A new approach to design a WLAN-based positioning system

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Abstract— **In recent years, as the deployment of Wireless Local Area Networks (WLAN) in dense-urban areas is growing rapidly, it can be a perfect supplement for providing location information of users in indoor environments where other positioning techniques such as GPS, are not much effective. However, most systems only focus on the network deployment for positioning but overlook that the original purpose of these WLAN infrastructures is providing the required connectivity. Furthermore, there is a lack of good analytical models that can be used as a framework for designing and deploying the positioning systems. In this paper, we propose an effective approach where WLAN planning and positioning error reduction are modeled as an optimization problem and tackled together during the WLAN planning process. A Mono-objective algorithm and a multi-objective algorithm both based on Variable Neighborhood Search (VNS) are implemented respectively and the simulations demonstrate that these two algorithms are highly efficient for designing the indoor positioning system.**

Keywords- Indoor Positioning System; communication quality demand; mono-algorithm; modeling

I. INTRODUCTION

The indoor positioning technology has won growing interest in the last years. Nowadays, access points can be found in our daily environment, thus if existing infrastructure such as WLAN without additional hardware installation can be used for location determination, then the realization costs are small and the service can be offered under attractive conditions. A common approach for the localization of a handheld terminal or mobile device by means of WLAN is based on measurements of received signal strengths of the WLAN signals from the surrounding access points at the terminal.

The previous studies in the literature mainly focus on measurements stage and then results analysis [1]. Recent developments have been emphasizing on the algorithms which are used for estimating the location that associates the fingerprints with the location coordinates [2], [3], [4], [5] and on reducing the time cost in the training phase[6],[7]. However, our work here is trying to model the positioning problem as optimization problem. To our knowledge, this is the first time that designing a WLAN-based indoor positioning is dealt as a modeling and optimizing approach.

Nevertheless, almost all the papers neglect a fact that the original purpose of these WLAN infrastructures is to provide the required connectivity [8], so that, positioning becomes the only target of the network configuration design. In [9], a network configuration refers to the deployment of a given number of APs with their assigned parameters (i.e. the allocated frequency, the emission power and the azimuth). In fact, an increase of the density of AP can improve the system accuracy and precision, whereas the communication quality (due to frequency interferences) and the installation costs are increasing too. These are major drawbacks!

In this paper, we attempt to answer the following question: how to deploy a WLAN in order to guarantee the requested Quality of Service (QoS) while reducing the location error? Such a problem includes two aspects: WLAN planning and positioning error reduction. To provide users an optimal wireless access to their local network, WLAN planning does not only consists in selecting a location for each transmitter and setting the parameters of all sites, but also acts on allocating one of the available frequencies to each AP configuration. And toward the indoor positioning system, once RSS from all visible APs are measured and inputted, the location is estimated and outputted using the RSS distribution and machine learning technique. We propose a new approach where WLAN planning and positioning error reduction are modeled as an optimization problem and tackled together during WLAN planning process.

The rest of the paper is organized as follows. The next section introduces two indicators which are used to evaluate network throughput and positioning accuracy. Section 3 describes the problem definition of WLAN-based positioning model. Section 4 presents a Mono-objective heuristic and a Multi-objective heuristic. The experiments and results are given in section 5. Final section gives some conclusions and perspectives.

II. EVALUTION INDICATORS

To find a feasible network configuration satisfying QoS and positioning error constrains, one important step is to define two indicators in order to evaluate the actual network QoS as well as the positioning error. In the proposed model, the calculation area is meshed. Each mesh node is called Marking Position

(MP). The defined indicators are calculated at each MP to evaluate the quality of the network configuration, i.e. the required QoS and positioning error. In this section, both indicators will be introduced.

A. QoS Indicator

Inside AP coverage area, the quality of service perceived by the user is of different levels because the interferences are not uniform. A user can loose his connection due to interferences while another user of the same AP may have high throughput. One indicator to measure interferences is the Signal-to-Interference-plus-Noise-Ratio (SINR). Its definition is local for each user, which is [10]:

$$SINR = \frac{P_{BestRSS}}{\sum P_{othersRSS} \times \gamma(\Delta f) + N} \tag{1}$$

Where:

$P_{best\ RSS}$ is the highest RSS in a MP. In IEEE 802.11 standard, the connection is usually established with the best RSS. $P_{other\ RSS}$ are other RSSs perceived by a MP with smaller values than the best RSS. $\gamma(.)$ is the protection factor corresponding to the attenuation coefficient between channels. It is a function of Δf, the channel distance between the carrier signal and the interfering signal. $\gamma(.)$ decreases when Δf increases: if $\Delta f = 0$, $\gamma(\Delta f)=1$ and if $\Delta f \geqslant 5$, $\gamma(\Delta f)=0$. All intermediate values depend on the receiver equipment features. N is the noise strength. Its value is around -100dBm in surrounding air. Actually, uplink signals coming from all other clients are also a kind of interfering signals. Usually in literature and also in practice, only the downlink signals coming from AP are taken into account to quantify interferences. In our approach as well, the uplink signals are not used for interference computation.

B. Positioning Error Indicator

Recent indoor positioning system research has mainly focused on algorithms that compute the best match. Although, most research only provided experimental results, they neglected an in-depth analysis of the impact of different factors for position errors. At a first glance, it is nearly impossible to find an appropriate way to pre-estimate the positioning error. However, viewing from a statistical perspective, the location error can be divided into two parts. One comes from real environment disturbances, which belongs to a random error. Many works have been done in this area. In [11], the author presents a probabilistic model for positioning errors in signal strength based localization systems. The probability density of the RSS variation is modeled as a Gaussian according to the empirical observation. Whereas, these contribute are only approximate simulation methods and there are many factors that can affect this kind of error, such as AP orientation, time of day (a lot of people or not), environment (tables, desks…), distance from transmitter, interferences from other AP, and sensibility of the wireless card. The error caused by these key factors is uncertain and time-varying, so that these contribute can not pre-estimate and eliminate it well. The other part is due to the drawback of the finger-printing technique, which is a system error. After studying the principle of positioning based on finger-printing technique, we noticed that there is only one drawback of finger-printing technique. It is especially significant in our positioning system which is based on the propagation-model. We call this drawback "aliasing". Aliasing means, that there are several distinct locations receiving the same signal strength of one AP. Even worse, due to variations in the signal strength caused by obstacles, locations need not to be in the same distance to the AP. If aliasing appears at some MPs that receive the same RSS values from several APs, positioning based on finger-printing technique will become invalid. In other words, aliasing is a source of positioning error. According to our pervious study [12], if we increase the number of APs or change the placement of APs, the number of the reference points which contain aliasing will reduce till disappear.

To sum up, we may draw the conclusion that the error induced by aliasing is suitable for being a part of the fitness of our optimization problem. In other words, the objective is to optimize the positioning error generated by aliasing. An indicator, called Refined Specific Error Ratio (RSER), was proposed in [12] and is used to evaluate the aliasing error. The expression of RSER at MP k is as follows:

If $n = 1$ so RSER (k) = 0

Otherwise,

$$RSER(k) = \frac{1}{(n(n-1))} \sum_{i} \sum_{j \neq i} dist(i, j) \tag{2}$$

where:

i, j: the sequence number of MPs having the same RSS vector at the position *k*.

n: the number of MPs having the same RSS vector at the position *k*.

dist (i, j): the Euclidean distance between the MP *i* and the MP *j*.

The above equation indicates that RSER computes an arithmetic mean of the distances by twos among a set of MPs having the same RSS vector. Namely, RSER is essentially a statistical aliasing error on a MP.

III. Modelling Optimization Problem

An indoor WLAN-based positioning system modeling process is based on a mathematical description of several objectives. WLAN design is widely studied, and some mathematical models of WLAN planning are worth learning from [13], [14], [15], [16]. In indoor WLAN-based positioning system, the basic objective is to provide radio coverage on all assigned areas, which is a common requirement for communication and positioning. One complementary objective concerns the positioning accuracy, which mainly relies on the distance between some points having the same RSS vector. Another complementary objective concerns the efficiency and the throughput of the network, which mainly relies on the interfering signals level and the communicating signal level between cells. Additionally, it is relevant to use an economy-oriented objective to reduce the purchasing and installation costs.

A. AP Location Model

In this model [13], the AP location is defined as a vector of N items $S = (s_1, \ldots, s_i, \ldots, s_n)$. Each item s represents a candidate site which is a geographical location where an AP may be assigned. The sites define places in the studied building and more than one AP may be installed to provide higher bit rate in strongly congested zones. Thus, we also define the sectors $L = (l_1, \ldots, l_i, \ldots, l_m)$ as the list of available sectors per site.

B. AP Parameters Model

In this model [13], since different types of APs have different parameter values, we predefine a list of AP types provided for user choice. When one AP is selected, we define its set of parameters that is, azimuth, emitted power and frequency. Summarily, the AP setting is characterized by the following parameters (s,l,a,p,h,f). Where (s,l) defines the location, a is the type of AP used, p is the emitted power, h is the azimuth or the horizontal orientation and f is the number of the frequency channel used. Then, a solution of the problem is expressed by the configuration of a set of AP for the whole building.

C. Radio Signal Model

To achieve a communication or positioning service, a user terminal needs to receive the radio transmission of an AP at an adequate level of power. The radio signal model defines the RSS expression and the different service demands related to the RSS level. For each candidate location, a three dimension coverage map is computed with a propagation model. The propagation model considers a discrete space, thus the coverage map is defined as a set of mean RSSs associated with the meshes. The element of the set p_{slm} is the RSS in the centre of the mesh m and coming from the location (s, l). This power is expressed in *dBm*. For the coverage criterion, we define three kinds of RSSs according to different power thresholds. The lowest power threshold is called interference threshold, which is the minimum signal power a client can receive as interference. The medium power threshold is called positioning threshold, which is the minimum signal power a client must receive for positioning estimation demand. The highest power threshold is called reception threshold, which is the minimum signal power a client must receive for communication.

D. Qos Model

The QoS model in [13] consists of two sub-models. One is called traffic model, which defines the way of representing the network load demand and gives a framework to the expression of the desired QoS. The other one is named throughput model, which transcribes SINR values into service level provided by the network, that is, the bit rate offered to the clients.

In the traffic model, we define service zones, which are represented by polygons covering parts of the building. Several essential characters of service zones are defined: n_z is the number of users inside the service zone z, and d_z is the bit rate in *kbps* desired by user for the service zone z. The service zones overlap each other, so the desired bit rate per user is computed taking into account the overlapping area. To integrate these service zones into our model, these service zones are represented by a set of meshes or MPs called Test Point (TP). The characters of service zones can be analyzed by d_t the total bit rate desired on the TP t. The mathematic formulation is given by: $d_t = argmax\{d_z : z \in Z\}$. Z is the set of service zones covering the TP t.

The principal parameter in throughput model is r_t, the real bit rate provided on the TP t, whose quality is defined by SINR on that TP. In fact, SINR determines the user nominal bit rate. A function gives the real bit rate provided by the serving AP in downlink according to the nominal bit rate and the number of users associated with this AP. This function also depends on other parameters such as the number of users communicating with the AP at different nominal bit rate allowed by the standard. A thorough study of the MAC layer and the protocol CSMA/CA allows detailing this function.

E. Positioning Model

Like the service zones considered in the traffic model, we define, in the positioning model, the positioning zones where we aim to reduce the positioning error. These positioning zones are also represented by a set of meshes or MPs called Reference Points (RPs). The key parameter for the model is the positioning error, denoted e_t, which represents the aliasing error at the RP t. As mentioned previously, we consider the aliasing error as the positioning error and RSER is used to calculate the aliasing error.

IV. Implementation

The WLAN-based indoor positioning optimization problem can be clearly identified as a multi-objective (MO) optimization problem where positioning accuracy and QoS need to be concurrently optimized. There are two commonly used approaches to solve a multi-objective optimization problem. The first one reduces the multiple objectives to a single objective by generating a composite objective function, usually from a weighted sum of the objectives. This composite objective function can be optimized using existing mono-objective optimization algorithms. In this case, the quality of the indoor positioning system relies on the optimization of several objectives and the optimal solution is the result of a fixed trade-off between them. The second one relies on a MO search strategy and looks for a set of Pareto-optimal solutions, each solution representing a different trade-off between the objectives that is involved. In this paper, both approaches will be implemented in the next section. These two approaches are based on the same meta-heuristic algorithm: Variable Neighborhood Search (VNS). The same initial solution and neighborhood structures are applied to both optimization algorithms.

A. *Initial solution*

The construction of initial solution should be fast and a good starting point for local search. Thus, the most intuitive way to find a good starting solution for QoS or positioning is to use an algorithm that considers a coverage constraint to build the initial solution. This initial solution can also be seen as a lower bound based on the coverage criteria. The problem of minimizing the number of candidate AP sites that are able to cover all MPs amounts to a well-known combinatorial optimization problem, namely the minimum cardinality set covering problem [17].

Because coverage planning problem is hard to (NP-hard) tackle, we devise effective heuristics based on Greedy Search Procedure to provide near-optimal solutions within a reasonable amount of time. Some exact algorithms such as Column generation could provide an initial solution but it is costly and time-consuming.

B. *Neighborhood construction strategy*

To balance neighborhood number with solutions space size, the transmission power and direction of emission are not chosen as the variables of problem. AP configuration is defined as AP with assigned parameters (power, azimuth, location) which are common in the throughput and the positioning, while the frequency is the specific parameter of throughput. Therefore, a neighboring solution is constructed by either one of these following moves:

- **Swap move:** a selected AP configuration is deselected, and a deselected AP configuration is selected for an unoccupied site.
- **Addition move:** a new AP configuration for an unoccupied site is added in the solution.
- **Delete move:** a selected AP is deselected from the solution.
- **Frequency allocation:** reallocate the frequency in the solution.

C. *Mono-objective VNS planning Algorithm*

1) *Mono-objective Formulation*

To achieve several objectives simultaneously, our optimization problem, which is to determine a feasible AP configuration satisfying QoS and positioning error constrains, should be formulated as a sum of objectives in order to minimize the following single evaluation function:

$$\sum_{\mathrm{Site}} C_{\mathrm{Site}} + \sum_{TP} \beta \times \Delta_{tp} + \sum_{RP} \gamma \times \mathrm{E}_{rp} \qquad (3)$$

Where, C_{Site} is the network installation cost of a site. β is the penalty coefficient assigned to the TP. Δ_{tp} is the deviation between the required bit rate and the real bit rate. γ is the penalty coefficient assigned to the RP. E_{rp} is the magnitude of positioning error. In this function, the first term is the network installation cost; the second term is the cost of unsatisfied demands on QoS and the third term is the cost of unsatisfied demands on positioning. All components are in Euros. So, the indoor positioning challenge is completely changed into an economical challenge.

In addition, our optimization must be done under the following constraints:

- The network covers all MPs with a minimum guaranteed service and a minimum positioning error needed by the user.
- The maximum number of newly installed AP does not exceed a given number fixed by the user.
- All AP parameters such as type, emitted power, azimuth and frequency should be included in their domain of definition.
- In each MP, the number visible AP should not less than three.

2) *Mono-objective VNS*

To solve this combinatorial and global optimization problem, Variable Neighborhood Search (VNS), enhanced with some strategies, is implemented. VNS is a meta-heuristic which systematically exploits the idea of neighborhood structure changes, both in descent to local minima and in escape from the valleys which contain them [18]. A neighborhood structure is a mechanism which can obtain a new set of neighbor solutions by applying a small perturbation to a given solution.

The simplest VNS is called Variable Neighborhood Descent (VND) where changes of neighborhood structure are made in a deterministic way, as described in Figure 1.

> Initialization: a finite set of pre-selected neighborhood structures $\{N_1, N_2, \ldots, N_{kmax}\}$ and an initial feasible solution x.
>
> Repeat the following sequence until no improvement is obtained.
>
> Step 1: Set k to 1;
>
> Step 2: Find the best neighbor x' of x in N_k;
>
> Step 3: If x' is better than x, set x to x' and go to Step 2, otherwise increase k;
>
> Step 4: if $k \le k_{max}$ go to Step 2 else end.

Figure 1. Variable Neighborhood Descent Algorithm

We can note that the final solution is a local optimum with respect to all the neighborhoods used and so the chances of obtaining a global optimum are increased.

This deterministic algorithm may be combined with a stochastic one to give the algorithm called Basic VNS described in Figure 2.

Initialization: a finite set of pre-selected neighborhood structures $\{N_1, N_2, \ldots, N_{kmax}\}$ and an initial feasible solution x.

Repeat the following sequence until the stopping criterion is met:

Step 1: Set k to 1;

Step 2: Generate a random neighbor x' of x in N_k;

Step 3: Apply a local search method with x' as initial solution: denote x'' the obtained local optimum;

Step 4: If x'' is better than x, set x to x'' and go to Step 2, otherwise increase k;

Step 5: if $k \le k_{max}$ go to Step 2 else end.

Figure 2. Basic Variable Neighborhood Search Algorithm

We can observe that point x' is generated at random in Step 2 in order to avoid cycling which might occur if any deterministic rule was used as in the VND algorithm. In our final algorithm, the local search in Step 3 is replaced by VND.

VNS may also be combined with Tabu Search (TS). Basically there are two ways to realize the combination: use TS within VNS or use VNS within TS. This part will be studied in our further works.

Furthermore, two enhanced strategies will be described in the remainder of this section.

a) Neighborhood selection strategy

Normally, the neighborhood selection strategy follows a sequential strategy. Keeping this concept in mind, it is obvious that the application order of the neighborhood structures is crucial for the performance of VNS. The first neighborhood structures are searched more often than the ones at the end of the queue. If the times required for examining the explored neighborhoods differ substantially, it is reasonable to order them according to increasing costs, i.e. exploring time. However, this criterion is not always applicable, in particular when the times for searching the neighborhoods are similar, or they vary strongly. Unfortunately, our neighborhoods correspond to this case. Some selection strategies based on random strategy or fixed probabilistic strategy are proposed, but these strategies suffer from lack of guidance. Here, we propose a dynamic probabilistic strategy for neighborhood selection. When an improvement happens in a neighborhood, the probability of this neighborhood is increased and the neighborhoods are reordered according to their probabilities. It is updated the neighborhood probability during every improvement, including in VND search process.

We define the upper bound parameter as the number of APs of the current best feasible solution. If only the addition move and the deletion move are applied, this upper bound can be used to restrict the neighborhood selection during the search. With this restriction, the addition move can be applied in the current solution only if the number of APs in the current solution is less than *upperbound-1*. In our problem, the upper bound is calculated from the maximum installed APs. If the feasible solution is improved during the search, the upper bound parameter is updated automatically.

b) A double control of the degradation

The purpose of the double control of the degradation is to avoid falling into a local minimum. It means replacing x by x'' even if the solution is worse than the current best one. A double control of the degradation is carried out by two parts: one is to control the quantity of the degradation which is a probability of a worse solution acceptance. The other is to control the quality of the degradation that defines the amplitude of degradation; this amplitude is calculated relatively to the best solution and current solution. A more detailed description of double control of the degradation by pseudo-code is shown as below:

If $(f(x'') < f(x^*) \times (1+degra1) + f(x) \times degra2)$ *or (accept with the probability Proba)*

Accept x'' as a current solution

Endif

Where,

x^*: the best so far solution

x: the current solution

Proba: the probability of the current solution degradation

degrad1: the coefficient of the degradation of the best so far solution

degrad2: the coefficient of the degradation of the current solution.

3) Termination criteria

The algorithm stops when one of the following termination conditions is satisfied:

- The number of iterations has reached the maximum number of iteration,
- The value of the returned cost function is equal to zero.

4) Algorithm description

The pseudo-code of our heuristic is the following:

Function VNS(x, Iteration$_{max}$,)

1. set the initial neighborhood probability

2. repeat

3. k ← 1(check upper bound criterion)

4. repeat

5. x' ← pick_at_random($N_k(x)$)

6. x'' ← VND(x', k'$_{max}$)

7. if double_ control_degradation (f(x) > f(x''))

8. x ← x'';

9. update each neighborhood probability;

```
      reorder neighborhoods;
       k ←1;
      update upperbound;
   else
      k ← k+1(check upper bound criterion)
 until k=k_max
 n ← n+1
Until n>Iteration_max
```

D. Multi-objective VNS planning Algorithm

1) Multi-objective(MO) optimization

Getting the solution that has the best possible rating for each objective is barely possible, especially when the optimization objectives have an opposed influence to each other on the variables. For instance, networks made up of a high number of APs have good coverage and positioning performance but suffer from high interference levels. A good planning solution is the result of a trade-off between the constraints involved in the search. Joint optimization of antagonistic objectives is the definition of a MO search problem.

Each MO problem has a set of Pareto-optimal solutions defined as the set of non-dominated solutions. This set of non-dominated solutions is called the theoretical Pareto front. For a MO problem where n objective functions f are minimized, a solution x dominates a solution y if and only if:

$$\forall i \in [1,n]: f_i(x) \leq f_i(y), \quad \exists j \in [1,n]: f_j(x) < f_j(y)$$

Each non-dominated solution represents a different optimal trade-off between the objectives. For such solutions, it is not possible to improve one criterion without worsening another one [19].

2) MO VNS algorithm

The MO algorithm looks for the number, the location, the power and the direction of emission of the APs. Its aim is to minimize concurrently the three defined objectives: the network installation cost; the demands on QoS and the demands on positioning. This algorithm is derived from the previously presented VNS meta-heuristic. It aims to improve the quality of the current search front at each iteration. This front consists of the set of solutions that dominate the other ones found during the search in the objective function space. The pseudo-code of our MO heuristic is the following:

Initialization: a finite set of pre-selected neighborhood structures $\{N_1, N_2, \ldots, N_{kmax}\}$ and an initial feasible solution x.

Repeat the following sequence until the stopping criterion is met:

Step 1: Set k to 1;

Step 2: Generate a random neighbor x' of x in N_k;

Step 3: Apply a local search (VND) method with x' as initial solution: denote $P(N_k(x'))$ the obtained non-dominated solutions during the local search;

Step 4: Add the $P(N_k(x'))$ into the optimal front F_p;

Step 5: Selected a solution x'' from the optimal front F_p randomly;

Step 6: if $P(N_k(x'))$ has more than a solution which isn't dominated by the optimal front F_p, set x to x'' and go to Step 2 increase k;

Step 7: Remove the solutions dominated in the optimal front F_p;

Step 8: If $k \leq k_{max}$ go to Step 2 else end.

Figure 3. the pseudo-code of Multi-objective VNS algorithm

V. EXPLEMENTATION

A. Test environment

Some experiments were realized with the objective to study the model and the algorithm. The experiments were held in the environment described by the Figure 4. The test bed is composed of a two-floor building. Each floor size is 120m x 40m. We defined 94 candidate sites for AP installation. AP parameter settings are one type of AP with a unidirectional pattern and 2 possible values of power. For the frequency allocation, each site must use one frequency among the 13 which are available in France. Then, the WLAN AP configuration design consists in installing some AP configurations among 188 candidate configurations and in assigning frequency channels that is 188x13 combinations. To focus on the different strategies, optimization does not take into account the financial requirements. We limit at 30 the maximum selected AP for a solution.

In order to define the traffic demand and positioning demand, we set several service zones and positioning zones respectively. And In order to ease the test analysis, we set several service zones and positioning zones of the same size which are presented by the green areas on Figure 4. Each zone is defined on each floor of the building. For the service zone, 300 users are uniformly distributed on each service zone and each user demand is about 500 kbps real bit rate. Then, the global demand for the whole building is 300 Mbps. Those two kinds of zones correspond to 7728m², and then 7728 TP are defined for SINR computation and 7728 RP are defined for RSER computation.

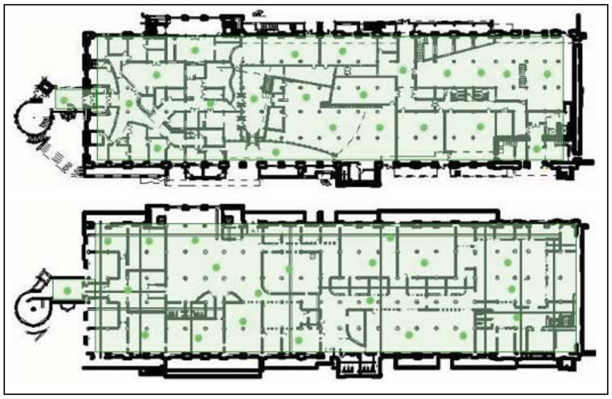

Figure 4. The topology of the test building

B. *Test Results of mono-objective optimization*

In mono-objective, the penalty coefficients of the evaluation function must be pre-set. Setting the penalty coefficients implicitly introduces the designer's requirements on the relative trade-off between objectives. To avoid some undesirable effects, we will study the impact of these penalty coefficients on optimization process through following experiments.

Three test scenarios have been defined to evaluate the mono-objective search:

$$\sum_{TP} 100 \times \Delta_{tp} + \sum_{RP} 1 \times E_{rp} \qquad (4)$$

$$\sum_{TP} 10 \times \Delta_{tp} + \sum_{RP} 1 \times E_{rp} \qquad (5)$$

$$\sum_{TP} 1 \times \Delta_{tp} + \sum_{RP} 1000 \times E_{rp} \qquad (6)$$

In these three test scenarios, we vary the γ to β ratio to study the relationship between QoS and the positioning accuracy. Figure 5 shows the total Δ_{tp} value on each improvement. Figure 5 shows the total E_{rp} value on each improvement. For each test scenario, we run 6000 iterations.

From figure 5, we easily conclude that a high γ to β ratio of 1000 can guarantee a small positioning error while leading to a high total Δ_{tp} (black curves: good positioning accuracy, bad QoS). In the same way, a low γ to β ratio of 0.01 only guarantees a low total Δ_{tp} but gives a high total positioning error (blue curves: bad positioning accuracy, good QoS). These results completely match our expectation. On one hand, the objective associated with a high penalty coefficient is emphatically optimized. On the other hand, a high penalty coefficient also prevents the improvement of other conflicting objectives. However, people usually do not have a preference for a certain objective. Under such circumstances, treating these objectives equally is the best choice. With an appropriate value of 0.1 for the γ to β ratio, our approach could find an AP configuration which might provide a good improvement not only on QoS demand but also on positioning accuracy.

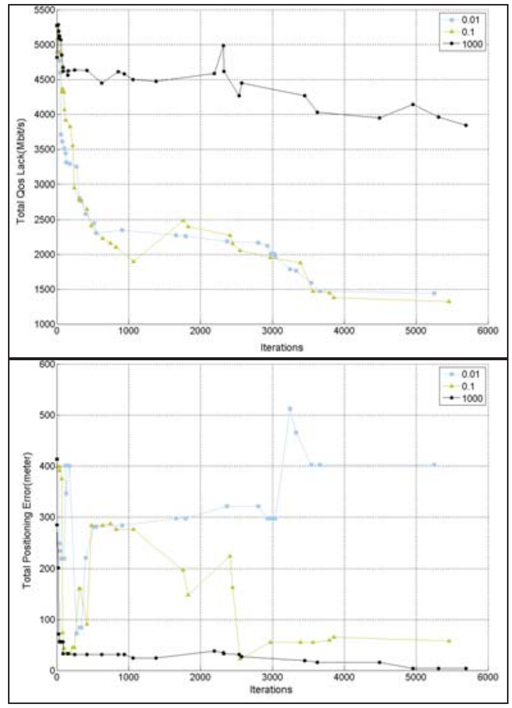

Figure 5. The variation of total Δ_{tp} and total E_{rp} by different γ to β ratio in each improvement.

C. *Test Results of multi-objective optimization*

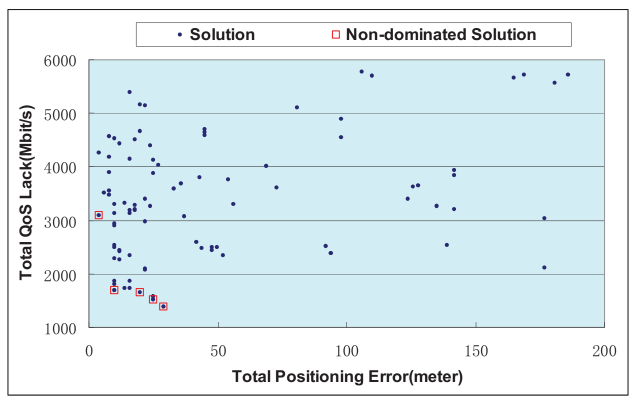

Figure 6. Estimated Pareto front for total Δ_{tp} and total E_{rp}.

The estimated Pareto front obtained after 7000 iterations is composed of 5 solutions that are presented in Figure 6. The QoS and positioning objectives are optimized in this search. The constraints are the same as the mono-objective optimization. We notice that the estimated Pareto front is worse than the result of mono-objective optimization. The reason is that the search process is more complex in MO optimization. Thus in the next stage, we will introduce the parallel method to our MO optimization algorithm.

VI. CONCLUSIONS AND PERSPCTIVES

In this paper, we provide a solution where WLAN planning and positioning error reduction is dealt with simultaneously as an optimization problem. QoS and positioning accuracy goals can be evaluated thanks to two evaluation indicators. The AP model, the RSS model, the QoS model and the positioning model have been defined according to our propagation model. Since the WLAN-based indoor positioning optimization problem can be clearly identified as a multi-objective (MO) optimization problem where positioning accuracy and QoS need to be concurrently optimized. The problem has been solved with the mono-objective heuristic and a simple MO heuristic.

In mono-objective VNS heuristic, a global formulation based on a penalty function has been proposed in order to transform a multi-objectives problem to a mono-objective problem. Then the MO VNS optimization provides several alternative solutions to the radio engineer in a single optimization step.

In the experimentation part, this paper has highlighted the importance of penalty value assigned to each objective. The tuning of the mono-objective takes several launches to get the desired trade-off. MO optimization has succeeded in overcoming this weak point of the mono-objective. However, in terms of computational time, the mono-objective search performs far better than the MO approach.

In our future work, we will supplement our positioning error estimation with Geometric Dilution of Precision (GDOP) and study the way to evaluate the confidence interval of the obtained error estimation. We will also focus on improving the mono-objective algorithm and the MO algorithm. For instance, introducing the TS algorithm to improve the quality, introducing the parallel method to reduce the search duration, etc...

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