JOURNAL OF NANO- AND ELECTRONIC PHYSICS
Vol. 9 No 3, 03042(4pp) (2017)
ЖУРНАЛ НАНО- ТА ЕЛЕКТРОННОЇ ФІЗИКИ
Том 9 № 3, 03042(4cc) (2017)

Artificial Neural Network Modeling of $Ni_xMn_xO_x$ based Thermistor for Predicative Synthesis and Characterization

T.D. Dongale[1,*], K.G. Kharade[2], N.B. Mullani[1], G.M. Naik[3], R.K. Kamat[4,†]

[1] *Computational Electronics and Nanoscience Research Laboratory, School of Nanoscience and Biotechnology, Shivaji University, Kolhapur, 416004 India*
[2] *Department of Computer Science, Shivaji University, Kolhapur, 416004 India*
[3] *Department of Electronics, Goa University, Goa, 403 206 India*
[4] *Department of Electronics, Shivaji University, Kolhapur, 416004 India*

(Received 02 March 2017; revised manuscript received 10 May 2017; published online 30 June 2017)

As foremost sensors of ambient conditions, temperature sensors are regarded as the most vital ones in wide-ranging applications touching the societal life. Amongst the temperature sensors, NTC thermistors have captured their unique place due to the favorable metrics such as highest sensitivity, low cost, and ease of deployment. Transition metal oxides especially the $Ni_xMn_xO_x$ are widely used for thermistor synthesis in spite of the main difficulty of predicting the final sensor characteristics before the actual synthesis. In view of the above, we report an Artificial Neural Network (ANN) technique to accomplish the synthesis with predictable results saving valuable resources. In the said ANN modeling we use hyperbolic tangent sigmoid transfer function for input layer and linear transfer function for the output layer. Levenberg-Marquardt feed-forward algorithm trains the neural net. We measure the performance of the ANN model with regard to mean square error (MSE) and the correlation coefficient between expected output and output provided by the network. Moreover, we uniquely model the resistance-temperature (R-T) characteristics of different thermistor samples using optimized ANN structure. To model such sort of behavior, we provide nickel content, room temperature resistance, and concentration of oxalic acid as an input data to the network and predict the nickel acetate and manganese acetate concentration. The accomplished ANN modeling evidences a lower number of hidden neuron architecture exhibiting optimum performance as regards to prediction accuracy. The lower number of hidden neurons signifies a lesser amount of memory required for prediction of different chemical composition. Thus, we demonstrate exploitation of modeling, simulation and soft computational approaches for predicting the best suitable chemical composition and thus establish the synergy between the materials science and soft computing paradigm.

Keywords: ANN, Thermistor, Soft computing, Modeling.

DOI: 10.21272/jnep.9(3).03042 PACS numbers: 07.05.Mh, 84.32.Ff, 07.05.Tp

1. INTRODUCTION

Among the principle physical parameters, the temperature is the one gauged and controlled for the most part in industrial, domestic and all the part touching regular human life. There exist collections of temperature sensors which have progressed over various years of inventive work. One such by and largely used a temperature sensor, solely known for its sensitivity is a thermistor. Thermistor essentially a world war II product, conceived using the transition metal oxides, strikingly caught the entire scope of domestics, communication, industrial and unified applications. Attributable to the most noteworthy sensitivity displayed by these cost effective sensors they turned into the most prominent though a portion of the deficiencies, for example, higher batch to batch tolerance, narrow measurement range and sometimes infant mortality in case the manufacturing quality assurance is not followed as per standard norms [1-3].

The NTC thermistor has the most noteworthy sensitivity, small heat capacity, rapid response, miniature size, low cost and modestly high resistance at room temperature [2, 3]. Inferable from the cost sufficiency of thermistors which really starts from the key move metal oxides framing these sensors; various research groups, including our own particular, are trying hard to make these sensors agreeable and compatible with the state of art advanced instrumentation. Some of these achievements of our investigations include customization of room temperature resistance for power optimization through a variety of chemical compositions and in this manner to keep away from the self-heating [1]. Our group has additionally reported temperature measurement utilizing the pulse width modulation wherein thermistor was put as a sensor. We have likewise addressed the linearization aspects of these sensors utilizing a non-linear ADC as a part of catering to the disproportionate difference between dynamic range, resolution and measurement accuracy [4].

The present investigation, however, focuses on using soft computing approach both concerning to materials synthesis as well as output characteristics to address the limitations of thermistors such as lack of interchangeability; poor linearity and precision; limited range; instability at high temperatures; hysteresis; and low resolution. In the present investigation, we effectively exhibit the utilization of Artificial Neural Network both for the synthesis of thermistors and additionally for the linearization of the Resistance Vs Tem-

* tdd.snst@unishivaji.ac.in
† rkk_eln@unishivaji.ac.in

perature characteristics.

Artificial Neural Network (ANN) is a bio-enlivened computing design which has numerous applications in the diversified fields, for example, natural science [5-6], materials science [7-8], electronics and communication engineering [9-10], control system [11], sensors [12] and much more. ANN is fundamentally the same as human brains and procedures the data as the human brain work. ANN is trained, validate and test as per the intended mathematical rules and once so trained no further programming is required [13]. The entire design of ANN is comprised of various ANN nodes. Every node comprises of input ports, output ports, weights or coefficients, summation block and activation function. In the event that all substances in the framework work appropriately, then any issue arising in the system can be tackled palatably. There are a good number of research groups working on the adoption of ANN for various application [14-18].

In the backdrop of the universal exploration of ANN as regards to the materials science, depicted above, the present paper reports the prediction of nickel acetate and manganese acetate concentration utilizing ANN. We have additionally modeled the resistance-temperature attributes of an atrial test utilizing improved ANN design.

2. ARTIFICIAL NEURAL NETWORK (ANN)

ANN is very similar to the biological neural networks in which weights and activation function associated with the network plays an important role in learning [19-20]. The magnitude of the weights increases or decreases to learn the specific pattern of the dataset. A schematic depiction of ANN is shown in Fig. 1. Fig. 1 (a) represents the typical ANN node, which consists of inputs (X_i), weights (W_i), a summation block (Σ), bias (b), net input function (η), activation function ($S(\eta)$), and output (Y). The dataset is provided through the inputs (X_i) section. The aim of the ANN is to model the dataset and this is accomplished by adjusting the weights of the network. The ANN adjusts their weights in such a way that the mean square error (MSE) between the target output and output produced will be minimum [9].

The activation function serves as a threshold utility when the net input is higher than the threshold value then only ANN produces an output. For the present investigation, the hyperbolic tangent sigmoid transfer function and linear transfer function are used for the input and output layer respectively. The network is trained by Levenberg-Marquardt feed-forward algorithm. A typical feed-forward ANN is shown in Fig. 1 (b). The details of mathematical equations related to ANN can be found in the ref. [9].

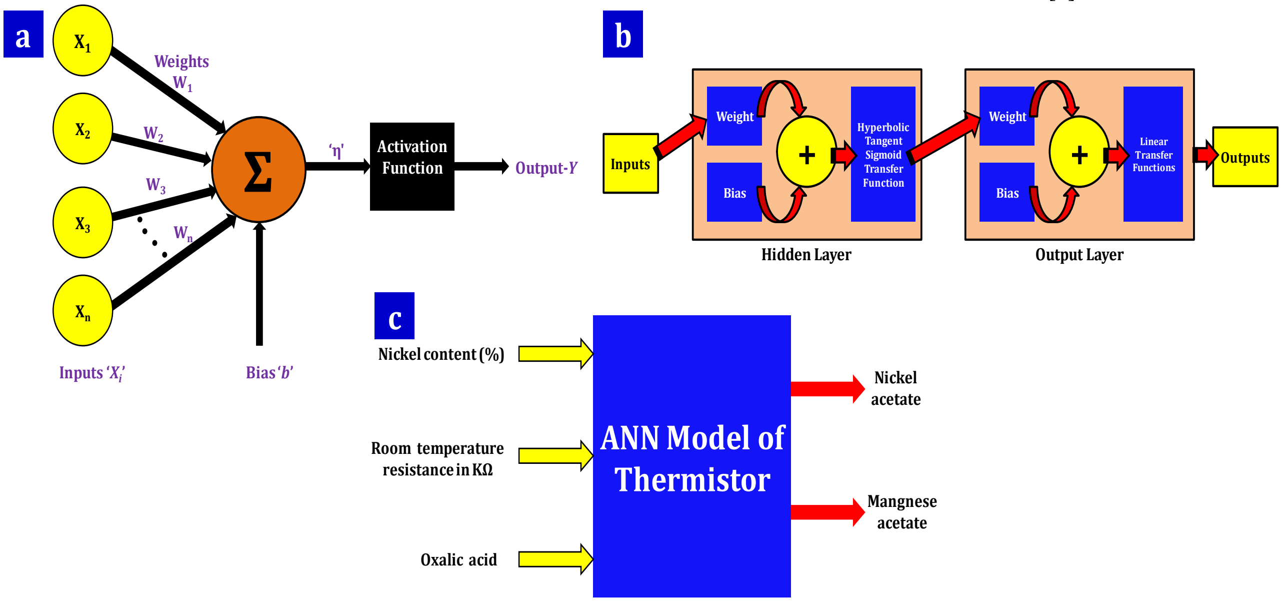

Fig. 1 – (a) ANN node; (b) Typical feed-forward Artificial Neural Network; (c) ANN model of the thermistor [9]

3. MODELING OF NI$_X$MN$_X$O$_X$ THERMISTOR USING ANN

The intent of the present paper is to report modeling of $Ni_xMn_xO_x$ thermistor utilizing ANN. A typical structure of the ANN model of $Ni_xMn_xO_x$ thermistor is shown in Fig. 1 (c).

The hidden layer consists of the hyperbolic tangent sigmoid transfer function and sums net input function. The above-referred duo works as a transfer function and net input function for hidden layer. In the present case, the dot product weight function is used to model the thermistor. The output layer consists of the linear transfer function and sums net input function. The above-referred functions work as a transfer function and net input function for output layer and corresponding weights of the output layer.

The aim of this model is to anticipate the nickel acetic acid and manganese acetic acid concentration, so as to develop the high-performance thermistor. In addition, we have likewise shown the resistance-temperature ($R - T$) characteristics of various thermistor samples utilizing optimized ANN architecture. To model such a behavior, we have provided nickel content, room temperature resistance, and concentration of oxalic acid as an input data to the network and predict the nickel acetate and manganese acetate concentration. The experimental data for the said purpose can be found in the ref. [1-4].

In order to attain the optimized ANN architecture, we have varied the hidden neurons. The resulting optimized structure is further used to model the resistance-temperature ($R – T$) characteristics of $Ni_xMn_xO_x$ thermistor. It was observed that the MSE between the target output and output produced by ANN decreases at a lower number of hidden neurons and MSE is tending to increase with the increase in hidden neurons. The epochs were also found higher in the lower number of hidden neurons. An epoch is a measure of the number of times all of the training vectors are used once to update the weights and the same is also responsible for lowering the MSE. The results clearly indicate that the average correlation coefficient between training, validation and testing data is higher only at the lower number of hidden neurons and average correlation coefficient tends to decrease as the hidden neurons increases. Furthermore, the average correlation coefficient is higher only at the lower number of hidden neurons (hidden neurons = 5 to 20) and it tends to decreases as the hidden neurons increases. Correlation coefficient one of the foremost performance parameters of an ANN; exhibits the relationship between actual data and the output produced by ANN. Higher the estimation of correlation coefficient demonstrates the most accurate model. For the present case, correlation coefficient was found to be ~ 1 for all cases. This implies that the proposed model accurately predicts the thermistor characteristics with the lower complexity of hidden neurons. The results clearly indicate that the maximum epochs are observed at a lower value of hidden neurons and further the epochs tend to decrease as the hidden neuron increases. The results also suggest that the lower number of hidden neurons gives the best performance in terms of gradient, mu (μ), validation fail parameters.

The predicted values of nickel acetate and manganese acetate concentration are shown in the fig. 2 (a and b) respectively. The results clearly indicate that the ANN accurately predicts the different values of nickel acetate and manganese acetate for a different combination of nickel content, room temperature resistance, and concentration of oxalic acid. The result also suggests that the lower number of hidden neuron architecture gives the best performance in terms of prediction. The prediction accuracy tends to decrease as hidden neuron increases. The lower number of hidden neurons signifies the less memory requirement for prediction of different chemical composition. This property can be utilized for the development of software defined as an intelligent block for predicting the best suitable chemical composition. This can be really useful in different domains such as chemical sciences, materials sciences, and electronics engineering.

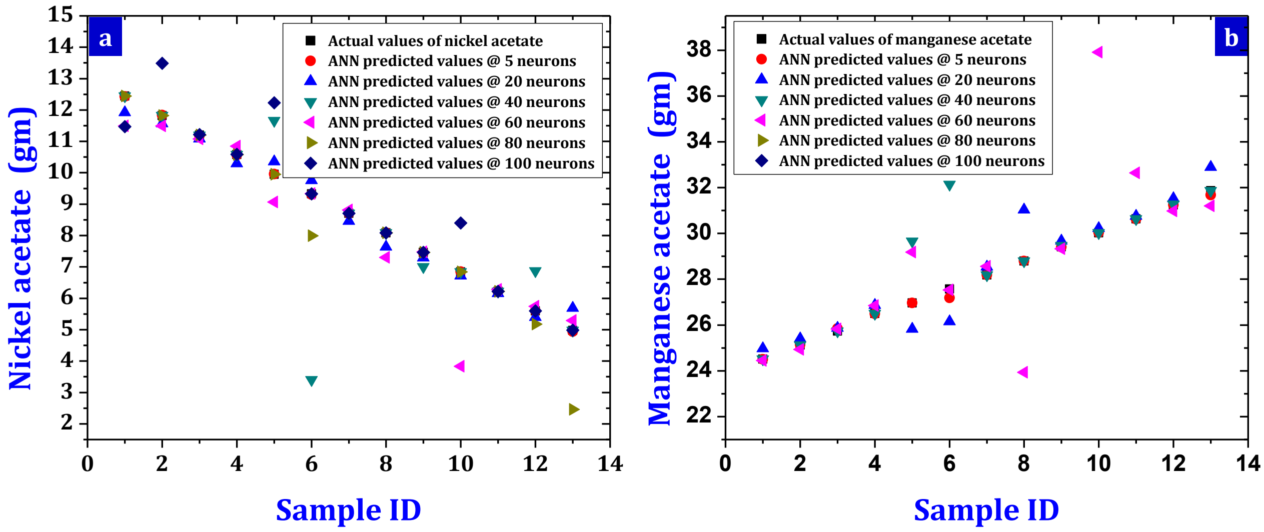

Fig. 2 – (a) Scatter plot of actual values of nickel acetate and ANN predicted values of nickel acetate for different hidden neurons. (b) Scatter plot of actual values of manganese acetate and ANN predicted values of manganese acetate for different hidden neurons

Moreover, the optimized lower number of hidden neuron ANN structure is used for the predicting and linearization of resistance-temperature ($R – T$) characteristics of $Ni_xMn_xO_x$ thermistor. For a case study, we have taken a couple of our samples namely TA1 and TA13 for the said ANN prediction. In this case, temperature becomes the input variable, whereas the resistance of thermistor become output variable. The correlation coefficient between actual $R – T$ characteristics and ANN predicted $R – T$ characteristics of TA1 and TA13 sample was found to be ~ 1. Hence, it can be concluded that ANN accurately predicts the $R – T$ characteristics of $Ni_xMn_xO_x$ thermistor. Considering the research outcome of present work, further, we are in the process of developing an open source software platform based on ANN. This software will help the research fraternity to predict the different synthesis combination for thermistor application.

4. CONCLUSION

The present manuscript reports the modeling of $Ni_xMn_xO_x$ thermistor characteristics using an Artificial Neural Network (ANN). The results evidenced that the lower number of hidden neuron architecture exhibits the best performance as regards to MSE and correlation coefficient. The optimized ANN structure is further used for modeling and linearization of resistance temperature ($R-T$) characteristics of $Ni_xMn_xO_x$ thermistor. The results depict that the correlation coefficient is higher in both cases. This clearly leads to the conclusion that the ANN accurately predicts $R-T$ characteristics of $Ni_xMn_xO_x$ thermistor. As reviewed in the opening part of the paper, the ubiquitous use of soft computing tools and techniques in materials science has made it an obligatory tool in the development of end products with predictable characteristics with significant optimization of resources. The present paper once again establishes the synergy between ANN and thermistor synthesis for value added end products and once again reiterates the cross-fertilization of ideas between diverse domains of research.

REFERENCES

1. R. K. Kamat, G.M. Naik, V.M.S. Verenka, *TI Analog. App. J.* 2001, 52 (2001).
2. R.K. Kamat, G.M. Naik, *Sensor Rev.* **22**, 334 (2002).
3. R.K. Kamat, Development of High-Performance NTC Thermistors, 2002 (Doctoral dissertation, Goa university).
4. R.K. Kamat, G.M. Naik, *Proceedings of International Measurement Confederation* 49 (Prague: 2002)
5. S. Palani, S.Y. Liong, P. Tkalich, *Mar. Pollut. Bull.* **56**, 1586 (2008).
6. Yılmaz, A.G. Yuksek, *Rock Mech. Rock Eng.* **41**, 781 (2008).
7. T.D. Dongale, P.R. Jadhav, G.J. Navathe, J.H. Kim, M.M. Karanjkar, P.S. Patil, *Mater. Sci. Semicond. Process.* **36**, 43 (2015).
8. M.O. Shabani, A. Mazahery, *Appl. Math. Modell.* **35**, 5707 (2011).
9. T.D. Dongale, K.P. Patil, S.R. Vanjare, A.R. Chavan, P. K. Gaikwad, R.K. Kamat, *J. Comput. Sci.* **11**, 82 (2015).
10. Patnaik, B. Choudhury, P. Pradhan, R.K. Mishra, C. Christodoulou, *IEEE Trans. Antennas Propag.* **55**, 775 (2007).
11. X. Sun, L. Chen, Z. Yang, H. Zhu, *IEEE-ASME Trans. Mech.* **18**, 1357 (2013).
12. V.N. Kumar, K.V.L. Narayana, *IEEE Sens. J.* **16**, 53 (2016).
13. S. Agatonovic-Kustrin, R. Beresford, *J. Pharm. Biomed. Anal.* **22**, 717 (2000).
14. S.H. Asl, M. Ahmadi, M. Ghiasvand, A. Tardast, R. Katal, *J Ind. Eng. Chem.* **19**, 1044 (2013).
15. R. Olawoyin, A. Nieto, R.L. Grayson, F. Hardisty, S. Oyewole, *Expert Syst Appl.* **40**, 3634 (2013).
16. Y. Shen, A. Bax, *J. Biomol. NMR.* **56**, 227 (2013).
17. N.S. Hanspal, B.A. Allison, L. Deka, D.B. Das, *J. Hydroinform.* **15**, 540 (2013).
18. K.P.S. Rana, N. Mittra, N. Pramanik, P. Dwivedi, P. Mahajan, *Exp. Tech.* **39**, 23 (2015).
19. T.D. Dongale, S.V. Katkar, K.V. Khot, K.V. More, S.D. Delekar, P.N. Bhosale, R.K. Kamat, *J. Nanoeng. Nanomanuf.* **6**, 103 (2016).
20. K.V. Khot, T.D. Dongale, S.S. Mali, C.K. Hong, R.K. Kamat, P.N. Bhosale, *J. Mater. Sci.* 1 (2017).