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# Underwater Noise Estimation with General Regression Neural Network

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**Abstract**—With growing exploration and utilization of the ocean by human beings, sound pollution increases accordingly and significantly. Hence, the impact of noise on marine organisms has become one of the most important research topics. In order to assess the impact of these activities on marine fauna, and especially on marine mammals, underwater noise propagation should be estimated. It is in this context that the proposed work is situated. In fact, the aim of this project is to study how neural network techniques can speed up these computations for estimating underwater noise propagation. For this, experimental data from practical investigations/experiments were used to train the GRNN for estimating noise level caused by each boat. The predicted values using GRNN closely followed the experimental ones with a root mean square error scores (RMSE) that is equal to 0.7. Results showed that the GRNN model had good prediction results during the testing process in terms of both RMSE scores and training times. To evaluate the model accuracy, the propagation distance from the source in the horizontal plane was set at 150 km. At this distance, the predicted loss of acoustic energy resulted in noise levels which were comparable to the reference values. Several parameters were used in order to build an accurate model. These parameters include: the propagation distance, the depth, the transmission frequency, the kinematic bathymetry, and the sediment nature. The proposed model therefore estimated the noise level until 150 km from the noise source with high accuracy and high speed computation without complex procedures. Moreover, the use of GRNN made it possible to avoid remaking the expensive computations for each sub-zone: it estimated the noise levels with a very reduced time compared to the state-of-the-art methods such as RAM.

Underwater noise prediction GRNN neural network function approximation

## I. INTRODUCTION

With growing exploration and utilization of the ocean by human beings, sound pollution increases accordingly and significantly. Hence, the impact of noise on marine organisms has become one of the most important research topics. In order to assess the impact of these activities on marine fauna, and especially on marine mammals, underwater noise propagation should be estimated. To do so, several propagation models were proposed in the literature, among which the Parabolic Equation model. In fact, separating the wave equation (or Helmholtz equation) into incoming and outgoing solutions, leads to the Parabolic Equation (PE) [25]. The solution for the PE is then derived from the wave equation in which only the out-going wave is considered. Several underwater sound propagation toolboxes make the use of PE in order to estimate/assess the noise level. One successful example is

the Range-dependent Acoustic Modeling (RAM) which is a parabolic equation implementation that models propagation at large angles from the horizontal plane.

However, simulating sound pollution starting from boat locations using the RAM toolbox requires intensive computations that increase with the square of frequency. It is in this context that the proposed work is situated. In fact, the aim of this project is to study how neural network techniques can speed up these computations.

Regression is a learning algorithm that, from an input dataset, predicts an output that can be quantitative/continuous [18].

A widely used neural network regression model is the General Regression Neural Network (GRNN) [18]. GRNN is used to approximate functions and can be used to perform a regression where the linearity constraint is relaxed. According to several benefits of GRNN respect to several regression models, this method will be used in this study in order to estimate/predict the underwater noise propagation. GRNN widely used tool that was applied in medical diagnosis [8], pattern identification [9], measuring pressure loss of Herschel–Bulkley drilling fluids in oil drilling [10], three-dimensional modeling [11], chemical engineering [12], and function approximation [13].

The proposed GRNN architecture is here a five-layer network (input layer, 3 hidden layers and 1 output layer). The first and last hidden layers are composed of 10 neurones each, the one has 100 neurones.

Experimental data from practical investigations/experiments were used to train the GRNN for estimating noise level caused by each boat. The predicted values using GRNN closely followed the experimental ones with a root mean square error scores (RMSE) that is equal to 0.7. Results showed that the GRNN model had good prediction results during the testing process in terms of both RMSE scores and training times.

The rest of this paper is organized as follows: In Section 2, the proposed approach is detailed. In Section 3, extensive evaluation is reported. Section 4 concludes the work by summarizing findings and giving directions for future work.

## II. PROPOSED APPROACH

### A. Theory

Environmental data are the drivers of underwater noise propagation. Hence, as indicated in Table I, the environmental

TABLE I  
ENVIRONMENTAL TOGETHER WITH THE ASSIGNED LAYER.

Environmental data	Layer
Propagation distance (rr)	Input
Depth (rd)	Input
Frequency (F)	Input
Kinematic Bathymetry (Cr)	Input
Temperature(T)	Input
Salinity(S)	Input
Sediment nature(Sn)	Input
Attenuation(TL)	Output

data are set to the inputs and are:

- the propagation distance: up to 150km starting from the noise source;
- the propagation depth: set to 200m starting from the noise source level;
- the frequency: each source has 6 several transmission frequencies varying in the range of 63Hz to 125Hz;
- the kinematic bathymetry: in which noise speed profile, the water temperature, and the water salinity intervene;
- the sediment nature: also referred to by the Geoacoustic model, in which several parameters intervene and are the number of layers, the density, and the attenuation of compressional waves.

In this study, the propagation distance starting from the source in the horizontal plane was set at 150Km. The propagation distance is associated to the horizontal resolution that was set to 100m. Hence, the noise estimates were given for each 100m up to the maximum distance resulting in 1500 estimations. This number is multiplied by the angular resolution (set to  $1^\circ$ ) to compute the total number of observations that will be used in the training/test process. Hence the total number of observations is 540000 (obtained as:  $360/1 * 1500$ ).

The kinematic Bathymetry (Cr) is a function of the depth, the water salinity, and the temperature as follows [5], [16]:

$$Cr = 1449.2 + 4.6 * T - 0.0551 * T^2 + 0.00029 * T^3 \\ + (1.34 - 0.01 * T) * (S - 35) + 0.016 * rd \quad (1)$$

where  $T$  is the temperature,  $S$  is the salinity,  $rd$  is the depth. Figure 1 illustrates the kinematic bathymetry profile. In this study, for simplicity, the temperature and the salinity were supposed to be constants. In a general case, however, these variables should be collected from monitoring stations over a set period [14].

The sediment nature has a major effect on noise propagation. In fact, the influence of the interaction of sea with frontiers and obstacles of the bottom is much more important than that of the surface. This is due to several phenomena occurring simultaneously: 1) penetration of the incident wave in the sediment due to the low impedance contrast between water and sediment, 2) the sound attenuation in sediment is much stronger than in water, and 3) the sound speed. Here, geo-acoustic properties were obtained from geological and geomorphological mappings that permitted the identification

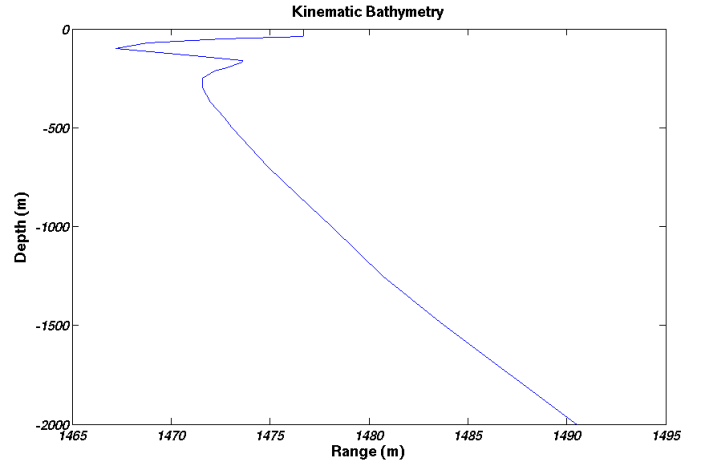


Fig. 1. Example of kinematic Bathymetry profile.

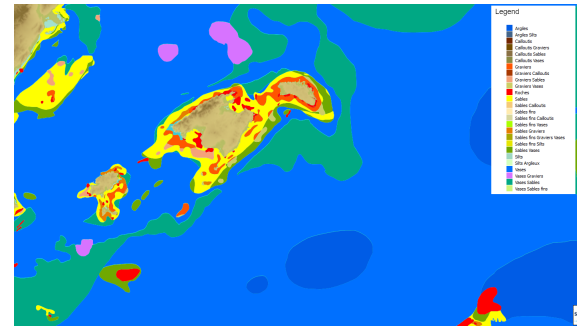


Fig. 2. Map of seafloor geological nature.

of the sediment nature and therefore selecting the relative coefficients. In Figure 2, a map indicating the seafloor geological nature is given. Hence, knowing the source position, values of the sea-bottom acoustic properties can be assigned to each point [15], [17].

#### B. Underwater noise estimation using GRNN

The proposed approach consists of General regression neural network (GRNN) to estimate the noise level depending on several inputs. GRNN is a type of supervised network and has been proposed by Specht [18]. GRNN is able to produce continuous value outputs. As indicated in Table I, the GRNN has an input layer, 3 hidden layers, and 1 output layer.

Firstly, the input data should be vectorized and fed into the network. A series of matrix operations is operated on the input data layer by layer through the 3 hidden layers. Each input sample is multiplied by weights and added to bias that are updated after every epoch. An *epoch* describes the number of times the regression algorithm sees the entire training dataset. Finally, the activation functions are applied to the result. The use of the activation functions is crucial. In fact they introduce non-linearities to the network, making it able to do universal function approximation. Several activation functions have been introduced in literature including the Sigmoid function, the Hyperbolic tangent (Tanh) function, and the Rectified linear

unit (ReLU) function [20] [24]. ReLU function is proved to learn faster and to avoid the vanishing gradient problem. Hence, this latter was used in this work.

After applying the activation function, the output is passed to the next layer to do the same thing. This operation is repeated until the last layer is reached where the output value is our prediction  $\hat{TL}$ . The estimation is then optimized by computing the error ( $e = TL - \hat{TL}$ ) between the predicted output  $\hat{TL}$  and the expected output  $TL$ . The error  $e$  is used to calculate the partial derivative with respect to the weights, and each layer goes backwards in order to update the weights with these values. This process is repeated until the error value is minimized.

GRNN was trained based on experimental data. As indicated in Table I, the variables that were set as independent inputs are the: propagation distance ( $rr$ ), the depth ( $rd$ ), the frequency ( $F$ ), the sediment nature and the kinematic Bathymetry ( $Cr$ ), while the attenuation was set as the output (target  $y$ ). Using the attenuation ( $TL$ ), the Noise level in the frequency ( $F$ ) at each point of the matrix is:

$$Lp(F) = SL(F) - TL(F) \quad (2)$$

where  $Lp$  noise level,  $SL$  is the source level, and  $TL$  is the attenuation level calculated at this frequency.

In order to find the total noise level on all the frequencies, we added up the pressure levels as:

$$Lp_S = \sum_{F=F_1}^{F_2} 10^{(Lp(F)/10)} \quad (3)$$

where  $F_1$  and  $F_2$  are the first and last central frequencies of the third octave, respectively.

The final summed noise level is then converted to dB as:

$$Lp_{dB} = 10 * \log_{10}(Lp_S). \quad (4)$$

### III. EVALUATION OF THE PROPOSED APPROACH

This section is devoted to the evaluation of the performance of the estimation. This evaluation consists to quantitatively evaluate GRNN estimation performance in terms of RMSE. As well, we quantify the proposed improvement compared to state-of-the art model that are namely ANN [23] and BPNN [23]. To do so, we estimated a noise card of 150km length starting from the boat (source) location. Figure 3 illustrates the attenuation in 3D as well as the source position (using a green circle).

A 2D-view of the attenuation profile that will be reproduced is illustrated in Figure 4. The depth of the card is of 200m and the propagation distance is 150Km. The corresponding noise level is illustrated in Figure 5.

The RMSE quantifies the mean deviation/error of estimated data compared to the measured data. The RMSE score can be calculated as follows [19]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{N}} \quad (5)$$

TABLE II  
DESCRIPTION AND RMSE FOR EACH ALGORITHM.

Algorithm	Description	RMSE
GRNN	3 hidden layers	<b>0.7405</b>
ANN	3 hidden layers	22.4606
BPNN	3 hidden layers	4.6526

where  $y_i$  is the measured value,  $\hat{y}_i$  denotes the predicted value, and  $N$  is the number of samples. Description and the RMSE scores are given for each algorithm are illustrated in Table III. The lowest RMSE score presents the more accurate estimation.

The underwater noise level was predicted using GRNN model as described above.

The neural network was trained on experimental data. The used training samples cover the whole range 0-150 km. In fact, we used the available data between 0 and 150 km with a step of 2kms. In this study, the depth is ranging from 0 to 200 meters along the experimental track. For simplicity, we supposed that the water depth does not change with directions.

In Figure 5, the predicted noise level values were compared with the experimental ones for the training set of 60% randomly chosen data from the whole dataset. In fact, The whole data set is divided into training and test sets. The training and test data sets were randomly chosen as 60% vs 40%. In turn, 10% of the training set was used as validation set.

The training is conducted through 10,000 epochs, where an epoch corresponds to a learning on all the data i.e. an iteration of the learning algorithm on the whole database. The larger the number epochs, the better the accuracy. In this work, the number of epochs was chosen to satisfy the trade-off between the estimation accuracy and the training time that did not exceed 17 minutes. In fact, after all the iterations, the model was not overfitted because the evaluation loss never exhibit a significant change in direction toward an increasing value. Hence, making predictions could be done safely based on the test dataset and assess how the model does as predicting underwater noise level.

To test and evaluate the network, the test set was used. The comparison of estimations of the network with the measured values for the test data set (population of 40% of the whole dataset) is shown in Figure 5. As well, a performance comparison of the predicted values using GRNN and those given by ANN or BPNN model is given in Table III. The GRNN RMSE score is 0.7, indicating a very satisfactory model performance. These results, therefore, verify the success of neural networks to recognize the implicit relationships between input and output variables. GRNN is then accurately able to predict underwater noise level with high accuracy without complex procedure.

### IV. CONCLUSION AND FUTURE WORK

GRNN was applied to predict underwater noise caused by boats. The input layer had six neurons including the propagation distance, the depth, the transmission frequency, the kinematic bathymetry, and the sediment nature. Hidden

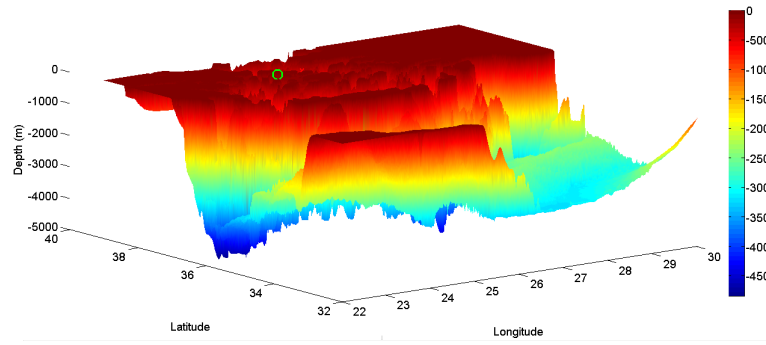


Fig. 3. Attenuation in 3D and the source position

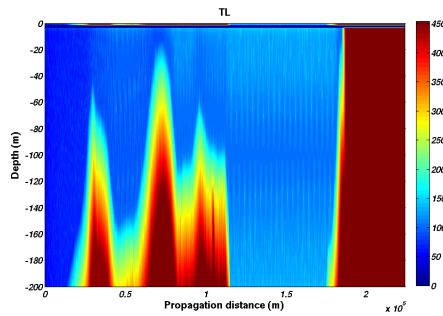


Fig. 4. Attenuation (TL) in the studied area.

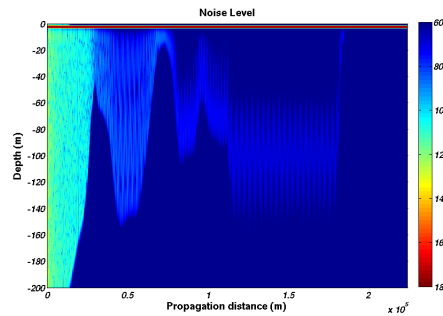


Fig. 5. Noise Level

layer had multiple neurons with activation function in all neurons and the output layer had one neuron.

The predicted noise level was close to the experimental values: the root mean square error (RMSE) was equal to 0.7. Hence, evaluation results showed that the GRNN model had good prediction accuracy during the testing process in terms of both RMSE scores and training times.

The GRNN model therefore estimated the noise level until 150 km from the noise source with high accuracy and high speed computation without complex procedures. Moreover, the use of GRNN made it possible to avoid remaking the expensive computations for each sub-zone: it estimated the noise levels with a very reduced time compared to the state-of-the-art methods such as RAM.

The effectiveness of the GRNN model in predicting underwater noise level could be more generalized by testing on

other areas and periods. Future work may address including detailed ship characteristics which could be a great step toward increasing the accuracy of the predicted underwater noise distributions.

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#### REFERENCES

#### REFERENCES

- [1] STOJANOVIC, Milica et PREISIG, James. Underwater acoustic communication channels: Propagation models and statistical characterization. *IEEE communications magazine*, 2009, vol. 47, no 1, p. 84-89.
- [2] ERBE, Christine. Underwater noise of whale-watching boats and potential effects on killer whales (*Orcinus orca*), based on an acoustic impact model. *Marine mammal science*, 2002, vol. 18, no 2, p. 394-418.
- [3] WITTEKIND, Dietrich Kurt. A simple model for the underwater noise source level of ships. *Journal of Ship production and design*, 2014, vol. 30, no 1, p. 7-14.
- [4] NEDWELL, J., LANGWORTHY, J., et HOWELL, D. Assessment of sub-sea acoustic noise and vibration from offshore wind turbines and its impact on marine wildlife; initial measurements of underwater noise during construction of offshore windfarms, and comparison with background noise. Subacoustech Report ref: 544R0423, published by COWRIE, 2003.
- [5] ERBE, Christine, LIONG, Syafrin, KOESSLER, Matthew Walter, et al. Underwater sound of rigid-hulled inflatable boats. *The Journal of the Acoustical Society of America*, 2016, vol. 139, no 6, p. EL223-EL227.
- [6] IKPEKHA, Oshoke. Underwater acoustics propagation analysis and modelling of sound emitting devices. 2017. Thèse de doctorat. Dublin City University.
- [7] ANCUTI, Codruta O., ANCUTI, Cosmin, DE VLEESCHOUWER, Christophe, et al. Color balance and fusion for underwater image enhancement. *IEEE Transactions on image processing*, 2017, vol. 27, no 1, p. 379-393.
- [8] NDABA, Moeketsi, PILLAY, Anban W., et EZUGWU, Absalom E. An improved generalized regression neural network for type II diabetes classification. In : *International Conference on Computational Science and Its Applications*. Springer, Cham, 2018, p. 659-671.
- [9] LIANG, Yi, NIU, Dongxiao, et HONG, Wei-Chiang. Short term load forecasting based on feature extraction and improved general regression neural network model. *Energy*, 2019, vol. 166, p. 653-663.
- [10] ROOKI, Reza. Application of general regression neural network (GRNN) for indirect measuring pressure loss of Herschel-Bulkley drilling fluids in oil drilling. *Measurement*, 2016, vol. 85, p. 184-191.
- [11] KULKARNI, Savita G., CHAUDHARY, Amit Kumar, NANDI, Somnath, et al. Modeling and monitoring of batch processes using principal component analysis (PCA) assisted generalized regression neural networks (GRNN). *Biochemical Engineering Journal*, 2004, vol. 18, no 3, p. 193-210.

- [12] WANG, Run, MO, Qiaoli, ZHANG, Qian, et al. Prediction of the Yield of Enzymatic Synthesis of Betulinic Acid Ester Using Artificial Neural Networks and Support Vector Machine. *Advance Journal of Food Science and Technology*, 2016, vol. 12, no 12, p. 653-662.
- [13] GOULERMAS, John Y., LIATSIS, Panos, ZENG, Xiao-Jun, et al. Density-driven generalized regression neural networks (DD-GRNN) for function approximation. *IEEE transactions on neural networks*, 2007, vol. 18, no 6, p. 1683-1696.
- [14] LOSSENT, Julie, MEDJBER, Bouzidi, GERVAISE, Cédric, et al. In situ demonstrator of a method to track in three dimensions cetaceans with passive acoustics in the context of close interactions impacts with marine renewable energy devices. *The Journal of the Acoustical Society of America*, 2018, vol. 144, no 3, p. 1809-1809.
- [15] DRIRA, Achraf, BOUZIDI, Medjber, MAGLIO, Alessio, et al. Modelling underwater sound fields from noise events contained in the ACCOBAMS impulsive noise register to address cumulative impact and acoustic pollution assessment. In : *Proceedings of Euronoise*. 2018. p. 2819-2824.
- [16] DRIRA, Achraf. Geoacoustic inversion: improvement and extension of the sources image method. 2015. Thèse de doctorat. Brest.
- [17] BELGHITH, Emna Hachicha, RIOULT, François, et BOUZIDI, Medjber. Acoustic diversity classifier for automated marine big data analysis. In : *2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI)*. IEEE, 2018. p. 130-136.
- [18] Specht, Donald F. A general regression neural network. *IEEE transactions on neural networks Vol2*, pp568–576, IEEE, 1991.
- [19] Wiem, Belhedi and Mowlae, Pejman and Aicha, Bouzid and others. Unsupervised single channel speech separation based on optimized subspace separation. *Speech Communication*, Vol96, pp3–101, Elsevier, 2018.
- [20] Krizhevsky, Alex and Sutskever, Ilya and Hinton, Geoffrey E. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, pp1097–1105, 2012.
- [21] Etter, Paul C. *Underwater acoustic modeling and simulation*, CRC press, 2018.
- [22] Pollara, Alexander and Sutin, Alexander and Salloum, Hady. Modulation of high frequency noise by engine tones of small boats. *The Journal of the Acoustical Society of America*, Vol142, pp30–34, ASA, 2017.
- [23] Plumb, A Philip and Rowe, Raymond C and York, Peter and Brown, Martin. Optimisation of the predictive ability of artificial neural network (ANN) models: a comparison of three ANN programs and four classes of training algorithm. *European Journal of Pharmaceutical Sciences*, Elsevier, 2005.
- [24] Nwankpa, Chigozie and Ijomah, Winifred and Gachagan, Anthony and Marshall, Stephen. Activation functions: Comparison of trends in practice and research for deep learning, *arXiv preprint arXiv:1811.03378*, 2018.
- [25] Collins, Michael D and Siegmann, William L, *Parabolic Wave Equations with Applications*, 2019, Springer.