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## RELATIONSHIP AND IMPACT OF CLIMATIC FACTORS WITH COASTAL ENVIRONMENTAL PARAMETERS (WATER TEMPERATURE, DISSOLVED OXYGEN) DUE TO WARM WATER DISCHARGE FROM A PROPOSED POWER PLANT

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**Abstract :** *Climatic factors play a vital role in determining the temperature of coastal water resources. The water temperature and salinity influences the dissolved oxygen concentration, vegetation growth and oxygenation in the coastal environment. In the present study, more than 30 years of climatic data near Jaitapur situated in the west coast of India, where a nuclear power plant is proposed, is analyzed and its relationship with sea surface temperature has been correlated. The relationship of warm water discharge and dissolved oxygen concentration is discussed. It is observed that even if the regulatory standards are met, the dissolved oxygen concentration may be reached at critical level due to high ambient temperature and climatic factors. The climatic data of a specific site is to be considered while studying thermal discharge in the coastal environment.*

**Keywords:** *sea surface temperature; ANN; correlation; saturated dissolved oxygen*

### INTRODUCTION

In India, currently, the share of nuclear power in terms of installed capacity is 3% which is expected to rise by 3-5 times in the next 20-40 years period (Annual Report, NPCIL, 2009). India has coastline of about 7550km with vast coastal area, which provides an inexhaustible source of cooling water requirement, and also sink for warm water discharge from a power plant. Moreover, if warm water discharges from the power station is very high in the coastal area, the climatic condition of the area also boost the water temperature and decrease the dissolved oxygen concentration in the area. There is a proposal to establish Nuclear Power Plant (NPP) at Jaitapur which is located on the west coast of India about 10 km south of Ratnagiri in Maharashtra (Fig.1). The cooling water required for the power station would be drawn from the sea through intakes protected by a breakwater. The large volume of warm water discharges with rise in temperature 7<sup>0</sup>C from the power plant would be let out through outfalls back to sea in deeper region.

This artificial increase in temperature can influence both chemical and biological processes such as dissolved oxygen concentrations, fish growth and even mortality. Many biological conditions are linked to water body thermal regime. For instance, Hodgson and Quinn (2002) demonstrated that the triggering of the spawning period for Sockeye salmon (*Onchorhynchus nerka*) on the

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**Fig.1 Location Plan of Study Area**

northwest coast of the United States was strongly influenced by water temperature. Water temperature simulations can also be done to investigate the potential impact of anthropogenic effects on the thermal regime of sea coast. Water temperature models have been included in decision support systems to assist managers in determining optimum outflows that maintain adequate temperature ranges for biota (e.g., Gu et al., 1999; Krause et al., 2005)

The water temperature is required for various practical purposes and is frequently obtained by calculating the heat budget. This method is tedious and yields rather inaccurate values of the water temperature if meteorological data is not collected carefully. An alternative approach to deterministic models in predicting or simulating water temperatures is the use of statistical or stochastic models. In contrast to the deterministic models, the main advantage of the statistical models is their relative simplicity and minimal data requirement.

Although stochastic models linking water to air temperatures offer a simple means of predicting or simulating water temperature, other statistical models, such as parametric (e.g., Box Jenkins, Auto regressive Moving Average Model, etc.) and non-parametric models like Artificial Neural Networks (ANN) are "statistically faithful" to the type of time series and adequately represent water temperature variability. Non-parametric models differ from parametric models in that the model structure is not specified a priori, but is instead determined from data. (Loubna Benyahya et. al. 2007)

In the present study, climatic data near Jaitapur situated in the west coast of India, where a NPP is proposed, is analyzed and its relationship with sea surface temperature has been correlated using ANN. The relationship of warm water discharge and saturated dissolved oxygen concentration is discussed. It is observed that even if the regulatory standards are met, the

dissolved oxygen concentration may reach at critical level due to high ambient temperature and climatic factors.

#### **METHODOLOGY**

Fry and Watt (1955) did a study of the effects of weather on the bass populations in South Bay and neighbouring waters in Manitoulin Island. These workers show that, for each month from June to October, there is a linear relation between the thermal sum for the surface waters and the monthly mean of the air temperatures. They also show that there is a linear relation between the year class strength of the bass in South Bay and the year to year deviations from the monthly mean air temperatures, when these deviations are summed over the period from June to October.

However, the assumption that the water-air temperature relationship is linear has been questioned. Indeed, Mohseni et al. (1998) also observed a non-linear behaviour between air and water temperatures at weekly intervals. Accordingly, these authors developed a model based on the logistic S-shaped function to predict average weekly stream temperatures at different locations in the United States. The logistic function used by Mohseni et al. (1998) to determine the air to water relation is given by

$$T_w = \alpha / 1 [e^Y(\beta - T_a)] \quad (1)$$

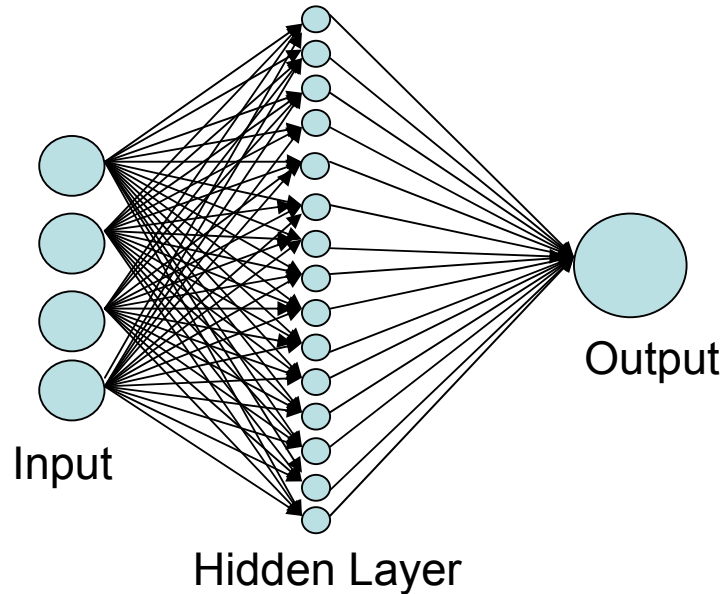
where  $T_w$  and  $T_a$  represent water and air temperatures,  
 $\alpha$  is a coefficient which estimates the highest water temperature,  
 $\beta$  is the air temperature at the inflexion point  
 $Y$  represents the steepest slope of the logistic function.

The advantage of this model over the linear regression is that it can better represent the tendency of water temperature in some water bodies to level off at higher air temperatures (Mohseni and Stefan, 1999).

Considering the non-linear relationship between air temperature and water temperature and also the fact that water temperature is not solely dependent on air temperature ANN models are gaining more importance. In the field of hydrology, ANN modelling has been used for a variety of purposes, particularly in water quality applications, Riskey et al. (2003) estimated water temperatures in small streams in western Oregon using an ANN model. More recently, Belanger et al. (2005) compared two models of water temperature: artificial neural networks and multiple linear regression using air temperature and discharge as independent variables. Of these two models, results indicated that both approaches were equally good in predicting daily stream water temperature with Root mean square of error (RMSE) of 1.06 °C for the regression model and 1.15 °C for the ANN model.

An Artificial Neural Network (ANN) model is a mathematical structure capable of describing complex nonlinear relations between input and output data. The architecture of ANN model is inspired by biological nervous systems. As in nature, independent variables (or predictors) are fed as inputs in the input layer through nodes used during neural network training. The hidden layer, represented by the middle circles in Fig. 2, is the location where the neural network is "trained," i.e., all outputs from the input layer are fed to each node, and weights are assigned to non-linear functions that combine the inputs (Ahmadi-Nedushan et al., 2007a). The network connection weights are adjusted in order to minimize the error between the ANN outputs and the training set

of the variable to be modelled. The weights of each node in the layers need to be adjusted. This can be done using several learning algorithms. One of the most popular learning algorithms is back propagation. In back propagation, a gradient descent is implemented to ensure that the direction of learning and rate of learning is appropriate.



**Fig. 2 Network Diagram for Artificial Neural Network**

In this paper an Artificial Neural Network model was used for prediction of sea surface temperature variation at Jaitapur. Past 30 years data available from Indian Meteorological Department of India for dry bulb temperature, wet bulb temperature, wind speed, sea surface pressure and sea surface temperature were analyzed. As these data are collected by various ship navigating in the Arabian Sea they are non continuous in nature. Apart from this meteorological data which is collected at Ratnagiri station which is situated about 20 Km from Jaitapur has also been used.

To determine if there is any relation between the data of sea surface temperature and the climatic variables observed at Ratnagiri station correlation analysis was done using monthly average data. While for predicting daily temperature a model based on ANN was made which used air temperature, previous available sea surface temperature and air pressure in hectopascal. To account for non-continuous data another variable  $d$  was given as input which indicated gap in data in no. of days.

## **RESULTS AND DISCUSSION**

Air and water temperature correlations of varying degrees of sophistication have been employed by Gameson et al. (1957 and 1959) in England, Miyake and Takeuchi (1951) in Japan, Dingman

(1972) in the U.S. and Cluis (1972) in Canada.

Based on the correlation coefficient analysis, it was found that there was maximum correlation of 0.73 between the monthly average air temperature observed at Ratnagiri meteorological station and monthly average sea surface temperature at Jaitapur site as indicated in Fig.3. This correlation was better when compared with the correlation coefficient of air temperature observed by the ship and sea surface temperature ( $r=0.68$ ). The autocorrelation of sea surface temperature was better with previous year SST ( $r=0.63$ ) compared to autocorrelation with previous month SST ( $r=0.52$ ).

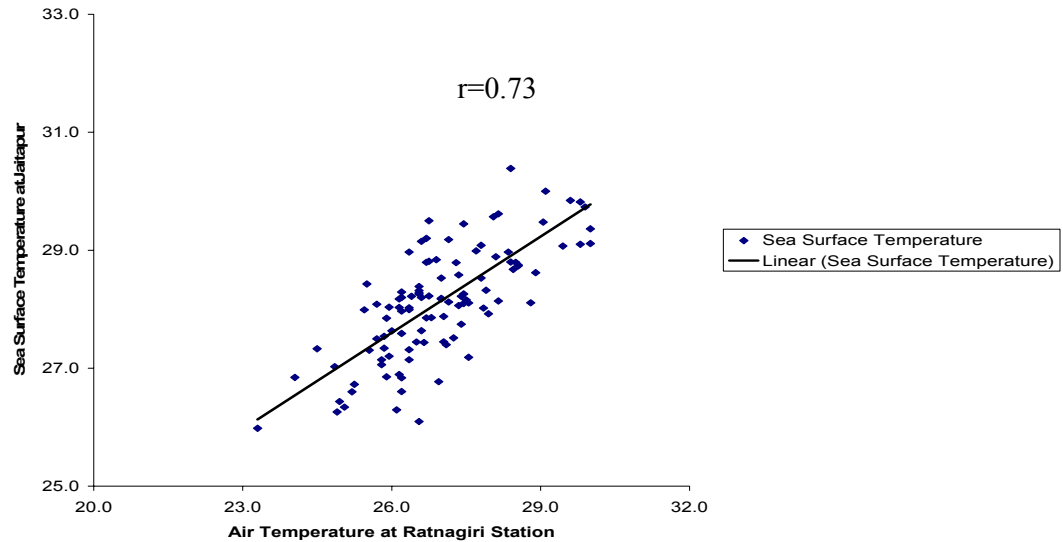


Fig. 3 Correlation between Air Temperature at Ratnagiri and SST

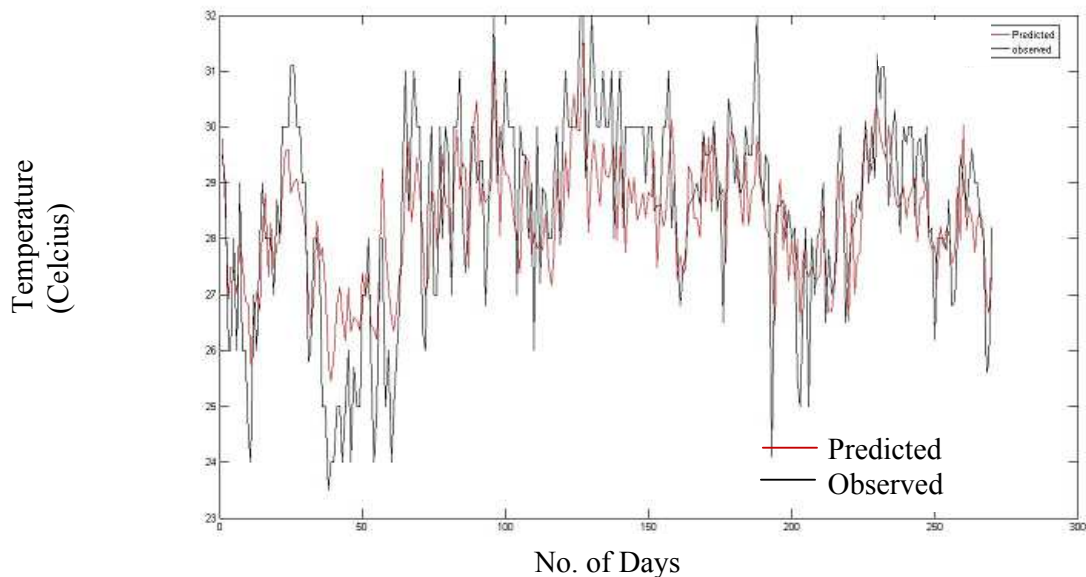
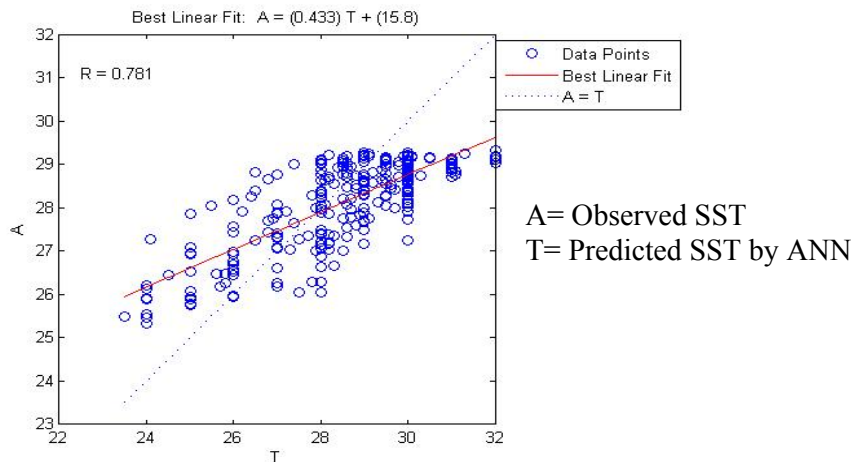


Fig. 4(a) Predicted and Observed SST using ANN

ANN model which is capable of describing complex nonlinear relations between input and output data is able to predict the sea surface temperature based on air temperature, previous SST and pressure observed by the ship. For training purpose data from 1989 to 1999 was used while validation was done using data from 2000-2005 (Fig. 4 (a)). The results obtained by the ANN model are considered as satisfactory as there is no continuous monitoring station to measure climatic variables at Jaitapur. A correlation of 0.781 was found between the predicted SST by ANN and observed SST (Fig. 4 (b))



**Fig 4(b) Correlation between Predicted and Observed data of SST**

Similarly, Conrads and Roehl (1999) have used ANN models to simulate salinity, temperature, and dissolved oxygen.

Based on the temperature and salinity observation carried out by NIOT in 2008-09, the impact of change in saturated dissolved oxygen level was analyzed using the following equation given in APHA(1992)

$$\ln O_{ss} = \ln O_{sf} - S(1.7674 \times 10^{-2} - 10.754/T_a + 2140.7/T_a^2) \quad (2)$$

where  $O_{ss}$  = saturated DO in Sea water

$o_{sf}$  = saturated DO in fresh water

S = Salinity (in ppt)

$T_a$  = air temperature

It is seen that in case the NPP is established at Jaitapur and if the rise in temperature is at  $7^{\circ}C$ , which is the maximum, as per the MoEF guidelines for warm water discharge. The fall in saturated DO level will be about 1mg/l. The lowest level of 5.5 mg/l will be observed in the month of May, June and November when the ambient water temperature is high. This decrease may result in reduced availability of DO for marine animals causing significant impact on them. Fig.5 shows expected annual decrease in saturated DO level due to setting up of NPP.

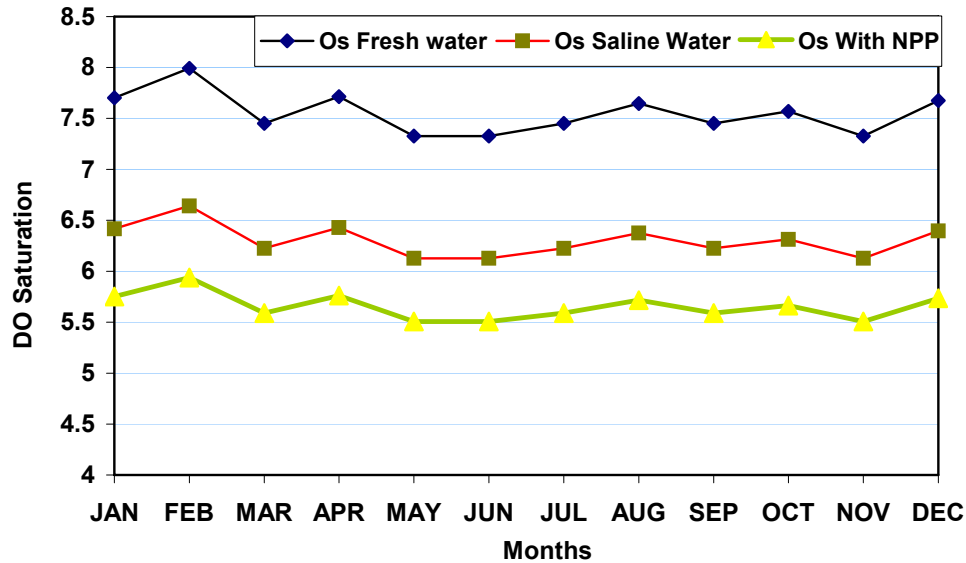


Fig 5 Predicted Impact of NPP on Saturated DO level

## CONCLUSIONS

The following conclusion are drawn from the study

- (i) There is a significant correlation between average monthly air temperature and Sea surface temperature.
- (ii) ANN model can be used to predict SST using air temperature, previous SST and sea surface level pressure.
- (iii) Rise in temperature is likely to decrease saturated DO level upto 1 mg/l which may cause considerable impact on marine flora and fauna.

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## REFERENCES

22<sup>nd</sup> Annual Report, *Nuclear Power Corporation of India Ltd.* August 2009

Ahmadi-Nedushan, B., A. St-Hilaire, M. Berube, E. Robichaud, N. Thiemonge and B. Bobee. 2007a. "A Review of Statistical Methods for the Evaluation of Aquatic Habitat Suitability for Instream Flow Assessment." *River Research and Applications*, 22(5): 503-523.



- APHA 1992 Standard methods for the examination of water and Wastewater 18<sup>th</sup> Ed. Washington DC
- Belanger, M., N. El-Jabi, D. Caissie, F Ashkar and J.M. Ribí. 2005. "Estimation de la température de l'eau en rivière en utilisant les réseaux de neurones et la régression linéaire multiple." *Revue des sciences de l'Eau*, 18(3): 403-421.
- Cluis, D. A. (1972) Relationship between stream water temperature and ambient air temperature. *Nordic Hydrology* 3(2): pp. 65-71.
- Conrads, P.A. and E.A. Roehl. 1999. "Comparing Physics-Based and Neural Network Models for Simulating Salinity, Temperature, and Dissolved Oxygen in a Complex Tidally Affected River Basin." *In Proceedings of the 1999 South Carolina Environmental Conference*, Myrtle Beach, March 15-16, 1999: Columbia, South Carolina, Water Environmental Association of South Carolina.
- Dingman, S. L. (1972) Equilibrium temperatures of water surfaces as related to air temperature and solar radiation. *Water Resour. Res.* 8: pp. 4249.
- Fry, F. . Watt. (1955). Yields of year classes of the smallmouth bass hatched in the decade of 1940 in Manitoulin waters. *Trans. Amer. Fish. Soc.*, 86: 135-143.
- Gameson, A. L. H., Hall, H, and Preddy, W. S. (1957) Effects of heated discharges on the temperature of the Thames estuary. *Engineer, Lond.*, 204: pp. 3-12.
- Gu, R., S. McCutcheon and C.G. Chen. 1999. "Development of Weather Dependent Requirements for River Temperature Controls." *Environmental Management*, 24(4): 529-540.
- Hodgson, S. and T P. Quinn. 2002. "The Timing of Adult Sockeye Salmon Migration into Fresh Water: Adaptations by Populations to Prevailing Thermal Regimes." *Canadian Journal of Zoology*, 80: 542-555.
- Krause, C., T J. Newcomb and D. Orth. 2005. "Thermal Habitat Assessment of Alternative Flow Scenarios in a Tailwater Fishery." *River Research and Applications*, 21:581-593.
- Loubna Benyahya, Daniel Caissie, Andre St-Hilaire, Taha B.M.J. Ouarda, Bernard Bobee 2007, A review of statistical water temperature models *Canadian Water Resources Journal*, Fall, 2007
- Miyake, Y. & Takeuchi, U. (1951) On the temperatures of river waters of Japan. *Jap. J. Limnol.* 15, 145-151.
- Mohseni, O., H.G. Stefan and T.R. Erickson. 1998. "A Nonlinear Regression Model for Weekly Stream Temperatures." *Water Resources Research*, 34(10): 2685-2692.
- Mohseni, O. and H.G. Stefan. 1999. "Stream Temperature/Air Temperature Relationship: A Physical Interpretation." *Journal of Hydrology*, 218: 128-141.
- NIOT Report 2009, 'Coastal environmental studies at Jaitapur', March 2009.
- Risley, J.C., E.A. Roehl and PA. Conrads. 2003. "Estimating Water Temperatures in Small Streams in Western Oregon Using Neural Network Models." *U.S Geological Survey Report* 02-4218.