Estimation of Carbon Nanotube Sensors Performance using Linear, Fuzzy and Neural Regression Models

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Abstract - Electrical transformers are considered one of the very important elements on the operation of power systems. The operation of electrical transformers is dependent on the performance of transformer oils. Hence, it is very necessary for continuous and online checking the transformer oil insulation level. Transformer oil wet process generates oil discharge space charge in the long run and bubbles are formed. When the electric field reaches a certain limit, partial discharge (PD) appears and lead to deterioration of oil insulation level. In this paper, Multi-wall carbon nanotube (MWNT) sensor is used for detecting PD of oils). The performance of (MWNTs) films sensor for continuous and on line monitoring the oil insulation level is studied. A linear, fuzzy and neural regression models are used to explain and predict the performance of the sensor.

Keywords - Partial Discharge, Carbon Nanotubes Sensors, Fuzzy Regression, Linear Regression.

I. INTRODUCTION

High voltage power transmission system showed prominence recently. With an increasing of power transformer rating and size, it is necessary to design and develop a compact, cost-effective and reliable insulation system of the power transformer. The cause of transformer failures by the incipient discharges that happens is the defects present in the insulation system.

Transformer oil discharge is generated during operation due to oil wet process. Then bubbles are generated inside transformer oil. When the electric field rises to critical value, a partial discharge will appear [1-3]. Up to now, decomposition components from partial discharge in transformer oils were successfully detected using a gas chromatography, an ion mobility spectrometer, a mass spectrometer, a detection tube and carbon nanotubes. The spectrometers and the gas chromatography are very expensive and suitable for laboratory analysis rather than on-line diagnosis. The detection tubes have poor accuracy and cannot be used in remote monitoring but it can detect decomposition components at ppm levels and handy. Nanotube sensor has good sensitivity and can detect partial discharges in transformer oils during operations. To expect the performance of the MWNTs sensor, three different methods are used as follows:

Fuzzy Linear Regression Methodology:

The fuzzy linear regression (FLR) is used in describing the relation between the dependent and independent variables using many fuzzy approaches such as least square technique [4-9].

Simple Linear Regression

The simple linear regression (SLR) is used to describe the relation between single factor X on a dependent variable Y using fitting and studying straight relation between variables.

Neural Regression

A neural regression is characterized by:

(i) Its pattern of connections between the neurons (called its architecture),

(ii) Its method of determining the weights on the connections,

(iii) Its activation function.

II. DATA DESCRIPTION

Laboratory tests were carried out using transformer oil testing device (oil tester) and MWNTs sensor for detecting the partial discharges, as shown in Figure 1.

The detection of partial discharge is based on the detection of the oil decomposition at the partial discharge. In the test, oil is kept in a pot in which one pair of electrodes is fixed with a gap of 2 mm in between. In the oil tester, one of the electrodes is stressed with the high voltage and the other is earthed. The sensor was placed above the oil. Now slowly rising the applied voltage and the sensor resistance is real timely recorded by a digital multimeter.

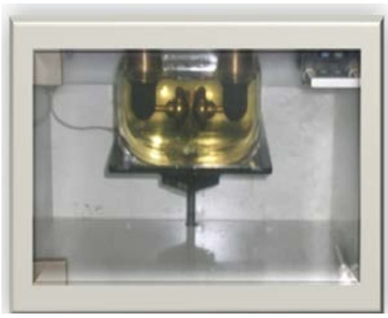

Fig. 1. Laboratory oil tester testing device of oil discharge decomposition.

According the experimental results, Fig. 2 presents the variations of the sensor resistances with time for the modified MWNTs thin film at different discharge voltages. It is clear that the resistance of the MWNTs sensor increased with the increasing of the exposure time of the applied voltage, until reach certain point (approximately 0.7 kΩ) then breakdown occur. It is noticed also, with increasing the applied voltage, the time to reach breakdown decreases. With lower applied voltage (6kV), the resistance slope is lower and takes longer time to reach the certain resistance point. Also, the resistance decreases rapidly at the point before the breakdown, while at higher voltages (8kV and 9 kV), the resistance slope is nearly the same. This online monitoring of the sensor resistance shall enable the operator to take a decision to disconnect the transformer before the breakdown stage. Hence, using this sensor, as an online monitoring technique, the partial discharge can be detected and the breakdown can be predicted by the observation for sensor electrical resistance change. It is obvious that the breakdown can be forecasted when the value of sensor resistance approaches to certain limit. So the sensor can be used to predict the occurrence of breakdown and the proper alarm and tools may be used to disconnect the transformer and prevent the breakdown.

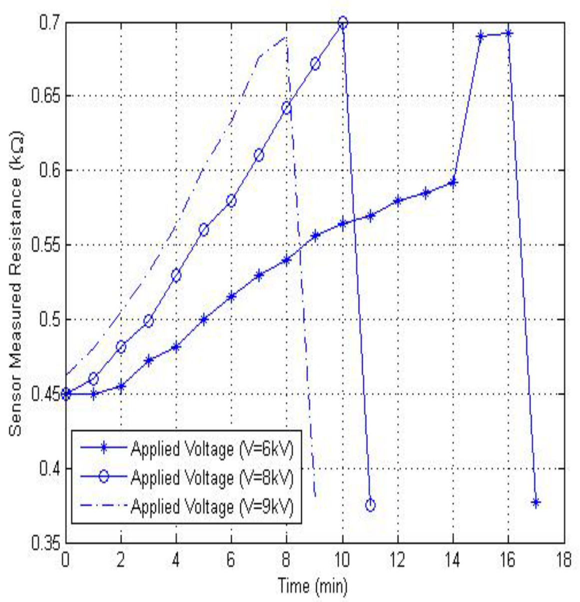

Fig. 2. Variation of MWNTS thin film resistance with time at different voltages

From Fig. 2, it is noticed that discharge time can represented as X variable and the resistances of the sensor at 6, 8 and 9 kV as Y1, Y2, Y3 respectively. These variables and Y's (which represent Y1, Y2 and Y3 together) are taken to build the linear, fuzzy and neural regression models.

III. RESULTS

Table 1 shows the mean and standard deviation of each variable. Correlation analysis is used to illustrate the strength and direction of the linear relationship among the variables and the factors of the conceptual model. It varies from 0 (random variable) to 1 (perfect linear relationship) or -1 (perfect negative relationship). Pearson Correlation Coefficients of the various variables represent the weakness positive significance relationship [11]. It shows that most correlations were statistically significant at (0.05). This shows that there is a moderate and high correlation between two variables (X and Y's).

When all data were included in model as a crisp number, regression would produce the same results as ordinary regression. So, the value of the center in fuzzy reserves must be the same as the result of ordinary least-squares regression. The following indictors are used to fit measurement model (to choose the best model):[12-15]

- The root mean squared error (RMSE).
- The mean absolute error (MAE).
- The mean absolute percentage error (MAPE).
- The Theil Coefficient (T.C).
- The Coefficient of Determination (R^2)

Table 1: Descriptive Statistics of variables

Variable	Descriptive		Correlation			
	Mean	STD. Dev.	Y1	Y2	Y3	X
Y1	0.535	0.080	1			
Y2	0.543	0.097	0.502	1		
Y3	0.551	0.101	0.284	0.265	1	
X	8.500	5.339	0.570*	0.463	0.359	1

* Correlation is significant at the 0.05 level.

Table (2) Indictors to fit statistics (measurement) model

Dep.	Model	RMSE	MAE	MAPE	T.C	R2
Y1 N=18	Fuzzy Reg.	0.062	0.032	6.037	0.0058	0.394
	Linear Regression	0.064	0.034	6.904	0.060	0.325
Y2 N=12	Fuzzy Reg.	0.098	0.067	14.572	0.093	0.146
	Linear Regression	0.075	0.05	11.303	0.072	0.093
Y3 N=10	Fuzzy Reg.	0.057	0.023	5.567	0.050	0.682
	Linear Regressi	0.653	0.556	117.905	0.415	0.021

	on					
Y'S N=9	Fuzzy Reg.	0.007	0.006	1.013	0.007	0.989
	Linear Regression	0.009	0.007	1.401	0.009	0.982
	Neural Regression	0.005	0.005	0.855	.0065	0.99

Table (2) shows summarizes the results of five tests of four dependent variables, each of the statistics is based on the one-ahead fit and errors of each model, which are the differences between the data value and predict of that value. The first four statistics measure the magnitude of the errors. A better model will give a smaller value. The last statistics, a better model will give a value close to 1. In this case, the model was estimated from the four models. Table (2) shows the statistics for the estimation models. If the results are considerably worse in the *Y1*, *Y2* and *Y3* and all *Y'^S*, it means that the model is not likely to perform as well as otherwise expected in forecasting the future. In table (2), N variable represents number of observations (readings) of each variable. The mathematical models would be computed using SPSS statistical software.

This table compares the results of four different models. Looking at the statistics, the model with the smallest root mean squared error (RMSE) during the estimation is model *Y'^s*, *Y3*. The model with the smallest mean absolute error (MAE) is model *Y'^s*, *Y3*. The model with the smallest mean absolute percentage error (MAPE) is model *Y'^s*, *Y3*. The model with the highest R- squared (R^2) is model *Y'^s*, *Y3*.

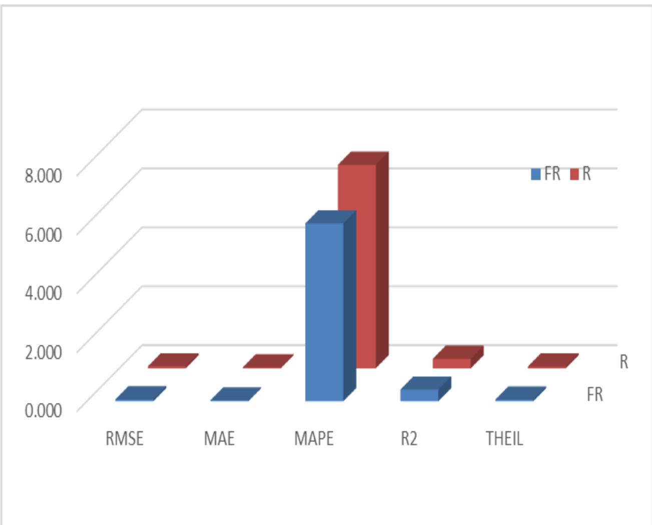

Fig. 3-a. Fit statistics of *Y1*

Fig. (3) represents the indicators to fit statistics of fuzzy(FR) and linear regression(R) models of variables Y1, Y2 and Y3 respectively. It is clear from Fig.(3) that the five indicators of fuzzy models of Y1 and Y3 are better than the linear regression model of these variables but the indicators of linear regression model of Y2 are better than the fuzzy model of this variable.

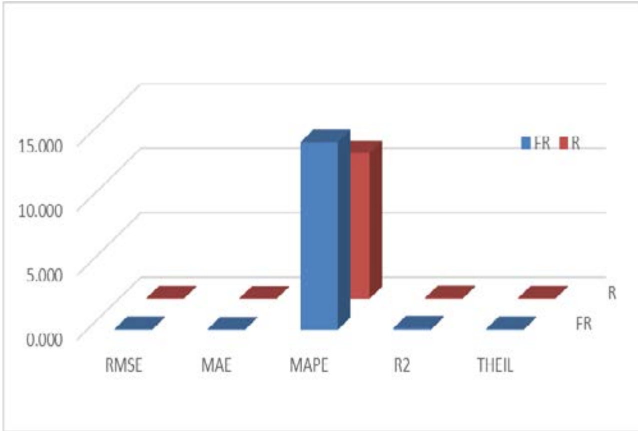

Fig. 3-b. Fit statistics of *Y2*

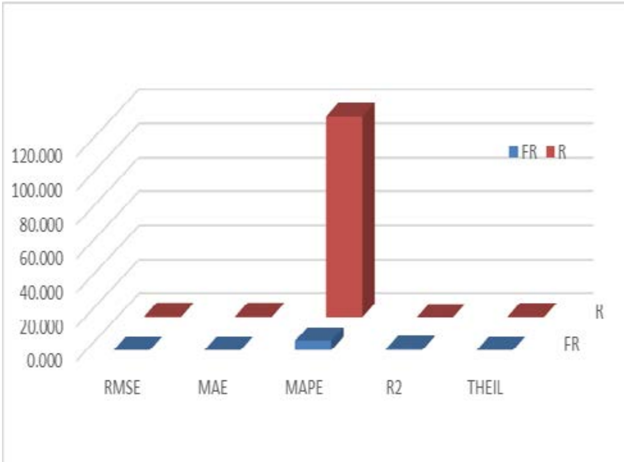

Fig. 3-c. Fit statistics of *Y3*

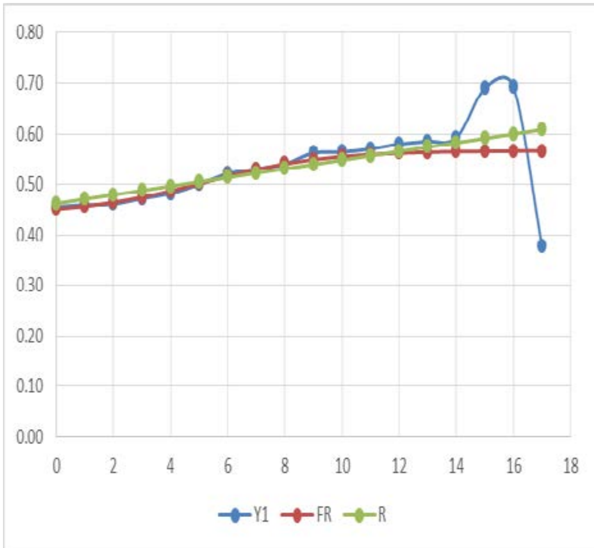

Fig. 4-a Data and Fit use FR and R of Y1

Fig. (4) compares the practical observations with the results of Y1, Y2 and Y3 respectively from fuzzy regression and linear regression models. Fig(4-a) and fig.(4-c) show that the fuzzy regression models are very near to the practical models readings than the linear

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regression models but fig.(4-b) shows that the linear regression model is near to the practical values than the fuzzy model.

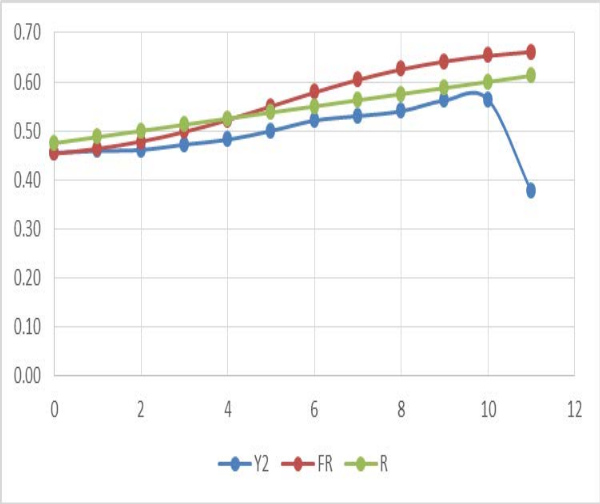

Fig. 4-b. Data and Fit use FR and R of Y2

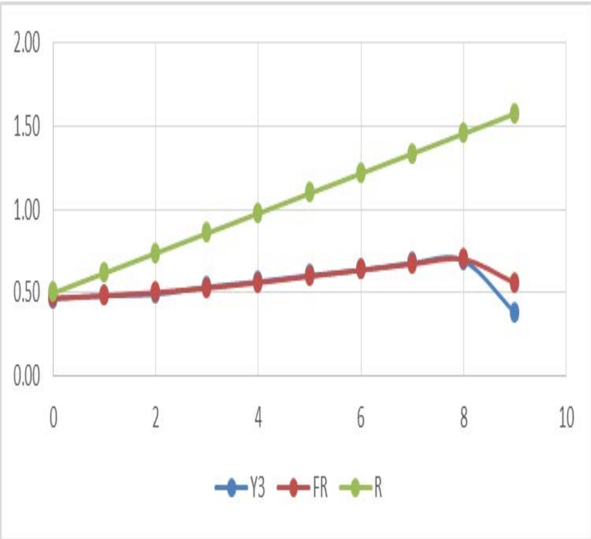

Fig. 4-c. Data and Fit use FR and R of Y3

Fig.(5) shows the deviation of the practical samples about the fuzzy regression model which represent as the line between these points. It is clear from the figure that the deviation of the practical points about the fuzzy line increases with the increasing of the discharge time.

Fig.(6) compares the practical observations of Y's with fuzzy regression and linear regression models.

Fig.(7) represents the indicators to fit statistics of fuzzy and linear regression models of variables Y's. It shows the five indicators of fuzzy regression of Y's are better than the linear regression model of this variable.

Fig.(8) shows network diagram used to design neural model to compute Y's variables. This network consists of input units which receive signals from outside and output units which show the response of the network. This network has only one layer of connection weights. The weights for one output unit do not affect the weights for other output units.

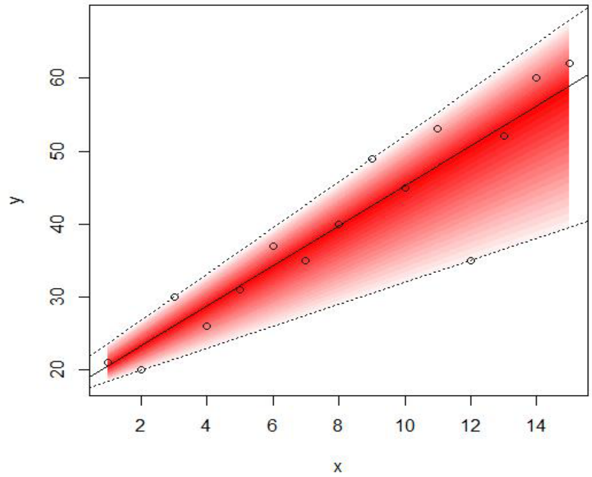

Fig. 5-a. Fuzzy regression of *Y1*

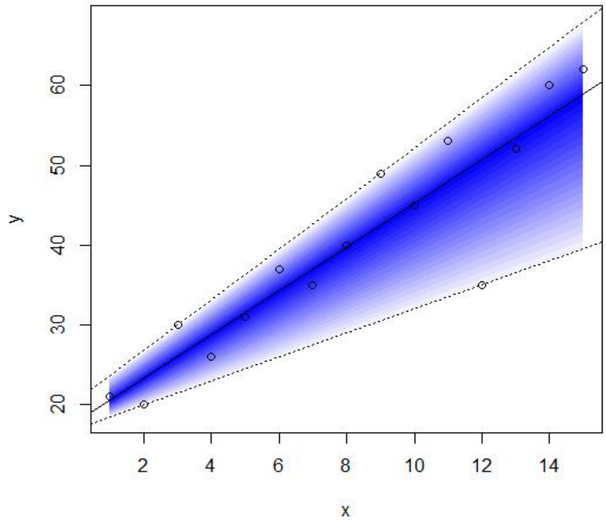

Fig. 5-b. Fuzzy regression of *Y2*

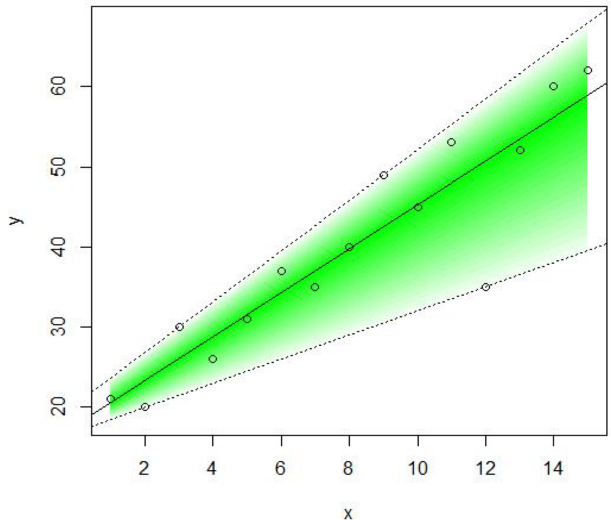

Fig. 5-c. Fuzzy regression of *Y3*

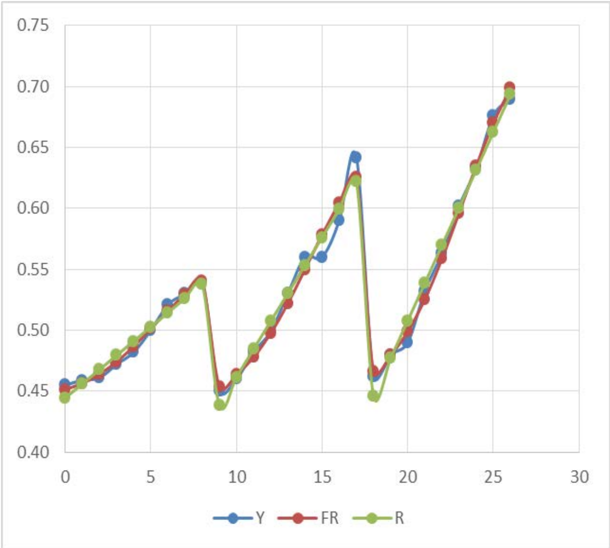

Fig. 6 Data and Fit use of FR and R of Y's

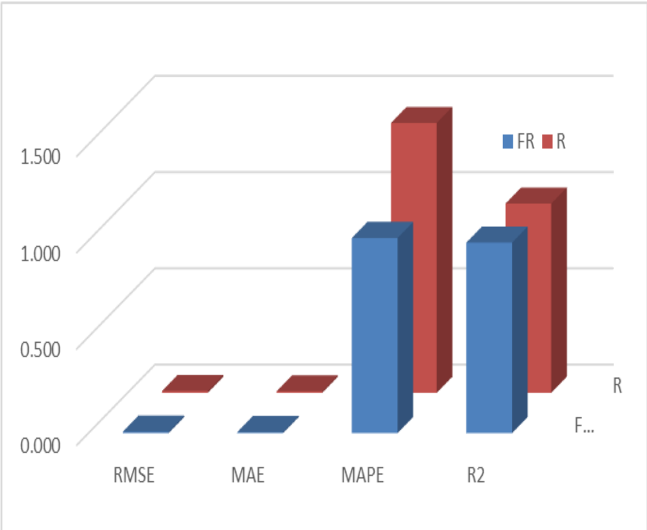

Fig. 7. Fit statics of *Y*'s

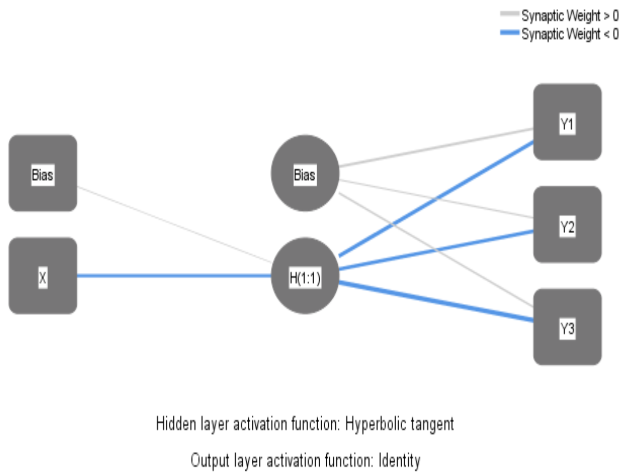

Fig. 8. Network diagram of *Y*

Fig.(9) represents the predicted values of Y1, Y2 and Y3 variables respectively using the neural network models.

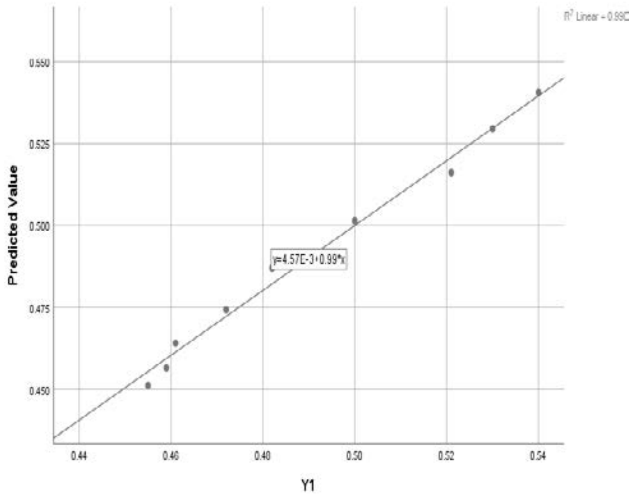

Fig. 9-a Predicted by observed charts of *Y1*

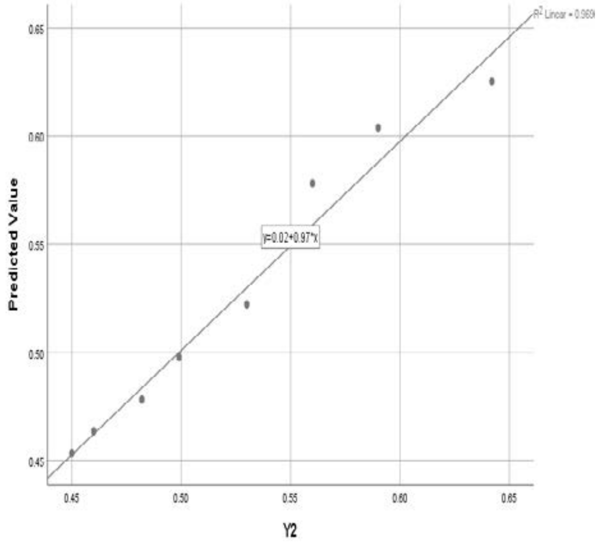

Fig. 9-b Predicted by observed charts of *Y2*

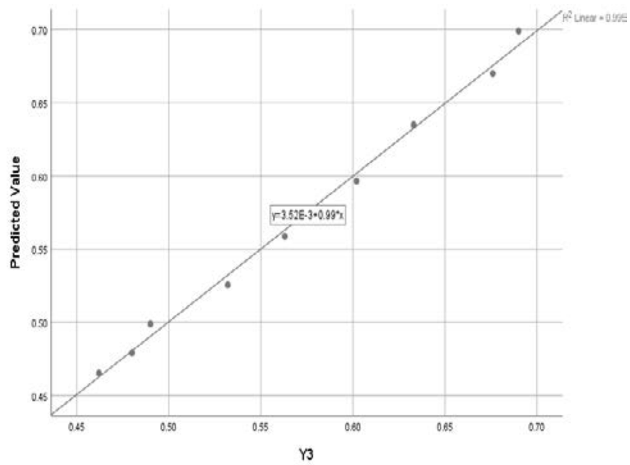

Fig. 9-c Predicted by observed charts of *Y3*

By solving this LP (Linear Programming) problem (using SPSS and SAS statistical software) of the 3 types of models: (where Y^ is the predicted value of Y), the following results are obtained:

(1) Simple Linear Regression (SLR) Model:

The form of SLR models are:

Y1^= 0.462* + 0:009* X

Y2^= 0.475* + 0:013 X

Y3^= 0.497* + 0:012 X

***** Significance of constants at 0.05 (P-Value < 0.05)

(2)Fuzzy Regression (FR) model:

The fitted general equation with interval coefficients are:

Y^ = < a0c , a0w > + < a1c , a1w >X

Where Y^ is the predicted value of Y,

a0c, a1c are constants of the fuzzy equation,

a0w, a1w are predicted errors of the equation, and the equation of our proplem are:

Y1^ = < 0.455, 0.000 > + < 0.006, 0.010 >X

Y2^ = < 0.450, 0.000 > + < 0.009, 0.016 >X

Y3^ = < 0.462, 0.000 > + < 0.011, 0.020 >X

(3)Neural Regression (NR) model:

The full model in Y's in one model (all Y's in the same with x):

Y1^= tanh(-0.142 – 0. 531 X), Y2^= tanh(4.000 + 3.619 X), Y3^= tanh(4.012 + 3.623 X)

IV. CONCLUSION

MWNTs sensor would be used to detect the partial discharge inside transformer oil in early stage and hence, prevent the occurrence of breakdown which has a great significance for increasing the transformers and power system reliability and continuous operation. The main conclusions are

- CNTs electric properties sensitive to the exposed gas environment.
- The electrical resistance of MWNT films sensor showed a strong response to a partial discharge in transformer oils.
- The MWNT sensor could detect partial discharge during operation of the transformer (on-line monitoring).
- Correlation matrix reveals the relationship between every variable in the mathematical methods.
- Neural theory is very suitable tool in modeling problems and better than fuzzy models.

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