



INSPIRe

WP8 – Assess the feasibility of using opportunistic sources of data to aid DFMC integrity

Spec8.1: Preliminary review of Functional and software design and test specifications Crowdsourced (inputs into DFMC integrity)

Prepared for:



Table of Contents

1.	Intro	oduction	.3
		ntext and Objective	
		erview of the Crowdsourcing Concept	
	1.3	Related document	
	1.4	Revision History	
2.		r-level crowdsourcing	
		nctional Architecture for the Software Design	
		st specifications	
3.		em-level crowdsourcing	
5.	-	nctional Architecture for the Software Design	
		easurements error data	
	J.Z 1016		тЭ

©Copyright Statement

This document, its contents and the ideas and intellectual property within are the ©Copyright of Taylor Airey Limited. This the document must not be copied, replicated or reproduced in any format including electronic transmission, or passed on to third parties without the express written permission of Taylor Airey Limited.

1. Introduction

This report provides a preliminary review of the functional and software design, along with the test specifications for crowdsourced inputs into DFMC integrity. This significant research initiative is undertaken as part of Work Package 8 (WP8) in the Integrated Navigation Systemof-Systems PNT Integrity for Resilience (INSPIRe) project.

1.1 Context and Objective

WP8 assesses the feasibility of augmenting dual-frequency multi-constellation GNSS integrity monitoring using crowd-sourced integrity data from users. The work focuses on the maritime sector, considering potential expansion into other sectors where integrity is a key performance metric in critical applications. The work includes two approaches: System-level crowdsourcing and user-level crowdsourcing.

The aim of this report is to present the preliminary functional architecture of the software design for both approaches. It details the data utilised in evaluating these approaches, describes the applications developed as part of this project, and outlines the testing scenarios and specifications involved in the assessment process.

1.2 Overview of the Crowdsourcing Concept

Crowdsourcing can be categorised into user-level and system-level types, which can be defined as follows:

- User-level crowdsourcing relies on leveraging nearby GNSS devices to support the userlevel navigation system. This can involve using the positioning information from nearby smartphones or, as implemented in this report, information from nearby vessels.
- System-level crowdsourcing involves the use of any available PNT sources to support system-level integrity monitoring, such as employing a CORS network.

1.3 Related document

The concepts of crowdsourcing, mathematical modeling, testing methodologies, results, validation metrics, and implementation plans are discussed in depth in "D 8.1: Crowd-sourced Inputs into DFMC Integrity, Feasibility Report" [1].

1.4 Revision History

Revision	Author(s)	Date	Section(s)
V0.1	Mamon Alghananim Washington Ochieng	13-11-2023	All

[1] Alghananim, M., Ochieng, W., & Hargreaves, C. (2023). D 8.1: Crowd-sourced Inputs into DFMC Integrity, Feasibility Report. Taylor Airey Limited.

2. User-level crowdsourcing

User-level crowdsourcing relies on leveraging nearby GNSS devices to support the user-level navigation system. This involves using the positioning information from nearby vessels. Further details about User-level crowdsourcing and its mathematical model are comprehensively discussed in Section 4 of the "D 8.1: Crowd-sourced Inputs into DFMC Integrity, Feasibility Report."

The evaluation of our developed approach underwent thorough testing via the Imperial College simulation platform. In this section, we will outline the functional architecture of the software design specific to this approach, as detailed in Section 2.1. In addition, Section 2.2 will delve into the test specifications, including the experiment specifications and their objectives.

2.1 Functional Architecture for the Software Design

The functional architecture of the User-level crowdsourcing simulation platform is presented in Figure (1). This architecture is structured around two primary types of inputs: configuration parameters and sensor accuracy. The configuration parameters are essential for testing the developed models under various operational conditions. These parameters include the minimum and maximum distances between vessels, the elevation range, the distribution of nearby vessels (Geometry), and the number of vessels. On the other hand, sensor accuracy pertains to the precision of range measurements and the positional accuracy of nearby vessels.

Utilising these inputs, the simulation platform is designed to accurately simulate all required information, including the positions and ranges of nearby vessels. Based on the simulated positions and ranges, the simulator then calculates the vessel's position and protection level for the defined scenarios.

Imperial College simulation platform has been developed to evaluate the User-level crowdsources positioning approach. This simulator incorporates a variety of configuration parameters, enabling the simulation of diverse scenarios under different operational conditions. The interface of the simulator is shown in Figure (2). The input configuration parameters and sensor accuracy are summarised in Table (1). The outputs of the simulator with a key sample are presented in Table (2).

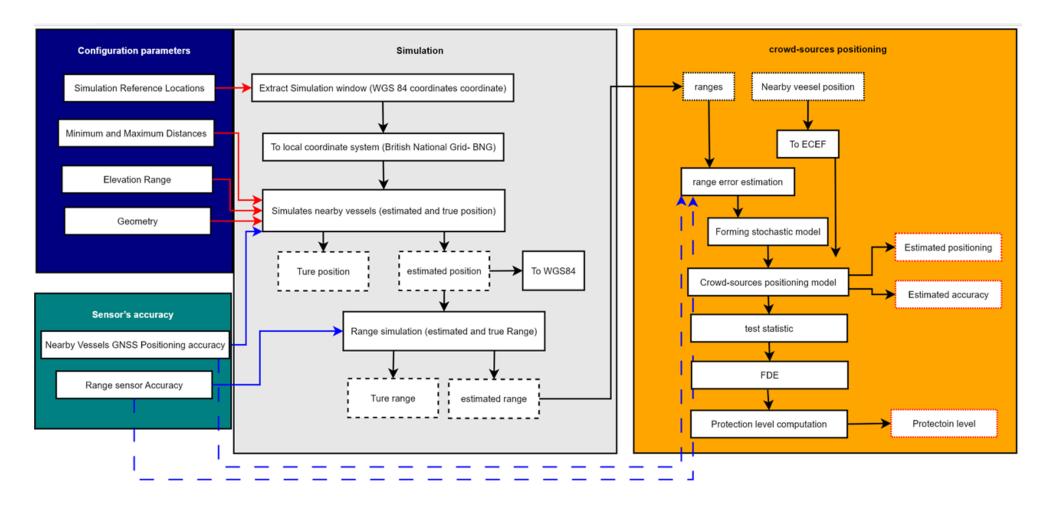


Figure 1: The functional architecture of the User-level crowdsourcing simulation platform

Simulation configuration parameters sensors accuracy the	Simulation configuration parameters sensors accuracy info
Number of nearby vessels 8	Nearby Vessels GNSS Positioning accuracy
	horizontal position accuracy mean 0 sigma 5
Distance between vessels and near by vessels minimum 200 maximum 1000	vertical position accuracy mean 0 sigma 10
Distances between nearby vessels minimum 200	
Simulation Reference Locations (WGS84) latitude 54.96 longitude 0.8903 Height -20	Range Sensors Accuracy
Elevation range 40	Radar accuracy customise v
Simulation option Single v	range accuracy whichever is greater: within 2
Geomatry Strong Number of scenarios 1000	or percentage of range scale 1e-0E %
Output file name results	
process	
Estimated position ECEF X 3.67e+06 Y 5.703e+04 Z 5.199e+06	
WGS84 Istitude 84.96 Iongitude 0.8903 Height -31.85	
Estimated standard deviation (OLS) Horizontal 0.8883 Vertical 14.69	
Error Horizontal Error (m) 0.2289 Vertical Error (m) 11.85	
Protection level Horizontal PL (m) 5.753	
Imperial College London	
London	

Figure 2: Imperial College simulation platform

Table 1: Imperial College Simulator Input Configuration Parameters and Sensor Accuracy

		Input type	Options	Description					
	Configuration parameters								
Number of Nearby	/ Vessels	Numerical -Integer	-						
Minimum and Maximum Distance	Minimum	Numerical -Float	-	The range of distances between the vessel (of unknown position) and the					
Distance	Maximum	Numerical -Float		nearby vessels.					
Minimum Distanc Nearby Vessels	Numerical -Float	-	The range of distances between nearby vessels.						
Simulation Reference	Latitude	Numerical -Float	-	Used to centre the simulation around this specific point					
Locations (Window)	Longitude	Numerical -Float	-	_					
	Height	Numerical -Float	-	_					
Elevation Range		Numerical -Float	-	Refers to the elevation difference between vessels, crucial for enhancing the simulation's reliability.					

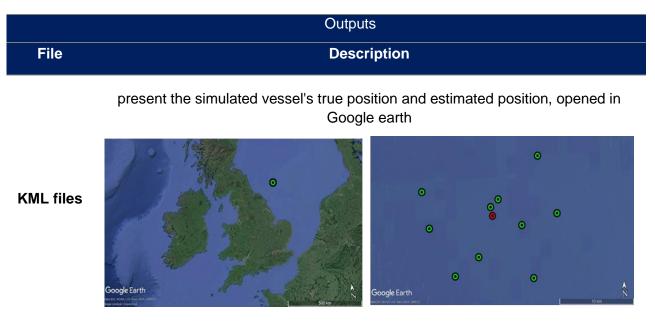
Geometry	Selection	strong, weak, and random.	This is vital for understanding the impact of geometry on computations and for accommodating various operational scenarios.
Number of Scenarios	Numerical- Integer	-	This parameter offers the flexibility to generate any number of scenarios and save the results in CSV files, enabling the generation of a million scenarios based on the selected configurations.
Output Filename:	String		The name of the CSV file containing

The name of the CSV file containing the results.

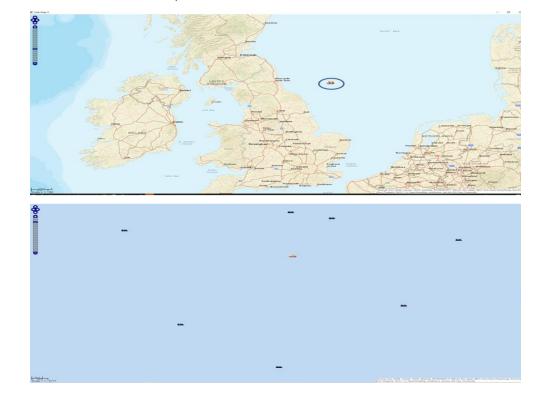
	Sensor's accuracy								
	Nearby Vessels GNSS Positioning accuracy								
Horizontal accuracy	Mean	Numerical -Float	-	These parameters are utilised to estimate the positions of nearby					
	Standard division	Numerical -Float	-	 vessels and to model the range errors resulting from positional errors in the functional model, this includes 					
Vertical accuracy	Mean	Numerical -Float	-	two parameters: • Nearby vessels' GNSS					
	Standard Numerical division -Float		-	 positioning horizontal accuracy Nearby vessels' GNSS positioning vertical accuracy 					

Range Sensors Accuracy								
Sensors type	Selection	-IMO standard	Used to simulate the ranges based on sensor accuracy, include:					
Accuracy	Numerical -Float	- Customise -	 Sensor type: consists of two options (Radar IMO standard, customise). Sensor accuracy, in case the customise option is selected, the sensor accuracy can be inserted manually 					

Table 2: Outputs of the Imperial College Simulator with Key Sample Examples



presents the simulated vessels



A web map

Tables	 Tables present a key output of the simulation, These tables include nearby vessels estimated position (in WGS84) nearby vessels GNSS horizontal error nearby vessels GNSS vertical error estimated range true range range error 						
	D Estimated Latitude Estimated Longitude Estimated Hospital True Latitude						
Estimated	Estimated position of the unknown vessels in WGS84 and ECEF coordinate system						
position	Estimated position ECEF X 3.67e+06 Y 5.703e+04 Z 5.199e+06 WG\$84 latitude 54.96 longitude 0.8903 Height -31.85						
estimated standard division	Horizontal and vertical estimated standard division from the least squares.						
True error	Horizontal and vertical true error						
	Error Horizontal Error (m) 0.2269 Vertical Error (m) 11.85						
Horizontal	Horizontal protection level						
protection level	Protection level Horizontal PL (m) 5.753						

2.2 Test specifications

The testing of this approach is focused on evaluating the developed method under various conditions. These include different distance ranges between the vessel and nearby ones, includes both strong and weak geometry. The testing also considers a range of vessel numbers and sensor accuracies. This comprehensive testing provides a thorough understanding of the developed approach's performance and reliability in different navigational contexts.

Put differently, the test specifications are based on assessing the developed approach's performance using various types of range sensors, taking into account different operational conditions such as geometry, the number of nearby vessels, and distance ranges between the vessel and nearby ones. A total of 30 experiments have been conducted to achieve the test specifications, summarised as follows:

- Experiments 1-6: These cases were set up for an initial assessment of Radar-based crowdsourcing positioning using the radar as per IMO standard (as specified in RESOLUTION MSC.192(79)) and FURUNO Radar (FR-2115-B, 2125-B, 2135S-B) that offer higher accuracy than the standard IMO specification.
- Experiments 7-18: These cases investigated LiDAR-based crowdsourcing positioning across various LiDAR accuracy levels (0.5, 1, 1.5, and 2 meters at 95% confidence level). The investigation covered all four accuracy levels across three scenarios of nearby vessel numbers (5, 6, and 7), with 100 strong geometry mode scenarios simulated for each scenario.
- **Experiments 19-21:** These cases assessed the influence of the distance to nearby vessels on the developed approach's performance.
- **Experiments 22-24:** These cases assessed the impact of the geometry factor.
- **Experiments 25-30**: These cases investigated in detail LiDAR-based crowdsourcing positioning across two LiDAR accuracy levels (0.5 and 1 meter at 95% confidence level).

Table 3 summarises the 30 experiments with their configuration parameters.

		Range accuracy (m) (95%)	Aim		Distances range between the vessel and nearby ones (m)	Geometry		
ID	Target range sensor			Number of nearby vessels		Strong	Weak	Number of Seniors
1		within 30 m or 1% of the	Radar-based	5	100-1000			100
2	Radar (IMO standard)	range scale,		6	100-1000			100
3	olandaray	whichever is greater;		10	100-1000			100
4		within 15 m or 1% of the		5	100-1000			100
5	Radar (FURUNO)	range scale ,	investigation Radar-based	6	100-1000			100
6		whichever is greater;		10	100-1000	Ø		100

Table 3: experiments with their configuration parameters

		Range accuracy Air (m) (95%)			Distances range	Geom	etry	Number of Seniors
ID	Target range sensor		Aim	Number of nearby vessels	between the vessel and nearby ones (m)	Strong	Weak	
7				5	100-1000			100
8	-	2	Investigation Lidar-based	6	100-1000	Ø		100
9				10	100-1000	Ø		100
10			5	100-1000	Ø		100	
11		1.5	Investigation Lidar-based	6	100-1000	Ø		100
12	Lidar			10	100-1000	Ø		100
13				5	100-1000	Ø		100
14		1	Investigation Lidar-based	6	100-1000	Ø		100
15	-			10	100-1000	Ø		100
16			5	100-1000	Ø		100	
17		0.5	Investigation Lidar-based	6	100-1000	Ø		100
18				10	100-1000	Ø		100
19			Evaluating 'distances to	5	100-300	Ø		100
20			nearby	6	100-300			100
21			vessels' factor impact	10	100-300	Ø		100
22			Evaluating	5	100-300		Ø	100
23			Geometry	6	100-300		Ø	100
24			factor impact	10	100-300		Ø	100
25	Lidar			5	100-1000			10,000
26		1	In depth investigations	6	100-1000			10,000
27			Ţ	10	100-1000			10,000
28				5	100-1000			10,000
29		0.5	In depth investigations	6	100-1000	Ø		10,000
30			5	10	100-1000	Ø		10,000
		1	1	1	1	1	total	62,400

3. System-level crowdsourcing

The system-level crowdsourcing approach in this report focuses on evaluating error characterisation at the system level. It utilises 6 distributions, including Gaussian, Generalised-t, GEV, Logistic, Laplace, and Cauchy distribution, as elaborated in "D 8.1: Crowd-sourced Inputs into DFMC Integrity, Feasibility Report." This section will provide summaries on Functional Architecture for the Software Design in Section 3.1, the measurement error data in Section 3.2, and the test specifications in Section 3.3

3.1 Functional Architecture for the Software Design

The system-level error characterisation process includes four main stages: data collection, distribution selection, distribution estimation, assessments, and evaluation, as presented in Figure (3). The initial stage involves collecting data from the OS Net CORS network. In the subsequent stage, the maximum likelihood method is employed to estimate the parameters of six selected distributions: Gaussian, Generalised-t, GEV, Logistic, Laplace, and Cauchy. The third stage focuses on evaluating these distributions across three key aspects: fitting (both overall and tail), impact on system availability, and bounding. The assessments used for this evaluation include the Kolmogorov-Smirnov (KS) test for overall fitting, graphical assessments for tail and core fitting as well as overbounding, and availability assessments to gauge the impact on system availability.

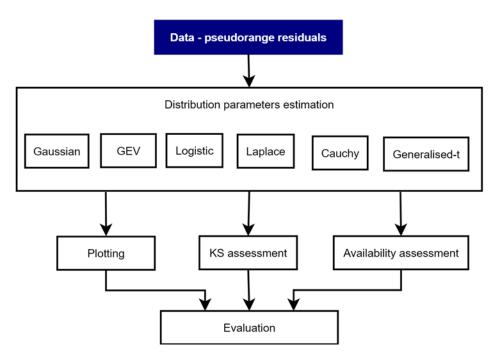


Figure 3: Functional Architecture of the System-Level Error Characterisation Software

This approach was rigorously tested using Imperial College's error characterisation application, specifically designed to handle the aforementioned distributions. The software assesses data through three distinct assessments, with the methodologies for these assessments thoroughly

discussed in "D 8.1: Crowd-sourced Inputs into DFMC Integrity, Feasibility Report." Figure (4) presents the application interface.

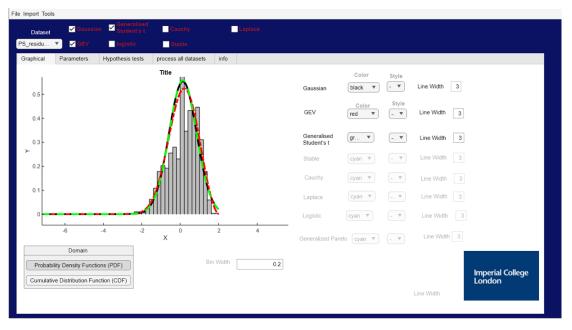


Figure 4: Imperial College error characterisation application interface

3.2 Measurements error data

The data have been collected and proceeded from 20 OS stations around the UK. The data include 3 hours of raw data (RINEX) files with 30-second epochs. Table (4) presents the data datasets used in this section. This was aimed at evaluating the error characterisation under diverse scenarios.

ID	StationID_year_dayoftheyear_startingtime_endingtime									
1	AMER_ 2023_220_18_21	11	LEED_ 2023_240_06_09							
2	ANLX_2023_255_21_00	12	LEEK_2023_212_17_20							
3	ATTL_2023_215_00_03	13	MANR _2023_238_08_11							
4	BUCI_ 2023_252_09_12	14	NCAS _2023_250_0_3							
5	CAMO_2023_228_14_17	15	SABS _2023_245_12_15							
6	CARL_2023_218_10_13	16	SHOE _2023_225_06_09							
7	CLAW_2023_230_12_15	17	SOTN _2023_235_00_03							
8	FAUG_2023_232_07_10	18	SWAN _2023_247_15_18							
9	GLAS _2023_242_04_07	19	SWAS _2023_248_18_21							
10	HOLY _2023_210_06_09	20	THUS _2023_222_15_18							