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# RADIOFREQUENCY TRENDS AWARE DYNAMIC BANDWIDTH SELECTION

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## RADIOFREQUENCY TRENDS AWARE DYNAMIC BANDWIDTH SELECTION

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### ABSTRACT

The current Dynamic Bandwidth Selection (DBS) algorithm only uses a snapshot of client metrics to make bandwidth recommendations for the remainder of the day. According to the present techniques, machine learning (ML) may be used to track/predict bias factors for DBS throughout the day.

### DETAILED DESCRIPTION

With 802.11ac, the IEEE introduced several new wide bandwidth modes, namely operation at 80 MHz, 160 MHz, and 80+80 MHz. Additionally, the 802.11ac standard also allows an access point (AP) to switch from these new modes to one of the existing narrower 20 MHz/40 MHz bandwidths. This is particularly useful for networks that have "brown field" deployments with legacy APs and/or clients. The exact conditions for when the AP should switch are not specified in the standard, and thus, this aspect is open for innovation.

Radio Resource Management (RRM) allows Unified WLAN architecture to continuously analyze the existing radio frequency (RF) environments, automatically adjusting each APs' power and channel configurations to help mitigate unfavorable effects such as cochannel interference and signal coverage problems. DBS is part of the RRM protocol and is designed to handle switches between channel bandwidths in 802.11ac radios. Given that both device types as well as the nature of their respective traffic changes over time, there is a need for a self-learning DBS that can optimize the bandwidth best suitable for the radio based on network conditions, RF environments, and capacity demands in the wireless network.

The DBS algorithm was conceptualized to be a flexible technique that would allow RRM to optimize bandwidth to APs in order to maximize radio capacity while minimizing co-channel contention in a high density RF environment. DBS is based on analysis of the client capabilities, whether the client uses voice/video or data, and number of clients present and amount of traffic generated by such clients. Here, a novel ML method is provided that seeks to optimize the radio's bandwidth based on network conditions, RF environments, and capacity demands in the wireless network at any given time of the day.

ML is a branch of artificial intelligence that employs a variety of statistical, probabilistic, and optimization techniques that allow computers to "learn" from past examples and to detect hard-to-discern patterns from large, noisy, or complex data sets. It is typically used to facilitate pattern recognition, classification, and prediction, based on models derived from existing data. Here, ML is leveraged to build a fast and accurate model that can perceive patterns in historical RF trends. The resulting ML model may be used to predict RF environments and capacity demands in a wireless network based on which DBS can proactively optimize a radio's bandwidth.

According to present techniques, a database of historical RF trends is built for a given radio. For every radio, features or predictor variables such as band, channel number, location, neighbor information, utilization, noise floor, interference, DCA metrics, client capabilities, client traffic, weather at the location, scheduled events, timestamp, etc. are extracted and recorded in the database. A subset of the RF trends data is used to train the ML model, conduct "goodness-of-fit" tests to fine tune the model as well as validate its accuracy on data not used for calibration. To enable the model to forecast RF trends for any given radio, a Wireless LAN Controller (WLC) can group together the necessary predictor variables to form a vector which can then be used to query for predictions. The resulting predictions are then used by RRM on WLC to assign an optimal bandwidth to the radio. FIG. 1 depicts the overall architecture for the ML based bandwidth optimization. Based on the historical RF trends, two primary factors influencing optimal bandwidth for the radio are isolated:

- RF Density: Inter-AP RF distances are represented between the adjacent nodes and basically represent their proximity. Higher RF Density would ideally lower the optimal bandwidth for a given radio.

- **Station Capacity Requirements:** Station capacity typically requires higher bandwidth operation on the radio. Higher channel width offers more spectrum for associated clients which ultimately results in an increase in overall throughput and performance.

As both of the aforementioned parameters provide contradictory bandwidth assessments, the ML model analyzes historical trends on these data sets to identify bias factors to guide optimal bandwidth for a given set of radios in an RF neighborhood.

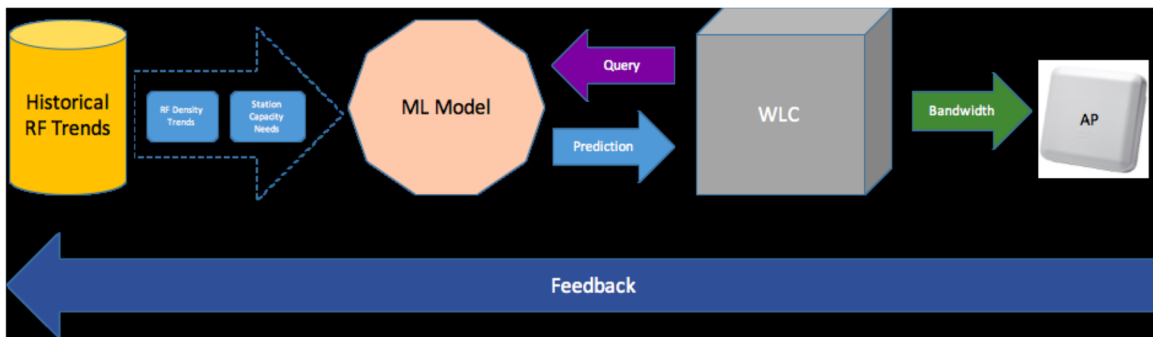


FIG. 1

In summary, ML may be used to track/predict bias factors for DBS in order to improve bandwidth recommendations made throughout the day.