Shipping noise field calibration via source inversion

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***Abstract*—There is significant evidence that the low-frequency mean acoustic noise pressure level in the ocean has been constantly increasing in the last decades. The main noise sources responsible for this increase were identified as ship traffic, offshore construction and oil & gas surveying. The Portuguese Navy funded SUBECO project aims at deploying a network of multiparametric offshore buoys for environmental and acoustic monitoring. A preferred location for the individual buoys is within or close by the ship traffic separation lanes along the west coast of Portugal. It is therefore expected that the received acoustic field will be dominated by shipping noise as a mixture of both short and long range ships. Most ships will have an AIS so their position may be known at all times. One of the objectives of this network is to use the recorded sound to infer and calibrate model predicted noise in a wider area. This work proposes a relatively simple technique for estimating the radiated noise level of ship tracks within acoustic reach of a single (or a small number of closely localized) hydrophone(s). It is expected that the data constrained predicted field with the estimated source levels will provide a better fit to the actual wide area acoustic field. This work is a contribution to fulfill the requirements of Portugal to the European Union Marine Strategy Framework Directive (MSFD) aiming at a good environmental status.**

I. Introduction

There is significant evidence that the low-frequency mean sound level in the ocean has been constantly increasing in the last decades [1]–[4]. The noise sources responsible for this increase are clearly identified: ship traffic, offshore construction, oil & gas surveying and also, to some extent, offshore renewable energy plants, the so called industrialization of the ocean [5]. The medium and long term effects of this increase in the biosphere is unknown and very difficult to determine [5], [6]. This difficulty is mainly related to two aspects: one is the effect of acoustic pressure on each individual of a given specie (the small scale effect) which may be localized in time and space, and the other is the effect of the mean background noise level at large scale, with possible impact on specie's migration paths, disorientation and maybe reproduction [7]. Long term variations of noise in the ocean may offer explanations for mysterious depletion of certain fish stocks in certain areas and miraculous rebuild in other areas.

Broadly speaking, noise sources may be separated in two groups: those that are pervasive with a global coverage, and those that are point like in time and space. The pervasive component is essentially attributed to shipping to which the largest part of the noise level increase along the past decades has been attributed [8]. The prediction of ocean noise at large scale due to shipping has been tackled by using numerical propagation models fed with environmental information (mostly bathymetric and water column data), ship location (from AIS) and assumed ship radiated noise. Ship radiated noise is drawn from tables with mean values per ship class [9] and generalized to all ships present in the AIS field. There are now noise map tools for research purposes [10], [11] or commercially available [12], for providing noise mapping estimates over limited regions or globally [13]. However, these tools are essentially formed by massive forward numerical runs that work in open loop and do not provide verifiable accuracy bounds. Thus the calibration of the predicted field requires the inclusion of in situ measured data. This data will inevitably be time and/or space limited and will have itself a finite accuracy. So, one of the challenges faced by current noise mapping tools is on how to calibrate wide areas or global model predictions with scarce time-space data.

The SUBECO project[1] aims at deploying a network of offshore buoys for environmental and acoustic monitoring. A preferred location for the individual buoys is within or close by ship traffic separation lanes along the west coast of Portugal. It is therefore expected that the received acoustic field to be dominated by shipping noise as a mixture of both short and long range ships. The position of most of these ships will be known through AIS. The objective of this network is to use the recorded sound to infer and to calibrate model predictions and thus constrain noise mapping in the area of the buoys but, if possible, also in a wider area and over long time intervals. One of the components of shipping noise prediction is the sound level density composed by the various sources (ships) within acoustic range of each buoy. This work proposes a relatively simple technique for estimating ship source level from acoustic recordings over ship tracks received on a single (or a small number of closely localized) hydrophone(s). It is expected that the estimated source level field will incorporate (and compensate) eventual misfit between measured and predicted fields allowing for a more stable and accurate noise mapping over a wider area and a longer time span thus contributing to the effective calibration of the noise field prediction. The data constrained noise map will be sequentially updated with the data received on the buoys. This work is a contribution to fulfill the requirements of Portugal to the European Union

[1]SUB-ECO Acoustic Surveillance System, funded under a PO-Navy contract.

Marine Strategy Framework Directive (MSFD) aiming at the good environmental status [14].

This paper is organized as follows: section II presents the background concept behind shipping noise modeling and details the proposed approach; section III presents a set of AIS data representative of the area off west coast of Portugal that will serve to produce a simulated example for the source level acoustic inversion. Section IV will draw some conclusions and future perspectives.

II. Concept and approach

In general ocean noise is assumed random because either the source itself is of random nature or because the propagation through a highly variable media made it appear as random when recorded at a remote receiver. A widely accepted expression for calculating noise power spectral density at a location $\mathbf{r}$ is [15], [16]

$$P(\omega;\mathbf{r}) = \sum_{\text{classes}} \int_V \lambda(\mathbf{r}) |g(\omega;\mathbf{r}_0,\mathbf{r}) s(\omega;\mathbf{r}_0)|^2 dv, \qquad (1)$$

where noise classes are, for example, environmental, man made, biological, etc, $\lambda(\mathbf{r})$ denotes source spatial extension/distribution, $g(\omega;\mathbf{r})$ is the Green's function, $s(\omega;\mathbf{r})$ is the source excitation and the integral is done over an arbitrary volume V. Among the considered classes of noise sources there are, for our purpose, two main groups: those that can be differentiated that we will call *point-sources* and those undifferentiated or *extended sources*. The first group generally stands up above the background either because of their power, persistence or directive, while the second group forms the background itself (sometimes also called the pedestal) or the noise component. There is no clear criteria to perform this separation of noise sources. In practice is the identifiability of the noise source that determines in which category it is classified and therefore determines the total number of sources present in the field which, of course, is variable with time. This separation will naturally lead to two terms: one that is a discrete summation of identifiable noise sources, and the other that is a diffuse background noise.

A. Shipping data model

It is clear from (1) that a linear model is adopted where the received power is a linear combination of the power emitted by the various sources weighted by the transmission loss between each source and the receiver, written at any given time t as (frequency dependence was omitted for clarity)

$$x(\mathbf{r};t) = \mathbf{g}(\theta,\mathbf{a};t)\mathbf{s} \qquad (2)$$

where $\mathbf{g}(\theta,\mathbf{a};t)$ is a row vector of dimension I with the Green's function transmission loss (TL) entries for each shipping noise source spatially distributed according to $\{\mathbf{a}\}$ in environmental conditions θ and at time t; $\mathbf{s}$ is a I-dimensional column vector with the source power excitation.

In the shipping noise prediction tools referred to above [10]–[13], a AIS distribution $\{\hat{\mathbf{a}}\}$ is used as an estimate of $\{\mathbf{a}\}$ and an a priori value $\tilde{\theta}$ is used for θ to produce an alternative transfer matrix $\hat{\mathbf{g}}$. Also, an educated guess $\tilde{\mathbf{s}}$ is used for the emitted ship noise power $\mathbf{s}$. So the approximate model can be written as

$$m(\mathbf{r};t) = \hat{\mathbf{g}}(\tilde{\theta},\hat{\mathbf{a}};t)\tilde{\mathbf{s}} \qquad (3)$$

The question that is posed in this paper is the following: *how does a field measurement of the received power at a given location* $\mathbf{r}_0$ *during a given time span* T *may be used to improve approximate model (3)* ?

This field measurement may be written as

$$p(\mathbf{r}_0;t) = x(\mathbf{r}_0;t) + u(\mathbf{r}_0;t) \qquad (4)$$

where $u(\mathbf{r}_0;t)$ is an additive noise component.

In order to increase the amount of data there are three possible observation variables: space, frequency or time. The space dimension implies several sensors at different locations which, taking into account the low frequency band, would imply impractically long arrays. Under project SUBECO it is foreseen to have a few closely spaced sensors on each deployed buoy. Buoys would be separated by several hundreds of km along the coast. Traditional frequency observations are made at third octave band center frequencies but ship radiated noise may vary significantly with frequency and ship type so, each frequency should be treated separately. The time dimension may be explored if the ship radiated noise is assumed stationary during the observation time. In practice this means that navigation conditions (speed, sea state, etc) of the ships within acoustic range of a given buoy do not vary significantly during the observation time. So, if the experimental recording is extended through a given number of time samples $t_n; n = 1,\ldots,N$, the above models may be written in matrix form as

$$\begin{aligned} \mathbf{x}(\mathbf{r}) &= \mathbf{G}\mathbf{s}, \\ \mathbf{m}(\mathbf{r}) &= \hat{\mathbf{G}}\tilde{\mathbf{s}}, \\ \mathbf{p}(\mathbf{r}_0) &= \mathbf{x}(\mathbf{r}_0) + \mathbf{u}(\mathbf{r}_0), \end{aligned} \qquad (5)$$

where matrices $\mathbf{G}$ and $\hat{\mathbf{G}}$ for true ship distribution $\{\mathbf{a}\}$ and AIS estimate $\{\hat{\mathbf{a}}\}$, respectively, now have dimension $N \times I$ and set obvious dimensions for the other vector quantities. Note that in order to write (5), time dependency was assumed in AIS ship distribution $\{\hat{\mathbf{a}}\}$ while there is no guarantee that this results in a well conditioned matrix $\hat{\mathbf{G}}$.

The improvement referred to above may be understood as on how to make the approximate model (3) appear closer to the true model (2). One may claim that this can be done in a variety of ways: one is to improve the environmental parameter vector $\tilde{\theta}$; another is to obtain a better approximation $\{\hat{\mathbf{a}}\}$ of the spatial distribution of noise sources $\{\mathbf{a}\}$ which, as we will see, is a relevant point with practical implications; still another way is to obtain a better estimate of the ship emitted source power $\mathbf{s}$, or all these options taken together. This paper assumes that there is no additional information to improve θ, and therefore attempts to estimate the source emitted power to improve the overall quality of the estimated field. So, the response to the question above is tackled via the estimation of the ship radiated noise term which, of course, will also depend on the spatial ship distribution $\{\mathbf{a}\}$ at any given time.

B. Exploring least-squares

Whenever the statistical distributions of the quantities at play are unknown or hard to predict/assume as it is the case here, least-squares (LS) offers an alternative that is purely geometrical. One way for approximating $x(\mathbf{r})$ using $p(\mathbf{r}_0)$ is to estimate the emitted source signal vector $\mathbf{s}$, such that

$$\hat{\mathbf{s}}_{\mathrm{LS}} = \min[(\mathbf{p}-\mathbf{G}\mathbf{s})^H\mathbf{W}(\mathbf{p}-\mathbf{G}\mathbf{s})] \tag{6}$$

where $\mathbf{W}$ is some full rank weighting matrix, that is known to be

$$\hat{\mathbf{s}}_{\mathrm{LS}} = (\mathbf{G}^H\mathbf{W}\mathbf{G})^{-1}\mathbf{G}^H\mathbf{W}\mathbf{p}, \tag{7}$$

if the matrix inverse exists. The associated field estimate $\hat{\mathbf{x}}_{\mathrm{LS}} = \mathbf{G}\hat{\mathbf{s}}_{\mathrm{LS}}$ is in the subspace $< G >$ span by the columns of $\mathbf{G}$. Plain LS theory shows that the goodness of fit is given by the norm of the vector $\hat{\mathbf{u}} = \mathbf{p} - \hat{\mathbf{x}}_{\mathrm{LS}}$ that belongs to the subspace $< G^{\perp} >$, and is such that $\|\hat{\mathbf{u}}\|$ approximately follows a modified $\sigma^2\chi^2_{N-I}$ distribution.

However, if matrix $\mathbf{G}$ is replaced by $\hat{\mathbf{G}}$ with "errors", such that $\hat{\mathbf{G}} = \mathbf{G} + \mathbf{G}'$ then the solution vector $\mathbf{x}'_{\mathrm{LS}}$ will not be in the subspace $< G >$ and the goodness of fit will normally deteriorate. Being able to obtain an estimate (7) in that case, will absorb the discrepancies between $\hat{\mathbf{G}}$ and $\mathbf{G}$ and a good chance for more accurate modeling of the predicted field on every location $\mathbf{r}$ or, at least, in the vicinity of the measurement location $\mathbf{r}_0$ and during a time span compatible with the acoustic presence of the most powerful ships in the area.

C. The total least squares extension

If we do not completely trust modeled matrix $\hat{\mathbf{G}}$, as it might be our case in practice, a possible solution is to let the projection of the observation $\mathbf{p}$ be out of the subspace $< G >$ span by the columns of matrix $\mathbf{G}$. This lack of trust may also come as a conclusion of a failed test of goodness of fit for plain LS (see above). The idea is to split our trust between $\hat{\mathbf{G}}$ and the observation $\mathbf{p}$. So, the right tool to deal with this is total least squares (TLS) [17], [18] that proceeds by constructing a projection matrix $\mathbf{P}_H = \mathbf{U}_H\mathbf{U}_H^T$, on to a subspace $< H >$ close but not coincident with $< G >$, where $\mathbf{U}_H$ is obtained as the singular value decomposition (SVD) of a matrix composed of $\mathbf{G}$ and $\mathbf{p}$, so $[\mathbf{G}\mathbf{p}] = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T$, and $\mathbf{U}_H$ has the columns of $\mathbf{U}$ but the last one (the one associated with the lowest singular value). Then we choose $\mathbf{W} = \mathbf{P}_H$ in the LS approach (7) above (see [17] pp. 392-393) to get

$$\hat{\mathbf{s}}_{\mathrm{TLS1}} = (\mathbf{G}^H\mathbf{P}_H\mathbf{G})^{-1}\mathbf{G}^H\mathbf{P}_H\mathbf{p}. \tag{8}$$

An alternative solution for the TLS problem is presented in [18], as

$$\hat{\mathbf{s}}_{\mathrm{TLS2}} = -\mathbf{T}_1\mathbf{V}_{xy}\mathbf{V}_{xy}^{-1}\mathbf{T}_2^{-1} \tag{9}$$

where matrices $\mathbf{T}_1$ and $\mathbf{T}_2$ are diagonal with normalization coefficients (useful in our case, since $\mathbf{G}$ and $\mathbf{p}$ have very different scales) and $\mathbf{V}_{xy}$ and $\mathbf{V}_{yy}$ are composed of the last column and last diagonal element of $\mathbf{V}$, resulting from the SVD. These two formulations are equivalent but (9) is easier to implement since it does not requires (in our case) a matrix inversion. As explained in [19] there is no guarantee that (9) does minimizes both the observation noise and the matrix inaccuracies but it provides a consistent solution for the Gaussian case and even for the under determined system case, where a lower rank approximation would be used.

III. Results

A. AIS data set

The Automatic Identification System (AIS) is intended as a complementary safety tool for ocean navigation. The AIS signal is transmitted through marine VHF and has therefore a receiving range of 10-20 nautical miles, although this value can vary with emitter - receiver height and weather conditions. A AIS record may include a variety of information about the ship where it is installed, among which the most important is its GPS coordinates and its identification tag, known as the ship ID. Message transmit time interval may vary from 2 seconds up to 30 minutes, depending on the AIS type and whether the ship is at anchor (less frequent) or in route (more frequent).

As in every communication system, the AIS is prone to receiving errors, due to emitter/receiver motion, interference, weather conditions, electromagnetic propagation, signal attenuation due to distance, etc. Moreover, in order to better cover a given area, several receiving stations are employed. This means that very often the same ship ID is simultaneously received in two or more stations. The raw data from these receivers is then sorted to make a unique stream, but this makes sorting errors inevitable. As we will see in the examples below

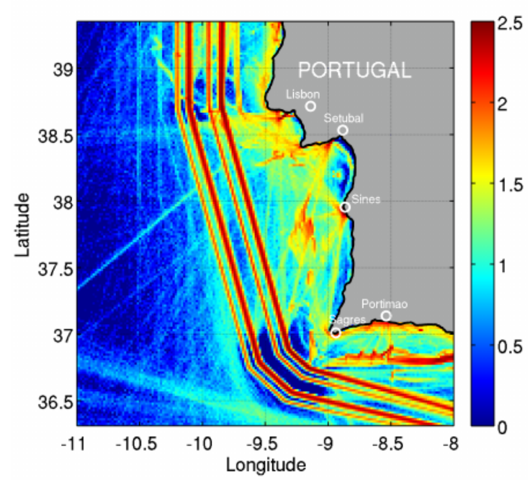

Fig. 1. *Southwest of Portugal, AIS ship density map in ship density per hour for the period of March 18 to December 31, 2014.*

repetitions or misses are frequent. All this contributes to make of the AIS data a stream with some stochastic nature, part of which is inherent to ship's position at sea and part is induced by communication and sorting errors. This stochastic behavior reflects directly in the GPS positioning and therefore in its usage for the prediction of the sound pressure level at any given point in time and space. Possible differences between predicted and actual acoustic measurements encompass other factors as for example non AIS bearing ships as well as, of course, other acoustic noise not due to shipping, e.g., environmental, biological and other anthropogenic noise.

An example drawn from the southwest Iberia, is shown in Figure 1 for the period March 19 to December 31, 2014, as ship density per hour [10]. This figure clearly shows the Traffic Separation Scheme (TSS) in place along the Portuguese coast that concentrates most of the AIS traffic. There is other areas with high AIS ship concentration reaching the main ports of Portimão, Sines, Setúbal and Lisboa as well as a persistent traffic off the southern coast, probably due to fishing.

B. TSS out of Lisboa

A time-space zoom of Figure 2, is done in front of the port of Lisboa for the month of August 2014 (a) and then for one hour on August 1, from 00:00 to 01:00 GMT (b). The TSS can be clearly distinguished as well as the traffic joining the TSS from East, probably originating from the port of Lisboa. This plot was obtained with a sampling rate of 3 min and has around 28000 contacts (not ships). The virtual observation point to be used in this study is situated in the center of the box at -10°W 38.5°N (red cross sign). The one hour zoom in (b) shows 17 individual ship IDs present in the area, some going along the TSS either South-North or vice-versa and a few others joining the TSS. Figure 3 shows AIS ship ranges to the virtual observation location (red cross) of Fig. 2(b). Raw data shows many incomplete tracks due to AIS communication failure or data sorting (thick lines). Using a nearest neighbor data completing algorithm the tracks are completed in (dashed lines), but it is obvious that a number of ship tracks are redundant and insufficient for retrieving source amplitude information.

C. Acoustic modeling and source inversion

A Copernicus data base[2] predicted temperature profile was used for the water column sound speed for that date and location. The KRAKEN normal model [20] was used for predicting acoustic propagation. Figure 4 shows both the SSP and the transmission loss (TL) for a source depth of 10 m and a frequency of 500 Hz, used in this work. Therefore, the main question is whether the AIS information allows to construct a well behaved matrix $\mathbf{G}$. In fact the 19×17 ship track matrix generated for one hour of data and with the 17 AIS ships is rank deficient. After extracting the 4 linearly dependent columns, corresponding to the most distant ships with small number of contacts (ship IDs 205521000, 247310400, 225353000 and 636090616), the matrix is now full rank with a condition number of 35. According to AIS information the 13 ships identified in this time-space slot (after removal) are: 9 container ships and 4 product tankers. To

[2]available on `http://marine.copernicus.eu/`

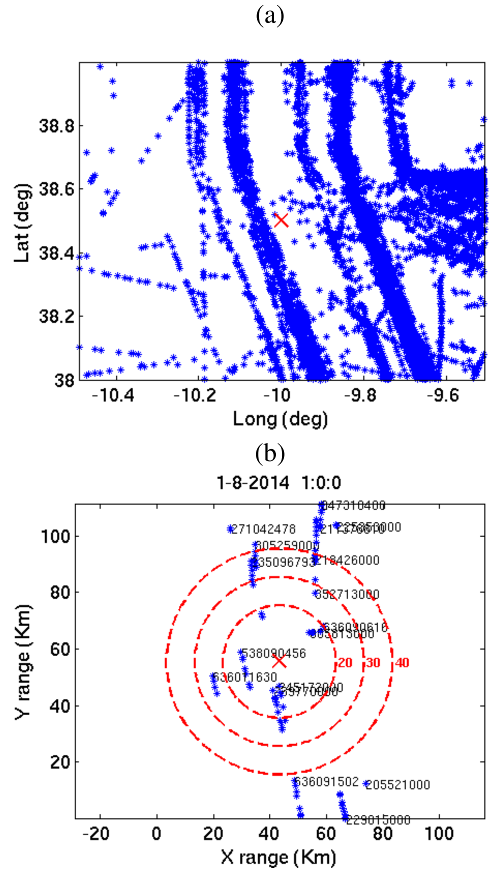

Fig. 2. *AIS contacts at 3 min sampling for August 2014, in the area of 1 degree side on the TSS off Lisboa (a) and 17 ships from 00:00 to 01:00 GMT on August 1,2014 (b). Virtual observation point situated at -10° W 38.5° N is shown by the red cross sign.*

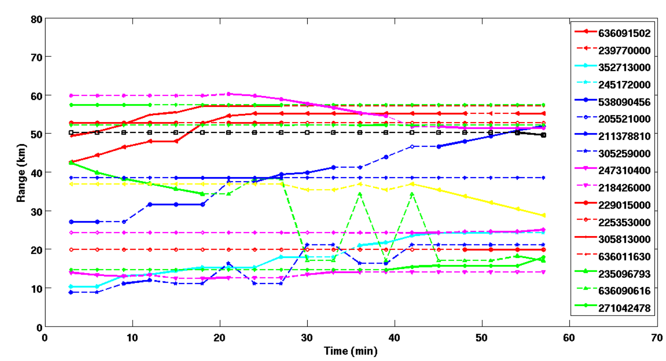

Fig. 3. *AIS ship ranges to red cross location for data of Figure 2(b) : raw data (thick lines), completed with the nearest neighbor algorithm (dashed lines).Legend shows shipID.*

each of these, source power levels of 178.1 and 169.6 dB re 1μPa/1m were respectively assigned, according to [9].

The resulting acoustic field was corrupted with additive white Gaussian noise with variable variance. The inverted source ship spectra is shown in Fig. 5 where it is clear that the estimates are unbiased and do, in average, decrease with increasing SNR with estimates within 10% of the true ship

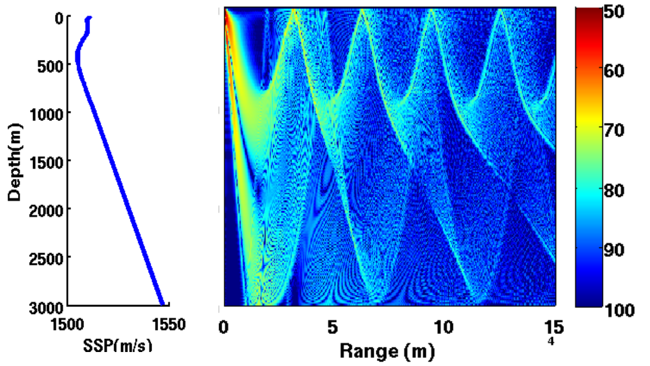

Fig. 4. *KRAKEN computed TL for source depth 10 m, at 500 Hz (right) and the CMEMS predicted sound speed profile (left).*

radiated power. Since in this case there is no misalignment,

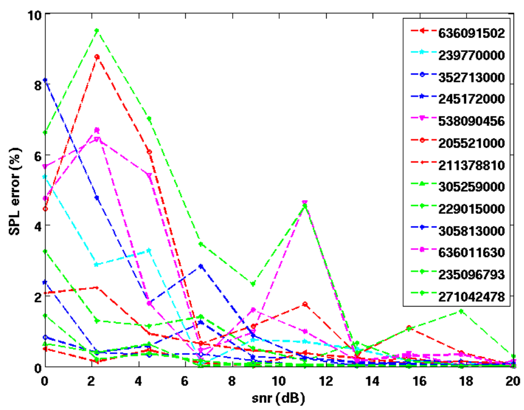

Fig. 5. *Estimates of ship noise power (%) in white Gaussian noise using least-squares.*

i.e., $\hat{\mathbf{x}}$ is in the subspace $< G >$ span by the columns of $\mathbf{G}$, the goodness of fit $\|\hat{\mathbf{u}}\|$ measures the "distance" between the observation vector and that subspace and is distributed as $\sigma^2\chi^2_{N-I}$ (with $N = 19$ and $I = 13$). Figure 6 shows the empirical histogram of the goodness of fit for the SNR=20 dB normalized by the signal variance (blue) and the probability density function for a χ^2 with 6 degrees of freedom (adjusted in amplitude to fit the empirical histogram). In this case the mean over SNR (normalized by noise variance) distance between the observation and the LS solution is 6 dB while the misalignment, *i.e.*, the mean distance between the true and the LS solution is 3 dB.

We now produce a misalignment by introducing a randomness factor in the entries of matrix $\hat{\mathbf{G}}$ with variance 25 dB. In this case the LS estimate results produces errors up to 120% of the true values and do not converge for increasing SNR (not shown). Instead, the TLS estimate performance against noise using (9) is shown in Fig. 7, where one can see that, although with higher error levels than in the no mismatch case, there is consistency with increasing SNR.

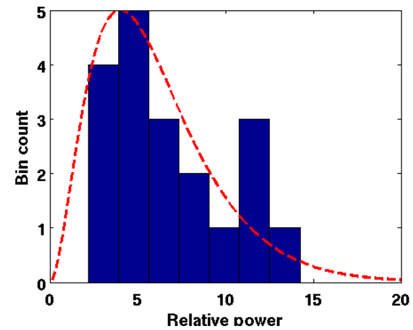

Fig. 6. *Goodness of fit empirical histogram for SNR=20 dB (blue) and .*

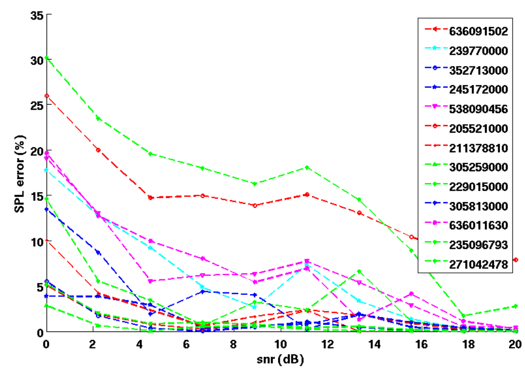

Fig. 7. *Estimates of ship noise power (%) in white Gaussian noise and with model uncertainties using total least-squares.*

IV. Conclusions

One of the drawbacks of current shipping noise field prediction tools is the lack of strategies for including field measurements in a consistent and efficient manner. The approach described here uses AIS tracks over range-time to invert for discrete ship source radiated noise using the information retrieved at a single location. The stationarity assumption made is that the ship source level is constant over the observation time necessary for the inversion and that it will remain approximately constant for some time after the observation period so it can be used to calibrate the model predictions in a consistent manner for the present and near future.

The proposed method uses a naive least squares approach, then extended as a total least squares, to deal with discrepancies in the model transmission loss matrix. The method is tested in a AIS data set recorded off the west coast of Portugal during a period of one hour in August, 2014. A total of 17 ships were identified as cruising within acoustic range from the receiver. This number was further decreased to 13 due to AIS inconsistencies translated into singularities of the data matrix. The results show that it is indeed possible to invert such data sets as drawn from AIS data information and that the LS estimates are consistent and unbiased. In case the model shows inaccuracies in the data matrix, total least squares were shown useful to also provide a solution, although with a larger error.

Of course the full test of the proposed method will only be obtained with actual field data that, will be available when the first buoy of the SUBECO project will be deployed in September 2017. Complementary information and contributions of the proposed method will be made under the EU H2020 funded project EMSODEV for monitoring of the acoustic component in ocean observatories and under the EU Atlantic program project JONAS (under approval).

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