# The Scour Depth Prediction of the Submarine Pipeline Area on the Algorithm of the Radial Basis Function

Authors: Lee, Hojin, Kim, Sungduk, and Jun, Kye-Won

Source: Journal of Coastal Research, 75(sp1) : 1382-1386

Published By: Coastal Education and Research Foundation

URL: https://doi.org/10.2112/SI75-277.1

| Journal of Coastal Research | SI | 75 | 1382 - 1386 | Coconut Creek, Florida | 2016 |
|---|---|---|---|---|---|

# The Scour Depth Prediction of the Submarine Pipeline Area on the Algorithm of the Radial Basis Function

**Hojin Lee** [†], **Sungduk Kim** [†*], **and Kye-Won Jun** [††]

[†]The School of Civil Engineering, Chungbuk National University, Cheongju, South Korea

[††]Graduate School of Disaster Prevention, Kangwon National University, Samcheok, South Korea

www.cerf-jcr.org

www.JCRonline.org

**ABSTRACT**

Lee, H.; Kim, S., and Jun, K.W., 2016. The scour depth of the submarine pipeline area on the algorithm of the Radial Basis Function. *In:* Vila-Concejo, A.; Bruce, E.; Kennedy, D.M., and McCarroll, R.J. (eds.), *Proceedings of the 14th International Coastal Symposium* (Sydney, Australia). *Journal of Coastal Research*, Special Issue, No. 75, pp. 1382-1386. Coconut Creek (Florida), ISSN 0749-0208.

The submarine pipeline is a facility that requires frequent usage for transporting substances like crude oil or gas. Failures in the submarine pipeline can cause marine pollution and the cost to restore the induced damage can be great. Therefore, it is important to consider several impact factors that can help secure the stability of the submarine pipeline during its installment. Scour is one of the factors that cause great damage to submarine pipelines. In this study, existing experimental data from previous experiments are analyzed in order to predict scour depth and deduce the main parameters affecting scour. The deduced parameters are used and analyzed by the Radial Basis Function Neural Network (RBFN) for the prediction of scour depth.

**ADDITIONAL INDEX WORDS:** *Submarine pipeline, marine pollution, scour, Radial Basis Function Neural Network (RBFN).*

## INTRODUCTION

Submarine pipelines are frequently installed near the coastal regions for the convenient transport of crude oil and gas. For the convenience of import and export, the industrial parks located in the coastal regions are growing in scale, and as a result, the number of submarine pipeline installments is increasing as well. The submarine pipelines must be able to endure the conditions of the marine environments of installment in order for the functions to be easily conducted; thus details must be attentively considered during the installment process. Because the maintenance of the submarine pipeline is particularly difficult, the systematic review process is taken seriously during the pipeline's construction to prevent damage.

One of the main factors to consider within the design process during installment is scour. When scours localize beneath the submarine pipeline, a dynamic force is pressed onto the pipeline in the form of vibration or the pipeline undergoes self-burial as additional static and dynamic load occurs. As a result, marine pollution can occur due to pipeline failure and the cost to restore the damage would be high. In order to establish proper countermeasure steps against scour, an accurate and deeper analysis of scour is needed. There are various factors that affect scour.

In the past, the main method to predict for scour involved using the hydraulic experiment based on empirical formulas. With the development of technology, computers and numerical methods can now incorporate and run the numerical model, the statistical method, the artificial intelligence model, and the hydraulic model test altogether.

*DOI: 10.2112/SI75-277.1 received 15 October, 2015; accepted in revision 15 January, 2015*

*Corresponding author: soungdoug@hotmail.com



In this study, an artificial neural network is applied to the methods used to predict the scour depth caused by waves within the submarine pipeline's vicinity. The results of the hydraulic model are set as input data: ($D$) for pipeline diameter, ($T$) for wave period, ($H$) for wave height, ($d$) for water depth, the Keulegan-Carpenter number, and the modified Ursell number. These values will be applied into the RBF Algorithm-based neural network model for scour depth prediction.

## METHODS

In this paper, the data from Table 1 are used for the neural networks method along with the results obtained by the hydraulic model test (Oh *et al.*, 2002; Sümer and Fredsøe, 1990). The measurements of the two-dimensional wave generation tank are the following: 1 m in height, 0.8 m in width, and 25 m in length.

In Table 1, the following information are presented: $D$ for pipe diameter, $T$ for wave period, $H$ for wave height, $d$ for water depth, the Keulegan-Carpenter ($KC$) number, and the Modified Ursell number($U_{RF}$).

The $KC$ number and the Ursell number($U_{RF}$) are defined with the following equations (1) and (2).

$$KC = \frac{U_m T}{D} \tag{1}$$

$$U_{RP} = \frac{U^3 T^2}{D^2 d^3} \tag{2}$$

In the equation listed above, $U_m$ is the maximum water particle velocity on the bed in the absence of the pipe, and $L$ represents wave length.

In the results of the previous hydraulic model test, the *KC* number and the Ursell number are proposed as main contributing factors to scour depth (Sümer and Fredsøe, 1990; Çevik and Yüksel, 1999).

Table 1. *Data used in Neural Network model*

| no | *D(m)* | *T(m)* | *H(m)* | *d(m)* | *KC* | $U_{RF}$ | *S/D* |
|---|---|---|---|---|---|---|---|
| 1 | 0.09 | 1 | 0.048549 | 0.33 | 0.817392 | 0.775804 | 0.088889 |
| 2 | 0.08 | 1 | 0.08 | 0.48 | 0.861587 | 1.636296 | 0.092822 |
| 3 | 0.09 | 1.5 | 0.051977 | 0.33 | 1.889391 | 2.850241 | 0.111111 |
| 4 | 0.06 | 1 | 0.093535 | 0.33 | 2.362179 | 12.4827 | 0.116667 |
| 5 | 0.09 | 1 | 0.11071 | 0.33 | 1.863943 | 9.199387 | 0.122222 |
| 6 | 0.09 | 1 | 0.113556 | 0.33 | 1.911856 | 9.927201 | 0.122222 |
| 7 | 0.04 | 1 | 0.08 | 0.48 | 1.723174 | 6.545185 | 0.13127 |
| 8 | 0.06 | 1 | 0.079063 | 0.33 | 1.996701 | 7.538914 | 0.133333 |
| 9 | 0.06 | 1 | 0.111309 | 0.33 | 2.811048 | 21.03656 | 0.15 |
| 10 | 0.08 | 1.5 | 0.08 | 0.48 | 2.404883 | 5.618757 | 0.155077 |
| 11 | 0.09 | 2 | 0.047179 | 0.33 | 2.537269 | 4.162302 | 0.155556 |
| 12 | 0.09 | 3 | 0.05713 | 0.33 | 4.932188 | 17.73599 | 0.155556 |
| 13 | 0.09 | 2.5 | 0.034299 | 0.33 | 2.410797 | 2.606227 | 0.166667 |
| 14 | 0.06 | 1.5 | 0.100955 | 0.33 | 5.504588 | 46.98936 | 0.166667 |
| 15 | 0.04 | 1 | 0.091876 | 0.33 | 3.480411 | 26.61768 | 0.175 |
| 16 | 0.02 | 1 | 0.08 | 0.48 | 3.446349 | 26.18074 | 0.185643 |
| 17 | 0.09 | 2.5 | 0.092272 | 0.33 | 6.485514 | 50.74153 | 0.188889 |
| 18 | 0.09 | 3 | 0.080935 | 0.33 | 6.987349 | 50.42824 | 0.2 |
| 19 | 0.04 | 1 | 0.112927 | 0.33 | 4.277857 | 49.42623 | 0.2 |
| 20 | 0.08 | 1.5 | 0.16 | 0.48 | 4.809766 | 44.95005 | 0.219312 |
| 21 | 0.09 | 1.5 | 0.131352 | 0.33 | 4.77467 | 45.99878 | 0.222222 |
| 22 | 0.09 | 1.5 | 0.16604 | 0.33 | 6.035566 | 92.91166 | 0.222222 |
| 23 | 0.08 | 2 | 0.11 | 0.48 | 5.199565 | 29.89282 | 0.228026 |
| 24 | 0.09 | 2 | 0.143559 | 0.33 | 7.720575 | 117.2689 | 0.244444 |
| 25 | 0.06 | 1.5 | 0.127181 | 0.33 | 6.934557 | 93.94663 | 0.25 |
| 26 | 0.04 | 1.5 | 0.097293 | 0.33 | 7.957368 | 94.63289 | 0.25 |
| 27 | 0.09 | 3 | 0.105265 | 0.33 | 9.087794 | 110.9461 | 0.255556 |
| 28 | 0.02 | 1 | 0.16 | 0.48 | 6.892698 | 209.4459 | 0.262539 |
| 29 | 0.08 | 2 | 0.16 | 0.48 | 7.563004 | 91.99172 | 0.275009 |
| 30 | 0.09 | 2.5 | 0.111311 | 0.33 | 7.823707 | 89.07752 | 0.277778 |

The RBFN (Radial Basis Function Network) is applied in this paper to predict for scour depth. According to the studies

conducted by Broomhead and Lowe (1988), and Moody and Darken (1989), the Radial Basis Functional Network (RBFN) is a network based on the radial function making much progress within similar topics of study.

Multi-layer Perception (MLP) is a network with a high classification performance level; however, a couple of its

Table 1. *Continued*

| no | *D(m)* | *T(m)* | *H(m)* | *d(m)* | *KC* | $U_{RF}$ | *S/D* |
|---|---|---|---|---|---|---|---|
| 31 | 0.08 | 3 | 0.11 | 0.48 | 8.182214 | 84.99641 | 0.286046 |
| 32 | 0.04 | 1 | 0.11143 | 0.33 | 4.221143 | 47.48635 | 0.3 |
| 33 | 0.06 | 2.5 | 0.06733 | 0.33 | 7.098625 | 44.35697 | 0.3 |
| 34 | 0.04 | 1.5 | 0.088804 | 0.33 | 7.263085 | 71.96099 | 0.3 |
| 35 | 0.06 | 3 | 0.061559 | 0.33 | 7.97179 | 49.92438 | 0.3 |
| 36 | 0.06 | 2 | 0.101033 | 0.33 | 8.150254 | 91.9721 | 0.3 |
| 37 | 0.04 | 3 | 0.094214 | 0.33 | 18.30082 | 402.6852 | 0.3 |
| 38 | 0.02 | 1.5 | 0.08 | 0.48 | 9.619532 | 89.9001 | 0.310154 |
| 39 | 0.08 | 2.5 | 0.16 | 0.48 | 10.12043 | 153.0102 | 0.318126 |
| 40 | 0.04 | 2.5 | 0.08 | 0.48 | 10.12043 | 76.5051 | 0.318126 |
| 41 | 0.09 | 2 | 0.106031 | 0.33 | 5.702325 | 47.24868 | 0.322222 |
| 42 | 0.04 | 2 | 0.11 | 0.48 | 10.39913 | 119.5713 | 0.322477 |
| 43 | 0.08 | 3 | 0.16 | 0.48 | 11.9014 | 261.5667 | 0.344984 |
| 44 | 0.04 | 3 | 0.08 | 0.48 | 11.9014 | 130.7834 | 0.344984 |
| 45 | 0.04 | 1.5 | 0.15588 | 0.33 | 12.74911 | 389.2006 | 0.35 |
| 46 | 0.06 | 2.5 | 0.163172 | 0.33 | 17.2033 | 631.3563 | 0.35 |
| 47 | 0.06 | 3 | 0.06502 | 0.33 | 8.420003 | 58.8277 | 0.366667 |
| 48 | 0.04 | 2.5 | 0.11 | 0.48 | 13.9156 | 198.8834 | 0.373036 |
| 49 | 0.06 | 1.5 | 0.123814 | 0.33 | 6.750985 | 86.6815 | 0.383333 |
| 50 | 0.06 | 2 | 0.089851 | 0.33 | 7.248242 | 64.69052 | 0.383333 |
| 51 | 0.02 | 2 | 0.08 | 0.48 | 15.12601 | 183.9834 | 0.388922 |
| 52 | 0.06 | 3 | 0.139949 | 0.33 | 18.12325 | 586.615 | 0.4 |
| 53 | 0.02 | 2 | 0.11 | 0.48 | 20.79826 | 478.2851 | 0.456051 |
| 54 | 0.04 | 2 | 0.191923 | 0.33 | 23.22352 | 1418.52 | 0.475 |
| 55 | 0.06 | 2.5 | 0.186227 | 0.33 | 19.63393 | 938.5573 | 0.483333 |
| 56 | 0.06 | 2 | 0.194256 | 0.33 | 15.67053 | 653.7233 | 0.5 |
| 57 | 0.04 | 2 | 0.146987 | 0.33 | 17.78608 | 637.2235 | 0.55 |
| 58 | 0.02 | 2 | 0.16 | 0.48 | 30.25202 | 1471.868 | 0.550018 |

drawbacks are found in its learning time and local minimum values. In contrast, the RBFN has a higher learning speed along with a simpler constitution. Its high level of classification performance also proves to be an excellent advantage. Similar to MLP, RBFN is constructed with an input layer, hidden layer, and an output layer; its basic structures are seen in figure 1.

The structure of this neural network is similar to prior neural networks while the internal functions are radically different. In the input of prior neural networks, only the vector's input pattern and the bias term were used. The RBFN incorporates not only these but its stochastic internal function provides the distribution, the average value, and the standard deviation of the given input. The RBFN consists of a number of algorithms and usually the algorithm is learned by two stages. In other words, algorithms are learned by the division of the hidden layer and the output layer (Hush and Horne, 1993). Figure 2 shows the study of RBFN. Table 2 shows the statistical indicators used in this paper.

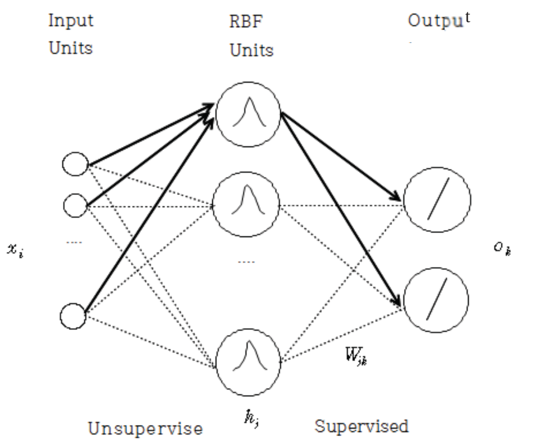


Figure 1. The traditional radial basis function network

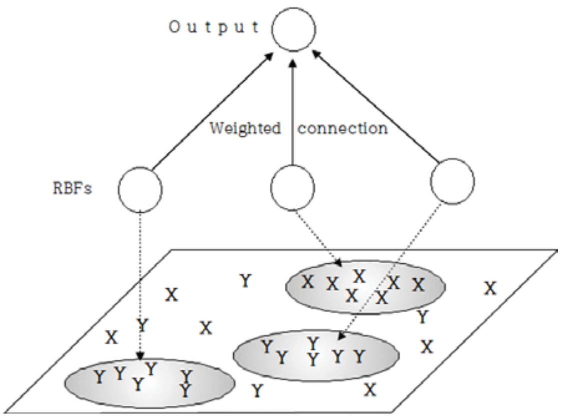


Figure 2. Leanring of the Radial Basis Functional Network (RBFN).

Table 2. *Indices for statistical test*

| No | Index | Relation equation |
|---|---|---|
| 1 | CC | $\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i - X_{in}}{\sigma_X}\right)\left(\frac{Y_i - Y_{in}}{\sigma_Y}\right)$ |
| 2 | $R^2$ | $1-\frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{\sum_{i=1}^{N}(X_i - Y_{in})^2}$ |
| 3 | RMSE | $\frac{1}{N}\sqrt{\sum_{i=1}^{N}(X_i - Y_i)^2}$ |
| 4 | MAPE(%) | $\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\lvert X_i - Y_i\rvert}{X_i}\right)$ |

Here, the measure value is $X_i$, the calculated value is $Y_i$, the average of the measured values is $X_{in}$, the average of the calculated values is $Y_{in}$ , the standard deviation of the measured value is $\sigma_X$, the standard deviation of the calculated value is $\sigma_Y$, the number of data is *N*. Using the Radial Basis Function Network, the input data is constructed like the following for the calculation of the relative scour depth *S/D*.

Firstly, the foundational input values are set with the following independent factors: the pipe diameter (*D*), the wave period (*T*), the wave height (*H*), and the water depth (*d*); these values are combined to set the non-dimensional parameters for the *KC* number and the modified Ursell number, $U_{RP}$.

A correlation analysis was implemented on the relative scour depth based on the parameters of the input data; the high input data showed combined correlation. The parameters of the correlationships are shown in Table 3.

Table 3. *The correlation coefficient of between relative scour depth and parameter*

| parameter | Correlation coefficient |
|---|---|
| *D*(m) | -0.48 |
| *T*(m) | 0.44 |
| *H*(m) | 0.55 |
| *d*(m) | 0.11 |
| *KC* | 0.88 |
| $U_{RP}$ | 0.74 |

Table 4. *Construction of the Radial Basis Functional Network (RBFN)*

| Model | Input | Spread Coefficient | Output |
|---|---|---|---|
| Case1 | $D, T, H, d, KC, U_{RF}$ | | |
| Case2 | $D,T,H$ | | |
| Case3 | $KC, U_{RF},H$ | 2.0 | $S/D$ |
| Case4 | $KC, U_{RF}$ | | |
| Case5 | $KC$ | | |
| Case6 | $U_{RF}$ | | |

The $KC$, $U_{RP}$, and the $H$ values that showed over 50% of correlation were focused to construct a combination of the input data. Table 4 shows the set and type of the input data used for RBFN application. The Matlab software was used to construct a model for RBFN learning and prediction.

## RESULTS

Out of the 58 input data, 46 data have been chosen for training, whereas the remaining 12 were used for testing. Table 5 shows the results of the training and the prediction. The correlationship coefficient (CC) of RBFN's training results was over 0.9 for all the six model cases; the coefficient of determination (R2) was within the 0.81~0.94 range, the RMSE (Root Mean Square Error) was within 0.018~0.034, and the MAPE (Mean Absolute Percentage Error) turned out between 7.28~13.25%.

Analysis of the training result show that the Case 3 model constructed by the input data, $KC$, $U_{RP}$, $H$, exhibited the highest prediction. Based on even the existing results of the hydraulic model test, it can be inferred that the $KC$ number and the $U_{RP}$ number greatly impacts scour depth.

Table 5. *Predicted results of training*

| Model | CC | R2 | RMSE | MAPE(%) |
|---|---|---|---|---|
| Case1 | 0.94 | 0.89 | 0.02596 | 7.96 |
| Case2 | 0.95 | 0.90 | 0.02517 | 8.47 |
| Case3 | 0.97 | 0.94 | 0.01874 | 7.28 |
| Case4 | 0.93 | 0.86 | 0.02939 | 9.32 |
| Case5 | 0.92 | 0.85 | 0.03026 | 9.16 |
| Case6 | 0.90 | 0.81 | 0.03421 | 13.25 |

Figure 3 and 4 show the training results for Case 1 and 3 respectively. Table 6 shows the application of the 12 data inputs that did not undergo training applied into the RBFN.

The results show that the CC for the Case 3 Model was is 0.94, the RMSE is 0.083, and MAPE is 8.37%, therefore showing an outstanding case of predictability. The accuracy of the prediction can be ranked by the following order, Case 3 > Case 4 > Case 6 > Case 5 > Case 2 > Case 1. Figure 5 shows the predicted results of relative scour depth when applied to RBFN.

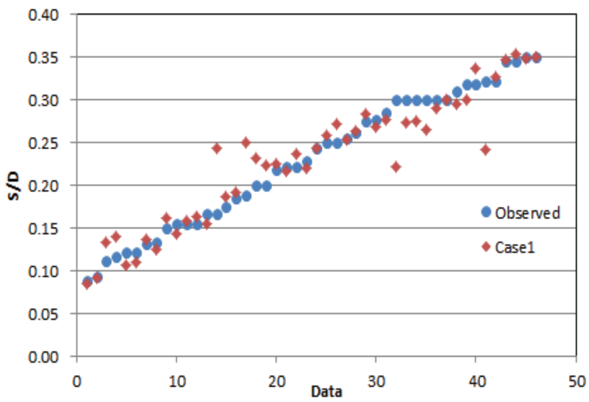


Figure 3. Training Results for Case 1 Model Using RBFN.

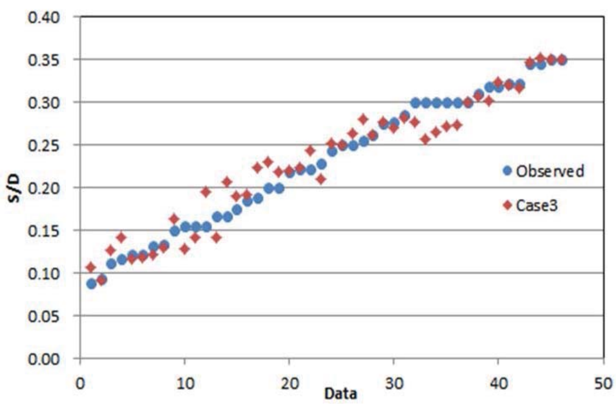


Figure 4. Training Results for Case 3 Model Using RBFN

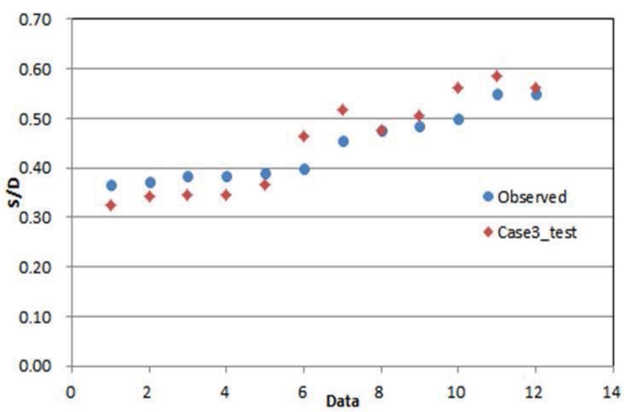


Figure 5. The predicted results of S/D

Table 6. *RBFN Testing*

| Model | CC | R2 | RMSE | MAPE(%) |
|---|---|---|---|---|
| Case1 | 0.72 | 0.51 | 0.09615 | 13.97 |
| Case2 | 0.74 | 0.54 | 0.09904 | 14.07 |
| Case3 | 0.94 | 0.91 | 0.06145 | 8.37 |
| Case4 | 0.85 | 0.72 | 0.08640 | 11.34 |
| Case5 | 0.78 | 0.61 | 0.08357 | 10.45 |
| Case6 | 0.79 | 0.63 | 0.09230 | 10.69 |

## DISCUSSION

The frequently used facility for transport of crude oil or gas is the submarine pipeline. The high convenience that comes with such utility has caused the numbers of installments to increase. Because the pipeline transports substances like crude oil, damages to the pipeline can lead to marine pollution. The cost to fixing the damage and restoring the pollution is high. With scour being one of the main factors that affect the submarine pipelines, it is necessary to correctly assess and predict for scour depth before installing the pipeline.

The correlationship coefficient was over 0.9 for all the six model cases and the Case 3 model constructed by the input data.

Based on even the existing results of the hydraulic model test, it can be inferred that the *KC* number and the $U_{RP}$ number greatly impacts scour depth. The CC for the Case 3 showing an outstanding case of predictability. The accuracy of the prediction can be ranked by the following order, Case 3 > Case 4 > Case 6 > Case 5 > Case 2 > Case 1 (Figure 2 and 4).

## CONCLUSIONS

In this paper, data from previous hydraulic model tests results are analyzed to deduce the parameters that affect scour formation. A correlation analysis is conducted between the deduced parameters and the relative scour depth; a set of parameters with high correlationships was constructed.

The results were inputted into the RBFN method to predict for the relative scour depth. The tendencies of the predicted results and the measured values were well simulated in the Case 3 model. In the future, it is regarded that data needs to be continuously collected for input use in order to improve the accuracy of the scour depth prediction model.

## ACKNOWLEDGEMENTS

This research was supported by a grant(15RDRP-B066173-03) from Regional Development Research Program funded by Ministry of Land, Infrastructure and Transport of Korean government.

## LITERATURE CITED

Broomhead, D.S. and Lowe, D., 1988. Multivariable functional interpolation and adaptive networks. *Complex Systems*, 2, 321-355.

Çevik, E. and Yüksel, Y., 1999. Scour under Submarine Pipelines in Waves in Shoaling Conditions. *Journal of Waterway, Port, Coastal, Ocean Engineering*, 125(1), 9–19.

Hush, D.R. and Horne, B.G., 1993. Progress in supervised neural networks. *IEEE Signal Processing Magazine*, 10(1), 8-39.

Moody, J. and Darken, C.J., 1989. Fast learning in networks of locally-tuned processing units. *Neural Computation*, 1(2), 291-294.

Oh, H.S.; Lee, H.J., and Kim, K.H., 2002. Local scour properties below submarine pipeline in waves. *Journal of the Korean Society of Civil Engineers*, 22(4-B), 539-549.

Sümer, B.M. and Fredsøe, J., 1990. Scour below pipelines in wave. *Journal of Waterway, Port, Coastal and Ocean Engineering*, 116(3), 308-323

.