A Comparative Study of Mobile Robot Positioning Using 5G NR

Panagiotis T. Karfakis[1,2], Micael S. Couceiro[1,2], David Portugal[2] and Carlos Henggeler Antunes[3]

Abstract— **In this work we study the use of the 5G New Radio (NR) communication model for position tracking of a mobile robotic system. We have deployed the 5G NR in three different configurations in a simulated agricultural environment. We evaluate the impact of using different number of gNodeB (gNB) base stations and the increased topological complexity on the position estimation, using three different heuristic approaches. The setups consist of 5, 10 and 15 gNBs that communicate with the user equipment (UE) carried by the robot. The ground truth trajectory of the system is recorded and estimated by three meta-heuristics, namely Hyperbola Crossing points (HCP), Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA). We measure the performance according to statistical metrics such as the average prediction time, the average Euclidean Distance (ED) and their standard deviations. We provide and discuss the qualitative results derived experimentally to assess the positioning capability of 5G NR for a simulated field robotics application.**

Index Terms— **5G NR, Mobile Robotics, Position Estimation, Meta-Heuristics, Agriculture, HCP, PSO, GA**

I. INTRODUCTION

As we are steadily moving forward into the next generation of wireless communications, there is a promising future for robotic systems integrating 5G New Radio (NR) technology [2]. NR is described in Release 16 of the 3rd Generation Partnership Project (3GPP), which is the standardization organization. The 5G NR network can support multiple communication protocols and services with a primary focus of advancing industrial, infrastructure, device to device (D2D), vehicular and people oriented applications in urban and rural areas.

The roll out of the 5G cellular network is performed currently as two types, Stand Alone (SA) and Non Stand Alone (NSA). In the first case, the 5G user devices have access through the ground Node B (gNBs) base stations and the core network relies on the newly installed 5G infrastructure. In the latter case, the 5G enabled devices have access to the 5G network interface but the core systems are still based on 4G infrastructure. Hence communications differ in latency than 'true' 5G in terms of tens of milliseconds, but still faster when compared to its predecessors. The User Equipment (UE) is the target of the tracking process and communicates with the gNB base stations at regular intervals to infer its global position from the cellular network [8].

5G-enabled devices are predicted to have many favorable characteristics for mobile robot applications in outdoor environments, such as higher speeds, low latency, larger bandwidth capacity and less tower congestion in terms of infrastructure, as its predecessors required. These attributes are very attractive for applications such as smart factories, manufacturing and warehousing, autonomous vehicles, medical and agriculture automation.

Tracking the position of a mobile robotic systems in an outdoor environment is a challenging task due to the inherent complexity of the environment. The Global Positioning System (GPS) is the standard for outdoor field robotics, but signal quality is not always available especially in rural areas such as dense forests, canyons, but also in building congested cities as it requires communication with satellites that are in orbit and non line of sight is a frequent problem.

The contribution of this work is to evaluate the position estimation performance from a terrestrial communication source such as the new 5G NR and assess its suitability for position estimation of robotic systems, in terms of execution time and error. For this purpose, we evaluate three well established meta-heuristics for 5G position tracking, based on Hyperbola Crossing Points (HCP), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). This represents a preliminary step towards a full assessment of the impact of placement of base stations on robot positioning performance.

II. RELATED WORK

Position estimation using telecommunications relies on multiple nodes. Nodes can be synchronized or operate asynchronously to determine the position. A node is responsible of transmitting signals with qualitative and quantitative properties that can be utilized by a receiver to measure the transmission time and infer the ranges from nearby cellular base stations. The measured signals are transformed into the inferred position that can be used for localisation purposes of a mobile robotic system operating outdoors.

There are two types of signal processing for position estimation which are range-based and range-free [3]. In static wireless networks, range free approaches such as the centroid [13], Amorphase [13], DV-HOP [13] and APIT [16] have been used in the past to determine sensor location. In

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[1]Panagiotis T. Karfakis and Micael S. Couceiro are with Ingeniarius Ltd, 4445-147, Alfena, Portugal. {panagiotis,micael}@ingeniarius.pt.

[2]Panagiotis T. Karfakis, Micael S. Couceiro and David Portugal are with the Institute of Systems and Robotics (ISR), Department of Electrical and Computer Engineering, University of Coimbra, Portugal. {panagiotis.karfakis,micaelcouceiro,davidbsp}@isr.uc.pt

[3]Carlos Henggeler Antunes is with INESC Coimbra, Department of Electrical and Computer Engineering, University of Coimbra, Portugal. ch@deec.uc.pt.

range positioning the position of a node relies on information produced from the Received Signal Strength Indicator (RSSI) [5], Time Difference of Arrival (TDOA) or Angle of Arrival (AOA) of the base station topology. For the determination of the ranges in cellular networks, the Time of Arrival (TOA), Angle of Arrival (AOA) and Phase of Arrival (POA) and their combinations [7] have been utilized successfully in the past.

As a means of absolute outdoor robot positioning systems, sensors based on the the Global Navigation Satellite Systems (GNSS) are the most commonly used [4]. They rely on a constellation of satellites around the Earth's orbit, which constantly transmit their location. This information is then used to estimate the time elapsed in communication between the receiver and transmitter. Through trilateration or multilateration between the receiver and available satellites in orbit, the final position can be established within a reasonable error margin. With the evolution of cellular networks the combination of satellite and terrestrial communications was made possible and an object can be tracked with improved accuracy [9].

Currently we are making the transition to the 5G era bringing increased signal density, lower latency, larger bandwidth and much higher frequencies and energy savings. As with its predecessors, 5G NR is predicted to be a hybrid between ground based radio frequency communications and satellite global communications. The 4G Long Term Evolution (LTE) has provided connectivity with devices in such way that broadband internet coverage was expanded to IoT devices in remote regions as a hybrid scheme.

The communication model is based on the downlink time difference of arrival signal (DL-TDOA) or the uplink signal (UL-TDOA) between the UE and the base stations. All gNBs are synchronized and each signal is transmitted in specific intervals to avoid cross interference [2].

Setup of the gNBs consists of the position reference signal (PRS) and the downlink shared channel (PDSCH). The PRS in 5G NR serves to solve two important positioning issues in regards to the communication of gNBs and UE. Each gNB signal is prone to interference from nearby stations that can cause the collision of the millimeter wave (mmWave) signals in both time and frequency domains. For this purpose the PRS was developed as a separate signal, to avoid the shadowing of weak signals received from distant gNBs. Without these signals, further uncertainty in the detection process of distant gNBs signals would be added and eventually result in partial signal loss, which can include the position information.

Moreover the downlink reference signal's correlation properties are generally weak due to low resource element (RE) density. Due to this reason, it is possible that the RE pattern is not widely accessible across the carriers of the transmitted frequency. The physical downlink shared channel (PDSCH) is the data transmission channel and is subject to signal modulation. The signal before transmission is encoded under an orthogonal frequency division multiplexing (OFDM) scheme which provides larger bandwidth and gains

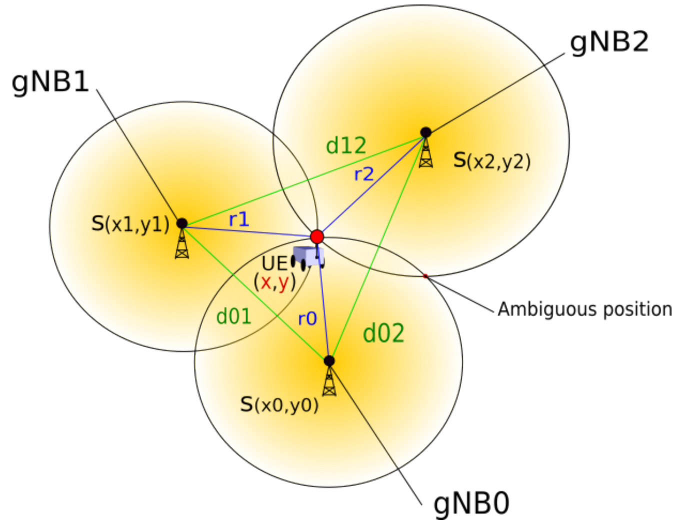

Fig. 1. Multilateration with 5G NR and User Equipment (UE).

in overall response time. More information regarding the 5G NR positioning and the parametrization of the signals can be found in [2].

In this work, we experiment with the 5G NR communication propagation model to derive the 2D position from the meta-heuristic approaches in an agricultural simulation.

III. Methodology

In this section we describe the concepts and processes involved within the work.

A. Problem modelling

Given a set of gNB stations which are placed over large distances, the position tracking can be seen as a combinatorial problem. A robot carrying the UE is able to use the 5G NR to track its position over time by comparing the ranges from each base station and infer its position as in Figure 1.

The ranges to each gNB $S_n(x, y)$, where n is the individual index, are estimated from the DL-TDOA signals. Additional parameters include the fixed locations of the stations, which can be considered as vertices of the triangles that are created from the known distances between gNBs d_{nm} where n is the source and m is the destination index, and the estimated ranges $[r_0, .., r_n]$ to the UE. A mobile robot carrying the UE with access to this information is capable of estimating its global position. By iterative computation, tracking the position will generate the trajectory of the robot over time in the world reference frame $O[x, y]$. All parameters of the problem are summarized in Table I.

In general, the positioning of the robot can be seen as a non linear optimization problem of the unknown position based on the gNB ranges, that has been adapted from [17] and represented as a system of equations of the form of Equation 1,

$$r_i^2 = (S_i - p_0)^T (S_i - p_0) \tag{1}$$

where r_i are the ranges from each gNB, S_i are the fixed gNB positions and p_o is the unknown robot position specified

TABLE I
PROBLEM PARAMETERS.

Parameter	Notation	Description
Space dimension:	2D	Cartesian
Redundant ranges:	Yes	Dependent on gNBs
Global reference:	O(x,y)	World frame
Robot position vector:	$p_o(x, y)$	Based on UE
Station position vectors:	$S_n(x, y)$	Fixed
Ranges:	$r_0, r_1, r_2..r_n$	Distances, gNBs to UE

from a number of N position reference points (gNBs). In our case, the ranges are measured from the TDOA signals of the 5G NR with Equation 2,

$$r_i^2 = \frac{c \cdot dtoa_i}{s_R} \tag{2}$$

where c is the speed of light, $dtoa$ is the time difference of arrival of each gNB and s_R the sample rate. Then we can represent the optimization equation as Equation 3,

$$\mathbf{p}_{opt} = \arg\min_{\mathbf{p}_0} S(\mathbf{p}_0) \tag{3}$$

where we try to minimize the approximate position estimates $S(p_o)$ and find the optimized position p_{opt}, based on the gNBs ranges and their fixed distances in the world reference frame. These estimates are given by Equation 4,

$$S(p_o) = \sum_{i=1}^{N} [(S_i - p_0)^T (S_i - p_0) - r_i^2]^2 \tag{4}$$

where r_i are the measured ranges, between the i-th gNB and the robot, from the 5G NR signal TDOA as per Equation 2, S_i is the i-th fixed gNB position and p_o is the estimated robot position specified by each of the N gNB position reference points. This least-squares formulation of the multilateration equation is implemented internally in all meta-heuristics.

B. Hyperbolic Crossing Points

The HCP [10] has been extensively used to determine the position of equipment since early applications within wireless and cellular telecommunication networks. It is a method that utilizes the TDOA multilateration algorithm to derive the position of UE in the global reference coordinates. It uses stationary terrestrial antennas to measure the propagation of signal from the gNB to the UE.

In our case the 5G NR model [14] provides an interface for estimating the position of the robot by using the DL-TDOA method, which calculates the time delays and the path loss from each gNB to the UE independently. When the number of base stations increases, the time required to estimate the position is an additional overhead, unless corrective measures are added to the method to selectively perform multilateration only with a number of nearest gNBs. In this work we perform multilateration with all gNBs and select the five nearest ones to the robot for position estimation.

The signal transmissions have hyperboloid form and arrive to the receiver at different time intervals which are differenced and multiplied by the speed of light. This process is the TDOA and results in the position estimation from the gNBs. As a requirement, all ambiguous points of the communication, which are the crossing points of successive hyperbolas, are eliminated by redundant base stations in the region. The resolution of these points is performed automatically and is capable of improving the position estimation capability within the cellular network.

C. Particle Swarm Optimisation

The PSO [6], [1] is a meta-heuristic aimed at searching the large candidate solution spaces effectively, while making minimal assumptions about the optimization problem characteristics. PSO is suitable for tracking the position of a moving target in the world frame coordinates. The algorithm works with population of solutions that interact, which is referred to as a swarm and the candidate solutions as particles.

Each particle is initialized within the available 2D search space and explores it to find the optimal robot position. The exploration process of each particle, with a certain velocity, is driven by its own best estimated position (personal best) and the swarm's best estimated position (global best) within the search space. This process continues until a stopping condition is attained. A balance is sought between the diversification (search space exploration) and intensification (exploiting promising solutions) movements, which should be obtained by a judicious choice of the algorithm control parameters, to avoid convergence to local optima and find the global optimal solution, or a good approximation in a reasonable computation time. Design decisions involve the population size, number of iterations, setting of inertia weight, cognitive and social parameters, which influence the position and the velocity of particles in the search space.

D. Genetic Algorithm

GA mimic the evolutionary process of survival of the fittest in an optimization context. The estimation of the position is based upon the evolution of solutions over generations until a stopping condition is reached aiming to determine the optimal (fittest) solution [15]. The initial population of candidate solutions is, in general, generated randomly or guided into areas where some prior information indicates good solutions are likely to occur.

The most prominent position estimates are preserved for generating the next iteration of potential solutions by passing their characteristics to their offspring. This iterative evolutionary process generates successive populations of candidate solutions, hopefully improving their quality in face of the optimization problem, by means of selection, crossover and mutation operators. The individuals of the solution population are evaluated by a fitness function to assess their quality, which influences selection for reproduction, i.e. being the parents of the next generation solutions.

The creation of offspring solutions involves the exchange (crossover) and the change (mutation) of parent solution components. The selection operator is called to select the parents to generate offspring and the offspring that will be carried out to the next generation. These operators should preserve solution diversity to avoid premature convergence to local optima.

E. Algorithmic approach

Before the execution of the algorithms two mandatory steps are performed. The first step is the configuration of the communication parameters and the algorithm parameters. The configuration of the PRS and the PDSCH is performed at startup and then we evaluate the performance of position estimation of the three meta heuristic approaches (see Algorithm 1).

For the meta-heuristics, we have decided to perform the position predictions at an interval of 100 ground truth measurements, due to the overall large execution time and data. The PSO was configured with a population size of 200 and the iterations were set to 1000. For GA the population size is set to 50, the generations to 200 and the elite count was set to be 0.05 of the population. The prediction time of the PSO is adjusted to be similar to the execution of the GA, in order to have a fair comparison of the methods and the parameters were set as above to achieve this and remained the same for experiments.

In all approaches, N is the number of gNBs and T are the robot points. The HCP estimates the crossing points of the hyperbolic signals based on the estimated ranges and the the five closest gNBs. The PSO inputs are the gNB positions and ranges, then calculates the minimum distance of the UE to the gNBs. The GA was customized in similar fashion by taking the ranges and positions of the base stations and returns the estimated position. We have used Equation 5 to calculate the Euclidean distance of the position compared with the ground truth for all setups. Additionally, we measured the time of execution for the position prediction of each measurement independently.

Algorithm 1 5G NR Position Estimation

```
procedure 5GEstimatePosition(N, T, interval)
    PRSconfig
    PDSCHconfig
    for i = 1 : size(T) : interval do
        UEpos ← T(i)
        for i = 1 : size(N) do
            ranges = TDOA(N, UEpos)
        end for
        t_start ← start
        p_hcp = HCP(N, ranges), or
        p_pso = PSO(N, ranges, 200, 1000), or
        p_ga = GA(N, ranges, 50, 200)
        t_(i) ← t_now − t_start
    end for
end procedure
```

F. Performance Metrics

For the evaluation of the meta heuristic algorithms, we have considered two important metrics, the position prediction time and the position error. We have measured the prediction time of the HCP, PSO and GA on an individual measurement basis. Once a measurement is received, the time elapsed for each heuristic is measured and overall averaged for the duration of the trajectory, resulting in the Mean Execution Time (MET).

The Euclidean distance (ED) between the predicted position and ground truth measurements are calculated according to the Equation 5 that gives the squared root of the Cartesian coordinate differences, between the ground truth position measurement $p_{gt} = [x_{gt}, y_{gt}]$ and the estimated positions $p_{est} = [x_{est}, y_{est}]$ of the algorithms. This determines the position error in the prediction as linear distance from the ground truth measurement.

$$dist(x,y) = \sqrt{\sum_{i=1}^{n} (x_i^{gt} - x_i^{est})^2 + (y_i^{gt} - y_i^{est})^2} \tag{5}$$

The standard deviation of the predicted measurements and the ground truth position of the robot is given by Equation 6, where the x and y are the Cartesian coordinates of the robot trajectory and their mean values μ_x and μ_y. This represents the expected deviation between the measurement estimated by the heuristic approaches and the ground truth.

$$Sn_{(x,y)} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu_x)^2 (y_i - \mu_y)^2} \tag{6}$$

The results of our tests are summarized with Table II where the MET and ED is presented along with their standard deviations.

IV. Results

In this section we report the experiments performed and the results.

A. Robot Simulation and 5G toolbox

For the experiment, the `cpr_agriculture_gazebo`[1] simulation package was used, which utilizes a Husky robot model from Clearpath Robotics[2]. This simulator was selected due to its integration with ROS and its outdoor features such as uneven terrain with elevation, its large provided area and its integrated physics rules. The simulator provides a ground truth pose, which was used to assess the estimation performance of each method.

For the PRS signal generation and communication aspects the MATLAB 5G Toolbox [12] was used and integrated within ROS [11] to predict the robot position from the simulator ground truth data.

[1] https://github.com/clearpathrobotics/cpr_gazebo
[2] https://clearpathrobotics.com

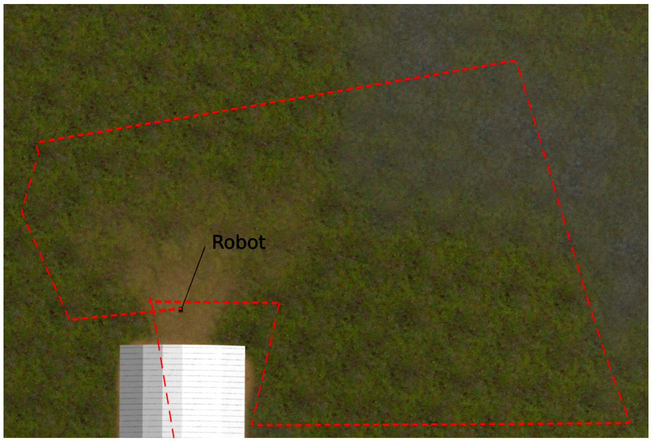

Fig. 2. Robot ground truth trajectory.

B. Experimental Setups

Three setups were prepared to evaluate the performance of the 5G NR positioning. We have selected different number of stations in order to compare the accuracy of the position tracking and the time required to generate the position estimation. The placement of gNB positions in all three environments were generated randomly outside the robot's working environment, and are located kilometers away, which is a representative assumption for 5G applications in real world outdoor scenarios.

In Setup 1 the placement of the 5 gNB positions are displayed in Figure 3. The ground truth trajectory within Figure 2 is performed by the mobile robot and depicted in Figures 3, 4, 5 to convey the scale of positioning.

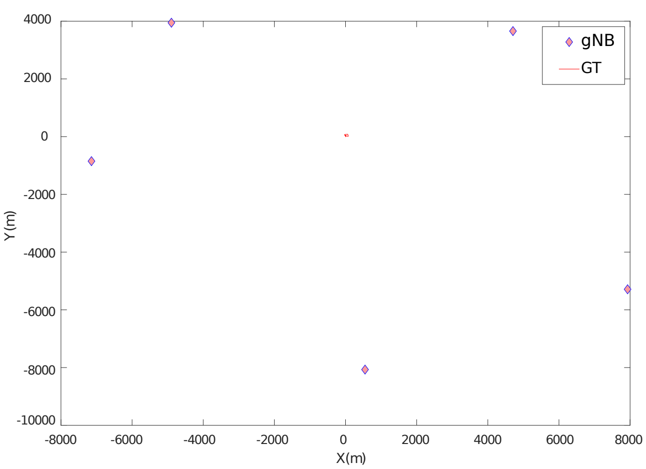

Fig. 3. Setup 1 featuring the gNB positions and the scale of the ground truth trajectory.

Likewise, setup 2 which consists of 10gNBs is depicted in Figure 4, and setup 3 which consists of 15gNBs is depicted in Figure 5. A notable fact about the rollout of the 5G NR is that signal coverage is going to determine the geometrical structure of the gNB locations and it is envisaged to be in a grid pattern, with each station being kilometers apart. In

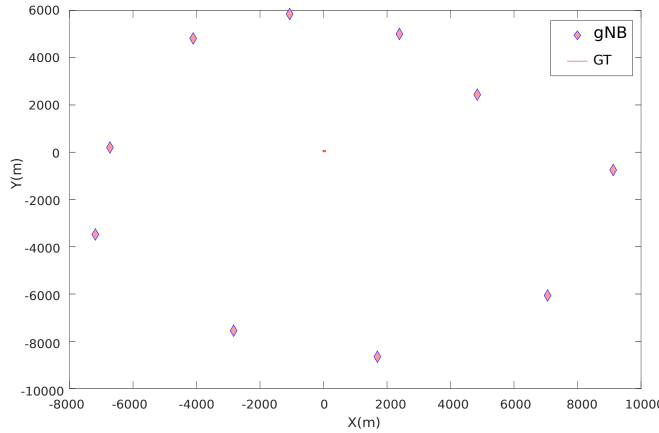

Fig. 4. Setup 2, consisting of the 10 gNB stations.

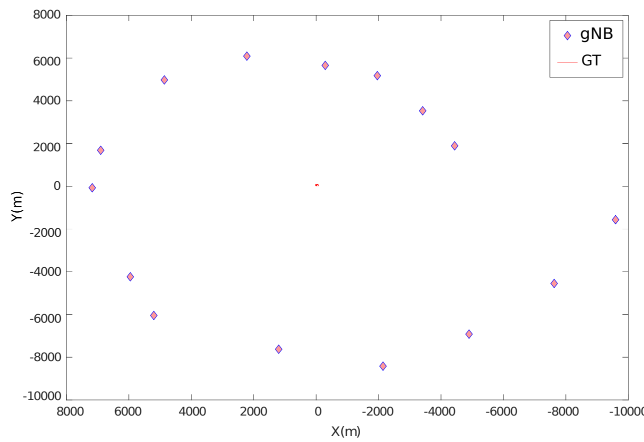

Fig. 5. Setup 3 consisting of the 15 randomly allocated gNBs.

rural agricultural areas the gNB deployment geometry may vary depending on the morphology of the area. The path loss model used (*cf.* Section IV-A) is set to the default urban Macrocell Scenario (uMa), with infrastructure height set to 5m and environmental height to be 2m and is representative of a flat agricultural area.

In the configuration of the 5G NR parameters, the PRS depends on the DL-TDOA scheme and we have configured the carrier slots of each gNB and a carrier frequency of $3e^9$ Hz. For the PRS configuration, the slot periodicity was set to 10 for setup 1, 20 for setup 2 and 30 for setup 3. The transmission offset was set to be every one consecutive repeated PRS signal. The modulation scheme for the PDSCH is set to Quadrature Phase Shift Keying (QPSK) and the length of the codewords to be 2 bits per symbol, with a total of 14 symbols per slot. Orthogonal frequency-division multiplexing modulation (OFDM) is performed to generate the 5G NR waveforms at each gNB [12]. The hearability problem is addressed by allocating the PRS resources and PDSCH channel to the slot grid in a way such that no other gNB transmits a PRS signal within the same slot.

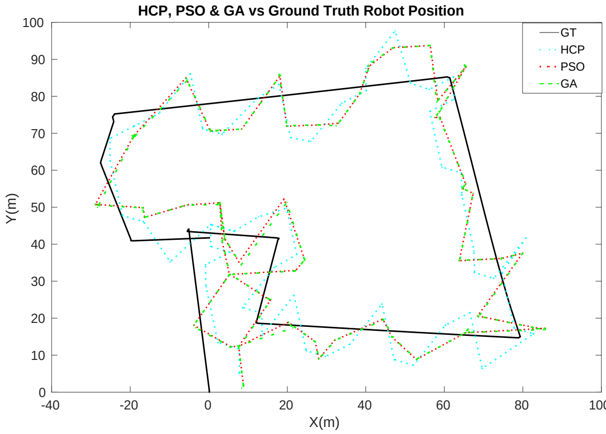

Fig. 6. Position estimation of HCP, PSO, GA meta-heuristics for Setup 1.

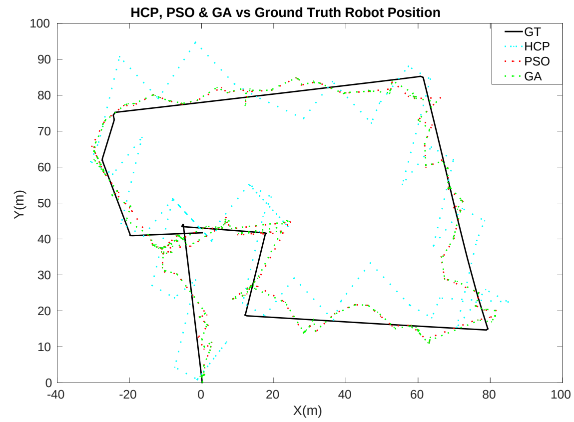

Fig. 7. Position estimation of HCP, PSO, GA meta-heuristics for Setup 2.

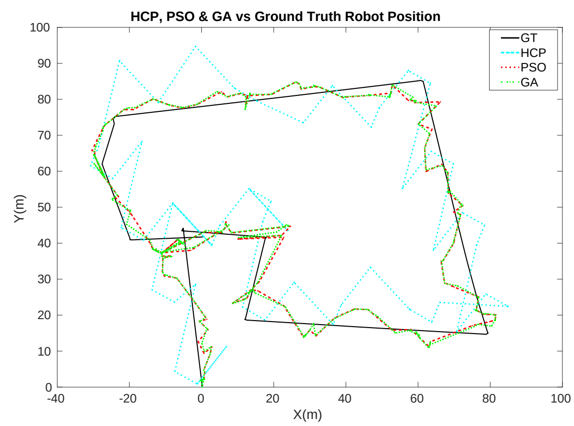

Fig. 8. Position estimation of HCP, PSO, GA meta-heuristics for Setup 3.

C. *Performance*

In setup 1, which consists of the 5 gNBs, we observed that the PSO was faster than the other two approaches. In terms of accuracy, the HCP proved to have the best positioning accuracy of 6.317 ± 2.810 meters, but is not the fastest approach to predict the position due to the characteristic multilateral aspects of the method with MET at 1.504 ± 0.119 seconds. The fastest approach was the PSO with MET at 0.075 ± 0.039 which was not far from the GA which was at 0.079 ± 0.036 seconds. In terms of average error they deviated about a meter from the HCP. The estimated trajectories can be seen in Figure 6.

In setup 2, which consists of 10 gNBs, results were slightly different. The best performing in terms of execution time and accuracy was the GA with MET at 0.053 ± 0.020 seconds and ED at 5.082 ± 2.015 meters. The time required by the PSO is 2.36 times the GA prediction time; the accuracy is also slightly worse but similar. The additional overhead of the HCP is due to the number of base stations and time required to communicate with all of them affected significantly the performance of HCP, having an execution time of 11.03 times longer than the PSO and 26.15 times than GA, with a larger position prediction error. In comparison with setup 1 the MET is faster due to the closer distance of some gNBs which were selected for position estimation. The estimated trajectories can be seen in Figure 7.

In setup 3, which consists of 15 gNBs, the PSO and GA approaches were the best overall, as their position accuracy is very similar. The GA has the fastest position prediction time which is at 0.050 ± 0.042 seconds, which is 3.91 times faster than the PSO prediction time. The HCP has a high execution time and the least position accuracy. In terms of positioning accuracy the PSO and GA are highly competitive with 3.850 ± 1.859 meters and 3.813 ± 1.862 meters respectively. The estimated trajectories can be seen in Figure 8.

In Table II, the GA is the top performing algorithm independently from the number of gNBs. The PSO, although being very similar to GA in error metrics, lacks in position prediction time. The HCP cannot cope with the growth of the number of gNB numbers, as the time required to communicate with all gNBs in a multilateration fashion is large.

TABLE II
EXPERIMENTAL RESULTS.

Setup	Methods	MET (s)	ED (m)
1	HCP	1.504 ± 0.119	**6.317 ± 2.810**
	PSO	**0.075 ± 0.039**	7.489 ± 2.580
	GA	0.079 ± 0.036	7.450 ± 2.560
2	HCP	1.386 ± 0.072	7.146 ± 3.248
	PSO	0.125 ± 0.075	5.183 ± 2.035
	GA	**0.053 ± 0.020**	**5.082 ± 2.015**
3	HCP	1.636 ± 0.098	7.395 ± 4.131
	PSO	0.199 ± 0.105	**3.850 ± 1.859**
	GA	**0.050 ± 0.042**	**3.813 ± 1.862**

V. CONCLUSION

In this work we have performed the integration of 5G NR technology in a simulated robotic environment and utilized meta-heuristics to track the location of the robot over time. The GA is the fastest method and has the least error, as the number of gNBs are increased. The PSO presents similar results but lacks the prediction time, which is important in mobile robot positioning applications. In terms of HCP, even by selecting only the closest five gNBs to the robot did not present better results in terms of accuracy and the TDOA is an additional overhead, with an increasing number of gNBs. The next step regarding this work is the placement of the gNBs in a grid fashion, perform further tests and progressively work with real data from 5G NR service providers to compare our findings.

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