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Analysis of Time Local Positioning Systems for High-Demanded Accuracy Applications: Position Disambiguation, Optimized Node Deployments and Failure Conditions Enhancements

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Análisis de Sistemas Temporales de Posicionamiento Local para Aplicaciones de Elevada Exactitud: Desambiguación en el Cálculo de la Posición, Distribuciones Optimizadas de Sensores y Comportamiento Mejorado en Condiciones de Fallo

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AGV	Autonomous Ground Navigation
APS	Asynchronous Positioning Systems
AOA	Angel-of-Arrival
A-TDOA	Asynchronous Time-Difference-of-Arrival
CRB	Cramér-Rao Bound
CRLB	Cramér-Rao Lower Bound
CS	Coordinate Sensor
FIM	Fisher Information Matrix
GA	Genetic Algorithms
GNSS	Global Navigation Satellite Systems
HGA	Hybrid Genetic Algorithms
HMA	Hybrid Memetic Algorithms
LOS	Line-of-Sight
LPS	Local Positioning Systems
LS	Local Search
LSD	Local Search Depth
MA	Memetic Algorithms
MP2	Multipoint Crossover 2
MP3	Multipoint Crossover 3
NLE	Node Location Environment
NLP	Node Location Problem
NLOS	Non-Line-of-Sight
PDOA	Phase Difference of Arrival
PDOP	Position Dilution of Precision
R	Roulette Selection
RMSE	Root Mean Squared Error
RSSI	Received Signal Strength Indicator
seq-TLE	Sequential Target Location Environment
SINFAB	Sistemas Inteligentes de Fabricación y Mecánica
SNR	Signal Noise Ratio
SP	Single Point Crossover
T2	Tournament 2 Selection
T3	Tournament 3 Selection
TBS	Time-Based Positioning Systems
TDOA	Time-Difference-of-Arrival
TLE	Target Location Environment
TOA	Time-of-Arrival
TS	Target Sensor
UAV	Unmanned Autonomous Vehicles
UWB	Ultra-Wide Band
WGN	White Gaussian Node
WS	Worker Sensor
WSN	Wireless Sensor Networks

Abstract

Actual and future technological progress demands the progressive introduction of positioning systems capable of providing more exact and more stable localization. Traditionally, Global Navigation Satellite Systems (GNSS) allowed to reach global coverage and the access to harsh environments with complex orography.

However, GNSS navigation for high-demanded accuracy applications requires a deep error treatment of the positioning signals in order to reduce the uncertainties generated by noise, clock and ionospheric instabilities. Furthermore, adverse phenomena on signals such as multipath or Non-Line-of-Sight (NLOS) propagation can incapacitate the employment of GNSS in indoor applications, low-level flights or complex environments.

Consequently, over the last few years, Local Positioning Systems (LPS), with an ad-hoc adaptation to their environment of operation, are deployed allowing the reduction of the uncertainties in the position calculation of the GNSS and mitigating the adverse effects on the positioning signals thus attracting a relevant research interest. Nevertheless, the deployment of the LPS arises novel challenges which had been previously solved in the GNSS or that emerge as a consequence of the proximity among the target and the architecture sensor nodes.

Among the different LPS configurations, those concerning temporal measurements -Time-Based Positioning Systems (TBP)- stand out by reaching an optimal trade-off among accuracy, availability, robustness, easy-to-implement hardware configurations and system costs. Consequently, the local TBP architectures are analyzed in this dissertation as promising candidates for meeting the future technological demands.

Thus, the most relevant specific problems of time LPS are addressed in this doctoral thesis such as the disambiguation in the position calculation with the minimum number of architecture nodes, the optimized deployment of sensors for reducing the architecture uncertainties or the consideration of possible sensor failures in the architecture sensors of the positioning systems.

Firstly, in Chapter 4, a methodology for the calculation of the position with the minimum number of nodes of a TDOA LPS architecture is proposed. This methodology allows the solution of the mathematical ambiguity generated by the intersection of non-linear surfaces of possible target locations. The solution of this problem requires the maximization of

the distance between solutions of the ambiguous case through an optimized sensor distribution which enables the application of an iterative positioning algorithm with total reliability.

In Chapter 5, a procedure for the optimization of the sensor deployment in LPS architectures considering not only their performance in nominal operating conditions but also their behavior in eventual failure conditions of some of the architecture sensor nodes is proposed. The results indicated that this kind of optimization minimally reduces the system performance in nominal conditions but reaches a notable improvement in emergency operating conditions.

Additionally, the emergence of novel asynchronous LPS architectures recommends the application of this methodology for treating an eventual failure in the Coordinator Sensors (CS) of the positioning architecture. This enables the mitigation of the main disadvantage of asynchronous methods: the impossibility of accessing some of the system CS in any spatial region promoting the temporal unavailability of the asynchronous architecture in some locations. Thus, the principles of the optimization of the Chapter 5 are applied on Chapter 6 in order to reach the minimization of clock and noise uncertainties of the A-TDOA architecture in both nominal and failure operating conditions. In addition, the optimal combination of sensors in coverage for the determination of the target location is studied in this chapter for reducing the uncertainties in NLOS imbalanced signal-degradated scenarios.

Chapter 7 extends the methodology of Chapter 6 for the finding of optimal sensor placements for reaching acceptable accuracy, availability and robustness properties in the main temporal LPS architectures (TOA, TDOA and A-TDOA). This allows the definition of a common framework for the comparison of the temporal LPS architectures in their deployment in complex urban scenarios. This framework is necessary due to the imbalanced clock and noise error distribution of the temporal LPS architectures which produces that there cannot be defined any suitable a priori configuration to be deployed in complex scenarios.

Finally, in Chapter 8, a memetic algorithm for the Node Location Problem (NLP) in harsh NLOS scenarios in which there exist discontinuity in the fitness function evaluation among contiguous solutions is proposed. This requires the introduction of a procedure for the local search based on the exploration of variable contiguous neighborhoods of solutions which are unfavored by the evolutionary process traditionally introduced in the literature approaches of the NLP. The analysis of the suitability of the neighbors can be exclusively focused on the evaluation of the positioning signal paths since clock and geometric errors remain practically constant in neighborhood solutions which enables an efficient exploration during the local search procedure. The results indicate the preeminence of the memetic algorithm performance with regards to the exclusive traditional genetic exploration of the literature of the NLP.

Resumen

El desarrollo tecnológico actual y futuro demanda de forma progresiva la introducción de sistemas de posicionamiento que sean capaces de proporcionar localizaciones más exactas y estables a lo largo del tiempo. Tradicionalmente, se han empleado los sistemas de navegación satelital (GNSS) que permitían alcanzar cobertura global y el acceso a territorios con orografías especialmente complejas.

Sin embargo, la navegación GNSS para aplicaciones de elevada precisión requiere de un profundo tratamiento de las señales de posicionamiento para reducir las incertidumbres generadas por el ruido, las mediciones temporales y las inestabilidades ionosféricas. Además, fenómenos adversos en las señales como el multicamino o la propagación en condiciones de falta de línea de visión (NLOS) pueden inhabilitar el uso de los GNSS en el interior de edificios, en navegación de baja cota o en entornos con profundas irregularidades.

Como consecuencia, en los últimos años, aplicaciones de posicionamiento local (LPS), con especiales características adaptadas al entorno en el que son desplegados, permiten reducir la incertidumbre en el cálculo de la posición de los GNSS y mitigar los efectos negativos en las señales de posicionamiento, alcanzando con ello un gran interés de investigación. No obstante, el despliegue de los LPS supone nuevos desafíos que ya se encontraban resueltos en los GNSS o que surgen como consecuencia de la proximidad entre el objetivo de posicionamiento y los sensores del sistema.

Entre los diferentes LPS, aquellos basados en mediciones temporales, son los que permiten lograr una mejor relación entre exactitud, estabilidad, robustez, sencillez de implementación y coste. Por ello, los LPS temporales son analizados en esta tesis doctoral como candidatos para satisfacer las futuras aplicaciones de precisión tecnológicas.

Es por ello que, en esta disertación se abordan problemas específicos de los LPS temporales como la desambiguación del cálculo de la posición con el mínimo número de sensores, el despliegue optimizado de los sensores de sus arquitecturas o la consideración de posibles fallos de operación de los nodos de las arquitecturas de posicionamiento.

En primer lugar, en el capítulo 4, se propone una metodología para el cálculo de la posición con el mínimo número de sensores de una arquitectura LPS TDOA logrando la resolución de la ambigüedad matemática que se genera por la intersección de superficies no lineales. Esta metodología requiere la maximización de la distancia entre las dos soluciones que se generan en el caso ambiguo mediante una distribución optimizada de los sensores en

el espacio que permita la aplicación de un algoritmo de posicionamiento iterativo con total confianza.

En el capítulo 5, se plantea un procedimiento de optimización de la distribución de los sensores de las arquitecturas LPS que no tiene únicamente en cuenta el funcionamiento del sistema en condiciones nominales sino también su funcionamiento estable en caso de fallo de alguno de sus sensores. Los resultados mostraron que este tipo de optimización reduce mínimamente las prestaciones del sistema en condiciones nominales, pero alcanza una mejora notoria de su funcionamiento en condiciones de emergencia.

Por otra parte, el surgimiento de nuevas arquitecturas asíncronas LPS recomienda el uso de esta metodología del capítulo 5 para tratar el fallo eventual de los sensores coordinadores de posicionamiento asíncrono. Esto permite resolver la principal desventaja de estos sistemas: la imposibilidad de acceso a alguno de estos sensores coordinadores en alguna región del espacio produce la pérdida temporal de la disponibilidad de posicionamiento de las arquitecturas asíncronas en estos lugares. Por ello, se aplica el principio de optimización de las distribuciones de posicionamiento del capítulo 5 en el capítulo 6 para permitir la minimización de los errores de ruido y relojes de la arquitectura asíncrona A-TDOA en condiciones nominales y de emergencia. Además, se estudia en este capítulo la combinación óptima de sensores en cobertura para el cálculo de la posición en condiciones NLOS con degradación desbalanceada de la señal.

En el capítulo 7 se extiende la metodología del capítulo 6 para encontrar despliegues de sensores optimizados que alcancen buenas propiedades de exactitud, disponibilidad y robustez en las principales arquitecturas LPS temporales (TOA, TDOA y A-TDOA). Esto permite la generación de un marco común de comparación de las arquitecturas temporales para su despliegue en escenarios urbanos complejos. Este marco es necesario ya que en las arquitecturas LPS temporales se produce una distribución desbalanceada entre los errores de reloj y de ruido de estos sistemas que hace que no se pueda definir a priori la idoneidad de una arquitectura sobre las demás en escenarios complejos.

Por último, se presenta en el capítulo 8, un algoritmo memético para la resolución del problema de colocación de sensores de posicionamiento (NLP) en entornos complejos NLOS en los que se produzca discontinuidad en la función de evaluación de la calidad de una distribución de sensores entre soluciones contiguas. Esto requiere la introducción de un procedimiento de búsqueda local basado en la exploración de vecindades colindantes en espacios de soluciones no favorecidos por la evolución genética presentada tradicionalmente en la literatura. El análisis de la idoneidad de los vecinos puede centrarse exclusivamente en la evaluación de los caminos de las señales de posicionamiento ya que los errores de relojes y geométricos son prácticamente constantes, lo que permite alcanzar una gran eficiencia en el proceso de búsqueda local. Los resultados demostraron la prevalencia de esta técnica con respecto a la exclusiva exploración genética tradicional.

Chapter 1

Objectives and thesis organization

1.1. Objectives

This dissertation looks for a deep analysis on the deployment of Local Positioning Systems (LPS) for high-demanded accuracy applications. In this general framework, there are some general objectives of the thesis and particular specific aims in each of the research chapters. The general objectives of the dissertation are presented hereafter while the particular goals of each chapter are described in Chapter 3 and in each of the research items presented from Chapter 4 to Chapter 8:

- ❖ Study of the performance of Local Positioning Systems with the minimum number of nodes for determining the target location.
- ❖ Definition of a methodology for achieving the disambiguation of the calculation of the position with the minimum number of nodes in Time Local Positioning Systems.
- ❖ Design of an enhanced procedure for the deployment of architecture sensor nodes in LPS considering eventual critical operating conditions by possible sensor failures in the positioning architecture.
- ❖ Analysis of novel asynchronous methodologies for their application in Local Positioning Systems: design, implementation, deployment, availability and robustness studies.
- ❖ Development of a novel cost-effective methodology for the reduction of clock and noise uncertainties in Time Local Positioning Systems.
- ❖ Adequate selection of system nodes for the calculation of the position in the coverage area of Local Positioning Systems.
- ❖ Analysis of the interaction between Worker and Coordinator Sensors in Asynchronous Local Positioning Systems.
- ❖ Definition of a common framework for the selection of the most appropriate

Time Local Positioning System in NLOS complex urban scenarios based on accuracy, availability, robustness and system costs.

- ❖ Analysis of the metaheuristic techniques employed for solving the Node Location Problem in Wireless Sensor Networks.
- ❖ Study of the influence of the Genetic Algorithm operators and Local Search techniques in the Node Location Problem.
- ❖ Proposition of a novel Hybrid Memetic methodology for addressing the Node Location Problem in NLOS complex scenarios in which there exist discontinuity in the fitness function evaluation among contiguous solutions.

1.2. Main contributions

A synopsis of the major contributions of this dissertation is presented hereafter:

I. Definition of a methodology for solving the ambiguity in the target location in 3D with the minimum number of nodes through the definition of a convergence sphere acting as a confidence interval for the definition of the starting point of an iterative method for the position calculation.

II. A novel strategy for the deployment of architecture sensor nodes based on primary and emergency conditions which allows the system adequate functioning in failure conditions.

III. The characterization of the system clock and noise uncertainties in LOS and NLOS conditions for the main Time Local Positioning Systems: TOA, TDOA and A-TDOA.

IV. Definition of the most appropriate combination of sensors under coverage for the position calculation based on the reduction of the Cramér-Rao Bounds in each analyzed point under coverage.

V. Solution of the potential coordinator sensor unavailability in failure conditions of asynchronous node deployments.

VI. The proposition of a novel methodology for the coverage problem in localization in nominal and emergency conditions.

VII. Definition of a common framework for the comparison of the performance of Time Local Positioning Systems in NLOS complex urban scenarios.

VIII. Adaptation of a flexible optimization of the sensor distribution to urban scenarios.

IX. Proposition of a Hybrid Memetic Algorithm for the solution of the Node Location Problem based on an intelligent usage of the GA operators during the evolutionary process and a Variable Neighborhood-Descent Local Search Strategy for exploring potential unfavored spaces of solutions.

1.3 Thesis Organization

The structure of this dissertation is presented in this Section. Chapter 1 defines the main objectives of the dissertation, presents the contributions of the doctoral thesis, provides the organization of the document and introduces the research funding projects and the research group in which the thesis has been developed.

Chapter 2 provides a general introduction to the LPS including the state-of-art technologies, the definition of the areas in which the LPS are applied, the main LPS architectures, a particularization on the Time-Based systems and the positioning algorithms used in the literature.

Later, the importance of the solution of the NLP in LPS is highlighted. The main heuristic techniques for addressing this NP-Hard complex problem are presented and the relevance of the GA due to their trade-off between diversification and intensification is mentioned.

Then, the characterization of the system uncertainties for determining the quality of the node distributions through the Cramér-Rao Bounds is analyzed, finalizing the Chapter with the proposal of the main research lines of this dissertation along with some of the contributions of the thesis.

Chapter 3 introduces the connection among the research chapters of this dissertation and the general investigation performed in the localization field during the development of the doctoral thesis.

Chapter 4 analyzes the mathematical ambiguity in the position calculation of TDOA systems with four architecture sensor nodes. A methodology for solving the 3D TDOA problem with the minimum number of nodes is proposed through the definition of a convergence sphere from which any inside point can act as starting point for the determination of the target location with total reliability.

Chapter 5 proposes a novel methodology for achieving the optimal performance of the TDOA architecture in cases of some sensor malfunction with a minimal reduction of the accuracy in nominal operating conditions. In addition, the solution of the 4-node 3D TDOA problem is guaranteed in failure conditions of any of the architecture sensors.

Chapter 6 presents a cost-effective strategy for the deployment of asynchronous sensor networks. It solves the coverage problem in cases of Coordinator Sensor failure by assuming the optimization for primary and secondary (emergency) conditions of the localization system. In addition, a technique for calculating the position with the most beneficial nodes under coverage is provided.

Chapter 7 introduces a methodology for the comparison of the performance of the most relevant Time-Based Positioning Architectures (TOA, TDOA and A-TDOA) in NLOS complex urban scenarios. This comparison is provided once the sensor distribution of each architecture is optimized since a priori optimal configurations cannot be directly determined. The optimization criteria are accuracy, robustness, availability and cost of each architecture.

Chapter 8 investigates the Node Location Problem in the localization field. It provides a definition of the complexity of the problem and analyzes the metaheuristic techniques that have been employed for addressing this NP-Hard problem. After this analysis, a Hybrid Memetic Algorithm, which combines the beneficial effects of the Genetic Algorithms in the Node Location Problem along with a Local Search Procedure for examining potential unfavored regions of the space of solutions, is proposed.

Finally, Chapter 9 provides the concluding remarks and the future investigations derived from the results obtained in this dissertation.

1.4 Research Framework

This work has been developed in the SINFAB research group of the University of León under the supervision of the Dra. Hilde Pérez García. The group has been involved in two national research projects during the thesis development: DPI2016-79960-C3-2-P of the Spanish Ministry of Economy, Industry and Competitiveness and PID2019-108277GB-C21 of the Spanish Ministry of Science and Innovation. These two research projects have funded the research activities of this doctoral thesis.

Chapter 2

General Introduction

The development of mobile technologies requires user localization for multiple applications for proportionating personal and adapted services of high quality. These technologies often use the signals of the Global Navigation Satellite Systems (GNSS) for providing global coverage with reduced cost.

However, other technological applications with heavy accuracy needs are suffering the limitations of the GNSS for supplying a stable and low-uncertainty position determination. These problems are boosted by complex orographic terrains [1], indoor environments [2], tunnel and low-level navigation [3,4] or underwater localization [5]. GNSS have traditionally mitigated their problems in this kind of activities through two different strategies: a deep signal error treatment for reducing clock [6], noise [7] and ionospheric uncertainties [8] and the terrestrial deployment of augmentation systems for reducing the global navigation uncertainties.

Nevertheless, GNSS were conceived for providing global coverage and although the increase of the satellites in space could partially mitigate their limitations, every new satellite in orbit supposes a notable increment of the system costs. This consideration has led the research interest over the last decades through the combination of the signals of the most important GNSS (GPS, Galileo, GLONASS or BeiDou) with multi-constellation techniques [9] for reducing the individual errors of the systems thanks to the liberation of the use of GNSS in the last few years.

However, GNSS efforts for achieving better accuracy results are not applicable for reaching the accuracy needs of some application fields such as surveillance, rescue operations, precision farming or indoor and outdoor navigation of autonomous vehicles. Consequently, Local Positioning Systems (LPS) [10] are being actually developed. LPS are based on the deployment of terrestrial sensor networks in which the proximity between target and sensors allows the reduction of the uncertainties in the position determination. LPS are classified through the physical property measured for determining the target location: time [11], power [12], phase [13], frecuency [14], angle [15] and combinations of them [16,17].

Among the LPS, those based on temporal measurements provide the best trade-off among accuracy, stability, robustness, availability, easy-to-implement hardware configurations and system costs. As a consequence, this dissertation delves into the analysis of time-based LPS architectures for its application in high-demanded accuracy applications.

Focusing on time-based LPS, three main architectures are distinguished: Time of Arrival (TOA) [18], Time Difference of Arrival (TDOA) [19] and Asynchronous Time Difference of Arrival (A-TDOA) [20].

TOA systems measure the total time of flight of a positioning signal from an emitter to a receiver. This total time can be converted in a distance between emitter and receiver through the speed of flight of the positioning signals, usually the speed of the radioelectric waves (c). Since the emitter can be located in any spatial position whose difference to the receiver is this distance measurement, every positioning signal produces a sphere of possible target locations. Thus, the solution of the three-dimensional (3D) TOA problem requires at least three different receivers for generating three different spheres. However, the non-linear conditions of the spherical equations promote an ambiguity in the intersection of the three spheres that cannot be mathematically solved, thus inducing the introduction of one more receiver for totally solving the 3D TOA problem.

TDOA systems are based on the measurement of the relative time of flight between the signal arrival to two different receivers. While TOA systems require the synchronism among the target and all the sensor clocks since the instant of the emission is needed for computing the time measurements, the relative time measurements of the TDOA systems induce the synchronization to be only mandatory among the system sensors clocks. In addition, TOA systems consider only the direct path between the emitter and the receiver while TDOA systems require a pair of positioning signals for computing the time measurements. This produces the 3D TDOA problem to require one more sensor for the position calculation. Furthermore, the relative time measurements generate hyperboloid equations instead of spheres but the ambiguity in the position calculation in this case with four nodes is still present. In Chapter 4, a methodology for addressing the disambiguation in TDOA systems which can be extended to any localization architecture in LPS is provided [21].

A-TDOA systems avoids the synchronism through a receive and retransmit strategy of the positioning signal using the collaboration of the target. This allows the computation of the time measurements in a single clock of a coordinator sensor reducing the clock uncertainties in the time measurements. This characteristic has supposed the A-TDOA architecture to be especially promising in LPS applications since an important amount of the system uncertainties is due to the synchronism effect on LPS. A-TDOA architecture produces ellipsoid equations [22] which unequivocal intersection requires four equations and five sensors from a mathematical point of view.

The solution of non-linear equations in each of the architectures has led to multiple positioning algorithms in the literature. Generally, these algorithms are classified in closed-form algorithms and iterative algorithms. Closed-form algorithms [23] provide a direct solution of the localization problem but they have shown to be more instable in the cases in which the temporary measurements are collected in noisy environments. Iterative algorithms [24] allow an error treatment but depend on the starting position from which the method is initialized. An incorrect selection of the starting point can cause algorithm convergence problems especially when the initial position is far away from the target location.

However, regardless the positioning architecture used and the algorithm selected for the position determination, the spatial distribution of the architecture sensors in space is critical for achieving valid localization uncertainties in LPS.

This problem requires the optimization of the sensor distribution and it is known as the Node Location Problem (NLP). It has been assigned as NP-hard [25], not allowing the solution in a polynomial time and suggesting the employment of metaheuristic techniques for finding optimal sensor placements. As a consequence, simulated annealing [26], the firefly algorithm [27], the dolphin swarm algorithm [28], the bacterial foraging algorithm [29], the elephant herding optimization [30], diversified local search [31] but especially Genetic Algorithms (GA) in the localization NLP [32-34] have been employed for addressing this problem. The GA have stand out due to their trade-off between diversification and intensification in the space of solutions. However, in this dissertation a novel promising technique for the NLP is introduced in Chapter 8 (memetic algorithms). The memetic algorithm proposed highlights the necessity of addressing the difficulties in the exploration of potentially unfavored spaces of solutions in imbalanced signal degradation environments in Non-Line-of-Sight (NLOS) conditions.

These essential optimizations of the sensor locations in the NLP require a fitness function for the determination of the quality of the sensor distributions in order to reduce the system uncertainties thus boosting the accuracy, availability and robustness properties of each localization architecture. For achieving a valid characterization of the system uncertainties, LPS require the modeling of the covariance matrix of the Cramér-Rao Lower Bound (CRLB) [35,36]. This modeling is flexible to introduce the system uncertainties of LPS and finally allows the obtainment of the minimum achievable error by any positioning algorithm in a determined target location. The derivation of the CRLB cannot be jointly calculated in every possible target location under coverage [37] which also suggest the employment of heuristic algorithms for the NLP.

The characterization of the noise and clock uncertainties of our recent works has allowed the optimization of each of the time LPS architectures analyzed in this dissertation for extracting valid conclusions on the implementation and deployment of LPS in actual operating conditions in the next chapters.

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Chapter 3

Research evolution and chapters linkage

The research studies presented in this dissertation are part of the investigation developed in the SINFAB group of the University of León. The objective of this chapter is to clarify the linkage among the next chapters (4-8) and the general framework and evolution of the research activities performed over the last few years.

The investigation started with the conception of analyzing the possible implementation of LPS to the guided navigation of emerging autonomous vehicles. The accuracy needs of these systems suggested the deployment of an ad-hoc sensor network for improving the accuracy results of the GNSS.

The first step demanded the analysis of the particularities of the LPS with regards to GNSS. One of the first discoveries was that the position determination with the minimum number of sensor nodes presented an elevated complexity with regards to GNSS. While the ambiguity in the position determination with 3 satellites in TOA systems and with 4 satellites in TDOA systems had been traditionally solved through the avoidance of the incoherent solution (e.g. one of the two possible solutions was traditionally outside the earth`s surface, inside the ground surface or extremely separated from the last known target location), in LPS the reduced separation among solutions did not allow us to directly solve this adverse scenario.

As a consequence, a methodology based on the principles of an iterative positioning algorithm was developed to solve the minimum number of nodes-TDOA problem in Chapter 4 [1]. This methodology showed that under optimized node distributions in which the distance between solutions is maximized, the 4-node 3D TDOA problem presented the properties of an analogous one with more sensors where the position disambiguation is achieved. Firstly, this optimal node distribution was searched by analyzing regular sensor network patterns where we found that the achievement of the best combination of sensors in space for solving this problem does not follow any design pattern. As a consequence, we discovered the NLP in wireless sensor networks which was NP-Hard and suggested the usage of heuristics for addressing this complex problem.

In this context, we conducted our research in order to discover the relation among the spatial distribution of the sensors with the main properties of the LPS: target position calculation uncertainties, system availability and robustness.

Although, traditionally, the noise uncertainties related with the geometric disposition of the target and satellites in the GNSS had been modeled through the Position Dilution of Precision (PDOP), the PDOP is based on the homoscedastic error consideration since the signal travels similar paths from the satellite to the target in GNSS. This is not the case for LPS in which the positioning signal travel significantly differs among the architecture sensors. As a consequence, we defined a heteroscedastic noise consideration for time LPS based on a Log-Normal path loss model which especially fits in LPS application scenarios. We later applied this model to the comparison of the noise uncertainties of two novel asynchronous architectures (Asynchronous Time Difference of Arrival and Difference-Time Difference of Arrival) which had shown an excellent adaptation for LPS applications [2].

The two architectures were compared in five different node distributions showing the A-TDOA architecture a better accuracy and stability for LPS applications.

The analysis of the asynchronous architectures was selected since the avoidance of the necessary synchronism of the target and system clocks in TOA systems and the system clocks in TDOA represented a key amount of the global error in LPS.

However, this error analysis of the asynchronous architectures was performed in regular environments of simulations in which the best combination of sensors of each architecture had not been achieved. As a consequence, we developed a heuristic methodology for finding optimal node deployments in irregular scenarios of simulations. We created a framework for simulating any actual irregular scenario of application of an LPS. In this scenario, we distinguished between the zone for the navigation of the vehicles, Target Location Environment (TLE), and the possible locations in which the architecture sensors can be deployed, Node Location Environment (NLE).

This distinction must be applied in LPS which supposes the principal difference with literature optimizations of Wireless Sensor Networks since the possible locations of the target must be considered jointly in the optimization process. In addition, this particularity makes that the error characterization of [2] cannot be derived in the entire TLE, thus recommending again the heuristic approach for the finding of optimal node distributions.

As a consequence, we applied the noise error characterization introduced in [2] to the Cramér-Rao Lower Bound (CRLB) covariance matrix since it provides the minimum achievable error by any positioning algorithm for characterizing the quality of a node distribution in a GA in which we included an irregular definition of the scenario of simulations of an A-TDOA architecture [3].

Results showed that significant improvements on the accuracy of the LPS can be achieved by optimizing the node deployments in these irregular scenarios. However, these optimizations considered exclusively the performance of the LPS in nominal operating conditions (i.e. all the architecture sensors correctly operating). This promoted that an eventual failure of some of the system elements could promote that the whole system could instantly increase the system errors thus promoting the useless of the LPS application.

We proposed in [4] (Chapter 5), a methodology for an enhanced performance of the LPS in failure conditions by optimizing the system performance for every combination of sensors that exceeds the minimum number of sensor nodes in every analyzed TLE point. In addition, we guaranteed the system operation for the minimum number of nodes with the maximization of the sphere of convergence defined in [1] for every combination of four sensors under coverage. Results showed that optimizations considering emergency conditions (i.e. possible sensor failures) perform similar to only nominal optimizations in primary conditions but significantly outperformed these nominal optimizations in failure conditions. [5].

However, the uncertainties in the position determination are notably affected by the temporal architecture measurements in LPS in addition to the noise uncertainties previously defined. This led us to the characterization of the clock errors in the covariance matrix of the CRLB. We generated a model in which the clock drift, initial-time offset and the instrument truncating errors are considered [6]. This model allows the comparison of the three main Time-Based Positioning Systems in LPS considering the noise characterization [2] and the proposed clock error definition [6] under optimized node deployments in irregular scenarios of simulations [3].

Results showed that asynchronous architectures are more stable in Line-of-Sight

(LOS) conditions than the synchronous time architectures due to the avoidance of the synchronism necessity. However, the results were not conclusive since the asynchronous architecture demands the receive and retransmit strategy in the positioning signal which increases the signal paths. As a consequence, an increased in the noise uncertainties is produced which can affect the asynchronous performance in NLOS scenarios (significant signal degradations) and increases the probability of suffering adverse effects on signals such as multipath.

Therefore, we included the NLOS paths in the noise characterization of the CRLB for the A-TDOA architecture provided in [2] by extending the Log-Normal Path Loss Model in [7]. This required the development of a novel algorithm for distinguishing the LOS and NLOS paths of the positioning signal. We also included an algorithm for the detection of the multipath phenomena based on the definition of the ellipsoid of the Fresnel Zone which produces destructive interferences on the communications channel and the ellipsoid containing the 3D space around the emitter and the receiver of the positioning signal where an object can produce a signal which cannot be distinguished from the LOS path (i.e. the one used for the temporal measurement).

The creation of these two algorithms promoted a multi-objective optimization looking for a minimization of the system uncertainties and the avoidance of the multipath phenomena in irregular scenarios.

The results of [7] indicated that this is an optimal technique for determining the optimal number of sensors required by the architecture for avoiding negative effects on signals and for minimizing the system uncertainties. However, this optimization showed the dependence of the A-TDOA architecture on the Coordinator Sensor (CS) Nodes since they collect the signals of all the Worker Sensors (WS) for computing the time measurements. This promotes that a sub-optimal location of the CS increases in a greater extent the architecture uncertainties than the WS location. In addition, the optimization found problems for finding the optimal location of the CS and not every TLE point could access to at least two different CS which could potentially produce a temporal unavailability of the architecture in some points in case of a CS malfunction which is a consequence of the dependence of the architecture on the CS.

As a consequence, we realized the importance of optimizing the asynchronous architectures for both primary and emergency conditions such as the procedure followed in Chapter 5 [4] considering possible CS failures. In addition, in [7] we found that not the total amount of sensors under coverage provides the better accuracy results since especially in NLOS environments there are imbalanced degradations of the positioning signals. This conclusion suggests the investigation on the best combination of sensors for calculating the target location. Moreover, the evolutionary process followed in [7] indicated that the convergence of the GA for solving the coverage problem in asynchronous localization was difficult to achieve without inducing penalizations in fitness values of the optimization. As a consequence, the sensor distributions in which not the minimum number of sensors reach the SNR_{min} are significantly penalized for guiding the evolutionary process to valid sensor combinations.

Every of these considerations were later considered for building a methodology for the deployment of asynchronous Time LPS in Chapter 6 [8]. We proposed an enhanced optimization for primary and secondary conditions (i.e. possible CS failures) guaranteeing at least two CS available in each point of the TLE region. In addition, we found in [8] the optimal configuration of sensors for calculating the uncertainties in the TS location through a CRLB model which combines the LOS and NLOS conditions for the noise characterization of [7] with the clock uncertainties of [6].

This methodology overcomes the principal problem of the asynchronous LPS since the unavailability of the CS produces the temporal discontinuity in the calculation of the position. In addition, results indicated the suitability of the asynchronous methodologies for LPS since the reduction of the clock errors avoiding the synchronism has a relevant impact in the reduction of the uncertainties.

However, the effective reduction of the uncertainties requires in asynchronous LPS the deployment of an important amount of CS since at least two of them must be always under coverage and the location of these sensors is critical since they must avoid NLOS links with the positioning signals and reduce considerably the multipath phenomena. This conclusion promotes that especially singular irregularities in the environment in which the asynchronous LPS are deployed may suppose a relevant increase in the number of CS needed for achieving valid results, thus increasing the system costs.

As a consequence, a deep study of the environment of application of the LPS is required for determining the optimal time architecture for particularly adapt to the environment conditions. This conclusion is also based on the different characteristics of the main time architectures (TOA, TDOA and A-TDOA).

TOA systems collect the higher clock errors since they require the synchronization among all the system elements but they cumulate the less noise uncertainties since each of the positioning signals only travels from emitter to receiver for producing a localization equation of possible target locations.

TDOA systems have an equilibrated distribution of their uncertainties. They have a reduction in the clock errors since they avoid the synchronism with the target sensor clock like in the TOA systems but they do not reach the complete avoidance of the synchronism like in the A-TDOA system. However, TDOA systems increase the noise errors with regards to TOA systems since the collection of a time measurement requires two different signal paths from emitter to receiver thus cumulating the noise errors of the two signals. But these noise errors are reduced with regards to A-TDOA systems in which the receive and retransmit strategy even increases the signal paths of TDOA systems.

Therefore, A-TDOA systems provide the less clock uncertainties but the larger noise cumulated errors. In addition, the CS dependence must be also balanced by the correct node deployments and can suffer in particularly irregular scenarios.

Consequently, we cannot define any a priori perfect architecture for LPS applications and there did not exist any approach to that problem in the literature before. Thus, we have created in Chapter 7 [9] a novel methodology for comparing the performance of the three main time LPS architectures (TOA, TDOA and A-TDOA). This methodology includes the system accuracy, robustness and availability performance of each system considering their architecture particularities during the optimization process of their node distributions.

We apply the Log-Normal Path Loss Model with LOS [2] and NLOS conditions [7] and the clock uncertainties [6] onto the CRLB of each architecture and we use the methodology of [4,5] for considering possible CS failures for guaranteeing optimal performance of each architecture in [9].

We also make usage of the methodology of [8] for guiding the optimization process for finding optimal node distribution which provide accuracy, availability and robustness. This creates an optimal framework for comparing the time LPS for applications in complex urban scenarios [9]. This has required the modeling of obstacles (i.e. buildings) over the terrain characterization provided in [3] which increases the TLE and NLE areas with a novel Obstacle Area (OA) where localization nodes and targets cannot be located.

On the other hand, the relevance of solving the NLP in LPS has been demonstrated throughout the research presented in this Chapter. Consequently, the finding of optimal node distributions is critical for applying ad-hoc LPS applications. Since it is an NP-Hard problem, heuristic methodologies have stand out for providing optimized sensor locations. GA, as shown in [3], have highlighted the importance of a trade-off among diversification and intensification for the NLP and thus have prevailed in the literature.

However, we have observed in [7-9] that optimizations in which NLOS conditions are considered, provide unstable performance of the evolutionary algorithms. This is due to the discontinuity in the fitness function evaluations among contiguous solutions (i.e. node deployments that differ minimally in the coordinates of one architecture sensor) which complicates the analysis of some regions of the space of solutions, not being enough with the mutation and crossing operators for exploring this unfavored regions.

We first tried to avoid this problem through the consideration of hybrid configurations in the GA operators which changed along the evolutionary process [10]. This allowed us to create two different stages in the GA optimization: a deep - exploration phase followed by a heavy - intensification phase. Different configurations of crossover and selection techniques are analyzed for each particular scenario proving the preeminence of this technique for achieving better optimization results than individual configurations [3].

However, this methodology is limited to the scenario of simulations in which the optimization is being performed. Consequently, their results are not applicable to any LPS application. Therefore, we considered a different optimization technique which could be applied in any scenario improving the results of the GA in NLOS discontinuity conditions in harsh environments.

As a consequence, in Chapter 8, a Memetic Algorithm (MA) for the NLP in Localization is proposed [11]. This MA combines the GA with a Local Search (LS) procedure for exploring potential unfavored regions of the space of solutions and for improving the characteristics of the elitist individuals reaching an improvement of the evolutionary process.

The variable neighborhood-descent (VND) LS is applied to the most different individuals of the population in order to explore different spaces of solutions. The selection of the most different individuals is based on dissimilarity metrics among population individuals.

One of the most relevant contributions of the LS is the application of a pseudo-fitness function which relies on the minimal variation of the geometric and clock errors in the neighborhood of an individual. Therefore, the reduction of the NLOS links among the architecture sensors and target concerns the LS procedure for improving the individuals of the MA. The finding of the most appropriate individual of the neighborhood following this process allows the intensification in these spaces such a way it could not be perform in the GA optimization.

Results showed that the combination of an enhanced hybrid usage of the GA operators of [10] and the MA proposed in [11] outperforms each of the previous heuristic configurations, reaching an improvement in the accuracy of the A-TDOA architecture of 14% with regards to only GA optimizations of [3].

More research is being performed nowadays for finding the optimal number of sensors directly in the evolutionary process, the application of different heuristic approaches to the NLP, the definition of patterns for the deployment of LPS in large-scale application, the consideration of new asynchronous architectures or actual implementations of the LPS which permits the validation of the CRLB models. This is particularly detailed in Chapter 9 with the future investigations derived from this dissertation.

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Chapter 4

3D TDOA Problem Solution with Four Receiving Nodes

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Abstract

Time difference of arrival (TDOA) positioning methods have experienced growing importance over the last few years due to their multiple applications in local positioning systems (LPSs). While five sensors are needed to determine an unequivocal three-dimensional position, systems with four nodes present two different solutions that cannot be discarded according to mathematical standards. In this paper, a new methodology to solve the 3D TDOA problems in a sensor network with four beacons is proposed. A confidence interval, which is defined in this paper as a sphere, is defined to use positioning algorithms with four different nodes. It is proven that the separation between solutions in the four-beacon TDOA problem allows the transformation of the problem into an analogous one in which more receivers are implied due to the geometric properties of the intersection of hyperboloids. The achievement of the distance between solutions needs the application of genetic algorithms in order to find an optimized sensor distribution. Results show that positioning algorithms can be used 96.7% of the time with total security in cases where vehicles travel at less than 25 m/s.

4.1 Introduction

Positioning is an essential factor for the correct navigation and location of vehicles. The accuracy in the calculation of the position has commonly determined the fields where positioning has been applied. High technological levels have been achieved when uncertainty has been enough reduced. The usage of localization methods has evolved throughout the last few years from a reference object to precision applications such as farming, indoor navigation or manufacturing environment.

Positioning systems can be divided into those based on time measurements and those that measure different properties such as the Angle of Arrival (AOA) [1] [2] or the Received Signal Strength Indicator (RSSI) [3] [4] [5]. Among them, time measurement systems are the most extended due to availability, accuracy, simplicity and robustness. In this category, TOA (Time of Arrival) systems [6] [7] as GPS, GLONASS or Galileo, and TDOA (Time Difference of Arrival) systems [8] [9] as LORAN, OMEGA or the WAM (Wide Area Multilateration) system [10]—highly widespread in aircraft environments—are considered.

TOA systems measure the total time-of-flight of a signal between a transmitter and a receptor. They require time synchronization between transmitter and receptor and their accuracy is highly dependent from the clock drift in this synchronization. These time-of-flight measurements lead to the equations of 3-dimentional spheres centred on the transmitter, with the possible locations of the vehicle in the space.

In contrast, TDOA systems measure relative times between signal arrival to two different receivers. In this case synchronization is optional, differentiating Asynchronous (A-TDOA) [11] and Synchronous (S-TDOA) [12] systems. This can lead to a reduction in the error levels. In such scenario, time difference measurements generate the equations of hyperboloids whose intersection determine the position of the vehicle.

A number of n equations can be obtained from n different receivers in TOA systems due to global time measurements in each receptor. In contrast, relative measurements in TDOA systems must consider different combinations of time difference of arrival measurements that are originated from every pair of receivers. These combinations do not allow repetitions in pairs 1-2 or 2-1, mainly due to the duplicity of results. However, it is proved that from a set of n different receiving sensors in a TDOA problem, only a number of (n-1) independent equations can be obtained. In addition, the biggest limitation in the equations of spheres and hyperboloids is that they are considered as non-linear equations. This produces a non-direct resolution of the positioning problem through these equations. This fact causes that intersection of spheres or hyperboloids do not have a unique solution in the space. Two different solutions can be obtained that cannot be distinguished through mathematical criteria.

According to rigidity theories in positioning systems [13], to completely determine the unequivocal location of an object in the three-dimensional space, it is necessary a minimum of 4 receptors in TOA systems, and a minimum of 5 in the case of TDOA systems. This disposition would guarantee one single solution for the positioning problem. However, global positioning systems as GPS do not necessarily require an additional satellite for the calculation of the position, since the distances between emitter and receptor are so far-off, that the sphere equations generated allow to correctly discard the incorrect solution, for being incoherent or too separated from the previous position of the vehicle.

This problem, apparently solved in global navigation systems, poses a great importance in Local Positioning Systems (LPS) [14] [15], as those used in precision applications such as indoor navigation or aircraft landings in nowadays airports. This is due to proximity between the two different solutions in these cases so that any solution can be discarded with a stable generalized criterion. In this article, a new criterion is proposed to solve this geometric problem based on the properties of some positioning algorithms. TDOA algorithms will be considered due to their great usage in LPS [16].

In section 4.2, TDOA positioning problem is described. In section 4.3, some different algorithms to solve in real-time the TDOA problem are presented while in section 4.4, fictitious point studies based on TDOA algorithms are developed to guarantee a 4 receivers TDOA solution and the convergence sphere is defined. We show the great computer processing difficulty of the convergence sphere in section 4.5 and a new parameter to process the convergence radius is proposed in section 4.6. Section 4.7 develops an optimized node localization to solve the 3D TDOA problem. The article concludes with the presentation and analysis of the results obtained extracting conclusions of the complete work.

4.2 The TDOA Problem

TDOA systems are based on difference time measurements between the signal arrival to different nodes or sensors in a network. These measurements can be converted on difference of distances by multiplying these times by speed emission of the radioelectric waves (c).

This leads in *Euclidean Geometry* to the next equation:

$$\begin{aligned} R_{ij} = d_{ij} = d_{Ii} - d_{Ij} \\ &= \sqrt{(x_I - x_i)^2 + (y_I - y_i)^2 + (z_I - z_i)^2} \\ &- \sqrt{\left(x_I - x_j\right)^2 + \left(y_I - y_j\right)^2 + \left(z_I - z_j\right)^2} + h(0,\sigma) = ct_{ij} + h(0,\sigma) \end{aligned} \tag{4.1}$$

where d_{Ij} is the distance difference between receivers i,j —which is the result of multiplying the real time difference of arrival (t_{ij}) and adding a white noise, $h(0, \sigma)$, that considers atmospheric instabilities and time error measurements. This noise is related with signal transmission and measurement of times which cannot be controlled by TDOA algorithms so that it is not considered in this paper. In addition, (x_I, y_I, z_I) are space coordinates of the vehicle that is being positioned and $(x_i, y_i, z_i), (x_j, y_j, z_j)$ the coordinates of the nodes i,j that receive the positioning signal. These equations correspond with hyperboloids that cannot be solved in an analytic direct process so that numerical methods must be used to determine the problem.

4.3 Algorithms for TDOA problem resolution

Non-linear equations of hyperboloids must be treated in order to address the TDOA problem resolution. Generally, two main methodologies have been considered: those based on hyperboloids intersection properties with closed-form solutions and those based on numerical methods, which offer a progressively reduction on the error gradient derivation in successive approximations to the final solution. Although these methods could be considered as analogue, they use different properties and methodologies. However, both of them share that univocal TDOA problem resolution must use at least 5 different sensors. Hence, from now on, a combined study with a method of each case is proposed to solve TDOA problem with only four beacons.

Bucher and Misra [17] proposed a method based on the properties of the intersection of hyperboloids. They show that hyperboloids intersection can always be contained in a plane. This process increases one degree of freedom to the problem since a number of n receivers generates a number of (n-1) independent hyperboloid equations and (n-2) independent intersection planes are obtained using this methodology. That means that to solve linearly 3D TDOA problem, where 3 planes are needed, we still have to use 5 different receivers. Nevertheless, the contention of the intersection of two different hyperboloids in a plane is a process where plane equation is independent from hyperboloids equations. As consequence, the intersection of two planes (4 nodes) resulting in a line of possible vehicle localizations can be verified in any hyperboloid to finally get the two solutions that are achieved in TDOA problems with 4 beacons (i, j, k, l). This methodology leads to two different solutions that for LPS cannot be discarded by any assumable criterion.

The other method would be based on applying a Taylor approximation truncated on first order to linearize the equations and to allow a real-time solution of the problem. In this way, a point with enough proximity to the final solution (x_0, y_0, z_0) from which a process of sequential iterations will be started is selected. These steps will finally allow to obtain the vehicle localization through a matrix where the range differences are considered in the next way:

$$R_{ij} = ct_{ij} = R_{ij_0} + \frac{\partial R_{ij}}{\partial x}\Delta x + \frac{\partial R_{ij}}{\partial y}\Delta y + \frac{\partial R_{ij}}{\partial z}\Delta z \tag{4.2}$$

being R_{ij} the value of the distance difference in the approximation point and $\frac{\partial R_{ij}}{\partial x}$, $\frac{\partial R_{ij}}{\partial y}$ and $\frac{\partial R_{ij}}{\partial z}$ the partial derivatives of the range differences, particularized for the values of the approximation point.

Applying this same process to the other two nodes k and l with reference to the node i, R_{ik} and R_{il} can be estimated. This leads to the following matrix system:

$$\Delta R = \begin{pmatrix} \frac{\partial R_{ij}}{\partial x} & \frac{\partial R_{ij}}{\partial y} & \frac{\partial R_{ij}}{\partial z} \\ \frac{\partial R_{il}}{\partial x} & \frac{\partial R_{il}}{\partial y} & \frac{\partial R_{il}}{\partial z} \\ \frac{\partial R_{ik}}{\partial x} & \frac{\partial R_{ik}}{\partial y} & \frac{\partial R_{ik}}{\partial z} \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta z \end{pmatrix} \tag{4.3}$$

where ΔR is the range differences matrix, H is the partial derivative matrix—commonly known as visibility matrix—and P is the position variance matrix.

Therefore, we can express the matrix system as follows:

$$\mathrm{H}\Delta P = \Delta R \tag{4.4}$$

This equation is usually solved through the Least Squares Method [18], as described below:

$$\Delta P = (H^t H)^{-1} H^t \Delta R = \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta z \end{pmatrix} \tag{4.5}$$

The coordinates of the solution point in the first iteration would be the result of adding all the approximation coordinates to the increments obtained. After several iterations the residual error is reduced, reaching the convergence to the real solution once it has become lower than the desired precision. However, the convergence of this method depends on the initial position chosen to start with the first iteration [19]. Regarding the resolution of the TDOA problem, 4 receiving sensors do not always guarantee the convergence of the method, and if produced, this can happen towards any of the two possible solutions—which prevent us from knowing whether the position calculation is correct. However, in contrast to the former method, the calculation of the position now guarantees a single solution instead of two possible answers.

4.4 Fictitious Point Method

Of all the methods proposed so far, it is not possible to conclude whether the TDOA System can be applied to LPS systems with 4 nodes with enough confidence to guarantee the correct calculation of the position. Nevertheless, it is possible to affirm that successive approximation method does guarantee the convergence—if produced—towards one of the possible of the solutions.

This means that if there were any way to ensure the convergence to occur towards the correct solution, the method would allow to solve the problem with 4 sensors. In the case the process is convergent, and highly dependent upon the initial point of the iterations, it is safe to say that when this initial point is close enough to the solution—the previous solution of the vehicle, for instance— the convergence should always take place towards the correct solution. To prove this statement, the behaviour of any point located at the plane that contains the two possible solutions is going to be proved for the TDOA problem. Applying the successive approximation method to these initial points, the intersection of planes is calculated.

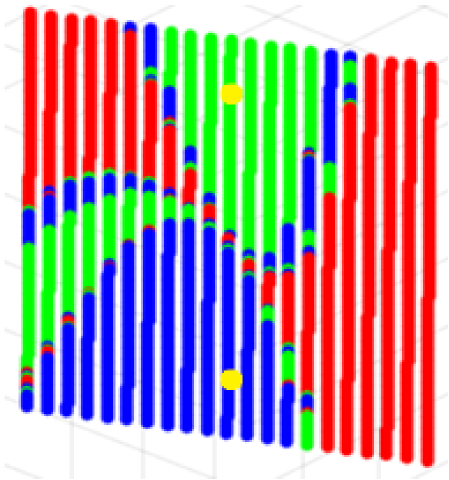

Figure 4.1. Plane of convergence containing the two solutions of a 4 beacon TDOA problem

As represented in the previous figure, the solutions (in yellow) are categorized between two regions (blue and green), which convergence produces towards the closest solution. Regions in red show an absence of convergence with the successive approximation method. As it is a 3-D positioning system, it is necessary to extrapolate the same reliable zone—for the position calculation with 4 nodes—to a 3-D space, to find the solution to the problem. The resulting figure would necessarily be a sphere—since the vehicle can move in any direction—with the solution as centre.

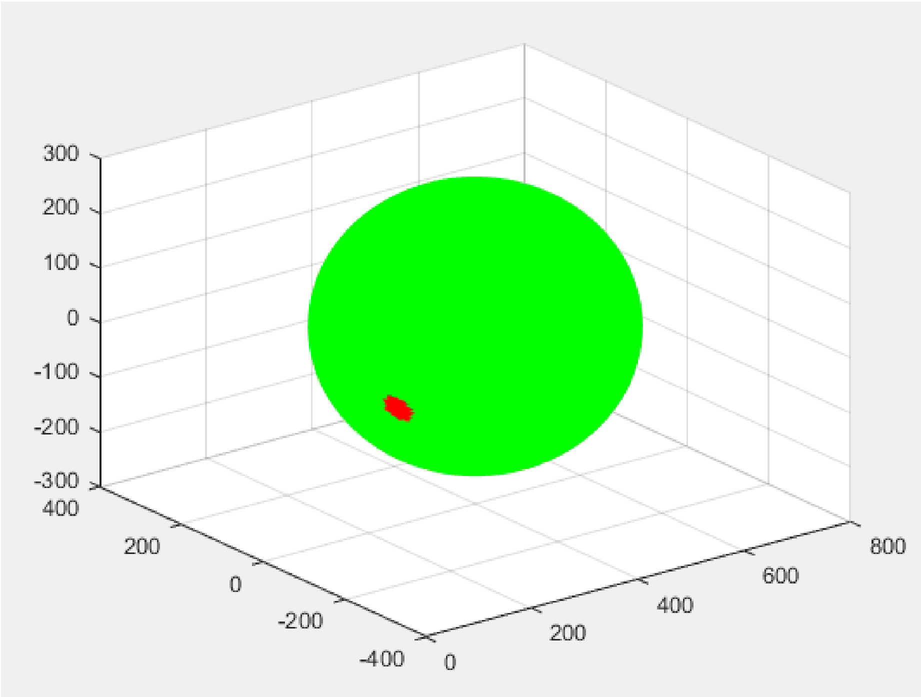

Figure 4.2. Analysis of a convergence radius of a sphere towards the solution. All the points in the surface of the sphere are proved as initial points in the successive approximation method to calculate the position towards the center of the sphere. In this figure, the first not convergent radius is presented where instabilities are represented in red.

Figure 4.2 shows the first non-convergent radius in a convergence analysis where instabilities in convergence have appeared and represented in red. Therefore, we define the convergence sphere around the correct solution, as that the one that has the maximum radius which guarantees that all the points in the surface of the sphere are convergent towards the inner solution.

Therefore, it is possible to conclude that a volume with four receiving sensors within coverage can be defined where the calculation of the position will be reliable if the distance from the initial point to the solution is inferior to the minimum radius of convergence, for all points of that volume.

4.5 Convergence Parameter Modification

Convergence radio is calculated from the evaluation of the points from the sphere centered on the desired solution. In the case that all these points of the sphere converge towards the inner solution, the value of the radius of convergence increases until there exists any divergence in any point. This gradual process of incrementing the radius, involves a higher number of calculation points for each iteration process, which cannot be assumed in a reasonable time.

Taking this into account, a different way to determine convergence is proposed in this paper. The surrounding of the solutions finds a region in which convergence is not reached in the fictitious point method. This region is considered to be the border between the two intervals of convergence when sequential approximations are used to find the solution. Thus, if the two solutions could be separated enough, the discontinuity region could be ousted from the solutions.

This would increase the convergence radius in this case. This problem statement leads to associate the convergence radius with the distance between solutions. To show that, convergence radius and distance between solutions are calculated in a representative number of points in the coverage area of a concrete node distribution. For this purpose, the spatial volume where positioning is going to be used to locate a target is divided in small steps in the three Cartesian coordinates in order to evaluate in each point the convergence radius and the distance between solutions to show the correlation between the parameters.

Table 4.1. Correlation between radius of convergence and distance between solutions.

Parameter		Convergence radius	Solutions distance
Convergence radius	Pearson Correlation Coefficient (PCC)	1	0.999
	S. (bilateral)	-	.000
	Samples	33306	33306
Solutions distance	Pearson Correlation Coefficient (PCC)	0.999	1
	S. (bilateral)	.000	-
	Samples	33306	33306

The correlation between these two factors is shown in Table 4.1 and reaches a value of 0.999. This value allows to conclude that any variation of these two parameters will be strongly related with the other.

In this sense, the new parameter can be calculated leading us to a new conclusion: the maximization of the distances between solutions in every coverage point of a concrete node distribution, leads to the increase of the interval of confidence of the sequential approximation method to solve the 4 beacon TDOA problem.

However, for a determined sensor distribution, the distances between solutions in the 4 beacon TDOA problem are fixed. Hence, in order to maximize this parameter, a search for the optimum node distribution is needed. This will lead to maximize the convergence interval of the algorithm.

4.6 Optimization of the node distribution for the 4 beacon TDOA problem

The calculation of the distance between solutions allows us to process the radius of convergence in a reasonably period of time. Due to the geometric properties of the intersection of hyperboloids, some particularities should be considered when a maximization of this parameter is performed.

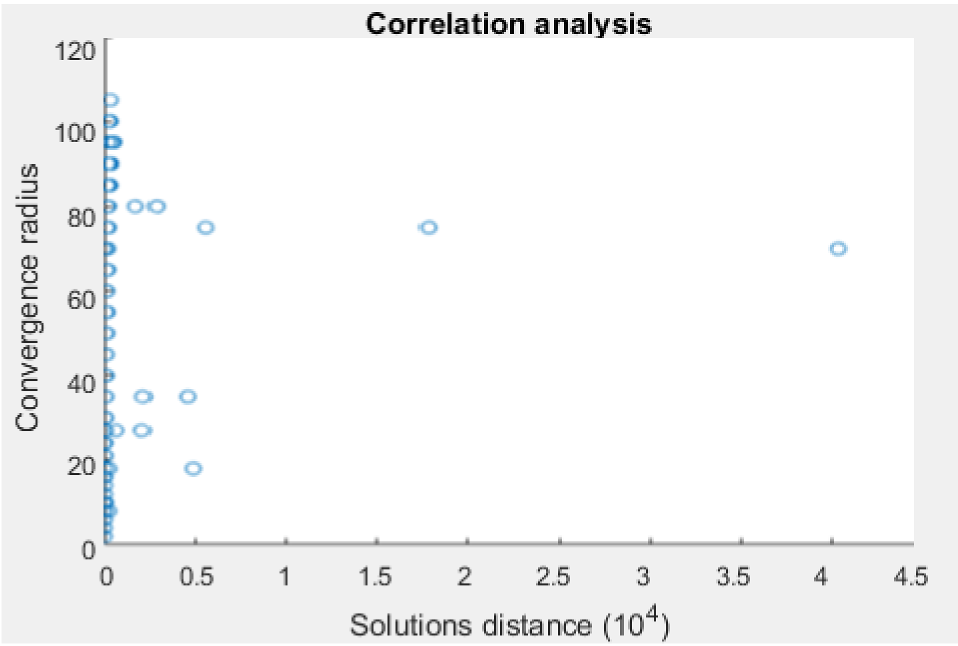

Figure 4.3 Outliers of the correlation between radius of convergence and distance between solutions.

A set of points with high distance between solutions values is shown in Figure 4.3. These points do not have a direct correlation with the radius of convergence but they represent less than 5% of the total points. This is due to near-tangent condition in the intersection of two different branches of the hyperboloids. The effect of this condition is the distancing of the two solutions.

A different circumstance is when it is observed a distance between solutions of 0—which is the tangent case—and does not permit a correlation with the convergence radius in this context. The distancing of the solutions or the existence of only one of them modifies the convergence problem in a 4 beacon TDOA problem. The problem is converted into a different case of convergence where more receivers were concerned.

However, these points imply great distortion for the comparison of statistical properties of the node distributions based on the distance between solutions in the 4 beacon TDOA problem. In order to remove this type of points, a filter is applied before performing an optimization. The filtering process is run in two different steps:

1. Elimination of points where distance between solutions is equal to 0.
2. Introduction of a parameter to remove the outliers where the distance between solutions is aberrant without losing the representativeness of the sample values.

This second step is controlled with the parameter r which measures the correlation between the mean of the sample values of the distance between solutions and their both ends as a dispersion indicator.

$$r = \frac{max(dist_{sol}) - min(dist_{sol})}{mean(dist_{sol})} \tag{4.6}$$

It is concluded that node distributions with outliers show values of r above 2.5 so that an elimination of points must be performed until a value of r smaller than 2.5 is obtained. In this case, the methodology followed is based on the standard deviation. In the first steps of the filter, the standard deviation has high values as a consequence of the outliers. This circumstance allows us to define the limit of the points discarded as a sum of the media and the standard deviation.

This process is performed iteratively until the r value is reduced. In the final step of the filter, more than 85% of the sample points are preserved and the representativeness is guaranteed, as is shown on Figure 4.4.

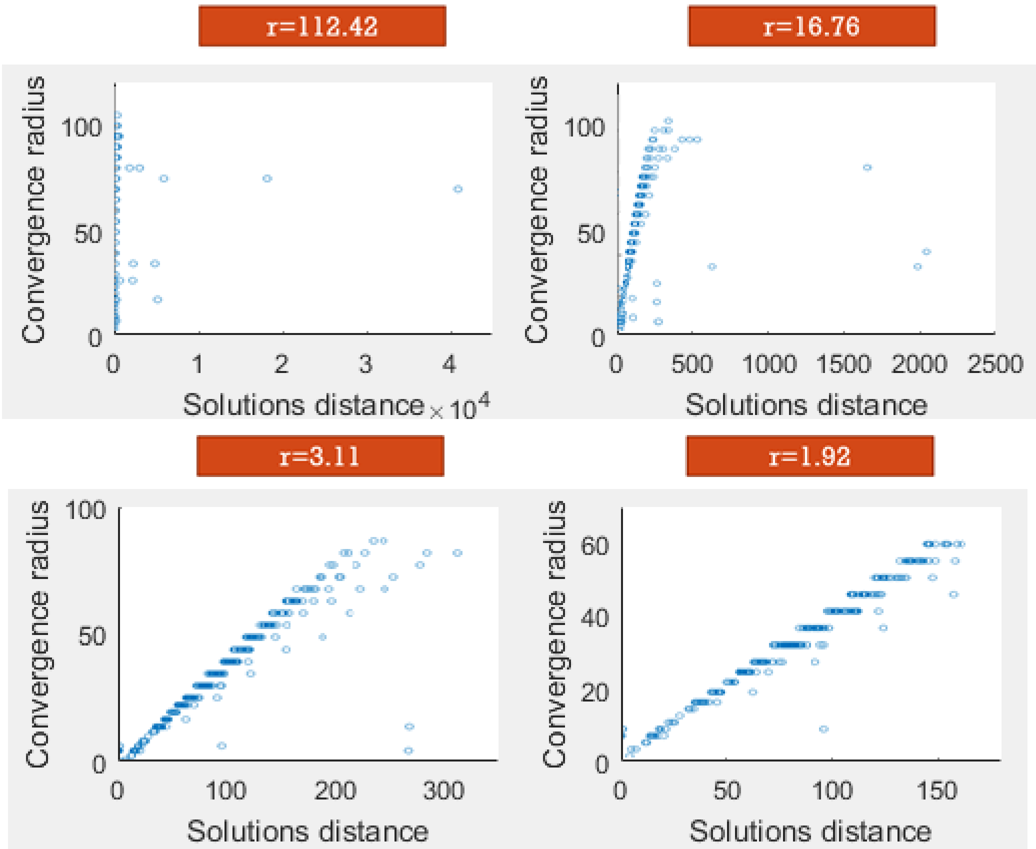

Figure 4.4 Sequential reduction of the r-correlation factor. The outliers are removed with this iteration process. The remaining distribution (r=1.92) does not present outliers.

Previous studies show a clear relationship between the convergence radius towards the correct solution in the 4-sensor TDOA problem and the 3D-node distribution. In the case this hypothesis were right, a 3D space will have associated certain node distribution which optimize the convergence radius.

This hypothesis was validated by means of optimization techniques. This problem presents two characteristics that dissuades resolution techniques based on exact algorithms: large solutions space size (related with the required resolution level in sensor location) and unavailability of applying recursive methodologies or separate the optimization in parts. Due to these circumstances, the optimization procedure is suitable to be performed by means of heuristic algorithms. Furthermore, Tekdas et al [20] demonstrated that the node distribution problem is considered as NP-hard and must be solved with the usage of heuristic techniques, where genetic algorithms are selected.

Amongst heuristic algorithms, the main reason to use genetic algorithms lie on their robustness and flexibility, the possibility of using non-derivable functions and, above all, the compromise solution they offer between diversification and intensification in the solution-searching process of the problem. As an alternative to genetic algorithms, techniques such as randomized search, proposed by Bergstra and Bengio [21], are also suitable for approaching this problem. The positioning problem can be seen as an optimization problem where the size of the convergence spheres plays the role of loss function while the position of the beacons can be considered as hyperparameters for the underlying positioning algorithms. This paper focuses on reporting the results obtained by using genetic algorithms.

The starting point for the analysis is the definition of a 3-D experimental volume of dimensions 1000×400x100 meters, described with a spatial discretization of 100 meters in x coordinate, 50 meters in the y coordinate, and 10 meters in the z coordinate. Each of the discretization point represent a real solution to the 3D TDOA system of study. Additionally, the height of the nodes has been limited to 15 meters measured from the z=0 plane, similarly to the conditions found in a local, terrestrial positioning system.

The genetic algorithm developed for the study is based on binary codification techniques of the population, tournament-based selection, single-point crossover, 10% elitism and a mutation probability of 4%. The fitness function has been defined as the arithmetic mean of the distance between solutions for all points at the discretization, corrected according to the parameter r.

The stop criterion of the algorithm has been defined as the instant when the maximum of the fitness function stops improving at the same time as the solution is reached for at least half of the individuals of the population. The resolution of the genetic algorithm is shown by means of the fitness function of the problem, in relation with the number of generations.

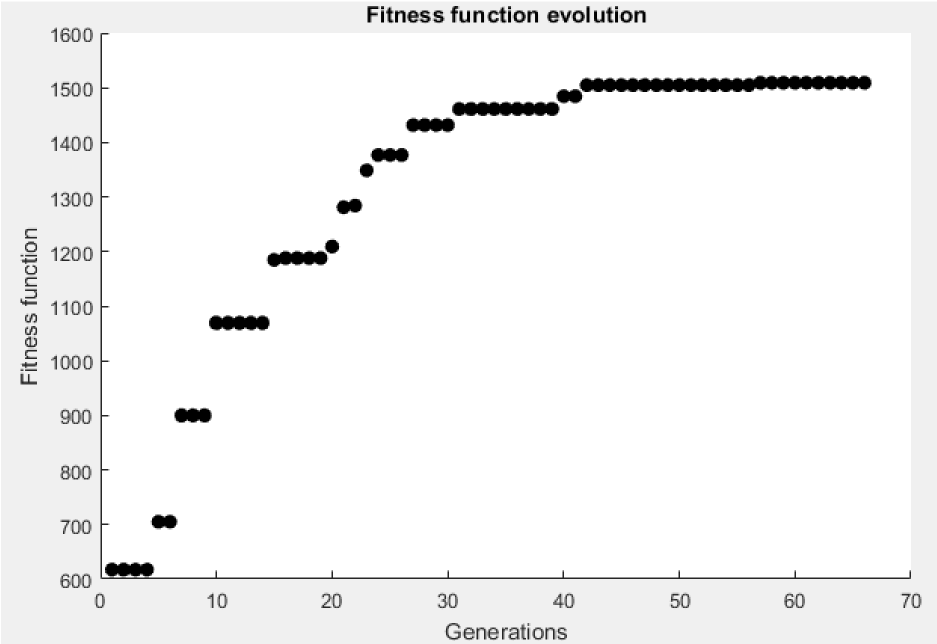

Figure 4.5 Evolution of the fitness function through several generations.

The final result of the process can be seen in figures 4.6 and 4.7. Figure 4.6 shows the evaluation of the convergence radius for the random distribution of points. Hereafter, the solution obtained after the maximization process is presented in Figure 4.7.

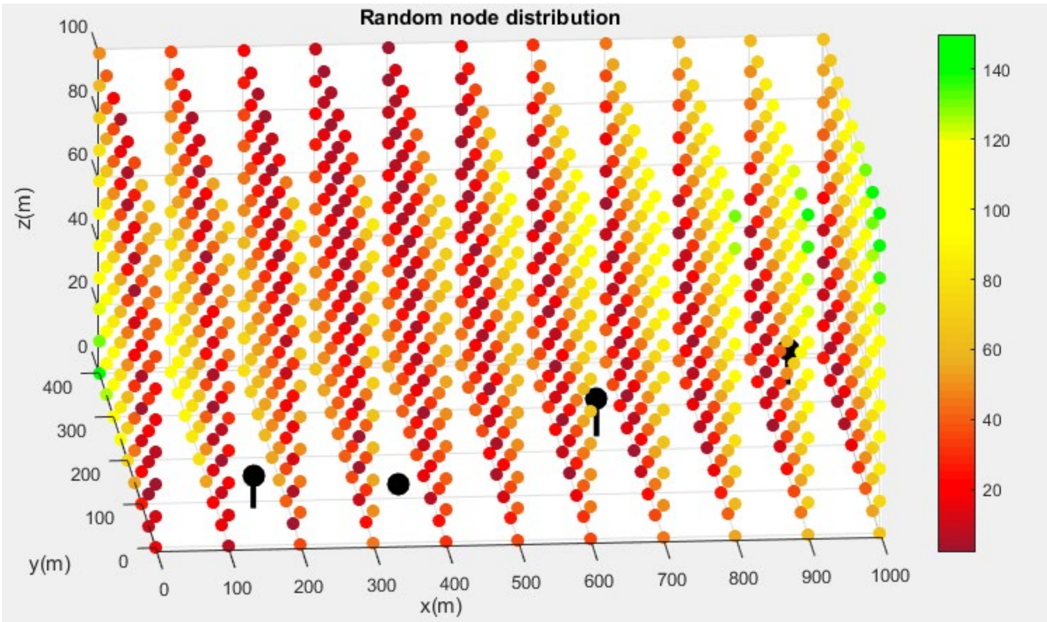

Figure 4.6. Evaluation of the convergence radius in the coverage area for a random distribution.

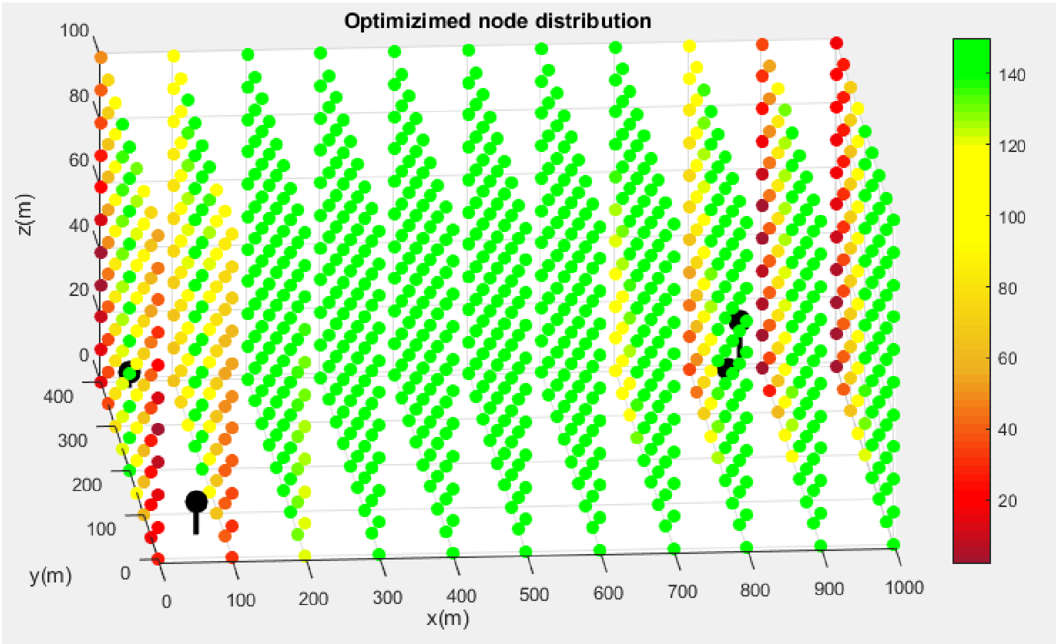

Figure 4.7 Evaluation of the convergence radius in the coverage area for the optimized distribution.

It is noteworthy to highlight the continuity presented by the convergence radius in all the domain, and the negative influence they have in those areas close to nodes. This is related to the geometry of the hyperboloids in these regions. In Table 4.2, a comparison between these distributions of nodes and the main statistical variables of the set of convergence radius is presented.

Table 4.2. Statistical parameters of the optimized and random distribution.

Convergence radius	Optimized Distribution	Random Distribution
Mean (m)	186.03	45.63
Min (m)	10	2
Max (m)	350	150
Std (m)	87.06	30.58
% Points convergence radius > 120	74.10 %	1.56 %

The results of the analysis lead to the conclusion that the initial hypothesis is correct, and hence a clear relationship exists between the node distribution and the convergence radius of the 4 node-3D-TDOA problem for the calculation of the position. Moreover, the whole procedure has been defined on the basis of genetic algorithms, being possible to maximize the convergence radius in any environment, optimizing the product *speed x refreshing* *rate.*

4.7 Discussion

A new methodology based on convergence properties of the TDOA algorithms has been proposed in order to solve the 4-sensor TDOA problem. This approach considers the procedure to maximize the capabilities of the algorithms in a confidence interval without considering the existence of errors due to signal transmission, signal processing or the synchronization of the system. For that reason, in future works it is necessary to consider this optimization in a context where an NLOS scenario was presented, clock synchronization was considered and other properties related with node distribution were also contemplated.

However, this paper presents a new perspective which concludes that algorithm properties are strongly related with node distribution and that 4-node TDOA problem can be solved under certain conditions with complete security for the first time in Local Positioning Systems. With this optimization, convergence has also been maximized, one of the biggest problems of Least Squares algorithms is that they are deeply dependent from the initial iteration point [19]. In practice, this point is the last estimated position. The last position can be far away from the new target localization if the vehicle is moving on at high speeds which can represent a convergence uncertainty. For this reason, a confidence region around the target localization has been defined to use the Least Squares algorithms under convergence conditions. The confidence region has been maximized through the radius of convergence and the calculation of the position has been guaranteed all over the domain in the optimized distribution which do not happens in the random distribution. This has important relevance in indoor positioning and precision landings in Wide Area Multilateration where sensor location must be considered. The reduction of one receiver guarantees system availability in case of failure of any sensor and reduces the overall costs.

4.8 Conclusions

In this paper, it has been shown that TDOA problem can be solved with only four sensors within a confidence interval defined through the convergence radius. The great computational processing time needed to calculate this parameter has led to the search of another indicator. This has been the distance between solutions which permits to explain the convergence radius almost entirely.

This geometric factor must be filtered with the aim of allowing the statistical comparison between different node distributions. The high number of possible solutions has promoted the utilization of Artificial Intelligence through Genetic Algorithms, which have permitted the improvement of the convergence radius through an optimized node distribution.

A comparison between a random and an optimized distribution shows the suitability of the methodology proposed to solve the TDOA problem with four sensors. By applying the sequential approximation algorithm between the two distributions improves the confidence level by over 400%. Furthermore, if a refresh rate of positioning signal is fixed in one second, the algorithm can be used with four beacons in the optimized distribution during the 96.7% of the time with total security if the vehicle has a maximum speed of 25 m/s. In contrast, it could be used only in a 31.2% of the cases in the random distribution.

The geometric statement of the problem of intersection of hyperboloids has shown that an improvement in the space localization of the hyperboloids through node localization optimization allows to transform the 4-sensor TDOA problem into an analogous problem in which more receivers were used. This methodology ultimately involves a great improvement in the positioning algorithm properties used throughout the article.

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Chapter 5

Local Wireless Sensor Networks Positioning Reliability Under Sensor Failure

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Abstract

Local Positioning Systems are collecting high research interest over the last few years. Its accurate application in high-demanded difficult scenarios has revealed its stability and robustness for autonomous navigation. In this paper, we develop a new sensor deployment methodology to guarantee the system availability in case of a sensor failure of a five-node Time Difference of Arrival (TDOA) localization method. We solve the ambiguity of two possible solutions in the four-sensor TDOA problem in each combination of four nodes of the system by maximizing the distance between the two possible solutions in every target possible location. In addition, we perform a Genetic Algorithm Optimization in order to find an optimized node location with a trade-off between the system behavior under failure and its normal operating condition by means of the Cramer Rao Lower Bound derivation in each possible target location. Results show that the optimization considering sensor failure enhances the average values of the convergence region size and the location accuracy by 31% and 22%, respectively, in case of some malfunction sensors regarding to the non-failure optimization, only suffering a reduction in accuracy of less than 5% under normal operating conditions.

5.1 Introduction

Autonomous navigation has meant a challenge for scientific development over the last few years. The high accuracy required has entailed the interest in Local Positioning Systems

(LPS) where the positioning signal paths are reduced between targets and architecture sensors. This fact significantly reduces noise and uncertainties by minimizing the global architecture errors with respect to Global Navigation Satellite Systems (GNSS).

GNSS provide global coverage but the distortion of their signals in their travel affects the stability and the accuracy of the localization over time. In addition, GNSS navigation is denied in indoor environments, where Automatic Ground Vehicles (AGVs) mostly operate, as signals deteriorate crossing large buildings. This causes Non-Line-of-Sight (NLOS) connections between satellites and targets which makes position determination impractical. The application of also GNSS has limitations in outdoor environments such as low-altitude flights in Unmanned Aerial Vehicles (UAVs) due to the higher uncertainty in the vertical coordinate of the global systems. It is a consequence of the similar altitude of the satellites in their constellations.

These reasons have promoted this new localization concept based on LPS especially for high accuracy automated navigation [1,2]. LPS require the deployment of architecture sensors in a defined and known space where the capabilities of the system are maximized. The characteristics of the LPS for a defined space rely on the measurement of the physical magnitude used for the determination of the target location: time [3], power [4], frequency [5], angle [6], phase [7] or combinations of them [8].

Among these systems, the most extended are time-based models due to their reliability, stability, robustness and easy-to-implement hardware architectures. Time-based positioning has two main systems that differ in time measurements computed: Time of Arrival (TOA) [9] and Time Difference of Arrival (TDOA) [10] systems.

TOA systems measure the total time of flight of a positioning signal from an emitter to a receiver. It requires the synchronization of the clocks of all the system elements (i.e. targets and sensors). This leads to the generation of a sphere of possible locations in the 3-D space for each received signal in a different architecture sensor. The intersection of spheres determines the target location. Mathematical standards show that the unequivocal target location is achieved in TOA systems with at least four sensors.

TDOA systems compute the relative time between the reception of the positioning signal in two different architecture sensors. The synchronization of these systems is optional considering asynchronous TDOA architectures in which the time differences are computed in a single clock of a coordinator sensor [11] and synchronous TDOA where all architecture sensors must be synchronized. Time relative measurements lead to hyperboloid surfaces of possible location of targets. A hyperboloid equation is obtained every two architecture sensors while only (*n-1*) independent equations can be processed from *n* different sensors [12]. The required number of sensors to determine unequivocally the target location is five sensors for 3-D positioning in these methodologies.

However, the intersection of three different spheres -3 architecture sensors- in TOA systems and three different hyperboloids -4 architecture sensors- in TDOA systems leads to two different potential solutions. Nevertheless, these solutions are not able to be discarded from a mathematical point of view.

In one of our previous works [13], we have demonstrated that a reliable unique solution to the intersection of three hyperboloids or spheres can be obtained through the maximization of the distance between the two potential solutions in a defined environment by means of Genetic Algorithms (GA). We achieve this result by applying Taylor-based algorithms [14] from an initial iteration point which must be close enough to the final solution. Results show that the node deployment has a direct impact in this finding.

The sensor distribution also has relation with the global accuracy of the LPS. Traditionally, the Position Dilution of Precision (PDOP) has been used to determine the achievable accuracy of time-based positioning systems in GNSS [15] by considering satellite location with respect to target nodes. This methodology considers the homoscedasticity of the satellite signals as they actually travel similar distances from satellites to target nodes. This consideration is impractical for LPS since the paths traveled can significantly differ from one architecture sensor to another producing the heteroscedasticity in the time measurements [16].

This fact promotes the use of Cramer Rao Lower Bound (CRLB) [17,18] derivations to characterize the White Gaussian Noise (WGN) present in the time measurements. In practice, CRLB determines the minimum achievable error in positioning systems [19]. We have computed these derivations for asynchronous and synchronous TDOA positioning methodologies in our recent works [20,21] in order to define the beauty of a node deployment in terms of accuracy. This has allowed us to perform the node deployment optimization in TDOA systems by means of GA. The reason of the use of heuristic techniques relies on the NP-Hard problem solution of the 3D sensor deployment in LPS and it is widely considered in the literature [22–27].

However, any of the approaches presented considers a possible sensor failure during the node distribution optimization addressed. This means that in these sensor deployments a sensor fault will cause the unavailability of TOA architectures with 4 sensors and TDOA architectures with 5 sensors. However, our finding in [13] has determined that an unequivocal solution for these systems with a possible sensor failure -3 sensors in TOA and 4 sensors in TDOA- can be achieved under an optimized node localization. As a consequence, an optimized sensor distribution can guarantee the availability of the system in sensor failure conditions through the consideration of a methodology to enhance the system properties in these situations.

In this paper, we propose for the first time a GA optimization for the 3D node deployment in a TDOA system with five architecture sensors with failure consideration, maximizing the performance during regular operation and in any possible sensor malfunction. For that purpose, we performed a multi-objective optimization in which we looked for a trade-off between the global accuracy of the system with five sensors and every combination of four nodes in a defined environment of an LPS. Additionally, we ensured the unequivocal position determination for every distribution of four sensors by maximizing the distance between the two possible mathematical solutions of the target location [11]. Based on [19] a 3D sensor distribution in irregular environments is provided, enabling the application of this failure-consideration approach to outdoor and indoor scenarios. This methodology will also ensure the availability of the system with acceptable accuracy in case of a sensor failure in any of the architecture nodes.

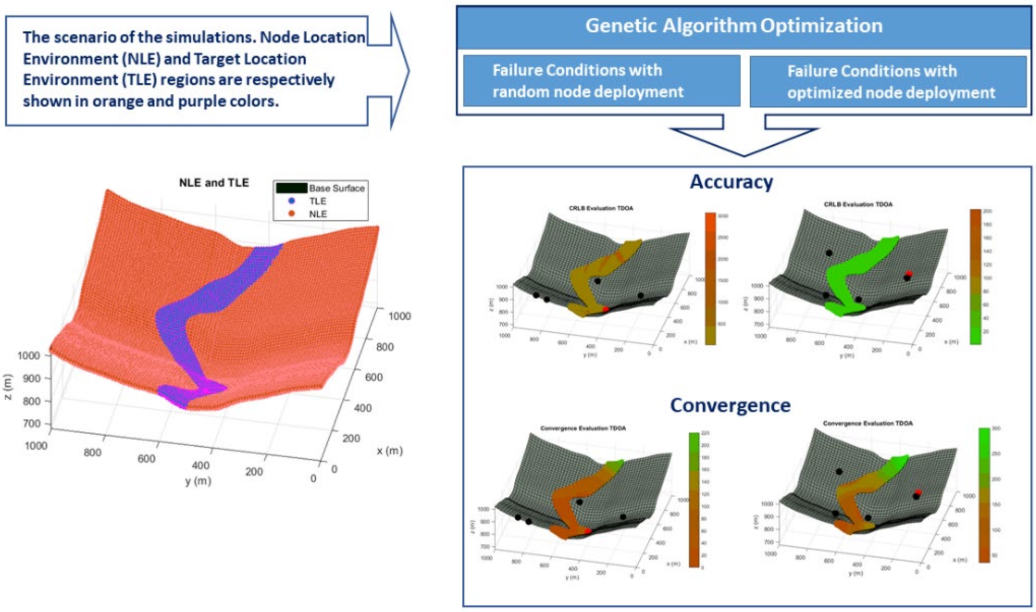

Figure 5.1 Graphical Abstract

The remainder of the paper is organized as follows: the algorithm for the target unequivocal location determination is presented in Section 5.2, the CRLB modeling is introduced in Section 5.3, the GA and the fitness function are presented in Section 5.4 and Sections 5.5 and 5.6 show the results and conclusions of the presented paper.

5.2 Taylor-Based Positioning Algorithm in Time Difference of Arrival (TDOA) Systems.

Relative time measurements in TDOA systems lead to hyperboloid equations of possible target locations. These equations are non-linear so numerical methods are required to solve the intersection of the hyperboloids. The algorithms used have been classified in two main categories: closed-form algorithms and iterative methods.

Closed-form algorithms [28,29] provide a direct final solution by solving a linearization of the hyperboloid equations. Iterative methods perform a gradient descent to achieve the solution through Taylor-Based linearization. These methods start from an initial position which must be closed enough to the final solution [30] to iteratively converge to the target location. The convergence of the algorithm depends on the initial position -usually the last known position of the target- which promotes a constant updating of the target location.

The position calculation with four architecture sensors in TDOA systems provides two possible ambiguous target localizations. The achievement of an unequivocal position cannot be determined according to mathematical standards. As a consequence, the position determination by means of iterative methods provides a unique solution that it might not match with the real target location. Nevertheless, we have shown in [13] that the optimal solution can be achieved by maximizing the radius of convergence of the initial iteration point which forces the iterative method to converge to the real solution in a high confidence interval. It has been demonstrated that this fact coincides with the maximization of the distance between the two possible solutions in LPS. This allows us to solve the 3-D TDOA problem with 4 nodes through Taylor-Based positioning algorithms with enough confidence under the optimization proposed.

This finding enables LPS architectures of 5 sensors -minimum number of sensors to supply unequivocal target location- to provide stable and accurate service in case of sensor failure or temporal unavailability of one of the architecture nodes.

Taylor-Based algorithms in TDOA systems are linearizations of the equation of the time difference of arrival:

$$\begin{aligned} R_{ij} = d_{ij} = d_{Ei} - d_{Ej} = c\, t_{ij} = c\left(t_i - t_j\right) \\ = \sqrt{(x_E - x_i)^2 + (y_E - y_i)^2 + (z_E - z_i)^2} \\ - \sqrt{\left(x_E - x_j\right)^2 + \left(y_E - y_j\right)^2 + \left(z_E - z_j\right)^2} \end{aligned} \tag{5.1}$$

where R_{ij} and d_{ij} represent the distance difference of the signal travel from the emitter to sensors i and j, d_{Ei} and d_{Ej} are total distance from the emitter (*E*) to sensors *i* and *j*, *c* is the speed of the radioelectric waves, t_{ij} is the time difference of arrival measured in the architecture sensors, t_i and t_j is the total time of flight of the positioning signal from emitter to receivers i and j respectively and $(x_E\,, y_E\,, z_E)$, $(x_i\,, y_i\,, z_i)$ and $(x_j\,, y_j\,, z_j)$ are the Cartesian coordinates of the target and the sensors i and j.

Taylor approximation truncated on first order is applied in equation 5.1 to linearize the equation from an initial iteration point $(x_0\,, y_0\,, z_0)$:

$$R_{ij} = ct_{ij} = R_{ij_0} + \frac{\partial R_{ij}}{\partial x}\Delta x + \frac{\partial R_{ij}}{\partial y}\Delta y + \frac{\partial R_{ij}}{\partial z}\Delta z \tag{5.2}$$

where R_{ij_0} is the range difference of arrival in the initial iteration point, $\frac{\partial R_{ij}}{\partial x}, \frac{\partial R_{ij}}{\partial y}$ and $\frac{\partial R_{ij}}{\partial z}$ are the partial derivatives of the range differences measured in the *i* and *j* architecture sensors particularized in the initial iteration point.

The application of this process to sensors k and l to complete the four-sensor 3D TDOA problem solution in [13] generates the range difference matrix $(\Delta\mathbf{R})$:

$$\Delta\mathbf{R} = \begin{pmatrix} \frac{\partial R_{ij}}{\partial x} & \frac{\partial R_{ij}}{\partial y} & \frac{\partial R_{ij}}{\partial z} \\ \frac{\partial R_{il}}{\partial x} & \frac{\partial R_{il}}{\partial y} & \frac{\partial R_{il}}{\partial z} \\ \frac{\partial R_{ik}}{\partial x} & \frac{\partial R_{ik}}{\partial y} & \frac{\partial R_{ik}}{\partial z} \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta z \end{pmatrix} = \mathbf{H}\Delta\mathbf{P} \tag{5.3}$$

where $\mathbf{H}$ is the partial derivative matrix, usually known as the visibility matrix, and $\Delta\mathbf{P}$ represents the coordinate variances in each space direction which is the unknown of the equation.

The previous equation is solved and iterated until no changes in coordinate variances are appreciated by means of the least squares method as follows:

$$\Delta\boldsymbol{P} = (\boldsymbol{H}^{\boldsymbol{t}}\boldsymbol{H})^{-\mathbf{1}}\boldsymbol{H}^{\boldsymbol{t}}\Delta\boldsymbol{R} = \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta z \end{pmatrix} \tag{5.4}$$

5.3 Cramer Rao Lower Bound (CRLB) Modeling in TDOA systems

CRLB is an unbiased estimator of the lowest variance of a parameter. Its usage in the localization field is widespread [31–33] since it allows us to determine the minimum achievable error by the system analyzed.

It characterizes the WGN present in the time measurements of the time-based positioning systems. The uncertainties introduced in the measurements depend on the distance traveled by the positioning signal from the emitter to the architecture sensors in a heteroscedastic noise consideration. Recent studies [18] developed a matrix form of the CRLB considering heteroscedasticity in time measurements:

$$FIM_{mn} = \left(\frac{\partial h(TS)}{\partial TS_m}\right)^T \boldsymbol{R^{-1}(TS)} \left(\frac{\partial h(TS)}{\partial TS_n}\right) + \frac{1}{2} tr\left\{R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial TS}\right)\boldsymbol{R^{-1}(TS)}\left(\frac{\partial R(TS)}{\partial TS_n}\right)\right\} \tag{5.5}$$

where $\mathbf{FIM}$ indicates the Fisher Information Matrix, m and n are the sub-indexes of the estimated parameters in $\mathbf{FIM}$, TS is the target sensor Cartesian coordinates, $\mathbf{h(TS)}$ is a vector that contains the travel of the signal in the TDOA architecture to compute a time measurement:

$$\begin{gathered} h_{TDOA_i} = \|TS - CS_i\| - \|TS - CS_j\| \\ i = 1, \dots, N_{CS} \\ j = 1, \dots, N_{CS} \end{gathered} \tag{5.6}$$

being CS_i and CS_j the coordinates of the architecture sensors *i* and *j* and N_{CS} the number of sensors involved in the position determination. $\mathbf{R(TS)}$ is the covariance matrix of the time measurements in the architecture sensors.

The covariance matrix is built with a heteroscedastic noise consideration in the sensors modeled by a Log-normal path loss propagation model [21] obtaining the following variances:

$$\begin{gathered} {\sigma_{TDOA_{ij}}}^2 = \frac{c^2}{B^2\left({}^{P_T}/_{P_n}\right)} PL(d_0)\left[\left(\frac{d_{Ei}}{d_0}\right)^n + \left(\frac{d_{Ej}}{d_0}\right)^n\right] \\ i = 1, \dots, N_{CS} \qquad j = 1, \dots, N_{CS} \quad where\ i \neq j \end{gathered} \tag{5.7}$$

where B is the signal bandwidth, P_T is the transmission power, P_n is the mean noise level determined through the Johnson-Nyquist equation, n is the path loss exponent, d_0 is the reference distance from which the path loss propagation model is applied and $PL(d_0)$ is the path-loss in the reference distance.

The inverse of the Fisher Information Matrix $(\mathbf{J})$ provides in its diagonal the uncertainties associated with each variable to estimate, i.e. the three Cartesian coordinates of the target for a 3D positioning. The location accuracy is directly evaluated through the Root Mean Squared Error (RMSE), which is computed based on the trace of the $\mathbf{J}$ matrix.

$$RMSE = \sqrt{J_{11} + J_{22} + J_{33}} = \sqrt{\sigma_x{}^2 + \sigma_y{}^2 + \sigma_z{}^2} \tag{5.8}$$

This model will be applied in the GA optimization with five sensors and each distribution of four sensors in any possible target location in the defined scenario in order to compare the beauty of different node deployments.

5.4 Genetic Algorithm

The strong influence of the sensor placement in the LPS performance enables the maximization of their capabilities through the optimization of their sensor distribution. This approach is especially suitable in complex 3D environments, where the most important source of positioning error is promoted by the sensor distribution.

In this work, we developed an optimization methodology to locate the positioning sensors of a five-sensor TDOA system with the consideration of an eventual failure in some of the system nodes. This procedure must guarantee the convergence of the iterative algorithm with all the possible combinations of four nodes in every target location under coverage. Furthermore, the achievement of an optimized node distribution for the normal operating conditions with five system nodes must be accomplished. This leads to a multi-objective optimization which considers both normal and failure operating conditions.

In our previous works [21], a GA for optimizing sensor distributions in 3D irregular environments is presented. The proposed methodology allows a free definition of the optimization region and the reference surface for locating the sensors of the positioning architecture. In addition, the procedure is modular, allowing the election of different selection techniques, percentage of elitism, crossover methodologies, mutation types, and convergence criteria.

After the choice of the optimization method, the next step is the definition of the fitness function. In this case, a multi-objective optimization is carried out for maximizing the accuracy of the TDOA architecture when the minimum number of sensors for positioning is available, i.e. when some of the architecture sensors fail. Accordingly, the methodology proposed in [13] guarantees the attainment of a unique location in TDOA architectures with 4 sensors by the Taylor-based positioning algorithm described in Section 5.2, based on an initial iteration point closed to the target estimation. The region where this procedure converges to the final solution depends on the geometric properties of the target and the architecture sensors, i.e. the sensor placement in the environment. Based on this relation, the regions of convergence can be maximized through the optimization of the sensor distribution [13].

Consequently, the goal of the multi-objective optimization is the combined maximization of the TDOA system accuracy in 3D environments when the whole architecture is available and when only four sensors are accessible, limited by the size of the convergence regions that allow the correct execution of the Taylor-based positioning algorithm. The fulfillment of these objectives guarantees the robustness of the TDOA architectures in adverse conditions of operation. The fitness function is detailed hereafter:

$$
\begin{aligned}
ff = \sum_{1}^{Comb} \Bigg\{ & \frac{C_1}{NT} \sum \left\{ 1 - \frac{\left[\left(\frac{1}{RMSE_{ref}}\right) - \left(\frac{1}{\boldsymbol{RMSE_{4sensors}}}\right)\right]^2}{\left(\frac{1}{RMSE_{ref}}\right)^2} \right\} \\
& + \frac{C_2}{NT} \sum \left\{ \frac{\left[\left(\frac{1}{D_{ref}}\right) - \left(\frac{1}{\boldsymbol{D}}\right)\right]^2}{\left(\frac{1}{D_{ref}}\right)^2} \right\} \Bigg\} \\
& + C_3 \sum \frac{\left\{ 1 - \frac{\left[\left(\frac{1}{RMSE_{ref}}\right) - \left(\frac{1}{\boldsymbol{RMSE_{Ncs}}}\right)\right]^2}{\left(\frac{1}{RMSE_{ref}}\right)^2} \right\}}{NT} - C_4 \frac{\sum_{i=1}^{N_{CS}} BL_i}{N_{CS}}
\end{aligned}
\tag{5.9}
$$

where $Comb$ is the number of groups of four sensors which are obtainable based on the total number of architecture sensors, *NT* is the number of analyzed points, $RMSE_{ref}$ is the reference accuracy, $\boldsymbol{RMSE_{4sensors}}$ is the vector that contains the CRLB evaluation for each point at analysis with each combination of 4 sensors, D_{ref} indicates the reference distance for the convergence criteria, $\mathbf{D}$ represents the vector that specifies the convergence evaluation in terms of the distance between the two possible solutions (combinations of 4 sensors) for each point at study, $\boldsymbol{RMSE_{Ncs}}$ is the vector that contains the CRLB analysis for each point at study when all architecture sensors are available, C_1, C_2, C_3 and C_4, are coefficients for calibration of the individual summands of the fitness function, and BL_i is the penalization factor associated with the existence of sensors in banned regions (if they exist).

The implemented fitness function presents two important characteristics: the individual summands of the function are confined in the interval (0,1], enabling different ponderations for the optimization; and the $RMSE_{ref}$ and D_{ref} magnitudes are adaptive to the problem characteristics, facilitating the diversification and intensification phases of the GA in complex environments.

5.5 Results

In this section, the results of the optimization for sensor failure in TDOA architectures are presented. Initially, a 3D complex scenario was designed for carrying out the optimization, proving the adaptability of the proposed methodology in any environment. For this purpose, an irregular scenario of simulation was designed by considering any possible target location and extensive available zones for positioning the architecture sensors in the environment of simulations. This fact ensures the versatility of the procedure for its application to indoor and outdoor environments.

In Figure 5.2, the term TLE represents the Target Location Environment which defines the region where targets are possible to be located. For this simulation, the TLE region extends from 0.5 to 15 meters of elevation from the base surface, emulating the operating conditions for a positioning system in the proximity of the ground. TLE region is spatially discretized based on a division of 20 meters in x and y coordinates, and 2 meters in z coordinate. This ensures the correct evaluation and continuity of the accuracy and convergence analysis, and the restriction in the total number of the studied points.

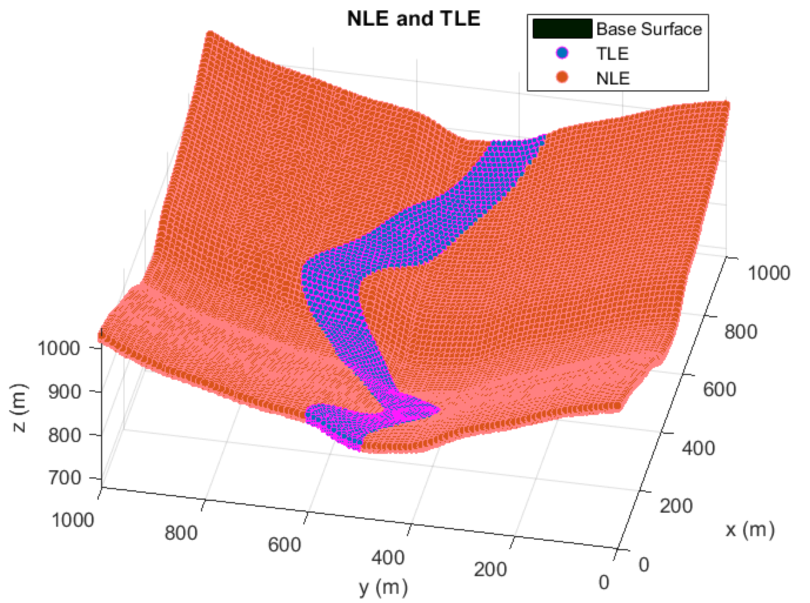

Figure 5.2 The scenario of simulations. The reference surface is depicted in grey tones. Node Location Environment (NLE) and Target Location Environment (TLE) regions are respectively shown in orange and purple colors. The discretized points of the TLE zone are the points employed for the optimization of the Time Difference of Arrival (TDOA) architecture performance. In the case of the NLE area, the points shown are only a representation of the area where every sensor can be located.

The NLE area expresses the Node Location Environment, which indicates all possible sensor locations. In the case of the NLE region, the height of the sensors is limited in the range of 3 to 10 meters from the base surface, depicting for a typical outdoor LPS implementation. The discretization of the NLE region depends on the codification of the individuals of the GA, precisely on the longitude of the chromosomes implemented. In this way, the resolution of the NLE area varies in the three Cartesian coordinates from 0.5 to 1 meter, alluring a fine setting in the optimization of each sensor.

Tables 5.1 and 5.2 show the principal parameters of configuration for the positioning system and the GA characteristics applied for the optimization.

Table 5.1. Parameters of configuration for the positioning system operation. Their selection is based on [19,34].

Parameter	Value
Transmission power	100 W
Mean noise power	-94 dBm
Frequency of emission	1090 MHz
Bandwidth	100 MHz
Path loss exponent	2.05
Antennae gains	Unity
Time-Frequency product	1

Table 5.2. Configuration of the principal elements of the Genetic Algorithm (GA).

GA	Selection
Population size	90
Selection technique	Tournament 2
% Elitism	5
Crossover technique	Single-point
% Mutation	3
Convergence criteria	80% individuals equals

Values presented in Table 5.1 were chosen in an attempt to stand for a generic positioning technology, expressed by the typical parameters of transmission power, frequency of emission and bandwidth. The configuration of the GA shown in Table 5.2 has been the subject of deep analysis, looking for the trade-off between the fitness function maximization and convergence speed.

In the following paragraphs and figures, the results after the optimization process are shown for distributions of 5 sensors. Firstly, in order to highlight the importance of the sensor distribution, a random sensor placement is evaluated in terms of accuracy and convergence under a sensor failure in Figures 5.3 and 5.4.

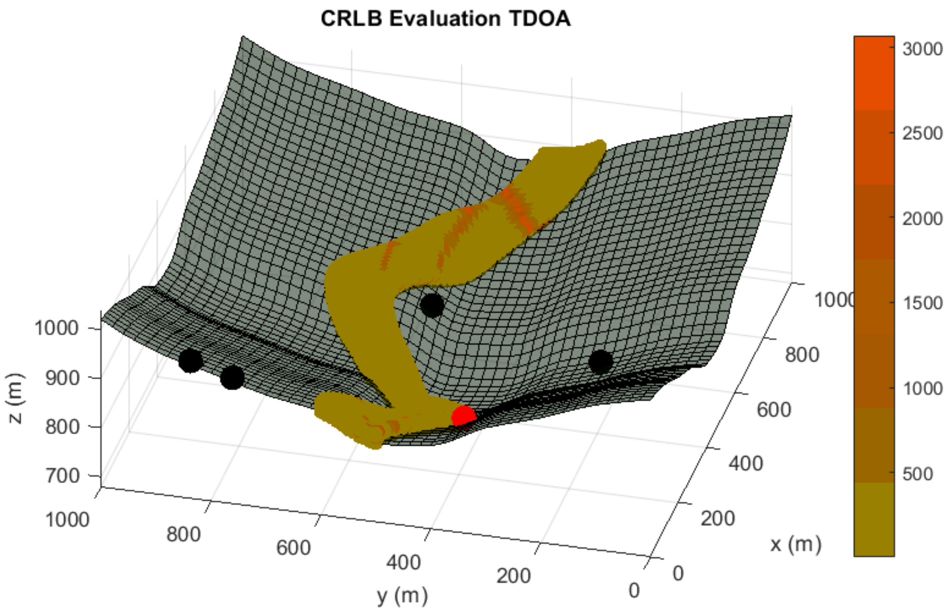

Figure 5.3 Accuracy analysis in terms of Crámer Rao Lower Bound (CRLB) in meters for a random sensor distribution of five sensors, under the assumption of one randomly malfunction sensor. Black spheres indicate the location of active sensors and red spheres highlights the sensor which is not available. Red tones in the color bar indicate bad accuracy evaluations, while green tones imply acceptable accuracy values.

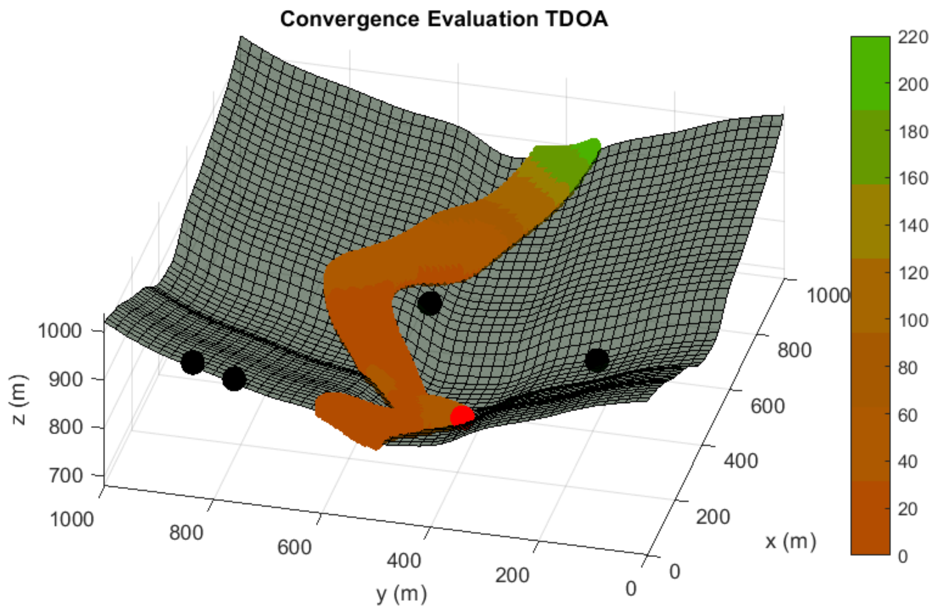

Figure 5.4 Convergence radius analysis in meters for a random sensor distribution of 5 sensors, under the assumption of one randomly malfunction sensor. The convergence radius represents the maximum

radius of the sphere of convergence in which every inside point used as initial iterating point of the positioning algorithm guarantees the unequivocal position determination by using the four available sensors. It represents the same operating condition than Figure 5.3. Red tones in the color bar indicate bad convergence radius values, while green tones imply acceptable convergence magnitudes.

As it is shown, the performance of this sensor distribution is not acceptable for any positioning service. The results for the optimized sensor placement with failure consideration, 5 sensors nominal operating conditions and convergence maximization (Case I) are provided in Figures 5.5 and 5.6 when one of the sensors is not available.

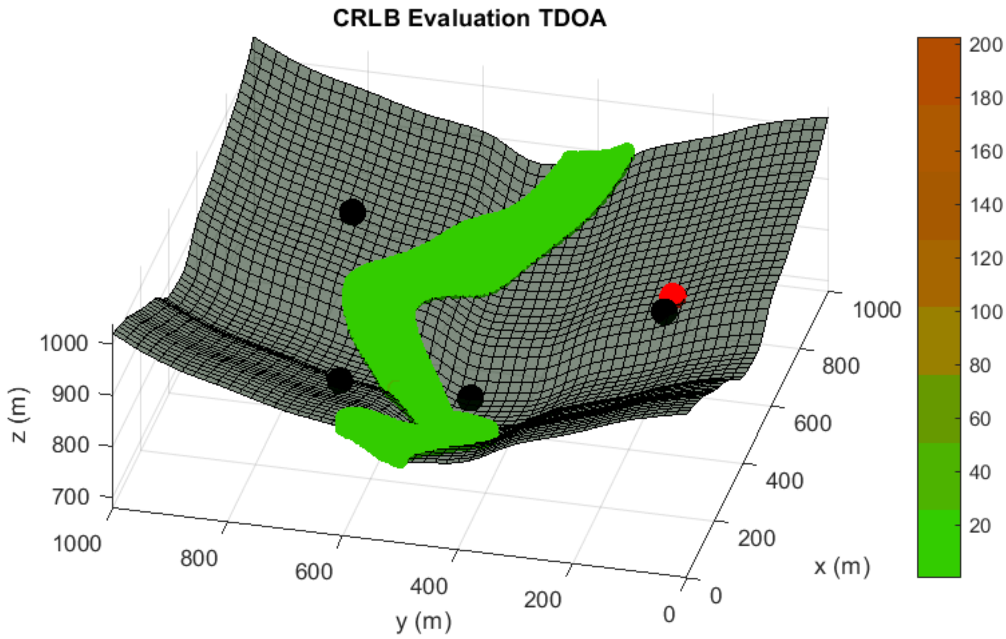

Figure 5.5. Accuracy analysis in terms of CRLB in meters for the optimized distribution of 5 sensors under possible failure. The condition represented corresponds with the Case I -Sensor Failure 1 of Table 5.3-. Red tones in the color bar indicate badly accuracy evaluations, while green tones imply acceptable accuracy values.

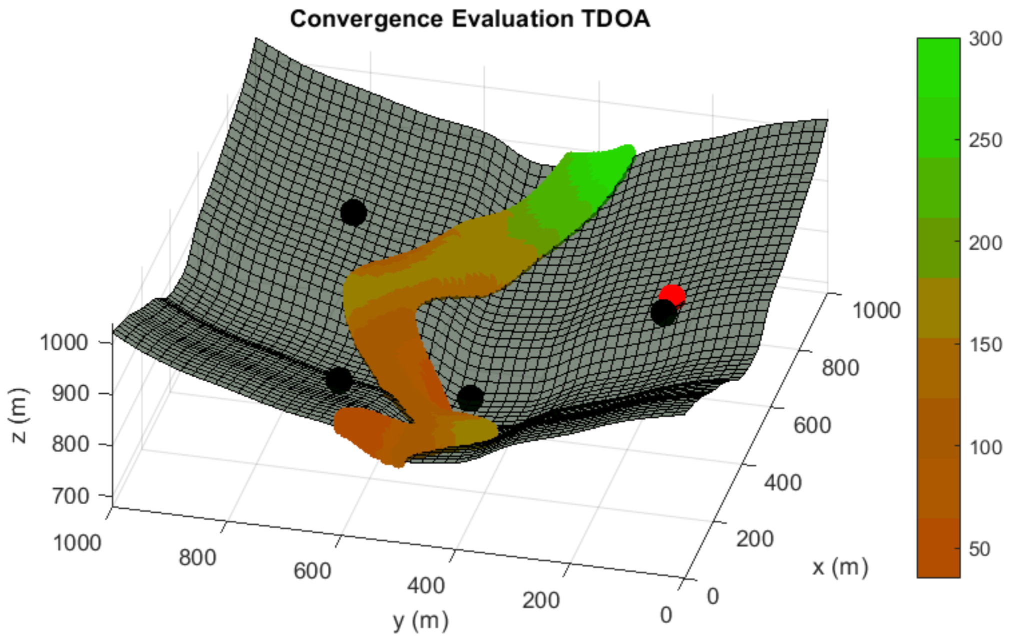

Figure 5.6. Convergence radius analysis in meters for the optimized distribution of 5 sensors under possible sensor failure. The condition represented corresponds with the Case I -Sensor Failure 5 of Table 5.3-. Red tones in the color bar indicate badly convergence radius values, while green tones imply acceptable convergence magnitudes.

The benefits of the consideration of the sensor failure in the architecture design have been shown through the differences in accuracy and convergence from the Figures 5.3 to 5.6. However, a comparison of the performance of the methodology proposed in this paper with a conventional optimized node distribution in which the failure conditions are not considered is needed to conclude the beauty of the technique. In Table 5.3, we set the parameters considered in each optimization considering nominal operation, failure conditions and convergence (Case I) and only nominal operating conditions (Case II). Case II match up with the GA optimization that we previously proposed in [21].

Table 5.3. Definition of the parameters considered for optimization in Case I and Case II.

Parameter Considered	Case I	Case II
Nominal Operating Conditions (5 sensor distribution)	✓	✓
Failure Conditions (4 sensor distributions)	✓	x
Convergence Maximization	✓	x

In Table 5.4, a comparison between the optimized sensor distribution for sensor failure (Case I) and the optimized sensor placement of 5 sensors without malfunction consideration and convergence maximization (Case II) is supplied. It should be stressed that this last optimization is carried out through a fitness function with the direct evaluation of the CRLB for 5 sensors and the last term of the Eq. 5.8.

Table 5.4. Comparative between the optimizations of Case I and II.

Sensor Distributions	Sensor Fail	CRLB Evaluation TDOA (meters)			Convergence Evaluation (meters)		
		Max	Mean	Min	Max	Mean	Min
Case I	Sensor 1	62.408	0.651	0.233	300	138.684	35
	Sensor 2	133.556	0.875	0.216	240	125.786	40
	Sensor 3	117.304	0.627	0.223	280	154.237	40
	Sensor 4	191.480	2.005	0.196	300	138.851	35
	Sensor 5	188.676	7.425	0.237	220	129.149	4
	None	0.795	0.326	0.154	300	140.229	40
Case II	Sensor 1	206.049	1.340	0.225	240	103.711	2
	Sensor 2	159.772	1.512	0.149	280	84.650	2
	Sensor 3	65.487	1.688	0.169	220	102.037	4
	Sensor 4	199.168	0.629	0.182	260	113.604	2
	Sensor 5	2340.42	9.674	0.181	240	70.850	2
	None	0.872	0.312	0.143	300	128.306	10

Table 5.5. Comparative between the optimizations of Case I and II. Values presented show the comparison in relative terms of the failure consideration distribution regarding the optimization for normal operation of the system.

Performance analysis		Case I	Case II	Sensor Distribution: Case I vs Case II
Mean CRLB Evaluation TDOA (meters)	Failure conditions	2.316	2.969	-22.0 %
	Non-Failure conditions	0.326	0.312	+4.3 %
Mean Convergence Evaluation (meters)	Failure conditions	137.341	94.970	+30.9 %
	Non-Failure conditions	140.229	128.306	+8.5 %

Tables 5.4 and 5.5 show the importance of the optimization of the sensor distribution under possible sensor failure. This feature is especially remarkable in the analysis of the convergence radius when some of the sensors are not available for positioning.

The results of these tables reveal that the optimization carried out in Case I not only minimizes the CRLB (i.e. maximum achievable accuracy based on the conditions of operation) when only 4 sensors are accessible, it also maximizes the region where the Taylor-based positioning algorithm is able to operate (together with alliterative methods).

Optimizations with failure-consideration (Case I) increase the radius of convergence by 30.9 % in failure conditions while they also experience a boost of 8.5% in this confidence interval in the normal operating condition of five sensors availability. This is due to the convergence radius maximization in the failure-consideration optimization which is not considered in conventional sensor deployment methodologies. This shows that an increase in this confidence interval in the distributions of four sensors has also a direct effect in the convergence radius of the five-sensor normal operating distribution of the failure-consideration optimization.

The beauty of this combined multi-objective optimization is that the accuracy of the four-sensor combinations in failure conditions has been increased by 22% while the accuracy of the normal operating five sensor distribution (Case I) has been reduced by less than 5% with regards to conventional node deployments (Case II) that only consider the five-sensor optimization.

Furthermore, the achievement of higher values of the convergence radius in the failure-consideration optimization enhances availability and security in failure conditions by solving the ambiguity of two valid mathematical solutions and by increasing the confidence interval of applying Taylor-Based positioning algorithms in normal operating conditions with regards to conventional node deployment methodologies.

This new optimization procedure considering sensor failures does guarantee the robustness of the positioning system in complex conditions of operations, and the design of architectures considering these situations.

5.6 Discussion

The location of sensors in LPS has been an active topic of research over the last few years [3,13,21–24]. This is a consequence of its direct relation with the accuracy, stability and robustness of wireless local sensor networks. Conventional approaches to the optimal node distributions have considered the best location of the sensors for nominal operating conditions.

Nevertheless, in actual implementations of the LPS, some sensors are possibly denied for positioning due to the presence of obstacles that disturb signals introducing adverse effects such as multipath or signal deterioration. Furthermore, a possible sensor malfunctioning introducing noise in the measurements must be considered.

These facts have not been studied in previous sensor distribution optimizations. In this work, we propose for the first time in the authors' best knowledge a node deployment methodology that enhances position determination in case of a sensor failure. Additionally, we apply this process to the more restrictive TDOA system to unequivocally determine target location, i.e. five-sensor TDOA deployments. This leads to a sensor-failure configuration in which we first need to solve the position ambiguity determination in systems with only four nodes according to the finding that we proposed in [11].

For this purpose, we performed a multi-objective optimization in a defined 3D irregular scenario in order to extrapolate the results to normal LPS applications. This optimization reduces the CRLB while it is also maximizing the radius of convergence of the Taylor-Based algorithm that we use for the target location determination.

Results show the beauty and importance of this new technique as it is able to enhance the system behavior in failure conditions with regards to only nominal optimizations. This is particularly remarkable since conventional optimization approaches are only focused in nominal operating conditions of LPS and they can suffer from temporal unavailability that can motivate important drawbacks in autonomous navigation.

5.7 Conclusions

Local Positioning Systems have emerged over the last few years for high-demanded accurate applications. Among them, time-based positioning architectures become predominant for its robustness, stability and trade-off between accuracy and complexity.

In this paper, we propose a method to guarantee system availability under sensor failure. This is a key factor for the real operation of LPS as a consequence of the possible ineffective link between target and sensors in complex environments and possible sensor malfunctioning.

In order to simulate an actual operation environment, we have defined a 3D irregular scenario consisting of a five-sensor deployment of a TDOA architecture. This configuration validates the methodology proposed for terrestrial and aerial applications in indoor and outdoor environments. In TDOA architectures, an unequivocal target location can be determined with a minimum of five sensors according to mathematical standards. However, we have proved that the ambiguity in the position determination with four sensors can be solved by the used of Taylor-Based positioning algorithms in a convergence region around the true target location which, in practice, corresponds with the maximization of the two possible solutions distance.

The achievement of this disambiguation can be obtained through an optimized sensor distribution. The node deployment must also minimize the time measurement uncertainties which are characterized by means of the CRLB. For this reason, we implement a multi-objective optimization for the combined maximization of the accuracy and convergence under each possible sensor failure condition. In addition, the optimization needs to guarantee the reduction of the uncertainties for the nominal performance with five sensors.

Results show that the proposed method can attain both accuracy and convergence requirements under every possible sensor failure condition. The global optimization with five sensors without sensor failure consideration overcomes the five-sensor deployment optimization with failure consideration in terms of medium accuracy during nominal operation by less than 5%. In contrast, in circumstances where some of the sensors are not available and only 4 sensors can be applied in the target position calculation, the optimization considering sensor failure increases the average values of convergence region size and accuracy by 30.9% and 22% respectively, regarding the non-failure optimization. These results show the importance of considering the anomaly cases of sensor failure during the LPS node distribution optimization in order to guarantee availability and operation quality in high-demanding accuracy applications.

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Chapter 6

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.

6.1 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].

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 6.2, the combined noise and clock CRB model for the optimization is presented in Section 6.3, the Genetic Algorithm settings for this combined optimization and the results of the optimization are introduced in Section 6.4 while Section 6.5 discuss and conclude the paper.

6.2 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.

6.2.1 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.

$$A - TDOA_i = c\left(t_{END_i} - t_{START_i}\right) - ||WS_i - CS|| \tag{6.1}$$

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 6.1, 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.

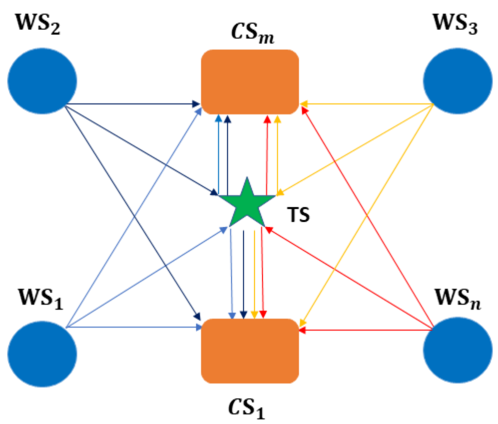

Figure 6.1 Asynchronous Time Difference of Arrival System (A-TDOA) communications scheme with m Coordinator Sensors (CS) and n Worker Sensors (WS) under coverage with the Target Sensor (TS).

6.2.2 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, 30-31]. One of the main advantages of WSN is the freedom to locate sensors in space in order to maximize system properties.

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:

$$O(NLP) = \left[\prod_{i=0}^{k-1}(n_{NLE} - i)\right] n_{TLE}\, O(ff_{TLE}) \tag{6.2}$$

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. 6.2 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 6.1:

Table 6.1. 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 6.1 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 favoring 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 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 6.2 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 modelling can be applied to characterize outdoor and indoor positioning, with terrestrial or aerial optimizations.

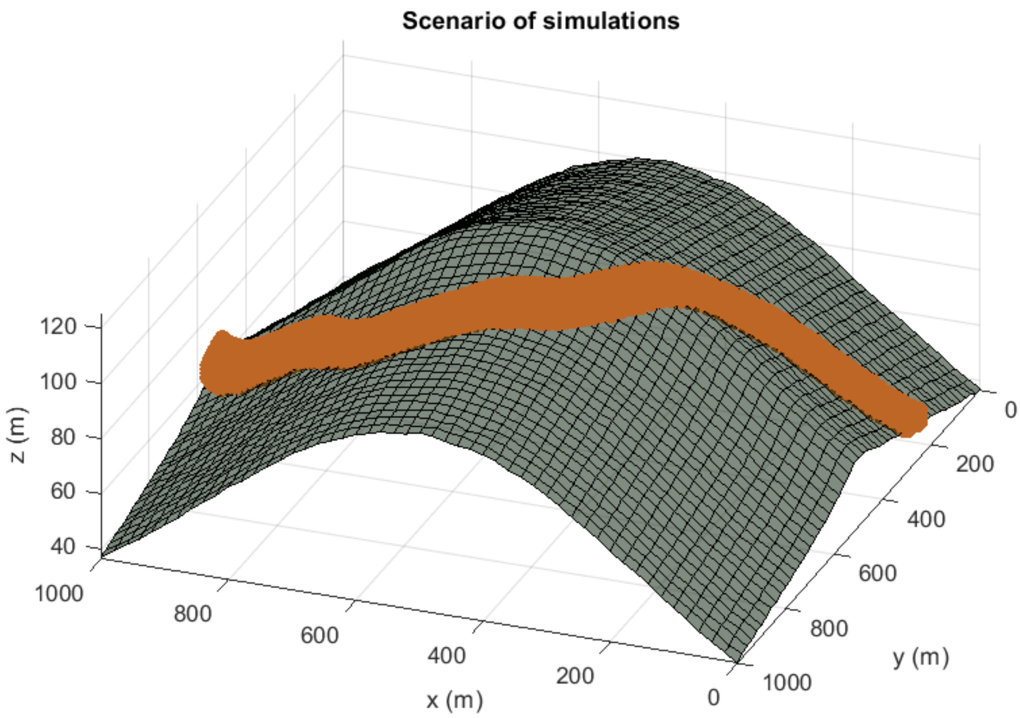

Figure 6.2 3D irregular scenario of simulations. Gray zones represent the base surface for the optimization. Orange regions define the TLE zone, which extends in elevation from the base surface from 0.5 to 5 meters. The rest of the base surface is intended to the NLE, with constraint in the minimum and maximum height regarding the reference surface from 3 to 10 meters respectively.

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 6.1) 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.

6.2.3 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.

$$ff = C_1 ff_1 + C_2 ff_2 - (C_1 + C_2)(ff_{2CS} + ff_R)$$

$$ff_1 = \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{(RMSE_{ref} - \boldsymbol{RMSE_{CS1}})}{RMSE_{ref}}\right]^2}{K_{TLE}}$$

$$ff_{2CS} = \frac{C_3 \left\{\frac{abs[n_{TLE} - sum(\boldsymbol{Eval_{CS1}})]}{n_{TLE}(n_{TLE}+1)}\right\}^2}{C_3 + C_4} + \frac{C_4 \left\{\frac{abs[n_{TLE} - sum(\boldsymbol{Eval_{CS2}})]}{n_{TLE}(n_{TLE}+1)}\right\}^2}{C_3 + C_4} \quad (6.3)$$

$$ff_R = \frac{\sum_{i=1}^{N} \boldsymbol{R}}{N}$$

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).

6.3 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:

$$J_{mn} = \left(\frac{\partial h(TS)}{\partial x_m}\right)^T R^{-1}(TS)\left(\frac{\partial h(TS)}{\partial x_n}\right) + \frac{1}{2} tr\left(R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial x_m}\right) R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial x_n}\right)\right) \tag{6.4}$$

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:

$$h_{A-TDOA_{ij}} = \left||TS - WS_i|\right| + \left||TS - CS_j|\right| - \left||WS_i - CS|\right| \\ i = 1,2 \dots, N_{WS} \quad j = 1,2, \dots, N_{CS} \tag{6.5}$$

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 correlated but asynchronous architectures assume uncorrelated time measurements since every measurement is produced in the CS.

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":

$$\sigma^2_{A-TDOA_i} = \frac{c^2}{B^2 \frac{P_T}{P_n}} \frac{PL(d_0)}{{d_0}^{n_{NLOS}}} \left[(d_{i_{LOS}} + {d_{i_{NLOS}}}^{x})^{n_{LOS}} \right. \\ + (d_{TS_{LOS}} + {d_{TS_{NLOS}}}^{x})^{n_{LOS}} + \left. (d_{CS_{LOS}} + {d_{CS_{NLOS}}}^{x})^{n_{LOS}} \right] \\ + \frac{1}{l} \sum_{k=1}^{l} \left\{ \left| \left(T_i + T_{TS_m} - T_{CS_{im}} \right) \right. \right. \\ \left. \left. - floor_{TR} \left(\left(T_i + T_{TS_m} - T_{CS_m} \right) \eta_{cs_m} \right) \right| c \right\} \tag{6.6}$$

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]:

$$RMSE = \sqrt{\sum_{m=1}^{m=n} FIM^{-1}_{mm}} \tag{6.7}$$

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).

6.4 Results

The implementation of the previous optimization technique for locating A-TDOA sensors in the 3D scenario presented in Section 6.2, 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.

6.4.1 Parameter and hyperparameter configuration for the simulations

The operation setting of the A-TDOA architecture employed for all simulations is provided in Table 6.2. 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 6.2. 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

The GA and fitness function configuration are presented in Table 6.3. Similarly to the spatial resolution selection for the TLE and NLE regions defined in Section 6.2, 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.

Table 6.3. 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 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).

6.4.2 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 6.2, 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 6.3 and 6.4 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.

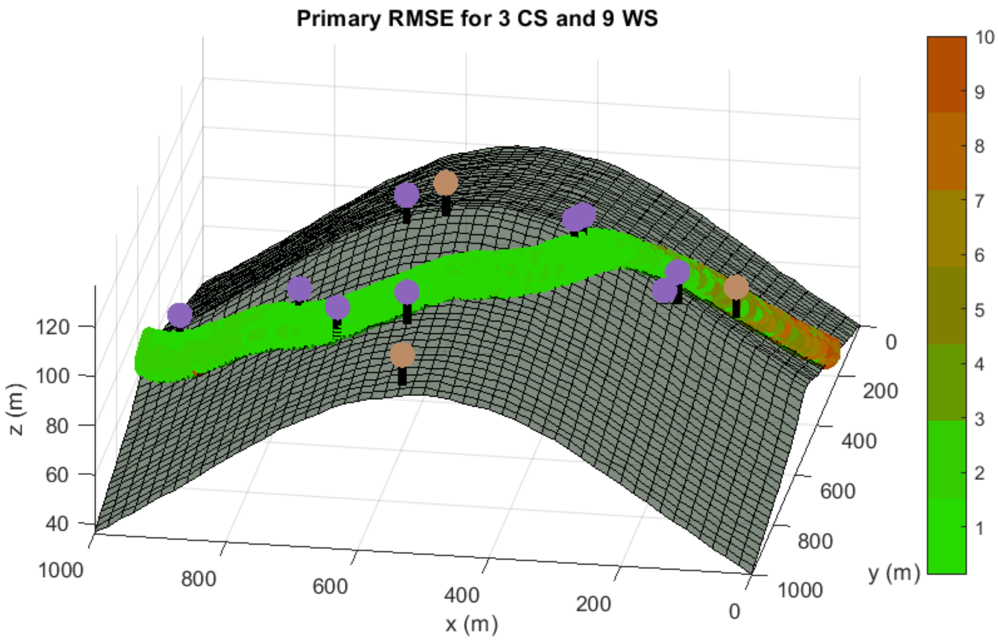

Figure 6.3 Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with three CS. CS and WS are characterized by brown and purple spheres, respectively.

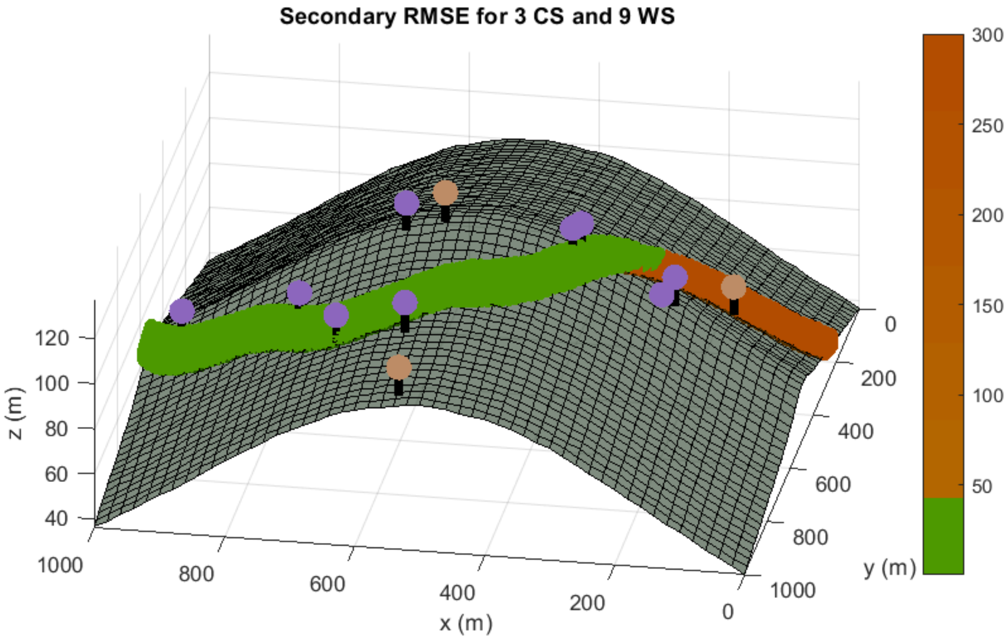

Figure 6.4 Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with three CS.

Figure 6.4 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).

After analyzing previous outcomes, the optimized sensor distribution with four CS and nine WS is presented in Figures 6.5 and 6.6 for primary and secondary CS positioning.

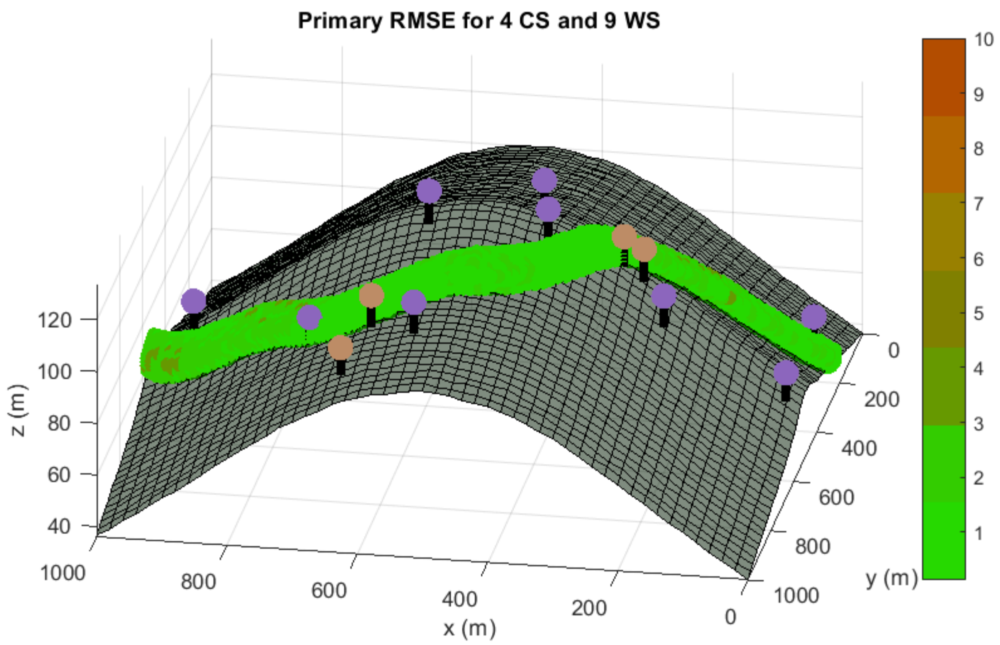

Figure 6.5 Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with four CS.

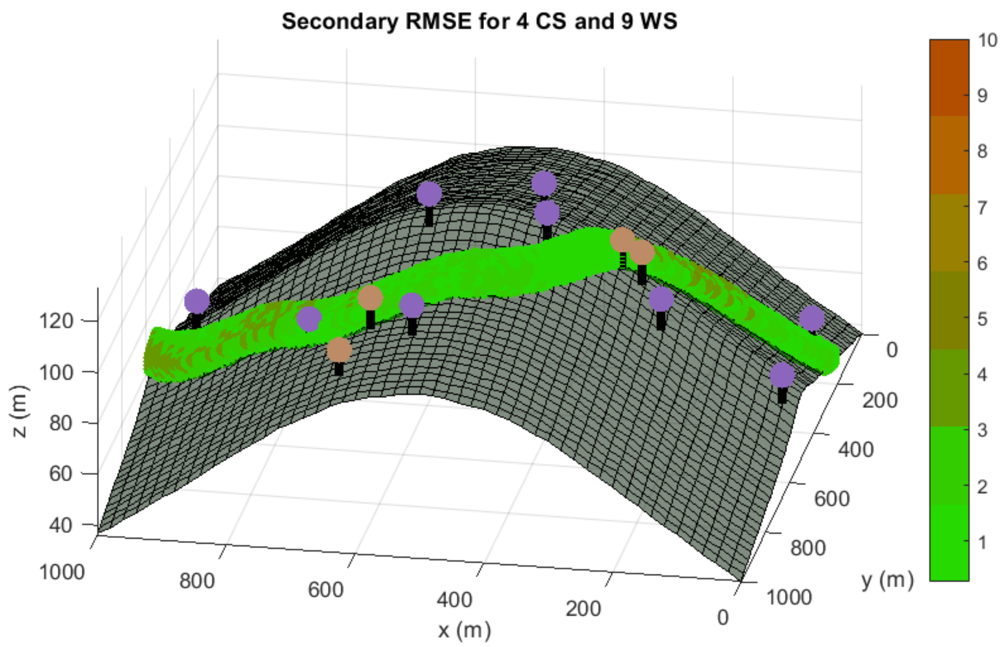

Figure 6.6 Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with four CS.

Conversely to the three CS optimization, Figures 6.5 and 6.6 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 6.7 and 6.8.

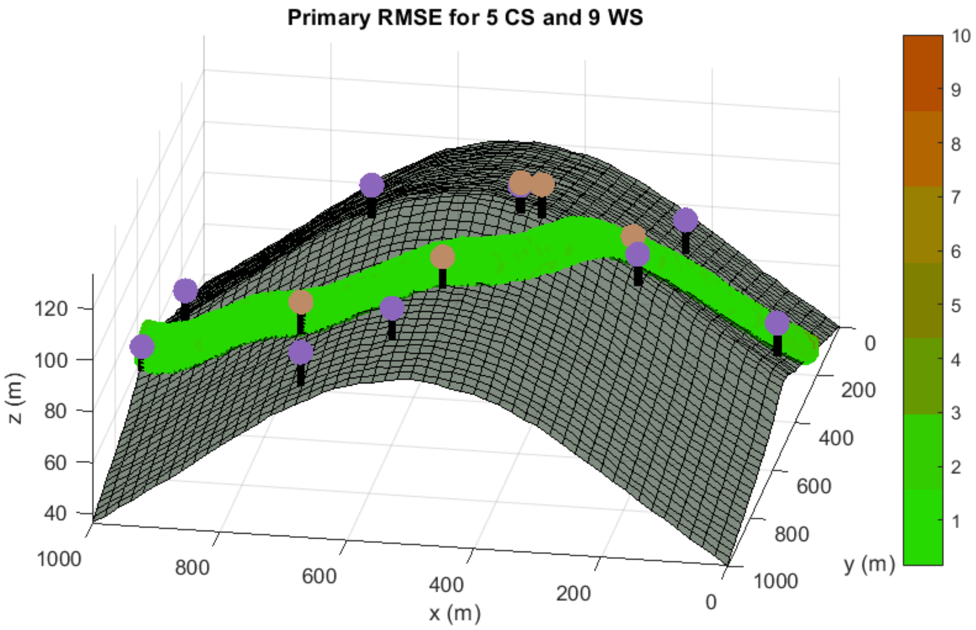

Figure 6.7 Accuracy evaluation in meters for the primary CS (i.e. normal operation) in each TLE point for the optimization with five CS.

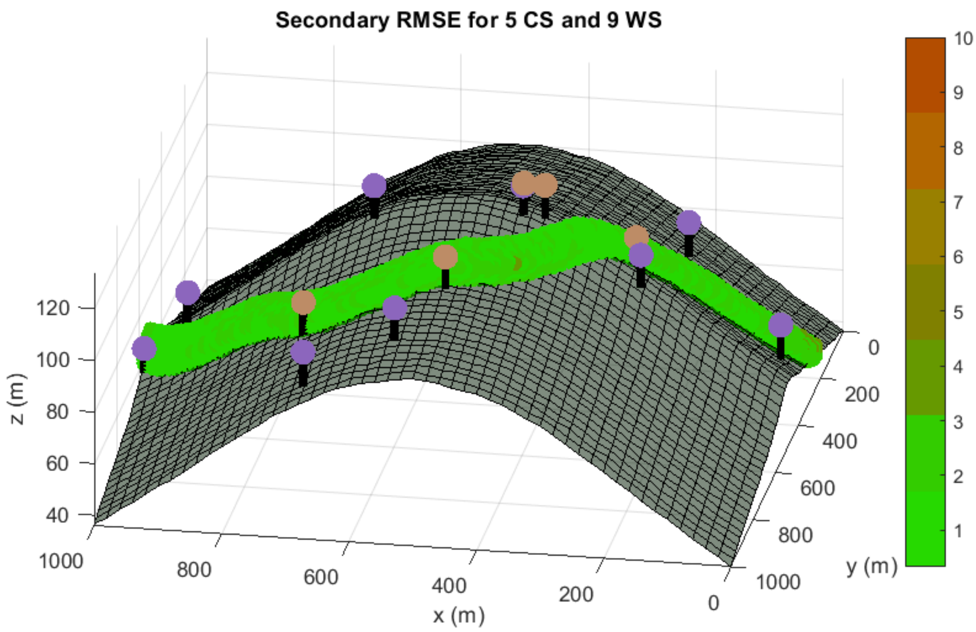

Figure 6.8 Accuracy evaluation in meters for the secondary CS (i.e. emergency operation) in each TLE point for the optimization with five CS.

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 6.9 and 6.10 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.

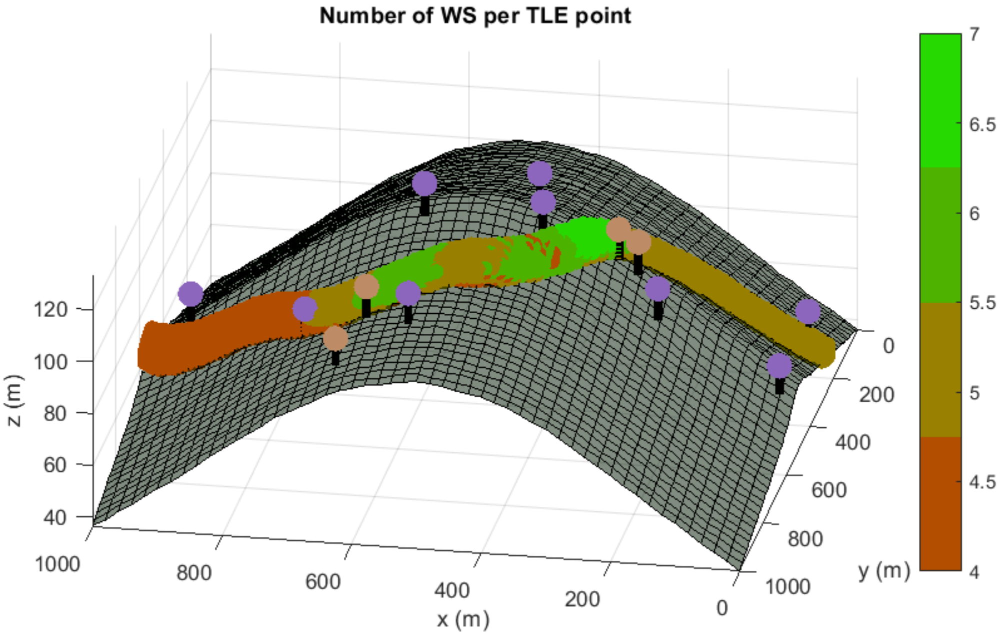

Figure 6.9 The number of available WS for each TLE studied point for the optimized sensor distribution of four CS.

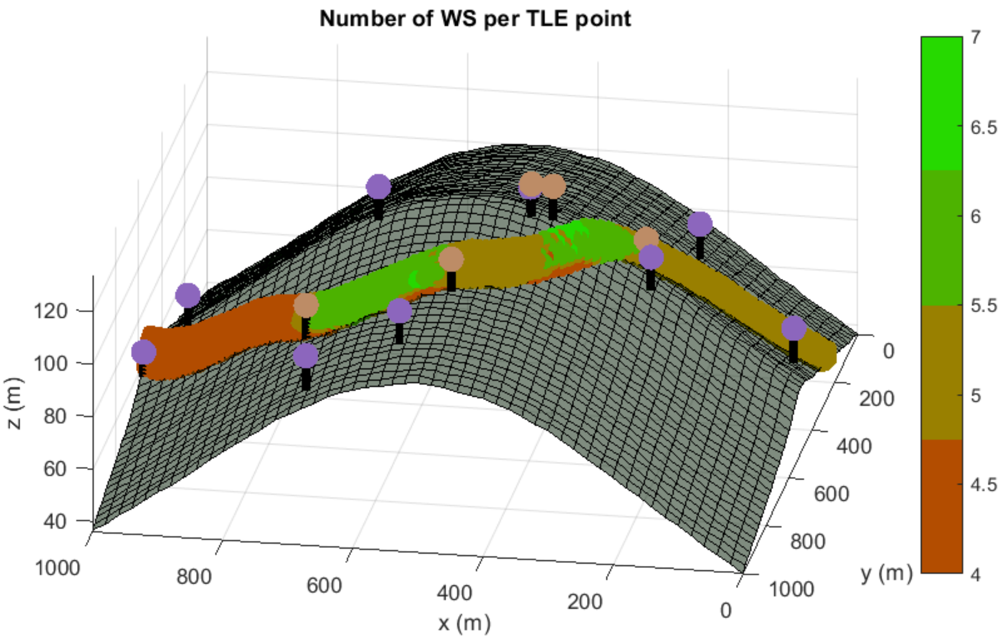

Figure 6.10 The number of available WS for each TLE studied point for the optimized sensor distribution of five CS.

Figures 6.9 and 6.10 show the variability of the number of WS in coverage for each

TLE area, as a result of the accuracy 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 6.4 a summary of the main performance results and characteristics of the analyzed sensor configurations is provided.

Table 6.4. 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 RMSE	P	1.91	1.14	0.89
	S	81.67	1.70	1.47
Minimum RMSE	P	11.73	3.89	3.66
	S	300	4.99	4.21
Max CS use (%)	P	41 %	40 %	32 %
	S	-	39 %	35 %
Max WS use (%)	P	39 % (5 WS)	47 % (5 WS)	47 % (5 WS)
	S	-	46 % (5 WS)	48 % (5 WS)

Table 6.4 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.

6.5 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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Chapter 7

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 and outstanding remark for future high-demanded accuracy applications in urban environments.

7.1 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].

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.

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 [23].

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 [24], 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 [25,26]. Therefore, a heuristic methodology is required for finding optimal node deployments. Simulated annealing [27], firefly algorithm [28], dolphin swarm algorithm [29], bacterial foraging algorithm [30], elephant herding optimization [31], diversified local search [32] but especially genetic algorithms in localization node location problems [33-36] have been used to address this complex task.

The node optimization in LPS requires favoring the Line-Of-Sight (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 [37-39] 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 [22,40] since the travel paths can notably differ among system receivers.

In our previous works, we have modeled the path losses [22], the clock instabilities [24], and Non-Line-of-Sight links [35] 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 [23] considering sensor failures in the CS nodes [41].

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 7.2, we present the NLOS complex urban scenario of simulations in Section 7.3, the node location problem and the Genetic Algorithm optimization proposed with the characteristics of each architecture at study are defined in Section 7.4, and the results and conclusions of the paper are analyzed in Sections 7.5 and 7.6.

7.2 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 [23]. 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 [23] 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 [24], the detection of LOS/NLOS paths in the positioning signal links of each architecture [35], the guarantee of the availability of the TBS under possible sensor failures [41] and a methodology that enables a cost-effective node deployment for each architecture [23].

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 the 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.

7.2.1 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 [36-38, 41] 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. [39] 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:

$$J_{mn} = \left(\frac{\partial h(TS)}{\partial TS_m}\right)^T R^{-1}(TS)\left(\frac{\partial h(TS)}{\partial TS_n}\right) + \frac{1}{2} tr\left(R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial TS_m}\right) R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial TS_n}\right)\right) \tag{7.1}$$

where J_{mn} represents the FIM_{mn} matrix element, $\mathbf{R(TS)}$ 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 $\mathbf{h(TS)}$ is the vector containing the information of the time measurement computed in each architecture.

As a consequence, the $\mathbf{h(TS)}$ vector and the covariance matrix $\mathbf{R(TS)}$ 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 [40, 43-44] since the path of the positioning signal significantly differs among the architecture sensors.

Following this consideration in LOS [22] and NLOS [35] 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] [24], 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 [24] and [35].

In TOA architectures, in which the time measurements are uncorrelated (i.e. non-diagonal elements of the covariance matrix are zero), $\mathbf{h(TS)}$ and $\mathbf{R(TS)}$ take the following expression:

$$h_{TOA_i} = \|TS - CS_i\|$$
$$i = 1, \dots, N_{cs} \tag{7.2}$$

$$\sigma_{TOA_i}{}^2 = \frac{c^2}{B^2\left(\frac{P_T}{P_n}\right)} PL(d_0)\left[\left(\frac{d_{i_{LOS}}}{d_0}\right) + \left(\frac{d_{i_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}}\right]^{n_{LOS}}$$
$$+\frac{1}{l}\sum_{k=1}^{l}\{|T_i - floor_{TR}(T_i + U_i - U_0 + T_0(\eta_i - \eta_0) + T_i\eta_i)|c^2\} \tag{7.3}$$

$$d_{i_{LOS}} = \|TS - CS_i\|_{LOS} \tag{7.4}$$

$$d_{i_{NLOS}} = \|TS - CS_i\|_{NLOS} \tag{7.5}$$

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, $d_{i_{LOS}}$ and $d_{i_{NLOS}}$ 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 [45] which produces non-zero elements in the non-diagonal terms of the covariance matrix. The vector $\mathbf{h(TS)}$ and $\mathbf{R(TS)}$ are obtained as follows:

$$h_{TDOA_i} = \|TS - CS_i\| - \|TS - CS_j\|$$
$$i = 1, \dots, N_{cs} \;\; j = 1, \dots, N_{CS} \;\; i \neq j \tag{7.6}$$

$$\sigma_{TDOA_{ij}}{}^2 = \frac{c^2}{B^2 \left(\frac{P_T}{P_n}\right)} PL(d_0) \left[\left(\frac{d_{i_{LOS}}}{d_0}\right)_{CS_i} + \left(\frac{d_{i_{NLOS}}}{d_0}\right)_{CS_i}^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{J_{LOS}}}{d_0}\right) + \left(\frac{d_{J_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} \right]^{n_{LOS}}$$
$$+ \frac{1}{l}\sum_{k=1}^{l}\{|T_i - floor_{TR}(T_i + U_i - U_0 + T_0(\eta_i - \eta_0) + T_i\eta_i)|c^2\}$$
$$+ \frac{1}{l}\sum_{k=1}^{l}\{|T_j - floor_{TR}(T_j + U_j - U_0 + T_0(\eta_j - \eta_0) + T_j\eta_j)|c^2\} \tag{7.7}$$

$$d_{j_{LOS}} = \|TS - CS_j\|_{LOS} \tag{7.8}$$

$$d_{j_{NLOS}} = \|TS - CS_j\|_{NLOS} \tag{7.9}$$

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 assume uncorrelated time measurements since a unique CS is employed for collecting the time measurements. $\mathbf{h(TS)}$ and $\mathbf{R(TS)}$ are particularized:

$$h_{A-TDOA_i} = \|TS - WS_i\| + \|TS - CS\| - \|WS_i - CS\|$$
$$i = 1, \dots, N_{ws} \tag{7.10}$$

$$\sigma_{A-TOA_i}{}^2 = \frac{c^2}{B^2\left(\frac{P_T}{P_n}\right)} PL(d_0)\left[\left(\frac{d_{WS_i-TS_{LOS}}}{d_0}\right) + \left(\frac{d_{WS_i-TS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{TS-CS_{LOS}}}{d_0}\right) + \left(\frac{d_{TS-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{WS_i-CS_{LOS}}}{d_0}\right) + \left(\frac{d_{WS_i-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}}\right]^{n_{LOS}} + \frac{1}{l}\sum_{k=1}^{l}\{|(T_i + T_{TS} - T_{cs}) - floor_{TR}[T_i + T_{TS} - T_{CS})(1+\eta_{CS})]|c^2\} \tag{7.11}$$

$$d_{WS_i-TS_{LOS}} = \|WS_i - TS\|_{LOS} \tag{7.12}$$

$$d_{WS_i-TS_{NLOS}} = \|WS_i - TS\|_{NLOS} \tag{7.13}$$

$$d_{TS-CS_{LOS}} = \|TS - CS\|_{LOS} \tag{7.14}$$

$$d_{TS-CS_{NLOS}} = \|TS - CS\|_{NLOS} \tag{7.15}$$

$$d_{WS_i-CS_{LOS}} = \|WS_i - CS\|_{LOS} \tag{7.16}$$

$$d_{WS_i-CS_{LOS}} = \|WS_i - CS\|_{NLOS} \tag{7.17}$$

Substituting the corresponding $\mathbf{h(TS)}$ and $\mathbf{R(TS)}$ for each TBS architecture in the FIM matrix (Eq. 7.1), the accuracy of each architecture can be evaluated through the Root Mean Squared Error (RMSE), expressed by the following relation:

$$RMSE = \sqrt{trace(\mathbf{J}^{-1})} \tag{7.18}$$

7.2.2 Configuration of the environment of simulations

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 [23], 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 7.1). This scenario has been designed for testing TBS architectures throughput in harsh environments, where positioning signals are degraded by obstacles, buildings, which are typical operating conditions for future autonomous vehicles and other high-demanding applications in urban areas.

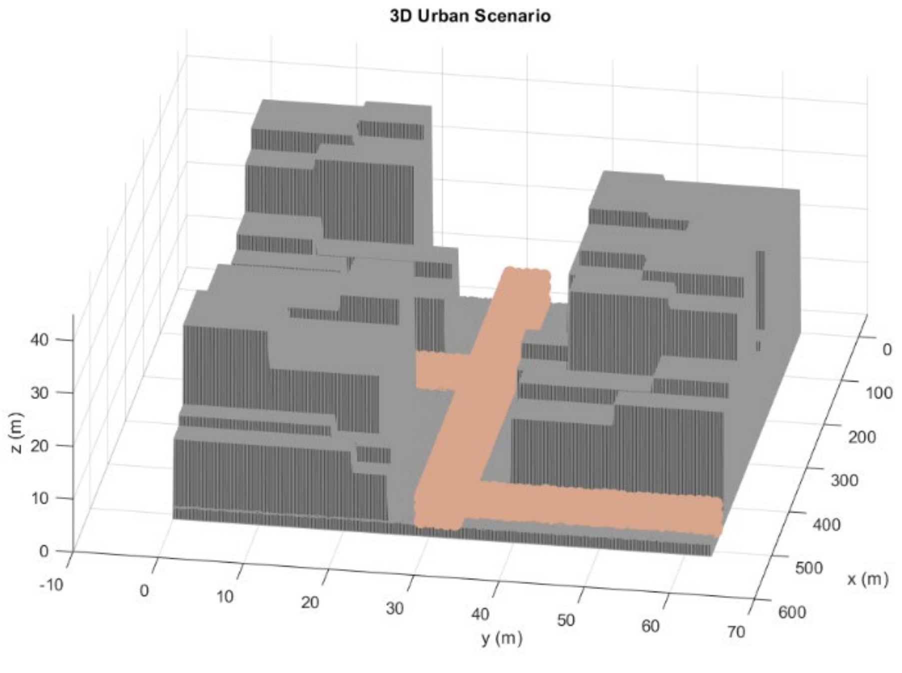

Figure 7.1 3D urban scenario of simulations. Grey tones represent the reference surface and buildings, while brown colors indicate the Target Location Environment (TLE).

Based on the terminology detailed in [33], the Target Location Environment (TLE) is defined as the allowed TS navigation area, and the Node Location Environment 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 [33] 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 application.

7.3 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 7.1. 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.

7.3.1 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 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[46]), the consideration of possible sensor failures in the deployment [40], the reduction of the energy consumption [47] or the minimization of the clock [24] and noise [35] 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 which has been assigned as NP-Hard [25,26]. Therefore, a heuristic solution is recommended for finding an optimized sensor placement in polynomial time. Simulated annealing [27], firefly algorithm [28], dolphin swarm algorithm [29], bacterial foraging algorithm [30], elephant herding optimization [31], diversified local search [32] have been used for addressing the NLP.

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 [23]- 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 [33-36] have particularly stand 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 [43]. 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 in order 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 [33].

7.3.2 Optimization functions for TBS Architectures

The optimization objectives of the TBS comparison are represented through specific fitness functions for TOA, TDOA, and A-TDOA architectures. 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 7.2).

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:

$$ff = c_{acc} ff_{acc} + c_{ava} ff_{ava} + c_{rob}\, ff_{rob} - (c_{acc} + c_{ava} + c_{rob}) ff_{pen} \tag{7.19}$$

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 pre-requisites.

As it can be observed, the optimization process is based on the maximization of Eq.7.19, searching for a trade-off between accuracy, availability, robustness, and avoiding forbidden sensor distributions.

TOA architectures are optimized based on the relations submitted in Eq. 7.20. Accuracy estimation is obtained through the CRB calculation based on the environment simulation detailed in Eq.7.3, 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 sensors distributions without consistency in the system throughput over the entire TLE. Finally, architecture sensors that are located inside the TLE zone are also penalized.

$$
\begin{aligned}
ff|_{TOA} = \; & c_{acc}|_{TOA}(ff_{acc}|_{TOA}) + c_{ava}|_{TOA}(ff_{ava}|_{TOA}) \\
& + c_{rob}|_{TOA}(ff_{rob}|_{TOA}) - (c_{acc}|_{TOA} + c_{ava}|_{TOA} \\
& + c_{rob}|_{TOA})\left(ff_{pen}\big|_{TOA}\right)
\end{aligned}
$$

$$
ff_{acc}|_{TOA} = \left.\frac{\sum_{k=1}^{K_{TLE}}\left[\frac{(RMSE_{ref} - \mathbf{RMSE})}{RMSE_{ref}}\right]^2}{K_{TLE}}\right|_{TOA}
$$

$$
ff_{ava}|_{TOA} = \left.\frac{\sum_{k=1}^{K_{TLE}}\left[\frac{\left(RMSE_{ref} - \sum_{1}^{Comb}\frac{\mathbf{RMSE_{3,C}}}{Comb}\right)}{RMSE_{ref}}\right]^2}{K_{TLE}}\right|_{TOA} \tag{7.20}
$$

$$
ff_{rob}|_{TOA} = \left\{\frac{abs[K_{TLE} - sum(\mathbf{Eval})]}{K_{TLE}(K_{TLE}+1)}\right\}^2\Bigg|_{TOA}
$$

$$
ff_{pen}\big|_{TOA} = \left.\frac{\sum_{1}^{N}\mathbf{R}}{N}\right|_{TOA}
$$

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, $\mathbf{Eval}$ 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 [23], N is the total number of sensors deployed, and $\mathbf{R}$ 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. 7.7), 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.

$$\begin{aligned} ff|_{TDOA} = {} & c_{acc}|_{TDOA}(ff_{acc}|_{TDOA}) + c_{ava}|_{TDOA}(ff_{ava}|_{TDOA}) \\ & + c_{rob}|_{TDOA}(ff_{rob}|_{TDOA}) - (c_{acc}|_{TDOA} + c_{ava}|_{TDOA} \\ & + c_{rob}|_{TDOA})\left(ff_{pen}\big|_{TDOA}\right) \end{aligned}$$

$$ff_{acc}|_{TDOA} = \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \mathbf{RMSE_{prim}} \right)}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA}$$

$$ff_{ava}|_{TDOA} = \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \mathbf{RMSE_{sec}} \right)}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA} + \left. \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \sum_{1}^{Comb} \frac{\mathbf{RMSE_{4,C}}}{Comb} \right)}{RMSE_{ref}} \right]^2}{K_{TLE}} \right|_{TDOA} \tag{7.21}$$

$$ff_{rob}|_{TDOA} = \left. \left\{ \frac{abs[K_{TLE} - sum(\mathbf{Eval})]}{K_{TLE}(K_{TLE} + 1)} \right\}^2 \right|_{TDOA}$$

$$ff_{pen}|_{TDOA} = \left. \frac{\sum_{1}^{N} \mathbf{R}}{N} \right|_{TDOA}$$

where $\mathbf{RMSE_{prim}}$ and $\mathbf{RMSE_{sec}}$ represents the location accuracy obtained with the primary and secondary eligible CS for all TLE points, $\mathbf{RMSE_{4,C}}$ 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 are defined as previously but for the TOA architecture.

A-TDOA architectures are optimized based on the criteria presented in Eq. 7.19, 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 postponing accuracy (RMSE) is calculated based on CRB. Availability evaluation is performed based on the capacity of the system to provide high-accuracy postponing 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 [23]. Robustness and undesirable sensor distributions are feed into the optimization using the same methodology that the rest of the TBS treated.

$$
\begin{aligned}
ff|_{A-TDOA} = \; & c_{acc}|_{A-TDOA}(ff_{acc}|_{A-TDOA}) + c_{ava}|_{A-TDOA}(ff_{ava}|_{A-TDOA}) \\
& + c_{rob}|_{A-TDOA}(ff_{rob}|_{A-TDOA}) \\
& - (c_{acc}|_{A-TDOA} + c_{ava}|_{A-TDOA} \\
& + c_{rob}|_{A-TDOA})\left(ff_{pen}\big|_{A-TDOA}\right)
\end{aligned}
$$

$$
ff_{acc}|_{A-TDOA} == \left.\frac{\sum_{k=1}^{K_{TLE}}\left[\frac{\left(RMSE_{ref} - \mathbf{RMSE_{prim}}\right)}{RMSE_{ref}}\right]^2}{K_{TLE}}\right|_{A-TDOA}
$$

$$ff_{ava}|_{A-TDOA} = \left. = \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \mathbf{RMSE_{sec}}\right)}{RMSE_{ref}}\right]^2}{K_{TLE}} \right|_{A-TDOA} \left. + \frac{\sum_{k=1}^{K_{TLE}} \left[\frac{\left(RMSE_{ref} - \sum_{1}^{Comb} \frac{\mathbf{RMSE_{4,C}}}{Comb}\right)}{RMSE_{ref}}\right]^2}{K_{TLE}} \right|_{A-TDOA} \tag{7.22}$$

$$ff_{rob}|_{A-TDOA} = \left\{\frac{abs\left[K_{TLE} - sum\left(\mathbf{Eval_{prim}}\right)\right]}{K_{TLE}(K_{TLE}+1)}\right\}^2 \left. + \left\{\frac{abs\left[n_{TLE} - sum\left(\mathbf{Eval_{sec}}\right)\right]}{K_{TLE}(K_{TLE}+1)}\right\}^2 \right|_{A-TDOA}$$

$$ff_{pen}\big|_{A-TDOA} = \left.\frac{\sum_{1}^{N} \mathbf{R}}{N}\right|_{A-TDOA}$$

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 [23].

7.4 Results

The results of the TBS node optimization in the 3D urban environment detailed in Figure 7.1 are submitted in this section. Firstly, descriptions about the positioning systems configuration and the GA hyper-parameters are provided. Secondly, 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

7.4.1 Parameter selection for simulations

TBS nodes optimizations are subjected to the definition of location technology and 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 [48]. Positioning signals characteristics, clocks uncertainties models, and path loss estimations are shown in Table 7.1.

Table 7.1. TBS configuration parameters relative to positioning technology, time measurement devices [21], and environment characterization [49].

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 μs
LOS Path loss exponent	2.1
NLOS Path loss exponent	4.1

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 7.2

displays the optimization parameters chosen for the simulations with the TBS.

Table 7.2. 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 equals individuals
Fitness function coefficients	1

Regarding the GA configuration of Table 7.2, two settings should be highlighted. 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. Lastly, the fitness function coefficients (Eq. 7.19) 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.

7.4.2 TBS Optimizations

The large urban scenario of simulations selected has promoted the employment of 16 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 4.2 to Figure 4.4:

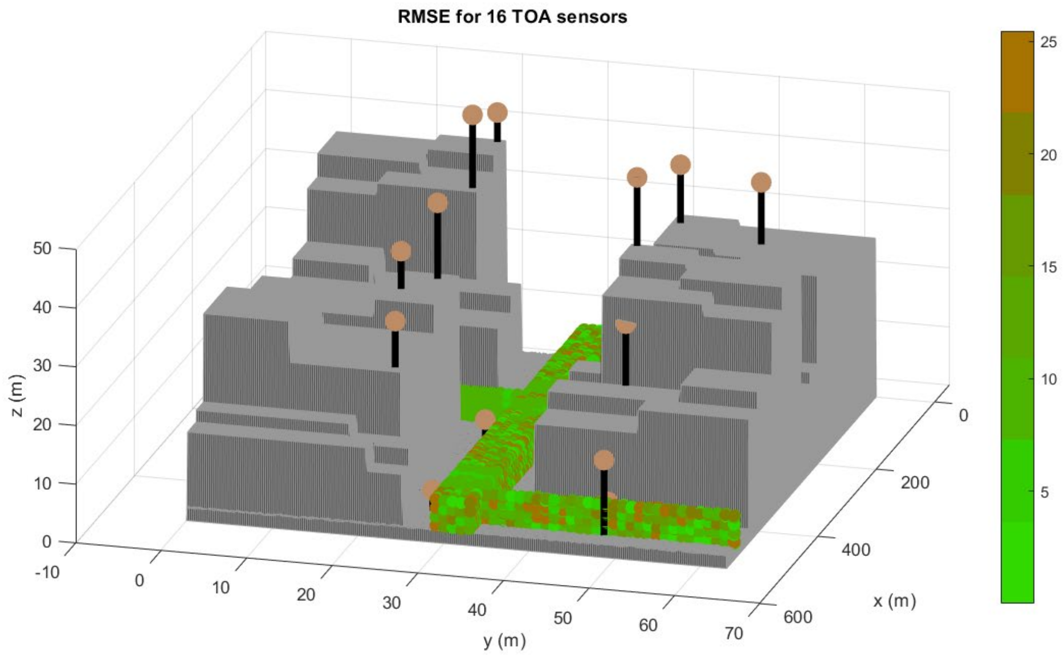

Figure 7.2 Accuracy representation in meters of the TOA architecture with 16 nodes in the proposed urban scenario.

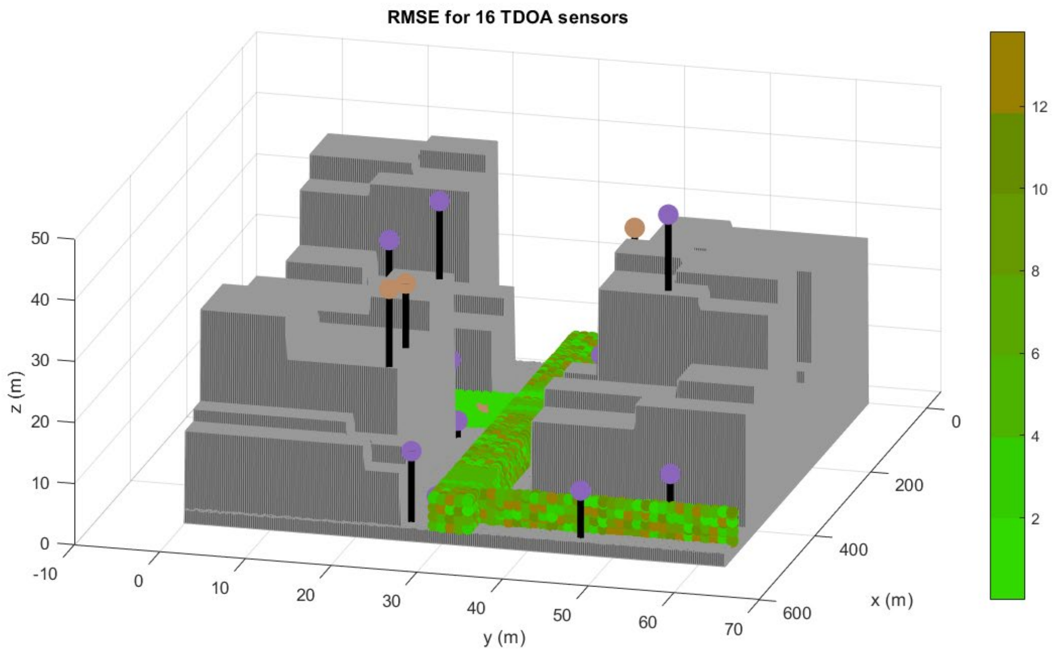

Figure 7.3 Accuracy representation in meters of the TDOA architecture with 16 nodes in the proposed urban scenario.

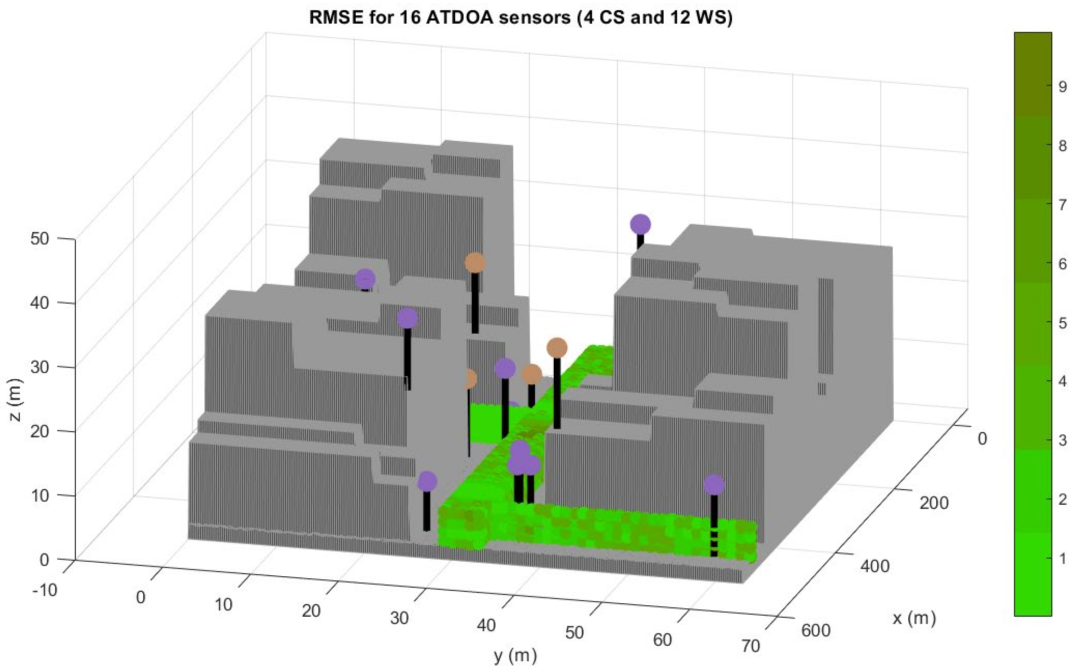

Figure 7.4 Accuracy representation in meters of the A-TDOA architecture with 16 nodes in the proposed urban scenario.

The previous figures have shown the accuracy of each architecture in the TLE. Then, in Table 7.3, the results of the accuracy and availability of the optimizations are presented:

Table 7.3. Accuracy analysis for TOA, TDOA, and A-TDOA architectures in nominal conditions.

RMSE (m)	TOA	TDOA	A-TDOA
Mean	11.46	6.14	**2.69**
Max	25.45	13.82	**9.91**
Min	0.12	**0.09**	0.13

As it is shown, A-TDOA outperforms the synchronous architectures in accuracy, indicating the relevance of the synchronism errors in LPS.

Its behavior in emergency conditions is also controlled through the optimization process. In Figures 5 and 6, the accuracy performance of the A-TDOA and the TDOA architecture under failure conditions of one of the CS is presented:

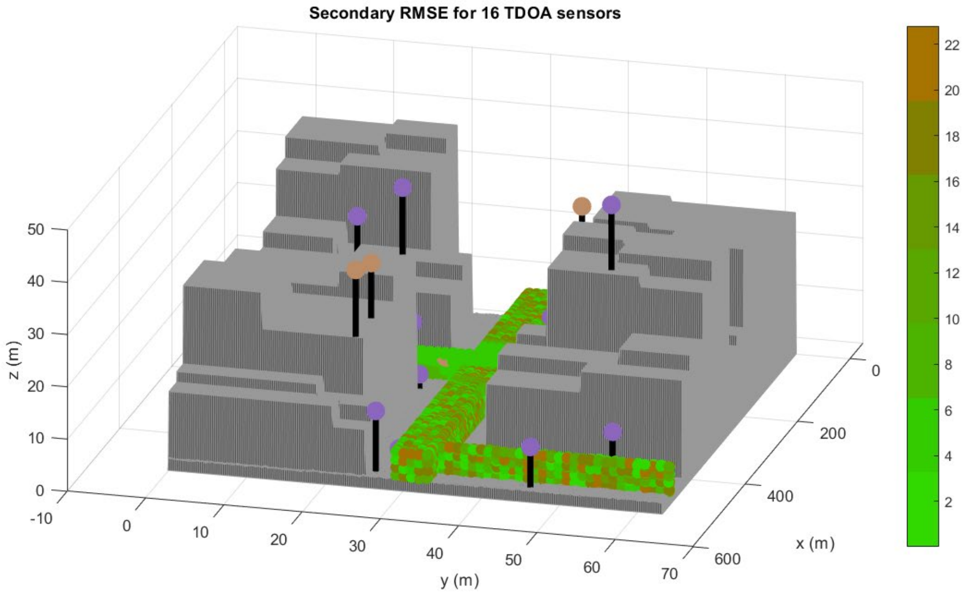

Figure 7.5 TDOA architecture accuracy performance in meters in failure conditions.

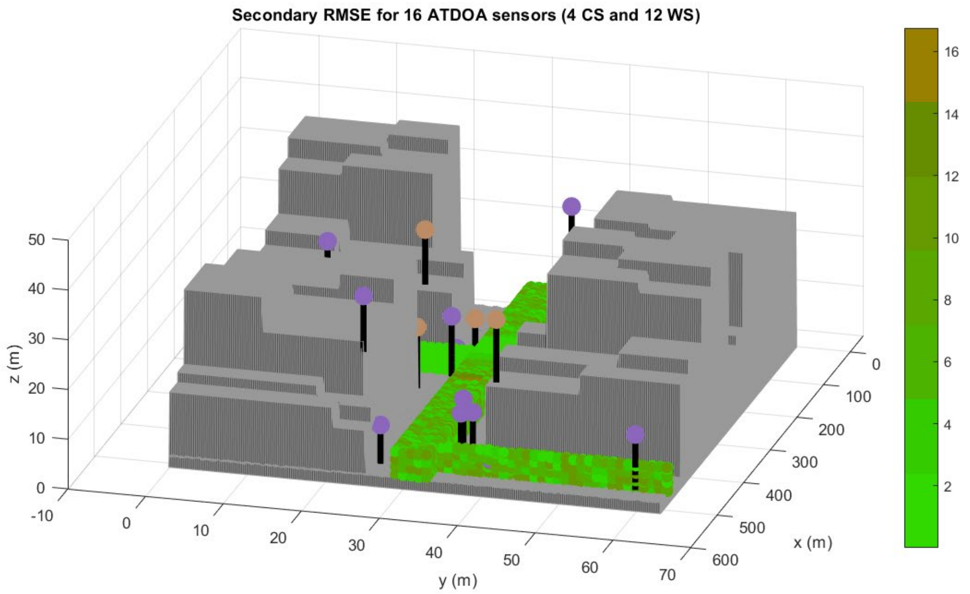

Figure 7.6 A-TDOA architecture accuracy performance in meters in failure conditions.

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.

However, the dependence of the A-TDOA architecture on finding specially enhanced locations for the CS in order to avoid NLOS links in the architecture connections among the

CS and WS nodes makes this architecture deployment be critical in especially irregular urban scenarios with the difficulty of finding LOS paths among the architecture sensors. As a consequence, the employment of the TOA and TDOA architectures is desirable in these especially harsh urban environments of operations since the independence of their nodes enables the possibility of having some sensors dedicated for the especially harsh TLE zones, thus achieving optimal accuracy in these locations.

7.5 Conclusions

Local Positioning Systems (LPS) have shown an excellent adaptation for high demanded accuracy applications in complex environments. The development of autonomous navigation with high navigation 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 cumulates the less 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 synchronism 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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Chapter 8

Memetic Algorithm for the Node Location Problem in Local Positioning Systems

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Abstract

Local Positioning Systems (LPS) have shown an excellent performance for high demanded accuracy applications. They rely on ad-hoc node deployments which fit the environment characteristics in order to reduce the system uncertainties. The obtainment of competitive results through these systems require the solution of the Node Location Problem (finding the optimal cartesian coordinates of the architecture sensors). This problem has been assigned as NP-Hard, therefore, a heuristic solution is recommended for addressing this complex problem. Genetic Algorithms (GA) have shown an excellent trade-off between diversification and intensification in the literature. However, in NLOS environments in which there is not continuity in the fitness function evaluation of a particular node distribution among contiguous solutions, challenges arise for the GA during the exploration of new potential regions of the space of solutions. Consequently, in this paper, we first propose a Hybrid GA with a combination of the GA operators in the evolutionary process for the Node Location Problem. Later, we introduce a Memetic Algorithm (MA) with a Local Search (LS) strategy for exploring the most different individuals of the population in search of improving the previous results. Finally, we combine the HGA and MA designing an enhanced novel methodology for solving the Node Location Problem, a Hybrid Memetic Algorithm (HMA). Results show that the HMA proposed in this article outperforms all of the individual configurations presented and attains an improvement of 14.2% in accuracy for the Node Location

Problem solution in the scenario of simulations with regards to the previous GA optimizations of the literature.

8.1 Introduction

The definition of the location of a target is an essential fact for performing complex tasks. Traditionally, Global Navigation Satellite Systems (GNSS) have been used for providing a stable signal for many different applications such as navigation, earth observation, emergency and rescue operations or surveillance. However, their signals are notably affected in their paths from satellites to targets and the accuracy achieved by these systems can be compromised by ionospheric instabilities [1], synchronization effects among the system devices [2], multipath phenomena [3] or signal path noise degradation [4]

However, the uncertainty in the position determination using GNSS may preclude their usage for high-demanded accuracy applications (e.g. autonomous navigation, indoor localization, low-level UAV flights or precision agriculture). Therefore, new localization schemes based on the terrestrial deployment of sensors with target proximity are collecting notable research interest over the last few years [5,6]. These deployments, known as Local Positioning Systems (LPS), require an ad-hoc distribution of the sensors in space adapting the sensor location to the characteristics of the environment of operation, thus reducing the system uncertainties in the position determination. The knowledge of the environment and the optimal deployment of the sensors enables mitigating or avoiding the main system error sources thus producing competitive and cost-effective systems for high-demanded accuracy applications [7].

LPS are categorized through the physical property measured for calculating the target location: power [8], angle [9], phase [10], frequency [11] , time [12] and hybridizations of them [13, 14].

Among them, time-based positioning (TBP) shows the best trade-off considering accuracy, reliability, robustness, stability and easy-to-implement hardware configurations. TBP is based on the measurement of the positioning signal time travel from an emitter to a receiver. There exist different architectures for computing the time measurements which produces different target determination calculations.

Time of Arrival (TOA) architectures measure the total time-of-flight of the positioning signal from an emitter to a receiver [15]. It requires the synchronism of the clock of all the system elements since every reception of the signal produces a different equation of a sphere for the target location determination. Generally, 3-D positioning needs 4 receivers for unequivocally determine the target spatial coordinates.

Time Difference of Arrival (TDOA) architecture measures the relative time lapse among the reception of the positioning signal in two different receivers [16]. Relative-time measurements generate hyperboloid surfaces of possible target locations in 3D. The necessity of using two different receivers for obtaining a hyperboloid equation, produces that 5 sensors are required for unequivocally determine the target location. However, we have proven [17] that under optimized sensor distributions this problem may be solved with 4 receivers.

TDOA architectures do not require the synchronism of the target with the system clocks. Even, completely asynchronous architectures are recently being proposed [18, 19] and are attracting high research interest since they collect all the time measurements in a single clock of a Coordinator Sensor (CS). This allows us to avoid synchronism among the system receivers, consequently reducing the architecture clock errors [20] but increasing the signal paths and noise errors [21], since they rely on a receive-and-retransmit strategy of the positioning signals in the Target Sensor (TS) producing longer path signals. In addition, a possible CS malfunction may produce temporal system unavailability [22] due to the particular architecture dependence on the CS.

These facts make the usage of synchronous and asynchronous TDOA deployments dependent on the environment characteristics. In this paper, we will analyze the asynchronous TDOA architecture since it supposes a promising technology in LPS that requires the solution of the Node Location Problem (NLP) to any application scenario and due to the extent usage of TDOA positioning in terrestrial localization [23, 24].

However, regardless the architecture used in local TBP, the optimal performance of the positioning system is achieved through the minimization of the system uncertainties in every possible TS location. This optimization demands an enhanced node distribution (i.e. an ad-hoc sensor location for the operating environment) in which noise uncertainties in Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions and clock errors are reduced favoring the optimal performance of the LPS.

The uncertainties are usually modeled in the Cramér-Rao Lower Bound (CRLB) since it provides the minimum achievable error by any positioning system in a defined TS location

[25] and its usage is widespread in the field [26 − 28]. Kaune et al. [25] provided a matrix form of the Fisher Information Matrix (FIM), which is a maximum likelihood estimator which inverse is the CRLB. This FIM matrix includes the covariance matrix of the system in which the definition of the uncertainties is introduced.

The signal path noise degradation must deal with heteroscedastic noises [29] since the signal paths notably differ among sensors in LPS. For the characterization of the clock errors we have recently introduced [20] a model in which the initial-time offset, clock drift and the instrument truncating error are considered. The minimization of this combined CRLB model enables the optimal performance of any LPS architecture for a defined TS location.

The finding of an optimized sensor location for high-demanded LPS applications, known as the Node Location Problem, must assume the overall minimization of the CRLB for each possible TS location, the Target Location Environment (TLE) [30]. This process is not derivable for all the TLE jointly [27, 31] and it has been categorized as NP-Hard [32, 33].

Therefore, a heuristic solution is recommended for addressing the optimization. Many different metaheuristic techniques such as simulated annealing [34], dolphin swarm algorithm [35], bat algorithm [36], elephant herding optimization [37] or diversified local search [38] have been used for approaching the node location problem but specially Genetic Algorithms (GA) have been used in the node location problem [39 − 41] due to the excellent trade-off of the GA between diversification (i.e. the capacity to explore the space of solutions) and intensification (i.e. the finding of the optimal solution in a reduced part of the space of solutions) [42].

In our previous research we have applied GA to the NLP in LPS [7, 20 − 22, 30]. In these papers, we have observed that the dimensions of the space of solutions which increases with the number of sensors, the resolution of the pre-defined possible space locations for them and the complexity of the fitness function evaluation, significantly affect the stable performance of the GA. This is due to the difficulty of exploring the huge space of solutions generated in the NLP.

In addition, the analysis of contiguous solutions (i.e. node distributions that differ only in a cartesian coordinate of a particular node) may suppose notable changes in the fitness function evaluation. These conditions especially occur in NLOS scenarios in which the signal quality may be significantly distorted if a node is located just behind an obstacle. This fact has promoted the usage of pre-defined populations of the GA for obtaining practical results in the GA evolution [21].

Thus, the observance of these facts has shown the necessity of introducing some knowledge in the optimization process of the node location problem in localization. In this paper, we first address the problem by constructing a Hybrid Genetic Algorithm (HGA) affecting the diversification and intensification phases through an ad-hoc usage of the GA operators for favoring the obtainment of practical results.

We later introduce a Memetic Algorithm (MA) for the node location problem in the localization field for the first time in the authors' best knowledge with the characterization of time and noise uncertainties for LOS and NLOS conditions. There exist some previous studies of the application of the MA to the optimization of Wireless Sensor Networks (WSN) [43 − 46] but these studies are focused on the coverage among the system nodes.

In this paper, we are not only considering the effective coverage among the sensors but also enhancing the performance of the LPS through the characterization of the system time and noise errors for designing competitive LPS for high-demanded accuracy applications.

In this sense, the MA allows us to introduce knowledge in the optimization process through the concept of meme. A meme is the unit of cultural information of the Dawkins theory of transmittable knowledge [47]which has ability to replicate, evolve and capacity to affect the human fitness (i.e. reproduction and survival). This idea later inspired Moscato [48] for generating an impact in the evolutionary computation. MA combine a local search strategy with the GA evolution for avoiding premature convergence. In addition, local search techniques are built to introduce knowledge in the optimization process for finding promising individuals in a reduced space of solutions, which may be difficult to be found in the GA evolution. However, a beneficial balancing among Global Search (i.e. GA performance) and Local Search (LS) is critical for achieving acceptable results in time and optimization [49].

We apply these ideas through a MA to the NLP with a variable neighborhood-descent LS in which the movement of the nodes for finding optimal sensor configurations is considered. The LS is applied to the most different individuals of the quantiles in which we divide the GA individuals through the fitness function evaluation. This allows us to explore new spaces of solutions not favored by the evolutionary process [50].

The variable neighborhood-descent LS implements a new pseudo-fitness function for characterizing promising node distributions in the reduced space of solutions of the LS in order to diminish the time complexity of the search. This is possible since geometric and clock errors are minority affected among contiguous solutions, and the notable increase of the fitness functions is produced by reducing NLOS links among the system elements.

Finally, we combine the beneficial effects of an enhanced GA operator selection during the evolutionary process in the HGA with the introduction of knowledge through the MA, obtaining a Hybrid Memetic Algorithm for the Node Location Problem which outperforms all the previous configurations.

The remainder of the paper is organized as follows: we define the category and complexity of the NLP, the definition of the scenario of simulations and the CRLB model for the fitness evaluation in Section 8.2, the GA solution, its implementation and its weaknesses in the achievement of practical results in NLOS scenarios in Section 8.3, the HGA for introducing the ad-hoc usage of the GA operators for diversification and intensification phases in Section 8.4, the MA for the node location problem is introduced in Section 8.5, the results are shown in Section 8.6, while the conclusions of the paper are presented in Section 8.7.

8.2 Localization Node Location Problem

Let $\langle x_i \rangle = (x_i, y_i, z_i)$ be the spatial coordinates of a sensor node used for the localization in LPS, S the set of possible sensor locations in the environment (NLE region), S_j a subset containing a possible combination of the defined N sensors used in the LPS located in different positions, S_l the rest of the subsets of S excluding S_j, T the total possible target locations (t_k) covered (TLE region), $f_{S_j}(t_k)$ the value of the fitness function of the optimization for the subset S_j of sensors in a defined target location (t_k), the node location problem is defined as finding the:

$$\left(\langle x_i \rangle \;\; (i \in 1, \dots, N) = S_j\right) \subset S : \frac{\sum_{k=1}^{T} f_{S_j}(t_k)}{T} \geq \max\left(\frac{\sum_{k=1}^{T} f_{S_l}(t_k)}{T}\right) \tag{8.1}$$

Therefore, the node location problem in localization entails the definition of the three Cartesian coordinates of the sensors used for localizing a TS such a way that the fitness function of the quality of the system performance is maximized. This implies the combination of sensors that enables the reduction of the system uncertainties in the TS calculation for every analyzed point of the TLE in the optimization discretization. In this section, we address the category and complexity of the node location problem, the definition of the scenario of simulation in which the GA, HGA and MA are applied and the model for the determination of the quality of a particular node distribution.

8.2.1 Category and complexity of the NLP

The NLP has been categorized as NP-Hard [32, 33, 51, 52] which shows the impossibility of finding the optimal solution of the problem in polynomial time without considering simplifications in the definition.

First attempts to address this problem were based on linear models applied on grid divisions of the NLE [53] which turned to be very complex and required problem simplifications. As a consequence, non-linear models were proposed for finding valuable solutions without previous considerations through greedy algorithms [54].

However, the dimensions of the space of solutions did not allow us to solve the NLP with these methodologies achieving valid results specially in discontinuous optimization spaces (e.g. NLOS system links considerations). Therefore, a heuristic solution to the NLP is recommended.

The main reasons are the non-derivability of the quality indicators for the complete TLE [27, 31], the discontinuity of the space of solutions, the dimensions of the problem which depend on the resolution of the NLE and TLE regions and the complexity of the fitness function evaluation.

Simulated annealing [34], dolphin swarm [35], bat algorithm [36], elephant herding optimization [37], diversified local search [38], firefly algorithm [55], bacterial foraging algorithm [56] but especially genetic algorithms [39 − 41, 57,58] have been used for solving the NLP.

GA have shown an excellent trade-off among diversification and intensification for this problem. Thus, they suppose the most extended methodology for the NLP in the literature, but we have found some problems of the exclusive evolutionary computation of the NLP that we will discuss in Section 8.3 and that recommend the introduction of some knowledge in the optimization process through a HGA and a MA.

However, regardless the methodology used for the optimization, the complexity of the NLP must be considered for taking beneficial design decisions. We define computational complexity of an algorithm as the amount of resources used for finding the optimal solution of a problem [59]. Considering the impossibility of solving the unconstrained problem (i.e. considering every possible sensor location), the complexity of the NLP depends on the characteristics of the resolution of the NLE [30]. The number of possible sensor distributions is defined as follows:

$$P(Sensor\ Distributions) = \left[\prod_{i=0}^{N-1}(n_{NLE} - i)\right] \tag{8.2}$$

where n_{NLE} is the total number of discretized points of the Node Location Environment which can hold an architecture sensor and N the total number of architecture sensors used in the LPS architecture.

Therefore, an increase in the number of architecture sensors used and a reduction in the resolution of the NLE induces the growth of the space of solutions. The order of the problem, as defined in Equation 8.2 is factorial.

In addition, localization NLP supposes the consideration of the analysis of the quality of a node distribution in every point of the TLE since the optimal performance of the LPS must produce competitive results in the entire target coverage area. As a consequence, the total number of operations for considering the exhaustive analysis of every possible combination of sensors is:

$$Number\ of\ operations = \left[\prod_{i=0}^{N-1}(n_{NLE} - i)\right] n_{TLE}\, ff(t_k) \tag{8.3}$$

where n_{TLE} is the total number of possible target locations analyzed for every possible sensor distribution and $ff(t_k)$ is the function of the quality of a node distribution in a defined target location (t_k).

Therefore, the time required for finding an optimized node distribution increases with the number of TLE analyzed points and it is dependent on the fitness function defined for the sensor distribution quality. This function will contain in this paper the combined uncertainties of noise in LOS and NLOS environments [21] and clock errors [20]. These effects are introduced in the covariance matrix of the FIM of the A-TDOA architecture.

FIM matrix, which inverse is the CRLB of the system, is a maximum likelihood estimator in which the effect of optimal geometric deployments for the intersection of hyperboloid surfaces in TDOA localization is also considered. In this paper, we are also considering a pseudo-fitness function in the LS of the memetic algorithm since a reduction in the time complexity is achieved through the exclusive consideration of the LOS/NLOS links of the positioning signal paths. This can be used as an indicator of the quality in local spaces of solutions since the clock and geometric uncertainties remain practically constant among contiguous solutions.

The definition of these hyperparameters (NLE and TLE regions) for solving efficiently the NLP is discussed in the next subsection.

8.2.2 Definition of the scenario of simulations

The proposed optimization technique for complex NLOS environments provides a potential way for a priori estimating the capabilities of positioning architectures deployed regardless the conditions and the scenarios of application of the location systems. Under this assumption, this new optimization methodology should be tested in pre-defined 3D complex scenarios where NLOS discontinuities are induced, searching all the weaknesses and finding those variables that limit the future implementation of the procedure in other environments. In this aspect, a 3D scenario with harsh operating conditions and a base surface with obstacles and elevate ground slopes is presented in Figure 8.1.

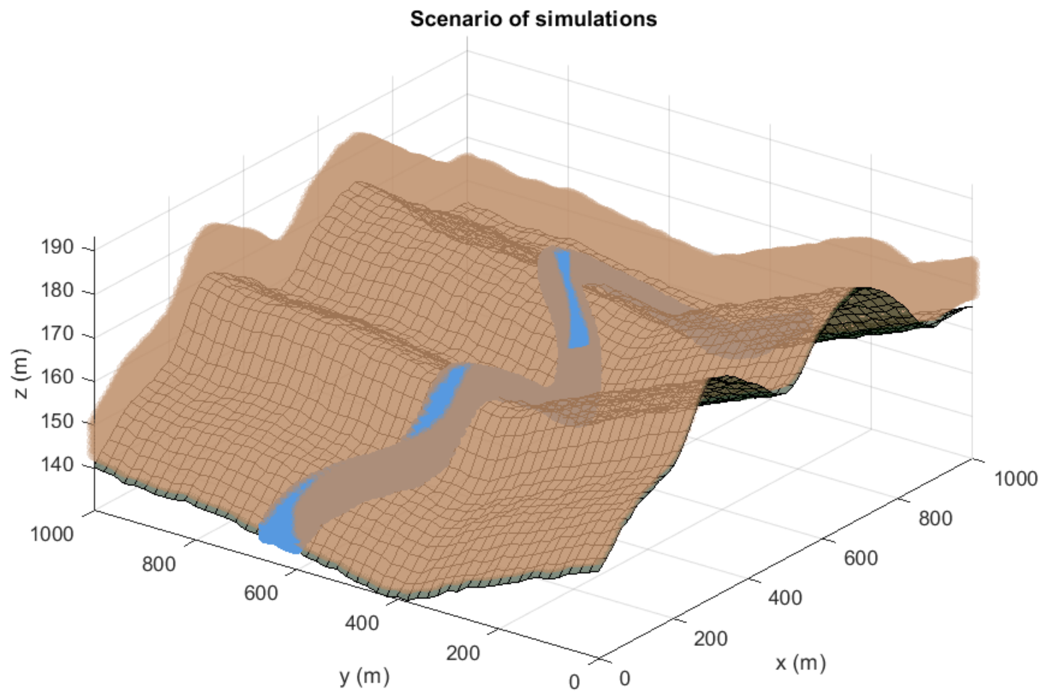

Figure 8.1 The scenario of simulations. Grey colors indicate the reference surface, blue colors represent the TLE region and brown zones show the NLE region.

Figure 8.1 shows the NLE and TLE regions of the designed scenario for all the simulations performed in the manuscript. This environment is unrealistic in terms of operating conditions and orography of the reference surface for the optimization, becoming a rough benchmark, and challenging the obtainment of adequate solutions for the deployment of sensors.

The TLE region extends in height from 0.5 to 3 meters respects the base surface. TLE area is discretized under a spatial resolution of 10, 5, 1.5 meters in the Cartesian coordinates x, y and z respectively. With this configuration, the number of operations and thus the complexity of the problem is contained, maintaining higher consistencies and representativeness of the scenario. This is accomplished when the principal statistical variables of the accuracy evaluation of the positioning systems are slightly modified when increasing the spatial resolution of the TLE and NLE regions.

For the NLE zone, the architecture sensors are allowed in elevations from the local-based surface from 3 to 10 meters, in an attempt of maximizing the conditions of adequate application of the CRLB model (avoiding multipath and other disruptive phenomena induced near the reference surface). The resolution in the NLE area is directly dependent on the codification of the sensor distributions in the individuals of the GA technique [30]. In this instance, a representation with binary chains of length 10,10,6 chromosomes for the respecting x, y and z. Cartesian coordinates are selected, leading to resolutions of approximately 2 meters. As in the TLE region, this ensures a trade-off between representativeness of the results and the number of operations of the procedure.

8.2.3 Evaluation of the quality of a node distribution

Localization NLP assumes an optimal sensor distribution for reducing the uncertainties in the determination of the TS location. The main system uncertainties in TBP are the noise degradation of the positioning signal in LOS and NLOS environments [21], the clock errors in the time measurements which are generated by synchronization of the system devices, drift and truncation errors in the CS clocks [20] and the geometric deployment of the sensors in space which affects the positioning algorithm performance [60].

The signal paths followed by the positioning signal vary notably in LPS. This fact recommends the usage of distance-dependent path-loss models for characterizing the signal path noises and for achieving practical results [29, 31]. These models can be introduced in the covariance matrix of the FIM for characterizing the architecture errors. In addition, we proposed [20] a clock error model for considering the time uncertainties in the FIM covariance matrix which is used in this paper for achieving practical optimization results.

The definition of the FIM for a time localization architecture was first proposed by Kaune et al. [25]:

$$FIM_{mn} = \left(\frac{\partial h(TS)}{\partial TS_m}\right)^T \mathbf{R^{-1}(TS)} \left(\frac{\partial h(TS)}{\partial TS_n}\right) + \frac{1}{2} tr\left\{R^{-1}(TS)\left(\frac{\partial R(TS)}{\partial \mathrm{TS}_m}\right)\mathbf{R^{-1}(TS)}\left(\frac{\partial R(TS)}{\partial TS_n}\right)\right\} \tag{8.4}$$

where $\mathbf{R(TS)}$ 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 $\mathbf{h(TS)}$ is the vector containing the information of the time measurement computed in the A-TDOA architecture.

Particularizing $\mathbf{h(TS)}$ and $\mathbf{R(TS)}$ for the A-TDOA architecture $[20, 21]$ and assuming uncorrelated time measurements in the A-TDOA architecture $[7]$:

$$h_{A-TDOA_i} = \|TS - WS_i\| + \|TS - CS\| - \|WS_i - CS\| \quad i = 1, \dots, N_{WS} \tag{8.5}$$

$$\begin{aligned}\sigma_{A-TDOA_i}{}^2 = {} & \frac{c^2}{B^2 \left(\frac{P_T}{P_n}\right)} PL(d_0) \Bigg[\left(\frac{d_{WS_i-TS_{LOS}}}{d_0}\right) + \left(\frac{d_{WS_i-TS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} \\ & + \left(\frac{d_{TS-CS_{LOS}}}{d_0}\right) + \left(\frac{d_{TS-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} + \left(\frac{d_{WS_i-CS_{LOS}}}{d_0}\right) \\ & + \left(\frac{d_{WS_i-CS_{NLOS}}}{d_0}\right)^{\frac{n_{NLOS}}{n_{LOS}}} \Bigg]^{n_{LOS}} \\ & + \frac{1}{l} \sum_{k=1}^{l} \{ |(T_i + T_{TS} - T_{cs}) \\ & - floor_{TR}[T_i + T_{TS} - T_{CS})(1 + \eta_{CS})]| c^2 \} \end{aligned} \tag{8.6}$$

$$d_{WS_i-TS_{LOS}} = \|WS_i - TS\|_{LOS} \tag{8.7}$$

$$d_{WS_i-TS_{NLOS}} = \|WS_i - TS\|_{NLOS} \tag{8.8}$$

$$d_{TS-CS_{LOS}} = \|TS - CS\|_{LOS} \tag{8.9}$$

$$d_{TS-CS_{NLOS}} = \|TS - CS\|_{NLOS} \tag{8.10}$$

$$d_{WS_i-CS_{LOS}} = \|WS_i - CS\|_{LOS} \tag{8.11}$$

$$d_{WS_i-CS_{NLOS}} = \|WS_i - CS\|_{NLOS} \tag{8.12}$$

where sub-index i represent the measurements and signal paths linked with architecture sensor i, while N_{WS} represents the number of Worker Sensors (WS); c is the speed of the radioelectric waves in m/s, B the signal bandwith in Hz, P_T the transmission power in W, P_n the mean noise level in W calculated through the Johnson-Nyquist relation, $PL(d_0)$ the path-loss in the reference distance d_0 from which the Log-Normal model is considered; d_{WS_i-TS}, d_{TS-CS}, d_{WS_i-CS} the LOS and NLOS distances travelled from the WS to the TS, from the TS to the CS and from the WS to the CS respectively calculated with the algorithm described in [21]; n_{LOS} and n_{NLOS} the path-loss exponents used in the Log-Normal model, l is the number of iterations of the Monte-Carlo simulation performed for estimating the temporal variances, T_i, T_{TS} and T_{CS} the time of flight of the positioning signal from the TS to the system WSs, the duration of the flight from TS to the CS and the period of time from the emission of the signal from the WS to the TS respectively; η_{cs} define the clock drift of the CS clock.

This FIM characterization allows us to consider the main architecture uncertainties in the optimization process of the NLP and finally obtain a measurement of the minimum achievable error achieved by any positioning algorithm through the trace of the inverse of the FIM, expressed through the Root Mean Squared Error (RMSE) as the most spread accuracy metric:

$$RMSE = \sqrt{\sum_{m=1}^{n} FIM_{mm}^{-1}} \tag{8.13}$$

8.3 Genetic Algorithm for the NLP in localization

Genetic Algorithms have shown an excellent trade-off between diversification and intensification for the NLP. These GA were proposed by Holland [61] and later refined by Goldberg [62]. They are built on the theory of evolution and rely on the characteristics of the descendants of a population which present a better adaptation than their parents by receiving the adapted genes from the previous generation. The usage of the GA operators allows the recombination of the individuals, the selection of the best candidates for finding an optimal offspring, the mutation of some genes for exploring new spaces of solutions avoiding local optima and the elitism for preserving the best adapted individuals from generation to generation.

We provide in Figures 8.2 and 8.3 a general framework of the GA performance and based on the binary codification proposed in the original work of Holland [61] (i.e. a candidate node distribution for the NLP).

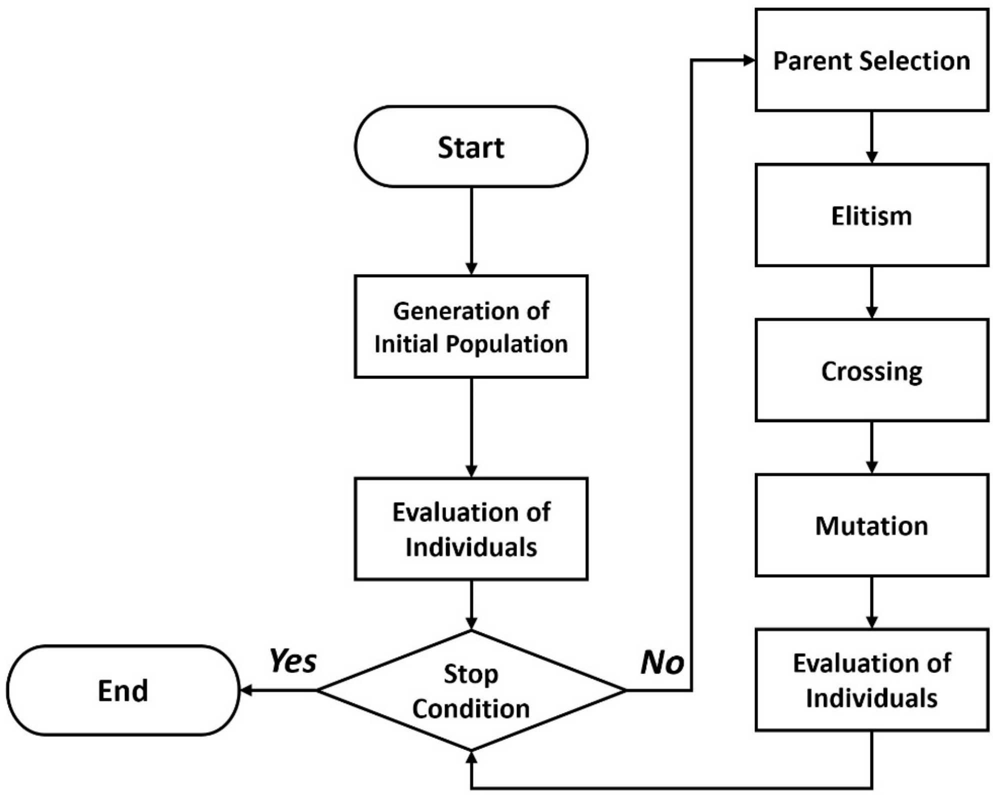

Figure 8.2 Flux Diagram of a GA

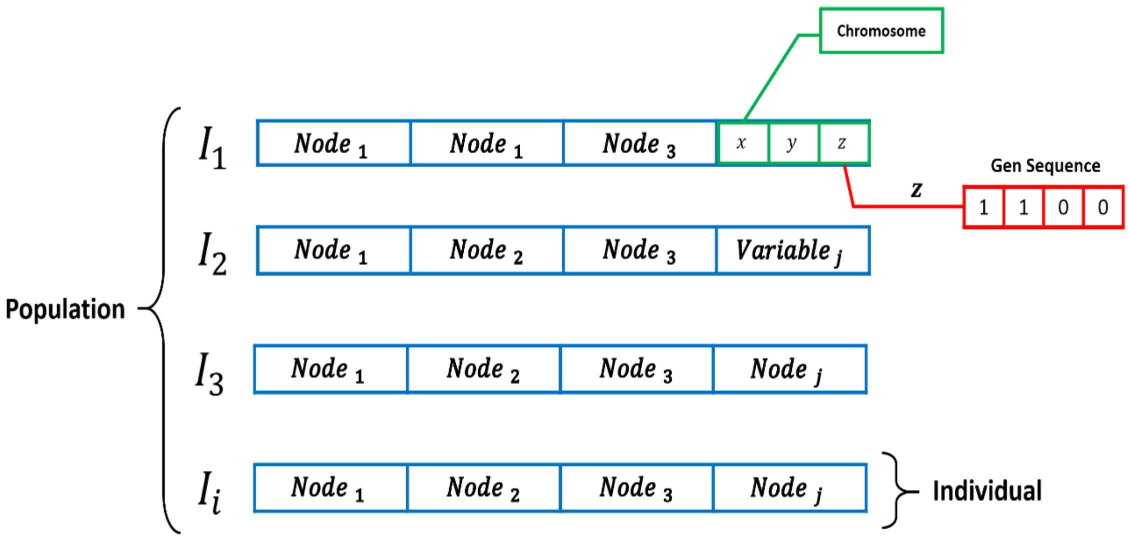

Figure 8.3 Binary codification of the GA for the NLP.

As it is shown in Figure 8.3 the variables to optimize in the NLP are the Cartesian coordinates of each architecture sensor node (i.e. the chromosomes of the codification) and the definition of the resolution of the optimization allows us to transfer the binary coding of the potential solution to decimal numbers through the escalation process defined in [49].

The definition of the quality of every individual of the GA is based on a fitness function considering the CRLB described in Section 2.3 which enables the application of pressure selection for allowing the evolutionary process find an optimal sensor configuration. The achievement of valid solutions in the GA performance requires an exhaustive definition of the hyperparameters of the optimization [62]. In this section, we analyze the potential problems of the NLP optimization through GA and propose two potential solutions through HGA and MA.

8.3.1 Implementation of the GA

Therefore, we have implemented a GA configuration that aims to find the best possible distribution of sensors. For the scenario proposed, shown in Figure 8.1, in Table 8.1 a set of generic technology parameters have been selected for performing simulations. Reason of this selection rely on the main objective of this research, that is the generation of a new optimization technique to the NLP, not the resolution of the NLP for a particular positioning technology.

Table 8.1. A-TDOA parameter configuration for the simulations, whose selection is based on [7,64,65]

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	3.1
NLOS Path loss exponent	4.5

Once established the initial conditions of the optimization, the number of sensors to achieve the desirable accuracy of the LPS is studied. This is a critical aspect in the NLP since an insufficient number of sensors may lead to coverage issues and unacceptable RMSE values in some TLE analyzed points. On the other hand, an unnecessary number of nodes shall incur in a considerable increase on the system implementation and maintenance cost.

Therefore, we have designed a genetic algorithm that obtains through the evaluation of a fitness function the optimal node distribution and performance for multiple numbers of sensors. The genetic algorithm, whose hyperparameters are shown in Table 8.2, is instructed by the following fitness function.

$$ff = 1 - \left(\frac{\overline{RMSE}}{RMSE_{ref}}\right)^2 \tag{8.14}$$

where $\overline{RMSE}$ is the mean value of the RMSE of a certain individual or node distribution for every possible target location (i.e. each of the TLE analyzed points). On the other hand, $RMSE_{ref}$ is a defined hyperparameter of the GA and serves as an accuracy reference [7,21]. This control parameter represents the maximum RMSE value that can be reached for the

TLE by an individual node distribution. Reducing the $RMSE_{ref}$ shall introduce pressure selection in the optimization process, improving the overall result. However, a disproportionate value may compromise the convergence of the GA to any solution, therefore, it is critical to obtain an adequate value for each particular scenario.

Furthermore, due to the construction of the fitness function in Equation 8.14, all fitness values should be represented in the interval [0, 1]. Therefore, the value selected for the $RMSE_{ref}$ must ensure that every fitness evaluation remains in the desired region

Table 8.2. GA hyperparameters selected [30]. The resulting number of possible combinations P, obtained from Equation 2 shows the magnitude of the solution environment for the scenario proposed. Due to the number of possible solutions, the applications of heuristic methodologies are in order.

GA Hyperparameters	Value
Population size	160
Convergence criteria	160 Generations or 80% population equal
Elitism	18%
Mutation	3%
Selection Technique	Tournament 2
Crossover Technique	Single-point
$RMSE_{ref}$	50
TLE points analyzed	1500
NLE points analyzed	24000
Number of sensors N	5 / 8 / 11 / 14
Number of possible combinations P	$7.95\ 10^{21}$ / $1.09 \cdot 10^{35}$ / $1.51 \cdot 10^{48}$ / $2.09 \cdot 10^{61}$

Hence, in Table 8.3 we study the performance of the GA under different node distributions in search of the most adequate configuration respecting performance and costs of the system. From these results, it is concluded that the best compromise solution regarding the systems performance and costs is an 11-node distribution. A lower number of sensors shall incur un greater and unfeasible positioning errors, furthermore, a higher number of nodes does not accomplish an improvement worth the investment.

For these simulations, we have employed a tournament 2 selection criteria [66] as well as a single point crossover technique. We will analyze the performance of the possible genetic operators in Section 8.4.

Table 8.3. Comparison of multiple node distributions for the scenario proposed

Node Distributions	Max RMSE (m)	Mean RMSE (m)	Min RMSE (m)
5 Nodes	23.02	5.32	0.63
8 Nodes	17.37	3.91	0.43
11 Nodes	10.28	2.31	0.29
14 Nodes	9.85	1.99	0.02

8.3.2 Weaknesses of the GA optimization in the NLP

GA evolution is a heuristic process in which randomness allows us to explore potential regions of the space of solutions for finding an optimized solution but the results achieved may vary among different runs since the introduction of the same inputs do not produce the same results. This is a consequence of the evolutionary process in which two phases can be defined: diversification and intensification.

In the first stage, the GA looks for promising regions in which an optimal solution can be found (i.e. diversification). Later, an exhaustive search in the promising regions (i.e. intensification) is promoted for finding the best adapted individual of these regions.

The mutation of some individuals is required for exploring new regions and avoiding local optima. However, the new individuals produced in the mutation operation must be good enough to hold the pressure selection. Otherwise, these individuals will disappear even if they belong to really promising regions. Even, the finding of new promising regions can be affected in especially discontinuous fitness function regions since the evolutionary process may suffer problems to reach the local optima if a deep increase in the fitness function can be produced among contiguous solutions (e.g. NLOS environments by the avoidance of obstacles in the positioning signal links). Therefore, we can affirm that the mutation process depends also on randomness and the exploration of new potential regions in discontinuous optimizations may be limited by the evolutionary pressure selection.

Thus, GA optimization in especially huge spaces of solutions such as in NLP optimizations in which NLOS links are considered may suppose a challenge in which the results can notably vary among different runs and the exploration of the space of solutions supposes an actual threat.

As a consequence, we propose the introduction of knowledge in the optimization for solving these potential weaknesses in the GA optimization in the NLP.

Firstly, we introduce a HGA for taking advantage of the usage of the GA operators in Section 8.4. We generate diversity in the generation of the new individuals in the diversification and intensification phases for achieving better optimization results. We later propose a memetic algorithm with a variable neighborhood-descent LS in which we introduce a methodology for detecting the most different individuals (i.e. new potential spaces of solutions) and we analyze its local region of potential solutions for allowing the finding of promising solution in discontinuous spaces in Section 8.5.

8.4 Implementation of Hybrid Genetic Algorithm in the NLP

The performance of every GA optimization is heavily dependent on the balance between the diversification and intensification capabilities of the GA. These values are established by the genetic operators utilized in the GA configuration, such as the selection and crossover operators, along the hyperparameters selected. An adequate equilibrium between these two competences is essential in favor of obtaining the optimal solution to the NLP.

An excessive focus on the intensification aspect, despite facilitating the convergence to the solution, may diminish the results obtained since relatively none exploration of the solution environment has been made. On the other hand, a disproportional commitment on the diversification capability shall boost the entropy of the optimization to a point where the convergence to a solution is compromised or even unfeasible.

Therefore, the balance between these two capabilities is crucial for the optimization performance, hence the configuration of genetic operators must be selected accordingly.

HGA have received a growing interest throughout the GA literature, being utilized for solving real-word problems [36]. HGA open up new possibilities as they support multiple configurations of genetic operators and hyperparameters.

Thus, HGA are suitable for applications where the solution environment is notably unfavorable. Scenarios that contain a consequential number of local maximums, such as the one studied in this paper, require both diversification, towards locating the global maximum region, and intensification, in order to obtain the optimal value of that region.

Therefore, for these particular scenarios, the approach of utilizing a HGA composed of multiple phases of diversification and intensification of the solution may exceed any achievable solution obtainable by any individual combinations of genetic operators.

Accordingly, in Table 8.4 we analyze the performance of multiple combinations of genetic operators in search of the most appropriate configuration for this particular scenario.

Table 8.4. Analysis of multiple combinations of genetic operators for the scenario proposed

Crossover Operator	**Tournament 2**		**Tournament 3**		**Roulette**	
	Min	Mean	Min	Mean	Min	Mean
Single point	2.31	2.67	2.55	2.67	2.66	2.9
Two-point	2.74	2.77	2.90	2.97	2.527	2.76
Three -point	**2.22**	**2.43**	2.83	3.00	**2.35**	**2.57**
Uni-form	2.70	3.18	4.65	5.82	2.82	2.87

Results in Table 8.4 show that the most appropriate techniques are the combination of tournament 2 (T2) selection criteria and multi-point crossover with 3 crossover points (MP3), along the roulette (R) selection methodology with also the MP3, exceeding these two combinations any other configuration.

T2 and especially Roulette are particularly elitist techniques [66], hence, we can conclude that for the scenario proposed, a heavy approach on intensification is far more advantageous than a diversification focused methodology.

However, the T2-MP3 combination achieves a greater exploration of the solution environment. Thus, it is possible to elaborate a HGA that utilizes both methodologies in search of a greater solution.

Consequently, in this paper we propose the configuration of a HGA that relies in two different phases, a deep - exploration phase followed by a heavy - intensification phase. The first phase incorporates a tournament 2 selection criteria along a three-point crossover and aims to explore the depth of the solution environment in search of the global maximum.

Afterward, a second combination of roulette selection methodology and also three-point crossover seeks to obtain the value of the global maximum.

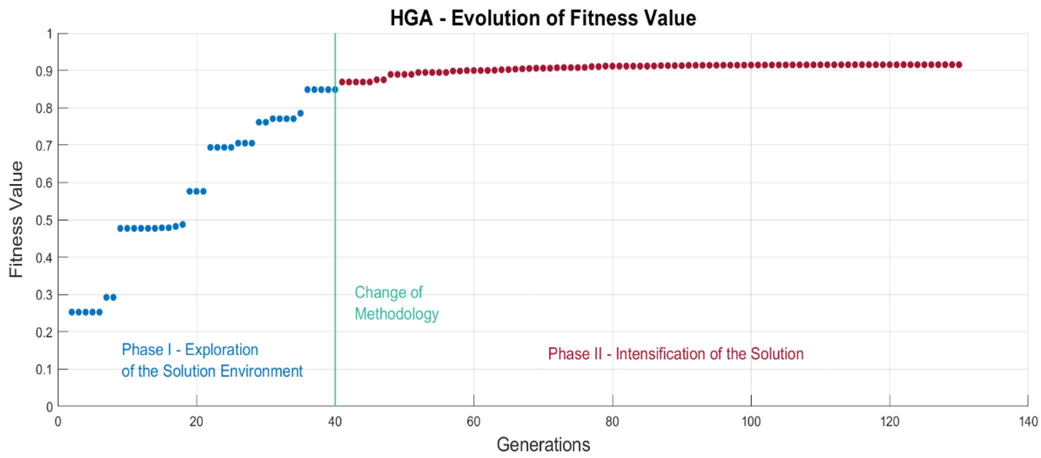

Figure 8.4 HGA optimization for the node location problem.

Results in Table 8.5 prove that indeed a HGA approach that combines two different phases may exceed the results obtained by any individual combination of genetic operators.

Table 8.5. RMSE comparison between the different methodologies analyzed

HGA Configuration	Min RMSE	Mean RMSE
GA - T2 / MP3	2.224	2.431
GA - R / MP3	2.354	2.575
HGA	**2.163**	**2.294**

Although it is true that HGA can exceed GA configurations, especially in adverse scenarios, the implementation of a HGA require the adjustment of a considerable amount of hyperparameters in addition to a profound analysis on the methodologies and genetic operators selected, which can only be done experimentally. Moreover, these parameters depend on the particular problem and scenario studied, hence, a subtle modification of the initial conditions may modify the performance of each configuration substantially. Therefore, it is critical to analyze each particular situation, as to determine if the implementation of an ad-hoc HGA configuration is in order.

In conclusion, HGA are a promising alternative to GA, and may surpass the results traditionally obtained by these algorithms, especially for adverse scenarios. However, the performance of the HGA is susceptible to the adequate selection of the genetic operators and the values of the hyperparameters inherent to this algorithm, depending this selection on each particular situation.

However, it is possible to elaborate a different strain of heuristic algorithm that provides both intensification and diversification capabilities along a solid versatility between different scenarios. In the next section we will study and analyze the implementation of a MA to the NLP.

8.5 Implementation of Memetic Algorithms and Local Search to the NLP

Within the compendium of metaheuristic methodologies, Memetic Algorithms are characterized by their inclusion of the problem's knowledge into the solution optimization. Consequently, the incorporation of particular information of the problem may achieve greater results than the previous methodologies introduced.

Moreover, once studied and particularized the optimization process for the NLP, the resulting MA achieves a higher versatility than GA or HGA. Even though it is possible to modify the initial conditions or the current scenario of study, all these applications share the foundations of the NLP whose knowledge is integrated into the MA optimization. The foundations of the MA are discussed in the next subsection and the implementation to the NLP subsequently.

8.5.2 Fundamentals of Memetic Algorithms

In this paper we have introduced the complexity of the NLP, consequently, a GA optimization was proposed in virtue of its diversification capabilities, which result vital in the optimization process, especially for adverse scenarios (e.g the one studied in this paper).

Nonetheless it is possible to implement a different heuristic methodology that allows a higher versatility along achieving possibly greater results, such is the case of Memetic Algorithms (MA) which we will analyze forthwith.

MA introduce the knowledge of the problem into the optimization process, improving the convergence to the solution along achieving greater results consequently. This knowledge is introduced through the concept of meme, the unit of cultural information of the Dawkins theory of transmittable knowledge [47]. Therefore, a meme is capable of evolving, along replicating itself and affect the human fitness (i.e reproduction and survival). Moscato [48] was subsequently inspired by this idea, who took these concepts into the evolutionary computation.

MA combine the optimization process of a GA along a LS technique. Through the LS methodology we introduce the knowledge of the problem, in search of the most promising individuals within a reduced solution environment, which may pass unsighted in the GA evolution.

Although there exists some former studies of MA optimization for Wireless Sensor Networks [43 − 46], these studies take only into account the coverage among the sensors. In this paper we will implement a MA for the NLP for the first time in the author's best knowledge with time and noise uncertainties characterization in the localization field.

8.5.2 Memetic Algorithm Structure

Memetic Algorithm combines both Global Search (i.e GA optimization) and Local Search in pursuit in exceed the results obtained by any of these methodologies individually. Therefore, we propose the following codification of a MA for the NLP.

Figure 8.5 shows the structure of the MA implemented for the NLP. The MA is composed of a GA optimization and the corresponding genetic operators along the LS methodology. For the NLP we propose a variable neighborhood-descent LS technique where the position of the nodes above the terrain is considered, thus introducing some knowledge of the problem into the optimization process.

Once mutated the population, the algorithm determines whether to proceed with the LS methodology for each generation. This depends on the LS frequency [49] which must be balanced in the combination of Global and Local Search for achieving the optimal optimization results in MA. It is vital to execute the LS after the mutation have finished, on the contrary, the progress made in the LS may be lost by the mutation of the population. Both the possibility of executing a LS and the number of individuals examined are hyperparameters that must be studied.

If the MA proceed with the LS technique, the first step through this algorithm is the selection of the most diverse individuals. The LS methodology pretends to explore and intensify undiscovered regions by the GA where a local or global maximum may be located, therefore, it is vital to select a certain number of individuals that are distant within each other in order to explore the maximum space of solutions possible.

Hence, we have developed a branch and bound algorithm that analyzes the population in search of the individual whose dissimilarity within each other are the greatest, thus optimizing the results obtained, which we will discuss in Subsection 5.3. Once evaluated the dissimilarity of each individual, the most diverse are transferred into the variable neighborhood-descent LS technique.

The variable neighborhood-descent LS evaluates reduced movements of the node positions for each individual (i.e. contiguous solutions in the neighborhood of the individual) in a new pseudo-fitness function in order to reduce the time complexity of the analysis. This procedure does not compromise the optimization since reduced movements of the sensors shall not incur in considerable deviation of geometric or clock errors. On the contrary, the pseudo-fitness function proposed is adequate for detecting NLOS trajectories that diminish the fitness value of the localization architecture. Therefore, this LS methodology excels in particularly adverse scenarios, where NLOS trajectories are considerable (e.g the one studied in this paper). In these scenarios, minimal changes in the node locations may result in considerable deviations of the fitness function since the avoidance of an obstacle may suppose a significantly increase in the localization accuracy.

```
algorithm MA is
    while Convergence criteria is not fulfilled do
        Fitness value ← Cramer-Rao Lower Bound of Population
        Population ← Selection of Population
        Population ← Elitism of Population
        Population ← Crossover of Population
        Population ← Mutation of Population
        if Local Search criteria is fulfilled do
            LS individuals ← Select disperse individuals from Population
            Fitness value LS individuals ←  CRLB of Population
            for each individual in LS individuals do
                for each iteration in Local Search Depth do
                    New LS Individual ← Variable Neighborhood Descent of individual
                    Pseudo Fitness value LS individuals ← Pseudo CRLB evaluation of individual
                end
                New Fitness LS ← Cramer-Rao Lower Bound of New LS Individual
                if New Fitness LS > Fitness value of LS individual do
                    substitute New LS individual from Population for LS individual
                end
            end
        end
    end
```

Figure 8.5 MA Structure Pseudo Code

Consequently, if in a certain direction an increase in the fitness function is detected, the new improved individual shall substitute its predecessor. Hence, the LS technique proposed can only improve the fitness function of the individuals analyzed, thus improving the overall performance of the optimization.

The LS technique in the MA introduces a spike of diversity and intensification into the optimization process. This effect shall prove useful when the GA convergence is compromised as a fact of the existence of local maximums, resulting in an overall greater performance of the optimization, achieving greater solutions consequently.

However, within the local search technique there exists an abundant quantity of algorithms from whose development and configuration relies the performance of the MA. Therefore, we shall analyze it thoughtfully forthwith.

8.5.3 Local Search in the MA optimization

The LS method grants to obtain accurate information about a bounded region defined by a distance function on the space of solutions. LS explores near neighbors for finding the best-adapted individuals within the area. Every set of adjacent individuals or distance 1 defines the neighborhood. Once the aim number of neighbors has been inspected, the next point in the LS is the selection of the best fitness neighbor. The algorithm ends when the stopping condition is reached (e.g. there is no evolution in the fitness between generations or the neighbor reached satisfies a criterion) or when over the maximum number of local iterations permitted is attained.

During the execution of the LS, the optimization of the number of individuals, breadth of search, and the count of depth iterations are vital factors for achieving practical results. Different LS techniques are considered in the literature, such as Tabu Search [67], Variable Neighborhood Descendt (VND) [68], selective LS [69], LS chain [70], or Iterated LS [71]. The adaptation to the characteristics of the problem determines their selection.

In this paper, VND is chosen since it allows the quantification of the improvement of the fitness in the spatial directions of the sensors in their neighborhood (i.e. the proximal allowable locations of the architecture sensors) for defining a path in the LS optimization. The application of LS in MA is critical for introducing knowledge in the evolutionary optimization process. Previous researches have used LS for introducing heterogeneity in the final solution for improving the elite individuals of the population [68] or for accelerating the overall speed of the optimization.

In this paper, we use LS in the MA not only for improving the elite individuals but also for introducing diversity in the evolutionary process for examining potential unfavored spaces of solutions. Potential unfavored areas of solutions appeared in the NLP in NLOS conditions. Significant differences in the fitness values are produced among contiguous solutions since obstacles significantly modify the architecture noises of adjacent node distributions.

The LS enables the examination of the most different individuals of the population to find potential optimum node distributions that are difficult to access through the GA operators and the evolutionary process.

8.5.3.1 Pseudo-fitness function

A critical issue in the MA is the selection of a LS fitness function, which should be kept in harmony with the GA search function [72]. The GA presented in Section 8.3 proposes the minimization of the CRLB error characterization of the TDOA architecture. However, we propose a pseudo-fitness function in the LS which analyzes the LOS/NLOS links of the positioning signal paths.

The pseudo function allows the finding of the optimum node distribution of reduced search spaces defined by neighborhood relations. Pseudo-function is composed by a path loss exponent value of the LOS and NLOS links and the total distances of the LOS and NLOS links under coverage which are used for the target location determination. The reduction of the paths allows the minimization of the noise uncertainties which supposes the main error source among neighboring potential solutions.

$$ff_{LS} = \frac{1}{\sum_{k=1}^{T}\sum_{i=1}^{N} d_{i_{LOS}}^{n_{LOS}} + \sum_{k=1}^{T}\sum_{i=1}^{N} d_{i_{NLOS}}^{n_{NLOS}}} \tag{8.15}$$

This optimization methodology has led to the maximization of the inverse of the sum values associated with the LOS and NLOS links in each possible TLE analyzed point (***T***) for each architecture sensor under coverage (***N***).

This pseudo function has proven the competence to ensure the finding of the neighborhood local optima. A new neighborhood for the next LS iteration is defined through the selection of the most adapted individual of the neighbors analyzed based on the pseudo-fitness function values. The definition of a different fitness evaluation for the LS instead of the fitness used in the GA optimization promotes the analysis of the CRLB of the local optima individual of the neighborhood just before introducing the LS optimal to the general optimization process.

8.5.3.2 Variable Neighborhood-Descent Local Search

The neighborhood search aims to maximize the pseudo-fitness function to obtain the local optima of the LS individual selected. Since the geometric and clock errors remain practically constant among contiguous solutions, the neighborhood LS looks for reducing the NLOS paths of the positioning signals.

In this paper, we apply a variable neighborhood descent algorithm (VND) [73] which finds the best individual of a defined neighborhood and later defines a new neighborhood based on the current LS individual optimum. VND is constantly improving or keeping the best LS individual in a new neighborhood for a maximum defined number of iterations, which is known in MA as Local Search Depth (LSD).

VND algorithm can also end by finding an individual sufficiently improved (e.g. avoiding all the NLOS connections in the positioning signals). The LS exploration is performed for each sensor of the architecture. The neighborhood is defined for every sensor which is moved around its neighborhood for improving its positioning connections. We explore 26 potential movements of each sensor for improving the pseudo fitness function value (i.e. 26 directions are considered for every sensor in each iteration of the LS). This LS is particularly crucial for the CS since this sensor is used for computing the time measurements in the A-TDOA and consequently the positioning links of the CS affect the quality of a node distribution in a bigger extent.

8.5.3.2 Definition of the LS individuals

The application of the MA LS in this article looks for providing genetic variability in the population and for discovering unexplored regions. In the intensification phase of the GA optimization, the existence of many individuals in a defined domain of the space of solutions promotes the access to every possible NLE solution through the crossover operator in this area. Nevertheless, GA make the most different individuals in this final optimization stages very probable to disappear without the exploration of their surrounding region thoroughly. In addition, the performance of the GA mutation in any optimization phase, which can produce diverse individuals, is not enough for providing variability in NLOS environments since the exploration of new potential regions is limited to the finding of a good enough individual in the new space of solutions to survive the pressure selection of the next generation. Therefore, we use the MA LS to explore the most different individuals of the population in order to find new promising solutions to the NLP.

The definition of the most different individuals of the population is achieved through the measurement of the dissimilarity among solutions. The dissimilarity is calculated by applying the Hamming distance in the binary codification of two different solutions (i.e. two different sensor distributions) **[74]**. However, the dissimilarity metric cannot be directly applied since identical sensors can be located in different positions of the binary codification of two different individuals. Hence, each sensor of any individual must be first compared with all the sensor locations of the rest of the individuals.

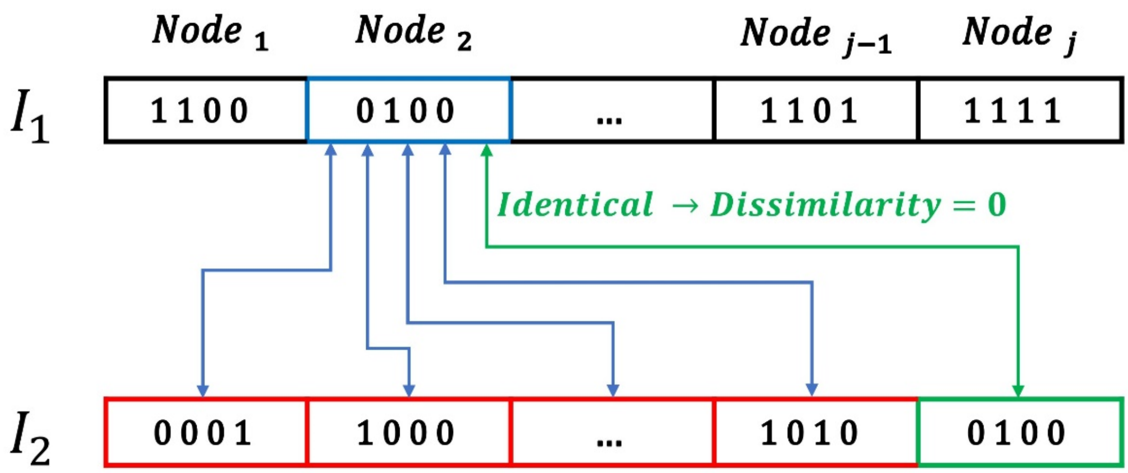

Figure 8.6 Calculation of the dissimilarities of the Node 2 of the Individual 1 $\left(I_{1_{N_2}}\right)$ with each node of the Individual 2 (I_2). The dissimilarity between $I_{1_{N_2}}$ is zero since they are identical and is determined through the Hamming distance with the rest of the nodes of I_2.

Therefore, the measurement of the dissimilitude among the different sensor distributions requires the finding of the pairs of sensors among two different potential solutions($\boldsymbol{I_1}$ and $\boldsymbol{I_2}$) which are more similar among them. However, greedy approaches cannot be applied for achieving this value since not the selection of the most similar nodes of two different individuals provides the minimum sum of the Hamming distance among the individuals. Consequently, we define the dissimilarity matrix among individuals $\boldsymbol{d}$ containing the values of the Hamming distance of each node of the $\boldsymbol{I_1}$ with each node of the $\boldsymbol{I_2}$:

$$d = \begin{pmatrix} d(I_{1\,N_1}, I_{2\,N_1}) & d(I_{1\,N_1}, I_{2\,N_2}) & \dots & d(I_{1\,N_1}, I_{2\,N_{j-1}}) & d(I_{1\,N_1}, I_{2\,N_j}) \\ d(I_{1\,N_2}, I_{2\,N_1}) & d(I_{1\,N_2}, I_{2\,N_2}) & \dots & d(I_{1\,N_2}, I_{2\,N_{j-1}}) & d(I_{1\,N_2}, I_{2\,N_j}) \\ \vdots & \vdots & & \vdots & \vdots \\ d(I_{1\,N_{j-1}}, I_{2\,N_1}) & d(I_{1\,N_{j-1}}, I_{2\,N_2}) & \dots & d(I_{1\,N_{j-1}}, I_{2\,N_{j-1}}) & d(I_{1\,N_{j-1}}, I_{2\,N_j}) \\ d(I_{1\,N_j}, I_{2\,N_1}) & d(I_{1\,N_j}, I_{2\,N_2}) & \cdots & d(I_{1\,N_j}, I_{2\,N_{j-1}}) & d(I_{1\,N_j}, I_{2\,N_j}) \end{pmatrix} \quad (8.16)$$

We explore the **d** matrix through a branch and bound algorithm [] for finding the combination of sensors of the two individuals which minimizes the Hamming distance of the pair of individuals. The procedure follows the definition of the most promising node (i.e. the more reduced value of the **d** matrix) and later exploring the possible combinations of the matrix without repeating row and column for finding the pairs of sensors which minimizes the sum of the dissimilarities. Once these pairs of similar sensors have been defined, the dissimilitude among solutions is defined as:

$$D_{ij} = min\left(\sum_{pair=1}^{N} d_{hamming_{pair}}\right) \quad (8.17)$$

where D_{ij} is the dissimilitude among the solutions i and j, $d_{hamming_{pair}}$ is the hamming distance measured in one of the pairs of contiguous sensors among solutions previously defined and N the total number of sensors used for the localization.

Once the dissimilitude among solutions is defined it can be expressed in matrix form ($\boldsymbol{D}$) for a general definition of the distances among every of the population individuals:

$$D = \begin{pmatrix} 0 & D_{12} & \dots & D_{1(n-1)} & D_{1n} \\ D_{21} & 0 & \dots & D_{2(n-1)} & D_{2n} \\ \vdots & \vdots & 0 & \vdots & \vdots \\ D_{(n-1)1} & D_{(n-1)2} & \dots & 0 & D_{(n-1)n} \\ D_{n1} & D_{n2} & \dots & D_{n(n-1)} & 0 \end{pmatrix} \quad (8.17)$$

The finding of the most different individual of the set to whom we apply the LS in search for new unexplored spaces of solutions is obtained through the maximization of the $\boldsymbol{D}$ matrix row or column sum values since the dissimilarity matrix is symmetric. This sum represents the total difference of an individual with the rest of the individuals of the population. According to this total dissimilitude factor, the population is ordered and a percentage of the first new individuals (i.e. the most different) is chosen for executing the VND algorithm.

In addition, we select the elite individual of the population for practicing the LS on it, thus obtaining an improvement in the accuracy results of the optimization within the LS.

8.6 Results

In this section, we present the results obtained by the MA optimization introduced in the previous section, along some comparisons with previously proposed methodologies. All algorithms and simulations were coded and executed in the MATLAB software environment, being every test performed with an Intel(R) i7 2.4GHz CPU and 16 GB of RAM.

Table 8.6 shows the results of the MA optimization. Due to the overall performance improvement of the optimization achieved by the LS, the final node distribution obtained reach a significant increase in positioning accuracy from previous simulations from Table 8.3. Therefore, in pursue of the optimal compromise between position accuracy and amount of sensors (i.e installation and maintenance costs) we can lower the number of sensors to 8 nodes without compromising the system accuracy.

Table 8.6. MA optimization results. Values displayed are the mean and minimal values of the mean RMSE of the simulations executed.

Node Distributions	**Min RMSE (m)**	**Mean RMSE (m)**
5 Nodes	4.287	4.923
8 Nodes	3.142	3.208
11 Nodes	2.184	2.284

Figure 8.7 shows the MA search of the optimal solution, combining the GA optimization with a LS methodology that enhances the overall performance of the optimization with

every iteration of the VND. However, it is possible to improve even further the MA optimization, relying this technique on a GA, thus a single combination of genetic operators and hyperparameters. Furthermore, it is possible to implement multiple configurations of genetic operators and hyperparameters into the GA optimization, thus obtaining a HGA, that along the LS of the MA results in an overall improvement of the optimization performance carried out by the proposed Hybrid Memetic Algorithm (HMA).

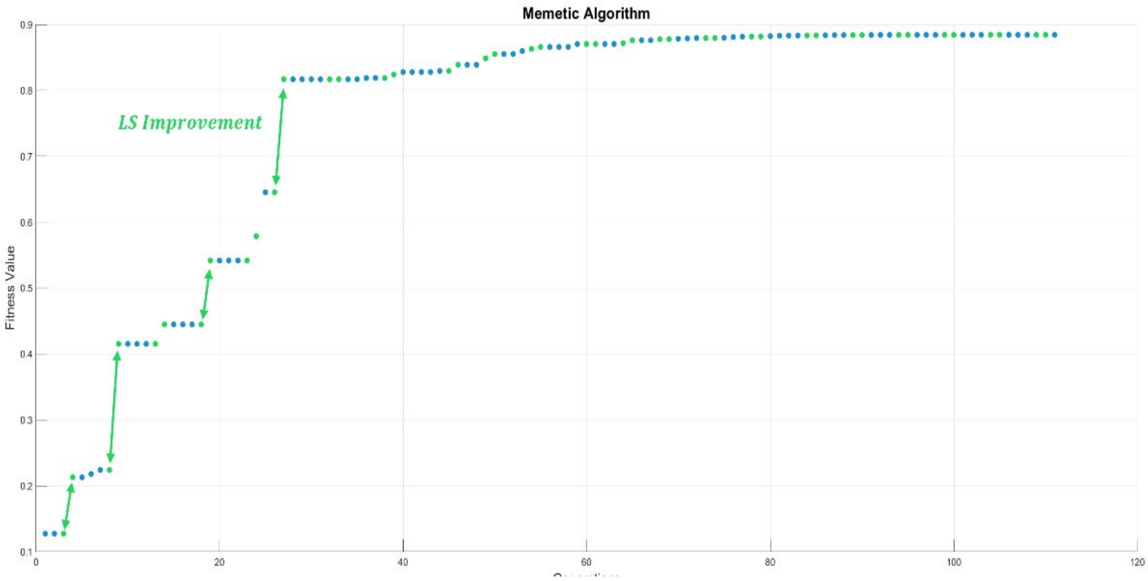

Figure 8.7 Memetic Algorithm convergence to the optimal solution for an 8-node distribution. Results show that the VNS utilized in the LS algorithm introduces significant improvements on the fitness values of the selected individuals, thus improving the convergence. These improvements escalate rapidly due to the effect of elitism on the enhanced individuals, thus preserving and spreading even further their properties.

Therefore, Table 8.7 shows the positioning error for each methodology proposed. Hence, we can appreciate an escalated increase in the optimization results with each step forward in the methodology selected.

Furthermore, Figure 8.8 shows the compendium of techniques introduced in this paper and their respective convergence for an 8-node distribution optimization.

Ultimately, Figure 8.9 show the optimal node distribution obtained by the HMA in Table 8.7, along the RMSE values for the TLE.

From the obtained results we can conclude that the resulting increase in diversification introduced by the MA derives in an increase in the number of generations the final convergence to a solution. However, as shown in Figure 8.8 this additional diversity implemented into the optimization achieves higher results than other methodologies as it allows a greater exploration of the solution environment.

Table 8.7. Comparison of positioning accuracy for each methodology studied in this paper for 8 nodes. Results displayed refer to the mean and minimal mean RMSE of every simulation executed.

Methodology	Min RMSE (m)	Mean RMSE (m)
GA	3.54	3.91
HGA	3.243	3.423
MA	3.142	3.208
HMA	**3.037**	**3.101**

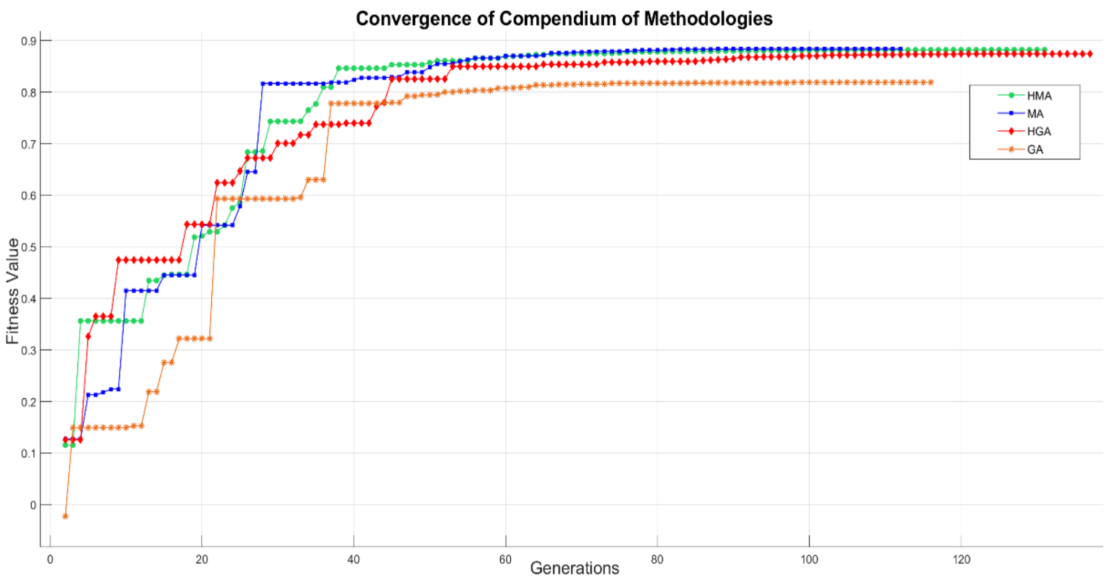

Figure 8.8 Convergence of the compendium of techniques proposed in this paper for 8 nodes.

Nevertheless, the implementation of a MA requires the introduction of knowledge into the problem, thus investing additional time into designing a specific LS methodology for each different problem. MA excel when faced against extremely adverse scenarios, or against different initial conditions that may turn ineffective the hyperparameters previously adjusted.

Therefore, it is critical to analyze each particular case, taking into consideration the complexity of the scenario along the possible variability of their initial configuration, in search of the optimal methodology for each particular case. Nevertheless, as results show, MA are ideal versatile techniques for adverse variable scenarios, such as the one proposed in this paper.

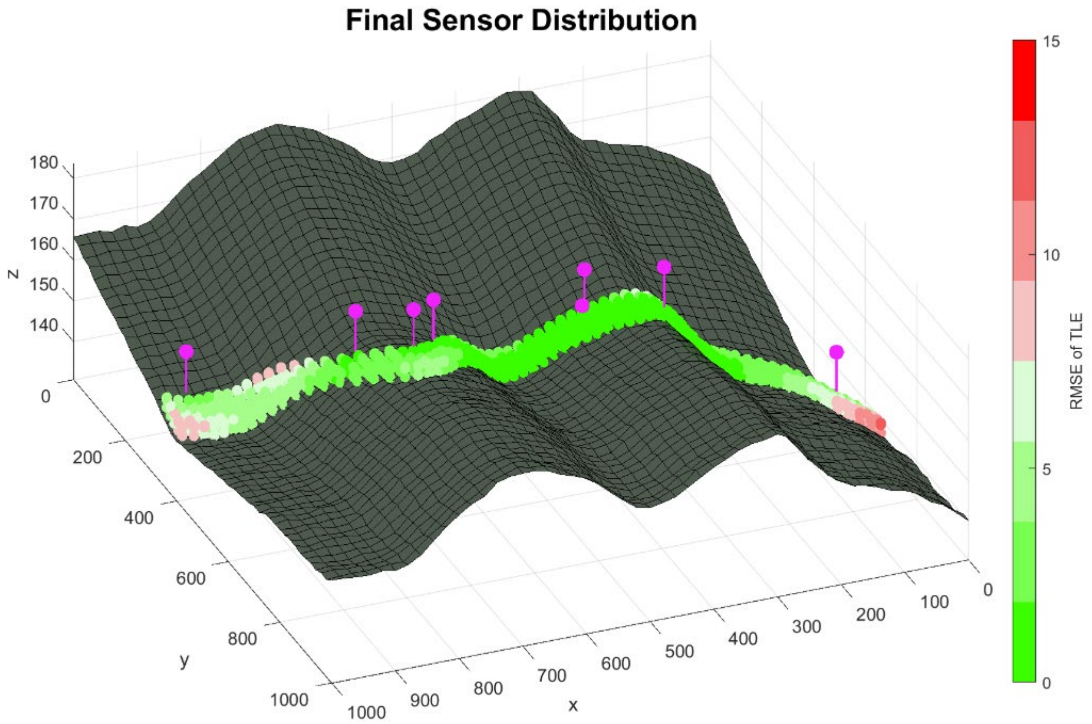

Figure 8.9 Optimal node distribution of 8 sensors obtained by the HMA and the RMSE accuracy of the TLE for the scenario proposed. The obtained distribution achieves an overall adequate positioing against the terrain adversities, even so for a reduced number of sensors.

8.7 Conclusions

Local Positioning Systems (LPS) are attracting large research interest over the last few years for performing high-demanded accuracy applications such as guided autonomous navigation in indoor and outdoor environments. Availability, robustness, hardware configuration, architecture coverage and uncertainties reduction are some of the most important issues addressed for achieving optimal sensor node deployments and fulfilling the LPS design requirements.

These tasks require optimized ad-hoc node distributions for adapting to the characteristics of the environment in which the LPS are deployed. Among LPS, those based on temporal measurements stand out since they provide a relevant trade-off among costs, hardware complexity, robustness and accuracy. The achievement of valid node deployments in Time-Based Positioning Systems (TBS) demands an error characterization in which the noise of the communications channel in LOS and NLOS architecture links and the clock errors in the temporal measurements must be considered.

The TBS have shown an excellent performance for LPS applications and among these architectures novel asynchronous architectures stand out due to the unnecessary synchronism of the system devices consequently reducing the clock errors. Thus, in this paper, we define a Cramér-Rao Bound (CRB) model for the Asynchronous Time Difference of Arrival (A-TDOA) architecture since CRB provides the minimum achievable positioning error of this architecture by using any positioning algorithm.

This CRB model is applied for measuring the quality of an A-TDOA node deployment for solving the Node Location Problem (NLP) of this architecture. The NLP requires the finding of the optimized cartesian coordinates of the architecture sensors of any sensor network distribution. It has been assigned as NP-Hard since a polynomial or exact solution cannot be found. Therefore, a heuristic solution to the NLP has been extended in the literature. Amongst the metaheuristic techniques, Genetic Algorithms (GA) have shown an excellent trade-off between the diversification and intensification stages of the optimization.

However, in our previous research we have found that the GA optimization is unstable in NLOS environments in which the discontinuities in the fitness values of contiguous solutions makes the exploration of new potential spaces of solutions be difficult to address.

As a consequence, in this paper we propose the introduction of knowledge in the optimization process. First, we propose a hybrid GA (HGA) based on the modification of the GA operators during the optimization process defining two optimization phases: an enhanced deep-exploration phase followed by a heavy-intensification phase.

Later, we introduce for the first time in the authors' best knowledge a memetic algorithm (MA) consisting of a mixture of the GA optimization with a variable neighborhood-descent (VND) Local Search (LS) strategy for the NLP in the localization field. The MA applies the LS to the most different individuals of the population defined by Hamming distance in order to explore new different spaces of solutions not favored by the evolutionary optimization process. In addition, we define a pseudo-fitness function based on the reduction of the architecture LOS and NLOS links since geometric and clock errors have a reduced impact in the neighborhood in which the LS is applied.

We finally design a Hybrid Memetic Algorithm (HMA) which combines the beneficial effect of the HGA and the MA for the achievement of improved node deployments.

Results show that the introduction of an enhanced combination of GA operators in the HGA enables the finding of better candidate solutions to the NLP in NLOS environments. Additionally, the introduction of knowledge in the optimization evolutionary (MA) process increases the overall performance in the solution of the NLP in a greater extent than the GA operators in the HGA. Finally, the HMA outperforms the previous configurations through the beneficial effect of the GA operators and the LS strategy of the MA. The HMA methodology proposed reaches an increase in accuracy in the optimization process in the scenario of simulations of this article of 14.2 % with regards to previous GA optimizations of the literature.

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Chapter 9

Concluding Remarks and Outlook

9.1 Conclusions

This dissertation presents an extensive analysis of the Time Local Positioning Systems. These systems are promising for the development of high-demanded accuracy applications in fields such as autonomous navigation, rescue operations, surveillance, underwater localization, tunnel and indoor localization, agriculture or surveillance. The implementation of LPS requires an ad-hoc deployment of sensors which fit the characteristic of the environment of application and demands an extensive knowledge of the localization field for achieving optimal deployments for meeting the design requirements.

In this thesis, the obtainment of optimized cost-effective deployment of sensors in LPS has been studied with the following concluding remarks:

- ❖ The solution of the LPS problem with the minimum number of sensors requires an optimized sensor distribution of sensors in space.
- ❖ The disambiguation of the position calculation of LPS with the minimum number of sensors demands a convergence sphere in which its interior points can act as the starting point of an iterative algorithm for the position determination with total confidence.
- ❖ The sphere of converge has a direct relationship with the distance among the ambiguous solutions in the LPS problem with the minimum number of sensors.
- ❖ The disambiguation in the position calculation in LPS is produced through the maximization of the distance between the ambiguous solutions. This distance must exceed a threshold which naturally happens in GNSS and must be induced in LPS.
- ❖ Traditional optimizations of the location of the nodes in LPS have not considered eventual sensor failures. This has promoted that the performance of the LPS in emergency conditions have instantly decreased with regards to nominal operating conditions without failures.
- ❖ A stable performance of the LPS in critical conditions can be achieved through

optimizations which consider the emergency conditions. Results have shown that minimal reductions in the nominal performance of LPS are produced when considering possible failure conditions in the architecture sensors while the performance in emergency conditions is notably enhanced.

- The main disadvantage of asynchronous LPS is their dependency on the CS for the position calculation. This can promote the availability absence of the architecture in CS failure conditions causing the lack of coverage in some regions of the TLE.
- This consideration must be contemplated in the optimization process allowing the coverage of at least two different CS in each analyzed TLE point. It is also required that the optimization of the sensor location of the asynchronous architecture must enhance the system performance with the primary and the secondary CS under coverage.
- The employment of all the architecture sensors which exceed the SNR_{min} may not produce the less uncertainty in the calculation of the position in NLOS conditions. This is due to possible imbalanced error distributions among the architecture sensors. Consequently, the finding of the best combination of architecture sensors for calculating the target location is required in NLOS LPS applications.
- The asynchronous LPS may require the introduction of a greater number of CS in especially harsh regions with irregular environments of operations, thus increasing the system costs.
- The characteristics of the Time LPS made that there is not a prevalent architecture for any high-demanded accuracy application a priori. Thus, an objective comparison of the performance of each architecture must be done for every scenario of application.
- This comparative may consider accuracy, robustness availability and system implementation costs for extracting valid conclusions on the application of each architecture.
- The solution of the NLP is essential for the application of any LPS. This problem is especially complex to be addressed in NLOS conditions with high spaces of solutions. This is due to the discontinuities in the fitness function evaluation

among contiguous solutions. As a consequence, the difficulty of the intensification during the evolutionary process followed in the solution of the NLP, significantly increases promoting the appearance of unfavored regions of the space of solutions.

- The implementation of LS procedures in the most different individuals of the genetic population used for the solution of the NLP has demonstrated the improvement in the heuristic search of the GA applicated to the NLP.
- The LS in the NLP can implement a pseudo-fitness function which can uniquely consider the reduction of the positioning signal paths -especially the NLOS links- since the clock and geometric errors in neighborhood regions remains practically constant.
- The combined effect of the LS with an adaptive use of the GA operators allows the improvement of the NLP results with regards to only genetic approaches employed in the literature.

9.2. Future Research Areas

This dissertation has presented the progress in the research of the LPS in the SINFAB group of the University of León over the last few years. Nonetheless plenty of investigations may be derived from this thesis:

- Actual implementation of LPS which allows us to validate the clock and noise models used throughout the node deployment optimizations. Investigations on UWB technologies will be done in order to prove the behavior of LPS.
- Optimization of the node distribution of LPS in indoor environments for the guided navigation of Automatic Ground Vehicles for collaborating in manufacturing activities of the Industry 4.0.
- Implementation of different metaheuristics for the Node Location Problem for improving the accuracy results in especially NLOS complex scenarios.
- Node Location Problem solution with a variable number of nodes during the evolutionary process. This requires the addressing of the variable-length genetic problem with the definition of novel selection, crossing and mutation operators applied to variable number of nodes distributions. This allows the solution of a unique NP-Hard problem instead of *n* different NP-Hard problems for *n* different number of nodes configurations.

- Research on modular sensor distributions for large-scale LPS applications. The definition of huge environments for the application of LPS increases the required number of sensors for these deployments, which makes the Node Location Problem to be extremely NP-Hard for addressing the whole optimization in a unique step.
- Research on novel asynchronous LPS architectures which can reduce the dependence on the target sensor for the retransmission of the positioning signal.
- Development of energy-effective node deployments in Time LPS which boost the reduction of the energy consumption of unmanned aerial vehicles (UAV) for increasing the navigation autonomy of these vehicles.
- Definition of maximum convergence points for the initialization of iterative positioning algorithms.
- Implementation of methods for the ponderation of a weighted least-squares matrix in the actual operation of LPS based on the a priori knowledge collected by the characterization of the uncertainties provided in this dissertation.

Anexo I

Síntesis

Capítulo 1

Resumen

El desarrollo tecnológico actual y futuro demanda de forma progresiva la introducción de sistemas de posicionamiento que sean capaces de proporcionar localizaciones más exactas y estables a lo largo del tiempo. Tradicionalmente, se han empleado los sistemas de navegación satelital (GNSS) que permitían alcanzar cobertura global y el acceso a territorios con orografías especialmente complejas.

Sin embargo, la navegación GNSS para aplicaciones de elevada precisión requiere de un profundo tratamiento de las señales de posicionamiento para reducir las incertidumbres generadas por el ruido, las mediciones temporales y las inestabilidades ionosféricas. Además, fenómenos adversos en las señales como el multicamino o la propagación en condiciones de falta de línea de visión (NLOS) pueden inhabilitar el uso de los GNSS en el interior de edificios, en navegación de baja cota o en entornos con profundas irregularidades.

Como consecuencia, en los últimos años, aplicaciones de posicionamiento local (LPS), con especiales características adaptadas al entorno en el que son desplegados, permiten reducir la incertidumbre en el cálculo de la posición de los GNSS y mitigar los efectos negativos en las señales de posicionamiento, alcanzando con ello un gran interés de investigación. No obstante, el despliegue de los LPS supone nuevos desafíos que ya se encontraban resueltos en los GNSS o que surgen como consecuencia de la proximidad entre el objetivo de posicionamiento y los sensores del sistema.

Entre los diferentes LPS, aquellos basados en mediciones temporales, son los que permiten lograr una mejor relación entre exactitud, estabilidad, robustez, sencillez de implementación y coste. Por ello, los LPS temporales son analizados en esta tesis doctoral como candidatos para satisfacer las futuras aplicaciones de precisión tecnológicas.

Es por ello que, en esta disertación se abordan problemas específicos de los LPS temporales como la desambiguación del cálculo de la posición con el mínimo número de sensores, el despliegue optimizado de los sensores de sus arquitecturas o la consideración de posibles fallos de operación de los nodos de las arquitecturas de posicionamiento.

En primer lugar, en el capítulo 4, se propone una metodología para el cálculo de la posición con el mínimo número de sensores de una arquitectura LPS TDOA logrando la resolución de la ambigüedad matemática que se genera por la intersección de superficies no

lineales. Esta metodología requiere la maximización de la distancia entre las dos soluciones que se generan en el caso ambiguo mediante una distribución optimizada de los sensores en el espacio que permita la aplicación de un algoritmo de posicionamiento iterativo con total confianza.

En el capítulo 5, se plantea un procedimiento de optimización de la distribución de los sensores de las arquitecturas LPS que no tiene únicamente en cuenta el funcionamiento del sistema en condiciones nominales sino también su funcionamiento estable en caso de fallo de alguno de sus sensores. Los resultados mostraron que este tipo de optimización reduce mínimamente las prestaciones del sistema en condiciones nominales, pero alcanza una mejora notoria de su funcionamiento en condiciones de emergencia.

Por otra parte, el surgimiento de nuevas arquitecturas asíncronas LPS recomienda el uso de esta metodología del capítulo 5 para tratar el fallo eventual de los sensores coordinadores de posicionamiento asíncrono. Esto permite resolver la principal desventaja de estos sistemas: la imposibilidad de acceso a alguno de estos sensores coordinadores en alguna región del espacio produce la pérdida temporal de la disponibilidad de posicionamiento de las arquitecturas asíncronas en estos lugares. Por ello, se aplica el principio de optimización de las distribuciones de posicionamiento del capítulo 5 en el capítulo 6 para permitir la minimización de los errores de ruido y relojes de la arquitectura asíncrona A-TDOA en condiciones nominales y de emergencia. Además, se estudia en este capítulo la combinación óptima de sensores en cobertura para el cálculo de la posición en condiciones NLOS con degradación desbalanceada de la señal.

En el capítulo 7 se extiende la metodología del capítulo 6 para encontrar despliegues de sensores optimizados que alcancen buenas propiedades de exactitud, disponibilidad y robustez en las principales arquitecturas LPS temporales (TOA, TDOA y A-TDOA). Esto permite la generación de un marco común de comparación de las arquitecturas temporales para su despliegue en escenarios urbanos complejos. Este marco es necesario ya que en las arquitecturas LPS temporales se produce una distribución desbalanceada entre los errores de reloj y de ruido de estos sistemas que hace que no se pueda definir a priori la idoneidad de una arquitectura sobre las demás en escenarios complejos.

Por último, se presenta en el capítulo 8, un algoritmo memético para la resolución del problema de colocación de sensores de posicionamiento (NLP) en entornos complejos NLOS en los que se produzca discontinuidad en la función de evaluación de la calidad de una distribución de sensores entre soluciones contiguas. Esto requiere la introducción de un procedimiento de búsqueda local basado en la exploración de vecindades colindantes en espacios de soluciones no favorecidos por la evolución genética presentada tradicionalmente en la literatura. El análisis de la idoneidad de los vecinos puede centrarse exclusivamente en la evaluación de los caminos de las señales de posicionamiento ya que los errores de relojes y geométricos son prácticamente constantes, lo que permite alcanzar una gran eficiencia en el proceso de búsqueda local. Los resultados demostraron la prevalencia de esta técnica con respecto a la exclusiva exploración genética tradicional.

Capítulo 2

Objetivos y organización de la tesis

1.1. Objetivos

Esta disertación busca un análisis profundo sobre la implementación de sistemas de posicionamiento local (LPS) para aplicaciones de precisión de alta demanda. En este marco general, hay algunos objetivos generales de la tesis y objetivos específicos particulares en cada uno de los capítulos de investigación. Los objetivos generales de la disertación se presentan a continuación, mientras que los objetivos particulares de cada capítulo se describen en el Capítulo 3 y en cada una de las unidades de investigación presentadas desde el Capítulo 4 al Capítulo 8:

- ❖ Estudio sobre desempeño de los Sistemas de Posicionamiento Local con el número mínimo de nodos para determinar la ubicación del vehículo.
- ❖ Definición de una metodología para lograr la desambiguación del cálculo de la posición con el número mínimo de nodos en Sistemas de Posicionamiento Local basados en medidas Temporales.
- ❖ Diseño de un procedimiento mejorado para el despliegue de una arquitectura de nodos sensores en LPS considerando eventuales condiciones críticas de operación por posibles fallas de sensores en la arquitectura de posicionamiento.
- ❖ Análisis de novedosas metodologías asincrónicas para su aplicación en Sistemas de Posicionamiento Local: estudios sobre el diseño, implementación, despliegue, disponibilidad y robustez.
- ❖ Desarrollo de una metodología novedosa y rentable para la reducción de las incertidumbres de reloj y ruido en sistemas de posicionamiento locales basados en medidas temporales.
- ❖ Selección adecuada de nodos del sistema para el cálculo de la posición en el área de cobertura de los Sistemas de Posicionamiento Local.
- ❖ Análisis de la interacción entre los Sensores Trabajadores y el Coordinador en Sistemas de Posicionamiento Locales Asíncronos.

- ❖ Definición de un marco común para la selección del Sistema de Posicionamiento Local de Tiempo más apropiado en escenarios urbanos complejos NLOS basado en precisión, disponibilidad, robustez y costos del sistema.
- ❖ Análisis de las técnicas metaheurísticas empleadas para resolver el problema de localización de nodos en redes de sensores inalámbricos.
- ❖ Estudio de la influencia de los operadores de algoritmos genéticos y técnicas de búsqueda local en el problema de localización de nodos.
- ❖ Proposición de una metodología memética híbrida novedosa para abordar el problema de ubicación de nodos en escenarios complejos NLOS en los que existe discontinuidad en la evaluación de la función de aptitud entre soluciones contiguas.

1.2. Contribuciones principales

A continuación, se presenta una sinopsis de las principales contribuciones de esta tesis:

I. Definición de una metodología para la resolución de la ambigüedad en la ubicación del vehículo en 3D, con el número mínimo de nodos, mediante la definición de una esfera de convergencia que actúa como intervalo de confianza para la definición del punto de partida de un método iterativo en el cálculo de la posición.

II. Una estrategia novedosa en el despliegue de nodos sensores para una arquitectura basada en condiciones primarias y de emergencia que permite que el sistema funcione adecuadamente en condiciones de falla.

III. La caracterización del reloj del sistema y las incertidumbres de ruido en condiciones LOS y NLOS para los principales Sistemas de Posicionamiento Local de Tiempo: TOA, TDOA y A-TDOA.

IV. Definición de la combinación de sensores con cobertura más adecuada para el cálculo de la posición en base a la reducción de los Límites Cramér-Rao en cada punto de cobertura analizado.

V. Solución a la potencial indisponibilidad del sensor coordinador en condiciones de falla de despliegues de nodos asíncronos.

VI. La propuesta de una metodología novedosa para el problema de cobertura de localización en condiciones nominales y de emergencia.

VII. Definición de un marco común para la comparación del desempeño de los

Sistemas de Posicionamiento Locales basados en medidas Temporales en escenarios urbanos complejos NLOS.

VIII. Adaptación de una optimización flexible de la distribución de sensores a escenarios urbanos.

IX. Proposición de un algoritmo memético híbrido para la solución del problema de ubicación de nodos basado en un uso inteligente de los operadores GA durante el proceso evolutivo y una estrategia de búsqueda local de vecindad variable descentente para explorar posibles espacios de soluciones desfavorecidos.

1.3. Organización de la tesis

La estructura de esta disertación se presenta en esta sección. El capítulo 1 define los principales objetivos de la disertación, presenta las aportaciones de la tesis doctoral, proporciona la organización del documento e introduce los proyectos de financiación de la investigación y el grupo de investigación en el que se ha desarrollado la tesis.

El Capítulo 2 proporciona una introducción general al LPS incluyendo el estado del arte de las tecnologías, la definición de las áreas en las que se aplica el LPS, las principales arquitecturas del LPS, una particularización sobre los sistemas basados en el tiempo y los algoritmos de posicionamiento utilizados en el literatura.

Posteriormente, se destaca la importancia de la solución de la PNL en LPS. Se presentan las principales técnicas heurísticas para abordar este problema complejo NP-Hard y se menciona la relevancia del GA debido a su compromiso entre diversificación e intensificación.

Luego, se analiza la caracterización de las incertidumbres del sistema para determinar la calidad de las distribuciones de los nodos a través de los Cramér-Rao Bounds, finalizando el Capítulo con la propuesta de las principales líneas de investigación de esta disertación junto con algunos de los aportes de la tesis.

El Capítulo 3 introduce la conexión entre los capítulos de investigación de esta disertación y la investigación general realizada en el campo de la localización durante el desarrollo de la tesis doctoral.

El Capítulo 4 analiza la ambigüedad matemática en el cálculo de la posición de los sistemas de arquitectura TDOA con cuatro nodos de sensor. Se propone una metodología para resolver el problema 3D TDOA con el mínimo de nodos mediante la definición de una esfera de convergencia desde la cual, cualquier punto interior puede actuar como punto de partida para la determinación de la ubicación objetivo con total fiabilidad.

El Capítulo 5 propone una metodología novedosa para lograr el rendimiento óptimo de la arquitectura TDOA en casos de mal funcionamiento de algún sensor con una reducción mínima de la precisión en condiciones de funcionamiento nominales. Además, la solución del problema TDOA 3D de 4 nodos está garantizada en condiciones de falla de cualquiera de los sensores de la arquitectura.

El Capítulo 6 presenta una estrategia rentable para el despliegue de redes de sensores asíncronos. Resuelve el problema de cobertura en casos de falla del sensor Coordinador asumiendo la optimización para condiciones primarias y secundarias (emergencia) del sistema de localización. Además, se proporciona una técnica para calcular la posición con los nodos más prometedores bajo cobertura.

El Capítulo 7 introduce una metodología para la comparación del desempeño de las Arquitecturas de Posicionamiento Basadas en mediciones Temporales más relevantes (TOA, TDOA y A-TDOA) en escenarios urbanos complejos NLOS. Esta comparación se proporciona una vez que se optimiza la distribución del sensor de cada arquitectura, ya que las configuraciones óptimas a priori no se pueden determinar directamente. Los criterios de optimización son precisión, solidez, disponibilidad y costo de cada arquitectura.

El Capítulo 8 investiga el problema de la ubicación del nodo en el campo de la localización. Proporciona una definición de la complejidad del problema y analiza las técnicas metaheurísticas que se han empleado para abordar este problema NP-Hard. Después del análisis, se propone un Algoritmo Memético Híbrido, que combina los efectos beneficiosos de los Algoritmos Genéticos en el Problema de Ubicación del Nodo junto con un Procedimiento de Búsqueda Local para examinar las potenciales regiones desfavorecidas del espacio de soluciones.

Finalmente, el Capítulo 9 brinda las observaciones finales y las futuras investigaciones derivadas de los resultados obtenidos en esta disertación.

1.4. Marco de Investigación

Este trabajo ha sido desarrollado en el grupo de investigación SINFAB de la Universidad de León bajo la supervisión de la Dra. Hilde Pérez García. El grupo ha participado en dos proyectos de investigación nacionales durante el desarrollo de la tesis: DPI2016-79960-C3-2-P del Ministerio de Economía, Industria y Competitividad de España y PID2019-108277GB-C21 del Ministerio de Ciencia e Innovación de España. Estos dos proyectos de investigación han financiado las actividades de investigación de esta tesis doctoral.

Capítulo 3

Introducción General

El desarrollo de la tecnología móvil en los sistemas tecnológicos requiere en múltiples aplicaciones la localización del usuario para proporcionar un servicio personalizado y adaptado de alta calidad. Estos sistemas acostumbran a utilizar las señales de los sistemas de navegación satelital (GNSS) para proporcionar cobertura global con un coste reducido.

No obstante, otras aplicaciones tecnológicas con elevados requerimientos de exactitud en la localización están empezando a sufrir las limitaciones de los GNSS para proveer una posición estable y con baja incertidumbre. Estos problemas se acrecientan en entornos complejos orográficos [1], en interiores de edificios [2], túneles y puentes [3,4], bajo el agua en navegación submarina o en suelos de baja cota de UAV [5]. Para mitigar estos efectos, los GNSS trabajaron en dos más: un profundo tratamiento de los errores de las señales para reducir las incertidumbres de relojes [6], ruido [7] e ionosféricas [8] y la dispersión terrestre de aumentadores que permiten reducir los errores del sistema.

De todas maneras, los sistemas GNSS fueron concebidos para proporcionar una cobertura global y la reducción de sus incertidumbres requerirán la puesta en órbita de un número mayor de satélites incrementando con ello notablemente los costes de funcionamiento. No obstante, la liberalización del uso de los sistemas GNSS a escala global ha permitido avances en este sentido mediante la fusión de sensores de posicionamiento de diferentes GNSS combinando sus señales y mejorando con ello los resultados de posicionamiento alcanzado [9]. Esto está suponiendo un importante aspecto de investigación en estos años.

Sin embargo, a pesar de todos los esfuerzos realizados por los GNSS, todavía no son capaces de alcanzar las exactitudes requeridas en algunos campos como la vigilancia, operaciones de rescate, agricultura de precisión o navegación de exteriores e interiores de vehículos autónomos. Como consecuencia, en los últimos años se han desarrollado los sistemas locales de posicionamiento (LPS) [10].

Los LPS se encuentran basados en el despliegue de sensores terrestres en los que su proximidad con respecto al target permite la reducción de la incertidumbre en el cálculo de la posición. Los LPS se clasifican en función de la propiedad física medida para determinar la localización del target: tiempo [11], potencia [12], fase [13], frecuencia [14] o ángulo [15], así como una combinación entre todas estas [16,17].

Entre los LPS, aquellos basados en mediciones temporales, proporcionan la mejor relación entre exactitud, robustez, estabilidad, facilidad de implementación de sus arquitecturas de hardware y coste. Por este motivo, en esta desertización se profundiza en el análisis de las arquitecturas temporales LPS para su implementación en aplicaciones de elevadas prestaciones.

Particularizando en las arquitecturas temporales LPS se distingue entre las arquitecturas síncronas - Time of Arrival (AOA) [18] y Time Difference of Arrival (TDOA) [19] – y las arquitecturas asíncronas – Asynchronous Time Difference of Arrival (A-TDOA) [20].

Los sistemas TOA miden el tiempo total de viaje de la señal entre un emisor y un receptor. Este tiempo puede ser convertido a través de la velocidad de vuelo de las ondas electromagnéticas (c) en una distancia entre emisor y receptor. Como el emisor puede encontrarse en cualquier lugar del espacio que se encuentre a una distancia determinada del receptor de la señal, por cada señal de posicionamiento se genera una esfera de posibles localizaciones del target en el espacio. Por ello, la resolución del problema TOA 3D requiere de al menos 3 receptores que generen 3 esferas distintas. No obstante, las condiciones de no linealidad de las ecuaciones esféricas provocan una ambigüedad con dos soluciones distintas en la intersección de 3 esferas que no puede ser resuelta desde el punto de vista matemático.

Los sistemas TDOA se basan en la medición del tiempo relativo que trascurre entre la llegada de una señal de posicionamiento a dos receptores distintos. Esta medición de tiempo relativo provoca que sólo sea necesario el sincronismo entre los relojes del sistema mientras que en los sistemas TOA se requiere el sincronismo también del reloj del target porque la medición temporal requiere el instante de emisión del pulso de posicionamiento. Mientras en los sistemas TOA se toma exclusivamente el camino entre emisor y receptor para obtener una ecuación de posicionamiento, los sistemas TDOA requieren de un par de señales para la medición de tiempos relativa. Esto produce que la resolución del problema tridimensional requiera la introducción de un sensor más y que en lugar de ecuaciones esferas se trabaje con la intersección espacial de hiperboloides. Al igual que en el caso TOA, se produce una ambigüedad matemática en el cálculo de la posición con 4 receptores que puede resolverse en sistemas LPS a través de la metodología introducida en el capítulo 4 de esta disertación [21].

Los sistemas A-TDOA eliminan la necesidad de sincronismo de los relojes del sistema mediante una estrategia de recepción y retransmisión de los pulsos de posicionamiento en el TS. Esto permite procesar todas las mediciones temporales en un único sensor coordinador reduciendo con ello las incertidumbres de las mediciones temporales. Esta particularidad los ha hecho especialmente prometedores para aplicaciones LPS como consecuencia del importante peso de la incertidumbre de la medición temporal en los errores de los LPS. Las arquitecturas A-TDOA producen ecuaciones de elipsoides [22] cuya intersección requiere de 4 ecuaciones y 5 sensores para resolver completamente el problema desde un punto de vista matemático.

Precisamente, la necesidad de resolver ecuaciones no lineales ha dado lugar a múltiples algoritmos de posicionamiento en la literatura. En general, pueden clasificarse en algoritmos cerrados y algoritmos iterativos. Los algoritmos cerrados [23] permiten una resolución directa del problema de posicionamiento, pero son más inestables a la incertidumbre generada en el proceso de medición temporal de las señales de posicionamiento. Por el contra, los algoritmos iterativos [24] permiten el tratamiento del error de las señales, pero dependen íntimamente de la posición de partida de las iteraciones que conducen a la posición espacial del target pudiendo llegar a tener incluso problemas de convergencia si la posición de partida se encuentra muy alejada de la posición final de las iteraciones.

Sin embargo, sea cual sea la arquitectura de posicionamiento empleada y los algoritmos utilizados para el cálculo de la posición, la distribución espacial de los sensores de cada arquitectura es esencial para reducir las incertidumbres de posicionamiento de los LPS.

Este problema, que requiere la optimización de la distribución espacial de los sensores, ha sido denominado como el problema de localización de nodos (NLP) y ha sido asignado como NP-Hard [25] por lo que se recomienda el empleo de metodologías heurísticas para su resolución. Como consecuencia, el recocido simulado [26], el algoritmo de luciérnaga [27], el algoritmo de enjambre de delfines [28], el algoritmo de búsqueda bacterial [29], la optimización por pastoreo de elefantes [30], búsqueda local diversificada [31] pero especialmente los Algoritmos Genéticos (GA) [32-34] destacan en la resolución de este problema por su compromiso entre diversificación e intensificación del espacio de soluciones. En esta disertación, en el Capítulo 8, se añaden los algoritmos meméticos como una técnica prometedora para el NLP en entornos complejos que incluyen sin línea de visión (NLOS) en los que se producen discontinuidad en la evaluación de la función de adaptación entre soluciones contiguas generan dos regiones desfavorecidas de exploración del espacio de soluciones.

Estas esenciales optimizaciones del NLP requieren de una función que determine la calidad de las distribuciones de balizado para reducir la incertidumbre de relojes y ruido de cada sistema y potenciar las propiedades de disponibilidad y robustez de las arquitecturas de posicionamiento. Para ello, los LPS demandan una caracterización heterocedástica del ruido de la señal que se modela en la matriz de covarianzas de la Cota Inferior de Cramér Rao (CRLB) [35,36]. Esta modelización es flexible y nos ha permitido introducir el ruido de la señal en condiciones LOS y NLOS junto a la incertidumbre de los relojes. La minimización de la CRLB se corresponde con la menor incertidumbre en el cálculo de la posición alcanzable por cualquier algoritmo de posicionamiento y no puede ser derivada conjuntamente en todos los lugares de cobertura de las arquitecturas LPS [37]. Como consecuencia, la utilización de la CRLB como criterio de optimización del NLP también aconseja el empleo de metodología metaheurística para la resolución del problema.

Toda esta caracterización de las incertidumbres de los LPS en conjunto con la optimización de la distribución de balizado de cada arquitectura son empleadas en esta disertación para extraer conclusiones de implementación y despliegue de los LPS en condiciones reales de operación.

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Capítulo 4

Evolución de la línea de investigación y enlace entre artículos

Los estudios de investigación presentados en esta disertación son parte de las investigaciones desarrolladas en el grupo de investigación SINFAB de la Universidad de León. El objetivo de este capítulo es clarificar la unión entre los siguientes capítulos (4-8) y dar una visión general de la evolución de las actividades de investigación llevadas a cabo en los últimos años.

La investigación comenzó con la conceptualización de la posible implementación de los Sistemas de Posicionamiento Local (LPS) para la navegación guiada de los emergentes vehículos autónomos. Las necesidades de exactitud de estos sistemas has sugerido el despliegue de una red de sensores para la mejora de los resultados de exactitud de los GNSS.

Los primeros pasos de estas investigaciones demandaban el análisis de las particularidades de los LPS con respecto a los GNSS. Uno de los primeros descubrimientos fue que la determinación de la posición con el menor número de sensores presentaba una elevada complejidad en los LPS con respecto a los GNSS. Mientras la ambigüedad en el cálculo de la posición con 3 satélites en los sistemas de tiempo de llegada (TOA) y los sistemas de diferencias de tiempo de llegada (TDOA) había sido resuelta tradicionalmente mediante la eliminación de la solución incoherente (e.g. una de las dos posibles soluciones se encontraba tradicionalmente fuera de la superficie terrestre, por debajo de la tierra o extremadamente separada de la última posición conocida de un vehículo), en los LPS la reducida separación entre las soluciones no permitía la resolución directa de este escenario adverso.

Como consecuencia, se desarrolló una metodología basada en los principios de un algoritmo de posicionamiento iterativo para la resolución del problema mínimo de sensores en arquitecturas TDOA en el Capítulo 4 [1]. Esta metodología demostró que en distribuciones de sensores optimizadas en las que se maximice la distancia entre las dos soluciones, el problema tridimensional TDOA con cuatro receptores presenta unas propiedades análogas a otros en los que más sensores se encuentren disponibles en los que la desambiguación en la determinación de la posición se consigue de manera directa. En primer lugar, la búsqueda de la distribución optimizada de sensores fue analizada en configuraciones de redes de sensores siguiendo patrones regulares, encontrando que la mejor combinación de sensores en el espacio para resolver este problema no sigue ningún patrón de diseño. Justo en este instante, descubrimos el problema de localización de nodos en redes de sensores (NLP) que ha sido designado como NP-Hard y sugiere el empleo de técnicas metaheurísticas para abordar este complejo problema.

En este contexto, dirigimos nuestra investigación para descubrir la relación entre la distribución espacial de sensores con las propiedades principales de los LPS: determinación de las incertidumbres del cálculo de la posición, disponibilidad del sistema y robustez.

Aunque, tradicionalmente, las incertidumbres de ruidos de la señal relacionadas con la disposición geométrica relativa entre el vehículo y los satélites en los GNSS se han modelado a través de la dilución de la posición (PDOP), el PDOP se encuentra basado en una consideración del error homocedástica ya que las señales viajan caminos similares entre los satélites y el objetivo de posicionamiento en los GNSS. Este no es el caso para los LPS en los que la señal de posicionamiento viaja a través de caminos que difieren significativamente entre los diferentes sensores de la arquitectura. Como consecuencia, definimos una consideración heterocedástica del ruido para las arquitecturas temporales LPS basada en un modelo de pérdidas de propagación Log-Normal que especialmente cubre las características de los escenarios de aplicación de los LPS. Posteriormente, aplicamos este modelo a la comparación de las incertidumbres de ruido de las dos principales arquitecturas asíncronas introducidas en los últimos años (Diferencia Asíncrona de las Diferencias de Tiempo de la Llegada de la Señal -A-TDOA- y Diferencia Temporal de las Diferencias de Tiempo de Llegada de la señal -D-TDOA-) que han mostrado una excelente adaptación en aplicaciones LPS [].

Las dos arquirtecturas fueron comparadas en cinco distribuciones de sensores mostrando la arquitectura A-TDOA mejor exactitud y estabilidad en aplicaciones LPS.

El análisis de las arquitecturas asíncronas fue seleccionado ya que la eliminación del sincronismo necesario entre los relojes del vehículo y los de la arquitectura en los sistemas TOA y el de los relojes de la arquitectura en los TDOA representan una parte relevante del error global de estos LPS.

Sin embargo, el análisis del error de las arquitecturas asíncronas fue llevado a cabo en entornos regulares de simulación en los que la mejor combinación de los sensores de las arquitecturas no fue probada. Por ello, desarrollamos una metodología metaheurística para encontrar despliegues optimizados de sensores en escenarios irregulares de simulaciones. Creamos con ello un entorno para simular cualquier escenario irregular real de aplicación de los LPS. En estos escenarios, se distingue entre la zona para la navegación de los vehículos, Target Location Environment (TLE) y la de posibles localizaciones de los nodos de la arquitectura, Node Location Environment (NLE).

Esta distinción es de especial aplicación en los LPS, lo que supone la principal diferencia con las optimizaciones de las redes de sensores Wireless ya que las posibles localizaciones del vehículo deben ser consideradas conjuntamente en el proceso de optimización. Además, esta particularidad hace que la caracterización del error del artículo [2] no pueda ser derivada para el TLE de forma completa, recomendando por ello de nuevo una aproximación heurística al problema para encontrar distribuciones optimizadas de sensores.

Como consecuencia, aplicamos la caracterización del ruido introducido en el artículo [2] en la matriz de covarianzas de la Cota Inferiror de Cramér Rao (CRLB) ya que proporciona el menor error alcanzable por cualquier algoritmo de posicionamiento empleado en el cálculo de la posición para caracterizar la calidad de una distribución de sensores en un Algoritmo Genético (GA) en el que se incluye una definición irregular del escenario de simulaciones para una arquitectura A-TDOA.

Los resultados mostraron que mejoras significativas en la exactitud de los LPS podían alcanzarse mediante la optimización de distribuciones de sensores en escenarios irregulares. Sin embargo, estas optimizaciones consideraban exclusivamente el desempeño de los LPS en condiciones de operación nominales (i.e. aquellas en las que todos los sensores de la arquitectura funcionan correctamente). Esto podría provocar que un fallo eventual en alguno de los elementos del sistema podría promover que el sistema completo podría instantáneamente incrementar sus errores provocando la pérdida de utilidad de los LPS en estas condiciones.

Propusimos por ello una metodología en [4] (Capítulo 5) para el funcionamiento mejorado de los LPS en condiciones de fallo para optimizar el funcionamiento del sistema para cada combinación de sensores que exceda el mínimo número de nodos requerido en cada punto analizado del TLE de la optimización. Además, garantizamos la operación del sistema para el mínimo número de sensores a través de la maximización de la esfera de convergencia de [1] para cada combinación de cuatro sensores en cobertura de una arquitectura TDOA. Los resultados mostraron que las optimizaciones que consideran condiciones de emergencia (i.e. con posibles fallos de sensores) se comportan de manera similar a las optimizaciones nominales tradicionales, pero mejoran significativamente el comportamiento en condiciones de fallo [5].

Sin embargo, las incertidumbres en el cálculo de la posición se encuentran notablemente afectadas por los errores cometidos en las mediciones temporales de las arquitecturas LPS además del ruido de la señal previamente definido. Esto nos llevó a la caracterización del ruido de los relojes en la matriz de covarianzas de la CRLB. Generamos un modelo en el que el clock drift, initial-time offset y los errores de truncamiento del sistema fueron considerados [6]. Este modelo permite la comparación de las tres principales arquitecturas temporales LPS con una consideración de ruido [2] y el modelo de definición del error de los relojes de [6] en distribuciones optimizadas de sensores en escenarios irregulares de simulaciones [3]. Los resultados mostraron que las arquitecturas asíncronas son más estables en condiciones de línea de visión (LOS) que las arquitecturas síncronas como consecuencia de la eliminación de las necesidades de sincronismo.

Sin embargo, los resultados no fueron concluyentes ya que las arquitecturas asíncronas demandas la estrategia de recibir y retransmitir en las señales de posicionamiento incrementando con ello el camino de la señal. Como consecuencia, un incremento en la incertidumbre de ruido se produce, lo que puede afectar al comportamiento asíncrono de los LPS en escenarios sin línea de visión (NLOS) donde se producen degradaciones significativas de las señales, incrementando con ello la probabilidad de sufrir efectos adversos en las señales como el multipath.

Por ello, incluimos los caminos NLOS en la caracterización del ruido de la CRLB de la arquitectura A-TDOA del modelo del [2] con la extensión del modelo de pérdidas de propagación Log-Normal en [7]. Esto requirió el desarrollo de un nuevo algoritmo para distinguir los caminos LOS y NLOS de vuelo de la señal de posicionamiento. También incluimos un algoritmo para la detección de los fenómenos de multipath basados en la definición del elipsoide de la zona Fresnel en el que se producen interferencias destructivas del canal de comunicaciones y el elipsoide que contiene el espacio 3D alrededor del emisor y el receptor de la señal de posicionamiento donde un objeto podría producir una señal que no podría distinguirse del camino LOS (i.e el que se usa para las mediciones temporales).

La creación de estos dos algoritmos promovió el empleo de una optimización multiobjetivo para lograr la minimización de las incertidumbres del sistema y la eliminación del fenómeno de multipath en escenarios irregulares.

Los resultados de [7] indicaron que se trata de una técnica óptima para determinar el número de sensores adecuado de cada arquitectura para eliminar los fenómenos adversos que se producen en las señales de posicionamiento y par la minimización de la incertidumbre en el cálculo de la posición. Sin embargo, esta optimización mostró la dependencia de la arquitectura A-TDOA sobre sus sensores coordinadores (CS) ya que son los que procesan las señales de todos los sensores trabajadores (WS) para la medición de tiempos del sistema. Esto promueve que una localización subóptima de los CS incrementa en mayor medida las incertidumbres de la arquitectura de lo que lo hace la localización de los WS. Además, la optimización encontró problemas para lograr la colocación de los CS lo que potencialmente podría ocasionar una pérdida temporal de disponibilidad de la arquitectura en la que algunos puntos en caso de fallo de un CS podrían quedar fuera de la cobertura del sistema.

Con ello, nos dimos cuenta de la importancia de la optimización de las arquitecturas asíncronas considerando tanto situaciones nominales de operación como condiciones de emergencia como en el procedimiento detallado en el Capítulo 5 [4] considerando posibles fallos de los CS. Además, encontramos en [7] que el total de sensores en cobertura no tiene por qué producir los mejores resultados de exactitud de la arquitectura como consecuencia de degradaciones desbalanceadas de las señales de posicionamiento en entornos NLOS. Esta conclusión sugiere la investigación en la mejor combinación de sensores para el cálculo de la posición de los vehículos. Además, el proceso evolutivo seguido en [7] indicó que la convergencia del GA para solucionar el problema de cobertura en localización asíncrona fue difícil de tratar sin inducir penalizaciones en los valores de adaptación de los individuos de la población. Como consecuencia, las distribuciones de sensores en las que no se alcanza el mínimo número de sensores que sobrepasan el SNR_{min} son significativamente penalizadas para guiar el proceso evolutivo para encontrar combinaciones de sensores válidas.

Cada una de estas consideraciones previas fueron posteriormente consideradas para construir una metodología de despliegue de los LPS asíncronos temporales en el Capítulo 6 [8]. Propusimos una optimización reforzada en condiciones primarias y secundarias (i.e. posibles fallos de sensores coordinadores) garantizando al menos dos CS disponibles en todas las regiones del TLE. Además, encontramos en [8] la configuración óptima de sensores para calcular las incertidumbres en la determinación de las coordenadas del vehículo a través de un modelo CRLB que combina las condiciones LOS y NLOS para la caracterización del ruido de [7] y las incertidumbres de reloj de [6].

Esta metodología solventa el principal problema de los LPS asíncronos ya que la falta de disponibilidad de los CS produce la discontinuidad temporal en el cálculo de la posición. Además, los resultados indicaron la idoneidad de las metodologías asíncronas para las aplicaciones LPS ya que la reducción de los errores de los relojes mediante la eliminación del sincronismo tiene un impacto relevante en la reducción de las incertidumbres del sistema.

Sin embargo, la reducción efectiva de las incertidumbres requiere en los LPS asíncronos el despliegue de una cantidad considerable de CS ya que al menos dos de ellos han de estar siempre en cobertura y la localización de esos sensores es crítica ya que deben eliminar las conexiones NLOS con las señales de posicionamiento y reducir considerablemente los efectos del fenómeno multipath. Esta conclusión promueve que entornos especialmente singulares con irregularidades en el terreno en las que se desplieguen los LPS asíncronos pueden suponer un incremento relevante de los CS requeridos para alcanzar resultados válidos, incrementando con ellos los costes del sistema.

Como consecuencia, el profundo estudio de los escenarios de aplicación de los LPS es un requerimiento para determinar la arquitectura óptima temporal para adaptarse de una forma particular a las condiciones del escenario de simulaciones. Esta conclusión se encuentra también basada en las diferentes características de las principales arquitecturas temporales (TOA, TDOA y A-TDOA).

Los sistemas TOA acumula los mayores errores de reloj ya que requieren la sincronización entre todos los elementos del sistema pero acumula los menores errores de las incertidumbres del ruido de la señal ya que la señal de posicionamiento sólo viaja entre emisor y receptor para producir una ecuación de posibles localizaciones espaciales del vehículo.

Los sistemas TDOA tienen una distribución equilibrada de las incertidumbres. Suponen una reducción del ruido de los relojes del sistema ya que eliminan el sincronismo con el vehículo como sucede en los sistemas TOA pero no alcanzan la completa falta de sincronismo como en los sistemas A-TDOA. Sin embargo, los sistemas TDOA incrementan los errores de ruido con respecto a los sistemas TOA ya que para computar una medición temporal requieren dos señales de posicionamiento diferentes entre un emisor y dos receptores distintos acumulando con ello el ruido de las dos señales. Pero estos errores de ruido se reducen con respecto a los sistemas A-TDOA en los que la estrategia de recepción y retransmisión de las señales de posicionamiento incrementa en mayor medida el camino de la señal que en el caso TDOA.

Por ello, los sistemas A-TDOA proporcionan el menor de los errores de reloj, pero con la mayor acumulación de ruido de todos los sistemas. Además, la dependencia de estos sistemas del CS debe ser equilibrada por una correcta disposición espacial de los sensores pudiendo sufrir en escenarios especialmente irregulares.

Por ello, no podemos definir ninguna arquitectura perfecta a priori para las aplicaciones LPS y no ha existido en la literatura ninguna aproximación a este problema previamente. Como consecuencia, hemos creado en el Capítulo 7 [9] una nueva metodología para comparar el desempeño de las tres principales arquitecturas temporales LPS (TOA, TDOA y A-TDOA). Esta metodología incluye la exactitud del sistema y el compartimiento estable y robusto de las arquitecturas considerando sus particularidades durante el proceso de optimización de sus distribuciones de sensores.

Aplicamos el modelo de pérdidas de propagación Log-Normal en condiciones LOS [2] y NLOS [7] y la caracterización de los errores de reloj [6] en la CRLB de cada arquitectura y usamos la metodología de [4,5] para considerar posibles fallors de los CS asegurando el funcionamiento óptimo de cada arquitectura en [9].

También hacemos uso de la metodología de [8] para guiar el proceso de optimización para encontrar la distribución óptima de sensores en el espacio que produzca la mejor combinación de exactitud, disponibilidad y robustez de cada sistema. Esto crea un marco óptimo para comparar los LPS basados en medidas temporales en escenarios urbanos complejos. Esto ha requerido la modelización de los obstáculos sobre el la caracterización del terreno de [3] que incrementa a las áreas TLE y NLE una nueva región de obstáculos (OA) donde no se pueden situar ni las balizas ni los vehículos.

Por otra parte, la relevancia de la resolución del problema NLP en LPS ha quedado patente a lo largo de la investigación presentada en este capítulo. Consecuentemente, encontrar distribuciones de sensores optimizadas es una actividad crítica para las aplicaciones ad-hoc LP. Dado que se trata de un problema NP-Hard, las metodologías heurísiticas han destacado para proporcionar distribuciones optimizadas de sensores. Los GA, como se muestra en [3], han demostrado su relevancia por su balance entre diversificación e intensificación del espacio de soluciones del problema NLP y por lo tanto han prevalecido en la literatura.

Sin embargo, hemos observado en [7-9] que las optimizaciones del NLP en las que se consideran condiciones NLOS, producen un comportamiento inestable de los algoritmos evolutivos. Esto se debe a la discontinuidad que se produce en las evaluaciones de la función de adaptación entre soluciones contiguas (i.e. distribuciones de sensores que mínimamente se diferencian en las coordenadas de un sensor de la arquitectura) lo que complica el análisis de algunas regiones del espacio de soluciones, no siendo suficiente con la mutación y los operadores de cruce para explorar estas regiones desfavorecidas.

En primer lugar, intentamos eliminar este problema mediante configuraciones híbridas en los operadores genéticos que cambiaban a lo largo del proceso evolutivo [10]. Esto nos permitió crear dos etapas distintas en la optimización del GA: una exploración profunda seguida por una fase de fuerte intensificación. Se analizaron diferentes configuraciones de cruce y mutación para el escenario de simulaciones proporcionado probando la prevalencia de esta técnica para alcanzar mejores resultados de optimización que las configuraciones individuales [3].

Sin embargo, esta metodología se encuentra limitada al escenario de simulaciones en el que se lleva a cabo el proceso de optimización. Consecuentemente, los resultados alcanzados por esta técnica en [10] no son aplicables a cualquier escenario LPS. Por ello, consideramos una técnica de optimización diferente que pudiese aplicarse a cualquier escenario mejorando los resultados del GA en condiciones de discontinuidad en entornos complejos.

Como consecuencia, en el Capítulo 8, un Algoritmo Memético (MA) para el NLP en localización es propuesto [11]. Este MA combina el GA con un procedimiento de búsqueda local (LS) para explorar regiones potencialmente desfavorecidas del espacio de soluciones y para mejorar las características de los individuos elitistas alcanzando una mejora del proceso evolutivo.

La búsqueda local mediante la técnica del vecindario variable (VND) se aplica a los individuos de la población más diferentes para explorar espacios de soluciones distintos. La selección de los individuos más diferentes se lleva a cabo mediante métricas de disimilitud entre los individuos de la población.

Una de las contribuciones más relevantes de la LS es la aplicación de un pseudo función de adaptación que confía en la variación mínima de los errores geométricos y de reloj en las vecindades de un individuo. Con esto, la reducción de las conexiones NLOS entre los sensores de la arquitectura y el vehículo concierne al procedimiento de LS para mejorar los individuos del MA. Encontrar los individuos más apropiados de las vecindades siguiendo este proceso permite la intensificación en esos espacios de una manera que no puede efectuarse a través de la optimización genética.

Los resultados mostraron que la combinación de un uso híbrido reforzado de los operadores genéticos como en [10] y el MA propuesto en [11] sobresalen sobre las configuraciones heurísticas previas, alcanzando una mejora en la exactitud de la arquitectura A-TDOA de un 14% con respecto a las optimizaciones exclusivamente genéticas de [3].

En la actualidad se está realizando más investigación en este campo para encontrar el número óptimo de sensores directamente en el proceso evolutivo, la aplicación de diferentes aproximaciones heurísticas al NLP, la definición de patrones para el despliegue de LPS en aplicaciones de larga escala, la consideración de nuevas arquitecturas asíncronas e implementaciones reales de los LPS que permitan la validación de los modelos de la CRLB. Esto se encuentran particularmente detallado en el Capítulo 9 con las investigaciones futuras que pueden derivarse de esta disertación.

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Capítulo 5

Conclusiones

Esta tesis presenta un análisis extenso de los Sistemas de Posicionamiento Locales basados en medidas Temporales. Estos sistemas son prometedores para el desarrollo de aplicaciones de precisión con alta demanda en campos como navegación autónoma, operaciones de rescate, vigilancia, localización subacuática, localización en túneles e interiores, agricultura o vigilancia. La implementación de LPS requiere un despliegue ad-hoc de sensores que se ajusten a las características del entorno de aplicación y exige un amplio conocimiento del espacio de localización para lograr despliegues óptimos con el objetivo de cumplir con los requisitos de diseño.

En esta tesis se ha estudiado la obtención de un despliegue optimizado y rentable de sensores en LPS con las siguientes conclusiones finales:

- ❖ La solución del problema LPS con el número mínimo de sensores requiere una distribución de sensores optimizada en el espacio de sensores.
- ❖ La desambiguación del cálculo de la posición de LPS con el número mínimo de sensores exige obtener una esfera de convergencia en la que sus puntos interiores puedan actuar como punto de partida de un algoritmo iterativo, consiguiendo una determinación de la posición con total confianza.
- ❖ En el problema LPS con el número mínimo de sensores, la esfera de convergencia tiene una relación directa con la distancia entre las soluciones ambiguas.
- ❖ La desambiguación en el cálculo de la posición en LPS se produce mediante la maximización de la distancia entre las soluciones ambiguas. Esta distancia debe exceder un umbral que ocurre naturalmente en GNSS y debe ser inducida en LPS.
- ❖ Las optimizaciones tradicionales sobre la ubicación de los nodos en LPS no han considerado eventuales fallas de sensores. Esto ha promovido que el desempeño del LPS en condiciones de emergencia haya disminuido instantáneamente con respecto a las condiciones nominales de operación sin fallas.

- Se puede lograr un rendimiento estable del LPS en condiciones críticas mediante optimizaciones que se consideren en condiciones de emergencia. Los resultados han demostrado que se producen reducciones mínimas en el rendimiento nominal de LPS al considerar posibles condiciones de falla en los sensores de la arquitectura, mientras que el rendimiento en condiciones de emergencia se mejora notablemente.
- La principal desventaja de los sistemas LPS asíncronos es su dependencia con el CS para el cálculo de la posición. Esto puede motivar la carencia de disponibilidad para la arquitectura en condiciones de fallo de CS, provocando la incapacidad de convergencia en ciertas regiones del TLE.
- Esta consideración ha de ser contemplada en el proceso de optimización para permitir la cobertura de al menos dos CS diferentes en cada punto del TLE analizado. De la misma forma, se precisa que la optimización de la posición de los sensores en arquitecturas asíncronas deba mejorar las prestaciones del sistema con los CS principales y secundarios bajo cobertura.
- La implementación de todas las arquitecturas de los sensores que exceden el SNR_{min} pueden no producir la menor incertidumbre en el cálculo de la posición en condiciones NLOS. Esto es debido al desequilibrio de las distribuciones del error a lo largo de las arquitecturas de los sensores. En consecuencia, la búsqueda de la mejor combinación de arquitecturas de nodos para obtener la posición del vehículo es requerida en condiciones NLOS para aplicaciones LPS.
- Los LPS asíncronos pueden requerir la introducción de un gran número de CS, especialmente en regiones adversas con escenarios irregulares, incrementando así los costes del sistema.
- La caracterización de los LPS basados en mediciones temporales ha ocasionado que no exista una arquitectura prevalente para cualquier aplicación de precisión a priori. En consecuencia, una comparación objetiva de las prestaciones de cada arquitectura ha de realizarse para cada escenario de aplicación.
- Esta comparación ha de considerar la precisión, robustez, disponibilidad y costes de implementación del sistema para extraer válidas conclusiones en la implementación de cada arquitectura.

- ❖ La solución del NLP es esencial para la aplicación de cualquier LPS. Este problema es especialmente complejo para ser resuelto en condiciones NLOS con amplios espacios de soluciones. Esto se debe a la discontinuidad en la evaluación de la función de adaptación a lo largo de soluciones contiguas. Como consecuencia, la dificultad de la intensificación durante el proceso evolutivo seguido en el NLP, mejora significantemente la aparición de regiones desfavorecidas en el espacio de soluciones.
- ❖ La implementación de procedimientos de LS en los individuos más diferentes de la población total usada en la solución al NLP ha demostrado cierta mejoría respeto a las técnicas metaheurísticas, así como el GA aplicado al NLP:
- ❖ La LS en el NLP puede implementar una pseudo-función de adaptación que puede considerar exclusivamente la reducción del recorrido de las señales de posicionamiento -especialmente en el caso de conexiones NLOS- ya que los errores geométricos y de reloj en las vecindades permanecen prácticamente constantes.
- ❖ El efecto combinado de la LS con el uso adaptativo de los operadores genéticos permite la mejora en la resolución del NLP alcanzando mejores resultados con respecto a las aproximaciones exclusivamente genéticas empleadas en la literatura.

Capítulo 6

Líneas Futuras

Esta disertación ha presentado el progreso en la investigación de los LPS que se ha producido en el grupo de investigación SINFAB de la Universidad de León en los últimos años. Aun así, multitud de investigaciones pueden desarrollarse derivadas de los trabajos de esta tesis:

- Implementación real de los LPS para validar los modelos de ruido y relojes utilizados en las optimizaciones de las distribuciones de balizado. Se harán investigaciones en la tecnología UWB para probar el comportamiento de los LPS temporales.
- Optimización de la distribución de los sensores de arquitecturas LPS en interiores para la navegación guiada de vehículos autónomos terrestres (AGV) que colaboren en actividades manufactureras de la Industria 4.0.
- Implementación de diferentes metaheurísticas para el problema de nodos de posicionamiento tratando de mejorar los resultados de exactitud en escenarios especialmente adversos con condiciones NLOS.
- Solución del problema NLP con un número variable de sensores durante el proceso evolutivo. Esto requiere abordar el problema genético multicadena a través de la definición de nuevos operadores de selección, cruce y mutación aplicados a distribuciones de sensores variables. Esto permite la resolución de un único problema NP-Hard para *n* diferentes números de sensores.
- Investigación en distribuciones de sensores modulares para aplicaciones de LPS de larga escala. La definición de escenarios de grandes dimensiones para la aplicación de los LPS incrementa el requerimiento del número de sensores de tal manera que provoca que el NLP sea extremadamente NP-Hard para ser abordado en una única optimización evolutiva.
- Investigación en nuevas arquitecturas LPS asíncronas que reducen la dependencia del vehículo en la retransmisión de la señal de posicionamiento.
- Desarrollo de despliegues de sensores efectivos desde el punto de vista energético en LPS temporales lo que potencia la reducción del consumo energético

de los vehículos aéreos no tripulados (UAV) para incrementar su autonomía de navegación.

- ❖ Definición de puntos de máxima convergencia para la inicialización de algoritmos iterativos de posicionamiento.
- ❖ Implementación de métodos que permitan la ponderación de la matriz de mínimos cuadrados en condiciones reales de operación de los LPS basados en el conocimiento que se obtiene a priori a través de la caracterización de las incertidumbres proporcionada en esta disertación.