ML-Optimized Beam-based Radio Coverage Processing in IEEE 802.11 WLAN Networks

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***Abstract*— Dynamic Radio Resource Management (RRM) is a major building block of Wireless LAN Controllers (WLC) function in WLAN networks. In a dense and frequently changing WLANs, it maximizes Wireless Devices (WD) opportunity to transmit and guarantees conformance to the design Service Level Agreement (SLA). To achieve this performance, a WLC processes and applies a network-wide optimized radio plan based on data from access points (AP) and upper-layer application services. This coverage processing requires a "realistic" modelization approach of the radio environment and a quick adaptation to frequent changes. In this paper, we build on our Beam-based approach to radio coverage modelization. We propose a new Machine Learning Regression (MLR)-based optimization and compare it to our NURBS-based solution performance, as an alternative. We show that both solutions have very comparable processing times. Nevertheless, our MLR-based solution represents a more significant prediction accuracy enhancement than its alternative.**

Keywords—Radio Resource Management, Beamforming, Co-channel interference, Machine Learning, NURBS surface, WLAN.

I. Introduction

Co-channel interference is one major issue that dense indoor WLAN networks face. To reduce its impact many strategies are adopted: centralized or distributed intelligence processing and decision making, dynamic RRM (dRRM) among others.

The centralized or distributed intelligence processing and decision making ensures that a reliable intelligence is gathered, from APs and new generation WDs, for decision making and that this decision is coherent network wide.

Dynamic RRM is a set of features and techniques that enable the central or distributed WLC optimize the radio resource plan, adapt quickly to radio environment changes, and trigger necessary healing actions to mitigate network issues. Additionally, dynamic RRM optimizes the network capacity by processing effectively new transmission opportunities. It accepts inputs from radio interface (RSSI, SNR, EIRP, noise, etc.), upper application service layers (MAC layer, TCP/IP, etc.), on-field site surveys: passive or active, and design recommendations: standard or per-vendor specifications.

The implementation of dynamic RRM requires deep and feasible approaches to represent and model the network radio coverage. In work [1] and its extension [2], we discuss different coverage representations and evaluate the corresponding solution models' performance.

The processing of the huge amount of raw data that is input to dRRM requires important network and system resources: sufficient bandwidth, control traffic prioritization in the network, sufficient CPU and RAM to handle intensive computing, and sufficient disk space to store the data and results. In work [3], we present a processing optimized solution of dRRM and discuss its advantages over the previous ones.

Motivated by the advances in machine learning and wide use of its concepts [4], [5], [6] and [7], we investigate in this work how could regression models enhance further our dRRM solution.

In section II, we discuss our Beam-based radio coverage representation of a Wi-Fi Unified Architecture (WUA) which is WLC-based and some important machine learning concepts that are the foundation of this work study. In section III, we compare two Beam-based solution models and show how they could be enhanced thanks to a NURBS-based optimization [3]. In section IV, we discuss an MLR-based alternative to our NURBS-based optimization. In the end, we conclude and further our work.

II. Theoretical Background and Related Work

In this section we recall some important concepts about WUA, discuss our Beam-based radio coverage representation, dRRM solution models, and scope important machine learning concepts that are the foundation of this optimization work.

A. Wifi Unified Architecture

In standalone AP deployments, dense indoor network capacity does not scale with frequent radio environment changes, number, mobility requirement, and application need of clients. A WLC is required to centralize AP intelligence and build a unified real-time vision of the entire coverage transmit opportunity. This opportunity processing builds on design recommendations, data from the radio interface and upper-layer application services. Some examples of these controllers are: Cisco 8540 Wireless Controller [8] and Aruba 7280 Mobility Controller.

Cisco WUA defines two protocols for the radio raw data exchange between the APs and WLC, on the wired interface, and between the APs themselves, over the air:

- CAPWAP: stands for Control and Provisioning of Wireless Access Points and is used by APs to build a protocol association to a WLC.
- NDP: is the Neighbor Discovery Protocol, it enables the APs to send Over-The-Air (OTA) messages and exchange standard and proprietary control and management information.

In addition to the basic RRM functionality that is described in [9], Cisco APs embark an on-chip RRM advanced feature: CLEANAIR. CLEANAIR, such a Wi-Fi engineer, monitors and measures environment real-time radio characteristics: SNR, interference, noise, etc. and reported them back to the WLC via the already established CAPWAP tunnels. Cisco appliances such as: Cisco Prime Infrastructure (CPI) or Mobility Services Engine (MSE), may extend this feature capability to analytics on Wi-Fi clients' presence, interferers management and heatmaps generation.

Cisco RRM implementation is well discussed in [10]. The idea is to trigger a new RRM Transmit Power Control (TPC) processing when the third neighbor RSSI is stronger than -70dBm and that the current transmit hysteresis is greater than the configured threshold which is by default equal to 6dB. This processing allows an AP to tune its transmit power level to reduce the co-channel interference that the neighboring APs may cause and consequently, eventually, maximize the transmit opportunity toward and from a WD.

But taken alone, it is hard to see how such implementation could hint on the opportunity to transmit at any given coverage point except from the APs? In the next sub-section, we motivate the need for a coverage representation approach and solution model to process this opportunity at every coverage area point.

B. *Beam-based modelization approach of radio coverage*

In a WLC-based WLAN network it is not possible to monitor every coverage area point and report the corresponding measures. Only a set of WDs have this ability: APs and certain Wi-Fi clients with extended capabilities such as Cisco Connected Mobile Experiences (CMX).

It is necessary then, to model the radio coverage and predict the corresponding measures based only on the enabled WDs. In [1] and [2] works, we discuss two major modelization approaches families that may be referred to as "simplistic", Range-based, and "idealistic", Voronoi-based.

The first approach supposes that an AP's coverage corresponds to one of these three ranges: a transmission, interference or no-talk range; that the pattern is omnidirectional in the form of a circle or a disk. In this scheme, the interference at any given point is approximated by the weighted intersection of all the interferers' patterns at this point.

In the second approach, the coverage area is segmented into non-uniform zones in the form of polygons. Each zone corresponds to an AP and its borderlines are proportional to the neighboring APs' transmit power levels. In this scheme, the co-channel interference condition is totally cancelled.

The implementation of the "simplistic" approach is feasible and straightforward, but it has many limitations that burden its performance: non-support of per direction transmit power adjustment, more prone to coverage holes, non-support of obstacle detection, non-support of client localization, and non-support of hidden transmit opportunity detection.

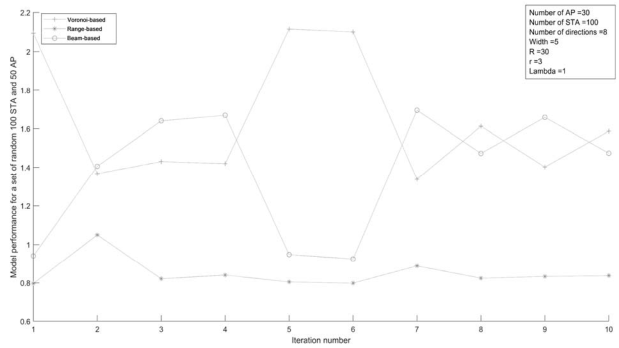

Fig. 1. Voronoi, Range and Beam-based model compared performance

The "idealistic" approach is the most performant, but it is not feasible: how could we achieve any polygon propagation pattern? It may be technologically possible but not economically!

In [1] and [2] works, a "realistic", Beam-based approach is presented that is a generalization of the previous two approaches. In this scheme, the AP coverage is the region covered by the beams in the AP's supported transmit directions. The transmit direction and the corresponding power level are tunable which offer two additional degrees of freedom to mitigate a co-channel interference condition especially in comparison with the "simplistic" approach.

In "Fig. 1", we show a compared performance of the three models: Voronoi-based, Range-based and Beam-based, in processing the coverage of a random set of 30 APs and 100 STAs (mobile Stations).

In this simulation, each AP supports 8 transmit directions, "R" is the corresponding transmit power level, "r" represents the sensitivity of an STA at reception, "lambda" reflects the attenuation of a signal from the source to the receiver and "width" is the aperture that characterizes the beam in each direction.

We check that the Voronoi-based model performs better than both Range and Beam-based models. With a "width" value equal to 5, the Beam-based model performs better than the Range-based model.

We show in "Fig. 2", that by tuning, decreasing, beam aperture ("width" value is equal to 0.1) we could achieve an "idealistic"-like performance. In this simulation, the performance of the Beam-based model is better than both the Voronoi and Range-based models.

In "Fig. 3", we show that by increasing the beam "width" significantly (to a value equal to 10 as an example) we approximate our model performance to a "simplistic"-like model performance. In this simulation, the performance of both Beam and Range-based are very comparable.

In "Fig. 1", "Fig. 2" and "Fig. 3", we show that the Beam-based representation model of the coverage generalizes both the Range and Voronoi-based models by tuning the aperture.

For the rest of this work, we set the "width" value to 2 that represents a "realistic" Beam-based representation model of the coverage.

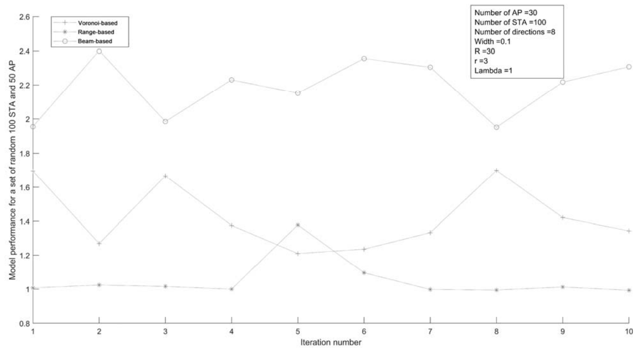

Fig. 2. Near "Idealistic" Beam-based model performance when “width” value is equal to 0.1 unit.

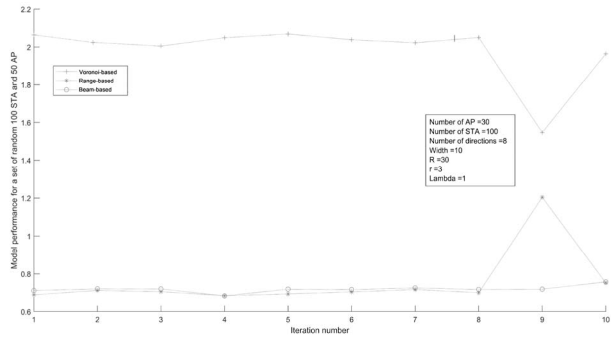

Fig. 3. Near "Simplistic" Beam-based model performance when “width” value is equal to 10 units.

Further, we’ve implemented a per-AP-power-level-adjustment “supervised” variant of our solution, “WLC2”, and proved that it is comparable to a “Cisco”-like implementation that is discussed in detail in [10]. Both “WLC2” and “Cisco” implementation solutions build on the “realistic” Beam-based representation model.

In “Fig. 4”, we show an example of a test distribution of a random set of WDs: 30 APs and 100 STAs. At the initialization, the number of the supported AP transmit directions is equal to 8 and each AP power level is set to 30.

In “Fig. 5” and “Fig. 6”, We show the transmit opportunity processing results of “WLC2” and “Cisco” solutions respectively. In this simulation, we optimize the number of the APs supported directions and power levels. All the APs have the same optimized number of the supported directions which is equal to 16. Each AP power level may be different from an AP to another. “R” is valued at 99 to denote that this variable is AP and model “WLC2” or “Cisco” dependent. The same power level is applied to all the supported transmit directions of a given AP. We check that both “WLC2” and “Cisco” are of equivalent performance with regards to the transmit opportunity processing results.

To enhance the readability of our results, we shortened the simulation variables names in Table [I].

In Table [II], [III], [IV] and [V], we record the test results for five iterations of the same previous simulation by choosing, at each iteration, a random set of WDs: 30 APs and 100 STAs and measuring “simplistic”, “WLC2”, “Cisco” and “idealistic” model performance. The “width” is equal to 0.1 and 10 for “idealistic”, which is tagged as “Dir1”, and “simplistic”, tagged as “Dir3”, models respectively.

We observe that the processing times are equivalent for both “WLC2” and “Cisco”. Even if “Cisco” is more performant, it is more prone to cause coverage holes. “WLC2” measured interference is less than “Cisco” in average.

TABLE I. VARIABLES SHORTENED NAMES

Variable old name	Variable new name
Mean Opportunity (in units)	M.O
Mean Interference (in units)	M.I
Dir. Optimal number	Dir.O
Detected Hole number	H.
Time (seconds)	T.
Relative Processing Time in %	RPT
Performance Score	Perf.
Mean diff to WLC2	M.Diff
Median to WLC2	Med.
Standard deviation To WLC2	Std.

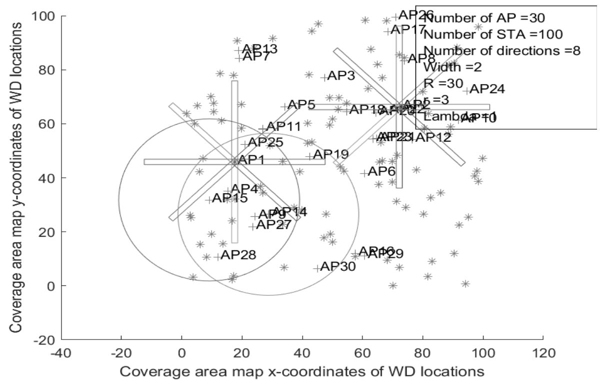

Fig. 4. A distribution example of a random set of WDs: 30 APs and 100 STAs

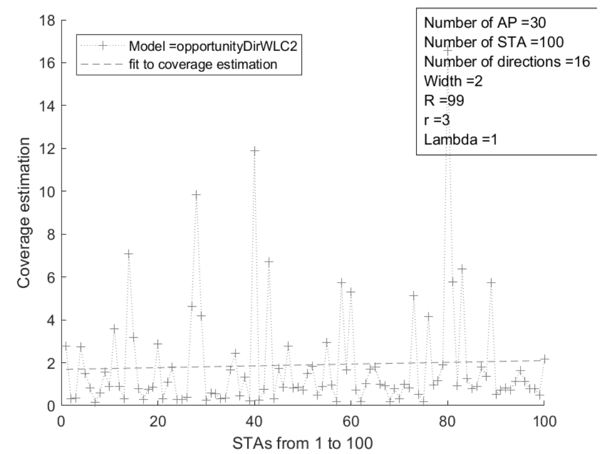

Fig. 5. "WLC2" Beam-based model RRM solution transmit opportunity processing example

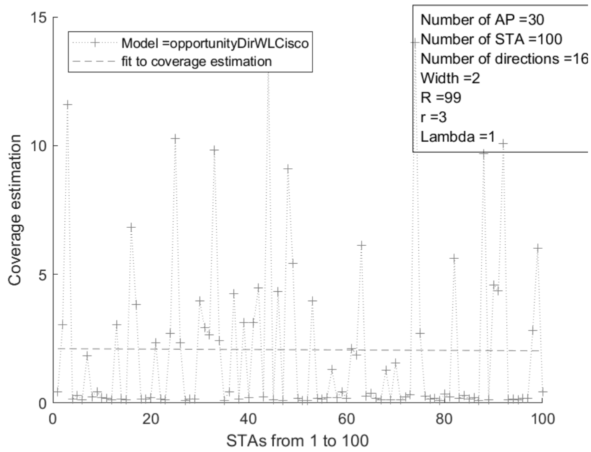

Fig. 6. "Cisco" Beam-based model RRM solution transmit opportunity processing example

TABLE II. BEAM-BASED MODEL PERFORMANCE RESULTS OF "DIR3"

Results: Dir3	**Simulation iteration number Settings: AP=30, STA=100, Width=2, R=30, r=3, lambda=1**				
	1	***2***	***3***	***4***	***5***
M.O	0.5	0.3	0.3	0.35	0.3
M.I	150	155	151	149	160
Dir.O	8	16	16	16	8
H.	0	0	0	0	1
T.	25.3856	25.1481	25.0731	25.0016	27.0775

TABLE III. BEAM-BASED MODEL PERFORMANCE RESULTS OF "DIR1"

Results: Dir1	**Simulation iteration number Settings: AP=30, STA=100, Width=2, R=30, r=3, lambda=1**				
	1	***2***	***3***	***4***	***5***
M.O	2	1.4	1.5	1.4	1.35
M.I	1.5	1.6	1.5	1.4	1.75
Dir.O	8	16	16	16	8
H.	2	5	2	2	3
T.	26.5227	25.2914	25.0289	24.9015	26.1321

TABLE IV. BEAM-BASED MODEL PERFORMANCE RESULTS OF "WLC2"

Results: WLC2	**Simulation iteration number Settings: AP=30, STA=100, Width=2, R=30, r=3, lambda=1**				
	1	***2***	***3***	***4***	***5***
M.O	0.5	0.8	0.4	1	0.5
M.I	40	52	64	60	45
Dir.O	8	16	16	16	8
H.	0	0	0	0	1
T.	82.566	169.5631	209.6245	217.2543	78.6225

TABLE V. BEAM-BASED MODEL PERFORMANCE RESULTS OF "CISCO"

Results: Cisco	**Simulation iteration number Settings: AP=30, STA=100, Width=2, R=30, r=3, lambda=1**				
	1	***2***	***3***	***4***	***5***
M.O	5	1	2.5	4	5
M.I	20	75	58	42	15
Dir.O	8	16	16	16	8
H.	5	0	0	3	8
T.	113.1636	179.8094	242.0869	216.0174	73.0206

For the rest of this work, we consider that "WLC2" model is a "realistic" model representation of a coverage area and could constitute a baseline for further optimizations. In one hand, it was proven that Range-based and Voronoi-based models could be generalized to Beam-based equivalents: "Dir3" and "Dir1". In the other hand, working with "width" value of 2, optimizing the power levels and the number of supported transmit directions as per our solution described in [1], we observe a comparable performance between the "WLC2" variant and the Cisco-like implementation of RRM, "Cisco".

In the next sub-section, we introduce a Machine Learning Regression approach that is aimed at optimizing the processing time of our "WLC2" solution. It may eventually, represent an alternative to our NURBS-based optimization that is detailed in [3].

C. Machine Learning Regression Models

In his book [11], Tom Mitchell describes machine learning in that a computer program, a machine, is said to learn from an experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

A simple form of this learning, focus of this work, is described as "supervised" learning. In this learning, the right answers to some input or training data, are provided in advance. Based on this training data, the inputs and corresponding outputs or "truth", the learning algorithm model parameters are tuned such as to minimize the error between the predicted outputs and the observed "truth".

This "trained" learning, also called hypothesis, is a function, with the previously optimized model parameters, that maps the input variables or features to a predicted outcome.

Supervised learning algorithms could be further classified by the nature of the outcome they work on. If the outcome is continuous then "regression" models are more suitable. For categorical or discrete valued outcomes, "classification" algorithms are more likely.

In our study we work on continuous valued outcomes, then we focus solely on regression models. Many types of regression models exist including: linear regression models (LM), regression trees (Tree), Gaussien process regression models (GPR), support vector machines (SVM), and ensembles of regression trees (Bagged).

To choose between models, we compare their Root Mean Square Error (RMSE) validation score. For all the simulations of our work, we observe that Coarse Gaussian SVM and Bagged Trees come out with the best RMSE scores. For the rest of our study, we focus solely on these two models.

III. PROBLEM DESCRIPTION

Simulation results of both RRM implementations: "WLC2" and "Cisco", were presented in Table [IV] and [V]. For the evaluation of these model performance, we measure the required relative processing time, "RPT", and the performance score, "Perf.", given by this formula:

$$Perf. = K_1 * \frac{\sum Interference}{Interference(model) + 1} +$$

$$K_2 * \frac{\sum Hole}{Hole(model) + 1} + K_3 * \frac{Opportunity(model)}{\sum Opportunity} \quad (1)$$

In Table [VI] and [VII], we summarize these results.

TABLE VI. "WLC2" AND "CISCO" RRM PERFORMANCE AND PROCESSING TIME RESULTS

Results: WLC2 Cisco	Simulation iteration number Settings: AP=30, WD=100, Width=2, R=30, r=3, lambda=1				
	1	*2*	*3*	*4*	*5*
Perf.	12.22 11.86	10.58 9.02	6.31 7.18	9.29 7.71	11.39 16
RPT	33.34 45.69	42.41 44.97	41.77 48.24	44.96 44.70	38.38 35.64

TABLE VII. "DIR3" AND "DIR1" RRM PERFORMANCE RESULTS

Results: Dir3 Dir1	Simulation iteration number Settings: AP=30, STA=100, Width=2, R=30, r=3, lambda=1				
	1	*2*	*3*	*4*	*5*
Perf.	8.46 87.18	6.9 110.31	3.87 110.79	6.73 107.04	7.92 84.08

Results' precision, that measures the gap between the model predicted coverage and the truth, as it might be measured by a specialized equipment such as: Ekahau or AirMagnet, was not considered deeply in this preliminary work. Instead, we consider that the real measure or truth is in between the "simplistic" and "idealistic" measures plots.

Further work may consider processing the raw radio data that is gathered in a laboratory test condition. But as we've shown before, tuning parameters of our Beam-based coverage representation may approximate them accurately. Also, we consider that simulating different implementation solutions based on the same modelization foundation would lead to comparable results in a real implementation of the same models.

The measured performance of both solutions "WLC2" and "Cisco" is equivalent and is almost at 10.156 point in average. We check that this performance is better than the "simplistic" case which is at 6.776 point and that the "idealistic" model performance is outstanding at almost 99.88 point.

The measured processing times of both models "WLC2" and "Cisco" are comparable but represent almost 84% of the total required processing time of all the models. This result indicates that both implementations are not scalable regarding the necessary processing time in comparison with the "idealistic" and "simplistic" models.

Because both solutions "WLC2" and "Cisco" are of equivalent performance, for the rest of this work, we focus only on the "WLC2" implementation.

In [3] we propose a NURBS surface-based optimization of the "WLC2" solution processing time. The idea is to process the "WLC2" coverage at only the "control" or "definition" points, and then, the corresponding NURBS surface to find out an estimation of the coverage at the remaining area points. By reducing the number of points "WLC2" processes, we reduce the initial required processing time.

For test purposes, we've implemented three variants of this solution: "NURBS1", "NURBS2", and "NURBS3". The difference is in how "definition" points (CP) are chosen. In the first variant, CPs correspond to any random number of the coverage points, STA_NURBS, weighted by their respective "WLC2" coverage measure. In the second variant, the definition points are the APs. In the third variant, the definition points are the APs but weighted to their optimized transmit power levels. In "WLC2", transmit power levels are optimized per AP: each AP may have a different transmit power level.

For the same random set of 30 APs, we vary the number of CPs and observe the "NURBS" variants processing time and results precision. In this scheme, the results precision corresponds to the deviation from "WLC2" measurement that is our truth.

In Table [VIII], [IX], and [X], we summarize the results of varying STA_NURBS number in this range: 100, 500, 1500, 2500 and 10000.

TABLE VIII. "NURBS1" OPTIMIZATION TO WLC2 MODEL PERFORMANCE RESULTS

Results: NURBS1	Simulation STA_NURBS number Settings: AP=30, Width=2, R=30, r=3, lambda=1				
	100	*500*	*1500*	*2500*	*10000*
M.Diff	41.0604	11.4398	23.5133	**0.7598**	0.75881
Med.	40.0395	7.5946	19.7305	**0.51118**	0.43403
Std.	22.8496	19.5894	20.6407	**8.4735**	3.5212
T.	30.168	136.5365	448.6352	**694.6876**	1508.60

TABLE IX. "NURBS2" OPTIMIZATION TO WLC2 MODEL PERFORMANCE RESULTS

Results: NURBS2	Simulation STA_NURBS number Settings: AP=30, Width=2, R=30, r=3, lambda=1				
	100	*500*	*1500*	*2500*	*10000*
M.Diff	48.7473	45.592	57.2992	**61.6536**	52.5964
Med.	45.9399	42.3936	55.231	**60.613**	50.065
Std.	23.5647	29.0324	22.7873	**24.9228**	22.7223
T.	9.3569	9.6129	11.0613	**9.1328**	5.8624

In Table [VIII], the results show that in general, “NURBS1” processing time and accuracy are increasing with the number of STA_NURBS. In Table [IX] and [X], the “NURBS2” and “NURBS3” results are not changing considerably because the number of APs is constant. Please note that a high accuracy corresponds to a low mean and a low standard deviation from this mean.

TABLE X. “NURBS3” OPTIMIZATION TO WLC2 MODEL PERFORMANCE RESULTS

Results: NURBS3	Simulation STA_NURBS number Settings: AP=30, Width=2, R=30, r=3, lambda=1				
	100	*500*	*1500*	*2500*	*10000*
M.Diff	53.9482	49.231	58.0436	**62.5081**	52.7283
Med.	50.253	46.8791	55.7009	**61.2722**	50.1472
Std.	23.7241	30.228	23.2916	**25.5144**	22.8494
T.	1.5346	0.70329	0.93668	**0.89961**	1.2902

When STA_NURBS number is at the lowest value, the required processing time represents almost 4.3% of the “WLC2” time, which is an important optimization. But the “M.Diff” representing the mean gap between the “NURBS1” measurement and the truth, is very high at almost 41.06 unit. The standard deviation from this mean is almost 22.84 unit and it is very high. At the highest STA_NURBS value, the accuracy is very good: the mean is almost equal to 0.75 unit and deviation is only 3.52 unit. But the required processing time is 390% of the “WLC2” time. When STA_NURBS number is 2500, “NURBS1” performance, time and accuracy, is very close to “WLC2”.

There’s a tradeoff between decreasing the required processing time and increasing the accuracy. For applications that have less constraints on the accuracy, STA_NURBS number of 500 is an accurate tradeoff. It would require only 19.51% of the “WLC2” initial required processing time. For applications that require a higher accuracy, “NURBS1” is a feasible alternative to “WLC2” in a network with rare radio environment changes.

In dense frequently changing networks, the “WLC2” processing time is not scalable with the number of changes. In these networks “NURBS1”, “NURBS2” and “NURBS3” are powerful and allows fast adaptation to radio environment changes. Upcoming work may spot in detail this “NURBSx” strength that was introduced in [3].

In the upcoming section, we explore an out-of-box MLR-based approach as an alternative to “NURBSx” in improving the coverage prediction accuracy.

IV. MLR-BASED OPTIMIZATION SOLUTION

In the previous section, NURBS surfaces helped optimize “WLC2” performance. But this optimization came with a tradeoff between the required processing time and measurement’s accuracy. In this section we propose an alternative out-of-box machine learning approach to improve “NURBS1” accuracy.

Using machine learning algorithms, we predict “WLC2” coverage measurement at a given coverage area point (STA). This value is continuous because it is the resultant sum of continuous, linear, function values. Each of these function values, corresponds to the effect of a single AP on this coverage area point.

Then, we use supervised regression models to predict interference measurement, the output, at points that are not pertaining to the training set. Our training set represents a 10% random sample record of all the available coverage points. We build our hypothesis on these features: STA index, STA localization coordinates X and Y, first AP of association, corresponding direction, corresponding power level, corresponding load, corresponding reported neighboring APs’ interference, second AP of association, and corresponding direction.

What regression algorithm should we use? For this preliminary work, we’ve chosen to work only with a Coarse Gaussian SVM and Bagged Tree algorithms. These two algorithms have showed the best RMSE validation results for several simulation iterations of the models. “SVM” model has scored an average RMSE of 14.75 point, whereas “Bagged”, 16.03 point.

We train our models using only the training set. Using the trained models “SVM” and “Bagged”, we predict the remaining points that are 90% of the total record set. We use the same training set corresponding “STA index” feature, to predict “NURBS1” values. At the end, we measure the accuracy and time as in the previous section.

In this simulation, the number of the control points or training set samples varies from 40 to 2250 sample. In each iteration, a new set of 10 random APs distribution is processed.

“Fig. 8” shows the per-model required processing time for each test. “WLC2” does not show in this figure because it ranges from 77.6062 to 8496.5513 seconds. The best processing times are recorded for “NURBS” and “Bagged”

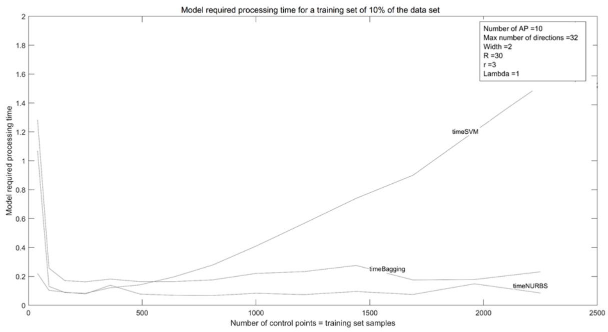

Fig. 8. Plot of models: “SVM”, “Bagged” and “NURBS” required processing time

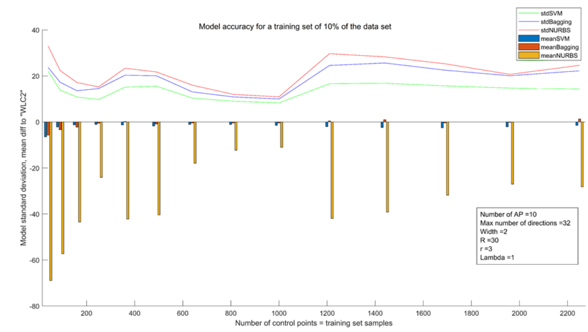

Fig. 9. Plot of models: “SVM”, “Bagged” and “NURBS” accuracy

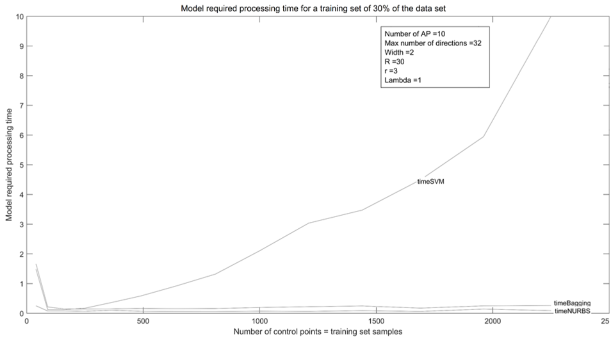

Fig. 10. Plot of models' required processing time when the training set is 30% of the data set

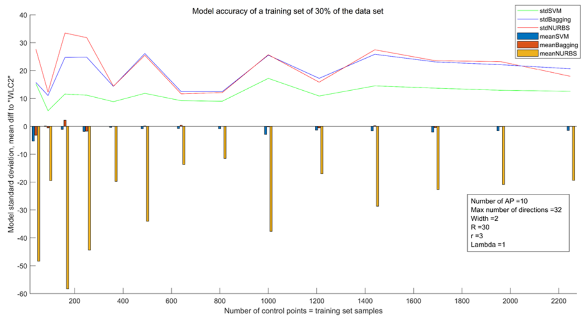

Fig. 11. Plot of models' accuracy when the training set is 30% of the data set

models and seem to be independent from the number of control points. "SVM" time is increasing with the number of control points, but it does not exceed a 1.51 second in time, which is still an important enhancement of "WLC2" solution.

"Fig. 9" shows the accuracy measurement for each test. The "SVM" optimization represents the best accuracy measurement at around 13.77 unit in standard deviation against 18.44 unit in "Bagged" or 21.43 unit in "NURBS".

To confirm our findings tendency, we redo the previous simulation with a large training set of 30% of the total data set. "Fig. 10" and "Fig. 11" show the corresponding required processing time and accuracy respectively.

By increasing the training set to 30% of data set, the "SVM" accuracy that was 76.63% in comparison to its direct challenger "Bagged", is now only 59.52%. Increasing the number of control points seems to have no effect on "Bagged" and "NURBS" as they show a steady pace of both accuracy and time. Instead, "SVM" accuracy has increased remarkably without exceeding the limit of 10 seconds of the required processing time which is acceptable.

V. Conclusion

In this work we've proposed an MLR-based out-of-box alternative optimization approach to Beam-based, representation of radio coverage in IEEE WLAN networks, NURBS-based optimized implementation variant of "WLC2". This has solved an important part of "WLC2" solution scalability issue and opened the possibility to implement new solution variants in further work.

The obtained results have proved that "SVM" solution offers the best tradeoff between the prediction accuracy and required processing time in comparison with its challengers "Bagged" and "NURBS".

Further work may extend this discussion to model the adaptability to the frequently changing radio environments. In such case, we'll explore in detail advanced concepts behind NURBS surface, ML or deep ML, to implement an efficient incremental processing of the coverage.

In upcoming work, we'll discuss new Beam-based implementation variants: "WLC3" and "WLC4". In "WLC3", we'll try to optimize the transmit power level per AP and per direction. In "WLC4", will process different optimized supported number of directions per AP.

Acknowledgment

We would thank colleagues: researchers, engineers, and reviewers for sharing their precious comments and on-field experience to improve the quality of this paper.

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