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A selective neighbour channels in Wi-Fi networks based on adaptive machine learning techniques

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Abstract
Due to the growing commercial exploitation of WiFi-based technologies in recent years and the lack of solutions for effective WiFi orchestration, spectrum utilization and user performance are often sub-optimal. The integration of WiFi-based radio resource management (RRM) and radio environmental maps (REMs) may create a cost-effective Smart-WiFi solution that optimizes underlying spectrum utilisation and network performance. The REM enables effective use of radio environmental data such as device location, estimated channel models, real-time network interference levels, WiFi channel occupancies, and so on. In WiFi-related settings, this information may be used to make intelligent and optimum RRM decisions. This study provides a new REM-based RRM strategy for managing and optimizing commercial WiFi devices that makes use of the underlying radio environmental data. The research uses a commercially available platform to illustrate the suggested solution, which includes on-the-fly radio environmental data gathering and optimal WiFi RRM allocation. In comparison to traditional WiFi networks, the simulation study findings reveal that the proposed Smart-WiFi leverages considerable performance advantages for large-scale situations.

Keywords: Radio environmental maps (REMs) · Smart-WiFi · Prototype platform · Radio resource management (RRM)

1. Introduction
Because of its ubiquitous vision for any time and everywhere access, wireless devices, apps, and services are attracting greater attention. This raises major issues for spectrum management in wireless networks, necessitating the acquisition of more frequency resources and/or more efficient use of existing spectrum resources. Radio environment maps (REMs) have lately become one of the most extensively researched tools for realizing that aim. REMs are increasingly seen as databases or knowledge bases that store a range of radio environmental data [1, 4]. This data includes everything from raw spectrum/signal measurements taken by wireless devices to transmitter and receiver locations, propagation models, and various spatiotemporal statistics on spectrum usage.

WiFi networking has made major inroads into the ICT business in recent years. In comparison to Ethernet and cellular-based systems combined, WiFi installations now transfer larger data volumes from and to consumers [5]. The huge WiFi exploitations are due to its communication in unlicensed bands, which also allows for the continual and quick invention of WiFi technology and services. However, due to uncoordinated operation and unmanaged inter-network interference between different WiFi installations, WiFi technology penetration results in overcrowding and congestion of the unlicensed bands. The use of optimum WiFi-based Radio Resource Management (RRM) or the provision of additional unlicensed bands for WiFi transmission are required to solve this issue. Because spectrum is a scarce resource, the latter is an infeasible and unsustainable approach.

Each REM design's major goal is to accurately analyze the spectrum occupancy before identifying underused Spatio-temporal and spectrum regions as potential spectrum possibilities. In terms of spectrum opportunity identification, the research community has identified two viable strategies: sensing-based and database-based techniques. Database-based approaches need terminals reporting their geolocation to a centralized server (database), which may then deliver the available spectrum information as a response. This is a network-centric strategy in which the centralized server does all REM and RRM-based computations, and the inferred information is transmitted to the network's various entities (such as secondary spectrum devices). Under various conditions, both REM construction strategies have distinct benefits and drawbacks. The sensing-based technique is more versatile since it delivers real-time spectrum information even with low-cost market equipment (when properly calibrated), allowing for the monitoring of the radio environment's dynamism. Since most market-available wireless terminals can do spectrum sensing intrinsically, i.e. they give the ability to at least measure received signal strength (RSS) values, this is a realistic, readily adaptable, and scalable technique. In more static contexts, the database-based method might be employed (such as TV white spaces [4, 5]. Implementation Specifications

Figures 1 and 2 show screenshots of the created Smart-WiFi prototype's REM functions, namely the RIFs and transmitter localization page and the propagation model estimate tab of the Web application, respectively. The black circles in Fig. 1 denote the positions of the spectrum sensors (MCD devices), the heat map depicts the current level of the radio interference field at a specific channel (in this case, WiFi channel 1), and the marker "x" denotes the current and on-the-fly localization of a transmitter operating on the underlying channel. Figure 2 depicts two graphs depicting propagation model estimates for a specific channel of interest, one current (left plot) and the other historical (right plot) (the right one).

Figure 3 illustrates the WiFi monitoring and configuration tab, where a web user may choose a device and configure it as an AP or a station using the GUI.

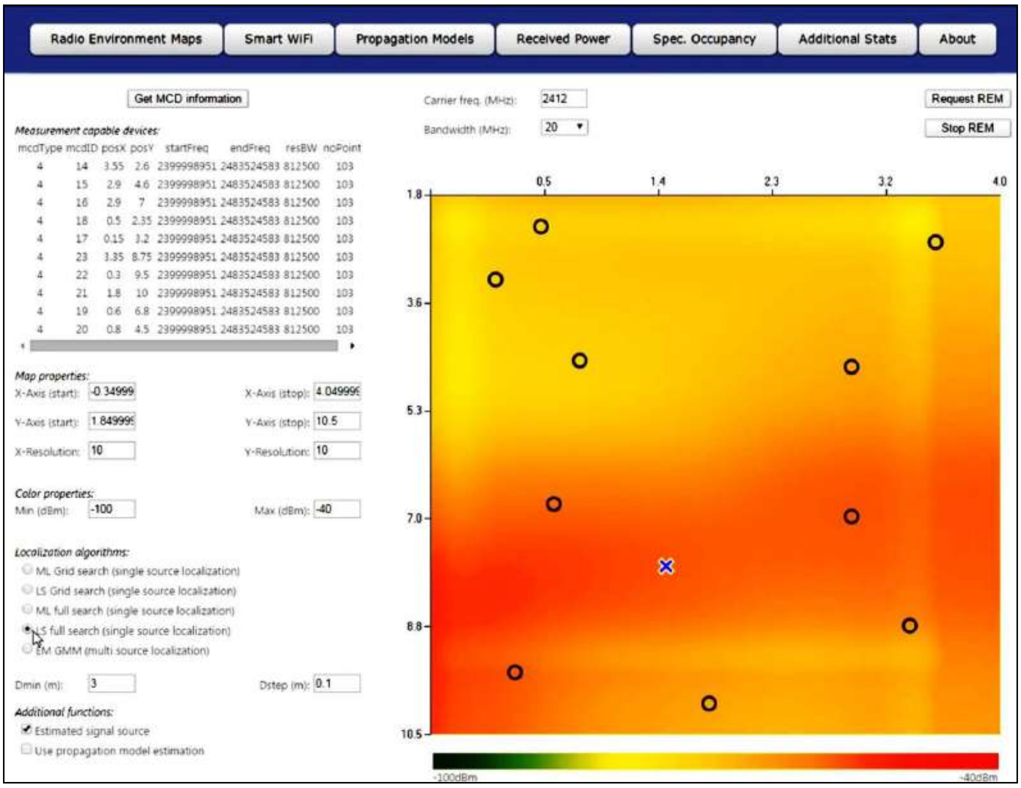


Fig 1: RIFs and transmitter localization tab of the web application

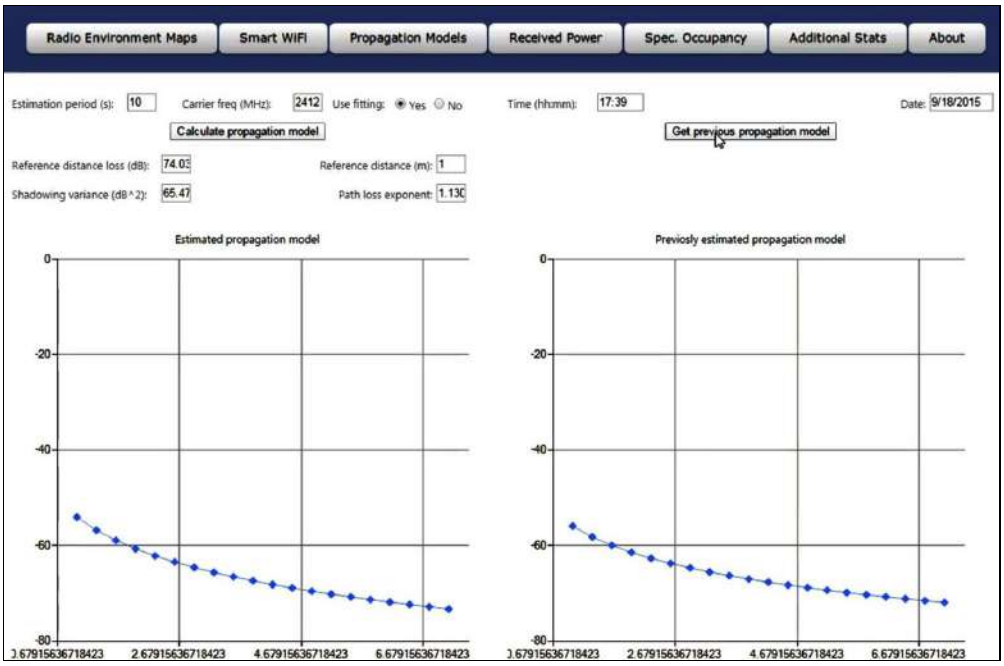


Fig 2: Propagation model estimation tab of the web application

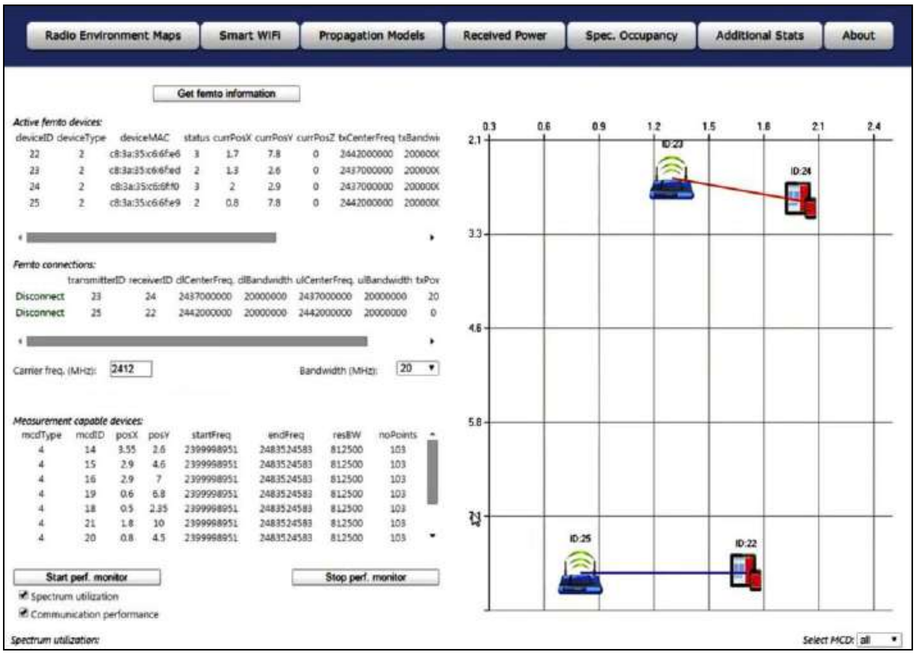


Fig 3: WiFi monitoring and configuration tab of the web application

1. REM-Based SmartWiFi Radio Resource Management

As previously elaborated, WiFi can significantly benefit from a REM-based RRM, because of the lack of solutions capable to orchestrate an efficient deployment and operation of the WiFi networks. The section introduces a novel RRM algorithm that utilizes the REM based features and is particularly designed for optimal WiFi performance.

2. Materials and Method

2.1 RRM algorithm

The presented RRM algorithm strives to maximize the aggregate WiFi throughput based on estimation and calculation of the Signal to Interference plus Noise Ratio (SINR). This process is performed by allocating to every active WiFi network (i.e. WiFi-AP), the optimal physical layer parameters:

$$\max_{f_c W, P_i} \sum_{i=1}^{N} W \log_s (1 + SINR_i) \qquad (1)$$

where $SINR_i$ represents the SINR in the ith WiFi network, P_i represents the transmit power of the ith AP, f_c represents the allocated channel's central frequency, W represents the allocated WiFi channel bandwidth (either 40 or 20 MHz), and N represents the number of active WiFi networks. Specifically, the bandwidth allocation feature is only available when controlling IEEE 802.11n, and/or IEEE 802.11ac networks, as the only standards capable of bandwidth aggregation. When managing the IEEE 802.11b and IEEE 802.11g networks, the bandwidth will be fixed to 20 MHz. To achieve the optimal resource allocation, based on the optimization process in Eq. (1), the proposed RRM exploits one of the possible two resource allocation strategies.

Strategy 1 The RRM allocates the active WiFi APs, to separate and non-overlapping channels. As a result of the induced channel i.e. frequency orthogonality, each WiFi AP can exploit the highest transmit power. This strategy has lower computational complexity, compared to Strategy 2. However, it can be utilized only in scenarios where there is either only a small number of active WiFi APs or/and notable spectrum under-utilization.

Strategy 2 In scenarios where the spectrum utilization is high and it changes frequently and/or in scenarios with a high number of active WiFi APs, Strategy 1 is not able to leverage the optimal solution from Eq. (1), as a result of the lack of free WiFi channels. Consequently, the REM-based RRM allocates the active WiFi networks to overlapping channels. This interference can be alleviated by utilizing a power optimization algorithm capable of leveraging the highest aggregate throughput [2, 6].

$$\max_{P} \sum_{i=1}^{M} W \log_2 \left(1 + \frac{g_i P_i}{\sum_{j=1, i \neq j}^{M} g_{i,j} P_j} \right) \qquad (2)$$

where M denotes the number of WiFi APs that are overlapping, g_i denotes the channel gain

between the ith AP and WiFi station, P denotes the transmission power of the ith WiFi AP. The parameter $g_{i;j}$ represents the channel gain between the jth WiFi AP and the ith WiFi station and P_j represents the transmission power of the jth WiFi AP. For optimal decision making, the presented RRM requires a priori all channel gains i.e. g_i $g_{i;j}$. In practical deployments, it is very demanding to estimate the channel gains. However, for the Smart-

The relevant radio environmental information may be retrieved from the REM backend using the channel estimate capability in the WiFi scenario.

The REM backend monitors and provides available WiFi channels using models that reflect past channel occupancy and collaborative spectrum sensing for both Strategy 1 and 2. Before making a resource allocation decision, the RRM consults the REM backend for a list of free WiFi channels that have been underutilized for a certain period. Consider a situation in which a group of Smart-WiFi APs use the same WiFi channel, with uncontrolled irregular broadcasts. The duration of the timeframe may have a big influence on the system's overall performance. For example, extremely small timespans may cause the ping-pong effect to reappear, but very lengthy timespans might mark an unused channel as unavailable, lowering overall system efficiency.

2.2 PHY Layer Reconfiguration Algorithm

Concerning two separate triggering use scenarios, the RRM conducts resource allocation as well as physical layer configuration/reconfiguration. In the first use scenario, the triggering occurs when a certain WiFi AP becomes operational. In the second use scenario, the triggering occurs when the communication performance of some of the active WiFi APs deteriorates. By setting thresholds for a collection of communication-related measures, it is possible to detect deterioration in communication performance (like delay, jitter, throughput, FER, etc.). The WiFi AP will notify the RRM when one of the monitored communication parameters exceeds the associated threshold. This will result in a new way of making decisions and allocating resources. The most typical cause of performance deterioration is a change in the communication channel as a consequence of introduced interferers (e.g. irregular uncoordinated transmissions) or changes in the propagation medium (e.g. the appearance of new obstacles).

Algorithm 1 PHY reconfiguration algorithm (NBW40 number of non-overlapping 40MHz spectrum parts)

STEP 1: Trigger occurrence
if NBW40 ≥ N then
Utilize Strategy 1 for 40MHz channels
Else
Calculate the sum throughput for Strategy 1 and 20MHz channel → C1
Calculate the sum throughput for Strategy 2 and 40MHz channel → C2
Go to STEP 2
STEP 2: Find optimal strategy
if C1 ≥ C2 then
Utilize Strategy 1 for 20MHz channels
else
Utilize Strategy 2 for 40MHz channels

2.3 Resource Allocation Strategy

Stemming from the elaborations in the previous section, Fig. 4 presents four conventional examples of the resource allocation and the physical layer reconfiguration, either as a result of the performance degradation or appearance of a new WiFi AP (i.e. new WiFI pair).

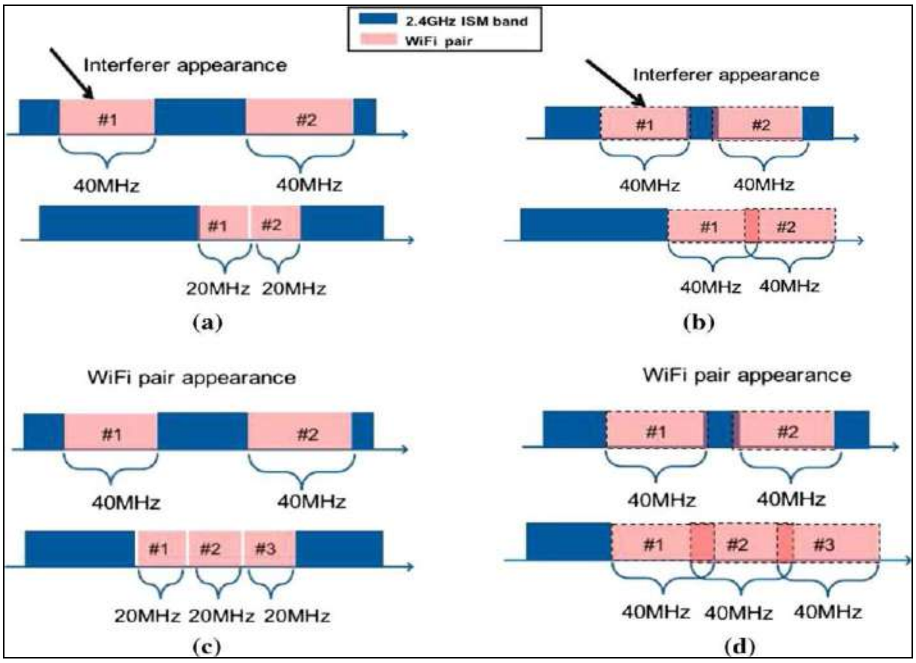
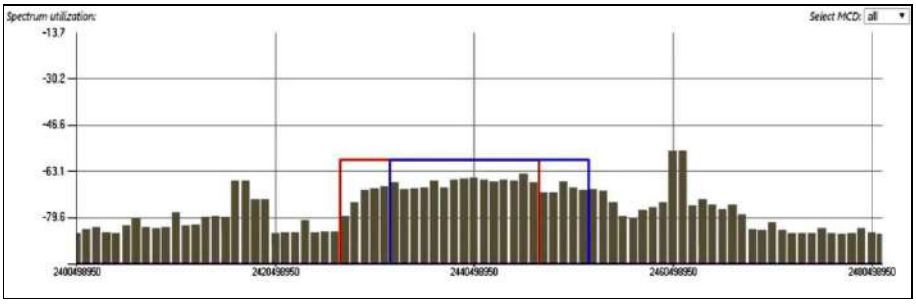


Fig 4.

3.0 Result and Discussion

This section analyzes the performance gains of the Smart-WiFi for large scale scenarios through simulations. The main goal of the analysis is to scrutinize the scalability behaviour of the Smart-WiFi. The section compares the Smart-WiFi to *conventional WiFi* systems and to WiFi systems that can assign APs to less occupied channels based on instantaneous *WiFi channel sensing*



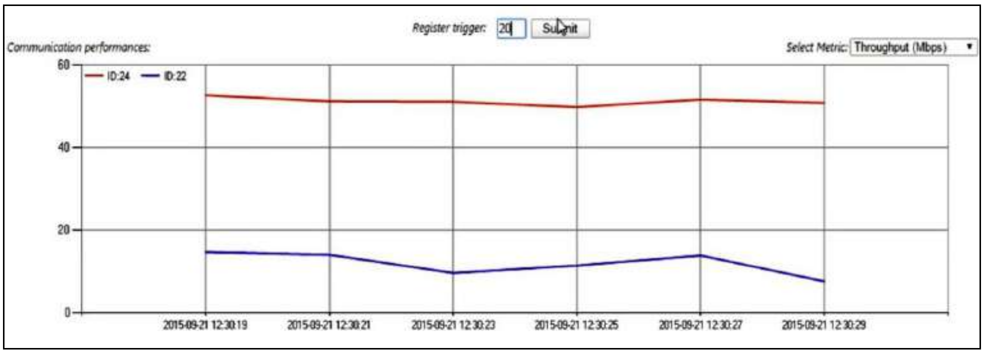


Fig 5: WiFi networks operating with power control and communicating on overlapping channels

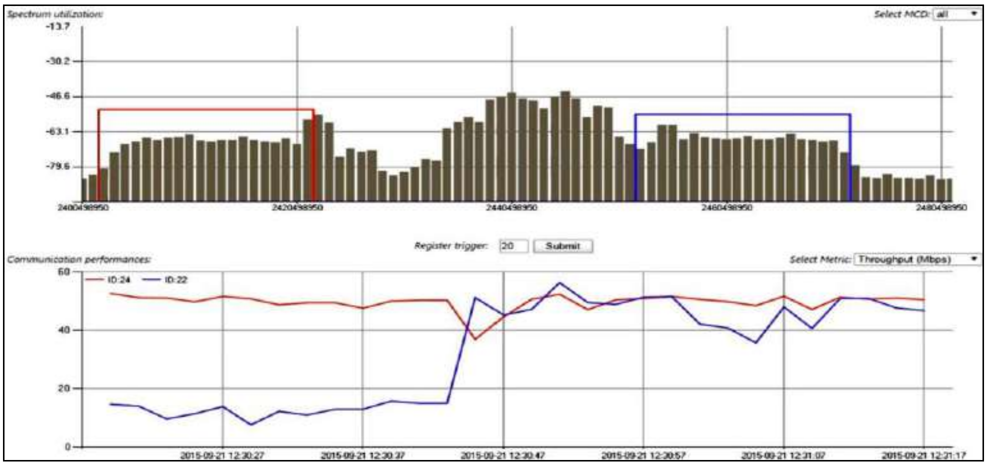


Fig 6: WiFi networks operating with maximal power on non-overlapping channels

The *conventional WiFi* systems cannot identify the less occupied channels. In this case, the APS are preset to a given channel irrespective of the underlying channel activity and utilization. For the simulation analysis the channel allocation of the conventional WiFi is modelled as a normal distribution:

$$\Xi = N(\mu, \sigma^2) \tag{3}$$

where N denotes the WiFi channel index, l denotes the mean of the distribution and r is the standard deviation. The normal distribution resembles the real world WiFi channel allocation behaviour, where each AP is allocated to a given channel on a random basis. Additionally, most of the APS gravitate around a specific channel due to the default factory settings that are left unchanged by the end-users. The mean and variance in Eq. (3) are specifically chosen to reflect a real-world scenario where the APs can randomly occupy one of the thirteen WiFi channels. However, most of the APS will use the sixth channel, as the default off the shelf set.

The WiFi system that exploits the *WiFi channel sensing*, is modelled to allocate every new AP to the least utilized and occupied WiFi channel based on the sensing measurements conducted when the new AP appears online. If all channels are equally occupied, the AP is allocated to a channel on a random basis:

$$\Xi = U(a, b), \tag{4}$$

where; denotes the discrete uniform random distribution, and *a* and *b* denote the minimal and maximal channel indexes. Compared to the Smart-WiFi, this approach does not take into consideration the historical data for the channel utilization, nor does it provide coordination between the APs to optimize the system throughput.

The simulation analysis is performed concerning the achieved system throughput and the throughput gain. The achieved system throughput is calculated as:

$$R_{\sum} = \sum_{i=1}^{N} R_i \tag{5}$$

where N denotes the number of APs in the system, and R_i denotes the achieved throughput of the *i-th* AP. The throughput gain is a metric that quantifies the advantages of the Smart- WiFi compared to the conventional WiFi and WiFi channel sensing. The throughput gain for N active APs is calculated as:

$$T_g^N = \frac{\frac{1}{N}\sum_{i=1}^{N} R_i^{sw}}{\frac{1}{N}\sum_{i=1}^{N} R_j} - 1 \tag{6}$$

where R^{sw} denotes the achieved throughput of the *i-th* AP when using Smart-WiFi, and R_i denotes the achieved throughput of the *i*-th AP when using either the conventional WiFi or the WiFi channel sensing.

Table 1 presents the simulation parameters and their values. The total throughput for all of the techniques is shown in Figure 8. The chart illustrates that Smart-WiFi delivers the best results, whereas the traditional WiFi channel selection strategy delivers the lowest results. In real-world circumstances, WiFi is unlikely to be implemented in an extremely dense configuration with hundreds of APs spatially and temporally colocated. A more plausible scenario would have a far smaller number of AP, maybe in the tens [7]. For various SNR levels, Figure 8 shows the throughput increase of Smart-WiFi over channel sensing and traditional WiFi techniques. The throughput gain presented in the

Table 1: Simulation setup

Simulation parameters	Parameter value
No. of Channels	13
No. of APs (N)	1:100
Channel bandwidth	20 MHz
Channel aggregation	None
Antenna configuration	SISO
SNR	10:10:30 dB
l	6
r	2
a	1
b	13

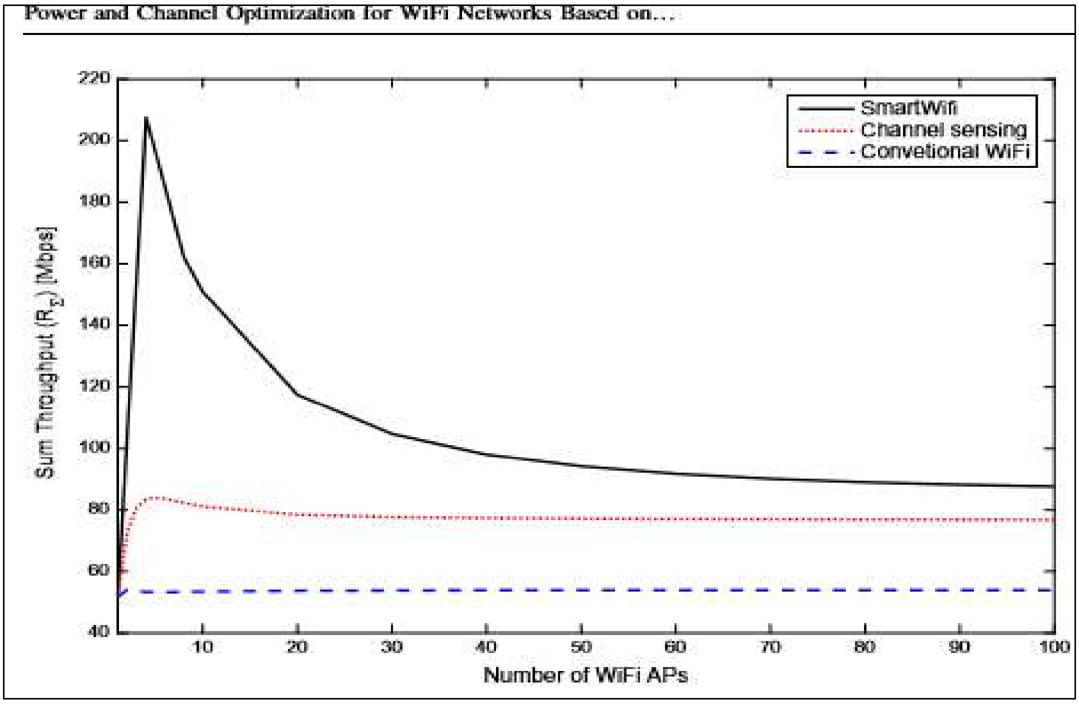


Fig 7: Sum Throughput for Smart-Wifi, WiFi channel sensing and conventional WiFi (SNR = 10 dB)

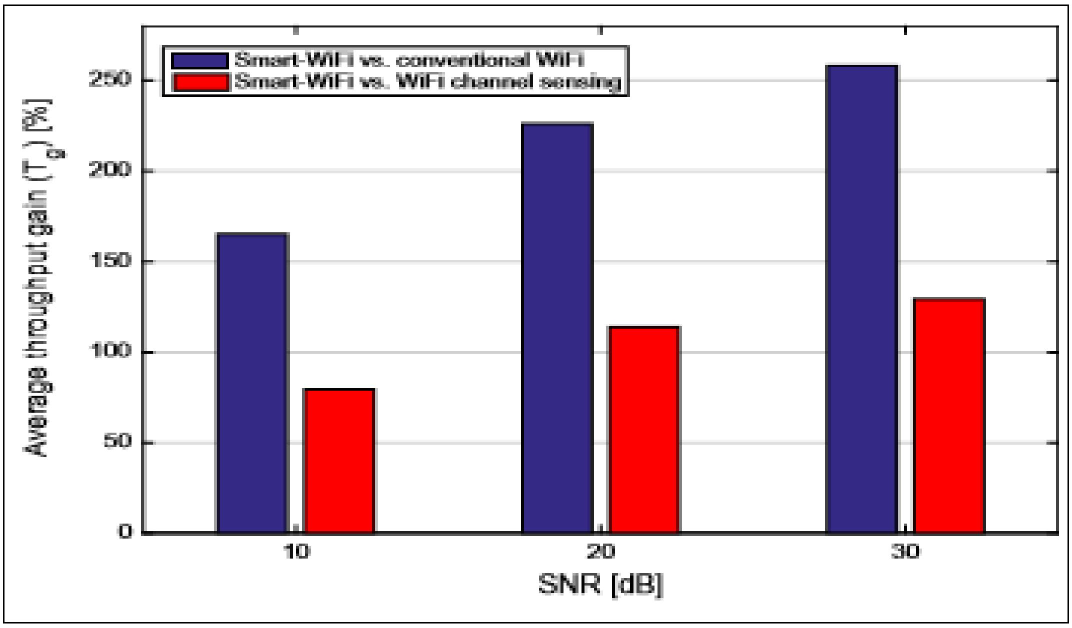


Fig. 8: Throughput gain of Smart-Wifi versus conventional WiFi and WiFi channel sensing (*N* ¼ 20)

the figure presents the average gain that the Smart-WiFi achieves over a span different number of active APs and it is calculated as:

$$T_g = \frac{1}{N}\sum_{i=1}^{N} T_g^i \qquad (7)$$

Figure 8 indicates that when compared to traditional WiFi and channel sensing techniques, Smart-WiFi produces a significant throughput boost. It is also clear that at larger SNR values, the achieved throughput increase is bigger. Greater SNR values may arise in real-world circumstances owing to a denser network, i.e. a network with WiFi stations closer to the AP, or networks capable of broadcasting with higher transmit strengths.

4. Conclusion

For successful WiFi administration, the overcrowded unlicensed bands need more nimble and efficient solutions. This research described an RRM architecture and prototype based on REM that can control and monitor active WiFi devices. The Smart-WiFi prototype on display uses a unique REM backend technology to manage the best possible connectivity between commercially accessible and off-the-shelf WiFi devices. The validation findings presented in the research demonstrate the prototype's usefulness in the context of intelligent and optimum WiFi network communication management. Furthermore, the simulation study findings show that, when compared to traditional WiFi deployment, the suggested method may give considerable performance advantages, even in large-scale settings. Future research will concentrate on developing a more holistic RRM algorithm that takes additional communication characteristics into account in the optimization loop, such as latency, packet loss, and so on. It will also expand the practical implementation and experimental validation into a larger-scale testbed employing commercial WiFi devices to demonstrate the advantages of Smart-WiFi in real-world circumstances.

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