Assessment of End-To-End performances of a GNSSbased Road User Charging System

Miguel Ortiz, David Bétaille, François Peyret, Ola Martin Lykkja, Svend-Peder Oseth, Asa Oslo

▶ **To cite this version:**

Miguel Ortiz, David Bétaille, François Peyret, Ola Martin Lykkja, Svend-Peder Oseth, et al.. Assessment of End-To-End performances of a GNSSbased Road User Charging System. European Navigation Conference (ENC), May 2016, HELSINKI UNIVERSITY OF TECHNOLOGY, ESPOO, FINLAND, Finland. 10.1109/EURONAV.2016.7530552 . hal-04469110

HAL Id: hal-04469110
https://univ-eiffel.hal.science/hal-04469110

Submitted on 20 Feb 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Assessment of End-To-End performances of a GNSS-based Road User Charging System

Based on Ifsttar-GEOLOC and Q-Free cooperation

Miguel Ortiz , David Bétaille, François Peyret
IFSTTAR/COSYS/GEOLOC
Nantes, France
david.betaille@ifsttar.fr

Ola Martin Lykkja, Svend-Peder Oseth
R&D, Q-Free ASA
Oslo, Norway

***Abstract*— The paper deals with the issues that have to be faced when designing a national Road User Charging (RUC) in Norway based upon GNSS and with an innovative methodology especially developed to address these issues proposed by CEN-CENELEC TC5/WG1 and supported by the SaPPART COST Action. The paper presents a case study applying the methodology to a specific RUC algorithm developed by the Norwegian company Q-Free. A dedicated GNSS position error model has been produced by Ifsttar GEOLOC for this purpose.**

Keywords—GNSS positioning; intelligent transportation systems; road user charging; error modelling

I. INTRODUCTION

A. Context

Global Navigation Satellite Systems (GNSS) have a very high potential in the development of Intelligent Transport Systems (ITS), Personal Mobility and associated services. This has been widely demonstrated through the use of GPS in supporting the provision of ITS services such as personal navigation, fleet management, cooperative traffic monitoring and more recently: Road User Charging (RUC), Pay-As-You-Drive insurance, emergency call (eCall), tracking and tracing of dangerous good, Advanced Driver Assistance Systems (ADAS), etc. [1].

Given the principle of GNSS positioning, performance is highly influenced by the conditions of the operational environment. Therefore, GNSS integrators and users are facing two major challenges: the difficult problem of estimating the expected performance of the service when using GNSS, and the lack of standards and certification references on positioning performance, which are necessary to guide their choices [2] [3].

B. Road User Charging with GNSS

As alternative to conventional physical-gantries-based RUC systems, GNSS-based RUC systems offer numerous advantages, the most important one being their flexibility. In Europe, these systems are being adopted by more and more countries. Slovakia, Germany, Switzerland and Hungary have successfully implemented GNSS-based tolling, Belgium and Russia have launched similar projects implementing GNSS-based schemes and France, Finland, Bulgaria, Denmark, The Netherlands and Lithuania have all declared their interest in GNSS-based schemes [1].

But, RUC is very demanding in terms of false detections which are prohibited to avoid the risk of rejection of the system by the end-user. For instance, for the French system, the acceptable false detection rate of the system had been fixed at 10-6 with a confidence level of 5%, which could be reached for example if there were no missed detection at all during 3.106 consecutive charging events all over the network. To be capable of such performance level, the detection of the charging event (the vehicle crossing the charging point) has to be extremely reliable, which can be quite tricky in difficult environments.

The detection performance of the system at the charging point depends on the performance of both the GNSS-based positioning terminal (GBPT) and the RUC detection algorithm in the given charging points environment. In challenging environments, such as urban locations, where poor GNSS performances are usual, a very smart detection algorithm can overcome these poor GNSS performances and ensure a high performance for the whole system. This means that, performance assessment of such system needs tests applied to the whole system, with a perfect respect of the environmental conditions [3].

Figure 1 illustrates the 2 main components which impact the end-to-end (E2E) service of the system.

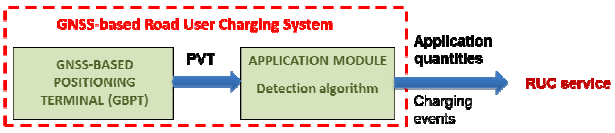

Figure 1: The 2 main components of a RUC system impacting the E2E service

C. *Assessment of Road User Charging system performances*

The execution of realistic test campaigns for assessing such performance as a false detection rate of 10-6 faces a difficult issue: how to carry out millions of tests in real or realistic environments ? Obviously, this is not possible to be done in real full-scale conditions, and laboratory-only conditions would not allow the respect of the realistic environment, so, a combined approach has to be followed.

CEN-CENELEC TC5 WG1, which has addressed this issue in his 1st standard [4], proposes a general method, applicable to any ITS system based on GNSS, called "Sensitivity analysis". This method is based upon field tests in real conditions of the GBPT to identify a PVT error model that will be used to generate automatically a high number of synthetic degraded trajectories that will be processed by the application module. From the outputs of the application module, using the E2E performance metrics, will be assessed the E2E performances of the system, depending from performances of both the GBPT and the application itself.

This method offers the advantage to multiply field tests executed in real operational conditions, the only ones capable of capturing the reality of the physical phenomena, in order to run a high number of trials, necessary to assess performances which are generally expressed by very low probabilities.

The sensitivity of the system to the performance of the GBPT can be analysed by increasing artificially step by step the amplitude of the errors of the PVT error model until the moment when the target E2E performance is no longer fulfilled. To summarize it, the Sensitivity analysis consists in 6 main steps:

1. Definition of the operational scenario and of the test protocol
2. GNSS-based positioning terminal (GBPT) field tests execution
3. PVT error model identification
4. Generation of degraded simulated trajectories
5. E2E performances assessment
6. Safety margin analysis

More details can be found in the draft standard itself [4].

This methodology was already followed, under an early form, by the test laboratory which was in charge of assessing the false detection rate performance of the French RUC system [5]. The following sections will be devoted to the application of this methodology to the RUC algorithm proposed by Q-Free Company.

The three first steps have already been achieved and already reported in previous papers [6]. The next section will recall the main principles used for the development of the error models and the following ones will describe in more details how the degraded trajectories have been generated and used for assessing the performances of the RUC algorithm.

II. ERROR MODELLING AND SIMULATION OF DEGRADED TRAJECTORIES

The error model is based upon the decomposition of the horizontal position error vector into its two local polar components: radius (or modulus) R and angle ϕ relative to the local Frenet frame, tangent to trajectory of the vehicle. Figure 2 shows these two local polar components.

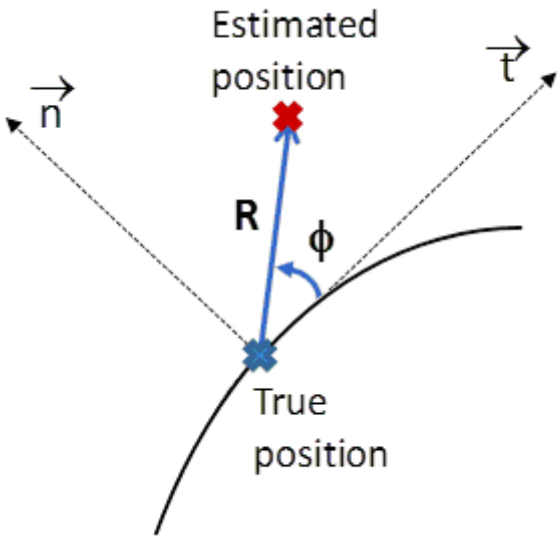

Figure 2: The local Frenet frame and the two polar components of the position error vector

The 2 components of the error data acquired from field tests that have been chosen as seeds of the synthetic degraded trajectories are respectively modelled by:

- For the radius, a filtered piecewise constant signal where a new step appears with the probability p (a Bernoulli trial at every sample); in case of a step, a new amplitude R for the radius is drawn from a Laplace distribution and a Cauchy additive noise, which is accumulated over each step, is added to it:

$$R[n+1] = \begin{cases} R[n] \text{ with probability } (1-p) \\ L_r[n] \text{ with probability } p \end{cases} + C_r[n] \quad (1)$$

where $L_r[n]$ is a realization of a truncated Laplace distribution (positive values only) giving the height of the new step, and $C_r[n]$ is a realization of a truncated Cauchy distribution.

The accumulation of the Cauchy noise does not operate over the whole signal, but it is accumulated only during one step. It is reset when there is a new draw from the Laplace distribution.

In a final step, the radius signal is filtered using an auto-regressive filter which relates the expected error signal with the simulated signal.

- For the angle, a random walk in which the additional noise is a realisation of a Cauchy distribution:

$$\phi[n+1] = \phi[n] + S_{\phi}[n] \quad (2)$$

where $S_{\phi}[n]$ is a realization of a truncated Cauchy distribution. The dispersion of the angle distribution (parameter γ) will be modulated with the speed of the vehicle, so that when stopping, the error may vary in amplitude but not in direction (avoiding that way a possible large rotating error).

The final angle error signal is also low-passed filtered.

The identification of the parameters of the Laplace distribution of the radius is realized with [7]. This method gives us the parameters of the distribution for the step amplitudes and also the instants when these steps occur, from which we can estimate p. An ARMAX identification is used to identify the linear filter for the radius [8]. The identification of the parameters of the Cauchy distribution of the angle is realized by fitting the experimental PDF [9].

Once the models of the radius and the angle components of the error have been correctly identified and tuned, the generation of the along-track and cross-track components of the error is straightforward:

$$\begin{cases} X_a = w_a R[n] \cos(\phi) \\ X_c = w_c R[n] \sin(\phi) \end{cases} \quad (3)$$

where w_a and w_c are normalisation constants used for the situations where the error vector does not distribute equally in both directions [10].

<<< until here, in GREEN, is what I added to the draft

>>> from here, in YELLOW, is what I took from the draft

III. Application of the Degraded Trajectories to Road User Charging

A. GNSS data collection

The GNSS position error modelling, as mentioned in item 3 of the Sensitivity analysis, shall rely on various full scale experiments reproducing operational scenarii. In the frame of this study, a test vehicle is equipped with several low-cost GNSS receivers from uBlox, ST, and SiRF, among which a low cost receiver uBlox LEA6-T is considered. The equipped vehicle is shown on Figure 3. The test devices were placed behind the windshield.

A reference trajectory is needed, not only for the error modelling step of the work, but also later on as a basis for cloning. The reference trajectory, supposed to be errorless, will actually be degraded N times, applying N different radius and angle errors, so that N clones of the initial uBlox trajectory will be able to be built in order to be fed into the RUC process. The synthetic errors are built by drawing random values in each of the probabilistic laws that are used in the radius and angle models.

On the roof one can see the antenna of the reference NovAtel CPOS receiver. This receiver is hybridized with an IMU and post-processed by the kinematic Precise Point Positioning (PPP) Terrapos software.

Figure 3: test vehicle from Q-Free

The data set is composed of 28 trajectories from Frankfurt, Germany, each of them being approximately 5 km long (see Figure 4). They were performed at the average speed of 15 km/h. Despite it is without tunnels and covered sections, the driven route goes through deep urban canyons, as visible in Figure 5.

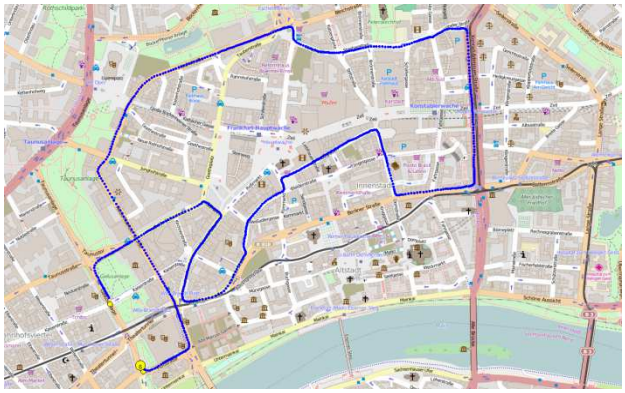

Figure 4: Driven route in Frankfurt recorded by the reference receiver

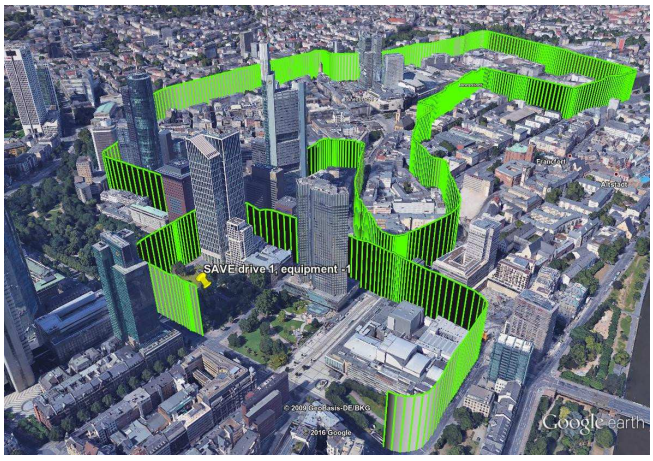

Figure 5: Same route in Frankfurt in a 3D building model

Figure 6 displays the extreme performances of the uBlox receiver observed throughout these 28 revolutions downtown Frankfurt. Most trajectories typically show positioning error time series close to the best one, but 2 trajectories contain

large error peaks of 400 meters for a duration of up to 30 seconds (see Figure 6).

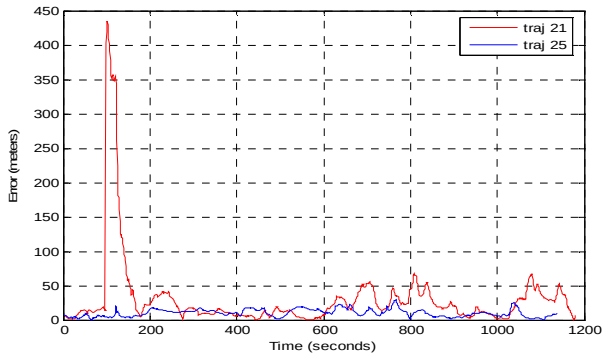

Figure 6: Position error of best (25) and worst (21) trajectories

B. RUC virtual gantries and performance metrics

The RUC application is based on virtual gantries (VG) defined as geo-objects specified by latitude and longitude. They comprise a tolling point (pink circle on Figure 7), a central polyline, and cross-sections (ABCD) with left and right extensions of the road (dashed line), and outer tolerances to the left and right (solid line), in meters. The tolerances can be made very wide if there is no neighboring road. A virtual gantry is oriented.

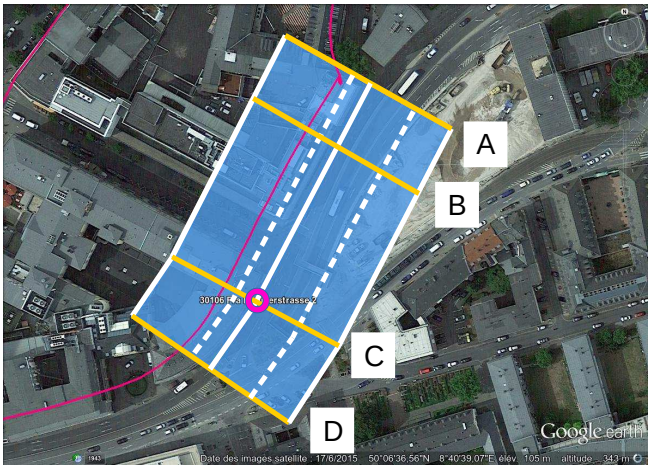

Figure 7: Description of a virtual gantry

When a vehicle passes through the gantry, the intersection point between the GNSS trajectory and the crossing lines are identified and the distance from the center point to the intersection point is calculated. This distance is compared to the road width and the tolerance and gives a passage score, with a maximum value at 1 if the intersection coincide with the center point, and going to zero at the outer tolerance point. If the intersection is outside the tolerance limits, the passage of this crossing line is ignored. After the passage through the VG, the total score is calculated and if the total score is above a predefined limit and more than p out of q crossing lines are crossed and the crossing lines are crossed in correct order, then a VG passage is assessed. The score can be used as an indication of VG passage confidence.

The arrangement makes the passage detection independent of driving speed and GNSS sampling rate. The method also spreads the decision out on a large geographical area (several hundreds of meters, even kilometers in rural road scenario, with multiple crossing lines) thus reducing the effects of the correlation between individual GNSS samples. The VG can be applied to curved roads and also in (or close to) intersections. This makes the method also suitable for urban use. The tolerance and width information are set individually for each crossing line based on local geographical and road topology properties taking into account typical GNSS performance at that location.

A first set of virtual gantries have been defined manually all along the itinerary repeated in Frankfurt (in blue). These virtual gantries should be detected and they will make it possible a measurement of the missed detections of the process. Additional virtual gantries (in orange) were added in the vicinity of the first set. The aim of this second set is to create false detections and make it possible a measurement of those. Some of these additional virtual gantries belong to other streets, but some are also totally fake. They are located in such a way to trigger false detections. Thus the false detection rates seen in this article does not reflect at all those of a real system.

^^^ From Ola's txt in BLUE

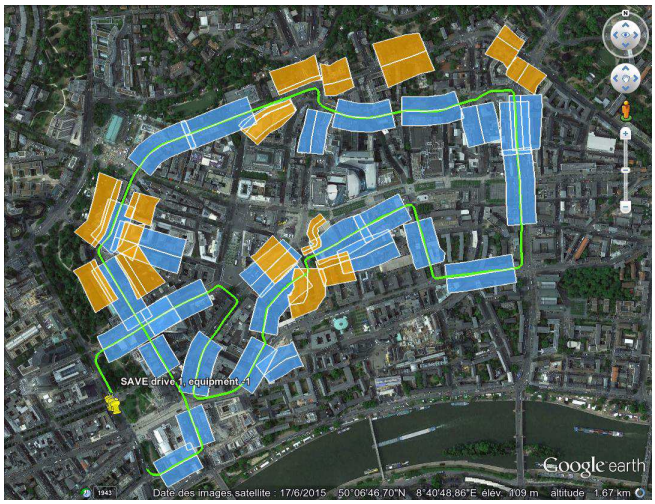

Figure 8: Virtual gantries designed in our experimental area in Frankfurt: the reference trajectory crosses through 20 virtual gantries

In Figure 8 and in the following Figures 9 and 10, this color code has been applied:

- green line: reference trajectory
- blue line: real trajectory of uBlox
- magenta line: cloned trajectory of uBlox
- blue virtual gantry: virtual gantry in the original QFREE database
- orange virtual gantry: virtual gantry added specially for false detection purpose.

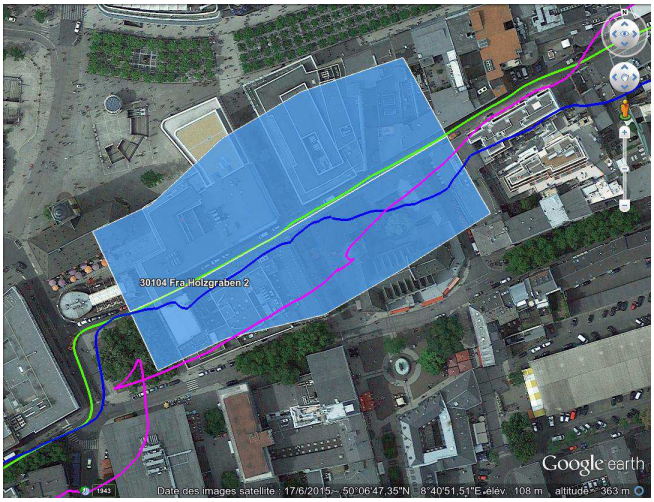

Figure 9: An example of missed virtual gantry (magenta line)

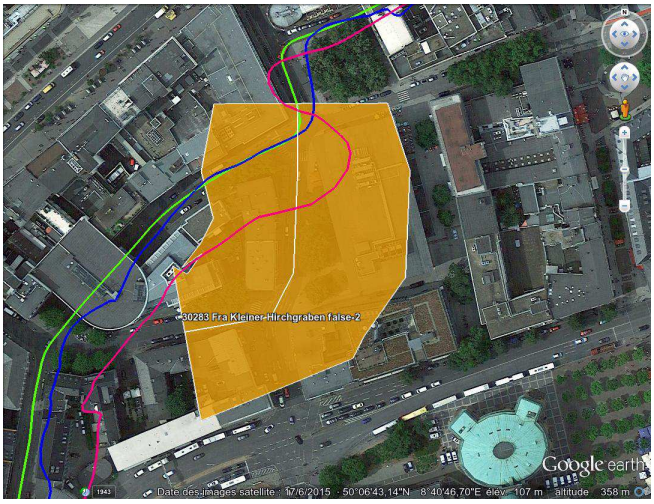

Figure 10: An example of false detection (magenta line)

The chosen metrics for missed detections and false detections have been chosen with QFREE agreement and according to [ISO/TS 17444-2]. They are the followings, for N clones of the uBlox-6T trajectory:

Global metrics:

• **CCR** Correct Charging Rate = TotalNbCorrectDetections / (N*RefNbCorrectDetections)

• **OCR** Over Charging Rate = TotalNbFalseDetections / N

Metrics local to each virtual gantry:

•**CCER** Correct Charge Event Recognition = (NbCorrectDetections for VGi) / (RefNbCorrectDetection for VGi)

• **FPCER** False Positive Charge Event Recognition = (NbFalseDetections for VGi) / N

For instance here is the result of the assessment of the RUC algorithm with 17,000 cloned trajectories, with a certain set of error modeling parameters:

```
#Output RUC algorithm
total missed number : 9
total false  number : 480

#Global metrics
Correct Charging Rate (CCR) : 99.99735%
Over Charging Rate (OCR) :  2.82353%

#Metrics for each Virtual Gantry with at least one missed or one false
#VGi : Virtual Gantry Id
#MISSED : Nb of missed dectections for VGi
#CCER
#FALSE : Nb of false dectections for VGi
#FPCER
VGi MISSED CCER          FALSE   FPCER
30279   0    100.00000% 210   1.23529%
30275   0    100.00000% 145   0.85294%
30273   0    100.00000% 59    0.34706%
30283   0    100.00000% 27    0.15882%
30276   0    100.00000% 39    0.22941%
30113   4     99.97647% 0     0.00000%
30112   3     99.98235% 0     0.00000%
30099   1     99.99412% 0     0.00000%
30111   1     99.99412% 0     0.00000%
```

Numerical details :
N = 17000
TotalNbCorrectDetections = RefNbCorrectDetections*N-TotalMissed= 20*17000 – 9 = 339991
TotalNbFalseDetections = 480
RefNbCorrectDetections = 20
NbCorrectDetections for VGi = RefNbCorrectDetection for VGi - Nb of missed detections for VGi
RefNbCorrectDetection for VGi = N for all VG because each of them has been crossed only once

C. Tuning of the simulation process

A first set of error modeling parameters (denoted the default set) has been estimated with the best trajectory (25) using the Hutter method implemented by Monsifrot [6] [7] [12]. Afterward the upper bound of the truncation of the Laplace law is the only parameter we make varying, from 22 m to 400 m.

TABLE I. SIMULATION PARAMETERS (RADIUS)

Parameter	Default	
Laplace		
μ	11 m	
b	36 m	
min	0.1 m	
max	**22 m**	**400 m**
Cauchy		
x_0	0	
γ	0.5 m	
min	-1.0 m	
max	1.0 m	
Filter coef a	{ 1, -1.728, 0.7544 }	
Filter coef b	0.02518	
Step prob p	0.032	

TABLE II. SIMULATION PARAMETERS (ANGLE)

Parameter	Default
Cauchy	
x_0	0
γ	0.0161 rad * (speed/15 km/h)
min	-pi
max	pi
Filter coef a	1
Filter coef b	{ 0.1, 0.1, 0.1, 0.1, 0.1, 0.1,

	0.1, 0.1, 0.1, 0.1 }

The speed is normalized by the average speed during the test campaign in Frankfurt (approximately 15 km/h) and it is used to modulate the parameter γ of the Cauchy law (i.e. the dispersion of the distribution).

One simulation result (for the radius) is shown in Figure 11 along with the true error radius of the best trajectory (25), using the default parameters. Another result, using the maximum upper bound of 400 m, is shown in Figure 12 along with the true error radius of the worst trajectory (21).

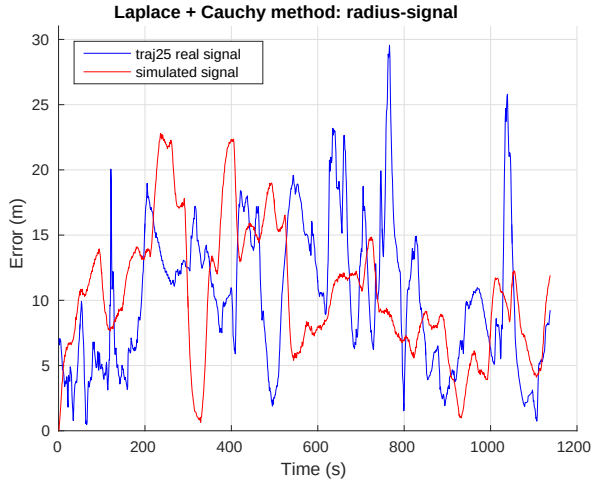

Figure 11: Time evolution of simulated and best target radii (trajectory 25)

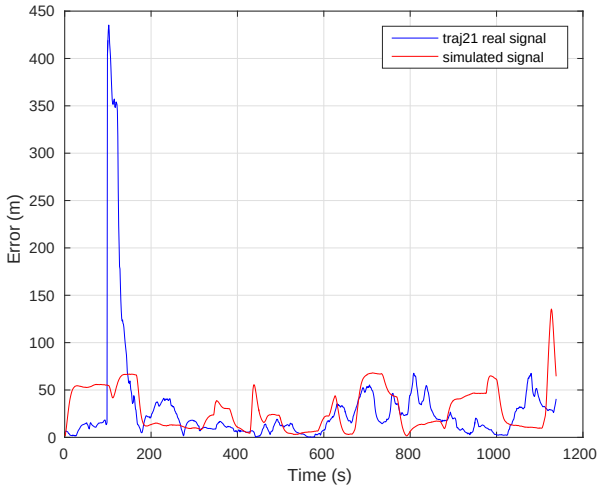

Figure 12: Time evolution of simulated and worst target radii (trajectory 21)

IV. ANALYSIS OF THE RESULTS OBTAINED

A. *Fixing the number N of clones*

The first parameter to set is the number N of simulated trajectories we have to produce in order to be confident that computed metrics are representative of the SA set. For instance, N=1 will not produce representative metrics: there is a good probability that CCR would be 100% and OVR 0%. By contrast, N= 10,000,000 will produce much more representative metrics ; but it will take too much time to run the whole process on a computer. For information, it takes about 1,5 h of computation for N=10,000 on a quite robust laptop. In order to estimate the minimum N value to be used, a run with N=30,000 has been conducted.

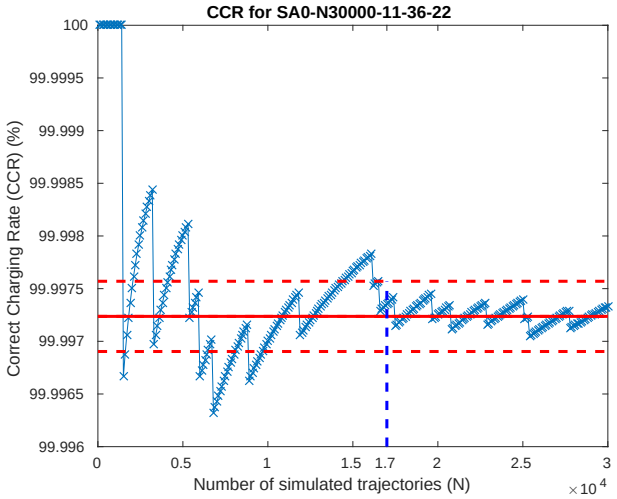

Figure 13: Evolution of CCR over 30,000 runs

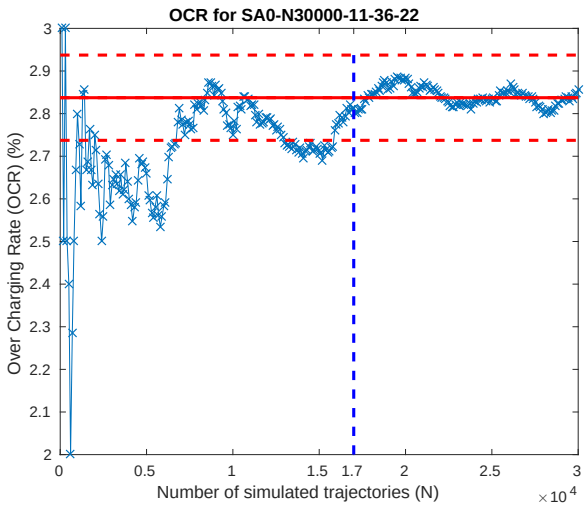

Figure 14: Evolution of OCR over 30,000 runs

The red line corresponds to the mean of the last third part (from 20,000 to 30,000); the red dash lines correspond to +10% and -10% of the first oscillation. As we can observe, from N=17,000 oscillations stay inside the 10% bounds. This

value of N=17,000 will be used for the next phase of RUC assessment.

B. Sensitivity analysis

This sensitivity analysis (SA) has focused on varying the upper bound of the Laplace law which drives the radius error. The two following figures illustrate the random draws for 5 different sets of SA. Afterward, the notation SA(11-36-x) means SA set with all radius and angle parameters set to values of Table I and II, excepted for the maximum of radius Laplace parameter equal to x (cf. Table III).

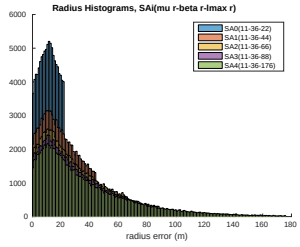

Figure 15: SA random draw for 100,000 samples trajectory

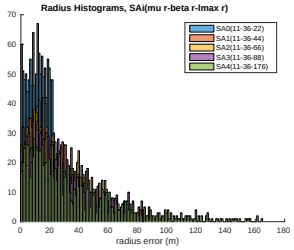

Figure 16: SA random draw for 1138 samples trajectory

As our original reference trajectory on which cloned radius and angle errors had been added is a 1138 samples trajectory, the Laplace random draw (Figure 16) is not so close to the ideal plot (Figure 15). However, we could observe that some high errors should be draw with low occurrence. 85,000 trajectories have been injected in the RUC algorithm – 17,000 for each SA – with the pre-defined set of virtual gantries (Figure 8):

TABLE III. VARYING RADIUS UPPER BOUND AND SIMULATION RESULTS

SAi	Total missed number	CCR (%)	Total false number	OCR (%)
SA0(11-36-22)	9	99.99	480	2.82
SA1(11-36-44)	2062	99.39	7505	44.15
SA2(11-36-66)	26631	92.16	13651	80.30
SA3(11-36-88)	47105	86.15	17360	102.12
SA4(11-36-176)	72672	78.63	21265	125.09

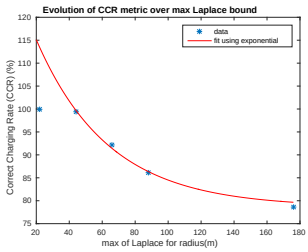

Figure 17:

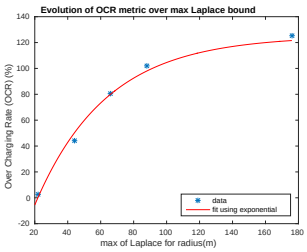

Figure 18:

We can observe an exponential trend of the evolution of CCR and OCR over the Laplace upper bound (Figures 17 and 18). In order to confirm this trend (Figures 19 and 20), other runs have been realized with different sets of SA (from 11-36-22 to 11-36-400):

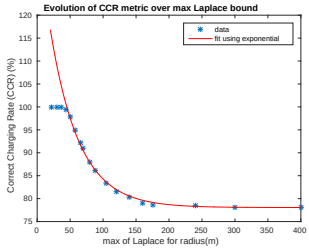

Figure 19:

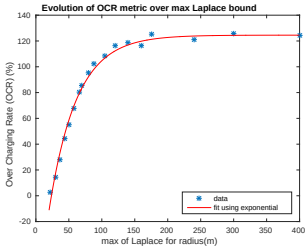

Figure 20:

Note 1: For CCR the 3 first points have been discarded for exponential fit. Note 2: OCR results are not representative of a realistic set of virtual gantries. They are only representative of the fake virtual gantries that had been added to the original ones. Note 3: CCR results are representative of a very dense network of virtual gantries. Here, each large error makes a missed detection. We could imagine that a low density network will be more resilient to large position error.

The exponential trends are confirmed. These asymptotic trends could be explained by the Laplace parameter we have chosen to make varying trajectories. The average of such a random draw with the upper bound varying is indeed nearby 40 m.

C. Conclusions

This study has allowed assessing a real Road User Charging (RUC) application. Cloned (or simulated) trajectories have been built from a model issued from a u-Blox-6T GPS receiver. It is based on Radius generation on one hand, and Angle generation on the other hand. Radius and Angle generation are driven by different random laws, and their parameters are the ones defined in Table 1. This kind of model fits quite well real trajectories with low errors, and has more difficulties to fit large error trajectories.

Assessment of the RUC algorithm could have been done by injecting trajectories increasingly degraded. Up to 18 sets of 17,000 trajectories have been injected. These parametric tests have been based on the increase of the maximum Laplace error. The following global metrics have been computed: Correct Charging Rate (CCR) and Over Charging Rate (OCR). Metrics relative to each virtual gantry have also been computed: this allows identifying a possible virtual gantry which has been badly designed. As a matter of fact, all false detections have been generated by virtual gantries that have been intentionally designed for that purpose (virtual gantries added to create false alarms).

Furthermore, assessment of the RUC application has shown that CCR and OCR reach an asymptotic value when the upper bound of the Laplace law is increasing. In our study, these asymptotic values themselves make no general sense because the use case is here totally artificial and non-representative of a real RUC system, but the existence of these asymptotes tends to prove that the couple {virtual gantries + RUC algorithm} presents minimum performances in front of a given receiver. These performances are actually guaranteed – and in particular over-charging cannot exceed the maximum

rate estimate – even if the experienced trajectories are all very bad ones.

Acknowledgment

This study has been carried out in the frame of SaPPART COST Action, in particular during a Short Term Scientific Mission (STSM) executed by Miguel Ortiz from Ifsttar at Q-Free, using data sets acquired in the frame of the Norwegian SAVE project, dedicated to GNSS-based Road User Charging issues.

References

[1] GSA; "GNSS Market Report, issue 4", March 2015, http://www.gsa.europa.eu/system/files/reports/GNSS-Market-Report-2015-issue4_0.pdf

[2] COST TU-1302; Satellite Positioning Performance Assessment for Road Transport, http://www.sappart.net/

[3] COST Action TU1302, "SaPPART White paper: Better use of Global Navigation Satellite Systems for safer and greener transport", Ifsttar, 2015, Techniques et méthodes, TMI 1. 58p. ISBN 978-2-8578-270-61

[4] CEN-CENELEC / TC 5; FprEN 16803-1:2015 "Space - Use of GNSS-based positioning for road Intelligent Transport Systems (ITS) - Part 1: Definitions and system engineering procedures for the establishment and assessment of performances"

[5] G. Duchâteau et al., "Challenges in GNSS Road User Charging and French Implementation Experience", CERGAL conference proceedings, July 2014, Dresden, Germany

[6] F. Peyret, J. Monsifrot, D. Bétaille, C. Moriana-Varo, "How GNSS performance standardisation can support the deployment of critical its applications", Intelligent Transport Systems World Congress, Bordeaux, France, Oct. 5 – 9, 2015

[7] M. Hutter, "Exact Bayesian regression of piecewise constant functions", Bayesian Analysis, Vol. 2, No. 4, 2007, pp. 635–664

[8] L. Lennart, "System identification: theory for the user", Prentice Hall PTR, USA, 1999

[9] D. Bloch, "A note on the estimation of the location parameter of the Cauchy distribution", Journal of the American Statistical Association, Vol. 61, No. 315, 1966, pp. 852–855

[10] P.D. Groves, Z., Jiang, L., Wang, M. Ziebart, Intelligent Urban Positioning using Multi-Constellation GNSS with 3D Mapping and NLOS Signal Detection. Proceedings of the 20th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2012), Nashville, TN

[11] ISO/TS 17444-2: …

[12] S.P Oseth, D. Bétaille, O.M. Lykkja, "COST TU-1302 - STSM; Generation and evaluation of simulated degraded trajectories by using PVT error models"

[13] M. Ortiz, O.M. Lykkja, D. Bétaille, "COST TU-1302 - STSM; Automation of degraded trajectories generation process in order to assess the robustness of tolling detection algorithms"