MODELING AND SIMULATION OF TEMPERATURE VARIATION IN BEARINGS IN A HYDRO ELECTRIC POWER GENERATING UNIT

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***Abstract**:* Hydroelectric power contributes around 20% to the world electricity supply and is considered as the most important, clean, emission free and an economical renewable energy source. Hydro electric power plants operating all over the world has been built in the 20th century in many countries and running at a higher plant-factor. This is achieved by minimizing the failures and operating the plants continuously for a longer period at a higher load. However, continuous operation of old plants have constrained with the failures due to bearing overheating. The aim of this research is to model and simulate the dynamic variation of temperatures of bearing temperature of a hydro electric generating unit.

Multi-input, multi-output (MIMO) system with complex nonlinear characteristics of this nature is difficult to model using conventional modeling methods. Hence, in this research neural network (NN) technique has been used for modeling the system.

Keywords— Hydro electricity, Bearing Temperature, Plant factor, Neural network, Simulation

1.0 Introduction

Hydro power contributes around 20% of the world electricity generation [1]. As a renewable source of energy it has become more important economical resource compared to other renewable sources as far as the scarcity of fossil petroleum fuel deposits, environmental threats, climate change due to green house gas emissions, and acid rains global warming, etc. are concerned. Hydro power produces no direct waste and contribution to CO_2, green house gases compared to fossil fuel plants. The global installed capacity of Hydro-electrical power generation is approximately 777GW with a production of 2998TWh/year [1]. It is around 88% of the renewable sources [2].

In Sri Lanka about 40% of electricity is generated from hydro electricity. At present almost all hydro potential available in the country has been utilized for electricity generation and few remaining are under construction. The deficit between electrical power generation and demand is met by thermal power generation.

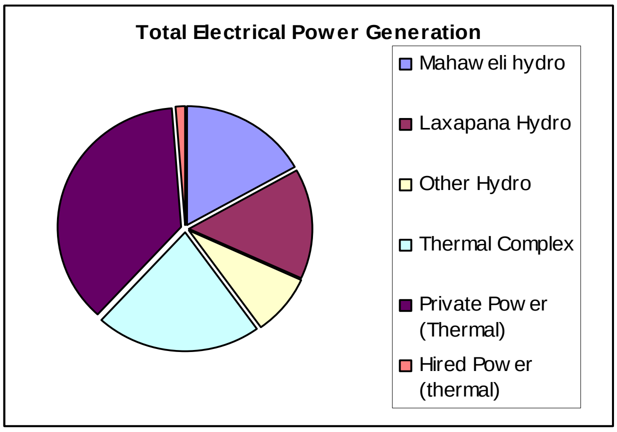


Figure 1. *Hydro electric contribution in 2009* (Source: Ceylon Electricity Board, Statistics 2009)

The electricity power generation by different sources in the year 2009 is shown in Fig. 1. Electricity generated in three major hydro power complexes (Mahaweli Hydro complex, Laxapana

Hydro Complex, Other Hydro Complex) in Sri Lanka, contributes 40% to the national energy supply while the rest is coming from thermal power generation. Hence, getting the maximum possible share from hydro would be great saving to the national economy.

Around 95% of the existing hydro power plants have passed the 25 year limit of their life span. Many developing countries in the region are not in a situation to replace all old-hydro power plants, within a short period and also their energy production are mainly depends on hydropower. In Sri Lanka all most all available hydro plants have the 25 year limit. Age analysis of the hydro plants in Sri Lanka is shown in Table 1.

TABLE 1: *Age analysis of Hydro electric Plants in Sri Lanka (Source: Ceylon Electricity Board, generation Data)*

Name of the Station	Installed capacity / MW	Commissioned year	Age (Years)
Inginiyagala	11.25	1950	65
Norton	50	1950	65
Udawalawe	6	1955	60
Old Llaxapana	50	1955	60
Polpitiya	75	1960	50
Ukuwela	40	1976	34
Bowetenna	40	1981	29
New Laxapana	100	1984	26
Canyon	60	1984	26
Kothmale	201	1985	25
Victoria	210	1985	25
Samanalawewa	120	1985	25
Randenigala	122	1986	24
Nilambe	3.2	1988	22
Rantambe	50	1990	20
Kukule	70	2002	8

Therefore, it is essential to obtain the maximum capacity from the existing plants by minimizing the down time through proper operations. In that context predicting the availability of hydroelectric generating units for fault free operation is one of the crucial factors for achieving this.

Bearing oil temperature plays a vital role in continues operation of hydro power plants. Stability of bearing temperatures in turbine and generators are essential for their successful continues operations. All hydraulic and lubricating fluids have practical limits on the acceptable higher operating temperatures. The machine loses its stability and experiences conditional failures whenever the system's fluid temperature violates this limits. Violations of the temperature limit could occur due to inadequate heat transfer rate, operating under higher ambient temperatures and longer duration of operation at higher mechanical loads. The power plant staff should closely monitor the bearing oil and metal temperatures in order to ensure a safe operation of the plant and the bearings life time [4]. Typical acceptable bearing temperatures of a vertical shaft hydro electric turbine generator unit are shown in Table 2.

Monitoring the bearing temperature is an important task for continues running of a hydro electricity generating unit and maximizing the plant-factor. In this context, old hydro power plants continuous operations have been constrained with the failures due to the bearing temperatures rise.

TABLE 2: *Bearing Metal/Oil Temperature Limits*

Bearing Type	Temperature / Deg C (Alarm)	
	Metal	Oil
Upper Guide (UGB)	85	50
Lower Guide (LGB)	85	65
Thrust Bearing (THB)	85	65
Turbine Guide (TGB)	70	70

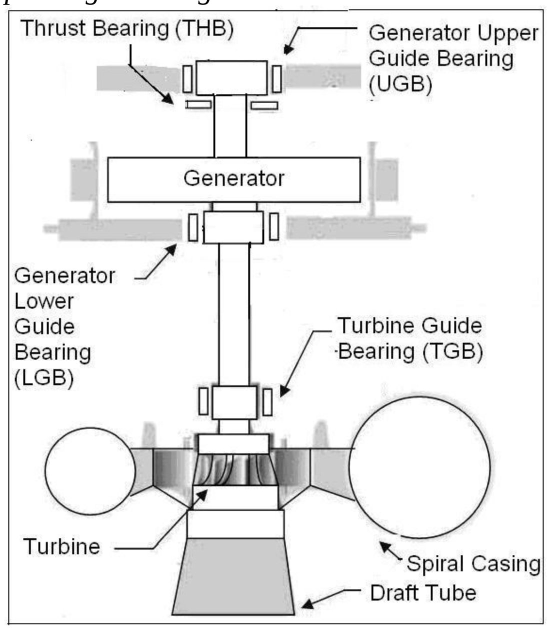
The aim of this research project is to model and simulate the dynamic variation of bearing (generator upper guide bearing UGB, generator Lower guide bearing LGB, turbine guide bearing TGB, thrust bearing THB) temperatures of a hydro electric generating unit which depends on multiple variables such as ambient air temperature, cooling water temperature, cooling water flow rate, initial bearing temperatures and generating unit electrical load and duration of operation etc.

1.1 The hydro electricity generating unit

Hydro electricity generating plant utilizes the potential energy of the water stored in a higher elevation and the turbine and the generator converts the potential energy in to kinetic energy and electric energy respectively. [5].

In this study real data is taken from the Kotmale hydro power generating system for simulating the proposed methodology. Kotmale hydro electric power generating unit consists of four main bearings namely upper guide bearing (UGB), lower guide bearing (LGB), thrust bearing (THB), and turbine guide bearing (TGB) as shown in Fig 2.

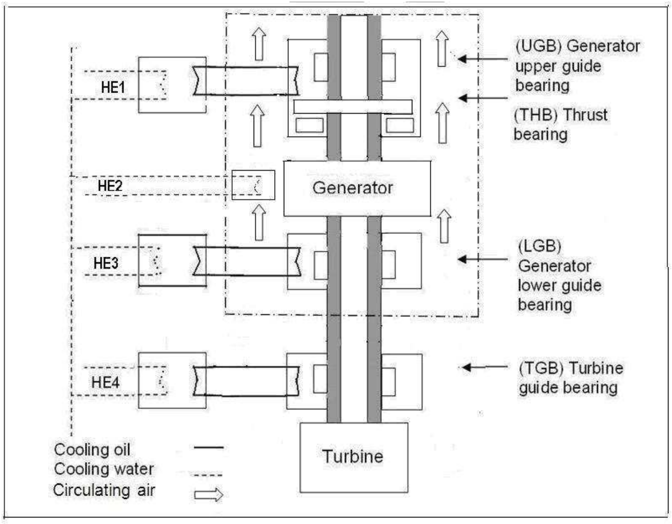
Figure 2. *Bearing arrangement of the hydro-electric power generating unit*



2.0 Determination of NN ARCHITECTURE

2.1 Overview of modeling

The investigated system is a multi dimensional system with multiple-input, multiple-output (MIMO). The physical arrangement of the different types of heat exchangers which transfers the heat generated by heat sources (bearings and generator stator) is shown in Fig 3.0.



HE3, HE4 – LGB, TGB oil coolers,
HE1 – THB and UGB oil cooler,
HE2 – Stator cooler
Figure 3. *Physical arrangement of bearing system*

A simplified diagram illustrating the heat transfer taking place within the system is shown in Fig 4. Bearings (UGB, LGB, THB, TGB) and generator stator are considered as heat sources, and cooling water as well as ambient air act as heat sinks. A detailed diagram of heat transfer is shown in Fig 5.

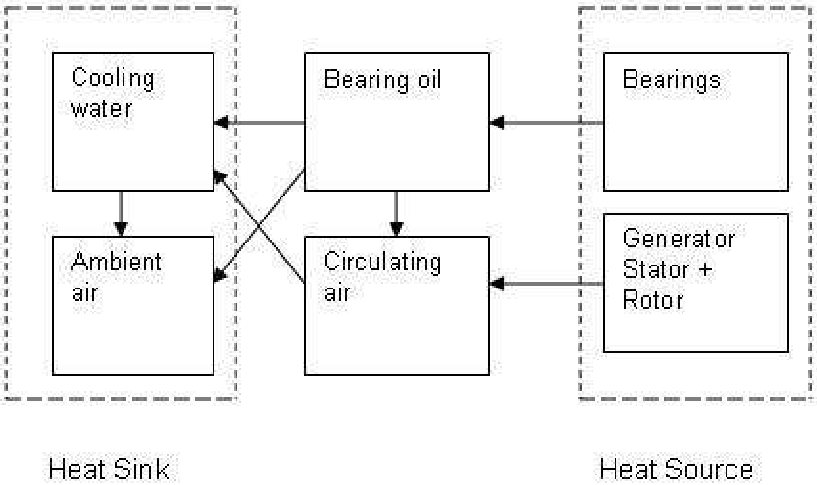


Figure 4. *Simplified heat transfer diagram*

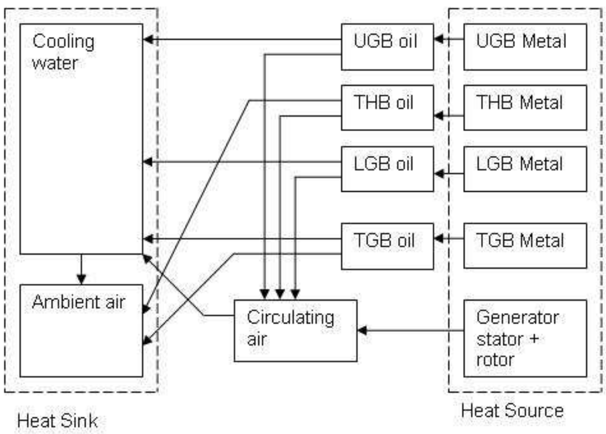


Figure 5. *Detailed heat transfer diagram*

2.2 General Framework for ANN model

A multi-layer feed forward network consists of input layer, out put layer and several hidden layers. The input layer passes their output to the first hidden layer or (with skip layer connection) to directly to output layer. Each of the hidden layer units takes a weighted sum of its inputs, adds a constant (the bias) and calculates a fixed function Φ_h of the result. This is then passed to the hidden units in the next layer or to the out put unit(s).The fixed function is given by

$$f(z) = \exp(z)/(1 + \exp(-z)) \tag{1}$$

The output units apply a threshold function Φ_0 to the weighted sum of their inputs plus their bias. If the input are p_i and outputs are a_k for one hidden layer ,

$$a_k = \phi_o(b_k + \sum_i^k w_{ij} p_h + \sum_j^k w_{jk} \phi_h(b_i + \sum_i^j w_{ij} p_i)) \tag{2}$$

i ,j,k denotes number of input ,hidden layer and output layer units. Following equation gives general form of a multi layer neural network.

$$a_i = \phi_0(b_k + \sum_j w_{ij}^{(1)} p_j + \sum_j \sum_k w_{ijk}^{(2)} p_j p_k + \sum_j \sum_k \sum_l w_{ijkl}^{(3)} p_k p_k p_l + \ldots) \tag{3}$$

(1),(2),(3) denotes the layer numbers and others are usual notations.

3 TRAINING THE NN

3.1 Developing the model

This section describes the approach and steps followed to develop a dynamic model to simulate hydro-electric power generating unit bearing temperature variation with time, electrical load, with the duration of operation and other environmental factors.

3.2 Selection of input/outputs

Input variables which affects to the characteristics of the system under investigation can be shown as given below in Table 3.

TABLE 3: *INPUTS/OUTPUTS*

Notation	Description
T_{LGBm}	Lower guide bearing metal temperature
T_{UGBm}	Upper guide bearing metal temperature
T_{TGBm}	Turbine guide bearing metal temperature
T_{THBm}	Thrust bearing metal temperature
T_{LGBoil}	Lower guide bearing oil temperature
T_{UGBoil}	Upper guide bearing oil temperature
T_{TGBoil}	Turbine guide bearing oil temperature
T_{THBoil}	Thrust bearing oil temperature
$T_{cooling\ water}$	Cooling water temperature
T_{air}	Circulating air temperature
$mdot_{CW}$	Cooling water flow rate
m_{BCW}	Bearing cooler water flow rate
L_e	Electrical load (MWs)
L_{vars}	Electrical load (Vars)

TLGB, *TUGB*,*TTHB*, *TTGB*, *TLGBoil*, *TUGBoil*, *TGBoil* and *TTHBoil*. But, values of the above variables depend not only on the instantaneous values of them , but current values as well as the previous values. It can be illustrated more general form as shown in the fig. 6. where, *Xi* as temperature related inputs, mi as inputs related to flow rates, *Li* inputs related to load variables.

Where,

Xi = { $T_{UGBm}(0)$, $T_{THBm}(0)$, $T_{LGBm}(0)$, $T_{UGBO}(0)$, $T_{LGBO}(0)$, $T_{TGBO}(0)$, $T_{UGBm}(t-2T)$, $T_{UGBm}(t-T)$, $T_{UGBm}(t)$, $T_{THBm}(t-2T)$, $T_{THBm}(t-T)$, $T_{THBm}(t)$, $T_{LGBm}(t-2T)$, $T_{LGBm}(t-T)$, $T_{LGBm}(t)$, $T_{TGBm}(t-2T)$, $T_{TGBm}(t-T)$, $T_{TGBm}(t)$, $T_{UGBo}(t-2T)$, $T_{UGBo}(t-T)$, $T_{UGBo}(t)$, $T_{LGBo}(t-2T)$, $T_{LGBo}(t-T)$, $T_{LGBo}(t)$, $T_{TGBo}(t-2T)$, $T_{TGBo}(t-T)$, $T_{TGBo}(t)$, $T_{CW}(t-2T)$, $T_{CW}(t-T)$, $T_{CW}(t)$, $T_{CA}(t-2T)$, $T_{CA}(t-T)$,$T_{CA}(t)$,}

Mi = {$m_{dot1}(t-2T)$, $m_{dot1}(t-T)$, $m_{dot1}(t)$, $m_{dot2}(t-2T)$, $m_{dot2}(t-T)$, $m_{dot2}(t)$}

Li = { $L_{mw}(t-2T)$, $L_{mw}(t-T)$, $L_{mw}(t)$, $L_{mv}(t-2T)$, $L_{mv}(t-T)$, $L_{mv}(t)$ }

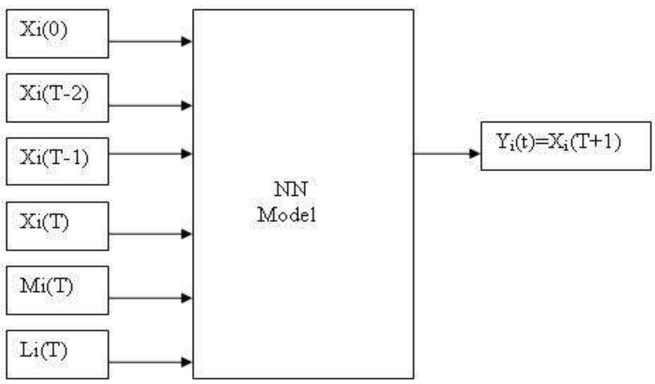


Figure 6. *Inputs / outputs for training the NN model*

3.3 Approach

As discussed earlier, in section 3 and as shown in Fig. 6, there are two types of input variables to the model, viz temperature dependent variables (bearing metal temperatures, bearing oil temperatures, cooling water temperature and circulating air temperature) as denoted by Xi. Second, type of inputs is the bearing water flow rates that do not change due to the performance of the system and the electrical load that directly affect to the bearing metal and bearing oil temperatures.

The variables that interact with system can also be classified into two categories. They are external variables and internal variables. Electrical load, cooling water and circulating air temperatures act as external factors while initial bearing metal temperature, bearing oil temperature act as internal variables. In a system of this nature, output values depend on the present status as well as previous status of the system.

In mathematical form, general behavior of the system can be defined as,

State equation,

$$S(t+T) = f(S(t), X(t), w) \quad (4)$$

Output equation,

$$y(t) = h(S(t), w) \quad (5)$$

Where, *S* represents the state vector, *x* external input vector and *w* neural parameter vector synaptic connection vectors and operational parameters, *f*(.) is the function that represents the structure of the neural network, and *h*(.) is a function that represents the relationship between state vector *S*(t) and output vector *y*(t) [10].

Some times in order to get a reasonable accuracy several previous states have to be considered. Therefore, some sort of memory capability has to be introduced to the model. The variation of temperatures are continues varying functions. But, as we consider sample inputs at a chosen time interval the model becomes a discrete system. Hence, the memory capability can be incorporated by giving a series of time delay inputs. Equations (8) and (9) describe behavior of a first order system which takes into account the previous state (with one step time delay) of the variables. In generally nth order system can be described as,

State equation,

$$S(t+T) = f(S(t), S(t-T), S(t-2T)......S(t-[n-1]T)X(t), w) \qquad (6)$$

Output equation,

$$y(t) = h(S(t), w) \qquad (7)$$

We have developed two models of second order and third order in order to select the one that gives the best performance.

In a third order system we have to consider the three previous states. Therefore, in order to predict the bearing temperature value at t, bearing temperature at t, (t-T) and , (t-2T) also has to considered. Then, with the bearing metal temperature, bearing oil temperature, cooling water temperature, circulating air temperature and electrical load MWs, MVars altogether makes 32 inputs to the model. Our intention is to predict the four bearing metal temperatures but as bearing oil temperatures, cooling water temperature and circulating air temperatures also affect to it, altogether the number of out puts become 9 ($T_{UGBm,}$ $T_{THBm,}$ $T_{LGBm,}$ $T_{TGBm,}$ $T_{UGBOil,}$ $T_{LGBOil,}$ $T_{TGBOil,}$ $T_{cw,}$ T_{CA}) So that, the initial architecture of the NN takes shape of 32 input nodes, and 9 output nodes as shown in Fig. 4.2 shown below. Let's arbitrarily select two hidden layers, this can be changed if necessary during the process of training the network. Number of nodes in the hidden layers also could be selected as an average number of nodes of the two adjacent layers of the network [11][12].

Then, the initial architecture becomes (32, 24, 15, 9), where number of inputs and outputs are a fixed value and the number of input also can be changed according to the consideration of previous status of inputs at interval such as t-T, t-2T, etc depending on the accuracy or the error of training. Training, validation and testing errors explain to what extent that the model fit to the actual system behavior.

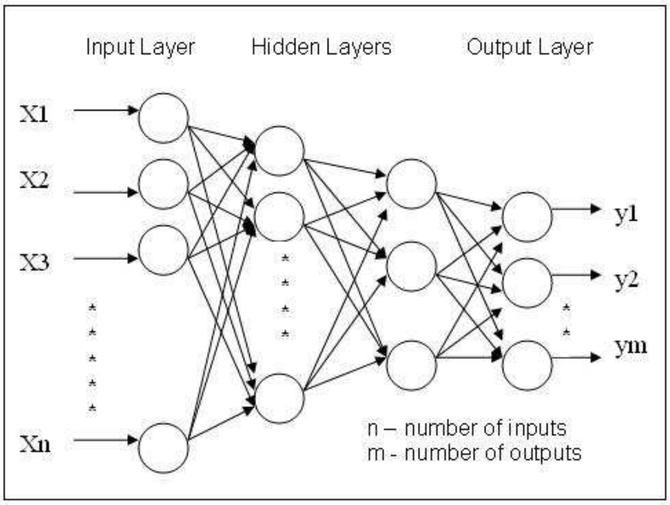


Figure 7. *Inputs / outputs for training the NN model*

Input and output data was fed into the network and trained in the MATLAB environment, Fig. 8 shows the training performance of the model. The mean squared error (Mse) was converegd to 3.10263e-007 , for a model with (32,40,26,9) aechitecture.

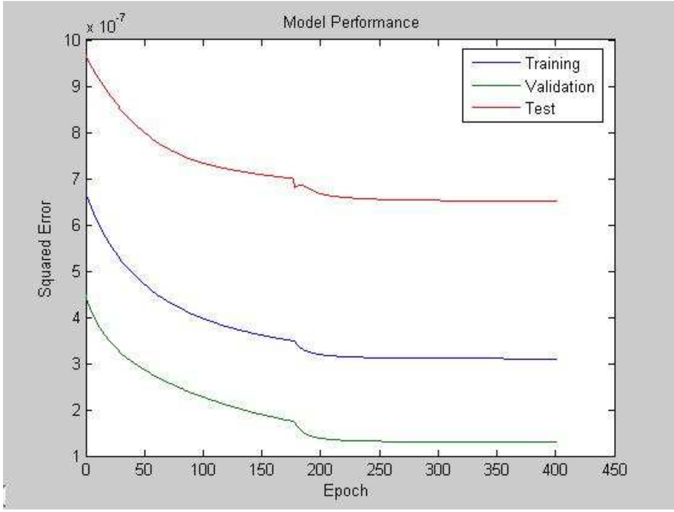


Figure 8. *Inputs / outputs for training the NN model*

3.4 Developing the dynamic model

As described in the previous section in order to model the temporal nature of the system as well as the effect of the internal variables the general architecture of the model should be as in Fig 9 shown below where Xi(0) denotes the initial conditions.

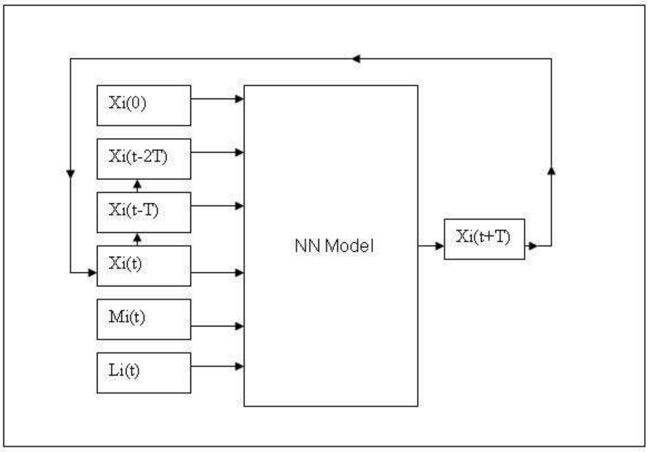


Figure 9. *Dynamic model*

3.5 Developing the dynamic model

Simulation was carried out according to the following algorithm.

Algorithm of the simulation:

```
Read

Xi(0), initial conditions  (bearing metal
                     and oil temperature)
read Xi(t),Xi(t-T),Xi(t-2T), bearing metal
                     and  oil temperature
Mi(t),Li(t)   cooling water flow rates,
                     circulating air
                     temperature and
                     electrical load,
```

```
make input matrix
load trained neural network
decide time duration n
loop up to n records
      simulate and get output of X_i(t+T)
      update inputs
      record output
end
```

4 Simulation results

4.1 Static model Performance

Our approach is to develop (training) a static model to simulate the behavior of the real system and then to convert it to a dynamic model by arranging a feedback of internal variables as inputs to the model. The simulated out puts were compared with the actual outputs to evaluate the performance of the static model. Then the correlation of simulated outputs with actual targets was compared. Static simulation results and corresponding correlation results of temperature variation for *UGBm, THBm, LGBm, TGBm* are shown in Fig 10, and 11 respectively.

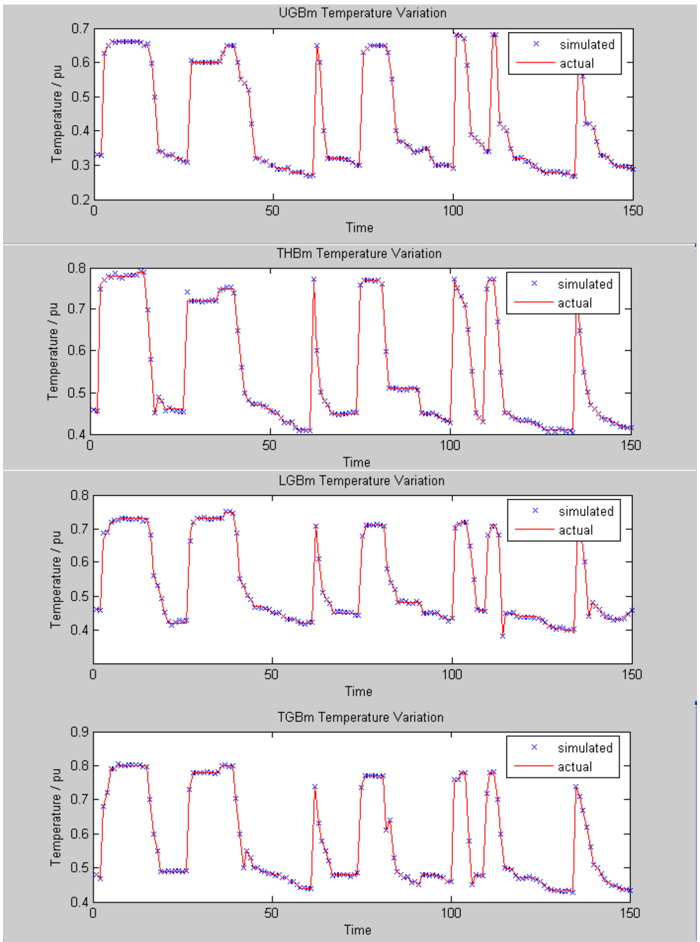


Figure 10. *simulaed results for static model*

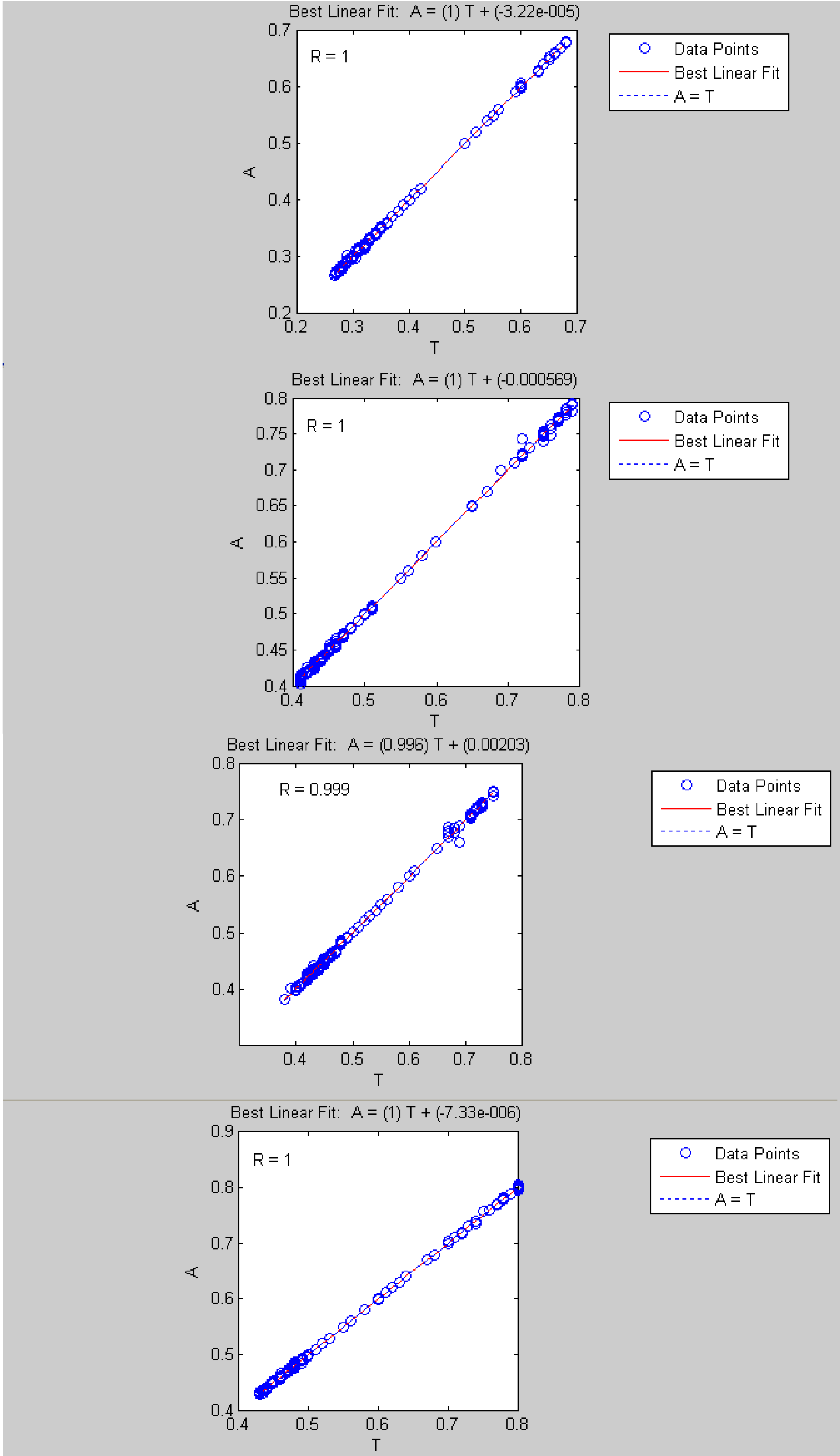


Figure 11. *corelation coefficient for static model*

4.2 Dynamic Model Performance

A set of unused data test data was fed into the trained model and simulated according the algorithm given in section III, E and the performance of the model was evaluated. The regression analysis results in Table II shows the correlation between actual and the simulated results.

5 CONCLUSION

The model developed in this research to simulate bearing temperatures of a bearing heat exchanger system was successful giving promising results. Initially a static model was developed and it was extended to simulate the dynamic behavior of the system. According to these results, neural network models are more capable of modeling non linear, multi-dimensional MIMO systems rather than using conventional methodologies using first principles. The model developed and methodology used provides and serves as a good initiative for others for modeling problems of this nature.

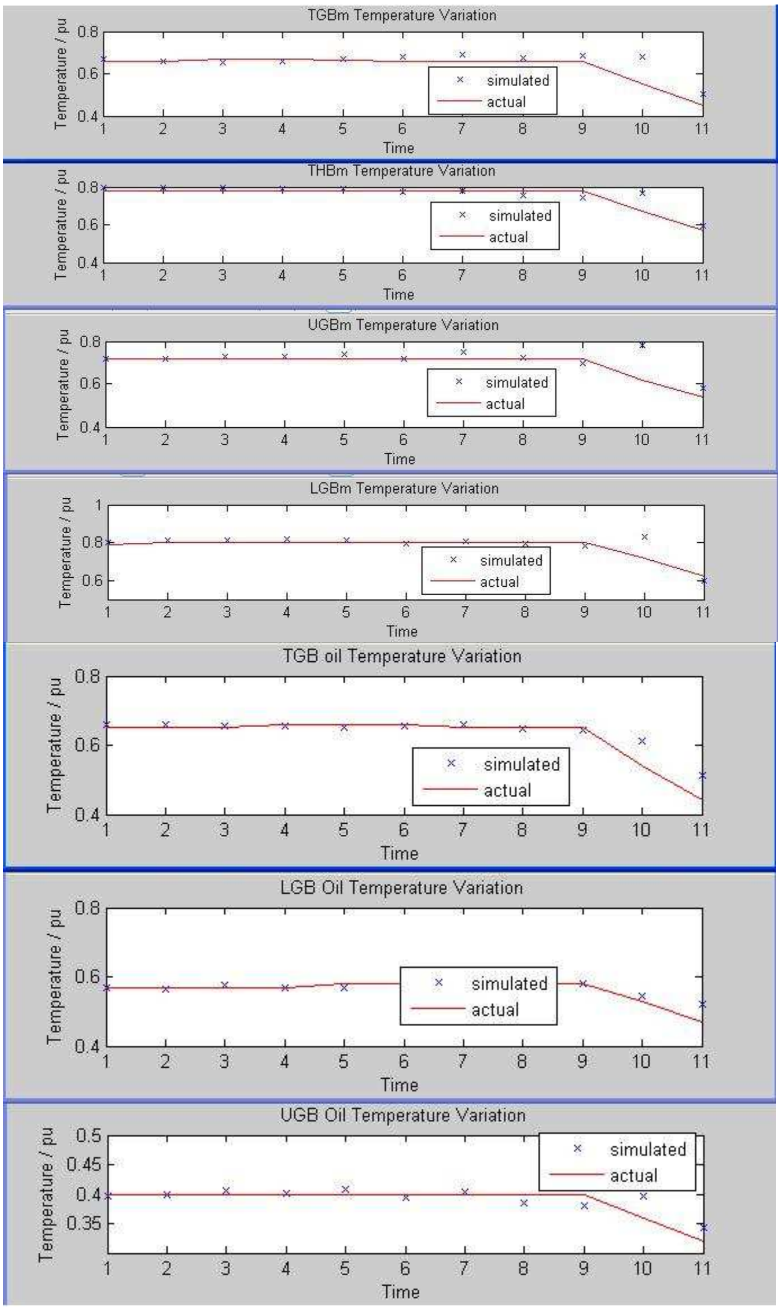


Figure 12. *Dynamic simulation results of the dynamic model*

TABLE 4: CORRELATION RESULTS OF THE OUTPUTS

OUTPUT NO	CORELATION COEFFICIENT
1	0.82
2	0.87
3	0.71
4	0.84
5	078
6	095
7	0.97

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