Neural Network Modeling for Predicting Electric Power Generation From Sea Waves

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***Abstract*—Thispaper presents a development of a prototype 1 kW electricpower generation system from sea waves in the gulf of Thailand. The system consists of electrical generator and buoy, and installed on a steel frame. This system is far from shore about 200 meters and sea level 3 meters deep. The purpose of this study is to investigate the relationship between electric power and wave height including the other parameters in the system. The neural networks are used to train the wave height and electric power and consequently the electric power from sea wave can be predicted. The predicted values from neural network models and polynomial regressionwill be compared. The predicted values from neural network are more accuracy in linking the inputs to the outputs in a non-linear manner. The prototype power units have been performed at the Sirindhorn international environment park to verify the ability of neural network models.**

***Index Teams*—sea waves, neural network modeling, electricpower generation, wave height**

I. Introduction

From the announce agreement, Kyoto protocol which sets a long-term goal of 50% reduction in global greenhouse emissions by 2050 is being negotiated [1, 2]. Thus, the importance of clean energy source for the next decades is interested. The potential of wave energy is tremendous and has led researchers to study in forecasting energy. They try to develop the wave farms commercially viable. However, temporal and spatial variability of wave height, frequency and direction is highly irregular, it is very difficult to design sea wave energy converter. Recently, researchers have been to try developed the power generation system from sea waves using the permanent magnet linear generators.

In this research, the main components consist of a floating buoy, linear generator and frame based. Normally, a location of installation is off-shore in deep-sea to obtain the high energy from the sea waves. Invice versa the cost of electric transmission and maintenance are increased because of long distance between wave farms and the land. To solve this problem, the researcher proposed the electrical generating farms at near shore. Each wave energy converter consists of a buoy with 1.2 meter diameter, 320 W permanent magnet generator from a washing machine and a gear box with a ratio of 7:1. Furthermore the system also requiresa measurement part.

The generators were tested to find the characteristics of them. The buoy and gear box were designed to maximize generation. Finally, the systems were constructed on the steel frame based at the Sirindhorn international environment park as shown in Fig. I. The generated electrical power, sea wave amplitude and displacement moving of buoy were recorded and created the model of electrical production from sea waves.

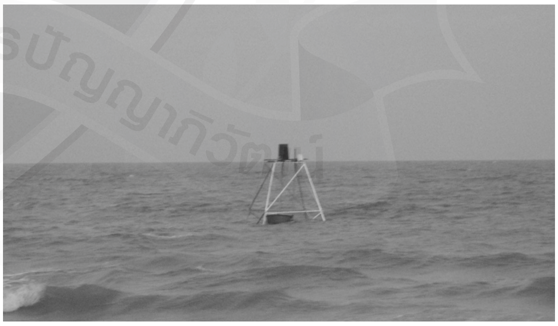

Fig. I. Electrical power generation system

II. Properties of waves

A. Linear wave theory

The condition of linear wave theory in two-dimension is used to solve the solution of velocity potential ϕ [3]. These conditions are the water is homogeneous and incompressible, the surface tension forces are negligible, and flow is irrotational, respectively. The velocity potential ϕ to satisfy the Laplace equation as follows:

$$\frac{\partial^2\varphi}{\partial x^2}+\frac{\partial^2\varphi}{\partial z^2}=0 \qquad (1)$$

where x and z are the horizontal and vertical coordinates, respectively.

Under these conditions, the wave height is small compare wave length and water depth. The particle velocities are proportional to the wave height, and wave celerity which is related to the depth and wave length. The surface deformations at the air-sea boundary incur the surface wave and they are characterized by the wave length L, or the wavenumber $k=\frac{2\pi}{L}$. The waves are propagating with the height H at the height d over the sea floor. A two-dimension diagram of wave propagating in the x direction is shown in Fig. II In Fig. II, L is defined as the horizontal distance between two successive wave crests, which is related to the water depth d and the wave period T, or reciprocally to the angular frequency $\omega=\frac{2\pi}{T}$. The speed of waves defined as the distance L divided by the wave moves in time T, or mathematical term $C=\frac{L}{T}$. The instantaneous elevation of thewater surface heaveis explained by the function of position and time $\eta(x, t)$.

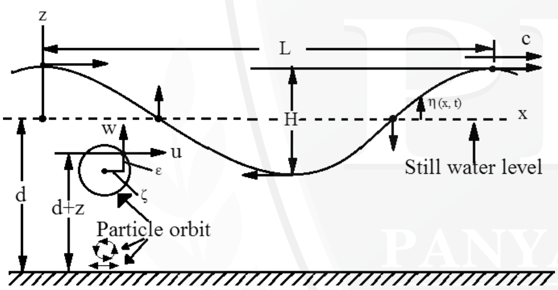

Fig. II. Definitions of linear water wave theory

Thus, the wave steepness defined as the ratio between the wave height and wavelength. The relative depth defined as the ratio between the water depth and wave length. The solution of equation (1) subject to the boundary conditions as:

$$\varphi=\frac{ga}{\sigma}\frac{\cosh k(y+d)}{\cosh kd}\sin(kx-\sigma t) \qquad (2)$$

$$=\frac{gHT}{4\pi}\frac{\cosh[(\frac{2\pi}{L})(y+d)]}{\cosh\frac{2\pi d}{L}}\sin 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (3)$$

$$\eta(x, t)=a\cos(kx-\sigma t)=\frac{H}{2}\cos 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (4)$$

$$\sigma=(gk\tanh kd)^{\frac{1}{2}} \qquad (5)$$

or $$C=(\frac{gL}{2\pi}\tanh\frac{2\pi d}{L})^{\frac{1}{2}} \qquad (6)$$

or $$L=\frac{gT^2}{2\pi}\tanh\frac{2\pi d}{L} \qquad (7)$$

where x, z are Cartesian co-ordinates with z = 0 at the still water level (positiveupwards),

η(x, t) is the free water surface,

t is the time,

u, w, are the velocity components in the x, z directions,

ϕ or ϕ(x, y, t) is the two-dimensional velocity potential,

ρ is the fluid density,

g is the gravitational acceleration,

a is wave amplitude = $\frac{H}{2}$,

H is the wave height,

k is the wave number = $\frac{2\pi}{L}$,

L is the wave length,

f is the wave frequency = $\frac{2\pi}{T}$,

T is the wave period,

d is the mean water depth, and

C isthe wave celerity = $\frac{L}{T}$.

In deep water case: $\frac{d}{L}>0.5$, $\tanh\frac{2\pi d}{L}\approx 1.0$.

The surface waves depend on the relative depth ($\frac{d}{L}$). The waves travelled from deep water offshore into shallow water near shore, the wave length will decreases. So that, the $\frac{d}{L}$ is used to classify into two cases:

- Deep water case, $\frac{d}{L}>0.5$, $\tanh\frac{2\pi d}{L}\approx 1.0$

$$\therefore \qquad L_0=\frac{gT^2}{2\pi}=1.56T^2 \qquad (8)$$

- Shallow water case, $\frac{d}{L}<0.04$, $\tanh\frac{2\pi d}{L}\approx\frac{2\pi d}{L}$

$$\therefore \qquad L_0=\frac{T(gd)^{\frac{1}{2}}}{2\pi}=\sqrt{gd} \qquad (9)$$

B. Particle velocities

The horizontal and vertical component of water particle velocity can be computed from the derivative of Laplace equations:

$$u=\frac{\partial\varphi}{\partial x} \text{ and } w=\frac{\partial\varphi}{\partial z} \qquad (10)$$

Substitute the velocity potential ϕ into the equation (10), the horizontal and vertical of flow are given:

$$u=\frac{\pi H}{T}\frac{\cosh\frac{2\pi(z+d)}{L}}{\sinh\frac{2\pi d}{L}}\cos 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (11)$$

$$w=\frac{\pi H}{T}\frac{\sinh\frac{2\pi(z+d)}{L}}{\sinh\frac{2\pi d}{L}}\sin 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (12)$$

The equation (11) and (12) can be reduced into the simplify form as follows:

$$u=\frac{\pi H}{T}\frac{\cosh\frac{2\pi z}{L_0}}{\sinh\frac{2\pi d}{L}}\cos 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (13)$$

$$w=\frac{\pi H}{T}\frac{\sinh\frac{2\pi z}{L_0}}{\sinh\frac{2\pi d}{L}}\sin 2\pi(\frac{x}{L}-\frac{t}{T}) \qquad (14)$$

C. Pressure

The pressure distribution in the vertical is given:

$$\frac{p}{\rho g}=\frac{\cosh 2\pi\frac{z+d}{L}}{\cosh\frac{2\pi d}{L}}\eta-z \qquad (15)$$

D. Energy

The total energy per wave per unit width of crest E is:

$$E = \frac{\rho g H^2 L}{8} \tag{16}$$

The waves in water 100 m depth have a period of 10 s and a height of 2 m. These waves have a wave length of 156 m, wave celerity of 15.6 m/s, and the steepness is 0.013. While these waves propagated into a near shore depth of 2.3 m. The wave celerity is 4.15 m/s, wave length of 4.75 m, and the steepness is 0.048< 0.05.

III. The Energy Conversion Principle

A. Theory and data analysis

The total wave energy would be the sum of the kinetic and potential energy of buoy[4-6]. The electrical production system converted the wave energy to mechanical work, magnetic energy and electrical energy, respectively. Fig. III shows the block diagram of energy conversion. Sea wave is a sinusoidal waveform and time varying. The excitation inputs can be expressed as in equation (17).

$$D(t, x) = (A/2) \sin (\omega x + 2\pi x/\lambda) \tag{17}$$

where A is the amplitude of incident waves

ω is the angular frequency and

λ is the wave length.

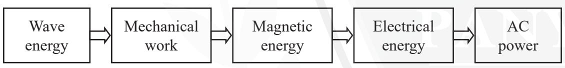

Fig. III. Block diagram of electrical power generation

The coupling configuration have the resultant ΣF is consisted of the hydrodynamic forces F_H, the gravitational force G, and the electromagnetism force F_G exerted via the system as follows:

$$\Sigma F = F_H - G - F_G \tag{18}$$

The hydrodynamic force depends on the movement of buoy and can be expressed as in equation (19).

$$F_w - G = \int_{-r}^{r} 2\sqrt{r^2 - x^2}\,[D(t,x) - S(t)]dx \tag{19}$$

where r is the radius of buoy, and

S(t) is the displacement of buoy.

The electromagnetism force exerted into the generator on the buoy always counter work its movement as follows:

$$F_G = NB^2 l^2 v \tag{20}$$

where N is the number of conductor in all slots,

B is the average magnetic field intensity of air gap,

l is the effective length of conductor and

v is the real time velocity of buoy.

From the equation (20) v depend on the wave height because of v = S/t. The velocity of buoy depended on the displacement of buoy but itindependent from a mass of buoy. However, the displacement of buoy related the amplitude of waves and mass of buoy. Thus, the design of buoy for maximizing converted the wave energy is very important [7, 8].

B. Development of artificial neural networks

The prediction problemin a case of electric power generation from sea waves is difficult because of the complexity of relationships in the input variables. Artificial neural network have been developed properly and typical parameters are employed to build the predicting electric power generation from sea waves. Similarly, the other power production such as the small hydropower plant [9], the prediction of electric power generation of solar cell [10], and the wind power plant [11], they have the same problems. From these problems, artificial neural networks offer an analyzing effectively to model performance of these plants, which have the complexity input variables.

This research applied the neural networks by approaching of feed-forward and back-propagation to compute performance predictions of electric power generation from sea waves. The power production depend on the characteristic of buoy, wave height, displacement moving of buoy, and the sea breeze in eachseason. Neural network as a functional estimator transforms inputs into outputs to the best of its ability as shown in Fig. IV The output of a neuron is a function in equation (21).

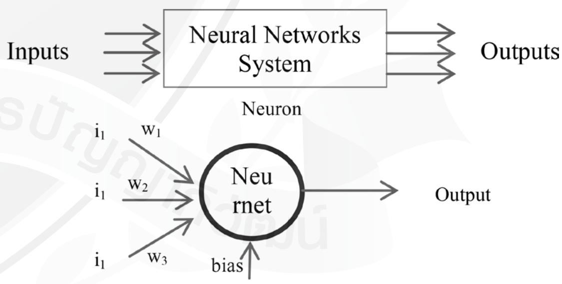

Fig. IV. Neural network as a function estimator transforms inputs into outputs

$$output = f(i_1 w_1 + i_2 w_2 + i_3 w_3 + bias) \tag{21}$$

where i_1, i_2, i_3 are the inputs,

w_1, w_2, w_3 are the weighted in each inter-connection.

In next step, applied the output of each neuron to produce theoutput using sigmoid function $f(x) = \frac{1}{1+e^{-x}}$ where x is an input.The input of sigmoid functionis theoutput in equation (21) from each node. The weights of neural network are the most important factor of presenting network with some sample data and modifying the weights to better approximate the desired function. If the outputs are not correct, the weights are adjusted according to the formula $w_{new} = w_{old} + \alpha(\text{desired-output})*\text{input}$, where α is the learning rate. Train and adjust the network until the neural networks give the corrected output. Neural network in this research is used to predict the electric power production, especially in case of uncertainties of inputs and outputs operation.

C. The measurement of systems

In practical, the researchers recorded the AC power, the height of waves and displacement moving of buoy and consequently to build the model of electrical generating from these data. The height of waves and displacement of buoy were collected by a video camera. The system gets the color label data from the label tab as in Fig. V using the histogram methods. The number of pixels and the height of wave data were used to train the neural networks as the measurement model. After training, the measurement model is used to measure the height of waves and displacement of buoy automatically. The next step, the electric power, the height of waves and displacement of buoy data use to train the neural network as the prediction models. Since, the relation approximation between the AC power and the height of waves /displacement of buoy are cumbersome. The approximation depends on the amplitude of waves and the other parameter of system. This research proposes to find the available prediction model using neural networks as the detail in the next section.

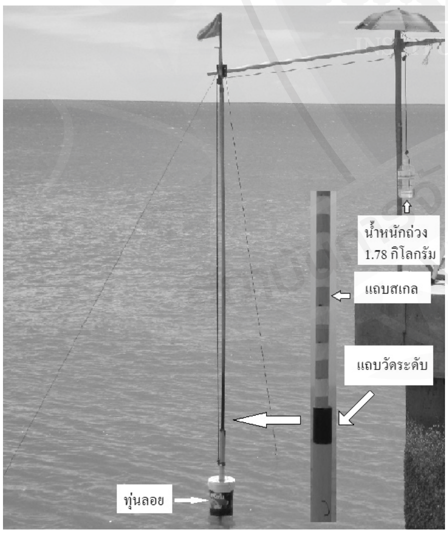

Fig. V. Label tab for measuring the height of waves

IV. Neural Networks as The Predicted Models

A complexity of mathematical model is used to predict the AC power from the height of waves and the other parameters. It is difficult to solve and find mathematical model [12]. However, the neural networks can be used to learn the knowledge of this relation as the predicted models. Thus, this research proposed to use the neural network as an approximation function. In Fig. VI, the unknown function is approximated using neural networks by adjust the parameters of the networks. So that it will produce the same response as the unknown function, if the same inputs are applied to both systems. In applications, the unknown function may correspond to a system as transform signals. Thus, the neural networks will be predicted the outputs from the inputs represent the mathematical model.

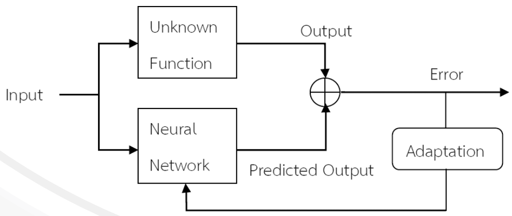

Fig. VI. Neural networks as an approximation function

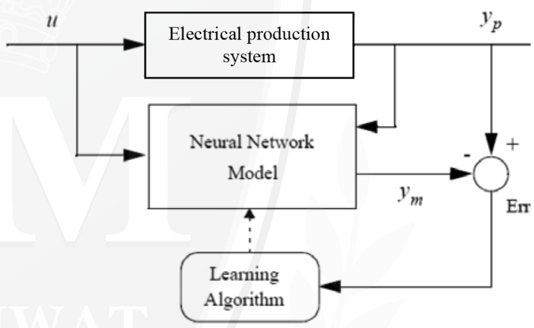

Fig. VII. Electrical production system identification

The first stage of prediction model is to train a neural network to represent the dynamic work of electric generator. Multilayer perceptron network with sigmoid transfer function is used to determine a procedure for selecting the weights and biases that will best approximation a given function. The selecting parameters or training uses back-propagation which is based on gradient descent. Fig. VII shows the electrical power generation system identification. From Fig. VII the difference errors between the electric generator outputs and the network calculated outputs are used as a neural network training signal. The error signals use to adjust the weights and biases of network for the special knowledge of this system. The weights and biases from the finish training is used as to predict the AC power output with related the wave height or displacement of buoy.

The next stage compares the calculated outputs from the predicted model with the calculated output from polynomial regression as the detail in section V.

V. The Experimental Results

In this study, the data testing is kept from the fieldwork at the Sirindhorn international environment park in the gulf of Thailand. The wave height get from the label tab video images (Fig. VIII) and covert to numerical data using the measured model as the results in Fig. IX and Table I.

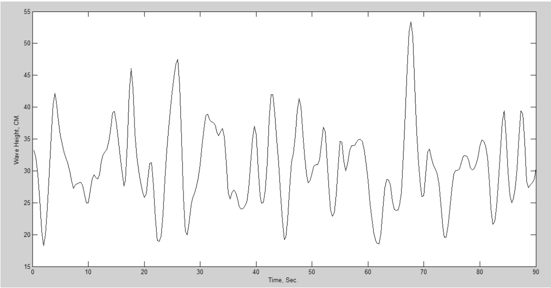

Fig. VIII. Graph of wave height

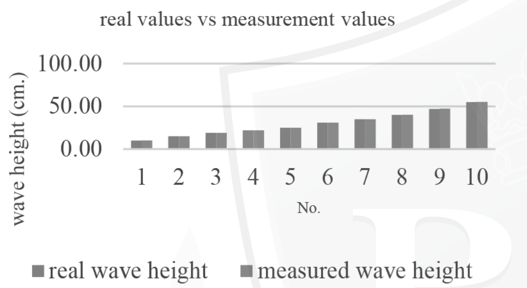

Fig. IX. Wave height from measurement model versus real wave height

TABLE I

Predicted valueswith real wave height

No.	real wave height (cm.)	wave height from the measurement model (cm.)	% |error|
1	10	10.24	2.40
2	15	15.14	0.93
3	19	18.98	0.11
4	22	22.02	0.09
5	25	25.03	0.12
6	31	30.95	0.16
7	35	35.00	0.00
8	40	40.20	0.50
9	47	47.30	0.64
10	55	55.22	0.40
	Average % |error|		0.54

The electric power outputs were recorded using watt meter and the wave elevations and displacements moving of buoy were recorded by the measurement model via the video camera. The wave elevation and electrical power output used as the order pair of inputs-outputs to adjust the weights and biases of networks. After training, the parameters of network used to build the predicted model. Fig. X and XI show the comparison results of the calculation results from the predicted models with the polynomial regression. Table II, IV shows the error calculations from predicted models with the Instantaneous electric powers.

TABLE II

Predicted values of predicted model and polynomial regression of unit 1

	Wave height (cm.)	Power measurement (W)	NN prediction (W)	% |error|	Polynomial Regression (W)	% |error|
1	20	20.78	20.78	0.00	20.70	0.39
2	30	22.17	22.17	0.00	22.26	0.42
3	40	28.20	28.68	1.69	28.80	2.12
4	50	45.90	45.99	0.20	43.88	4.40
5	60	64.01	63.84	0.27	66.30	3.57
6	70	91.45	91.67	0.24	90.02	1.56
7	80	104.20	103.47	0.70	104.25	0.05
			Average % |error|	0.44	Average % |error|	1.79

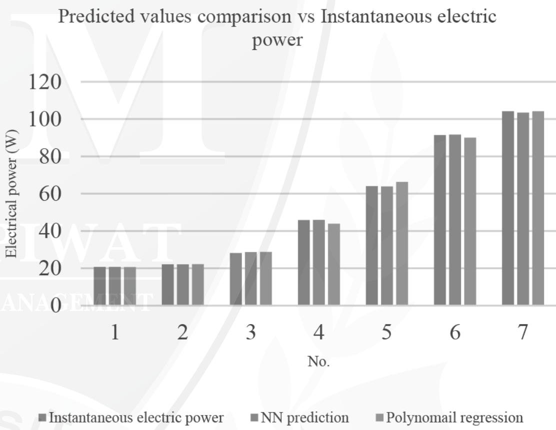

Fig. X. Predicted value comparison between the predicted model and polynomial regression

TABLE III

Instantaneous electric powers and predicted values (use wave height & displacement moving for training) of unit 1

	inputs		Instantaneous electric power (W)	Predicted electric power (W)	% |error|
	wave height (cm.)	displacement moving of buoy (cm.)			
1	20	9	20.78	20.78	0.00
2	30	14	22.17	22.17	0.00
3	40	18	28.20	28.20	0.00
4	50	23	45.90	45.90	0.00
5	60	27	64.01	64.01	0.00
6	70	32	91.45	95.81	4.77
7	80	36	104.20	104.20	0.00
Average % |error|					0.68

TABLE IV
Predicted valuesof predicted models and polynomial regression of unit 2

	Wave height (cm.)	Instantaneous electric power (W)	NN prediction (W)	% |error|	Polynomial Regression (W)	% |error|
1	10	8.50	8.50	0.00	8.50	0.00
2	20	10.04	10.06	0.21	10.10	0.60
3	30	24.63	24.63	0.00	24.96	1.34
4	40	60.00	59.77	0.39	61.06	1.77
5	50	100.50	100.50	0.00	103.10	2.59
		Average % |error|		0.12	Average % |error|	1.26

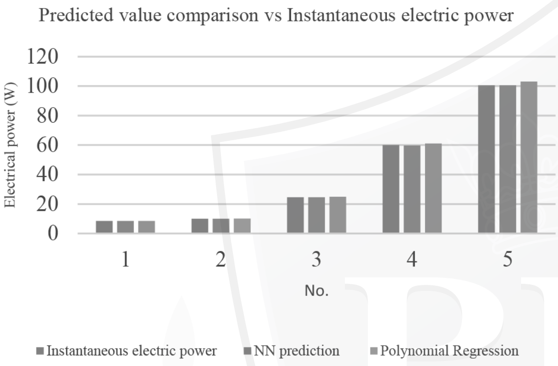

Fig. XI. Predicted values of predicted models and polynomial regression of unit 2

TABLE V
Instantaneous electric powers and predicted values (use wave height & displacement moving for training) of unit 2

	inputs		Power measurement (W)	Power calculation (W)	% |error|
	wave height (cm.)	displacement moving of buoy (cm.)			
1	10	5	8.50	8.96	5.39
2	20	9	10.04	10.04	0.00
3	30	14	24.63	24.63	0.00
4	40	18	60.00	60.00	0.00
5	50	23	100.50	100.50	0.00
Average % |error|					1.08

VI. Discussion and Conclusion

The power outputs can be derived from equation (16) in Section II. We can to compute the power outputs using the different level of wave height data in Table II. For example at the wave height 30 cm. has the power output 110.25 W, while a measurement power output equals 22.7 W. Thus, the average efficiency of sea wave system of this research is about 19.25 %. The results of this research are corresponding with the result of research in [13, 14]. The model building takes data at least a year. The researchers study the uncertainties of parameter operation and design the network structure and trained by means of 340 experimental data. A generated electrical modeling from wave energy divided into parts: measurement model and predicted model. The two model performed calculation using neural network. In training stage, Neural networks try to adjust the parameters until satisfy with the knowledge and able to compute the output of models. Table I, it can be seen that the error of neural network model is 0.54%. Thus, this model can be used to measure the wave height. In the case, electrical power generation have the complex parameters. However, possible to train the neural networks as the predicted model from the inputs-outputs of systems. Table II and IV show the results of the predicted models using neural networks and polynomial regression compare with instantaneous electric powers of unit 1 and 2, respectively. The NN predicted models have the average error 0.44 % and 0.12 % which less than the best polynomial regression ($y = -0.2x^4 + 2.597x^3 - 8.098x^2 + 10.68x + 15.72$ in Table II and $y = -0.94x^4 + 11.03x^3 - 35.30x^2 + 44.84x - 11.1$ in Table IV). Table III and V show the average error from NN predicted models are 0.68 % and 1.08 %. The NN predicted models in Table III and V is trained using the two inputs (wave height and displacement of buoy) for computing the output of models. The results of these tables show the ability of neural networks as predicted models. From the testing results, the neural networks can to learn the knowledge of systems and use the networks as the approximation of models.

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