

Motion-Induced Bias in UWB Asynchronous TWR: Modeling, Analysis, and Implications

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Motion-induced uncertainties fundamentally limit the performance of asynchronous two-way ranging (TWR) localization systems, yet existing literature lacks a unified definition and characterization of these uncertainties for TWR methods. This work introduces a comprehensive characterization of motion-induced errors in TWR, establishing explicit analytical relationships between target velocity, message timing asymmetries, and the resulting ranging error. Using this formulation, four widely adopted TWR methods, single-sided TWR (SS-TWR) and symmetric double-sided TWR (SDS-TWR), each evaluated under sequential and parallel reply schemes, are assessed and compared within an optimized deployment framework derived from the spatial Cramér–Rao bound. The analysis reveals that sequential methods, commonly implemented in commercial ultra-wideband devices, offer the best performance under static conditions but degrade rapidly with motion due to accumulated timing asymmetries. In contrast, parallel configurations remain largely unaffected by velocity but are constrained by longer cumulative reply times in larger networks. Furthermore, SDS-TWR is found to be consistently more sensitive to motion than SS-TWR despite its superior correction of

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clock drift. The proposed framework provides the first systematic basis for quantifying motion effects in asynchronous TWR and offers practical guidelines for selecting and deploying ranging strategies in dynamic environments.

I. INTRODUCTION

Ultra-wideband (UWB) technology has become a key enabler for high-accuracy indoor localization, offering strong robustness against multipath and non-line-of-sight (NLOS) propagation and enabling reliable ranging in complex environments [1], [2], [3]. Modern commercial UWB chipsets typically implement asynchronous two-way ranging (TWR) protocols, most commonly single-sided (SS-TWR) and symmetric double-sided (SDS-TWR), as defined in the IEEE 802.15.4z standard [4]. These methods mitigate synchronization requirements by relying on timestamping and round-trip delay measurements, and consequently dominate practical deployments in industrial mobile robots, autonomous platforms, and other dynamic agents requiring self-positioning capabilities [5], [6], [7], forming a fundamental pillar of the hyperconnected industrial ecosystem where reliable, low-latency localization is essential for coordinated and autonomous operation [8], [9].

Despite their widespread adoption, the accuracy of asynchronous TWR systems is fundamentally constrained by timing inconsistencies, such as clock drift, timestamping noise, and reply-time asymmetries [10], [11], [12]. These error sources have been extensively characterized under static conditions in recent literature, including complete formulations for line-of-sight (LOS)/NLOS noise, multipath, and clock-induced uncertainties [13], [14], [15], [16].

However, the influence of target motion on asynchronous TWR ranging has not yet been formally defined, analyzed, or quantified, even though commercial systems routinely operate in scenarios where the target moves during the ranging sequence. Existing studies involving mobile targets either evaluate movement qualitatively or under constrained speed ranges [17], [18], [19], or propose alternative protocols under idealized timing conditions without clock drift or timestamp noise [20], [21]. Importantly, no prior formulation describes how motion interacts with reply-time asymmetries, sequential measurement acquisition, or protocol-dependent timing structures in conventional SS-TWR and SDS-TWR [22].

Target motion introduces two distinct effects. The first is the geometric displacement during the measurement interval, which can often be compensated by filtering or kinematic estimation [23], [24]. The second, critical for asynchronous TWR, is the temporal incoherence between transmission and reception timestamps, as the true target position varies during the inevitable reply delays. This effect becomes tightly coupled with the ranging strategy: sequential implementations accumulate timing offsets across sensors, whereas parallel implementations require increasing reply times to avoid collisions [25], [26]. As a result, velocity-induced uncertainties cannot be properly characterized without jointly modeling the TWR protocol and its

implementation strategy, yet this interaction has remained unaddressed in all prior work.

To fill this gap, this work presents a unified analytical characterization, which to the best of our knowledge has not been addressed in prior UWB literature, of motion-induced ranging errors in conventional SS-TWR and SDS-TWR, explicitly modeling how velocity interacts with reply-time asymmetries, clock drift, and measurement noise. Building upon established Cramér–Rao bound (CRB)-based uncertainty formulations and node-distribution optimization frameworks [13], [14], [16], [26], we derive new expressions that quantify the dynamic error contributions for both sequential and parallel ranging strategies. Using these models, we evaluate each method within an optimized sensor-deployment framework [26], [27] ensuring a fair comparison across implementations, sensor densities, and target velocities.

Building on our previously devised CRB-based uncertainty framework [13], [14], [22], the black widow optimization (BWO)-based deployment optimiser [26], [28], and the 3-D ray-traced indoor scenario model [15], the specific contributions of this work are as follows.

- 1) A complete analytical formulation of motion-induced uncertainties in SS-TWR and SDS-TWR, capturing the interaction between velocity, reply-time structures, and clock drift.
- 2) A comparative evaluation of sequential and parallel TWR implementations, including their scalability and sensitivity to velocity-dependent degradation.
- 3) A performance analysis under realistic 3-D deployment scenarios, revealing conditions where traditional sequential TWR approaches suffer severe loss of accuracy in dynamic environments.

The rest of this article is organized as follows. Section II reviews prior work on motion in UWB ranging and contextualizes the contribution against dynamic-ranging studies in adjacent domains. Section III formalizes the motion-induced error in asynchronous TWR and distinguishes it from the trivial geometric displacement during the localization window. Section IV derives the motion-aware CRB characterizations for SS-TWR, SDS-TWR (both in sequential and parallel implementations), and time difference of arrival (TDoA). Section V introduces the evaluation scenario, the BWO-based deployment optimization framework, and the network parameters used in the comparison. Section VI reports the comparative performance across velocities and sensor counts, together with a spatial analysis of the motion-induced uncertainties. Finally, Section VII concludes this article.

II. RELATED WORKS

Target movement is a well-known source of localization inaccuracy across most positioning systems. Variations in the actual target position during the localization process inherently increase positioning error. In certain protocols, however, this effect is further amplified besides the trivial

position displacement. Changes in the actual target location during specific stages of the protocol, such as response delays, introduce additional errors due to the lack of consistency among gathered measurements referenced to a wrongly presumed true static location.

While velocity compensation algorithms can be employed to reduce the discrepancy between the initial location and the actual location [18], the collection of temporally misaligned measurements caused by the variation of the true location during the protocol remains a critical source of error [29].

Multiple studies have highlighted increase positioning errors in UWB localization methods when tracking moving targets [11], [17]. However, most of these works do not specify the actual target speed profile used during the experiments, which limits the ability to quantitatively assess the influence of movement on localization accuracy.

Among those works that do report target velocity, the evaluated speeds are typically equivalent to or lower than human walking pace [18], or limited to low-dynamic motion where the target moves only mildly during the measurement sequence [19]. As a result, the findings have limited relevance to applications involving faster-moving targets, such as industrial ground vehicles [8], autonomous aerial vehicles (AAV) [28], or other dynamic agents in both indoor and outdoor environments [25].

Some theoretical studies have acknowledged the influence of target motion in the characterization of positioning errors. For instance, Ayman Shalaby et al. [20] analyzed this error source in the context of an alternative protocol to the DS-TWR method defined in the IEEE 802.15.4z standard [4]. Their findings suggest that, under constant-speed motion, target movement does not introduce additional positioning errors in their proposed protocol. However, this conclusion is only valid in the absence of clock offsets, clock skews, timestamping noises, and other common sources of errors, such as multipath and NLOS interference, thus limiting this conclusion to ideal conditions.

Dynamic ranging has also been extensively studied in interaircraft, vehicle-to-vehicle, and intersatellite links. In those domains, however, motion enters the measurement primarily through carrier Doppler and range-rate, and the system architectures address it accordingly—through synchronized or simultaneous ranging schemes and motion-aware waveform design—so that the bias accrued during a reply interval is either structurally eliminated or negligible relative to the system accuracy class. In IEEE 802.15.4z asynchronous TWR [4], by contrast, clocks are free-running, reply times are set by hardware turnaround constraints, and carrier-frequency-offset correction compensates clock drift but not target displacement, so the timing bias induced by motion during the reply intervals—the effect characterized in this work—becomes the dominant motion-related error source.

To the best of the authors' knowledge, no prior studies have comprehensively analyzed or characterized

the influence of target movement on conventional UWB ranging protocols (e.g., SS-TWR, SDS-TWR, and TDoA). Previous works have primarily focused on static scenarios or limited speed ranges, which limits their applicability in dynamic environments.

In response to this gap, this article introduces a formulation and characterization, novel in the asynchronous-TWR context, of the positioning error induced by target motion, specifically for asynchronous TWR positioning systems. Unlike prior analyses that often rely on idealized assumptions, the proposed framework explicitly considers a realistic, nonideal environment where target movement coexists with multiple additional sources of error, including clock skew, signal propagation noise, multipath effects, and NLOS conditions.

By employing the proposed characterization models, comprehensive performance evaluations have been carried out under a wide range of operational scenarios. This systematic approach enables a detailed analysis of the effects of target movement on the scalability of sensor networks, taking into account critical parameters, such as the number of deployed sensors, system response times, and target velocities. The achieved results provide a more in-depth analysis of the relative performance between the compared asynchronous TWR methods and the synchronous TDoA system. This analysis highlights the key factors that must be considered when selecting the most suitable localization technique according to the specific requirements of each application.

III. IMPACT OF TARGET MOTION IN LOCALIZATION ACCURACY

Targets moving at a relative velocity with respect to a stationary localization system experience a reduction in localization accuracy due to this motion. Velocity induces a position displacement during the localization procedure, leading to a discrepancy between the estimated position, based on the initial location at the start of the process, and the actual position at the time the estimated location is received.

This effect causes an average increase in localization error, which becomes more pronounced as the target's speed increases. Nevertheless, this source of error is only caused by the net change of position due to the target movement, and thus can be predicted and compensated through additional information regarding the target velocity and trajectory [23].

However, velocity can also introduce additional errors in localization systems where the target sensor (TS) is actively involved in the measurement process. In such cases, variations in the target's position during the emission or reception of signals may lead to temporally inconsistent or spatially incoherent measurement. This inconsistency increases the overall positioning uncertainty, as the collected data no longer corresponds to a single, well-defined location. Unlike the direct displacement error induced solely by motion, this additional source of error depends not only on the target velocity but also on the specifics of the localization protocol, the network and hardware capabilities, and how timing information is computed and processed within the system.

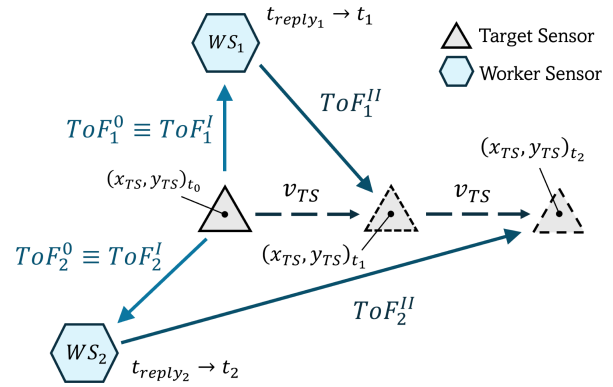


Fig. 1. Influence of TS velocity on ToF measurement in the parallel TWR implementation. Although all initial ToF references are associated with the same TS location, the TS displacement during the WS predefined reply times causes the final ToF associated with each WS to differ.

In consequence, this second error source depends on multiple variables and cannot be as easily predicted or compensated as the direct displacement error caused by target motion. Despite its relevance, a comprehensive analysis of its impact in real-world localization scenarios remains largely unaddressed in current literature.

Consequently, the subsequent analysis of target motion-induced errors focuses exclusively on the influence of motion on the coherence of the acquired measurements, and does not account for the positioning inaccuracy caused by the position displacement of the target during the localization sequence, as this latter effect can be compensated through external means [18]. Therefore, in the subsequent analysis, the ground truth is defined as the target position at the start of the localization exchange, which provides a consistent reference for evaluating the impact of motion during the ranging process.

The TWR protocol estimates the time-of-flight (ToF) between a tag or TS and a receiver or worker sensor (WS). This estimation is based on timestamps recorded at the reception of a signal in a sensor.

In the SS-TWR method, a single round time, t_{round} , is measured at the TS, whereas the SDS-TWR method includes an additional t_{round} measurement at the WS. Each t_{round} includes the ToF for both sending and receiving signals, as well as a reply time that accounts for the reception, processing, and transmission of the message by the opposing sensor [12].

These processes refer to the interaction between a specific pair of sensors. However, scaling the TWR protocol to actual networks of deployed sensors typically involves one of two approaches: 1) a parallel implementation, in which the TS initiates the localization by broadcasting to all WSs simultaneously or 2) a sequential implementation, where the localization process is carried out as a series of individual TS-WS pairwise localization sequences for each WS.

The impact of velocity-induced errors is highly dependent on the chosen TWR implementation. In parallel implementations, as illustrated in Fig. 1, the TS motion during the varying reply times of each WS leads to inconsistencies between the measured ToF in the first exchange of sensor

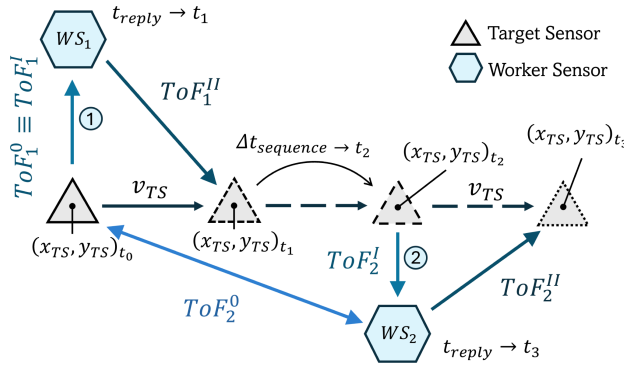


Fig. 2. Influence of TS velocity on ToF measurements in a sequential TWR implementation. Each WS transmits its reply at the same predefined reply time, but the ToF is computed from different TS locations due to motion.

i (ToF_i^I) and the second exchange (ToF_i^{II}). This occurs because, in parallel implementations, each WS employs an incremented reply time to prevent collisions between response signals (i.e., $t_{\text{reply}_2} = t_{\text{reply}_1} + \Delta t_{\text{reply}}$). Consequently, sensors with longer reply times experience a greater influence from target motion, resulting in increased ToF measurement errors [21]. Note that the measured ToF from a given WS could theoretically increase or decrease depending on the target trajectory.

This leads to a discrepancy between the averaged ToF and the initial ToF for each sensor, which is proportional to the target speed and the sensor reply time. Consequently, as the number of deployed sensors increases, the reply time for the later sensors becomes longer, leading to larger errors caused by the target's movement.

In contrast, in sequential implementation schemes, as depicted in Fig. 2, the TS interacts individually with each WS at different time intervals, effectively dividing the process into multiple pairwise range measurement sequences. In this approach, the discrepancy between the initial ToF_i^I and the subsequent ToF_i^{II} for each sensor tends to be lower than in the parallel model as all WS share the same reply time estimate, being signal collision not a concern in this approach, thus allowing an overall lower reply time than in parallel approaches.

On the other hand, the division of the localization process into sequences requires the specification of an elapsed $\Delta t_{\text{sequence}}$ between each pairwise range measurement. The aggravation of all $\Delta t_{\text{sequence}}$ over all sequences extends the overall localization process duration, which may cause the last WS in the queue to measure an initial ToF that differs from the equivalent ToF at the start of the localization process (ToF_i^0) (i.e., $\text{ToF}_i^I \neq \text{ToF}_i^0$), which was not an issue in the parallel approach. This temporal shift leads to an increase in position variance when aggregating measurements from all sensors to estimate the target location.

As shown, these two implementation schemes differ significantly in how the signals are collected, leading to variations in localization accuracy when tracking moving targets. Each approach is influenced by different variables (e.g., Δt_{reply} for the parallel approach and $\Delta t_{\text{sequence}}$ for the

sequential implementation), while both methods are also affected differently by shared factors, such as target speed, number of deployed nodes, and base t_{reply} . This motivates a comprehensive comparative analysis to evaluate the individual and combined effects of these variables, ultimately providing practical insights for the optimal deployment of TWR-based localization systems in dynamic scenarios.

Such comparison requires the development of dedicated performance assessment models for each implementation scheme. These evaluation models are derived from the TWR characterizations proposed in the following section, which account for the main error sources (e.g., clock skews, NLOS, multipath) in addition to the influence of target motion discussed in the current section. In this sense, due to the inherently different behavior of parallel and sequential strategies with respect to target movement, two distinct characterization models for each TWR method must be developed to accurately capture their respective dynamics.

IV. CHARACTERIZATION OF THE ASYNCHRONOUS SYSTEMS POSITIONING UNCERTAINTIES

The characterization of the target location error in systems with heteroscedastic noises is usually addressed through the CRB [16], [20]. The CRB provides the minimum achievable error of a system given a set of captured measurements [30].

For the definition of the positioning calculation uncertainties of each time measurement of the base methods analyzed in this article (i.e., synchronous TDoA and asynchronous SS-TWR and SDS-TWR), we employ the characterizations of our past papers [14], [22], [27]. These error models characterize the principal error sources of UWB methods in indoor environments: noise under LOS/NLOS conditions, synchronization, drift and truncation errors, and multipath interference. These models have proven superior performance to other literature approaches in real-world experimentation [24].

In this article, we propose a novel error characterization that accounts for the influence of target motion throughout the entire measurement acquisition process. This effect is particularly relevant in asynchronous methods due to the retransmission requirements of the positioning signal. In addition, the influence of employing either sequential or parallel measurement collection strategies is also addressed in this study.

Therefore, in the subsequent subsections, we define the time-based uncertainties of the asynchronous SS-TWR, SDS-TWR, and synchronous TDoA positioning methods, considering clock, noise, and multipath variances.

A. SS-TWR

The pairwise SS-TWR procedure involves the exchange of a localization signal between the TS, which emits first, and a deployed sensor WS_i , regardless of the implementation strategy considered. Upon the reception of the message, the WS replies after a predefined reply time has been count by the WS. The reception of the response message by the

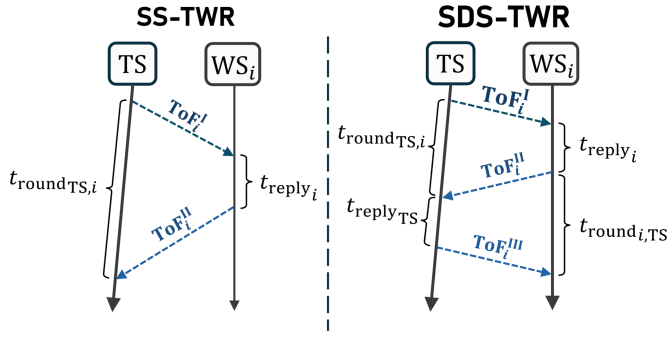


Fig. 3. Message exchange diagrams for the SS-TWR and SDS-TWR protocols under TS movement. The illustrations show the ToF components (ToF_i^I , ToF_i^{II} , and ToF_i^{III}), the reply times at the sensor and the transmitter (t_{reply_i} , $t_{\text{reply}_{\text{TS}}}$), and the measured RTTs ($t_{\text{round}_{\text{TS},i}}$, $t_{\text{round}_{i,\text{TS}}}$). The SDS-TWR protocol includes an additional message exchange, enabling a more refined ToF estimation at the cost of increased sequence duration and sensitivity to motion.

TS ends the localization sequence, and a signal round-time is measured within the TS as the difference between the timestamps of signal transmission and reception. The ToF of the signal is then computed following the TWR protocol [4]:

$$\hat{\text{ToF}}_i = \frac{\hat{t}_{\text{round}_{\text{TS},i}} - \hat{t}_{\text{reply}_i}}{2} \quad (1)$$

where $\hat{\text{ToF}}_i$ represents the measured ToF for sensor i , $\hat{t}_{\text{round}_{\text{TS},i}}$ is the round-trip time (RTT) measured at the TS for the exchange with the WS i , and $\hat{t}_{\text{reply}_i}$ represents the reply time measured at WS i .

The message exchange sequences and timing relationships for both the SS-TWR and SDS-TWR protocols are illustrated in Fig. 3. This figure highlights the respective ToF components, reply times, and measured round-trip intervals in each approach.

Equation (1) provides an average of the perceived ToF of both transmission and reception phases from the TS. While this procedure is appropriate for static applications where the TS remains stationary, the introduction of target motion, as shown in Figs. 1 and 2, leads to variations in the physically measurable ToF between the emission and reception instants, thereby introducing inconsistencies in the final estimation.

The influence of this issue can be assessed and characterized by considering two different physical ToF (i.e., ToF_i^I and ToF_i^{II}) that correspond to the first and second phase of the pairwise SS-TWR sequence between the TS and a given sensor i . The first-second-phase relationship is

$$\text{ToF}_i^{II} = \text{ToF}_i^I + \delta_v(\text{ToF}_i^I + t_{\text{reply}_i}) \approx \text{ToF}_i^I + \delta_v t_{\text{reply}_i} \quad (2)$$

where δ_v equals v/c , with v and c denoting the TS velocity and the propagation speed of the localization signal, respectively. The term $\delta_v \text{ToF}_i^I$ is neglected because its magnitude is bounded by $v \cdot \text{ToF}_i^I/c$. For the most demanding scenario considered in this work ($v = 16$ m/s) and a representative indoor ToF of ~ 100 ns, this contribution is on the order of 5×10^{-15} s, which is several orders of magnitude below the dominant $\delta_v t_{\text{reply}_i}$ term, and is therefore negligible.

Note that in (2), as well as in the following characterizations, the contribution of target motion to the signal ToF is modeled under a worst-case scenario, in which the TS moves directly away from sensor i , increasing the distance and the ToF between nodes.

The contribution of target motion to the signal ToF is modeled under a worst-case scenario in which the TS recedes radially from sensor i , maximizing the velocity-induced ToF increase. This radial formulation yields a per-sensor bound that holds for any motion direction: for an arbitrary 3-D velocity, the radial component at sensor i is $v \cos \theta_i$, so the effective motion coefficient $\delta_{v,i} = (v/c) \cos \theta_i$ satisfies $|\delta_{v,i}| \leq v/c$, with equality only under exact radial alignment. Since δ_v enters the clock variance of (7), (9), (17), and (18) additively within the squared timing error, each per-sensor variance is nondecreasing in $|\delta_{v,i}|$, and setting $\cos \theta_i = 1$ for all sensors bounds every $\sigma_{\text{clock}_i}^2$ simultaneously. The aggregate positioning CRB obtained from the Fisher information matrix (FIM) consequently provides an upper bound of the achievable variance under any 3-D motion, a guarantee that no direction-specific model can provide. Notably, this uniform-radial condition is not realizable by a single trajectory, as one velocity vector cannot align radially with all sensors at once; the resulting metric therefore characterizes the system limit independently of the target trajectory, in keeping with the trajectory-agnostic nature of the CRB framework adopted throughout this work.

Considering the clock drift in both the TS and the WS clocks, the RTT and the reply time as measured by the TS and WS, respectively, based on (1), can be expressed as

$$\hat{t}_{\text{round}_{\text{TS},i}} = (\text{ToF}_i^I + \text{ToF}_i^{II} + t_{\text{reply}_i})(1 + e_{\text{TS}}) \quad (3)$$

$$\hat{t}_{\text{reply}_i} = t_{\text{reply}_i}(1 + e_i) \quad (4)$$

where e_{TS} and e_i refers to the clock drift of the TS and WS clock, respectively.

Integrating (3) and (4) into the ToF measurement of (1), and considering the multiple ToF measurements from (2), the fundamental ToF measurement equation for the SS-TWR method is obtained as

$$\hat{\text{ToF}}_i = \frac{[2 \text{ToF}_i^I + t_{\text{reply}_i}(1 + \delta_v)](1 + e_{\text{TS}}) - t_{\text{reply}_i}(1 + e_i)}{2} \quad (5)$$

This equation yields the ToF measurement resulting from a single localization exchange between the TS and a single WS. The consideration of additional sensors through a parallel or a sequential implementation introduce modifications to the base equation, affecting the overall accuracy of the system.

In the parallel implementation approach, the TS broadcasts the localization message to all WS simultaneously, resulting in the initial ToF for each sensor being equivalent to the first ToF of the localization sequence (i.e., $\text{ToF}_i^0 \equiv \text{ToF}_i^I$). However, in order to avoid message collisions, each WS is assigned a distinct reply time. A common strategy to achieve this is to introduce a fixed reply time increment for

TABLE I
Scenario Parameters for Performing the Comparison

Scenario Parameters	Values
Dimensions x-y-z	23.78 x 13.21 x 5.4 m
No. Obstacles	6
$\sum$ Obstacle Volume	79.5 m ³
NLE Surface	219.41 m ²
TLE Volume	158.6 m ³
No. NLE Points	16929
No. TLE Points	18264

each deployed sensor

$$t_{\text{reply}_i} = t_{\text{reply}_0} + \Delta t_{\text{reply}}(i - 1); \quad i \in [1, n_s] \quad (6)$$

where t_{reply_0} is a base reply time, typically the minimum achievable by the sensor hardware, n_s is the number of deployed sensors, and Δt_{reply} represents the incremental reply time assigned per sensor.

Incorporating these two modifications into (5) provides the measured ToF for a given sensor i , which is subsequently used to derive the clock-related uncertainties within the CRB model employed in our previous works [14], [22], [27]

$$\sigma_{\text{SS-P (clock)}}^2 = \frac{1}{n_M} \sum_{k=1}^{n_M} \{ |\text{ToF}_i^0 - \text{floor}_{\text{TR}} [\text{ToF}_i^0 (1 + e_{\text{TS}}^k) + \frac{1}{2} t_{\text{reply}_i} [e_{\text{TS}}^k - e_i^k + \delta_v (1 + e_{\text{TS}}^k)]] | c \}^2 \quad (7)$$

where $\sigma_{\text{SS-TWR-P (clock)}}^2$ represents the error variance associated with a single time measurement in the parallel SS-TWR method, and n_M denotes the number of Monte Carlo simulations performed to estimate the expected value of this variance [13].

In contrast, a sequential implementation introduces different modifications into the base equation. In this approach, a series of pairwise localization exchanges between the TS and each WS is performed sequentially. Unlike the parallel case, this method does not require the use of distinct reply times, allowing the reply time of each sensor to be considered equal to the base reply time defined previously (i.e., $t_{\text{reply}_i} \equiv t_{\text{reply}_0}$). However, each localization exchange occurs at a different moment relative to the initial message transmitted by the TS. Consequently, if the TS is in motion, the ToF at the start of the localization sequence for a given sensor i may differ from the ToF at the beginning of the overall localization process. This deviation can be characterized as

$$\text{ToF}_i^f = \text{ToF}_i^0 + (i - 1)(t_{\text{seq}} + t_{\text{wait}})\delta_v \quad (8)$$

where t_{seq} denotes the duration of a single localization exchange, and t_{wait} represents the elapsed time between consecutive localization sequences. The sum of both times provides a sequence spacing time value.

Equation (8) models a linear accumulation of motion-induced ToF drift across sequential exchanges, valid under two practical conditions. First, the intersequence spacing

TABLE II
Network Parameters Employed for the Localization methods [36], [37]

Method	Parameter	Value
Baseline	LOS exponent (n_{LOS})	2.1
	NLOS exponent (n_{NLOS})	4.1
	Transmission frequency	3.9 GHz
	Transmission power (P_T)	1 W
	Bandwidth (B)	500 MHz
	Mean noise power	-94 dBm
	Receiver sensitivity	-90 dBm
	Clock frequency	1 GHz
	Clock Drifts ($e_{\text{TS}}, e_{\text{WS}}$)	U[-3, 3] ppm
	TS reply time $t_{\text{reply}_{\text{TS}}}$	250 μ s
P-TWR	WS base reply time (t_{reply_0})	300 μ s
	Incremental WS reply time (Δt_{reply})	89.6 μ s
S-TWR	Shared WS reply time (t_{reply})	300 μ s
	Sequence spacing ($t_{\text{seq}} + t_{\text{wait}}$)	500 μ s
TDoA	Initial-time offset range (U)	[15, 30] ns
	Time-from-last-synchronization (U_0)	200 μ s

($t_{\text{seq}} + t_{\text{wait}}$) is assumed uniform; practical jitter from MAC-layer scheduling is submicrosecond, and thus negligible against the accumulated drift term. Second, the target velocity vector is assumed approximately constant over the localization window $n_s(t_{\text{seq}} + t_{\text{wait}})$, which spans only a few milliseconds for the parameter set used in this study (Table II). Over such brief intervals, even aggressive platform maneuvers—such as a AAV undergoing accelerations up to 20 m/s²—produce velocity and heading variations below 1% relative to the worst-case speed of 16 m/s. Consequently, these dynamic deviations remain negligible compared to the dominant error contributions quantified in Section VI.

Taking these two modifications into account, the clock-related uncertainty for the sequential SS-TWR method can be derived as

$$\sigma_{\text{SS-S (clock)}}^2 = \frac{1}{n_M} \sum_{k=1}^{n_M} \{ |\text{ToF}_i^0 - \text{floor}_{\text{TR}} [2 [\text{ToF}_i^0 (1 + e_{\text{TS}}^k) + \delta_v(t_{\text{seq}} + t_{\text{wait}})(i - 1)] (1 + e_{\text{TS}}^k) + \frac{1}{2} t_{\text{reply}_0} [e_{\text{TS}}^k - e_i^k + \delta_v(1 + e_{\text{TS}}^k)]] | c \}^2 \quad (9)$$

Both (7) and (9) exhibit novel terms scaled by the δ_v coefficient. These terms represent velocity-induced errors resulting from the movement of the TS in both implementations of the SS-TWR method.

In both approaches, the inclusion of additional sensors leads to increased clock-related uncertainty. In the parallel implementation, the velocity-induced error arises primarily from the growing reply times, which scale with the number of sensors. In contrast, the sequential approach exhibits a δ_v -dependent error influenced by both the reply time and ToF incoherence. Although the same base reply time is used for all sensors in this case, ToF incoherence increases with the number of sensors due to the cumulative effect of t_{wait} and t_{seq} .

However, based on both equations, the resulting error for each method depends on the specific network parameters and hardware characteristics used in the localization process, with neither approach being clearly superior to the other. In the results section, a comprehensive comparison will be conducted using representative parameter values for each implementation, in order to evaluate and quantify the mobility-induced error associated with each system.

This comparison also incorporates noise and multipath-related uncertainties, as derived in our previous work [22]. These uncertainty models are applicable to both the parallel and sequential approaches, since both share the same underlying SS-TWR localization exchange mechanism

$$\sigma_{SS(noise)_{ii}}^2 = \frac{c^2}{B^2(\frac{P_T}{P_N})} \text{PL}(d_0) \left[\left(\frac{2d_{i,LOS}}{d_0} \right)_{WSi} \right. \quad (10a)$$

$$\left. + \left(\frac{2d_{i,NLOS}}{d_0} \right)_{WSi}^\gamma \right]^{n_{LOS}} \quad (10b)$$

$$\gamma = \frac{n_{NLOS}}{n_{LOS}} \quad (10c)$$

$$\sigma_{SS(multipath)_{ii}}^2 = \bar{G}_i \log(1 + 2d_i) \quad (11a)$$

$$\bar{G}_i = G(d_0) \left[\left(\frac{2d_{i,LOS}}{d_0} \right) + \left(\frac{2d_{i,NLOS}}{d_0} \right)^\gamma \right]^{-n_{LOS}} \quad (11b)$$

$$G(d_0) = \left(\frac{G_T G_R \lambda_0^2}{16\pi^2 d_0^2} \right) \quad (11c)$$

where B denotes the signal bandwidth, P_T is the transmission power, P_N represents the average noise power as defined by the Johnson–Nyquist equation, $\text{PL}(d_0)$ is the reference path loss at distance d_0 [31], d_{LOS} and d_{NLOS} are the LOS and NLOS distances traversed by the localization signal to/from the WS, respectively, n_{LOS} and n_{NLOS} are the path loss exponents for LOS and NLOS conditions, respectively, based on the log-normal propagation model, G_T and G_R are the transmitter and receiver antenna gains, respectively, λ_0 is the wavelength of the UWB localization signal, and γ denotes the ratio between the NLOS and LOS path loss exponents.

B. SDS-TWR

The SDS-TWR method extends the baseline SS-TWR by incorporating an additional RTT measurement to calculate the ToF between the TS and WS. Specifically, after receiving the WS reply, the TS waits for a defined reply time before transmitting a second response message. This initiates a second RTT interval, which is measured at the WS. The measured time corresponds to the interval between the emission of the WS reply, as in the SS-TWR baseline, and the reception of the TS second response. The resulting ToF is computed as half of the average RTT interval, after subtracting both reply times

$$\hat{\text{ToF}}_i = \frac{\hat{t}_{\text{round}_{TS,i}} - \hat{t}_{\text{reply}_i} + \hat{t}_{\text{round}_{i,TS}} - \hat{t}_{\text{reply}_{TS}}}{4} \quad (12)$$

where $\hat{t}_{\text{round}_{i,TS}}$ is the RTT interval measured at the WS i between sensor i and the TS.

As with the SS-TWR method, ToF estimation using (12) may integrate measurements that are not temporally coherent in dynamic scenarios, particularly when the TS is in motion. In the SDS-TWR scheme, three distinct ToF values are implicitly involved due to the separation between signal exchanges, as illustrated in Fig. 3.

The first RTT measurement $\hat{t}_{\text{round}_{TS,i}}$ is measured between the TS's transmission and reception events. It involves two ToF components: 1) ToF_i^I (corresponding to the TS's initial transmission to WS) and 2) ToF_i^{II} (from the WS's reply to the TS). This component is identical to the SS-TWR RTT defined in (3).

As for the second RTT measurement, $\hat{t}_{\text{round}_{i,TS}}$, it is measured at the WS side and spans from the emission of the WS reply to the reception of the second TS response. This interval also involves two ToF components, the first being the same WS to the TS component as in the prior case, ToF_i^{II} , and a final ToF_i^{III} that corresponds to the last signal transmission from the TS to the WS

$$\text{ToF}_i^{III} = \text{ToF}_i^{II} + \delta_v t_{\text{reply}_{TS}} = \text{ToF}_i^I + \delta_v (t_{\text{reply}_i} + t_{\text{reply}_{TS}}). \quad (13)$$

In this characterization, the first RTT measurement and the associated reply time can be computed using the same equations as in the SS-TWR method, specifically (3) and (4). In contrast, the second RTT measurement and the reply time elapsed at the TS can be obtained from the following expressions:

$$\hat{t}_{\text{round}_{i,TS}} = [2\text{ToF}_i^I + t_{\text{reply}_{TS}}(1 + \delta_v) + 2\delta_v t_{\text{reply}_i}](1 + e_i) \quad (14)$$

$$\hat{t}_{\text{reply}_{TS}} = t_{\text{reply}_{TS}}(1 + e_{TS}). \quad (15)$$

By integrating these expressions into the ToF formulation given in (12), we obtain the fundamental expression for the ToF estimation in the SDS-TWR method

$$\begin{aligned} \hat{\text{ToF}}_i &= \frac{1}{2} \text{ToF}_i^I (2 + e_{TS} + e_i) + \frac{1}{4} (t_{\text{reply}_i} - t_{\text{reply}_{TS}}) (e_{TS} - e_i) \\ &\quad + \frac{1}{4} \delta_v [(1 + e_{TS}) t_{\text{reply}_i} + (1 + e_i) (t_{\text{reply}_{TS}} + 2t_{\text{reply}_i})]. \end{aligned} \quad (16)$$

Similarly to the SS-TWR characterization, (16) yields an individual ToF estimate from a single localization exchange between the TS and a given WS. Additional sensors employed in the localization through a parallel or sequential approach require further adaptations from this equation.

In the parallel SDS-TWR approach, the behavior remains analogous to the SS-TWR case. Thus, the starting ToF of each localization exchange can be set to the initial value (i.e., $\text{ToF}_i^0 \equiv \text{ToF}_i^I$). As before, the reply time of each sensor must be adjusted to avoid signal collisions. However, due to the additional RTT interval introduced in the SDS-TWR protocol, the time offset between successive reply slots, Δt_{reply} , should be prolonged compared to the SS-TWR method to ensure proper scheduling and avoid overlap.

Incorporating these two adaptations into the fundamental ToF equation yields the final ToF expression for a given WS i , which serves as the basis for deriving the clock-related uncertainty in the parallel SDS-TWR approach

$$\sigma_{\text{SDS-P (clock)}_{ii}}^2 = \frac{1}{n_M} \sum_{k=1}^{n_M} \left\{ \left| \text{ToF}_i^0 - \text{floor}_{\text{TR}} \left[\frac{1}{2} \text{ToF}_i^0 \right. \right. \right. \\ \left. \left. \left. (2 + e_{\text{TS}}^k + e_i^k) + \frac{1}{4} (t_{\text{reply}_i} - t_{\text{reply}_{\text{TS}}}) (e_{\text{TS}}^k - e_i^k) + \frac{1}{4} \delta_v \right. \right. \right. \\ \left. \left. \left. [(1 + e_{\text{TS}}^k) t_{\text{reply}_i} + (1 + e_i^k) (t_{\text{reply}_{\text{TS}}} + 2t_{\text{reply}_i})] \right] \right| c \right\}^2. \quad (17)$$

On the other hand, the sequential implementation of the SDS-TWR method entails a different set of adaptations. As in the SS-TWR approach, the sequential scheme does not require distinct reply times for each sensor (i.e., $t_{\text{reply}_i} \equiv t_{\text{reply}_0}$). However, the delay between consecutive localization exchanges introduces a deviation between the first ToF of each sequence, ToF_i^I , and the original reference ToF, ToF_i^0 . This motion-induced deviation follows a similar process to the one described for the SS-TWR variant in (9). Consequently, the comprehensive sequential SDS-TWR formulation in (18) is derived by directly substituting the ToF_i^I expression within (16) in terms of the ground truth ToF_i^0 from (8). It is worth noting that (17) corresponds to the particular case where $\text{ToF}_i^0 \equiv \text{ToF}_i^I$, which eliminates the sequential timing offset. In addition, the total sequence time parameter t_{seq} is inherently longer in the SDS-TWR configuration due to the integration of the additional RTT measurement exchange.

Taking these two factors into account, we derive the following model for the clock-induced uncertainty in the sequential SDS-TWR method

$$\sigma_{\text{SDS-S (clock)}_{ii}}^2 = \frac{1}{n_M} \sum_{k=1}^{n_M} \left\{ \left| \text{ToF}_i^0 - \text{floor}_{\text{TR}} \left[\frac{1}{2} [\text{ToF}_i^0 \right. \right. \right. \\ \left. \left. \left. + \delta_v (t_{\text{seq}} + t_{\text{wait}})(i-1) \right] (2 + e_{\text{TS}}^k + e_i^k) \right. \right. \\ \left. \left. \left. + \frac{1}{4} (t_{\text{reply}_0} - t_{\text{reply}_{\text{TS}}}) (e_{\text{TS}}^k - e_i^k) + \frac{1}{4} \delta_v \right. \right. \right. \\ \left. \left. \left. [(1 + e_{\text{TS}}^k) t_{\text{reply}_0} + (1 + e_i^k) (t_{\text{reply}_{\text{TS}}} + 2t_{\text{reply}_0})] \right] \right| c \right\}^2. \quad (18)$$

As in the SS-TWR characterization, both the parallel and sequential models for SDS-TWR include additional terms involving the coefficient δ_v , which account for velocity-induced errors. These terms increase with the number of sensors and with longer reply times, following a similar trend to that observed in the SS-TWR method.

However, as a consequence of the additional total sequence time of the SDS-TWR method due to the measurement of an additional RTT interval, the velocity-induced errors may yield larger error values than for SS-TWR systems under similar conditions and hardware. This effect may become significant for dynamic localization applications, where the potential advantages of superior performance

under similar or symmetric reply times are offset by the amplification of velocity-induced errors.

To assess the impact of these factors, we conduct a comparative analysis in the results section, evaluating the performance of each system under various application scenarios and motion profiles. These analyses also consider the noise and multipath-induced uncertainties previously derived in our earlier work [22]. As in the SS-TWR case, the derived equations are valid for both the sequential and parallel implementations of the SDS-TWR protocol

$$\sigma_{\text{SDS (noise)}_{ii}}^2 = \frac{c^2}{B^2(\frac{P_T}{P_N})} \text{PL}(d_0) \left[\left(\frac{4 d_{\text{LOS}}}{d_0} \right)_{\text{WS}_i} \right. \\ \left. + \left(\frac{4 d_{\text{NLOS}}}{d_0} \right)_{\text{WS}_i}^\gamma \right]^{n_{\text{LOS}}} \quad (19)$$

$$\sigma_{\text{SDS (multipath)}_{ii}}^2 = \bar{G}_i \log(1 + 4 d_i) \quad (20a)$$

$$\bar{G}_i = G(d_0) \left[\left(\frac{4 d_{\text{LOS}}}{d_0} \right) + \left(\frac{4 d_{\text{NLOS}}}{d_0} \right)^\gamma \right]^{-n_{\text{LOS}}}. \quad (20b)$$

C. TDoA

The TDoA method is a synchronous localization system that estimates the target position based on the differences in reception times of the same localization signal across multiple WS. Unlike TWR-based approaches, TDoA requires the WS nodes to be synchronized to a common time reference in order to compute the time differences.

This synchronization requirement introduces potential vulnerabilities to clock-related errors, particularly due to drift in local oscillators. In contrast, the TDoA protocol does not require any reply or retransmission from either the WSs or the TS, which makes it inherently more robust in challenging environments with high NLOS density as well as under dynamic operating conditions.

Moreover, since the TS does not transmit any response signal in TDoA, this approach is not affected by velocity-induced ToF distortions. Although the target displacement during the localization process may still impact the geometric accuracy of the estimated position, it does not compromise the internal consistency of the timing measurements, thereby preserving the overall accuracy of the position estimation.

This robustness is structural. The motion-induced bias in TWR arises from averaging two propagation phases separated by the reply time, between which the target displaces by $\delta_v t_{\text{reply}}$ in (1) and (12). TDoA has no second phase: a single signal is broadcast by the TS and time-stamped by the synchronized sensors; therefore, velocity has no quantity to act upon and a motion-aware derivation reproduces (21) unchanged. The only kinematic coupling is the displacement during one-way propagation $v \cdot \text{ToF}_i$ which shifts the reference instant of the estimate rather than corrupting the timing; it is not treated as a system error here, being recoverable through inertial aiding and likewise uncompensated for TWR.

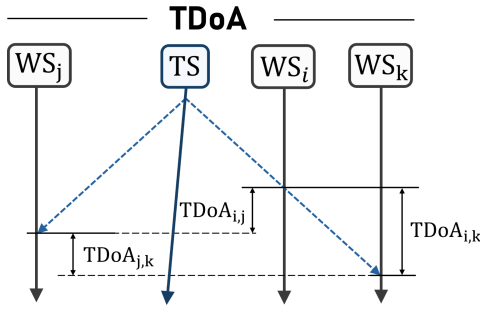


Fig. 4. TDoA protocol diagram. A single localization signal is broadcasted by the TS and received by multiple synchronized sensors (WS_j , WS_i , and WS_k). The differences in reception times are used to estimate the relative distances to the target.

The message exchange structure of the TDoA protocol is illustrated in Fig. 4, where the differences in arrival times are depicted between three receiving sensors (WS_j , WS_i , and WS_k) for a single transmission emitted by the TS.

Being unaffected by the consideration of target motion, the TDoA method is characterized in this comparison using the uncertainty model previously derived in our previous work [32], which accounts for clock drift, measurement noise, and multipath propagation effects. In (21), T_i and T_j denote the signal-flight times measured at the synchronized sensors i and j , respectively. T_0 is the reference emission instant at the TS. U_i and U_j are the per-sensor initial-time offsets relative to the common time base (with range specified in Table II). U_0 is the time elapsed since the last network synchronization. n_{MC} and n_s are the Monte Carlo sample count and the number of synchronized sensors involved in the position estimation. The clock-drift variables e_i^k , e_j^k , and e_{TS}^k retain the same meaning introduced for SS-TWR in (3) and (4)

$$\sigma_{\text{TDoA (clock)}}^2_{ij} = \frac{1}{n_{MC}} \sum_{k=1}^{n_s} \{ |T_i - \text{floor}_{TR}(T_i + U_i - U_0) + T_0(e_i^k - e_{TS}^k) + T_i e_i^k| c^2 \} + \frac{1}{n_{MC}} \sum_{k=1}^{n_s} \{ |T_j - \text{floor}_{TR}(T_j + U_j - U_0) + T_0(e_j^k - e_{TS}^k) + T_j e_j^k| c \}^2 \quad (21)$$

$$\sigma_{\text{TDoA (noise)}}^2_{ij} = \frac{c^2}{B^2(\frac{P_T}{P_N})} \text{PL}(d_0) \left[\left(\left(\frac{d_{i,LOS}}{d_0} \right)_{WS_i} + \left(\frac{d_{i,NLOS}}{d_0} \right)_{WS_i} \frac{n_{NLOS}}{n_{LOS}} \right) + \left(\frac{d_{j,LOS}}{d_0} \right)_{WS_j} + \left(\frac{d_{j,NLOS}}{d_0} \right)_{WS_j} \frac{n_{NLOS}}{n_{LOS}} \right]^{n_{LOS}} \quad (22)$$

$$\sigma_{\text{TDoA (multipath)}}^2_{ij} = \bar{G}_i \log(1 + d_i) + \bar{G}_j \log(1 + d_j) \quad (23)$$

$$\bar{G}_j = G(d_0) \left[\left(\frac{d_{j,LOS}}{d_0} \right) + \left(\frac{d_{j,NLOS}}{d_0} \right) \frac{n_{NLOS}}{n_{LOS}} \right]^{-n_{LOS}} \quad (24)$$

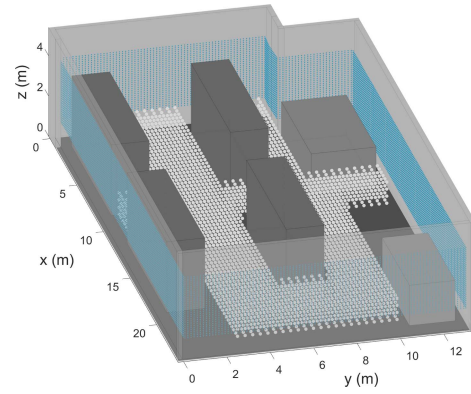


Fig. 5. Scenario employed for the comparison. The blue dots represent all possible sensor locations (i.e., NLE), the white dots represent all possible target locations (i.e., TLE) and the gray shapes represent walls and obstacles that may produce NLOS.

With the analytical expressions obtained for SS-TWR, SDS-TWR, and TDoA, which include the effects of clock drift, measurement noise, as well as multipath and velocity-induced errors, a unified framework is established for the comparison of localization performance. These models allow quantifying the expected accuracy under different operational conditions.

The next section presents the methodology used in this study, based on a realistic deployment scenario. It includes the use of optimization algorithms to allocate the sensors optimally, enabling a fair and practical comparison of the three methods or five strategies (considering parallel and sequential approaches) under representative sensor distributions.

V. EVALUATION SETUP AND METHODOLOGY

This section outlines the methodology used to conduct the experiments and model evaluations presented in this article. To this end, the section is organized into three subsections: 1) the development and characteristics of the application scenario chosen for the experiments; 2) the sensor distribution optimization framework employed to ensure a fair comparison across all tests; and 3) the selection and adjustment of network parameters according to the actual scenario.

A. Application Scenario

The use of simulation environments is appropriate for this evaluation, as the dynamic nature of the problem requires evaluating localization accuracy over a large set of target positions, velocities, and motion directions under strictly controlled conditions. Such exhaustive and repeatable testing is not feasible in physical setups, whereas simulation enables a fair and consistent assessment of all methods across the full scenario.

In consequence, we propose a synthetic industrial layout for conducting all the simulations, as shown in Fig. 5. This scenario includes different obstacles, walls and also navigable regions where the localization accuracy is to be evaluated. These regions are discretized into clouds of

possible location points, shown as white dots within Fig. 5, which we define as the target location environment (TLE).

The scenario also includes a region where the sensors can be deployed for the experiment, which in this application is constrained by the scenario walls. This region, referred to as the node location environment (NLE), is also discretized by a cloud of points, shown as blue dots in Fig. 5, where each point represents a potential sensor location. Table I details the key characteristics that define the scenario and its discretization for the proposed simulations.

The definition of these regions serves as a preamble to a fundamental issue that must be addressed before conducting the experiments. The actual localization uncertainty achieved by any given sensor deployment depends not only on target speed and other network parameters but also on the number of deployed WSs and their spatial arrangement.

In this context, optimizing the WS distribution for this scenario can substantially influence the reliability and validity of the results obtained in the evaluation. Based on these considerations, the following subsection presents the optimization framework used to determine the most suitable WS distribution for each case study.

B. Sensor Distribution Optimization Framework

To ensure a fair comparison among all localization methods and test configurations, we perform a sensor-distribution optimization for each case study. This requires addressing the node location problem (NLP) [13], which aims to achieve the spatial disposition of sensors that minimizes the error distribution across the application scenario, where the error distribution is derived from the CRB error characterization models discussed before.

The NLP is an NP-hard combinatorial problem whose complexity scales not only with the number of nodes to be deployed but also with the scenario characteristics [33] (e.g., obstacles, dimensions, discretization). Consequently, recent works rely on metaheuristic algorithms to obtain compromise solutions within an acceptable computational cost [6], [34]. In this context, in our previous works we devised and evaluated the BWO algorithm for the NLP, which demonstrated superior performance compared to other metaheuristic approaches due to its intensification and exploration capabilities [26].

For this reason, in this article, we adopt the BWO algorithm proposed in our previous work [26] for the analysis and comparison of the different case studies involving the localization method, network parameters, and target speeds, ensuring that all sensor distributions are obtained in a consistent and robust manner.

It is worth noting that, although the target velocity v reshapes the cost values through the motion-aware variance terms of (7)–(18), it enters the NLP as a fixed parameter of each case study rather than as a time-varying state. The optimization landscape addressed by the BWO therefore remains static, preserving the dimensionality, continuity, and constraint structure under which the algorithm was validated in [26].

Algorithm 1: RMSE evaluation based on the CRB.

```

1 Input: WSDistribution, TLE, Obstacles, Method, NetParams, v;
2 for  $TS$  in TLE do
3    $WS_{cov} \leftarrow \{ s \in WSDistribution \mid SNR(TS, s, Obstacles) > SNR_{min} \}$ ;
4   for each subset  $C \subseteq Sensors_{cov}$  required by Method do
5     for  $WS$  in  $C$  do
6        $d_{LOS}, d_{NLOS} \leftarrow LOS/NLOS$  3D Ray-Tracing (Obstacles,  $TS, WS$ );
7       Parameters  $\leftarrow$  Group [ $d_{LOS}, d_{NLOS}$ , Method, NetParams];
8        $\sigma_{noise} \leftarrow$  NoiseVariance (Parameters);
9        $\sigma_{multipath} \leftarrow$  MultipathVariance (Parameters);
10       $\sigma_{clock} \leftarrow$  ClockVariance (Parameters, v);
11    end
12     $FIM_C \leftarrow$  Fisher Information Matrix ( $\sigma_{noise}, \sigma_{multipath}, \sigma_{clock}$ );
13     $RMSE(C) \leftarrow \sqrt{\text{trace}(FIM_C^{-1})}$ ;
14  end
15   $RMSE_{TS} \leftarrow \min(RMSE(C))$ ;
16 end
17  $\text{fitness}_{CRB} \leftarrow 1 - \text{mean}(RMSE_{TS})(RMSE_{ref})^{-1}$ ;
18 Output:  $\text{fitness}_{CRB}$ ,  $\text{mean}(RMSE_{TS})$ ;

```

Fig. 6 depicts the proposed methodology, covering the definition of each case study and the optimization process that provides the final sensor distribution. The optimization is performed based on the evaluation of the root-mean-squared-error (RMSE) distribution across the TLE, where the RMSE at each point is obtained from the characterized CRB models of each localization method. As depicted in Algorithm 1, this computation involves identifying the WSs satisfying the signal-to-noise-ratio (SNR) threshold, evaluating all valid WS combinations, and deriving the corresponding noise, multipath, and static and motion-induced clock variances used to assemble the FIM [35]. The RMSE for each target position is then obtained as the minimum CRB across all combinations.

Regarding the employed BWO algorithm, the specific adaptation to the NLP and the hyperparameters used in this article coincide with those reported in [28].

With the optimized sensor distributions established for each case study, the following subsection defines the network parameters employed and adjusted for the comparison, ensuring that the resulting performance remains consistent and generalizable to other scenarios.

C. Network Parameters

The analyses presented in the results section are based on the network parameters summarized in Table II. While some parameters serve as a common baseline across all localization methods, others are specific to particular implementations or techniques.

While most values in Table II correspond to technology-based parameters, others depend on scenario-specific characteristics, such as the incremental WS reply time (Δt_{reply}). Selecting an excessively large Δt_{reply} increases the overall $t_{reply_{WS}}$, ultimately degrading the localization system performance. On the contrary, an overly small value may lead to signal collisions and, consequently, anomalous behavior that renders parallel operation unfeasible.

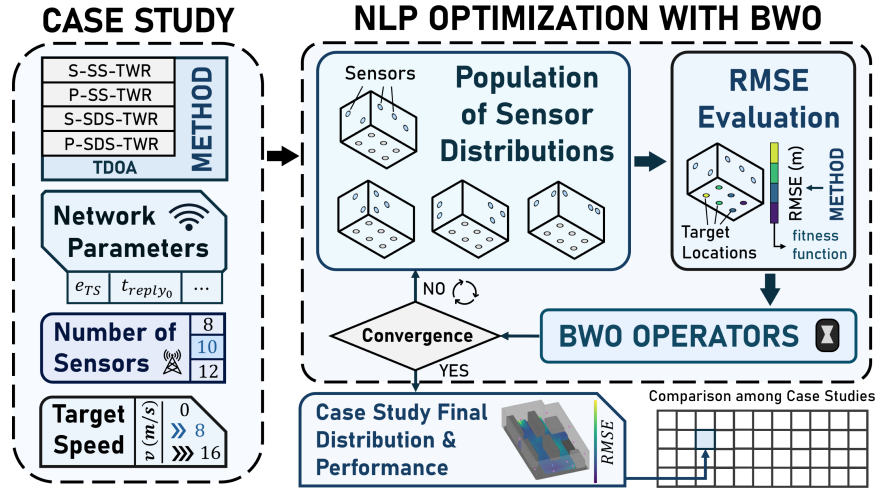


Fig. 6. Overview of the methodology employed for optimizing the sensor distribution and for evaluating each case study analyzed in the results section.

TABLE III
RMSE Metrics in Cm for the Optimized Sensor Distributions of Each Compared Method At Different Target Speeds (v)

Method		S-SS-TWR			P-SS-TWR			S-SDS-TWR			P-SDS-TWR			TDoA		
Number of Sensors		8	10	12	8	10	12	8	10	12	8	10	12	8	10	12
$v = 0$ m/s 0 km/h	Mean	8.63	7.97	6.65	12.84	12.01	11.45	10.00	7.67	5.84	11.05	9.72	8.72	16.03	12.60	11.33
	Max	30.00	17.27	12.60	34.44	37.00	22.45	46.33	28.10	32.77	49.67	39.57	36.51	31.65	19.31	19.69
	Std	3.06	2.50	1.72	4.14	2.52	2.61	7.17	3.18	3.78	5.47	3.82	4.24	3.41	1.83	1.76
$v = 8$ m/s 28.8 km/h	Mean	11.62	10.50	9.64	12.84	12.01	11.45	12.77	12.71	11.88	11.67	10.35	9.45	16.03	12.60	11.33
	Max	32.51	21.51	18.06	34.44	37.00	22.45	48.35	42.17	42.34	53.42	41.88	37.49	31.65	19.31	19.69
	Std	3.87	3.14	2.52	4.14	2.52	2.61	7.21	4.80	5.06	5.40	3.97	4.37	3.41	1.83	1.76
$v = 16$ m/s 57.6 km/h	Mean	13.87	12.56	11.68	12.84	12.01	11.45	16.03	18.34	18.56	12.34	11.03	10.20	16.03	12.60	11.33
	Max	35.91	25.45	22.20	34.44	37.00	22.45	53.26	58.67	55.51	58.03	44.28	38.93	31.65	19.31	19.69
	Std	4.60	3.62	3.23	4.14	2.52	2.61	8.13	6.66	6.69	5.36	4.12	4.50	3.41	1.83	1.76

The bold numbers refer to the best performing deployment solution for each tested target velocity (0, 8 and 16 m/s).

For the comparison conducted in this work, the Δt_{reply} value was set following the experimental procedure described in [32]. That study introduced a ray-tracing-based methodology that estimates all possible equivalent signal flight times within a given scenario by accounting for obstacles and the relative positions of nodes and targets. Based on the resulting distribution of equivalent ToF values, Δt_{reply} is selected using a high-percentile threshold (Q95), corrected for LOS/NLOS conditions and scaled by a safety factor, ensuring collision-free operation under realistic propagation variability.

Beyond these considerations, parameters, such as the number of deployed sensors and the target speed are also varied throughout the conducted analysis and comparisons in the results section, presented hereafter.

VI. RESULTS

This section presents the evaluation results of the models introduced in Section IV on the proposed scenario, considering variations in key network parameters. All results were derived from the optimization framework described in the previous section. The section is organized into two subsections. The first one provides a comparative performance analysis across different numbers of deployed sensors and

target speeds, together with insights into the selection of the most suitable localization architecture depending on the scenario of application considered and network configuration.

The second subsection examines the spatial distribution of motion-induced errors within the realistic 3-D scenario, highlighting that the influence of target movement is not uniform across the environment.

A. Comparative Performance and Localization Method Selection

Table III provides a comparative overview of the performance achieved by each localization method across different numbers of deployed sensors and target speeds. The results are directly comparable, as all methods have been optimally deployed according to their respective requirements derived from the characterization models.

As shown in Table III, the sequential implementation of the TWR localization methods (i.e., S-SS-TWR and S-SDS-TWR) achieve notably superior performance in the static case study. The relative performance between each method depends on the number of deployed sensors: with eight sensors, S-SS-TWR provides the lowest error, whereas

for 10 and 12 sensors, S-SDS-TWR becomes the most accurate option. In contrast, the parallel implementation of these systems (i.e., P-SS-TWR and P-SDS-TWR) exhibit higher localization errors due to the incremental reply time Δt_{reply} which amplifies clock-related inaccuracies, particularly when a large number of sensors is employed. These results indicate that, under static conditions, traditional sequential TWR methods outperform both their parallel counterparts and the TDoA system, which is consistent with their widespread adoption in commercial hardware. However, the introduction of target motion substantially alters these findings.

Two additional dynamic case studies are also included in the comparison of Table III, corresponding to target speeds of 8 and 16 m/s. Under these conditions, the influence of target motion significantly affects the sequential TWR methods, whereas the parallel approaches undergo little to no significant degradation. This behavior is caused by the computation of temporally incoherent ToF measurements in sequential deployments, where the initial ToF of each localization exchange varies throughout the sequence. In contrast, parallel implementations share a common initial ToF, which mitigates the impact of target motion on the resulting accuracy.

The consideration of target motion substantially reshapes the comparative performance among the evaluated methods. As expected, the TDoA system remains unaffected, and the P-SS-TWR configuration experiences only negligible variations under μm accuracy, unnoticeable within the 0.1-mm precision of Table III, confirming its low sensitivity to motion-induced inconsistencies. The P-SDS-TWR approach does exhibit some degradation, although its impact is considerably smaller than that observed in both sequential implementations. In fact, sequential systems experience the most pronounced deterioration, with the 12-sensor S-SDS-TWR configuration showing an increase in localization error of up to 217%.

This behavior reflects the accumulation of motion-induced clock uncertainties, which scale not only with the target speed but also with the number of deployed sensors involved in the sequential exchange. Among the sequential variants, S-SDS-TWR is the most affected, as its additional ToF measurements extend the overall sequence duration and amplify the temporal incoherence introduced by motion. It is also noteworthy that the degradation is not proportional to the target speed, which suggests that motion-related effects may become particularly critical in high-speed applications.

This behavior is further illustrated in Fig. 7, which provides additional insight into the RMSE contribution of each TWR method at 16 m/s for different numbers of deployed sensors. The figure distinguishes between the static clock-related error, corresponding to a target velocity of 0 m/s, and the dynamic clock contribution, computed as the difference between the total error at 16 m/s and the static case. As observed, increasing the number of sensors generally reduces the path-propagation component, since the optimized deployments can more effectively avoid NLOS conditions. However, in sequential approaches, particularly

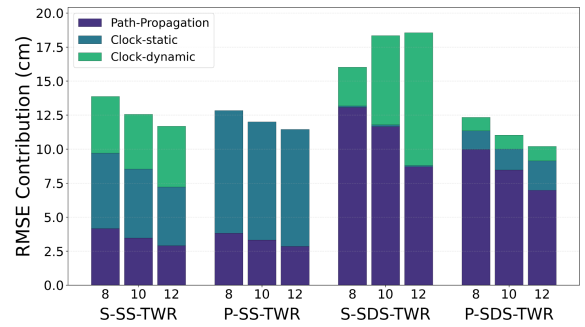


Fig. 7. RMSE contribution of each error source for the SS-TWR and SDS-TWR methods under sequential and parallel schemes, for different numbers of sensors. The total RMSE is decomposed into path-propagation errors, static clock-related errors, and the additional clock-dynamic component from target motion at $v = 16$ m/s.

the S-SDS-TWR method, exhibit a substantial growth in the motion-dependent clock contribution, which may even become the dominant source of error. This behavior highlights an important tradeoff: in high-speed applications, adding more sensors does not necessarily improve performance and may, in fact, significantly degrade the final accuracy due to the accumulation of dynamic clock uncertainties inherent to sequential TWR exchanges. These results also suggest that sensor selection strategies should account for the expected target speed [38], as removing sensors with detrimental timing impact may yield more accurate estimates than relying on larger, but dynamically inconsistent, sequential exchanges.

Although the numerical results discussed above are directly transferable only to scenarios with comparable network parameters and propagation conditions, Fig. 8 offers a generalizable perspective on the selection of the most appropriate localization architecture under varying operational regimes. The figure presents contour plots that depict the RMSE difference obtained from pairwise comparisons of the TWR methods while varying both the target speed and the incremental reply time Δt_{reply} , whose feasible values depend on the characteristics of the application scenario. These maps reveal the sensitivity of each method to these parameters and expose the decision boundaries that determine which configuration performs best in each case.

As shown, the relative superiority of the methods is strongly conditioned by these variables, which suggests that a prior analysis of the operating conditions is advisable to support informed method selection in real-world deployments. It is worth noting that in high velocity conditions, more traditional approaches, such as TDoA may remain competitive, as they are inherently unaffected by reply time related motion effects, despite receiving comparatively less attention in recent literature.

B. Spatial Decomposition of the Motion-Induced Uncertainties

While the prior subsection provided a comparative analysis based on the achieved mean RMSE between methods, this subsection provides additional insight on the spatial

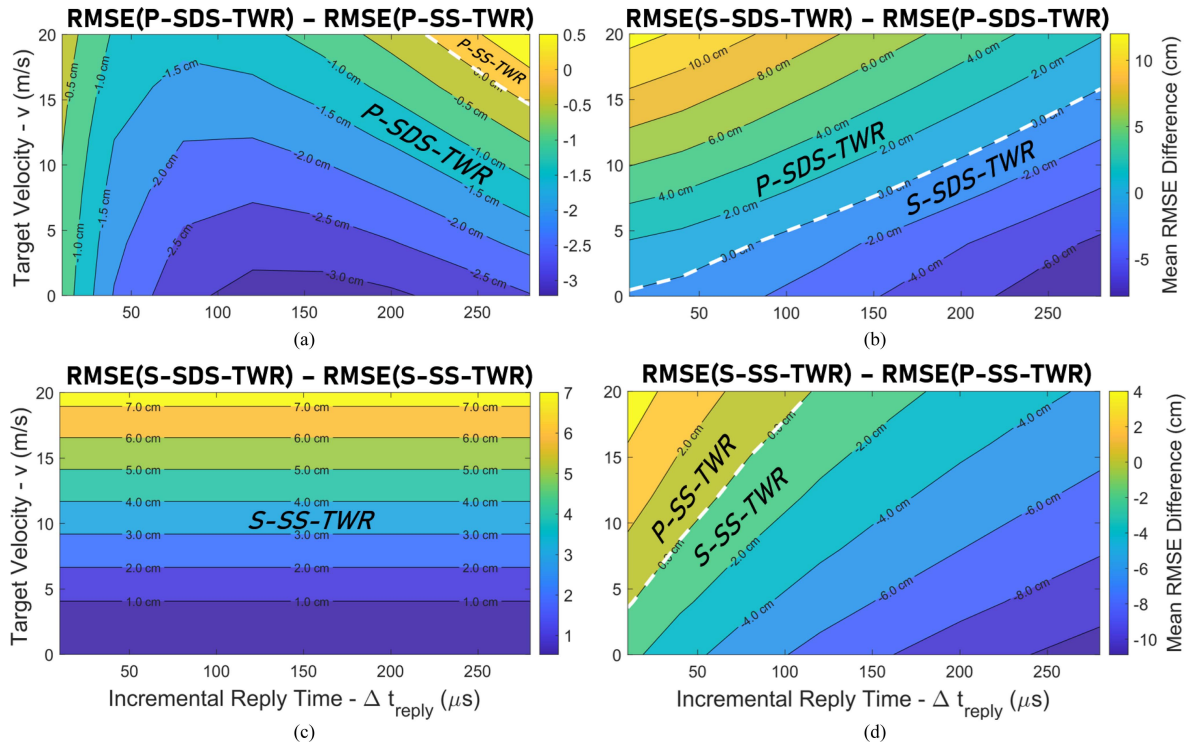


Fig. 8. Contour plots of the mean RMSE difference across target velocities and Δt_{reply} values for four method pairs. (a) P-SDS-TWR versus P-SS-TWR (parallel methods). (b) S-SDS-TWR versus P-SDS-TWR (SDS-TWR implementations). (c) S-SDS-TWR versus S-SS-TWR (sequential methods). (d) S-SS-TWR versus P-SS-TWR (SS-TWR implementations). The white dotted line marks the selection boundary (zero-difference contour) separating the regions where each method performs best; the dominant method in each region is also indicated.

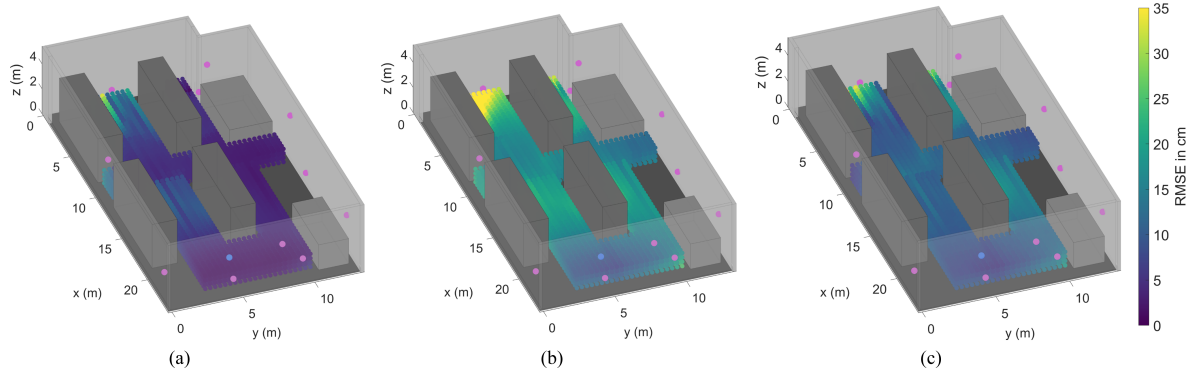


Fig. 9. Optimized spatial distribution of 12 sensors operating within the S-SDS-TWR method and the resulting RMSE distribution along the experimental scenario for target speeds of (a) 0 m/s and (b) 16 m/s. (c) RMSE difference between both cases highlights the error increment caused exclusively by the target motion. (a) RMSE distribution at $v = 0$ m/s. (b) RMSE distribution at $v = 16$ m/s. (c) RMSE difference: $\text{RMSE}_{16} - \text{RMSE}_0$

decomposition of the achieved RMSE distribution for the scenario of application.

Fig. 9 displays the achieved RMSE distribution for three case studies for the same S-SDS-TWR deployment of 12 sensors. Fig. 9(a) and (b) show the error distribution for target speeds of 0 and 16 m/s, respectively. The results show an uneven distribution of the error, where corners in between large obstacles may exhibit larger localization errors. This behavior is further influenced by the fact that the sensor deployment is optimized globally rather than symmetrically, meaning that some areas benefit from more

favorable geometric conditioning while others depend on weaker sensor configurations. Fig. 9(c) shows the RMSE difference between cases (a) and (b), thus representing the error increment caused exclusively by the motion-dependent component of the clock uncertainties. It is worth noting that, even though the target speed remains constant at 16 m/s, the resulting dynamic error distribution is not constant throughout the scenario.

Similarly to static clock-related uncertainties, target motion also affects the computed ToF. However, this impact varies across the scenario due to the local target-sensor

geometry, as larger propagation distances amplify the temporal disparity between the emission and reception instants of each ranging message. Moreover, the presence of obstacles modifies the LOS/NLOS conditions at each location, causing the motion-dependent clock contribution to interact with different noise and multipath levels throughout the environment.

As a result of these combined factors, certain regions become particularly sensitive to target motion and exhibit noticeably larger dynamic errors. This observation is especially relevant in scenarios where high-speed motion is confined to specific corridors or transit regions. In such cases, explicitly identifying these areas allows the deployment to be optimized accordingly, ensuring that the localization infrastructure is optimized where motion-induced errors are expected to be most critical.

The scope of the present study is analytical: it builds on a static CRB core whose measurement-noise characterization was contrasted against experimental indoor UWB ranging data in [24], extended here with a deterministic kinematic term $\delta_v \cdot t$ that follows algebraically from the protocol timing equations and introduces no empirical parameters requiring calibration. The comparative conclusions across protocols therefore stem from the structure of the bias terms and hold for any estimator operating on the protocol timestamps. Quantifying how closely commercial transceivers approach these bounds under motion requires a geometry-controlled setup with hardware-synchronized, submillimetre ground truth and configurable reply times; a dedicated campaign based on a rotary test rig meeting these requirements is being pursued as the experimental continuation of this work.

VII. CONCLUSION

This work presents a formal definition and characterization of the motion-induced uncertainties in asynchronous TWR localization systems, together with a systematic comparison under an optimized deployment framework across methods, implementation strategies, and target velocities.

The results indicate that sequential TWR methods achieve superior accuracy in static conditions but degrade rapidly as motion increases, whereas parallel approaches remain largely unaffected by movement yet constrained by the incremental reply time. In addition, under symmetric or near symmetric reply time conditions, SDS-based schemes consistently outperform their SS counterparts, leading to improved localization accuracy in these scenarios. SDS-TWR tends to be more sensitive to motion than SS-TWR due to its longer timing sequence, while TDoA, although it may exhibit lower accuracy in low speed scenarios, remains unaffected by target velocity, which may make it a relevant alternative in high-speed applications.

These findings highlight that method selection cannot rely on static performance alone. Instead, deployment decisions must consider expected target velocities, feasible reply-time configurations, and scenario geometry. Notably, the observed sensitivity of sequential TWR approaches raises concerns regarding the robustness of

commercial UWB systems that rely exclusively on sequential exchanges, as their accuracy may degrade substantially in dynamic or high-speed environments if deployment conditions are not carefully controlled. This reinforces the need for careful selection of hardware and configuration parameters in dynamic scenarios, particularly in applications, such as mobile robotics, AAVs, and high-speed autonomous mobile robots (AMRs) where motion-induced effects become increasingly relevant.

To summarize the main conclusions and practical implications of this work:

- 1) sequential methods excel in static scenarios but exhibit strong vulnerability to motion, limiting their applicability in dynamic environments;
- 2) parallel implementations offer higher robustness to movement but require carefully selected reply-time increments to avoid collision-induced degradation;
- 3) SS-TWR consistently outperforms SDS-TWR under motion due to its shorter and less sensitive ranging sequence;
- 4) in sequential TWR systems, adding more sensors may worsen accuracy at high speeds because of accumulated motion-induced inconsistencies; selecting only the sensors that remain coherent at the expected velocity can mitigate this issue.

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REFERENCES

- [1] A. Benouakta, F. Ferrero, L. Lizzi, and R. Staraj, "Antenna characteristics contributions to the improvement of UWB real-time locating systems' reading range and multipath mitigation," *IEEE Access*, vol. 11, pp. 71449–71458, 2023.
- [2] X. Deng, Z. Ping, and R. Sun, "UWB NLOS recognition based on improved convolutional neural network assisted by wavelet analysis and Gramian angular field," *IEEE Sensors J.*, vol. 23, no. 14, pp. 16384–16392, Jul. 2023.
- [3] R. F. Brena, J. P. García-Vázquez, C. E. Galván-Tejada, D. Muñoz-Rodríguez, C. Vargas-Rosales, and J. Fangmeyer Jr, "Evolution of indoor positioning technologies: A survey," *J. Sensors*, vol. 2017, no. 1, 2017, Art. no. 2630413.
- [4] "IEEE Standard for Information Technology–Local and Metropolitan Area Networks–Specific Requirements–Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs): Amendment 1: Add Alternate Phys.," IEEE Standard 802.15.4a-2007 (Amendment to IEEE Std 802.15.4-2006), pp. 1–210, 2007.
- [5] F. Vicentini, "Collaborative robotics: A survey," *J. Mech. Des.*, vol. 143 no. 4, 2021, Art. no. 040802.
- [6] R. Ahmad, W. Alhasan, R. Wazirali, and N. Aleisa, "Optimization algorithms for wireless sensor networks node localization: An overview," *IEEE Access*, vol. 12, pp. 50459–50488, 2024.
- [7] I. Sánchez-Calleja, R. Ferrero-Guillén, A. Martínez-Gutiérrez, and J. Díez-González, "Integrating industrial robots through a contact method," *IEEE Access*, vol. 13, pp. 175770–175780, 2025.

- [8] A. Martínez-Gutiérrez, J. Díez-González, R. Ferrero-Guillén, P. Verde, R. Álvarez, and H. Perez, "Digital twin for automatic transportation in Industry 4.0," *Sensors*, vol. 21, no. 10, 2021, Art. no. 3344.
- [9] A. Martínez-Gutiérrez, J. Díez-González, P. Verde, R. Ferrero-Guillén, and H. Perez, "Hyperconnectivity proposal for smart manufacturing," *IEEE Access*, vol. 11, pp. 70947–70959, 2023.
- [10] J. Cano, G. Pagès, E. Chaumette, and J. LeNy, "Clock and power-induced bias correction for UWB time-of-flight measurements," *IEEE Robot. Automat. Lett.*, vol. 7, no. 2, pp. 2431–2438, Apr. 2022.
- [11] Y. Gu and B. Yang, "Clock compensation two-way ranging (CC-TWR) based on ultra-wideband communication," in *Proc. 8th Int. Conf. Instrum. Meas., Comput., Commun. Control*, 2018, pp. 1145–1150.
- [12] C. L. Sang, M. Adams, T. Hörmann, M. Hesse, M. Porrmann, and U. Rückert, "An analytical study of time of flight error estimation in two-way ranging methods," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2018, pp. 1–8.
- [13] R. Alvarez, J. Díez-González, L. Sanchez-Gonzalez, and H. Perez, "Combined noise and clock CRLB error model for the optimization of node location in time positioning systems," *IEEE Access*, vol. 8, pp. 31910–31919, 2020.
- [14] R. Alvarez, J. Díez-González, N. Strisciuglio, and H. Perez, "Multi-objective optimization for asynchronous positioning systems based on a complete characterization of ranging errors in 3D complex environments," *IEEE Access*, vol. 8, pp. 43046–43056, 2020.
- [15] P. Verde, J. Díez-González, R. Álvarez, and H. Perez, "Characterization of AGV localization system in industrial scenarios using UWB technology," *IEEE Trans. Instrum. Meas.*, vol. 72, 2023, Art. no. 8505313.
- [16] S. Srinivas, S. Welker, A. Herschfeld, and D.W. Bliss, "Cramér–Rao lower bounds on 3D position and orientation estimation in distributed ranging systems," *Appl. Sci.*, vol. 13, no. 3, 2023, Art. no. 2008.
- [17] M. Delamare, R. Boutteau, X. Savatier, and N. Iriart, "Static and dynamic evaluation of an UWB localization system for industrial applications," *Sci*, vol. 2 no. 2, 2020, Art. no. 23.
- [18] Z. Y. Liu, R. Z. Chen, F. Ye, G. Y. Guo, and L. X. Huang, "A low-delay and robust solution for rapid movement detection using UWB: The international archives of the photogrammetry," *Remote Sens. Spatial Inf. Sci.*, vol. 43, pp. 377–382, 2020.
- [19] Y. Zhao, Z. Zhou, J. Zou, J. Guo, G. Huang, and J. Wu, "Ultra-wideband ranging data reconstruction and positioning calculation framework in indoor low-dynamic scenarios," *IEEE Trans. Instrum. Meas.*, vol. 74, 2025, Art. no. 1013017.
- [20] M.A. Shalaby, C.C. Cossette, J. R. Forbes, and J. L. Ny, "Reducing two-way ranging variance by signal-timing optimization," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 60, no. 3, pp. 3718–3724, Jun. 2024.
- [21] T. Laadung, S. Ulp, M. M. Alam, and Y.L. Moullec, "Novel active-passive two-way ranging protocols for UWB positioning systems," *IEEE Sensors J.*, vol. 22, no. 6, pp. 5223–5237, Mar. 2022.
- [22] R. Ferrero-Guillén, J. Díez-González, R. Álvarez, J. Torres-Sospedra, H. Perez, and A. Moreira, "Asynchronous time-based indoor localization systems—comparative analysis under realistic industrial-oriented conditions," *Ad Hoc Netw.*, vol. 173, 2025, Art. no. 103816.
- [23] M. Manzoni et al., "Motion estimation and compensation in automotive MIMO SAR," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 1756–1772, Feb. 2023.
- [24] N. Ballber Torres, B. Etzlinger, E. Dehmollaian, and A. Springer, "Defining secure areas for TDOA-enhanced non-ideal distance bounding," in *Proc. Int. Wireless Commun. Mobile Comput.*, 2022, pp. 348–353.
- [25] B. V. Herbruggen, D. V. Leemput, J. V. Landshoot, and E. D. Poorter, "Real-time anchor node selection for two-way-ranging (TWR) ultra-wideband (UWB) indoor positioning systems," *IEEE Sens. Lett.*, vol. 8, no. 3, Mar. 2024, Art. no. 600240.
- [26] R. Ferrero-Guillén, J.-M. Alija-Pérez, A. Martínez-Gutiérrez, R. Álvarez, P. Verde, and J. Díez-González, "Black widow optimization for reducing the target uncertainties in localization wireless sensor networks," *Log. J. IGPL*, vol. 32, no. 6, pp. 971–985, 2024.
- [27] J. Díez-González, R. Ferrero-Guillén, P. Verde, A. Martínez-Gutiérrez, R. Álvarez, and J. Torres-Sospedra, "Time-based UWB localization architectures analysis for AAVs positioning in industry," *Ad Hoc Netw.*, vol. 157, 2024, Art. no. 103419.
- [28] J. Díez-González, R. Ferrero-Guillén, P. Verde, A. Martínez-Gutiérrez, J.-M. Alija-Pérez, and H. Perez, "Analysis of synchronous localization systems for AAVs urban applications," *Neurocomputing*, vol. 564, 2024, Art. no. 126969.
- [29] K. Muthineni, A. Artemenko, J. Vidal, M. Nájara, M. Catalan, and J. Paradells, "Deep learning-based UWB-IMU data fusion for indoor positioning in industrial scenario," *IEEE Open J. Veh. Technol.*, vol. 6, pp. 1209–1221, 2025.
- [30] S. Cavassila, S. Deval, C. Huegen, D. V. Ormondt, and D. Graveron-Demilly, "Cramér–Rao bounds: An evaluation tool for quantitation," *NMR Biomed.: Int. J. Devoted Develop. Appl. Magn. Reson. Vivo*, vol. 14, no. 4, pp. 278–283, 2001.
- [31] M. K. Elmezghi and T.J. Afullo, "An efficient approach of improving path loss models for future mobile networks in enclosed indoor environments," *IEEE Access*, vol. 9, pp. 110332–110345, 2021.
- [32] R. Ferrero-Guillén, J. Díez-González, A. Martínez-Gutiérrez, H. Perez, J. Torres-Sospedra, and A. Moreira, "Comparing synchronous and asynchronous UWB time-based localization systems for autonomous mobile robots," *Neurocomputing*, vol. 629, 2025, Art. no. 129622.
- [33] Y. Yoon and Y.-H. Kim, "An efficient genetic algorithm for maximum coverage deployment in wireless sensor networks," *IEEE Trans. Cybern.*, vol. 43, no. 5, pp. 1473–1483, Oct. 2013.
- [34] J. Díez-González, P. Verde, R. Ferrero-Guillén, R. Álvarez, and H. Pérez, "Hybrid memetic algorithm for the node location problem in local positioning systems," *Sensors*, vol. 20, no. 19, 2020, Art. no. 5475.
- [35] J. Díez-González, R. Álvarez, L. Sánchez-González, L. Fernández-Robles, H. Pérez, and M. Castejón-Limas, "3D TDOA problem solution with four receiving nodes," *Sensors*, vol. 19, no. 13, 2019, Art. no. 2892.
- [36] F. Geyer and D. Schupke, "Precise onboard aircraft cabin localization using UWB and ML," in *Proc. IEEE Glob. Commun. Conf.*, 2022, pp. 2032–2037.
- [37] J. Zhou, L.J. Shen, and Z. Sun, "A new method of D-TDOA time measurement based on RTT," in *Proc. MATEC Web Conferences*, 2018, Art. no. 03018.
- [38] R. Álvarez, J. Díez-González, P. Verde, R. Ferrero-Guillén, and H. Perez, "Combined sensor selection and node location optimization for reducing the localization uncertainties in wireless sensor networks," *Ad Hoc Netw.*, vol. 139, 2023, Art. no. 103036.



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