

Summary of the Existing Literature on the Evolution of Artificial Neural Networks

Title	Description	Results	Year	Data sets
Evolving Artificial Neural Networks (REVIEW) (yao-1999)	<ul style="list-style-type: none"> Global theory, encodings, Hybrid GA-BP, evolution of weights, evolution of topology, evolution of weights and topology, EPNet (Evolutionary Programming on Neural Nets) Evolution of learning rules Evolving ANN ensembles 	<p>“Global search procedures such as EA's are usually computationally expensive. It would be better not to employ EA's at all three levels of evolution.” (weights only, topology only, evolution of learning rules)</p> <p>“Evolution can be used to find a near-optimal ANN architecture automatically”</p> <p>“With the increasing power of parallel computers, the evolution of large ANN's becomes feasible.”</p>	1999	None
Evolving Neural Networks through Augmenting Topologies (stanley-2002)	<ul style="list-style-type: none"> Neuroevolution starts out with a smallest number of neurons and incrementally builds a solution Each neuron can be connected to any one or more neuron of a next layer (The concept of layer is almost non-existent) Hidden layers do not necessarily use the same number of units Genotype includes the connectivity of the network (as a graph) and the corresponding weights Speciation is used to protect innovation 	<p>(only applied to Reinforcement learning problems)</p> <p>“Experimental comparisons verify that such evolution is several times more efficient than the neuroevolution methods so far.”</p>	2002	XOR, Double Pole balancing with velocity problem, Double Pole balancing without velocity problem
Comparison of Particle Swarm Optimization and Backpropagation as Training Algorithms for Neural Networks (gudise-2003)	<ul style="list-style-type: none"> BP: weights evolution PSO: weights evolution 	<p>“The number of computations required by each algorithm has shown that PSO requires less to achieve the same error goal as with the BP”</p>	2003	Not stated
Design of Artificial Neural Networks using a Modified Particle Swarm Optimization Algorithm (licon-2009)	<ul style="list-style-type: none"> PSO: topology, transfer function and weights evolution Uses a different implementation of feed-forward neural networks 	<p>“Compared against back-propagation (BP) algorithm in ANN composed by 3 layers, learning rate of 0.1, the same data sets and the same number of epochs, our proposed PSO algorithm was better”</p> <p>“Furthermore our proposal seems to need fewer epochs to get good results compared against basic PSO and second generation PSO algorithms.”</p>	2009	XOR, Iris plant, Wine, Breast Cancer
Design of Artificial Neural	<ul style="list-style-type: none"> DE: topology, transfer functions and weights 	<p>(Was tested on non linear problems)</p>	2010	XOR, Iris plant,

Networks Using Differential Evolution Algorithm (garro-2010)	<ul style="list-style-type: none"> evolution Uses a different implementation of feed-forward neural networks 	<p>“DE produces results comparable to BP”</p> <p>“DE produces ANNs with a lower MSE than PSO on all problems (XOR, Iris, Wine, Breast Cancer)”</p> <p>“DE sometimes automatically reduce the dimensionality of the input pattern”</p>		Wine, Breast Cancer
Artificial immune system based neural networks for solving multi-objective programming problems (abdElWahed-2010)	<ul style="list-style-type: none"> Clonal Selection: weights evolution 	<p>“The approach is able to produce results similar or better than those generated by other evolutionary algorithms after determining the max and min values with NN and use it to initialize population with at least feasible antibodies which help MISA to find the Pareto-optimal solution more accurate and more faster”</p>	2010	Test functions: <ul style="list-style-type: none"> BNH SRN M_OU M_LOC M_3OU
Artificial Neural Network Training Using Differential Evolutionary Algorithm for Classification (si-2012)	<ul style="list-style-type: none"> DE: weights evolution Hybrid DE: local and global mutation 	<p>“The hybrid DE with global and local mutation tends to perform better on 3 problems out of 5”</p>	2012	Iris plant, Cleveland Heart disease, Breast Cancer, BUPA Liver disorder, Hepatitis
NeuroEvolution of Augmenting Topologies with Learning for Data Classification (chen-2006)	<ul style="list-style-type: none"> NEAT NEAT-BP NEAT-Divide-and-conquer 	<p>NEAT performs poorly on the classification problems</p> <p>NEAT-divide-and-conquer and NEAT-BP clearly outperform NEAT</p>	2006	Iris plant Scale balance

Data sets used in the experiment

- Iris plant (Multi-class)
- Wine (Multi-class)
- Breast Cancer Wisconsin Diagnostic
- Breast Cancer Recurrence

Other interesting data sets

- Cleveland heart disease
- Hepatitis

Pre-processing applied to all data sets: Feature scaling using mean normalization

Details: https://en.wikipedia.org/wiki/Feature_scaling

