempts.
The results clearly indicate that the LSTM-based predictive guard channel scheme offers substantial improvements in network performance. The ability of the LSTM model to accurately forecast future handoff demands enables the network to allocate resources more intelligently and proactively, minimizing service disruptions and enhancing the user experience. The dynamic adjustment of guard channel ensures that

resources are utilized more efficiently, avoiding the wastage associated with statically reserved channels and mitigating the risk of handoff failures during peak periods.

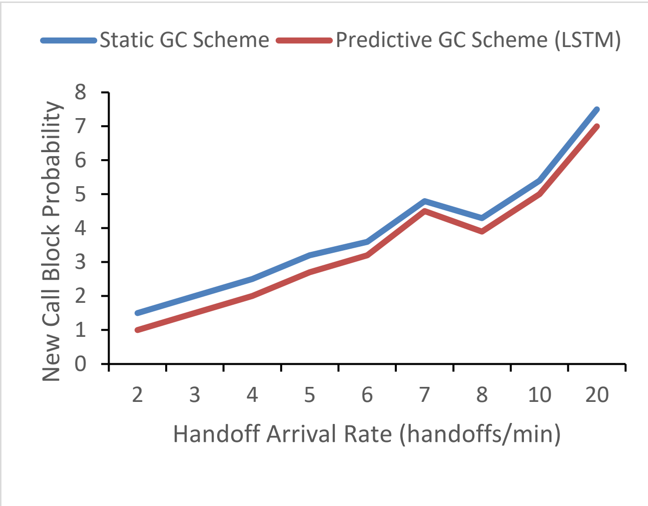

Figure 4: New Call Blocking Probability versus Handoff Arrival Rate

5. Conclusion

This paper presented a proactive resource allocation scheme for mobile networks, employing a predictive guard channel mechanism powered by LSTM networks. By leveraging the time-series forecasting capabilities of LSTMs, the proposed scheme anticipates future handoff demands and dynamically adjusts the size of guard channels. The system architecture, mathematical model, and algorithmic flow were detailed, providing a comprehensive understanding of the scheme's operation.

Simulation results demonstrated the significant advantages of the Predictive Guard Channel (PGC) scheme over a conventional Static Guard Channel (SGC) scheme. The PGC scheme achieved a substantially lower handoff drop probability, particularly under high traffic loads, while also maintaining a slightly improved new call blocking probability. These improvements highlight the effectiveness of integrating advanced machine learning techniques, especially LSTMs, into mobile network resource management. Proactive resource allocation is crucial for meeting the demands of modern mobile users and the evolving landscape of 5G and future networks. Future work could explore the integration of real-time learning for the LSTM model, multi-cell coordination for guard channel allocation, and the impact of diverse mobility models on the scheme's performance.

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