

# Artificial Neural Network Modeling of MoS<sub>2</sub> Supercapacitor for Predicative Synthesis



S. K. Kharade, R. K. Kamat, K. G. Kharade

**Abstract:** Energy storage systems are fundamental to the activity of intensity frameworks. They guarantee coherence of vitality supply and improve the dependability of the framework. The first area is centered on various energy storage frameworks, considering capacity limit, voltage and current proportions, and energy accessibility. Among the energy storage devices, supercapacitor is widely used because it is a high-limit capacitor with capacitance esteem a large amount than different capacitors. In the supercapacitor we have used MoS<sub>2</sub> material synthesized with various Electrolytes. In perspective on the above mentioned, we report an Artificial Neural Network (ANN) strategy to achieve the predictable results. Levenberg- Marquardt feed-forward calculation prepares the neural network. We measure the exhibition of the ANN model with respect to mean square error (MSE) and the relationship coefficient between anticipated yield and yield given by the system. Results confirm the stability of supercapacitor over the other energy storage devices. To show such kind of conduct, we give Synthesis technique, Electrolyte, Cycle Life as an info esteems and Specific limit as yield esteem. For the amalgamation technique info esteem we have taken both compound and physical strategies by normalizing it. The practiced ANN demonstrating confirmations a higher number of concealed neuron design showing ideal execution as respects to expectation exactness

**Keywords :** ANN, Mean-Square error, Simulation, Supercapacitor

## I. INTRODUCTION

Energy storage systems are turning into a basic help for present day living. An Energy storage framework is used so as to store vitality during high power generation periods and return it to utilization at low or extremely high wind speed periods. In the course of recent years, supercapacitors have been considered to guarantee vitality stockpiling gadgets for different applications for example, computerized media transmission frameworks and memory reinforcement frameworks because of their long cycle lives, higher power densities and quick revive capacities. A supercapacitor is a high-limit capacitor with capacitance esteem a large amount than different capacitors.

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Supercapacitor can acknowledge and convey charge quicker than batteries, and endures more charge and release cycles. Each electrochemical capacitor has two cathodes, precisely isolated by a separator, which are ionically associated with one another by means of the electrolyte. Umakant M. Patil successfully employed EPD method for the deposition of 2D MoS<sub>2</sub> and GO nanosheets onto the NF surface [1]. Xiuhua Wang concludes that flower-like MoS<sub>2</sub> can be suitable for electrochemical supercapacitor devices and also can be an ideal adsorbent in water treatment [2]. Ananthakumar Ramadoss incorporated a mesoporous molybdenum disulfide (MoS<sub>2</sub>) nanostructure by a simple aqueous course for supercapacitor applications. From these outcomes, they have inferred that the savvy arrangement of a MoS<sub>2</sub> nanostructure implies it could be a promising anode material for supercapacitors [3]. Guofu Ma inferred that a PPy/MoS<sub>2</sub> nanocomposite with high explicit capacitance and long redox cycle life can be acquired by in situ oxidation polymerization of pyrrole within the sight of flowerlike MoS<sub>2</sub> with graphene-like subunits structure suspension [4]. M. Balasubramaniam from his outcomes, evident that both exposed MoS<sub>2</sub> nanosheets and MoS<sub>2</sub>/ZSO nanocomposites can be one of the electrochemically dynamic and potential terminal materials for supercapacitors [5].

The present examination, centers around utilizing soft computing approach both concerned to materials combination just as yield attributes to address the constraints of supercapacitor. In the present examination, we viably show the usage of Artificial Neural Network for the synthesis of Supercapacitor. Artificial Neural Network (ANN) is a bio-enlivened computing design which has numerous applications in the diversified fields, for example, natural science, material science[6]. Advancements in ANNs have animated a great deal of excitement and analysis. ANNs might be characterized as structures involved thickly interconnected versatile straightforward handling components that are equipped for performing greatly parallel calculations for information preparing and learning demonstration [7].

## II. COMPUTATIONAL TOOL

A neural framework is a figuring model whose layered structure takes after the sorted out structure of neurons, with layers of related hubs. A neural framework can pick up from data—so it might be set up to see structures, orchestrate data, and guess future events. A neural framework isolates your commitment to layers of reflection. During assessment of this investigation we have used MATLAB for computational tallies.



Techniques Used with Neural Networks:

- Supervised Learning
- Classification
- Regression
- Pattern Recognition
- Unsupervised Learning
- Clustering

### III. ANN MODELING OF SUPERCAPACITOR

For supercapacitor, we consider the following parameters or experimental data as an input to the neural - Synthesis method such as Chemical Method and Physical Method, Electrolyte(Na<sub>2</sub>SO<sub>4</sub>, KOH, H<sub>2</sub>SO<sub>4</sub>, KCL,HClO<sub>4</sub>), Cycle Life(500 Cycles=1 is the considered value) and the output of

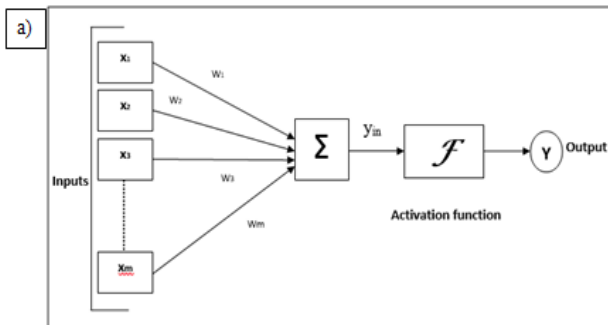
the neural network contains Specific capacity. The Table I below shows the experimental results for supercapacitor.

To model the capacitance of supercapacitor, we have employed artificial neural network (ANN). Highly crystalline morphology is used for the experiment. The ANN prompts streamlined game plans in some progressing nonlinear issues. For the present assessment, normal feed-forward ANN is used. The framework contains input layer and yield layer.

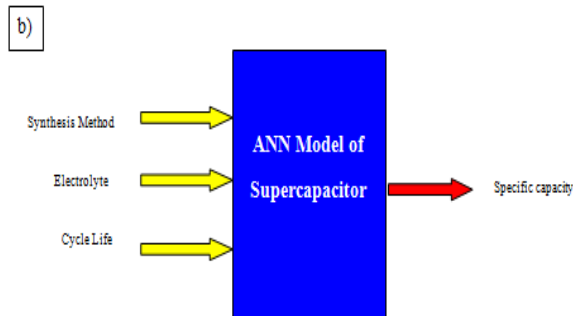
**Table- I: Experimental Results of MoS<sub>2</sub> Supercapacitor**

Name of Energy Storage device	Experimental Results			
	Synthesis Method	Electrolyte	Cyclic Life (Cycles)	Spec. Cap. F g <sup>-1</sup>
Supercapacitor [Material used: MoS <sub>2</sub> , Synthesis Method used: 1.Chemical 2.Physical Method Electrolytes: 1. Na <sub>2</sub> SO <sub>4</sub> 3. H <sub>2</sub> SO <sub>4</sub> 4. KCL 6. HCL]	1	3	2	1.95
	2	4	1	5.537
	1	6	10	4.29
	2	1	4	5.12

### IV. WORKING MODEL



**Fig. 1.Model of Artificial Neural Network. (a)**



**Fig. 1. ANN Model of Supercapacitor (b)**

The Levenberg-Marquardt feed-forward algorithm is used to train the present architecture

The Synthesis method, Electrolyte, Cycle Life of supercapacitor is considered as inputs to the network, whereas Specific capacity is considered as the output of the network. By measuring the performance of the ANN model supercapacitor in terms of mean square error (MSE) and the correlation coefficient. The MSE is defined as,

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (1)$$

where  $Y_i$  is an actual value of the  $i^{th}$  observation and  $\hat{Y}_i$  represents the predicted value of the  $i^{th}$  observation. The difference  $(Y_i - \hat{Y}_i)$  is termed as an error. The correlation coefficient between X and Y is,

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (2)$$

Where  $\bar{X}$  and  $\bar{Y}$  denotes the arithmetic mean of the X and Y respectively.

Table- II: Network performance for different numbers of hidden neurons

No. of Hidden Neurons	% of Training	% Validation	% of Testing	Dataset	MSE	Correlation coefficient	Average correlation coefficient
10	80%	15%	5%	Training	$4.4222 \times 10^{-0}$	$8.6517 \times 10^{-1}$	0.81316
				Validation	$3.1184 \times 10^{-0}$	$7.0373 \times 10^{-2}$	
				Testing	$22.8136 \times 10^{-0}$	$-1.000 \times 10^{-0}$	
15	90%	5%	5%	Training	$4.5856 \times 10^{-0}$	$8.3959 \times 10^{-1}$	0.84067
				Validation	$2.3676 \times 10^{-0}$	$1.0000 \times 10^{-0}$	
				Testing	$1.4215 \times 10^{-0}$	$1.0000 \times 10^{-0}$	
20	80%	10%	10%	Training	$3.9644 \times 10^{-0}$	$8.7275 \times 10^{-1}$	0.85869
				Validation	$3.3683 \times 10^{-0}$	$-2.8354 \times 10^{-1}$	
				Testing	$3.5302 \times 10^{-0}$	$-7.6314 \times 10^{-1}$	
25	80%	15%	5%	Training	$4.7031 \times 10^{-0}$	$8.3121 \times 10^{-1}$	0.84868
				Validation	$2.7758 \times 10^{-0}$	$9.3737 \times 10^{-1}$	
				Testing	$9.2079 \times 10^{-1}$	$-1.000 \times 10^{-0}$	
30	85%	10%	5%	Training	$3.8425 \times 10^{-0}$	$8.7072 \times 10^{-1}$	0.86044
				Validation	$4.0126 \times 10^{-0}$	$8.4746 \times 10^{-1}$	
				Testing	$3.3762 \times 10^{-0}$	$9.9999 \times 10^{-1}$	

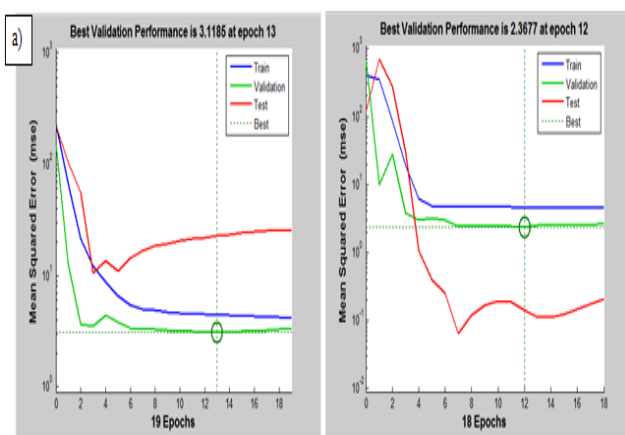


Fig. 2. Performance of ANN model of supercapacitor for mean square error of network provided by the network by changing the values of hidden neuron i.e.10,15 (a)

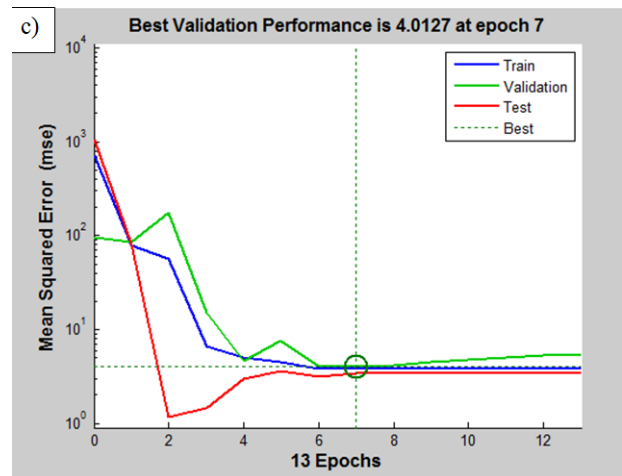


Fig. 2. Performance of ANN model of supercapacitor for mean square error of network provided by the network by changing the values of hidden neuron i.e.30 (c)

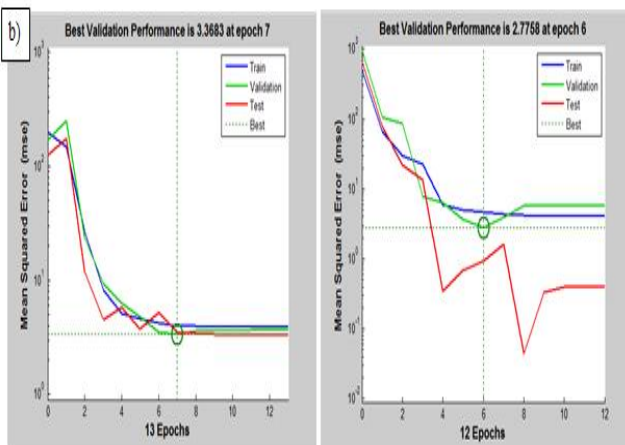


Fig. 2. Performance of ANN model of supercapacitor for mean square error of network provided by the network by changing the values of hidden neuron i.e.20, 25 (b)

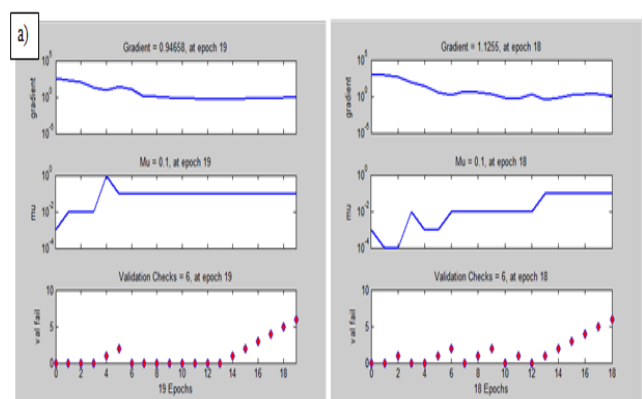
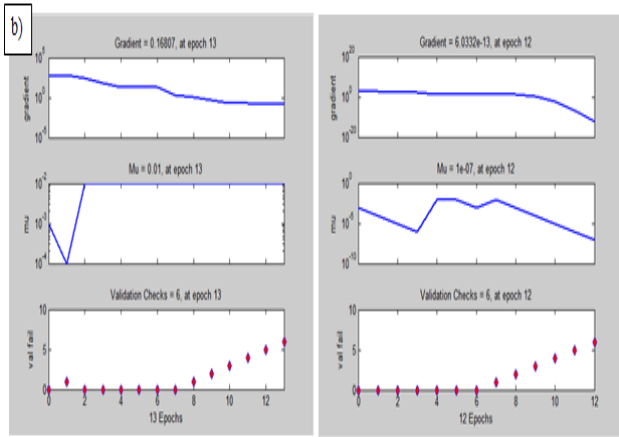
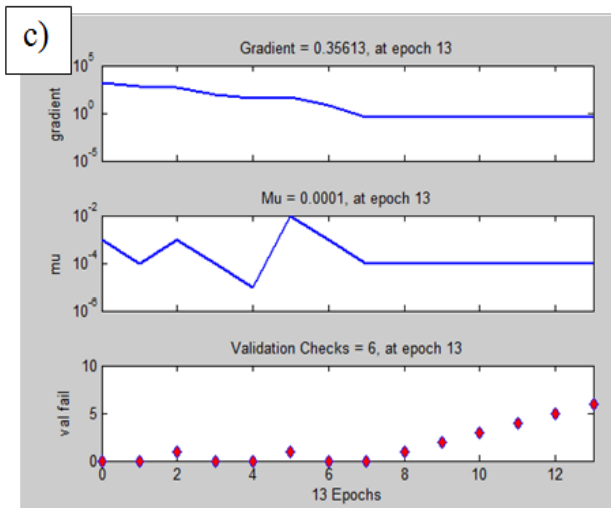


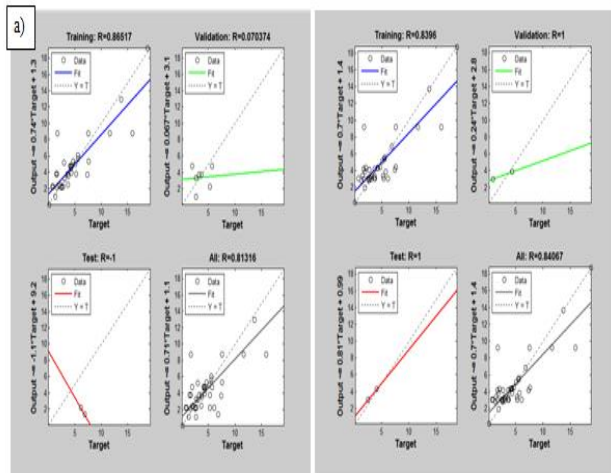
Fig. 3. Performance of ANN model of supercapacitor for gradient, mu (), and validation checks parameters of the network; by changing the values of hidden neuron i.e.10,15 (a)



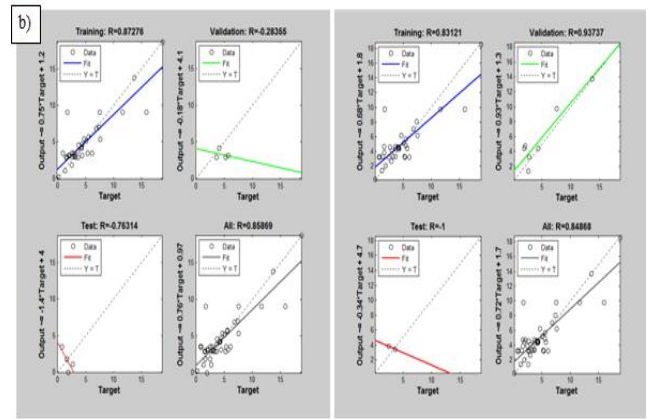
**Fig. 3. Performance of ANN model of supercapacitor for gradient, mu (), and validation checks parameters of the network; by changing the values of hidden neuron i.e.20,25 (b)**



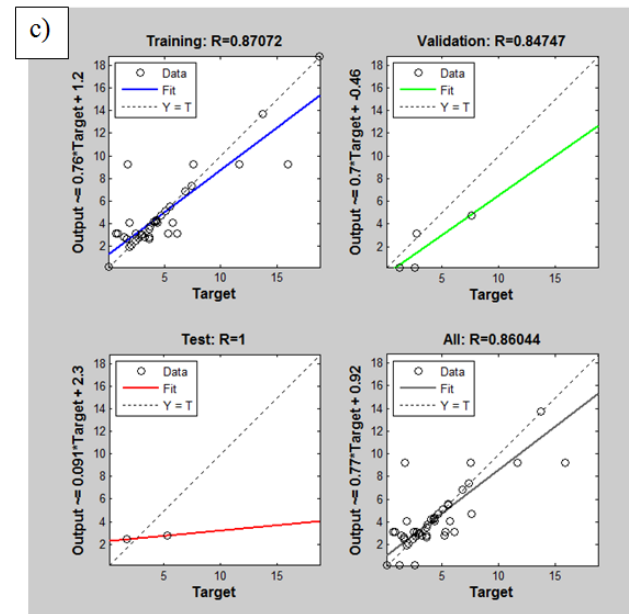
**Fig. 3. Performance of ANN model of supercapacitor for gradient, mu (), and validation checks parameters of the network; by changing the values of hidden neuron i.e.30 (c)**



**Fig. 4. Performance of ANN model of supercapacitor for the correlation coefficient of the output by changing the values of hidden neuron i.e.10,15 (a)**



**Fig. 4. Performance of ANN model of supercapacitor for The correlation coefficient of the output by changing the values of hidden neuron i.e.20, 25 (b)**



**Fig. 4. Performance of ANN model of supercapacitor for The correlation coefficient of the output by changing the values of hidden neuron i.e.30 (c)**

## V. PERFORMANCE MEASUREMENT OF ANN MODEL

Figure 1 presents the performance of ANN model of supercapacitor. Figure 4(a) and 4(b) represents correlation coefficient of the output provided by the network. This is also called the Regression. Regression is a statistical metric used in finance, investment and other disciplines to determine the power of the connection between one dependent variable and a number of other factors.

When hidden neuron value is '10' then the correlation coefficient for training data set is approximately equal to 0.86517, whereas for validation dataset, it becomes 0.070 and for testing dataset it to becomes -1. The overall correlation coefficient of the output and provided by the network is equal to 0. 81316.



When hidden neuron value is '15' then the correlation coefficient for training data set is 0.8396, whereas for validation dataset, it becomes 1 and for testing dataset it becomes 1. The overall correlation coefficient of the output and provided by the network is equal to 0.84067. When hidden neuron value is '20' then the correlation coefficient for training data set is 0.87276, whereas for validation dataset, it becomes -0.28 and for testing dataset it becomes -0.76. The overall correlation coefficient of the output and provided by the network is equal to 0.85869. When hidden neuron value is '25' then the correlation coefficient for training data set is

0.83121, whereas for validation dataset, it becomes 0.93737 and for testing dataset it becomes -1. The overall correlation coefficient of the output and provided by the network is equal to 0.84868.

The mean-square error and  $\mu()$  of the network have value 0.01 which is very small, and confirms the effectiveness of ANN in modeling supercapacitor. Following graph shows that the optimized results of supercapacitor found at '30' hidden neurons.

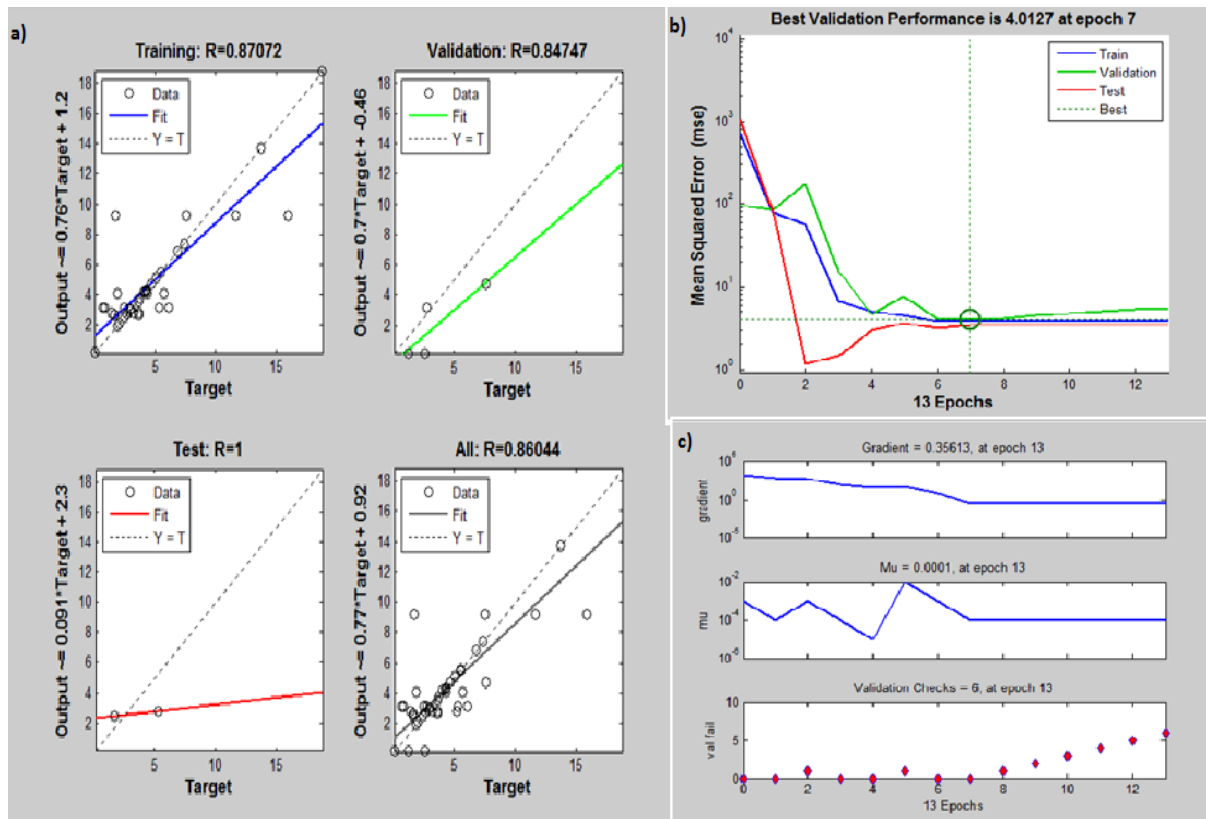


Fig.5. Performance of ANN model with '30' hidden neuron value of supercapacitor. (a)correlation coefficient of the output provided by the network; (b)gradient,  $\mu$  ( $\mu$ ), and validation checks parameters of the network; (c) mean square error of network

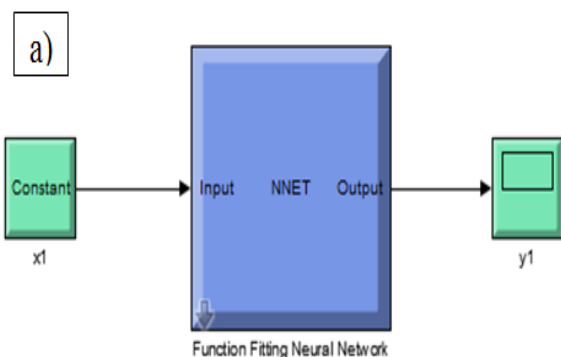


Fig. 6. Simulink diagram of the ANN model of the MoS2 supercapacitor at hidden neurons equal to 15 presents the input and output mapping of the network. (a)

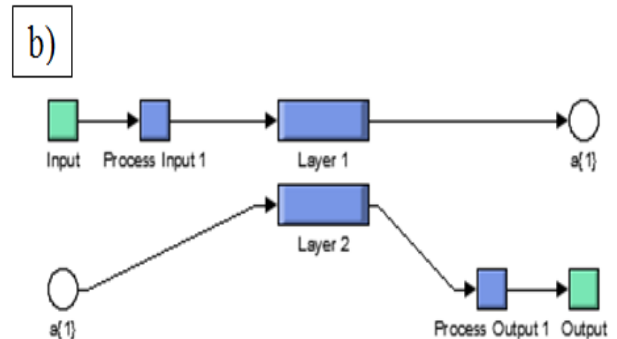


Fig. 6. Simulink diagram of the ANN model of the MoS2 supercapacitor at hidden neurons equal to 15 depicts general structure of hidden layer and an output layer of the model (b)

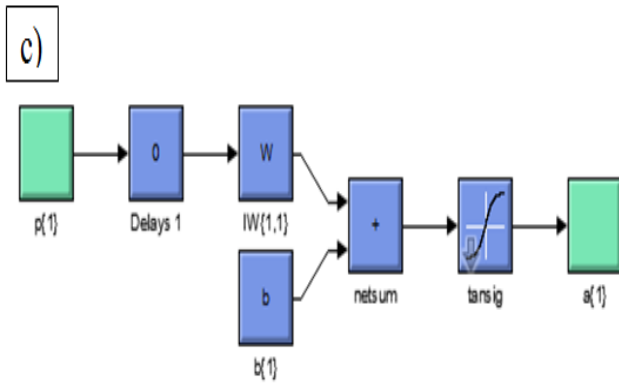


Fig. 6. Simulink diagram of the ANN model of the MoS<sub>2</sub> supercapacitor at hidden neurons equal to 15 reveals detail the structure of the hidden layer1 (c)

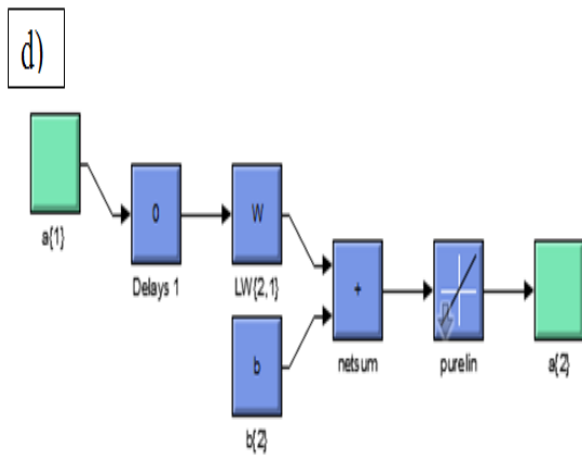


Fig. 6. Simulink diagram of the ANN model of the MoS<sub>2</sub> supercapacitor at hidden neurons equal to 15 depicts general structure of hidden layer and an output layer 2 of the model. (d)

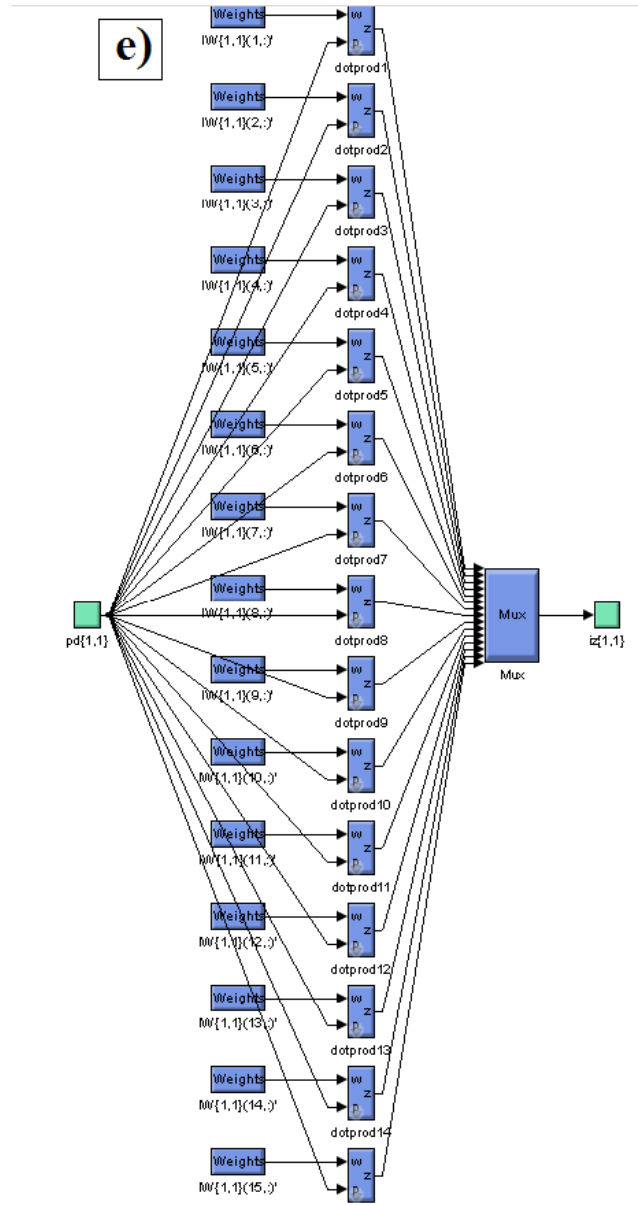


Fig. 6. Simulink diagram of the ANN model of the MoS<sub>2</sub> supercapacitor at hidden neurons equal to 15 exemplifies weights associated with the hidden layer 1 (e)

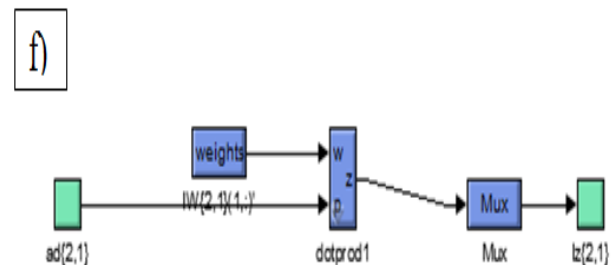


Fig. 6. Simulink diagram of the ANN model of the MoS<sub>2</sub> supercapacitor at hidden neurons equal to 15 exemplifies weights associated with the hidden layer 2 (f)

## VI. IMPACT OF HIDDEN NEURONS SUPERCAPACITOR

For different neuron values we found different average

errors of supercapacitor. These values are in between -0.78074 to 6.3450.

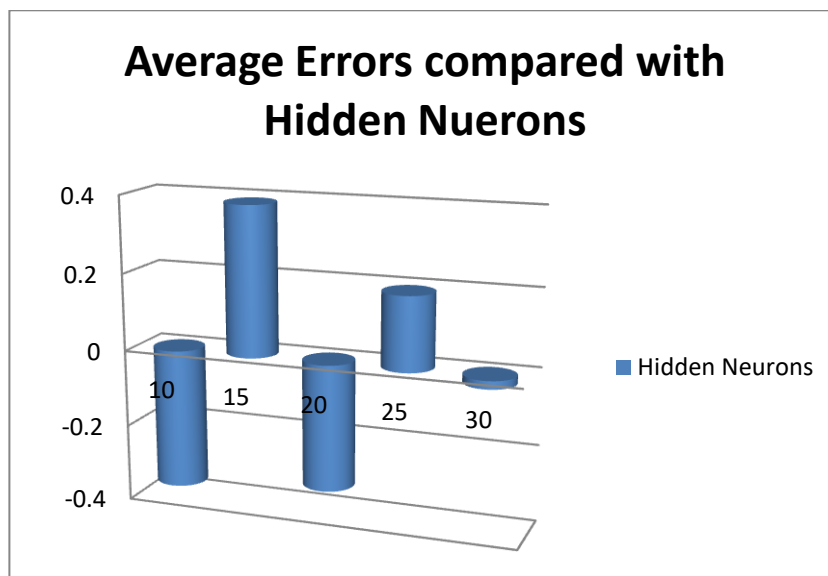


Fig. 7. Average Errors found in different values of hidden neuron

Above graph shows that the negative average error values of supercapacitor found at '10', '15', '20', '25', '30', hidden neurons. When Value of hidden neuron was '10' then average value was -0.362442. When Value of hidden neuron was '15' then average value was 0.38593. When Value of hidden neuron was '20' then average value was -0.32781. When Value of hidden neuron was '25' then average value was 0.18977. When Value of hidden neuron was '30' then average value was -0.02087. So above graph represents the minimum error found at '30' hidden neurons. From above predictions we can conclude that these results are useful for optimization of supercapacitor parameters.

## VII. CONCLUSION

The present original copy reports the displaying of MoS<sub>2</sub> supercapacitor attributes utilizing an Artificial Neural Network (ANN). The outcomes prove that the lower number of hidden neuron engineering displays the best execution as respects to MSE and relationship coefficient. The outcomes portray that the relationship coefficient is higher. This unmistakably prompts the end that the ANN precisely predicts attributes of supercapacitor.

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