Robust and Reliable Vertical Handoff Technique for Next Generation Wireless Networks

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Abstract—Next Generation Wireless Networks (NGWNs) focus on providing consistent Quality of Service (QoS) to network users; to achieve this goal, Cooperative Communication (CC) framework is popularly utilized. Here, multiple wireless networks cooperate to provide consistent QoS to the user. Vertical Handoff (VH) is one of the extensively used techniques in CC framework. Here, the user, whose original network is unable to provide requested QoS is migrated to neighboring wireless network—which can deliver the requested QoS. In the literature, raft of techniques have been presented for VH. However, almost all these techniques have ignored formal methods to analyze reliability and robustness of handoff decisions, which are extremely essential to support the merits of handoff decisions. In this work, formal methods to analyze reliability and robustness of handoff decisions are presented. The proposed VH technique is achieved through Long Short Term Memory (LSTM) architecture. Simulation results exhibit the relative merits of the proposed VH technique in-terms of reliability and robustness against contemporary VH technique.

Index Terms—Vertical Handoff; Quality of Service; Lstm; Reliability.

I. INTRODUCTION

A. Overview on VH

The appeal of Wireless Communication (WC) is not just exploding, demand for resource intensive WC is also increasing [1]. Multiple wireless applications such as–audio/video conferencing, multimedia e.t.c. are primarily involved in demanding resource intensive WC. Each user who expects resource intensive WC, demands specific QoS in-terms of various parameters such as–bandwidth, cost, RSSI e.t.c. When large number of users in a wireless network demand QoS, due to extensive resource demands, the network might fail to deliver expected QoS for certain users. In such scenarios, rather than making the user’s suffer, NGWNs attempt to provide consistent QoS through CC framework. In this framework, multiple wireless networks form cooperative cluster; wherein, network resources are mutually shared for the benefit of all network users in the cluster. VH is one of the extensively utilized techniques in CC framework. If a user cannot be provided with consistent QoS; other suitable wireless networks in the cooperative cluster— which are able to meet the user QoS demands—are utilized by migrating the user to such potential networks. However, such vertical migration can only be possible when seamless network migration framework is adopted in the cooperative cluster.

B. Open Issues

VH has received substantial attention in the literature. Most of the VH techniques utilize two stages. In the first stage, the QoS parameters are defined, and in the second stage, classifiers are utilized to perform VH. The wireless network in cooperative cluster, which provides the highest potential in maintaining QoS demands of the user–as decided by the classifier–is selected for VH. Even though promising wireless networks might be selected for handoff by the VH technique, there is possibility that, due to future network traffic conditions, new handoffs might be required to consistently meet user QoS demands. Hence, reliability issue is critical to make promising handoff decisions, which avoid frequent handoff scenarios. Frequent handoffs, not only increase communication ineffectiveness, it could result in increased cost of communication for the user and network service providers. Another important consideration is of robustness aspect in the reliability issue; the reliable network selected for handoff might exhibit limited reliability in–unexpected or different–network traffic conditions. The selected network should be analyzed for its reliability in different network traffic conditions.

The contributions made in the literature for VH have largely ignored reliability and robustness issues in handoff decisions. Designing VH technique which can achieve the dual goal of reliability and robustness in handoff decisions, through the aid of effective formal methods, can aid in deploying VH techniques in different real world scenarios.

C. Contributions

In this paper, the following contributions are made:

1. Novel VH technique is presented which provides handoff such that, the selected wireless network for handoff provides reliability in-terms of future handoffs, and this reliability is robust in the sense that, reduction of future handoffs is ensured for all kinds of network traffic conditions. The presented VH technique utilizes three QoS parameters–bandwidth, communication cost and Received Signal Strength (RSSI). LSTM architecture is utilized as the backbone classifier by the presented VH technique. Suitable reliability and robustness model is presented to achieve the main goals for the presented VH technique.

2. The presented VH technique is simulated in MATLAB, and compared against the contemporary technique. Simulation analysis exhibit relatively superior performance of the presented VH technique in-terms of reliability in making...
handoff decisions and robustness in providing this reliability for different network traffic conditions.

This paper is organized as follows: Section 2 presents the related work. Section 3 presents the proposed VH technique. Section 4 describes the simulation results, and their corresponding discussions. The work is concluded with future directions in Section 5.

II. RELATED WORK

VH in Wireless transmission has received substantial attention in the literature. Most of the contributions in the literature for VH can be differentiated in two aspects: utilized QoS/handoff parameters and classification techniques for achieving handoff.

The contemporary contributions in the literature [1]–[14] utilize myriad of QoS parameters such as bandwidth, RSSI, monetary cost, coverage area, power consumption, sojourn time, device speed, bit error rate, signal to interference ratio, security, network transmission range, network capacity, traffic intensity etc.; classification techniques such as–fuzzy logic based classification, neural networks [15]–[19], genetic algorithm, combination of all these classification techniques etc. are utilized.

There are two significant limitations in the contemporary contributions [1]–[14]: many of these handoff techniques utilize more than five QoS/handoff parameters due to which, the curse of dimensionality issue arises during classification, which can significantly reduce handoff accuracy, and thereby reduce handoff effectiveness. The second limitation is that, all these techniques claim superior reliability in simulation analysis; however, they lack mathematical models for reliability calculation to support this claim. It must be noted that, lack of mathematical model for reliability can result in limited performance in those scenarios which were not considered for simulation analysis.

In [20], mathematical model for reliability in VH is introduced. Here, the future traffic is predicted through a prediction model, which given the number of users accessing the network currently, can predict future number of users. This prediction model assumes correlation between QoS availability and number of network users; however, this assumption might not hold in many scenarios. Consider a scenario; wherein, a particular network has large number of current users, and most of the network users do not demand significant QoS; in such scenarios, the assumption of [20] clearly does not hold good. The mathematical model for reliability must consider the QoS oriented traffic conditions for a particular network, in order to accurately predict the potential network reliability.

III. VH TECHNIQUE FOR RELIABLE AND ROBUST HANDOFF

A. LSTM Overview

LSTM [21]–[24] is a special version of Recurrent Neural Network (RNN). Sequential data, in many cases, contains correlations in different sections of the data. The classical feed forward Neural Networks are unable to effectively model such sequential data, mainly due to the absence of recurrent structure at deeper levels of the network. The presence of cyclic connections in RNNs, makes them suitable for modeling such sequential data. RNNs are able to model long term dependencies in the data through deep cycles in the network, which provide network activation information from previous steps to the current step. The network activation information is stored inside the network internal states. This special mechanism of RNNs allows them to utilize dynamic analysis window over the input data; rather than, static window.

LSTM is an improved version of RNNs, which overcomes some of the earlier design issues. LSTM has received popularity in performing sequence–labeling and prediction. Some of the other problems in which LSTM is effectively applied are–language modeling, learning context–free and sensitive–languages etc. Based on the empirical analysis carried out in this work to select the most suitable classifier to build the proposed VH technique, LSTM was judged to be the most accurate classifier.

The special units of LSTM are indicated as memory blocks, which are located inside recurrent hidden layer. The memory blocks are made up of memory cells; in which, self connections are designed for storing the network temporal state. There are basically three gates inside LSTM memory blocks–input, output and forget–gates. The flow of–input and output–activations are controlled by input and output gates respectively. The forget gate aids in processing input data, which are not divided into subsequences. Also, LSTM might also contain peephole connections from the gates to the internal cell for learning accurate timing of outputs.

The architecture of LSTM memory block is illustrated in Figure 1. Here,  \( t \) indicates the iterative steps; wherein,  \( t = 1 \) to  \( T \),  \( x = (x_1, x_2, ..., x_T) \) and  \( y = (y_1, y_2, ..., y_T) \) indicate the input and output sequences respectively,  \( o, f, i, m \) and  \( c \) indicate the output gate, forget gate, input gate, output activation vector and cell activation vectors respectively, and  \( h \) and  \( g \) indicate the cell–output and input activation functions respectively.

Fig. 1. LSTM Memory Block Architecture

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Equations 1, 2, 3, 4, 5 and 6 represents the network unit activation sequence. Here, $W$ indicates the weight matrices, $W_{ix}$ indicates the weight matrix corresponding to input and input gates, $W_{fc}, W_{ic}$ and $W_{oc}$ indicate the peep hole connection-diagonal weight matrices, $b$ indicate the bias vectors, $b_i$ indicate the bias vector for input gates, $\sigma$ indicates the logistic sigmoid function, $\odot$ indicates product of vectors considered element wise, and $\phi$ indicates the output activation function of the network.

$$
\begin{align*}
    i_t &= \sigma(W_{im}m_{t-1} + W_{ix}x_t + b_i + W_{ic}c_{t-1}) \\
    f_t &= \sigma(W_{fm}m_{t-1} + W_{fx}x_t + b_f + W_{fc}c_{t-1}) \\
    c_t &= c_{t-1} \odot f_t + i_t \odot g(W_{cm}m_{t-1} + W_{cx}x_t + b_c) \\
    o_t &= \sigma(W_{on}m_{t-1} + W_{ox}x_t + W_{oc}c_t + b_o) \\
    m_t &= o_t \odot h(c_t) \\
    y_t &= \phi(m_tW_{ym} + b_y)
\end{align*}
$$

(1) (2) (3) (4) (5) (6)

B. Generation of Training Set through Formal Methods

LSTM requires training set of sufficient size to achieve accurate classification. Hence, this section describes the adopted approach to generate the required training set for the proposed VH technique.

Basically, three QoS parameters for each wireless network are considered for handoff: the bit rate provided by the wireless network and indicated by br, the monetary cost to transmit p bytes of data and indicated by co, and Received Signal Strength indicated by rssi. The feature vector for the jth wireless network is indicated by $x_j$, and it is represented in Equation 7. Here, $br_j$, $co_j$ and $rssi_j$ indicate the br, co and rssi values respectively for jth wireless network.

$$
    x_j = \begin{bmatrix} br_j \\ co_j \\ rssi_j \end{bmatrix}
$$

(7)

Each wireless network in the training set will be labeled with reliability index, which indicates the actual reliability for handoff provided by the network. There are 10 defined reliability index values indicated as (0, 1, 2, ..., 9); wherein, 0 and 9 indicate the highest and lowest reliability respectively. Each index value represents a class indicated as $C_k (1 \leq k \leq 10)$, and $C_k$ represents $k - 1$ reliability index value.

Each wireless network in the training set is quantified for its robustness for providing reliable handoff for different traffic conditions. The traffic conditions are divided into 10 levels. Equation 8 represents the $z^{th} (1 \leq z \leq 10)$ traffic level for $j^{th}$ network. Here, $H_{ljz}$ indicates the $z^{th}$ traffic level for $j^{th}$ network, $N(x_j)$ indicates the threshold for number of users inside $j^{th}$ network, who demand QoS as per the constraints represented in Equation 7; such that, QoS can be effectively provided without any handoff requirement. The parameter $N(x_j)$ can be estimated by analyzing the network behavior for $j^{th}$ network for different QoS traffic load. The parameter $\alpha_z$ indicates the coefficient; such that, $\alpha_z > 1$. Also, in-order to reflect increasing traffic levels for $tl_{jz}$ as $z$ increases, the setting $\alpha_1 < \alpha_2 < ... < \alpha_{10}$ is utilized.

$$
    tl_{jz} = \alpha_z N(x_j)
$$

(8)

In-order to calculate actual reliability values for all the networks in the training set, each network is monitored for $m$ equal time intervals. In each time interval, the number of handoffs made to a specific network, and which led to new handoffs are calculated. Equation 9 represents the actual reliability index value for $j^{th}$ network—under the traffic level $tl_{jz}$. Here, $\text{reliability}_{jz}(x_j)$ is the actual reliability index value for $j^{th}$ network—under the traffic level $tl_{jz}$, and the function case,$z_{jz}(x_j)$ is represented in Equation 10. Here, $\text{nhandoff}_{iz}(x_j)$ indicates the set of users who were provided with handoff to $j^{th}$ network—under traffic level $tl_{jz}$, and in the $i^{th}$ $(1 \leq i \leq m)$ time interval. Similarly, $\llbrace \text{nhandoff}_{iz}(x_j) \rrbrace$ indicates the subset of $\text{nhandoff}_{iz}(x_j)$; such that, each user $\in \llbrace \text{nhandoff}_{iz}(x_j) \rrbrace$ had to be provided with new handoff—eventually.

$$
    \text{reliability}_{jz}(x_j) = \frac{\sum_{i=1}^{m} \text{case}_{iz}(x_j)}{m}
$$

(9)

$$
    \text{case}_{iz}(x_j) = \frac{\text{nhandoff}_{iz}(x_j)}{|\llbrace \text{nhandoff}_{iz}(x_j) \rrbrace|} \times 9
$$

(10)

After calculating actual reliability values for all training set networks, actual robustness value is calculated for each of these networks. Equation 11 represents the actual robustness value for $j^{th}$ network—indicated by robustness$(x_j)$. Here, $\beta_z$ are the tunable coefficients, which agree to the constraint represented in Equation 12. Higher and lower values of robustness$(x_j)$ indicate poor and good robustness for $j^{th}$ network respectively.

$$
    \text{robustness}(x_j) = \sum_{z=1}^{10} \text{reliability}_{jz}(x_j) \beta_z
$$

(11)

$$
    \beta_1 > \beta_2 > ... > \beta_{10}
$$

(12)

Theorem III.1. The coefficient constraint represented in Equation 12 aids in proper calculation of actual robustness.

Proof. Actual robustness metric provides an aggregated projection of actual reliability provided by a specific network in varying traffic levels. It can be clearly inferred that, poor actual reliability values at lower traffic levels, the possibility of poor actual reliability values at higher traffic levels is generally significant. Hence, penalizing the specific network represented by $x_j$ for poor reliability values at lower traffic levels, through corresponding higher values of coefficients $\beta_i (1 \leq i \leq 10)$,
results in achieving—proper aggregate projection of actual robustness of \( x_j \).

Theorem III.1 presents the justification for coefficient constraint represented in Equation 12. The final training set contains the feature vectors and their corresponding—actual robustness value label.

In some scenarios, two or more—exactly same—feature vectors in the training set might have different actual robustness values. Such scenarios, can lead to ambiguity in LSTM training, which can result in poor effectiveness w.r.t. LSTM prediction. Hence, in-order to address worst case scenario, the largest actual robustness value among exactly same feature vectors is reassigned as the actual robustness value label for all these feature vectors.

C. Problem Description

Equation 13 represents the specified QoS parameter values of the user who requires handoff. Here, \( u \) indicates the QoS feature vector of the user. Also, \( b_{ru}, c_{ru} \) and \( rssi_{ru} \) represent the user specified—bit rate, cost of transmitting p data bytes and RSSI respectively. The set of wireless networks which satisfy \( u \), and which can be used for providing handoff to the user is indicated by \( handoff_{set} \). The main goal of this work is to assign predicted robustness values for each network \( \in handoff_{set} \), and select the network from \( handoff_{set} \) which provides the most reliable and robust handoff.

\[
u = \begin{bmatrix} b_{ru} \\ c_{ru} \\ rssi_{ru} \end{bmatrix}
\]  \hspace{1cm} (13)

D. Algorithm

The proposed VH technique is represented in Algorithm 1. Here, there are two phases—preprocessing and handoff phase. In the preprocessing phase, training of LSTM is accomplished by generating the required training set through \( generate_training_set() \), and \( Train\_LSTM(T_r) \) performs the actual training of LSTM.

The second phase is invoked during actual handoff requirement scenario for the user. Assuming there are \( n \) wireless networks in the \( handoff_{set} \), each network is labeled with predicted robustness value—indicated by \( \text{robustness\_label}(x_i) \)—through LSTM by using \( LSTM\_predict(x_i) \). The wireless network \( \in handoff_{set} \) which has the lowest/best predicted robustness value—indicated by \( selected\_network \)—is selected for executing handoff through \( \text{execute\_handoff}(selected\_network) \).

Theorem III.2 presents the justification for correctness of Algorithm 1. In-order to exploit maximum effectiveness in utilizing Algorithm 1, it is critical to train LSTM with sufficiently large training set. Also, the feature vector has only three components, which ensures that, the size of sufficiently large training set does not explode due to curse of dimensionality.

**Theorem III.2. (Algorithm Correctness) For sufficiently large size of training set, the chances of performing handoff to a network \( \in handoff_{set} \) having larger actual robustness value, when other network/s \( \in handoff_{set} \) have relatively lower actual robustness value is limited.**

Proof. Consider the feature vectors indicated by \( x_i \) and \( x_j \) which \( \in handoff_{set} \). Consider the scenario: \( \text{robustness}(x_i) > \text{robustness}(x_j) \), and Algorithm 1 has executed handoff to the network represented by \( x_i \). This scenario can only occur when \( \text{robustness\_label}(x_i) < \text{robustness\_label}(x_j) \). However, since, the training set is sufficiently large, and LSTM tends to provide substantial prediction accuracy, when trained by sufficiently large training set [21], the chances of the event—\( \text{robustness\_label}(x_i) < \text{robustness\_label}(x_j) \)—occurring is limited, which immediately proves the theorem.

IV. RESULTS AND DISCUSSIONS

A. Simulation Settings

The proposed VH scheme is simulated in MATLAB, and compared against the contemporary technique [20]. The simulation study involved 4 different types of wireless networks–GSM, UMTS, WiFi and WiMAX. The simulation parameter settings are presented in Table I. For the ease of reference, the proposed VH scheme is referred as VPO, and the contemporary vertical handoff technique [20] as VCO.

In VCO, the three QoS/handoff parameters that are considered are: bandwidth, user device velocity and number of network users. The classification is achieved through fuzzy classification model. The number of network users is predicted through the neural network, which utilizes non-linear regression model. In its original presentation, VCO does not utilize formal methods for actual robustness value calculation. However, to perform simulation study in this work, the actual robustness value of the network to which handoff was performed by VCO is calculated as described in Section III-B.

B. Discussions on Simulation Results

The first experiment analyzes the performance of VPO and VCO w.r.t. actual robustness value of the network to which handoff was performed—when the user specified bit rate parameter \( b_{ru} \) is varied. The actual robustness value of that network to which handoff was performed by VPO and
Table 1

<table>
<thead>
<tr>
<th>Simulation Parameter Setting</th>
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<tr>
<td><strong>Parameters</strong></td>
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<tr>
<td>Number of wireless networks in the training set</td>
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<tr>
<td>Number of wireless networks of each type in the training set</td>
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<tr>
<td>Message size</td>
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<tr>
<td>Data rate</td>
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<td>Frequency band WiFi</td>
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<td>Frequency band GSM</td>
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<td>Frequency band UMTS</td>
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<td>Frequency band WiMAX</td>
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<tr>
<td>Monetary cost</td>
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<tr>
<td>RSSI</td>
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<tr>
<td>Number of wireless networks available to perform handoff during test case</td>
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<tr>
<td>$N(x_j)$</td>
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<td>$\alpha_z$</td>
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<td>$\beta_z$</td>
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VCO is indicated as Handoff-Robustness(VPO) and Handoff-Robustness(VCO) respectively; these values are calculated as outlined in Section III-B. The experimental analysis result of first experiment is illustrated in Figure 2. Here, VCO provides handoff to less-reliable and robust networks, which is mainly due to ignoring the actual QoS related traffic conditions for each network. The performance of VPO and VCO is non-linear, because of limited correlation between Handoff-Robustness() and $br_u$.

The result of the first experiment w.r.t. execution latency of performing handoff for both handoff techniques is illustrated in Figure 3. The pre-processing costs for VPO are not included in execution latency, because these costs are incurred only once, and pre-processing phase is not invoked when actual handoff is performed. Both handoff techniques exhibit similar and limited execution latency, which is mainly due to the fact that, the classifiers utilized are computationally light.

The second experiment analyzes the performance of both handoff techniques w.r.t. actual robustness value of the network to which handoff was performed—when the user specified monetary cost parameter $co_u$ is varied; the result of this experimental analysis is illustrated in Figure 4. The same experiment also analyses the execution latency of three handoff techniques, and experimental analysis illustrated in Figure 5. Similarly, the third experiment analyzes the performance of all the three handoff techniques w.r.t. actual robustness value of the network to which handoff was performed—when the user specified RSSI parameter $rssi_u$ is varied; the result of this experimental analysis is illustrated in Figure 6. The same experiment also analyses the execution latency of three handoff techniques, and experimental analysis illustrated in Figure 7. Here, similar results are obtained as seen for the first experiment, and for the same reasons as outlined for the first experiment.

V. Conclusion

In this work, reliability and robustness issue w.r.t. VH decisions was addressed through a new VH technique. The proposed VH technique was built over LSTM. Formal methods to analyze reliability and robustness of wireless networks w.r.t. handoff decisions were presented. In the simulated study, the proposed VH technique was compared against contemporary technique, and the proposed VH technique exhibited its relative merits by making reliable and robust handoff decisions. In future, security aspects in VH has to be investigated comprehensively, because this issue has until now, received limited attention, and currently, wireless networks are facing substantial security issues.

References

Fig. 4. Robustness vs \( co_u \)

Fig. 5. Execution Cost vs \( co_u \)

Fig. 6. Robustness vs \( rssi_u \)

Fig. 7. Execution Cost vs \( rssi_u \)


