Journal of Coastal Research	SI 50	317 - 321	ICS2007 (Proceedings)	Australia	ISSN 0749.0208

Evaluation of Neuro Fuzzy and Numerical Wave Prediction Models in Lake Ontario

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ABSTRACT

KAZEMINEZHAD, M. H., ETEMAD-SHAHIDI, A. and MOUSAVI, S. J., 2007. Evaluation of neuro fuzzy and numerical wave prediction models in Lake Ontario. Journal of Coastal Research, SI 50 (Proceedings of the 9th International Coastal Symposium), 317 – 321. Gold Coast, Australia, ISSN 0749.0208

For planning or designing maritime structures, wave observation with a long-term history is generally necessary. However, we may often encounter the problems that only short-term observed data were available or the records are incomplete in a station. In this study, the performances of a new generation spectral wind-wave model based on unstructured meshes and a neuro fuzzy model for predicting wave parameters are investigated. The data set used in this study comprises of wave data and over water wind data gathered from deep water location in Lake Ontario. The data set was divided into two groups. The first one that comprises of 26 days wind and wave measurement was used as training and checking data to develop neuro fuzzy models and also to calibrate the numerical model. The second one that comprises of 14 days wind and wave measurement was used to verify the neuro fuzzy and numerical models. Wind field was specified as constant in space and variable in time. Results show that whitecapping factor is the most important calibration factor in this case and satisfactory results can be obtained by tuning this factor. Results also indicate that the errors of proposed neuro fuzzy models in predicting wave parameters are more than those of on the numerical model.

ADDITIONAL INDEX WORDS: *Fuzzy Inference System, MIKE 21, Spectral Wave Model, ANFIS*

INTRODUCTION

Wind waves play a significant role in all ocean related activities. They damage shore protection structures, reshape beaches and affect marine structures and are hence important for commercial, military and recreational activities. Therefore, it becomes necessary to understand the characteristics of waves that impact various operations in offshore and coastal regions. However, in most cases little wave data is available for engineering construction and planning. Field observation and physical modelling of waves are extremely difficult, costly and time-consuming. Remote-sensing instruments, used in recent years, do not systematically provide the desired resolution in some cases and no instrument can in any case anticipate future sea states. The desired sea-state information may thus be obtained using reliable wave models. In the literature, several approaches have been proposed to wave predictions which are empirical based, soft-computing based and numerical based approaches. During the past decades several numerical models such as WAM (WAMDI GROUP, 1988), SWAN (BOOIJ *et al.,* 1999) and MIKE 21 (DHI, 2004) were developed and employed to predict wave characteristics in different cases. Numerical models are generally based on a form of the spectral energy or action balance equation. Recently, a new generation spectral wind-wave model called SW model has been presented in MIKE 21 software. SW model is based on unstructured meshes and simulates the growth, decay and transformation of wind generated waves and swell in offshore and coastal areas.

Recently, Fuzzy Inference Systems (FISs) and Artificial Neural Networks (ANNs) have been used to develop wave prediction models. FISs are based on expertise expressed in term of 'IF-THEN' rules which can be used to predict uncertain systems. ANNs may essentially be used as semi-parametric regression estimators which can approximate virtually any function up to an arbitrary degree of accuracy. AGRAWAL and DEO (2002) and TSAI *et al.* (2002) have used ANNs for forecasting wave parameters. KAZEMINEZHAD *et al.* (2005, 2006) have also used fuzzy inference systems and neuro-fuzzy computing techniques in the prediction of wave parameters in fetch limited conditions.

In this study, the performance of the MIKE 21 SW model and a neuro-fuzzy model for predicting wave parameters were investigated.

THE SPECTRAL WAVE MODEL

Spectral Wave (SW) model is a new generation wind-wave model. The model includes two different formulations which are the fully spectral formulation (FS) and the directional decoupled parametric formulation (DDP). The FS formulation is based on wave action conservation equation (KOMEN *et al.*, 1994) where the directional frequency wave action spectrum is a dependent variable. The DDP formulation is based on a parameterisation of the wave action conservation equation. The parameterisation is made in the frequency domain and the zeroth and first moments of the wave action conservation are considered as dependent variables (HOLTHUIJSEN, 1989). In the SW model the basic conservation equations can be formulated in Cartesian (small scale domain) and polar spherical co-ordinates (large scale domain).

Equations and Numerical Method

The transport equation of wave action density describes the dynamics of gravity waves. The model formulation is based on the wave direction, θ, and the relative angular frequency, σ. The action density, $N(\sigma,\theta)$, is calculated as follows:

$$N = \frac{E}{\sigma} \qquad (1)$$

where $E(\sigma,\theta)$ is the energy density.

In Cartesian co-ordinate, the conservation equation for the wave action can be written as:

$$\frac{\partial N}{\partial t} + \nabla.(\vec{v}N) = \frac{S}{\sigma} \qquad (2)$$

where $N(x,\sigma,\theta,c)$ is the action density, t is the time, $\vec{x}(x,y)$ is the Cartesian co-ordinate, $\vec{v}(c_x, c_y, c_\sigma, c_\theta)$ is the propagation velocity of a wave group in the four-directional phase space $\vec{x}$, σ, and θ, and S is the source term for the energy balance equation. ∇ is the four dimensional differential operator in the $\vec{x}$, σ, and θ space.

The energy source term, S, consists of source functions of various physical phenomena as:

$$S = s_{in} + s_{nl} + s_{ds} + s_{bot} + s_{surf} \qquad (3)$$

In the above equation s_{in}, s_{nl}, s_{ds}, s_{bot}, and s_{surf} are the generation of energy by wind, the wave energy transfer due to the non linear wave-wave interaction, the dissipation of wave energy due to whitecapping, the dissipation due to bottom friction and the dissipation of wave energy due to depth induced breaking respectively.

The input source term is calculated by:

$$s_{in} = \gamma E \qquad (4)$$

where γ is the growth rate. In SW model a simple parameterisation of the growth rate obtained by JANSSEN (1991) has been used. The model has implemented three different formulations to estimate the friction velocity and critical height. The formulations are the uncoupled model using a drag law, the uncoupled model using charnock and the coupled model (DHI, 2004).

The nonlinear energy transfer amongst the different wave components of a directional-frequency spectrum plays a crucial role for temporal and spatial evolutions of a wave field. The quadruplet wave-wave interaction controls the shape-stabilisation of the high-frequency part of the spectrum and the downshift of energy to lower frequencies. SW model has implemented the nonlinear wave-wave interaction using Discrete Interaction Approximate (KOMEN *et al.*, 1994). The energy transfer caused by triad wave-wave interactions is not considered in the model.

The whitecapping is the other mechanism that leads to dissipation of wave energy. The model has implemented whitecapping mechanism just in the fully spectral formulation using the formulation described in KOMEN *et al.* (1994). The whitecapping dissipation source function includes two free parameters, c_{ds}^* and δ. The c_{ds}^* coefficient is a proportional factor for the whitecapping dissipation source function and thus controls the overall dissipation rate. The δ coefficient is controlling the weight of dissipation in the wave energy-action spectrum. The coefficients can be specified as constants for the entire domain or variables in the domain. The default values for c_{ds}^* and δ are 4.5 and 0.5, respectively.

As waves propagate into shallow water, the orbital wave velocities penetrate the water depth and the source function due to bottom friction becomes important. The dissipation source function used in SW model is based on the quadratic friction law and linear wave kinematics theory. The model has used four different formulations to calculate the dissipation due to bottom friction (JOHNSON *et al.* 1998).

Depth induced breaking occurs when waves propagate into very shallow water regions. The formulation of wave breaking used is the one derived by BATTJES and JANSSEN (1978). The source term s_{surf} is calculated as described in ELDEBERKY and BATTJES (1995). The formulation has two calibration factors that are α_{BJ} and γ. The parameter α_{BJ} controls the rate of energy dissipation after breaking while γ controls the amount of depth related breaking. The default value for the both parameters is 1.

The discretisation of the governing equation in geographical and spectral space is performed using cell-centred finite volume method. In the geographical domain, an unstructured mesh technique is used. The spatial domain is discretised by subdivision of the continuum into non overlapping triangle elements. The action density represented as a piecewise constant over the elements and stored at the geometric centres. In frequency and directional space, a logarithmic and an equidistant discretisation are respectively used. The time integration is performed using a fractional step approach where a multisequence explicit method is applied for the propagation of wave action.

NEURO FUZZY WAVE PREDICTION MODEL

Fuzzy Inference Systems

One of the most useful tools presented within the context of fuzzy sets theory to deal with nonlinear, but ill-defined, mapping of input variables to some output ones is what is known as Fuzzy Inference Systems (FISs). A FIS is a framework which simulates the behaviour of a given system as IF-THEN rules through knowledge of experts or past available data of the system.

Generally, a fuzzy IF-THEN rule involves two parts. The first is IF part and the second is THEN part which are called premise and consequent parts, respectively. One type of proposed FISs in the literature is the so called Takagi and Sugeno FIS (SUGENO, 1985) in which the consequent variable of each rule is defined as a linear combination of input (premise) variables. Then the final output is the weighted average of each rule's output. For example, a Sugeno FIS including two input variables x, y, one output variable f and two fuzzy rules is as follows:

Rule i: If x is A_i and y is B_i then $f_i = p_i x + q_i y + r_i \quad i=1,2$

where p_i, q_i and r_i are the consequent parameters of ith rule. A_i and B_i are the linguistic labels which are represented by fuzzy sets whose membership function parameters are premise parameters.

The so called firing strength or degree of fulfillment of a pair (x,y) to rule i, which measures the degree to which that pair belongs to rule i, can be defined as:

$$w_i = \mu_{A_i}(x) \wedge \mu_{B_i}(y) \quad i = 1,2 \qquad (5)$$

where $\mu_A(x)$ and $\mu_B(y)$ are membership functions of x and y in fuzzy sets A_i and B_i. "Λ" denotes a fuzzy T-norm operator which is a function that describes a superset of fuzzy intersection (AND) operators, including minimum or algebraic product. In this study algebraic product was used. The final output of the system is the weighted average of all rules' outputs as

$$Final\ Output = \left(\sum_{i=1}^{n} w_i f_i\right) \times \left(\sum_{i=1}^{n} w_i\right)^{-1} \qquad (6)$$

According to the simplified wave prediction methods e.g. U.S. ARMY (2003) it is assumed that the wave generation is governed by three parameters: fetch length, wind duration and wind speed. Therefore, there are three input variables in the wave height prediction problem and fuzzy IF-THEN rules used may have the following form:

If wind speed is high and fetch length is large and wind duration is high then wave height = p_i (wind speed) + q_i (fetch length) + r_i (wind duration)+s_i

Similar IF-THEN rules are used in the wave period prediction problem. In this study the parameters p_i, q_i, r_i and s_i are estimated using available input-output data. Subtractive clustering method (Chiu, 1994) was also used to estimate the optimum number of IF-THEN rules and determine the membership functions.

ANFIS Architecture

An Adaptive-Network-Based Fuzzy Inference System (ANFIS) (Jang, 1993) is a Sugeno type FIS in which the problem of fine-tuning membership functions of premise variables is carried out by a feed-forward neural network. ANFIS provides a methodology for the fuzzy modelling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated FIS to track the given input-output data.

Figure 1 shows the structure of ANFIS including two inputs x, y, and one output f and two rules which were described in previous part. The first layer is the fuzzifying layer in which A_i and B_i are the linguistic labels. The output of the layer is the membership functions of these linguistic labels. The second layer calculates the firing strength for each rule quantifying the extent which any input data belongs to that rule. The output of the layer is the algebraic product of the input signals as can be seen in equation (5). The third layer is the normalisation layer. Every node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths

$$\overline{w}_i = \frac{w_i}{w_1 + w_2} \quad , \quad i = 1,2 \qquad (7)$$

The output of every node in fourth layer is

$$\overline{w}_i \; f_i = \overline{w}_i \left(p_i x + q_i y + r_i \right) \qquad (8)$$

The fifth layer computes the overall output as the summation of all incoming signals, which represents the results of wave height or wave period as can be seen in equation (6).

In ANFIS the premise and consequent parameters are optimised using a hybrid learning algorithm. In this way a two-step process is used for the learning or adjustment of the network parameters.

In the first step, the premise parameters are kept fixed and the information is propagated forward in the network to Layer 4, where the consequent parameters are identified by a least-squares estimator. In the second step, the backward pass, the consequent parameters are held fixed while the error is propagated and the premise parameters are modified using a gradient descent algorithm. The only user-specified information is the number of membership functions for each input and the input-output training information.

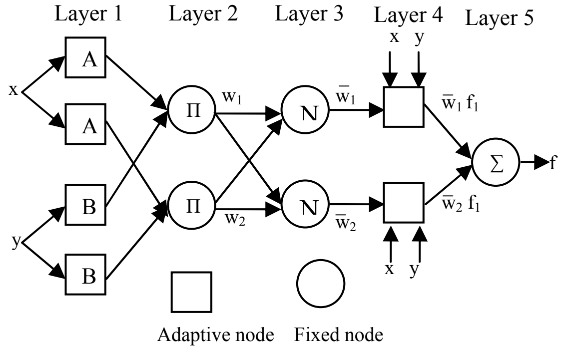

Figure 1. ANFIS architecture

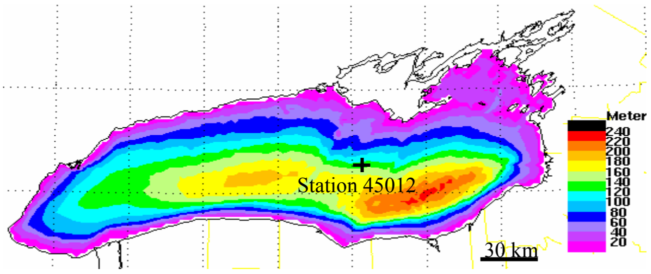

Figure 2. Lake Ontario bathymetry and location of NDBC buoy 45012 located at 43°37′09′′ N and 77°24′18′′ W.

STUDY AREA AND DATA SET

The data set used in this study comprises of wind and wave data gathered in Lake Ontario with an area of 19010 km^2 from 27th October to 9th November, 2004 and further 6th October to 1st December, 2005. The data set was collected by National Data Buoy Centre (NDBC) in station 45012 at 43° 37′ 09′′ N and 77° 24′ 18′′ W (Figure 2), where water depth is 145 m. Wind and wave data were collected using 3-metre discus buoy at 1-hour intervals. The wind speed at buoy was measured at a height of 5 metres above the mean sea level. The measured wind speed was adjusted to 10 m level using following simple approximation:

$$U_{10} = U_z \left[\frac{10}{z} \right]^{1/7} \qquad (9)$$

where U_{10} is the wind speed at 10 m above the sea surface (m/s); and U_z is the wind speed at level z (m/s).

To develop the neuro fuzzy model, it is necessary to calculate the wind duration and fetch length. To determine the duration of winds, definition of constant wind (U.S. Army, 2003) was used. In this way, wind duration at ith hourly data point was considered to be equal to the number of preceding consecutive and acceptable hours which satisfies the following conditions:

$$\left| U_i - \overline{U} \right| < 2.5 \qquad \left| D_i - \overline{D} \right| < 15 \qquad (10)$$

where $\overline{U}$ and $\overline{D}$ are the average of preceding consecutive and acceptable hourly wind speed and direction, respectively. U_i and D_i are wind speed and direction at ith hourly data point.

The fetch length for a certain direction was determined by constructing 30 radials from the point of interest (at 1 degree intervals) and extended them until they first intersect the coastline. Then, fetch length was calculated as arithmetic average of extended radials (U.S. Army, 2003).

RESULTS AND DISCUSSION

Calibration and verification of the SW Model

In this study SW model was run using fully spectral formulation in Cartesian coordinate. Since it is assumed that the wind characteristics are constant in the domain the measured wind speed and direction in station 45012 was applied in all points of Lake Ontario. Therefore, wind forcing was applied in format of varying in time and constant in domain. The coupled air-sea interaction was used in the simulations. Since the wind speed used in SW model should be measured at height of 10 metres above the sea level the equation (9) was used to convert the measured wind speed to the 10 metre height's one.

Geographical domain (Lake Ontario) was discretised using 1322 unstructured triangle elements. The frequency domain was discretised using logarithmic type discretisation. The minimum frequency, the frequency ratio and the number of discrete frequencies were selected 0.055 Hz, 1.1 and 25, respectively. Hence the frequency spectrum was resolved within the frequency range [0.055; 0.6] Hz. In this study time step was 300 seconds in all simulations.

The Model was calibrated using data set of year 2005 consisting of 611 hourly wind and wave measurements. As mentioned before, SW model has several calibration factors. Since the model was calibrated in deep water, the most important calibration factor is the whitecapping factor (c_{ds}^*).

The scatter index (*SI*) and bias are used to evaluate the degree of accuracy of the results. These parameters were calculated as

$$SI = \left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \right) \left(\sum_{i=1}^{N} O_i \right)^{-1}$$
$$bias = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i) \qquad (11)$$

where O_i is the observed value, P_i is the predicted value and N is the number of observations.

An initial calculation was performed using the default value c_{ds}^* = 4.5. Results indicate that the model under predicts the wave parameters. Consequently the whitecapping factor was reduced. Calibration was performed in several steps by reduction of c_{ds}^*. Finally the best c_{ds}^* was obtained as equal to 2.6. Table 1 shows the scatter index of wave parameters prediction in different calibration stages.

The data set of year 2004 was used to evaluate SW model. Using the calibrated parameter, $c_{ds}^*=2.6$, in SW model, wave characteristics related to data set of year 2004 were simulated. Figure 3 shows the measured significant wave height and peak spectral period along with SW model's predictions. As can be seen, the model has performed quite well in predicting the significant wave height and peak spectral period. Moreover, the model predicts the wave growth and decay very well. Table 2 shows the error statistics of predicted wave parameters using SW model. It can be seen that the model under predicts the peak spectral period while the significant wave height prediction is unbiased in the studied case. In addition, the scatter index for predicted H_s (SI=22.1 %) is larger than the one for predicted T_p (SI=12.9 %). The accuracy of the numerical model depends on the calibration parameters, resolution in geographical, spectral space discretisation and wind field accuracy. Model sensitivity to the order of discretisation was investigated using finer elements in the geographical space and smaller time steps. It was found that using finer elements and smaller time steps does not lead to better results. Also, results showed that other calibration parameters such as depth induced wave breaking and bottom friction have no significant effect on the results. It is due to the fact that the model was calibrated and verified in a deep water station where the most important dissipation phenomenon is the whitecaping. In this study the most important source of error is the wind field. Wind field was assumed constant in domain which is not true in all times. Therefore, this assumption may lead to some errors in the simulation of the wave characteristics. However, to have a fair comparison between the models, the same wind forcing was used.

Table 1: Error statistics calculated in calibration stages

c_{ds}^*	wave height (H_S)		wave period (T_P)	
	SI (%)	Bias (m)	SI (%)	Bias (s)
4.5	23.6	-0.19	15.5	-0.35
4	20.5	-0.14	14.9	-0.29
3.5	17.7	-0.09	14.5	-0.23
3	15.6	-0.03	13.9	-0.16
2.6	14.7	0.02	13.8	0.12

Neuro Fuzzy Model Development

The neuro fuzzy (ANFIS) model was developed and trained using data set of year 2005. The data set of year 2005 was divided in 2 parts. The first one was used in FIS development and also as training data in ANFIS modelling (430 data point) and the second one as checking data in ANFIS modelling (181 data point) to ensure over-training is not occurred.

Using the subtractive clustering method and training data including wind speed, fetch length and wind duration as input variables and wave heights as the output variable, an FIS was developed for wave height prediction. The developed FIS was then used as an initial FIS for ANFIS modelling. ANFIS optimises the parameters of initial FIS using neural networks.

After developing FIS and ANFIS models, testing data, the same data set used in testing the calibrated SW model were used to verify the accuracy of the predicted values of wave parameters. Figure 3 shows the observed and predicted wave heights using the developed ANFIS model.

Similarly, another FIS and ANFIS models were developed for prediction of wave period. The developed model was then used to predict the wave period using testing data. Figure 3 shows the comparison between observed and predicted wave periods.

Table 2: Error statistics of predicted wave parameters by the SW and ANFIS models

Model	wave height (H_S)		wave period (T_P)	
	SI (%)	Bias (m)	SI (%)	Bias (s)
SW	22.1	0.00	12.9	-0.06
ANFIS	31.3	0.01	13.8	0.10

Table 2 shows the error statistics of significant wave height and peak spectral period calculated by ANFIS models. As can be seen, the ANFIS models slightly overestimate both significant wave heights (bias=0.01 m) and peak spectral periods (bias=0.10 s) in the studied case. It can be seen from table 2 that the accuracy of SW model is better than that of ANFIS model while the accuracy of ANFIS model is acceptable.

SUMMARY AND CONCLUSIONS

In this study the performance of SW and ANFIS models for the prediction of wind wave characteristics were investigated. To calibrate the models, the data set of Lake Ontario in year 2005 was used. Calibration of SW model showed that the most important calibration parameter in deep water is the whitecapping parameter. Komen *et al.* (1994) proposed $c_{ds}^*=4.5$ while in the studied case the best results obtained by using $c_{ds}^*=2.6$. Results indicate that the errors of SW model in predicting wave parameters are less

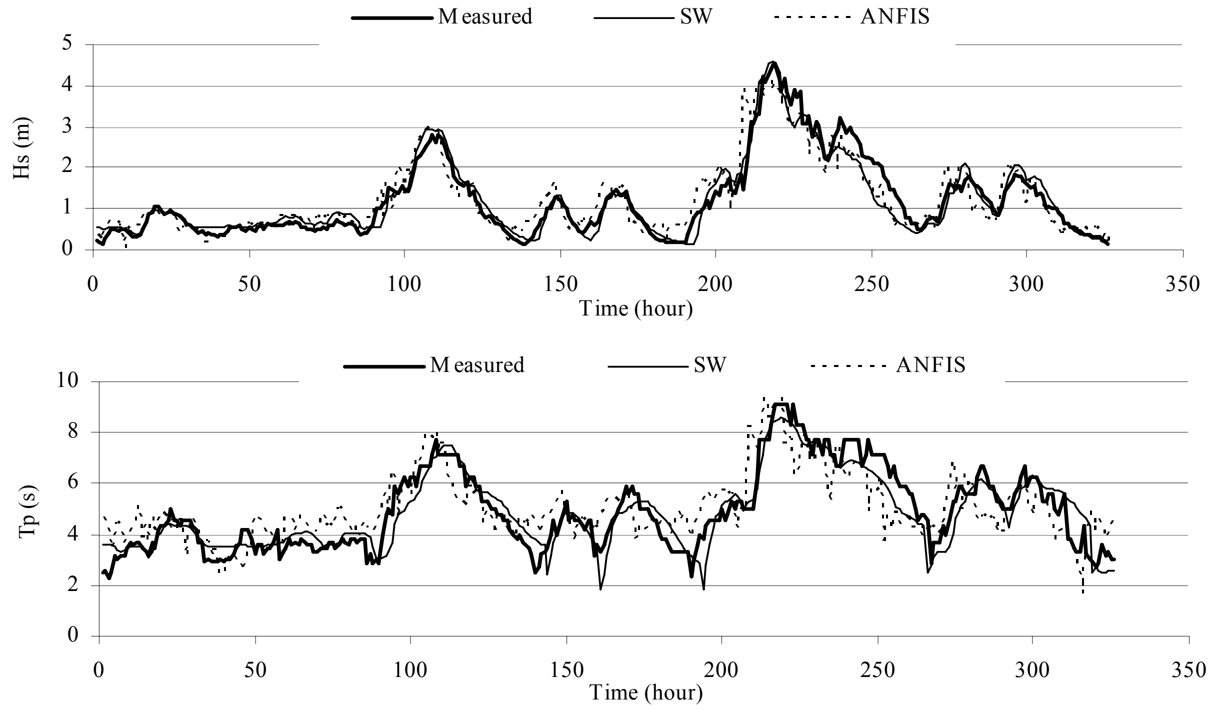

Figure 3. Comparison between measured and predicted significant wave height and peak spectral period

than the ANFIS model's ones. The scatter index of SW model in predicting significant wave height is 22.1 % while the ANFIS model's one is 31.3 %. The observed errors in the results of SW model may be due to the usage of constant wind in domain. It was seen that the scatter indices for predicted H_s by both SW and ANFIS models are larger than the ones for predicted T_p .

ACKNOWLEDGEMENTS

The authors have their special appreciation to Dr. K.W.Olsen from DHI water and environment.

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