Pollution, 6(2): 399-415, Spring 2020
DOI: 10.22059/poll.2020.289549.684
Print ISSN: 2383-451X Online ISSN: 2383-4501
Web Page: https://jpoll.ut.ac.ir, Email: jpoll@ut.ac.ir

Artificial Neural Network Modeling for the Management of Oil Slick Transport in the Marine Environments

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Received: 25.09.2019 Accepted: 17.02.2020

ABSTRACT: Due to an increase in demand of petroleum products which are transported by vessels or exported by pipelines, oil spill management becomes a controversial issue in coastal environment safety as well as making serious financial problems. After spilling oil in the water body, oil spreads as a thin layer on the water surface. Currents, waves and wind are the main causes of oil slick transport. These phenomena depend on the overall interaction among gravity, viscosity, surface tension and interfacial tension of oil in water bodies. In the current study, Artificial Neural Network (ANN) models have been designed and trained for the prediction of oil spreading and advection under different hydrodynamic conditions. In this regard, results obtained from a multiphase Lagrangian numerical model are deployed to train ANN model. The mentioned numerical model which is based on the moving particle semi-implicit (MPS) method is developed in the earlier stage of the study. In this research study, the MPS numerical model is first validated and verified against the analytical formulas which are based on experimental data cited in the literature. Then, various hydrodynamic conditions and oil spill scenarios were chosen to obtain different numerical model results. Finally, numerical model results are then deployed for training ANN model to provide a useful tool for urgent prediction of oil slick trajectory in order to manage the oil slick transport in the coastal environments.

Keywords: Neural network, Numerical modeling, Oil spill, Pollution transport, Marine environment.

INTRODUCTION

The oil spill is a serious problem in coastal areas, it may pose significant threats to marine environments and people's health and can pollute vessels and harbor facilities in beaches or near-shore regions. Simultaneously, adequate preparedness of harbor and maritime authorities to potential oil spills requires significant material and human resources (den Boer *et. al.,* 2014; Weng, 2017). The trajectory of a particular spill is of fundamental importance since it determines the influence of oil on coastal regions and on other delicate wildlife. Prediction of an oil slick transport can be useful for taking the proper actions in the management and removal of pollutions. When oil spilled on the surface of water bodies, it spreads as a thin diaphragm the so-called oil slick. An imbalance in the force between gravity, viscosity and surface tension and oil-water interfacial tension controls the direction of oil spreading (Imanian *et al.*, 2017). Numerical modeling of oil spill is an essential tool to predict the

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fate and transport of oil slick under different hydrodynamic conditions for supervising and controlling of produced pollutions. Two approaches for computing oil slick trajectories and simulating fluid flow are normally used in different research studies including Lagrangian and Eulerian approaches. Researchers have developed several methods to simulate fluid flow based on the Eulerian mesh-based formulation (Sarhadi Zadeh & Hejazi, 2012; Barrios, 2016; Verma, 2016). Some other researchers preferred to apply mesh-less methods (De Dominicis *et. al.*, 2013 & 2016; Ratherford *et. al.*, 2015; Golshan *et al.*, 2018). The comparison of results obtained from Eulerian and Lagrangian approaches showed that the particle-based approaches can well represent the location of oil slick. Moreover, it can predict the oil slick breakage due to the flow pattern (Nagheeby & Kolahdoozan, 2010; Rowshan *et al.*, 2007).

One of the most important particle-based methods is moving particle semi-implicit (MPS). MPS which was introduced originally by Koshizuka & Oka (1996) and has applied in a wide range of engineering applications such as free surface water waves, phase transitions, multiphase flow, elastic structures, and sediment-laden flows. Governing equations in the MPS method are transformed into particle interactions, also grids are not used in this approach; therefore, large scale deformations of interfaces can simply be simulated. In this method fluid and solid are treated as separate phases and governing equations of momentum and continuity are solved for them concurrently. Recently, researchers were developed a large number of models to economize time and cost. One of the most accurate and simplest models without professional mathematical equations in different fields is the artificial neural network (ANN) model (Huang *et al.*, 2010, Rajasekaran & Bharadwaj, 2012, Singha *et al.*, 2013, Zhang *et al.*, 2015, Xu *et al.*, 2016, Song *et al.*, 2017). ANN is a relatively new technology based on the process of the biological brain and it has many human-like qualities (Kohonen, 1989). As a quick response from governments is required in situations of marine pollution due to oil spills (Liu *et. al.*, 2011; Gallego *et. al.*, 2018), ANN models are highly applicable in environmental monitoring, assessment, forecasting and management (Acciani *et al.*, 2003; Booty *et al.*, 2001; Gumrah *et al.*, 2000; Liao *et al.*, 2012; Palani *et al.*, 2008). In the current study, ANN models were designed and developed to predict oil slick spreading and transport in the marine environment. With the developed ANN models, fast tools are prepared to manage necessary activities to preserve marine waters from hazardous impacts.

Herein, a MPS model which was originally developed by Imanian *et al.* (2011) is deployed and verified against several test cases. Then, the model applied to simulate a multiphase system (water and oil) with different oil properties under various hydrodynamic conditions. To prepare necessary data for the ANN model, different scenarios were executed by the developed numerical model and a wide range of test results were obtained. The prepared dataset was then deployed to train and test the ANN models.

MATERIAL & METHODS

Numerical method of solving governing equations and details of artificial neural network is described.

Governing equations for incompressible viscous fluid flows are continuity and momentum equations given as follows (Monaghan, 1994):

$$1/\rho.D\rho/Dt+\nabla.\vec{u}=0 \tag{1}$$

$$D\vec{u}/Dt=-1/\rho\nabla P+\nu_t\nabla^2\vec{u}+f \tag{2}$$

where $\vec{u}$= velocity, t= time, ρ= fluid density, P= pressure, ν_t= turbulent viscosity and f= body forces.

In the MPS modeling, differential governing equations are needed to be converted to equations stating the particle interactions. The particle interactions are based on the Kernel function which is used as:

$$w(r)=\begin{cases} r_e/r-1 & 0\le r< r_e \\ 0 & r_e\le r \end{cases} \quad (3)$$

where r= the distance between two particles, and r_e= the cutoff of efficient radius.

Gradient is evaluated between two adjacent particles and is expressed as (Koshizuka *et al.*, 1998):

$$\nabla\phi_i = d/n^0.\sum_{i\neq j}\left[\phi_j-\phi_i^{'}/\left|r_j-r_i\right|^2.\left(r_j-r_i\right).W\left(\left|r_j-r_i\right|\right)\right] \quad (4)$$

where ϕ= physical quantity, n^0= the standard density, d= number of space dimension, r_i= location vector for particle i, and ϕ'= minimum amount of ϕ in the neighboring particles in the efficient radius.

The Laplacian model in the MPS method has a conservative form as (Koshizuka *et al.*, 1998):

$$\nabla^2\phi_i = 2d/n^0\lambda.\sum_{j\neq i}\left[\left(\phi_j-\phi_i\right).w\left(\left|r_j-r_i\right|\right)\right] \quad (5)$$

In this study, a 2D MPS model is deployed as a numerical tool for modeling the oil slick transport in the water body. Governing equations of oil-water flow are then discretized using MPS method and numerically solved. Then, ANN capability is examined for predicting oil slick spreading and advection.

Over the last few decades, one particular machine learning technology known as artificial neural networks has been successfully applied to a wide range of engineering problems (Lee, 2018). An artificial neuron is a model inspired by the human brain neurons. In this study, a widely used ANN with the use of Back Propagation (BP) algorithm was deployed. BP algorithm was used in Feed-Forward artificial neural network system which calculates from the input layer over hidden layers to the output layer. The first step in the training process of BP neural networks is assembling training data and then creating a network object. A two-layer feed-forward network with tan sigmoid transfer function in the hidden layer and linear output transfer function is trained with Levenberg-Marquardt BP algorithm (see Figure 1).

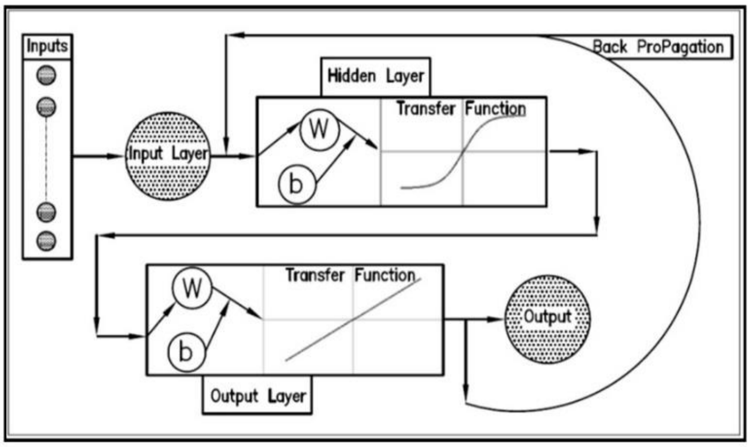

Fig. 1. Schematic of feed-forward back propagation artificial neural network

This algorithm was created to approach second-order training speed without having to compute the Hessian matrix. The performance function is a sum of squares as typical in training feed-forward networks, then the Hessian matrix and gradient can be computed as (Khataee & Kasiri, 2010):

$$H = J^T J \quad (6)$$

$$g = J^T e \quad (7)$$

where J= the Jacobian matrix which contains first derivatives of the network errors regarding the weights and biases, and e= a vector of network errors.

The Jacobian matrix can be calculated through a standard back-propagation technique that is simpler than calculating the Hessian matrix. Feed-forward ANN is a layered network which means the artificial neurons are arranged in layers and emitted the signals forward, but their errors propagated backward. All neurons in a specific layer are connected to all neurons of the adjacent layer in feed-forward neural network. This is one of the most popular and simplest learning algorithms with a high level of performance for complicated and multi-layered networks. Errors in this method would be reduced since the ANN has been learned through training data. ANNs are able to learn from different datasets including numerical modeling data without knowledge of the real rules that govern the system. It is apparent from results that the prediction of ANN was improving through training network with different sets of models.

RESULTS & DISCUSSION

In this part, the numerical MPS model is verified against analytical formulas to validate its performance in the hydrodynamic domain and in two-phase oil pollution interaction. To verify the hydrodynamic model in the presence of waves, numerical tests are conducted in a wave flume, and a piston wave-maker is located at the beginning of the flume to generate a regular wave train. To calculate wavelength, the dispersion equation is deployed as follows (Dean & Dalrymple, 1991):

$$(2\pi / T)^2 = \mathrm{gk}(\tanh(\mathrm{kh})) \quad (8)$$

where k= the wave number= $2\pi/L$, h = water depth, T= wave period and L= wave length.

The wave height for a defined wavelength and wave-maker amplitude determined as (Dean & Dalrymple, 1991):

$$H / S = 2(Cosh 2kh - 1) / Sinh 2kh + 2kh \quad (9)$$

where H= wave height and S= paddle stroke.

It should be mentioned that numerical models that are used in this paper are modeled in shallow (h/L <0.05) and transitional (0.05<h/L <0.5) waters.

The regular and non-breaking wave is generated in a 10.5 m flume with 1 m water depth; the wave-maker paddle stroke amplitude is 50 cm with a period of 3 s. In this numerical model, 4683 particles with 4.7 cm diameter are used. A sensitivity analysis was carried out to obtain the suitable value for the time step and in this regards it was found that 0.003 second is appropriate. The wave height and length resulted from numerical modeling are 0.27 m and 8.6 m respectively illustrated in Figure 2.

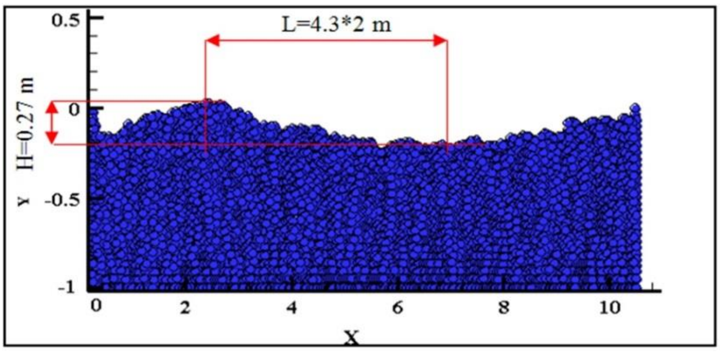

Fig. 2. The wave generated by the wave-maker

Alternatively, using analytical formulas (equations 8 and 9), wave height and length are 0.33 m and 8.69 m respectively. Comparing these two sets of results represent 1% and 18% difference in wavelength and wave height predictions respectively. Interestingly, it can be concluded that the numerical model has a reasonable agreement with the analytical result in computing wavelength.

The existence error in calculating the wave height is because of the difference between the basic formulations in the numerical model and analytical formula. The analytical formula for wave height is based on Euler equation, fluid in this equation is considered ideal, then the shear tensions and viscosity are become neglected (Dean & Dalrymple, 1991). In the present numerical model, governing equations are based on Navier-Stokes equations which consider shear stresses in fluid flow. The effect of shear stresses and viscosity of fluid is to damp the wave energy and consequently to decrease the wave height.

To represent the applicability of the MPS model for simulation of fluid flow in open channels, a critical flow simulation is described herein. It is important to know as wind and tidal currents are also primary factors in marine environments, they affect marine environments by producing currents (surface currents and tidal currents). Consequently, their impacts have been considered in the form of currents in this paper.

In this case study, a broad crested weir with 2 m length and vertical framework in both sides is modeled in a 7.5 m channel (at x=5 m). Both static head of water above weir's crest and weir's height are 1 m. Also, the water depth is 2 m and fluid inflow (current) velocity is set to 0.45 cm/s. For numerical modeling purposes, 4991 water particles with 5 cm diameter are modeled with the time step set to 0.005 seconds. The discharge in control section calculated by equation 10 is 0.0819 m^3/s.

$$Q = 1.705 C_d C_v k b_c H'^{3/2} \tag{10}$$

where Q= the discharge in the control section, C_d= flow coefficient, C_v= velocity coefficient, K= submergence coefficient presented by Ranga Ranju (1993), b_c= channel width and H'= height of weir.

Since q is the inflow in unit width, critical depth in rectangular sections can be computed as:

$$y_c = \sqrt[3]{q^2 / g} \tag{11}$$

where y_c= critical depth which is formed on just the beginning of the weir or in the control section and g= gravitational acceleration.

The critical depth obtained from equation 11 is 0.649 m, which is in a good agreement with the model result which is 0.65 m illustrated in Figure 3.

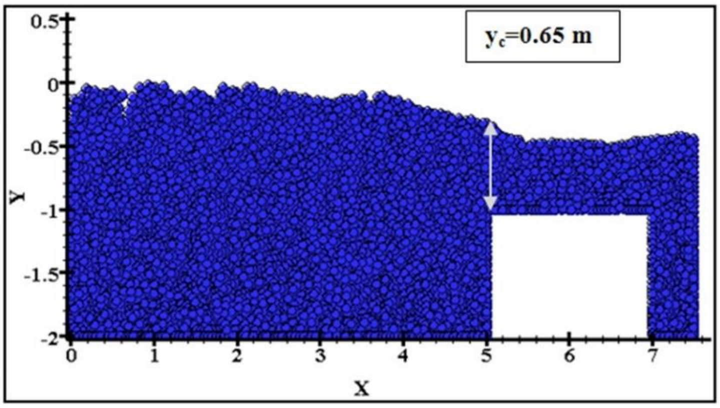

Fig. 3. Critical depth formed on the broad crested weir

With the above two test cases, it can be concluded that the numerical MPS model can well predict the fluid flow in both wave and current conditions. Herein, the developed MPS model is applied in some cases to validate its performance in oil pollution transport in the marine environment. For this purpose, the developed two-phase MPS model is applied to simulate oil slick spreading on the water surface and its advection due to waves and currents.

Spreading is one of the most significant processes during the early stage of the oil spill. This process is the horizontal expansion of oil slick. In the oil spill process, as soon as oil releases into the water body, it starts to spread non-uniformly. The principal force behind the initial spreading of oil is its weight. Oil slick spreads over the water surface due to a balance between gravitational, viscous and surface tension forces, while the composition of the oil changes from the initial time of the spill (Wang *et al.*, 2005).

Fay (1971) suggested that oil slick spreading passes through three stages; in the first stage, gravity and inertial forces are balanced and they control oil slick spreading across the water surface. In the second stage, the inertial forces are neglected to compare with the viscous drag force across the surface. In the third phase, interfacial forces become dominant and provide the driving force for the spreading phenomena. Thus, at equilibrium, the floating oil could spread across the surface or it could form a lens. The gravity-viscous ($g - v$) spreading regime is represented as (Fay, 1971):

$$L_{eg-v} = 1.39\left(\Delta g A^2 t^{3/2} v_w^{-1/2}\right)^{1/4} \qquad (12)$$

where L_e= increasing length of the oil slick, A= half volume of the oil per unit length of oil slick, ν_w= kinematic viscosity of water, $\Delta = 1 - (\rho_o/\rho_w)$, ρ_w and ρ_o= water and oil density respectively.

Since these empirical equations have been obtained from experimental tests, the results obtained from these verifications are accordingly achieved from experimental data. Numerical tests are carried out to investigate the oil slick spreading in wave flumes. In each test, a regular and non-breaking wave generated by the wave-maker situated at the beginning of the flume causes the oil slick to move on the water surface. Flume, wave and oil slick specifications are presented in Table 1. The comparison of computed oil slick length using the deployed MPS model and Fay (1971) empirical relationship results (equation 12) for 3 cases are illustrated in Figure 4.

In case (a) oil slick consist of 400 particles with 3.75 cm diameter, in case (b) it consists of 285 particles with 3.5 cm diameter and in case-c oil slick consists of 215 particles with 3.5 cm diameter.

From Figure 4 it can be concluded that the length of oil slick in both numerical models and Fay's empirical formula is increased by time. In three cases, Fay's empirical relationship resulted more oil spreading than the numerical model. In fact, the trend for both models in each graph of three case studies is almost the same. Regarding Figure 4, in the case (a), there is a little difference between the empirical formula and MPS model, but in case-b this difference increases. The variability of these cases is because of the wave period. With increasing the wave period, oil slick spreads more rapidly and results of numerical MPS model become closer to the results obtained through Fay's empirical formula.

The error analysis of comparing MPS numerical results and Fay's empirical formula in different cases are presented in Table 2.

Table 1. Flume, water and oil slick specifications in oil slick spreading model verification

Case	Flume Properties		Wave Properties			Oil Slick Properties	
	length(m)	depth(m)	height(m)	period(s)	length(m)	viscosity(m^2/s)	density(kg/m^3)
a	15	0.6	0.6	2.11	4.65	0.085	850
b	15	0.5	0.73	1.73	3.4	0.085	800
c	13.5	0.55	0.62	2	4.22	0.085	800

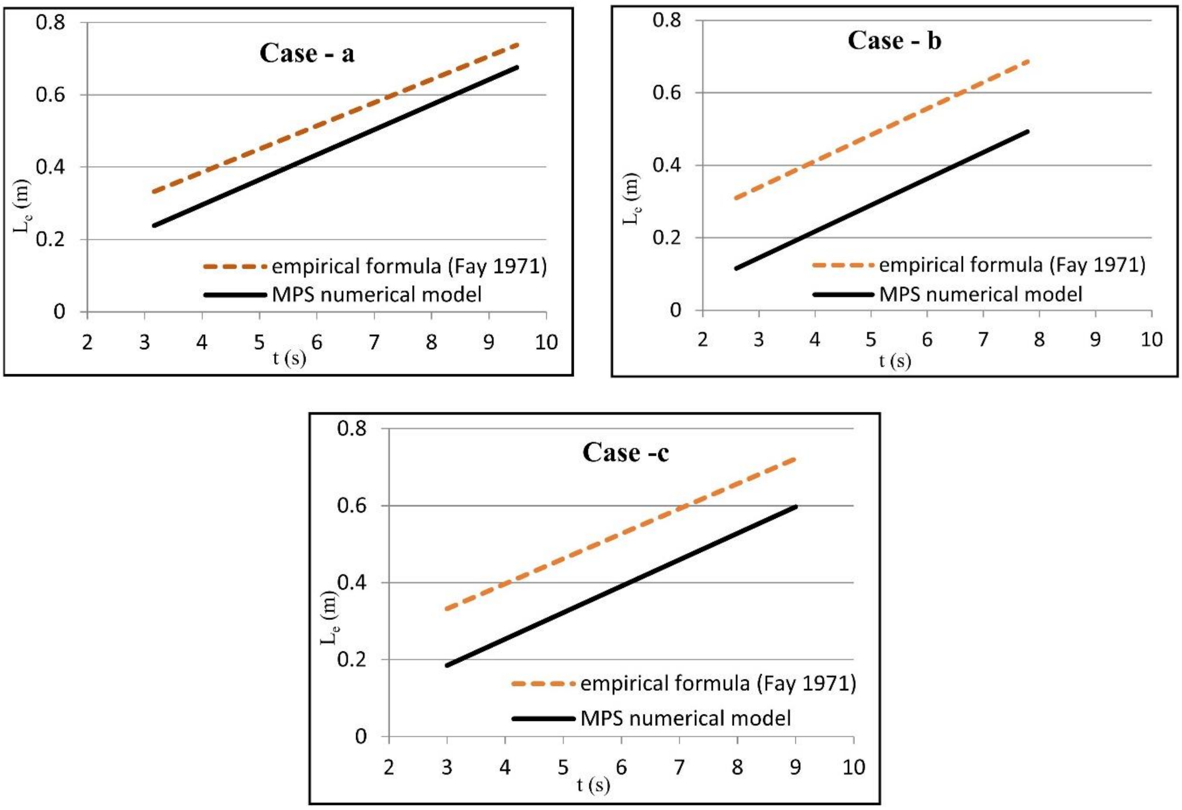

Fig. 4. Comparison of numerical results and Fay (1971) empirical formula for oil slick spreading

Table 2. Error analysis of numerical and empirical results of oi slick spreading

Case	RMSE	NMSE
a	0.0788	0.0254
b	0.1935	0.2473
c	0.1362	0.0900

Error values of root mean square error (RMSE) and normalized mean square error (NMSE) show that the numerical model is capable to predict oil spreading and numerical simulation is validated.

Moreover, it can be seen that error values for case a, which is related to the larger wave period (according to Table 1), is less than other cases. At the same time, error values for case b, which is related to the smaller wave period, is more than others. This can be explained by the fact that for the larger wave period, oil slick spreads more rapidly, which in turn causes results of numerical simulation and empirical formula became closer to each other.

A wide range of natural substances such as plants, animals or mineral origins, as well as a range of synthetic compounds is described with oil. Therefore, each type of oil or petroleum product has unique properties. One of the main physical properties which affect the behavior of oil in the water body is the oil density and it depends on the oil chemical compositions. Comprehending the distribution nature of sources and their inputs, as well as the behavior of petroleum in the environment, are the keystone to understand the impacts of petroleum on marine environments.

Numerical tests are carried out to investigate the density effects on oil slick spreading due to wave-induced currents. Flume, wave and oil slick specifications for two tests are presented in Table 3. In addition, in the first case, oil slick consists of 511 particles with 2.75 cm diameter and in the second one; oil slick consists of 125 particles with 4 cm diameter. The time step is 0.001 second for both cases. Moreover, the variation of oil slick length is demonstrated with time in Figure 5.

Table 3. Flume, wave and oil slick specifications in the investigation of oil density effect

Case	Flume characteristics		Wave Properties			Oil Slick Properties	
	length(m)	depth(m)	height(m)	period(s)	length(m)	initial length(m)	viscosity(m^2/s)
1	13.5	0.55	0.438	2.033	4.3	2	0.085
2	11.1	1	0.888	2.5	6.99	1	0.085

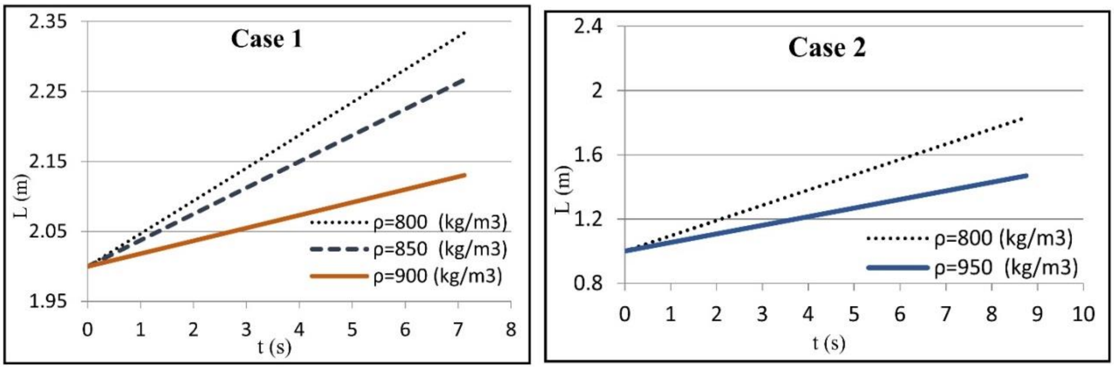

Fig. 5. Time variation of oil slick length for different oil densities

Figure 5 shows that in case (a) the rate of oil slick length increase is 4.7 cm/s for oil density of 800 kg/m^3; while this parameter is 3.8 and 1.8 cm/s for oil density of 850 and 900 kg/m^3, respectively. With the same trend in case (b), the slick length growth rate for 800 kg/m^3 oil density is 9.5 cm/s in comparison with 5.4 cm/s for oil with a density of 950 kg/m^3.

It can be concluded that with increasing the oil density, the spreading process occurred more slowly. Also, the gradient of oil slick spreading length in oil with a higher density is less than oil with lighter density. It means that the length of oil slick in lighter oil increases more rapidly compared to heavy oil. In both models, the initial length of oil slick for different types of oil is the same but oil with lower density spreads faster than oil with heavier density.

Results of numerical MPS models indicate that density of oil plays a major role in spreading phenomenon and it affects the rate of spreading in marine environments, also wave period may play a significant role in the oil slick spreading.

Other important processes in oil slick transport are advection and turbulent diffusion. Oil particles are transported in the water surface mainly as the effect of wind, surface currents, and waves. The advection velocity of oil slick U_d= is described as (Al-Rabeh *et al.*, 1992; Chao *et al.*, 2001; Chao *et al.*, 2003):

$$U_d = K_t U_t + K_w U_{wind} \tag{13}$$

where U_{wind}= wind velocity at a height of 10 m above the water surface, U_t= surface velocity and K_t *and* K_w = current and wind drift factor equals 1 and 0.03 respectively.

The turbulent diffusion transport and calculation of velocity components are commonly gained from a homogeneous random walk procedure. Distance ΔS through which a particle travels by horizontal diffusion and can be expressed as (Al-Rabeh *et al.*, 1992; Chao *et al.*, 2001; Chao *et al.*, 2003):

$$\Delta S = [R]_0^1 \sqrt{12 D_h \Delta t} \quad (14)$$

where $[R]_0^1$= random number between 0 to 1, D_h= horizontal diffusion coefficient and Δt= time step.

They also described the displacement of oil slick due to advection and horizontal turbulent diffusion as follows (Al-Rabeh *et al.*, 1992):

$$L_x = U_{dx} \Delta t + \Delta S \cos(2\pi \left[R\right]_0^1) \quad (15)$$

$$L_y = U_{dy} \Delta t + \Delta S \sin(2\pi \left[R\right]_0^1) \quad (16)$$

where L_x and L_y= the displacements of the oil slick in the x and y directions respectively, U_{dx} and U_{dy}= advective velocity components in the x and y directions respectively. The new position for each particle at a new time step will be the summation of the previous location coordinate and computed displacement.

A 3 m long flume with a water depth of 50 cm is considered to simulate oil slick advection in two cases. The oil slick with 50 cm length and 10 cm thickness is spilled in the water at x=1.5 m from the beginning of the channel and monitored for 10 seconds. The density and viscosity of the oil are 850 $\mathrm{kg/cm^3}$ and 0.08 $\mathrm{m^2/s}$, respectively and oil slick is divided into 39 particles with a diameter of 3.9 cm. Results obtained from multiphase MPS models are then compared with Chao et al., (2003) in Figure 6. The inflow velocity is considered 4.5 and 5 $\mathrm{cm/s}$ in case (a) and (b), respectively. Other parameters are the same in two cases.

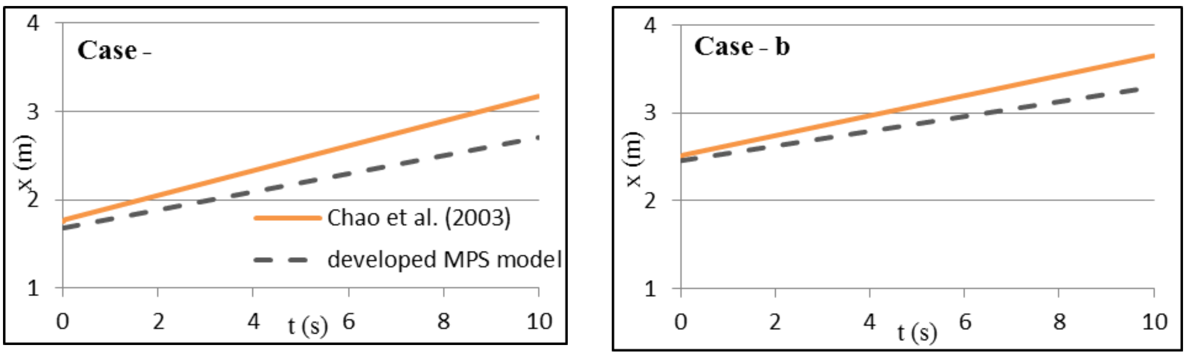

Fig. 6. Comparison of numerical results and Chao et al. (2003) formula for oil slick advection

Figure 6 represents the same trend in both oil slick transport value obtained from the developed model and Chao *et al.*, (2003) formula (equation 14). The difference between calculated oil slick displacement in the numerical model and displacement value (Δs) obtained from theoretical formula (with $D_h = 0.1$) for case (a) and case (b) are 9.1 % and 9.8%, respectively. Theoretical equations are simulated according to experimental data; thereby, results obtained from the mentioned equations are accordingly based on experimental datasets. The location of oil slick in different time steps is calculated and illustrated in Figure 7 for two cases.

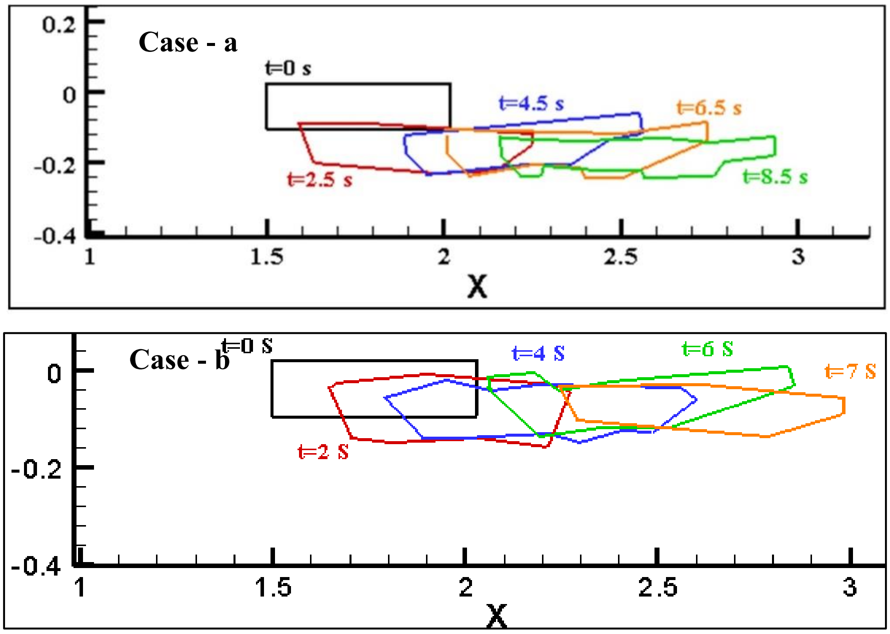

Fig. 7. Oil slick trajectory obtained from developed MPS model

The details of designed Artificial Neural Network model are presented in the following sections.

The arrangement or relative situation of cells in the network such as numbers, groups, and connections type is called the network's topology. The topology of ANN shall be optimized; this step plays an important role in the development of the network. In the current study, the hyperbolic tangent function is preferred to other activation functions such as logistic function. The hyperbolic tangent function has a limiting value of -1 to +1 and represents as follows (Bar *et al.*, 2010):

$$\tanh(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x}) \qquad (17)$$

For the output layer, a linear activation function is deployed as a transfer function (Bar *et al.*, 2010):

$$Y = x + b \qquad (18)$$

where b= the bias term that processes the element of the output layer each of which accumulates the weighted connections from the hidden layer.

Details of given herein for design and development of artificial neural network models to predict oil spill spreading related to currents and wave-induced currents.

The first step in the ANN model development process presented here is the choice of appropriate model outputs (i.e. the variables to be predicted) and a set of potential model input variables from the available data. Although ANNs are data-driven models, it is up to the modeler to choose which input variables should be considered as part of the model development process. This can be done based on a priori knowledge and/or the availability of data (Maier *et al.*, 2010; Li *et al.*, 2015). Herein, the input data includes channel geometry, oil slick thickness and length, and oil viscosity and density. Also, various hydrodynamic conditions, wave characteristics and current velocities are considered to have a comprehensive train of the ANN. Training, analyzing and testing data have been clarified by sensitivity analysis, correlation coefficient and mean square error. According to ANN model rules, the first stage is preparing necessary data to train, validate and test the model. In this regard, numerical experiments were carried out by the use of the developed MPS numerical model. The network was created using a two-layer, feed-forward neural network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. This kind of topology is useful for function approximation and regression problems.

For defining the number of neurons in hidden layer, trial and error methods have been applied. The Neural Network has been repeatedly trained till the mean square error reaches its minimum. Additionally, the validation of the ANN can be determined through regression analysis and the correlation between output data and target data. Therefore, based on the number of analyses, 15 hidden neurons were selected for modeling purposes. The performance of the ANN model is then determined using mean square error (MSE) and correlation factor (R) which can be represented mathematically as follows (Bar *et al.*, 2010):

$$MSE = 1/N.\sum_{i=1}^{N}\left(x_i - y_i\right)^2 \tag{19}$$

$$R = \sum_{i=1}^{N}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right) / \sqrt{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 \sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2} \tag{20}$$

In the current study, two individual ANN models were developed for i) prediction of oil slick spreading in the presence of waves and ii) oil slick advection in the presence of currents. To train the ANN models, Levenberg-Marquardt training algorithm was deployed. Input data in this research study for both ANN models are divided randomly into three categories according to sensitivity analysis results as follows:

a. In the first category, 70 percent of input data are used for training ANN models.
b. In the second category, 15 percent of input data are used for the validation process. In this group data, network generalization was examined.
c. The remaining 15 percent of input data is used for model testing purposes. This stage represents the performance of the developed ANN model.

The percentage of divided input data sets into 3 above categories can be changed in each epoch according to the performance of the ANN model.

To develop an ANN model for oil spreading due to the waves, 124 case studies (resulted from developed numerical model) were designed. These case studies were chosen in a way to consider the variety of different parameters involved in the process *i.e.* oil properties, wave, and flume characteristics, *etc*. In Table 4, some samples (10 from 124 models) of input data such as length and depth of the channel, wave and oil slick properties for ANN modeling of oil spreading due to wave are summarized:

Table 4. Flume, wave and oil slick specifications in 10 samples (from 124 datasets) in the model of oil slick spreading due to waves

Case	Flume characteristics		Wave Properties			Oil Slick Properties	
	length(m)	depth(m)	height(m)	period(s)	length(m)	Density(kg/m^3)	viscosity(m^2/s)
1	18	0.3	0.88	1.32	2	800	0.085
2	15	0.45	1.25	1.47	2.65	850	0.0425
3	17.3	0.5	1.03	1.57	3	800	0.085
4	15.3	0.45	0.74	1.62	3	900	0.085
5	15	0.5	0.73	1.73	3.4	850	0.045
6	13.5	0.75	1.36	1.82	4.2	900	0.085
7	15	0.4	0.34	2	3.7	950	0.0425
8	12	0.5	0.34	2.25	4.65	800	0.085
9	15	0.6	0.32	2.34	5.25	850	0.085
10	11.1	1	0.88	2.5	6.99	950	0.045

The 124 datasets were normalized to train the ANN models. As mentioned before, based on the sensitivity analysis for the number of data needed to train the model, 70 percent of input data is selected. The remaining 30 percent of data is considered for validation and testing processes equally. Table 5 represents a summary of model results including MSE and R with the results showing in detail for each category of modeling such as training, validating and testing in Figures 8 and 9.

Table 5. Performance of neural network in training, validation and testing stages for oil slick spreading

Categories	Samples	MSE	R
Training	86	0.0085	0.992
Validation	19	0.0165	0.982
Testing	19	0.0245	0.966

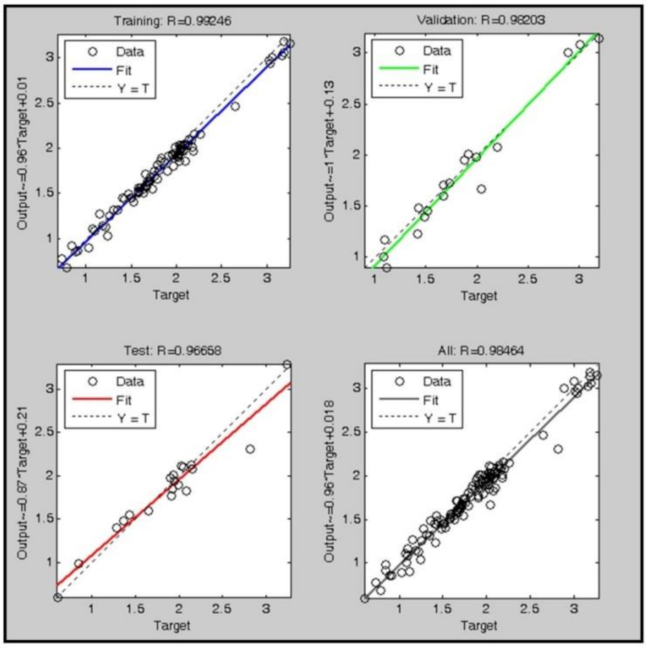

Fig. 8. Results of linear regression in the developed ANN model for oil slick spreading

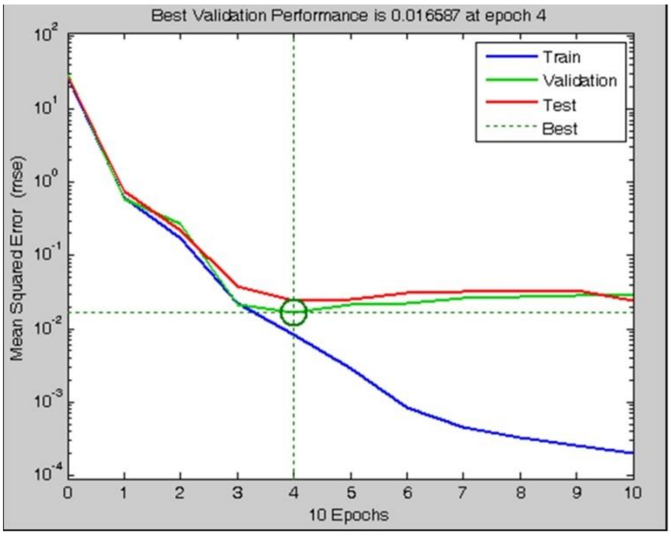

Fig. 9. The best performance of the developed ANN model for oil slick spreading in the presence of wave

Figure 9 shows that the training stage is stopped when a validation error is subjected to increase at epoch 4. In epoch 4, the mean square errors become minimize and it shows that the best performance of designed network has occurred at this epoch. If network training continues after epoch 4 (in this case), the network will be over trained. Overtraining of networks makes it worthless because the performance of ANN model will be decreased by this action. Although the MSE of training process tends to zero after passing epoch 4 the MSE value for validation and testing network will be increased. From Figure 9 it can be concluded that the developed ANN model can well predict the oil slick spreading due to waves.

Applying the ANN model instead of employing time-consuming Lagrangian numerical models represents the applicability of the ANN for fast prediction of oil slick spreading in marine environments.

To develop an ANN model for oil slick advection process due to currents, 92 case studies (resulted from developed numerical model) are designed. These case studies are chosen to cover a different aspect of oil slick, current properties, and channel specifications. In Table 6, some samples (10 from 92 models) of input data such as channel, current and oil properties for ANN modeling of oil slick advection due to currents are summarized. The parameters in Table 6 might be changed in each model; therefore, to develop an accurate artificial neural network model a wide range of various parameters shall be chosen.

Again in the currently developed model, input datasets are randomly divided into 70 percent for training, 15 percent for validating and 15 percent for testing purposes as a result of sensitivity analysis. Table 7 represents a summary of the model results with the details given in Figures 10 and 11.

Table 6. Flume, current and oil slick specifications in 10 samples (from 92 models) in the model of oil slick advection due to currents

Case	Flume characteristics		Current	Oil Slick Properties	
	length(m)	depth(m)	Speed(cm/s)	Density(kg/m^3)	viscosity(m^2/s)
1	9	2	0.4	800	0.085
2	9	0.5	0.5	900	0.0425
3	10.5	1.2	0.75	950	0.085
4	9.75	1	1.5	850	0.085
5	10.5	0.5	2	800	0.085
6	12	0.4	4.5	800	0.085
7	16.5	0.5	4.5	850	0.085
8	9	1.5	5	950	0.0425
9	15	0.4	5	900	0.0425
10	10.5	0.5	6	800	0.085

Table 7. Performance of neural network in training, validation and testing stages for oil slick advection

Categories	Samples	MSE	R
Training	64	0.0011	0.999
Validation	14	0.0281	0.996
Testing	14	0.0322	0.997

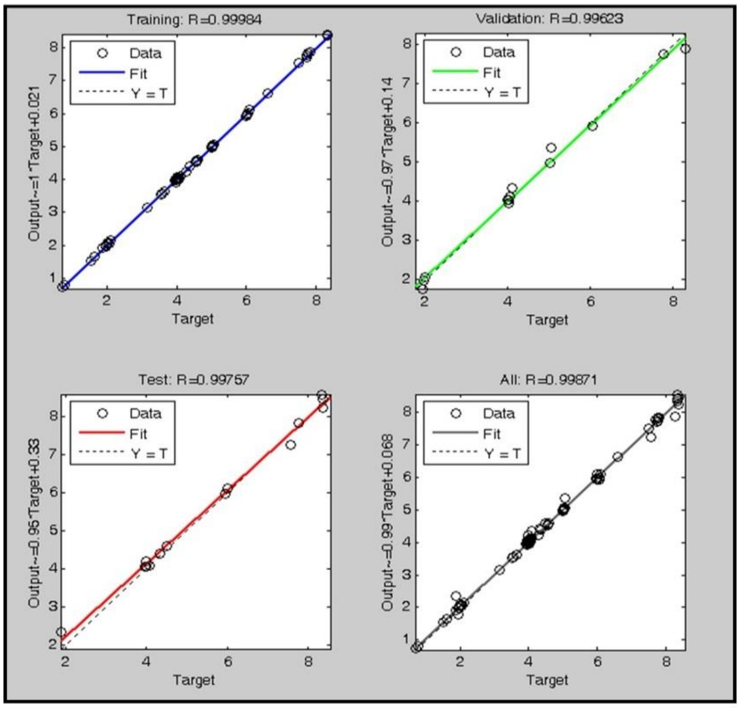

Fig. 10. Results of linear regression in the developed ANN model for oil slick advection

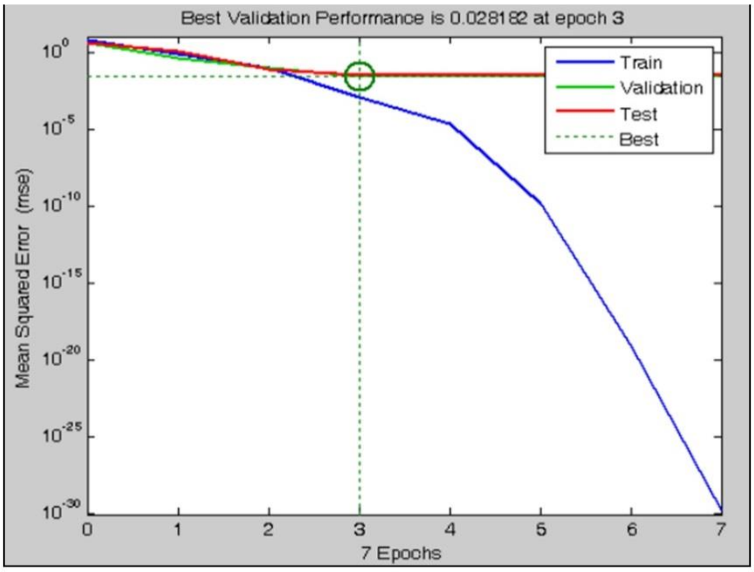

Fig. 11. The best performance of the developed ANN model for oil slick advection in the presence of current

Training stage is stopped when validation error increased which occurred at epoch 3 (Figure 11) and the best validation performance occurred at epoch 3. From Figure 11, it can be concluded that oil slick advection due to the presence of currents can be well predicted by the developed ANN model.

According to results obtained from both ANN models, the ANN modeling approach can be well applied to oil spill phenomena in the marine environment. Results obtained through both currents and waves represent the performance of ANN modeling method in the prediction of oil slick transport for supervising oil spill contamination in marine environments. The main output of the ANN model is managing oil spill accidents by prediction of location and situation of oil slick after passing time in marine environments.

CONCLUSION

In the current study, artificial neural networks were developed based on numerical dataset results to predict oil slick transport and spreading. Prediction of oil spill behavior is substantial to take a quick action to manage it and make a decision to remove the resulting pollutions from marine environments. In conclusion, as the computational time for ANN modeling is much less than both numerical models of hydrodynamics and oil slick transport, one can be concluded that the earlier one is faster in case of real problems which is more suitable for the real-time management of oil slick spreading. In other words, the most significant advantage of using ANN models to predict phenomena than other numerical models is; by using ANN models, results have been acquired very quickly but numerical models need more time to obtain results.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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