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Research Article

Estimating Fluid Parameters of Submarine Outfall Using Neural Networks

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ABSTRACT

Disposal of the urban and industrial liquid waste has become important by paying attention to environmental and human health recently. Submarine outfall diffusers are the major parts of the marine disposal systems. Pipe of the diffuser, risers and ports, internal and external flows which form the discharge system are modelled and fluid-structure interaction (FSI) method is utilized by ABAQUS finite elements program. Coupled CFD & Explicit technique is performed in FSI analysis. Method of bidirectional fluid-structure interaction (FSI) is used in finite elements method (FEM). Internal and external flows constitute fluid domain and diffuser constitutes the structure domain. While internal velocity and pressure values are obtained from the program, predictions of these results are performed by Artificial Neural Network (ANN) analysis. The average discharge velocities provide to avoid water intrusion into the ports. According to results obtained by FEM it can be said that the discharge system works efficiently. Numerical and estimated values are compared and the relationship between these values is investigated. The correlation coefficients are calculated by using numerical and estimated values and it is observed that a strong relationship is obtained between them.

Introduction

Submarine outfall diffusers, placed at the end of the ocean disposal systems, have wide range of utilization area in transferring urban and industrial liquid wastes. Intended use of diffusers is to prevent ocean environment from environmental impacts related with health, aesthetic and ecological affects [1, 2]. Diffusers are a part of submarine outfall systems. Submarine outfalls are composed of onshore headwork (e.g. gravity or pumping basin), the feeder pipeline conveying the effluent to the disposal field and the diffuser section, where a number of ports releases and disperses the effluent into the environment in order to minimize the impacts on the quality of the receiving water body [3].

Marine structure models, such as submarine outfalls, contain fluid and structure domains which interact with each other. Coupled system occurs when two or more physical systems interact with each other. Fluid-structure interaction (FSI) can be given as an example of a coupled system. In this system, the physical systems are fluid and structure ones. The structure may be movable or deformable. On the other hand, the fluid flow may be internal or external for this system. Forces because of a moving fluid are effected as pressure on the structure that will be deformed later.

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Determination of coupling fluid dynamics and structural dynamics codes are not easy by the reason of various domain discretization (fluid grids vs. FE-meshes) and particular numerical method while solving the governing equations. Numerical procedures are effective in estimating hydrodynamic motion and forces on the offshore structures and they become more attractive with the development of computer science [4, 5]. In the study of Gücüyen [6] bidirectional FSI analysis is performed to determine the discharge velocity, displacement and stress values of the diffuser in marine environment. Thereby, discharge velocity that can't be calculated from one-directional FSI analysis is obtained. Discharge velocity which is an important parameter for the effective use of diffuser is semi-analytically determined by Bleninger et al.[7].

Artificial neural networks (ANN) can be counted as one of the artificial intelligence applications which are widely utilized while modeling a number of human activities in several scientific fields. ANN analysis is used by scientists and engineers to estimate results. It is also proper to generate software about engineering problems. The importance of techniques as ANN and fuzzy logic approaches have increased considerably. They are being used to solve a whole range of engineering applications [8-12]. ANN can be both applied to experimental and numerical models. Erdem [13] has studied the impact parameters of a reinforced concrete slab that is tested under impact loading by using a test setup. Test results are estimated by and ANN analysis. It is stated that ANN analysis is an effective way to estimate the test results successfully. In the study of Edincliler et al. [14] damping ratio and shear modulus of sand–waste tire mixtures are predicted and the results are verified by experimental results. Zhao et al. [15], propose effective approach by combined using of CFD (Computational Fluid Dynamics), multi-objective genetic algorithm and artificial neural networks (ANN) for a double-channel pump's impeller and state the accuracy of results. El-Abbasy et al. [16] have determined the corrosion behavior of three existing pipelines by ANN analysis. Predicted results approach to %97 accuracy by regression analysis. As it is seen from literature research, verification of predicted ANN results can be made by experimental, regression and finite elements methods.

In this study, internal velocity and pressure values of the diffuser pipe of submarine outfall are computed according to finite elements analysis [17] in the first place. It can be said that the FEM model works efficiently according to conditions given by [18-20]. Afterwards, these values are estimated by using ANN analysis. For this purpose, a multi-layer feed-forward and back propagation ANN algorithm is used. The relationship among analyses is extensively presented in figures and suggestions are proposed.

Finite Elements Analysis

In this study hydraulic design of outfall diffuser is performed by ABAQUS via FSI. For this purpose, 24 m long, fixed supported, two-span diffuser is modeled as seen in Figure 1. The model is discharging salty cooling water whose flow rate is 0.254 m^3/s.

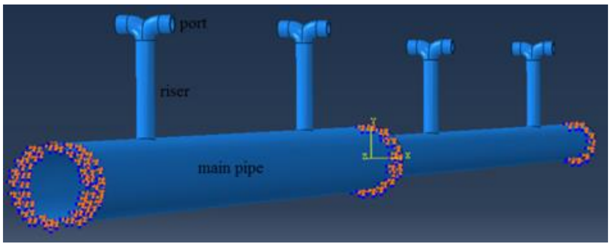


Figure 1 Diffuser model with supports

0.40 m long supports are placed at the beginning, in the middle and at the end of the model. Vertical ports with 1 m long are placed to make the distances between them as 6 m. While main pipe whose diameter value is 0.60 m in the first span, it is 0.50 m in the second one with wall thickness of 0.01 m. Diameter values of both risers and ports are considered as 0.12 m with the same thickness of main pipe. A riser has two bell mouthed ports [21]. Material of the model is steel whose Young's Modulus is 2.1x1011 N/m^2, Poisson ratio is 0.30 and density value is 7850 kg/m^3. The models are separated into small elements to analyze complex models in the finite elements method. 10-node modified tetrahedron shaped elements (C3D10M), suitable for contact problems, are utilized in the simulations. Mesh distances are determined as 0.01 m on ports and risers that is the same value of wall thickness and 0.05 m on diffuser pipe. 431060 nodes and 218612 elements are generated in diffuser model by utilizing the mentioned sizes.

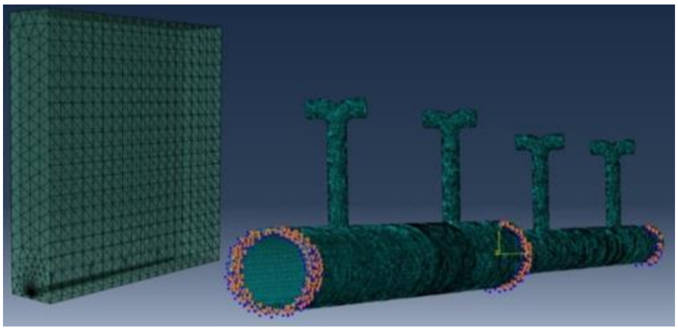


Figure 2 Mesh structure of fluid and diffuser

The diffuser model is seen in the right side of Figure 2, is located in fluid domain which is in the left side of figure. The fluid domain consists of internal and external domains that interact each other. The size values of the domain are 30 m in the diffuser direction, 2.0 m perpendicular to diffuser direction and 25 m in the vertical direction (d).

Domain sizes are decided by considering diffuser geometries and the conditions that are given by [22-24]. Discharge should be at a depth of 20 m or more, if the natural ocean topography enables. When sewage materials including floatable substances such as particles of fruit, faeces etc, are discharged at a depth of 20 m or more, the resulting pressure modifies the material so that it no longer floats. The effect of port spacing depends on the ratio s/d (the spacing between ports is s, water depth is d). If the ports widely spaced i.e. s/d»1 the individual plumes do not merge and they behave isolated, point plumes. As the ports are brought closer together, the plumes merge and dilution decrease. When s/d≈0.3 the ports are close enough that the plume limits is reached.

Properties of the fluid are selected to represent water at sea whose density is 1025 kg/m^3 and dynamic viscosity is 0.0015 Ns/m^2. FC3D4 (4 node modified tetrahedron) elements that are compatible with FSI applications are used to model the fluid domain. The value of mesh distances is utilized as 0.01 m on ports and the same value of wall thickness. However, mesh distance is taken as 1 m for the rest of the geometry. Fluid domain is generated by 28136 nodes and 141126 elements.

The equations of motion simplified to incompressible Navier-Stokes equations that are presented between Eqs. (1-3) are used by CFD technique.

$$\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+w\frac{\partial u}{\partial z}= X-\frac{1}{\rho}\frac{\partial P}{\partial x}+\nu\left(\frac{\partial^2 u}{\partial x^2}+\frac{\partial^2 u}{\partial y^2}+\frac{\partial^2 u}{\partial z^2}\right) \tag{1}$$

$$\frac{\partial v}{\partial t}+u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+w\frac{\partial v}{\partial z}= Y-\frac{1}{\rho}\frac{\partial P}{\partial y}+\nu\left(\frac{\partial^2 v}{\partial x^2}+\frac{\partial^2 v}{\partial y^2}+\frac{\partial^2 v}{\partial z^2}\right) \tag{2}$$

$$\frac{\partial w}{\partial t}+u\frac{\partial w}{\partial x}+v\frac{\partial w}{\partial y}+w\frac{\partial w}{\partial z}= Z-\frac{1}{\rho}\frac{\partial P}{\partial z}+\nu\left(\frac{\partial^2 w}{\partial x^2}+\frac{\partial^2 w}{\partial y^2}+\frac{\partial^2 w}{\partial z^2}\right) \tag{3}$$

The velocity components u, v, w and the body force components X, Y and Z correspond to x, y and z directions respectively. ρ corresponds to density, ν represents kinematic viscosity and P symbolizes pressure in the related equations.

The analysis is driven by applied two velocity inlets. One is on the diffuser pipe as the fluid inlet velocity with 0.90 m/s that corresponds to flow rate. The other one is on the external flow wave velocity. Equation of velocity, representing the Linear Wave Theory is applied to outlet domain as presented below.

$$u = \frac{H}{2}\frac{gT}{L}\frac{\cosh[2\pi(y+d)/L]}{\cosh(2\pi d/L)}\cos(\frac{2\pi}{L}x - \frac{2\pi}{T}t) \quad (4)$$

Where H, T are known as wave height and period and d is also water depth where the structure deploys. In this study, employed parameters are considered respectively: H=3.0 m, T=8 s and d=25 m. Wave length (L=99.92 m) is determined by using these parameters. Wave motion is in the lateral direction (x) of the diffuser. In this paper, while the value of relative depth d/L is between 0.05 and 0.5, the wave is intermediate water depth as mentioned.

Fluid pressure is defined as zero at external flow outlet surface at x direction. Bottom of the external flow is matched with wall boundary condition on which all velocity components equal to zero. The rest of the surfaces excluding contact surfaces are assigned as far field where velocity is supposed to be equal to inlet velocity.

In this study, FSI method is adopted to model interaction between fluid and structure domains. This method represents several multi-physics solutions in which fluid flow effects compliant structures, which in turn effects the fluid flow. Contact surfaces are determined in the first step of FSI analysis. Afterwards, the forces are transferred from fluid to structure and transfer of deformations from structure to fluid is also determined.

The pressure loads (P) obtained from CFD solver are transferred to solid domain via FSI technique on contact surfaces. After Eq. (5) is utilized to determine the displacements via Explicit technique, the values are transferred to fluid according to FSI analysis.

$$m^{NJ}\ddot{X}^{N}|_{t} = \left(P^{J} - I^{J}\right)|_{t} \quad (5)$$

$$\dot{X}^{N}_{(i+\frac{1}{2})} = \dot{X}^{N}_{(i-\frac{1}{2})} + \frac{\Delta t_{(i+1)} + \Delta t_{(i)}}{2}\ddot{X}^{N}_{i} \quad (6)$$

$$X^{N}_{(i+1)} = X^{N}_{(i)} + \Delta t_{(i+1)}\dot{X}^{N}_{(i+\frac{1}{2})} \quad (7)$$

In Eqs. (6-7), X^N and $\dot{X}^N$ are degrees of freedom, (N) of displacement and velocity components respectively. Nodal accelerations are determined according to Eq. (8).

$$\ddot{X}^{N}_{(i)} = (m^{NJ})^{-1}(P^{J}_{i} - I^{J}_{i}) \quad (8)$$

Values of velocity and displacement may also be calculated after determining acceleration values. In this paper, analysis duration is 8 s with the time increment of 0.01 s.

Artificial Neural Networks

Artificial neural networks are defined as computing systems which can simulate the biological neural systems of the human brain. ANN analysis is a complicated system which is developed by neurons which are connected to each other with various effect levels. The method is based upon biological models of the functions of human brain. ANN have been inspired by biological findings in relationship with the behavior of the brain as a network of units that are names neurons. This technique enables investigation of the relationship between data by simulating the structure of biological neural networks.

Computation is modeled as a big network of interconnected processors. ANN may also be trained to determine input patterns and produce proper outputs. Applications having enough training data are applicable to ANN. Estimation of the complicated examples and rapid evaluation of problems can be given as the principal advantages of ANN.

Basic sciences allow modeling the neurons in human brain mathematically in recent years. ANN analysis which is widely used to solve complex engineering problems is utilized in various research areas such as modeling, classification and prediction. In other words, ANN analysis is a parallel computational system which consists of several simple processing elements that are connected together in a specific way to perform an important task. The common type of artificial neural network contains three or more layers. These layers named as input, output and hidden layers where neurons are subjected to each other with modifiable weighted interconnections as presented in Figure 3.

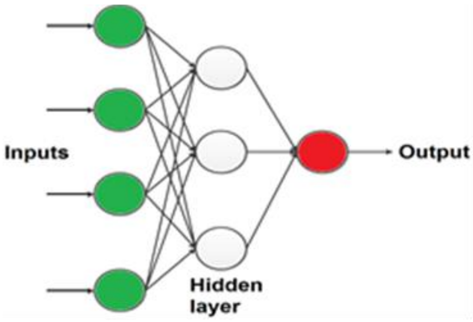


Figure 3 ANN architecture

Input layer, one or more hidden layers according to problem and an output layer are the counterparts of the ANN analysis. Layers that take place among the input and output layers are known as hidden layers. Data of the problem is separated into training and testing datasets. While training data includes the 70-80% of the total data, the rest is utilized for testing data.

The architecture of ANN represents an absolutely interconnected feed forward multilayer perceptron. Neurons in the layers depend on the type of the problem. A suitable model is required for ANN analysis. While there are several ANN architecture types, the most successful type in data mining is the multi-layer feed forward networks. Back propagation is the classic neural network learning algorithm due to its simplicity and universal capacity of approximation. This algorithm provides the minimum error function in weight space by using the method of the gradient decent. Besides, it identifies a systematic way to update the synaptic weights of multi-layer feed forward networks that are consisted of neurons. This analysis makes computational devices more effective and improves human performance.

Results

In this paper, internal velocity and pressure values of the diffuser pipe of submarine outfall are obtained according to finite elements analysis (ABAQUS) in the first step. Fluid structure interaction (FSI) is performed to complete numerical analysis. Subsequently, obtained values are estimated by ANN analysis.

The visualization of FEM results of velocity and pressure values are seen in Figure 4. The average results of FEM for internal velocity and pressure values are given in Table 1. Nodes are chosen to be along a streamline following the diffuser pipe centerline. The nodes are numbered in ascending order starting with inlet of the main pipe and ending at the last riser which is located at the end of the model.

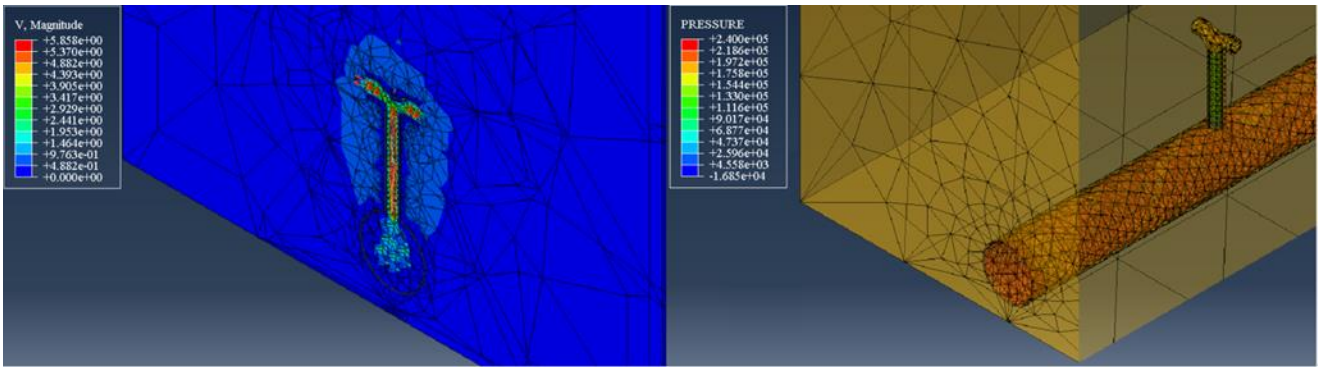


Figure 4 Velocity and pressure distribution of flow domain

Table 1 Internal velocity and pressure values of FEM

Node	1	2	3	4	5	6	7	8	9	10
Velocity *u*/ (m/s)	0.899	0.834	0.869	0.941	0.983	0.992	0.984	0.986	0.810	0.754
Pressure $P/(\mathrm{N/m^2})$	217663	217024	216924	216523	216046	215922	215520	215712	215472	215062

Node	11	12	13	14	15	16	17	18	19	20
Velocity u/ (m/s)	0.721	0.715	0.714	0.715	0.718	0.717	0.995	0.716	0.724	0.874
Pressure P/(N/m^2)	214999	214771	214529	214338	213188	213721	215224	212893	212552	212176
Node	21	22	23	24	25	26	27	28	29	30
Velocity u/ (m/s)	0.846	0.837	0.826	0.836	0.767	0.756	0.667	0.612	0.631	0.675
Pressure P/(N/m^2)	211777	211688	211090	210001	210886	211384	210767	210528	210507	210615
Node	31	32	33	34	35	36	37	38	39	40
Velocity u/ (m/s)	0.685	0.672	0.789	0.823	0.803	0.851	0.903	0.946	0.954	0.982
Pressure P/(N/m^2)	210462	210073	210115	209943	209237	209104	208686	208384	208279	208178
Node	41	42	43	44	45	46	47	48	49	50
Velocity u/ (m/s)	1.109	1.181	1.237	1.524	1.517	1.492	1.458	1.413	1.439	1.417
Pressure P/(N/m^2)	207868	207738	207614	211946	210089	209086	208848	208091	207752	207099
Node	51	52	53	54	55	56	57			
Velocity u/ (m/s)	1.479	1.389	1.379	1.369	1.34	1.296	1.288			
Pressure P/(N/m^2)	206221	206049	205775	205317	205285	205115	204143			

This paper is primarily concerned with the estimation of velocity and pressure values of the diffuser pipe according to ANN analysis. The dataset is separated into training and testing sets by feed-forward back propagation algorithm that is available by the neural network toolbox of the Matlab [25] software. Thus, several Matlab subroutines have been developed to perform analysis. There are 43 data in training set and 14 data in testing set taking place in the database. There is a hidden layer as well as an input and output layer in the architecture of network. While material type, span lengths are constant inputs, section sizes are taken as varied ones. Besides, internal velocity and pressure values are the output parameters of the network.

Several trials are performed to reach the most convenient architecture of network. Before performing analysis, the test data is normalized by using simple normalization methods. The pre-processing operation directs the data in a new form to train the network. Scaled Conjugate Gradient (SCG) is utilized as the training function in the analysis and 3000 iterations are utilized to reach the optimum result. Dispersion and performance of the training and testing sets are determined after ANN analysis. While results related to velocity values are given in Figures 5 and 6, pressure values are given in Figures 7 and 8.

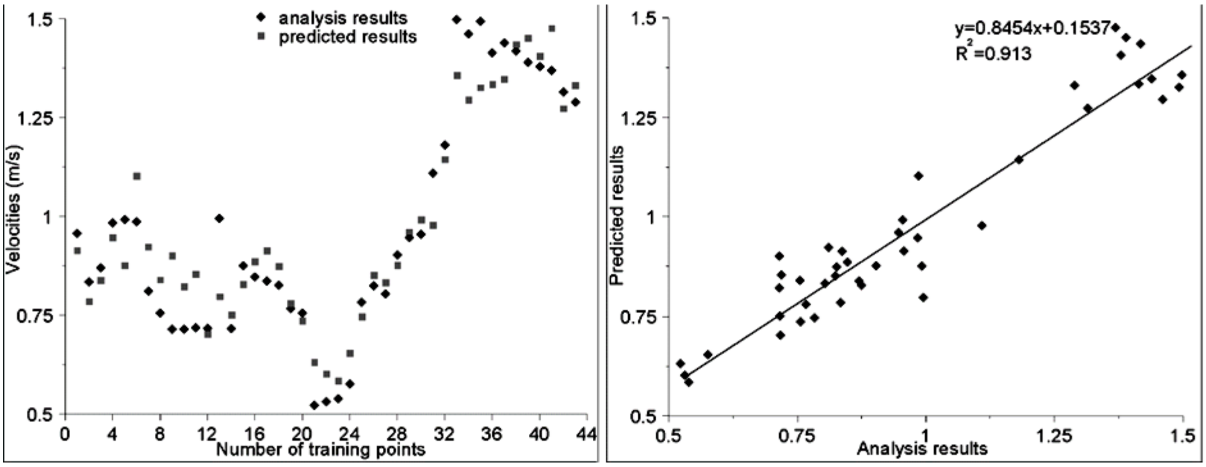


Figure 5 Training set for velocity values

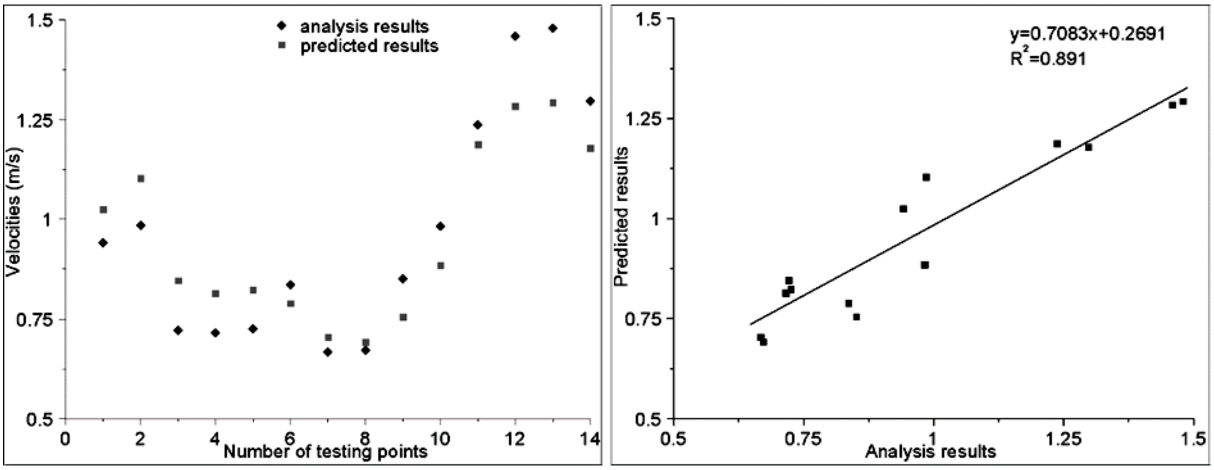


Figure 6 Testing set for velocity values

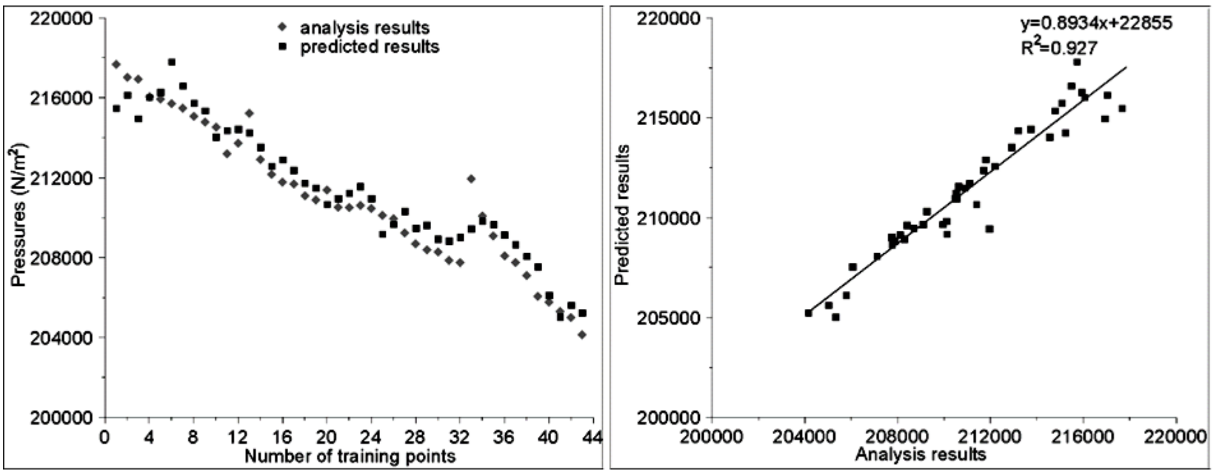
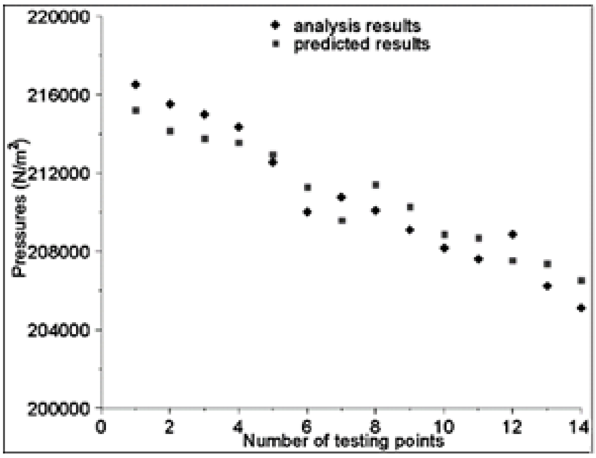


Figure 7 Training set for pressure values



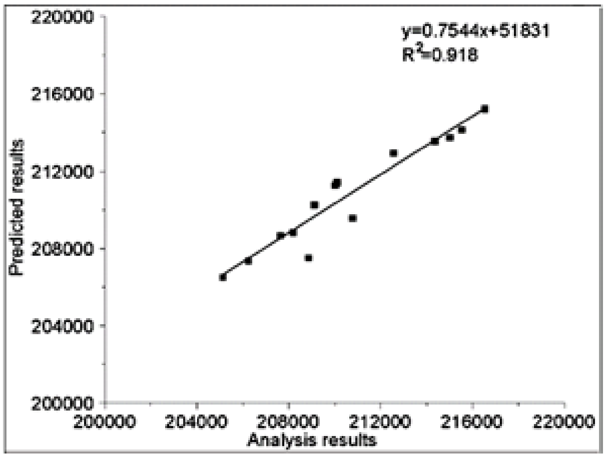


Figure 8 Testing set for pressure values

The performance of the network is utilized according to correlation coefficients (R^2) of determination for the finite elements analysis and estimated values of the dataset. These coefficients present the relationship between analysis and estimated results. Accordance level of the values is determined according to correlation coefficients by using Eq. (9) that is given below.

$$R^2 = \left[\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \right] \tag{9}$$

Correlation coefficients (R^2) are accepted as performance standards in ANN analysis. They determine the suitability level of the values. These coefficients that are calculated according to Eq. (9) give information about the relationship between experimental and estimated results. While correlation coefficient of the training set is calculated as R^2=0.913, it is determined as R^2=0.891 for the testing set after analyses of velocity values. On the other hand, the related coefficient is calculated as R^2=0.927 and R^2=0.918 for training and testing sets of pressure values respectively. The results of correlation coefficients which give information about the success of prediction according to each analysis are summarized in Table 2.

Table 2. Correlation coefficients

Velocity values		Pressure values	
R^2(training)	R^2(test)	R^2(training)	R^2(test)
0.913	0.891	0.927	0.918

Discussion

In this study, internal velocity and pressure values of the diffuser pipe of submarine outfall are obtained by finite elements analysis via FSI and these values are estimated by ANN. In finite elements analysis, fluid and structure domains are modeled by ABAQUS finite elements program which is widely used for dynamic analyses. After, domain sizes and flow conditions are defined, analyses are performed. For this purpose, 24 m long, fixed supported, two-span diffuser is modeled. Cooling water whose flow rate is 0.254 m^3/s is being discharged into the sea at the depth of 25 m by submarine outfall. Steady discharge flow is interacting with the unsteady ambient which is represented by Linear Wave Theory. Both internal and external flows are interacting the diffuser model.

To make discharge system effective, inner-outer flow velocity and pressure values shall provide the conditions given in the literature. The velocity in the pipe shall be high enough to scour and prevent deposition of particles; this will be concluded by peak flow velocity values between about 0.6 and 2.5 m/s. In this study these values vary between 0.621 m/s and 1.524 m/s. On the other hand, internal pressure values vary between 204143 N/m^2 and 217663 N/m^2. Higher values of internal pressure than external pressure values are obtained as it is seen in Figure. 4. The values of discharge velocities are bigger than external flow velocities as shown in Figure. 4. The average discharge velocities are obtained as 4.04 m/s which satisfy Froude number>1. Water intrusion into the ports is avoided by this way.

According to results obtained by FEM it can be said that the discharge system works efficiently.

ANN analysis is combination of mathematical and numerical methods which provide information and simulation of the results from computational models. This analysis is used for several engineering problems to reduce workload by predicting results accurately. The internal velocities and pressure values of diffuser pipe are obtained by FEM and these values are also tried to be estimated. For this purpose, neural network toolbox of the Matlab software is utilized. A computer program is established to calculate the values. Ultimately, the correlation coefficients are calculated by using obtained and estimated values and it is observed that a strong relationship is obtained between them. The correlation coefficient values are determined as R^2=0.913, it is determined as R^2=0.891 according to training and test process of velocity values. The values of these coefficients are calculated as R^2=0.927 and R^2=0.918 for pressure values.

Thus, the created ANN model can be used as an alternative approach to predict the internal velocity and pressure values of the diffuser pipe. ANN results are in accordance with finite elements analysis results according to this study. FSI analysis requires high computer capacity. However, ANN reduces the analysis time of computers. Therefore, ANN analysis is considered to be more practical for non-visual models.

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