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Prediction of Sediment in The Mahanadi River Basin Using Machine Learning

Arti Kumari[1] , Jeetendra Singh Yadav[2]
[1]Mtech Scholar, CSE Department BHABHA University , Bhopal, India
[2] Prof. & HOD, CSE Department BHABHA University , Bhopal, India

Abstract – *This paper integration of Artificial Neural Networks (ANNs) with Genetic Algorithms (GAs) for predicting sediment load in river basins, such as the Mahanadi River Basin, presents a powerful hybrid modeling approach. ANNs are highly effective in capturing the complex and nonlinear relationships characteristic of sediment transport processes in river systems. However, determining the optimal architecture and parameters for ANNs can be a challenging task, which directly impacts the model's accuracy and reliability. To address this, the use of GAs provides a robust solution by optimizing the hyperparameters of the ANN, such as network architecture, learning rate, and the number of hidden layers and neurons. By simulating the process of natural selection, GAs explore the parameter space to find the best-performing configurations, thereby enhancing the learning and generalization capabilities of the ANN.*
This hybrid ANN-GA model not only reduces the likelihood of overfitting but also improves prediction accuracy and model stability compared to traditional methods and standalone ANNs. The results from this study highlight the effectiveness of the ANN-GA combination, which significantly improves the accuracy of sediment load predictions in river basins. This method offers valuable insights for water resource management and environmental planning by enabling more precise forecasting of sediment loads, facilitating better management of river systems like the Mahanadi Basin. The ANN-GA hybrid model, therefore, represents a promising advancement in sediment prediction, contributing to improved decision-making in environmental and hydrological management.
Keywords: Sediment load prediction, Artificial Neural Networks, Genetic Algorithms, hybrid model, river basin management, Mahanadi River Basin, environmental planning.

I. INTRODUCTION

The Mahanadi River basin, one of India's largest and most vital river systems, spans approximately 141,600 square kilometers across central and eastern India. Originating from the highlands of Chhattisgarh, the river meanders through the state of Odisha before ultimately discharging into the Bay of Bengal. Serving as an essential water source, the Mahanadi sustains the livelihoods of millions of people. It is a critical asset for agriculture, providing irrigation for staple crops like rice, as well as pulses and oilseeds, thereby playing a vital role in the region's food security. Beyond agriculture, the river supports a range of industries, hydroelectric power generation, and drinking water supplies, underlining its significance in both rural and urban settings.
Despite its importance, the Mahanadi River basin faces several environmental challenges, with sedimentation being among the most pressing. The basin experiences substantial rainfall during the monsoon season, resulting in large volumes of water and sediment entering the river system. This sediment load primarily stems from soil erosion in the river's extensive catchment area, exacerbated by deforestation, mining activities, and unsustainable agricultural practices. The accelerated sedimentation not only alters the river's morphology but also has far-reaching consequences for water management. It complicates flood control efforts, as the sediment reduces the river's capacity to carry floodwaters, increasing the risk of overflow and damage to surrounding communities. Additionally, sediment accumulation in reservoirs and irrigation channels necessitates frequent maintenance, leading to increased costs and operational challenges.
The Mahanadi River, India's fourth-largest river basin, spans an area of 141,589 km². It flows through Maharashtra, Jharkhand, Chhattisgarh, and Odisha, with its catchment area divided as 53% (75,136 km²) in Chhattisgarh and 46% (65,580 km²) in Odisha, while the remainder is in Maharashtra and Jharkhand. The river extends 851 km to the Bay of Bengal. In 2005–2006, land use in the basin was predominantly agricultural (54.27%), followed by forest cover (32.74%), wasteland (5.24%), water bodies (4.45%), and built-up land (3.30%). The elevation ranges from 30 to 700 meters above sea level. The basin features significant water bodies like the Hirakud Dam, the world's largest earthen dam, and Chilka Lake. Gauge heights in the basin vary from 50 to 411 meters.
The average annual rainfall from 1971 to 2004 ranged between 1200 and 1400 mm, with 90% occurring during the monsoon season (June to October). Temperature extremes are 12°C in December and January and 39°C to 40°C in April and May. The upstream region of the basin primarily consists of Proterozoic sedimentary rocks, while the downstream areas are characterized by metamorphic silicate rocks. The basin's lithological composition includes 34% granite, 7% Khondalite, 15%

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charnockite, 17% limestone, 22% sandstone and shale, and 5% coastal alluvium.

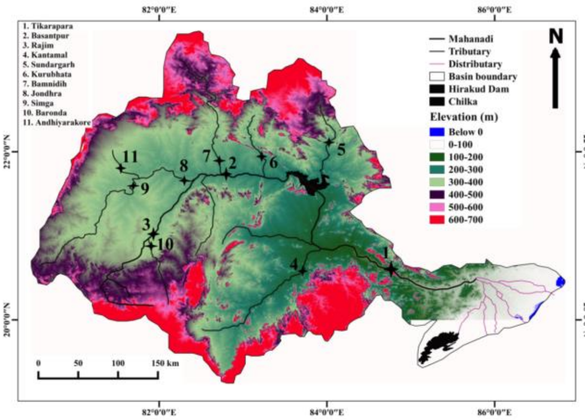

Figure 1 Mahanadi River

II. Impacts of Sedimentation

The impacts of sedimentation in the Mahanadi River basin are profound, spanning environmental, economic, and social spheres. Economically, the increased sediment load in the river necessitates frequent and costly dredging operations to maintain navigability and the efficiency of hydraulic infrastructure, such as dams and irrigation systems. These maintenance activities divert significant financial resources that could otherwise be invested in development projects. Moreover, sedimentation can lead to the inundation of fertile agricultural land, resulting in waterlogging that reduces soil fertility and crop yields, further diminishing the economic viability of farming in affected areas. The loss of arable land and reduced agricultural productivity contribute to food insecurity and can lead to increased poverty among farming communities.

Environmentally, sedimentation disrupts the natural flow of the Mahanadi River, altering its geomorphology and leading to the degradation of aquatic habitats. The excessive buildup of sediment can cause the river to change course or create new channels, destabilizing riverbanks and increasing erosion rates. This erosion further exacerbates sedimentation, creating a feedback loop that intensifies the problem. The altered flow regime can also reduce the river's ability to flush out pollutants, leading to a decline in water quality that harms fish populations and other aquatic life. The degradation of aquatic ecosystems not only threatens biodiversity but also diminishes the ecosystem services that these habitats provide, such as water purification, flood regulation, and support for local fisheries.

Socially, the impacts of sedimentation are deeply felt by the communities that rely on the Mahanadi River for their livelihoods. Farmers face declining agricultural productivity due to waterlogging and reduced soil fertility, which can lead to lower incomes and increased vulnerability to economic shocks. Fishing communities, too, suffer as the degradation of aquatic ecosystems reduces fish populations, threatening their primary source of income and food security. Additionally, the increased flood risks associated with sedimentation pose a significant threat to riverside communities, as the reduced capacity of the river to carry floodwaters heightens the likelihood of devastating floods. These floods can destroy homes, displace families, and cause loss of life, further exacerbating the social and economic challenges faced by these communities..

III. Method

Artificial Neural Networks (ANNs) are a prominent artificial intelligence technique that belongs to the class of nonlinear statistical models. ANNs are particularly powerful due to their ability to learn complex nonlinear relationships between variables based on observed data. The primary goal of ANN is to develop learning techniques through pattern recognition, allowing the model to learn from data and make accurate predictions (Bhattacharya et al., 2003). ANNs are capable of modeling any complex nonlinear process, such as the relationship between suspended sediment yield and continuous hydro-meteorological data (Wang and Traore, 2009).

The main objective of this study is to evaluate the effectiveness of ANNs in estimating suspended sediment yield in the Mahanadi River. The model utilizes both temporal data (such as rainfall, temperature, and water discharge) and spatial data (including rock type, relief, and catchment area) as inputs. ANNs are recognized as versatile models because they adapt their learning processes by analyzing correlations between input and output datasets, thereby producing accurate and desirable results. The ANN is a flexible mathematical structure having strong similarity to the biological brain (Haghizade et al. 2010). It works on the basis of concept of biological brain and its associated nervous system (Haghizade et al. 2010). The ANN has capability for identifying the complex non-linear or linear relationship between inputs and outputs data through proper learning without detail knowledge of the character of the internal structure of the physical processes. In the last two decades, ANN based models have seen increasing popularity for simulation of hydrological process (Singh and Panda 2011). The ANN has the capability for tackling the simulation of hydrological processes with high speed and accuracy.

There are some ANN such as a general regression neural network (GRNN) and back- propagation network (BPN) (Karayiannis and Venetsanopoulos, 1993); among them BPN is most often used since it is computationally efficient for the training of the multi-layer perception (MLP). Monthly rainfall, temperature, water discharge and suspended sediment data were collected from eleven gauging stations of the Mahanadi river during 1990-2010 for the development of the robust ANN model. The

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descriptive statistical analysis of hydro- climatic data such as rainfall, temperature, water discharge and suspended sediment yield for the Mahanadi river basin is given.

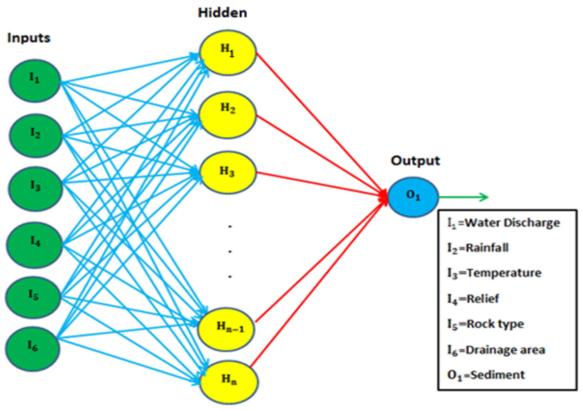

Figure 2. The architecture of MLP Artificial neural network.

The multi-layer perceptron (MLP) is a feed-forward artificial neural network that contains input layer, hidden layer and output layer. Each layer contains the specific number of neurons with activation function. The number of neurons of the input layer and output layer must be same as the input and target parameters. The number of the neurons in the hidden layer is determined by error statistics of the neural network. Theoretical works have shown that a single hidden layer is sufficient for the ANNs to approximate to any complex nonlinear function (Cybenko 1989; Hornik et al. 1989). Single hidden layer is used to avoid increasing in the complexity of the network (Tang et al. 1991).
Each network was trained under several structures with different number of neurons in the hidden layer. Neurons of one layer are connected to another layer through weighted interconnected links and these weights contain extremely important information in ANN. In MLP, each neuron in a layer maps the sum of weighted input into an activation level which is determined by the activation function. The activation function should monotonically increase and differentiable. The tan-sigmoid function at the hidden layer and the pure linear transfer function at the output layer were used in feed-forward back-propagation neural network models in this study to obtain the optimized structure (Boukhrissa et al. 2014, Yadav et al.
2017). The combinations of these transfer functions was provided least error and best accuracy for estimation of suspended sediment yield..The schematic diagram of MLP artificial neural network model for suspended sediment yield prediction is presented in Figure
4.1. In this figure, I represent the inputs neurons, H represents the hidden neurons and O represents the output neurons. Blue color represents the connection weight between the inputs layer and hidden layer. Red color represents the connection weight between the hidden layer and output layer. Six input layers were used in the ANN models to understand the effect of these input parameters jointly on suspended sediment yield. Spatial inputs variables such as rock type, relief and catchment area are fixed for each gauging stations and not changed over unlike other temporal variables (water discharge, rainfall, temperature and suspended sediment yield). The value of rock type was mapped within 0 and 1. If any gauge station has very hard rock with lowest weatherability, the rock type value is considered as zero. If rock type is soft like clay, limestone etc. which easily decomposed and weathered, the rock type value was used as 1. Similarly, the relief, and catchment area value are mapped between the 0 and 1. The higest relief in the gauge station within the river basin is considered as 1, and the lowest relief values in the gauge station is consideres as 0, and the in between values are linearly interpolated within 0 and 1. The cattchment area was also coded similart to releif to get values within 0 and 1. These data are also used for all prediction and forecasting models.

4.1.2. Neural Network training

To train the neural network models, feed-forward back-propagation training algorithms were used in this study by Levenberg Marquardt (FFBP-LM) algorithm (Pramanik and Panda 2009). The training of multilayer perceptron feed forward neural network with Levenberg Marquardt algorithm (LM) is more capable than the other types of ANN such as gradient descent and radial basis function (RBF) in terms of performance (Kisi 2004a; Kisi 2008; Sahoo and Jha 2013). The FFBP-LM algorithm is used for developing the robust MLP neural network model due to its fast response. Thus, it is preferably a first choice for supervised algorithm although it requires more memory (Adeloye and Munari 2006). The weights were initialized randomly with constant seed value to control the training of the neural network and regenerate the same initial weights later if required. The neurons parameter of the network
were changed to understand the effect of input parameters on suspended sediment yield estimation. The weights of neural network are updated by FFBP-LM method. The weight update rule of FFBP-LM optimization algorithm is derived by steepest descent and Newton's
where J is Jacobian matrix, I is identity matrix, e is error matrix, W is weight of neural network and μ is non-negative scalar value i.e. combination coefficient that affects the learning process of FFBP-LM in artificial neural network. When μ = 0, FFBP-LM algorithm is responding as Newton's method; whereas, if μ is large, it becomes gradient descent method with a small step size (Pramanik and Panda 2009). Therefore, the selection of parameter μ is a crucial task in LM method. The optimum hidden neurons and μ were.

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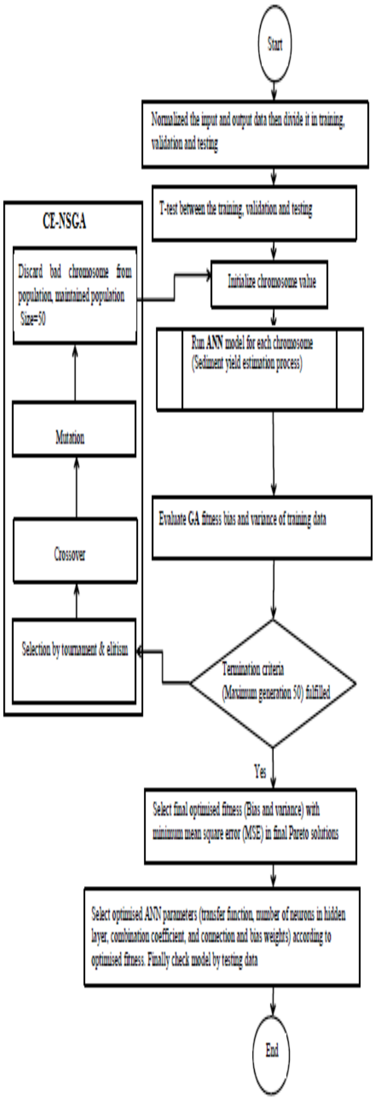

Figure 3. Schematic diagram of proposed Neuro multi objective genetic algorithm based model for automatic process parameter selection.

IV. RESULT

Variation in monthly average water discharge (cumec), rainfall (mm), temperature (°C), and suspended sediment yield (tons/month) data over the period of 20 years (1990-2010) for all gauge stations except the Kantamal, which is having availability of data from 1990-2008, are shown in Figure 5.1 in the Mahanadi basin. The mean monthly suspended sediment yield in the basin varied from 39010 tons/month (Andhiyarakore) to 1078384 tons/month (Tikarapara). The variation in mean monthly water discharge ranged from 339.36 cummec at upstream gauge station (Andhiyarakore) to 49009.91 cummec at downstream gauge station (Tikarapara) in basin. The mean monthly rainfall in the basin varied from 82.14 cm (Andhiyarakore) to 129.0 cm (Tikarapara). The variation in mean monthly temperature ranged from 28.04 (Andhiyarakore) to 28.43°C (Tikarapara). Thus the water discharge and suspended sediment yield of Mahanadi river show wide fluctuations; whereas temperature and rainfall do not show much variation among different gauge stations in the basin.

Commonly, there is a good linear relationship between suspended sediment yield and water discharge (Wood 1977; Mossa 1990; Gupta and Chakarpani 2005; Yadav et al. 2017). However, suspended sediment yield is also controlled by relief, lithology, anthropogenic activities and catchment area (Gupta and Chakarpani 2005; Zhu et al. 2007; Bastia and Equeenuddin 2016). Thus, it is observed that the suspended sediment yield behavior is not similar to that of water discharge at some stations. For example, the disproportional behavior between suspended sediment yield and water discharge is found at Sundargarh and Bamnidih. Relatively higher suspended sediment yield is found at Sundergarh than Bamnidih while water discharge is less at Sundargarh. Similar, disproportional behaviour is found at Sundargarh-Sigma, Kantamal-Basantpur, Sundargarh-Rajim, Kurubhata-Bamnidih, Rajim- Bamnidih and Kurubhata-Rajim. It is due to fact that that water discharge and suspended sediment yield do not hold a functional relationship. The suspended sediment yield is directly controlled by the supply of loose material than the capacity of flow to transport the material (Nordin 1985; Subramanian 1993). Further, Tikarapara station, which is located at extreme downstream part of Mahanadi river basin, has the highest water discharge, rainfall, catchment area and suspended sediment yield, whereas Andhiyakore station which is located at upstream part of the basin has the lowest suspended sediment yield.

The distributions of water discharge at different locations are shown in the Figure 5. Tributaries of the Mahanadi river showed a greater variation in water discharge, and ranged from as low as 4.055 km3/year in the Hamp upstream tributary at Andhiyakore to as high as
588.1 km3/year at the Tikarapara. The main stream stations like Tikarapara (588119 cummec), Basantpur (248384 cummec) and major tributaries like the Seonath at Jhondhra (97569.83 cummec) and the Tel at Kantamal (145137 cummec) showed a relatively larger values of water discharge. The Baronda (18122 cummec), Simga (58392 cummec), the Mand at Kurubhata (27593 cummec), the Ib at Sundargarh (38978.4 cummec), Rajim (36556.1 cummec) and Bamnidih (48781 cummec) showed relatively lower values of water discharge.

Mahanadi river shows a significant downstream increase in mean annual water discharge due to confluence of numerous tributaries towards downstream. As a peninsular river, the majority of the water flows in the Mahanadi basin is contributed by rainfall since there is no contribution from either snowfall or snowmelt or major water springs. The water discharge in the basin shows a larger seasonal fluctuation as it is fed from monthly rainfall, and which is controlled by strongly monsoon. The maximum monthly water discharge of 430767 cummec was found on July 1994 which was the highest average monthly water flow in the basin over the period of 20 years (1990–2010). The lowest monthly water discharge at Andhiyarakore was zero cummec occurred on May 2010.

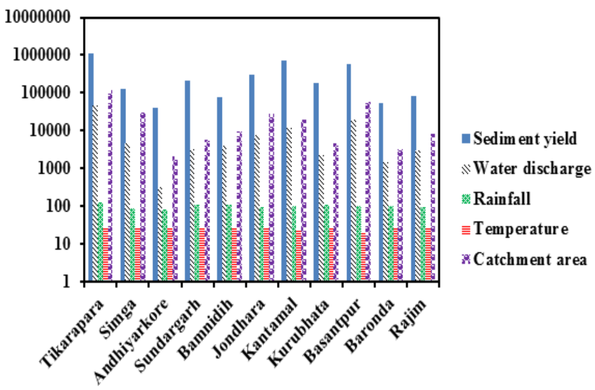

Figure 4. Spatial variation in monthly average water discharge (cumec), rainfall (mm), temperature (°C), catchment area (sq.km) and suspended sediment yield (tons/month).

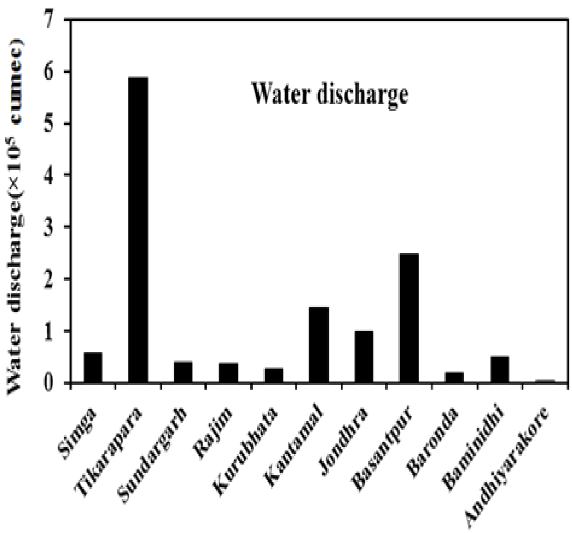

Figure 5. Average annual water discharge variation at different stations of Mahanadi river basin.

The spatial distribution of rainfall in the Mahanadi basin is shown in the Figure 5. Rainfall in the basin is a major source of water to the river. Hence it is regarded as the major controlling factor for water discharge. The monsoon is the main contributor to the annual rainfall. The lowest and highest averages annual rainfall took place in the basin were 982 mm at Andhiyarakore and 1549 mm at Tikarapara, respectively during 1990-2010. Maximum annual average rainfall of 2456 mm/year during June 2001 to May 2002 over the period of 20 years (1990-2010) was recorded at Tikarapara. Maximum monthly average rainfall of 939 mm at Tikarapara station is found in July 2001. Panda et al. (2011) demonstrated that the annual average rainfall in the Mahanadi basin is higher as compare to most of tropical Indian River basins. Among all gauging stations, the Tikarapara (1549 mm) showed maximum annual average rainfall followed by Kurubhata (1388 mm), Sundargarh (1378 mm), Bamnidih (1356 mm), Basantpur (1270 mm), Baronda (1239 mm), Kantamal (1210 mm), Jhondhra (1188 mm), Rajim (1163 mm), Simga (1091 mm) and Andhiarakhore (981 mm) gauging stations. Panda et al. (2013) is also found similar spatial and temporal variation in rainfall distribution. The distribution of rainfall was uneven in the Mahanadi river basin (Jin et al. 2018).

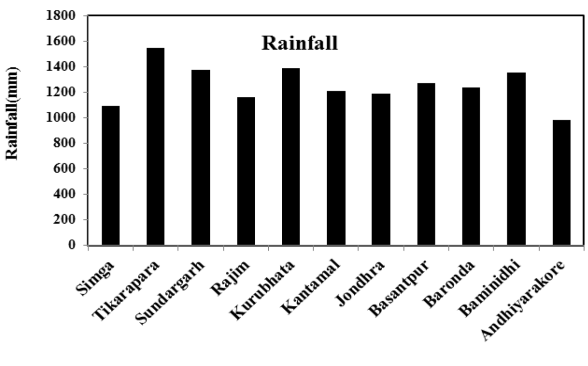

Figure 6. Average annual rainfall variation at different stations of Mahanadi river basin.

Variation in annual average temperature at different locations of Mahanadi basin is shown in Figure 6. Annual average temperature ranged from as low as 20°C at Basantpur to as high as 29.5°C at Bamnidih in the basin. December or January is the coldest month whereas April or May is the hottest month in this region. Maximum mean monthly temperature in the basin is found to be 39.5 at Kantamal in May, 2005. Minimum mean monthly temperature is 14 °C at Sundargarh which is found in January 2010. Western portion of the Mahanadi basin achieves the lowest and highest temperature as compared to eastern portion and delta area during winter and summer season respectively (Water year book 1997; Bastia and Equeenuddin 2016). Temperature has indirect effect on rainfall distribution (Loo et al. 2015).

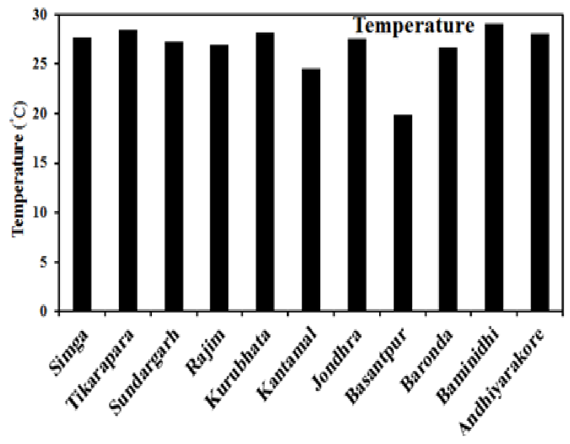

Figure 7 Average annual temperature variation at different stations of Mahanadi river basin.

Annual average suspended sediment yield varied from 458364 to 12940610 tons/year, on the basis of 20 years (1990-2010) data at different locations in the Mahanadi basin are shown in Figure 7. The mean annual suspended sediment yield values at main stream stations like Tikarapara (12940610 tons/month), Basantpur (7021931 tons/month) and major tributaries like the Seonath (3522111 tons/month), the Mand (2000069 tons/month), the Ib (2523751 tons/month), the Tel (8302742 tons/month) showed a relatively higher values of suspended sediment yield. The Baronda (604508 tons/month), Simga (1537833 tons/month), Rajim (918665 tons/month) and Bamnidih (919019 tons/month) showed relatively lower values of suspended sediment yield. The annual suspended sediment yield at Tikarapara varied from 2170793 tons/year (2002–2003) to 50265601 tons/year (1994–1995). Monthly maximum suspended sediment yield was 17346901 tons/month at Tikarapara in July 1994. The lowest annual average suspended sediment yield (458364 tons/year) was found at the Andhiyarakhore. The annual suspended sediment yield at Andhiyarakore varied in the range 20796 tons/year (2009–2010) to 1764906 tons/year (1994–1995). Monthly maximum suspended sediment yield is 711518 tons/month at Andhiyarakore on October in 1994. Higher suspended sediment yield occurs during the monsoon period corresponding to the higher rainfall.

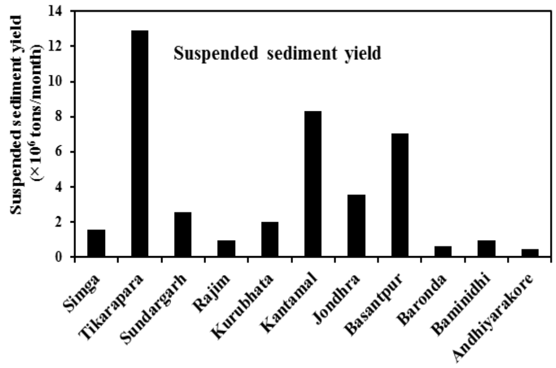

Figure 8. Average annual suspended sediment yield variation at different stations of
Mahanadi river basin.

Variations in rainfall, water discharge, temperature and suspended sediment yield in percentage during monsoon (June–October) and non-monsoon (November–May) period, averaged over twenty years (1990–2010) at different locations along upstream, midstream and downstream in the Mahanadi basin are. It is observed that high rainfall, water discharge, temperature and suspended sediment yield are found in monsoon season. The Tikarapara gauge station has shown the highest suspended sediment yield of non-monsoon season amongst all gauging station. Highest water discharge for non-monsoon season is found at the Bamnidih gauging station as comparative other stations. It may be due to large Minimata Bango dam nearest to this station which releases the stored dam water in non-monsoon season for irrigation, drinking, hydropower generation etc. Similarly results of second highest water discharge in non-monsoon season for Tikarapara station also may be due to the released the stored Hirakud dam water in this season. Tikarapara station has highest rainfall during non-monsoon season as comparative other gauging station which caused high suspended sediment yield in non-monsoon seasons. Bamnidih station has shown highest water discharge, but it has not highest suspended sediment yield during non-monsoon season, it may be due to sediment settled down and trapped in the Bango dam dam. The suspended sediment yield at Tikarapara gauge station has shown the highest suspended sediment yield and second highest water discharge in non- monsoon season among all gauging stations it might be due to the supply of sediment by two major tributaries namely Ong and Tel. The monsoon rains varies in the basin varies from

83.63% (Tikarapara) to 93.19% (Baronda) (Figure 4.6). Rainfall has been widely understood to have a predominant influence on water discharge and sediment discharge. A major portion of the rainfall takes place during the southwest monsoon in Mahanadi river basin.

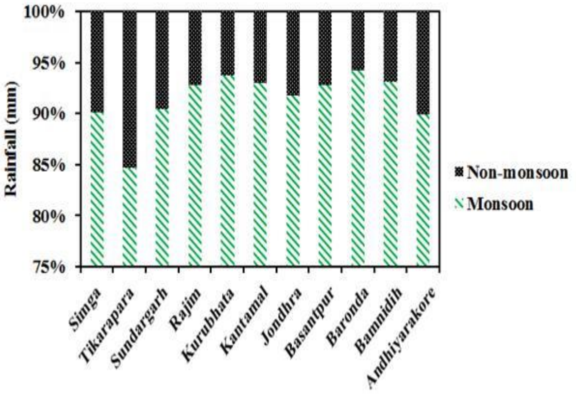

Figure 9. Mean annual monsoon and non-monsoon rainfall with logarithm scale at different stations of Mahanadi river basin.

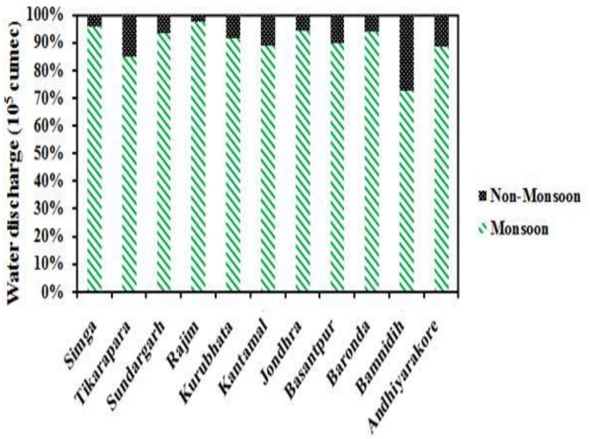

Figure 10. Mean annual monsoon and non-monsoon water discharge at different stations of
Mahanadi river basin.

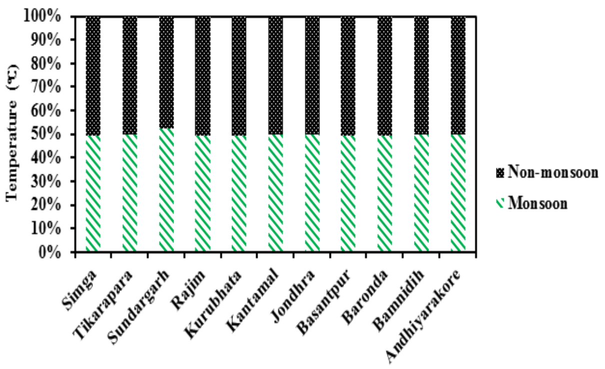

Figure 11. Mean annual monsoon and non-monsoon temperature at different stations of
Mahanadi river basin

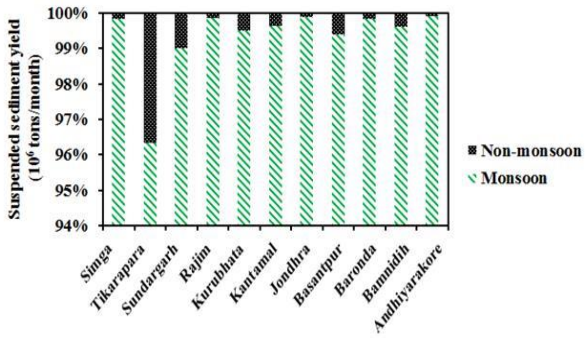

Figure 12 Mean annual monsoon and non-monsoon variation of suspended sediment yield.

Water discharge during the monsoon varies from as low as 72.95% at Bamnidih) to as high as 95.85% at Simga of total annual flow at different locations in the basin (Figure 9). The monsoon season accounts for most of the annual water flow; however, there is also considerable flow in some locations during non-monsoon. This could be due to additions from groundwater to the river during non-monsoon periods (Central Ground Water Board 2006; Jha and Sinha 2009). Similar observations have been made for other rivers in India, such as Ganga, Brahmaputra, Krishna, Cauvery, Narmada and Godavari (Biksham 1985; Biksham and Subramanian 1988; Subramanian 1993; Gupta and Chakrapani 2005, 2007). Most of the water flow in the river is during the monsoon season, except in some tributaries, where groundwater flow to the river during non-monsoon is significant (Chakrapani and Subramanian 1990; Gupta and Chakrapani 2007). Suspended sediment yield during the monsoons varies from 96.32% (Tikarapara) to 99.93% (Andhiyarakhore) among all gauging stations (Figure 5.9). Similar observation are noticed for other rivers in India such as the Godavari (Biksham and Subramanian 1988), Krishna (Ramesh and Subramanian, 1988), Cauvery (Vaithiyanathan et al., 1988), Narmada River basin (Gupta and Chakrapani 2005, 2007) and Brahmaputra (Goswami, 1985). It is also observed from the Figure that the water discharge, rainfall and suspended sediment yield in Mahanadi river show greater spatialy variation in monsoon and non-monsoon seasons; whereas temperature has not shown much variation among different locations in the basin.

V. CONCLUSION

This paper show application of Artificial Neural Networks (ANNs) combined with Genetic Algorithms

(GAs) for predicting sediment load in river basins, such as the Mahanadi River Basin, demonstrates significant potential in enhancing the accuracy and reliability of sediment prediction models. ANNs are well-suited for capturing the complex, nonlinear relationships inherent in environmental data, making them an effective tool for modeling sediment transport processes. However, the performance of ANNs heavily depends on the optimal selection of network architecture and training parameters, which can be challenging and time-consuming.

The integration of Genetic Algorithms (GAs) addresses this challenge by providing a robust optimization technique for tuning the hyperparameters of the ANN, including the selection of network architecture, learning rate, and the number of hidden layers and neurons. GAs mimic the process of natural selection to efficiently search the parameter space and identify the best-performing configurations for the ANN. This combination of ANNs and GAs results in a model that not only learns the underlying patterns in the data more effectively but also generalizes better to unseen data, thereby improving its predictive capabilities.

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