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Title: Time Series Analysis

Author(s): James L. Carroll
Christ D. Tomkins

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Los Alamos NATIONAL LABORATORY
EST. 1943

Time Series Analysis

2011 BIE Users Group

James L. Carroll

Chris D. Tomkins

Abstract

- We use the S-BIE to perform a systematic study of time series analysis, using multiple noise regimes, and temporal degrees of freedom. Analyzing quality of the result obtained (and comparing that quality to that obtained with a static analysis). We are also interested in the optimization difficulty under the static and time series situations.

The Bayesian Inference Engine is:

- The Lab's primary toolkit for DARHT Radiography Analysis:

The BIE Consists of:

- A set of tools for radiographic forward modeling and parameter optimization
- A functional reactive graphic programming language for interfacing with those tools

Comparison

Graphical

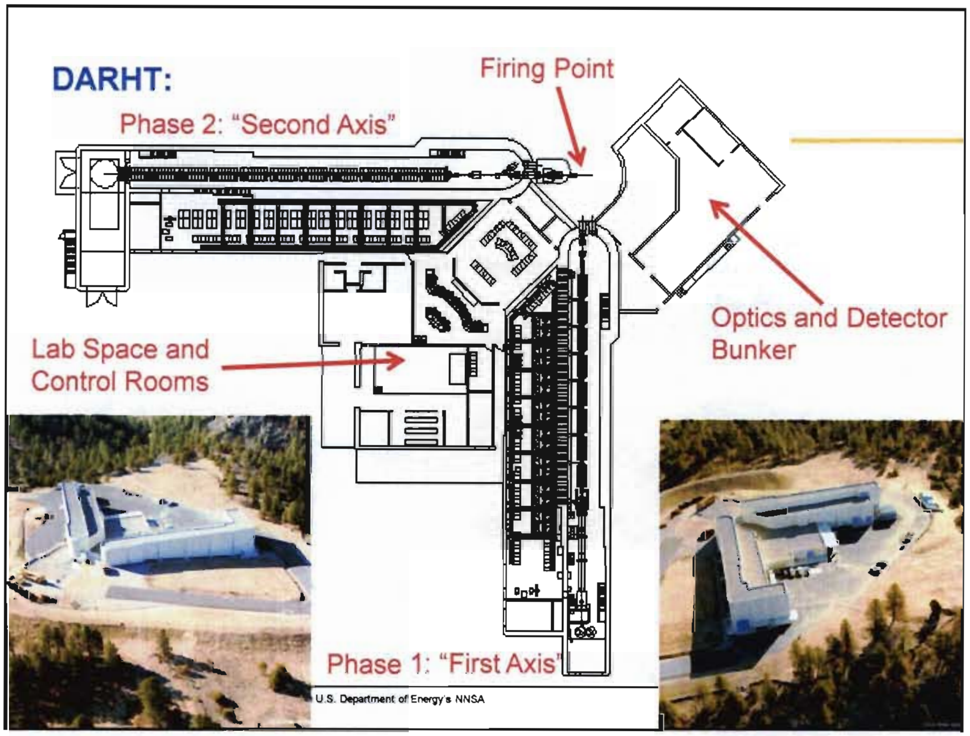
- Intuitive
- Interactive

Scripting

- Powerful
- Reproducible

Preliminary results and uses

- We have created a prototype scripting language (the S-BIE), and implemented several of the BIE's forward modeling tools within the new language.
- Scripting enables systematic studies
- We have applied this new scripting language to analyze several time series problems



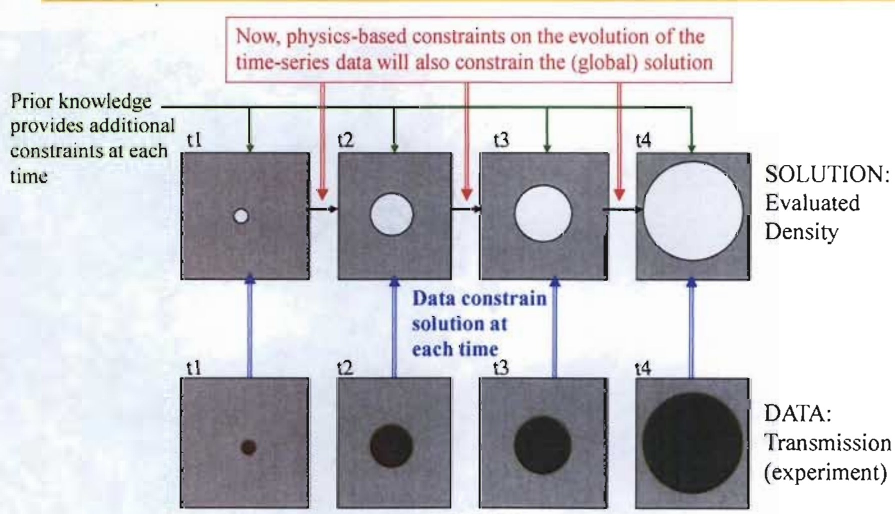
DARHT Axis 2 Accelerator

- 2-ms, 2-kA, 18.4-MeV electron beam
- for 4-pulse radiography.
- Linear Induction Accelerator with wound Metglass cores and Pulse Forming Networks (PFNs) .
- The Injector uses a MARX bank with 88 type E PFN stages at 3.2 MV.
- Thermionic cathode.
- 4 micropulses - variable pulse width.
- Operations began in 2008.

Time Series Analysis

- To date we have analyzed each element of DARHT axis 2 time series data independently
- But we should be able to use information in the time series to compensate for some of the noise, and get better results.

The forward-modeling framework makes possible a global optimization procedure



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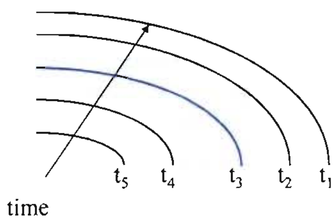
These physics-based constraints will maximize information extracted from each dataset

Consider an evolving interface:



Concept: Can we learn something about the solution at time 3 (blue) from the data at surrounding times?

Approach: use physics to constrain solution at each time based upon time-series of data.

WHEN WILL THIS APPROACH HAVE GREATEST VALUE?

When certain conditions are met:

Data must be correlated in time! → 1) Must have the time between measurements (Δt) on the order of a relevant time scale of the flow; and

Perfect data would be the only required constraint… (Noisier data means the global optimization adds more value). → 2) Must have non-perfect data (due to noise, background levels, etc).

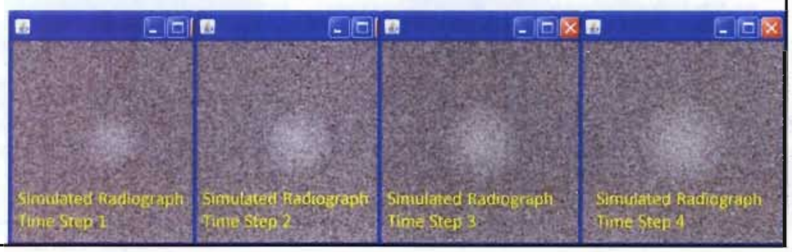
Example

- **Graded Polygon:**

S-BIE Simulated Expanding Object

- Object model:

- Simulated four time series radiographs:



Explore Relationships Between:

- Degrees of temporal freedom
- Noise
- Optimization Difficulty

Hypothesis 1:

- The complexity of the physics model (Degrees of temporal freedom)
  - Lower freedom provides more information from time series
  - Higher freedom provides less information from time series

Hypothesis 2:

- Noise
  - Lower noise provides more static information
  - Higher noise provides less static information

Hypothesis 3:

- Optimization Difficulty
  - Time series analysis can produce a more difficult optimization problem
  - The difficulty is related to the temporal degrees of freedom

How to Model Physics

- There are many ways to model the time series
  - Simplest time series case:
    - Matching a polynomial of degree n (perfect physics)
  - More complex case:
    - Penalize divergence from some presumed smooth motion through time (imperfect physics)
- We will begin our analysis with the simplest case

Radius Polynomials

- Degrees of Temporal Freedom:
  - 1: $r = knownConst + p_1 t$
  - 2: $r = p_0 + p_1 t$
  - 3: $r = p_0 + p_1 t + p_2 t^2$
  - 4: $r = p_0 + p_1 t + p_2 t^2 + p_3 t^3$

    ...
  - n: $r = p_0 + p_1 t + p_2 t^2 + p_3 t^3 + \ldots + p_{n-1} t^{n-1}$

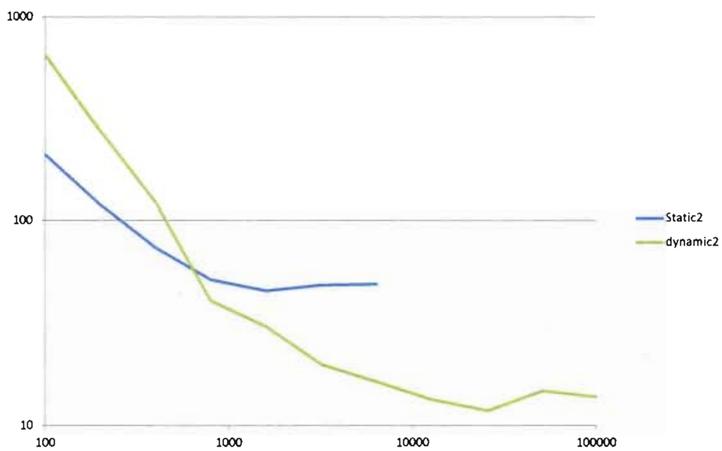
Signal to Noise

- Signal
  - 15 in center
  - 1 at edge
- Noise
  - Std deviations

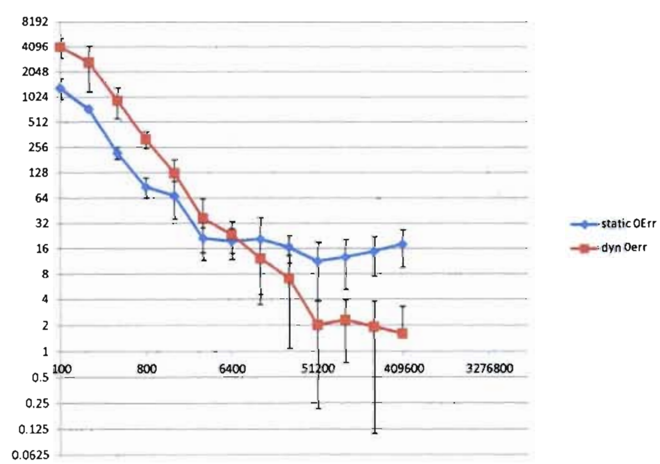
Results

1 Degree of Temporal Freedom

2 sdev noise



0 noise



1 Degree of Temporal Freedom

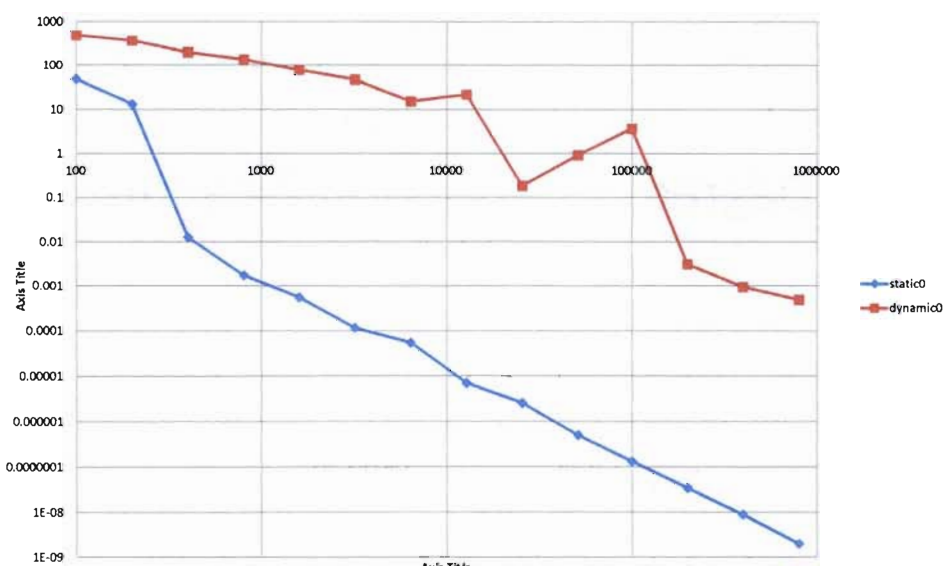
- Results
  - Time Series Analysis is best for all noise ranges considered
  - Time Series Analysis is slightly more difficult for the optimizer

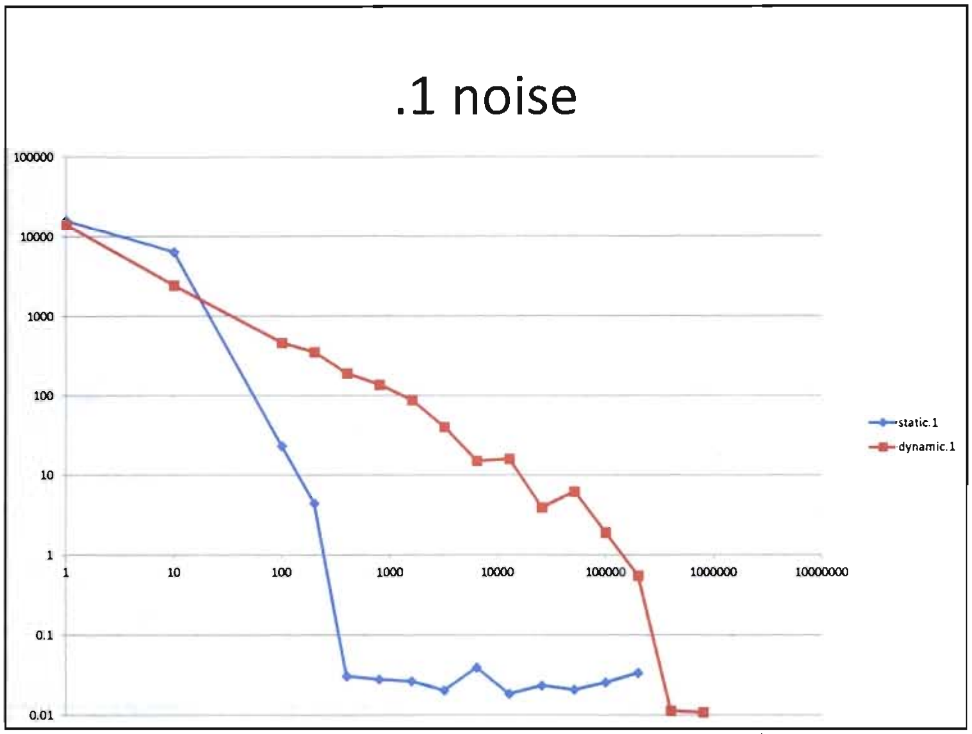
2 Degrees of Temporal Freedom

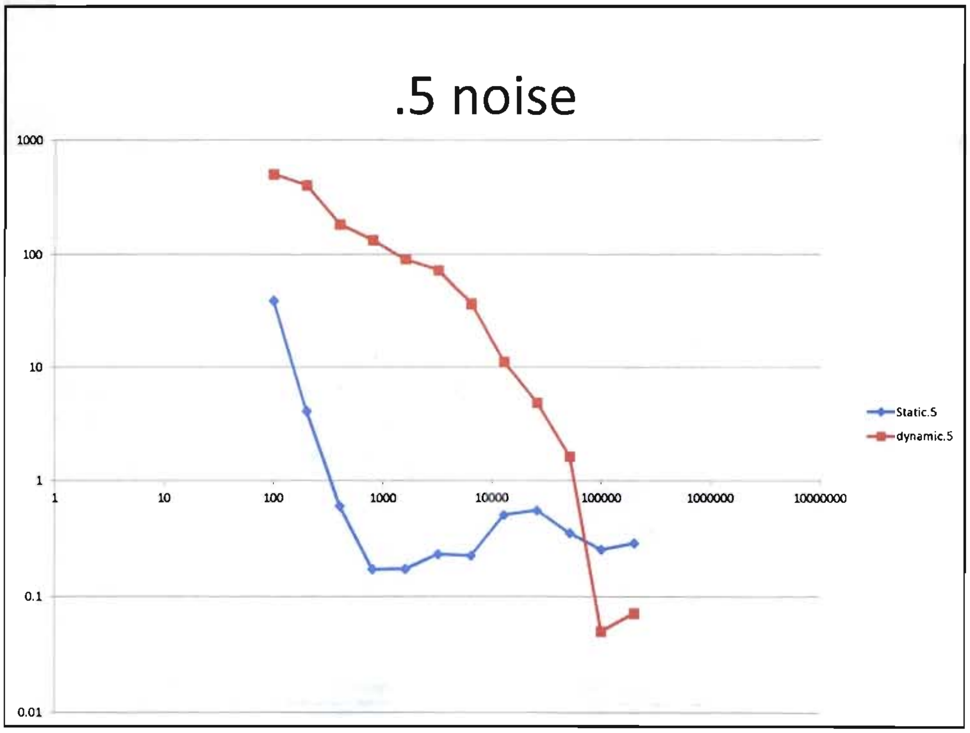
Prediction

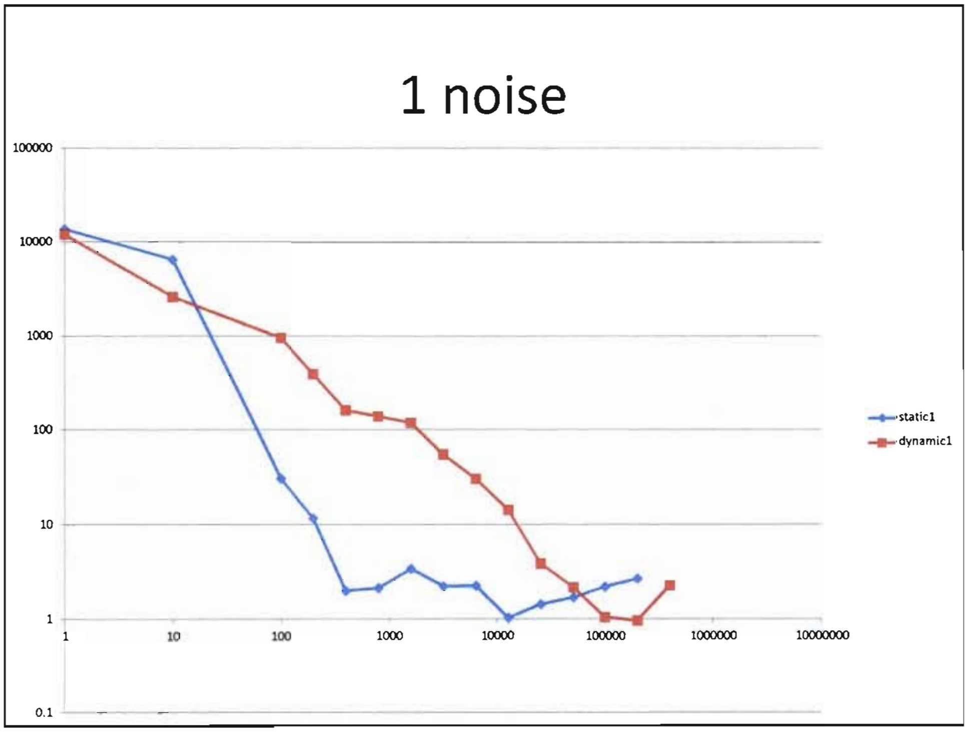
- Increased degrees of freedom will make the time series analysis more difficult

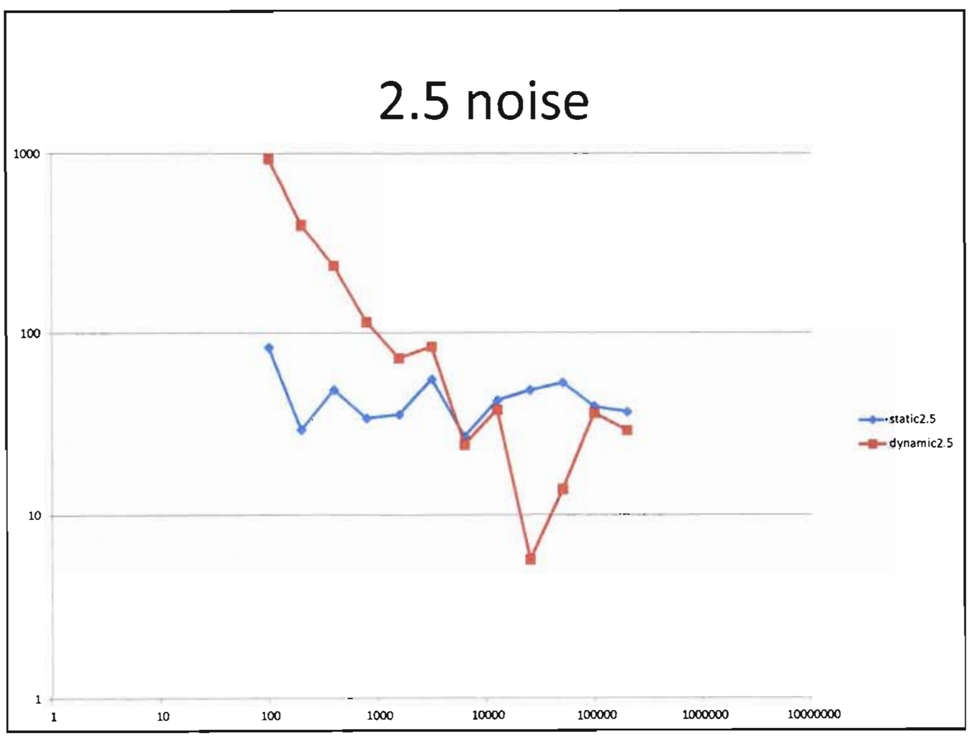
No noise

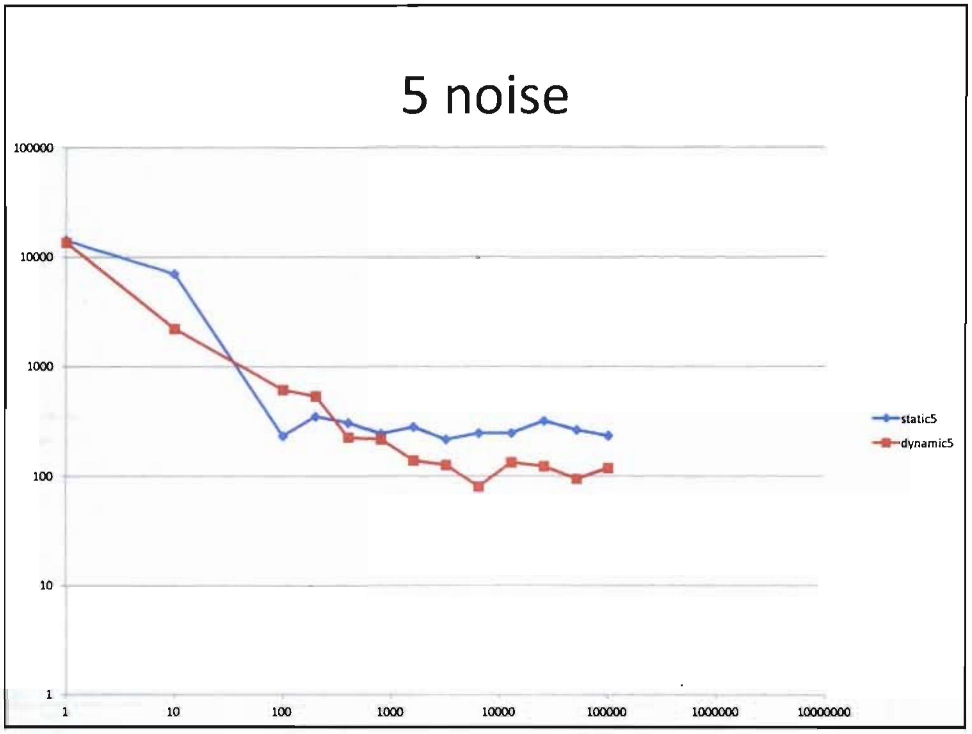


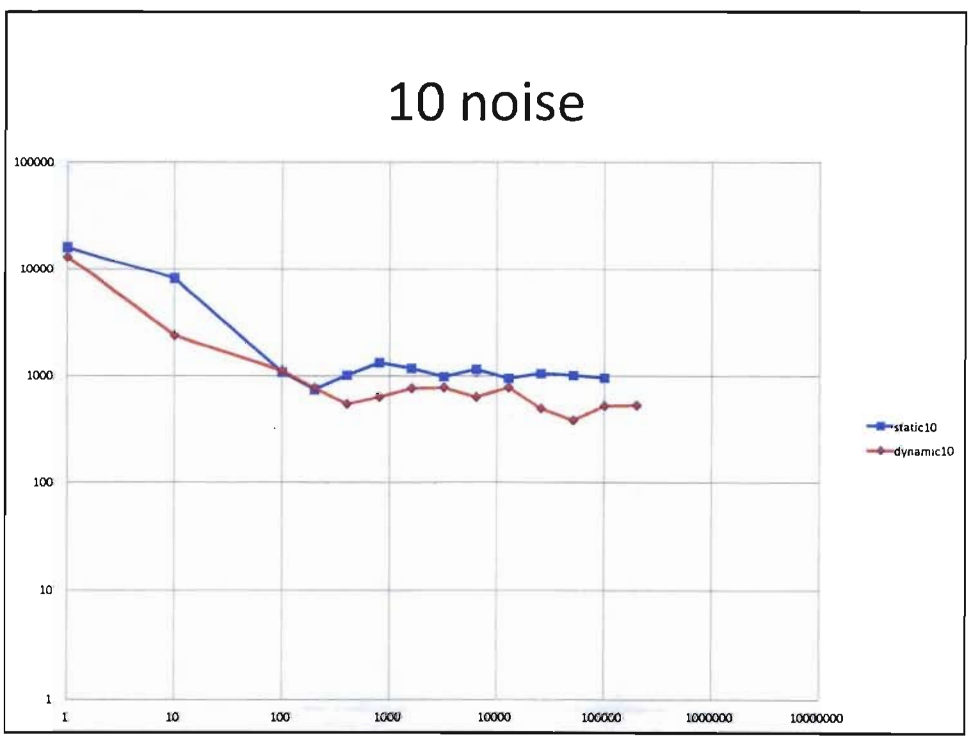

.1 noise
100000
10000
1000
100
10
1
0.1
0.01
1
10
100
1000
10000
100000
1000000
10000000
static.1
dynamic.1

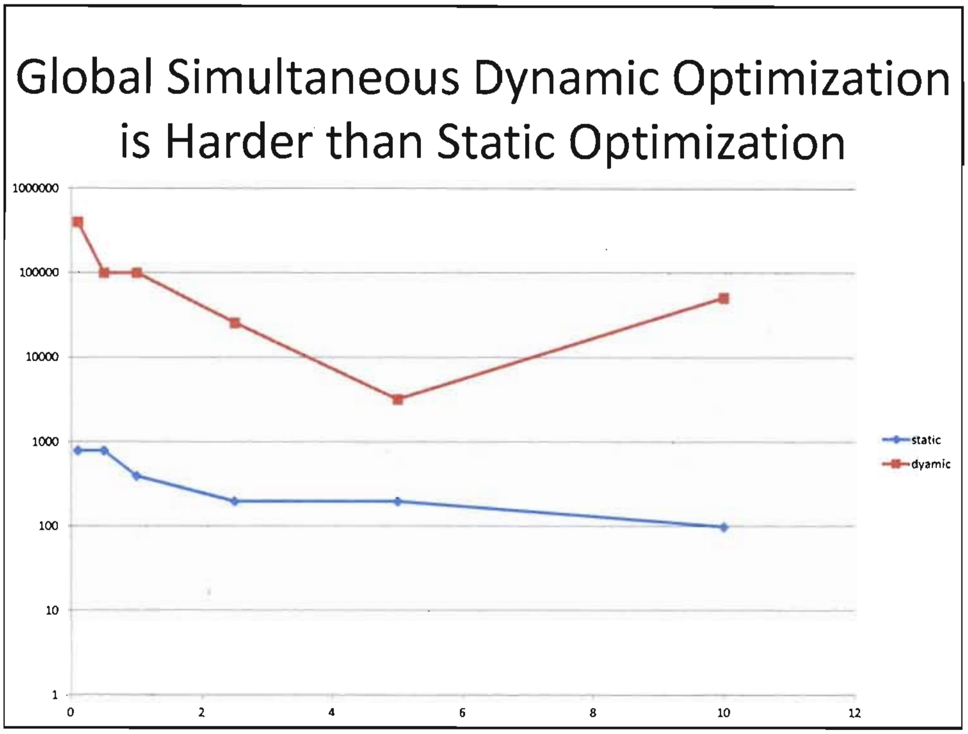

.5 noise
1000
100
10
1
0.1
0.01
1
10
100
1000
10000
100000
1000000
10000000
Static.5
dynamic.5

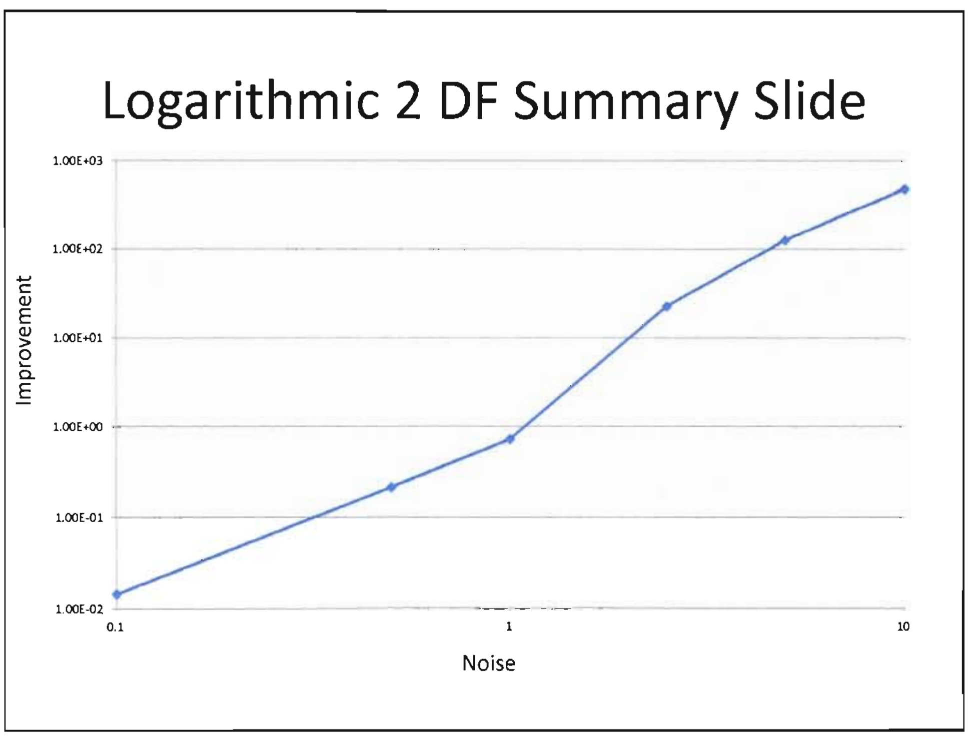

1 noise
100000
10000
1000
100
10
1
0.1
1
10
100
1000
10000
100000
1000000
10000000
static1
dynamic1


2.5 noise
1000
100
10
1
1
10
100
1000
10000
100000
1000000
10000000
static2.5
dynamic2.5

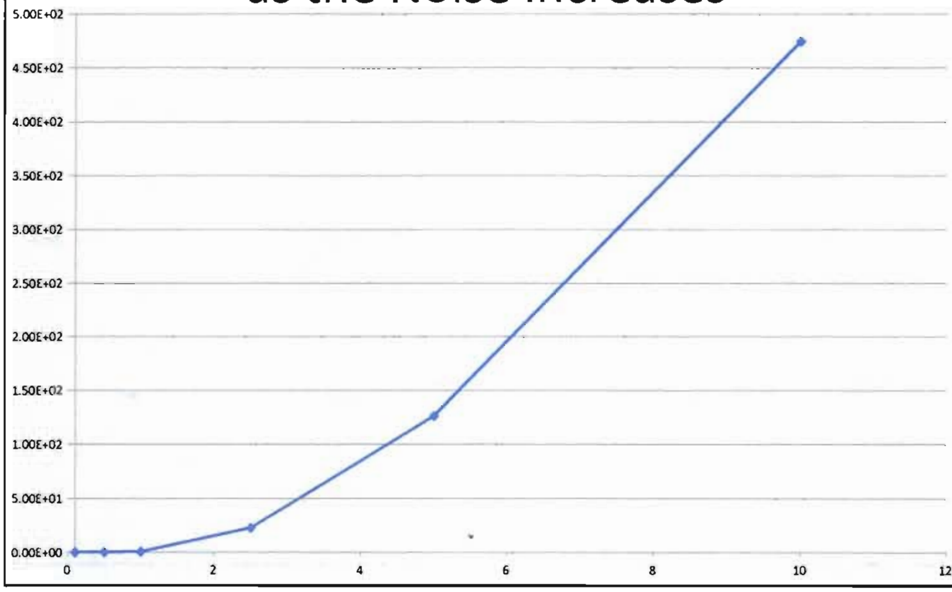

5 noise
100000
10000
1000
100
10
1
1
10
100
1000
10000
100000
1000000
10000000
static5
dynamic5


10 noise
100000
10000
1000
100
10
1
1
10
100
1000
10000
100000
1000000
10000000
static10
dynamic10

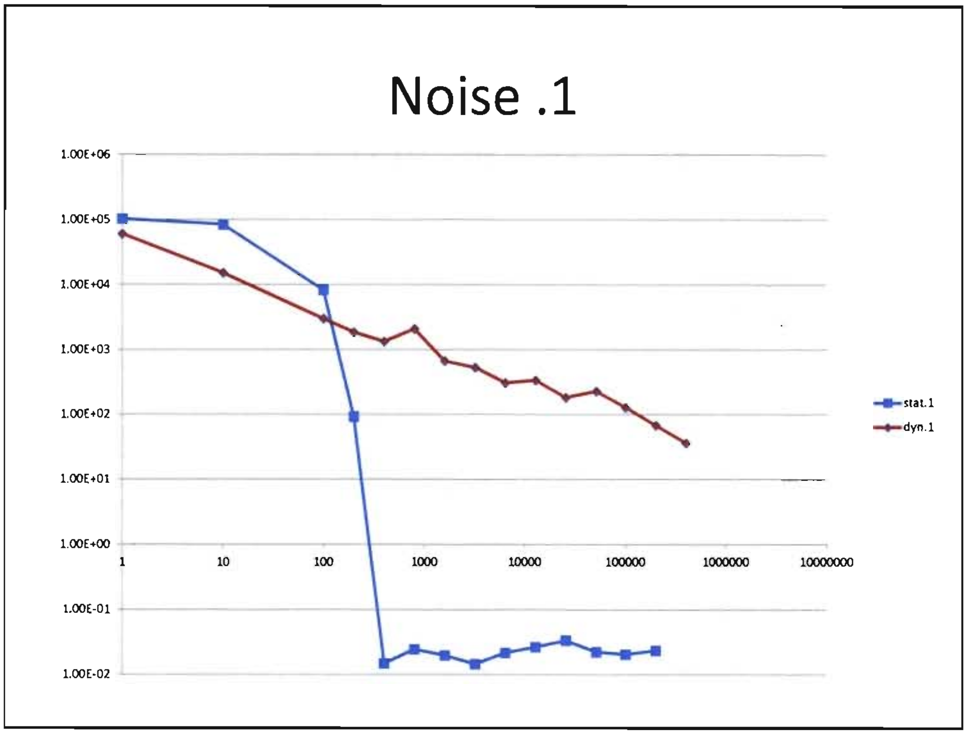

Global Simultaneous Dynamic Optimization is Harder than Static Optimization
1000000
100000
10000
1000
100
10
1
0
2
4
6
8
10
12
static
dyamic

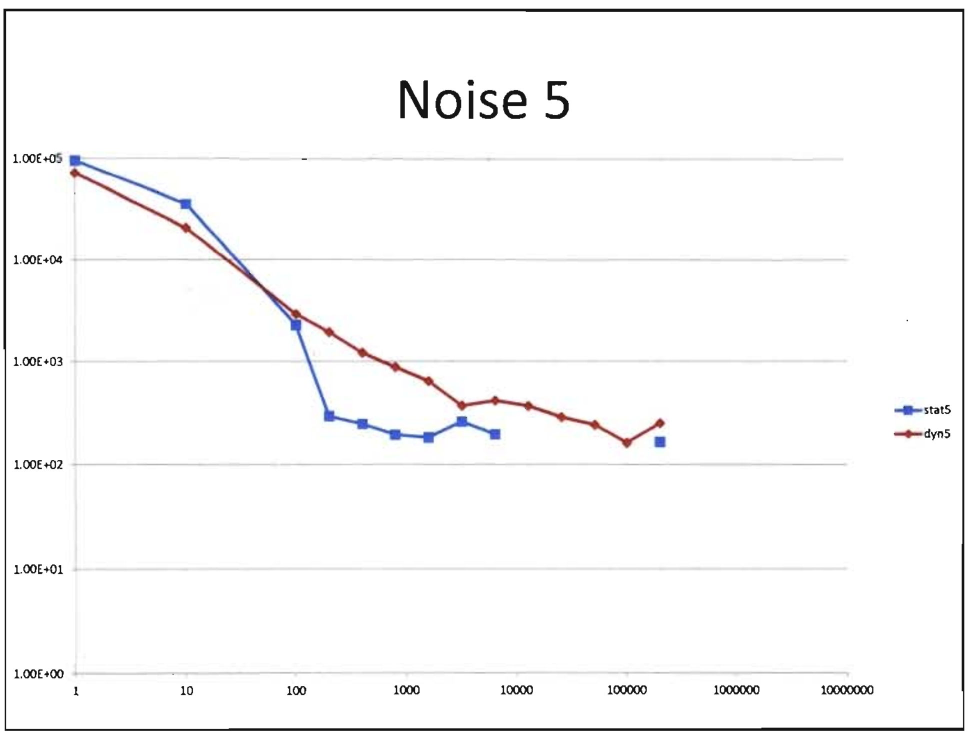

Logarithmic 2 DF Summary Slide
1.00E+03
1.00E+02
1.00E+01
1.00E+00
1.00E-01
1.00E-02
0.1
1
10
Improvement
Noise

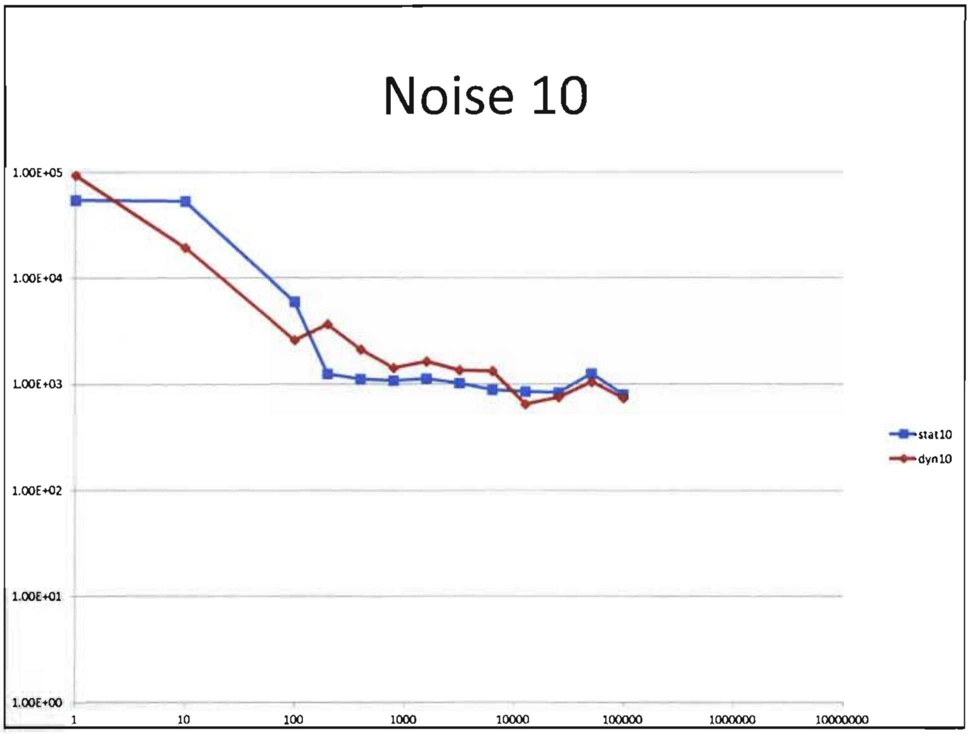
Benefit of Dynamic Analysis Increases as the Noise Increases

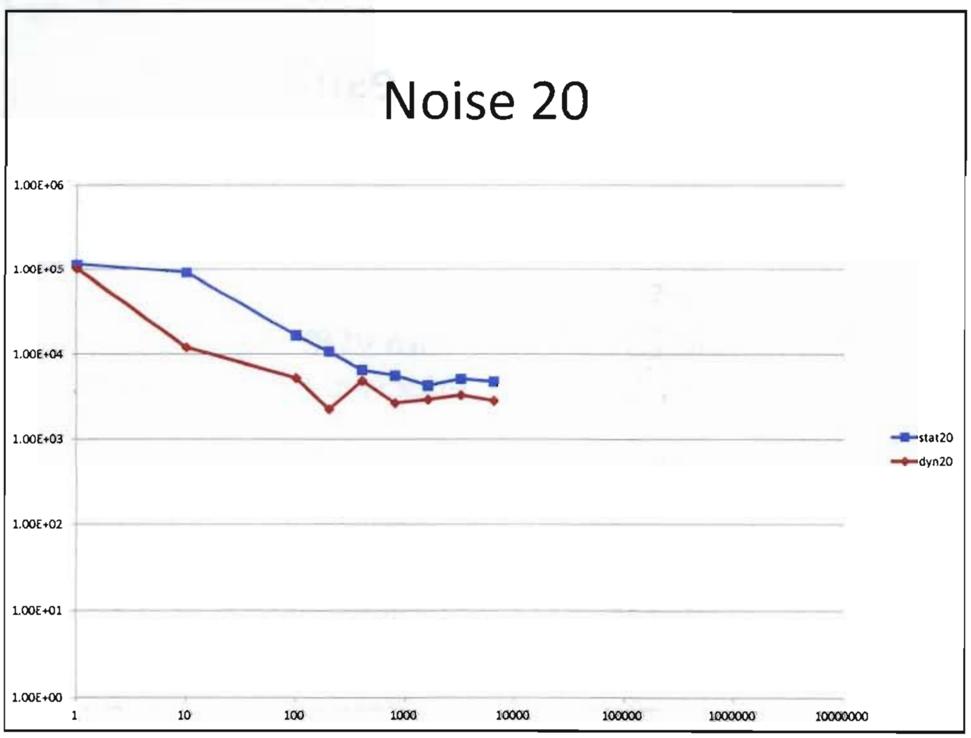


Three Degrees of Temporal Freedom.


Noise .1
1.00E+06
1.00E+05
1.00E+04
1.00E+03
1.00E+02
1.00E+01
1.00E+00
1.00E-01
1.00E-02
1
10
100
1000
10000
100000
1000000
10000000
stat.1
dyn.1


Noise 5
1.00E+05
1.00E+04
1.00E+03
1.00E+02
1.00E+01
1.00E+00
1
10
100
1000
10000
100000
1000000
10000000
stat5
dyn5


Noise 10
1.00E+05
1.00E+04
1.00E+03
1.00E+02
1.00E+01
1.00E+00
1
10
100
1000
10000
100000
1000000
10000000
stat10
dyn10


Noise 20
1.00E+06
1.00E+05
1.00E+04
1.00E+03
1.00E+02
1.00E+01
1.00E+00
1
10
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10000
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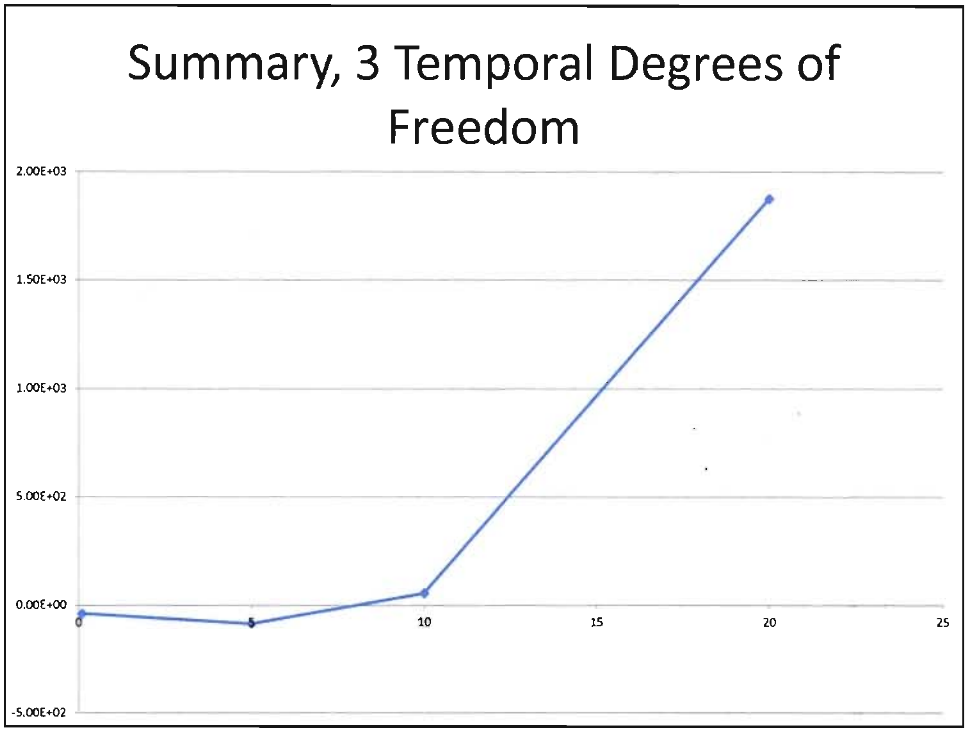
1000000
10000000
stat20
dyn20



Time Series Results

- 1DF: Simple TSA is always superior to static analysis
- 2DF: Simple TSA is almost always superior to static analysis.
- 3DF: Simple TSA is better with VERY high Signal to Noise Ratios, 1:10 at the edges, and 15:10 in the center.
  - Average SNR?
    - ≈7:10
- 4DF: Unknown…
  - Approaching an under/constrained problem

Time Series Results

- Time series analysis involves a far more difficult optimization problem than is present in static analysis.
- Interestingly enough, with lower noise levels the optimization problem is more "difficult" in the sense that it is possible to refine the answer to a greater degree
- When the optimization problem can be solved, time series analysis can outperform static analysis for some combinations of noise and temporal degrees of freedom.
- The number of optimization steps necessary before time series analysis outperforms static analysis depends on the noise and the temporal degrees of freedom.

Unanswered Time Series Questions

- There exists a level of temporal degrees of freedom where static analysis is always better (must be greater than 3, we need to try higher values)?
  - What happens when the time series polynomial is under constrained (more temporal degrees of freedom than there are observation time steps)
- Does that change if you move to a more complex form of time series analysis (away from simply matching a polynomial).

Conclusions

- The new scripting language (S-BIE) allowed for complex iterative algorithmic evaluation
  - The BIE's graphical interface was insufficient for this systematic study
- Time series analysis shows potential for real applications at DARHT
  - Improvement will depend on the noise level present in the data.
  - Improvement will depend on how tightly the physics can constrain the temporal motion of the object
  - Complex global optimization will likely require improvements in the BIE's function optimization algorithms

Future Work

- Scripting interface:
  - Incorporation of more of the BIE's tools into the new scripting language
  - Integrating the two interfaces together in one tool
- Time series analysis:
  - Explore higher temporal degrees of freedom
  - Analysis of more complex shapes
  - Implementation of more advanced function optimization routines
  - Exploration of other techniques for taking advantage of time series data besides fitting a polynomial.