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# Application of adaptive neuro-fuzzy inference systems (ANFIS) in modeling the effects of selected input variables on the period of oscillation in an unsteady flow through surge chamber

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## Abstract

In this research paper, an attempt was made to model the significant effects and the interactions of some selected input variables on the period of oscillation in an unsteady flow through surge chambers using adaptive neuro-fuzzy techniques. The choice of adaptive neuro-fuzzy technique is based on the fact that, it is a hybrid modeling algorithm that combines both neural network and fuzzy logic to obtain better result. The inlet valve to the reservoir was opened and adjusted to give a steady level of discharge from an overflow weir for a predetermined period of time. The flow rate of the water was thereafter computed using the volume against time relationship. A surge was then initiated following a sudden closure of the valve and the dynamics of flow behaviour was studied based on the period of oscillation. Statistical studies on the effects of selected input variables such as surge tower diameter, time of flow, velocity of flow, and rate of flow on the operational dynamics of unsteady flow in surge chambers was done using design of experiment (DOE) employing the 2-level factorial design with 3 central points' and one replication. Results obtained were then modeled using Adaptive Neuro-Fuzzy Inference Technique (ANFIS) incorporated into MATLAB in fuzzy logic toolbox to determine the input variable (s) that possess the highest significant effects on the response variable (period of oscillation) and also to develop a Fuzzy Inference Systems (FIS) structure which can be employed to study the adequacy of results from similar experiment. Results obtained from the modeling shows that surge tower diameter with a root mean square error of 0.7360 appears to be the single variable with the highest significant effects on the amplitude of displacement. More also, for the combine variable effects, surge (tower diameter and velocity of flow) having a combine root mean square error of 0.4410 were seen to possess the highest significant effects on the amplitude of displacement.

## Keywords

Period of Oscillation, Design of Experiment, 2-Level Factorial Design, Unsteady Flow, and Adaptive Neuro-Fuzzy Technique

## 1. Introduction

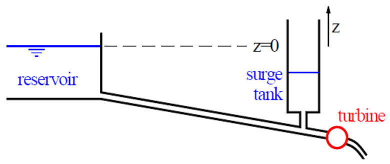
Water flowing in a horizontal pipe will continue in its state of uniform and steady motion except there is an alteration in the conditions that kept the flowing water in that state of motion. One of such property that keeps the flowing water in its state of uniform motion is; the uniform velocity of flow and the uniform cross sectional area of the pipe (1, 2, and 3). At constant velocity, the flow will be uniform with distance and remain steady with time and also for a pipe of uniform cross sectional area, the flow will also remain uniform provided the velocity is maintained throughout the flow distance. If the velocity of water flowing in a pipe of uniform cross section is suddenly diminished, pressure would be developed in the pipe line due to frictional resistance and wave propagation (4, 6, and 7). This pressure rise or water hammer is normally manifested as a series of shocks, sounding like hammer blows, which may have sufficient magnitude to rupture the pipe or damage connected equipment 5, 11). It may be caused by the nearly instantaneous or too rapid closure of a valve in the line or by an equivalent stoppage of flow which would take place with the sudden pressure (13, 14). The pressure wave due to water hammer travels back upstream to the lintel end of the pipe, where it reverses and surges back and forth through the pipe, getting weaker on each successive reversal (16). The velocity of the wave is that of an acoustic wave in an elastic medium, the elasticity of the medium in this case being a compromise between that of the liquid and the pipe (17). The excess pressure due to water hammer is additive to the normal hydrostatic pressure in the pipe and depends on the elastic properties of the liquid and on the magnitude.

Pressure transients are also referred to as surge pressure or, if referring to water systems, water hammer. The latter term suitably reflects the harmful effects that the hammer-like blows accompanying the pressure surges can have on pipes and system components. Water hammer causes piping, valves, pipe fixtures, supports, system components, etc. to suffer the added strain of dynamic loads (13, 16, and 17). The major causes of water hammer are as follows; rapid closure of valves, sudden shut off or unexpected failure of power supply to centrifugal pump, and also pulsation problems due to hydraulic rams and reciprocating pumps (12).

In this research paper, we employed adaptive neuro-fuzzy inference systems (anfis) to study the unsteady nature of flow of water in a closed pipe, the flow behaviour and dynamics were investigated by varying some selected input variables such as surge tower diameter, time of flow, velocity of flow and the rate of flow. The resulting pressure hammer which was occasioned by the sudden closure of the control valve was translated in the form of period of oscillation along the surge tower.

## 2. Sudden Closure of a Valve; the Time Series of Events

Consider flow from a large reservoir (constant pressure; excess pressure $p = 0$) at speed $u0$.




If a valve at the end of the pipeline is suddenly closed, pressure waves travel back and forth along the pipe. The time taken for pressure waves to travel from one end of the pipe to the other is given as

$$\Delta t = \frac{L}{c} \tag{1}$$

And the maximum water pressure (which occurs at the critical time of closure Tc or at any time less than Tc) is given by the expression (12);

$$H_{max} = \frac{CV_0}{G} \tag{2}$$

Where:
C = Velocity of pressure wave travel in (m/Sec)
G = Acceleration due to gravity, 9.8 m/Sec$^2$
$V_0$ = Normal velocity in pipe line before sudden closure in (m/Sec)
L = Length of pipe line (m)

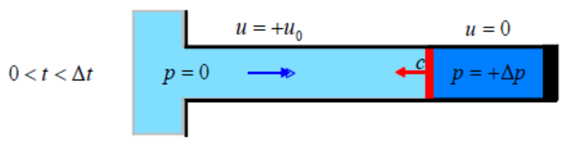
$$C = \frac{1425}{1 + \frac{kd}{EC_t}} \tag{3}$$

Where;
k = bulk modulus of water (2.07 x $10^8$ kg/m$^2$)
d = diameter of pipe in (m)
$C_t$ = Wall thickness of pipe in (m)
E = modulus of elasticity of pipe material in kg/m$^2$, for steel pipe, E is 2.1 x $10^{10}$ kg/m$^2$

The sequence of events that follows the sudden closure of a valve is as follows;

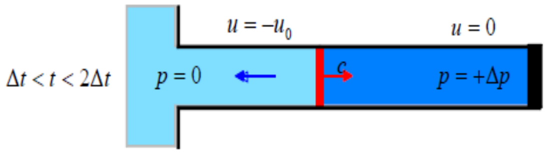
*At t = 0, the valve is closed*

The water immediately next to the valve is compressed to an excess pressure $+\Delta P$ and a pressure wave starts to propagate back along the pipe. For $0 < t < \Delta t$, the propagating wave moves into unaffected fluid ($u = u_0$ and $p = 0$). Behind the shock is stationary, compressed fluid ($u = 0$, $p = +\Delta P$).




*At t = Δt the wave reaches the reservoir*

All the fluid in the pipe is at rest; however, it is compressed to a higher pressure than the reservoir, so it begins to drive a flow $u0$ back toward the reservoir. The water-hammer wave is reflected. For $\Delta t < t < 2\Delta t$ the wave propagates back toward the valve, gradually decompressing the pipe.




If the actual time of closure T is greater than the critical time Tc, the actual water hammer is reduced approximately in proportion to Tc/T. water hammer wave velocity may be as high as 1370m/s for rigid pipe or as low as 850m/s for a steel pipe and for plastic pipes may be as low as 200m/s.

## 3. Adaptive Neuro- Fuzzy Technique

The complexity and the dynamism of real world problems require sophisticated methods and tools for the construction of knowledge systems that can be used in the solution to such problems. The search for systems that can solve increasingly complex problems has stimulated research in a number of scientific fields, especially Hybrid Intelligent Systems. This area seeks to combine different techniques of learning and adaptation to overcome their individual limitations. Among such systems, one important model — Neuro-Fuzzy Systems — is an approach that can learn from the environment and then reason about its state (18).

Adaptive Neuro-fuzzy systems constitute an intelligent systems hybrid technique that combines fuzzy logic with neural networks in order to have better results (10). A neuro-fuzzy system is based on a fuzzy inference system, which is trained by a learning algorithm derived from artificial neural network theory. While the learning capability is an advantage provided by artificial neural network, the formation of a linguistic rule base is an advantage provided by the fuzzy inference system.

In recent years, the fuzzy system has been applied in numerous fields such as power system, industry's control (9). Neuro- fuzzy systems constitute an intelligent systems hybrid technique that combines fuzzy logic with neural networks in order to have better results. ANFIS can be described as a fuzzy system equipped with a training algorithm. It is quite quick and has very good training results that can be compared to the best neural networks. Neuro-fuzzy network have been widely used for many different industrial areas such as control, modeling, prediction, identification, and pattern recognition (8, 9).

Neuro-fuzzy system represents connection of numerical data and linguistic representation of knowledge. The neuro-fuzzy system works similarly to that of multi-layer neural network. This hybrid system uses the adaptive neural networks (ANNs) theory to characterize the input-output relationship and build the fuzzy rules by determining the input structure (10).

Adaptive Neuro-Fuzzy Technique is a hybrid modeling algorithm that combines both Neural Network and Fuzzy Logic to produce better modeling results. Adaptive neuro-fuzzy technique works similarly to that of neural network; it provides a method for the fuzzy modeling procedure to learn information about a data set. Adaptive neuro-fuzzy technique works better than linear regression and statistical model especially when the main focus is to establish the multiple interaction and significant effects of selected parameters. Unlike linear regression and statistical modeling techniques, adaptive neuro-fuzzy technique is a nonlinear modeling technique which models the interactions and significant effects of the selected input parameters on the measured response based on their root mean square error (RMSE). In which case, the single or combine parameter with the lowest root mean square error is adjured the parameter (s) with the highest significant effects on the measured response (amplitude of displacement). In addition, adaptive neuro-fuzzy techniques do not only allow a graphical visualization between the root mean square error and the single/combine parameters, it is also employed to generate a fuzzy inference system (Fis Structure) for experimental data which can be used to validate the adequacy of experimental data set obtained from similar experiment.

## 4. Methodology of Research

The equipment used for this research studies is the plint and partners surge tower model equipment with the following specific properties;

1. Length of pipe (penstock) = 9.10m
2. Diameter of penstock = 0.0611m
3. Diameter of surge tower = 0.121m
4. Cross sectional area of penstock ($A_1$) = 0.00293$m^2$
5. Cross sectional area of surge tower ($A_2$) = 0.01150 $m^2$
6. Hydraulic radius; (R = $\frac{A_1}{A_2}$ )
7. Working fluid is water, having a bulk modulus of 2.07 x $10^8$ kg/$m^2$
8. The penstock material is stainless steel with modulus of elasticity of 2.1 x $10^{10}$ kg/$m^2$

The input variables studied include;

1. Diameter of surge chamber (m)
2. Time of flow (s)
3. Velocity of flow (m/s) and
4. Rate of flow ($m^3$/s)

The response, (Dependent variable) measured was the period of oscillation (p). Randomization of the selected variables was done in other to accurately generate experimental data sets that can be perfectly modeled using adaptive neuro-fuzzy technique and method of statistical design of experiment (DOE) was employed in this regard.

For the statistical design of experiment, 2-level factorial design with 3 central points' and one replication making a total of 19 experimental runs was employed. Statistical software package; Design Expert 7.0 was employed for the design of experiment. The coded values of the selected input parameters are shown in the table 1 and the experimental matrics are shown in table 2;

***Table 1.** Coded variables for input factors*

| Variables | -1 | 0 | +1 |
|---|---|---|---|
| Surge tower diameter ($X_1$) | 0.08 | 0.121 | 0.200 |
| Time of flow ($X_2$) | 7.5 | 8.5 | 9.5 |
| Velocity of flow ($X_3$) | 320.50 | 367.50 | 410.50 |
| Flow Rate ($X_4$) | 0.750 | 1.078 | 2.345 |

***Table 2.** 2- Level Factorial Experimental Matrics*

| Run | $X_1$ | $X_2$ | $X_3$ | $X_4$ | Response |
|---|---|---|---|---|---|
| 1 | -1 | -1 | -1 | -1 | |
| 2 | -1 | -1 | -1 | +1 | |
| 3 | -1 | -1 | +1 | -1 | |
| 4 | -1 | -1 | +1 | +1 | |
| 5 | -1 | +1 | -1 | -1 | |
| 6 | -1 | +1 | -1 | +1 | |
| 7 | -1 | +1 | +1 | -1 | |
| 8 | -1 | +1 | +1 | +1 | |
| 9 | +1 | -1 | -1 | -1 | |
| 10 | +1 | -1 | -1 | +1 | |
| 11 | +1 | -1 | +1 | -1 | |
| 12 | +1 | -1 | +1 | +1 | |
| 13 | +1 | +1 | -1 | -1 | |
| 14 | +1 | +1 | -1 | +1 | |
| 15 | +1 | +1 | +1 | -1 | |
| 16 | +1 | +1 | +1 | +1 | |
| 17 | 0 | 0 | 0 | 0 | |
| 18 | 0 | 0 | 0 | 0 | |
| 19 | 0 | 0 | 0 | 0 | |

The randomized experimental matrics using the real values of selected input variables are shown in table 3 below;

***Table 3.** Real values of input variables*

| Run | $X_1$ | $X_2$ | $X_3$ | $X_4$ | Response |
|---|---|---|---|---|---|
| 1 | 0.080 | 7.500 | 320.5 | 0.750 | |
| 2 | 0.080 | 7.500 | 320.5 | 2.345 | |
| 3 | 0.080 | 7.500 | 410.5 | 0.750 | |
| 4 | 0.080 | 7.500 | 410.5 | 2.345 | |
| 5 | 0.080 | 9.500 | 320.5 | 0.750 | |
| 6 | 0.080 | 9.500 | 320.5 | 2.345 | |
| 7 | 0.080 | 9.500 | 410.5 | 0.750 | |
| 8 | 0.080 | 9.500 | 410.5 | 2.345 | |
| 9 | 0.200 | 7.500 | 320.5 | 0.750 | |
| 10 | 0.200 | 7.500 | 320.5 | 2.345 | |
| 11 | 0.200 | 7.500 | 410.5 | 0.750 | |
| 12 | 0.200 | 7.500 | 410.5 | 2.345 | |
| 13 | 0.200 | 9.500 | 320.5 | 0.750 | |
| 14 | 0.200 | 9.500 | 320.5 | 2.345 | |
| 15 | 0.200 | 9.500 | 410.5 | 0.750 | |
| 16 | 0.200 | 9.500 | 410.5 | 2.345 | |
| 17 | 0.121 | 8.500 | 367.5 | 1.078 | |
| 18 | 0.121 | 8.500 | 367.5 | 1.078 | |
| 19 | 0.121 | 8.500 | 367.5 | 1.078 | |

Experimental results obtained were then modeled using Adaptive Neuro- Fuzzy Inference Techniques (ANFIS) incorporated into MATLAB in fuzzy logic toolbox to analyze the significant effects and interactions of each/combine variables on the measured response (period of oscillation).

The input data used for the modeling include;

1. input_ name (data set generated from design of experiment)
2. trn_data (data set the shows high conformity with theoretical values )
3. chk_data (data set the shows high deviation from theoretical values)

To model the significant effects and interactions of the selected variables on the measured response (period of oscillation), we employ the simple program below:

```
>> a = 'diameter';
>> b = 'time';
>> c = 'velocity';
>> d = 'flow rate';
>> e = 'period and amplitude';
>> input_name = char (a, b, c, d, e);
>> a = [x1; x2; x3; x4; x5];
>> b = [x1; x2; x3; x4; x5];
>> c = [x1; x2; x3; x4; x5];
>> d = [x1; x2; x3; x4; x5];
>> e = [x1; x2; x3; x4; x5];
>> data = [a b c d e];
```

To get the train data and the checking data, we proceed as follows;

```
>> trn_data_n = k
>> trn_data = data (1:trn_data_n, : );
>>chk_data=data (trn_data_n+1:trn_data_n+p, :);
```

To find the single and combine input parameter(s) with the highest influence on the response variable we proceed as follows:

```
>> exhsrch (1, trn_data, chk_data, input_name);
>> exhsrch (2, trn_data, chk_data, input_name);
>> exhsrch (3, trn_data, chk_data, input_name);
```

Training of data set allows you to check the generalization capability of the resulting fuzzy inference systems (FIS). To perform the data training we proceed as follows:

```
>> load trn_data
>> load trn_data
>> anfisedit
```

## 5. Results and Discussion

Experimental values of the period of oscillation (T) as obtained based on the statistical design are shown in table 4 below;

***Table 4.*** *Experimental results of period of oscillation*

| **Run** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Period** | 13 | 13 | 14 | 15 | 13 | 14 | 14 | 15 | 10 | 8 | 9 | 9 | 8 | 10 | 11 | 12 | 9 | 10 | 9 |

These experimentally obtained values were then taken as the response variable; the values were slotted into table 3 and presented to MATLAB for ANFIS modeling and data training.

From the model results, surge tower diameter was seen from the model output as the single input variable with the most significant effect on the period of oscillation having the least root mean square error as presented in table 5 and figure 1 respectively.

***Table 5.*** *Model Analysis Based on RMS Errors (Period of Oscillation)*

| S/No: | Model: | Input Variable | Training Error | Checking Error |
|---|---|---|---|---|
| 1 | Model 1 | Surge Tower Diameter (m) | 0.7360 | 2.4191 |
| 2 | Model 2 | Time of Flow (s) | 1.3333 | 4.2176 |
| 3 | Model 3 | Velocity of Flow (m/s) | 1.0646 | 4.2944 |
| 4 | Model 4 | Rate of Flow ($m^3$/s) | 1.2270 | 4.5521 |

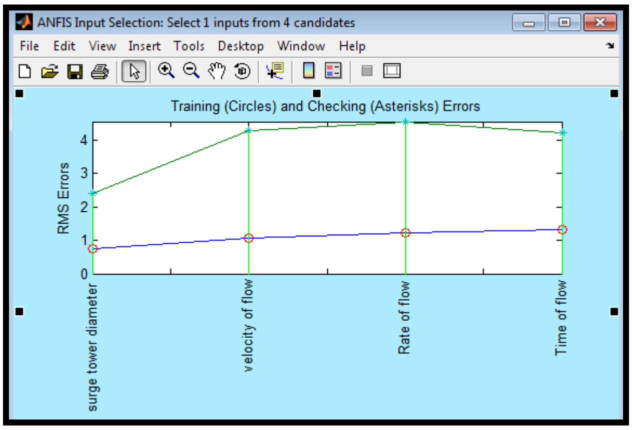



***Figure 1.*** *Modeling the Effects of Single Parameter on the period of Oscillation*

On the effects of combined input variables on the period of oscillation, the output result of table 6 and figure 2 shows that surge tower diameter and velocity of flow are the two most significant combined parameters controlling the period of oscillation in an unsteady flow in pipes;

***Table 6.*** *Model Analysis Based on RMS Errors (Period of Oscillation)*

| Model: | Input Variables | Training Error | Checking Error |
|---|---|---|---|
| Model 1 | Surge Tower Diameter + Time of flow | 0.7265 | 5.1490 |
| Model 2 | Surge Tower Diameter + Velocity of flow | 0.4410 | 5.0767 |
| Model 3 | Surge Tower Diameter + Rate of flow | 0.6455 | 4.9984 |
| Model 4 | Time of flow + Velocity of flow | 0.9129 | 4.4256 |
| Model 5 | Time of flow + Rate of flow | 1.1386 | 4.2317 |
| Model 6 | Velocity of flow + Rate of flow | 0.8498 | 4.2729 |

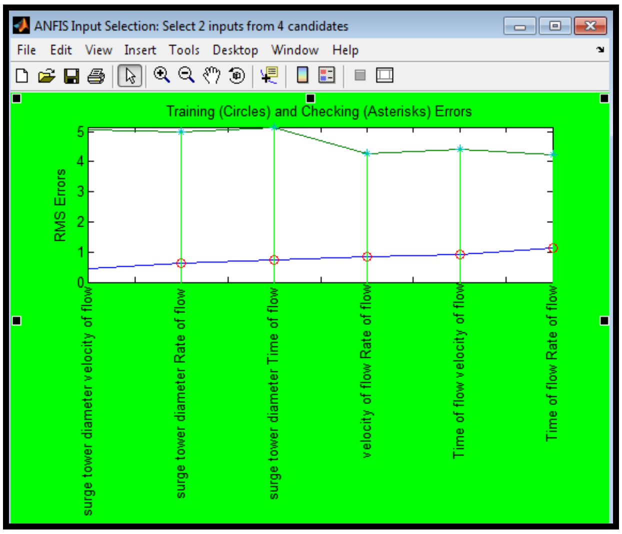



***Figure 2.*** *Modeling the Effects of combine Parameter on the period of Oscillation*

On the three combined input variables with the highest significant effect on the period of oscillation, the ANFIS output as presented in the table 7 and figure 3 shows that (Surge tower diameter +Velocity of flow + Rate of flow) possesses the highest significant effects on the period of oscillation

***Table 7.*** *Model Analysis Based on RMS Errors (Period of Oscillation)*

| Model: | Input Variable | Training Error | Checking Error |
|---|---|---|---|
| Model 1 | Diameter + Time + Velocity | 0.4082 | 6.0916 |
| Model 2 | Diameter + Time + Rate | 0.6236 | 6.0034 |
| Model 3 | Diameter + Velocity +Rate | 0.2357 | 6.0672 |
| Model 4 | Time + Velocity + Rate | 0.7071 | 4.3917 |

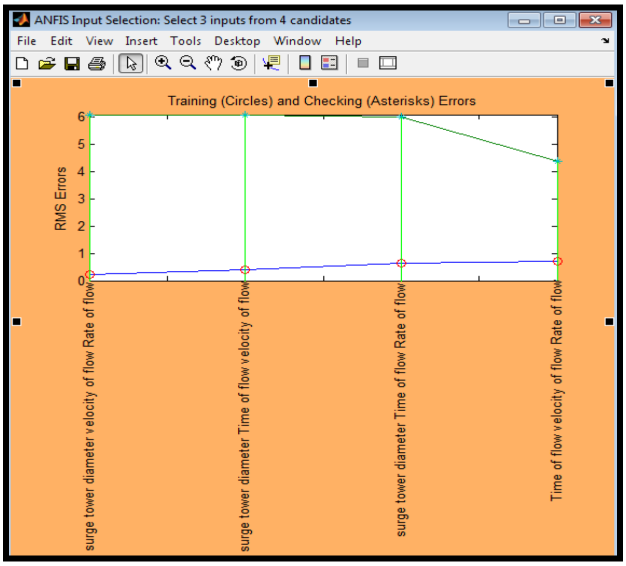



***Figure 3.*** *Modeling the Effects of combine Parameter on the period of Oscillation*

To perform the data training we partitioned the result of the period of oscillation obtained from the experimental run into two. The first part which represents the data set that shows high conformity with theoretical value was taken as the training data while the second part which represents the data set that shows high deviation from theoretical value was taken as the checking data. The training data set let you check the generalization capability of the resulting fuzzy inference systems and also help generate a fuzzy inference system (FIS) structure that can be employed to validate the accuracy of data sets from similar work. The correlation between the training data sets and the checking data sets was investigated using neuro-fuzzy and the result is presented in the figure 4 below; (circle represent training data, plus is checking data)

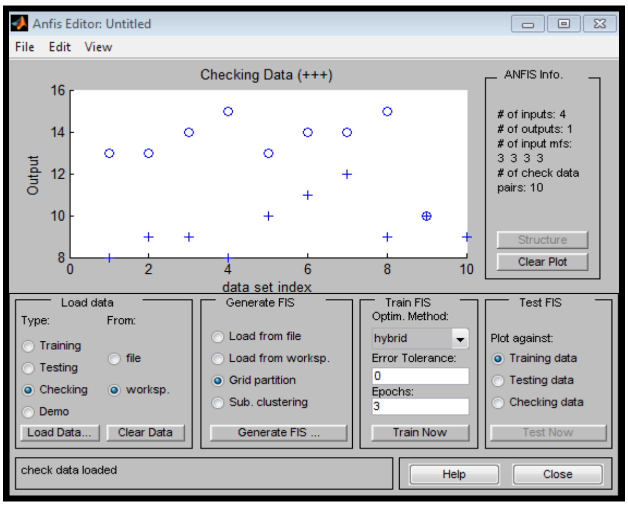



***Figure 4.*** *Correlation between training and checking data for period of oscillation*

The check data appears in the graphics user interface (GUI) plot as pluses superimposed on the training data. This data set was used to train a fuzzy system by adjusting the membership function parameters that best model this data.

The membership function plot which shows the lower and the upper limit of each input variable was done and the resulting structures are shown in figures 5, 6, 7, and 8 respectively.

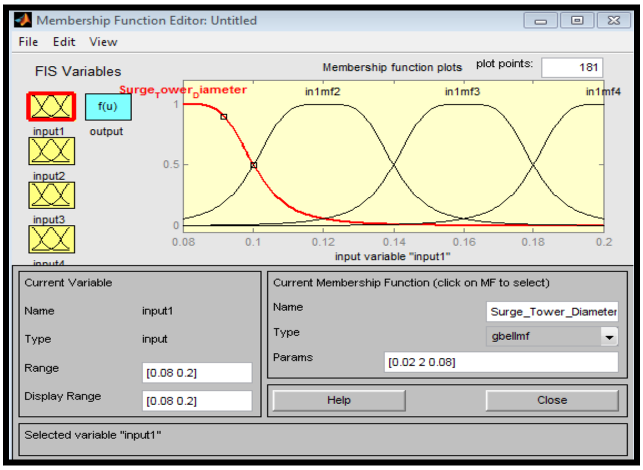



***Figure 5.*** *Surge tower diameter function plot*

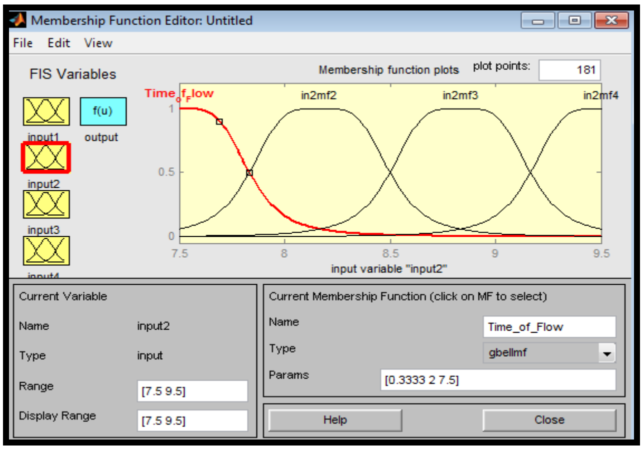



***Figure 6.*** *Time of flow function plot*

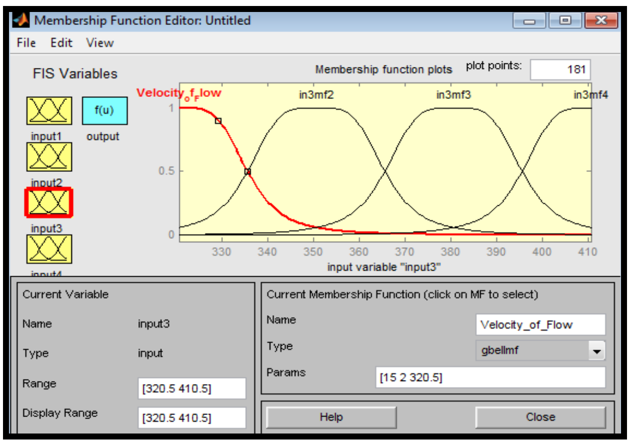



***Figure 7.*** *Velocity of flow function plot*

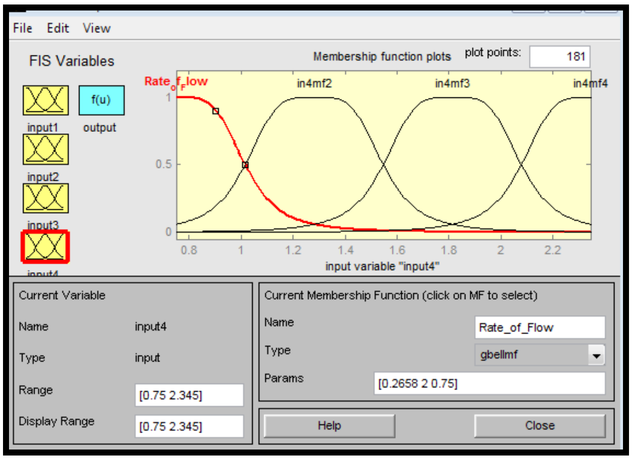



***Figure 8.*** *Rate of flow function plot*

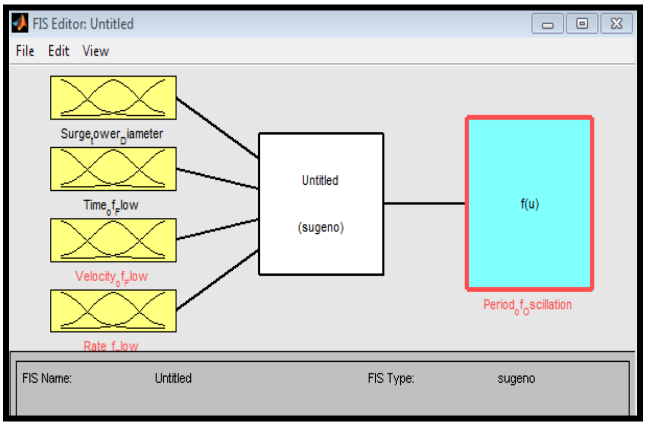



***Figure 9.*** *Period of oscillation function plot*

The fuzzy inference system structure (FIS) that shows the interactions between the input membership functions and the period of oscillation is presented as shown in figure 10 below;

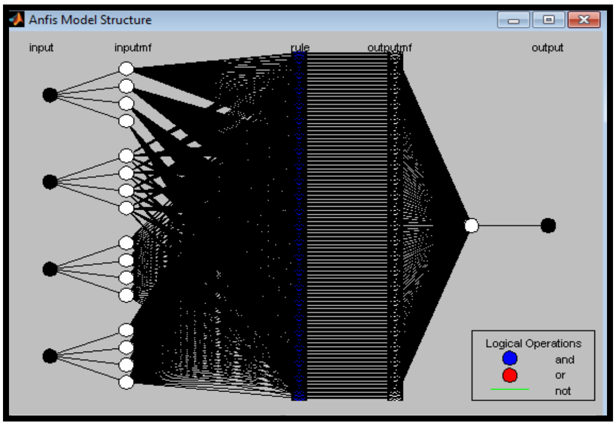



***Figure 10.*** *Fuzzy Inference System Structure*

To perform the fuzzy inference systems training, we employed the hybrid optimization method, the number of training epochs which defines the number of iteration was set at 40, the error tolerance was set at zero and the graph of checking errors against the training errors was generated as shown in figure 11 below.

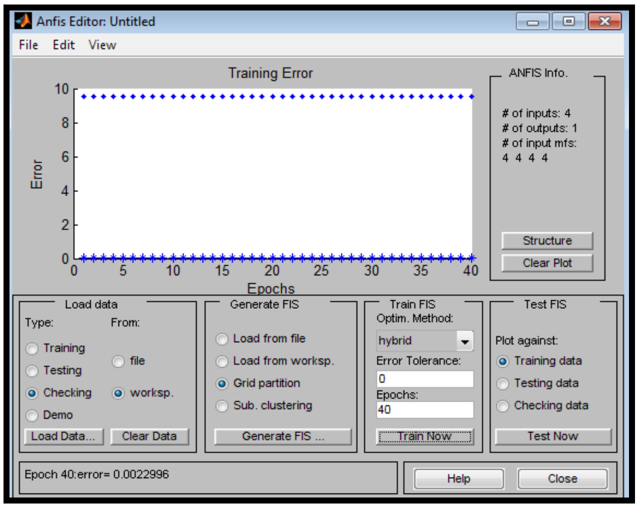



***Figure 11.*** *Fuzzy Inference Systems Training*

The plot shows the checking error at the top and training error at the bottom. A training error of 0.0022996 as shown in figure 11 reveals that the FIS strucrure generated is adequate for the training and thus we can proceed to checking the experimentally obtained data against the trained FIS structure. To perform the testing task, we select checking data in the Test FIS portion of the ANFIS graphics user interface. When you test the checking data against the FIS structure, you will need to check for the average testing error as shown in figure 12 below

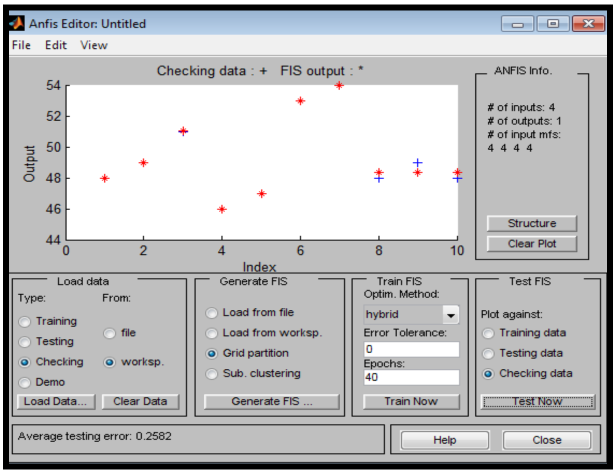



***Figure 12.*** *Checking data against the FIS structure*

An average checking error of 0.2582 indicates that the training model was adequate and the FIS structure developed can be employed to test the adequacy of experimental data obtained from similar experiments. A rule based optimization was also done by allowing the software to generate its own rule that best fit the modeling process. The method of “and” was selected and about 252 rules were generated for the modeling. Using the rule based optimization as genereated by ANFIS, the following results were obtained.

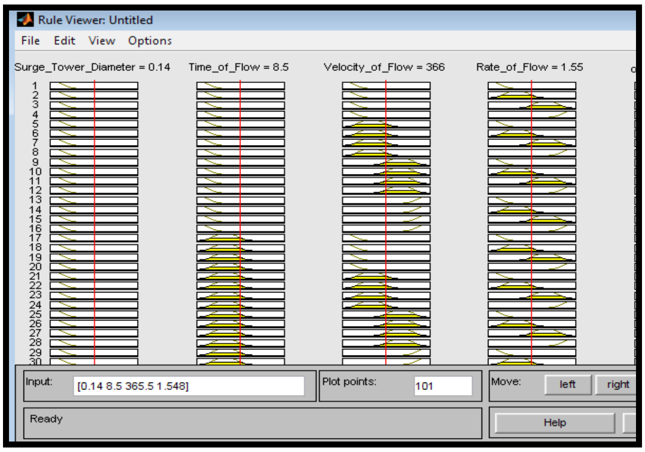



***Figure 13.*** *Rule based optimization results*

The surface plots which shows the interactions between the input membership function and the period of oscillation are shown in figures 14, 15, and 16 respectively.

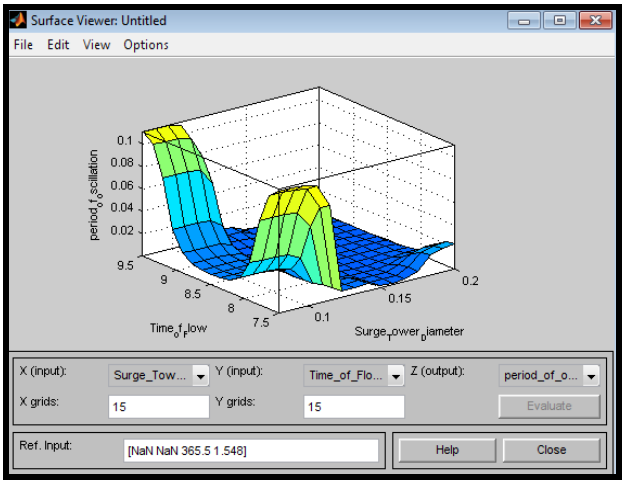



***Figure 14.*** *3D surface plot*

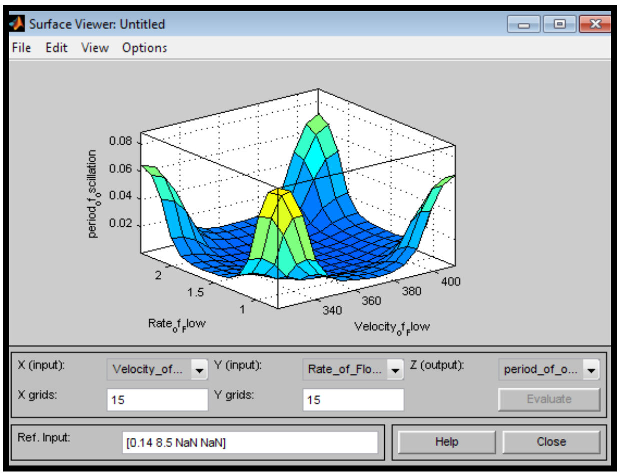



***Figure 15.*** *3D surface plots*

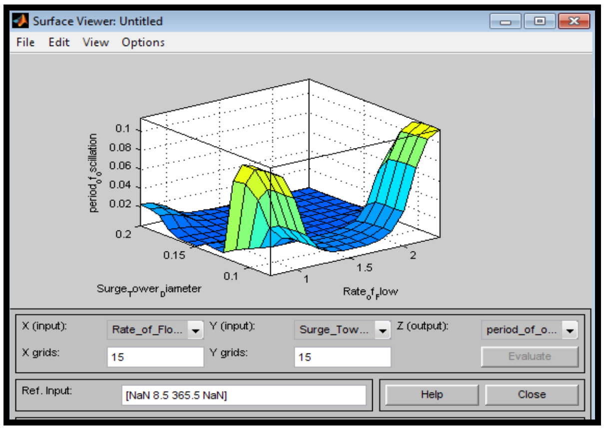



***Figure 16.*** *3D surface plot*

## 6. Conclusion

The suitability of adaptive neuro-fuzzy techniques over others modeling techniques has been demonstrated in this research work. Adaptive neuro-fuzzy technique works better than linear regression and statistical model especially when the main focus is to establish the multiple interactions and significant effects of selected input parameter on the measured response (period of oscillation). Unlike linear regression and statistical modeling techniques, adaptive neuro-fuzzy technique is a nonlinear modeling technique which models the interactions and significant effects of selected input variables based on their root mean square error (RMSE). In which case, the single or combine parameter with the lowest root mean square error is adjured the parameter (s) with the highest significant effects on the period of oscillation.

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