Ocean Engineering 161 (2018) 98–110

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Robust data-driven model to study dispersion of vapor cloud in offshore facility

Jihao Shi [a,b], Fasial Khan [c], Yuan Zhu [a,*], Jingde Li [b], Guoming Chen [a]

[a] Center for Offshore Engineering and Safety Technology, China University of Petroleum, Qingdao 266580, China
[b] Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, WA 6102, Australia
[c] Centre for Risk, Integrity and Safety Engineering (C-RISE), Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1B 3X5, Canada

ARTICLE INFO

Keywords:
Bayesian regularization
Artificial neuron network
Response Surface Method
Frozen Cloud Approach
Overfitting problem
Better generalization

ABSTRACT

Data driven models are increasingly used in engineering design and analysis. Bayesian Regularization Artificial Neural Network (BRANN) and Levenberg-Marquardt Artificial Neural Network (LMANN) are two widely used data-driven models. However, their application to study the dispersion in complex geometry is not explored.

This study aims to investigate the suitability of BRANN and LMANN in estimating dimension of flammable cloud in congested offshore platform. A large number of numerical simulations are conducted using FLACS. Part of these simulations results are used to training the network. The trained network is subsequently used to predict the vapor cloud dimension and compared against remaining simulation results. The predictive abilities of these network along with Response Surface Method and Frozen Cloud Approach (FCA) are studied. The comparative results indicate BRANN model with 20 hidden neurons is the most robust and precise. The developed BRANN would serve an effective and tool for quick Explosion Risk Analysis ERA.

1. Introduction

Gas dispersion simulation of offshore platform plays an essential role for Explosion Risk Analysis (ERA), as it can be conducted to identify credible gas cloud volume, gas concentrations and cloud locations and the simulation results can be viewed as the input for different simulations (NORSOK, 2010) (ISO 19901-3,2015). Generally, it is not feasible and acceptable to perform limited dispersion simulations as part of ERA. Large set of simulations is cost prohibitive. Two popular techniques namely Frozen Cloud Approach (FCA) and Response Surface methodology (RSM) are often employed to predict the acceptable non-simulation flammable cloud volume. For range of conditions, this improves the efficiency of the risk analysis based on a limited number of computationally fluid dynamics simulations.

FCA was initially proposed by DNV then widely used by many (GexCon, 2015; Hansen and Middha, 2008; Qiao and Zhang, 2010) to predict the flammable cloud volume. In this technique, linear relations amongst gas concentration, leak rate and the wind speed for each leak scenario are assumed and data of gas cloud volume from the non-numerically-simulated scenarios are then obtained. Generally, FCA contributes to saving time and financial cost of ERA. It can provide good prediction results for leakages in ventilation-dominated regions. Moreover, it can easily determine the time series of flammable cloud volume. However, FCA may determine poor estimation under specific leakage condition, e.g. leakage in the fuel-dominated region (GexCon, 2015).

RSM was firstly adopted by Cleaver (Cleaver et al., 1999) and then widely used to predict the flammable cloud volume (Ferreira and Vianna, 2014). However, conventional RSM may cause overfitting problem. This means the generated correlations may have a worse generalization for new input data even though higher coefficient of determination R^2 for training data can be obtained. Robustness of these correlations are not be guaranteed. Although, specific statistical methods are used to keep correlation avoid overfitting problem (Jihao et al., 2017), there seems to a room to further improve the robustness and accuracy.

Artificial Neural Network (ANN), which computer-based algorithm, appears to have a better prospect in terms of flammable cloud volume estimation. ANN consists of a set of processing units that allow signals to travel in parallel as well as serially by connecting various neural (Adedigba et al., 2017). It can mimic the complex non-linear relationships between the inputs and outputs. Among various types of ANNs,

* Corresponding author. Center for Offshore Engineering and Safety Technology, China University of Petroleum, Qingdao 266580, China.
E-mail addresses: shi_jihao@163.com (J. Shi), zhy3323@163.com (Y. Zhu).

https://doi.org/10.1016/j.oceaneng.2018.04.098
Received 8 January 2018; Received in revised form 19 April 2018; Accepted 29 April 2018
Available online 10 May 2018
0029-8018/© 2018 Elsevier Ltd. All rights reserved.

back-propagation (BP) algorithm is widely used, which uses the derivative of an error function to find the direction that minimizes the error of the network and then updates the weights accordingly. However, conventional BP algorithm also may cause overfitting problem, especially under limited simulation data.

Different regularization techniques are developed to overcome the overfitting problem. Among these techniques, Levenberg-Marquardt (LM) and Bayesian regularization (BR) are widely used because of their respective advantages (Demuth and Beale, 2009; Baghirli, 2015; Kayri, 2016). Recently, various researchers from different areas have compared the predictability LMANN and BRANN, BRANN is identified as better generalization in most cases (Baghirli, 2015; Kayri, 2016; Gianola et al., 2011; Kaur and Salaria, 2013; Ticknor, 2013). However, in terms of flammable cloud volume prediction, the more robust and efficient one is unknown since ANNs are sensitive to statistical properties of the input and output datasets (varied volume and statistical properties). Additional issue employing ANN is that it is difficult to determine the suitable hidden neuron numbers with varied inputs for general application. In other words, if employing ANN, the engineers should initially determine the suitable hidden neuron numbers along with the various inputs during the training process. This is much labor intensity.

This study aims to determine the efficient techniques to estimate the flammable cloud volume in complex geometry such as the offshore platform. Using the identified technique, a robust model is to be developed to estimate the flammable cloud volume. The developed model is tested on a fixed and floating offshore facility. The developed model is integral part of the ERA.

2. Artificial neuron network

2.1. Multilayer perception with back propagation algorithm

Fig. 1 shows the architecture of multi-layer perception (MLP) with BP algorithm, which is the basis to develop the BRANN and LMANN. As can be seen, this architecture consists of three layers, namely input, hidden and output layers. The input layer contains n neurons, presenting n factors affecting the flammable cloud volume. (In this study, $n \leq 4$ since 4 main factors, namely leak rate, wind speed, wind direction and leak direction are considered). The neurons in hidden layer are varied while the output layer only contains 1 neuron presenting the maximum flammable cloud volume.

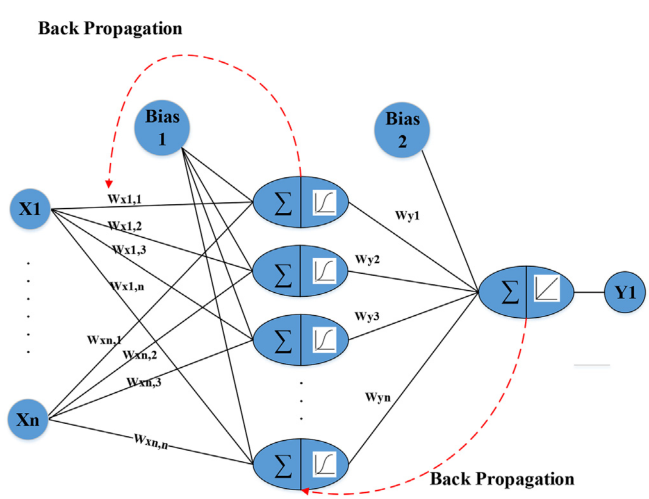

Fig. 1. Architecture of multi-layer perception (MLP) with back-propagation (BP) model; *X1* to *Xn* ($n \leq 4$) indicates varied factors, i.e. leak rate, wind speed, wind direction and leak direction; *Y1* presents the maximum flammable cloud volume; The activation function is Tansig in hidden layer; The activation function of output layer is Purelin function; $W_{i,j}$ means a series of weights; Bias 1 presents the series of bias in the hidden layer while Bias 2 means those bias in output layer.

2.2. Bayesian regularization and Levenberg-Marquardt algorithms

The conventional MLP with BP algorithm may cause the overfitting problem, i.e. lower bias but larger variance. As an alternative, BRANN has better generalization capacity since it minimizes a combination of squared errors E_D and weights E_w and then determine the optimal weight and objective function parameters α, β as probability (Kayri, 2016). The objective function for BRANN is shown as:

$$F = \beta E_D + \alpha E_w \tag{1}$$

In BRANN, the initial weights are randomly set. With these initial weights, the density function for the weights can be updated according to Baye's rule.

$$P(w/D,\alpha,\beta,M) = \frac{P(D/w,\beta,M)\cdot P(w/\alpha,M)}{P(D/\alpha,\beta,M)} \tag{2}$$

where D is the training sample, M is the particular neural network model (architecture) adopted, and w is the vector of network weights. $P(w/\alpha,M)$ is the prior distribution of weights, which presents our knowledge of the weights before any data is collected. $P(D/w,\beta,M)$ is the likelihood function, which is the probability of the occurrence, given the weights w. $P(D/\alpha,\beta,M)$ is a normalization factor, which can be expressed as Equation (7) as below.

If Gaussian distribution is assumed to the noise of training set data and weights, the probability densities can be calculated as below;

$$P(D/w,\beta,M) = \frac{1}{Z_D(\beta)}\exp(-\beta E_D) = (\pi/\beta)^{-N/2}\exp(-\beta E_D) \tag{3}$$

$$P(w/\alpha,M) = \frac{1}{Z_w(\alpha)}\exp(-\beta E_W) = (\pi/\alpha)^{-N/2}\exp(-\beta E_W) \tag{4}$$

If we substitute these probabilities into Eq. (2), we obtain:

$$P(w/D,\alpha,\beta,M) = \frac{\frac{1}{Z_W(\alpha)}\frac{1}{Z_D(\beta)}\exp(-(\beta E_D+\alpha E_W))}{P(D/\alpha,\beta,M)} = \frac{1}{Z_F(\alpha,\beta)}\exp(-F(w)) \tag{5}$$

In this BRANN, the optimal weights should maximize the posterior probability. Maximizing the posterior probability $P(w/D,\alpha,\beta,M)$ is equivalent to minimizing the regularized objective function F (Foresee and Hagan, 1997).

The joint posterior density:

$$P(\alpha,\beta/D,M) = \frac{P(D/\alpha,\beta,M)\cdot P(\alpha,\beta/M)}{P(D/M)} \tag{6}$$

Maximizing the joint posterior above is determined by maximizing the likelihood function $P(D/\alpha,\beta,M)$, which can be calculated by:

$$P(D/\alpha,\beta,M) = \frac{P(D/w,\beta,M)\cdot P(w/\alpha,M)}{P(w/D,\alpha,\beta,M)} = \frac{Z_F(\alpha,\beta)}{(\pi/\beta)^{\frac{n}{2}}(\pi/\alpha)^{\frac{m}{2}}} \tag{7}$$

where n is the number of observations (input-target simulation pairs), and m is the total number of network parameters. Furthermore, the parameter, $Z_F(\alpha,\beta)$ depends on the Hessian of the objective function (Foresee and Hagan, 1997), which can be calculated below:

$$Z_F(\alpha,\beta) \propto \frac{e^{-F(w\max)}}{\sqrt{|H\max|}} \tag{8}$$

where the subscript 'max' indicates maximum a posteriori. The Hessian matrix (H) is calculated from the Jacobian(J):

$$H = J^T J \tag{9}$$

Download English Version:

https://daneshyari.com/en/article/8062155

Download Persian Version:

https://daneshyari.com/article/8062155

Daneshyari.com