Websites:
http://www.sciencepub.net
http://www.sciencepub.net/report

Emails:
editor@sciencepub.net
reportopinion@gmail.com

Report and Opinion

MARSLAND PRESS
Multidisciplinary Academic Journal Publisher

The Estimation of Nonlinear curves of Sediment using Computational Intelligence Approach

Mohammad Rashki Ghale noo1, Dr. Gholam Hossein Akbari2

1: Civil Engineering, Hydraulic Structures, Sistan and Baloochestan, Pardis, Chabahar, Iran
2: Associate Professor of Civil Engineering, Sistan and Baloochestan, Iran
rashkimohammad20@yahoo.com

Abstract: The neural networks are new systems and computational methods that are obtained for learning, knowledge show and finally for knowledge refinery. Also these methods are used for forecasting the resulted answers from complicated systems outputs. The aim of this study is to estimate the amount of sediment entering the reservoir with help of ANFIS, AANs and SRC models, and also provide an optimal training set for training the models. On the other hand some complex aspects of sediment transport yet and require further study in the future.
[Mohammad Rashki Ghale noo, Gholam Hossein. **The Estimation of Nonlinear curves of Sediment using Computational Intelligence Approach.** Akbari. *Rep Opinion* 2021;13(3):56-63]. ISSN 1553-9873 (print); ISSN 2375-7205 (online). http://www.sciencepub.net/report. 8.doi:10.7537/marsroj130321.08.

Keywords: Nonlinear Curves, Neural Networks, Deposition, Optimal Training Set

1. Introduction

Solid crust of the earth was formed out of the air surrounding the earth began to move, and loss of rainfall, erosion and sediment transport was initiated and carried out. By water and wind erosion, and material handling processes continue without interruption and has continued ever since. Looking at the effects that surface each year by water, wind, glaciers, and ... Billions of tons of material eroded from point to point across the land is transferred again [1].

Major factors affecting soil erosion in the watershed hydrology of rivers, rainfall is the first step and it might be especially or hail storm. According to research by Mr. Ellison's fall or collision energy particles or beads of rain on the surface of the basin have shown that the seed rain small bombs that are collision of particles of the soil dropped and separated [2].

Sediments that are moving with the flow of water in the river bed with water may move. This material suspended load and is said that the river bed with water flowing forward are times is called. Once all sediment bed load and suspended load of a river is formed [3].

The rate of deposition and aggregation of factors that can directly affect the size of the dam and result in a rapid decline in reservoir capacity is. Experience shows that many of the barriers for various applications are built with heavy expenditure due to incorrect estimation of the sedimentation rate, the expected useful life before the design of premature have a problem and a sense of the dam will not be able to estimate their goals.

The sediment transport on water quality parameters affect both drinking and agriculture. The experts always try to estimate the suspended load of the river [4]. To tackle these problems, firstly, the condition is known mechanisms of sediment movement; secondly, in order to determine exactly the amount of sediments transported to be used in the design of hydraulic structures [5].

There are basically two different approaches for the estimation of suspended load rivers: the first approach uses a mathematical approach to the equations of hydrodynamics and sediment physical concepts to solve the field being carried out. These models usually have a variety of materials such as grain size, water temperature, specific gravity and viscosity, it flows quickly, the section of the river, and steep-walled river need sex. In the majority of cases never has enough of such data. Not all, mostly water discharge and sediment load data to be summarized. Recent years intelligent models such as artificial neural network simulators evolve neural networks - Fuzzy (ANFIS) or artificial neural networks (ANN) are used. Using artificial neural networks to the discovery of a new chapter in relations inherent in the data may be considered to be non-linear and complex issues, including the phenomenon of sediment can be employed and instrumental. All models and AI-based mechanism so that the vector of parameters or input variables to the vector of parameters or variables to the output image. ANN models It is suitable for complex nonlinear problems. Accurate estimates of the sediment carried by rivers in relation to shipping, filling reservoirs, hydroelectric equipment longevity, water quality, fish location, scientific interest is important. Estimate the sediment load of rivers, especially in the transport of contaminants in environmental engineering and hydraulic engineering design and management of water resources is an important [6].

Artificial neural networks have been successful in different areas of water resources. Recent research has shown that artificial neural networks in hydrology forecasting a new approach for modeling rainfall - runoff, river flow prediction, the input current tanks, and have provided estimates of suspended sediment. In recent years, fuzzy logic has been applied successfully to predict the suspended sediment and Casey fuzzy model was developed for use in estimating daily suspended sediment rating curves can be compared with her fuzzy models and found that it fuzzy model of the curve, measures are [6].

Quantity and quality of water resources planning systems consisting of a summary of the complex and conflicting objectives and decision variables is noteworthy that for optimal results, use of computer facilities and the latest innovations in the field optimization models and simulation is essential. Prosperity and economic development of a society dependent on its ability to maximize the benefits and minimize the damage caused. A permanent river cross section, longitudinal profile, the flow regime and its general form, depending on the situation, including erosion and sediment deposition, and altered its terms, will apply. Thread sediment centuries, studied by engineers and rivers and ways to solve a variety of issues that are presented. Unfortunately, the results of the different approaches often differ dramatically, and in the meantime, these results are not consistent with the actual observations. Sedimentation and River Engineering Science consistently over time, significant progress has been achieved, so some of the fundamental concepts of sediment transport, approach of using these concepts and their relations in recent years has become clear to us.

2. Methodology

Nagy et al., (2002) estimated the total sediment load using multi-layer perception network and error back propagation algorithm. The total sediment load of 161 and 9 of them have been developed based on hydraulic parameters of river sediment load, which was collected by different researchers have used the results of the model MLP Compared to the developed formulas [14].

Cigizoglu (2002) estimated using artificial neural network models, MLP, sediment concentration. He showed that the artificial neural network model predicts that the sediment rating curve. Better model than traditional artificial neural network model to estimate the curve, the ability of artificial neural network to model the hysteresis was reported. The estimated total annual precipitation is also required in cases where the artificial neural network model is compared with the curve of the annual suspended sediment is much closer to the actual value and the predicted reservoir studies efficient model was introduced [15].

Keram Cigizoglu (2004) estimated and forecasted daily suspended sediments using a multi-layer perception networks. That the rivers of the United States that the data from the site USGS The data is taken from 1952 to 1981., And concluded that Multilayer perception model is statistically better than the conventional model [16].

Sarangi and Bhattacharga (2005) designed two ANN models, one is based on geomorphology (GANN) where the input parameters such as river geomorphologic form factor, and the relative salience factor is drainage associated with river runoff and sediment concentrations were associated with the output of the network. Other models based on non geomorphology (NGANN) The single input single output channel runoff and sediment concentration, respectively. Comparing the results of these two models showed that GANN have relatively better response [17].

Agarwal et al., (2005) using the method of back-propagation gradient descent method to optimize the weights of the precipitation forecasts daily, weekly, ten-day and monthly River in India began. The method FFBP The two methods used to model train set and found that they work better river network model of learning offers as well as the neural network to answer to generalize than transmission model linear pointed . Another thing is that scholars have asserted that the rapid convergence and high-trained models do not necessarily lead to a better generalization of a model with. [18].

Cigizoglu and Alp (2005) established another type of algorithm ANN the regression neural network has (GRNN) in America used to estimate suspended. Unlike this algorithm FFBP (The other method was used in this study) on the one hand requires much iteration to find appropriate initial random weights did not predict the negative values for the deposition. For small, medium and large scale networks, and concludes that methods designed to separate GRNN The correlation coefficient R More and mean square error MSE Less than FFBP Is [19].

(2005) Kisi In this paper, a fuzzy network capabilities – neuron (NF) And neural networks (NN). To estimate the discharge has been investigated., And discharge of water and sediment discharge data for the two stations Queered balance And Rio Valencia no Used to establish the model and the multiple linear regression curve and has also been used. The statistical parameters used to evaluate the root mean square error models (RMSE) and the coefficient of determination (R^2) [20].

the main goal of the paper of Dogan et al., (2007) is to establish an effective model nonlinear relationship between the dependent variable (concentration of total sediment load) and the independent variable (the slope of the floor, flow and sediment particle size) is. And to estimate the total sediment load of artificial neural network with three layers (one hidden layer) were used. Sensitivity analysis determined the effect of different variables used in the neural network. [22].

Kisi et al., (2009) used the method of calculating fuzzy - neural adaptive for estimation of suspended sediment. In this paper, suspended sediment and flow data from two stations Kuylus and Salur Koprusu in Turkey it is used. Results obtained using fuzzy neural techniques, and tests were compared with artificial neural networks and rating curve. Statistical criterion of root mean square error, mean absolute error and correlation coefficient was used to assess model performance. The results indicated that the fuzzy - neural monthly suspended sediment will best answer. [6].

A biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Connections, called synapses, are usually formed from axons to dendrites, though dendrodendritic microcircuits [7] and other connections are possible. Apart from the electrical signaling, there are other forms of signaling that arise from neurotransmitter diffusion [8].Artificial intelligence, cognitive modeling, and neural networks are information processing paradigms inspired by the way biological neural systems process data. Artificial intelligence and cognitive modeling try to simulate some properties of biological neural networks [9]. In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents (in computer and video games) or autonomous robots [10].Historically, digital computers evolved from the von Neumann model, and operate via the execution of explicit instructions via access to memory by a number of processors. On the other hand, the origins of neural networks are based on efforts to model information processing in biological systems [11]. Unlike the von Neumann model, neural network computing does not separate memory and processing [12].Neural network theory has served both to better identify how the neurons in the brain function and to provide the basis for efforts to create artificial intelligence. The preliminary theoretical base for contemporary neural networks was independently proposed by Alexander Bain [3] and William James [13]. In their work, both thoughts and body activity resulted from interactions among neurons within the brain.

3. Results

Fuzzy inference system based on rules "if - then" is built, so that the rules can be used to obtain the relationship between the number of input and output variables. Thus the FIS Can be used as a model to predict the absence of data input and (or) output can be used with high uncertainty. Word ANFIS Its name from the term "Adaptive Neural Fuzzy Inference System" is. Using information from a set of input / output function, Fuzzy Logic Toolbox ANFIS a fuzzy inference system (FIS) That the membership function parameters to pre – release alone or in combination with least squares method [6] are moderated and it is a Sugeno fuzzy. This allows you to work through the information that the object model is an attempt to teach his system. Adaptive fuzzy inference system (ANFIS) Other types of intelligent systems is a training algorithm for neural networks and fuzzy reasoning to map an input space to an output space with the ability to combine the power of language, the system uses the numerical strength of fuzzy neural network adaptive. It is also capable of extracting fuzzy rules from numerical data or knowledge or experience of experts and through a data base to make the adjustment. The main drawback of the model predictions ANFIS Network training time required to determine the structure and operating parameters are [12]. Inference Model of Adaptive Neuro - Fuzzy (ANFIS) Multi-layer network, consisting of a node and the arcs connecting the nodes are. Model structure ANFIS The schematic in Figure (1) is shown.

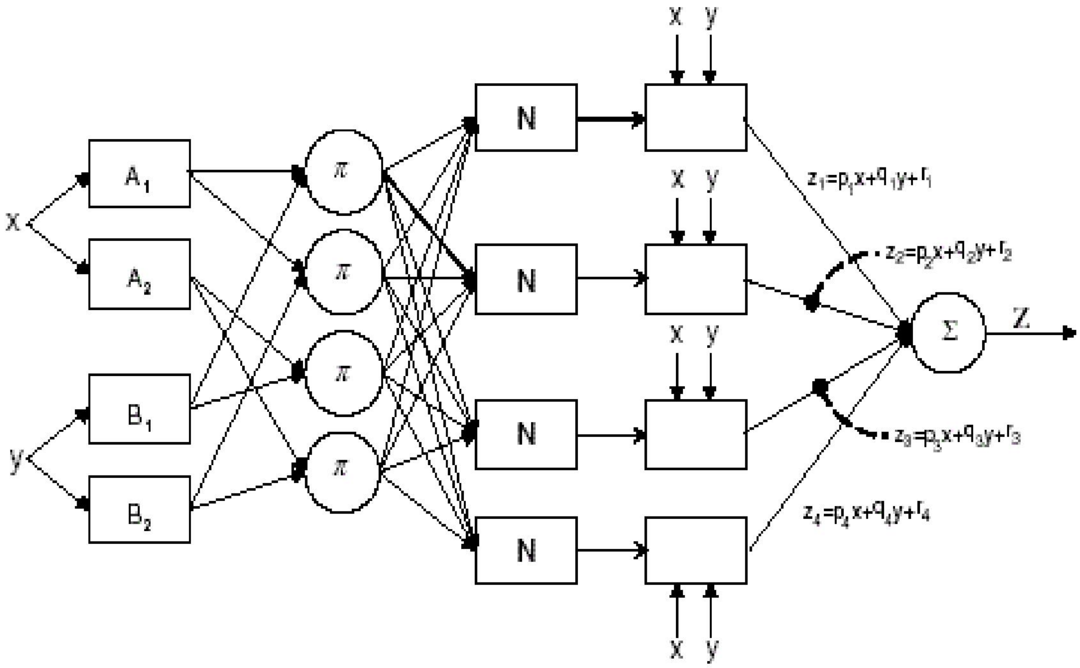

Figure (1): The structure of ANFIS model with two input variables

As the figure shows that model ANFIS is composed of five layers:

The first layer, the input node: This layer is the input layer which belongs to the range of each input phase to be determined. For example, in Figure 2, two fuzzy sets for each input is considered. The membership functions and the desired amount of overlap using the following equation is determined by the user.

$$\mu_A(x) = 1/(1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}) \qquad (1)$$

Here x is Input a, b, c are adaptive parameters and coefficients of non-linear of equations that could determine the shape of the membership function. Variable coefficients, Fuzzy Sets Set S_1 or set parameters is called left hand side (LHS). Output values for the first layer membership values of the membership functions of each input to the input.

The second layer, rule nodes in the input layer to each node multiplied by the weight of the rules is obtained. For example, for the first node we have:

$$w_i = \mu_{A_i}(x_1)\mu_{B_i}(x_2) \qquad (2)$$

The third layer, the intermediate node: these nodes do the function of calculation of the relative weight:

$$\overline{W}_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \qquad (3)$$

Where n is the number of nodes in this layer.

The fourth layer, the nodes of this layer, called laws, rules of operation on the input signal this layer are given by:

$$Z_i = \overline{w}_i f_i = \overline{w}_i(p_i x_1 + q_i x_2 + r_i) \quad (4)$$

That Following parameters are called Consequent Parameters.

Collection of $\{(p_1, q_1, r_1), (p_2, q_2, r_2), \ldots\}$ are called S_2. These set of parameters are known as Right Hand Side.

Fifth layer of output nodes: the network layer is the last layer is composed of a node. The task of this layer is the sum of all input nodes to this node is responsible.

$$\sum_i^n \overline{w}_i f_i \qquad (5)$$

In this way we can learn is the ability of a fuzzy system is implemented. The main teaching method is propagation of errors. In this algorithm gradient descending method using error and the error value is propagated to the input parameters are correct. Total output as a linear combination of the parameters can be written:

$$\begin{aligned} f &= w_1^n f_1 + w_2^n f_2 \\ &= (w_1^n x)p_1 + (w_1^n y)q_1 + (w_1^n)r_1 \\ &+ (w_2^n x)p_2 + (w_2^n y)q_2 + (w_2^n)r_2 \end{aligned} \qquad (6)$$

Thus, the resulting parameters using total least squares error can be calculated. In same way mentioned above, the model structure ANFIS Set of adaptive parameters S_1 and set the following parameters S_2 Exist. In fact, when done properly simulate the actions that both these parameters are estimated so that the model error function is training and testing Minimum. Obtaining parameters typically takes place in two steps. In the first step, a step forward is called a parameter set S_1 Assumed to be constant and set parameters S_2 The algorithm uses the least square error (LSE) Are calculated in the second step of the backward step is called a parameter set S_2 Assumed to be constant and set parameters S_1 Using the reduced gradient algorithm are obtained. This series of floor operations at each stage of the learning occurs epoch Is called. The calculated model parameters, the model output pairs for training the model as a data model has been obtained. The value predicted by the model compared to the actual value, the error model training ANFIS Be calculated. Per epoch Of course, the values of model parameters and subsequently modified the training error and testing error of the model is changed, the number of epoch Training will be added to the model, the reduction of training error is reduced models, where to start testing error curve fluctuates or increases. In such a situation, so it is said that the model has been in a state of over training. Thus, the optimal frequency is selected to be trained not to over-state model. The training model ANFIS This situation should be avoided [35,33,34].

4. Conclusion

ANFIS Membership function of the input model is considered. Membership functions are different types of membership functions such as trapezoid, triangular, Z Function sig Function pi Function dsig Function S And a Gaussian bell function noted. Select the membership function based on different types of membership functions are tested. Means that the membership functions are separately analyzed and model ANFIS Membership functions for each of these individually trained. The error rate of the model is compared with the lowest error rate in functional training, the less time will be adopted as the membership function. Fuzzy Logic Toolbox has 11 membership functions, prefabricated includes. It is made up of 11 different major functions:

Piecewise functions - linear, Gaussian distribution function, circular curve, a quadratic polynomial functions of two and three, that the membership functions of all the letters at the end of their name.

The simplest membership functions are formed from straight lines. The simplest function is the triangular membership functions and function names related where the triangles are not more than three points. Trapezoidal membership functions, flat upper surface and a curved triangular fact that its head is cut off.

Corresponding Author:
Mohammad Rashki Ghale noo
Civil Engineering, Hydraulic Structures, Sistan and Baloochestan, Pardis, Chabahar, Iran
rashkimohammad20@yahoo.com

References

[1]. A. Bivens, C. Palagiri, R. Smith, B. Szymanski, and M. Embrechts. Networkbased intrusion detection using neural networks. Intelligent Engineering Systems through Artificial Neural Networks, 12(1):579–584, 2002.

[2]. Becker, and D. Siboni. A neural network component for an intrusion detection system. In Proceedings of 1992 IEEE Computer Society Symposium on Research in Security and

Privacy, pages 240–250, Oakland, CA, USA, 4-6 May 1992. IEEE Press.
[3]. Cannady and J. Mahaffey. The application of artificial neural networks to misuse detection: Initial results. In Proceedings of the 1st International Workshop on Recent Advances in Intrusion Detection (RAID 98), Louvain-la-Neuve, Belgium, 14-16 September 1998.
[4]. Cannady. Applying CMAC-based on-line learning to intrusion detection. In Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks (IJCNN '00), volume 5, pages 405–410, Como, Italy, 24-27 July 2000. IEEE Press.
[5]. Cannady. Next generation intrusion detection: Autonomous reinforcement learning of network attacks. In Proceedings of the 23rd National Information Systems Security Conference, pages 1–12, Baltimore, MA, USA, 16-19 October 2000.
[6]. Cayzer and J. Smith. Gene libraries: Coverage, efficiency and diversity. In H. Bersini and J. Carneiro, editors, Artificial Immune Systems, volume 4163 of Lecture Notes in Computer Science, pages 136–149. Springer Berlin/Heidelberg, 2006.
[7]. Chan, W. W. Y. Ng, D. S. Yeung, and E. C. C. Tsang. Comparison of different fusion approaches for network intrusion detection using ensemble of RBFNN. In Proceedings of 2005 International Conference on Machine Learning and Cybernetics, volume 6, pages 3846–3851. IEEE Press, 18-21 Aug. 2005.
[8]. Chavan, K. Shah, N. Dave, S. Mukherjee, A. Abraham, and S. Sanyal. Adaptive neuro-fuzzy intrusion detection systems. In IEEE International Conference on Information Technology: Coding and Computing (ITCC'04), volume 1, pages 70–74. IEEE Computer Society, 2004.
[9]. Chebrolu, A. Abraham, and J. P. Thomas. Feature deduction and ensemble design of intrusion detection systems. Computers & Security, 24(4):295–307, 2005.
[10]. Chen, J. Zhou, and A. Abraham. Estimation of distribution algorithm for optimization of neural networks for intrusion detection system. In L. Rutkowski, R. Tadeusiewicz, L. A. Zadeh, and J. Zurada, editors, The 8th International Conference on Artificial Intelligence and Soft Computing (ICAISC '06), volume 4029 of Lecture Notes in Computer Science, pages 9–18. Springer Berlin / Heidelberg, 2006.
[11]. Chen, Q. Chen, and W. Guo. A PSO-based approach to rule learning in network intrusion detection. In B.-Y. Cao, editor, Fuzzy Information and Engineering, volume 40 of Advances in Soft Computing, pages 666–673. Springer Berlin / Heidelberg, 2007.
[12]. Cheng, H. Jin, Z. Han, and J. Sun. Network-based anomaly detection using an elman network. In X. Lu and W. Zhao, editors, Networking and Mobile Computing, volume 3619 of Lecture Notes in Computer Science, pages 471–480. Springer Berlin / Heidelberg, 2005.
[13]. Chimphlee, A. H. Abdullah, M. N. M. Sap, S. Chimphlee, and S. Srinoy. Unsupervised clustering methods for identifying rare events in anomaly detection. In 6 th Internation Enformatika Conference (IEC '05), 26-28 October 2005.
[14]. Chimphlee, A. H. Abdullah, M. N. M. Sap, S. Srinoy, and S. Chimphlee. Anomaly-based intrusion detection using fuzzy rough clustering. In International Conference on Hybrid Information Technology (ICHIT '06), volume 1, pages 329–334, 2006.
[15]. Chimphlee, M. N. M. Sap, A. H. Abdullah, S. Chimphlee, and S. Srinoy. To identify suspicious activity in anomaly detection based on soft computing. In Proceedings of the 24th IASTED international conference on Artificial intelligence and applications, pages 359–364, Innsbruck, Austria, 2006.
[16]. Chittur. Model generation for an intrusion detection system using genetic algorithms. Technical report, High School Honors Thesis, Ossining High School. In cooperation with Columbia Univ., 2002.
[17]. Cho. Incorporating soft computing techniques into a probabilistic intrusion detection system. IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Reviews, 32(2):154–160, 2002.
[18]. Craenen and A. Eiben. Computational intelligence. Encyclopedia of Life Support Sciences, EOLSS; EOLSS Co. Ltd., 2002.
[19]. Crosbie and E. H. Spafford. Applying genetic programming to intrusion detection. In E. V. Siegel and J. R. Koza, editors, Working Notes for the AAAI Symposium on Genetic Programming, pages 1–8, MIT, Cambridge, MA, USA, 10-12 Nov. 1995. AAAI.
[20]. Dam, K. Shafi, and H. A. Abbass. Can evolutionary computation handle large dataset? In S. Zhang and R. Jarvis, editors, AI 2005: Advances in Artificial Intelligence- 18th Australian Joint Conference on Artificial Intelligence, Sydney, Australia, 5-9 December,

2005, volume 3809 of Lecture notes in computer science, pages 1092–1095. Springer Berlin / Heidelberg, 2005.
[21]. Dasgupta and F. Gonzalez. An immunity-based technique to characterize intrusions in computer networks. IEEE Transactions on Evolutionary Computation, 6(3):281–291, 2002.
[22]. Dasgupta, S. Yu, and N. Majumdar. MILA-multilevel immune learning algorithm and its application to anomaly detection. Soft Computing Journal, 9(3):172–184, 2005.
[23]. Dasgupta. Advances in artificial immune systems. IEEE Computational Intelligence Magazine, 1(4):40–49, 2006.
[24]. Dasgupta. Immunity-based intrusion detection system: A general framework. In Proceedings of the 22nd National Information Systems Security Conference, pages 147–160, Arlington, VA, USA, 18-21 October 1999.
[25]. Dass. LIDS: A learning intrusion detection system. Master of science, The University of Georgia, Athens, Georgia, 2003.
[26]. Denning. An intrusion detection model. IEEE Transactions on Software Engineering, Special issue on computer security and privacy, 13(2):222–232, 1987. 36
[27]. Dorizzi. An application of a recurrent network to an intrusion detection system. In Proceeding of the International Joint Conference on Neural Networks (IJCNN 92), volume 2, pages 478–483. IEEE Computer Society, 7-11 June 1992.
[28]. Forrest, and P. Helman. An immunological approach to change detection: Algorithms, analysis and implications. In Proceedings of 1996 IEEE Symposium onSecurity and Privacy, pages 110–119, Oakland, CA, USA, 6-8 May 1996. IEEE Computer Society.
[29]. Gomez and D. F. Hougen. Analysis and mathematical justification of a fitness function used in an intrusion detection system. In H.-G. Beyer and U.-M. O'Reilly, editors, Proceedings of the Genetic and Evolutionary Computation Conference (GECC 05), pages 1591–1592, Washington, D.C., USA, 25-29 June 2005. ACM.
[30]. Goss, N. Franks, A. Sendova-Franks, C. Detrain, and L. Chretien. The dynamics of collective sorting: Robot-like ants and ant-like robots. In J. A. Meyer and S. Wilson, editors, Proceedings of the First International Conference on Simulation of Adaptive Behaviour: From Animals to Animats, volume 1, pages 356–365. MIT Press, Cambridge, MA, USA, 1991.
[31]. Immune, swarm, and evolutionary algorithms, part II: Philosophical comparisons. In L. Wang, J. C. Rajapakse, K. Fukushima, S.-Y. Lee, and X. Yao, editors, Proceedings of the International Conference on Neural Information Processing (ICONIP '02), Workshop on Artificial Immune Systems, volume 3, pages 1469–1473. IEEE Press, 18-22 Nov. 2002.
[32]. J. C. Bezdek. What is computational intelligence? Computational Intelligence Imitating Life, pages 1–12, 1994. IEEE Press, New York.
[33]. J. Cannady. Artificial neural networks for misuse detection. In Proceedings of the 21st National Information Systems Security Conference, pages 368–381, Arlington, VA, USA, 5-8 October 1998.
[34]. Nde Castro and J. I. Timmis. Artif icial immune systems asa novel soft computing paradigm. Soft Computing, 7(8):526–544, 2003.
[35]. P. J. Bentley, J. Greensmith, and S. Ujjin. Two ways to grow tissue for artificial immune systems. In C. Jacob, M. L. Pilat, P. J. Bentley, and J. Timmis, editors, Artificial Immune Systems, volume 3627 of Lecture Notes in Computer Science, pages 139–152. Springer Berlin/Heidelberg, 2005.
[36]. S. Cayzer, J. Smith, J. A. Marshall, and T. Kovacs. What have gene libraries done for AIS? In C. Jacob, M. L. Pilat, P. J. Bentley, and J. Timmis, editors, Artificial Immune Systems, volume 3627 of Lecture Notes in Computer Science, pages 86–99. Springer Berlin/Heidelberg, 2005.
[37]. S. M. Bridges and R. B. Vaughn. Fuzzy data mining and genetic algorithms applied to intrusion detection. In Proceedings of the 23rd National Information Systems Security Conference, pages 13–31, Baltimore, MA, USA, 16-19 October 2000.
[38]. S. M. Bridges and R. B. Vaughn. Intrusion detection via fuzzy data mining. In Proceedings of the 12 thAnnual Canadian Information Technology Security Symposium, pages 111–121, 2000.
[39]. S. T. Brugger. The quantitative comparison of ip networks. Technical report, University of California, Davis, 2007. Retrieved January 26, 2008.
[40]. T. Brugger. KDD cup '99 dataset (network intrusion) considered harmful, 15 Sep 2007. Retrieved January 26, 2008.
[41]. Timmis. An artificial immune network for multimodal function optimization. In D. B. Fogel, M. A. El- Sharkawi, X. Yao, G.

Greenwood, H. Iba, P. Marrow, and M. Shackleton, editors, Proceedings of the IEEE Congress on Evolutionary Computation (CEC '02), volume 1, pages 699–674, Honolulu, HI, USA, 12-17 May 2002. IEEE Press.

[42]. Wespi. Towards a taxonomy of intrusion-detection systems. Computer Networks, 31(8):805–822, 1999.

[43]. Zuben. Artificial immune systems: Part I - basic theory and applications. Technical Report TR – DCA 01/99, The Catholic University of Santos, Brazil, December 1999.

4/3/2021