

Determining Aircraft Sizing Parameters through Machine Learning



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Overview

Aircraft conceptual design is an inherently iterative process. In some cases, it is advantageous to split the optimization process into an optimization loop and a sizing loop, with the sizing loop containing design parameters that do not work well in the traditional optimization structure. In this work we use machine learning techniques to guess good starting values for this loop, and to predict how the sizing loop progresses. Two aircraft, one jet fuel powered and one battery powered, are tested for initial sizing. Only the sizing loop for the more complex battery case is explored with a recurrent neural network.

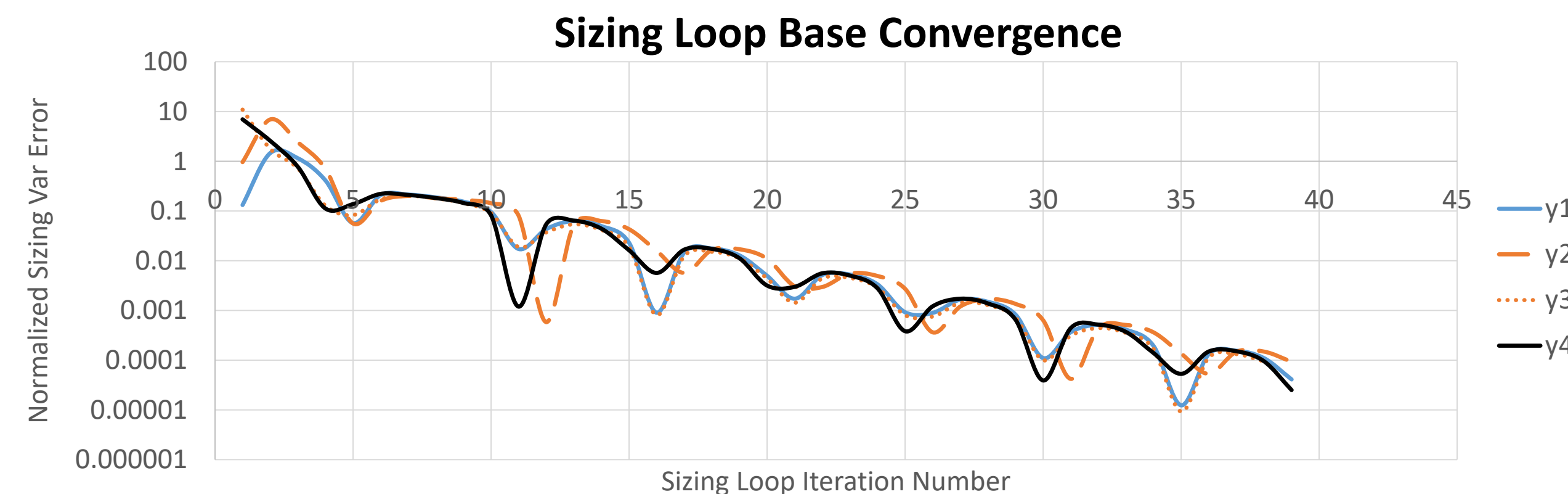
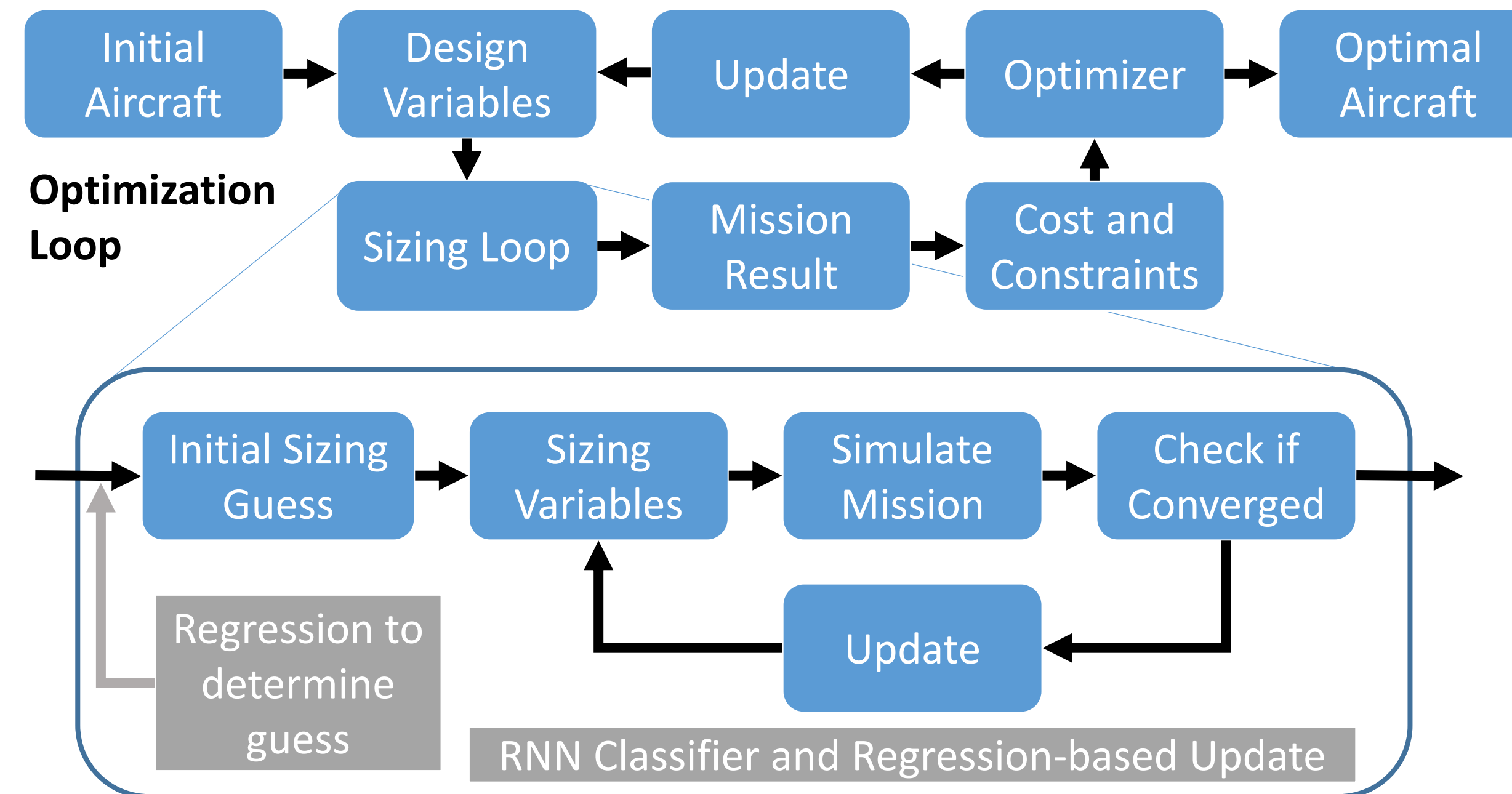
Data Collection

In Loop Data Collection

Data is collected within the optimization loop and used to develop an in loop regression model to speed iterations. Data from previous optimizations is not used.

Out of Loop Data Collection

Data on sizing step sequences is collected both with and without the outer loop, and is stored for future use. When done without the outer loop, initial data is sampled with LHS.



Results

Only the battery powered aircraft sees much benefit from regression. Errors are between guess and exact method.

Algorithm	Sizing Calls	Opt Calls	Ratio	Test Mean Error	Test Med Error	Test Max Error
Sample Point	95,849	4,396	21.80	>20	>20	>20
Table	7,227	1,343	5.38	0.784	0.062	11.166
KNN(5)	11,838	2,409	4.91	0.454	0.131	6.505
GPR	3,415	524	6.52	0.462	0.433	2.297
Extra Trees	10,555	2,045	5.16	0.316	0.137	1.901

RNN classification with a sample test set:

Steps Used	# Training	# Test	Converged Correct	Diverged Correct
4	12400	5800	87.3%	98.8%

RNN regression – Error from L2 norm of normalized sizing vars:

Steps Used	# Training	# Test	Train Error	Test Error
3	134831	2289	0.2373	1.131
4	128071	2232	0.08698	0.2843

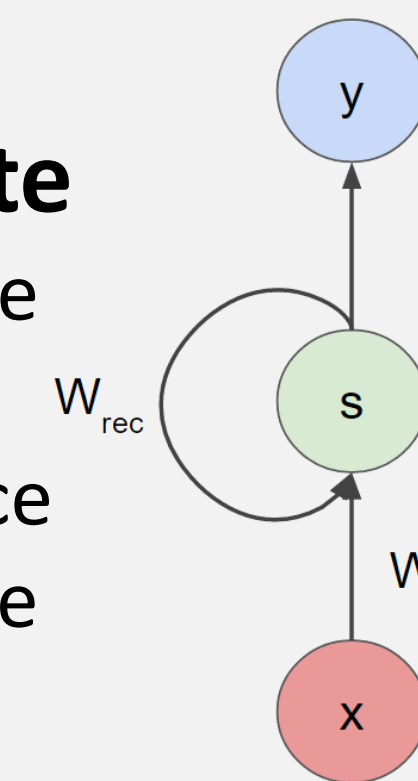
Methods

Initial Sizing Variable Regression

Several different regression algorithms were explored to determine effectiveness in guessing the initial parameters for the initial sizing variables, with the goal of being as close to a converged value as possible on the first step. Data is collected as the optimization problem progresses, and used to build a regression model at each major step. The algorithms selected are shown in the results.

Recurrent Neural Network for Classification and Update

In this case, RNNs are training on saved sizing sequences to determine whether or not the loop is likely to converge, and to speed it up. The classification RNN is trained using the first n iterations of the sequence and the result. The update version uses n iterations at any point in the sequence and attempts to determine the next value in the sequence.



Discussion

Initial Sizing Variable Regression

Each regression model reduced the overall required number of sizing values by an order of magnitude. However, numerical noise within the outer loop finite differencing caused the number of Opt Calls to vary significantly. Future work will done to compare results for non-gradient-based optimization schemes to compare effectiveness

Recurrent Neural Network

The converged prediction percentage is low for binary prediction, but the addition of confidence intervals could improve its usefulness. The regression model must be tested in loop to check effectiveness.

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