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Optimized Cost-Effective Node Deployments in Asynchronous Time Local Positioning Systems

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ABSTRACT Asynchronous Time Local Positioning Systems are emerging as a decisive tool for high-demanded accuracy applications. Its relevance relies on the unnecessary synchronism of the system devices and the ad-hoc node deployment for fitting the design requirements in irregular scenarios. In this paper, we provide a new methodology for obtaining optimized cost-effective asynchronous node deployments based on system accuracy, enhanced primary and emergency operating conditions and security robustness. In addition, we perform a deep analysis of the NP-Hard node location problem and we propose a new Cramér-Rao Bound (CRB) error characterization considering Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) system connections and clock instabilities for evaluating the quality of a node deployment. We apply a Genetic Algorithm optimization in an irregular scenario of simulations to display this innovative methodology with a trade-off between resolution in the search in the space of solutions and the achievement of time-effective results. Results show that deployments with 4 and 5 coordinator sensors fulfill the design requirements in the proposed scenario in both primary and emergency conditions (1.14 and 1.70 meters and 0.89 and 1.47 meters of mean errors respectively) while 5 coordinator sensor configurations outperform 4 coordinator sensor configurations in system security robustness proving their preeminence in this study.

INDEX TERMS Asynchronous positioning systems, CRB, clock errors, genetic algorithm, LOS, NLOS.

I. INTRODUCTION

Global Navigation Satellite Systems (GNSS) provide global coverage with a constellation of satellites in the space. Their usage is widespread since they reach acceptable accuracy for localizing objects in the earth with the available number of satellites under coverage in a determined target location. However, their signals simply deteriorate by crossing large buildings [1], by facing obstacles in their paths [2], by suffering ionospheric adverse effects [3] or by unstable synchronization effects on GNSS devices [4].

Consequently, new deployments of sensors in local and defined spaces with the aim of enhancing accuracy have attracted research interest over the last few years. These deployments are known as Local Positioning Systems (LPS) which enable to locate targets for high demanded accuracy applications such as indoor localization [5], precision farming [6], precision landings [7], or autonomous navigation [8].

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LPS conception allows the proximity between targets and sensors to reduce adverse effects on the physical properties measured to compute location. LPS are distinguished and classified by the physical property measured: time [9], angle [10], power [11], phase [12], frequency [13] or combinations of them [14], [15].

Among these systems, Time-Based Positioning Systems have the better combination between accuracy, stability, robustness and easy-to-implement hardware design. Time measurements can be collected from two different strategies: total time-of-flight measurements and relative time-of-flight measurements.

Total time-of-flight systems, usually known as Time of Arrival (TOA) [16], perform their target position determination through the distance traveled by the signal from the emitter to the receivers. They require the complete synchronization among the clocks of the system (i.e. targets and sensors) to compute the time measurements. At least four receivers are required to unequivocally determine the 3D target cartesian coordinates in these systems.

Relative time-of-flight systems, usually known as Time Difference of Arrival (TDOA) [17], measure the distance difference of the signal path traveled from the emitter to the architecture sensors. These systems make use of at least five sensors to unequivocally determine 3D target position determination even though we have proven [18] that by optimizing the location of the sensors the problem can be solved with four receivers.

Since the time differences are computed without considering the emission time in TDOA architectures, the synchronism of the clock of the receivers is enough to compute the system measurements. Furthermore, the synchronism of the receivers is optional in asynchronous TDOA configurations which have emerged over the last few years enabling the avoidance of the synchronization process among all the receivers by centralizing the time measurements in a single clock of a coordinator sensor (CS). This process reduces the uncertainty and allows more stable target location calculations.

Asynchronous Time Difference of Arrival (A-TDOA) [19] and Difference-Time Difference of Arrival (D-TDOA) [20] represent these elliptical asynchronous [21] methods and its accuracy was studied in [22] showing a better overall performance of the A-TDOA for LPS applications.

Asynchronous systems reduce uncertainties but increase the paths traveled by their signals since the emission of the positioning signal from the worker sensors (WS) to the coordinator sensors (CS) must also be considered. Hence, noise errors are increased in the asynchronous systems and clock errors are reduced with regard to synchronous LPS. We studied this problem in [23] and determined that the overall error was greater in synchronous LPS applications.

Therefore, asynchronous LPS provide greater accuracy and stability for high-demanded autonomous applications. This consideration relies on an optimized node deployment since bad sensor configurations in the space increase the global architecture errors due to the accumulated error of non-optimized paths and time measurements.

This fact contributes to enhance the importance of the sensor locations in LPS. This is the main advantage of LPS since the designer can locate the sensors to maximize the system properties in a defined space. However, the designer deals with a complex NP-Hard problem [24], [25] which has been widely studied in the literature [26]–[28]. Because of the dimensions of the space of solutions, heuristic methods are applied to find an appropriate and optimized solution in acceptable time [29]–[31].

The cost function of the problem is commonly the reduction of the uncertainties of the system errors. For this purpose, a characterization of the noise and clock errors is needed in each possible target location inside the coverage of the LPS.

Firstly, Position Dilution of Precision (PDOP) was used as the tool to characterize the system errors [32]. However, it represents a homoscedastic noise consideration which do not deal with LPS applications since distances between targets and receivers may vary notably. Therefore, a heteroscedastic noise consideration is needed and Cramér-Rao Bound (CRB) has been used to model it [33], [34]. CRB represents the minimum achievable error of a positioning system by any algorithm in a determined location. Traditionally, CRB models have considered path degradations on signals [35]. In one of our recent papers we completed this model by adding a characterization of the clock errors to the covariance matrix of the system [23].

This model considers initial-time offset to compute the effect of the delay between the reference clock used for synchronization and the clocks of the rest of the coordinator sensors of the architecture -which has no effect in asynchronous LPS-, the clock drift which introduces a cumulative error in the time measurements with the instability in the frequency of the clocks and the temporal resolution of the architecture sensor clocks. In addition, a path loss propagation model is introduced to characterize the White Gaussian Noise (WGN) present in the communication channel.

This combined model for the optimization of the node location has shown that asynchronous LPS reach better accuracy performance in terms of stability and reduction of the system errors. Consequently, we use A-TDOA in this paper to fit the LPS high-demanded accuracy needs.

Nevertheless, asynchronous architectures have a firm dependence on CS performance since all the time measurements are computed on it. This causes that a possible malfunction of the CS disables the complete system operation making the localization temporarily unavailable. This disadvantage is solved in this paper through an optimized node location which do guarantee at least two CS under coverage in each possible target location.

We previously started this approach with the optimization of the node location in synchronous LPS applications considering possible sensor failures in the architecture sensors [31]-each of them are CS, i.e. TOA or TDOA methodologies-. We later demonstrated [36] that a sub-optimal design of the nominal performance of the localization system can reach optimal behavior in failure conditions-temporal unavailability of an architecture sensor- with a minimal accuracy lost on the nominal conditions.

However, each of our past studies have particularized in a small-scale positioning system performance optimization. If the scenario becomes larger, a greater number of sensors are needed to reach the accuracy required for every possible target location [35]. However, the increased number of sensors employed also affect the global costs of the system. Particularly, the higher complexity of the CS in design, equipment and operation affects in a greater extent to the A-TDOA architecture overall costs. For this reason, the usage of the minimum number of CS makes this asynchronous system cost-effective while the necessity of at least two CS under coverage makes it available in CS failure conditions. In addition, the best combination of WS in each target location must be selected to reach the best operating conditions in each system coverage position.

In this paper, we propose a methodology to deploy an optimized cost-effective distribution of coordinator and worker sensors in large-scale asynchronous LPS applications (e.g. coverage of more than 1 km2 or required combinations of more than the minimum architecture sensors to cover the entire TLE with the accuracy bounds desired) by considering CS availability and accuracy in each target position under coverage. This includes the optimization for nominal and eventual failure operating conditions of the system CS in each possible target location and the finding of the optimized location and the appropriate combination of WS for maximizing accuracy in the space of coverage of the system.

The remainder of the paper is organized as follows: we introduce a detailed description of the A-TDOA architecture, the definition of the node distribution problem and the methodology to reach a cost-effective node deployment in asynchronous architectures in Section 2, the combined noise and clock CRB model for the optimization is presented in Section 3, the Genetic Algorithm settings for this combined optimization and the results of the optimization are introduced in Section 4 while Section 5 discuss and conclude the paper.

II. PROBLEM DEFINITION

Asynchronous Positioning Systems (APS) provide a stable and cost-effective performance of LPS in high-demanded accuracy applications. Its robustness is based on its capability of computing the time measurements in a single clock of a coordinator sensor. This fact reduces the overall error of the time local positioning systems [23] by decreasing the clock errors in optimized node locations.

However, these systems require that their signals travel longer distances which may produce significant signal degradations. Therefore, not any sensor deployment configuration can be used for improving the performance of APS since an effective link between target-CS and WS-CS must be assumed. This link is more effective if Line-of-Sight (LOS) connections between signal emitter and receivers are favoured and adverse phenomena on signals are avoided [35].

Furthermore, in APS, all the time measurements are computed in the CS which makes the system unavailable in case there is not a CS under coverage in a space location. As a consequence, if a CS is not available there is not possibility of determining the Target Sensor (TS) location in APS even if the number of sensors available exceeds the minimum number of receivers to provide a solution of the TDOA problem solved in APS (i.e. more than the required number of WS needed in the TDOA problem and unavailability of a CS to compute the time measurements).

In this paper, we provide an enhanced genetic algorithm optimization of the node location of the A-TDOA architecture by guaranteeing the availability of the CS in all the space possible target locations and by reducing the overall errors and the costs of the system through a novel methodology in evaluating the beauty of the node distributions. In this section, we present the A-TDOA architecture, the node location problem and the particularities of the novel evaluation method used for the optimization.

A. A-TDOA ARCHITECTURE

APS techniques have been proposed over the last few years [19], [20]. They reach great stability and accuracy since they reduce the number of clocks needed for the position determination by centralizing all the system measurements in a single clock of a CS. This approach is especially suitable for LPS applications since the incremental distance traveled by their signals do not affect the overall accuracy more than the effect of the clock errors in LPS. However, APS are not appropriate for GNSS since the signal travel longer paths than in synchronous configurations and the signal degradation would be higher than the benefits of the reduction of the clock errors in GNSS.

Therefore, the usage of APS fits with high accuracy demands in precision local applications. Among the APS architectures, we demonstrated [22] that A-TDOA provides less uncertainty in different sensor configurations. For this reason, we apply this architecture to reach a cost-effective accuracy APS.

A-TDOA is a passive positioning system that uses the TS as a repeater of the positioning signals which are emitted by the WS. It requires at least four WS (3D positioning) to send different positioning signals that will be received, after TS retransmission, in the CS (t_{ENDi}). Furthermore, the same signal emitted by the WS arrives directly to the CS (t_{STARTi}). The time difference between the arrival of the two positioning signals is the time computed for each time difference of each pair WS-CS. The process finishes when each signal of each WS is processed in the CS and the time measurements are accomplished.

$$A - TDOA_i = c\left(t_{END_i} - t_{START_i}\right) - ||WS_i - CS|| \quad (1)$$

where $A\text{-}TDOA_i$ represents the time measurement of the WS_i, c is the speed of the radioelectric waves and $||WS_i - CS||$ is the distance between the WS_i and the CS which is known since the position of the nodes is fixed.

The procedure allows the usage of a single clock in the CS and its accuracy and robustness is highly dependent on the sensor distribution in the space. In Figure 1, the increase in the path traveled by the positioning signal is shown. Therefore, the introduction of path loses on signals must be reduced through an optimized node location to make the A-TDOA architecture competitive.

B. NODE LOCATION PROBLEM AND DEFINITION OF THE SCENARIO OF SIMULATIONS

The node location problem has been widely studied in the localization field since the appropriate deployment of sensors has a direct impact in the performance of the Wireless Sensor Networks (WSN) [26], [28], [37], [38]. One of the main advantages of WSN is the freedom to locate sensors in space in order to maximize system properties.

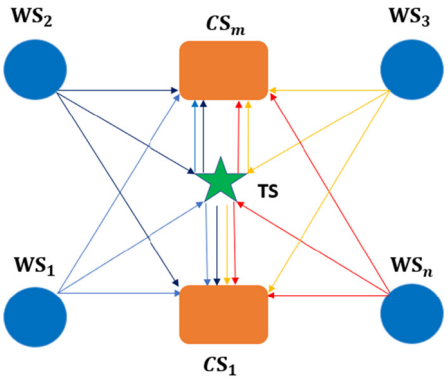

FIGURE 1. Asynchronous Time Difference of Arrival System (A-TDOA) communications scheme with m Coordinator Sensors (CS) and n Worker Sensors (WS) under coverage with the Target Sensor (TS).

The problem of the node distribution has proven to be NP-Hard [24], [25] in the complexity of the space of possible solutions. Firstly, this node distribution was treated through linearizations of the problem in grid searches to reduce the overall complexity [39]. Then, non-linear approaches were considered through greedy-type algorithms [40]. However, these solutions do not estimate the complete combination of sensors in space and this problem is not suitable for using greedy algorithms since a deep exploration of the space of solutions is suggested to find acceptable solutions.

Subsequently, the advancement in processing capability enabled the usage of heuristic methods to find more refined solutions to the node location problem. Simulated annealing [29], [41], particle swarm optimization [42], Tabu search methodologies [43], firefly algorithm optimizations [44] but specially Genetic Algorithms (GA) [18], [26], [27], [31], [35] have been used to determine suitable node locations. For this reason, we use in this paper a Genetic Algorithm to solve the node location problem.

However, regardless the heuristic method used for the optimization there is a task to particularly considering for enhancing the performance of localization networks: while communication networks rely exclusively on the position of the nodes since they are the only active element of the system, LPS also require the interaction with the TS. Therefore, each possible TS location in the coverage region must be evaluated in the fitness function used for optimization. We defined in [31] the difference between the space available for the sensors to be located, Node Location Environment (NLE), and the possible TS navigation environment, Target Location Environment (TLE). The existence of the NLE increases the overall optimization process complexity. The computational complexity of a problem is defined through the order of the number of operations needed to explore all the space of solutions [45] to reach a solution.

Therefore, the complexity of the node location problem of k sensors in localization is:

$$O\,(NLP) = \left[\prod_{i=0}^{k-1} (n_{NLE} - i)\right] n_{TLE}\, O(ff_{TLE}) \qquad (2)$$

where $O(NLP)$ is the complexity order of the node location problem, k is the number of sensors of the problem, n_{NLE} is the number of possible locations of each sensor in the space, n_{TLE} the number of possible TS locations and $O(ff_{TLE})$ is the complexity order of the fitness function evaluation in every possible TLE.

Eq. 2 shows that the larger the number of possibilities for the sensors to be located in the space and the larger the number of sensors displayed, the greater the computational complexity of the global problem. In addition, this complexity increases with the number of operations in the fitness function of each possible TS location for each combination of sensors.

Each of these initial parameters must be selected to guarantee a sufficient exploration of the space of solutions and not overcomplicate the computational complexity of the problem. For this study, we define each of these parameters in Table 1:

TABLE 1. Parameters to define the complexity of the node location LPS problem.

Parameter	Value
n_{NLE}	1000
k	12/13/14
n_{TLE}	1000
Possible sensor distributions	$9.36 * 10^{35}/9.25 * 10^{38}/9.13 * 10^{41}$
Overall Number of operations	$\left[\prod_{i=0}^{k-1}(n_{NLE} - i)\right] * n_{TLE} * O(ff_{TLE})$

Table 1 shows the high complexity of the node location problem in LPS, suggesting the implementation of a heuristic approach to find an acceptable solution in a reasonable time, as it has been widespread in the literature. For this reason, the designer must select the parameters involved in the optimization process carefully, specially the number of evaluated target sensor positions in space (n_{TLE}) and the possible space locations for the architecture sensors (n_{NLE}) since a trade-off between the resolution in the search of the space of solutions leading to improved results of the problem and the reduction of the overall complexity of this NP-Hard problem must be balanced. The designer must also control the complexity of the fitness function which will depend on the characteristics of the optimization. As a result of the diversity of the goals for the designer solving the node location problem, the number of operations is not quantified in this table favouring the generalization of the problem and will depend on the constraints and algorithms for determine the quality of the optimization selected.

The selection of these parameters must be based on the scenario of simulations in which the node optimization is

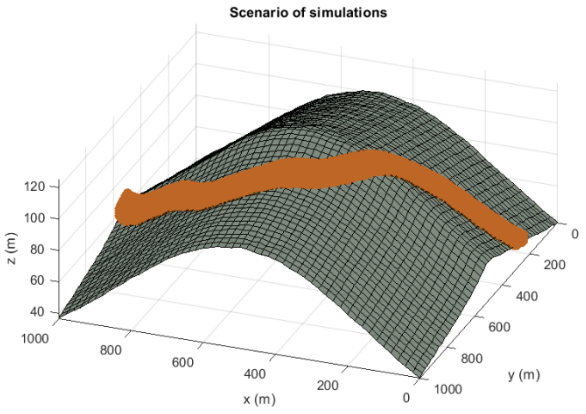

FIGURE 2. 3D irregular scenario of simulations. Gray zones represent the base surface for the optimization. Orange regions define the TLE zone, which extends in elevation from the base surface from 0.5 to 5 meters. The rest of the base surface is intended to the NLE, with constraint in the minimum and maximum height regarding the reference surface from 3 to 10 meters respectively.

performed. Based on [31], we define a 3D scenario in an attempt to figure out the real-operating conditions of LPS (i.e. complex orographic scenarios with LOS/NLOS environments and subareas of target navigation such as roads for autonomous vehicles). This scenario is shown in Figure 2 with the definition of the TLE and NLE.

TLE and NLE regions have been defined towards the objective of depicting any possible condition or complex scenario of application, which substantiates the flexibility and versatility of the proposed methodology, and allows the implementation of this procedure in difficult outdoor and indoor environments. In this case, the designed environment for simulations shows a terrestrial LPS application, where the TLE varies deeply in elevation and its projection over the reference surface is highly irregular. However, this modeling can be applied to characterize outdoor and indoor positioning, with terrestrial or aerial optimizations.

The NLE and TLE regions are modeled following a discretization procedure, based on a trade-off between accuracy in the evaluation of sensor distributions and the number of analyzed points -which directly influences the overall number of operations (Table 1) and the algorithm complexity-. The best results for the TLE region are reached through a spatial discretization of 10 meters for x and y coordinates, and 1.5 meters for z coordinate. With this configuration, experiments revealed that the mean optimization metrics remain almost constant for higher spatial resolutions, saving processing time. Regarding the NLE, the spatial discretization is variable, derived from the process of scaling proposed in [31], enabling resolutions for 0.5 to 1 meter for a high accuracy sensor deployment.

The novelty of the optimization proposed in this paper is based on the consideration of the noise and clock errors, the additional path losses typical in NLOS environments, and the effective coverage of the sensors for the position determination through the CSs availability over the TLE. All these considerations constitute the fitness function evaluation in each TLE position and its definition is proposed in the next subsection.

C. METHODOLOGY FOR THE COST-EFFECTIVE NODE DEPLOYMENT IN A-TDOA SYSTEMS

Each heuristic optimization is based on a fitness function in which each parameter considered for reaching optimized solutions must be represented. In this subsection, we define each parameter and develop the final form of the fitness function to evaluate the beauty of the node distribution examined in all the TLE.

The constraints for the cost-effective node deployment in the A-TDOA architecture are:

- Optimization of the clock errors in the CS, through the combined minimization of the magnitudes of the time measurements in the CS for each A-TDOA sensor combination.
- Optimization of the path losses of the positioning signals in the travel from TS-CS and WS-CS, using the combined minimization of distances and NLOS disruptions in each A-TDOA signal path.
- Selection of the adequate combination of sensors from all available for location determination in each TLE area, ensuring the maximization of the performance of the A-TDOA architecture in terms of accuracy.
- Optimization of the availability of the system under CS failures, i.e. guaranteeing two CS for positioning in each location of the TLE region, holding high-demanding requirements of accuracy in both configurations.
- Elimination of sensor deployments that interferes or occupies some forbidden regions, e.g. the TLE region or some specific zones.

The attainment of these objectives is performed through a sequential TLE (seq-TLE) approach, where all optimization parameters are evaluated for each analysis point of the TLE, repeating the procedure throughout the remaining TLE region. This methodology avoids repeated calculations, becoming especially suitable for large and complex TLE areas, where high-density point representations are needed for accurate results.

In this sense, the first step of the fitness function characterization is the selection of the most suitable CS for each A-TDOA sensor deployment (i.e. GA individuals). The election is based on the following criteria: ''the most suitable CSs selection (initially all sensors in the GA individual are candidates to be CS) for each sensor deployment in the environment is the one which maximizes the number of TLE points in coverage combining different CS and ensuring at least four WS connected to each of them''. In fact, for attaining CS condition failures, this statement is modified for guaranteeing at least two CS available in each TLE analysis point. The obtainment of the coverage quantification for each CS-TLE

point link is performed through the LOS/NLOS algorithm described in reference [35].

Once this process is finished, the best configuration of CS and WS for each sensor distribution of the GA is selected. Then, the seq-TLE process is performed for every individual (i.e. A-TDOA different sensor deployment) of the GA.

The optimization of noise and clock errors, together with the optimization of LOS/NLOS path losses of the positioning signals in the travel from TS-CS and WS-CS are assumed through the minimization of the CRB for each point of the TLE provided for each CS in the distribution. The CRB mixed model for combined positioning uncertainties is derived from our previous works [23], [35], which is detailed in Section 3. This model is directly applied when at least one CS and a minimum of four WS are available for positioning, otherwise a 300 meters' accuracy error is fixed (this hyperparameter is adjustable according to accuracy requirements and stands out for a non-valid operating condition, where CRB model is not implementable).

The quantification of uncertainties induced by noise and clock errors and NLOS signal propagation is performed for every combination of one CS and multiple WS in each point of analysis of the TLE region. This ensures the attainment of the best valid configuration for every block of CS with multiple CS available in each TLE point -e.g. if there are one CS and 6 WS, the best configuration in terms of accuracy can be reached with all WS available or with some of them (if some of the deployed WS present NLOS conditions in this zone in particular)-.

Concerning to the optimization of the system CS failure conditions, the fitness function provides a method for progressively penalizing those sensor distributions where the positioning cannot be provided by at least two different CS (although these CS can share multiple WS), which is mandatory for the availability of APS under failure conditions. The penalization is based on the quantification of available CS-WS groups for location in each TLE point, assigning a penalization $-2n_{TLE}$ to each TLE point where at least two CS are not available. This method guarantees the completion of the failure condition requirements since softer penalizations encourage the achieving of sensor distributions with zones with a high-density of distinct CS coverage and regions with only one CS available.

The last parameter of the optimization is the penalization factor relative to the deployment of sensors in forbidden areas, and/or the enhancement sensor distributions in certain regions of interest. In this specific problem, sensors cannot be located inside the TLE region, as an actual representation of LPS terrestrial applications of positioning, where sensors must be outside the road/travel of vehicles.

The above optimization approach leads to the following fitness function, where all summands are constrained in the interval [0-1], enabling a flexible optimization weighting and ensuring a correct characterization of the process.

$$
\begin{aligned}
ff &= C_1 ff_1 + C_2 ff_2 - (C_1 + C_2)\left(ff_{2CS} + ff_R\right) \\
ff_1 &= \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - \mathbf{RMSE_{CS1}})}{RMSE_{ref}}\right]^2}{K_{TLE}} \\
ff_2 &= \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - \mathbf{RMSE_{CS2}})}{RMSE_{ref}}\right]^2}{K_{TLE}} \\
ff_{2CS} &= \frac{C_3 \left\{\frac{abs[n_{TLE} - sum(\mathbf{Eval_{CS1}})]}{n_{TLE}(n_{TLE}+1)}\right\}^2}{C_3 + C_4} \\
&\quad + \frac{C_4 \left\{\frac{abs[n_{TLE} - sum(\mathbf{Eval_{CS2}})]}{n_{TLE}(n_{TLE}+1)}\right\}^2}{C_3 + C_4} \\
ff_R &= \frac{\sum_{i=1}^{N} \mathbf{R}}{N}
\end{aligned}
\tag{3}
$$

where ff_1 and ff_2 are respectively the fitness function accuracy representation for the primary and secondary CS in each TLE point, coefficients C_1 and C_2 allow distinct ponderations of ff_1 and ff_2 for the optimization process, ff_{2CS} is the penalization due to unavailability of CS in each analyzed region of the TLE, ff_R represents the penalization factor proper of invalid sensor placements, n_{TLE} is the number of studied points that characterized the TLE, $RMSE_{ref}$ is the reference Root Mean Square Error (RMSE) for normalizing the ff_1 and ff_2 (prefixed to 300 meters, as the possible lower accuracy condition in the problem), $\mathbf{RMSE_{CS1}}$ and $\mathbf{RMSE_{CS2}}$ are the vectors that contain the accuracy evaluation in terms of the RMSE–detailed in Section 3- for the primary and secondary CS in each TLE analysis point, C_3 and C_4 are the coefficients related to the weighting of the ponderations of the summands of the ff_{2CS} function, $\mathbf{Eval_{CS1}}$ and $\mathbf{Eval_{CS2}}$ are respectively the vectors that quantifies the existence of one or two CS in each TLE analysis point–with their correspondent minimum of four WS (shared or not)-, assuming a value of $-2K_{TLE}$ when these conditions are not fulfilled since the analysis of each point of the TLE returns 0 in unavailability conditions and 1 in available configurations, N is the number of sensors deployed (CS and WS), and $\mathbf{R}$ is the penalization for void sensor locations (0 for valid placement, 1 for forbidden colocation).

III. CRAMÉR-RAO BOUND MODEL FOR THE COMBINED NOISE AND CLOCK ERROR MODEL

Cramér-Rao Bound (CRB) is a maximum likelihood estimator based on the inverse of the Fisher Information Matrix (FIM). Its usage in the localization field has been widely considered for the characterization of the architecture errors in positioning systems [46]–[48]. This statistical operator provides the lowest error in localization regardless of the algorithm used for the position determination. Therefore, the analysis of this parameter allows us to characterize the beauty of a node deployment since the better distribution of sensors in space allows the reduction of the CRB values in the TLE.

For this purpose, a characterization of the WGN present in the communications channel must be considered. Particularly, in LPS, the heteroscedasticity of the noises resulted from different range of signal travels is essential to attain valuable results [33]. This fact is introduced in the covariance matrix of the system. Kaune et al [49] develop a matrix form of the FIM to generally compute the system architecture errors with distance-dependent noises:

$$J_{mn} = \left(\frac{\partial h\,(TS)}{\partial x_m}\right)^T R^{-1}\,(TS)\left(\frac{\partial h\,(TS)}{\partial x_n}\right) + \frac{1}{2} tr\left(R^{-1}\,(TS)\left(\frac{\partial R\,(TS)}{\partial x_m}\right) R^{-1}\,(TS)\left(\frac{\partial R\,(TS)}{\partial x_n}\right)\right) \quad (4)$$

where m and n are the parameters to be estimated -TS Cartesian coordinates-, **h(TS)** the vector containing the system path travel measured in the architecture at study through the time measurements in a CS and **R(TS)** the covariance matrix containing the uncertainties of the system -in this case clock and path errors-.

Particularizing for the A-TDOA architecture, the **h(TS)** vector is constituted as follows:

$$h_{A-TDOA_{ij}} = ||TS - WS_i|| + \left|\left|TS - CS_j\right|\right| - ||WS_i - CS|| \quad i = 1, 2 \ldots, N_{WS} \quad j = 1, 2, \ldots, N_{CS} \quad (5)$$

being N_{WS} the number of WS under coverage for each CS and N_{CS} the total number of CS under coverage.

The construction of the covariance matrix, **R(TS)**, depends on the error characterization introduced. Traditional studies considered path degradation in signal propagation in LOS environments through path loss models [33]. We introduced in our recent articles a new model for quantifying the clock errors [23] and also the NLOS propagation errors in complex LPS scenarios [35] in the covariance matrix along with traditional noise uncertainties.

In this paper, we combine these two models to provide a more accurate approximation of the actual errors of A-TDOA systems. According to Kaune *et al.* [49], the time measurements in TDOA systems are assumed to be uncorrelated.

In this way, the covariance matrix is constructed for the A-TDOA architecture by considering LOS and NLOS propagation travels by the positioning signal on a Log-Normal Path Loss Model which especially fits LPS demands in complex environments [50] and clock error considerations [20] for a generic CS "m":

$$\sigma^2_{A-TDOA_i} = \frac{c^2}{B^2\frac{P_T}{P_n}}\frac{PL(d_0)}{d_0^{n_{NLOS}}}\left[(d_{i_{LOS}} + d^x_{i_{NLOS}})^{n_{LOS}} + (d_{TS_{LOS}} + d^x_{TS_{NLOS}})^{n_{LOS}} + (d_{CS_{LOS}} + d^x_{CS_{NLOS}})^{n_{LOS}}\right] + \frac{1}{l}\sum_{k=1}^{l}\left\{\left|\left(T_i + T_{TS_m} - T_{CS_{im}}\right) - floor_{TR}\left(\left(T_i + T_{TS_m} - T_{CS_m}\right)\eta_{cs_m}\right)\right| c^2\right\} \quad (6)$$

$x = (n_{NLOS})/(n_{LOS})$ where c is the speed of the radioelectric waves, B the signal bandwidth, P_T the transmission power of the positioning signal, P_n the mean noise power level obtained through the Johnson-Nyquist relation, d_0 the distance of reference from which the application of the Log-Normal Path Loss Model can be used, $PL\ (d_0)$ the path-loss in the reference distance;n_{LOS} and n_{NLOS} the coefficients of the path loss exponents; d_i, d_{TS} and d_{CS_i} are the distances from the TS to the WS_i, from the TS to the CS_m considered for the position determination and from the WS_i to the CS_m respectively; l the number of iterations of a Monte Carlo simulation to correctly estimate the temporal variance associated with the time system errors, T_i the total time of flight from the TS to the WS_i, T_{TS_m} the time from the emission of the positioning signal in the TS and its arrival in the CS_m, $T_{CS_{im}}$ the time of signal travel from the WS_i to the CS_m, η_{cs_m} the clock drift of the CS_m and $floor_{TR}$ the truncation of the error in the clock based on their resolution parameters.

This variance model provides the uncertainties in a defined TS location based on the clock characteristics and the signal travel from the WS and the CS under coverage used for the position determination. The trace of the inverse of the FIM directly defines the RMSE of the TS location in the TLE considered [33]:

$$RMSE = \sqrt{\sum_{m=1}^{m=n} FIM^{-1}_{mm}} \quad (7)$$

being n the number of parameters to estimate, in this case each of the TS Cartesian Coordinates (2 and 3 for 2D and 3D positioning respectively).

IV. RESULTS

The implementation of the previous optimization technique for locating A-TDOA sensors in the 3D scenario presented in Section 2, yields the following results. Firstly, the configuration parameters of the A-TDOA architecture, the characteristics of the CS clocks used in the system and the GA optimization hyperparameters are provided and justified. Subsequently, simulations for a distinct number of sensors are provided, enabling different comparisons in terms of availability and accuracy of sensor distributions with a variable number of CS and WS deployed. With this procedure, a methodology for cost-effective sensor optimizations of asynchronous LPS is granted, enabling trade-off solutions based on the design requirements for high-accuracy applications.

A. PARAMETER AND HYPERPARAMETER CONFIGURATION FOR THE SIMULATIONS

The operation setting of the A-TDOA architecture employed for all simulations is provided in Table 2. The handled selection criteria are based on a generic representation of positioning systems [50], [51], aiming a flexible characterization of technologies and highlighting the application of the described optimization technique in several circumstances.

TABLE 2. A-TDOA parameter configuration for the simulations. Noise characterization is performed based on [50], and clock error modeling is configured relying on [20].

Parameter	Magnitude
Frequency of emission	1090 MHz
Transmission power	400 W
Mean noise power	- 94 dBm
Receptor sensibility	- 90 dBm
Bandwidth	100 MHz
Clock frequency	1 GHz
Frequency-drift	$U\{-15, 15\}$ ppm
Time-Frequency product	1
LOS Path loss exponent	2.1
NLOS Path loss exponent	4.5
TLE Coverage Area	0.12 km2

TABLE 3. Setup of the GA hyperparameters and fitness function coefficients for the simulations.

GA hyperparameter	Setup
Population size	120
Selection technique	Tournament 2
Crossover technique	Single-point
Mutation technique	Single-point
Elitism percentage	2.5 %
Mutation percentage	7 %
Stop criteria	300 generations or 80 % of equals individuals
C_1 - C_2 coefficients value	1
C_3 - C_4 coefficients value	1

The GA and fitness function configuration are presented in Table 3. Similarly to the spatial resolution selection for the TLE and NLE regions defined in Section 2, the setup of the GA hyperparameters is accomplished under the compromise between accuracy representations and restrained algorithm complexity with controlled processing time. The selection process of these hyperparameters has been similar to the methodology followed in [31] but different results were obtained since any different scenario of simulations require a particular fine-tuning for achieve practical results. The following hyperparameters are the best-founded configuration that allows the fulfillment of these factors.

The proposed GA and fitness function configuration search for an optimization where primary and secondary CS positioning would be practically homogenous, in other words, the importance of the accuracy of the normal operating conditions is comparable to the importance of the failure operating conditions in the optimization. The importance of the constraints of the optimization can be modified through the variation of the fitness function coefficients value (C_1-C_2-C_3-C_4).

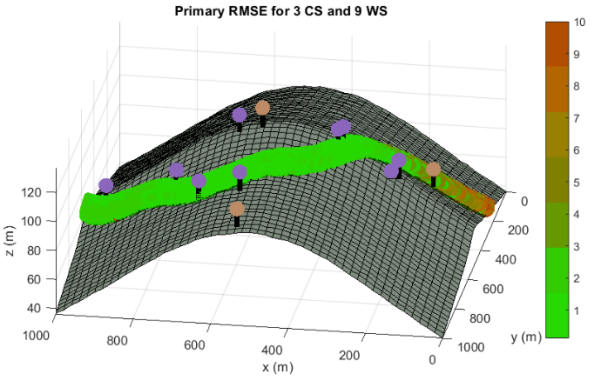

FIGURE 3. Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with three CS. CS and WS are characterized by brown and purple spheres, respectively.

B. ACCURACY AND AVAILABILITY ANALYSIS

In this section, A-TDOA sensor distributions with different number of CS are studied under the parameters of accuracy and availability of performance in CS failure conditions. The proposed scenario, together with the environment modeling presented in Table 2, represents a complex framework where the guarantee of two CS available – and at least four WS connected with these CS– for primary and secondary positioning in every TLE zone presents difficulties. Due to the complex orography and the challenging propagation of positioning signals between different side of the central hill with higher ground elevation, at least three CS are theoretically needed for ensuring positioning services in CS failure conditions and satisfy the availability requirement. Furthermore, experiments carried out show that at least nine WS are needed to deploy and establish a valid connection with CS and ensuring a minimum of four WS for primary and secondary positioning (shared or not).

Based on these factors, in the following paragraphs, the results for the optimization of accuracy and the fulfillment of availability requirements are presented for three, four, and five CS. All of these optimizations are performed with nine additional WS. Figures and Tables are provided to capture all the information of the simulations.

Firstly, the results of the optimization for three CS and nine WS are given. Figures 3 and 4 present the accuracy evaluation, in terms of the RMSE, for the primary and secondary or emergency CS (sub-optimal configuration as a consequence of a temporal unavailability of the primary-the most accurate- CS) handled for positioning in each discretized TLE point.

Figure 4 reveals an important feature. The deployment of only three CS does not allow the guarantee of double CS availability in every point of the TLE for the designed environment. Even there are some regions where secondary positioning is possible, the fact that in some areas positioning service in emergency conditions cannot be provided can assume a serious drawback for high-robustness applications (e.g. autonomous navigation).

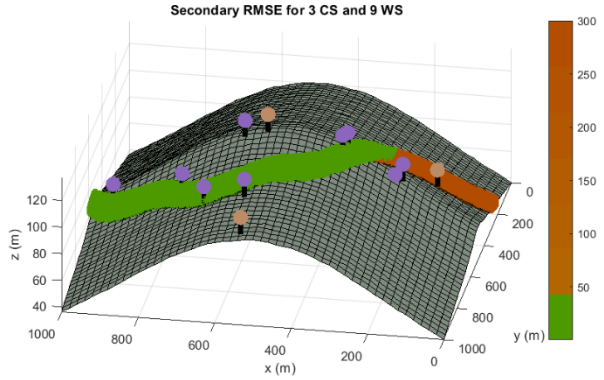

FIGURE 4. Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with three CS.

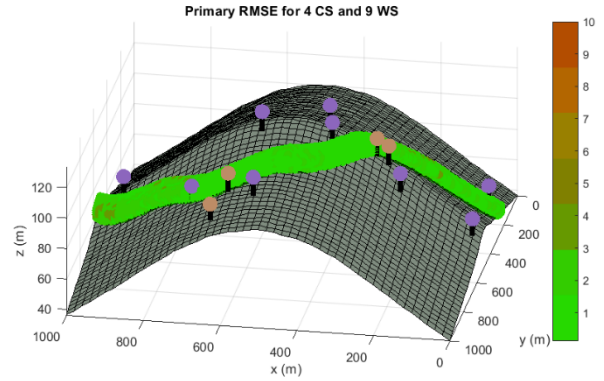

FIGURE 5. Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with four CS.

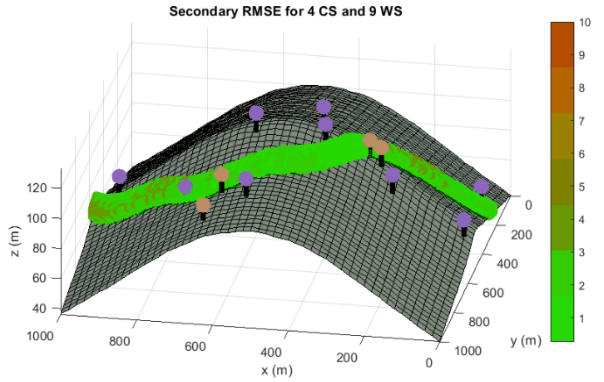

FIGURE 6. Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with four CS.

After analyzing previous outcomes, the optimized sensor distribution with four CS and nine WS is presented in Figures 5 and 6 for primary and secondary CS positioning.

Conversely to the three CS optimization, Figures 5 and 6 show that the deployment of four A-TDOA CS with the corresponding nine WS allows high performance in accuracy for primary and secondary positioning. However, the system performance in normal an emergency can be improved with the increase of CS, as it is displayed in Figures 7 and 8.

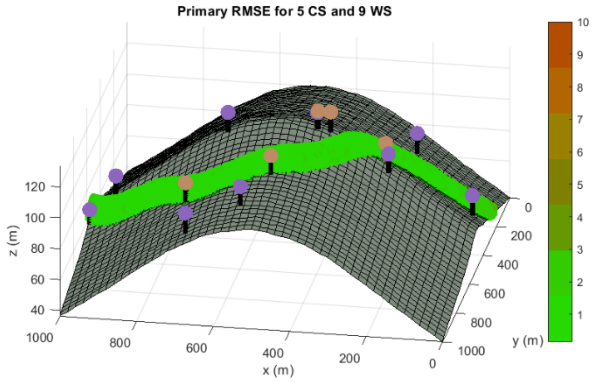

FIGURE 7. Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with five CS.

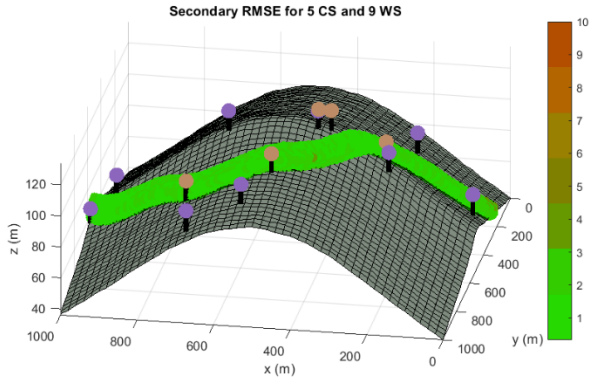

FIGURE 8. Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with five CS.

As it can be inferred, an increase in the number of CS entails a boost in primary and secondary positioning accuracy, reaching the desired requirements for high-accuracy applications. In this sense, a cost-effective node deployment can be achieved with this optimization methodology, through the trade-off between accuracy, availability, and the number of sensors deployed (which directly influences the total cost of the LPS).

In addition to the accuracy evaluations, in Figures 9 and 10 the number of WS per TLE point is presented for the four and five CS configurations (those which enables a secondary positioning in all the environment). The importance of the WS location is crucial, both in accuracy and in positioning availability (not only double CS are required in each TLE zone, also a minimum of four WS linked to each CS).

Here resides the complexity of the optimization since the cost-effective methodology for asynchronous node deployments presented in this paper for achieving valuable and stable accuracy results must not only deal with the location of the CSs in optimized positions but also consider the relative location of the WSs in space defining a combined optimization which is critical for obtainment the required accuracy needed for LPS applications.

Figures 9 and 10 show the variability of the number of WS in coverage for each TLE area, as a result of the accuracy

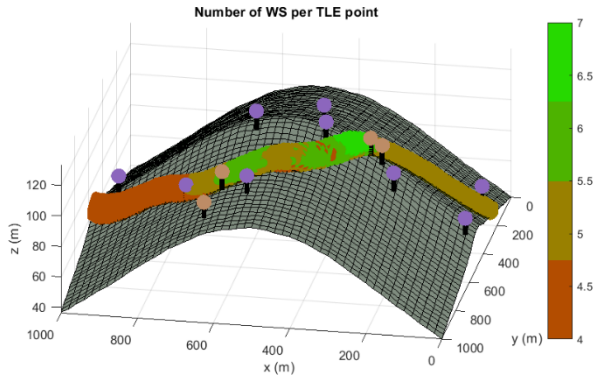

FIGURE 9. The number of available WS for each TLE studied point for the optimized sensor distribution of four CS.

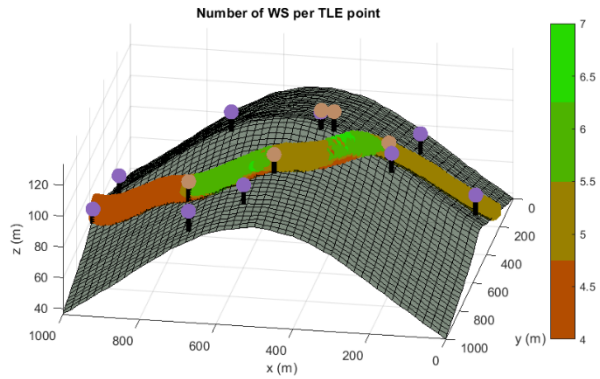

FIGURE 10. The number of available WS for each TLE studied point for the optimized sensor distribution of five CS.

and availability optimizations in the 3D irregular environment with deep land slopes. It can be observed that areas where the reference base and TLE regions experiment larger changes in geometry or orography, concentrate a higher density of WS in an attempt of maintaining the required accuracy and availability objectives of LPS applications since generally the more sensors in coverage the better accuracy achieved (especially if they reach LOS and proximity links with the TS).

Lastly, in Table 4 a summary of the main performance results and characteristics of the analyzed sensor configurations is provided.

Table 4 highlights the superiority of the five CS optimization in terms of accuracy (both mean and minimum magnitude) for the primary and secondary positioning. Also, the maximum percentage of use of CS is reduced, i.e. this sensor deployment allows more homogeneity in the importance of the different CS involved (related to the security robustness of the system). Conversely, the three CS optimization cannot guarantee the positioning service in emergency conditions, due to the inexistence of combined coverage of pairs of CS for every TLE zone. Finally, the four CS distribution represents the minimum number of deployed sensors (CS and WS) that can accomplish the high accuracy and availability demands in this environment.

TABLE 4. Accuracy and availability comparison between sensor configurations with three, four, and five CS (in meters). Primary conditions (P) are referred to as normal operation, while secondary conditions (S) represent emergency positioning service.

Sensor distributions		3 CS	4 CS	5 CS
Mean	P	1.91	1.14	0.89
RMSE	S	81.67	1.70	1.47
Minimum	P	11.73	3.89	3.66
RMSE	S	300	4.99	4.21
Max CS	P	41 %	40 %	32 %
use (%)	S	-	39 %	35 %
Max WS use (%)	P	39 % (5 WS)	47 % (5 WS)	47 % (5 WS)
	S	-	46 % (5 WS)	48 % (5 WS)

V. CONCLUSIONS

Local Positioning Systems are attracting high research interest in high-demanded accuracy applications such as indoor and outdoor autonomous navigation.

Among these local systems, those based in time measurements allows the design of robust, accurate and easy to implement hardware architectures. The main system errors of these architectures are provided by ineffective links among target and sensors and inappropriate synchronism of the system devices. As a consequence, asynchronous time local positioning systems have emerged over the last few years. The asynchronous time systems are based on the collection of the time measurements in a single clock of a coordinator sensor avoiding the necessity for overall system synchronization but increasing the signal paths. Thus, the increase of the signal uncertainties must be offset by the reduction of the clock uncertainties in the system overall performance which can be achieved by optimizing the sensor distribution in space.

The sensor location problem is deeply analyzed in this paper, showing the high-complexity of the NP-Hard node deployment for which a trade-off between resolution in the search of the space of solutions and time-effective optimizations must be considered.

However, the specificities of the asynchronous node deployment make this task even more complicated. For this purpose, we propose a new optimized cost-effective methodology to deploy both coordinator sensors and worker sensors in space by entailing the overall system accurate performance in nominal and emergency conditions (i.e. primary coordinator sensor unavailability). We provide an optimization framework in search of at least two coordinator sensors under coverage in every possible target location and the guarantee of at least four worker sensors under coverage for each coordinator sensor (which can be shared for the same target location).

Furthermore, we apply an algorithm for the usage of the best combination of coordinator sensors and worker sensors since not always the maximum number of available connections among coordinator and worker sensors can provide the best accurate results (e.g. imbalanced signal degradations among nodes).

The analysis of the combined effect of the clock and noise uncertainties in the time measurements is performed through the Cramér-Rao Bound which provides the minimum achievable error by any positioning algorithm in every possible target location. We propose a Cramér-Rao Bound model considering LOS and NLOS signal links through a Log-Normal Path Loss model with the addition of the clock drift and truncation errors present in the coordinator sensor clock. This allows us to measure the architecture accuracy for a defined node distribution.

The optimization of the node location is performed through a Genetic Algorithm approach by looking for an enhanced node deployment which focuses on accuracy, connection effectivity, emergency localization and security robustness for making the system cost-effective fulfilling the design requirements.

In an attempt for representing real-operating conditions of a Local Positioning System we have defined a simulation scenario containing deep variances in elevation over the ground reference surface forcing NLOS connections over the different possible target locations.

The optimization considers three different configurations with 3, 4 and 5 coordinator sensors and 9 worker sensors (i.e. minimum WS number for achieving full coverage in this scenario). The finding of the optimal number of coordinator sensors for the fulfillment of the cost-effective security-enhanced node deployment and its relation with the worker sensors location is the main objective of this paper.

Results show that deployments with 3 coordinator sensors are not able to reach full coverage increasing the overall errors of the system. Optimized four coordinator sensor deployment can attain the design objective with an acceptable mean error of 1.14 meters and 1.70 meters in primary and emergency conditions while optimized five coordinator sensor deployment can reach 0.89 meters and 1.47 meters mean errors respectively. Both conditions satisfy the design main objective but five coordinator sensor deployments show a less critical usage of the system coordinator sensors in both primary and emergency conditions which is crucial for the security robustness of the system making the five coordinator sensor deployment have a superior cost-effective performance.

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