The Comparison of the Ability of the Neural Hammerstein-Wiener Model to Simulate the Remediation Process of Mining Acid Waste Water using Biochar-Cao Composite

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Abstract. Acid mine drainage waste is waste from which the impact is detrimental to the environment and human health. To overcome the pollution of acid mine drainage waste, one of the studies is using biochar-CaO composites to reduce the level of metal content in the waste. Time constraints, expensive materials, and nonlinear data are the problems in this case. This Final Project research uses the Hammerstein-Wiener Neural model to predict the absorption of metal content in acid mine drainage waste. The model will be trained with various scenarios, namely variations in the distribution of training data, test data, validation data, and variations in the number of hidden nodes. The results showed that the Hammerstein-Wiener Neural model is the best model to predict the absorption of metal content in acid mine drainage using Biochar-CaO composite with MSE, MAE, and MAPE evaluation values of 0.7815, 0.0790, and 0.0130, respectively. These values are obtained from the data division of 35% training data, 30% validation data, and 35% testing data with 160 hidden nodes. The model outperforms other models to solve the problem.

Keywords: *Remediation, Absorption, Hammerstein-Wiener Neural.*

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1 Introduction

Manufacturing, Production, Electricity Distribution, Construction, Mining, and Quarrying are the industry categories that contribute the most to water pollution worldwide. The mining and quarrying industry has been studied more extensively to determine the extent of its impact on human health and water quality [1]. Water quality degradation in these industries can produce acid mine drainage, which has a pH of 1-5 and contains heavy metals in acid mine drainage that can threaten human health and damage the environment [1].

Acid mine drainage (AMD) is a hazardous problem once it has contaminated water and air. Acid mine drainage comes from mining-related activities such as underground and open pit mining, rock dumping, rock cutting, and stockpiling. Although many efforts have been made for its formation by constructing drainage and dewatering systems, only a few have been successful. Some mining companies have also found ways to remove metal levels in acid mine drainage, namely by Bioremediation. Still, the obstacle is the high cost and the possibility of failure which results in bacteria proliferating and the limited safety of bioremediation to treat acid mine drainage. Treatment of acid mine drainage waste has been carried out in various ways including adsorption. Adsorption is a method that can be used to absorb a pollutant from water using activated carbon or biochar [1]. Other materials are zeolite, shrimp shell waste, and dairy cow manure compost. However, this research uses CaO compounds as adsorbents because they can increase the pH of acid mine drainage and are easily obtained in coastal areas of Indonesia. Several studies have also been conducted to simulate AMD treatment using adsorbent. However, this process has a highly nonlinear behavior, hence it is difficult to get good results. One of the nonlinear models that has a good performance to simulate highly nonlinear processes is block block-oriented model, this model also has low computational time hence successfully applied to Model Predictive Control (MPC). There are many types of oriented models such as Wiener, Hammerstein, and Hammerstein-Winer models [2-7].

The Hammerstein-Wiener Neural Model is expected to be able to build a system or composition that is used so that the metal content in acid mine water can be purified or neutralized so that it is good for human health and the surrounding environment. In this research, the Wiener – Hammerstein model was built using neural network and state space models as non-linear blocks and linear blocks, respectively. The neural network has a good ability to simulate nonlinear processes [8, 9, and 10]. State space also has good performance in simulating nonlinear processes [11]. The performance of the Hammerstein–Wiener model is also compared with the Neural Wiener model and Neural Hammerstein model. These models have been developed using experimental laboratory data, and simulation study conducted using Matlab software.

2 Materials and Methods

2.1 *Materials*

Biochar and CaO

The materials used in this research have been carried out at the National Research and Innovation Agency (BRIN) Tanjung Bintang (Tanjung Bintang, Lampung Selatan) using Biochar and Calcium oxide (CaO). In this work, the concentration of Biochar and CaO were fixed.

Datasets

The data is quoted from the results of previous research conducted by [1] The research was conducted to develop affordable and sustainable composite materials from solid waste to efficiently treat acid mine drainage (AMD). Which produced biochar-CaO composites from solid waste. The composite showed a high adsorption capacity for AMD species, including Fe, Mn, and Mg metals, with an equilibrium point at 300 minutes of contact time. In the adsorption experiments, it was shown that the biochar-CaO composite was highly effective for the removal of Fe, Mn, and Mg metal contents from acid mine drainage with the corresponding adsorption isotherm model being the Langmuir isotherm model. The following experimental data are used as input and output data as listed in Table 2.

Table 1. Input Data

Input								Output		
Fe	Mn	Mg	CaO	Biochar	Volume(mL)	Δt(minute)	pH	Fe	Mn	Mg
9.24	6.78	7.05	0.3	1	100	0	2	9.24	6.78	7.05
9.24	6.78	7.05	0.3	1	100	10	2	8.7	5.3	6.8
9.24	6.78	7.05	0.3	1	100	30	2	8.3	4.5	6.5
9.24	6.78	7.05	0.3	1	100	50	2	7.5	4	6.2
9.24	6.78	7.05	0.3	1	100	70	2	6.8	3.6	5.8
9.24	6.78	7.05	0.3	1	100	100	2	6.5	3	5.6
9.24	6.78	7.05	0.3	1	100	200	2	5	2.8	5
9.24	6.78	7.05	0.3	1	100	300	2	4.8	2.7	4.6
9.24	6.78	7.05	0.3	1	100	500	2	4.8	2.7	4.5
9.24	6.78	7.05	0.3	1	100	0	7	9.24	6.78	7.05
9.24	6.78	7.05	0.3	1	100	10	7	1.63	2.3	6.5
9.24	6.78	7.05	0.3	1	100	30	7	1.6	2	6
9.24	6.78	7.05	0.3	1	100	50	7	1.6	1.9	5.8
9.24	6.78	7.05	0.3	1	100	70	7	1.6	1.8	5.8
9.24	6.78	7.05	0.3	1	100	100	7	1.5	1.7	5.6
9.24	6.78	7.05	0.3	1	100	200	7	1.5	1.7	5

9.24	6.78	7.05	0.3	1	100	300	7	1.5	1.7	4.6
9.24	6.78	7.05	0.3	1	100	500	7	1.5	1.7	4.5
9.24	6.78	7.05	0.3	1	100	0	9	9.24	6.78	7.05
9.24	6.78	7.05	0.3	1	100	10	9	1.72	2.4	6.7
9.24	6.78	7.05	0.3	1	100	30	9	1.6	2.1	6
9.24	6.78	7.05	0.3	1	100	50	9	1.5	1.8	5.7
9.24	6.78	7.05	0.3	1	100	70	9	1.5	1.7	5.5
9.24	6.78	7.05	0.3	1	100	100	9	1.5	1.6	5.4
9.24	6.78	7.05	0.3	1	100	200	9	1.4	1.6	5.1
9.24	6.78	7.05	0.3	1	100	300	9	1.4	1.6	4.7
9.24	6.78	7.05	0.3	1	100	500	9	1.4	1.6	4.7

2.2 *Methods*

Feedforward Neural Network

Neural networks are information processing systems that mimic the way the human brain works in solving a problem by learning through weight changes and testing. Artificial neural networks can recognize activities based on past data. The past data will be learned by artificial neural networks that can provide decisions on data that has not been learned [8]. One of the neural networks is the feedforward neural network.

Feed Forward Neural Network model is a model for linear and nonlinear problems that consists of input data, a hidden layer (there are several neurons), and an output layer [9][10]. In the neurons, there is an activation function to process the input data. The following is the architecture of the feedforward neural network.

State Space

State space is a mathematical framework used to describe and analyze dynamic systems. In a state space representation, the state of the system at a given time is represented by a vector consisting of state variables. state equation and output equation. The state equation describes how the state of the system changes over time based on the current state and system inputs [3]. Typically, these equations are written in matrix form as equations 1 and 2.

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{A}(t)\boldsymbol{x}(t) + \boldsymbol{B}(t)\boldsymbol{u}(t) \tag{1}$$

$$\boldsymbol{y}(t) = \boldsymbol{C}(t)\boldsymbol{x}(t) + \boldsymbol{D}(t)\boldsymbol{u}(t) \tag{2}$$

Where

$A(t)$: state matrix,
$B(t)$: input matrix,
$C(t)$: output matrix, and

$D(t)$: direct transmission matrix.

Neural Hammerstein-Wiener

Hammerstein-Wiener Neural Model is a type of non-linear dynamic system modeling model that combines elements of the Hammerstein and Wiener models with a neural network [2][3][4][5]. This model is used to capture and represent the dynamic behavior of complex non-linear systems.

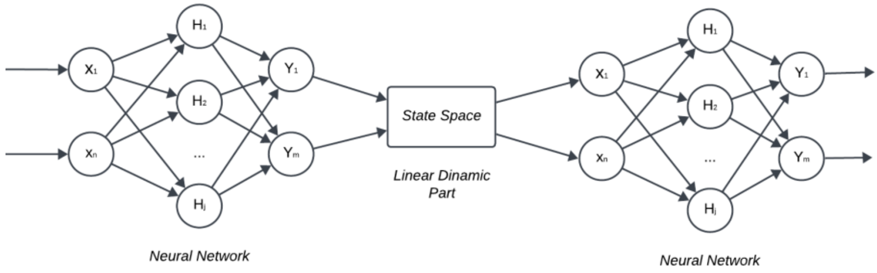

Fig. 1. Structure of Hammerstein-Wiener Neural Model

The Neural Network model was chosen for the Nonlinear block in the Hammerstein-Wiener Neural model. In this section, a multiple input - multiple output (MIMO) Neural Network model is used to model the process. This model has an input which is (u). The output of the state space model is used as the input (v) of the Nonlinear Neural Hammerstein (NH) block. The output $y(k)$ of the neural network is described in Eq 3.

$$v_{(k)} = w_0 + \sum_{i=1}^{k} w_i^2 \varphi(w_{i,0}^1 + w_{i,1}^1 u_{(k)}) \tag{3}$$

where w_0 is the bias, w_{ij} is the layer weight, w_i is the second layer weight φ is the Nonlinear activation function which is a hyperbolic tangent sigmoid function (tansig), and k is the number of hidden nodes. The second block of Neural Hammerstein uses a state space model. Using the input-output data from data generation, the state space model was developed using the Matlab command (n4sid). This model has two inputs, namely (v). The output of the state space model will be the output $(y)$of the Nonlinear Neural-Hammerstein block. Therefore, the output of the Neural-Hammerstein model can be described in Eq 4.

$$z_{(k)} = \boldsymbol{C}\, x_{(k)} + \boldsymbol{D}\, (w_0 + \sum_{i=1}^{k} w_i^2 \varphi)\{w_{i,0}^1 + w_{i,1}^1 u_{(k)}\} \tag{4}$$

The results of the overall NH model were plotted and compared with the data from the data generator. The second block of Neural Hammerstein-Wiener uses a state space model. Using the input-output data from data generation, the state space model was developed using the Matlab command (n4sid). This model has two inputs, namely v_1 as input from the Neural Network and z_2 as input from the state space. The output of the state space model will be the output (y) of the Nonlinear Hammerstein-Wiener block. Therefore, the output of the Hammerstein-Wiener model can be described through Eq 5.

$$y_{(k)} = w_0 + \sum_{i=1}^{k} w_i^2 \varphi\left(w_{i,0}^1 + w_{i,1}^1 \left[\boldsymbol{C}\, x_{(k)} + \boldsymbol{D} \left(w_0 + \sum_{i=1}^{k} w_i^2 \right) \left\{ w_{i,0}^1 + w_{i,1}^1 u_{(k)} \right\} \right] \right) \tag{5}$$

The results of the NHW model as a whole can be plotted and compared with the data from the data generator.

Errors

Measurement of the level of forecasting accuracy can be calculated using the Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) formulas [11].

3 RESULT AND DISCUSSIONS

3.1 Neural Hammerstein-Wiener

The creation of the Hammerstein-Wiener (NHW) Neural Model that has been developed starts from the Feedforward Neural Network (FFNN) model as a nonlinear block and State Space as a linear block and ends up in the FFNN model. The result of the State Space block which has become the output of the nonlinear block will be input back to the FFNN model.

Model testing begins by training input and output data on the FFNN model which is a nonlinear block to produce temporary variables. The following is the state space equation for the Hammerstein-Wiener Neural model in equations 9 and 10.

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{K}\, e(t) \tag{6}$$
$$\boldsymbol{y}(t) = \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{D}\boldsymbol{u}(t) + e(t) \tag{7}$$

After testing, the model that has been tested is used as a model design in a nonlinear block to simulate the concentration value of Fe, Mn and Mg. The following is the simulation results of the Hammerstein-Wiener Neural model in Table 5.

Table 2. Hammerstein-Wiener Neural Model Evaluation Results

Splitting Data	Hidden Node	MSE	MAE	MAPE	Computation Time (s)
35% Training Data, 30% Validation Data, and 35% Testing Data	20	0.5423	0.3051	0.0941	15.3879
	40	2.0060	0.8512	0.3482	5.1676
	60	1.3223	0.3703	0.1546	**3.4278**
	80	2.8243	0.2060	0.0486	48.1405
	100	2.4716	0.4565	0.1858	11.8167
	120	3.3007	0.7260	0.2559	8.5536

	140	**0.4921**	0.1029	0.0326	38.4704
	160	0.7815	**0.0790**	**0.0130**	**306.5827**
	180	5.5609	0.4113	0.1088	10.0827
	200	2.1494	0.1719	0.0389	8.5620
40% Training Data, 30% Validation Data, and 30% Testing Data	20	5.1840	1.0908	0.3843	28.3428
	40	1.7809	0.7407	0.2685	4.8637
	60	1.5415	0.7255	0.2549	7.0522
	80	0.6907	0.1864	0.0452	31.6331
	100	1.1063	0.1168	0.0227	14.7451
	120	2.1709	0.5717	0.2034	5.7027
	140	1.2385	0.2374	0.0738	33.0572
	160	2.2557	0.4643	0.1775	6.6121
	180	1.6903	0.1717	0.0371	5.6310
	200	6.4284	0.9806	0.3697	7.4358
50% Training Data, 25% Validation Data, and 25% Testing Data	20	2.3506	0.3891	0.1105	71.3515
	40	5.3501	1.7088	0.7865	18.2844
	60	1.3032	0.5202	0.1498	34.0293
	80	1.8996	0.8292	0.2956	106.9480
	100	3.5254	0.1519	0.0280	43.1434
	120	2.2417	0.6337	0.2623	36.2051
	140	2.1478	0.4030	0.1316	92.4804
	160	1.0608	0.1134	0.0314	28.1329
	180	3.4899	0.3819	0.1052	10.0707
	200	1.2484	0.1091	0.0220	67.9502

Table 5 shows the best output results from the Hammerstein-Wiener Neural model with data division of 35% training data, 30% Validation data, and 35% Testing data and hidden nodes of 160. The best evaluation value is obtained with MAE and MAPE values of 0.0790 and 0.0130 which are below 10%. while the MSE value is obtained when the hidden node is 140 with an MSE value of 0.4921. then for the fastest and longest computation time obtained in 3.4278 seconds and 306.5827 seconds when the hidden node is 60 and 160.

The results of the graph plot with the Hammerstein-Wiener Neural model have many graph plots that resemble the original data. However, only one model configuration has the best results, namely with a data division of 35% Training Data, 30% Validation Data, and 35% Testing Data which uses a Hidden Node of 160. The following are the best results of Fe, Mn, and Mg concentration graph plots with real data.

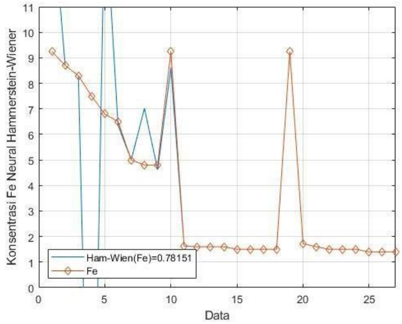

Fig. 2. Plot of Fe Comparison Graph of simulation results with original data Hammerstein-Wiener Neural Model

Figure 2 shows the comparison of simulation results with the original data on Fe concentration. at first, the Hammerstein-Wiener Neural model could not adjust the results to the original data. but at the 11th data, the simulation results using the Hammerstein-Wiener Neural model can adjust to the original data.

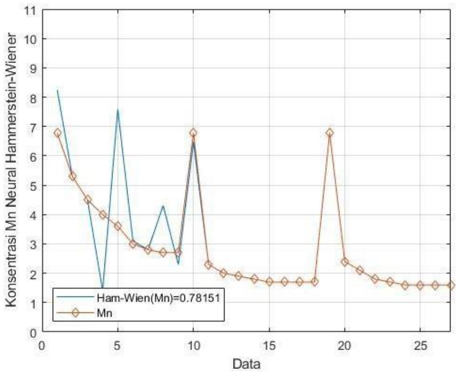

Fig. 3. Plot of Mn Comparison Graph of simulation results with original data Hammerstein-Wiener Neural Model

Figure 3 shows the comparison of simulation results with the original data on Mn concentration. In the first data, the output results of the Hammerstein-Wiener Neural model almost resemble the original data. but in the next data, there is still a considerable difference between the results of the Hammerstein-Wiener Neural model and the original data. until the 11th data, the results of the Hammerstein-Wiener Neural model can match the original data.

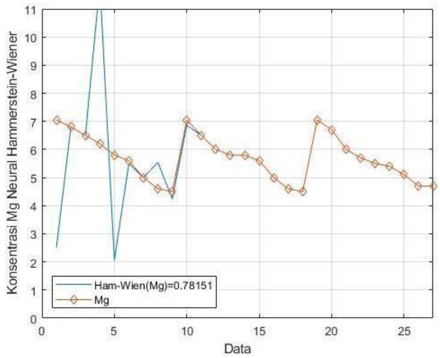

Fig. 4. Plot of Mg Comparison Graph of simulation results with original data Hammerstein-Wiener Neural Model

Figure 4 shows the comparison of simulation results with the original data on Mg concentration. In the first data, the output results of the Hammerstein-Wiener Neural model cannot match the original data until the 10th data. Then on the 11th, the output of the Hammerstein-Wiener Neural model can finally match the original data.

4 CONCLUSIONS

Simulation results of the Hammerstein-Wiener Neural Model with a configuration of 35% Training Data, 30% Validation Data, 35% Testing Data, and a Hidden Node of 160 produce MSE, MAE, MAPE evaluation values of 0.7815, 0.0790, 0.0130, and computation time for 306.5827 seconds. Because the MAE and MAPE evaluation values are below 10%, the configuration is the best configuration for the Hammerstein-Wiener Neural model. and can overcome the problem of predicting the absorption of metal content in the Remediation process in Acid Mine Drainage using Biochar-CaO composites.

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