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EDITORIAL PREFACE

This is the *Fifth* Issue of Volume *Six* for International Journal of Engineering (IJE). The Journal is published bi-monthly, with papers being peer reviewed to high international standards. The International Journal of Engineering is not limited to a specific aspect of engineering but it is devoted to the publication of high quality papers on all division of engineering in general. IJE intends to disseminate knowledge in the various disciplines of the engineering field from theoretical, practical and analytical research to physical implications and theoretical or quantitative discussion intended for academic and industrial progress. In order to position IJE as one of the good journal on engineering sciences, a group of highly valuable scholars are serving on the editorial board. The International Editorial Board ensures that significant developments in engineering from around the world are reflected in the Journal. Some important topics covers by journal are nuclear engineering, mechanical engineering, computer engineering, electrical engineering, civil & structural engineering etc.

The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Started with Volume 6, 2012, IJE appears with more focused issues. Besides normal publications, IJE intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

The coverage of the journal includes all new theoretical and experimental findings in the fields of engineering which enhance the knowledge of scientist, industrials, researchers and all those persons who are coupled with engineering field. IJE objective is to publish articles that are not only technically proficient but also contains information and ideas of fresh interest for International readership. IJE aims to handle submissions courteously and promptly. IJE objectives are to promote and extend the use of all methods in the principal disciplines of Engineering.

IJE editors understand that how much it is important for authors and researchers to have their work published with a minimum delay after submission of their papers. They also strongly believe that the direct communication between the editors and authors are important for the welfare, quality and wellbeing of the Journal and its readers. Therefore, all activities from paper submission to paper publication are controlled through electronic systems that include electronic submission, editorial panel and review system that ensures rapid decision with least delays in the publication processes.

To build its international reputation, we are disseminating the publication information through Google Books, Google Scholar, Directory of Open Access Journals (DOAJ), Open J Gate, ScientificCommons, Docstoc and many more. Our International Editors are working on establishing ISI listing and a good impact factor for IJE. We would like to remind you that the success of our journal depends directly on the number of quality articles submitted for review. Accordingly, we would like to request your participation by submitting quality manuscripts for review and encouraging your colleagues to submit quality manuscripts for review. One of the great benefits we can provide to our prospective authors is the mentoring nature of our review process. IJE provides authors with high quality, helpful reviews that are shaped to assist authors in improving their manuscripts.

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Experimental Study to Correlate the Test Results of PBT, UCS, and CBR with DCP on Various soils in soaked condition

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Abstract

The development of new roads, enhancement of existing roads and new runways are part of infrastructure boom in India as well as in Gujarat. Need of strength parameters of subgrade soils is very important in monitoring and evaluation of roads and runways subgrade quality. Laboratory determination of California Bearing Ratio useful for flexible pavement design, Coefficient of subgrade reaction K-Value needed for rigid pavement, raft footing and unconfined compressive strength (UCS) is required for determination of shear strength parameter of subgrade are time consuming and demand significant effort but mandatory. Dynamic Cone Penetration test can be a faster and easier way to evaluate subgrade strength.

In present study an investigation has been carried out on strength parameters for the soil from various locations of Gujarat, In-situ condition has been created in laboratory using bigger testing mould and various tests like Liquid Limit, Plastic limit as well as CBR, PBT, UCS and DCP were carried out on repetitive samples of Maximum Dry Densities achieved through modified proctor effect in soaked condition.The empirical correlations have been established among test results using linear regression procedure. The formulations are validated using other sets of tests data. The developed empirical correlations may be useful to estimate time consuming strength parameters as well as physical properties at numerous locations within area under consideration using simple and rapid DCP test.

Keywords: Subgrade, CBR, DCP, UCS, PBT.

1. INTRODUCTION

The quality of the road or runways depends to a large extent on the strength and shear characteristics of subgrade material. To per-form optimistic Pavement design, an accurate and representative material characterization technique is essential; such technique would be more acceptable if it is simple, rapid and economic. The evaluation of subgrade strength is an important for the road pavement during design, construction and service stages.

The use of CBR or K-Value is mandatory parameters for pavement design, to estimate the CBR or K-value for the subgrade soil. The laboratory determination of CBR and K-value tests demand significant effort, In strength of subgrade determination, initially the California Bearing Ratio (CBR) test was developed by the California Division of Highway. The CBR is a measure of shearing resistance of material under controlled density & moisture condition, it is a ratio of the force per unit area required to penetrate a soil mass with a standard circular piston of 50 mm diameter at the rate of 1.25 mm/min to that required for the corresponding penetration of a standard material. The CBR value obtained is an integral part of several flexible pavement design method, as per the test method standard one CBR test will take minimum 7 days.

The Plate Bearing Test (PBT) is one of the most important tests to determine the stiffness of road subgrade. The PBT teat measures deformation under rigid plate for various loading conditions. The test is expensive and long duration. The PBT test is used to determine modulus of subgrade reaction (K-value) of subgrade which is important parameter to design rigid pavement and raft footing.

The unconfined compression strength of sub grade soil is a load per unit area at which an unconfined cylindrical specimen of soil will fail in simple compression test, Test is lengthy and precise and need experienced engineer to conduct, UCS test gives the shear strength of the soil that is useful parameters for computing Safe bearing Capacity of soil as well as strength of soil.
In view of present pavement design procedures, it reflect that there is a need of performing direct monitoring of stiffness of subgrade to design, construction and operation period which demands rapid & easy way to verify subgrade strength parameters, It become easier to evaluate the strength parameters by correlating the results of PBT, CBR, UCS & DCP in soaked as well as Unsoaked condition.

This paper is aims to develop linear correlations between DCP and other subgrade soil parameter such as CBR, UCS, K_{PBT} etc. in both soaked and unsoaked condition for direct determination of these parameters from DCP results. The Dynamic Cone Penetrometer Test is a Portable Equipment that measures Penetration resistance by cone penetration with blows count of hammer; it is designed for the rapid insitu measurement of subgrade. So the use of Dynamic cone penetrometer is the faster and the easier way to estimate the strength parameters. (Harison, J.R., 1983 – 1987, Kleyn, E.G., 1975, Livneh, M. 1987, Rodrigo Sal-gadi, Sungmin Yoon, 2003, Talal Ao-Referal & Al Suhaibani, 1996).

2. EXPERIMENTAL SETUP

As a test samples, various soils belongs to different locations of Gujarat were collected ,The index properties of the selected soils samples were determined as shown in Table -1 and Grain Size analysis results were depicted in FIGURE 1. (IS-2720-P-4, IS-2720-P-5, IS-1498, IS-2720-P-3). Wet sieve analysis is conducted to determine the percentage by weight coarser than 425 micron (C) One kilogram of oven dried soil sample is taken in a 425 micron I.S. sieve and washed under a jet of water until the wash water became clear. The material retained on the sieve is collected and dried in oven for 24 h. The dried soil sample is weighted accurately and the value of C is determined (Table-2) (IS-2720-P-4).

Based on the experimental study, analysis is done to develop the correlation for CBR, KPBT and UCS with plasticity/gradation characteristics. The generalization for natural soils can be made by accounting for the presence of coarser fraction and modifying the liquid limit as

$W_{LM} = W_L$ (1- C/100) ------------------- (1)

Where, WLM = Modified Liquid limit (%),
WL= Liquid Limit (%)
C = Fraction of soil coarser than 425 micron (%)

In the present study, Modified liquid limit has been used as the characteristic property of the soil and presented in table-1.

Sample No.	Gravel	Coarse Sand	Fine Sand	Silt + Clay content	Group of Soil	W_L	modified LL(W_{LM})	PL	PI
S1	0	15	30	55	CL	32	19.52	21	11
S2	0	29	32	39	SC	29	20.59	21	8
S3	4	48	7	41	SC	31	21.08	21	10
S4	4	2	74	20	SM	23	22.08	NP	NP
S5	6	38	8	48	SC	32	22.08	21	11
S6	3	5	45	47	SM-SC	28	24.36	21	7
S7	2	5	51	42	SC	28	24.64	21	7
S8	4	25	15	56	CL	33	24.75	21	12
S9	6	18	28	48	SC	34	25.16	21	13
S10	2	15	31	52	CL	35	26.25	21	14
S11	7	13	17	63	CI	38	26.64	23	15
S12	1	5	9	85	CL-ML	33	26.73	26	7
S13	0	2	9	89	CL-ML	32	26.88	25	7
S14	0	0	37	63	CL	32	27.2	21	11
S15	4	10	61	25	SC	38	28.12	21	17
S16	4	7	30	59	CI	36	28.44	22	14
S17	0	18	10	72	CI	42	29.82	22	20
S18	3	12	19	66	CI	42	29.82	22	20
S19	2	0	31	67	CI	36	29.88	23	13
S20	5	15	5	75	CI	44	29.92	22	22
S21	0	0	20	80	CI	38	33.06	23	15
S22	0	18	34	48	SC	48	33.12	21	27
S23	1	2	9	88	CI	36	34.92	22	14
S24	1	11	7	81	CI	46	40.48	22	24
S25	0	13	11	76	CI	48	41.76	24	24
S26	0	0	19	81	MI	40	42.14	25	15
S27	1	8	12	79	CH	54	49.14	24	30
S28	0	1	40	59	CI	47	51.3	23	24
S29	0	0	18	82	CI	49	58.9	24	25

TABLE 1: Index Properties

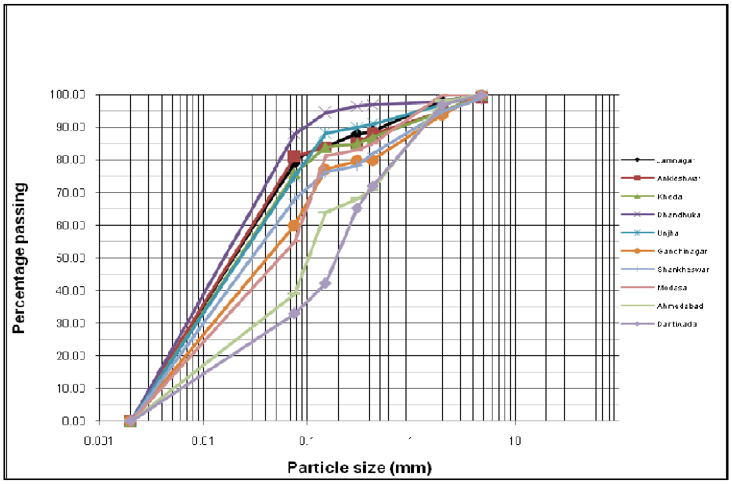

FIGURE 1: Grain Size analysis

It was planned to perform the CBR, PBT, and UCS as well as DCP tests for soaked and unsoaked remolded soil samples for Maxi-mum Dry Density by using Modified Proctor Compaction test(IS-2720-P-8), CBR, PBT, UCS and DCP test were conducted three times for each sample and average of three results was considered and tabulated in Table-2.

2.1 Test Set Up For Investigation Using Plate Bearing Test (PBT)

The investigation was carried out on prototype cylindrical mould of 490 mm diameter and 490 mm height made of 10 mm thick steel plate. The mould was stiffened by 12 mm thick and 40 mm wide steel ring at bottom and top. The photograph of mould and Reaction frame are shown in FIGURE 2.

FIGURE 2: The photograph of mould and Reaction frame

A base plate of 25 mm thickness was prepared to fix the cylindrical mould. It is stiffened by 4 mm wide and 2 mm thick steel plate. At the bottom of the base plate for soaking of the sample, 6 mm diameter holes were drilled at uniform spacing. During soaking top soil surface was closed by perforated steel plate, which is properly clamped with mould to prevent swelling or particles displacement of soil. It was placed in steel water tank of larger size by means of crane so that sample in mould got saturated uniformly during soaking are as shown in FIGURE 3.

FIGURE 3: Mould with saturation tank

The diameter of the test mould for the sample satisfies the recommendation for the experimental set up and the test procedure as per the Indian standard that is the diameter of the loading plate should be approximately one fifth of the diameter of the sample specimen mould in order to overcome the effect due to the confining of the boundary. (IS-1498, IS-1888, IS-9214).PBT was conducted on samples prepared in the test mould. Weight of sample required filling the mould of an inner diameter of 490 mm and a sample depth of 400 mm was determined. Total soil was filled in five equal layers by static efforts using compression testing machine specially developed as shown in FIGURE 4.

FIGURE 4: Compression testing machine for static Compression of sample in mould

The load was applied on the circular plate of diameter 10.5 cm and thickness of 15 mm by manually operated jack fitted on reaction frame .The load was applied without impact, fluctuation or eccentricity. Initially a seating load of 0.007 MPa was applied and released before the actual test was started. The loads were applied in convenient increment and measured by proving ring of capacity 50 KN or more and settlement of Plate for each increment were measured by two nos. of dial gauge (0.01 mm accuracy) placed at diametrically opposite ends of the plate. The settlements were measured until the rate of settlement becomes less than 0.025 mm per minute.

This procedure was continued up to the total settlement became 1.75 mm or more three tests were performed and average of three results are presented in Table-2A & 2B Similar tests were performed for the each type of soil for M.D.D. in soaked and unsoaked condition . The results of the test are used in calculation of K-value (Coefficient of subgrade reaction) and presented in the Table-2A & 2B.

2.2 Test Set Up For Investigation Using Dynamic Cone Penetrometer (DCP)

DCP test were performed using cylindrical mould at the same densities and moisture content in soaked and unsoaked condition as were done in the case of test using PBT. FIGURE 5 shows test set up for DCP specially developed with digital facilities for blows count and penetration measurement and also mechanical arrangement for hammer falling.

In DCP test the 8 kg hammer were dropped through the height of 575 mm on the anvil hammer was dropped by mechanical pulling arrangement, anvil was connected with rod attached by 60 degree cone of 20 mm diameter was kept on the top of the soil surface. In the DCP test, observation were made of number of blows corresponding to penetration of cone through digital display.

The penetration test using DCP was performed up to 300 mm depth; the penetration resistance was obtained that was the ratio of the total penetration to the corresponding number of blows. Similar tests were performed for M.D.D. for each type of soil in soaked and unsoaked condition. The results of the test were observed and are noted in the Table-2A & 2B.

FIGURE 5: Dynamic Cone Penetrometer

2.3 California Bearing Ratio Test (CBR)

CBR tests were performed on soaked soil samples as per the test procedure stipulated in Indian standard.(IS-2720-P-16) In the CBR test, load and penetration reading of 50 mm plunger were observed at a rate of 1.25 mm/minute, the load for 2.5 mm and 5 mm were observed, the load was expressed as a percentage of standard load value at a respective deformation level. CBR test were conducted at the same densities and moisture contents for soaked and unsoaked sample as were performed using PBT and DCP. Test results of CBR are tabulated in Table-2A & 2B.

2.4 Unconfined Compressive Strength (UCS)

UCS tests were performed on soaked soil samples as per the test procedure stipulated in Indian standard.(IS-2720-P-10) The maximum load that can be transmitted to the sub soil depends upon the resistance of the underlying soil. To measure the resistance of the soil by compressibility or shearing deformation, unconfined compression test is the load required per unit area to fail the unconfined soil specimen by application of compressive pressure. UCS test were conducted at the same densities and moisture contents as were performed using PBT, CBR and DCP. Test results of UCS are tabulated in Table-2A & 2B.

Sample no.	MDD (KN/m^3)	OMC	Wet Density	SPG	Soaked CBR	Soaked K_{PBT} (N/mm2/ mm)	Soaked UCS (N/mm^2)	Soaked DCP (mm/blows)
S1	19.9	10.2	2.19	2.61	8.9	0.205	1.72	2.18
S2	20.9	8.7	2.27	2.62	15.05	0.828	2.48	1.72
S3	20.8	9.6	2.28	2.62	11.9	0.569	2.06	1.97
S4	20.6	8	2.21	2.63	9.5	0.359	1.7	2.08
S5	20.5	9.7	2.26	2.62	10	0.458	1.78	2.03
S6	20.4	7.5	2.19	2.62	8.5	0.195	1.56	2.22
S7	20.2	9.7	2.22	2.60	8.3	0.181	1.53	2.29
S8	20.3	10	2.23	2.61	8.1	0.179	1.5	2.32
S9	20.1	10	2.21	2.62	7.8	0.168	1.46	2.39
S10	19.9	10.4	2.20	2.61	6.6	0.102	1.28	2.65
S11	19.9	12.5	2.24	2.62	6.5	0.093	1.27	2.68
S12	19.8	10	2.18	2.58	5.9	0.088	1.2	2.84
S13	19.7	9.8	2.16	2.60	5.8	0.081	1.18	2.93
S14	19.6	10.1	2.16	2.60	5.5	0.08	1.14	3.02
S15	19.5	10.4	2.15	2.61	5	0.075	1.08	3.21
S16	19.4	10.6	2.15	2.61	4.9	0.069	1.06	3.22
S17	19.4	12.8	2.19	2.57	4.6	0.062	1.01	3.35
S18	19.4	11	2.15	2.62	4.6	0.062	1.02	3.34

S19	19.4	10.5	2.14	2.59	4.5	0.058	0.98	3.72
S20	19.3	11.6	2.15	2.62	4.6	0.066	1.03	3.35
S21	19.1	10.7	2.11	2.60	3.9	0.054	0.91	3.72
S22	19.3	10.4	2.13	2.61	4.2	0.056	0.96	3.55
S23	18.9	13	2.14	2.61	3.59	0.052	0.93	4.00
S24	18.5	12.5	2.08	2.60	3.1	0.047	0.75	5.25
S25	18.6	12.7	2.10	2.60	3.47	0.048	0.81	4.95
S26	19	10.2	2.09	2.60	3.5	0.049	0.86	3.98
S27	17.9	13.6	2.03	2.60	2.28	0.013	0.62	6.39
S28	18.3	14.5	2.10	2.58	2	0.008	0.64	7.42
S29	17.9	14.6	2.05	2.59	1.2	0.004	0.52	9.63

TABLE 2B: Results of CBR, K_{PBT}, UCS & DCP (soaked)

3. RESULTS AND DISCUSSION

Assessment of soil focused on observations obtained by CBR, PBT, UCS, and DCP tests in soaked condition. Here attempt has been made to develop correlation between various strength parameters. These relationships help civil engineers to estimate various parameters of soil. The linear and multiple variable regression analysis has been adopted to evaluated relation between strength parameters. development of correlation between results of various tests in soaked condition is done in following way.

3.1 LINEAR REGRESSION ANALYSIS

3.1.1 Relation between MDD and DCP observations.

A relation between MDD and penetration index determined from DCP results is represented by equation as shown by Equation No.-2 a plot of MDD verses DCP results are presented in FIGURE 6.

MDD = 21.908DCP-0.099 ----- (2)

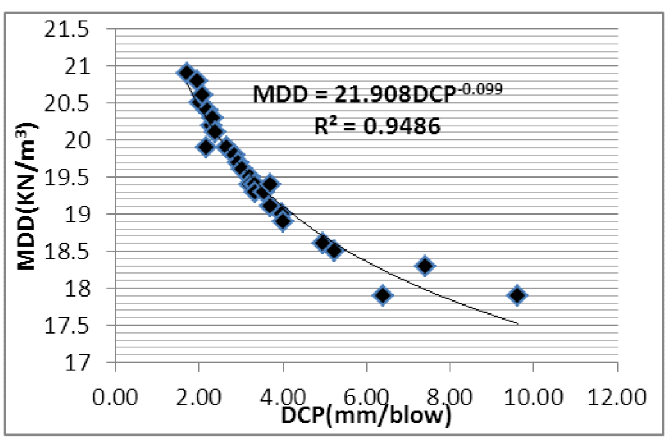

FIGURE 6: Correlation between MDD and DCP Results

3.1.2 Relation between CBR and DCP observations

A relation between CBR and penetration index determined from DCP observations is formulated as shown in Equation No.- 3.

$$CBR = 24.903DCP^{-1.331} \quad \text{------- (3)}$$

A graph presented in FIGURE 7 of CBR verses DCP results

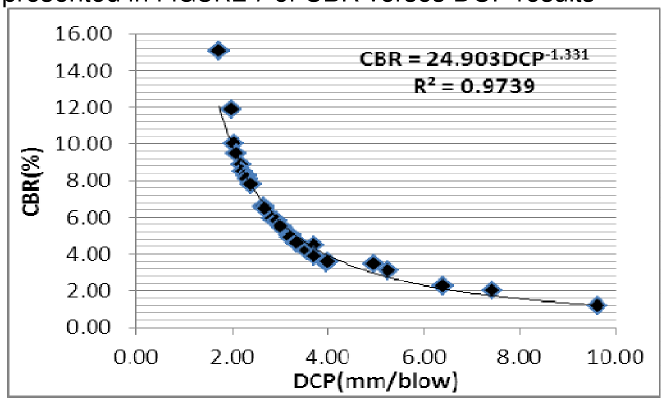

FIGURE 7: Correlation between CBR and DCP Results

3.1.3 Relation between K_{PBT} and DCP observations

A relation between KPBT and penetration resistance computed from DCP observations is formulated as shown in Equation No. - 4.

$$K_{PBT} = 2.0173DCP^{-2.721} \quad \text{------- (4)}$$

A Plot of K_{PBT} and DCP results are as shown in FIGURE 8.

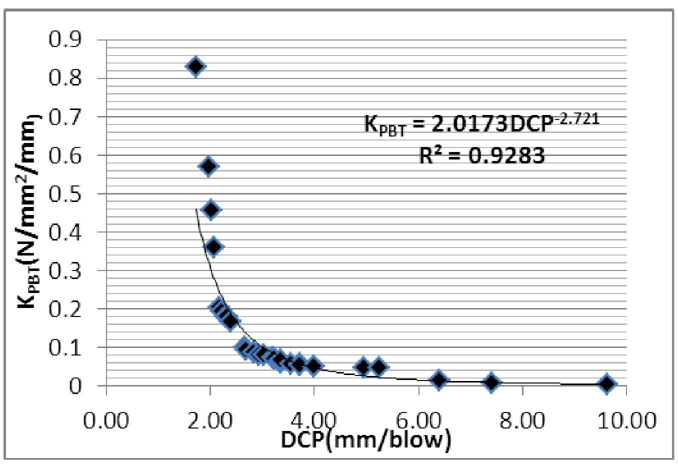

FIGURE 8: Correlation between KPBT and DCP Results

3.1.4 Relation between UCS and DCP observations

A relation between UCS and penetration resistance computed from DCP observations is formulated as shown in Equation No. – 5.

A Plot of UCS and DCP results are as shown in FIGURE 9.

$$UCS = 3.1237DCP^{-0.865} \quad \text{------- (5)}$$

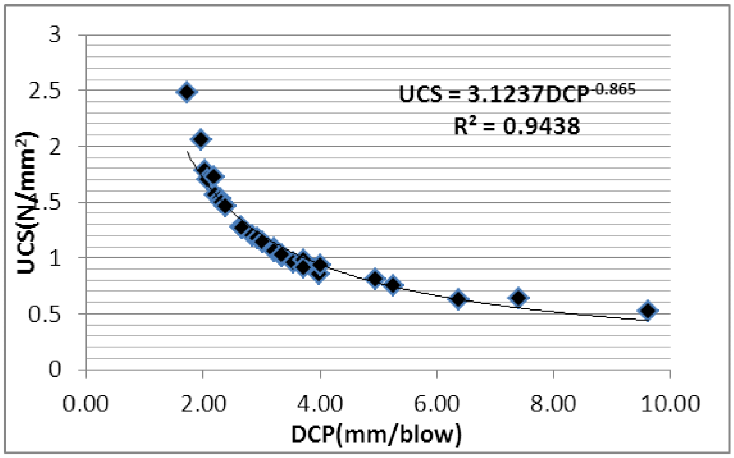

FIGURE 9: Correlation between UCS and DCP Results

3.1.5 Relation between MDD and W_{LM} observations

A relation between MDD and Modified Liquid limit W_{LM} results is provided by equation as shown by Equation No.-6

$$\mathbf{MDD = 31.722W_{LM}^{-0.143}} \qquad \text{----- (6)}$$

A plot of MDD verses W_{LM} results are presented in FIGURE 10.

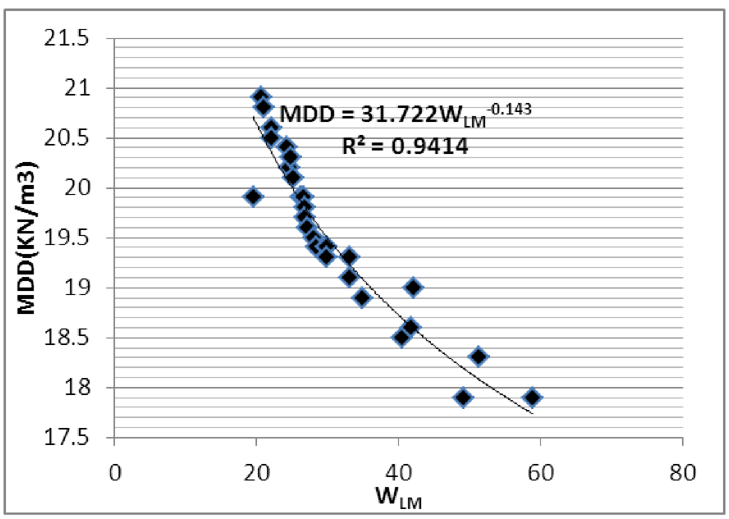

FIGURE 10: Correlation between MDD and WLM Results

3.1.6 Relation between CBR and W_{LM} observations

A relation between CBR and Modified Liquid limit WLM observations is formulated as shown in Equation No. - 7.

$$\mathbf{CBR = 3246.4W_{LM}^{-1.895}} \qquad \text{------- (7)}$$

A graph presented in FIGURE 11 of CBR verses W_{LM} results

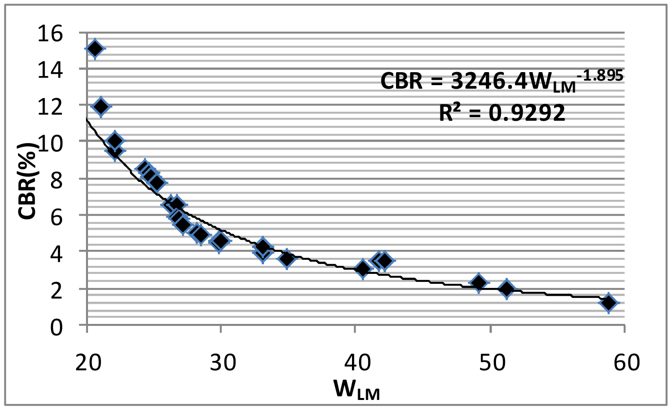

FIGURE 11: Correlation between CBR and W_{LM} Results

3.1.7 Relation between K_{PBT} and W_{LM} observations

A relation between K_{PBT} and Modified Liquid limit W_{LM} observations is formulated as shown in Equation No. - 8.

$$K_{PBT} = 35756W_{LM}{}^{-3.822} \qquad \text{------- (8)}$$

A Plot of K_{PBT} and W_{LM} results is as shown in FIGURE 12.

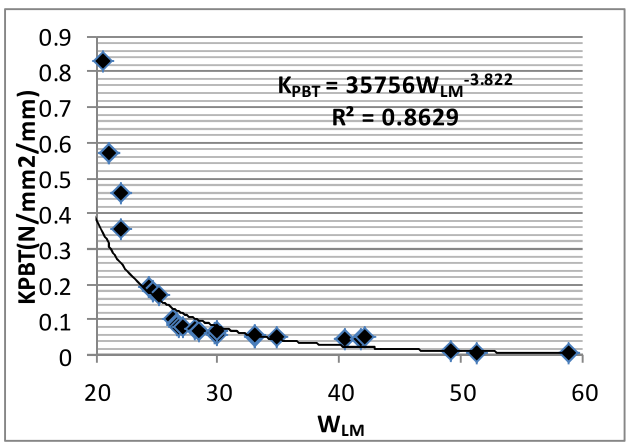

FIGURE 12: Correlation between K_{PBT} and WLM Results

3.1.8 Relation between UCS and W_{LM} observations

A relation between UCS and Modified Liquid limit WLM observations is formulated as shown in Equation No. - 9

$$UCS = 75.791W_{LM}{}^{-1.239} \qquad \text{------- (9)}$$

A Plot of UCS and W_{LM} results are as shown in FIGURE 13.

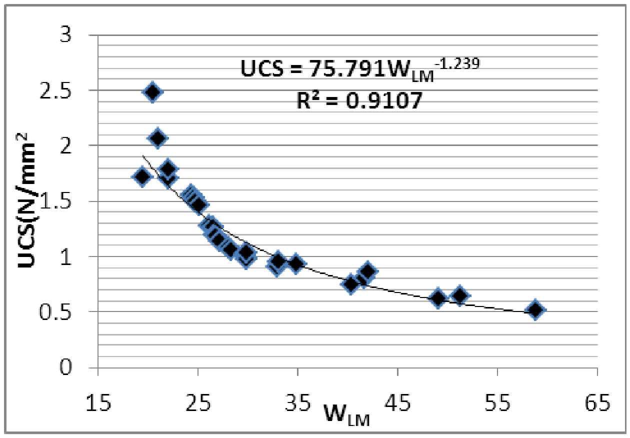

FIGURE 13: Correlation between UCS and W_{LM} Results

3.1.9 Relation between DCP and W_{LM} observations

A relation between DCP and Modified Liquid limit W_{LM} observations is formulated as shown in Equation No. – 10

$$DCP = 0.0259 W_{LM}^{1.4214} \qquad \text{------- (10)}$$

A Plot of DCP and W_{LM} results are as shown in FIGURE 14.

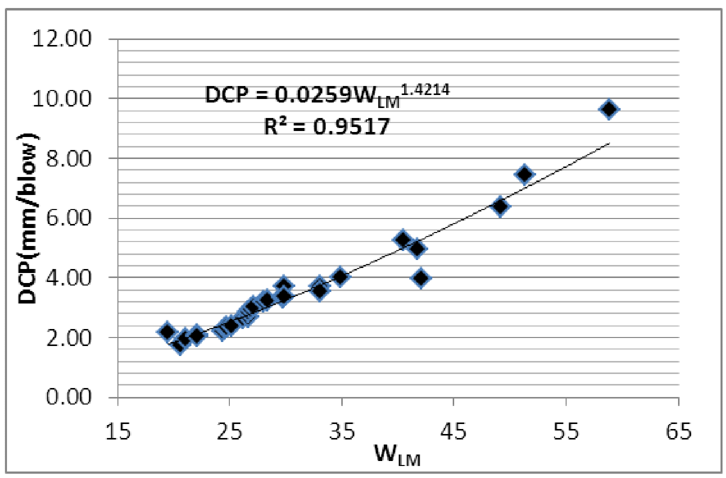

FIGURE 14: Correlation between DCP and W_{LM} Results

3.2 MULTIVARIABLE REGRESSION ANALYSIS

3.2.1 Prediction of UCS Using Maximum Dry Density, Optimum Moisture Content And Modified Liquid Limit

A relation of MDD, OMC and modified liquid limit with UCS is represented by equation as shown by Equation No.-11

A plot of Comparison of Predicted UCS and actual UCS is presented in FIGURE 15.

$$UCS = 4.287255904 \cdot 10\text{-}1\ MDD - 2.581485936 \cdot 10\text{-}2\ OMC + 1.039471265 \cdot 10\text{-}2\ W_{LM} - 7.165088134 \qquad \text{------ (11)}$$

Residual Sum of Squares: rss = 1.429119183

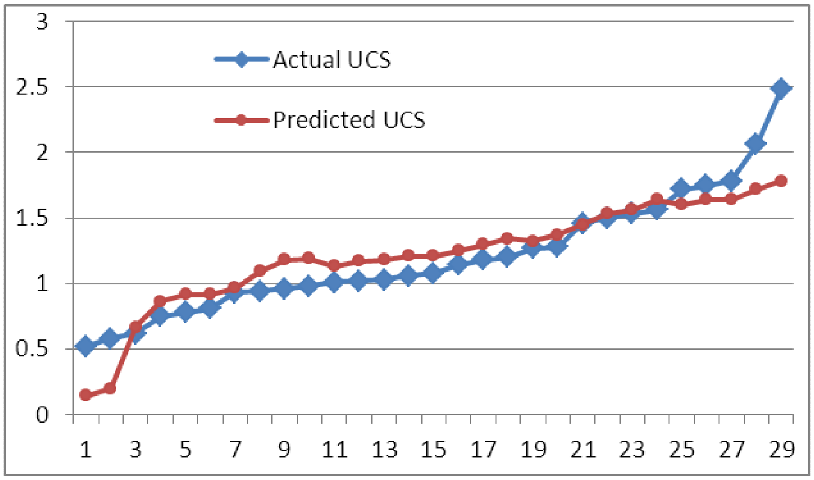

FIGURE 15: Comparison of Predicted UCS and actual UCS

3.2.2 Prediction of K-Value Using Maximum Dry Density, Optimum Moisture Content And Modified Liquid Limit

A relation of MDD, OMC and modified liquid limit with K-Value is represented by equation as shown by Equation No.-12

A plot of Comparison of Predicted K-value and actual K-Value is presented in FIGURE 16.

$$\textbf{K-Value} = 2.841852052 \cdot 10\text{-}1\ \mathbf{MDD} - 6.666796321 \cdot 10\text{-}3\ \mathbf{OMC} + 2.006130462 \cdot 10\text{-}2\ \mathbf{W_{LM}} - 5.922789562 \quad \text{------- (12)}$$

Residual Sum of Squares: rss = 4.882056826*10-1

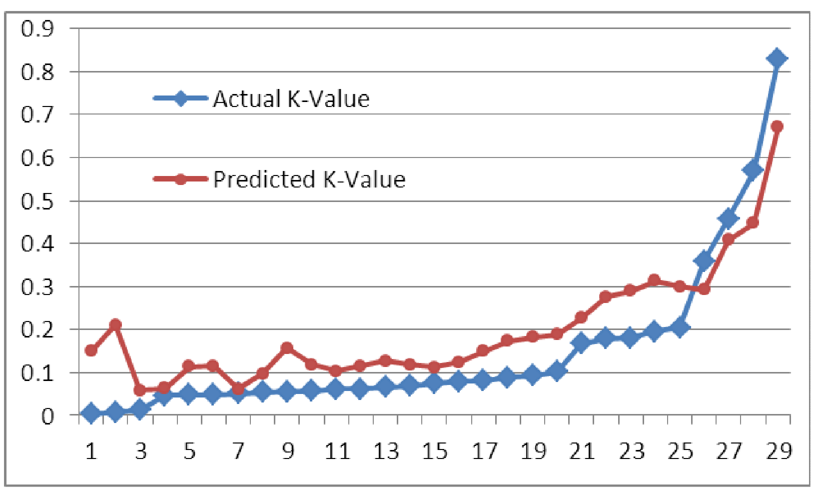

FIGURE 16: Comparison of Predicted K-value and actual K-Value

3.2.3 Prediction of CBR Using Maximum Dry Density, Optimum Moisture Content And Modified Liquid Limit

A relation of MDD, OMC and modified liquid limit with CBR is represented by equation as shown by Equation No.-13

A plot of Comparison of Predicted CBR and actual CBR is presented in FIGURE 17.

CBR = 3.753294993 MDD - 1.366922172·10-1 OMC + 1.519309837·10-1 WLM - 70.10518931 ------ (13)

Residual Sum of Squares: rss = 75.9823576

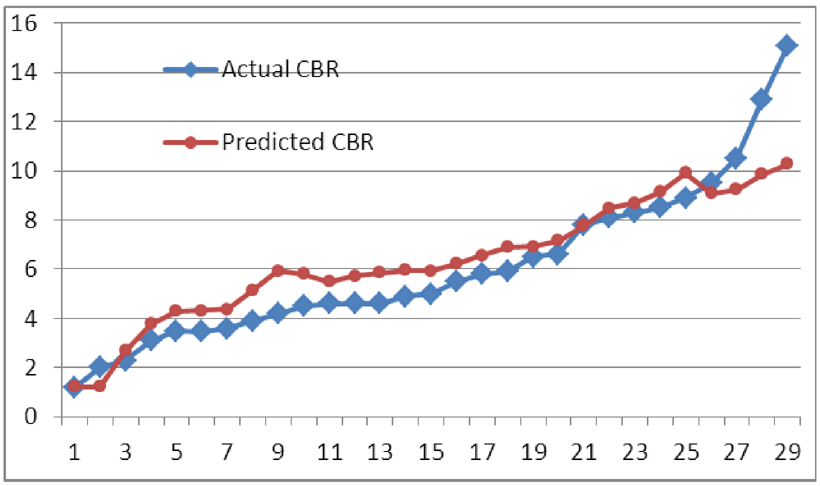

FIGURE 17: Comparison of Predicted CBR and actual CBR

3.2.4 Prediction of DCP Using Maximum Dry Density, Optimum Moisture Content And Modified Liquid Limit

A relation of MDD, OMC and modified liquid limit with DCP is represented by equation as shown by Equation No.-14

A plot of Comparison of Predicted DCP and actual DCP is presented in FIGURE 18.

DCP = -8.727239902·10-1 MDD - 4.783120596·10-2 OMC + 9.150404595·10-2 W_{LM} + 18.17841692 **------- (14)**

Residual Sum of Squares: rss = 3.895738853

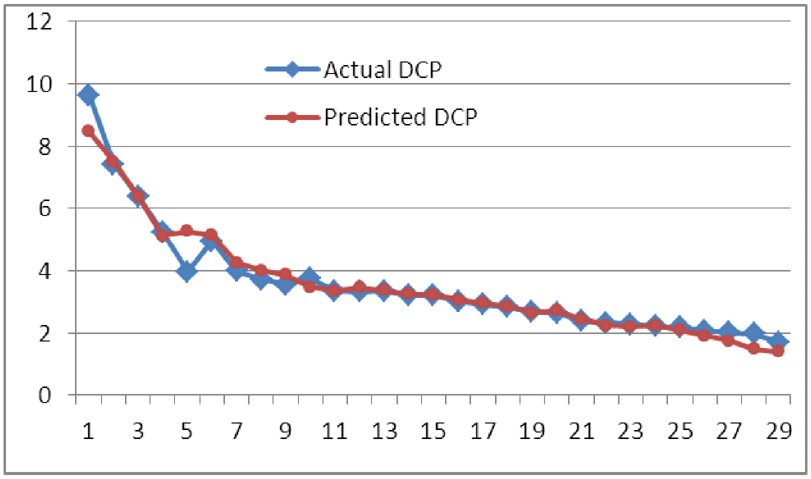

FIGURE 18: Comparison of Predicted DCP and actual DCP

3.2.5 Prediction of CBR Using MDD, OMC, Modified Liquid Limit and DCP

A relation of MDD, OMC, modified liquid limit and DCP with CBR is represented by equation as shown by Equation No.-15

A plot of Comparison of Predicted CBR and actual CBR is presented in FIGURE 19.

$$\mathbf{CBR = 5.61152798\ MDD - 3.484842045 \cdot 10\text{-}2\ OMC - 4.290247861 \cdot 10\text{-}2\ MLL + 2.129233306\ DCP - 108.8112801} \qquad \text{--------------- (15)}$$

Residual Sum of Squares: rss = 58.32050164

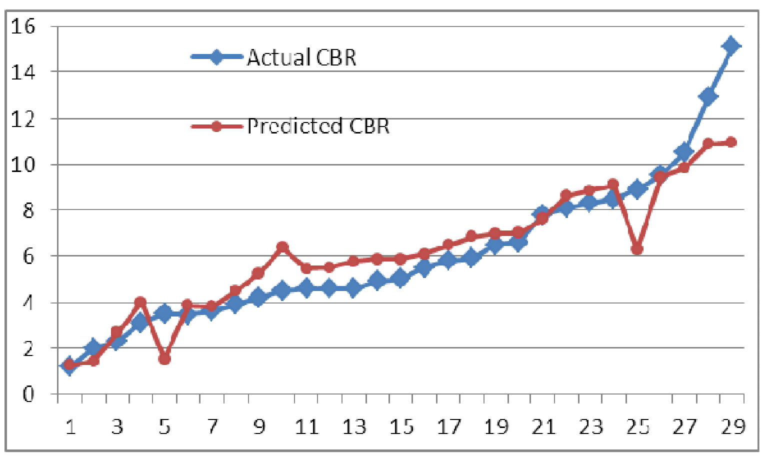

FIGURE 19: Comparison of Predicted CBR and actual CBR

3.2.6 Prediction of K-Value Using MDD, OMC, Modified Liquid Limit and DCP

A relation of MDD, OMC, modified liquid limit and DCP with K-Value is represented by equation as shown by Equation No.-16

A plot of Comparison of Predicted K-value and actual K-Value in FIGURE 20

$$\mathbf{K\text{-}Value = 4.209888602 \cdot 10\text{-}1\ MDD + 8.30973734 \cdot 10\text{-}4\ OMC + 5.717608247 \cdot 10\text{-}3\ MLL + 1.567547777 \cdot 10\text{-}1\ DCP - 8.772343264} \qquad \text{------------- (16)}$$

Residual Sum of Squares: rss = $3.924793526*10^{-1}$

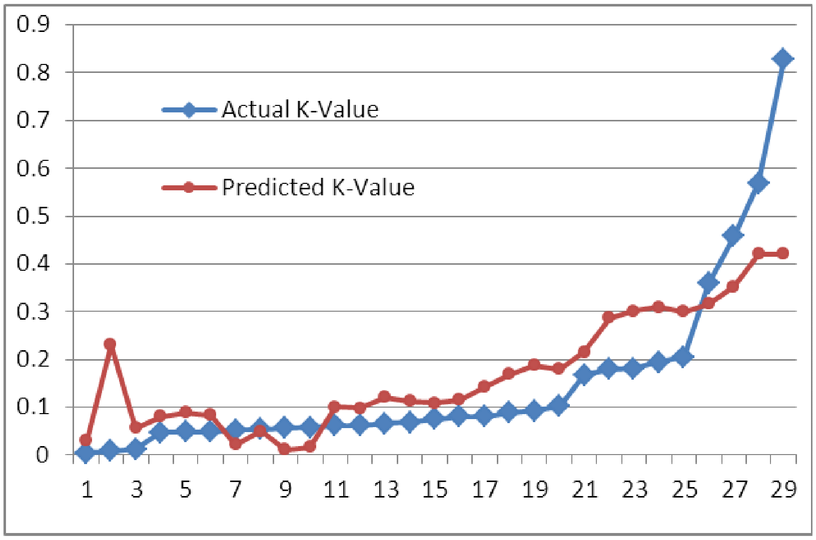

FIGURE 20: Comparison of Predicted K-value and actual K-Value

3.2.7 Prediction of UCS USING, OMC, Modified Liquid Limit and DCP

A relation of MDD, OMC, modified liquid limit and DCP with UCS is represented by equation as shown by Equation No.-17

A plot of Comparison of Predicted UCS and actual UCS in FIGURE 21.

$$\mathbf{UCS = 6.904701568 \cdot 10^{-1}\ MDD - 1.146947823 \cdot 10^{-2}\ OMC - 1.704888589 \cdot 10^{-2}\ MLL + 0.299916777\ DCP - 12.61710035} \quad \text{---------------} \ (17)$$

Residual Sum of Squares: rss = 1.078697188

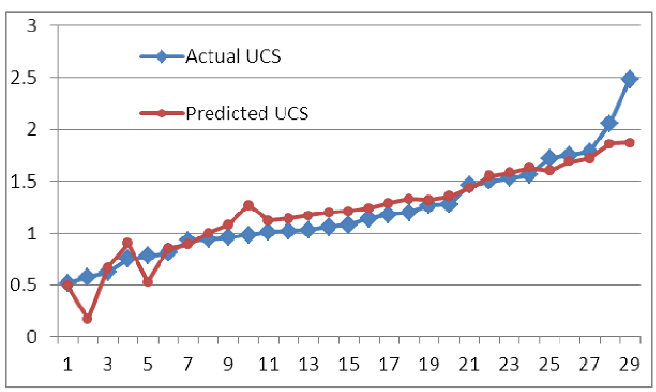

FIGURE 21: Comparison of Predicted UCS and actual UCS

4. CONCLUSION

The above experimental analysis was carried out to develop the co relations between various tests like MDD, K_{PBT}.UCS, CBR and DCP of soil in soaked condition. The correlations developed are very useful to the civil engineer in estimating strength parameters of various soils from the results of very fast and easier DCP test. Based on experimental results the following conclusions are drawn. In short we can say that the relations between MDD, K_{PBT},UCS, CBR with DCP results are in form of $y = ax^b$, where y denote the values of MDD, K_{PBT}, UCS and CBR and x represent the DCP results, a & b are constant.

a) With increase in Maximum Dry Density of soil, Penetration resistance observations from DCP decrease.
b) California Bearing Ratio Test results and Penetration resistance observations from DCP test shows that CBR-value increase with decrease in DCP values.
c) Results of Coefficient of sugrade reaction K-value from Plate bearing Test and Penetration resistance observations from DCP test shows that K-value increase with decrease in DCP values.
d) Results of Unconfined Compression Test and Penetration resistance observations from DCP test shows that UCS increases with decrease in DCP values.
e) Results of DCP decreases as modified liquid limit increases.

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Use of Evolutionary Polynomial Regression (EPR) for Prediction of Total Sediment Load of Malaysian Rivers

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Abstract

This study investigates the use of Evolutionary Polynomial Regression (EPR) for predicting the total sediment load of Malaysian rivers. EPR is a data-driven modelling hybrid technique, based on evolutionary computing, that has been recently used successfully in solving many problems in civil engineering. In order to apply the method for modelling the total sediment of Malaysian rivers, an extensive database obtained from the Department of Irrigation and Drainage (DID), Ministry of Natural Resources & Environment, Malaysia was sought, and unrestricted access was granted. A robustness study was performed in order to confirm the generalisation ability of the developed EPR model, and a sensitivity analysis was also conducted to determine the relative importance of model inputs. The results obtained from the EPR model were compared with those obtained from six other available sediment load prediction models. The performance of the EPR model demonstrates its predictive capability and generalisation ability to solve highly nonlinear problems of river engineering applications, such as sediment. Moreover, the EPR model produced reasonably improved results compared to those obtained from the other available sediment load methods.

Keywords: Evolutionary polynomial regression, sediment, rivers, Malaysia, prediction.

1. INTRODUCTION

Sedimentation is a process that changes the rivers shape and embankments in the form of altering the cross-section, longitudinal profile, course of flow and patterns of rivers. In order to sustain the cultural and economic developments along alluvial rivers, the principles of sediment transport should be carefully studied and solutions for its engineering and environmental problems need to be developed. Currently, there are a few models that can be used to identify the sedimentation process in the form of estimating the total sediment load. Some of the available models include Engelund & Hansen [1], Graf [2], Ackers & White [3], Yang & Molinas [4], Van Rijn [5], Karim [6] and Nagy et al. [7], among others. However, most of these models have been developed based on flume data from western countries, including America and Western Europe, and have not been widely used or evaluated in other parts of the world [8]. Since the 1990's, some Malaysian researchers have developed models based on the Malaysian conditions (e.g. [8]; [9]; [10]). However, these models failed to achieve consistent success in relation to accurate sediment prediction; hence, there is a need for more accurate sediment models.

In this paper, Evolutionary Polynomial Regression (EPR) was used to develop a more accurate model for predicting the total sediment load for rivers in Malaysia. EPR is an artificial intelligence technique that has the advantage of combining the genetic algorithms with traditional numerical regression [12]. The data used for model calibration and validation were collected from the Department of Irrigation and Drainage (DID), Ministry of Natural Resources & Environment, Malaysia (hereinafter referred to as the DID). The database comprises 338 data cases (from 1998 through to 2007) that represent ten different rivers across Malaysia for four river catchment areas, namely Kinta, Kerayong, Langat and Kulim (Figure 1). The first set of data was collected for Pari River in Taman Merdeka and Kerayong River in Kuala Lumpur from 1998 to 1999. The second set of data was undertaken at the Kinta River catchment, which consists of four rivers including Kinta River, Raia River, Pari River and Kampar River. The third set of data took place over the period 2000 to 2002, at the Langat River catchment area, comprising Langat River, Lui River and Semenyih River. The fourth and final set of data was completed at Kulim River in 2007.

The available data were divided into two sets: a training set for model calibration and an independent validation set for model verification. In order to test the performance of the developed model, consideration was given not only to the model predictive statistical accuracy in the training and validation set but also to the robustness and interpretive ability of the model. This was carried out by performing a parametric study to investigate the generalization ability (robustness) of the model and a sensitivity analysis to quantify the relative importance of the model inputs to the corresponding outputs (i.e. interpretive ability). Predictions from the developed EPR model were compared with those obtained from six other available models.

FIGURE 1: Map of river catchments of the study area. [13]

2. OVERVIEW OF EVOLUTIONARY POLYNOMIAL REGRESSION (EPR)

EPR is a data-driven hybrid regression technique, based on evolutionary computing, that was developed by Giustolisi and Savic [14]. EPR has been used successfully in solving several problems in civil engineering (e.g. [15]; [16]; [17]). It constructs symbolic models by integrating the soundest features of numerical regression [18] with genetic programming and symbolic regression [19]. This strategy provides the information in symbolic form expressions, as usually defined and referred to in the mathematical literature [20]. The following two steps roughly describe the underlying features of EPR, aimed to search for polynomial structures representing a system. In the first step, the selection of exponents for polynomial expressions is carried out, employing an evolutionary searching strategy by means of genetic algorithms [21]. In the second step, numerical regression using the least square method is conducted, aiming to compute the coefficients of the previously selected polynomial terms. The general form of expression in EPR can be presented as follows [14]:

$$y = \sum_{j=1}^{m} F(X, f(X), a_j) + a_o \tag{1}$$

where: y is the estimated vector of output of the process; m is the number of terms of the target expression; F is a function constructed by the process; X is the matrix of input variables; f is a function defined by the user; and a_j is a constant. A typical example of EPR pseudo-polynomial expression that belongs to the class of Eq. (1) is as follows [14]:

$$\hat{Y} = a_o + \sum_{j=i}^{m} a_j \;.\,(X_1)^{ES(j,1)} \ldots\ldots\ldots\ldots (X_k)^{ES(j,k)} . f\left[(X_1)^{ES(j,k+1)} \ldots\ldots (X_k)^{ES(j,2k)}\right] \tag{2}$$

where: $\hat{Y}$ is the vector of target values; m is the length of the expression; a_j is the value of the constants; X_i is the vector(s) of the k candidate inputs; ES is the matrix of exponents; and f is a function selected by the user.

EPR is suitable for modelling physical phenomena, based on two features [15]: (i) the introduction of prior knowledge about the physical system/process – to be modelled at three different times, namely: before, during and after EPR modelling calibration; and (ii) the production of symbolic formulae, enabling data mining to discover patterns which describe the desired parameters. In the first EPR feature (i) above, before the construction of the EPR model, the modeller selects the relevant inputs and arranges them in a suitable format according to their physical meaning. During the EPR model construction, model structures are determined by following user-defined settings such as general polynomial structure, user-defined function types (e.g. natural logarithms, exponentials, tangential hyperbolics) and searching strategy parameters. The EPR starts from true polynomials and also allows for the development of non-polynomial expressions containing user-defined functions (e.g. natural logarithms). After EPR model calibration, an optimum model can be selected from among the series of returned models. The optimum model is selected based on the modeller's judgement, in addition to statistical performance indicators such as the coefficient of determination (CoD). A typical flow diagram of the EPR procedure is shown in Figure 2, and detailed description of the technique can be found in [14].

The EPR symbolic approach can be seen as opposite to those numerical regressions performed in Artificial Neural Networks. According to the classification of modelling techniques based on colour, whereby meaning is related to three levels of prior information required [22], EPR can be classified as a "grey box" technique (conceptualisation of physical phenomena), and Figure 3 shows a pictorial representation of this classification where the greater the physical knowledge used during the development of the model, the better the physical interpretation of the phenomena by the user. EPR is a technqique based on observed data; however, the mathematical structure it returns is symbolic and usually uncomplicated in its constitution [14].

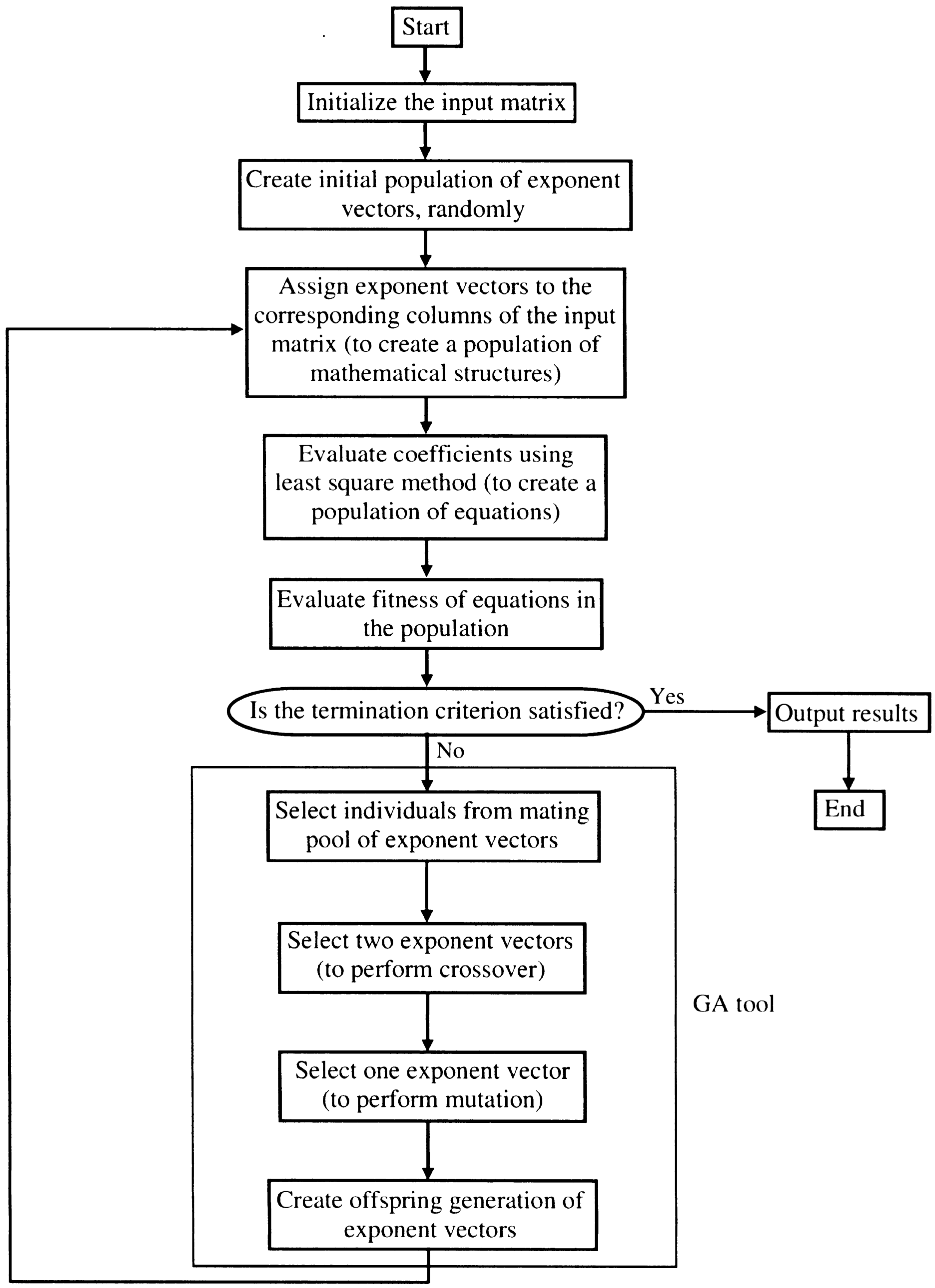


FIGURE 2: Typical flow diagram of EPR procedure. [31]

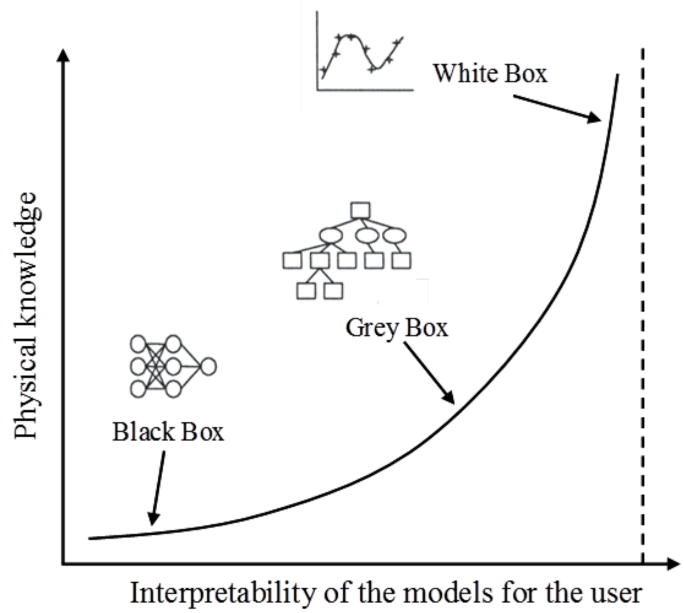


FIGURE 3: Graphical classification of EPR among modelling techniques. [17]

3. DEVELOPMENT OF SEDIMENT TRANSPORT MODEL USING EPR

In this study, the EPR model was developed based on a set of 338 data records collected from the DID, containing information on total sediment load. The collected data represent the sediment transport features of ten different rivers across Malaysia, as mentioned earlier. In modeling environmental phenomena, such as sediment, care has to be given to the data used. Incomplete sampled data always exist and analysis should provide new insights into the phenomena, give accurate forecasting of the output for a range of inputs. Another additional problem when dealing with environmental data is related to discontinuities, i.e. gaps often present in the data records, and reconstructing the information contained in the missing data, without influencing the construction of models, is needed [11]. The EPR model was developed using the available software package, EPR Toolbox Version 2 [23].

The first important step in the development of the EPR model was to identify the potential model inputs and corresponding outputs. Based on previous studies carried out by many researchers (e.g. [8]), for the purpose of this study, eight inputs were utilised, having deemed them to be the most significant factors affecting the sediment transport. These inputs include the hydraulic radius (R), flow depth (Y_o), flow velocity (V), median diameter of sediment load (d_{50}), stream width (B), water surface slope (S_o), fall velocity (ω_s) and flow discharge (Q). The only output is the total sediment load (T_j).

The next step taken in the development of the EPR model was the data division. In this study, the data were randomly divided into two sets: a training set for model calibration and an independent validation set for model verification. In dividing the data into their sets, the training and testing sets were selected to be statistically consistent, thus, represent the same statistical population, as recommended by Shahin et al. [24]. In total, 271 data cases (80%) of the available 338 data cases were used for training, and 67 data cases (20%) were used for validation. The statistics of the data cases used for the training and validation sets are given in Table 1, including the mean, standard deviation, minimum, maximum and range. It should be noted that the extreme values of the data cases were included in the training set.

Model variables & data sets	Statistical parameters				
	Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Range**
Flow discharge, Q (m^3/s)					
Training set	7.28	6.62	0.74	47.90	47.16
Testing set	7.96	7.28	1.19	35.91	34.72
Flow depth, y_o (m)					
Training set	0.57	0.27	0.22	1.87	1.65
Testing set	0.60	0.30	0.24	1.61	1.37
Flow velocity, V (m/s)					
Training set	0.62	0.20	0.19	1.26	1.07
Testing set	0.64	0.19	0.26	1.10	0.84
Median diameter of bed material, d_{50}					
Training set	0.0014	0.0008	0.0004	0.0040	0.0036
Testing set	0.0016	0.0010	0.0005	0.0039	0.0034
Hydraulic radius, R (m)					
Training set	0.54	0.24	0.21	1.77	1.56
Testing set	0.56	0.25	0.23	1.39	1.16
Stream width, B (m)					
Training set	17.85	3.70	13.50	28.00	14.50
Testing set	17.92	3.89	13.80	28.00	14.20
Bed slope, S_o (m)					
Training set	0.0034	0.0027	0.0003	0.01	0.01
Testing set	0.0033	0.0027	0.0010	0.01	0.01
Fall velocity, ω_s (m^2/s)					
Training set	0.22	0.29	0.04	1.74	1.69
Testing set	0.23	0.26	0.06	1.34	1.28
Total Load, Tj (kg/s)					
Training set	2.76	3.57	0.11	28.52	28.41
Testing set	3.08	3.62	0.18	17.85	17.66

TABLE 1: EPR input and output variables used and their statistics.

The following step in the development of the EPR model was selecting the related internal parameters for evolving the model. This was carried out by a trial-and-error approach in which a number of EPR models were trained, using the parameters given in Table 2, until the optimum model was obtained. A more detailed description of the modelling parameters used in Table 2 can be found in the EPR Toolbox manual [23].

Parameter	EPR setting
Regression type	Statistical
Polynomial structure	$Y = sum(a_i \times X_1 \times X_2 \times f(X_1) \times f(X_2)) + a_o$
Function type	Exponent
Term	[1:5]
Range of exponents	[0, 0.5, 1, 2]
Generation	10
Offset (a_o)	Yes
Constant estimation method	Least Square

TABLE 2: Internal parameters used in the EPR modeling.

3.1 Performance indicators

As mentioned earlier, the optimum EPR model was obtained by a trial-and-error approach in which a number of EPR models were trained with different internal modelling parameters, and three models were found to give the best results, as shown in Table 3. It can be seen that five performance measures that evaluate the relationship between the measured and predicted total loads were used, namely: the coefficient of correlation, *r*, coefficient of efficiency, *E*, root mean squared error, *RMSE*, discrepancy ratio, *DR*, and Akaike information criterion, *AIC*. The coefficient of correlation, *r*, is the performance measure that is widely used in civil engineering but sometimes can be biased in reflecting higher or lower values, leading to misleading model performance. The coefficient of efficiency, *E*, is an unbiased performance estimate and provides an assessment of the overall model performance, which can range from minus infinity to 1.0, with higher values indicating better agreement [25]. The *RMSE* has the advantage in that large errors receive much greater attention than small errors, as indicated by Shahin et al. [26]. The discrepancy ratio, *DR*, is the ratio between the predicted and measured total sediment loads, and a model is considered to be suitable if its discrepancy ratio falls within the range of 0.5–2.0, as indicated by Sinnakaudan et al. [8]. The *AIC* gives an estimate of the expected relative distance between the fitted model and the unknown true model. The smallest value of *AIC* is considered to be the most favourable amongst the set of candidate models [27].

Table 3 shows that the three best EPR models have *r*, *E*, *RMSE* and *DR* close to each other and that all three models have consistent performance in both the training and testing sets. However, based on the *AIC* results, Table 3 shows that Model-1 is superior to the other models and can be considered to be optimal.

Performance measurement	**Model-1**	**Model-2**	**Model-3**
Correlation coefficient, *r*			
Training	0.72	0.72	0.73
Validation	0.74	0.74	0.74
Coefficient of efficiency, *E*			
Training	0.52	0.52	0.52
Validation	0.55	0.55	0.55
RMSE			
Training	2.46	2.46	2.46
Validation	2.41	2.41	2.41
Discrepancy ratio, *DR*			
Training	0.68	0.69	0.69
Validation	0.64	0.66	0.66
AIC			
Training	0.00	4.10	4.00
Validation	0.00	5.20	5.20

TABLE 3: Performance results of the EPR models in the training and testing sets.

As can be seen in the following equations (i.e. Eqns. 3–5), Model-1 has only 6 input variables (Eqn. 3), whereas both Model-2 (Eqn. 4) and Model-3 (Eqn. 5) have 8 input variables each. It should be noted that the performance results of these models are considered to be acceptable in representing the sediment transport problem compared to those of most available methods, as will be seen in the next section. The symbolic formulae obtained from the EPR Models are as follows:

$$T_j = 226356.81\ V\, d_{50}^{\ 2} + 18.37\ Q^{\ 0.5}\ Y_o S_o^{\ 0.5}\ e^{\ 0.5V} + 0.000012\ Q\ d_{50}^{\ 0.5}\ e^{0.5B} \quad (3)$$

$$T_j = 222250.88\ V\, d_{50}^{\ 2} + 18.17\ Q^{\ 0.5}\ Y_o S_o^{\ 0.5}\ e^{0.5V} + 0.000012\ Q\ d_{50}^{\ 0.5}\ e^{0.5B} + 1.23\ Q\ Y_o W_S^{\ 2} R^2 S_O\, e^{2Ws+2R} \quad (4)$$

$$T_j = 162.24\ B^2\ Y_o\ W_s^{\ 2}\ R^2\ S_o^{\ 2} + 222624.92\ V\ d_{50}^{\ 2} + 18.15\ Q^{\ 0.5}\ Y_o\ S_o^{\ 0.5}\ e^{0.5V} + 0.000012 Q d_{50}^{\ 0.5} e^{0.5B} + 0.000023\ Q^2\ W_s R^2\ e^{2R} \quad (5)$$

where: T_j is the total sediment load, V is the flow velocity, d_{50} *is* the median diameter of sediment load, Q is the flow discharge, Y_o is the flow depth, S_o is the water surface slope, B is the stream width, R is the hydraulic radius and ω_s is the fall velocity.

3.2 Robustness study

In order to confirm the robustness of the EPR model to generalise within the range of the data used for model training, an additional validation approach was utilised, as proposed by Shahin et al. [26]. The approach consists of carrying out a parametric study, part of which includes investigating the response of the EPR model output to changes in its inputs. All input variables, except one, were fixed to the mean values used for training, and a set of synthetic data (between the minimum and maximum values used for model training), was generated for the input that was not set to a fixed value. The synthetic data set was generated by increasing its values in increments equal to 5% of the total range between the minimum and maximum values, and the model response was then examined. This process was repeated using another input variable until the model response has been tested for all input variables. The robustness of the model was tested by examining how well the trends of the total sediment loads, over the range of the inputs examined, are in agreement with the underlying physical meaning of sediment problem. The results of the robustness study are shown in Figure 4, which agree with hypothetical expectations based on the known physical behaviour of the total sediment load. Figures 4 (a□f) shows that the predicted total sediment load increases in a relatively consistent and smooth fashion, as the discharge, velocity, width, river depth, median diameter, slope, hydraulic radius and fall velocity increase.

3.3 Interpretive ability of EPR model

When evaluating the EPR model, consideration must be given not only to its predictive accuracy but also to the interpretive ability of the model. This can be made by carrying out a sensitivity analysis that quantifies the relative importance of model inputs to the corresponding outputs. In this study, the relative importance was determined using three different sensitivity measures, namely the range (r_a), gradient (g_a) and variance (v_a), as follows [28]:

$$r_a = \max(y_a) - \min(y_a) \quad (6)$$

$$g_a = \sum_{j=2}^{L} \left| y_{a,j} - y_{a,j-1} \right| / (L-1) \quad (7)$$

$$v_a = \sum_{j=2}^{L} (y_{a,j} - \bar{y}_a)^2 / (L-1) \quad (8)$$

For all of the above metrics, the higher the value the more relevant is the input. Thus, the relative importance (R_a) can be given as follows [29]:

$$R_a = s_a / \sum_{i=1}^{I} s_i \times 100(\%) \quad (9)$$

where: $y_{a,j}$ is the sensitivity response for $x_{a,j}$ and s is the sensitivity measure (i.e. *r, g* or *v*). Figure 5 shows the graphical representation of the relative importance measures in the form of bar charts. It can be seen from Figure 5 that the river depth, Y_o, seems to provide greater importance than the other input variables for almost all sensitivity measures used, while the flow velocity, *V*, and median diameter of sediment load, d_{50}, hold less importance than the other input variables.

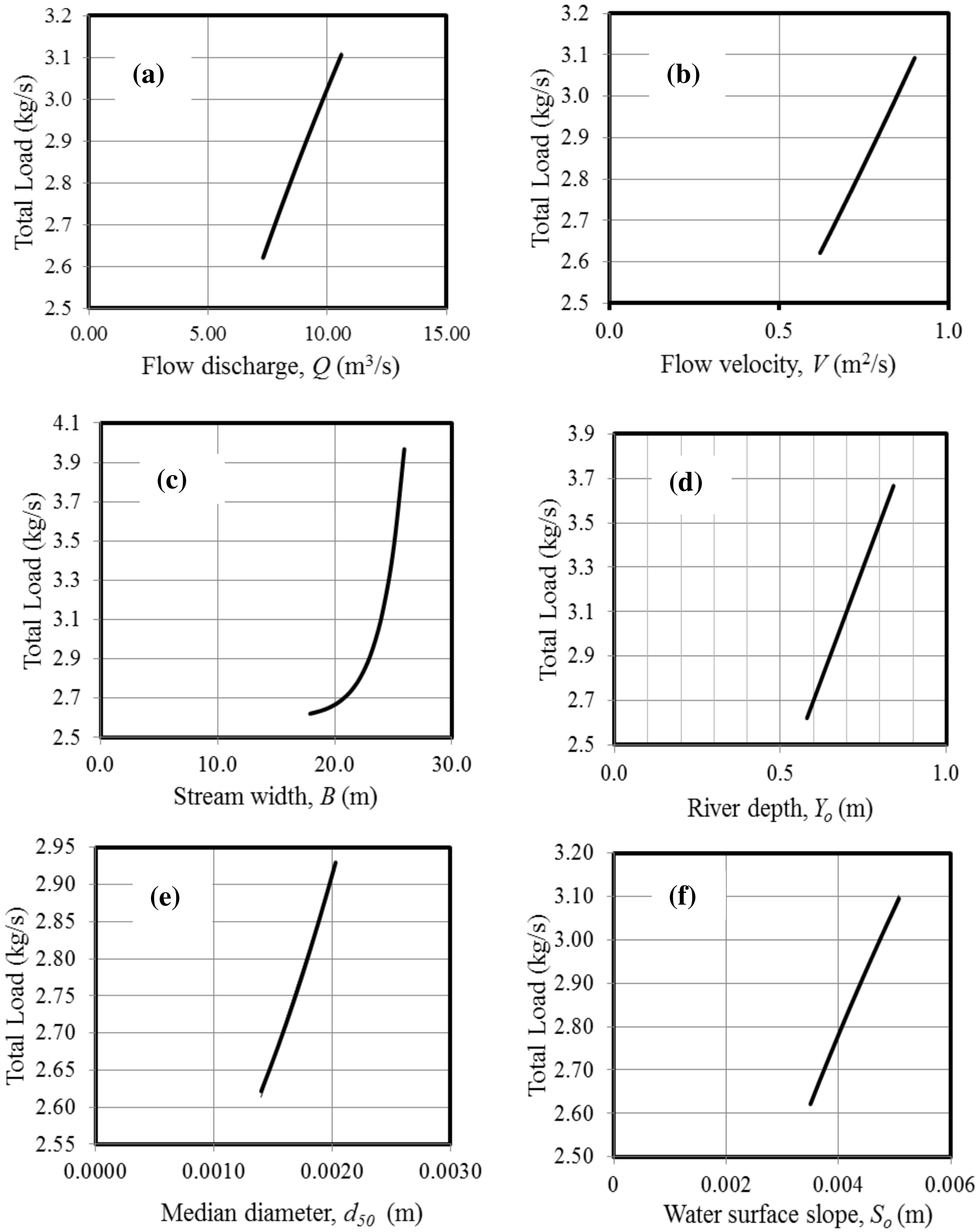


FIGURE 4: Robustness study showing the EPR model ability to generalise.

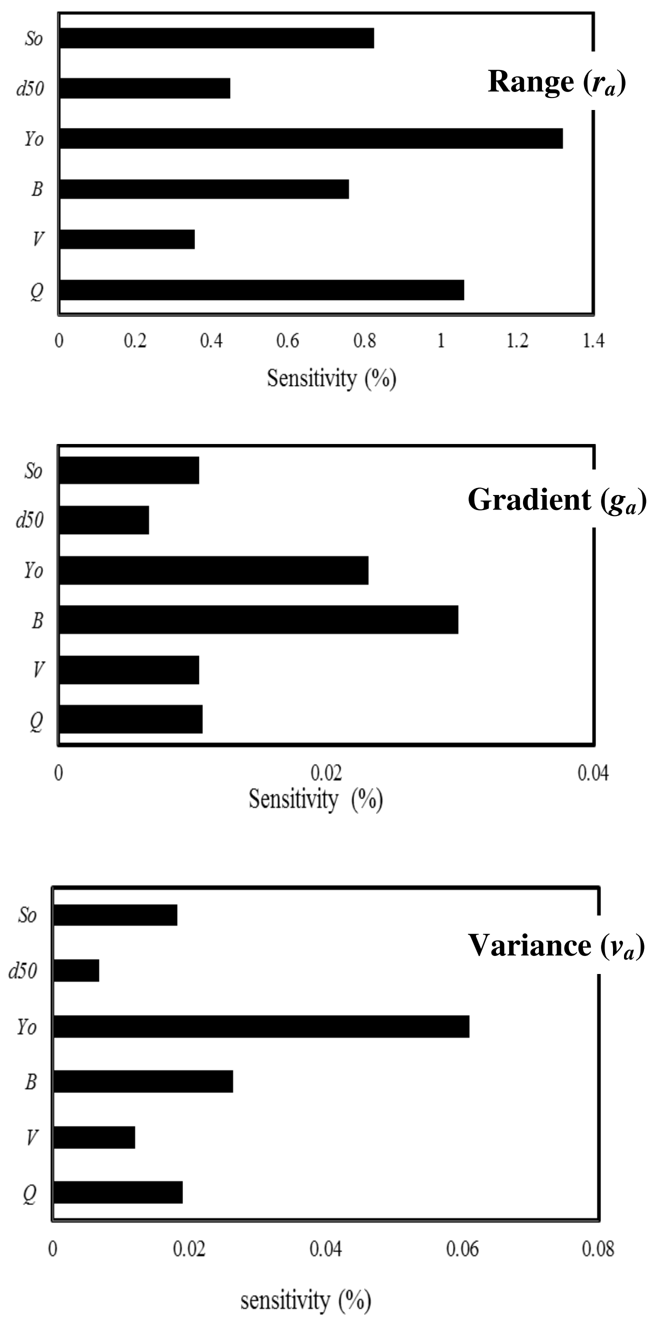


FIGURE 5: Sensitivity analysis showing the relative importance of the EPR model inputs.

3.4 Comparison of optimum EPR model with available models

In order to examine the accuracy of the developed EPR model against other available models, the EPR model predictions were compared with those obtained from six available sediment transport models, including Engelund & Hansen [1], Graf [2], Ariffin [9], Chan et al. [10], Sinnakaudan et al. [8], Zakaria et al. [30] and Aminuddin et al. [33]. A summary of the sediment parameters for other available methods used for comparison is given in Table 4. Statistical analyses, in relation to the 67 cases of the validation set, were carried out and the results are given numerically in Table 5 and represented graphically in Figure 6.

Model	Input parameters used
Engelund–Hansen [1]	$\gamma_s, V^2, \sqrt{d_{50}/g(\gamma_s/\gamma_w)}, \sqrt[1.5]{\tau/(\gamma_s-\gamma_w)d_{50}}$
Graf [2]	$(S_s-1)d_{50}/RS_o, C_vVR/\sqrt{g(S_s-1)d_{50}^3}$
Ariffin [9]	$R/d_{50}, U^*/\omega_s, U^*/V, V^2/gy_o$
Chan et al. [10]	$(S_s-1)d_{50}/RS_o, C_vVR/\sqrt{g(S_s-1)d_{50}}$
Sinnakaudan et al. [8]	$VS_o/\omega_s, R/d_{50}, \sqrt{g(S_s-1)d_{50}^3}/VR$
Zakaria et al. [30]	*Q, V, B, Yo, R, So, Ws,d50*
Ab. Ghani et al. [32]	*Q, V, B, Yo, A, P, So*

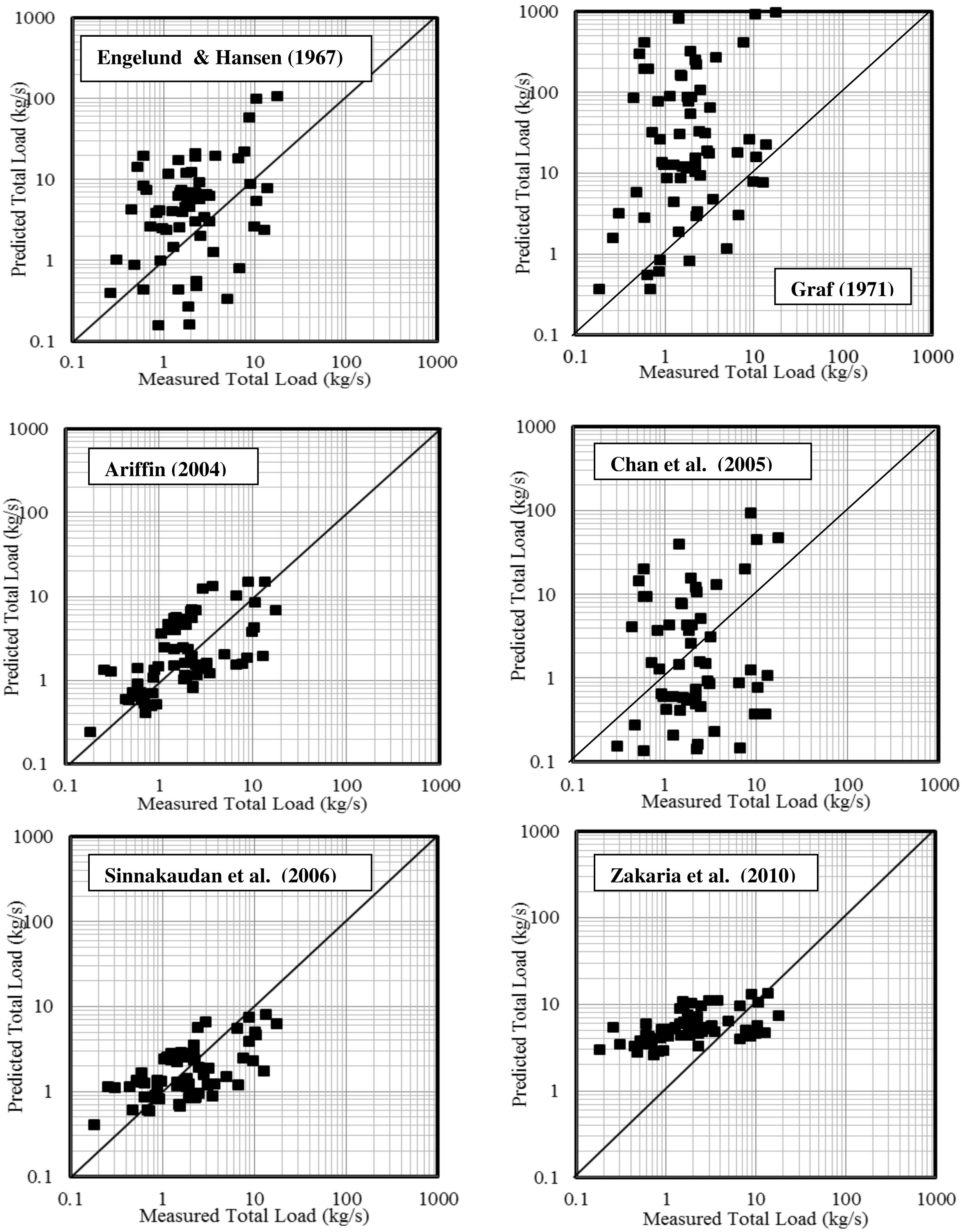
γ_s = unit weight of sediment; V = flow velocity; d_{50} = median diameter of sediment load; g = acceleration of gravity; γ_w = unit weight of water; τ = mean bed shear stress; S_s = specific gravity of sediment; R = hydraulic radius; C_v = volumetric sediment concentration; U^* = shear velocity, ω_s = fall velocity, Q = flow discharge; B = stream width, Y_o = flow depth, S_o = water surface slope; A = river cross sectional area, P = river perimeter.

TABLE 4: Summary of sediment parameters used in available methods.

It can be seen from Table 5 that the EPR model outperforms the other available methods in all performance measures used. It can also be seen that the model developed by Sinnakaudan et al. [8] comes second in order of best model performance. The graphical results also indicate that both the EPR model and Sinnakaudan et al. [8] have the least scattering around the line of equality between the predicted and measured sediment total loads, and this observation is confirmed numerically by the efficiency values, *E*, obtained in Table 5.

Model	**Performance measure**				
	R	***RMSE***	***E***	***DR***	***AIC***
Engelund & Hansen [1]	0.59	17.72	-23.28	0.21	94.8
Graf [2]	0.39	23.46	-8088.71	0.19	258.9
Ariffin [9]	0.47	3.63	-0.02	0.46	0.0
Chan et al. [10]	0.39	13.75	-13.62	0.15	75.1
Sinnakaudan et al. [8]	0.64	2.97	0.32	0.53	12.2
Zakaria et al. [30]	0.40	4.33	-0.45	0.24	39.2
Current study (EPR)	0.74	2.41	0.55	0.64	0.0

TABLE 5: Comparison of EPR model and other available methods (validation set – 67 data cases).


Engelund & Hansen (1967)
Graf (1971)
Ariffin (2004)
Chan et al. (2005)
Sinnakaudan et al. (2006)
Zakaria et al. (2010)
Predicted Total Load (kg/s)
Measured Total Load (kg/s)
0.1
1
10
100
1000

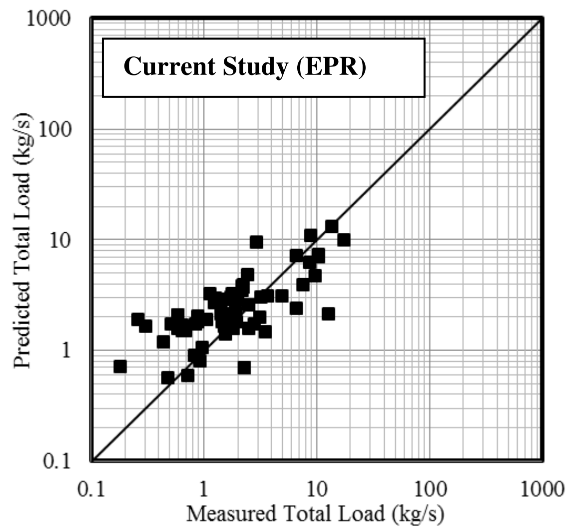


FIGURE 6: Predicted vs measured total sediment load for EPR and other methods.

4. CONCLUSIONS

This study investigated the use of the Evolutionary Polynomial Regression (EPR) technique in developing a new model for predicting sediment transport in Malaysian rivers. The data used for model calibration and validation involved 338 cases that were collected from the Department of Irrigation and Drainage (DID), Ministry of Natural Resources & Environment, Malaysia. The data were divided into 80% for model calibration (training) and 20% for model validation (testing). The EPR models were trained with eight input variables that thought to be significant including the hydraulic radius (R), flow depth (Y_o), flow velocity (V), median diameter of sediment load (d_{50}), stream width (B), water surface slope (S_o), fall velocity (ω_s) and flow discharge (Q). The only output is the total sediment load (T_j). Robustness study to investigate the generalisation ability of the developed EPR model was conducted, and a sensitivity analysis was also carried out to check the relative importance of model inputs to the corresponding output. Predictions from the developed EPR model were compared with those obtained from six available methods including: Engelund & Hansen [1], Graf [2], Ariffin [9], Chan et al. [10], Sinnakaudan et al. [8] and Zakaria et al. [30]. The statistical analyses used for comparison of performance of models included the coefficient of correlation, r, root mean squared error, *RMSE*, coefficient of efficiency, E, discrepancy ratio, *DR*, and Akaike information criterion, *AIC*.

The results indicate that the EPR model with six input variables (i.e. R, Y_o, d_{50}, B, S_o and Q) provided the best performance and was thus considered to be optimal. This optimum EPR model showed better performance, in relation to the validation set, than the other methods used for comparison with less scattering around the line of equality between the measured and predicted total sediment loads. For the EPR model: r, *RMSE*, E, *DR* and *AIC* were found to be equal to 0.74, 2.41, 0.55, 0.64 and 0.0, respectively. These measures were found to outperform those of the other available methods. The EPR model was also found to be robust in terms of its generalisation ability as its behaviour was found to be in agreement with the underlying physical meaning of sediment transport. The sensitivity analysis indicated that the river depth, Y_o, provided greater importance than the other input variables, while the flow velocity, V, and median diameter of sediment load, d_{50}, and hold less importance than the other input variables. The above results indicate a high potential for using the EPR model over available methods for predicting the total sediment load of Malaysian rivers.

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A Learning Linguistic Teaching Control for a Multi-Area Electric Power System

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Abstract

This paper presents a new methodology for designing a neuro-fuzzy control for complex physical systems. By developing a Neural -Fuzzy system learning with linguistic teaching signals. The advantage of this technique is that, produce a simple and well-performing system because it selects the fuzzy sets and the numerical numbers and process both numerical and linguistic information. This approach is able to process and learn numerical information as well as linguistic information. The proposed control scheme is applied to a multi-area power system with hydraulic and thermal turbines.

Keywords: Fuzzy Logic Control, Artificial Neural Network, Interconnected Power System, Load Frequency Control, Neuro-fuzzy Systems.

1. INTRODUCTION

The control engineer's knowledge of the system is based on expertise, intuition, knowledge of the system's behavior. Therefore, the main objective of the fuzzy control scheme is to replace an expert human operator with a fuzzy rule-based control system.

The fuzzy system belongs to a general class of fuzzy logic system in which fuzzy system variables are transformed into fuzzy sets "Fuzzification" and manipulated by a collection of "IF-THEN" fuzzy rules, assembled in what is known as the fuzzy inference engine.

These rules are derived from the knowledge of experts with substantial experience in the system. Then, the fuzzy sets are transformed into fuzzy variables" Defuzzification" [2, 4].

In such a system, input values are normalized and converted to fuzzy representations, the model's rule base is executed to produce a consequent fuzzy region for each solution variable, and the consequent regions are defuzzified to find the expected value of each solution variable [1, 7].

Artificial Neural networks may be employed to represent the brain activities, neural networks are attractive to the classical techniques for identification and control of complex physical systems, because of their ability to learn and approximate functions [6, 9].

The conventional control systems usually involve the development of a mathematical model of the system to derive a control law. In many of the physical systems, it may be difficult to obtain an accurate mathematical model due to the presence of structured and unstructured uncertainties. Fuzzy system and neural networks are both soft computing approaches for modeling expert behavior [7, 9]. This paper will show those combinations of neural networks with fuzzy systems, the so called neural fuzzy or neuro-fuzzy systems.

By a Neuro-fuzzy system, one understands a system which involves in some way both fuzzy systems and neural networks, or features of both, combined in a single system.

The most important reason for combining fuzzy systems with neural networks is their learning capability and such a combination should be able to learn linguistic rules and / or membership functions.
Therefore, combining neural networks with a fuzzy set could combine the advantage of symbolic and numerical processing.

Neural Networks and fuzzy systems estimate functions from sample data, it does not require a mathematical model; they are model-free estimators [6, 9]

2. FUZZY LOGIC CONTROLLER

The fuzzy logic controller comprises three stages namely fuzzifier, rule-based assignment tables and the defuzzifier. The fuzzifier is responsible for converting crisp measured data into suitable linguistic values. The fuzzy rule-base stores the empirical knowledge of the operation of the domain experts. The inference engine is the kernel of an FLC, and it has the capability of simulating human decision-making by performing approximation reasoning to achieve a desired output.

The defuzzifier is utilized to yield a nonfuzzy decision action from an inferred fuzzy system by the inference engine. The defuzzifier is responsible for converting linguistic values into crisp data [1, 7].

A typical architecture of a fuzzy logic is shown in Fig.1

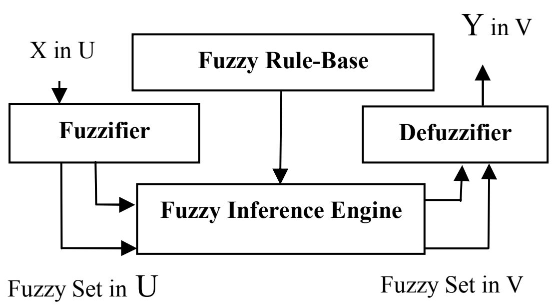

FIGURE 1: Fuzzy System Structure

The fuzzy logic system proceeds as follows to evaluate the desired output signal, as shown in Fig.2.
At First, the input variables are normalized, and the membership function of the fuzzy logic controller output signal is determined by linguistic codes

Finally, the numerical value of the adaptive fuzzy logic controller output signal corresponding to a specific linguistic code is determined.

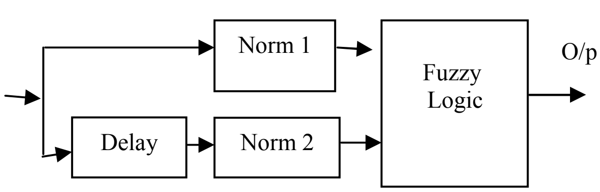

FIGURE 2: The Internal Structure of Fuzzy Logic

The error “e” and the error change “Δe” are defined as a difference between the set point value and the current output value

$$e(k) = u_r^0(k) - u_c^0(k) \quad (1)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (2)$$

That is,

$$u_r^0(k) = u_r^0(k-1)$$

This assumption is also satisfied in most cases:
Case (1):

$$e(k) < 0 \quad and \quad \Delta e(k) > 0$$

$$\Rightarrow \Delta u_r^0(k) < u_c^m(k)$$

$$and \quad u_c^m(k) < u_c^m(k-1)$$

Case (2):

$$e(k) > 0 \quad and \quad \Delta e(k) < 0$$

$$\Rightarrow \Delta u_r^0(k) > u_c^m(k)$$

$$and \quad u_c^m(k) < u_c^m(k-1)$$

Where

$u_r^m(k)$: is the reference of the fuzzy logic controller at k-th sampling interval
$u_c^m(k)$: is the fuzzy logic controller signal at k-th sampling interval
e(k) is the error signal
Δe(k): is the error change signal

3. NEURAL NETWORKS

The most significant characteristic of the neural networks is their ability to approximate arbitrary nonlinear functions. This ability of the neural networks has made them useful to model nonlinear systems, which is of primary importance in the synthesis of nonlinear controllers [11]. A neuro-controller (neural network-based control system), in general, performs a specific form of a multilayer network and the adaptive parameters being defined as the adjustable weights [12].

In general, neural networks represent parallel-distributed processing structures, which make them prime candidates for use in multivariable control systems.

The neural network approach defines the problem of control as the mapping of measured signals for change into calculated controls for actions. The system shown in Fig.3 represents the neural learning and control scheme, a control system is called a learning control system, if the information pertaining to the unknown features of the system for its environment is acquired during operation, and the obtained information is used for future estimation.

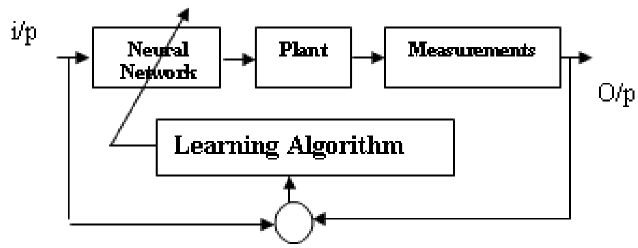

FIGURE 3: A Typical Neural Learning and Control Scheme

4. NEURO-FUZZY SYSTEMS

The neural networks and fuzzy systems solve problems by performing the function approximation. Neural networks can be used, if training data is available, and a mathematical model of the system is not needed [6-9, 11, 12]. But a fuzzy system can be used, if knowledge about the solution of the problem in the form of linguistic IF-THEN rules is available, a formal model of the system is unnecessary, and training data will not be needed.

On the other hand, if the problem of interest changes too much compared to the former training data, then the network may not to able to cope with that, there is no guarantee that resuming the training process will lead to fast adaption to the modified problem, it may be necessary to repeat the learning again [11].

A neuro-fuzzy system, is a system which involves in some way both fuzzy systems and neural networks or features of both combined in a single system [11, 12]

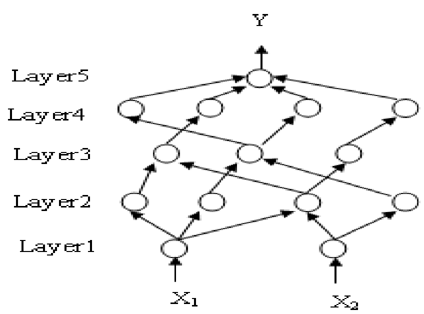

FIGURE 4: The five Layer Architecture

Fig. 4 shows the neural fuzzy system structure with five-layers. The proposed approach to develop a neuro-fuzzy logic control consists of the following five steps. At first, each node in the first layer transmits input number xi to the next layer directly.

The second step is called matching, each node in the 2^{nd} layer has exactly one input from some input linguistic nodes and feeds its output to rule node, and the weight is fuzzy number w. the third step.

The input and output of a node in the 3^{rd} layer are numerically calculated to find the minimum matching of fuzzy logic rules. The fourth step, finds the maximum value for the 3^{rd} layer, and the nodes in the 4^{th} layer should be fuzzy OR. Finally, Merging and Defuzzification of each node has a fuzzy weight w $Y_{i.}$

All previous steps can be governed by the following equations

$$O_i^1 = U(O_{i1}^1 - O_{i2}^1) = X_i \tag{3}$$

$$f_{ij}^2 = 0.5\sum(w \times X_{ij1} - u_{ij}(t))^2 + \sum(w \times X_{ij1} - u_{ij}(t))^2 \tag{4}$$

$$O_1^3 = \min(u_1^3, ..., u_k^3) \tag{5}$$

$$O_1^3 = \max(u_1^4, ..., u_k^4) \tag{6}$$

$$O_5 = U(O_1^5, O_2^5) = Y = \frac{\sum u_1^5 wy}{\sum u_1^5} \tag{7}$$

5. ELECTRIC POWER SYSTEM

It is reasonable to study in considerable details the megawatt frequency control problem for multi-area electric power system. Load Frequency Control “LFC” is a very important factor in power system operation. It aims at controlling the output power of each generator to minimize the transient errors in the frequency and tie-line power deviations and to ensure its zero steady state errors [15, 16].

Load frequency control “LFC” sometimes, called Automatic Generation Control “AGC” is a very important aspect in power system operation and control for supplying sufficient and reliable electric power with the desired quality [13, 14].

Load frequency control generally involves several designed power areas within an integrated power grid with each area responsible for controlling its area control error ‘ACE”

A two area interconnected power system model is developed. The load frequency control “LFC” of interconnected power system “IPS” relies on an operating schedule that is usually prepared all day. In advance, this schedule indicates the expected demand profile of the area as well as, the area commitment to its adjacent areas. The problem of the LFC of an IPS can be expressed mathematically as follows

$$\begin{aligned} X &= [X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8] \\ &= [\Delta F_1, \Delta X_{g1}, \Delta P_{g1}, \Delta F_2, \Delta X_{g2}, \Delta H_{g2}, \Delta P_{g2}, \Delta P_{tie12}] \end{aligned} \tag{8}$$

$$U = [U_1, U_2, U_3, U_4] = [\Delta P_{c1}, \Delta P_{d1} \Delta P_{c2} \Delta P_{d2}] \tag{9}$$

The commitment is the tie-line power interchange which should be maintained at a certain point in time. This value is fed to the other area. The functional block diagram of Hydro-Thermal interconnected power system is shown in Fig.5. Power deficits may be purely active, purely reactive, or combined. Any of these deficits affects the frequency of the system either directly.

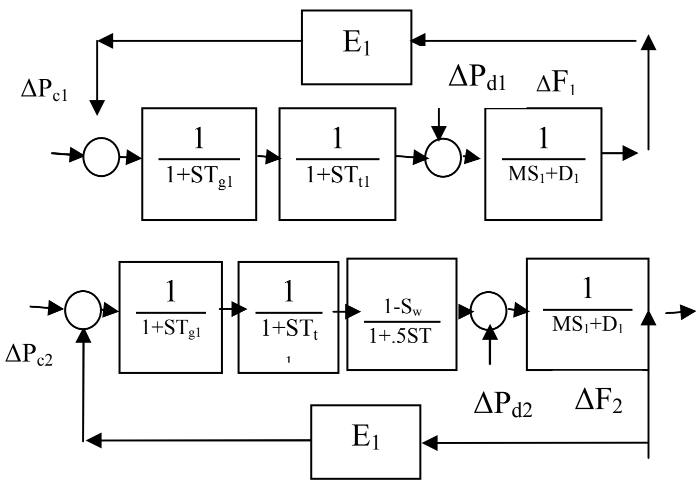

FIGURE 5: Block diagram of Hydro-Thermal Interconnected power system

Due to active power unbalance, or indirectly, through change in system demand due to changes in voltage caused by reactive power unbalance.

Active power deficits may take place in power systems as a result of forced outage of generating units and / or loaded tie lines, or due to the switching on of appreciable loads.
The interlinking of the various areas in case of a two-area system is though the tie-line power exchange. Changes in tie-line power flows affected the power balance in corresponding areas as shown in Fig.6.

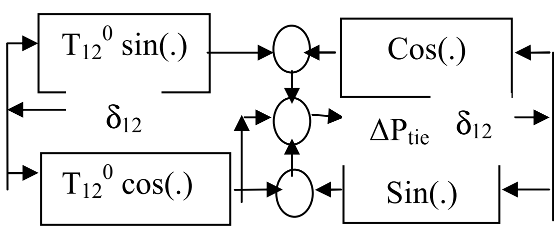

FIGURE 6: Tie -Line Power Exchange

The incremental tie-line power is

$$\Delta P_{tiel2} = T_{12}^{0}\sin(\delta_1^0-\delta_2^0)\cos(\delta_1^0-\delta_2^0)$$
$$-T_{12}^{0}\sin(\delta_1^0-\delta_2^0)+T_{12}^{0}\cos(\delta_1^0-\delta_2^0)\sin(\delta_1^0-\delta_2^0) \qquad (10)$$

6. NUMERICAL DATA

As a numerical example, a two area load frequency control system was studied. The numerical data has shown:

Thermal-area
M=0.04 , G=0.01 , Tg=0.5 , T_t=0.5, E=0.03
Hydro-area
M=0.03 , G=0.08 , Tg=0.5 , T_t=0.5, E=0.013, T_w=0.5
Tie-line power
T_{12}=0.02701

In this section, the development of a Neuro-fuzzy system, learning with linguistic teaching signals is shown.

This system is able to process and learn numerical information as well as linguistic information. It can be used as an adaptive fuzzy controller by using the reinforcement learning proposed in [12]. The proposed Neuro-fuzzy techniques confirmed the effectiveness of the human operator in the presence of system nonlinearities. The results are shown in Fig.7, indicates the closed loop response of the Neuro-fuzzy control.

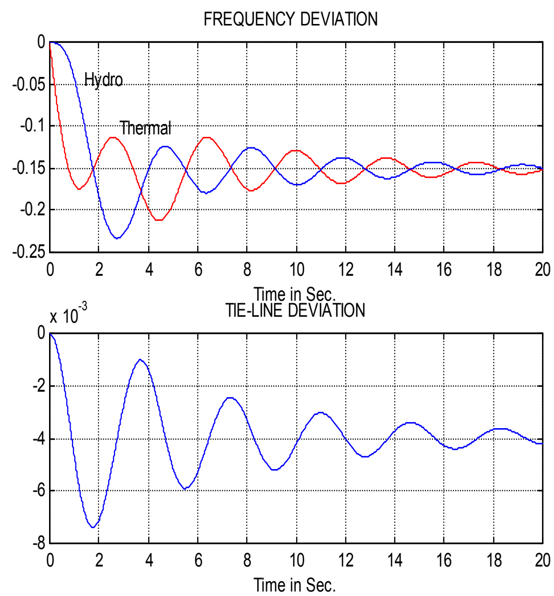

FIGURE 7: the System Response with Neuro-Fuzzy Control

6. CONCLUSION

This paper proposed combining a neural network with a fuzzy set; It could combine the advantage of symbolic and numerical processing. Neural Networks and fuzzy systems estimate functions from sample data, it does not require a mathematical model; they are model-free estimators a Neural-Fuzzy system that process both numerical and linguistic information. The proposed system has some characteristics and advantages, the inputs and outputs are fuzzy numbers or numerical numbers, the weights of the proposed Neural-fuzzy system are fuzzy weights, owing to the representation forms of the fuzzy weights, the fuzzy inputs and fuzzy outputs can be fuzzy number of any shape, and except the input-output layers, numerical numbers are propagated through the whole Neural-fuzzy system. The proposed Neuro-fuzzy techniques confirmed the effectiveness of the human operator in the presence of system nonlinearities. This controller does not require the system model, this model is a complex model, and needed to leanirezed to design a controller, but our controller require only the observation of input-output. The response of Hydro-Thermal plant has an error less than the conventional controller used, and it is an adaptive controller.

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