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A Robust Regression Model for Handover Prediction In Wireless Networks

Shakhawan H. Wady[1] Kamalrulnizam A. Bakar[2] & Kayhan Z. Ghafoor [3]

Mathematics Department, School of Science Education, University of Sulaimani, Sulaimani, Iraq.
Faculty of Computer Science and Information Systems, Universiti Teknologi Malaysia, Malaysia.
Faculty of Engineering, School of Computing, Koya University, Koya, Iraq.

E-mail: shakhawan.hares@univsul.edu.iq

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Abstract

The recent applications of wireless networks demand high Quality of Service (QoS) and mobility management between access networks. For this reason, emergent Advances in IEEE 802.11 standards have been witnessed to achieve seamless communication between mobile nodes. However, since existing handover mechanisms have shortcomings in terms of mobility handover cost and latency, more robust handover decision approach should be considered. To this end, in this research, we propose a decision approach to accurately trigger handover process between current and next access point. The proposed approach incorporates robust regression model is to predict the received signal strength (RSS) of the wireless channel between the mobile node (MN) and the access point. Thus, the MN makes an accurate handover decision as well as layer 3 handover process occurs in advance to the one in layer 2. Our theoretical analysis and simulation results show that the proposed handover decision approach is far superior to the existing handover decision schemes in terms of handover latency and cost.

1. INTRODUCTION

With the rapid development of wireless communication technologies, The IEEE 802.11 based WLAN standards activity are widely used in many companies, hot spots, universities and homes, which allows users to communicate anytime anywhere [1]. In IEEE 802.11 based WLANs uninterrupted connectivity is one of the important requirements that provide users to move within set boundaries of the network. Due to the very long handover latency this facility did not provide uninterrupted sensitive real-time application such as voice over IP (VoIP), audio streaming and video streaming to users when they move to different subnets [2]. However, still have various technical weaknesses for wireless networks, containing high handover latency and packet loss, therefore the handover latency has become one of the critical issues to the research world which needs to be resolved [3], [4], [5], [6] and [8]. The requirement of smooth handover and reduction of D-Link Layer 2 handover latency in IEEE 802.11b based WLANs in MIPV6 is the focus of our discussion.

2. HANDOVER PROCEDURE IN IEEE 802.11B

According to [2], [9] and [10] the complete handover procedure is divided into three distinct logical stages which are scanning (Probe) phase, authentication phase and re-association phase.

2.1. Scanning Phase

In handover procedure, the scanning phase is the most critical phase since it is responsible up to 90% of the total handover time [9] and [10]. During the IEEE 802.11 handover process, the MN executes the scanning process to determine the available APs and associate with it. IEEE 802.11 identifies two types of scanning mode active scan and passive scan mode [1]. In active scan mode, the MN broadcasts a probe request frame asking all APs in the coverage area then receives a probe response package from the APs. In passive scan mode, the MN listens passively for the beacon message, which is APs sent periodically. Scanning phase can be distributed in three sub phase detection, scanning, and decision sub phase [2]. In detection sub phase the MN is decided as soon as the scanning has begun due to the fact that the MN cannot continue in the current access point mode (AP). In scanning sub phase, after detection, the MN starts scanning to discover an access point (APs) that is near to the MN. As a result, the MN creates correlating associations with one of the access points (AP) near the range. The scanning stage is a decision sub phase within the MN with which access point and the decision of making a connection depends on several parameters, such as received signal strength (RSS) and bandwidth.

2.2. Authentication phase

After the scanning phase process the MN initiates the authentication phase. This then sends the authentication request frames that related to it, to the access point. The process then carries on as the access point sends the authentication response frame to the MN.

2.3. Re-association phase

When the authentication phase executes successfully the MN tries to re-associate with the access point by sending a re-association request frame. The access point then replies to the MN by sending a re-association response message, which contains the information concerning the result of re-association of the scanning procedure. It is measured to be the heaviest fragment of handover in wireless local area networks (Wireless LANs)

The total L2 handover latency in 802.11b based WLANs is a combination of three types of delays, scanning delay, authentication delay and re-association delay. It is conferring up to 90% of handover latency comes from scanning phase delay [3], [4] and [8] the total handover latency process is shown in fig 1.

3. RELATEDWORK

When the MN moves from its point of attachment to the new different network the handover process occurs in both Wi-Fi and Wi-Max environments. Therefore, the handover process takes place based on handover decision, which achieved often by strongest received signal strength (RSS). In addition this can be done with defining a handover threshold. Based on the handover threshold the MN decides when to start handover process. In the same way we can either use handover process based on RSSI with hysteresis, as well as using a combination of RSS with hysteresis and handover threshold. Also there exist some prediction methods to define the handover on setting time, which keep tracking the RSS or distance parameters. Finally existing techniques such as fuzzy logic and neural network can be used to take place the handover process.

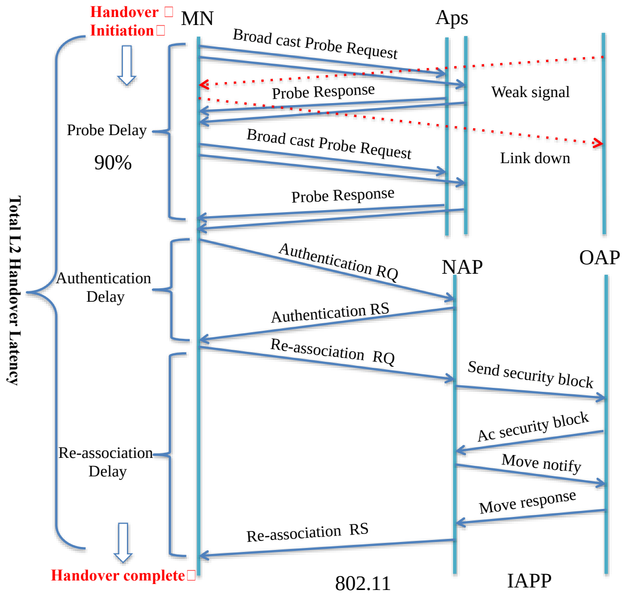

Fig. 1. Layer 2 Handover Process

In [11] S. Pyo et. al proposed a fast cross layer handover algorithm in Wi-Max environment, which predict based on MN movement, result achieved by applying linear regression algorithm using received signal strength. The proposed algorithm works effectually and reduces the total handover latency. In [5] Atalah et.al proposed RSSI gradient predictor approach in a combined Wi-Fi and Wi-Max environment from the RSSI gradient calculated from a data set. The proposed algorithm can be used to know the exact time to store the real time application and the RSSI Gradient filter will eliminate unnecessary actions. In [7] Changiz et. al applied gray predictions approach to reduce both handover latency and the number of handover. In [12] Chien S.F. et. al applies the autoregressive integrated moving average (ARIMA) algorithm for reducing handover latency, service interruption as well as minimizing unnecessary layer 2 triggers. This algorithm predicts the received signal strength (RSS) and layer 2 triggers based on the prediction of future RSS value accurately.

Sarddar et. al in [8] included GPS to take the advantage of this technology to determine the position of the MN then using linear regression algorithm to realize the potential AP where the MN has the maximum probability to change its point of attachment in the future. As a result not only they succeed to decrease the number of scanned AP but also they reduced the total handover latency. To support technologies brighter than wireless networks some algorithm has been proposed. In [11] S. Pyo et. al applies prediction based L2 trigger using exponential smoothing algorithm in WiBro environment .the algorithm reduce the handover latency by the amount of prediction interval. Sarddar et. al [9] using GPS they proposed a pre scanning algorithm in IEEE 802.11 to reduce handover latency and packet loss. In their experiment they used channel 1, 6 and 11 because there is no overlapping between these channels. They succeed to reduce scanning delay but as they claimed there were no reduction in both authentication and re association phase.

In another attempt to reduce number of scanned APs and handover latency in IEEE 802.11WLANs Sarddar et. al in [8] applied vector analysis algorithm. This algorithm is able to determine the potential AP taking advantage of GPS technology. The experimental result reduced the handover latency in a great deal. To provide a fast handover in WLAN networks [13] used global path cash mechanism with global history to determine the direction of MN. This resulted in reducing handover latency, minimizing unnecessary handover process and eliminates the number of AP scanning. Yan et. al in [6] the author proposed handover decision based traveling distance prediction with calculating two handover thresholds by the MN in IEEE

802.11 WLANs. The mechanism resulted in reducing handover latency, minimizing the probability handover failure and unnecessary handover process.

In this paper, we propose a new pre decision algorithm based on movement prediction for IEEE 80.11b networks to obtain accurate and efficient L2 handover triggers. Movement prediction is achieved by robust regression model without any assumption on the statistical properties of the movement. We measure the RSSI values between the MN and neighbor APs in the range. Using the RSSI values obtained through scanning process the estimated robust regression line is updated to predict the future RSSI value for the next coming time of movement. Therefore the right handover decision helps to reduce the handover latency in IEEE 802.11bWLANs.

4. ROBUST REGRESSION MODEL

Regression analysis techniques are commonly used for prediction and forecasting. Robust Regression technique is an iterative form of simple linear regression, where each observation is assigned a weight bases on the residuals from the previous iteration [14]. Robust Regression is used to fit the demised time series of received power linearly with time [15]. Linear least-squares estimates can behave badly when the error distribution is not normal, particularly when the errors are heavy tailed [16]. Therefore, the proposed approach, termed robust regression, is to employ a fitting criterion that is not as vulnerable as at least squares to unusual data.

M-estimation is the most common method of robust regression that considers the linear model [17]. Assume that the responses *RSSI* $_{(i)}$ corresponding to the input *RSSI* values of simulation time $T_{(i)}$ i=1, 2, 3. . . n, are to be observed and used to estimate the parameters $\hat{\beta}_0^k$ and $\hat{\beta}_1^k$ in a robust regression model

$$R\hat{S}SI_{\,i} \;=\; \hat{\beta}_0^k \;+\; \hat{\beta}_1^k\, T_i \qquad (1)$$

Where:

$R\hat{S}SI_{\,i}$: Predicted RSSI for (i) observations.

T_i : Simulation time value.

$\hat{\beta}_0^k$: The intercept (scale) after n iteration.

$\hat{\beta}_1^k$: The slope (amplitude).

The general linear regression model is formulated as follows [12]:

$$R\hat{S}SI_{\,i} = \beta_0 + \hat{\beta}_1\, T_{i1} + \ldots + \hat{\beta}_n\, T_{in} + ei \quad (2)$$

For *ith* of *n* observations the fitted model is:

$$R\hat{S}SI_{\,i} \;=\; \beta_0 + \hat{\beta}_1\, T_{i1} + ei \qquad (3)$$

Choose the OLS estimates $\hat{\beta}_0^k$ and $\hat{\beta}_1^k$ as the initial estimates of β_0 and β_1 respectively, and set $\hat{\beta}_0^k = \hat{\beta}_0^0$, $\hat{\beta}_1^k = \hat{\beta}_1^0$ Fix the estimate S_e of σe at the initial value S_e^0.

Where:

$$\hat{\beta}_1^0 = \frac{n\sum_{i=0}^{n} T(i)\, RSSI(i) - \sum_{i=0}^{n} T(i)\, \sum_{i=0}^{n} RSSI(i)}{n\sum_{i=0}^{n} T(i)^2 - \left(\sum_{i=0}^{n} T(i)\right)^2} \quad (4)$$

$$\hat{\beta}_0^0 = R\bar{S}SI - \hat{\beta}_1^0\, \bar{T} \qquad (5)$$

The general M-estimator minimizes the objective function.

$$\sum_{i=1}^{n} \rho(e_i/S_\varepsilon) = \sum_{i=1}^{n} \rho\left(\frac{\mathrm{RSSI}_{(i)} - (\hat{\beta}_0^0 + \hat{\beta}_{1\,1}^0 \mathrm{T}_{(i)})}{\mathrm{S}_\varepsilon^0}\right) \qquad (6)$$

Where S_ε is robust estimator of scale the median absolute deviation (MAD)

$$S_\varepsilon = \{|T_i\; median\; (T_i)|\} \;\; (7)$$

To calculate weighted least square the bisquare weight function must be used to determine the robust regression estimators [8], the set the derivative of $\sum_{i=1}^{n} \rho(e_i/S_\varepsilon)$ with respect to the arguments $\hat{\beta}_0^0$ and $\hat{\beta}_1^0$ equal to zero. Then by given $\hat{\beta}_0^k$ and $\hat{\beta}_1^k$, we calculate weights as follow.

$$w_i^k = \frac{\psi(e_i^k/S_\varepsilon^0)}{e_i^k/S_\varepsilon^0}, \qquad i = 1, \ldots\ldots, n \quad (8)$$

We define the bisquare weight function to compute weights:

$$f(x) = \begin{cases} (1 - \frac{\left(\frac{e_i}{S_\varepsilon}\right)^2}{25})^2 & vv \quad \frac{|e_i|}{S_\varepsilon} \le 5 \\ . \\ . \\ 0 & \frac{|e_i|}{S_\varepsilon} > 5 \end{cases} \qquad (9)$$

Where: $e_i^k = RSSI_i - (\hat{\beta}_0^k + \hat{\beta}_1^k\, T_i)$

Then the weighted least square of residuals from least square linear regression will be calculating as follow:

$$\sum_{i=1}^{n} w_i^k\, e_i = 0 \qquad (10)$$

$$\sum_{i=1}^{n} T_i\, w_i^k\, e_i = 0 \qquad (11)$$

For: $\beta_0^{\hat{k}+1}$ and $\beta_1^{\hat{k}+1}$

After calculating the weighted least square of residuals from the least square linear regression, the first set of weights (WLS) is produced. In the first iteration, each point is assigned equal weight and model coefficients are estimated using ordinary least squares. At subsequent iterations, weights are recomputed so that points farther from model predictions in the previous iteration are given lower weight. Model coefficients are then recomputed using weighted least squares [9]. The process continues until the values of the coefficient estimates converge within a specified tolerance.

$$\frac{\left|\beta_j^{\hat{k}} - \beta_j^{\hat{k}-1}\right|}{\left|\beta_j^{\hat{k}-1} + 1E - 6\right|} \le T\,, \qquad j = 0, 1,$$

The line ($R\hat{S}SI_i = \beta_0^{\hat{k}} + \beta_1^{\hat{k}}\, T_i$) is the estimated robust regression line (see Fig.2) that is used for prediction the received signal strength (*RSSI*) of the MN for each AP in the range of MN coverage areas.

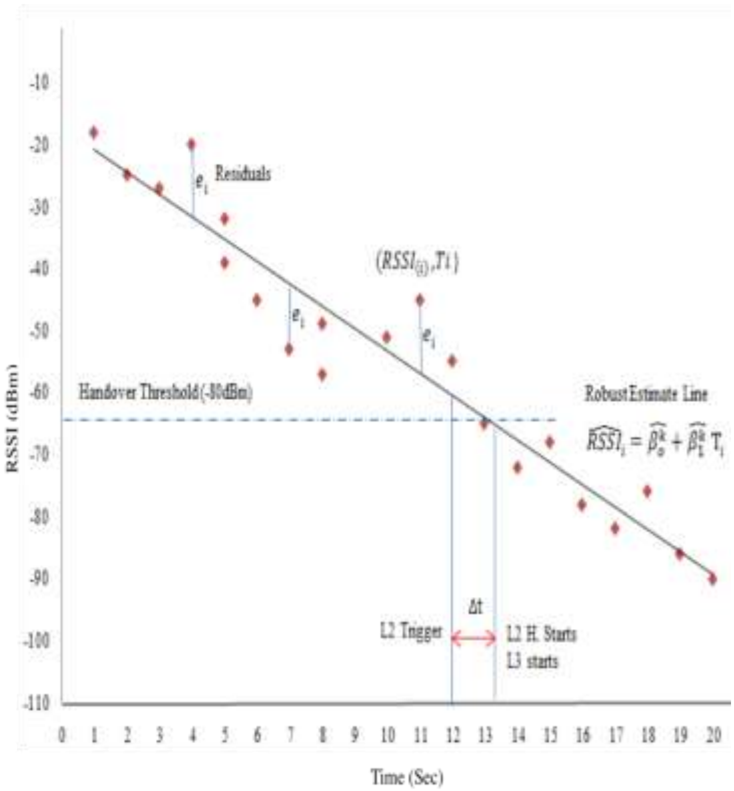

Fig. 2. Estimated Robust Regression Line

Robust regression model is used to determine the potential AP by extrapolate the best predict future received signal strength indicator values. The MN starts to examine the neighbor APs in the range to determine their suitability, as a handover target along with other performance considerations. During the scanning process the MN sends out a 802.11 probe request which include all saved access points (APs) and it obtains RSSI values periodically for each AP. Without prediction in D-Link layer, the MN will still working on the old AP until it reach the link down message then will start D-Link layer handover procedure with other AP from its range. Lack of handover decision will affect negatively on total handover latency to be increased.

This paper proposes a handover decision algorithm based on the prediction for 802.11b wireless network. The flow chart for proposed algorithm has been depicted in fig.3 using RSSI samples by the time in second that obtained from the scanning process; MN makes a scatter diagram for each neighbor access point AP. Then the MN obtains the estimated robust regression line ($R\hat{S}SI_i = \beta_0^{\hat{k}} + \beta_1^{\hat{k}}\, T_i$) from the scatter diagram. Each time the MN obtains a new RSSI sample by the time (T_i), the MN adds the sample to the scatter diagram and recalculates the estimated robust regression line. Depend on the estimated robust regression line the MN predicts the future RSSI value between the MN and neighbor access points which are a response of ($t = t + \Delta t$) where (Δt) is a prediction interval and (t) is a current timer.

Finally, the predicted RSSI from the proposed RRM will compare with the current RSSI value if the predicted value of RSSI between the MN and the serving access point is less than the predetermined level of handover threshold (Hth) then the MN expected to start the handover process after a prediction interval (Δt). From this point, the MN will be able to achieve the right handover decisions in advance before the link-Down signal being with current AP. Therefore, an efficient handover decision at the right time helps in decreasing the overall handover latency.

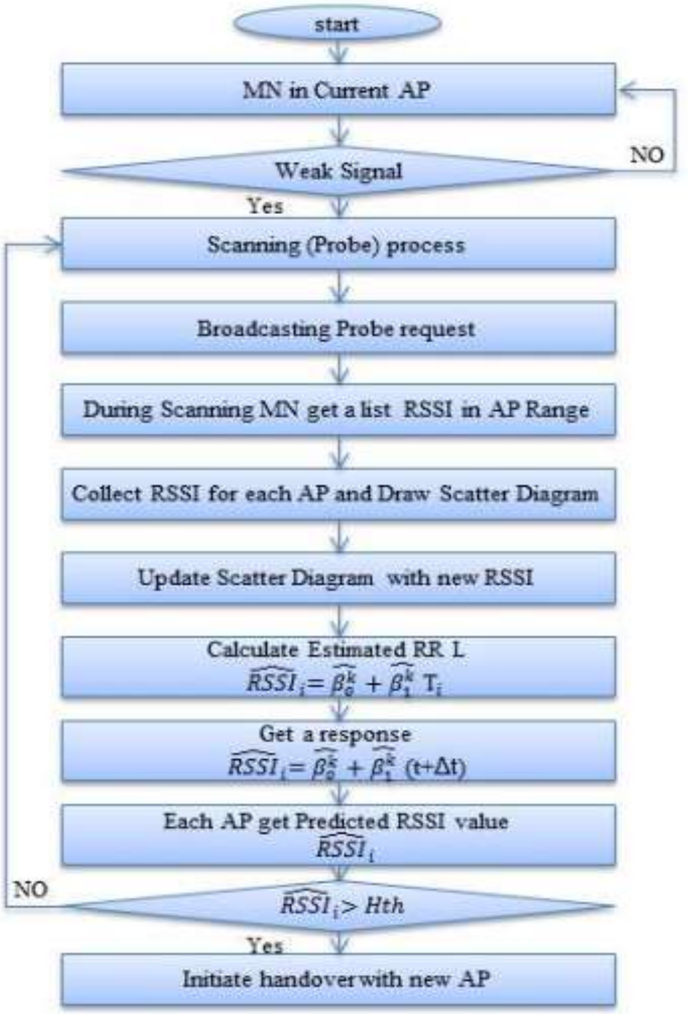

Fig. 3. L2 Handover process with RRM algorithm

6. SIMULATION RESULT

Here, we explain the effectiveness of the proposed handover decision based prediction means in terms of reducing the time delay in each of the D-Link layer and total handover latency. The simulation scenario will develop in order to evaluate the proposed robust regression approach for MIPv6. The simulator OMNeT++ (OMNeT, 2011) with xMIPV6 Framework will use to satisfy this point and establish the simulation environment. The xMIPV6 framework is one of the simulation models that support IEEE 802.11b model (both ad-hoc and infrastructure mode), which is built on OMNeT++ simulator. In the simulation the following parameters is used mobility environment is 500m x 500m, two access points (AP) each AP run over IEEE 802.11/b standard uses the 2.45 GHz with WLAN connection at 11Mbps, since this standard the coverage area for each AP will be as a 125 m with 200 m gab between current AP and new AP, 20% overlapping area with each one, and 200 seconds simulation time. The simulation parameters used in the experiments summarized in Table 1.

Table 1. Parameter setting

Parameter	Value
Grid area	500m X 500m
Scanning method	Active
Probe delay	0.1s
Authentication timeout	5s
Association timeout	5s
Mobility type	Linear
Speed	2 m/s
Acceleration	5 m/s2
Signal Strength Threshold	-80dBm
Hysteresis factor	2 dB
MN transmission range	125 m
Beacon Interval	0.1s
Channel number (MN)	Auto
Channel AP1 and AP2	1 and 6
Radio bit rate	11 Mbps
Transmit power	1.0 mW
Carrier frequency	2.4 GHz
Thermal noise	-110 dBm
Sensitivity	-85 dBm
Path loss alpha	2
Access points coverage area	125 m
Distance between APs	200 m
Simulation time	200 second

As shown in Fig. 4 The AP1 is connected to the access router (Home Agent), while AP2 is connected to a different access router (Access Router), when the MN move from the current AP1 to the new AP2 handover process is required. In our simulation setup, MN moves in a linear direction from the edge of the current AP1 cell to the center of the new AP2 cell at the speed of 2mps. Once the MN learns that it is going to change its point of attachment to the next foreign AP2, the next challenge is to estimate the right time to track the correct handover decision in advance before reaching new AP2.

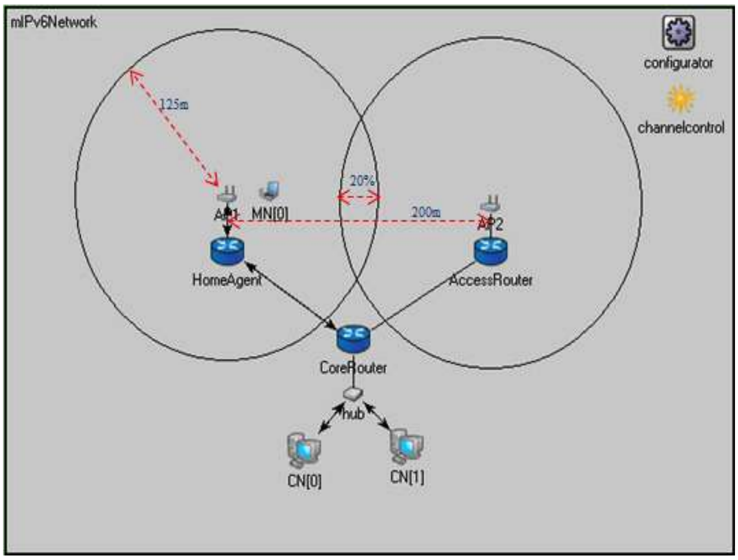

Fig. 4. Simulation Scenario

Robust regression model, which is mentioned in section 4 applied in layer 2 scanning phase in terms of predicting the future RSSI values for each AP in the MN coverage area. By applying RRM prediction algorithm, the predicted RSSI values with a less error percentage, which helps to get a robust Layer 2 handover, can be obtained.

Furthermore, with the help of prediction algorithm, the MN works in the accurate way that will help the upper layers to do their functions in an optimum way, and layer 3 handover activities are able to occur prior to layer 2 handover. Therefore, the total handover latency happening during the handover process will be reduced by the amount of the prediction interval (Δt).

We use recent 20 RSSI value samples using OMNeT++ simulator for obtaining the estimated robust regression line and predict the future RSSI value for 200 ms ahead. Fig. 5 shows the real RSSI values measured by the MN crosses the center of AP2. From the figure it's clear that at the first time of MN movement the current AP1 was giving the highest RSSI value, this indicate that the MN was close to the current AP1 and during the MN movement from the serving AP to the target new AP the RSSI value decrease. At the same time the collected RSSI for AP2 is increased. When the measured RSSI value is less than the handover threshold (*Hth*), then the layer 2 handover process starts and the RSSI value for the new serving AP will be increased.

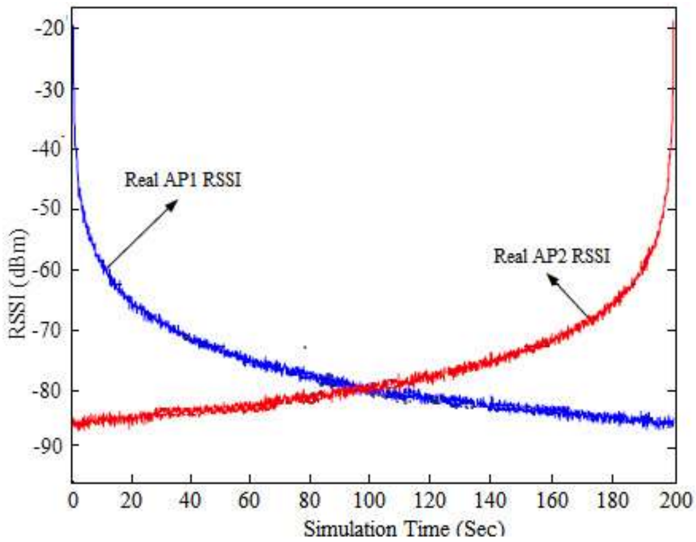

Fig. 5. Real RSSI values for AP1 and AP2

Fig. 6 shows the estimated robust regression process has been processed for the collected RSSI samples for the duration of 200 ms of MNs movement and it represent the future values of real RSSI. From our simulation result shows the proposed prediction handover algorithm can start the handover process faster than the conventional one. This is because the MN in the proposed algorithm is using pre active scan mode to scan APs in the range then decide the handover trigger when the RSSI value of new AP is greater than the current AP. when time (t) = 7.1 second the predicted RSSI value was below the handover threshold ((*Hth*)= -80dBm). The corresponding D-Link layer (L2) trigger was happened at time (t) = 7.1 second, while the real D-Link layer handover started at time (t) = 7.2 second. Since the mobile IP pre registration process started prior than Layer 2 handover and the total handover latency shortened by the amount of l00 ms. Therefore, the handover process occurs based right decision, which affected to reduce the overall handover latency and support the real-time traffic as well.

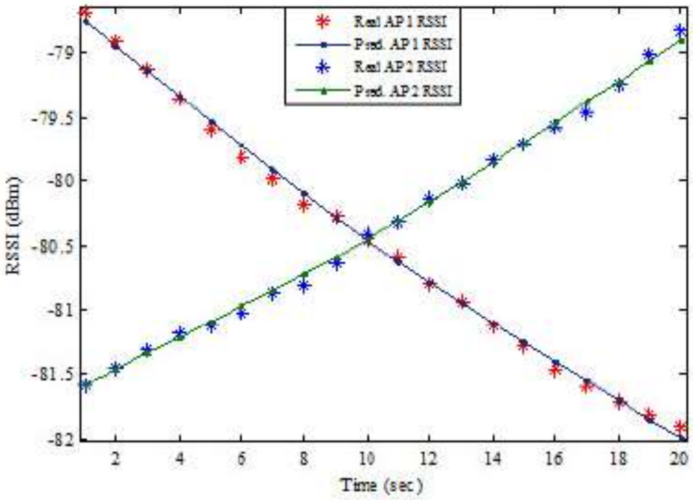

Fig. 6. Predicted RSSI values for AP1 and AP2

7. CONCLUSION

Handover latency in IEEE 802.11 is a critical issue in wireless LANs that affects sensitive real-time applications such as voice over internet. In this paper, we proposed prediction based L2 trigger algorithm using Robust Regression Model. The MN in our proposed algorithm can decide to start a handover process faster than the conventional one without any assumption on the statistical properties of the MN movement. By utilizing signal strength prediction, layer 3 handover activities are able to take place prior to layer-2 handover. The simulation results prove the efficiency of proposed algorithm in terms of reduce the time delay in each of data link layer and overall handover latency which it supports the real-time application

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