An Analysis of NeuroEvolution Through Augmenting Topologies in the Optimization of Airplane's Airfoils

William Metz

The Center for Advanced Studies and Research

Thousand Oaks High School

Abstract

The use of Neuroevolution of Augmenting Topologies (NEAT) algorithm was tested for its effectiveness at optimizing the airfoil lift-drag coefficient at varying degrees of control over the design and was then compared to a traditional Multidisciplinary Design Analysis and Optimization (MDAO) algorithm. The experimentation was performed with three different degrees of control: single, six, and 211. Each test was run 30 times to ensure a statistically significant sample size and then was analyzed with an ANOVA and Kruskal-Wallis test to assess for statistical difference. In the results of the study, NEAT with six variables of control optimized orders of magnitude more than any of other the optimization experiments. Furthermore, the study reveals that NEAT yielded a greater improvement than MDAO with the same degree of control; however, NEAT had a longer runtime and inconsistent results.

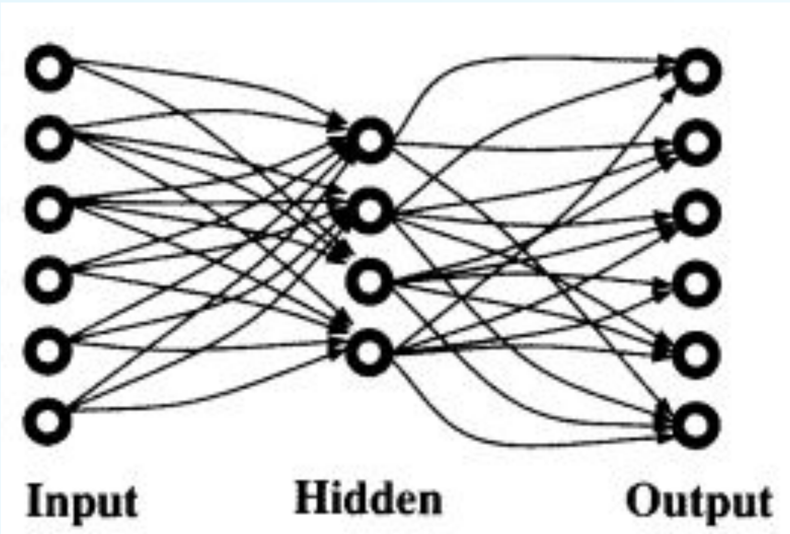

Figure 1. Image of a sample ANN

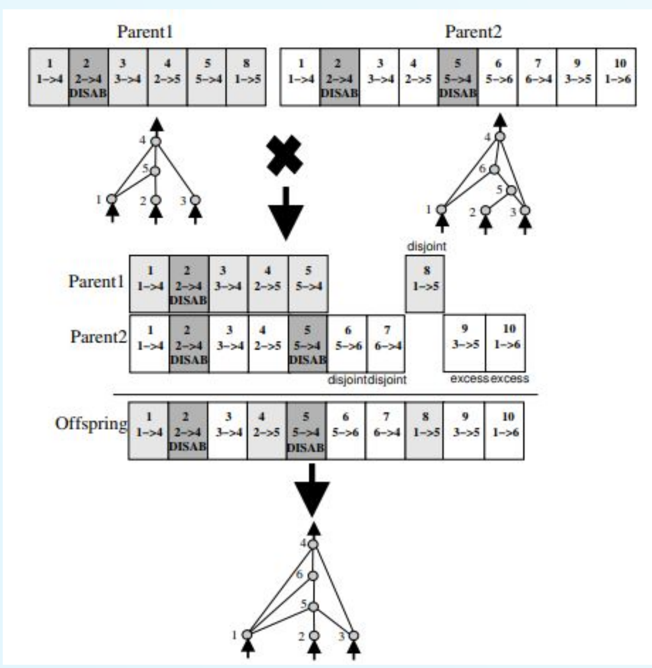

Figure 2. Image of NEAT network and the reproduction process.

Introduction

NEAT is a new type of neuroevolutionary algorithm which is similar to traditional ANNs in that it has an input, output and hidden nodes. However, instead of having uniform layers, the nodes are connected in non-uniform topological structures (Stanley, 2004). Before the advent of computers capable of modeling the complexities of fluid dynamics for three-dimensional objects, aircraft optimization occurred by creating a physical design and testing the design's flight properties in a wind tunnel (Stack, 1935). This process was highly cost prohibitive due to material costs and lengthy construction time. As result, limiting the amount of testing performed and making rapid improvements in flight performance less likely to occur. With continued advances in computational power and efficiency, the optimization of aircraft now relies more on computer-based methods of optimization (Sobieszczanski-Sobieski & Haftka, 1996).

Over the last 20 years, the trend, known as Moore's Law, in which the number of transistors and correlatively computing power in a microcomputer chip doubled every two years, allowed computational methods to become the primary method of optimization (Moore, 1998). This advancement in computing power allowed previously theoretical Artificial Intelligence algorithms such as Artificial Neural Networks (ANNs) to be applied for the first time (Pitts, 1942). ANNs replicate the function of the human brain by creating a network of interconnected nodes or neurons with both an input and output with three different types of layers: input, hidden, and output (Fig. 1).

NEAT is a type of neuroevolutionary algorithm which is similar to traditional ANNs in that it has an input, output, and hidden nodes. However, instead of having uniform layers, the nodes are connected in non-uniform topological structures (Stanley, 2004) (Fig. 2). It has never been applied to aircraft optimization before.

Research Question

How effective are NeuroEvolution of Augmenting Topologies algorithms at optimizing aerodynamic efficiency?

Hypothesis

Null: NeuroEvolution of Augmenting Topologies algorithms have no effect on the aerodynamic properties of airplane designs.

Alternative: NeuroEvolution of Augmenting Topologies algorithms are effective at optimizing the aerodynamic

Methods

- 5 different experiments
  - NEAT with one, six and 211 design variables
  - MDAO with one and six
- Ran 30 times for each experiment for statistical significance

	One Design Variable	Six Design Variables	211 Design Variables
Angle of Attack	Used	Used	Used
Alpha Maneuver		Used	Used
Spar Thickness		Used	Used
Wing Geometry		Used	Used
Wing Skin thickness		Used	Used
Wing Twist		Used	Used
All 205 mesh points			Used

Table 1. Variables used in each experiment

Results

	NEAT One	NEAT Six	NEAT 211	MDAO One	MDAO Six
Max Fitness L/D	14.5	109,029	151.5	1.1	6.23
Min Fitness L/D	.4	-1	-18	1.1	6.23
Average Fitness L/D	4.76	3777.37	16.90	1.1	6.23
Variance	16.06	$3.95*10^8$	1481.90	0	0
Trimmed Average Fitness L/D	4.33	127.28	11.22	1.1	6.23
Run Time Average	433.8	890	6785	4.39	12.11

Table 2. Data from the experiments

	P-value
Kruskal-Wallis	0.00
Anova	.37

Table 3. Statistical test p-values

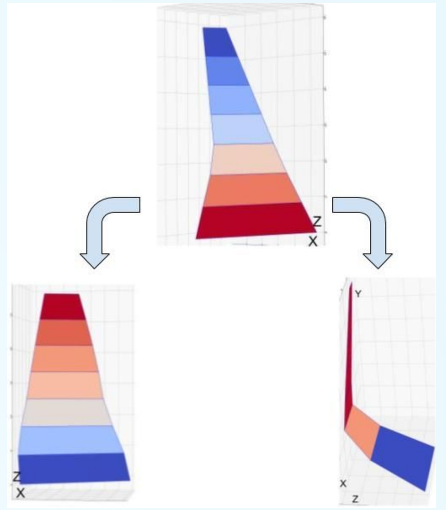

Figure 3. Six design variable wing designs

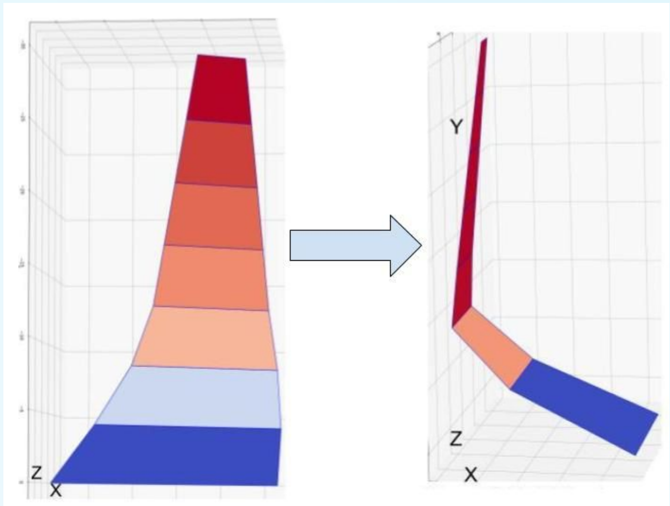

Figure 4. 211 design variable wind design

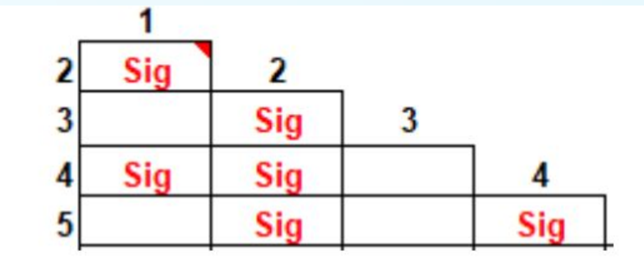

Figure 5. Significance between tests

Conclusion

In the comparison of the different methods of optimization, the NEAT method was overall more successful at creating efficient airplane designs. In the majority of scenarios, the design created by the NEAT network was more efficient than the product of the MDAO method. When the network failed to create a more efficient design, it was due to lack of sufficient time to run and not a failure of the algorithm as a whole. Failures in optimization, reflected insufficient time to analyze and find the ideal weights and biases for a network not a deficiency of the algorithm. When choosing the degree of control, it is crucial to consider the amount runtime allotted. The six variable NEAT seems to be an effective degree of control, but with sufficient runtime, 211 variables may achieve unseen improvements. .

Acknowledgements

I special thanks to Mr. John Jasa, Dr. James Brownley, Dr. Arlsen, and Dr. Malhotra.

Reference

Moore, G. (1998). Cramming More Components Onto Integrated Circuits. Proceedings of the IEEE, 86(1), 82-85. doi:10.1109/jproc.1998.658762

Pitts, W. (1942). Some observations on the simple neuron circuit. The Bulletin of Mathematical Biophysics, 4(3), 121-129. doi:10.1007/bf02477942

Sobieszczanski-Sobieski, J., & Haftka, R. (1996). Multidisciplinary aerospace design optimization - Survey of recent developments. 34th Aerospace Sciences Meeting and Exhibit. doi:10.2514/6.1996-711