1. Introduction

Artificial neural network (ANN) is a computational structure inspired by a biological nervous system. An ANN consists of very simple and highly interconnected processors called neurons. The neurons are connected to each other by weighted links over which signals can pass. The process consists of data collection, analysis and processing, network structure design, number of hidden layers, number of hidden units, initializing, training the network, network simulation, weights/bias adjustments, and testing the network. Artificial neural networks are used in many different fields to process large sets of data, often providing useful analyses that allow for prediction and identification of new data. Artificial neural networks are computational structure programs consisting of interconnected processors called neurons connected by weights. They compute structural data through a process of learning and training. Data normally used by these structures have nonlinear relationships between inputs and outputs. They are used in applications such as speech recognition, imaging, control, estimation, optimization, and host of other things. They are also applied in real-world applications in the areas of finance, medical, business, mining, etc. [1].

2. ANN basic fundamentals and architectures

The process of artificial neural network works similarly to the neurons in the brain. First, before an artificial neural network can be tested or used, it must be trained. The process starts with the neuron, the basic element ANNs (see Figure 1). The neuron inputs are the outputs of several other neurons. Once a neuron has combined the inputs and produces a single output, it is compared to what is known as a training set, group of known inputs and outputs. The user sets a threshold of maximum that is allowed by the system. If the output value from the neuron does not match the known value in the data set, then the system will adjust the weights. This process is repeated until the error is within the threshold range and at that time the system will hold the weights at their
current position to be tested against data that was not used in the training set. At this point in time, the system will be able to back decision and process patterns from the nonlinear data.

An important issue in designing an ANN is knowing how many values are assigned to each layer of an ANN. Assigning too many variables to a layer will lead to overfitting due to the system not being able to process so much information and also will lead to longer computational times during training. Sometimes, proper training may not be possible in a reasonable time given the overload of data. Assigning to few variables in a layer of a complicated set will lead to the system to underfitting the data due to the signals not being fully recognized. Many factors such as the inputs and outputs, noise, complexity of the error function, network architecture, and training algorithm influence what is the best number of hidden units. The neural network is implemented in MATLAB and Simulink toolbox. The performance of the system will be the mean squared error for measuring the average of the squared error. Training of the network will stop when the max number of repetitions is reached, the max time is reached, the performance is minimized to the goal, the performance gradient falls below the minimum value, or mu exceeds the max value [1].

Biological neurons as shown Figure 2 have a cell nucleus to receive input from other neurons through a web of dendrites. Its learning is accomplished via little changes to a current

![Figure 1](image1.png)

**Figure 1.** Neuron function [1].

![Figure 2](image2.png)

**Figure 2.** Neural network (biological and artificial) [2] (Image credit: Wikipedia).
portrayal—its setup contains critical data previously, and learning is directed. The qualities of associations between neurons, or weights, don’t begin as arbitrary, nor does the structure of the associations. Unlike biological neural networks, artificial neural networks (ANNs) are ordinarily prepared starting with no outside help, utilizing a settled topology decided for the current issue. Be that as it may, ANNs can likewise learn in light of a prior portrayal. Sooner rather than later, ANNs will start to play out extra classes of errands at close human and even superhuman levels, maybe ending up scientifically and fundamentally more like organic neural systems [2].

One of the primary issues with neural systems is that, generally, they have a constrained capacity to recognize causal connections expressly. Engineers of neural systems bolster these systems’ huge swathes of information and take into consideration the neural systems to decide autonomously which input factors are generally vital. Another issue with neural systems is the inclination to overfit in light of the fact that the model records for abnormalities and anomalies in the preparation information that may not be available crosswise over real informational indexes. Overfitting of information happens when an information examination model, for example, a neural system, produces great expectations for the preparation information yet more regrettable ones for testing information. Designers can moderate overfitting in neural systems by punishing huge weights and constraining the quantity of neurons in shrouded layers. Decreasing the quantity of neurons in concealed layers lessens overfitting yet in addition restrains the capacity of the neural system to display more intricate, nonlinear connections [3].

Artificial neural network contains various layers as shown in Figure 3. These layers are the following: input layer to receive inputs for network’s learning and recognition, output layer to react to the data about how it’s found out any assignment, and in-between hidden layer to change the contribution to something that yield unit can use somehow.

![Figure 3. Multilayer neural network [4]](image-url)
Moreover, neural network has different architectures such as perceptron model, radial basis function, multilayer perceptron, recurrent neural network, long short-term memory, Hopfield network, Boltzmann machine neural network, convolutional neural network, modular neural network, and physical neural network [4]. These different types are well depicted in Figure 4.

Also, neural networks could be used in classification, prediction, clustering (competitive networks, adaptive resonance theory networks, and Kohonen self-organizing maps), association, pattern recognition (supervised classification and unsupervised classification), and in addition machine learning [4].

3. In-brief recent applications

The editor himself has used ANN in different applications such as smart distributed generation systems [5], photovoltaic module and horizontal axis wind turbine modeling [6], wind energy estimation functions for future homes [7], small-scale hydropower generator electrical system modelling [8], robot energy modeling [9], small-scale wind power dispatchable energy source modeling [10], optimum ANN empirical model of capacitive deionization desalination unit [11], lead acid battery modeling for PV applications [12], solar panel modeling-based design technique for distributed generation applications [13], wind turbine (horizontal and vertical) design...
and simulation aspects for renewable energy applications [14], neural network storage unit parameter modeling [15], empirical capacitive deionization ANN nonparametric modeling for desalination purpose [16], PV module optimum operation modeling [17], ANN interior PM synchronous machine performance improvement unit [18], DC-DC converter duty cycle ANN estimation for DG applications [19], stand-alone PV system simulation for DG applications—Part I: PV module modeling and inverters [20], stand-alone PV system simulation for DG applications—Part II: DC-DC converter feeding maximum power to resistive load [21], maximum power point genetic identification function for photovoltaic system [22], PV cell module modeling and ANN simulation for smart grid applications [23], a neuro-modelling for new biological technique of water pollution control [24], high fundamental frequency PM synchronous motor design neural regression function [25], PM synchronous motor control strategies with their neural network regression functions [26], DC micro-grid pricing and market models [27], battery degradation model based on ANN regression function for EV applications [28], sizing residential photovoltaic systems in the state of georgia [29], an artificial neural network model for wind energy estimation [30], site wind energy appraisal function for future egyptian homes [31], horizontal axis wind turbines modeling [32], wind energy simulation and estimation in egypt [33], petroleum archie parameter estimation [34], storage device unit modeling [35], capacitive deionization (CDI) operational condition nonparametric modeling [36], solar photovoltaic module modeling-based design technique [37], high-speed synchronous motor basic sizing neural function for renewable energy applications [38], generating basic sizing design regression neural function for HSPMSM in aircraft [39], neural unit for PM synchronous machine performance improvement used for renewable energy [40], neural unit for PM synchronous machine performance improvement used for renewable energy [41], a neural model for flat-plate collector [42], a neuro-modelling for new biological technique of water pollution control [43], a neural model for new biological technique of water pollution control: experimental project [44], speed sensorless neural controller for induction motor efficiency optimization [45], and neural model of three-phase induction motor [46].

These book chapters reflect advanced ANN applications for next generation optical networks modulation recognition using artificial neural networks, hardware ANN for gait generation of multi-legged robots, high-resolution soil property ANN map production, ANN dynamic factor models for combined forecasts, ANN parameter recognition of engineering constants in civil engineering, ANN electricity consumption and generation forecasting, ANN for advanced process control, ANN breast cancer detection, ANN applications in biofuels, ANN modeling for manufacturing process optimization, spectral interference correction using a large-sized spectrometer and ANN-based deep learning, solar radiation ANN prediction using NARX model, and ANN data assimilation an atmospheric general circulation model.

Author details

Adel El-Shahat
Address all correspondence to: aahmed@georgiasouthern.edu

Department of Electrical and Computer Engineering, Georgia Southern University, Georgia, USA
References

[1] El-Shahat A. Artificial Neural Network (ANN): Smart & Energy Systems Applications. Germany: Scholar Press Publishing; 2014. ISBN: 978-3-639-71114-1

[2] Schiappa M, Rudd E. Man vs machine: Comparing artificial and biological neural networks, Sophos News. 21 September 2017, https://news.sophos.com/en-us/2017/09/21/man-vs-machine-comparing-artificial-and-biological-neural-networks/

[3] Mahesh S. Machine minds: An exploration of artificial neural networks. Catalyst. May 1, 2017;10. Posted in M and tagged with Volume 10, Connections, M, Physical Sciences, Mathematics and Models, http://ricecatalyst.org/volume-10/2017/6/machine-minds-an-exploration-of-artificial-neural-networks

[4] Jagreet KG. Overview of artificial neural networks and its applications. Categories - Artificial Neural Networks, Machine Learning, Deep Learning. May 05, 2017. https://www.xenonstack.com/blog/data-science/overview-of-artificial-neural-networks-and-its-applications

[5] Guha B, Haddad RJ, El-Shahat A, Kalaani Y. Smart distributed generation systems using artificial neural network-based event classification. IEEE Power and Energy Technology Systems Journal. In press;5(2):1-8

[6] Eldean MAS, El-Shahat A, Soliman AM. A new modeling technique based on performance data for photovoltaic modules and horizontal axis wind turbines. Wind Engineering Journal. Accepted & In Press; 2017:1-21. http://journals.sagepub.com/doi/abs/10.1177/0309524X17737052, Article first published online: October 30, 2017. https://doi.org/10.1177/0309524X17737052

[7] El-Shahat A, Haddad R, Kalaani Y. Wind energy estimation functions for future homes. Journal of Power Technologies. In Press; 2016:1-10. http://papers.itc.pw.edu.pl/index.php/JPT/article/view/605

[8] Saggus C, Coley R, Floyd Z, El-Shahat A. Small scale hydropower generator electrical system modelling based on real-measurements. European Journal of Advances in Engineering and Technology. 2016;3(8):1-12

[9] Rios-Gutierrez F, El-Shahat A, Wahab M. ANN robot energy modeling. IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE). 2016;11(4):66-81. Ver. III (Jul–Aug 2016)

[10] Cannon J, Moore D, Eason S, El Shahat A. Small scale-wind power dispatchable energy source modeling. International Journal of Scientific Engineering and Applied Science (IJSEAS). January 2016;2(1):34-39. ISSN: 2395-3470.

[11] El-Shahat A, Haddad R, Kalaani Y. Optimum ANN empirical model of capacitive deionization desalination unit. International Journal of Industrial Electronics and Drives. InderScience. 2015;2(2):116-133
[12] Haddad R, El-Shahat A, Kalaani Y. Lead acid battery modeling for PV applications. Journal of Electrical Engineering. June 2015;15(2):17-24. ISSN: 1582-4594

[13] Soliman AM, El-Shahat A, Sharaf MA. Solar panels modeling based design technique for distributed generation applications. International Journal of Engineering Research and Management (IJERM). December 2014;1(9):213-218. ISSN: 2349-2058

[14] El Shahat A, Soliman AM, Sharaf MA. Wind turbines (horizontal & vertical) design and simulation aspects for renewable energy applications. ARPN Journal of Science and Technology. June 2014;4(7):388-396

[15] El Shahat A. Neural network storage unit parameters modeling. International Journal of Industrial Electronics and Drives. 2014:1(4);249-274

[16] El Shahat A. Empirical capacitive deionization ANN nonparametric modeling for desalination purpose. Journal of Engineering Research and Technology. June 2014;1(2):58-65

[17] El Shahat A. PV module optimum operation modeling. Journal of Power Technologies. 2014;94(1):50-66. ISSN: 2083-4187, E-ISSN: 2083-4195

[18] El Shahat A, Kader FA, El Shewy H. ANN interior PM synchronous machine performance improvement unit. Journal of Automation & Systems Engineering (JASE). December 2013;7(4, P3):164-175. ISSN: 1112-8542

[19] El Shahat A. DC-DC converter duty cycle ANN estimation for DG applications. Journal of Electrical Systems (JES). March 2013;9(1):13-38. ISSN: 1112-5209

[20] El Shahat A. Stand-alone PV system simulation for DG applications, Part I: PV module modeling and inverters. Journal of Automation & Systems Engineering (JASE). 2012;6(1):36-54. ISSN: 1112-8542

[21] El Shahat A. Stand-alone PV system simulation for DG applications, Part II: DC-DC converter feeding maximum power to resistive load. Journal of Automation & Systems Engineering (JASE). 2012;6(1):55-72. ISSN: 1112-8542

[22] El Shahat A. Maximum power point genetic identification function for photovoltaic system. International Journal of Research and Reviews in Applied Sciences. June 2010;3(3):264-273. ISSN: 2076-734X, EI ISSN: 2076-7366

[23] El Shahat A. PV cell module modeling & ANN simulation for smart grid applications. Journal of Theoretical and Applied Information Technology. June 2010;16(1):9-20. ISSN: 1992-8645, EI ISSN: 1817-3195

[24] El Shahat A, Tawfik ATY. A neuro-modelling for new biological technique of water pollution control. Journal of Arab Research Institute for Science & Engineering. 2010;2(2):6-17. ISSN: 1994-3253; Second Quarter (April–June)

[25] El Shahat A, El Shewy H. High fundamental frequency PM synchronous motor design neural regression function. Journal of Electrical Engineering. 2010;10:1-10. ISSN: 1582-4594; Article 10.1.14, Edition 1, March
[26] El Shahat A, El Shewy H. PM synchronous motor control strategies with their neural network regression functions. Journal of Electrical Systems (JES). December 2009;5(4):1-16. ISSN: 1112-5209

[27] Minshew Z, El Shahat A. DC micro-grid pricing and market models. In: Jose HS, editor. IEEE Global Humanitarian Technology Conference. California, USA: DoubleTree; October 19–22, 2017

[28] May G, El Shahat A. Battery-degradation model based on ANN-regression function for EV applications. In: Jose HS, editor. IEEE Global Humanitarian Technology Conference. California, USA: DoubleTree; October 19–22, 2017

[29] El Shahat A, Haddad RJ, Guha B, Kalaani Y. Sizing residential photovoltaic systems in the state of Georgia. In: 2015 IEEE International Conference on Smart Grid Communications (SmartGridComm 2015), Miami Florida, USA: IEEE Communications Society; November 2–5, 2015

[30] El Shahat A, Haddad R, Kalaani Y. An artificial neural network model for wind energy estimation. IEEE SoutheastCon 2015 Conference. Fort Lauderdale, Florida: IEEE South East Region; April 9–12, 2015. pp. 1-3

[31] El Shahat A. Site wind energy appraisal function for future egyptian homes. In: 2014 Grid of the Future Symposium. Houston, Texas, USA: The Third Grid of the Future Symposium Sponsored by the CIGRE US National Committee (USNC) and the 10 Electric Power Research Institute (EPRI); October 19–21, 2014. pp. 1-13. http://cigre-usnc.tamu.edu/wp-content/uploads/2015/06/Site-Wind-Energy-Appraisal-Function-for-Future-Egyptian-Homes.pdf

[32] El Shahat A. Horizontal axis wind turbines modeling. In: 16th International Middle East Power Systems Conference. Cairo, Egypt: IEEE; December 23–25, 2014 (MEPCON’14)

[33] Shahien RA, El Shahat A, Sharaf MA, Abbas AMS. Wind energy simulation & estimation in Egypt. In: 12th International Conference on Mining, Petroleum and Metallurgical Engineering MPM12. Suez, Egypt: Suez University; October 20–22, 2014. pp. 13-22

[34] Attia AM, Al Aziz MMA, El Shahat A. Archie parameters estimation (comparative study). In: 12th International Conference on Mining, Petroleum and Metallurgical Engineering MPM12. Suez, Egypt: Suez University; October 20–22, 2014. pp. 43-51

[35] El Shahat A. Storage device unit modeling. In: The 2nd International Conference on Engineering and Technology (ICET 2014), German University in Cairo (GUC). Cairo, Egypt: IEEE Xplore included; April 19–20, 2014

[36] El Shahat A. Capacitive deionization (CDI) operational conditions nonparametric modeling. In: International Conference on Industry Academia Collaboration, IAC 2014, Fairmont Heliopolis, Cairo, Egypt: IEEE; March 3–5, 2014

[37] El Shahat A, Soliman AM, Sharaf MA. Solar photovoltaic modules modeling based design technique. In: The International Conference on Industry Academia Collaboration, IAC 2014, Fairmont Heliopolis, Cairo, Egypt: IEEE; March 3–5, 2014
[38] El Shahat A, El Shewy H. High speed synchronous motor basic sizing neural function for renewable energy applications. In: MDGEN05, The International Conference on Millennium Development Goals (MDG): Role of ICT and Other Technologies. Chennai, India: RMK Engineering College; December 27–29, 2009

[39] El Shahat A. Generating basic sizing design regression neural function for HSPMSM in Aircraft EP-127. In: 13th International Conference on Aerospace Science & Aviation Technology. Cairo, Egypt: ASAT 2009 – Military Technical College; May 26–28, 2009

[40] El Shahat A, El Shewy H. Neural unit for PM synchronous machine performance improvement used for renewable energy. In: Ref: 93, The Third Ain Shams University International Conference on Environmental Engineering (Ascee – 3), Cairo, Egypt: College of Engineering, Ain Shams University; April 14–16, 2009

[41] El Shahat A, El Shewy H. Neural unit for PM synchronous machine performance improvement used for renewable energy. In: Paper Ref.: 910, Global Conference on Renewable and Energy Efficiency for Desert Regions (GCREEDER2009), Amman, Jordan: The University of Jordan

[42] Nafey A, El Shahat A, Sharaf MA. A neural model for flat plate collector. In: EGY – 38, 6th International Conference on Role of Engineering towards a Better Environment, RETBE’06 Conference in Alexandria: College of Engineering, Alexandria University; December 16–18, 2006

[43] Tawfik ATY, El Shahat A. A neuro modeling for new biological technique of water pollution control. In: EGY – 37, 6th International Conference on Role of Engineering towards a Better Environment, RETBE’06 Conference in Alexandria: College of Engineering, Alexandria University; December 16–18, 2006

[44] Tawfik ATY, El Shahat A. A neural model for new biological technique of water pollution control: Experimental project. In: The 6th Syrian – Egyptian Conference of Chemical & Petroleum Engineering, Syria: Baath University; November 8–10, 2005

[45] Tawfik AY, El Shahat A. Speed sensorless neural controller for induction motor efficiency optimization. In: 1st International Conference on Advanced Control Circuits and Systems (ACCS’05), Cairo, Egypt: Electronics Research Institute; March 6–10, 2005. ACCS Catalog No: 080610 M 05, ISBN: 0-146-6310-7933-2

[46] El Shewy H, Tawfik AY, El Shahat A. Neural model of 3 phase induction motor. In: 1st International Conference on Advanced Control Circuits and Systems (ACCS’05), Cairo, Egypt. March 6–10, 2005. ACCS Catalog No: 080610 M 05, ISBN: 0-145-6310-7933-2
