

Summary of the Existing Literature on Evolution of Artificial Neural Networks

Title	Description	Results	Year
Evolving Artificial Neural Networks (REVIEW)	<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
Evolving Neural Networks through Augmenting Topologies	<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
Comparison of Particle Swarm Optimization and Backpropagation as Training Algorithms for Neural Networks	<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
Design of Artificial Neural Networks using a Modified Particle Swarm Optimization Algorithm	<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
Design of Artificial Neural Networks Using Differential Evolution Algorithm	<ul style="list-style-type: none"> DE: topology, transfer functions and weights evolution Uses a different implementation of feed-forward neural networks 	<p>(Was tested on non linear problems)</p> <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>	2010

Artificial Neural Network Training Using Differential Evolutionary Algorithm for Classification	<ul style="list-style-type: none"> • DE: weights evolution • Hybrid DE: local and global mutation 	“The hybrid DE with global and local mutation tends to perform better on 3 problems out of 5”	2012
Artificial immune system based neural networks for solving multi-objective programming problems	<ul style="list-style-type: none"> • Clonal Selection: weights evolution 	“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”	2010