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# Improving the electro-pneumatic clutch actuation control system of a heavy-duty vehicles using artificial neural network

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## Abstract

The performance enhancement of clutch actuation control process in electro-pneumatic clutch system for heavy duty vehicles through the application of Artificial Neural Network control is addressed in this presentation. The inability of some heavy-duty vehicles to operate optimally on hilly terrains due to inadequate compression or torque and which often leads to accidents can be traced to inadequacies in clutch actuation control. Conventional control techniques in clutch actuation uses on/off, servo mechanism and other non-intelligent methods of actuation control. These conventional techniques demand for frequent calibration of clutch actuators. Often times, this important requirement is neglected with attendant ugly consequences. To eliminate calibration and its observed defects, an intelligent method of clutch actuation modelled in an Artificial Neural Network control is implemented. Conventional data obtained for piston error signals, speed, torque and power from a Mercedes Benz Actros Truck model MP 2, 2031 provided the reference points. These data were fed into a developed ANN that was subjected to a standard training algorithm to achieve the intelligence control for electro-pneumatic clutch actuation. The Backpropagation method of weight adjustments and the application of Sigmund activation functions featured. Simulink models which imbedded design parameters for both conventional and ANN controllers were also developed and simulated. Different percentages of improvements were recorded for piston error, engine torque, angular speed and power respectively. In order to justify the research, the level and percentage of improvements were determining. ANN improved by 0.4821mm or 33.04 % decrease for error, increases of 334.1 RPM or 33 % for angular speed, 0.0594NM or 33.26 % for torque and 2.79 watts or 16.53 % for power respectively were recorded. These results depicts conclusively that ANN controller application in intelligent clutch actuation control of an electro-pneumatic clutch actuation system for heavy-duty vehicle will be remarkable. Its impact in the smooth operation of heavy-duty vehicles will indeed eliminate completely the attendant calibration problems and associated poor performances with conventional controllers in electro-pneumatic clutch actuation systems.

**Keywords:** Artificial Neural Network; Actuation; Control; Calibration; Transmission

## 1. Introduction

The need of heavy-duty vehicles in our environments for transportation purposes cannot be over emphasized. The ability of the vehicles to initiate movements and hence accomplish a given assignment is by virtue of their rotary motions or torque. The requirements for engine torque differ for different work needs. The different work needs justify the need for mechanical amplifications via gearing mechanisms that include clutch actuation system. A clutch actuation mechanism acts as an isolator between the drive shaft linked to the engine and the driven shaft connected to the load or wheels of motor vehicles. A good clutch system safeguards the gear from teeth grinding and ensures effective and

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smooth coupling of the drive and driven shafts. The shift quality of a gear is a measure for accessing how good a clutch system is (Li-kun *et al* 2015). It is through control process that the clutch activates instruction to the automobile or machine to move or stop, by engaging and disengaging the transmission of power particularly from a driving shaft to a driven shaft. Clutch ensures that the transmission link between the engine and the driven parts establishes a releasable torque (Mishra, 2014). Clutches like brakes are ideally control elements for smooth transmission of drive torque, power and speed in many rotating drive systems. Mechanical movement, linear or rotary must go through actuation process; in order to achieve a control action on a machine or device, with the ultimate aim of converting a linear motion to rotary motion and vice versa (Carlos, 2016). Enhancement in clutch actuation controls is critical for automobile developments. The present conventional control methods in the electrical control unit of heavy- duty vehicles are inadequate owing to observed failures on the roads especially on hilly terrains (Annual Report of the Federal Road Safety Corps 2011). Some of the problems associated with clutch system in heavy-duty vehicles include; clutch wearing or burnt, torsional spring weakening, clutch vibrations, fiber rebating, and leakage in seals. Other are friction forces, weakening piston springs and weakening of clutch release bearing, etc. (Nice and Bryant 2019). Samson (2019) disclosed that wears are often seen in gear-based travel sensors. Clutch defects manifest in clutch actuation positional errors in actuation chambers with resultant effects on poor clutch engagement and disengagement.

Conventional control designs presently in use are in the forms of; off/on control, proportional control, servo mechanism control, integral control, and a combination of Proportional and Integral (PI) control. These designs accommodate in its clutch actuation control, provision for frequent calibration of clutch load as a means of effecting corrections to ensure better operation (Calibrating the clutch Actuator from Sachs Workshop Tips 2019). Calibration also ensures quicker responsiveness of the actuator control as well as maneuvering driving situations in slick roads and launching on hilly terrain with heavy loads among others (Clutch Problems, Trouble Shooting and Service, 2019). Workshop Tips on Clutch from ZF Aftermarket on the topic Overview of all Workshop Tips on Clutches and repair Tips for Clutch System (2019) noted that lack of routine calibration manifests in poor clutch engagements and disengagements. Clutch calibration adjustments can be realized by disengaging the output or load shaft for a reference engine or input shaft speed to be fixed. It can also be done by increasing the pressures on the actuator piston while monitoring the engine speed for a low torque transmission to the load shaft or wheals. Calibration can also result from the narrowing of the clutch travel distance in the actuator or by increasing pressure on the piston through the variation of the energizing current in the electrical control module of the clutch system (Li-kun *et al* 2015). This calibration is presently done manually in a conventional controlled actuation process and are often neglected with attendant failures.

A dynamic process for self-adjustment of calibration is the way out of this malady. The process will checkmate the weakening piston springs and weakening of clutch release bearings and similar prominent calibration faults responsible for piston positional error in clutch actuation. An Artificial Neural Network (ANN) system of intelligent controller technique is advocated as a substitute for conventional controller for the dynamic process to handle this calibration problem and hence improve efficiency in heavy duty vehicles.

## 2. Basic Theory

Artificial Neural Network is a computational tool in control system engineering and sciences. The origin is traceable to biological neurons. It is composed of a number of elements that are well organized in layers for definite processing activities. Artificial neural networks are arranged in nodal formations and interconnected with one another. Each link has its activation functions and added weighting factors. The layers are arranged serially from the input layer, the intermediate layer and lastly the output layer (Babuska, 2002). ANN systems behave as a human brain. Like a brain, it functions as a computing network with embedded parallel distributed structure (Fuller, 2001). The merits of the neural networks are its capacity to learn, generalize and robustness in the presence of disturbances. Indeed, the greatest credit of a neural network system lies on its ability to adapt to a variety of circumstances. Improved

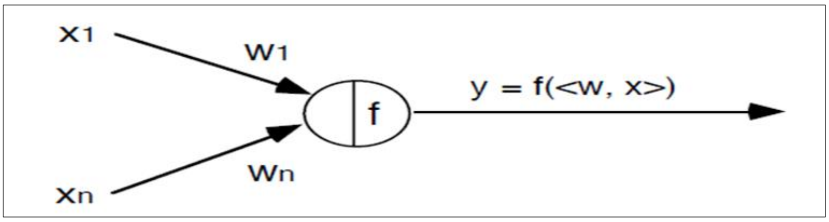


**Figure 1** Simple Neural Network (Fuller, 2001)

neural network design systems can accommodate automatic weight adjustment in order to achieve optimization in pattern recognition, decision making, predictions, system controllers, etc.

Figure 1 above illustrates a simple ANN. The ‘x’ and ‘w’ are real numbers and represents the input signals and the attached weights. The signal ‘$x_i$’ by interaction with the weight ‘$w_i$’ is multiplied to produce the product ‘$p_i$‘= $w_i x_i$, i = 1,2, . . . n. The input information ‘pi’ is a product. The net input is a summation = $p_1 + \cdots + p_n = w_1x_1 + \cdots + w_nx_n$ (Fuller, 2001). The neuron uses its transfer or activation function or sigmoidal function f, defined as

$\mathbf{f(t)} = \frac{1}{1+e^{-t}}$ **,** to give the desired output ‘y’ thus; $y = f(net) = f(w_1x_1 + \cdots + w_nx_n)$.

Training of ANN in most cases is about weight adjustment to achieve the desired result. Often, a number of neuros are required to accomplish a given task. Such an interconnected neuron is termed multi-layer neural network. It can also be used to illustrate the number of training session a set of neurons has passed through. Six stages of Neural Network Learning are as follows:

- Apply initial weights to the neuron inputs and outputs.
- Compute the training set inputs and outputs through the neural network in what is termed forward propagation.
- Set a desired result and then find the error function between the result computed and the desired result. The margin of error will guide you in adjusting the weight positively or negatively.
- Aim to minimize the error function, this is the back propagation session.
- Use the most optimal weights to adjust the inputs so as to affect the back-propagation algorithm results.
- Train severally to achieve convergence by way of repeated weight adjustments until the ANN learns the rule accurately and adequately.

Activation functions may be linear, Sigmund, hyperbolic tangent or step wise. Weights are usually attached to the input variables, summed before applying the activation function to obtain a value for the successive hidden neurons. Finally, another activation function is applied to get the output. In the backward propagation, the margin of error between the desired result and the obtained results must continuously be converging as the training progressed. It can as well be implemented in a MATLAB environment.

## 3. Materials and Methods

This section is devoted to the materials used in the study, the apparatus deployed and the procedure adopted in the study.

### 3.1. Materials

The study material for this work includes the actuation chamber, clutch plate, static and dynamic gearing parameters of a Mercedes Benz Actros Truck model MP 2, 2031 from which conventional actuation parameters were sourced empirically. Artificial Neural Network module was selected in a MATLAB environment.

### 3.2. Methods

#### *3.2.1. Conventional Controller design*

Empirical research method was used to obtain the initial data prevalent in the actuator chamber of Mercedes Benz Actros Truck model MP 2, 2031. This formed the characterized conventional control data. The details of the characterization are contained in the work of Ndubuisi et el (2021) entitled “Physiological Characterization of Electro-Pneumatic Clutch Actuation System for Heavy-Duty Vehicles”. Simulink models for conventional controller was designed in a MATLAB 7.5 system. Longitudinal vehicle dynamics building blocks were connected accordingly in the design. The characterized data for error, speed, torque and power were inserted into the conventional modelled Simulink and simulated. Figure 2 below is the Simulink designed model.

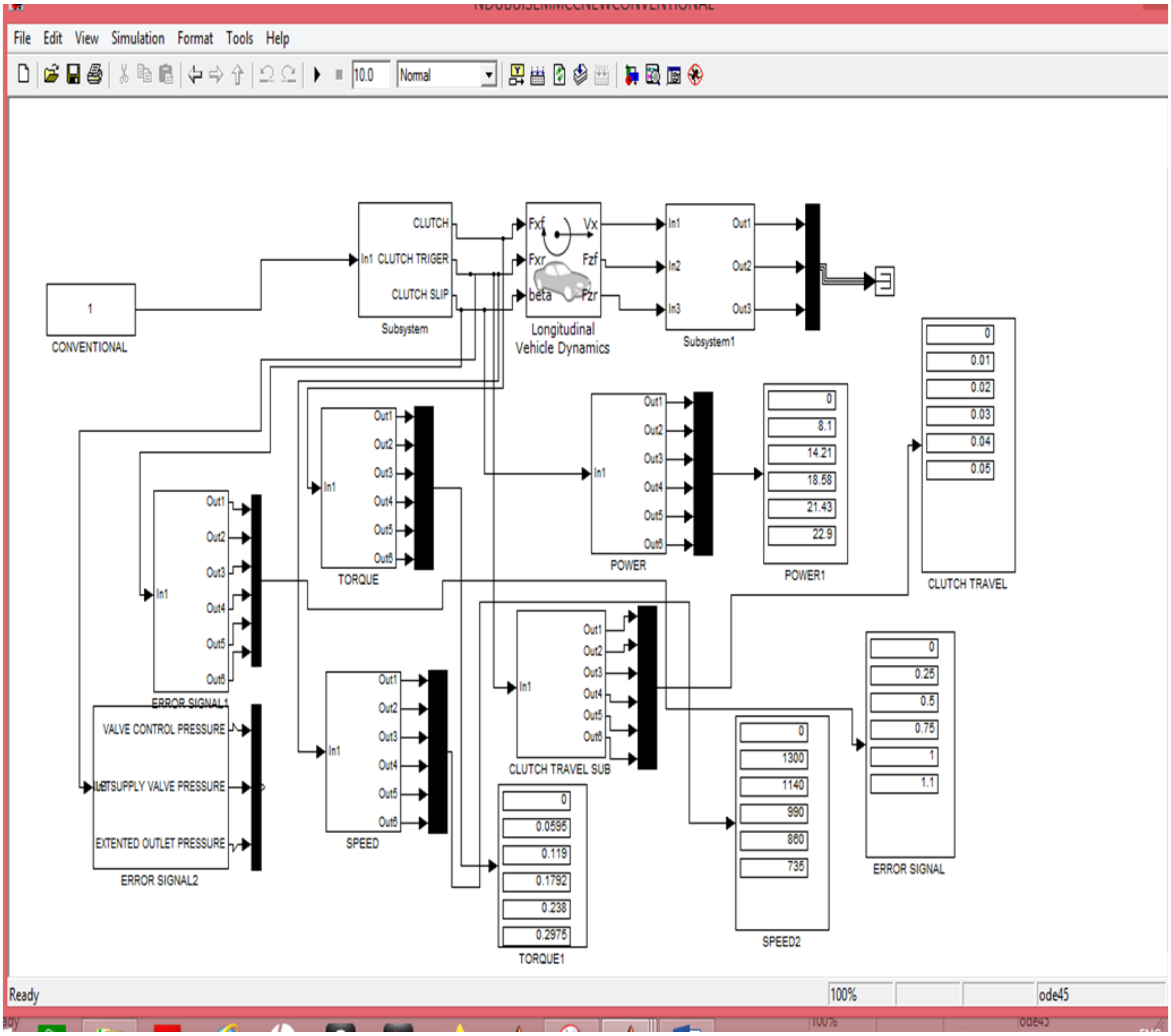


**Figure 2** Model for Conventional Controller

### *3.2.2. ANN Controller design*

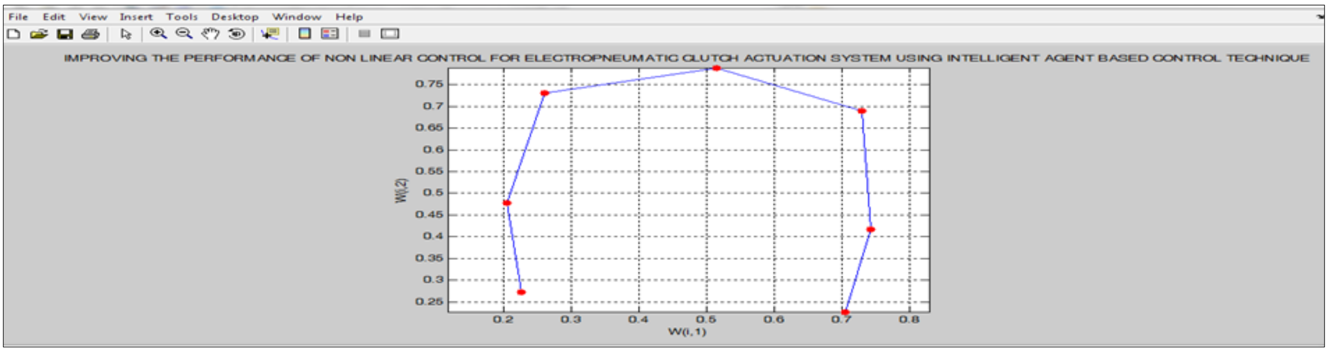


**Figure 3** Neuron arrangement of the first training in ANN

From characterization information, two input signals of error and change in error were identified as distinct signals as piston transverses within five milometers in the actuation chamber during clutch engagements and disengagements.

These formed the inputs to the ANN. Artificial Neural Network module was selected in a MATLAB environment. Seven neurons were used as the input neurons into which the two input signals of error and change in error were fed.

The back-propagation algorithm technique for weight variations was adopted for its obvious advantage of fast response demanded in clutch actuation. Similarly, seven neurons formed the output neuron through which the output signal was derived. The hidden neurons were thirty-five. The total number of neurons in the system resulted to forty-nine neurons. This is synonymous to seven neurons trained seven times. Figure below illustrates.

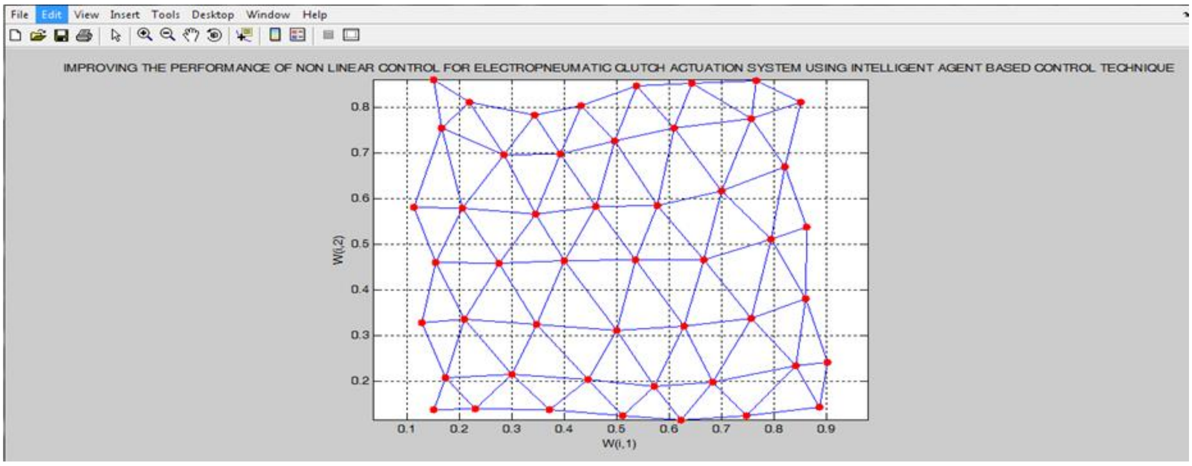


**Figure 4** Neuron arrangement of the Seventh Training in AN

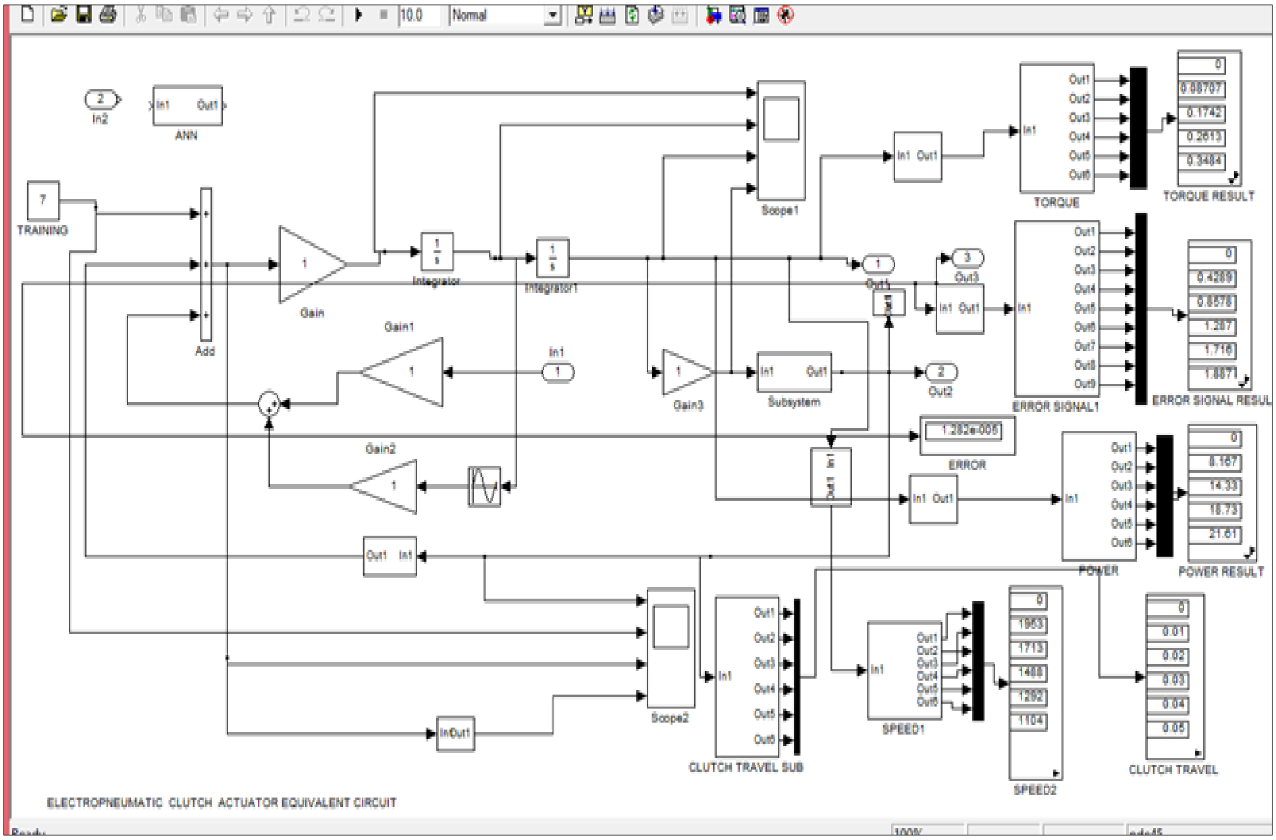


**Figure 5** Designed Equivalent Circuit model for ANN controlled training

The Sigmund activation function $(\frac{1}{1+e^{-t}})$ was adopted. The neural network systems training can be illustrated with a neural network equivalent circuit. Equivalent Circuit model of artificial neural network (ANN) controller is shown in Figure 5. It is composed of a number of gain amplifiers, integrators, inn/out subsystems for feeding inn the characterized data and from which the display units derive its output. There are also the function generator, scope and weight adjustment block to facilitate training.

Simulink models for ANN Controller was also designed in a MATLAB 7.5 system. Longitudinal vehicle dynamics building blocks were connected in the designs. Subsystem building blocks for error, power, torque, speed and clutch travel parameters were connected. A data input/output subsystem where relevant analytical data for clutch travel, error, speed, torque and power parameters were fed and read, were also connected. Subsequently, ANN model controller was cascaded with the conventional controller and the outputs extracted from the design output device. The Simulink model design for ANN is shown in figure 6.

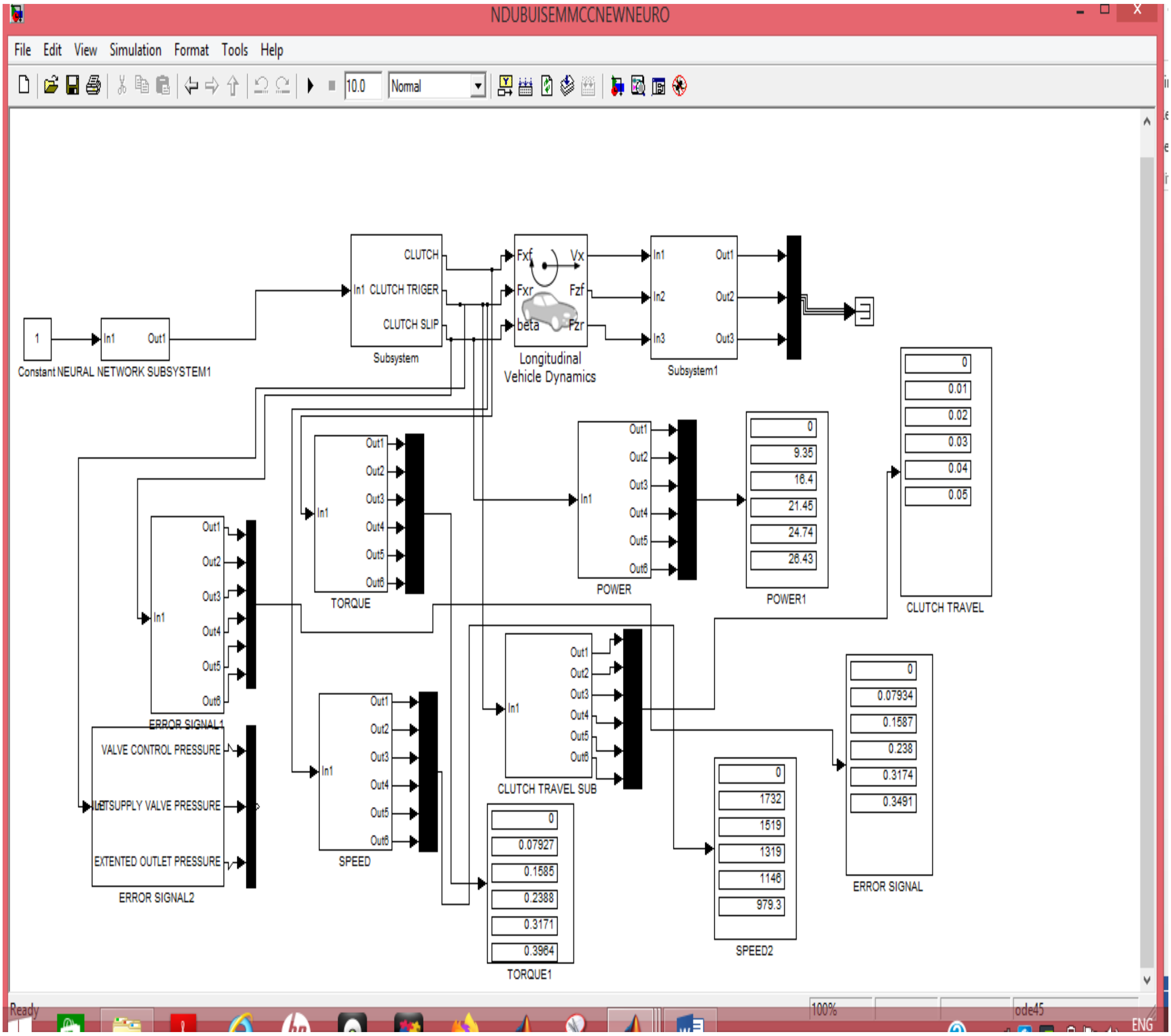


**Figure 6** Designed Simulink model for an improved electro-pneumatic clutch actuation system using artificial neural network (ANN) controller

## 4. Results and Discussions

The simulated results from conventional controller Simulink model, ANN equivalent circuit training model and ANN Simulink model are presented and discussed in this section.

### 4.1. Presentation of simulated data

The simulated data for conventional and ANN controllers are presented in this segment. It also includes the result from simulation of the designed equivalent circuit for ANN training

#### *4.1.1. Data from Conventional Controller Simulink model.*

Table 1 is the data obtained from simulation of conventional controller Simulink model. It is similar to the empirical data of characterization.

**Table 1** Conventional Controller Simulink model data

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | 0 | 0.0000 | 0.00 |
| 0.01 | 0.25 | 1300 | 0.0595 | 08.10 |
| 0.02 | 0.50 | 1140 | 0.1190 | 14.21 |
| 0.03 | 0.75 | 990 | 0.1792 | 18.58 |
| 0.04 | 1.00 | 860 | 0.2380 | 21.43 |
| 0.05 | 1.10 | 735 | 0.2975 | 22.90 |

#### *4.1.2. Data from ANN equivalent circuit on neuron training sequence.*

The weight adjustments were carried out seven times and convergence were observed as the common difference between successive readings were progressively shrinking in most cases.

The results of the first, third, fifth and seventh training were presented in tables 2, 3, 4 and 5 respectively.

**Table 2** Data from the first ANN training

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | ∞ | 0.0000 | 0.00 |
| 0.01 | 0.1169 | 1572 | 0.0719 | 08.908 |
| 0.02 | 0.2337 | 1379 | 0.1439 | 15.60 |
| 0.03 | 0.3506 | 1197 | 0.2168 | 20.44 |
| 0.04 | 0.4674 | 1040 | 0.2878 | 23.57 |
| 0.05 | 0.5142 | 888.9 | 0.3598 | 25.16 |

**Table 3** Data from the third ANN training

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | ∞ | 0.0000 | 0.00 |
| 0.01 | 0.1023 | 1626 | 0.0744 | 9.058 |
| 0.02 | 0.2045 | 1425 | 0.1488 | 15.89 |
| 0.03 | 0.3068 | 1238 | 0.2341 | 20.78 |
| 0.04 | 0.4090 | 1075 | 0.2976 | 23.97 |
| 0.05 | 0.4499 | 919.1 | 0.3720 | 25.61 |

**Table 4** Data from the fifth ANN training

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | ∞ | 0.0000 | 0.00 |
| 0.01 | 0.0887 | 1684 | 0.0771 | 09.22 |
| 0.02 | 0.1774 | 1477 | 0.1542 | 16.17 |
| 0.03 | 0.2661 | 1283 | 0.2322 | 21.15 |
| 0.04 | 0.3548 | 1114 | 0.3084 | 24.40 |
| 0.05 | 0.3902 | 952.4 | 0.3855 | 26.07 |

**Table 5** Data from the seventh ANN training

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | ∞ | 0.0000 | 0.00 |
| 0.01 | 0.07934 | 1732 | 0.0792 | 09.35 |
| 0.02 | 0.1587 | 1519 | 0.1585 | 16.40 |
| 0.03 | 0.2380 | 1319 | 0.2378 | 21.45 |
| 0.04 | 0.3174 | 1146 | 0.3171 | 24.74 |
| 0.05 | 0.3491 | 979.3 | 0.3964 | 25.85 |

*4.1.3. Data from ANN Controller Simulink model.*

The result obtained from ANN Simulink model is presented in table7. The result of the seventh training is in agreement with the result of the ANN controller Simulink model simulation.

**Table 6** Artificial neural network controller Simulated Data

| Clutch travel (M) | Error signal (mm) | Speed (RV/M) | Torque (NM) | Power (kw) |
|---|---|---|---|---|
| 0 | 0 | ∞ | 0.0000 | 0.00 |
| 0.01 | 0.0793 | 1732 | 0.0792 | 09.35 |
| 0.02 | 0.1587 | 1519 | 0.1585 | 16.40 |
| 0.03 | 0.2380 | 1319 | 0.2378 | 21.45 |
| 0.04 | 0.3174 | 1146 | 0.3171 | 24.74 |
| 0.05 | 0.3964 | 979.3 | 0.3964 | 26.43 |

## 4.2. Comparison of data presentation

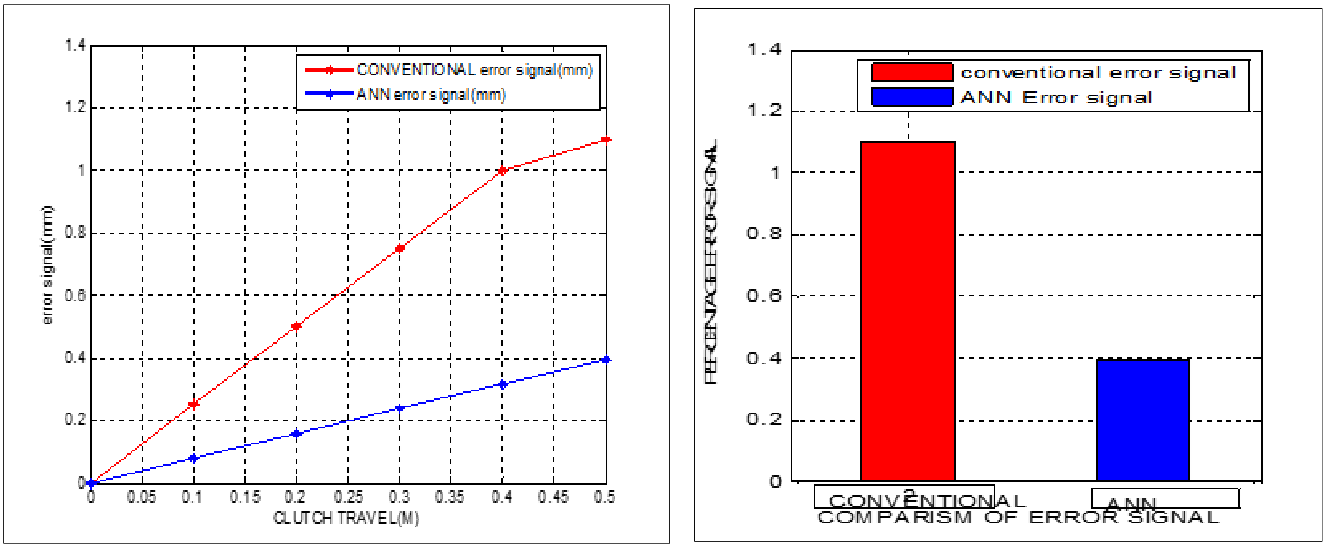
The data collated from conventional controller and ANN controller for proportional error, engine speed, torque and power are tabulated and plotted below for comparison.

*4.2.1. Comparing error signals.*

The data in table 8 is used to compare the performances of the conventional controller with that of the ANN controller in electro-pneumatic clutch actuation. The error arising from clutch load and associated weaknesses in piston springs as it traverses the actuation chamber is comparably lower in an ANN controller. Table 8 is plotted in figure 8 (a) with the red plot representing the conventional controller performance. To further illustrate it, the average and percentage error are determined and shown in the bar chart of fig.8 (b)

**Table 7** Comparing error signals

| Clutch travel (M)/Analysis | Conventional error signal (mm) | ANN error signal (mm) |
|---|---|---|
| 0 | 0 | 0 |
| 0.01 | 0.25 | 0.0793 |
| 0.02 | 0.50 | 0.1587 |
| 0.03 | 0.75 | 0.2380 |
| 0.04 | 1.00 | 0.3174 |
| 0.05 | 1.10 | 0.3964 |
| Average | 0.72 | 0.2379 |
| % difference /base 100 | 100 | 33.04 |



(a) Graph

(b) Bar Chart

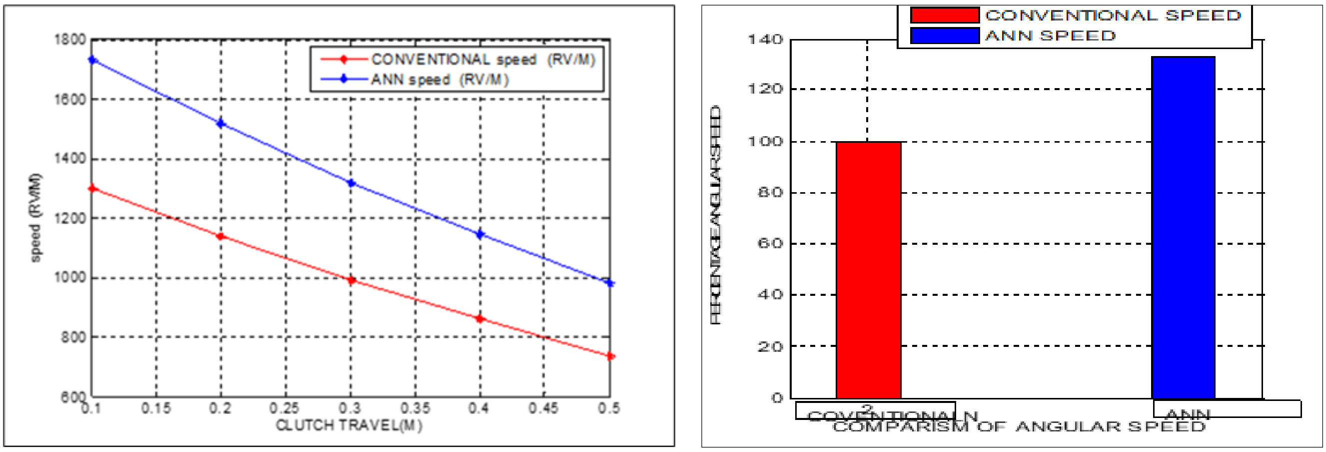
**Figure 7** Conventional and Artificial Neural Network controller compared for error signal

*4.2.2. Comparing Angular Speed*

**Table 8** Comparison of Engine angular speed

| Clutch travel (M)/Analysis | Conventional speed (RV/M) | ANN speed (RV/M) |
|---|---|---|
| 0.00 | ∞ | ∞ |
| 0.01 | 1300 | 1732 |
| 0.02 | 1140 | 1519 |
| 0.03 | 990 | 1319 |
| 0.04 | 860 | 1146 |
| 0.05 | 735 | 979.3 |
| Average | 1005 | 1339.1 |
| % difference /base 100 | 100 | 133.24 |

Table 8 and figures 8 (a) and (b) showcase the comparison of the performances of the conventional controller with that of the ANN controller in electro-pneumatic clutch actuation. Deductions from the table, graph and bar chart respectively clearly indicates that the angular speed is comparably higher in an ANN controller. While the average speed in a conventional controlled was 1005 RPM, the ANN controller produced an average of 1339.1 RPM or a 33.24 % increase.



(a) Graph

(b) Bar Chart

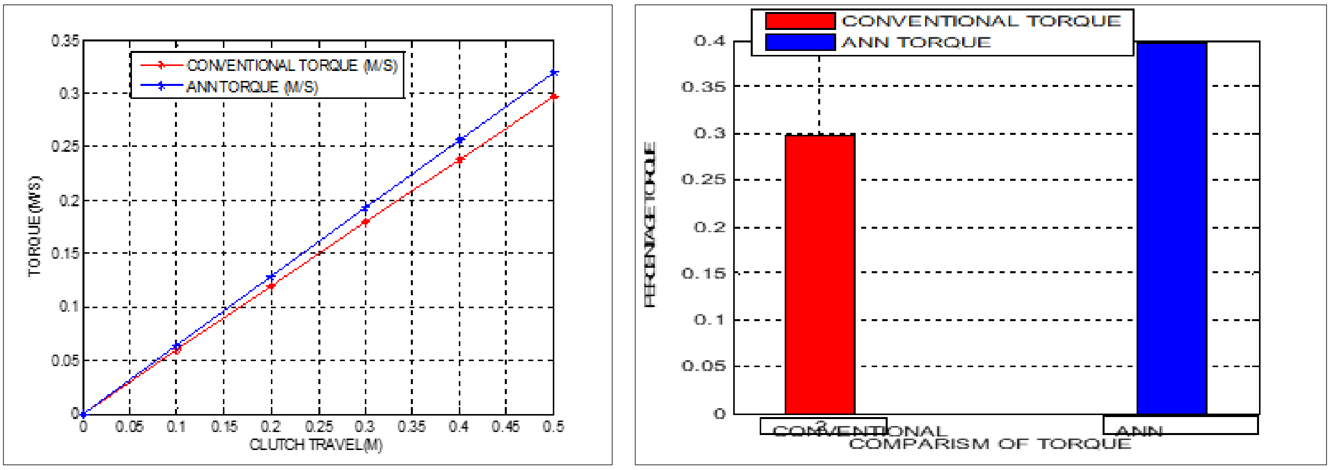
**Figure 8** Conventional and Artificial Neural Network controller compared for Angular Speed

*4.2.3. Comparing Engine Torque.*

In table 10 and figures 10 (a) and (b), the engine torque performance indices of the conventional controller (red colour) with that of the ANN controller (blue colour) in electro-pneumatic clutch actuation are presented in table, graph and bar chart. The table, graph and bar chart respectively clearly indicate that the engine torque is comparably higher in an ANN controller. The average torque in a conventional controlled was 0.1786 NM, the ANN controller yielded an average of 0.238NM or a 33.26) % increase.

**Table 9** Comparison of engine torque in electro-pneumatic clutch actuation control

| **Clutch travel (M)/Analysis** | **Conventional torque (NM)** | **ANN torque (NM)** |
|---|---|---|
| 0.00 | 0.0000 | 0.0000 |
| 0.01 | 0.0595 | 0.0792 |
| 0.02 | 0.1190 | 0.1585 |
| 0.03 | 0.1792 | 0.2388 |
| 0.04 | 0.2380 | 0.3171 |
| 0.05 | 0.2975 | 0.3964 |
| Average | 0.1786 | 0.2380 |
| % difference/ base 100 | 100 | 133.26 |



(a) Graph

(b) Bar Chart

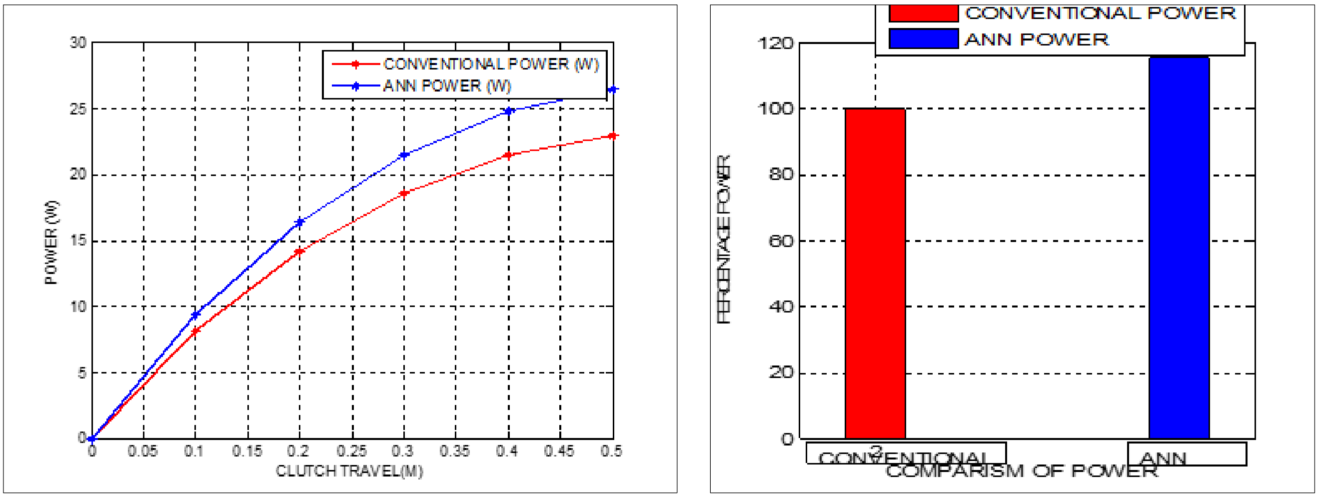
**Figure 9** Conventional and Artificial Neural Network controller compared for Engine Torque

*4.2.4. Comparing Engine Power*

Engine power is presented in table 11 and figures 11 (a) and (b). The table, graph and bar chat showcase the comparison of the performances of the conventional controller with that of the ANN controller in electro-pneumatic clutch actuation system. The conventional controller data is plotted in red colour while the blue colour represents the ANN controller. The table, graph and bar chart respectively clearly indicate that the engine power is comparably higher in an ANN controller as the average engine power produced in a conventional controlled was 16.88kw, the ANN controller produced an average of 19.67kw resulting in an improvement of a 16.53 %.

**Table 10** Comparison of engine power in electro-pneumatic clutch actuation control

| **Clutch travel (M)/Analysis** | **Conventional power (kw)** | **ANN power(kw)** |
|---|---|---|
| 0.00 | 0.00 | 0.00 |
| 0.01 | 08.10 | 09.35 |
| 0.02 | 14.21 | 16.40 |
| 0.03 | 18.58 | 21.45 |
| 0.04 | 21.43 | 24.74 |
| 0.05 | 22.09 | 26.43 |
| Average | 16.88 | 19.67 |
| % difference/ Base 100 | 100 | 116.53 |



(a) Graph

(b) Bar Chart

**Figure 10** Conventional and Artificial Neural Network controller compared for Engine Power

## 5. Conclusion

From the above, it is shown that the average error for conventional controller was 0.72mm and ANN controller gave 0.2379mm. Error was reduced by 0.4821mm or 67%, It proves that calibration challenges in clutching will be reduced comparably in heavy duty vehicles that utilizes ANN controller model in its actuation controls. The result of this error reduction will have tremendous impact in the engine module. This presentation indicates an increased engine torque, angular speed and power respectively. All these results, transforms to an optimized performance, ease of operation and reduction in accidents that usually occurred with this class of vehicles especially on hilly terrains in a typical Nigerian highway. It is conclusive that ANN controllers that utilizes electro-pneumatic method of transmission in its actuation process are indeed far better than conventional controllers in clutch actuation control of heavy-duty Vehicle.

## Compliance with ethical standards

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### *Disclosure of conflict of interest*

The authors declare no conflicts of interest regarding the publication of this article.

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