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Comparative Performance Analysis of Time Local Positioning Architectures in NLOS Urban Scenarios

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ABSTRACT Autonomous navigation has meant a challenge for traditional positioning systems. As a consequence, ad-hoc deployments of sensors for addressing particular environment characteristics have emerged known as Local Positioning Systems (LPS). Among LPS, those based on temporal measurements present an excellent trade-off among accuracy, availability, robustness and costs. However, the existence of different Time-Based Positioning architectures - Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Asynchronous Time Difference of Arrival (A-TDOA)- with different characteristics in clock and signal path noise uncertainties has supposed that it does not exist any preferred a priori architecture for urban NLOS complex scenarios. As a consequence, in this paper, we propose a general framework for the optimization of the node deployments of each architecture in urban scenarios based on accuracy, availability and robustness. This framework allows us to compare the performance of the TBS architectures in the urban scenario proposed as a novel methodology for the deployment of LPS time architectures in urban environments. Results in the proposed scenario have shown the preeminence of the A-TDOA architecture in primary and emergency conditions which supposes an outstanding remark for future high-demanded accuracy applications in urban environments.

INDEX TERMS A-TDOA, clock errors, Cramér-Rao bounds, genetic algorithm, localization, local positioning systems, NLOS urban scenarios, TDOA, TOA.

I. INTRODUCTION

Localization accuracy has become a crucial task for high-demanded autonomous navigation. Traditionally, Global Navigation Satellite Systems (GNSS) have provided global coverage through a constellation of satellites in the space reaching acceptable accuracy for localizing objects in the earth's surface. However, the signals emitted from satellites face different challenges for providing a stable link among targets and satellites such as ionospheric adverse effects [1], signal path noise degradation [2], multipath phenomena [3] or unstable synchronism among system elements [4].

This creates error instabilities on GNSS signals that make them useless for indoor navigation [5], precision landings [6], reconnaissance and surveillance [7], search and rescue operations [8] or precision farming [9].

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These applications have promoted the development of Local Positioning Systems (LPS) that are based on ad-hoc deployments of sensors that particularly adapt to complex environments reducing or avoiding adverse effects on signals.

LPS and GNSS are categorized through the physical property measured for providing target location: time [10], power [11], phase [12], angle [13], frequency [14], or combinations of these methodologies [15], [16].

Time-Based Positioning Systems (TBS) have particularly shown an outstanding trade-off among accuracy, robustness, availability, stability, and easy-to-implement hardware configurations. These time architectures are distinguished by the time-lapse computed in the system clocks for determining the target location.

Time of Arrival (TOA) [17] models measure the time elapsed from the positioning signal emission until its reception in one of the architecture nodes. They require the synchronization among all the system elements that cooperate actively in the target location determination and at least

4 different nodes are required to mathematically solve the 3-D position calculation.

Time Difference of Arrival (TDOA) [18] computes the relative time-of-flight among the reception of a positioning signal in two different architecture nodes. 5 different receivers are required for the 3-D position determination but we have shown in [19] that under a node optimization only 4 receivers can unequivocally determine the target location.

The synchronization of TDOA architectures is not necessary for the signal emitter and it is optional among the architecture nodes. This synchronization among the architecture nodes can be avoided through the computation of the time measurements in a single clock of a Coordinator Sensor (CS). This can be reached through the receive and retransmit strategy of the positioning signal from the system devices to the CS node.

Among these asynchronous architectures, Asynchronous Time Difference of Arrival (A-TDOA) [20] and Difference-Time Difference of Arrival [21] stand out and we have proven [22] that A-TDOA systems provide better accuracy performance under different node configurations.

Therefore, the A-TDOA architecture which was first proposed in [20] in 2017 has been widely studied for precise location contexts with an analysis of the optimal frequencies of emission for reducing the system errors [23] in a very similar derived architecture or achieving optimal results in indoor environments [24].

However, GNSS such as GPS, GLONASS, or Galileo use TOA configurations since these architectures provide the minimum signal travel, reducing the path noise uncertainties, that stand as the key error source of these systems.

However, if there exists proximity among target and architecture nodes, the effects of the signal path degradation are reduced and synchronization instabilities among the system elements become more important. That is the reason why traditional ground-based area positioning systems such as Omega or Loran-C made use of TDOA hyperbolic positioning. But these systems have been shut down since the error treatment of GNSS signals has allowed global navigation with less uncertainty.

But, the global navigation is not the purpose of LPS where complex environments do not allow the use of GNSS devices for complex high-demanded accuracy tasks. LPS suppose the finding of the fittest system settings for these particular conditions in which the designer must deal with accuracy, stability, robustness security, availability, and costs [25].

In this sense, the usage of TOA systems reduces the costs and complexity (i.e. fewer system elements needed) but the synchronism error must be offset. TDOA systems reduce the clock errors (i.e. not necessary synchronism for the emitter) but combine the uncertainties of two different paths for the positioning signal. Asynchronous TDOA configurations avoid the synchronism errors but increase the signal travel paths by retransmitting the positioning signals to the CS nodes [26], being the availability of a CS in each possible target location under coverage mandatory for computing the

time measurements, making the system dependent on these processing sensors.

Consequently, there is no a priori perfect TBS architecture for a defined scenario, and a deep study of each configuration is needed for each different LPS application.

However, regardless of the TBS architecture used, the optimization of the node location is critical for achieving practical results reducing the system uncertainties.

This is known as the node location problem and has been assigned as NP-Hard [27], [28]. Although, exact solutions such as the branch and cut algorithm for monitoring lanes with sensor network deployment optimization [29], hybrid exact-heuristic solutions such as the optimization of wireless body area networks for enhancing the system operation with low-battery consumptions [30] or approximate algorithms such as [31] in which the optimal Line-of-Sight (LOS) coverage with power constraints is inspected; heuristic methodologies are recommended for finding optimal node deployments especially in large instances of the problem (i.e. high number of nodes deployed or large regions covered by the sensor network).

For instance, in [32] the authors address the energy-efficient coverage problem in Wireless Sensor Networks (WSN) through simulated annealing, in [33] a memetic algorithm with a pseudo-fitness function in the local search is proposed for analyzing potential unfavored regions of the space of solutions in LPS or in [34] the introduction of swarm intelligence through the firefly algorithm allows the obtainment of optimized sensor distributions for power localization schemes. Other approaches look for at least three non-collinear beacons in coverage by employing the dolphin swarm algorithm [35], the transformation of unknown localization nodes into settled nodes by maximizing the coverage properties of a WSN through the bacterial foraging algorithm [36], the analysis of the energy decay models in energy-based localization through the elephant herding optimization [37], the optimization of the optimal layout of beacons for indoor localization of Automated Ground Vehicles (AGV) through diversified local search [38] but specially genetic algorithms in localization node location problems [39]–[42] have been used to address this complex task.

In [39] a novel methodology distinguishing the region for the location of the system nodes and the region for the navigation of the vehicles in LPS is introduced, in [40] a multi-objective methodology for optimizing the parameters which reduce the localization uncertainties of LPS is proposed, in [41] a multi-objective approach to the node location problem allows the joint optimization for system accuracy and the avoidance of disruptive phenomena on signals such as the multipath or in [42] the localization of the unknown anchors is optimized preserving the network connectivity.

These wide range of applications of the node location problem in WSN must be particularized for localization schemes. The node optimization in LPS requires favoring the LOS paths among target and sensors, reducing the signal paths,

avoiding multipath phenomena, considering possible sensor failure conditions, and finding the optimal combination of sensors under coverage for determining the target location.

LPS accuracy must be evaluated in these optimizations through Cramér-Rao Bound (CRB) which is a maximum likelihood estimator that provides the minimum achievable uncertainty granted by any algorithm used for the position determination. Its usage in localization is widespread [43]–[45] and the characterization of the system errors are introduced in the covariance matrix of the system. The characterization of the signal path noise must deal with a heteroscedastic noise consideration in LPS [22], [46] since the travel paths can notably differ among system receivers.

In our previous works, we have modeled the path losses [22], the clock instabilities [26], and Non-Line-of-Sight links [41] into the covariance matrix of the CRB for characterizing the architecture errors in LPS applications. We have later applied this model for constructing optimized cost-effective node deployments [25] considering sensor failures in the CS nodes [47].

In this paper, we study the time local positioning architectures (TOA, TDOA, A-TDOA) for optimized node deployments in NLOS complex urban scenarios considering sensor failures in CS nodes and Worker Sensor (WS) nodes, while maximizing the achieved accuracy of each system.

We particularly analyzed the characteristics of the time positioning architectures in urban environments where there is no a priori suitable architecture and the particularities of the environment must be considered. This study proposes the methodology for taking design decisions in LPS urban applications guaranteeing system accuracy, robustness, availability, and stability enhancements.

The remainder of the paper is organized as follows: we introduce the TBS architectures studied and their error model characterization into the CRB matrix in Section 2 together with the NLOS complex urban scenario of simulations. In Section 3 the GA optimization technique is presented with the fitness functions for each TBS optimization based on a cost-effective sensor deployment, while Section 4 and 5 relate the results and the conclusions of the paper.

II. PROBLEM DEFINITION

TBS have attracted research interest for LPS high-demanded accuracy applications. Their trade-off among system complexity, robustness, stability, and availability provide a reliable combination of factors for deploying ad-hoc sensor networks for autonomous guided navigation in outdoor and indoor environments.

TBS are configured under synchronous (TOA and TDOA) and asynchronous (A-TDOA) architectures which provide different alternatives for the attainment of the accuracy requirements defined by the particular tasks for which they are committed.

However, there is no a priori suitable architecture for LPS applications. This is a consequence of the different characteristics of the main TBS architectures.

TOA systems provide the least uncertainty in the signal noise since their travel path is the shortest among the TBS architectures. Nonetheless, their clock errors are the greatest since they require synchronism among all the sensors of the architecture including the Target Sensor (TS).

TDOA systems combine the path degradation effects of two different signals, which are mandatory for computing the time difference measurements to determine the TS location. But, they reduce the synchronism errors since these systems do not require the TS node synchronism with the CS nodes of the architecture.

A-TDOA systems have the longest positioning signal paths as they rely on the receive and retransmit strategy of the signal through the CS node of the system in which all the time measurements are computed. As a consequence, these systems assume the greatest signal degradations but they avoid the synchronism adverse effects in the time measurements [26]. Besides, asynchronous architectures completely rely on the CS clock for computing the time measurements. This requirement may suppose potential system unavailability if a temporal malfunction of the CS node is occurring. Consequently, methodologies for ensuring the system availability [25] in CS node failure conditions are required for easing this potential disadvantage.

Therefore, a deep study of the characteristics of the environment, the system clocks properties, and the goals of the LPS deployment must be performed for defining the most convenient TBS architecture for enhancing the localization accuracy and stability.

This study requires the characterization of the system noise errors [22], the consideration of the clock errors [26], the detection of LOS/NLOS paths in the positioning signal links of each architecture [41], the guarantee of the availability of the TBS under possible sensor failures [47] and a methodology that enables a cost-effective node deployment for each architecture [25].

In this paper, we apply each of these considerations for the deployment of a TBS architecture for an LPS application in an urban scenario for the first time in the authors' best knowledge. We define this scenario, characterize the system errors of each architecture and perform the optimization of the node deployment for each possible TBS architecture since the system errors are not comparable under random node deployments (e.g. signal noise is not minimized in these cases and beneficial geometric node deployments are not considered for achieving practical surfaces for the application of the positioning algorithms).

As a consequence, we first minimize the uncertainties of each TBS architecture and then compare these architectures for the urban scenario selected as a methodology for the appropriate design of LPS for critical accuracy applications.

In this section, we provide an analysis of each TBS architecture at study and the modeling of the system uncertainties for each TBS (i.e. TOA, TDOA, and A-TDOA) into the CRB matrix which provides the minimum achievable error by any positioning algorithm in a defined TS location. This estimator

is later used for characterizing the quality of a particular node deployment and for comparing the performance of each TBS architecture in the defined scenario.

A. CRÁMER-RAO BOUNDS FOR THE TBS ARCHITECTURES

The definition of the uncertainties in TBS is crucial for the design of LPS systems and the comparative performance of the different architectures. CRB allows us to determine the minimum variance value of any unbiased estimator. In localization, its usage is widespread [43]–[45], [48] since it provides the minimum achievable error in the estimation of the TS spatial coordinates (i.e. the minimum error reached by any positioning algorithm).

Kaune et al. [45] provided a matrix form of the Fisher Information Matrix (FIM) which is a maximum likelihood estimator which inverse defines the CRB of each architecture at study:

$$J_{mn} = \left(\frac{\partial h(TS)}{\partial TS_m} \right)^T R^{-1}(TS) \left(\frac{\partial h(TS)}{\partial TS_n} \right) + \frac{1}{2} tr \left(R^{-1}(TS) \left(\frac{\partial R(TS)}{\partial TS_m} \right) R^{-1}(TS) \left(\frac{\partial R(TS)}{\partial TS_n} \right) \right) \quad (1)$$

where J_{mn} represents the FIM_{mn} matrix element, $\mathbf{R}(\mathbf{TS})$ is the covariance matrix of the architecture at study in which the characterization of the uncertainties (i.e. noise in LOS/NLOS condition and clock errors) is provided, and $\mathbf{h}(\mathbf{TS})$ is the vector containing the information of the time measurement computed in each architecture.

As a consequence, the $\mathbf{h}(\mathbf{TS})$ vector and the covariance matrix $\mathbf{R}(\mathbf{TS})$ must be characterized for every TBS architecture in order to obtain the FIM. The derivations of the \mathbf{J} terms referred to the TS spatial coordinates provide an expression of the maximum variance of the TS coordinates (i.e. the error in the position calculation).

In LPS applications, the characterization of the noise in the covariance matrix must be introduced in an heteroscedastic consideration [46], [49], [50] since the path of the positioning signal significantly differs among the architecture sensors.

Following this consideration in LOS [22] and NLOS [41] conditions through a Log-Normal path loss propagation model, and introducing a model for quantifying the uncertainties of the CS clocks of the architectures through a Monte-Carlo simulation for estimating each temporal variance of the time measurements including the time resolution of the system clocks [21], [26], we characterize the error of each TBS architecture at study. This characterization is assuming uncorrelated errors between noise and clock uncertainties, since the error sources do not share any relation (i.e. noise errors are produced in the positioning signal path and clock errors in the CS time measurement). For a detailed consideration of each error characterization in LPS systems, please refer to [26] and [41].

In TOA architectures, in which the time measurements are uncorrelated (i.e. non-diagonal elements of the covariance

matrix are zero), $\mathbf{h}(\mathbf{TS})$ and $\mathbf{R}(\mathbf{TS})$ take the following expression:

$$h_{TOA_i} = \|TS - CS_i\| \quad i = 1, \dots, N_{cs} \quad (2)$$

$$\sigma_{TOA_i}^2 = \frac{c^2}{B^2 \left(\frac{P_T}{P_n} \right)} PL(d_0) \left[\left(\frac{d_{iLOS}}{d_0} \right) + \left(\frac{d_{iNLOS}}{d_0} \right)^{\frac{n_{NLOS}}{n_{LOS}}} \right]^{n_{LOS}} + \frac{1}{l} \sum_{k=1}^l \left\{ |T_i - floor_{TR}(T_i + U_i - U_0 + T_0(\eta_i - \eta_0) + T_i\eta_i)| c^2 \right\} \quad (3)$$

$$d_{iLOS} = \|TS - CS_i\|_{LOS} \quad (4)$$

$$d_{iNLOS} = \|TS - CS_i\|_{NLOS} \quad (5)$$

where N_{cs} is the number of CS under coverage, c the speed of the radioelectric waves in m/s, B the signal bandwidth in Hz, P_T the transmission power in W, P_n the mean noise level in W obtained through the Johnson-Nyquist relation, $PL(d_0)$ the path-loss in the reference distance d_0 from which the Log-Normal model is applied, d_{iLOS} and d_{iNLOS} represent the flight distance from each emitter/receiver pair in LOS and NLOS conditions respectively, n_{LOS} and n_{NLOS} the LOS and NLOS path-loss exponents, l is the number of iterations of the Monte-Carlo model for estimating the temporal variances, T_i is the time of flight of the positioning signal from emitter to receiver in TOA architecture, U_i and U_0 is the initial-time offset of the CS and TS clocks respectively and η_i and η_0 represent the clock drift of CS and TS clocks, and $floor_{TR}$ is the truncation function that represents the temporal resolution of the deployed sensors.

TDOA architectures assume the correlation among the time measurements [51] which produces non-zero elements in the non-diagonal terms of the covariance matrix. The vector $\mathbf{h}(\mathbf{TS})$ and $\mathbf{R}(\mathbf{TS})$ are obtained as follows:

$$h_{TDOA_i} = \|TS - CS_i\| - \|TS - CS_j\| \quad i = 1, \dots, N_{cs}, j = 1, \dots, N_{CS} \quad i \neq j \quad (6)$$

$$\sigma_{TDOA_{ij}}^2 = \frac{c^2}{B^2 \left(\frac{P_T}{P_n} \right)} PL(d_0) \left[\left(\frac{d_{iLOS}}{d_0} \right)_{CS_i} + \left(\frac{d_{iNLOS}}{d_0} \right)_{CS_i}^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{jLOS}}{d_0} \right) + \left(\frac{d_{jNLOS}}{d_0} \right)^{\frac{n_{NLOS}}{n_{LOS}}} \right]^{n_{LOS}} + \frac{1}{l} \sum_{k=1}^l \left\{ |T_i - floor_{TR}(T_i + U_i - U_0 + T_0(\eta_i - \eta_0) + T_i\eta_i)| c^2 \right\} + \frac{1}{l} \sum_{k=1}^l \left\{ |T_j - floor_{TR}(T_j + U_j - U_0 + T_0(\eta_j - \eta_0) + T_j\eta_j)| c^2 \right\} \quad (7)$$

$$d_{jLOS} = \|TS - CS_j\|_{LOS} \quad (8)$$

$$d_{jNLOS} = \|TS - CS_j\|_{NLOS} \quad (9)$$

where sub-index j is used for referring to the second positioning signal in the TDOA architecture (i.e. the emission in which the CS_j is operated).

A-TDOA architecture also assumes uncorrelated time measurements since a unique CS is employed for collecting the time measurements. $\mathbf{h}(\mathbf{TS})$ and $\mathbf{R}(\mathbf{TS})$ are particularized:

$$h_{A-TDOA_i} = \|TS - WS_i\| + \|TS-CS\| - \|WS_i - CS\| \quad (10)$$

$$i = 1, \dots, N_{ws}$$

$$\sigma_{A-TOA_i}^2 = \frac{c^2}{B^2 \left(\frac{P_T}{P_n}\right)} PL(d_0) \left[\left(\frac{d_{WS_i-TS_{LOS}}}{d_0}\right) + \left(\frac{d_{WS_i-TS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{TS-CS_{LOS}}}{d_0}\right) + \left(\frac{d_{TS-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{WS_i-CS_{LOS}}}{d_0}\right) + \left(\frac{d_{WS_i-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} \right]^{n_{LOS}} + \frac{1}{l} \sum_{k=1}^l \left\{ |(T_i + T_{TS} - T_{cs}) - floor_{TR} [(T_i + T_{TS} - T_{cs})(1 + \eta_{CS})]| c^2 \right\} \quad (11)$$

$$d_{WS_i-TS_{LOS}} = \|WS_i - TS\|_{LOS} \quad (12)$$

$$d_{WS_i-TS_{NLOS}} = \|WS_i - TS\|_{NLOS} \quad (13)$$

$$d_{TS-CS_{LOS}} = \|TS-CS\|_{LOS} \quad (14)$$

$$d_{TS-CS_{NLOS}} = \|TS-CS\|_{NLOS} \quad (15)$$

$$d_{WS_i-CS_{LOS}} = \|WS_i - CS\|_{LOS} \quad (16)$$

$$d_{WS_i-CS_{NLOS}} = \|WS_i - CS\|_{NLOS} \quad (17)$$

Substituting the corresponding $\mathbf{h}(\mathbf{TS})$ and $\mathbf{R}(\mathbf{TS})$ for each TBS architecture in the FIM matrix (Eq. 1), the accuracy of each architecture can be evaluated through the Root Mean Squared Error (RMSE), expressed by the following relation:

$$RMSE = \sqrt{\text{trace}(\mathbf{J}^{-1})} \quad (18)$$

B. SIMULATIONS ENVIRONMENT CONFIGURATION

The comparison between TBS architectures should take place in an environment where systems capabilities can be tested. In detail, specific scenarios for each application must be characterized to estimate the accuracy, cost, and robustness of the implemented system before its deployment. Even more interesting, with CRB models [25], the designer can compare different architectures, sensor placements, and environments conditions finding the best solution to its particular location problem.

This last approach is presented in this paper, where a 3D generic urban scenario has been conceived to compare TOA, TDOA, and A-TDOA characteristics (Figure 1). This scenario has been designed for testing TBS architectures throughput in harsh environments, where positioning signals are degraded by obstacles, buildings, which are typical

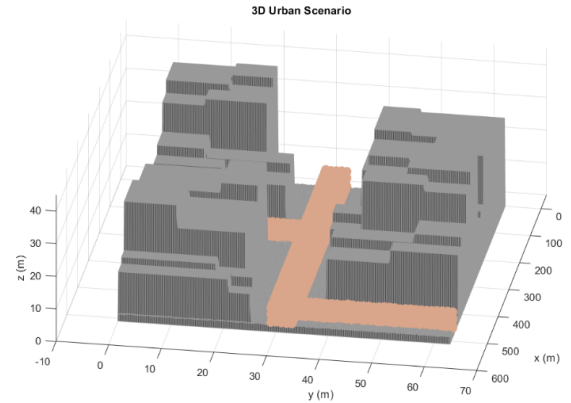


FIGURE 1. 3D urban scenario of simulations. Grey tones represent the reference surface and buildings, while brown colors indicate the Target Location Environment (TLE).

operating conditions for future autonomous vehicles and other high-demanding applications in urban areas.

Based on the terminology detailed in [39], the Target Location Environment (TLE) is defined as the allowed TS navigation area, and the Node Location Environment (NLE) is identified as the possible zone where architecture sensors can be located.

In the scenario depicted in Figure 1, the TLE region is located in the proximity of the reference surface, simulating a terrestrial positioning application (however it can model also aerial configurations). It extends from 0.5 to 5 meters in elevation from the ground, avoiding multipath phenomena that blurred the representativeness of the accuracy results reached through the CRB models.

The NLE zone extends over all the reference surface and buildings, except for the TLE region. This ensures that architecture sensors do not disturb the traffic of possible vehicles. The NLE region is contained in height from 3 to 10 meters, minimizing disruptive phenomena due to multipath in the sensors, and limiting the maximum size of sensors, especially critical in urban environments.

Once TLE and NLE regions are determined, a discretization process based on a required spatial resolution must be performed. This procedure is extremely important to obtain accurate results, without over-dimension the processing time of the optimization.

For the TLE area, spatial resolutions of 1 meter in x and y , and 1.5 in z Cartesian coordinates are defined. The discretization of the NLE region is directly determined by the scaling process of the implemented GA [39] for the optimization. Based on this, a grid resolution contained in the interval [0.5-1] meter is employed.

These settings are founded when the optimization variables vary less from the 1 % when increasing the spatial resolution of NLE and TLE zones, reaching a trade-off between representativeness and processing time. This analysis should be performed for every environment of the application.

III. GENETIC ALGORITHM OPTIMIZATION

In this manuscript, a TBS performance comparison in terms of accuracy, availability, and robustness is carried out for high-demanding applications in 3D urban environments. Comparative results must be acquired through optimized sensor distributions for each TBS in the Scenario presented in Figure 1. In this section, the characteristics of this optimization problem and the implemented methodology to solve are submitted, together with the optimization functions for locating TOA, TDOA, and A-TDOA architectures sensors.

A. NODE LOCATION PROBLEM

The finding of the optimized sensor distribution for the reduction of the architecture uncertainties is known as the Node Location Problem (NLP).

It is a crucial task in Wireless Sensor Networks (WSN) since the system performance is notably dependent on finding an optimized node deployment. The definition of the necessary nodes for covering the target area (i.e. coverage problem [52]), the consideration of possible sensor failures in the deployment [47], the reduction of the energy consumption [53] or the minimization of the clock [26] and noise [41] uncertainties are some of the most important issues in WSN that require an optimized sensor location for achieving acceptable results.

The NLP is a combinatorial optimization problem that has been assigned as NP-Hard [27], [28]. Therefore, a heuristic solution is recommended for finding an optimized sensor placement in polynomial time. However, the huge dimension of the space of solutions of the NLP - highly dependent on the number of sensor nodes and the resolution of the NLE and TLE [25]- has suggested the usage of metaheuristics which reach an optimal trade-off among the intensification and diversification phases in the combinatorial search. Among them, GA [39]–[42] has particularly stood out in the literature.

In the localization field, the usage of heuristics for the NLP is also justified since the derivation of the quality metric (CRB) cannot be extended to the entire TLE [49]. Therefore, it is impossible to define a path in the optimization process in which an ascent tendency in the fitness value can be attained. This produces that the NLP designer must particularly perform a hyperparameter tuning to guarantee the population diversity for achieving a balanced examination of the space of solutions and avoiding the premature convergence of the algorithm.

As a consequence, in this paper, we propose a GA optimization to the NLP of the three main localization architectures in urban scenarios with the methodology for the hyperparameter tuning described in [39].

B. CHARACTERIZATION OF THE NODE LOCATION PROBLEM

The NLP aims to discover the optimal Cartesian coordinates of the architecture sensor nodes for enhancing the sensor network localization properties.

Generally, the NLP is defined as the finding of the subset S_i containing the Cartesian coordinates of each of the architecture sensors ($\langle s_i \rangle = \langle x_i, y_i, z_i \rangle$) fulfilling the following relation [33]:

$$(\langle S_i \rangle = (\langle s_i \rangle, \dots, \langle s_n \rangle)) \subset S : \left\{ \begin{array}{l} \frac{\sum_{k=1}^{K_{TLE}} ff_{S_i}(k)}{K_{TLE}} \\ \geq \max \left(\frac{\sum_{k=1}^{K_{TLE}} ff_{S_j}(k)}{K_{TLE}} \right) \end{array} \right\} \quad (19)$$

where S is the set containing each possible combination of sensors in the space of coverage, S_j the subset containing every combination of S except S_i , n the number of sensors of the architecture, K_{TLE} all the points in which the target is considered to be located during the optimization process [39], $ff_{S_i}(k)$ the evaluation of the fitness function of the subset S_i in one of the analyzed target points k and $ff_{S_j}(k)$ the analysis of the fitness function in a determined point k in the subset S_j .

In addition, the characterization of the NLP requires the definition of the hyperparameter K_{NLE} -the number of possible locations for an architecture sensor in the coverage area- which defines the number of possible individual subsets of the S in the NLP which is defined as follows [33]:

$$P(\text{Sensor Distributions}) = \left[\prod_{m=0}^{n-1} (K_{NLE} - m) \right] \quad (20)$$

Consequently, the NLP is factorial with the number of nodes present in each architecture which is dependent on the achievement of the accuracy results acceptable in the designing process. Thus, the correct definition of K_{TLE} and K_{NLE} are critical for obtaining acceptable results in time-effective NLP optimizations [39]. In this paper, the definition of these hyperparameters are performed through the achievement of slightly modifications in the principal statistical variables when reducing the spatial resolution.

C. OPTIMIZATION FUNCTIONS FOR TBS

The optimization objectives of the TBS comparison are represented through specific fitness functions for TOA, TDOA, and A-TDOA architectures. For further details of the presented TBS architectures, please refer to the authors' previous work in [26]. Precisely, the optimization must maximize the accuracy, availability, and robustness of each architecture in the environment of simulations, while penalizing all sensor distributions with an invalid configuration.

The maximization of the accuracy is completed through the minimization of temporal uncertainties induced by noise, clock errors, and NLOS conditions in the positioning signals of TBS. The accuracy magnitude for each TBS sensor distributions is estimated through the RMSE characterized based on the corresponding CRB system model (Section 2).

The maximization of the availability is performed through the assurance of the throughput requirements when some sensors of the TBS are not accessible to the operation. Accordingly, the optimization should provide sensor distributions

that maximize the accuracy performance of TOA, TDOA and A-TDOA architectures when Coordinate Sensors (CS) –those with the capacity to perform temporal measurements– and/or Worker Sensors (WS) –sensors without the time measuring ability, typical of A-TDOA systems–fail or are unavailable. Based on their configuration, the maximization of the availability is represented differently for each TBS.

Concerning to the maximization of robustness, high-demanding applications demand not only accuracy in the TS positioning, but also stability in the location service. The optimization of TBS must penalize sensor deployments with high contrast in the accuracy values of all the TLE region of the system.

Finally, penalizations for forbidden sensor distributions, such as devices located inside the TLE zone, are performed for ensuring correct TBS implementations. Similarly, designers can encourage distributions in certain pre-determined areas.

Gathering previous requirements, a global fitness function for the cost-effective node deployment of TBS in urban environments can be characterized through the next relation:

$$ff = c_{acc}ff_{acc} + c_{avaff}ff_{ava} + c_{rob}ff_{rob} - (c_{acc} + c_{ava} + c_{rob})ff_{pen} \quad (21)$$

where ff stands for the value of the global fitness function, ff_{acc} represents the accuracy component of the ff , ff_{ava} relates the availability compound of the ff , ff_{rob} expresses the robustness part of the ff function, and finally ff_{pen} quantifies all penalizations applied to the TBS sensor distribution. Each of these components is linked to their correspondent coefficient (c_{acc} , c_{ava} , c_{rob}) for weighting its influence according to the optimization prerequisites.

As it can be observed, the optimization process is based on the maximization of Eq.21, searching for a trade-off between accuracy, availability, robustness, and avoiding forbidden sensor distributions.

Thus, the mathematical model proposed in this paper for the NLP in TBS architectures is presented below:

$$\text{Maximize } Z = ff(ff_{acc}, ff_{ava}, ff_{rob}, ff_{pen}) \quad (22)$$

$$\text{Subject to : } x_{lim_1} \leq x_i \leq x_{lim_2}; \quad \forall x_i \in s_i, s_i \in S; s_i \notin U \quad (23)$$

$$y_{lim_1} \leq y_i \leq y_{lim_2}; \quad \forall y_i \in s_i, s_i \in S; s_i \notin U \quad (24)$$

$$z_{lim_1} \leq z_i \leq z_{lim_2}; \quad \forall z_i \in s_i, s_i \in S; s_i \notin U \quad (25)$$

$$Cov_{arch_k} \geq n_{min_{arch}} \quad (26)$$

$$Cov_{arch_k} = \sum_{i=1}^n Cov_{arch_{kn}} \quad (27)$$

$$Cov_{arch_{kn}} = \begin{cases} 1 & \text{if } SNR_{kn} \geq SNR_{threshold} \\ 0 & \text{otherwise} \end{cases} \quad (28)$$

where x_{lim_1} , y_{lim_1} , z_{lim_1} and x_{lim_2} , y_{lim_2} , z_{lim_2} are the lower and upper bounds for a sensor to be located in the simulations scenario respectively and U the subset of S containing the forbidden regions for the architecture sensors such as the area for the navigation of the vehicles or the buildings of the urban scenario, Cov_{arch_k} represents the number of architecture sensors with effective coverage in an analysis point k which must exceed the minimum number of sensors under coverage for performing location in each architecture ($n_{min_{arch}}$) and the definition of the effective coverage of an architecture sensor node n in the point k ($Cov_{arch_{kn}}$) is achieved when the link between the sensor and the target has a signal-to-noise ratio (SNR_{kn}) which exceeds the threshold ($SNR_{threshold}$) imposed by the receptor sensibility.

TOA architectures are optimized based on the relations submitted in Eq. 29. Accuracy estimation is obtained through the CRB calculation based on the environment simulation detailed in Eq.3, ensuring that at least 4 TOA sensors are usable. Availability requirements are studied of the system performance when the minimum number of sensors is accessible to TS location (for TOA architectures, when only 3 sensors in coverage). Respecting robustness, the fitness function incrementally penalizes TLE zones where performance is non-adequate, avoiding sensor distributions without consistency in the system throughput over the entire TLE. Finally, architecture sensors that are located inside the TLE zone are also penalized.

$$\begin{aligned} ff|_{TOA} &= c_{acc}|_{TOA} (ff_{acc}|_{TOA}) + c_{ava}|_{TOA} (ff_{ava}|_{TOA}) \\ &\quad + c_{rob}|_{TOA} (ff_{rob}|_{TOA}) - (c_{acc}|_{TOA} + c_{ava}|_{TOA} \\ &\quad + c_{rob}|_{TOA}) (ff_{pen}|_{TOA}) \\ ff_{acc}|_{TOA} &= \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - RMSE)}{RMSE_{ref}} \right]^2}{K_{TLE}} \Bigg|_{TOA} \\ ff_{ava}|_{TOA} &= \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - \sum_1^{Comb} \frac{RMSE_{3,C}}{Comb})}{RMSE_{ref}} \right]^2}{K_{TLE}} \Bigg|_{TOA} \\ ff_{rob}|_{TOA} &= \left\{ \frac{abs[K_{TLE} - sum(\mathbf{Eval})]}{K_{TLE}(K_{TLE} + 1)} \right\}^2 \Bigg|_{TOA} \\ ff_{pen}|_{TOA} &= \frac{\sum_1^N \mathbf{R}}{N} \Bigg|_{TOA} \end{aligned} \quad (29)$$

where K_{TLE} is the number of points in the TLE region, $RMSE_{ref}$ is the reference RMSE for normalizing ff_{acc} , assuming a maximum error of 300 meters when positioning cannot be provided (worst accuracy condition in the problem), \mathbf{RMSE} is the vector that contains the accuracy evaluation for all TLE zone, $Comb$ is the number of possible combinations of 3 available sensors in each zone of the TLE region, $\mathbf{RMSE}_{3,C}$ represents the accuracy estimation for each

point of the TLE region for each combination of 3 possible TOA sensors in coverage, **Eval** is the vector that stores the existence of the required architecture sensors in each point of the TLE –assuming a value of $-2K_{TLE}$ when these conditions are not fulfilled [25], N is the total number of sensors deployed, and **R** represents the vector for penalizing wrong sensors distributions (0 for valid and 1 invalid allocation).

TDOA architectures optimization is founded on the same basis as TOA systems. Based on CRB evaluation for TDOA architectures with temporal uncertainties induced by noise, clock errors, and NLOS conditions (Eq. 7), accuracy in each of the TLE points is estimated for sensor distributions (assuming that at least 4 TDOA sensors are accessible for 3D positioning). Availability is addressed through the accuracy analysis of sensor distributions when the minimum number of sensors is available for positioning (4 in the case of 3D location with TDOA systems [19]). Also, in TDOA architectures one pre-determined CS is used to refer time measurements of the surroundings TDOA sensors and compute pairs of time difference of arrival from TS. For this reason, availability is also affected by malfunctions in this pre-defined CS in each TLE zone, so at least 2 eligible CS must be in coverage and connected with 3 more (shared or not) CS in order to perform positioning in failure conditions. As in the TOA case, robustness is maximized based on a progressive fitness function for evaluation accuracy and availability, which gradually penalizes sensor distributions with non-uniformity in the performance for every TLE region. Also, TDOA sensors placed inside TLE zones led to hard penalizations in the global fitness function for this sensor distribution.

$$\begin{aligned}
 ff|_{TDOA} &= c_{acc|TDOA} (ff_{acc}|_{TDOA}) \\
 &+ c_{ava|TDOA} (ff_{ava}|_{TDOA}) \\
 &+ c_{rob|TDOA} (ff_{rob}|_{TDOA}) - (c_{acc|TDOA} \\
 &+ c_{ava|TDOA} + c_{rob|TDOA}) (ff_{pen}|_{TDOA}) \\
 ff_{acc}|_{TDOA} &= \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - RMSE_{prim})}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA} \\
 ff_{ava}|_{TDOA} &= \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - RMSE_{sec})}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA} \\
 &+ \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - \sum_1^{Comb} \frac{RMSE_{4,C}}{Comb})}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA} \\
 ff_{rob}|_{TDOA} &= \left. \left\{ \frac{abs [K_{TLE} - sum(\mathbf{Eval})]}{K_{TLE}(K_{TLE} + 1)} \right\} \right|_{TDOA} \\
 ff_{pen}|_{TDOA} &= \left. \frac{\sum_1^N \mathbf{R}}{N} \right|_{TDOA} \tag{30}
 \end{aligned}$$

where $RMSE_{prim}$ and $RMSE_{sec}$ represents the location accuracy obtained with the primary and secondary eligible CS for all TLE points, $RMSE_{4,C}$ represents the accuracy estimation for each point of the TLE region for each combination of 4 possible TDOA sensors in coverage, and the rest of the variables of the fitness function are defined as previously but for the TDOA architecture characteristics.

A-TDOA architectures are optimized based on the criteria presented in Eq. 21, but the methodology for analyzing accuracy and availability requirements are slightly different than the purposed for TOA and TDOA systems. This alteration is induced by the existence of two different types of sensors (CS and WS) characteristics of A-TDOA architectures.

Accuracy estimation is carried out from the assumption that 1 CS and at least 4 WS are available to connect with the TS location. Consequently, temporal measurement uncertainties in systems sensors motivated by noise, clock errors, and NLOS conditions, are introduced in Eq.11 and positioning accuracy (RMSE) is calculated based on CRB. Availability evaluation is performed based on the capacity of the system to provide high-accuracy positioning service when some of the CS or WS present malfunctions. Conversely to previous TBS systems, in A-TDOA architectures there exists two types of sensors with different capabilities and functions, so the availability study must distinguish their impacts. Precisely, WS availability is approached as in TOA and TDOA systems, where the accuracy is evaluated for each possible combination with the minimum number of sensors needed for positioning (3 WS [19] and 1 CS for A-TDOA systems). Concerning CS availability, the optimization must guarantee that a minimum of 2 CS –with the correspondent WS connected (shared or not) between them– is accessible in each zone of the TLE region, alluring the positioning service in the event of CS malfunctions [25]. Robustness and undesirable sensor distributions are feed into the optimization using the same methodology that the rest of the TBS treated.

$$\begin{aligned}
 ff|_{A-TDOA} &= c_{acc|A-TDOA} (ff_{acc}|_{A-TDOA}) \\
 &+ c_{ava|A-TDOA} (ff_{ava}|_{A-TDOA}) \\
 &+ c_{rob|A-TDOA} (ff_{rob}|_{A-TDOA}) \\
 &- (c_{acc|A-TDOA} + c_{ava|A-TDOA} + c_{rob|A-TDOA}) \\
 &\times (ff_{pen}|_{A-TDOA}) \\
 ff_{acc}|_{A-TDOA} &= \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - RMSE_{prim})}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{A-TDOA} \\
 ff_{ava}|_{A-TDOA} &= \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - RMSE_{sec})}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{A-TDOA}
 \end{aligned}$$

$$\begin{aligned}
& + \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \sum_1^{Comb} \frac{RMSE_{4,C}}{Comb} \right)^2}{RMSE_{ref}} \right]}{K_{TLE}} \Bigg|_{A-TDOA} \\
& \left. \begin{aligned}
& \left. \begin{aligned}
& ff_{rob} \Big|_{A-TDOA} \\
& = \left\{ \frac{abs [K_{TLE} - sum(\mathbf{Eval}_{prim})]}{K_{TLE}(K_{TLE} + 1)} \right\}^2 \\
& + \left\{ \frac{abs [n_{TLE} - sum(\mathbf{Eval}_{sec})]}{K_{TLE}(K_{TLE} + 1)} \right\}^2 \Bigg|_{A-TDOA} \\
& ff_{pen} \Big|_{A-TDOA} \\
& = \frac{\sum_1^N \mathbf{R}}{N} \Bigg|_{A-TDOA}
\end{aligned} \right\} (31)
\end{aligned} \right.
\end{aligned}$$

where \mathbf{RMSE}_{prim} and \mathbf{RMSE}_{sec} indicate the accuracy evaluation for all TLE based on the primary CS associated and the second one, respectively, for each TLE point, $\mathbf{RMSE}_{4,C}$ represents the accuracy estimation for each point of the TLE region for each combination of 3 possible A-TDOA WS and 1CS in coverage, and \mathbf{Eval}_{prim} and \mathbf{Eval}_{sec} are respectively the vectors that quantify the existence of one or two CS –with their correspondent minimum or four WS (shared or not)-, assuming a value of $-2K_{TLE}$ when these conditions are not fulfilled [25].

D. OPTIMIZATION PROCESS

Once presented the quality evaluation models for each one of the TBS architectures and the mathematical modeling of the NLP, we detail through the following pseudocode the optimization process developed for optimizing the node distribution of these architectures for making their results objectively comparable for the first time.

The optimization is carried out through the enforcement of a GA algorithm, as it is shown in Table 1. Amongst all the heuristic methodologies usually applied for solving the NLP, GAs submit more flexibility for adapting to the characteristics of each specific implementation due to their large number of encodings and genetic operators, the diversification and intensification stages can be adjusted to the convergence features of the problem, and the control over the selective pressure allows a better global performance in harsh optimizations with severe discontinuities in the fitness function.

As it is shown in Algorithm 1, the process starts with the definition of a random population of individuals containing possible node distributions. We then start the GA until the convergence criteria is fulfilled. Inside the GA, we calculate the LOS/NLOS paths of the positioning signal from each of the possible TLE analyzed points to each of the nodes of the architecture through the Ray Tracing algorithm introduced in [41]. Later, the temporal variances are calculated through the Monte Carlo model introduced in [26]. This information allows the calculation of the CRB of each architecture following the model presented in Section 2.1.

TABLE 1. Pseudocode of the optimization process followed for the solution of the NLP

Algorithm 1: GA with LOS/NLOS and Clock Errors
 $(\pi, Eli, Mut, \pi_{limits}, \pi_{obstacles}, \tau_{param}, k_{TLE}, k_{NLE}, n, Convergence\ criteria, N)$

```

1 Pop ← Random Distribution of N Individuals with n
  sensors among the kNLE possible locations of scenario π,
  respecting πlimits and πobstacles;
2 while Convergence criteria is not fulfilled do
3   for Ind in Pop do
4     for Pt in kTLE do
5       for Sensor in Ind do
6         φ(Sensor) ← LOS/NLOS Error 3D Ray
          Tracing Detection Algorithm(π, Pt,
          Sensor);
7       end
8       σ ← Temporal Variances of Clock Errors
          obtained from Monte-Carlo simulations(π, Pt,
          Ind);
9       R(TS)τ ← Noise and Temporal uncertainties
          (φ, σ, Ind);
10      FIMτ(Pt) ← (R(TS)τ, h(TS)τ, τparam, Ind);
11      CRBτ(Pt) ← Inverse of FIMτ(Pt);
12      RMSEτ(Pt) ← Trace of CRBτ(Pt);
13    end
14    ffacc ← Accuracy analysis of Pop in π based on τ
          architecture;
15    ffavv ← Availability analysis of Pop in π based on
          τ architecture;
16    ffrob ← Robustness analysis of Pop in π based on
          τ architecture;
17    ffpen ← Penalization analysis of Pop in π,
          considering πlimits and πobstacles;
18    ffτ(Ind) ← function of
          (ffacc, ffavv, ffrob, ffpen)τ;
19  end
20 Pop ← Selection of Pop, based on ffτ;
21 Pop ← Elitism of Eli % of Pop;
22 Pop ← Crossover of Pop;
23 Pop ← Mutation of Mut % Pop;
24 end

```

This information allows us to calculate the fitness functions presented in Section 3.3 following the characteristics of the TBS architecture that is being optimized for finally utilize the GA operators (selection, elitism, crossover and mutation) for executing the evolutionary optimization.

The implemented GA [39] allows adapting the heuristic optimization process to the local geometric properties of the NLE and TLE zones. In this sense, a binary encoding and a scaling transformation of coordinates enable real-cases scenarios of optimization. Also, the binary codification entitles the implementation of distinct crossover techniques and mutation procedures for boosting the convergence of the method.

IV. RESULTS

The results of the TBS node optimization in the 3D urban environment detailed in Figure 1 are submitted in this section. Firstly, descriptions about the positioning systems configuration and the GA hyper-parameters are provided. Secondly,

TABLE 2. TBS configuration parameters relative to positioning technology, time measurement devices [21], and environment characterization [54]

Parameter	Value
Transmission power	1 W
Frequency of emission	5465 MHz
Bandwidth	100 MHz
Mean noise power	- 94 dBm
Receptor sensibility	- 90 dBm
Clock frequency	1 GHz
Frequency-drift	$U\{-10, 10\}$ ppm
Initial-time offset	$U\{15, 30\}$ ns
Time from synchronization	1 μ s
LOS Path loss exponent	2.1
NLOS Path loss exponent	4.1

performance evaluations for TOA, TDOA, and A-TDOA architectures in the urban scenario are supplied. Finally, an analysis of the results is submitted, highlighting the benefits of each architecture and how their characteristics influence their implementation to high-demanding positioning applications

A. SELECTION OF PARAMETERS FOR THE SIMULATIONS

TBS node optimizations are subjected to the definition of the location technology and the optimization strategy to properly compare the positioning architectures.

Relating TBS technologies, the objective of this manuscript is to provide a detailed methodology to estimate architectures a priori throughputs and compare positioning systems based on real applications in complex urban environments. Based on this, a generic configuration of communications and positioning devices is selected, aiming the most representativeness with urban restrictions and limitations. Positioning signal characteristics, clocks uncertainties models, and path loss estimations are shown in Table 2.

The hyper-parameter selection for the GA optimization is conditioned to the trade-off between the obtainment of near-global maximum solutions with high representativeness and spatial resolution, and the processing time and the complexity of the method. Table 3 displays the optimization parameters chosen for the simulations with the TBS.

Regarding the GA configuration of Table 3, experiments were carried out for diminishing the number of individuals in the population due to their direct impact on the complexity and processing time. Reducing individuals below 80 led to suboptimal optimizations and unstable convergences, so this value is fixed as the minimum threshold for adequate optimizations.

Tournament 2 has been selected as the selection technique due to their better trade-off between higher fitness function values and the number of generations to converge, compared to other methodologies as Tournament 3, Ranking, and Roulette. Parametric analysis for elitism has been also

TABLE 3. Settings for GA optimization for TOA, TDOA, and A-TDOA architectures

GA	Settings
Population size	80
Selection technique	Tournament 2
Crossover technique	Single-point
Mutation technique	Single-point
Elitism percentage	3 %
Mutation percentage	8 %
Stop criteria	300 generations or 75 % of equal individuals
Fitness function coefficients	1

developed, based on the same criteria as the election of the selection technique and with the analytical process for the selection of these values that we introduced in [55] adapted to this particular scenario. In this regard, the optimization process tends to fall in local optima, so applying slight selective pressure results in the better global performance of the method.

Among the large variety of crossover and mutation binary techniques, the single-point methodologies provide the best outcomes thanks to the escalation in the exploration of the space of solutions. In the urban NLOS problem, where discontinuities and drastic alterations in the fitness functions are present, these procedures are the key aspect for obtaining a trade-off between the diversification and intensification stages. The effect of these techniques is a progressive increment of the maximum fitness function value through the generations, thanks to the creation of new individuals with a resemblance with their progenitors (uniform crossovers show a tendency to blur the genetic similarity inducing less robust optimizations).

The mutation percentage is slightly larger than usual to overcome local optimizations induced by the discontinuities in the global fitness function caused by NLOS conditions [33]. Lastly, the fitness function coefficients (Eq. 19) are determined as unitary to perform a standard optimization where normal operating conditions are considered to a greater extent than emergency (failure) conditions. However, this layout can be adapted based on optimization demands and application requirements.

B. TBS OPTIMIZATIONS

The large urban scenario of simulations selected has promoted the employment of 25 architecture sensors for achieving the coverage of the entire analyzed TLE points.

We have performed the optimizations described throughout the past chapters for each of the TBS architectures (TOA, TDOA and A-TDOA) looking for enhanced node distributions in accuracy, availability and robustness reaching the following results displayed from Figure 2 to Figure 4:

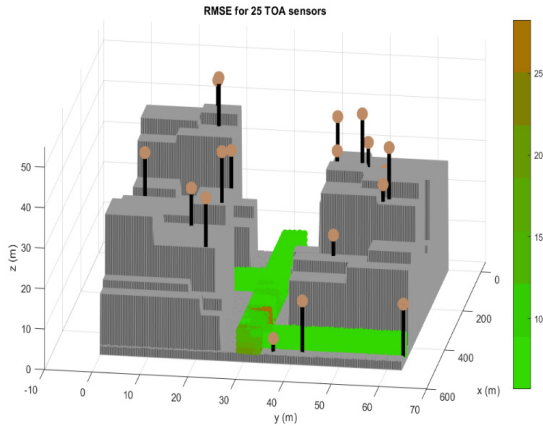


FIGURE 2. Accuracy representation in every TLE analyzed point for the optimized TOA architecture with 25 sensors in the proposed urban scenario. The architecture nodes deployed are displayed in brown tones.

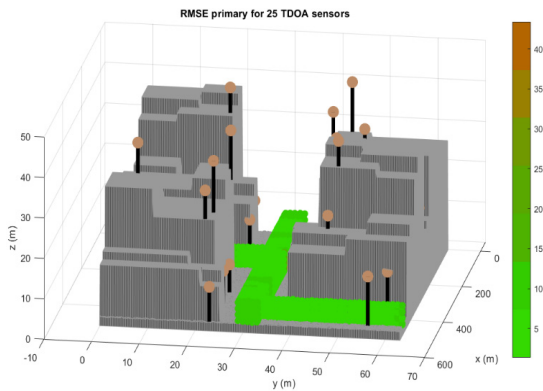


FIGURE 3. Accuracy representation in every TLE analyzed point for the TDOA architecture with 25 sensors in the proposed urban scenario. The architecture nodes deployed are displayed in brown tones.

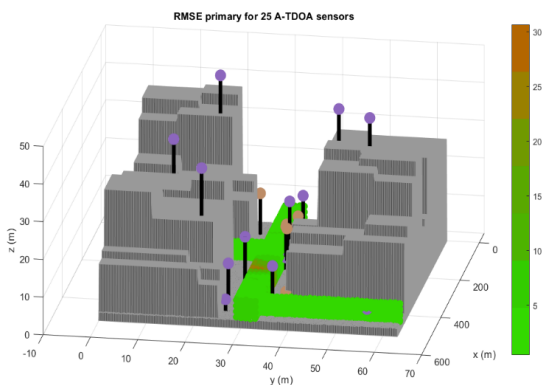


FIGURE 4. Accuracy representation in every TLE analyzed point for the A-TDOA architecture with 25 sensors (5 CS) in the proposed urban scenario. The architecture CS nodes deployed are displayed in brown tones and the WS are displayed in purple tones.

The previous figures have shown the accuracy of each architecture in the TLE. Then, in Table 3, the results of the accuracy and availability of the optimizations in nominal conditions are presented:

TABLE 4. Accuracy analysis for the TOA, TDOA and A-TDOA architectures in nominal conditions

RMSE (m)	TOA	TDOA	A-TDOA
Mean	8.82	6.32	3.84
Max	28.26	43.38	30.66
Min	5.69	1.35	0.47

TABLE 5. Accuracy analysis for the A-TDOA architecture in failure emergency conditions

RMSE (m)	A-TDOA
Mean	4.49
Max	35.46
Min	0.49

As it is shown, A-TDOA outperforms the synchronous architectures in accuracy, indicating the relevance of the synchronism errors in LPS. Therefore, the path errors have less influence than the clock uncertainties in urban scenarios as we previous demonstrated in outdoor environments in [26] even considering NLOS paths through the algorithm later introduced in [41].

This also means that the evolutionary optimization proposed in this manuscript is able to address the trade-off required for reducing the signal paths in the whole TLE analyzed points without compromising the accuracy in any region.

It is particularly noteworthy the achievement of a reduced error bound in the TOA architecture which is the result of the least dependency of this architecture on particular nodes for collecting the time measurements, making the TOA systems more flexible and robust.

However, their mean error values due to the influence of the synchronism uncertainties makes the TOA architecture non-competitive in this scenario but it could be suitable in especially harsh environments which could potentially promote an incremental number of CS in the A-TDOA architecture for the attainment of acceptable accuracy results [25].

The preeminence of the A-TDOA architecture in this scenario promotes the determination of their results in emergency conditions to conclude its suitability for this particular scenario. We present in Figure 5 and Table 4 the operation of this architecture in failure condition of a CS in every analyzed TLE points promoting the use of the secondary CS under coverage which is granted during the evolutionary optimization of this architecture following the methodology introduced in [25].

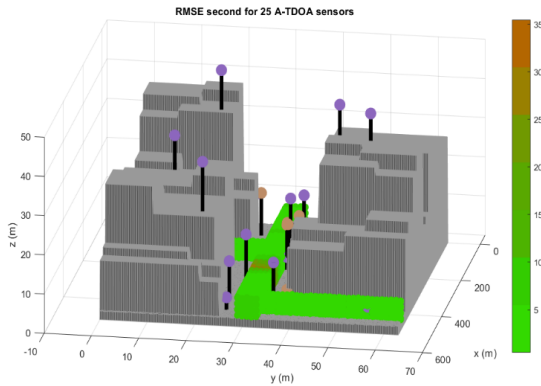


FIGURE 5. Accuracy representation in every TLE analyzed point for the A-TDOA architecture in failure conditions with 25 sensors (5 CS) in the proposed urban scenario. The architecture CS nodes deployed are displayed in brown tones and the WS are displayed in purple tones.

Consequently, the application of the A-TDOA architecture in failure conditions slightly deteriorate with regards to its nominal operation showing the availability of this architecture and the quality of the optimization process.

As it is shown, the overall results show the preeminence of the A-TDOA in this urban scenario. This supposes an outstanding remark to be considered for future high-demanded applications in urban contexts.

V. CONCLUSION

Local Positioning Systems (LPS) have shown an excellent adaptation for high demanded accuracy applications in complex environments. The development of autonomous navigation with high accuracy needs has supposed a challenge in NLOS urban scenarios.

In this paper, we propose a methodology for the deployment of Time-Based Positioning Systems (TBS) in urban environments. This methodology relies on the exploration and analysis of the three main temporal localization architectures: Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Asynchronous Time Difference of Arrival (A-TDOA).

Every architecture must be considered for every different scenario since the clock errors and noise path uncertainties are imbalanced among them. TOA systems accumulate the least noise uncertainties since the positioning signal travels the shortest path of these architectures but requires the synchronism of all the system elements, while A-TDOA avoid synchronization errors but increases the signal paths by its receive and retransmit strategy.

Consequently, we define a general framework for the optimization of the node distribution of these TBS architectures in order to compare their performance in the proposed urban scenario. This optimization requires the solution of the node location problem for each architecture which has been assigned as NP-Hard.

We propose a GA optimization for addressing this complex problem focusing on the reduction of the clock and noise

architecture uncertainties in a combined LOS and NLOS urban scenario, on guaranteeing the system accuracy and on system availability in case of some Coordinator or Worker Sensor malfunction and penalizing invalid node deployments.

Results show the preeminence of the A-TDOA architecture in the proposed scenario. The influence of the synchronization effects makes A-TDOA to be promising for urban Local Positioning System applications due to the achieved reduction of the system clock errors. However, the simulations have shown the importance of the location of the CS nodes in the A-TDOA in desirable special positions that are reached in this scenario but can suppose a challenge in some environments, promoting the implementation of the TOA and TDOA system in especially irregular urban scenarios

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