Improving Multi-objective Genetic Algorithm for Lattice Optimization with Machine Learning

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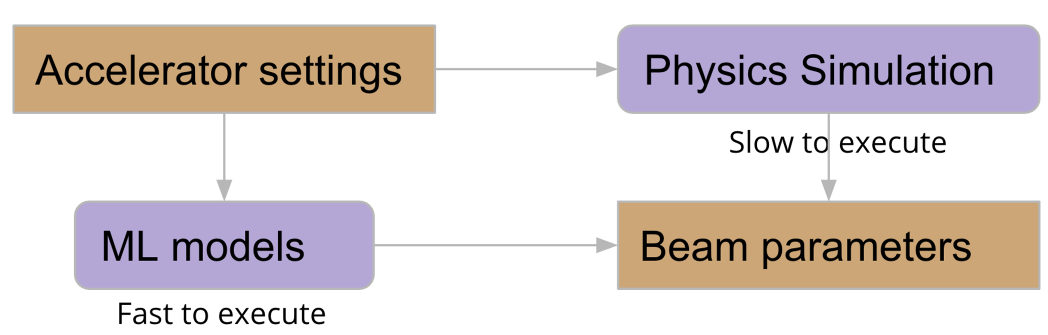
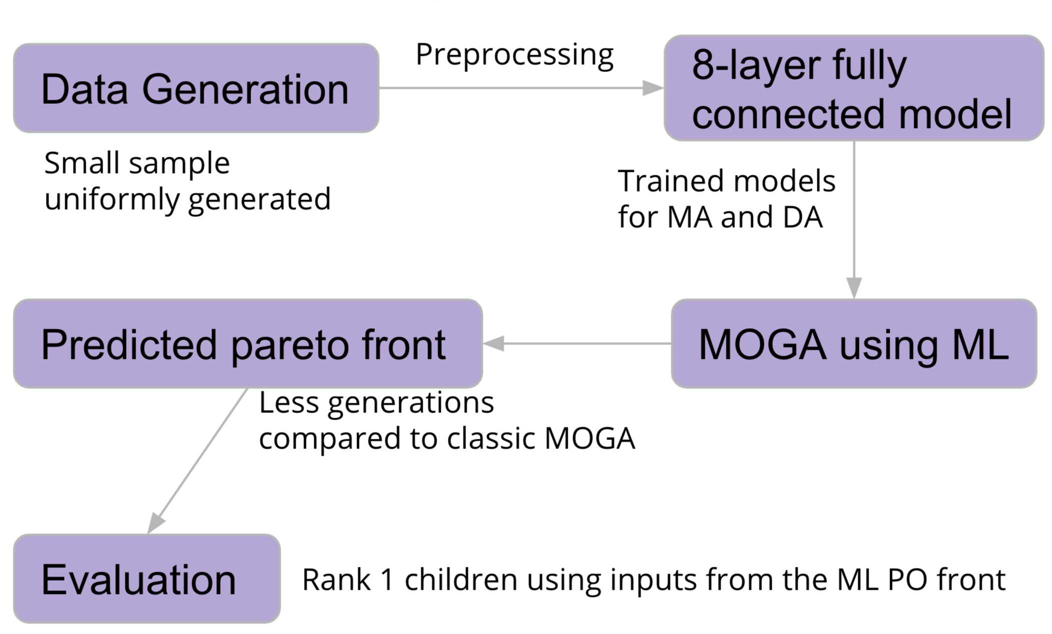
1. Background

Nonlinear lattice optimization at ALS-U is a complex time-consuming task which usually consists of 10+ variables and several constraints and objectives. Currently, it would take days or even months for a multi-objective genetic algorithm (MOGA) to reach the Pareto optimal front where the bottleneck is evaluating each potential candidate using particle tracking techniques for the next generation. We proposed a new machine learning pipeline to reduce the time of the evaluation process by automatically predicting dynamic aperture and momentum aperture. We got a 25+ speedup based on the preliminary tests of a two nonlinear knobs problem.



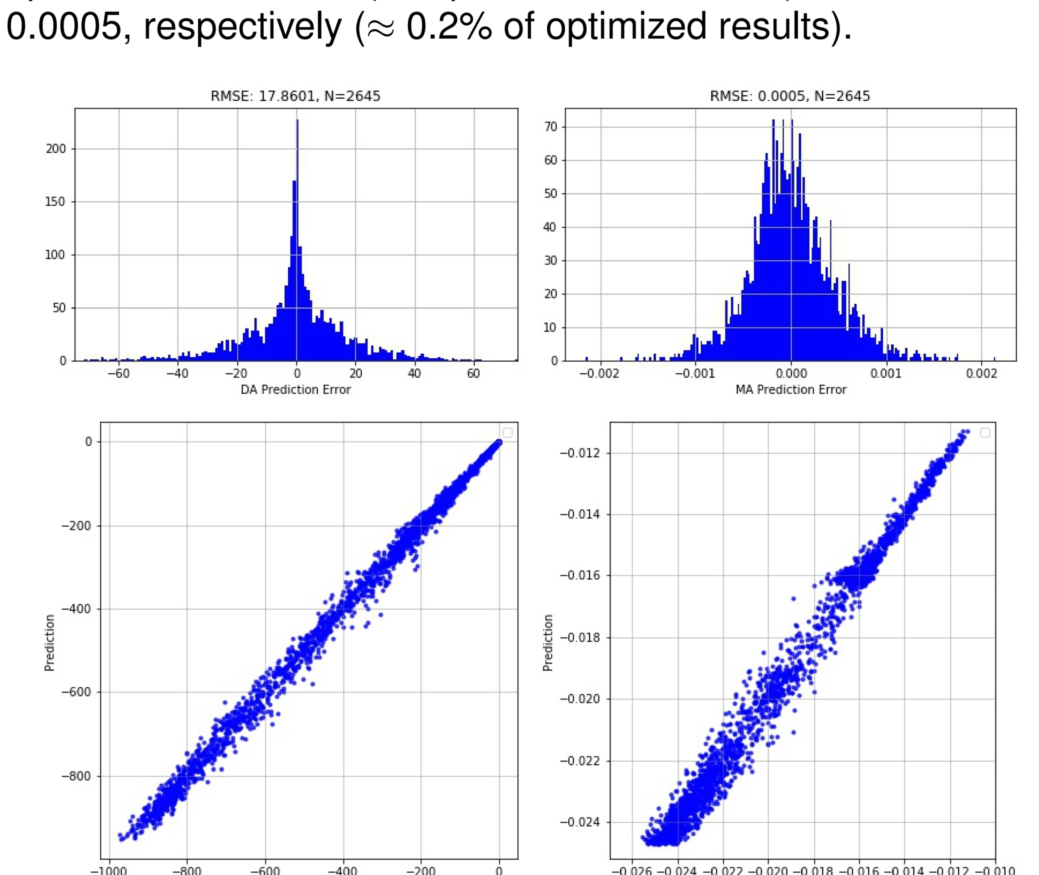
2. Workflow

Below is the workflow of our machine learning pipeline. The training data is uniformly generated in the input parameter space without using all generation data from a actual MOGA run. In the evaluation process, we compared the Pareto front from a MOGA run with the rank-1 children (non-dominated solutions) from the final ML generation.



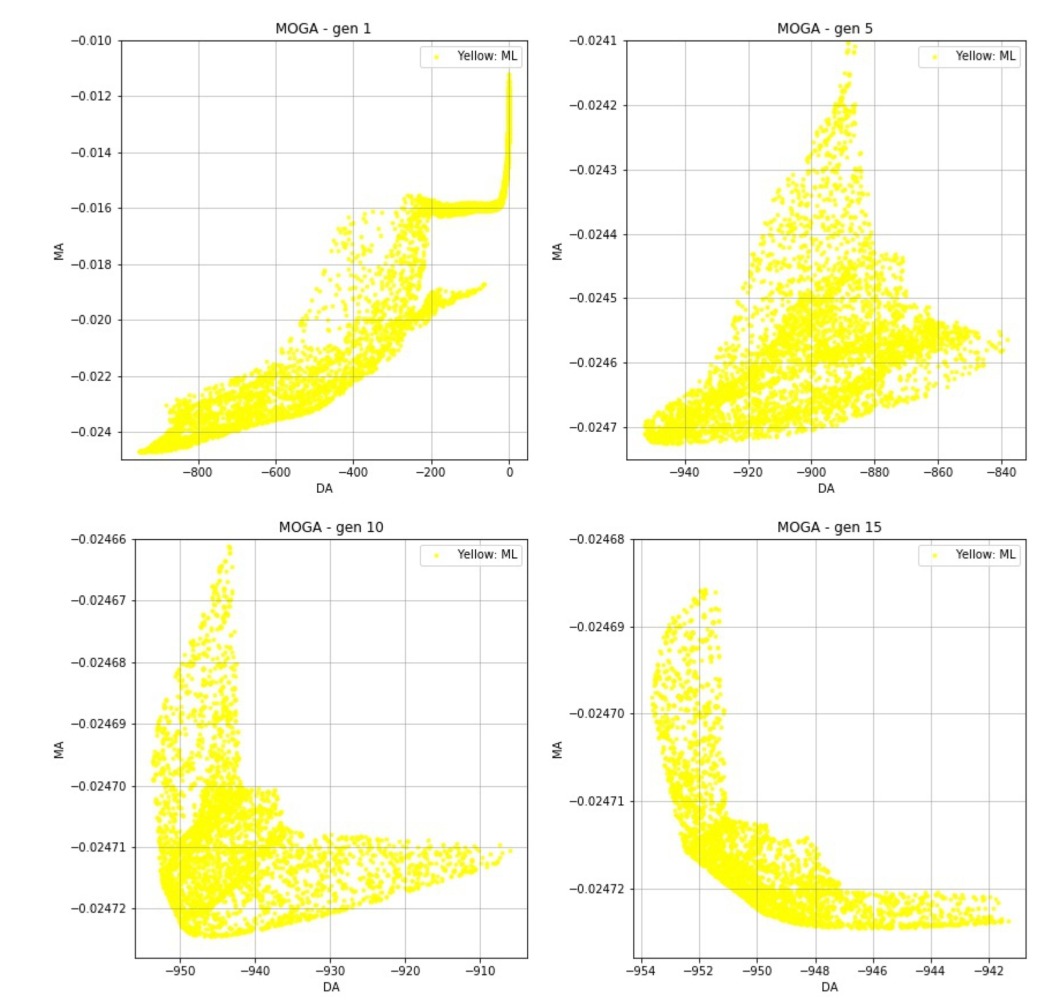
3. Neural Network & Training

As described in the workflow, fully connected models work best for our data. We split the sample data into 80% for training and 20% for testing. The training process usually finishes within 10 minutes. The RMSE of dynamic aperture and momentum aperture on test data (sample size is 115 * 115) is 17.8601 and 0.0005, respectively ($\approx$ 0.2% of optimized results).



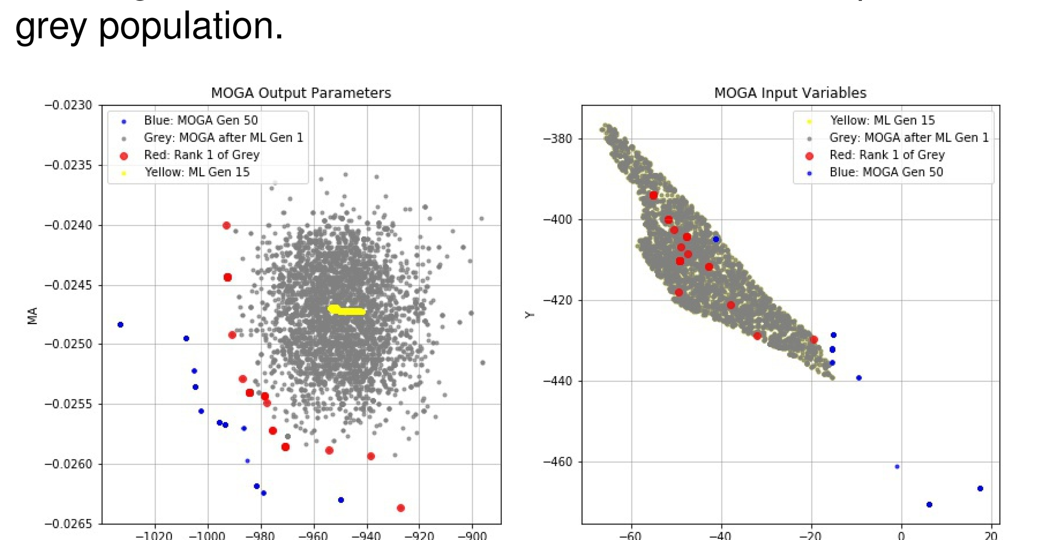
The correlation of actual values and predictions are linear with no big deviations. Once the training is complete, we replace the particle tracking part (using Tracy) in MOGA with the two machine learning models.

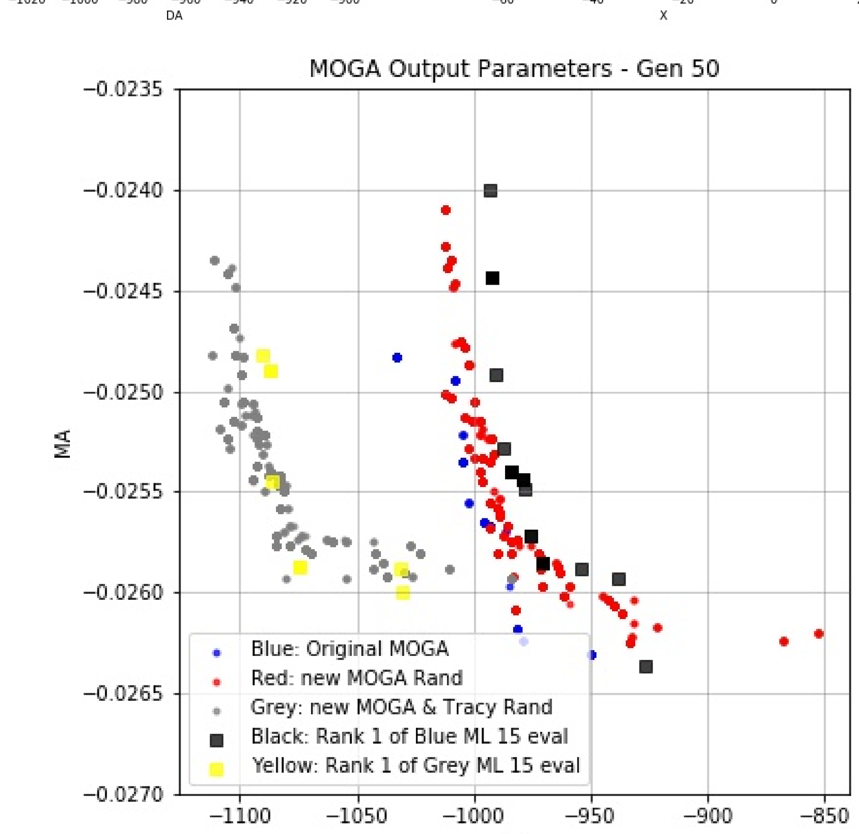
Figure below shows the MOGA with machine learning run from generation 1 to generation 15. The data quickly converged to the bottom left region.

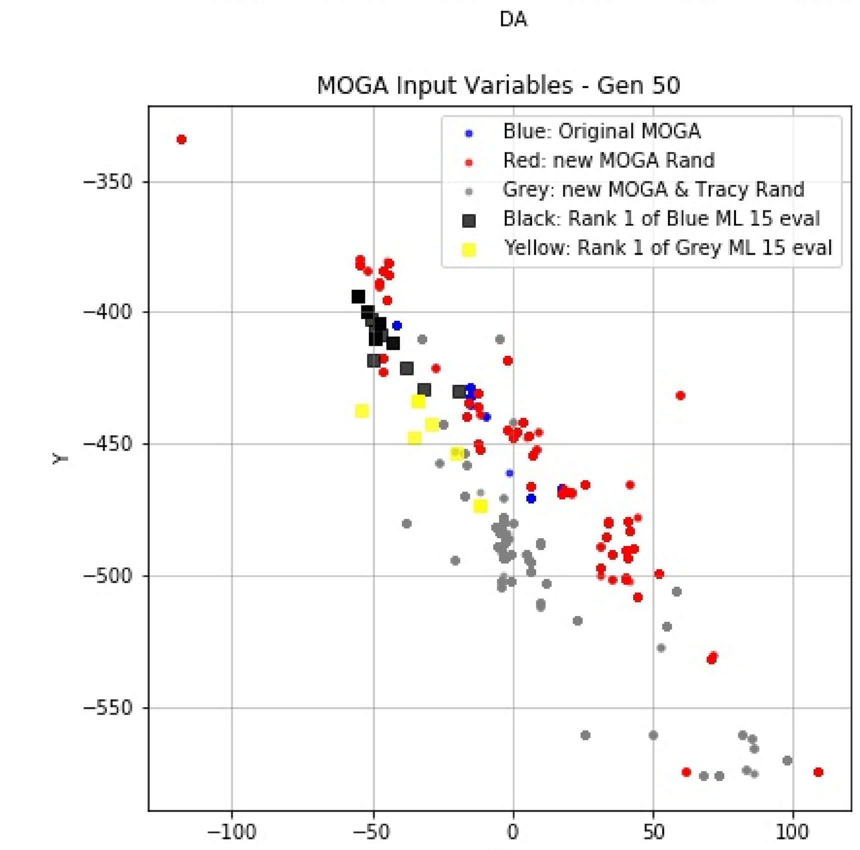


4. Machine Learning Results

The left figure compares the output parameters, and the right figure shows the input space. The blue dots are the Pareto front from original MOGA run at generation 50. The yellow dots are the final machine learning population at generation 15. MOGA with machine learning run takes fewer generations to converge. The grey dots are the evaluations of the machine learning Pareto front. The red dots are the rank-1 points of the grey population.







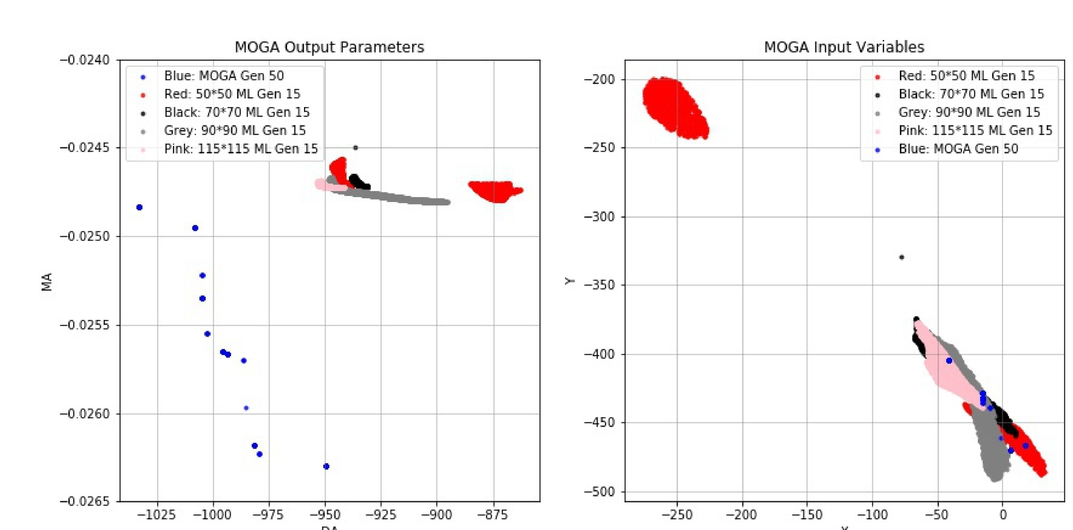
Our machine learning results are very close to the original MOGA results in both parameter space and input space. As random seeds are used in both Tracy and MOGA, we also tested the consistency of our machine learning pipeline with different MOGA settings. The figures above proved the robustness of our pipeline.

5. Smaller Sample Size

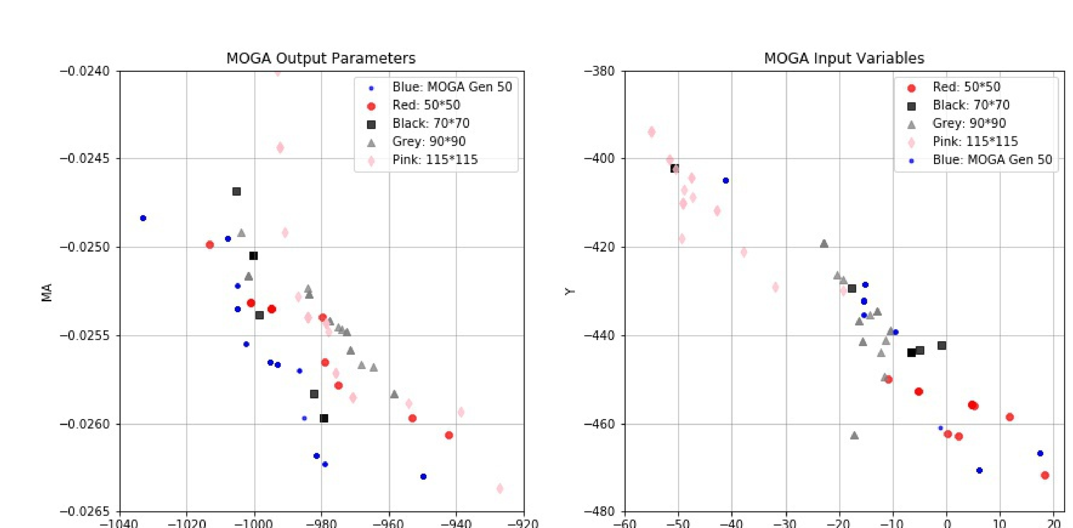
We also tested the effect of sample size on the accuracy of our pipeline. The table below shows the RMSE of dynamic aperture and momentum aperture with different sample size during the training process.

sample size	50 * 50	70 * 70	90 * 90	115 * 115
DA	1.91e+01	1.87e+01	1.88e+01	1.79e+01
MA	4.84e-04	4.69e-04	4.64e-04	4.53e-04

Even though the RMSE increased somewhat (<7%), small sample data still has a good prediction accuracy. The machine learning Pareto fronts are converged in the same region except 50*50 sample data.



The effect of sample size is even smaller by comparing the rank-1 points of evaluations of previous machine learning Pareto fronts. For our two nonlinear knobs problem, we can lower the sample size from 115 * 115 to 70 * 70 which contributes to the 25+ speedup.



6. Discussion

- We showed the application of machine learning on a two nonlinear knobs problem by replacing the Tracy part with two trained models.
- Our next step is to extend the pipeline to more complex problems with a higher expected speedup.

Acknowledgments

This research was funded by US Department of Energy (BES & ASCR Programs), and supported by the Director of the Office of Science of the US Department of Energy under Contract No. DEAC02-05H11231.

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