Changeover prediction model for improving handover support in campus area WLAN

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***Abstract*—A handover in wireless networks is the mechanism to maintain quality of service (QoS) by transferring an ongoing call or data connection from one point of access to another. IEEE802.11-based wireless local area networks (WLANs) do not explicitly support handovers, but permit a changeover if two access points (APs) have identical identifiers. This changeover is triggered by the mobility of a mobile host or an AP's inability to support hosts in its vicinity, and such changeovers are not seamless. The changeover is initiated by the mobile host which results in disruptions to ongoing connections. In this paper, we develop a changeover prediction model as an evidence-based tool to help minimise such disruptions. We determined the best set of predictors for a changeover using variable selection on a linear regression model. Our results show that the best set of predictors for changeover is consistent and reproducible across different locations around a campus area network. This finding can provide significant insights to the design and development of future handover algorithms built on top of IEEE 802.11 WLAN.**

***Index Terms*—Handover, WLANs, 802.11, SDN.**

I. Introduction

In a wireless network, a handover "is defined as the mechanism by which an ongoing connection is transferred" from one point of access to another point of access [1]. A handover helps to ensure that users' existing connections (such as an ongoing Hangout session) do not break whilst they move out of range of one point of access into another. However, the IEEE 802.11 wireless local area networks (WLANs) do not explicitly support handovers and were not initially designed to support real time and delay sensitive services.

For an IEEE 802.11-based WLAN, the standard allows for a mobile host to switch between two access points (APs) if the APs have identical identifiers. But switching between APs does not maintain connection continuity leading to disruption and re-establishment of existing connections. In this paper, we call this process a *changeover* and we use this term to precisely describe the process of a mobile host losing connectivity from a source AP and re-association with a destination AP. In our context, the term changeover is different from handover in the sense that a handover is a process that maintains a connection's state during a changeover and this process attempts to hide the artefact of changeover (e.g. jittery videos, disconnections, etc.)

Among the different proposals for supporting WLAN handovers, network-side handover approach is preferred for campus area WLANs. Network-side handover support is the term we coined to describe the operational reality of making changes to network-side operation to support handover between APs. Network-side changes (such as AP firmware upgrade) are easier to deploy because it usually falls under a single administrative domain and changes can be made simultaneously, thus reducing possible incompatibilities.

Fundamental to providing network-side handover support is anticipating a handover at the AP. This anticipation helps detect the onset of degraded quality of service (QoS) in the initial phases and could facilitate the starting of more effective handover management strategies to improve the QoS during the handover. The anticipation of a handover can be linked to some metrics readily available in the AP, for example, received signal strength indicator (RSSI) and access delay. For the purpose of handover management, the metrics used to trigger a handover are called *predictors*. To anticipate handovers, the network tracks a set of predictors to aid handover decisions. However, when too many redundant predictors are present, collecting, storing and processing this information wastes bandwidth, energy and storage space.

Identifying a modest number of handover predictors is useful in practice for several reasons. Firstly, tracking a smaller set of handover predictors eliminates predictors that may confuse the handover algorithm thus helping the network to respond quickly to prevent excessive delays during a handover. Secondly, WLAN APs are low cost devices that have limited compute and storage capability. Hence, handover algorithms are expected to be of modest complexity with a limited set of predictors as inputs. Thus, it is important that the limited set of predictors contribute to the predictive accuracy of impending handovers.

To date, there has been very little research to determine which are the significant predictors of handover for IEEE 802.11 WLANs. While some information can be gleaned from other systems such as 3G, LTE, etc., the protocols and interactions between entities in a IEEE 802.11 WLAN and the reasoning involved in the handover process are different. This paper provides new understanding of the critical predictors in IEEE 802.11 WLAN changeovers (note the use of the term changeover because our campus WLANs do not support handover). Better understanding of changeover predictors is necessary for more informed decisions in devising handover algorithms. We use multiple regression and variable selection on empirical changeover datasets to derive the best set of predictors. In summary, the goals of this paper are to:

(i) determine if a set of predictors can be consistently identified from changeover datasets with random variability,

(ii) develop a changeover prediction model using optimal predictors for supporting network-side handover, and

(iii) provide an empirical basis for future handover algorithm development.

In the following section, we establish the context by exposing the challenges facing network-side handover support and previous work that closely parallel the ideas to be presented in this paper. Section III describes the WLAN changeover datasets and test bed setup used to collect these datasets. The method we used for constructing the changeover prediction model from the empirical data is presented in Section IV followed by the regression diagnostics in Section VI. Finally, Section VII is where we give our conclusions, discuss future work and research opportunities.

II. Background & Related work

During a handover, session continuity and minimal disruption to an ongoing session or flow has always been the primary goal of handover management. Existing research on handovers are geared towards supporting 2G, 3G and LTE mobile hosts. This is because the goals of handover management handover management are more easily supported by some radio technologies compared to others [2], [3]. As the handover process is not standardised in the IEEE 802.11 standard, the adverse impact of switching between APs (for example, increased delay and decreased throughput) is implementation specific and may vary across mobile hosts depending on vendor implementation.

There is research to show that handover decisions based on link-layer predictors are more responsive and yield better QoS in terms of latency and perceived quality [4]. A study performed by Mishra *et al.* [5] found that the greatest delay when switching APs was the probing delay (during the scanning phase) which is required for finding an appropriate AP to switch to. Work has since been conducted to improve this delay [6] and the IEEE has published additional standards such as the 802.11k [7] and 802.11r [8] that provide link-layer information to facilitate future handover mechanisms. However, IEEE 802.11 semantics permits a mobile host to be associated with only one AP at any given time and therefore a changeover between two APs requires a "break-before-make" mechanism.

In its current form, the changeover in IEEE 802.11 relies on the RSSI and most of the proposed handover algorithms in the literature are commonly based on RSSI [6], [9], [10]. For example, changes in RSSI of the currently associated AP beyond certain thresholds can be used to trigger a handover. Depending on the how the IEEE 802.11 standard is implemented on a mobile host device, the device may not switch to another AP until the RSSI is below a threshold (for example below -90 dBm) where the currently associated AP is unreachable.

Besides RSSI, the number of frame retransmissions or frame losses have been widely used as triggers for handover decisions [9], [11]. A common reasoning is that a change in RSSI poorly reflects the necessity for a handover. A study by Tsukamoto *et al.* [9] found that using RSSI as the handover trigger was not sufficient in detecting performance degradation. Using frame retransmissions as a trigger for a handover allows a reduction in TCP goodput to be detected and dealt with before the decrease is noticeable to a user.

For ensuring delay constraints, there have been several studies on access delay to guide handover decisions [12], [13]. The performance of real-time (or near real-time) services such as video streaming and voice over Internet Protocol (VoIP) will be impacted if time related predictors such as access delay, round-trip-time (RTT) and jitter are neglected. Such time related predictors are increasingly important as the shift to an all-IP solution takes place and handovers will need to occur between different technologies, such as 4G LTE and WLAN, which could lead to increased delays [12].

Despite several link-layer predictors proposed in the literature for improving handover delay and throughput, there is little understanding of the relative trade–offs in handover performance when one predictor is selected over another. The bulk of current research focuses on using RSSI to trigger a handover, this is based on intuition and common sense rather than empirical measurements/data. Besides RSSI, there are many predictors at the disposal of the handover management algorithm which could be equally valid predictors for a handover. For example, studies have been done using predictors such as frame transmissions and frame losses [9], [11] but other predictors such as data rates and transmission rates have not been considered together with the usual RSSI.

Motivated by the lack of evidenced-backed analysis of the predictors of handovers, we use multiple regression to analyse a set of predictors which may explain changeover occurrence in WLANs. The use of regression models for studying handover in wireless networks has been documented in several papers. For example, the authors in [10], [14]–[16] characterised mobility patterns to anticipate handovers with the help of regression modelling. The key differences in these models are the handover criteria and performance. Signal strength remains as a notable criteria in most of the models for predicting handover and it is used in tandem with one or more criteria for determining handovers. Surprisingly, there has been no comparative study of which criteria are best or even which set of criteria optimally predicts a handover. In the following section, we describe the approach we used to study the different predictors tracked by the network that may be used by handover algorithms.

III. Approach

An experimental approach is adopted involving a test bed built with the goal of collecting changeover data. The test bed and measurement campaign were replicated in three separate locations that represent a campus area WLAN. In each

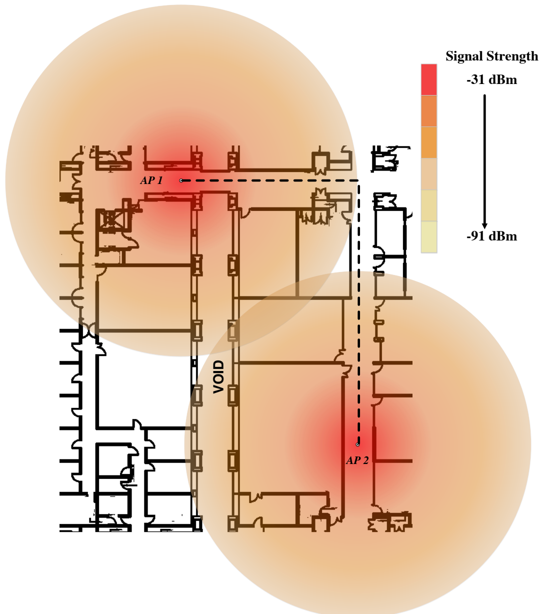

Fig. 1. Indoor Office Scenario – Cotton Building

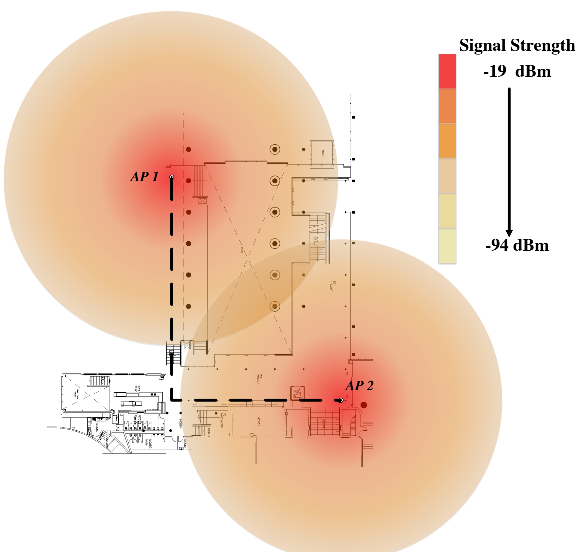

Fig. 2. Indoor Open Space Scenario – The Hub

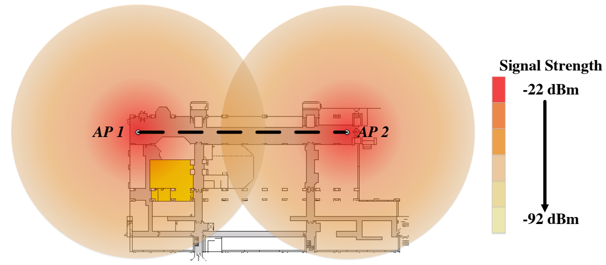

Fig. 3. Indoor Line-of-Sight Scenario

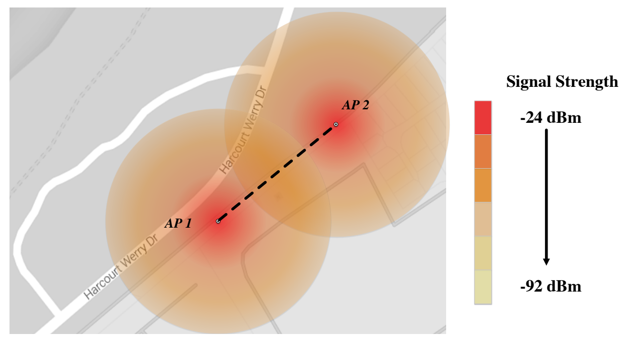

Fig. 4. Outdoor Scenario

location, mobile hosts are tracked via their MAC addresses and we assume that each MAC address matches only one user.

Detailed data were collected on the APs when mobile hosts changeover between two adjacent APs and each AP records the results in a text file on the AP's internal flash memory. The collected data is cleaned, processed for outliers and finally used to construct a regression model for identifying the most useful predictors of a changeover.

A. Campus area locations

We performed our experiments in three indoors scenarios and one outdoor scenario. The indoor scenarios are three different locations in Victoria University of Wellington's Kelburn campus, New Zealand. The floor plans and the measurement points for these locations are shown in Fig. 1 to Fig. 3. This indoor environment reflects the noise and interference associated with human movement patterns and other APs within range that are potentially operating on the same or overlapping channels. The fourth scenario (Fig. 4) is an outdoor setting in Lower Hutt, Wellington, New Zealand, with minimal interference due to few people and minimal WLAN pollution in the vicinity to act as a baseline reference.

Fig. 1 is a typical interior environment with small offices and cubicles (recorded as dataset D1), while Fig. 2 shows a large open indoor student space, roughly cube shaped with twelve large beams cutting across the space (recorded as dataset D2). Another representative campus scenario is a long hallway with laboratories on one side and this is shown in Fig.3 (recorded as dataset D3). Finally, Fig. 4 depicts the open space outdoors scenario located in Lower Hutt (41°11′37.4″S, 174°55′53.6″E) and the measurements were recorded as dataset D4. The dash line in each figure is the typical path traversed by mobile hosts (users) and the changeover occurs when the mobile host moves between the coverage area of two APs (this coverage area is depicted as concentric circles centred on the AP).

B. Devices & Device Configuration

The test bed equipment (APs) are identical in order to achieve homogeneity and reduce systematic bias that could be due to differences in changeover handling. The APs were of the same model and make (Linksys WRT1900ac) running OpenWrt 15.05 on Linux. Each AP has four detachable

Predictor	Notation (unit)	Description	Source	Documented use
RSSI$_s$	V_1 (dBm)	Denotes the RSSI of WLAN signal from originating AP.		[6], [9], [10]
RSSI$_d$	V_2 (dBm)	Denotes the RSSI of WLAN signal from destination AP. The RSSI is measured at the physical layer and indicates the power observed at the antennas used to receive the incoming frames. Note that the RSSI is only measured during the reception of the physical layer convergence protocol (PLCP) preamble.	*iwinfo*	[6], [9], [10]
Noise Floor	V_3 (dBm)	Sum of all noise present in the channel from the perspective of the source AP.	*iwinfo*	
SNR	V_4 (dB)	The received signal to noise ratio is the relative strength of the desired signal to the noise plus interference power over the channel. Different from the RSSI, the desired signal strength is measured over the received frame rather than the PLCP preamble.	*iwinfo*	
TX Rate	V_5 (Mbps)	Physical layer data rate which the source AP is sending to a logged host.	*iwinfo*	[6]
TX Bytes	V_6 (Bytes)	The number of bytes transmitted to a host since the last sample taken. Obtained by keeping track of historical data from *proc*.	*proc*	[6]
TX Packets	V_7 (Integer)	The number of packets transmitted to a host since the last sample taken. Obtained by keeping track of historical data from *proc*.	*proc*	[6]
RX Rate	V_8 (Mbps)	Physical layer data rate which the source AP is receiving from a logged host.	*iwinfo*	[6]
RX Bytes	V_9 (Bytes)	The number of bytes received from a host since the last sample taken. Obtained by keeping track of historical data from *proc*.	*proc*	[6]
RX Packets	V_{10} (Integer)	The number of packets received from a host since the last sample taken. Obtained by keeping track of historical data from *proc*.	*proc*	[6]
No. Clients	V_{11} (Integer)	The number of clients associated to the source AP.	*iwinfo*	
RTT	V_{12} (ms)	Round trip time of an ICMP message to a monitored host.	*ping*	

TABLE I
DESCRIPTION OF PREDICTORS (EXPLANATORY VARIABLE) AND HOW EACH PREDICTOR IS MEASURED.

antennas and operate in 2.4 GHz band (Channel 1) using the IEEE 802.11b protocol with a maximum data rate set to 11 Mbps (at the physical layer). The default rate adaptation for the AP was retained [17] (the AP uses the Marvell 88W8864 Chipset).

Before setting up the test bed to run the experiments, a site survey at each of the four chosen locations were conducted. This was done to determine a common transmit power that would be appropriate for the space available and to determine suitable AP placement. Based on the site survey, a changeover between APs is likely occur with the APs set to transmit at 15 dBm.

C. Measurement

A measurement campaign was conducted in August/September 2015 to collect data from APs the moment a mobile host switches from one AP to another. Table I lists the twelve predictors (explanatory variables) along with the respective symbols used to denote each measured predictor. From this point forward, we use the term variable and predictor interchangeably. The description of each predictor is also given to avoid ambiguity and the tool used to retrieve the data is listed in the "Source" column. The final column cites the documented use of the predictor in the literature.

A shell script was written to automate measurement and data collection. The shell script executes the *iwinfo*, *ping* and *proc* commands on the APs and returns the readings of all of the observed predictors for each second passed. If no packets have been transmitted by the observed mobile host on the wireless interface (inactive clients), the data would not get recorded. Only when there was activity on the interface from the observed mobile hosts would data get logged. All APs are monitored to ensure that they are in operational state during the data collection period.

D. Dataset processing

The first step in processing the datasets was to apply data cleaning procedures to the raw data set. The datasets were checked for duplicate entries, and entries with "NAN" (not a number), "unknown" and entries with missing values; if found the entries were removed. The second step was detecting outliers and extreme values. For outlier detection, we employ Minimum Covariance Determinant which calculates the N-dimensional (where N is the number of predictors) distance of a point from the centroid of the dataset and discards points that are far away from the centroid.

Additionally, we also perform changeover continuity checking whereby we check that data g is successfully received at the new AP (and only the new AP) when a mobile host moves from one AP (source) to the other AP (destination). This process eliminates the so-called "ping-pong" effect of repeatedly changing the association with two APs.

Upon cleaning the dataset and performing outlier detection the average changeover rate for each dataset is 25.2%, 22.1%, 21.3% and 25.0%. This is the ratio of the number of changeovers to the average number of mobile hosts associated with the source AP. Exclusion of entries with missing data resulted in a final sample size of 36205 for the subsequent multivariate analyses. All datasets used in this paper would be made publicly available through the CROWDAD project [18].

IV. Regression modelling

A multiple linear regression model links the statistical dependence of a variable under study Y on a set of N explanatory variables $\{V_1, V_2 \ldots V_N\}$ and random error ϵ called the *residual*. In our problem of changeover prediction, the variable Y denotes the changeover rate in a two-minute interval and the predictors are the explanatory variables. The two-minute changeover rate is defined as the ratio of the number of changeovers to the number of associated mobile hosts before the end of the two minute observation interval. The choice of two minutes is guided by the frequency a handover algorithm re-calculates the changeover probabilities; this aspect provides an opportunity for further research to determine more appropriate observation durations to suit different scenarios and overheads incurred from more frequent re-computations.

In the regression model, we assume a linear relationship between Y and $\{V_1, V_2 \ldots V_N\}$ in the form of

$$Y \sim f(V_1, V_2 \ldots V_N) + \epsilon, \tag{1}$$

and the residuals ϵ are assumed to be normally distributed with a constant variance. Using the regression model in Eqn. (1), we employ variable selection procedures to choose the subset of explanatory variables that minimises the residual (hence bringing $f(V_1, V_2 \ldots V_N)$ closer to Y). A chosen subset of explanatory variables is called a submodel while the full model contains all explanatory variables.

We employ four different model selection strategies to arrive at the best subset of predictors. These strategies are: (i) forward selection (FS), (ii) backward reduction (BR), (iii) stepwise regression (SR) and (iv) exhaustive subsets (ES). Of these four strategies, FS, BR, and SR are *automated variable selection* strategies while ES performs model selection over all combinations of predictors. Upon completing the variable selection, we will revisit the assumptions for the regression and check if they are violated with the help of regression diagnostics.

A. Changeover predictors

Candidate predictors were selected based on the following criteria: (i) well defined at the link layer or network layer, (ii) is measurable using existing network-side infrastructure and (iii) has been documented to be associated with handovers in the literature. These predictors are classified into the following categories: (i) signal strength, (ii) data rates, (iii) delay and (iv) associations (number of clients attached).

As a sanity check, a univariate logistic regression predicting changeover was performed to determine the statistical significance of the association between each predictor and the changeover rate. In univariate regression, a function relating the statistical relationship between one predictor and the changeover rate is analysed ignoring other predictors. The odds ratio and statistical significance (P-values) resulting from the univariate regression are tabulated in Table II, where D1 – D4 refer to the datasets for the four scenarios shown earlier in Fig. 1 to Fig. 4 respectively.

Category	Predictor	Odds ratio				P-value
		D1	D2	D3	D4	
Signal strength	$RSSI_s$	1.461	1.239	1.478	1.865	< 0.0001
	$RSSI_d$	1.461	1.239	1.478	1.682	< 0.0001
	Noise Floor	1.175	1.192	1.2099	1.683	< 0.0005
	SNR	1.587	1.490	1.358	1.078	< 0.0001
Data rates	TX Rate	1.278	1.187	1.2531	1.012	< 0.0005
	TX Bytes	1.198	1.239	1.2408	1.234	< 0.0005
	TX Packets	1.244	1.216	1.189	1.231	< 0.0005
	RX Rate	1.419	1.424	1.399	1.203	< 0.0005
	RX Bytes	1.422	1.408	1.415	1.402	< 0.0005
	RX Packets	1.401	1.413	1.39	1.433	< 0.0005
Associations	No. Clients	0.567	0.627	0.464	0.270	< 0.001
Delay	RTT	1.327	1.283	1.313	1.565	< 0.0001

TABLE II

Univariate association between handover and predictor.

The odds ratio quantifies how strongly the presence or absence of a predictor is associated with the two-minute changeover rate in the dataset. In our datasets, the odds ratio is defined as the change in likelihood of changeover for every unit increase in the predictor. An odds ratio of 1 indicates that a predictor does not influence the odds of changeover likelihood. An odds ratio greater than 1 implies the corresponding predictor is more useful in anticipating changeover while an odds ratio less than 1 implies otherwise. Similarly, a predictor with a low P-value is likely to be a meaningful addition to predicting the changeover.

From the univariate regression, the number of clients stands out as having very little predictive power for changeovers because the odds ratio is lower than 1, while RSSI appears to be strongly associated with the changeover. Recall that univariate regression provides an isolated view of the role of one predictor from all of the other predictors and the marginal effects of multiple regression in Eqn. (1) may be entirely different from the univariate regression.

B. Variable Selection

For regression models with high dimensionality (i.e. N in Eqn. (1) is large), a global solution to the problem of variable selection requires an exhaustive search over all possible subsets of the explanatory variables. This approach is computationally expensive and therefore in practice, an incremental approach is preferred. The result of the variable selection procedure is the submodel whose fitted values best reflect the changeover rate.

Widely used incremental approaches are FS, SR and BR. Each of these procedures generate a sequence of submodels in which each submodel differs from the previous one in the sequence by the addition or deletion of a single predictor. The variable selection procedure is terminated when the F-value of each predictor in the model is significant. The F-value is the test of significance of the predictor if it were included in the regression model and can be thought of as a test of quality of the predictor.

Besides the F-value, the significance of a predictor included in a model selection procedure can be measured using the Akaike's Information Criterion (AIC). The AIC can be interpreted as a measure of quality of the regression model by calculating how much "information" is lost with respect to an optimal model. Another model selection criterion similar to AIC is the Bayesian Information Criterion (BIC). The difference is that BIC penalises the inclusion of predictors and the size of datasets (i.e. rewarding fewer variables to avoid overfitting).

1) Automated Variable Selection: In FS, predictors are added one at a time according to some selection criterion. Backward reduction is performed under a similar set of rules, beginning with the full model and sequentially eliminating one predictor at a time. Both FS and BR have the characteristic that once a predictor enters (departs) the model, it is not subsequently reconsidered for removal (reentry). The SR procedure begins like FS but with the added flexibility of removing a previously added predictor if it fails to retain its significance as additional predictors are added. The potential problems in overlooking better models are well known and we take note of the caution on the misguided use of automatic variable selection procedures [19].

2) Exhaustive subset (ES): ES is a selection procedure where all possible predictor subset combinations are examined to get the best set of predictors. For this set of 12 predictors, the ES selection was performed and, it retained three predictors as the optimal combination across all datasets.

V. RESULTS

The results for the most significant predictors for changeover for the four datasets are shown in Table III. We use both AIC and BIC criteria for each variable selection procedure, and Table III shows the best set of predictor variables based on these two criteria. A tick in the AIC column indicates that the best model through the given procedure was found based on the AIC criterion, and likewise for the BIC column. Ticks in both AIC and BIC denote that the procedure returns the same submodel tuned via both AIC and BIC criteria.

The variable-selection procedure identifies the predictors that fit the two-minute changeover rate best and drops predictors that do not contribute to explaining the observed changeover rate. In all three datasets it was consistently found that $\{$SNR, RX Bytes and RTT$\}$ were the most significant predictors for changeover. The initial hypothesis (from Table II) that the number of associated clients is not a significant predictor is confirmed by the findings reported in Table III because it is dropped as a predictor by all four variable selection procedure. By consensus, the best submodel for predicting changeover based on indoor datasets (D1–D3) is:

$$\begin{aligned} Y &\sim V_4 + V_8 + V_{12}, \\ Y &\sim \text{SNR} + \text{RX Bytes} + \text{RTT}. \end{aligned} \tag{2}$$

The choice of SNR over RSSI in the best submodel given in Eqn. (2) is expected. This choice can be traced to the fact that RSSI measures the power within a given channel and does not differentiate between signal and interference power while SNR measures the desired signal to the noise floor. For the outdoor scenario, the variable selection procedures FS and BR retained the RSSI$_s$ predictor in favour of the SNR predictor. Recall also that the D4 dataset was obtained under conditions whereby the signal between APs and mobile hosts have a dominant line of sight and experience less reflection, and these explain why the RSSI predictors provide a closer approximation of changeover rate. This is because the FS and BR procedures do not remove a predictor once it is included.

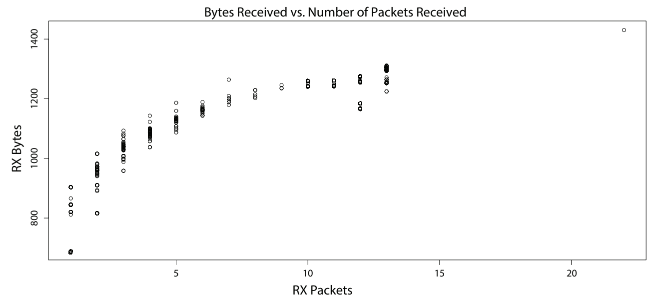

Fig. 5. Non-linear relationship between the number of received packets and total bytes received, averaged over a 2–minute interval.

An interesting observation from the results in Table III is that one predictor from each category (signal strength, data rate and delay) is chosen by each selection procedure. This is intuitive because each predictor gives a different dimension to the submodel for predicting the changeover rate. However, the choice of RX Bytes over both RX Packets and RX Rate requires further reasoning. All three predictors capture the same information albeit at different levels. The RX Bytes predictor was selected over RX Packets because the latter is coarse grained and hence less responsive to the changes in changeover. On the other hand, RX Bytes is more responsive because it counts all bytes from the mobile host inclusive MAC–layer frames and possibly frames with errors. While the RX Bytes and RX packet predictors are correlated they are not linear as seen in Fig. 5. This continuous feedback reduces the residual error in the regression model and is therefore retained in all four variable selection procedure.

VI. DIAGNOSTICS

After selecting the most suitable set of predictor variables, several diagnostics can be applied for assessing the adequacy of the submodel. These diagnostics are used to assess the violations of linear regression assumptions and relevance of the chosen submodel. For example quantile-quantile (QQ) plots, residual plots, outlier identification (Cooks distance), or partial residual plots to identify trends in the data. In this section, we use three diagnostics to check for normality and homogeneity.

We plot the QQ-plots of the predicted changeover comparing quantiles obtained through the model $Y \sim V_4 + V_8 + V_{12}$ against the quantiles from the ensemble dataset (merging D1,

Dataset	Method	Predictors												Tuning	
		V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	AIC	BIC
D1	FS				✓				✓				✓	✓	
	BR				✓				✓				✓	✓	
	SR				✓				✓				✓	✓	✓
	ES				✓				✓				✓	✓	✓
D2	FS				✓				✓				✓	✓	
	BR				✓				✓				✓	✓	
	SR				✓				✓				✓	✓	✓
	ES				✓				✓				✓	✓	✓
D3	FS				✓				✓				✓	✓	
	BR				✓				✓				✓	✓	✓
	SR				✓				✓				✓	✓	✓
	ES				✓				✓				✓	✓	
D4	FS	✓							✓				✓	✓	
	BR	✓							✓				✓	✓	
	SR				✓				✓				✓	✓	✓
	ES				✓				✓				✓	✓	✓
Selected Regression Model															
$Y \sim V_4 + V_8 + V_{12}$															

TABLE III
VARIABLE SELECTION USING FORWARD SELECTION (FS), BACKWARD REDUCTION (BR), STEPWISE REGRESSION (SR) AND EXHAUSTIVE SEARCH (ES) RESULTS.

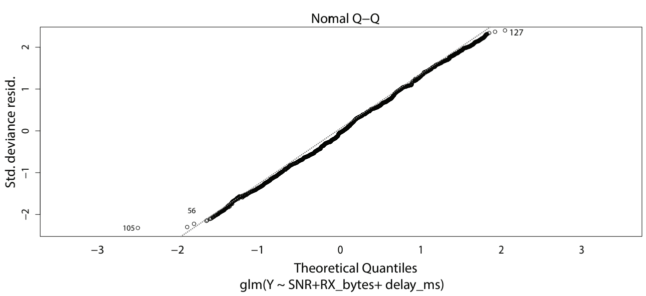

Fig. 6. QQ-plot

D2 and D3). A linear trend in the QQ-plot (Fig. 6) indicates that the selected submodel produces changeover predictions of "similar distribution" to the ensemble dataset. Slight deviations from the reference line (grey dotted line) at the upper and lower quantiles indicate that the changeover projections may differ slightly in extreme cases. The lower quartile deviations occur at entries 56 and 105 in the dataset, while the upper quartile deviation is due to entry 127. We will see these entries appear in subsequent diagnostic plots.

Fig. 7a shows the residuals (see ϵ in Eqn. (1)) versus predictions (both x-axis and y-axis have the same units) and the mean (red line). Standardised residuals are residuals divided by the standard deviation of the residuals and is useful for comparing across datasets with different means. The residuals are balanced with respect to the mean and no unusual variance across the predicted values. Additionally, no trend is observed in the residuals for plot in Fig. 7a and this observation suggests that: (i) the residuals are uncorrelated to the fitted values (normally distributed errors), (ii) the residuals are uniformly distributed and spread across the predicted values and (iii) there is no violation of homogeneity assumption.

The residuals versus leverage plot in Fig. 7b indicates points that have overly strong influence on the regression relationship. Leverage is a measure of influence an entry (in the dataset) has on determining the two-minute changeover. Again, three labelled points ($\{105, 457, 576\}$) were identified as entries that may warrant further investigation. However, the residuals are balanced with respect to the mean and the identified outliers are few not significant (large residual that correspond to a small leverage). The lack of significant outliers can be traced back to the cleaning of datasets and the use of outlier detection prior to model selection.

The final diagnostic is the plot of scale versus location shown in Fig. 7c, the plot indicates that the constant variance assumption is not satisfied. The plot indicates that the variance of the model first increases and subsequently decreases over the range of predicted values. This non-constant variance is called heteroscedasticity. This suggests that handover algorithms should pay attention to the non-constant variance when using these predictors for a handover, perhaps scaling the variables or transforming the variables as a function of variance would improve the predictive performance of such algorithms.

VII. CONCLUSION

In this paper, we used variable selection based on linear regression to determine the best changeover predictors from a set of commonly used predictors. The results of this model showed that RSSI was not the best predictor for a changeover as we had originally thought. In an outdoor environment, RSSI was still a good predictor for when a changeover occurs, but was not optimal. We found that SNR, RTT and RX Bytes were the best predictors for a changeover across the four datasets.

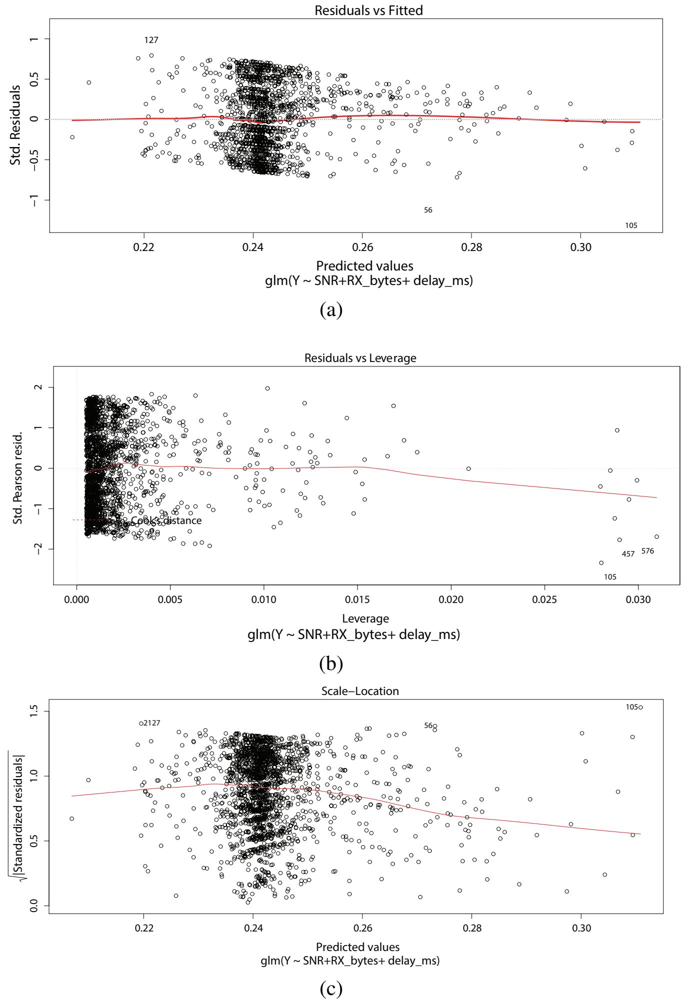

Fig. 7. Normality diagnostics: (a) Residual vs. Fitted , (b) Residual vs. Leverage and (c) Scale vs. Location

For future work, handover algorithms can be designed to take advantage of the results of our analysis on changeover. We envisage that these new algorithms are easily implemented in software-defined networks to enable network-side handovers to take place in order to meet the QoS and user experience requirements that mobile users expect.

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