The 2012 World Congress on
Advances in Civil, Environmental, and Materials Research (ACEM' 12)
Seoul, Korea, August 26-30, 2012

Geotechnical Considerations for Offshore Wind Turbines based on Neural Network

*Mert Tolon[1)] and Derin N. Ural[2)]

[1), 2)] *Istanbul Technical University, Department of Civil Engineering, Maslak, Istanbul, Turkey*
[1)] *tolon.mert@gmail.com, mtolon@itu.edu.tr*
[2)] *derin@itu.edu.tr*

ABSTRACT

Offshore wind tribunes are becoming increasingly popular in the quest for renewable sources of energy. The planning, design, inspection, and maintenance of offshore wind farms requires careful consideration of many variables, including local climate and site conditions, economic incentives, proximity to energy loads, environmental considerations, and legal issues. The various subjects involved in the design of offshore structures include oceanography, foundation engineering, structural engineering, and marine civil engineering.

The development of an offshore wind farm includes six phases: the incorporation of verification of the design basis, the preliminary design, and the final design, as well as manufacturing surveys, transport and installation, and the final in-service state. Some of the parameters affecting the projects are types of foundation, in-situ testing, laboratory testing, slope stability, earthquake stability, hydraulic stability, wind loading, wave loading and ice loading. These parameters also include sub-parameters and these sub-parameters are considered as input parameters that can be used in the learning and training phases in the neural network models.

Based on the results of the training phase, a forecasting study is presented for models. In order to reach the best results, various configurations and architectures are trained. The success rate of the model is measured by r^2, a statistical indicator applied to all the analysis. The best configurations, architectures, and error graphs are presented.

As a result, the objective of this paper is to define the parameters importance that affects the project of offshore wind farms and to make a reliable method for deciding the efficiency of offshore wind farm projects by using neural network method.

1. INTRODUCTION

As it is mentioned before, offshore wind farms are becoming increasingly popular as sources of energy. Because of we have to pay attention on the planning, design, inspection, and maintenance of offshore wind farms, the site conditions importance increases. The artificial neural network algorithm will help us to get a preliminary idea about the projects due to the effective parameters for the project.

[1)] Ph.D. Graduate Student
[2)] Professor

2. PARAMETERS

These site conditions cover virtually all environmental conditions on the site, including but not limited to meteorological conditions, oceanographic conditions, soil conditions, seismicity, biology, and various human activities. The site conditions include data on the local geological, oceanographic, meteorological, human, and environmental characteristics of a wind farm site.

According to these site conditions that we have to consider in analysis by using neural network models, the first parameter is the wind climate. The normal wind conditions generally concern recurrent structural loading conditions, while the extreme wind conditions represent rare external design conditions. Normal wind conditions are used as basis for determination of primarily fatigue loads, but also extreme loads from extrapolation of normal operation loads. Extreme wind conditions are wind conditions that can lead to extreme loads in the components of the wind turbine and in the support structure and the foundation. The extreme wind conditions are specified in terms of an air density in conjunction with prescribed wind events. The extreme wind conditions include wind shear events, as well as peak wind speeds due to storms, extreme turbulence, and rapid extreme changes in wind speed and direction. (Randolph,2005)

The wave climate is another parameter and is represented by the significant wave height HS and the spectral peak period TP. The significant wave height HS is defined as four times the standard deviation of the sea elevation process. The significant wave height is a measure of the intensity of the wave climate as well as of the variability in the arbitrary wave heights. The peak period TP is related to the mean zero-crossing period TZ of the sea elevation process. The wave height H of a wave cycle is the difference between the highest crest and the deepest trough between two successive zero-up crossings of the sea elevation process. The arbitrary wave height H under stationary 3 or 6 hour conditions in the short term follows a probability distribution which is a function of the significant wave height HS. The parameter of current consists of a wind-generated current and a tidal current, and a density current when relevant. The current is represented by the wind-generated current velocity v_{wind} at the still water level and the tidal current velocity v_{tide} at the still water level. Other current components than wind-generated currents, tidal currents and density currents may exist. Examples of such current components are; the subsurface currents generated by storm surge and atmospheric pressure variations and the near-shore, wave-induced surf currents running parallel to coast. (Randolph,2005)

Another important parameter is the water level and it consists of a mean water level in conjunction with tidal water and a wind- and pressure induced storm surge. The tidal range is defined as the range between the highest astronomical tide (HAT) and the lowest astronomical tide (LAT), see Fig. 1. When the wind turbine structure is to be located in an area where ice may develop or where ice may drift, ice conditions shall be properly considered. Relevant statistical data for the following sea ice conditions and properties shall be considered as the geometry and nature of ice, concentration and distribution of ice, type of ice (ice floes, ice ridges, rafted ice etc.), mechanical properties of ice (compressive strength r_u, bending strength r_f), velocity and direction of drifting ice, thickness of ice and probability of encountering icebergs.

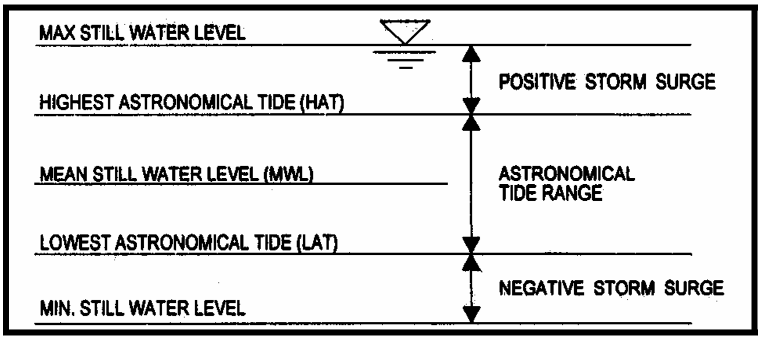


Fig. 1 Water level at offshore wind tribune farms (Randolph,2005)

Maybe the most important parameter that we have to focus on is the soil investigations and it shall provide all necessary soil data for a detailed design. The soil investigations may be divided into geological studies, geophysical surveys and geotechnical soil investigations. (Randolph,2005) A geological study, based on the geological history, can form a basis for selection of methods and extent of the geotechnical soil investigations. A geophysical survey, based on shallow seismic, can be combined with the results from a geotechnical soil investigation to establish information about soil stratification and seabed topography for an extended area such as the area covered by a wind farm. A geotechnical soil investigation consists of in-situ testing of soil and of soil sampling for laboratory testing. The extent of soil investigations and the choice of soil investigation methods shall take into account the type, size and importance of the wind turbine structure, the complexity of soil and seabed conditions and the actual type of soil deposits. For multiple foundations such as in a wind farm, the soil stratigraphy and range of soil strength properties shall be assessed within each group of foundations or per foundation location, as relevant.

Soil investigations are normally to comprise the following types of investigation the site geological survey, the topography survey of the seabed, the geophysical investigations for correlation with soil borings and in-situ testing, the soil sampling with subsequent static and cyclic laboratory testing, the shear wave velocity measurements for assessment of maximum shear modulus and the in-situ testing, for example by cone penetration tests (CPT), pressiometer tests and dilatometer tests. The geotechnical investigation at the actual site comprising a combination of sampling with subsequent laboratory testing and in-situ testing shall provide the data for soil classification and description, the shear strength and deformation properties, as required for the type of analysis to be carried out and the in-situ stress conditions for all important layers.

For the importance of characteristic soil properties the data should include, (Norsok 2004, OSIC 2004): Summary of soil conditions: soil classification, description, and stratigraphy: total unit weight, solids unit weight, water content, void ratio, porosity, relative densities, liquid and plastic limits, and grain size distributions; Basic soil parameters: effective in situ overburden stress, σ'_{vo}; in situ pore pressure, u_o; preconsolidation stress, σ'_p; over consolidation ratio, OCR; coefficient of lateral earth pressure at rest, K_o; relative density of sand layers, D_r; Deformation properties: undrained shear modulus, G; drained Young's modulus, E; Poisson's ratio, v; constrained modulus, M; horizontal and vertical coefficients of consolidation, c_h and c_v; coefficient of permeability, k; creep parameters; cyclic loading parameters for settlement calculations; small strain shear modulus, G_{max}; damping ratio, ξ; Shear strength parameters: friction angles for granular material, index, undisturbed, and remolded undrained shear strengths, s_u, and sensitivity for fine grained material; pore pressure parameters; parameters to describe excess pore pressure development and shear strength degradation due to cyclic loading; for drained clay analyses, cohesion and friction angles are needed; Parameters for specific applications: contour diagrams for cyclic effects; base contact stress parameters; skirt penetration resistance parameters; for piled and gravity base structures, mud mat stability and settlement parameters; for jack-up platforms, parameters for stability settlement and punching failure; for geohazard analysis, slope stability shear strength parameters; for earthquake analysis, dynamic soil parameters.

Another parameter that effects offshore wind turbine farm projects is the foundation, its type, dimensions, etc. The four main classes of offshore foundations consist of piled foundations, gravity base foundations, skirt and bucket foundations, and floating structures with moored foundations. There are advantages and disadvantages fore each foundation class and structural subclass primarily based on site conditions and turbine size. The loading regime of the offshore wind turbine foundation is unique to offshore structures in that the weight of the turbine structure is low compared to the overturning moment and the horizontal load. When designing the foundation for an offshore wind turbine, it is important to keep in mind that since wind turbine farms contain numerous turbines, a single design for the entire farm is necessary to enable mass production and ensure expedient installation, both of which are necessary for the economic feasibility of a wind farm. The choice of the foundation type should be based on site-specific information, including the adequate characterization of the soil conditions, water depth, scour and erosion potential, turbine capacity, foundation cost, and the environmental loading conditions. The design process must consider both the strength and the deformation characterization of the surrounding soils. The primary soil strength failures that can occur in an offshore environment include bearing capacity failure, sliding failure, and pile pull-out and punch-through failure. The primary deformation failures that can occur include large settlements or lateral displacements. Ultimately, the foundation design will depend primarily on the cost of installation due to the number of turbines and their properties. (Watson 2000).

The level of seismic activity of the area is another parameter and is where the wind turbine structure is to be installed shall be assessed on the basis of previous record of earthquake activity as expressed in terms of frequency of occurrence and magnitude. If the area is determined to be seismically active and the wind turbine structure will be affected by an earthquake, an evaluation shall be made of the regional and local geology in order to determine the location and alignment of faults, epicenter and focal distances, the source mechanism for energy release and the source to site attenuation characteristics. Local soil conditions shall be taken into account to the extent that they may affect the ground motion (Randolph,2005). The potential for earthquake-induced sea waves, also known as tsunamis, shall be assessed as part of the seismicity assessment.

The presence of pipelines and cables within the area of installation shall be mapped and must be evaluated as a parameter in the analysis. Extreme values of high and low temperatures are to be considered as a parameter and to be expressed in terms of the most probable highest and lowest values, respectively, with their corresponding return periods. Both air and seawater temperatures are to be considered when describing the temperature environment. The plant, animal and bacteria life on the site causes marine growth on structural components in the water and in the splash zone. Marine growth adds weight to a structural component and influences the geometry and the surface texture of the component. The marine growth may hence influence the hydrodynamic loads, the dynamic response, the accessibility and the corrosion rate of the component. Air density is another parameter and it shall be addressed since it affects the structural design through wind loading. For the parameter of the ship traffic, the risk associated with possible ship collisions shall be addressed as part of the basis for design of support structures for offshore wind turbines. Finally, the salinity of the seawater shall be addressed as a parameter of importance for the design of cathodic protection systems (Randolph,2005).

3. METHOD AND ANALYSIS

This study is mainly based on numerical models by using artificial neural network methods. The artificial neural network methods are systems and computational devices that are constructed to make use of some organizational principles resembling those of the human brain. Like human brain this algorithm has the ability to learn; recall and generalize from the data which are used to train the system. Neurons are also grouped into layers by their connection to the outside world. For example, if a neuron receives data from outside of the network, it is considered to be in the input layer. If a neuron contains the network's predictions or classifications, it is in the output layer. Neurons in between the input and output layers are in the hidden layer(s), see Fig. 2. There are different types of neural network architectures. These architectures differences are their algorithm and function formulas.

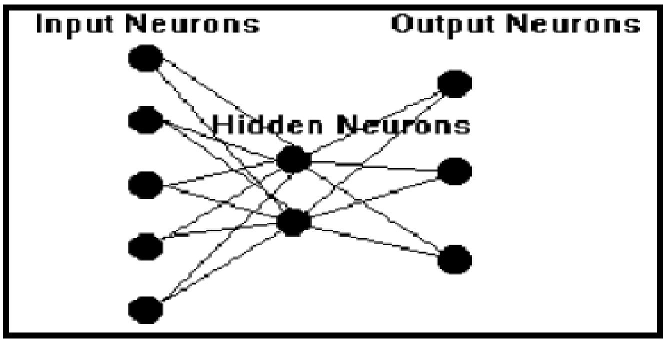


Fig. 2 Neural Networks Structure (Ural, D. and Tolon M.,2008)

The back-propagation learning algorithm is the most commonly used neural network algorithm. The back-propagation neural network has been applied with great success to model many phenomena in the field of geotechnical and geo-environmental engineering. Each neuron in a layer receives and processes weighted inputs from neurons in the previous layer and transmits its output to neurons in the following layer through links.

The weighted summation of inputs to a neuron is converted to an output according to a nonlinear transfer function. The common transfer function widely used in the literature is the sigmoid function. At the end of the training phase, the neural network should correctly reproduce the target output values for the training data and provided the errors are minimal. The associated trained weights of the neurons are then stored in the neural network memory. In the next phase, the trained neural network is feed by a separate set of data. In this testing phase, the neural network predictions using the trained weights are compared with the target output values. The performance of the overall ANN model can be assessed by several criteria. These criteria include the coefficient of determination (R^2), mean-squared error, mean absolute error, minimum absolute error, and maximum absolute error. A well-trained model should result in an R^2 value close to 1 and small values of the error terms.

The geotechnical considerations are similar between offshore wind turbine foundations and offshore platforms foundation and according to this knowledge, the D is the width of the foundation, h is the height, M term is a moment parameter, etc. are taken into the input parameters and the foundation area (m^2) is taken as the output parameter from Norway projects for this example case study problem (Fig. 3).

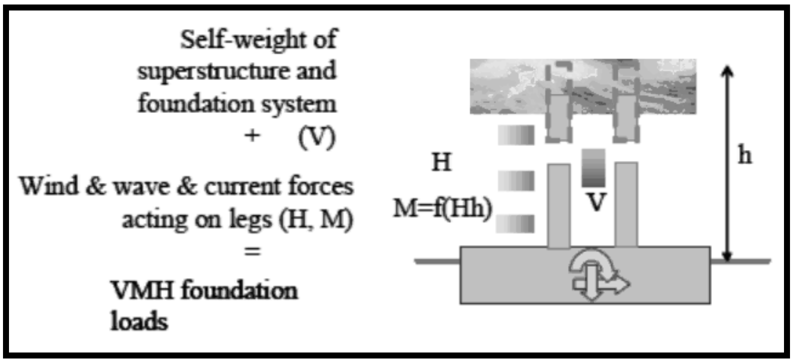


Fig. 3 Combined loading of foundation (Randolph,2005).

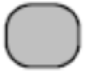
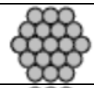
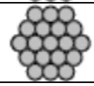
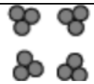
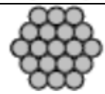
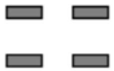
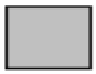
Foundation area (dimensions) can be examined by neural network approaches. Because of this, the architectures of back propagation neural network, probabilistic neural network and general regression neural network are tried for neural network approaches to evaluate our problem. Values are obtained from case study data. These values will be used in neural network approaches.

The proposed models consist of separate datasets. These datasets have to be divided randomly into testing, training, and validation datasets in the test set extraction phase and these numbers must be appropriate for process (Fig. 4). For a case study example, suitable numbers are given in Table 1. Neural Network parameters that are considered for evaluating the foundation area are given below in the Table 2.

Table 1 Distribution of the data among phases

Database	Database (%)
Training	55
Testing	27
Forecast	18
Total	100

Table 2 A.N.N. based evolution of offshore shallow foundation systems - Case Study (Randolph,2005)

Project Year	Foundation type	Location	Water depth m	Soil conditions	Foundation plan	Skirts d (d/D)	V (= W') MN	H MN	M MN	M/HD	Foundation dimensions, m$_2$	Reference
Ekofisk Tank 1973	GBS	North Sea (Norway)	70	Dense sand to 26 m, layers stiff clay 16-18 m. >26 m hard clays and sands (su ~ 300 kPa)		0.4 (0.004)	1900	786	28000	0.37	A = 7,390	Clausen, 1976 (p.400) Clausen, 1976 (p.263) O'Reilly & Brown, 1991 (p.124)
Beryl A 1975	Condeep	North Sea (Norway)	120	As at Ekofisk but sand layer only to 10 m		4 (0.04)	1500	450	15000	0.37	A = 6,360	Clausen, 1976 (p.263)
Brent B 1975	Condeep	North Sea (Norway)	140	Stiff to hard clays (su ~ 300 kPa) with thin layers of dense sands to 45 m		4 (0.04)	2000	500	20000	0.44	A = 6,360	O'Reilly & Brown, 1991 (p.124)
Gullfaks C 1989	Deep skirted Condeep	North Sea (Norway)	220	Soft nc silty clays (su ~ 30 kPa) and silty clayey sands with dense sand layers (qc ~ 4 MPa)		22 (0.13)	5000	712	65440	0.64	A = 16,000	Tjelta et al., 1990 Tjelta, 1998
Snorre A 1991	TLP with concrete buckets	North Sea (Norway)	310	Very soft to soft nc clays (sum = 0, k ~ 7 kPa/m to 20 m; 0 < qc < 2 kPa @ 17 m)		12 (0.7)	142 per CFT	21 per CFT	126 per CFT	0.20	A_{total} = 2,724	Christophersen, 1993 (p.435) Stove et al., 1992 (p.76)
Draupner E (Europipe) 1994	Jacket with steel buckets	North Sea (Norway)	70	22-25 m dense to very dense fine sand (qc ~ 60 MPa) over stiff clay		6 (0.5)	57 per bucket	10	30	0.25	A_{total} = 452	Bye et al., 1995 (p.870)
Sleipner SLT 1995	Jacket with steel buckets	North Sea (Norway)	70	As at Draupner E		5 (0.35)	134 per bucket	22	50	0.35	A_{total} = 616	Bye et al., 1995 (p.876)
Troll A 1995	Deep skirted Condeep	North Sea (Norway)	305	Soft nc clays (sum = 0, k ~ 3 kPa/m to 60 m; 0 < qc < 1.5 kPa @ 40 m)		36 (0.25)	2353	512	94144	1.27	A = 16,596	Andenaes et al., 1996 (p.62) Hansen et al., 1992 (p.924)
Wandoo 1997	GBS	NW Shelf W Australia	54	Thin layer dense calcareous sand (qc ~ 3 MPa) over thick strong calcarenite (qc ~ 30 MPa)		0.3 (0.003)	755	165	7420	0.45	A = 7,866	Humpheson., 1998 (p.362, 365)
Bayu-Undan 2003	Jacket with steel plates	Timor Sea N Australia	80	2 m very soft calcareous sandy silt over cemented calcarenite and limestone (qc ~ 20 MPa)		0.5 (0.04)	125 per plate	10	- - - -	- - - -	A_{total} = 480	Neubecker & Erbrich, 2004 (p.2)
Yolla 2004	Skirted GBS/jacket hybrid	Bass Strait S Australia	80	Firm calcareous sandy silt with very soft clay and sand layers (qc ~ 2 MPa)		5.5 (0.1)	- - - -	- - - -	- - - -	- - - -	A = 2500	- - - -

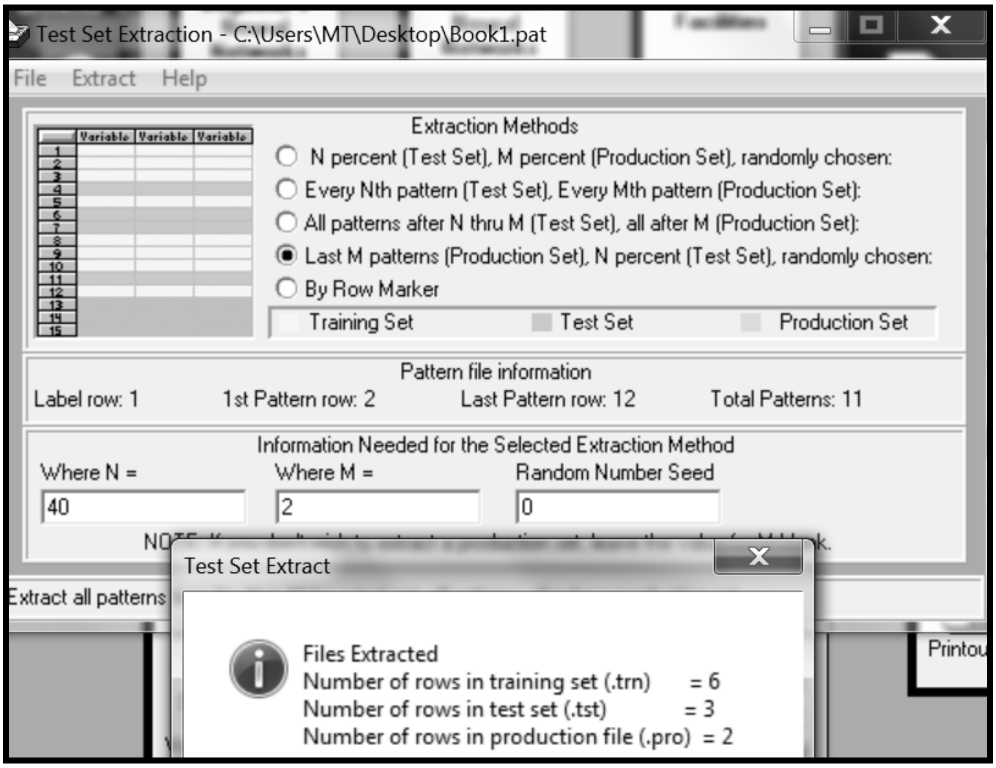
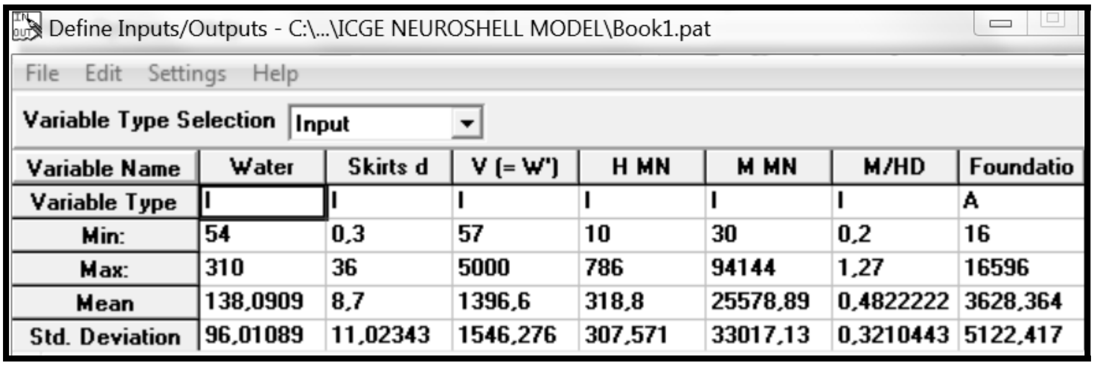


Fig. 4 The test set extraction phase

Then, we have to define the output and input parameters in the program and we define the values range. So, the program will use min, max, mean values while the program is learning the model. These input and output values range table is given below in Fig. 5.

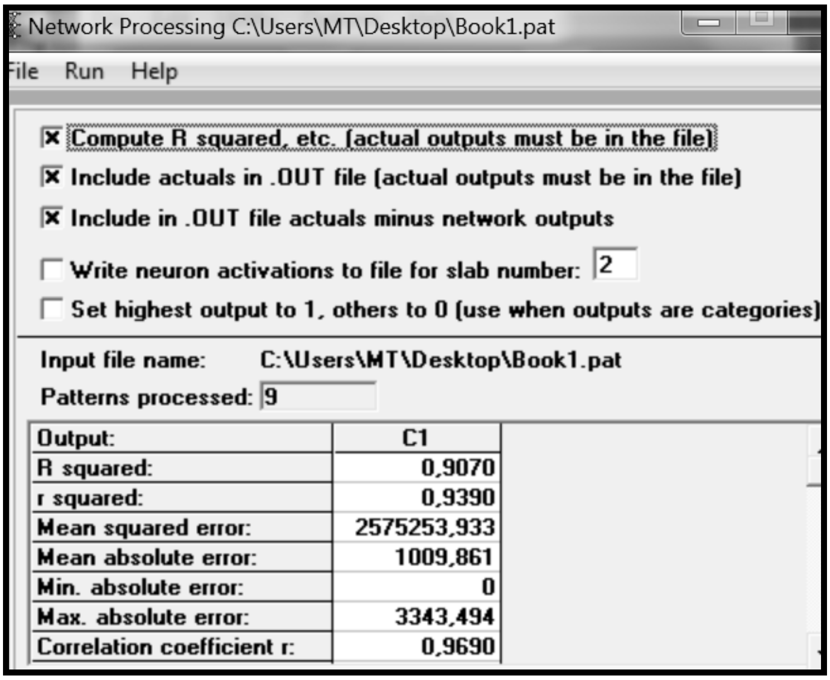


Variable Name	Water	Skirts d	V (= W')	H MN	M MN	M/HD	Foundatio
Variable Type	I	I	I	I	I	I	A
Min:	54	0,3	57	10	30	0,2	16
Max:	310	36	5000	786	94144	1,27	16596
Mean	138,0909	8,7	1396,6	318,8	25578,89	0,4822222	3628,364
Std. Deviation	96,01089	11,02343	1546,276	307,571	33017,13	0,3210443	5122,417

Fig. 5 The test set extraction phase

4. RESULTS

After making different model approaches, we get the results from models. From these results as we can see from Fig. 6 our best success rate is % 93,90 and the correlation coefficient is 0,9690.



Output:	C1
R squared:	0,9070
r squared:	0,9390
Mean squared error:	2575253,933
Mean absolute error:	1009,861
Min. absolute error:	0
Max. absolute error:	3343,494
Correlation coefficient r:	0,9690

Fig. 6 The test set extraction phase

As it is seen from Fig. 7 over-learning did not occur and graph is close to 0,00004 that means error is very little.

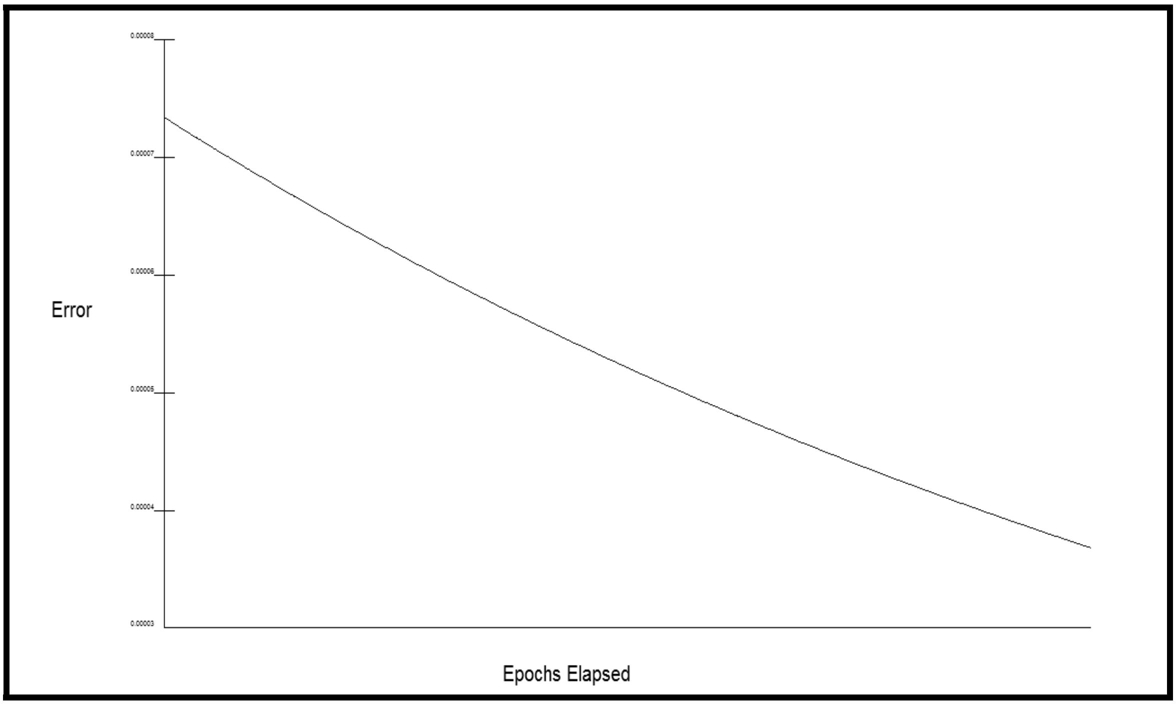


Fig. 7 The error – epochs elapsed graph for model

The model relative contribution factors graph will give the results for our case study in Fig. 8 and Fig. 9.

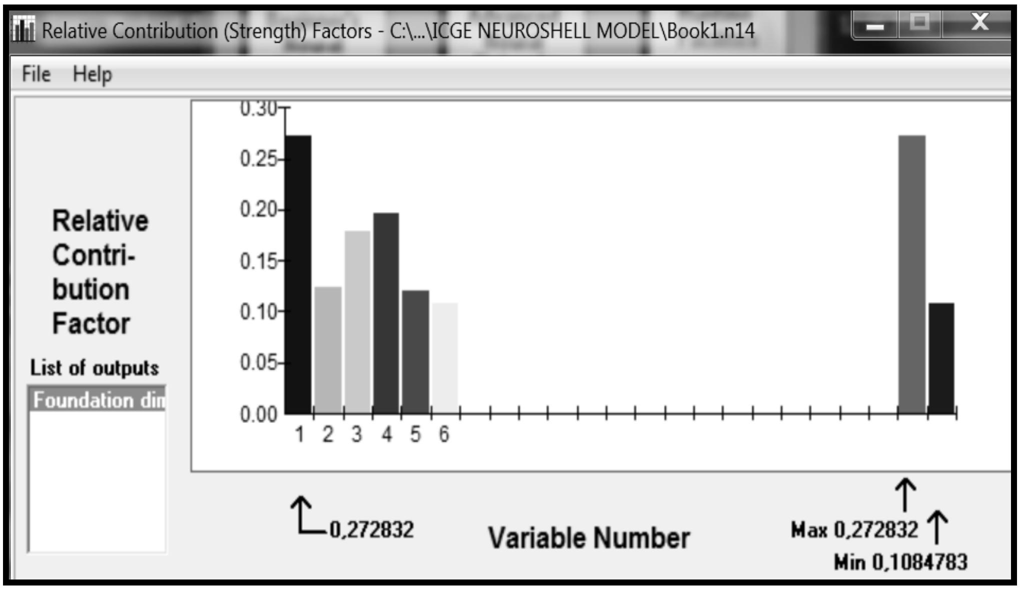


Fig. 8 Model relative contribution factors graph

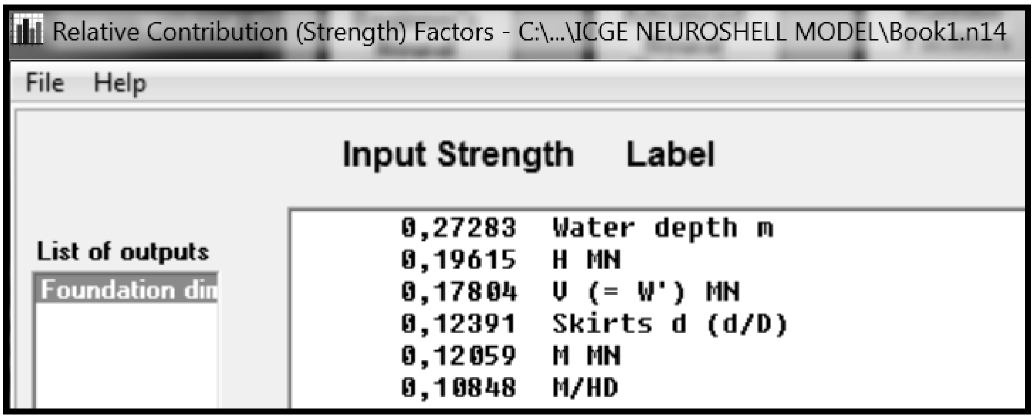


Fig. 9 Model relative contribution factors by input strength

5. LIMITATIONS AND FUTURE WORKS

During collecting the datasets, we have to collect or get all parameters also different areas or projects, because we have to use them in the training and testing phases. Due to this problem, we have to make a database for all offshore wind tribune farm projects from all over the world which has been done previously, and also have to get need more geotechnical, meteorological and oceanographic datasets from municipalities or different companies for collecting data for the region near the new project area. This situation makes a limitation for our models. Because of this limitation we have use offshore platform foundation parameters.

For a future work, as mentioned above, we have to keep records from previous projects and with these parameters we can evaluate different case studies like the efficiency of offshore wind tribune project as economic case, as seismicity potential or as wind / wave criteria and etc. For a future work of this study will be evaluating the efficiency level of a specific offshore wind tribune farm as an economical way and compare it with an existing one. By doing this study, we hope to see the expectations and existing economic values will give the same results.

CONCLUSIONS

The global development of offshore wind energy is heading towards larger turbines, larger wind farms, and further distances offshore into deeper waters. The unique loading aspects of offshore wind turbine foundations require further development. Although the costs of offshore wind energy can be competitive with onshore wind energy generation, refinement of the current foundation technology and offshore construction procedures are necessary to decrease the relatively higher foundation manufacture, transport, and installation costs.

In conclusion, with these limited parameters this study shows that, the water depth is the most effective parameter for evaluation of foundation area at offshore wind tribunes. Another important result is that this processes can be successfully performed utilizing AI tools, and that different effective parameters of offshore wind tribunes can be forecasted by these models. Another fact is that we get which architecture (BPNN, PNN, and GRNN) is suitable and which Model has the best success rate for geotechnical considerations of offshore wind turbines based on neural network.

For future works, while deciding if the base area is suitable for offshore wind turbine farms considering geotechnical conditions, or evaluating the sensitivity of effective parameters for projects, using an AI tool model to see a short and easy pre decision result, is recommended.

REFERENCES

Bye, A., Erbrich, C., Rognlien, B. and Tjelta, T.I. 1995. Geotechnical design of bucket foundations. Proc. Annual Offshore Technology Conf., Houston, PaperOTC 7793.

Clausen, C.J.F. 1976. The Condeep story. Proc. Offshore Soil Mechanics, Cambridge University. Ed.George. P. and Wood, D., 256-270.

Christophersen, H.P. 1993. The non-piled foundation systems of the Snorre field. Offshore Site Investigation and Foundation Behaviour, Soc. for Underwater Technology, 28, 433-447.

Humpheson, C. 1998. Foundation design of Wandoo B concrete gravity structure. Offshore Site Investigation and Foundation Behaviour, Soc. For Underwater Technology, 353-367.

NeuroSHELL 2 user’s manual – version 3.0 (1996) Frederick M.D., Ward Systems Group, Inc., USA

Neubecker, S.R. and Erbrich, C.T. 2004. Bayu-Udan substructure foundations: Geotechnical design and analysis. Proc. Annual Offshore Technology Conf., Houston, Paper OTC 16157.

Norsok Standard G-0111, (2004). Marine Soil Investigations, Revision **2**, Oct. pp 66.

Offshore Site Investigation Committee (OSIC): Allan, P., Cook, M., Power, P., (2004). Guidance Notes on Geotechnical Investigations for Marine Pipelines, Rev. **03**, Society for Underwater Technology, pp.47.

Randolph M., Cassidy M. and Gourvenec S., (2005) Challenges of Offshore Geotechnical Engineering, Centre for Offshore Foundation Systems, The University of Western Australia.

Tjelta, T.I. 1998. Foundation design for deepwater gravity base structure with long skirts on soft soil, Proc. Int. Conf. on Behaviour of Offshore Structures, BOSS'98, The Hague, 173-192.

Tolon M., (2007) A neural network approach for slope stability during Earthquake, Faculty of Civil Engineering, Istanbul Technical University, M.Sc. Thesis, 2007; in English.

Tolon M. and Ural, D., (2010) Slope Stability during Earthquakes: A Neural Network Application. International Review on Computers and Software, IRECOS, Special Section on "Advanced Artificial Neural Network Approaches with Applications to System Management", Vol. **5**. n. **4**, pp. 454-459, July, 2010.

Ural, D. and Tolon M., (2008) Slope Stability During Earthquakes: A Neural Network Application, American Society of Civil Engineers GeoCongress 2008, Special Publication No.**179**, pages 878-885, March 9-12, 2008 New Orleans, USA.

Watson, P.G. 2000. Performance of Skirted Foundations for Offshore Structures, PhD Thesis, The University of Western Australia.