Rational approximations are essential for representing frequency-dependent phenomena in electromagnetic transients (EMT) simulations via the universal line model. The vector fitting (VF) algorithm for computing rational approximations is the current state of the art. We investigate using a multifunction variant of the AAA algorithm [1] to compute rational function approximations for EMT.

AAA approximation

Our variant of the AAA algorithm builds a rational approximation of a function \( f(x) \) in barycentric form from sample values \( f(z) \) by selecting support points \( \{ z_m \} \) and subsequently solving

\[
r_k(z) = \frac{\sum_{m=1}^{M} w_m f(z_m) z_k^{\frac{1}{2}}}{z_k - z_m}
\]

for the \( w = (w_1, w_2, ..., w_M) \) over \( \mathbb{Z}(z_m) \) in a least squares sense. Supports points are chosen greedily such that \( z_m \) maximizes \( \sum w_m z_k^{\frac{1}{2}} \). When \( z_k - r_k(z) \) is less than some desired tolerance, \( r_k(z) \) is output as rational approximations of \( f(z) \).

Example: Fitting entries of an admittance matrix

We test our approach by approximating six entries in an admittance matrix as a function of frequency. This example is used as a test case in the Vector Fitting handbook [2].

Introduction

- The mission of the Computational Science at NREL includes leading the lab's efforts to solve energy challenges using high-performance computing (HPC), computational science and applied mathematics.
- We provide a short overview of three areas of computational mathematics research at NREL: scenario generation for stochastic grid operations and planning, improved rational function approximations for electromagnetic transients codes, and wind farm yaw control using ADMM and reinforcement learning.

Rational Approximation for EMT Modelling

Two-stage stochastic programming and SAA

Our variant of the AAA algorithm builds a rational approximation of a function \( f(x) \) in barycentric form from sample values \( f(z) \), \( z \in \mathbb{C} \) by selecting support points \( \{ z_m \} \) in \( z \) and subsequently solving

\[
r_k(z) = \frac{\sum_{m=1}^{M} w_m f(z_m) z_k^{\frac{1}{2}}}{z_k - z_m}
\]

for the \( w = (w_1, w_2, ..., w_M) \) over \( \mathbb{Z}(z_m) \) in a least squares sense. Supports points are chosen greedily such that \( z_m \) maximizes \( \sum w_m z_k^{\frac{1}{2}} \). When \( z_k - r_k(z) \) is less than some desired tolerance, \( r_k(z) \) is output as rational approximations of \( f(z) \).

Scenario Generation for Economic Dispatch

Increasing penetrations of renewable energy sources, e.g. wind, into power grids motivates investigating new approaches to computing 5-minute economic dispatch. We investigate using importance sampling with analog scenarios in two-stage stochastic economic dispatch. Stochastic economic dispatch experiments on the RTS-GMLC network [2] were run for 200 unique timestamps in a simulated year. Six years of WIND Toolkit (WTK) [3] time series data were used as a source of analog scenarios, and 1 year of WTK data was used to simulate actuals.

Two-stage stochastic economic dispatch over varying dates and times

We test our approach by approximating six entries in an admittance matrix as a function of frequency. This example is used as a test case in the Vector Fitting handbook [2].

We provide a short overview of three areas of computational mathematics research at NREL: scenario generation for stochastic grid operations and planning, improved rational function approximations for electromagnetic transients codes, and wind farm yaw control using ADMM and reinforcement learning.

Two-stage stochastic economic dispatch over varying dates and times

Table X1: Episodic power production for 6 turbines, ADMM-RL learnt controller achieves comparable result but can be operated in real time.

<table>
<thead>
<tr>
<th>Power (MW)</th>
<th>Toris</th>
<th>φ</th>
<th>Δγ</th>
<th>RL</th>
<th>ADMM-RL</th>
</tr>
</thead>
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<tr>
<td>81.6</td>
<td>10.5</td>
<td>10</td>
<td>7.8</td>
<td>7.8</td>
<td>7.5</td>
</tr>
</tbody>
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References