# Dynamic Wi-Fi RSSI normalization in unmapped locations

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## ABSTRACT

With the growing availability of open access WLAN networks, we assisted to the increase of marketing services that are based on the data collected from the WLAN access points. The identification of visitors of a commercial venue using WLAN data is one of the issues to create successful marketing products. One of the ways to separate visitors is to analyse the RSSI of the mobile devices signals coming to various access points at the venue. Nevertheless, the indoor signal distortion makes RSSI based methods unreliable.

In this work we propose the algorithm for the WLAN based RSSI normalization in uncontrolled environments. Our approach is based on the two steps, where at first based on the collected data we detect the devices whose RSSI can be taken as a basic one. At the second step the algorithm allows based on the previously detected basic RSSI to normalize the received signal from mobile devices. We provide the analysis of a real dataset of WLAN probes collected in several real commercial venues in Italy.

## 1 INTRODUCTION

Localization is becoming a more and more important feature in the mechanisms used for the location-based services and different location-based business models [13, 14]. One of the most commonly used and precise mechanism for the localization, the Global Navigation Satellite Systems (GNSS), has strong limitations in indoor environments. Hence, in order to organise the localization in indoor environments, researchers and industry approached the problem by using different signal technologies, such as Radio Frequency Identification tags, Ultra Wide-Band or WLAN.

While the technologies based on the Radio Frequency Tags and Bluetooth Low Energy show promising results in indoor localization [2, 7], it is WLAN that is of our particular interest. Indoor localization based on WLAN technologies does not show significant precision benefits in comparison with other approaches. However, in the last decades the availability and distribution of free internet zones in the cities and commercial venues have significantly increased. Therefore, the application of WLAN based localization does not require additional infrastructure deployment and can be based on the already existing infrastructure. This characteristic makes this method to be one of the most appealing for small and medium size enterprises, also considering its flexibility and applicability. The approach can be of particular interest when the high localization precision is not required.

There are a lot of commercial companies that are working with the data of commercial venues in order to provide marketing products to the clients. These companies are buying probes data from giant wireless infrastructure providers, such as Meraki, Ruckus and Aerohive, and process this data into the marketing product. The marketing product motivating the paper originates from a company mission to help retailers in brick and mortars stores to build an *omni-channel* communication with their customers. For example, one use case could be to trigger a specific marketing action on a defined behaviour such as a push up notification on the proprietary app when the customers enters the store or to send a discount or promotion email to a customer who has just left the location for retaining. As many real world scenarios, the raw data contains much 'noise' and is in need of semantic attribution to be able to aim the right communication to the right target: the visitors.

As a matter of fact, one of the key aspect for this data processing is actually to separate the *visitors* of the venue from the *passers-by*, where the visitor is usually considered a person that enters the venue and spends some time (and hopefully money) inside. One of the ways to separate visitors from passers-by is by analysing the Received Signal Strength Indicator (RSSI) of mobile WiFi devices carried by nearby persons. The RSSI indicates the power present in the received radio signal from remote mobile devices and typically decreases with the distance between the receiver and the transmitter of the signal. The RSSI parameter is very volatile and highly depends on the environment. The signal in a propagation channel is affected by path loss and multi-path effects, which result in RSSI variation and attenuation [3, 11, 12]. This is an important factor especially for commercial venues, in which the high fluctuation of people makes the problem of correctly distinguish between visitors and passers-by based on RSSI even more challenging.

Most of the existing WLAN solutions are based on the knowledge of the *access points* (APs) position, network devices that allow other Wi-Fi devices to connect to the wired network [4, 6]. Also, the typical solutions rely on the fixed indoor layout and do not consider the people fluctuations [3].

In this paper, we focus on the characterization and possible adjustments of RSSI based indoor localization for WLAN communication. More precisely, our contribution can be summarized as follows. We propose an algorithm that dynamically adjusts the RSSI of the received probes from mobile devices. During the adjustment phase the RSSI of probes of selected *anchor* devices are used as a reference to evaluate the path loss in the propagation channel. In general, an anchor device is (i)active during the closing hours of the venue, (ii)does not change its location, and (iii)it is also present during the opening hours of the same day. We also describe the algorithm for the anchor devices selection.

In our work we provide the analyses of a real dataset of WLAN probes collected in several real commercial venues in Italy. This dataset is provided by the company *Cloud4Wi* for research purposes. We provide the evaluation results for the anchors distribution and presences for different types of commercial venues. We also evaluate the correlation of RSSI of anchor devices on the number of incoming probes to an AP.

The benefit of described approach is that the algorithm relies only on the device probes received by AP and do not require deployment of additional hardware. Moreover, the adjustment phase can be executed at runtime or offline. This important characteristics are essential to follow the wireless channel variance during the day due for instance to the high fluctuation of people. While the described solution does not aim for a high precision localization, it can significantly improve the quality of marketing solutions proposed on the data processing market.

The remainder of this paper is organized as follows. Section 2 offers an overview of the related work. Section 3 provides the definition of the problem statement, whereas Section 4 presents the algorithm for anchors selection and dynamic RSSI adjustment. In Section 5 we evaluate the anchors selection algorithm based on the real WLAN data. Finally, we conclude the paper in Section 6 by discussing the results and the future work.

## 2 RELATED WORK

Indoor localization is a mature research field. Nevertheless, the growing distribution of wireless infrastructure and open access internet connections raises old and brings new challenges. Recent overviews on technologies and techniques can be found on existing surveys [8, 13, 14].

Most of the available literature in the field relies on some known data about indoor layout. This data can include the shape of positioning measurement, points coordinates or fingerprints [4, 5, 8], maps of the area [2, 7, 8], some known scenario [7].

For example the work of Nikoukar et al. [7] describes the study of low-energy Bluetooth advertisement channels. The authors conduct extensive experiments in four different environments. The work describes the study of the effect of the environment noise and interference on the signal propagation conditions. Our work is also connected with the studies of signal deformation in a propagation channel. Nevertheless, the authors consider the controlled environment in their studies, while in our case the setup layout and the indoor conditions are fully uncontrolled.

Another work that studies the propagation channel is the work of R. Faragher and I. Papapanagiotou [2]. The authors provide a detailed study of Bluetooth Low Energy (BLE) fingerprinting. In their investigations the authors rely on the deployed network of 19 beacons. While the study provides the quantitative comparison of BLE technology with the WiFi one, it still relies on a controlled network of hardware devices that has to be installed.

The work of Shrestha et al. [11] describes an approach for indoor localization with WLAN signal and unknown access point locations. The authors formulate the problem of WLAN positioning as a deconvolution problem and investigate three deconvolution methods with different path loss models. The work describes the comparison of the proposed approach with the fingerprinting one. Nevertheless, the authors relies on two stages approach where on the first *training* stage is required the information about the indoor environment and some controlled off-line measurements using the existing APs. By comparison, in the scenario described in our work we have no knowledge about the area and no control over the APs.

One more aspect described in the literature is the possibility of attacks in case of fingerprinting approach. For example the work of Richter et al.[10] discusses different attack types and compare positioning performance of RSS-based fingerprinting under these attacks via simulations. The authors also present the simulator for realistic RSS predictions for the simulation environments. Aboelnaga et al.[1] describe an algorithm to identify attacked APs and make accurate localization in the presence of attacks. These works are concentrated on the evaluation of different attacks types on the performance of RSS. Moreover, in order to detect and evaluate the attacks the authors rely on previously collected fingerprints datasets.

Our work differs from most of the state of the art because we do not improve the precision or reliability of the indoor localization methods. Instead, the main scope of our work is to provide an approach that could, with minimum monetary investments, improve marketing solutions provided by companies based on the collected data. As we describe in Section3, we deal with environment layouts that are not known and not controlled. In our work we rely only on the sniffed data of probes from APs in a totally passive fashion. To decrease the impact of path loss effect in propagation channel on the RSSI based localization we propose to rely on a set of dynamically detected anchors. Monitoring the changes of RSSI of these anchors and applying the correction coefficient for the sniffed RSSI on APs allows to adjust the RSSI-based localization.

## 3 PROBLEM STATEMENT

The wireless radio signal passing through propagation channel experiences path loss and multi-pass effects influencing on the RSSI sniffed by the receiver. These effects are caused by different factors like obstacles in the propagation channel, signal reflection on the walls and floors, etc. In order to estimate the distance between transmitter and receiver some applications rely on the strength value of the received signal RSSI. Hence, the deformation of the signal passing through propagation channel can significantly decrease the level of the provided service.

Regarding the importance of the signal deformation problem for the distance measurement, various models have been proposed to compute the strength of the signal depending on the distance [9]: (i) the free-space propagation model, (ii) the two-ray model and (iii) the log-normal shadowing model (LNSM). For our application, these models usually do unrealistic assumptions or have too high requirements in terms of knowledge of the layout. For example the free-space propagation model assumes the environment to be obstacle-free. A more promising models based on RSSI for the indoor localization is LNSM. However, it heavily relies on the knowledge about the indoor environment. This knowledge includes positions of APs, mapping of the area, environment parameters like temperature, humidity, etc.

These requirements are important for correct indoor localization and cannot be ignored in case of precise modeling. Nevertheless, in real applications it is not always possible to have full knowledge about the environment and the company-owned data usually is very limited. Moreover, the environmental factors change over time.

In our work we consider, as an use case, a company that provides marketing products to commercial venues. The product of the company is based on the processing data of probes sniffed from APs placed in some venues. As a medium size company it does not provide the services of hardware deployment and relies on the APs installation and services provided by big market players like Meraki, Ruckus and Aerohive. The company does not have the knowledge about the position of APs. Also, the company does not have the knowledge about the indoor layout of the venue. The indoor layout of the venue is periodically changing. The venues tend to have fluctuation of visitors during the day and visitors inside the venue can significantly influence on the deformation of the signal in the propagation channel.

At the same time, in order to provide services linked to its mission, the company has to distinguish the probes of *visitors* of the venue from the probes of *passers-by*. This selection has to work under constantly changing conditions inside the propagation channel. To monitor the signal strength loss in the propagation channel one could organise a message exchange between the available APs in the venue. Nevertheless, as we mentioned before, the mid-size company does not deploy the hardware itself and hence cannot influence on the protocols of messages exchange between APs.

In this paper we propose an approach that relies only on the sniffed data of probes from APs. The proposed approach is based on the monitoring of the RSSI changes between transmitter and receiver in time. These changes correspond to the changes of transmitting conditions in propagation channel between these two devices.

One of the first questions to answer is how to detect the fixed transmitters, *anchors*, based on the sniffed data of probes. The second question is how to adjust the RSSI of sniffed probes from visitors mobile devices in order to level out the influence of side factors, like people fluctuation, on the visitor/passer-by detection.

We acknowledge that the proposed solution cannot be applied in cases when high precision is required. Nevertheless, we believe the proposed adjustment can improve the existing marketing products without additional costs for hardware deployment.

## 4 ALGORITHM AND MODEL

The algorithm for the dynamic adjustment of RSSI is composed by two steps, which can be broadly summarized as the following. The first step is dedicated to detecting the devices that can possibly play the role of anchors. The second step applies the anchors RSSI data to adjust the RSSI data from the mobile devices.

In order to be selected as an anchor, a *candidate* device has to meet the following requirements:

(1) the probes of the candidate device have to be presented in the closing hours of the venue. We assume in these hours there is minimum additional noise in the area of investigation. In this case we can measure the basic level of RSSI for the anchor device.
(2) the standard deviation of RSSI probes for the anchor candidate in the closing hours of the venue has to be low. We argue that a low standard deviation relates to those devices that have a fixed position over time. These devices can be represented by printers, TVs or some venue security appliances.
(3) the probes of the candidate must be detected in both the closing hours of the venues and the next consecutive opening hours. With this requirement we eliminate those devices that are, for some reasons, active only during the closing hours of the venue. For example it can be specific security appliance that is activated when no physical guardians are presented.

At the end of the first step we have a list of anchor devices that can be used to adjust RSSI of the mobile devices during the opening hours. Each anchor is assigned to some APs. The corresponding RSSI detected in the closing hours corresponds to the basic RSSI, i.e., $RSSI_0$, between the anchor $A$ and the corresponding AP. Hence, for the following opening hours of the venue this $RSSI_0$ can be assigned as the basic RSSI for the adjustments for the propagation channel between anchor $A$ and the assigned AP.

Based on the detected anchors for the RSSI adjustments of mobile devices we describe the second step of the proposed algorithm, which we call *dynamic RSSI adjustment*. In order to simplify the explanation we consider an example with one AP and one anchor device (Figure 1):

(1) During the opening hours, every time the anchor's probe reaches the AP ($RSSI_{a1}$), the adjustment coefficient $\alpha$ is re-computed by considering the RSSI of the new received probe:
$$\alpha = \frac{RSSI_{a1}}{RSSI_0}$$
(2) The adjustment coefficient $\alpha$ is applied to all mobile devices probes ($RSSI_{m1}$ and $RSSI_{m2}$ on the Figure 1) coming to this AP until the next anchor probe arrives:
$$RSSI = \alpha * RSSI_m 1$$

This algorithm permits to cope with the unavoidable channel variation estimating the $\alpha$ parameter. Indeed, $\alpha = 1$ means that there are no channel variation, $\alpha < 1$ means that the RSSI value decreases with respect to the adjustment phase, or increases when $\alpha > 1$, but in the last two cases the channel has changed.

*No anchors detected.* An additional situation we would like to discuss is the case when there are no detected anchor devices during the opening hours of the venue. For example this can happen in case of very small venues or in case of possible black outs, or for some other reasons that are difficult to estimate.

Every time the algorithm does the calculation of $\alpha$ for AP based on the signals received from the anchor, it can save this value together with the current number of incoming probes to this AP. In cases when no anchors are detected, the algorithm can apply the $\alpha$ estimation based on the current level of incoming probes and the $\alpha$ versus number of probes collected statistics. We leave this improvement for our future work investigations.

## 5 EVALUATION

We have used 2.4 GBs of textual data representing a month (May 2018) of raw data from 6 different locations in Italy. This data has been collected by Cloud4Wi[1] a SaaS company providing behavioral analytic and an omni-channel communication with their customers to retailers worldwide. Each line, representing a single request-to-send/clear-to-send (RTS/CTS) handshaking exchange between a device (which has the Wi-Fi enabled) and an AP in a location, contains information about the time of interaction, the access point id, the device id and the RSSI of the signal.

[1]https://cloud4wi.com/

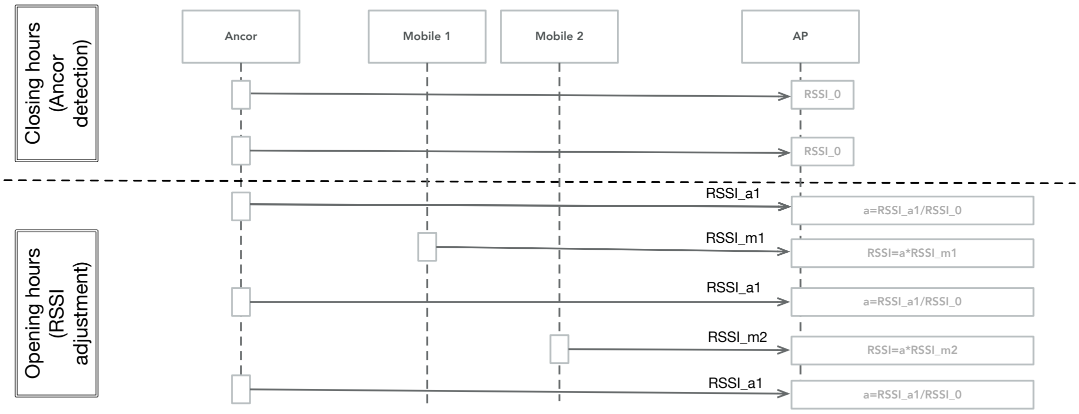



**Figure 1: An example of dynamic RSSI adjustment**

## 5.1 Evaluation setup

In order to understand the possibility of applying the described method, we provide an analysis of different types of venues to see the statistic on the perspective anchor devices. We arbitrarily separated the locations in groups to see if any difference between the groupings could have helped in better understanding the context of the analysis. The locations can be split on the basis of their size (both in traffic and in meters) and of their positioning. The two categories that we decided to implement are:

(1) *Single standing city venues.* The venues that are located in more inhabited areas such as a city centre. In the following experiments we address these locations as **A, B, C**. Venues **A** and **C** are located in seasonal touristic cities. Venue **B** is a city shop located close to the factory building.
(2) *Commercial centers.* The venues are located in dedicated shopping areas such as malls or shopping villages. In the following experiments we address these locations as **D, E, F**.

## 5.2 Data preparation and analyses

As we already described in Section 4 in order to select the anchor devices between the variety of available probes we apply the following numerical constrains:

- The anchor candidate should have at least 4 probes during the closing hours. As closing hours of the venue we have considered deep night hours from $00:00$AM to $04:00$AM. Since all the locations are placed in the same country, Italy, these conditions are applied to all of them.
- In order to be sure the candidate device is not changing its position over time we fix its standard deviation of RSSI to be less then 3. Empirically we found that the maximum of $3-4\%$ standard deviation from the RSSI allows to identify good anchor candidates. An extensive study of this parameter is out of the scope of this paper, and we leave such study for future work.
- We control the presence of anchor candidates during the opening hours of the same day. As opening hours for the venue we have considered the time interval between 8AM and 10PM. We have preferred to be more inclusive for opening hours interval in order to evaluate the maximum possible anchor candidates. Nevertheless, the real opening hours can be different from the one mentioned here. The selected time interval also includes the preparation time for the staff and security checking period after a venue closing for clients.

The parameters described above are derived empirically and are subject for evaluation and studies in a future work.

### Presences of anchor devices

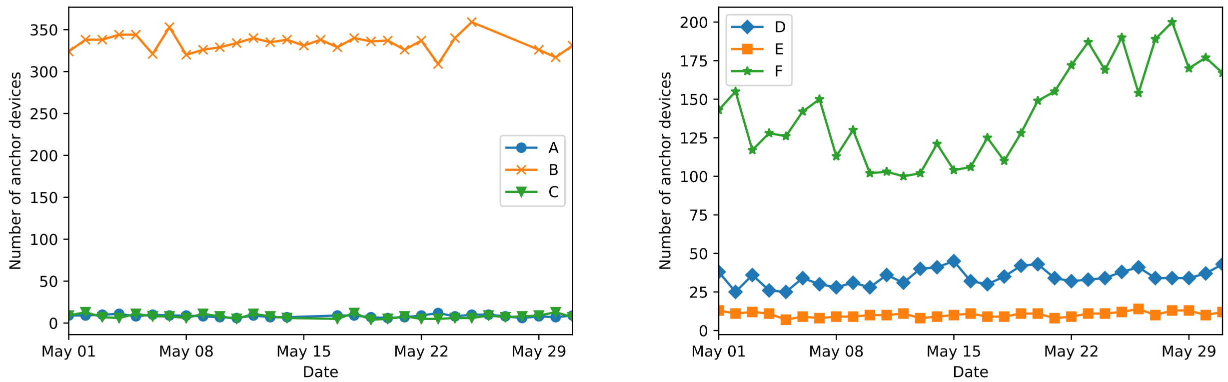
Based on the described constrains we have evaluated the presences of anchor candidates for different categories of locations Figure 2.

As we can see in all the venues there are devices that can be exploit as anchors. At the same time we can see that some venues have much more anchors then others. We explain this by the particularity of the location of the venue. For example, the venues **A** and **C** are placed in the city center of summer touristic cities (Figure 2a). Since we consider the month of May, which is just before the start of summer season, we can see the lack of available anchors. At the same time, the venue **B** is sharing the location with the factory and so we can see an high presence of available anchor candidates. Figure 2b shows the evaluation of the number of available anchor candidates for the venues located in the places such as malls or shopping villages. As we can see all three venues shows availability of the anchor candidates. According to the processed data, the venue **F** has higher availability of anchors in comparison with other venues. It can be explained by the particularity of the specific area organization (security devices, etc.).

### Distribution of anchors per APs

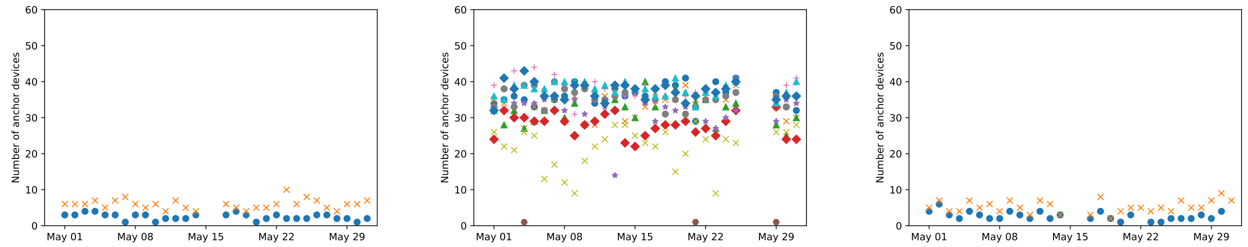
In order to evaluate the distribution of the anchors inside the area we have computed the number of available anchors per APs deployed in the venue. The results of the evaluation are presented in Figure 3. Different dots style and color correspond to the different APs statistic.

As we can see on the Figure 3 and as we have already mentioned on the previous Figure 2 the venues **B, D** and **F** have significantly higher the number of available anchor candidates. This can be also explained by the number of available APs inside the location. The number of APs can be used as indirect characterization for the venue size. An high number of APs is also connected with heterogeneity of the anchor candidates presences. For example on Figure 3b we can see that some of the APs

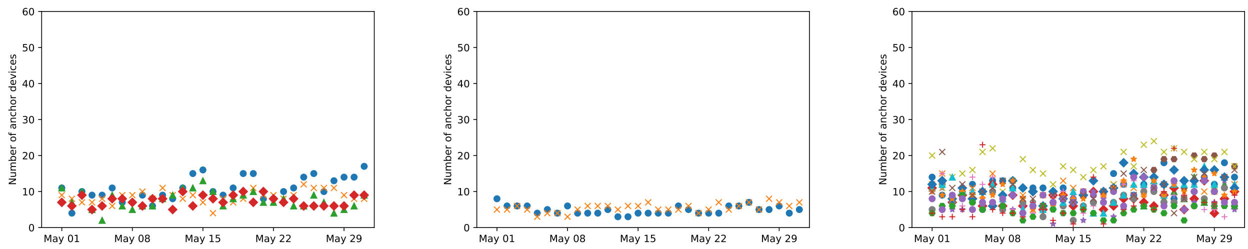



**(a) Single standing city venue.** **(b) Commercial centers.**

**Figure 2: Number of available anchor devices for two types of venue location.**




**(a) Venue A** **(b) Venue B** **(c) Venue C**




**(d) Venue D** **(e) Venue E** **(f) Venue F**

**Figure 3: The distribution of the anchor devices between available APs in the venues.**

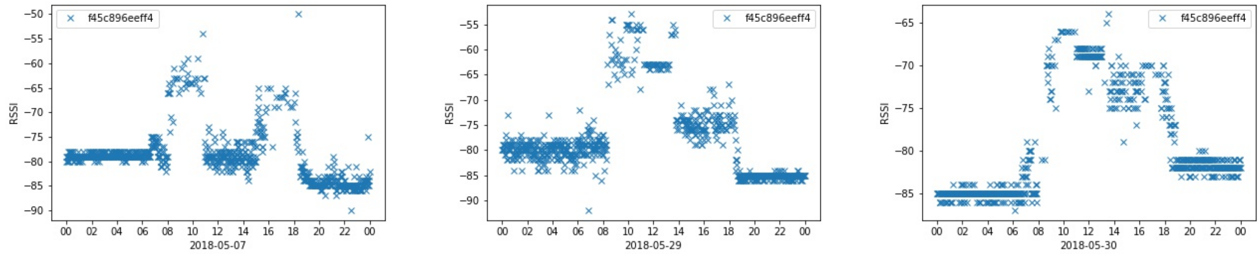
have a much lower number of available anchors in comparison with the rest of the APs. By comparison, in Figure 3f there are some APs that show an higher anchors availability then the rest. The rest of the venues with low number of APs show a more uniform distribution of anchors. The heterogeneity of the APs distribution can correlate with the size of the venues. When the size of the venue is relatively small the available APs cover the most important zones. Instead in case of big size venue and high number of APs its distribution can be less uniform. Some APs can be placed behind obstacle or in less popular spots of the commercial venue.

## Signal strength versus number of probes

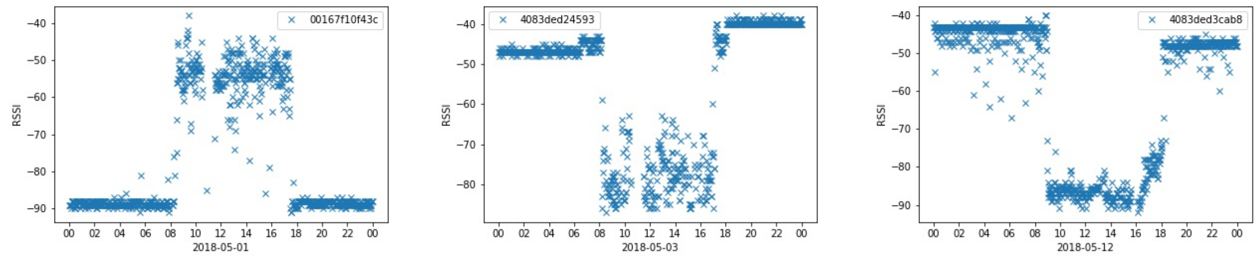
In order to evaluate the impact of clients fluctuation on the transmitter-receiver propagation channel we have evaluated the RSSI changes during the day for some venues/APs/anchors(Figure 4). The Figure 4 shows some randomly selected days and APs for the evaluation. For the sake of presentation we selected the anchors with the higher number of available probes during the day.

The results show that the anchor candidates, as expected, have a relatively stable RSSI for the closing hours of the venue and show an high deviation during the venue opening hours. The difference in RSSI measured in closing and opening hours is higher than 50% and goes more than 60% in some cases (Figure 4h) The RSSI measured on the APs reacts on the changes in the propagation channel, for example due to the clients presences. This is important to notice since our approach is based on this assumption.

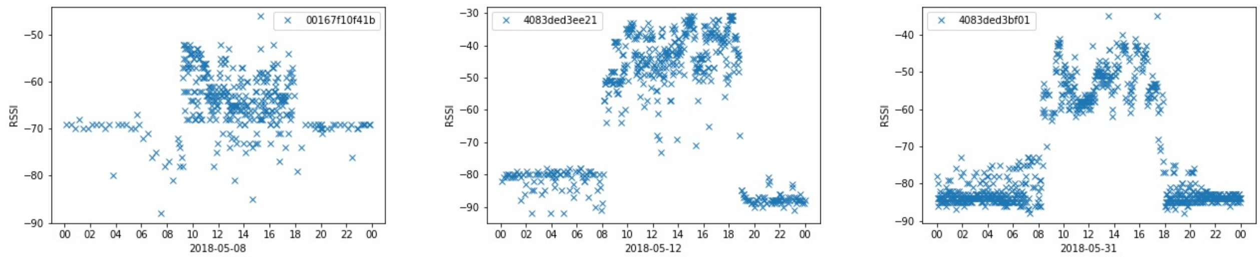
Figure 5 shows the statistic for number of incoming probes to different APs. The APs on the figures are the same as the ones presented on the Figure 4. This choice is done for easing




(a) Venue A. AP 88:15:44:bc:63:50 (b) Venue A. AP 88:15:44:bc:63:50 (c) Venue A. AP 88:15:44:bc:63:50




(d) Venue B. AP 88:15:44:a9:0a:85 (e) Venue B. AP 88:15:44:a9:0a:85 (f) Venue B. AP 88:15:44:a9:0a:85




(g) Venue D. AP 0c:8d:db:93:18:9b (h) Venue D. AP 0c:8d:db:93:27:82 (i) Venue D. AP 0c:8d:db:93:26:d4

**Figure 4: Signal strength RSSI of anchors versus number of probes per AP.** 24 **hours statistics.**

the comparison between the statistics for the same date and AP. In fact by comparing both sets of figures we can see that the variation of RSSI measured for anchors on the AP (Figure 3) correlates with the variation of the number of incoming probes to this AP.

This is especially noticeable when compared Figures 4a,4b,4c with the corresponding Figures 5a,5b,5c. The shape of the RSSI variation is following the shape of the incoming probes to the same AP. An high number incoming probes to the AP indirectly indicates an increase of the number of clients in the area. In turn, an high number of clients in the area increases the probability that some of them are positioned between the transmitter and receiver devices, which leads to the variation of the incoming RSSI.

## 6 CONCLUSION AND FUTURE WORK

In this work we propose an algorithm for dynamic adjustment of RSSI measured on APs. The proposed approach is based on two steps. The first step selects the anchor devices, that are used as a reference point for RSSI. The second step is an actual dynamic adjustment of measured RSSI values of mobile devices. We have evaluated 2.4 GBs of textual data representing a month (May 2018) of raw data from 6 different locations in Italy. This dataset has been collected by *Cloud4Wi* company. The analysis of this dataset shows the availability of anchor devices in all considered locations. The presence of anchor devices is homogeneous for most of the available APs. The results of data evaluation confirm that the anchor devices present a low deviation for RSSI in closed venue hours and an high deviation in opening hours. This confirms the impact the people fluctuation does on the propagation channel properties.

This work is our first attempt for the dynamic adjustment of RSSI measures in fully uncontrolled environment in case of WLAN based localization. The described evaluation is based on the empirically derived parameters. These parameters are subject for deeper evaluation and studies in the future work.

As future work, we plan to deploy a controlled test environment where we can evaluate the described approach and test the possible variation for the parameters. We also plan to evaluate the possibility to introduce the additional small devices that could interact with available APs. We expect such kind of devices could significantly increase the effectiveness of the proposed approach and also can be important in case of lack of available anchor candidates.

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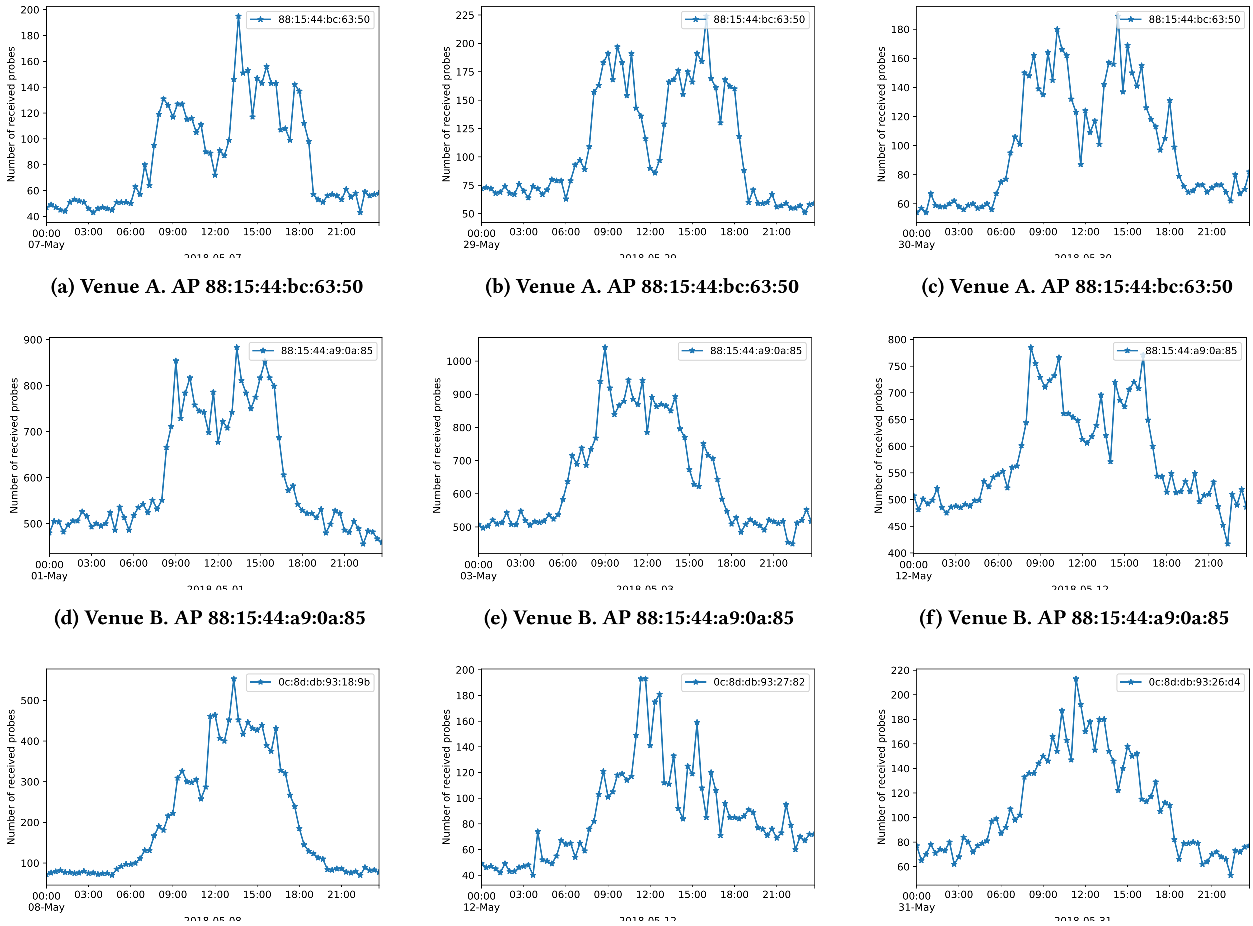


**(a) Venue A. AP 88:15:44:bc:63:50**

**(b) Venue A. AP 88:15:44:bc:63:50**

**(c) Venue A. AP 88:15:44:bc:63:50**

**(d) Venue B. AP 88:15:44:a9:0a:85**

**(e) Venue B. AP 88:15:44:a9:0a:85**

**(f) Venue B. AP 88:15:44:a9:0a:85**

**(g) Venue D. AP 0c:8d:db:93:18:9b**

**(h) Venue D. AP 0c:8d:db:93:27:82**

**(i) Venue D. AP 0c:8d:db:93:26:d4**

**Figure 5: Number of received probes per AP.** 24 **hours statistics.**

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