

Prediction on Vibro-Wind Energy Harvester

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Abstract--- *The Vibro-wind energy harvester designed in various geometric shapes and sizes. The ultimate aim is to collect the samples from various design and to avoid designing harvester for analysis in the future, the prediction model has been applied on collected samples. The data has been collected as physical properties of a harvester, oscillation frequency, and vibration parameters. Based on the physical properties the neural network back-propagation model predicted the vibration parameters and frequency. The model has been evaluated with Mean Square error Value (MSE) and Mean Absolute error value which are found as 0.005826 and 0.07 respectively.*

Keywords--- *Vibro-Wind energy harvester, prediction, Back- propagation, Mean Squared error value, Mean Absolute error value*

I INTRODUCTION

Global warming awareness is reached among all over countries in the world. Non-renewable energy resources playing a large role in global warming. The alternative source of Non-renewable energy resources is renewable resources like water, wind, solar. The ultimate goal of designing an energy harvester and analyzing the samples from an energy harvester in various geometrical shapes and size is to find the vibration parameters for the given design through prediction model.

The Cornell University has conducted harvesting research based on vibration known as Vibro-wind harvester in which arrays of cantilevered bluff bodies are assembled in a panel (Moon, 2010b)[3]. This experiment was based on power generation due to the effect of aerodynamic forces. The principle behind the power generation was a Piezo-electric effect. Here foam pads are used as a bluff body (a body that alters its position due to aerodynamic forces) which provides motion when it is subjected to aerodynamic forces. When the setup was exposed to wind flow, the bluff bodies provides the necessary motion (This motion produced by the bluff bodies is an example of transverse aerodynamic galloping) which transmitted to the beam and due to the beam's vibration the piezo-electric materials excited to generate power.

As per previous researches, the amplitude produced by the galloping oscillators with both translation and rotational

movements is comparatively less than oscillators providing a pure translation. Erturk et al. (2010)[5] increased the performance of energy harvester by decreasing the critical wind speed which was the starting point for understanding the role of oscillator's geometry. The amount of energy harvested can be increased by using a more efficient coupling mode Sodano et al (2005a) [6] 31mode and 33mode are the two practical coupling modes used. Among this, the 31mode configuration cantilever has proved to be efficient under low vibration level environment

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while the 33mode configuration cantilevers are suitable in high vibration level sectors. The harvested output power directly proportional to the coupling coefficient k and dielectric constant ϵ . Yang et al (2005) [8] conclude that the device having high coupling coefficient produce more power and that have nearer driving frequency to resonant frequency will lead to more power generation. Cho et al (2005a)[9] predicted that increasing the stiffness of the passive elastic layer will simultaneously increase the coupling coefficient which in-turn leads to more output and at the end his research it was found that the residual stress plays a key role in decreasing the coupling coefficient and concluded that reducing this residual stress will show significant gain in coupling coefficient

In this paper, we created Vibro-wind energy harvester which generates energy from wind. The harvester generates power based on the principle of the piezoelectric effect. Piezo-electric effect means when mechanical forces are applied on piezoelectric material it produces electric force and vice versa. The Vibro-wind generator consists of versatile cantilever beam and bluff bodies (trapezoidal and conical) and the piezoelectric material which is connected at the end of the versatile cantilever beam. The versatile cantilever beam made up of stainless steel 302 series which has Modulus of Elasticity (Tension) 28×10^6 PSI and the bluff bodies made up of Extruded polystyrene foam (XPS) consists of closed cells, offers improved surface roughness and higher stiffness and reduced thermal conductivity. The density range is about 28– 45 kg/m³.

The prediction model is applied to the data which has been collected through various experiment set up. When the wind strikes the harvester, the harvester begins to oscillate which produces vibration, the oscillation frequency, vibration parameters data were collected. Cui and Quin (2018)[10]

researched the dynamic characteristic of soft soil under metro vibration load. here they have conducted their experiment using indoor dynamic triaxial equipment. To realize the virtual reality of the dynamic characteristic of a complex model accurately, the Back-propagation neural network was used. Gebrael et al[11] developed a prediction model to diagnose the bearing faults of mechanical machines and rotational equipment, the vibration data were collected through an accelerated test. The Back-propagation neural network prediction model had given an effective result. Nguyen et al[12] developed a prediction model for blast-induced PPV in an open-pit coal mine of Vietnam, a dataset of 68 blasting events were used for feed-forward artificial neural network and they found less RMSE and R² value.

This survey shows that the neural network model works well in control system parameters. Hence the model has been trained with collected data, based on a physical parameter of a harvester, the oscillation frequency, and vibration parameter were predicted with neural network model with back- propagation algorithm was applied which was evaluated based on Mean absolute error, Mean squared error and root mean squared error. Thus this system will reduce the cost of designing harvester, rather prediction model can be used for future study which enormously reduces the time and resources.

II MODEL:

Vibro-wind energy harvester generates power based on the principle of the piezoelectric effect. In this piezo-electric materials are attached to the rear end of the thin versatile cantilever beam made up of SS 304 and bluff bodies (trapezoidal and conical) made up of Extruded Poly-styrene to the front end of the beam which is fixed in

rows and columns in panel grid. Once the wind strikes the harvester, the bluff bodies begin to vibrate and due to which the beam starts to deflect. This deflection ends up in impressing vibration, as a result of this impression, power is generated by the piezoelectric material. In the Design Of Experiments(DoE), using the Taguchi method, the L9 orthogonal array model was considered their response properties are velocity, amplitude, and displacement which are vibration parameters and oscillation frequency. Table 1 and table 2 values are generated from the orthogonal array. the dimensions of the trapezoidal and conical bluff bodies were finalized and the force working on the bluff bodies were measured and dynamically has been developed using Computational Fluid Dynamics(CFD) that consolidate structural properties of the bluff bodies, the result of mean native velocity and electrical properties of effective piezoelectric to estimate electric power output. The panel grid was made with the dimension of are the length, height, width thickness and angle which are 30mm,500mm,50mm,10mm, and 25 deg respectively and the beam body was made with 0.3mm thickness, 20 mm width and 200 mm length. The beam body and panel are constant setups for throughout experiments. The bluff bodies were designed with 9 different sizes and two different shapes which are trapezoidal and canonical.



Figure 1. Experimental Setup



Figure 2. Shape of Beam and Bluff Bodies.

i).Dimensions based on the design of Experiment for trapezoidal section and Conical section

Table. 1 Dimensions for Conical section

Sizes	Conical Shape Dimensions								
	1	2	3	4	5	6	7	8	9
Major diamete r	70	70	70	80	80	80	60	60	60
Minim m diamete r	40	50	45	40	50	45	50	40	45
Height	70	60	50	50	70	60	50	60	70
Maxim m Value(V)	0.0 7	0.1	0.0 9	0.0 9	0.1 1	0.1	0.0 9	0.0 9	0.0 7
Minim m Value(V)	0.0 2	0.0 3	0.0 2	0.0 2	0.0 6	0.0 3	0.0 4	0.0 2	0.0 2

Table. 2 Dimensions for trapezoidal section

Sizes	Trapezoidal Shape Dimensions								
	1	2	3	4	5	6	7	8	9
Major diamete r	120	120	120	100	100	100	80	80	80
Minimm diamete r	80	70	60	80	70	60	80	70	60
Height	30	25	20	25	20	30	20	30	25
Maxim m Value(V)	0.5 4	0.5 3	0.5 5	0.5 9	0.4 9	0.4 7	0. 4	0.4 2	0.4 4
Minimm Value(V)	0.1 3	0.1 8	0.1 6	0.2 0.2	0.1 4	0.1 2	0. 1	0.0 8	0.1 5

This setup leads to a power generation even in wind speeds as low as 3 m/s which is very much less than the 9 m/s start-up velocity of the wind turbine. A one square meter Vibro-wind panel operating at 10% efficiency in just 10 m/s is capable to generate 54W of electricity figure on par with solar panels (Moon, 2010a, 2010b)[2][3].

PREDICTION MODEL:

The dataset has been collected through the experimental setup of different geometric sizes and shapes of Vibro-energy harvester. the dataset consists of 5000 samples.

The input parameters for this network model are the length of the beam, maximum and minimum diameter of bluff bodies,

$\text{newmax}=1, \text{newmin}=0, \text{min}$ is minimum of x_i , max is maximum of x_i , x belongs to x_i .

ii).Model Fitting Artificial neural network

A neural network is a data processing machine that works based on the function of biological human brain neurons. The nodes of the graph represent biological neurons and connections between them represent synapses. Unlike in biological neural networks, connections between artificial neurons aren't usually added or removed after the network was created. Instead, connections are weighted and the weights are adopted by the learning algorithm. The input signal propagates through the network in the direction of connections until it reaches the output of the network.

ii).Artificial Neuron

The complex behavior of biological neurons was simplified to create a mathematical model of artificial neurons, also called units. The unit receives its inputs via input connections from other units' outputs, called activations. Then it calculates a weighted sum of the inputs, called potential. Finally, the unit's activation is computed from the potential and sent to other units. Weights of connections between units are stored in a matrix w ,

the output of this predicted model was velocity, amplitude, displacement, and frequency. Here the length of beam and

$$p_j = \sum_{i=1}^N x_i w_{ji} \dots (2)$$

wind speed were constant for all the dimensions performance was evaluated based on Mean square error(MSE) value and Mean Absolute Error.

i).Data Preprocessing

The collected samples were non-linear. The data has been checked for missing value, duplication, and outliers. The outlier or missing values were discarded or readjusted before the learning operations to increase performance or reduce the effort. The different parameter had a different range of values, parameters within different dynamic ranges should be normalized or standardized on-demand to equalize the influences in the cost function.

The different range of data can be modified into the same set of range by scaling the values of the parameter. The unscaled data have a large impact on the prediction value only because of its scale. The data prone to more errors if it is not scaled properly. There are some common techniques used to scale data: min-max normalization, Z-score normalization, median and MAD, and tan-h estimators. By applying min-max normalization on the data, the values are transformed into a common range.

Data scaling – MIN-MAX scaler to maintain original distribution of variable

$$\frac{x - \min}{\max - \min} = \frac{x - \text{newMin}}{\text{newMax} - \text{newMin}} \dots (1)$$

where,

newmax=1, newmin=0, min is minimum of x_i , max is maximum of x_i , x belongs to x_i .

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where w_{ij} denotes the weight of the connection from unit j to unit i . Every unit i has a potential p_j which is calculated as a weighted sum of all of its N input units and bias. x is the input.

$$p_j = \sum_{i=0}^N x_i w_{ji}$$

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iii). Activation Function

Typically used activation functions are rectified linear unit (Relu) which shows better improvement in compared with other conventional activation functions, The rectified linear activation function is a piecewise linear function that will give input as output is positive, otherwise, it will give output as zero. It has become the default activation

function for many types of neural networks because a model that uses it is easier to train. the limitation of relu is should be applied within hidden layers. The range value of relu is 0 to infinity. It is mathematically expressed as $R(x) = \max(0, x)$ i.e if $x < 0$, $R(x) = 0$ and if $x \geq 0$, $R(x) = x$.

where denotes the slope, net denotes the output of a neuron

iv) .Back-propagation

The back-propagation algorithm is a multilayer feed forward neural network learning algorithm, which is based on a supervised learning method. This algorithm is an error optimization algorithm which reduced the error by updating the weights

$$E = \frac{1}{2} \sum (T_o - Y_o)^2 \dots \dots \dots (3)$$

Where denotes target output, denotes predicted output.

v).Learning Rule – Stochastic Gradient descent algorithm:

Considering error E as a function of network’s weights w, For multidimensional space gradient descent algorithm was used. fitting a curve local minima have to be identified. A local minimum is approached by changing weights along the direction of negative error gradient $-\partial E / \partial w$.

It can be derived as,

$$\begin{aligned} \text{Gradient descent (GD)} &= -\frac{\partial E}{\partial w_{ij}} \\ &= (T_o - Y_o) X_i = \eta (T_o - W_o) X_i = \Delta W_{ij} \end{aligned} \quad (4)$$

by weight change Δw_{ij} proportionally to, which is a constant positive value called learning rate.

$$\text{new } w_{ij} = w_{ij} + \Delta w_{ij} \quad (5)$$

where w_{ij} denotes old weight, Δw_{ij} denotes weight correction

In the stochastic gradient descent algorithm, the subset of training sample used to update weight for particular iteration, hence its is faster in training and faster in convergence. the subset of sample is called minibatch stochastic gradient descent algorithm.

III RESULTS AND DISCUSSION

i).By Using Trapezoidal Bluff Bodies,

Table 3. The characteristics of Trapezoidal Section

Single Bean and Bluff Bodies	9 Beams and Bluff Bodies
Wind speed=7.2 m/s	Wind speed=1.5 to 2 m/s
Output voltage=0.59V	Output voltage=1.3V

ii).By Using Conical Bluff Bodies,

Table 3. The characteristics of Conical Section

Single Bean and Bluff Bodies	9 Beams and Bluff Bodies
Wind speed=7.2 m/s	Wind speed=1.5 to 2 m/s
Output voltage=0.11V	Output voltage=0.27V

iii).prediction measures:

Based on physical properties the Displacement, Amplitude, velocity, and frequency were predicted and are evaluated based on mean squared error, mean absolute error and root mean squared error.

Figure 3.. Predicted Value(Red) Vs Actual Value(blue) for vibration parameter Displacement.

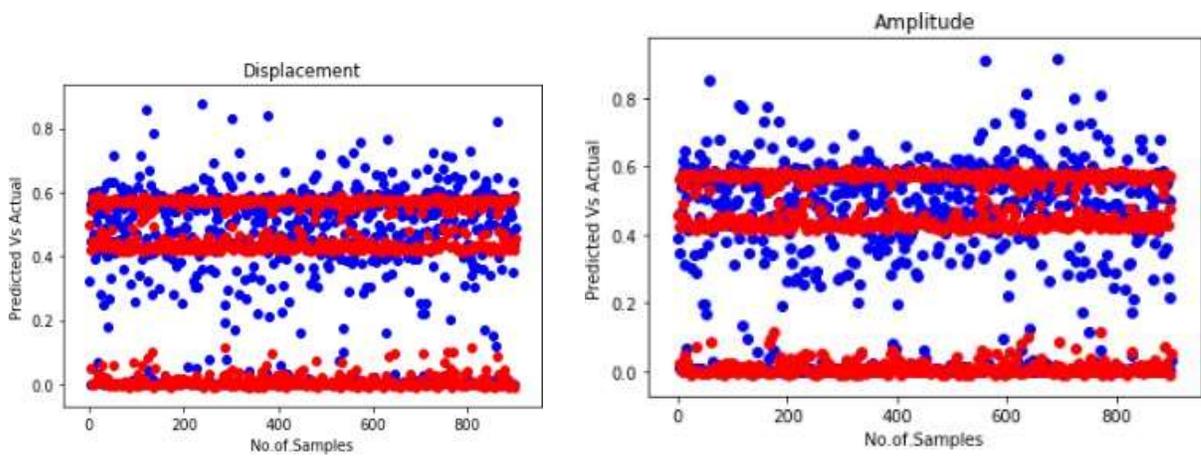


Figure 4. Predicted Value(Red) Vs Actual Value(blue) for vibration parameter Amplitude.

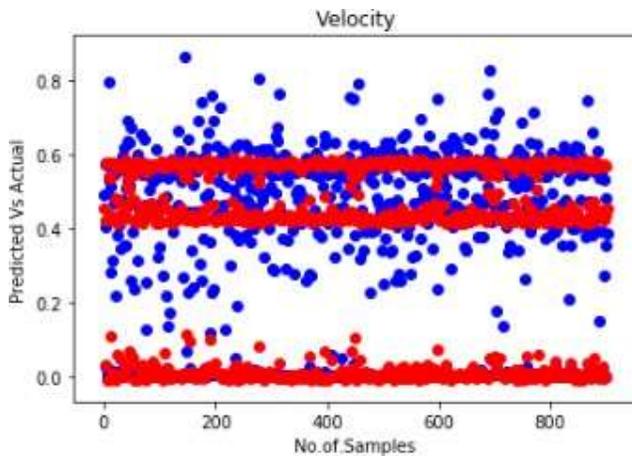


Figure 5. Predicted Value(Red) Vs Actual Value(blue) for vibration parameter Velocity.

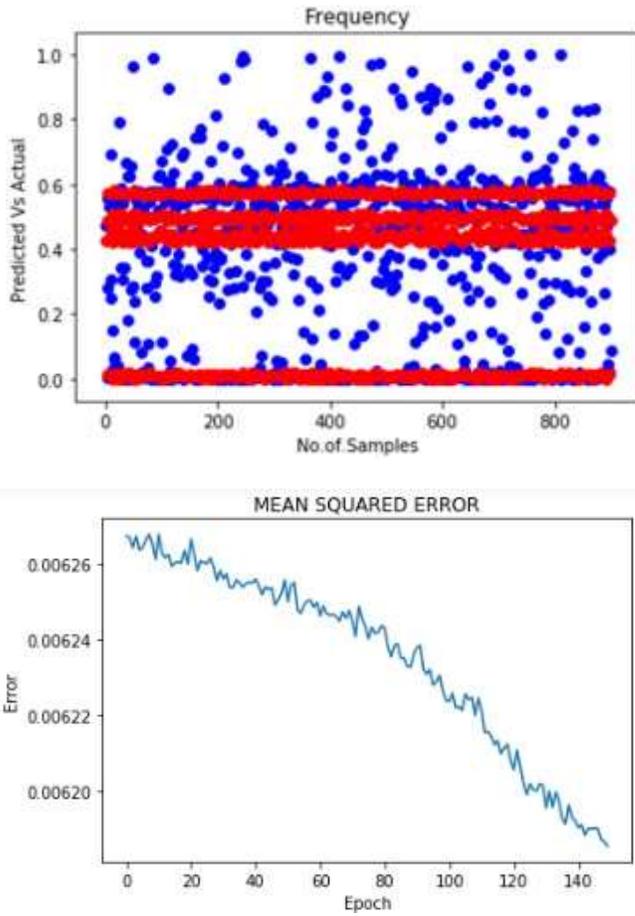


Figure 6. Predicted Value(Red) Vs Actual Value(blue) for vibration parameter Frequency.

iv).Evaluation Metrics:

a).Mean absolute error:: mean absolute error (MAE) is a measure of the difference between the target output and actual output.

$$E = \frac{1}{n} \sum^n |Y_i - X_i|$$

Where Y_i denotes predicted value, X_i denotes observed value.

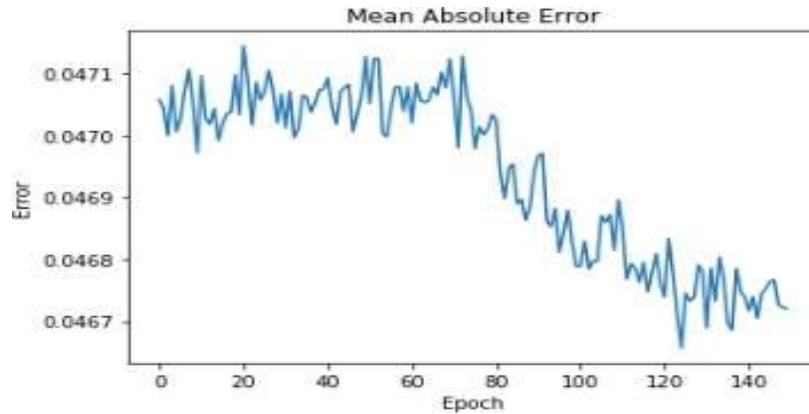


Figure 6. Mean Absolute Error

b). **Mean-Square-Error (MSE)**: The mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - X_i)^2$$

Figure 7. Mean Squared Error

The Mean square value and Mean absolute value and square value was evaluated as 0.00582 and 0.046064.

IV CONCLUSIONS

This project developed to reduce the cost and resource of designing Vibro-generator in different sizes rather the prediction model has been developed so that the user gets to know the desire response by feeding the physical parameter. An efficient neural network algorithm was implemented for prediction. And found its mean square error is 0.005826 which shows that this neural network model fit well on the dataset and had given an effective result.

As per the designed panel, bluff bodies, beam we finally found a result at higher rate ie) higher voltage at low wind speed. Finally, the output gained in our project is supposed to use in various applications. So far from our references we can conclude that using different mechanical structures, multilayer structures, multilayer connections with series and parallel connections, by varying the thickness of the layers, using more efficient piezo-electric layers (Macro-Fiber composites), by varying the piezo-electric configuration(mode31 and mode33) one can increase the overall efficiency of the system. Power can also be increased by mounting the piezo-electric material nearer to the clamping end of the beam.

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