Vol. 2(2), pp. 1-13, 2023
eISSN: 2976-4009

ASEAN Journal of Process Control

Research Article

Comparison of Neural Capabilities of Hammerstein, Neural-Wiener, Hammerstein-Wiener Model in Modeling Limiting Current of The Lanthanum - Electro Deposition

Sudibyo[1*], Anton Sapto Handoko[1], Freza Devica Gunada[2],La Zakaria[3*], Favorisen R. Lumbanraja[3], Fakhrony Sholahudin Rohman[4], Dinie Muhammad[5*]

[1] Research Center for Mineral Technology - National Research and Innovation Agency, 35361, Tanjung Bintang, Lampung Province, INDONESIA

[2] Mathematics Study Program, Faculty of Mathematics and Natural Sciences, University of Lampung, 35141 INDONESIA

[3] Computer Science Department, Faculty of Mathematics and Natural Sciences, University of Lampung 35141 , INDONESIA

[4] Process Systems Engineering Centre (UTM-PROSPECT), Research Institute of Sustainable Environment (RISE), Universiti Teknologi Malaysia, 81310, Johor Bahru, MALAYSIA.

[5] Faculty of Chemical and Energy Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM), Johor Bahru, Johor 81310, MALAYSIA

*Corresponding Author: dinie.muhammad@utm.my, sudibyo@brin.go.id, lazakaria.1969@fmipa.unila.ac.id

Academic Editor:
Received: xxx; Accepted: xxx; Published: xx

Abstract:

Lanthanum can be obtained by electrowinning or electrodeposition process. To increase this process, the magnetic field is introduced in the electrodeposition process. The magneto electrodeposition (MED) process will increase the mass transfer and a limiting value (ib). The optimum mass transport on magneto electrodeposition occurs at this limiting current. Hence, knowing this limiting current is very important. The parameters that have a significant effect on limiting current, namely: electrode area (A), electron-active concentration (C), kinematic electrolyte viscosity (V), diffusion coefficient (D), magnetic field strength (B), and the number of electrons involved in the MED process (n). However, limiting current is a highly nonlinear process. One model which able to simulate a highly nonlinear process is block-oriented. In this work, three block-oriented models namely the Neural Hammerstein Model modeling, Neural Wiener Model, and Neural Hammerstein Wiener Model were developed to simulate limiting current on lanthanum MED. The results and analysis of this study show that the Neural Hammerstein-Wiener Model uses the neural network with 1 hidden layer, 50 hidden nodes, and the data sharing of 50% train, 30% test, and 20% validation. this model has the smallest error value (0.0019 Mean Square Error (MSE) and 1.4122% of Mean Absolute Percentage Error (MAPE) and 0,014122 Mean Absolute Error (MAE).

Keywords: Lanthanum, Neural Network, Neural Hammerstein, Neural Wiener, Hammerstein Wiener, Mechine Learning.

1. Introduction

Lanthanum belongs to the group of rare earths that are soft, bluish-white metals. It was discovered in 1893 and is one of the group III B transition metal elements found in the lanthanide element series [1]. Lanthanum can be obtained by electrowinning process. Electrodeposition is the process of settling a substance using a direct electric current. Electrodeposition has the main problem of roughness in the resulting layer (non-uniform crystal growth) [2].

This problem can be solved by applying Magneto electrodeposition (MED). The MED process will produce a limiting value iB, which requires compounds and tools such as electrode area (A), active-electron concentration (C), electrolyte viscosity kinematics (V), diffusion coefficient (D), magnetic field strength (B), and the number of electrons involved in the MED process (n). Magneto electrodeposition (MED) research tends to require expensive compounds [3].

The test laboratory can be divided into a wet laboratory and a dry laboratory. The process of analyzing mathematical calculations is carried out in a dry laboratory. To solve the problem of high costs, this can be done in a dry laboratory. One of them is the block-oriented model approach. A lot of chemical research goes through this approach because of its reliability and the fact that it offers complex information through conventional programming processes [4]. Therefore, through this study, a comparison of the ability of the block-oriented model. Three block-oriented models have good performance namely the Neural Wiener Model, Neural Hammerstein, and the Neural Hammerstein Wiener Model to guess the value of the best-limiting current (iB) by comparing its Mean Square Error (MSE) Mean Absolute Percentage Error (MAP), and Mean Absolute Error (MAE) with limiting current data from laboratory data. The Neural Hammerstein, Neural Wiener, and Neural Hammerstein-Wiener systems are the most popular structures in block-oriented nonlinear systems [5-10]. In this work, all simulations were conducted using Matlab software.

2. Materials and Methods

The methodology adopted to develop Neural Hammerstein, Neural Wiener, and Hammerstein Wiener models to simulate the limiting current of Lanthanum MED is described in this chapter. This is followed by the variation of neural network data sharing from 50% to 40% of train data. The last part is the comparison study of those models. The overall flowchart of the research methodology is shown in Figure 1.

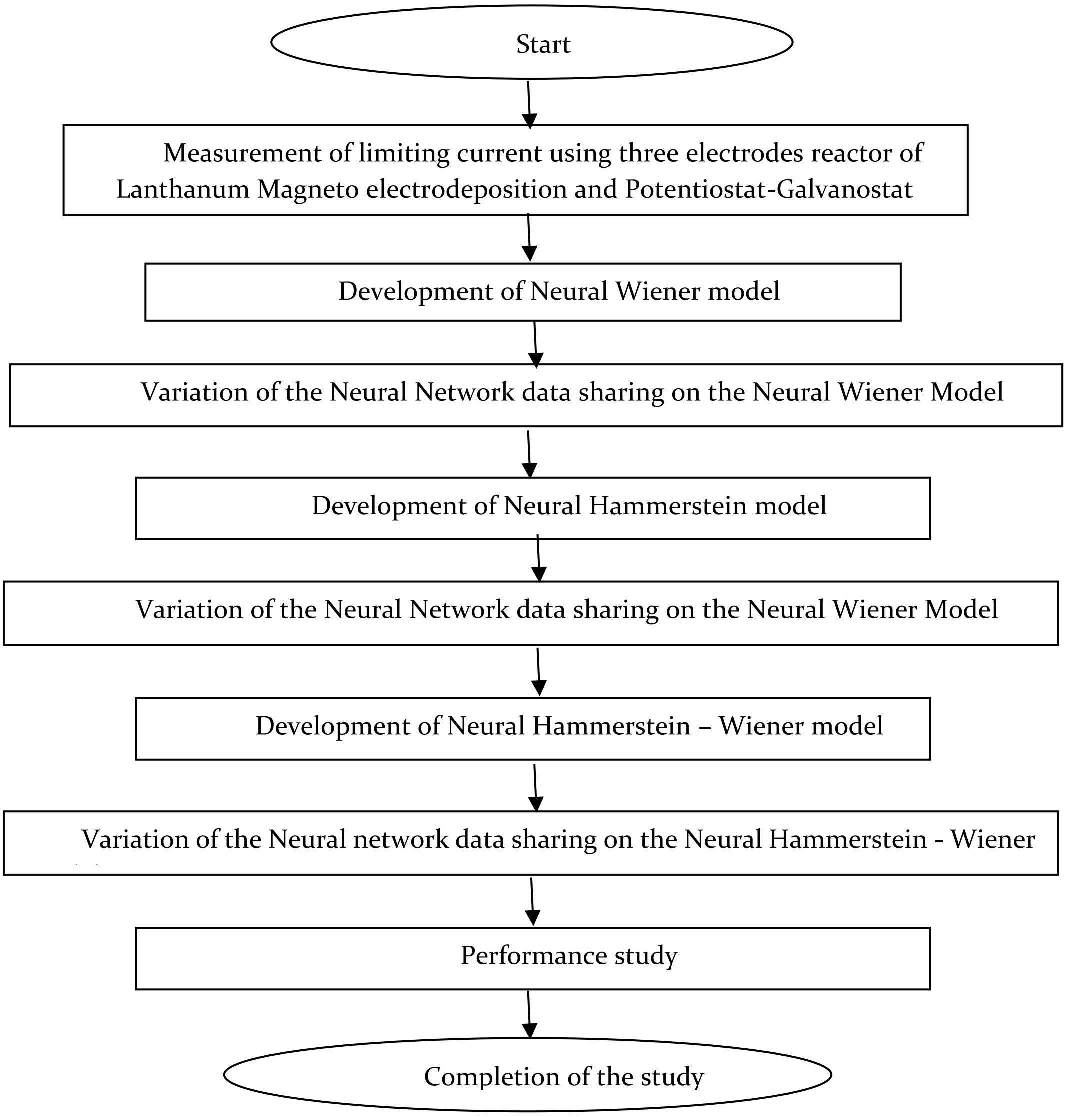

Figure 1. Overall research methodology

2.1 Process Magneto Electrodeposition (MED) in Lanthanum

This method was previously applied to lanthanum to obtain the current-limiting equation in a semi-empirical manner. The material used is Lanthanum (III) Chloride Heptahydrate 98% containing H_2SO_4 solution. In lanthanum processing, the substantial variation of the magnetic field is an influential parameter in determining limiting currents. The results obtained are in the form of optimal semi-empirical equations in the magneto electrodeposition process of lanthanum. The limiting current value was obtained using three-electrode electrochemical cells under the magnetic field effect. This three-electrode electrochemical cell was operated using Pontenstiotsat-Galvanostat, as shown in Figure 2.

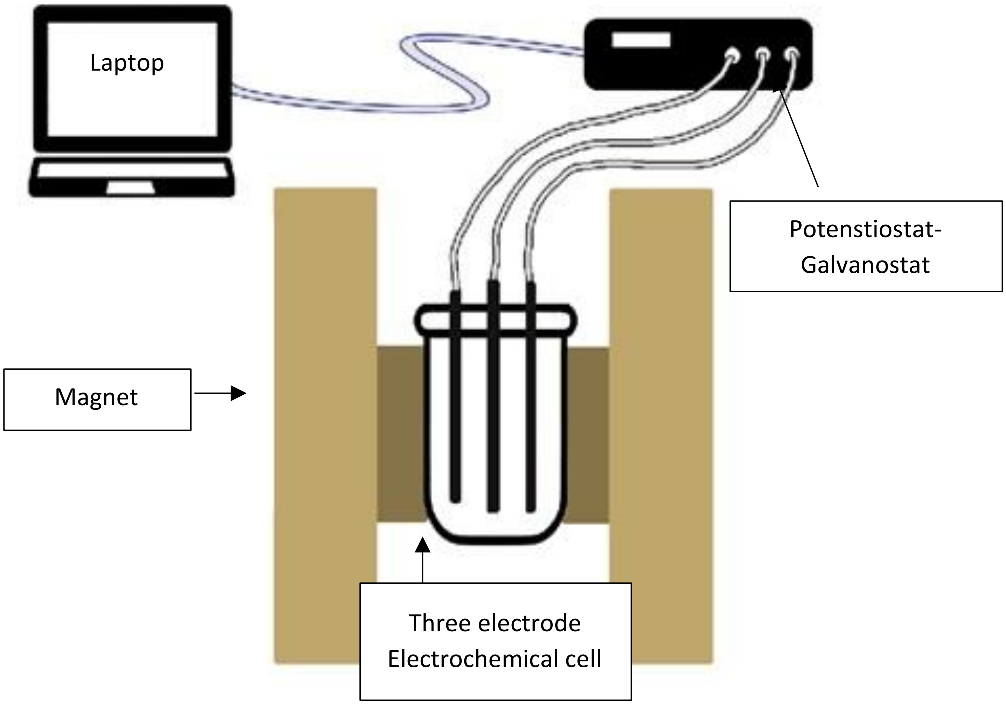

Figure 2. Schematic diagram of Magneto-Electrodeposition of Lanthanum [11]

2.2 Data Neural Network

The processed data are obtained from the results of existing semi-empirical research where the influence of Lanthanum (III) Heptahydrate Chloride concentration is 98%, auxiliary electrolyte (H_2SO_4 concentration), electrode area (A), electro-active diffusion coefficient (D), electrolyte kinematic viscosity (v), magnetic field strength (B) and number of electrons in the redox process (n) are inputs to produce output i.e., limiting limiting current (ib) for MED simulation solutions on lanthanum. The data increased the limiting current (ib) value at a variation in the influence of Lanthanum (III) Heptahydrate Chloride by 98%, the magnetic field's strength, and the working electrode's surface area. The data also resulted in a decrease in the limiting current value at the variation in the concentration of H_2SO_4. There were 19 samples, and they were multiplied 10 times to improve data accuracy. Then, the input data is formed into a matrix measuring 7 x 190, while the output becomes 1 x 190. Input data has been trained using the Levenberg-Marquardt algorithm with 1 hidden layer and 50 hidden nodes with the proportion of training data, validation data, and testing data used, namely 50% training, 20% validation, 30% testing, 40% training, 30% validation, 30% testing, as well as 45% training, 20% validation, 35% testing.

2.3 Neural Wienner's Model Development

The creation of Neural Winner is done by training the input and output data on the *state space* block first to produce temporary variables, the result of the *State Space* output is continued into the *Neural Network* so that the *neural* block becomes a single *input*-single *output* (SISO). The *output* of the *Neural Network* is taken on the 10th replay to improve its accuracy. The Neural Weiner output resul*t* is graphed in comparison and calculated with MSE against *the* i_B semi-empirical result. The arrangement of the N-W model is shown in Figure 3.

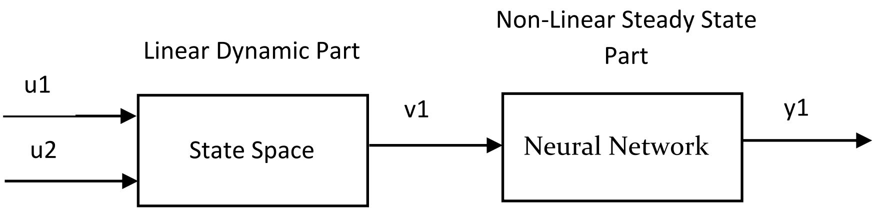

Figure 3: *Neural Wiener* Model Arrangement

As stated earlier, the first block of the Neural Wiener (NW) used the state space model. Using the input – output data from the experiment data, the state space model was developed using the Matlab command (n4sid). Hence the state space equation can be expressed as follows:

$$x_{(k+1)} = A\,x_{(k)} + B\,u_{(k)} \tag{1}$$

$$v_{(k)} = C\,x_{(k)} + D\,u_{(k)} \tag{2}$$

where x is the state vector, u is the input vector, and v is the output vector. The matrix coefficients, A, is an n-by-n matrix, n is the number of states, B is an n-by-m matrix (n is the number of rows and m is the number of the column), and m is the number of inputs. C is an r-by-n matrix, where r is the number of outputs and D is an r-by-m matrix. In the NW, the accuracy of the model obtained from the state model was improved by the nonlinear block of the NW model.

The nonlinear block of the NW model used in this work was the feed-forward neural network model. The feed-forward neural network was developed using the Matlab command. The output y(k) of the neural network can be written in Equation3:

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

where w_o is a bias, $w_{i,j}$ is the weight of the first layer, and w_i is the weight of the second layer, ϕ is a nonlinear transfer function i.e: hyperbolic tangent sigmoid transfer function (tansig), and K is the number of hidden nodes. The output of the NW model can be defined by substituting Equation (2) into Equation (3), as shown below:

$$y(k) = w_0 + \sum_{i=1}^{K} w_i^2 \varphi\left\{w_{i,0}^1 + w_{i,1}^1 [C\,x(k) + D\,u(k) + e(k)]\right\} \tag{4}$$

2.4 Development of the Hammerstein Neural Model

Neural Hammerstein is created by first training the input and output data on the Neural Network block to produce temporary variables. The results of the Neural Network outputs are transmitted into State Space as input. The output of State Space is taken on the 10th replay to improve its accuracy. Hammerstein's Neural output results are compared and calculated with MSE against i_B semi-empirical results. The arrangement of the N-H model is shown in Figure 4.

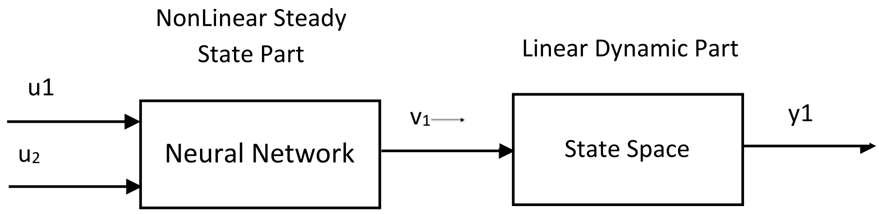

Figure 4: *Hammerstein Neural* Model Arrangement

The output $y_{(k)}$ of the neural network is described in Equation (5).

$$v_{(k)} = w_0 + \sum_{i=1}^{K} w_i^2 \varphi\left(w_{i,0}^1 + w_{i,1}^1 u_{(k)}\right) \tag{5}$$

where w_o is the bias, $w_{i,j}$ is the weight of the first layer, and w_i is the weight of the second layer, ϕ is a nonlinear transfer function i.e: hyperbolic tangent sigmoid transfer function (tansig), and K is the number of hidden nodes. The output of the NH model can be defined by substituting Equation (5) into Equation (2) as shown below:

$$y_{(k)} = C\,x_{(k)} + D\,(w_0 + \sum_{i=1}^{K} w_i^2 \;\left\{w_{i,0}^1 + w_{i,1}^1 u_{(k)}\right\} \tag{6}$$

2.5 Hammersstein-Wienner Model Development

The creation of Neural Hammerstein-Wiener is done by training the input and output data on the first Neural Network block first to produce temporary variables, the results of the Neural Network outputs are passed into State Space as input. The result of Hammerstein's Neural output is then transferred into the second neural network. The output of the second Neural Network is taken on the 10th replay to improve its accuracy. The result of the Hammerstein-Wiener Neural output is graphed in comparison and calculated with MSE against i_B semi-empirical results. The arrangement of the N-W models is shown in Figure 5.

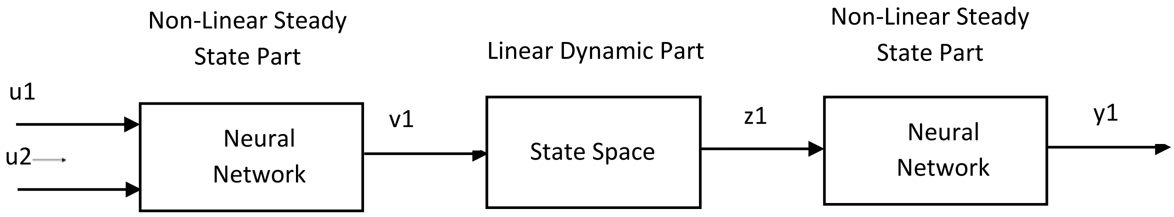

Figure 5: *Hammerstein-Winner Neural* Model Arrangement

Output $v(k)$ of the first neural network block is shown in equation (7):

$$v_{(k)} = w_0 + \sum_{i=1}^{k} w_i^2 \varphi\left(w_{i,0}^1 + w_{i,1}^1 u_{(k)}\right) \tag{7}$$

The second block of Hammerstein Wiener is the state space block, v (k) became the input of this state space block and the output is z(k). The output of state space block (z) is described in equation (8).

$$z_{(k)} = \boldsymbol{C}\, x_{(k)} + \boldsymbol{D}\ (w_0 + \sum_{i=1}^{k} w_i^2)\{w_{i,0}^1 + w_{i,1}^1 u_{(k)}\} \tag{8}$$

The output of state space block (z) became the input of the second neural network block and the output of the second neural network is the output of the overall Hammerstein Wiener model (y) as described in equation (9).

$$y_{(k)} = w_0 + \sum_{i=1}^{k} w_i^2 \varphi\left(w_{i,0}^1 + w_{i,1}^1[\boldsymbol{C}\, x_{(k)} + \boldsymbol{D}\ (w_0 + \sum_{i=1}^{k} w_i^2)\{w_{i,0}^1 + w_{i,1}^1 u_{(k)}\}]\right) \tag{101}$$

3. Results and Discussion

Performance tests from the Hammerstein Neural Model, Neural Wiener Model, and Hammerstein-Wiener Neural using MED Lanthanum semi-empirical data, six inputs, and one output. The Neural Network algorithm used is Levenberg-Marquardt with 1 hidden layer and 30 hidden nodes. The results of modeling the process of determining the limiting current (ib) on the magneto electrodeposition of lanthanum are obtained as follows.

3.1 Neural Wiener

The neural wiener model used the state space model as a non-linear block. In this work, the following state space model was used with the value as follows:

$$\begin{aligned} A = [&0.9046\ 0.07485\ -0.1603\ -0.02745\ -0.004148\ -.002207\quad 0.3733 \\ &-0.4721\ -0.08012\ -0.01074 \\ &-0.002789\ 0.001481\quad 0.06724\ 0.8378\ -0.338\ 0.003124 \\ &-0.0005042\ -0.0009871\quad -.01948\ -.02636 \\ &-0.8935\ 0.2589\ 0.0753\ 0.0005673\quad -.09534\ -0.06156 \\ &-0.209\ -0.9115\ 0.1666\ -0.2535\quad 0.03671\ -0.0169 \\ &-0.02036\ -0.1043\ 0.05481\ 0.8828\quad] \end{aligned} \tag{11}$$

$$B = [-7.383e + 07\ 6.191e + 06\ -4.657e + 06\ 1.476e + 08\ -4.733e + 09\ 1.621e + 10\quad] \tag{12}$$

$$C = [-0.0075\ 2.3e - 05\ 0.00078\ 0.00022\ 6.4e - 05\ -1.7e - 05\quad] \tag{13}$$

$$D = [0] \tag{14}$$

$$K = [0\ 0\ 0\ 0\ 0\ 0\ \ ] \tag{15}$$

Meanwhile, the nonlinear block model used a feed-forward neural network (FFNN) in which the train data varied from 40% to 50%. Meanwhile, the test data varied from 30 to 40%, as listed in Table 1. Neural Wiener Data Training Model Simulation 40%, 45& and 50% were shown in Figures 6, 7, and 8, respectively. Table 1 shows that the neural wiener using a neural network with 50% train data and 30% test data gives the smallest MSE, MAP, and MAE error.

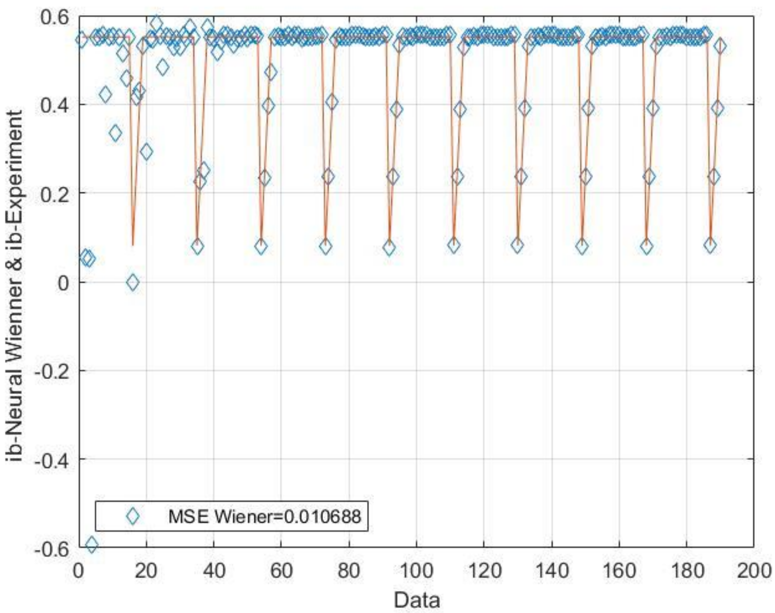

Figure 6. *Neural Wiener* Data Training Model Simulation *40%*

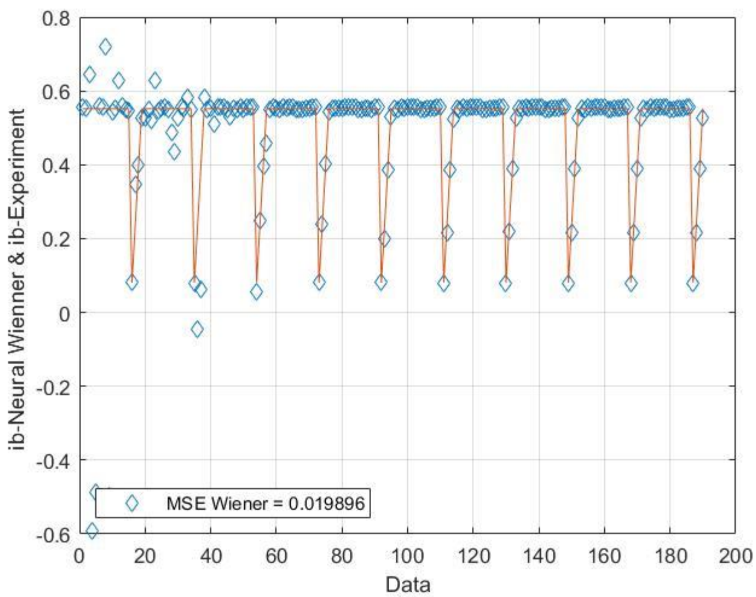

Figure 7. *Neural Wiener* Data Training Model Simulation *45%*

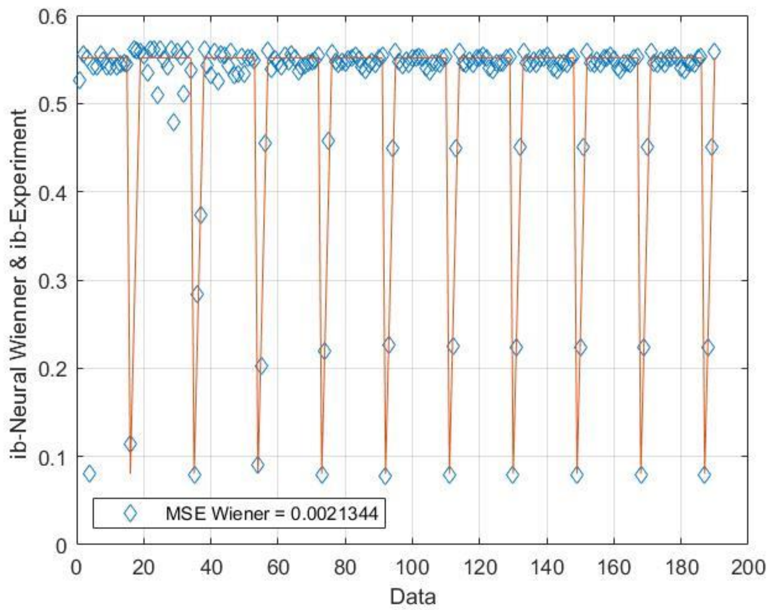

Figure 8. *Neural Wiener* Data *Training* Model Simulation 50%

Table 1. Comparison of *Neural Wiener* Model Accuracy Values using various data sharing of Neural Network development

Data Sharing	Model Evaluation		
	MSE	MAP	MAE
50% *train* 30% *test*	**0.0021**	**2.6522%**	**0.0265**
45% *train* 35% *test*	0.0199	5.3733%	0.0537
40% *train*, 30% *test*	0.0107	3.9822%	0.0398

3.2 *Neural Hammerstein*

The neural Hammerstein model used a feed-forward neural network (FFNN) in which the train data were varied from 40% to 50%. Meanwhile, the test data were varied from 30 to 40%, as listed in Table 2. Neural Wiener Data Training Model Simulation 40%, 45& and 50% were shown in Figures 9, 9 and 10, respectively. Table 2 shows that the neural Hammerstein model, which used a neural network with 50% train data and 30% test data, gives the smallest error of MSE, MAP, and MAE.

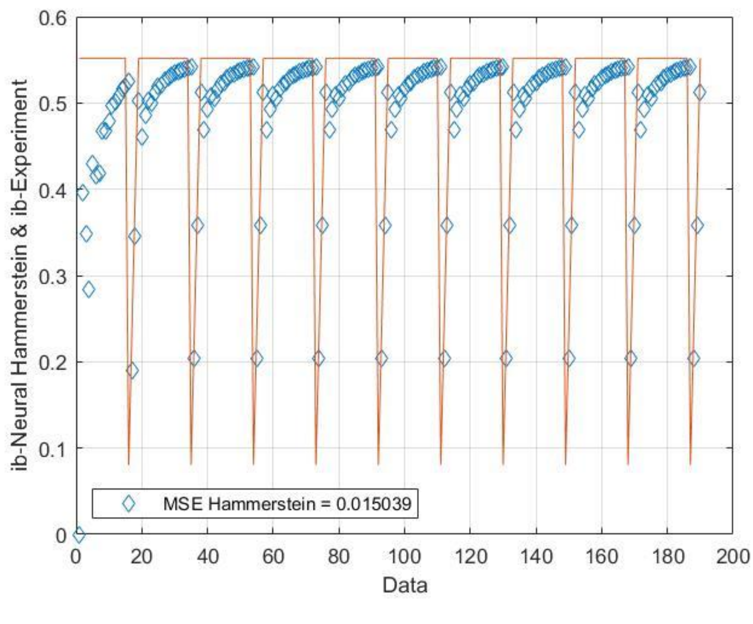

Figure 9. *Neural Hammerstein* Data *Training Model Simulation 40%.*

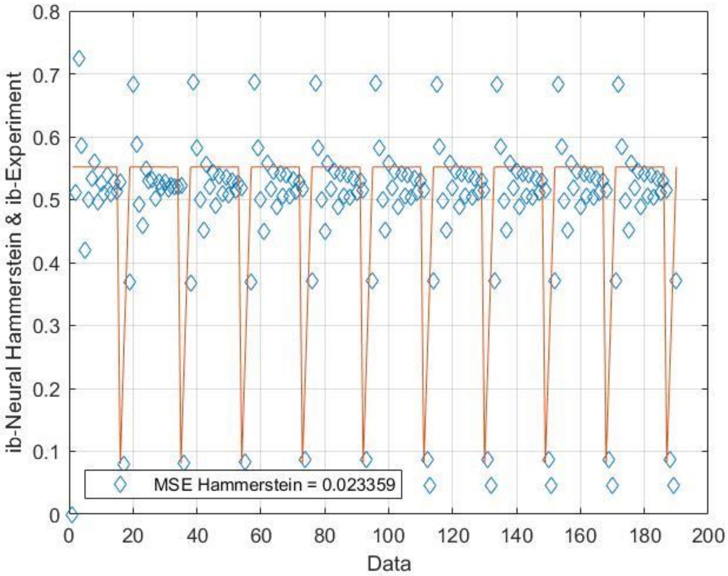

Figure 10. *Hammerstein Neural* Model Simulation Data *Training 45%*

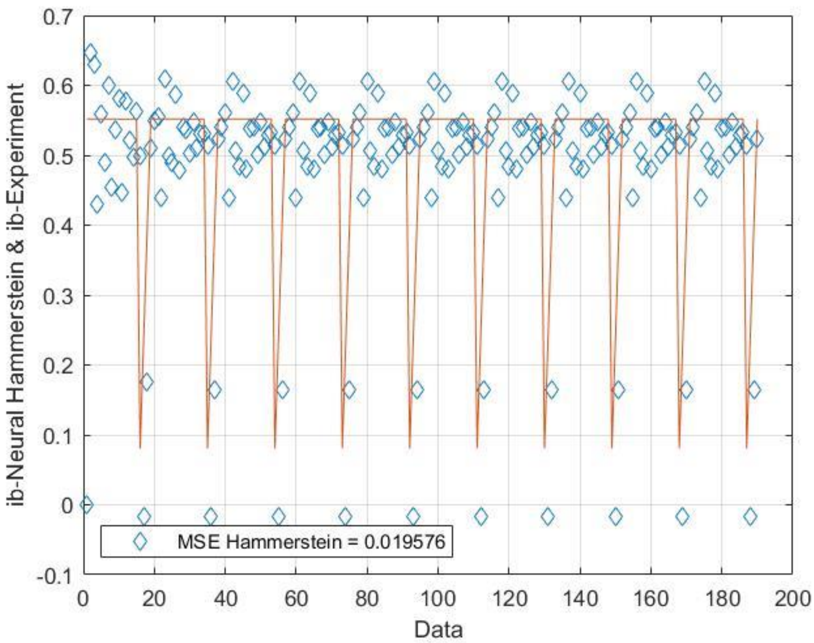

Figure 11. *Neural Wiener* Data *Training* Model Simulation 50%

Table 2. Comparison of Accuracy Values of Neural *Hammerstein* Models using various data sharing of Neural Network development

Data Sharing	Model Evaluation		
	MSE	**MAP**	**MAE**
50% *train* 30% *test*	**0.0195**	**15.1820%**	**0.1518**
45% *train* 35% *test*	0.0234	17.2283%	0.1723
40% *train* 30% *test*	0.015	11.3332%	0.1133

3.3 *Neural Hammerstein-Wiener*

The Wiener - Hammerstein model used a feed-forward neural network (FFNN) in which the train data varied from 40% to 50%. Meanwhile, test data were varied from 30 to 40%, as listed in Table 2. Neural Wiener Data Training Model Simulation 40%, 45& and 50% were shown in Figures 12, 13, and 14, respectively. Table 3 shows that the neural Hammerstein model, which used a neural network with 50% train data and 30% test data, gives the smallest error of MSE, MAP, and MAE.

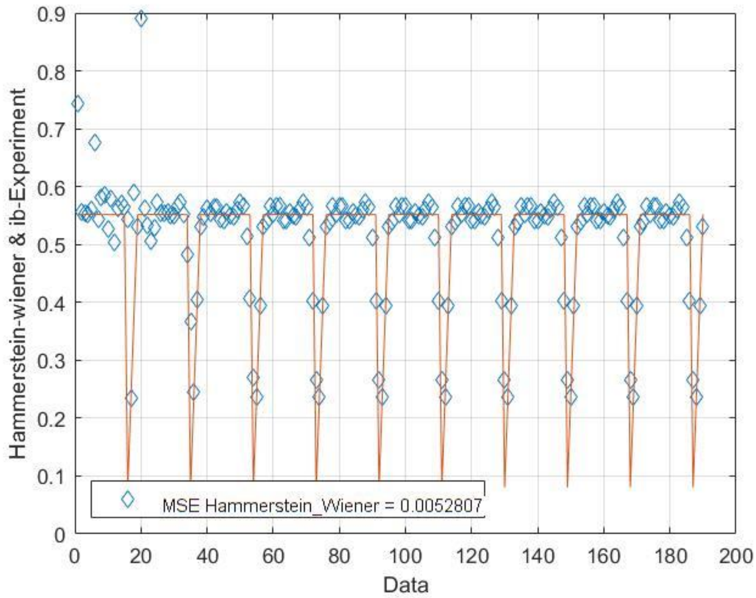

Figure 12. Neural *Hammerstein-Wiener* Model Simulation Data *Training 40%*

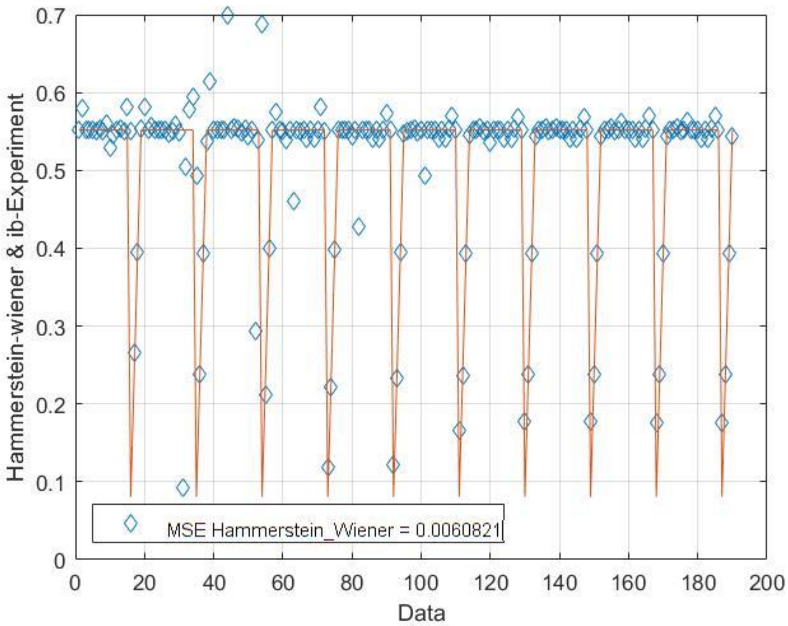

Figure 13. Neural *Hammerstein-Wiener* Model Simulation Data *Training 45%*

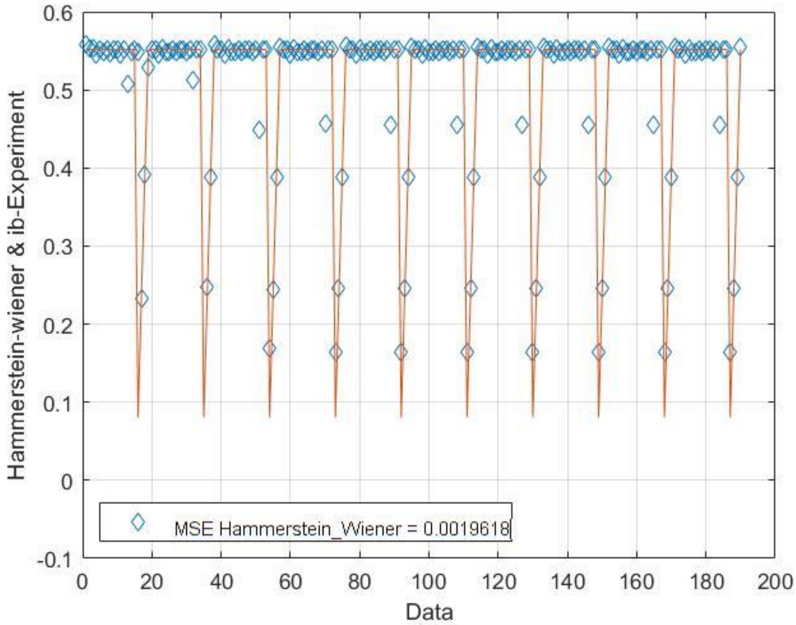

Figure 14. Neural Hammerstein-Wiener Model Simulation Data *Training* 50%

Table 3. Comparison of Accuracy Values of *the Neural Hammerstein-Wiener* Model using various data sharing of Neural Network development

Data Sharing	Model Evaluation		
	MSE	MAP	MAE
50% *train*, 30% *test*	**0.0019**	**1.4122%**	**0.0142**
45% *train*, 35% *test*	0.0061	7.9368%	0.0794
40% *train*, 30% *test*	0.0053	6.0594%	0.0606

3.4 Model Evaluation

The evaluation of the model used in this study is the MAE, MAP, and MSE values used to see the accuracy of the accuracy produced by the Neural Wiener, Neural Hammerstein, and *Neural* Hammerstein-Wiener models in detail listed in Table 4. The table shows that the best model to simulate limiting current is Hammerstein Wiener with the smallest value of the MAE, MAP, and MSE. The comparison of the actual data graph of Lanthanum limiting current (ib) with the prediction modes is shown in Figure 13. The figure shows that the Hammerstein-Wiener model has better performance in modeling the Lanthanum limiting current (ib) than the neural Wiener and neural Hammerstein model.

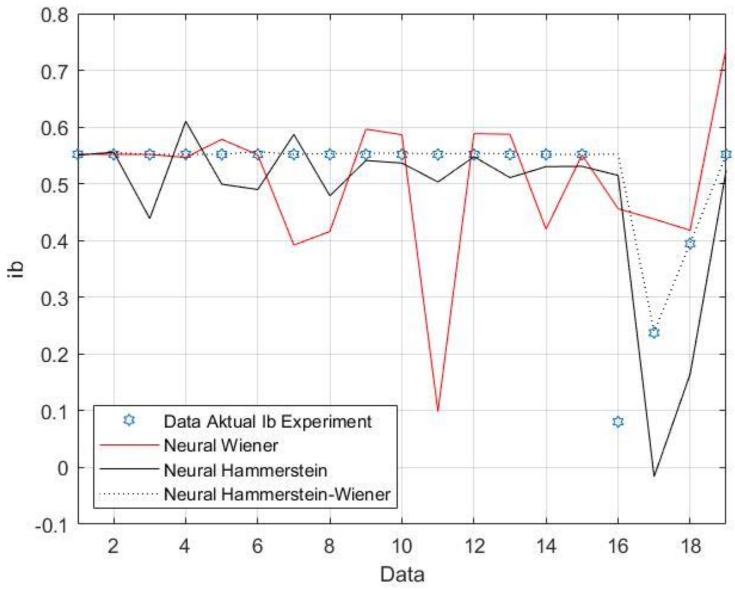

Figure 13. Actual Data Graph (ib) with Prediction Model

Table 4. Comparison of Model Accuracy Values using various data sharing of Neural Network development

Model	Data Sharing	Model Evaluation		
		MSE	MAP	MAE
Neural Wiener	50% *train*, 30% *test*	0.0021	2.6522%	0.0265
Neural Hammerstein	50% *train*, 30% *test*	0.0195	15.1820%	0.1518
Neural Hammerstein-Wiener	**50% *train* 30% *test***	**0.0019**	**1.4122%**	**0.0142**

4. Conclusion

The three models, namely the Neural Hammerstein, the Neural Wienner Model, and the Neural Hammerstein-Wiener Model, were created to simulate lanthanum magnetoelectrodeposition (MED) to determine the limiting current (ib) value. By using a dataset of 7 input parameters and 1 output parameter, it is known that the final result in the form of MSE, MAPE, and MAE values from the Hammerstein Wiener Model modeling is smaller than the Neural Hammerstein modeling and the Neural Wiener. The Neural Hammerstein Wiener Model uses a neural network with 1 hidden layer, 50 hidden nodes, and data sharing of 50% train, 30% test, and 20% validation. This model has an MSE value of 0.0019, MAPE of 1.4122%, and MAE of 0.0142.

Acknowledgments: The author would like to thank the Universiti of Teknologi Malaysia (UTM) and the National Research and Innovation Agency (BRIN) Republic Indonesia for providing a research grant for this project.

References

1. Ratmi Herlani, M. S. Studying the Effect of Rare Earth Metals Cerium (Ce) And Lanthanum (La) On Thorium Analysis with X-ray Fluorescent Method. Yogyakarta: Center for Accelerator Technology and Material Process –BATAN, Babarsari Yogyakarta. Indonesia. 2011. 237 – 248.
2. Uzir M. H., Sudibyo, Aziz N. and Othman M. R. Magneto-electro deposition of tin dendrites Surf. Coatings Technol. 2015 Volume 264, Pp 66-71, https://doi.org/10.1016/j.surfcoat.2015.01.018

3. Sudibyo dan Aziz, N. Semi-Empirical Equation of Limiting Current for Cobalt Electrodeposition in The Presence of Magnetic Field and Additive Electrolyte. *AIP Conf. Proc.* 2016, Vol. 1711, pp. 020003, https://doi.org/10.1063/1.4941612
4. C. A. O. Nascimento, R. Giudici, and R. Guardani, "Neural network-based approach for optimization of industrial chemical processes," Comput. Chem. Eng.,2000. vol. 24, no. 9–10, pp. 2303–2314. https://doi.org/10.1016/S0098-1354(00)00587-1
5. Giri, F. and Bai, E. Block-oriented Nonlinear System Identification. Springer-Verlag London, London. 2010. Vol. 404
6. Chen Xie, Deepu Rajan, Quek Chai "An interpretable Neural Fuzzy Hammerstein-Wiener network for stock price prediction," Information Sciences, 2021, Vol. 577, Pages 324-335, https://doi.org/10.1016/j.ins.2021.06.076
7. Feng Li, Lianyu Chen, Songlin Wo, Shengquan Li, and Qingfeng Cao "Modeling and parameter learning method for the Hammerstein–Wiener model with disturbance" Measurement and Control, 2020, Volume 53, Issue 5-6, 2020, Pp. 971-982, https://doi.org/10.1177/0020294020912790
8. Li, F., Jia, L. & Gu, Y. Identification of the nonlinear process described by neural fuzzy Hammerstein-Wiener model using multi-signal processing. Adv. Manuf., 2023, vol. 11, 694–707, https://doi.org/10.1007/s40436-022-00426-w
9. Khalfi, J., Boumaaz, N., Soulmani, A. et al. Nonlinear Modeling of Lithium-Ion Battery Cells for Electric Vehicles using a Hammerstein–Wiener Model. J. Electr. Eng. Technol., 2021, Vol. 16, 659–669. https://doi.org/10.1007/s42835-020-00607-2
10. Chihi, Ines, Lilia Sidhom, and Ernest Nlandu Kamavuako. "Hammerstein–Wiener Multimodel Approach for Fast and Efficient Muscle Force Estimation from EMG Signals", *Biosensors* 12, 2022, no. 2: 117. https://doi.org/10.3390/bios12020117
11. A. G. Cahyanegoro, Sudibyo, M. Badaruddin, Sugiyanto, Fajar Nurjaman, Yayat Iman Supriyatna, and Erik Prasetyo, "Study of magnetoelectrodeposition of lanthanum (III) chloride heptahydrate leached with sulfuric acid," IOP Conf. Ser.: Earth Environ. Sci., 20233, Vol. 1017, Pp. 012011, doi:10.1088/1755-1315/1017/1/012011