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Applying Neuro-Fuzzy Architecture in Swmm Model for Best Management Practices

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Abstract

Hydrologists are often confronted with problems of prediction and estimation of runoff, rainfall, contaminant concentrations, water stages, and so on. Moreover, engineers are often faced with real situations where little or no information is available. The processes and relationship between rainfall and surface runoff transport for a catchment area require good understanding, as a necessary pre-requisite for preparing satisfactory drainage and storm water management projects. In the hydrological cycle, the rainfall occurs and reaching the ground may collect to form surface runoff or it may infiltrate into the ground. The surface runoff and groundwater flow join together in surface streams and rivers which finally flow into the ocean. Urban drainage systems have changed from primitive ditches to complex networks of curbs, gutters, surface and underground conduits (links). Along with the increasing complexity of these systems has come the need for more thorough understanding of the basic hydrologic and hydraulics processes along with spatial and temporal information of catchment in order to combine them in a computer model to yield outputs at points of interest in time and space. The Environmental Protection Agency (EPA) Storm Water Management Model (SWMM) is chosen for this study to simulate all the hydrologic and hydraulics elements involved in the phenomenon of urban drainage.

The feasibility of using fuzzy logic based neuro-fuzzy model to directly predict the most sensitive parameters used in the model to simulate a hydrograph that matches the observed hydrograph was done. A fuzzy logic is usually defined as a rule base of a large number of processors.

Keyword- *Surface runoff, Drainage system, Hydrologic and Hydraulics elements.*

I. INTRODUCTION

Water in urban areas; and urban storm drainage [21] as a part of the urban infrastructure, are topics which are gaining in importance in recent years. Cities now house 50% of the world population, consume 75% of its resources, yet occupy only 2% of the land surface. By the middle of the next century, it is confidently predicted that 70% of the global population will live in urban areas [2,26]. The number of megacities (> 10 million inhabitants) will increase to over 20, 80% of which are in developing countries.Properly designed and operated urban drainage systems with its interactions with other urban water systems are crucial element of healthy and safe urban environment. The concept of sustainable development is provoking a profound rethinking in our approach to urban water management [7,12,14,27,28] Sustainable development is that which "meets the needs and aspirations of the present generation without compromising the ability of future generations to meet their own needs So, sustainable solutions have a "now" and a "then" component, and improvements though necessary in the present must not be carried out at the expense of future needs and situations.

SWMM was first developed between 1969-1971 and has undergone several major upgrades since then. The major upgrades were: (1) Version 2 in 1975, (2) Version 3 in 1981 and (3) Version 4 in 1988. The current SWMM edition, Version 5(14,27,28), is a complete re-write of the previous FORTRAN release in the programming language C, and it can be run under Windows XP, Windows Vista and Windows 7.

The EPA SWMM [7,12] is one of several advanced computer assisted model designed to simulate urban storm water runoff. The SWMM is capable of predicting and routing the quantity and quality constitute of urban storm water runoff [9,13,21]. The model consists of four functional program blocks, plus a coordinating executive block. The blocks can be overlaid and run sequentially or can be run separately with interfacing data file. The choice of the mode depends on the user needs. The first of the functional blocks, the runoff block, simulated continuous runoff hydrographs and pollutograph for each sub catchment in the drainage basin. Runoff hydrographs are predicting based on an input hyetrograph [15,29] and the physical characteristics of the sub catchment; including area, average slope, degree of imperviousness, overland flow resistance factor, surface storage and overland flow distance.

Neural networks (NNs) [16] are demonstrated to have powerful capability of expressing relationship between input–output variables. In fact it is always possible to develop a structure that approximates a function with a given precision. In ANFIS, input may be multiple but the respective output is only the results of all the inputs i.e. one. However, there is still distrust about NNs identification capability in some applications. Fuzzy set theory plays an important role in dealing with uncertainty in plant modeling applications. Neuro-fuzzy systems are fuzzy systems, which use NNs to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy integrates to synthesize the merits of both NN and fuzzy systems in a complementary way to overcome their disadvantages.

II. STORM WATER MANAGEMENT MODEL (SWMM 5.0)

The latest SWMM used [13,21], integrating with full US EPA SWMM 5.0 engine, SWMM is a decision support system for a storm water management modeling SWMM. Providing a large array of the file management, data file creation, output interpretation, and reference tool for storm water modeler.

SWMM accounts for various hydrologic processes that produce runoff from urban areas. These include:

- Time-varying rainfall
- Evaporation of standing surface water
- Snow accumulation and melting
- Rainfall interception from depression storage
- Infiltration of rainfall into unsaturated soil layers
- Percolation of infiltrated water into groundwater layers
- Interflow between groundwater and the drainage system
- Nonlinear reservoir routing of overland flow

Spatial variability in all of these processes is achieved by dividing a study area into a collection of smaller, homogeneous sub catchment areas, each containing its own fraction of pervious and impervious sub-areas. Overland flow can be routed between sub-areas, between sub catchments, or between entry points of a drainage system.

III. NEURO FUZZY

3.1 Adaptive Neuro-Fuzzy inference system (ANFIS) architecture:

Neural networks (NNs) are demonstrated to have powerful capability of expressing relationship between input–output variables. In fact it is always possible to develop a structure that approximates a function with a given precision. In ANFIS, input may be multiple but the respective output is only the results of all the inputs i.e. one. However, there is still distrust about NNs identification capability in some applications. Fuzzy set theory plays an important role in dealing with uncertainty in plant modeling applications. Neuro-fuzzy systems are fuzzy systems, which use NNs to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy integrates to synthesize the merits of both NN and fuzzy systems in a complementary way to overcome their disadvantages. The fusion of an NN and fuzzy logic in neuro-fuzzy models possess both low-level learning and computational power of NNs and advantages of high-level human like thinking of fuzzy systems. For identification, hybrid neuro-fuzzy system called ANFIS combines a NN and a fuzzy system together. ANFIS has been proved to have significant results in modeling nonlinear functions. In ANFIS, the membership functions (MF) are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to given error criterion. In a fused architecture, NN learning algorithms are used to determine the parameters of fuzzy inference system. Below, we have summarized the advantages of the ANFIS technique.

- Real-time processing of instantaneous system input and output data's. This property helps using of this technique for many operational researches problems.
- Offline adaptation instead of online system-error minimization, thus easier to manage and no iterative algorithms are involved.
- System performance is not limited by the order of the function since it is not represented in polynomial format.
- Fast learning time.
- System performance tuning is flexible as the number of membership functions and training epochs can be altered easily.

The simple if–then rules declaration and the ANFIS structure are easy to understand and implement.

3.2 Type and number of membership functions:

The MF (type and number) assigned to each input variable is chosen empirically i.e. by examining the desired input-output data and/or by trial and error. Four input variables i.e. temperature, wind speed, wind direction and total vehicle count have been used as inputs in the neuro-fuzzy model formulation for the present study. Different membership functions have been used for training Neuro-Fuzzy model.

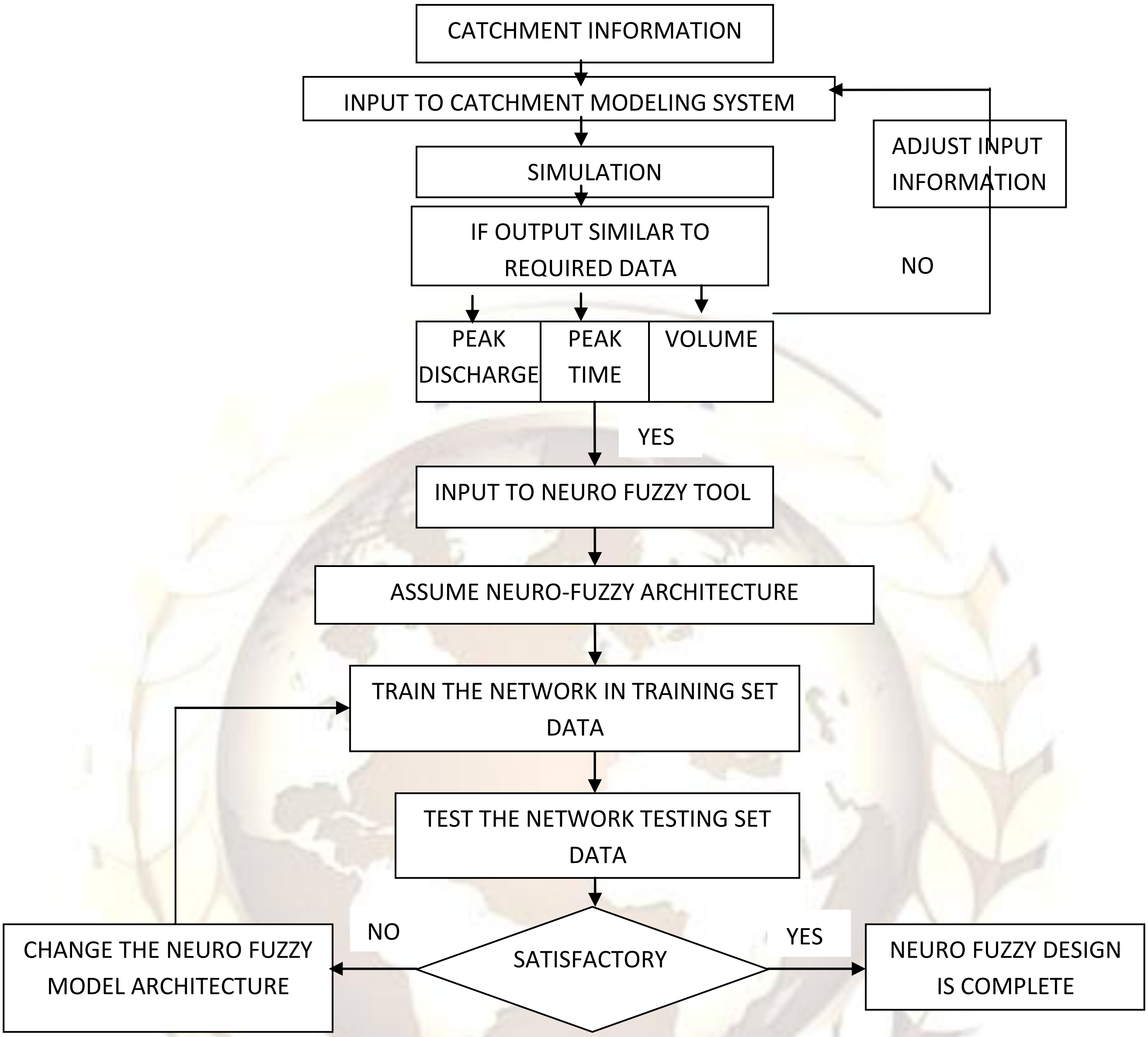
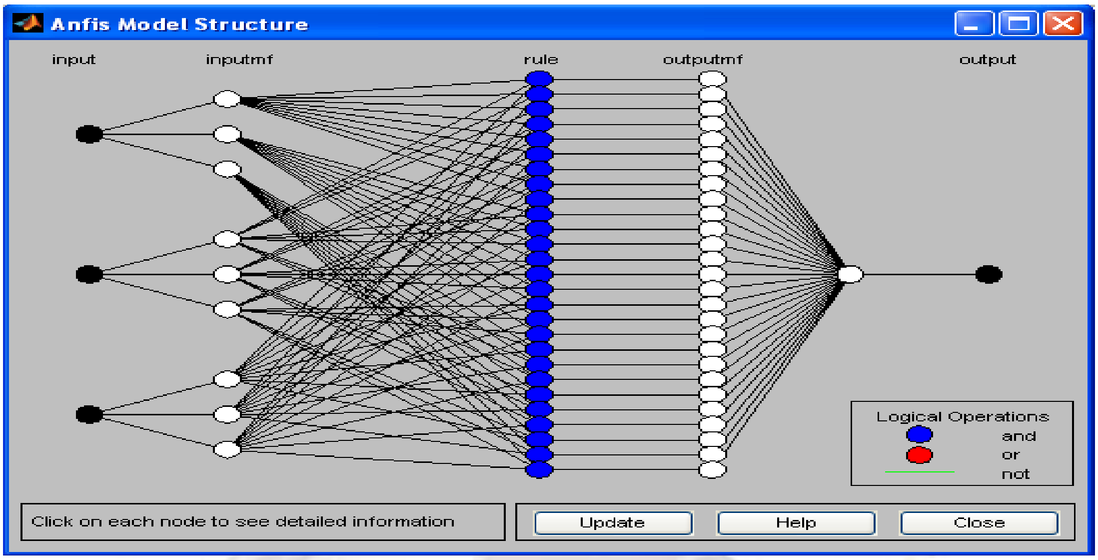


Figure 3.1: Development of Neuro Fuzzy Based methodology



IV. RESULT AND DISCUSSION

4.1 RESULTS FROM NEURO-FUZZY MODEL

Table 4.1 shows the error statistics at 25 % slope and Fig. 4.1 shows the scatter plot and Fig. 4.2 shows line chart

Table 4.1: Error statistics at 25% slope at training data set for width 1

S. No.	Actual	Predicted	% Error	ABS(diff)	(Actual-m)^2	(ABS(diff))^2
1	25.82508	22.8921	0.113570994	2.93298	28.67720311	8.60237168
2	15.2165	19.2834	0.267269083	4.0669	27.59894704	16.53967561
3	32.50321	31.2308	0.03914721	1.27241	144.7988649	1.619027208
4	21.37364	14.0302	0.343574609	7.34344	0.816619469	53.92611103
5	14.10332	15.7693	0.118126796	1.66598	40.53423222	2.77548936
6	37.5908	38.0178	0.011359162	0.427	293.1228199	0.182329
7	35.07309	35.7691	0.019844559	0.69601	213.2511137	0.48442992
8	22.06557	22.2785	0.009649875	0.21293	2.54593936	0.045339185
9	24.95303	16.5572	0.336465351	8.39583	20.09782696	70.48996139
10	23.53834	21.5402	0.084888739	1.99814	9.414894457	3.99256346
11	8.394339	8.3978	0.000412302	0.003461	145.820864	1.19785E-05
12	12.1276	26.0501	1.148001253	13.9225	69.59513722	193.8360063
13	18.90219	16.1503	0.145585776	2.75189	2.457934128	7.572898572
14	9.302474	8.983	0.034342907	0.319474	124.7129669	0.102063637
15	33.80997	30.6292	0.094077871	3.18077	177.9556	10.11729779
16	7.876296	8.3264	0.057146659	0.450104	158.6006248	0.202593611
17	9.120388	9.0314	0.009757041	0.088988	128.8130116	0.007918864
18	6.915668	8.5308	0.233546781	1.615132	183.7191027	2.608651377
19	9.189941	13.2085	0.437277998	4.018559	127.2390542	16.14881644
20	17.4957	21.0735	0.204495962	3.5778	8.846282033	12.80065284
21	12.5213	16.0389	0.280929296	3.5176	63.18135477	12.37350976
22	36.96711	36.7696	0.005342857	0.19751	272.1556282	0.0390102
23	17.27654	14.5001	0.160705789	2.77644	10.19799516	7.708619074
24	7.478987	14.8529	0.985950771	7.373913	168.7656393	54.37459293
25	36.22827	25.1544	0.305669302	11.07387	248.3240189	122.6305968
26	39.21744	38.8957	0.008204003	0.32174	351.4676314	0.103516628
27	17.62234	18.729	0.062798698	1.10666	8.108996617	1.224696356
Sum	552.6891	**av% error**	0.204375616	85.308031	3030.820303	85.308031
Average	20.46997	**NE**	0.154350838			
		ME	0.971853154			
		RMSE	1.777514192			

4.1.1 Scatter plot and line chart for training data set for w1

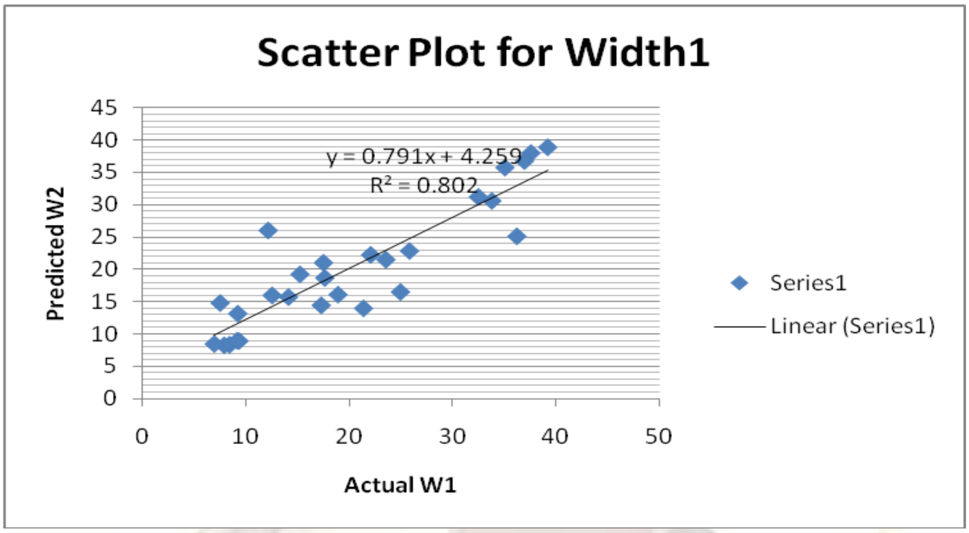


Fig 4.1.1:Scatter plot for width 1 (training data set)

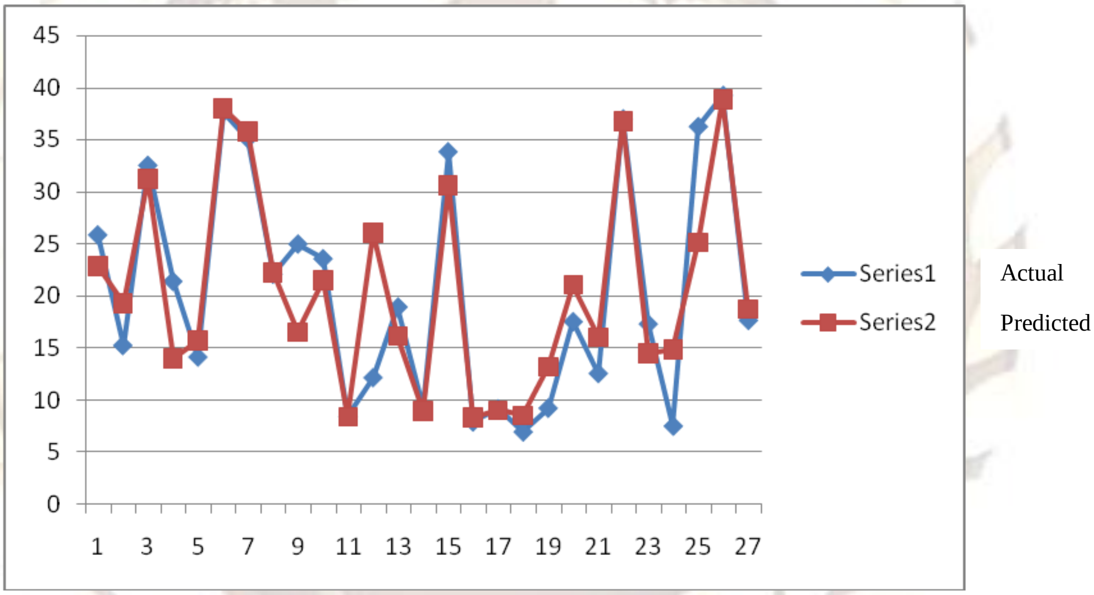


Fig 4.1.2:Line chart for width 1 (training data set)

From Fig 4.1.1, it is evident that predicted values are match well with actual values (R^2=0.802) in training set data for w1

Table 4.2: Error statistics at 25% slope at testing data set for width 1

S. No.	Actual	Predicted	% Error	ABS(diff)	(Actual-m)^2	(ABS(diff))^2
1	4.536736	16.3418	0.513264	11.80506	142.6625759	139.359536
2	10.40352	-6.0874	0.716997	16.49092	36.93430457	271.9504424
3	16.4186	8.3264	0.351835	8.0922	0.003878798	65.48370084
4	23.85198	17.506	0.275912	6.34598	54.33311521	40.27146216
5	10.5692	40.7143	1.310657	30.1451	34.94796042	908.727054
6	24.16924	26.735	0.111555	2.56576	59.11087949	6.583124378
7	28.496	36.0564	0.328713	7.5604	144.3631086	57.15964816
8	8.953393	37.6322	1.246905	28.67881	56.66306054	822.4739709
9	4.788048	16.3318	0.501902	11.54375	136.7223202	133.2582102
10	11.94518	-146.617	6.893999	158.562	20.57257449	25141.9015

11	12.82773	-309.926	14.03275	322.7533	13.34550492	104169.712
12	17.0354	26.2923	0.402474	9.2569	0.30749243	85.69019761
13	20.37693	38.4883	0.787451	18.11137	15.1792056	328.0217233
14	3.514428	32.9797	1.281099	29.46527	168.1288775	868.202254
15	10.58003	-12.0814	0.98528	22.66143	34.82003072	513.5404096
16	32.0813	22.7399	0.406148	9.3414	243.3731042	87.26175396
17	1.26673	243.1455	10.51647	241.8788	231.4703602	58505.33938
18	37.18562	37.3932	0.009025	0.20758	428.6862585	0.043089456
19	29.25945	18.1347	0.483685	11.12475	163.2918512	123.7600626
20	19.60823	28.1922	0.373216	8.58397	9.780318023	73.68454096
21	23.19844	25.5961	0.104246	2.39766	45.12561235	5.748773476
22	9.573799	26.3523	0.7295	16.7785	47.70776794	281.5180958
23	18.42024	27.1206	0.378277	8.70036	3.76111721	75.69626413
Sum	379.0602	**av% error**	1.85832	983.0513	2091.291279	192705.3872
Average	16.48088	**NE**	2.593391			
		ME	-91.1466			
		RMSE	91.53412			

4.1.3 Scatter plot and line chart for testing data set for w1

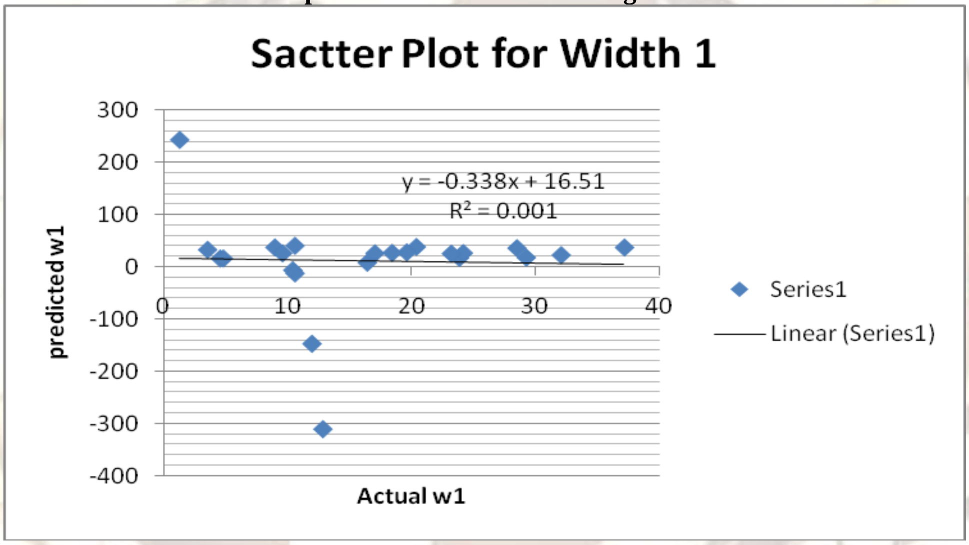


Fig 4.1.3: Scatter plot for width 1 (testing data set)

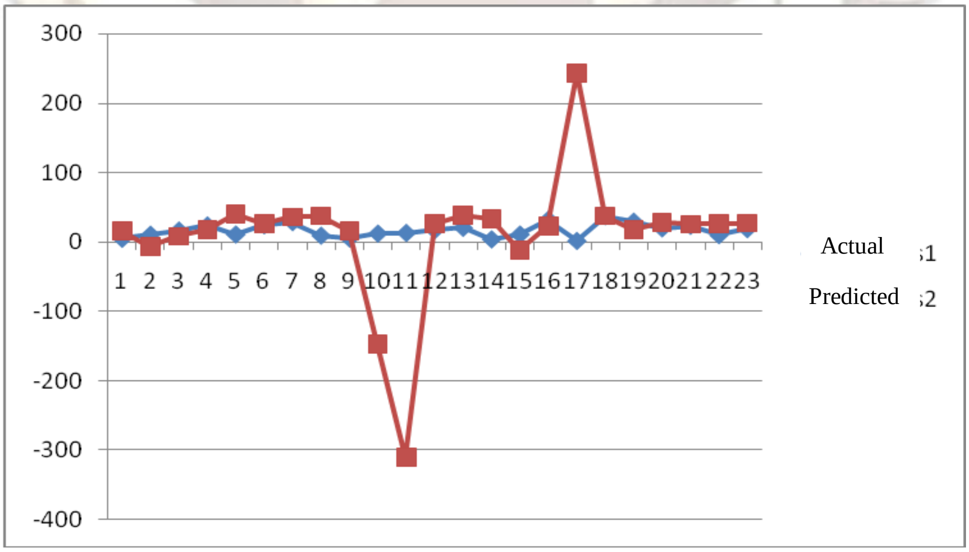


Fig 4.1.4: Line chart for width 1 (testing data set)

From Fig 4.3, it is evident that predicted values are match badly with actual values (R^2=0.001) in testing set data for w1.

V. CONCLUSION AND FUTURE RECCOMENDATIONS

The methodology presented in this work demonstrates the applicability of the neuro-fuzzy models. The result shows that Neuro-Fuzzy model simulates the transport processes for predicting the catchment characteristics at different slopes. The neuro-fuzzy models consistently perform better than traditional regression models. However, as slope increases, predictive accuracy decreases. The model efficiency dropped from 0.96221 to 0.871867, when slope increased from 25% to 50% and 0.871867 to 0.806623 for 50% to 100% slope.

The high error in testing set data show limitation of the methodology. An extensive evaluation of neuro-fuzzy parameters with more numbers of data sets needs to be explored.

The future recommendations are that the methodology presented in this work can be implemented in real field situations with observed data. Using these models management of the urban storm water may be explored.

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