

# A Second-Order Consistent Multilevel-Multifidelity Optimization Scheme

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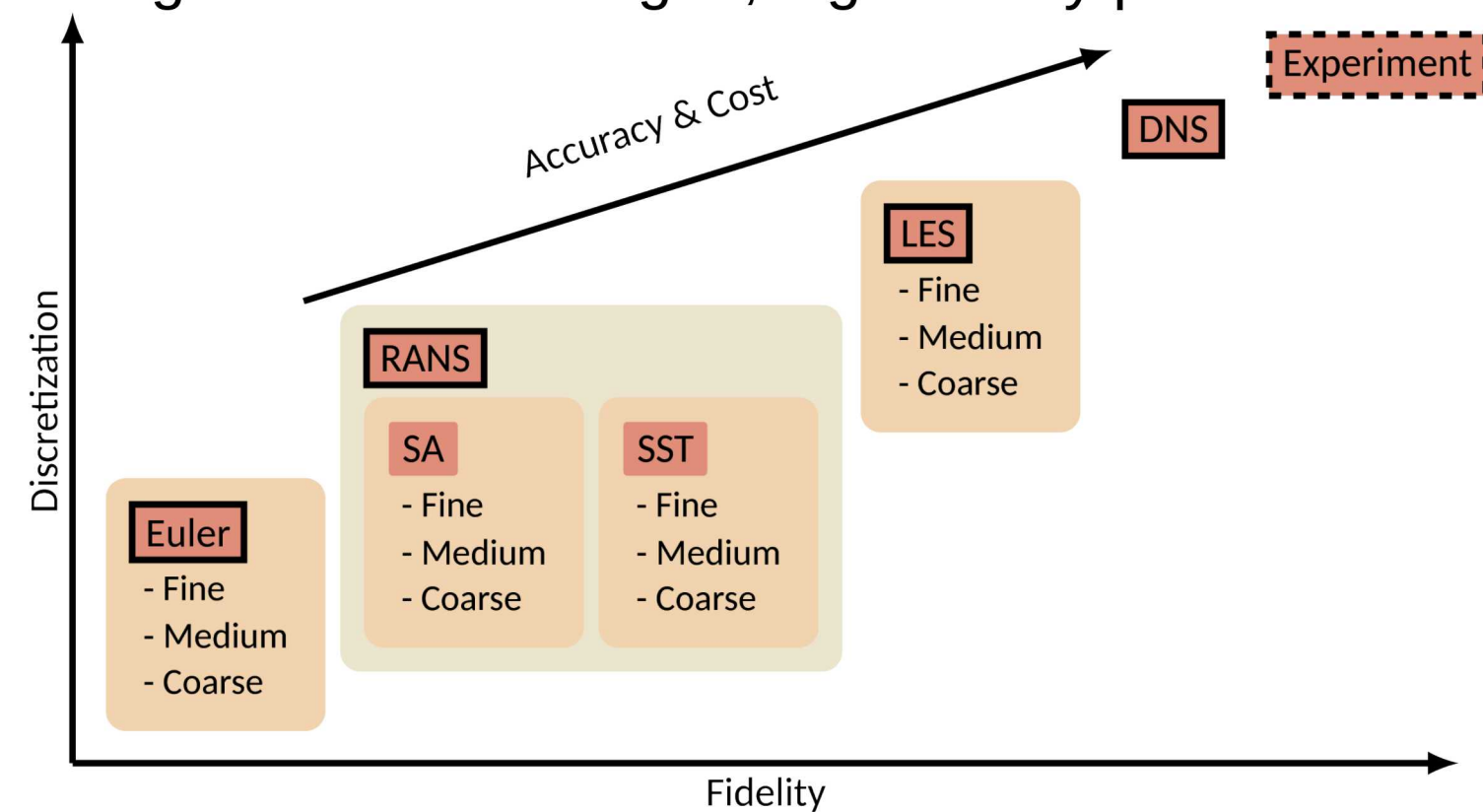
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## Background & Problem

Many engineering design problems can be formulated in the framework of partial differential equation (PDE) constrained optimization. Often there are multiple discretization levels and related model forms available.

### Research Question:

How do we exploit the lower cost of coarse-grid and reduced fidelity models to speed up convergence of the fine-grid, high-fidelity problem?



## Approach

There are numerous potential choices for navigating the hierarchy of discretization levels and model forms. This research attempts to take advantage of the close relationship between different discretizations of the same model.

**Algorithm 1** Multilevel-Multifidelity Optimization

```

procedure MLMFOPT
  ▷ Initialize optimization at a lower fidelity and/or level
  Partially solve:  $x_n^{(K,J)} = \arg \min_x f^{(K,J)}(x)$ 
   $x_{n+1} = \prod_{k=K-1}^1 P_{k,1} \prod_{j=J-1}^1 P_{K,j} x_n^{(K,J)}$ 
  repeat
     $x_n = x_{n+1}$ 
     $x_{n+1} = \text{MFOPT}(1, x_n, f^{(1,1)}(x))$ 
  until convergence
  return  $x_{n+1}$ 
end procedure

```

The approach builds off of the multigrid optimization ideas of Lewis & Nash [1]. Algorithm 1 is the outer optimization. Algorithms 2 & 3 are nested recursive algorithms and are very similar in structure to the Lewis & Nash multigrid method. At each fidelity level, Algorithm 3 takes advantage of multiple discretization levels to accelerate convergence at a single fidelity. Algorithm 2 uses the multilevel optimization to accelerate convergence to the highest fidelity.

**Algorithm 2** Multifidelity Optimization

```

procedure MFOPT( $k, x_0^{(k,1)}, f_{\text{corr}}^{(k,1)}(x)$ )
  if  $k \leq N_{\text{fid}}$  then
     $x_1^{(k,1)} = \text{MLOPT}(k, 1, x_0^{(k,1)}, f_{\text{corr}}^{(k,1)}(x))$ 
    return  $x_1^{(k,1)}$ 
  else
    Partially solve:  $x_1^{(k,1)} = \text{MLOPT}(k, 1, x_0^{(k,1)}, f_{\text{corr}}^{(k,1)}(x))$ 
     $x_1^{(k+1,1)} = R_{k,1} \left[ x_1^{(k,1)} \right]$ 
     $f_{\text{corr}}^{(k+1,1)}(x) = \text{CORRECTION}(x_1^{(k,1)}, R_{k,1}, f_{\text{corr}}^{(k,1)}(x), f^{(k+1,1)}(x))$ 
     $x_2^{(k+1,1)} = \text{MFOPT}(k+1, x_1^{(k+1,1)}, f_{\text{corr}}^{(k+1,1)}(x))$ 
     $e = P_{k,1} \left[ x_2^{(k+1,1)} - x_1^{(k+1,1)} \right]$ 
     $x_2^{(k,1)} = \text{LINESEARCH}(x_1^{(k,1)}, f_{\text{corr}}^{(k,1)}(x), e)$ 
    return  $x_2^{(k,1)}$ 
  end if
end procedure

```

**Algorithm 3** Multilevel Optimization

```

procedure MLOPT( $k, j, x_0^{(k,j)}, f_{\text{corr}}^{(k,j)}(x)$ )
  if  $j = N_{\text{level}}$  then
     $x_1^{(k,j)} = \arg \min_x f_{\text{corr}}^{(k,j)}(x)$ 
    return  $x_1^{(k,j)}$ 
  else
    Partially solve:  $x_1^{(k,j)} = \arg \min_x f_{\text{corr}}^{(k,j)}(x)$ 
     $x_1^{(k,j+1)} = R_{k,j} \left[ x_1^{(k,j)} \right]$ 
     $f_{\text{corr}}^{(k,j+1)}(x) = \text{CORRECTION}(x_1^{(k,j)}, R_{k,j}, f_{\text{corr}}^{(k,j)}(x), f^{(k,j+1)}(x))$ 
     $x_2^{(k,j+1)} = \text{MLOPT}(k, j+1, x_1^{(k,j+1)}, f_{\text{corr}}^{(k,j+1)}(x))$ 
     $e = P_{k,j} \left[ x_2^{(k,j+1)} - x_1^{(k,j+1)} \right]$ 
     $x_2^{(k,j)} = \text{LINESEARCH}(x_1^{(k,j)}, f_{\text{corr}}^{(k,j)}(x), e)$ 
    return  $x_2^{(k,j)}$ 
  end if
end procedure

```

Corrections are applied to the lower fidelity and coarser discretization models to make them up to 2<sup>nd</sup>-order consistent with the high-fidelity fine-grid model. This correction function is listed in Algorithm 4 and is based on Eldred et al. [2]

- 1<sup>st</sup>-order corrections guarantee that Algorithms 2 & 3 provide descent directions
- The linesearch in Algorithms 2 & 3 ensure provable convergence. The method reverts to the underlying optimization method at highest-fidelity and discretization if the sub-models are not informative.

**Algorithm 4** Apply up to 2<sup>nd</sup>-order corrections

```

procedure CORRECTION( $x_c, R, f_{\text{hi}}(x), f_{\text{lo}}(x)$ )
   $A_0, A_1, A_2, B_0, B_1, B_2 = 0$ 
  if  $\text{correction order} \geq 0$  then
     $A_0 = f_{\text{hi}}(x_c) - f_{\text{lo}}(R x_c), \quad B_0 = \frac{f_{\text{hi}}(x_c)}{f_{\text{lo}}(R x_c)}$ 
  end if
  if  $\text{correction order} \geq 1$  then
     $A_1 = R^T [\nabla f_{\text{hi}}(x_c)] - \nabla f_{\text{lo}}(R x_c), \quad B_1 = \frac{f_{\text{hi}}(x_c)}{f_{\text{lo}}(R x_c)} \nabla f_{\text{lo}}(R x_c)$ 
  end if
  if  $\text{correction order} \geq 2$  then
     $A_2 = R^T [\nabla^2 f_{\text{hi}}(x_c)] R^T - \nabla^2 f_{\text{lo}}(R x_c)$ 
     $B_2 = \frac{f_{\text{hi}}(x_c)}{f_{\text{lo}}(R x_c)} R^T [\nabla^2 f_{\text{hi}}(x_c)] R^T - \frac{f_{\text{hi}}(x_c)}{f_{\text{lo}}(R x_c)} \nabla^2 f_{\text{lo}}(R x_c) + \frac{2 f_{\text{hi}}(x_c)}{f_{\text{lo}}(R x_c)} \nabla f_{\text{lo}}(R x_c) \nabla f_{\text{lo}}^T(R x_c)$ 
     $- \frac{1}{f_{\text{lo}}^2(R x_c)} [\nabla f_{\text{lo}}(R x_c) (R \nabla f_{\text{hi}}(x_c))^T + R \nabla f_{\text{hi}}(x_c) \nabla f_{\text{lo}}^T(R x_c)]$ 
  end if
   $\alpha(\bar{x}) = A_0 + A_1^T (\bar{x} - R x_c) + \frac{1}{2} (\bar{x} - R x_c)^T A_2 (\bar{x} - R x_c)$ 
   $\beta(\bar{x}) = B_0 + B_1^T (\bar{x} - R x_c) + \frac{1}{2} (\bar{x} - R x_c)^T B_2 (\bar{x} - R x_c)$ 
  if additive correction then
     $\gamma = 1$ 
  else if multiplicative correction then
     $\gamma = 0$ 
  else if combined correction then
     $\gamma = \frac{f_{\text{hi}}(x_p) - f_{\text{lo}}(x_p) \beta(x_p)}{f_{\text{lo}}(x_p) + \alpha(x_p) - f_{\text{lo}}(x_p) \beta(x_p)}$ 
  end if
  return  $f(\bar{x}) = \gamma f_{\text{lo}}(\bar{x}) + \alpha(\bar{x}) + (1 - \gamma) f_{\text{lo}}(\bar{x}) \beta(\bar{x})$ 
end procedure

```

## Results

### 1D Diffusion Problem:

High-Fidelity:

$$\frac{d}{dx} \left( a \frac{du}{dx} \right) = -f, \quad x \in (0, 1)$$

$$u(0) = u(1) = 0$$

$$a = 2 + \cos(2\pi x) + 0.4 \sin(6\pi x)$$

Low-Fidelity:

$$\frac{d}{dx} \left( a \frac{du}{dx} \right) = -f, \quad x \in (0, 1)$$

$$u(0) = u(1) = 0$$

$$a = 2 + \cos(2\pi x)$$

Optimization Problem:

$$\text{minimize}_f \int (u(f) - u^*)^2 dx$$

$$\text{subject to } c(f, u(f)) = 0$$

$$u^* = \sin^2(2\pi x)$$

Discretization:

- 2<sup>nd</sup>-order finite differences
- Fine grid:  $N_1 = 100$
- Coarse grid:  $N_2 = 50$

Prolongation / Restriction:

- 2<sup>nd</sup>-degree Lagrange interpolation
- $R = cP^T$

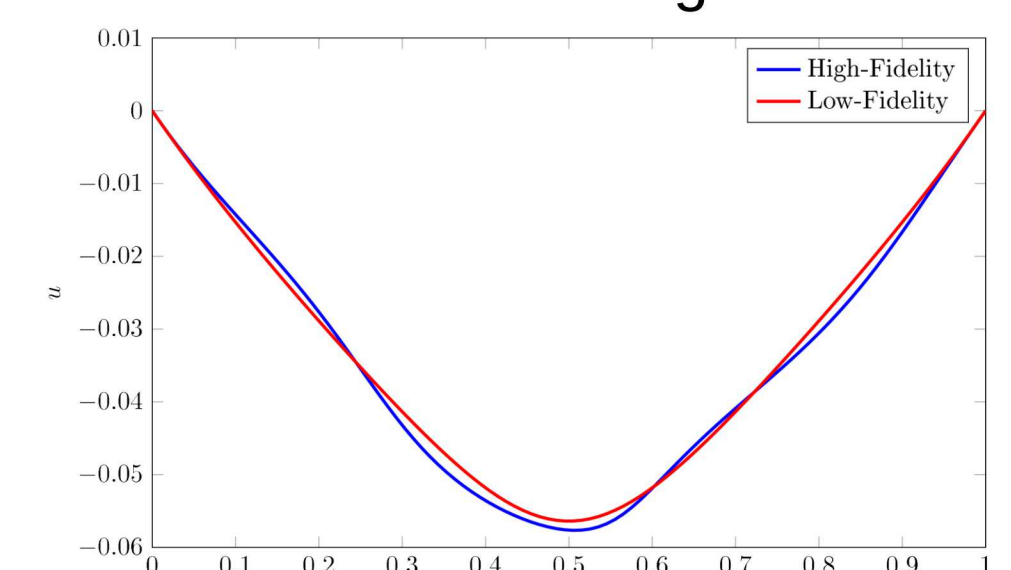
Number of function evaluations:

1 fidelity and 1 level		1 fidelity and 2 levels	
	Fine	Fine	Coarse
High-Fidelity	229	112	146

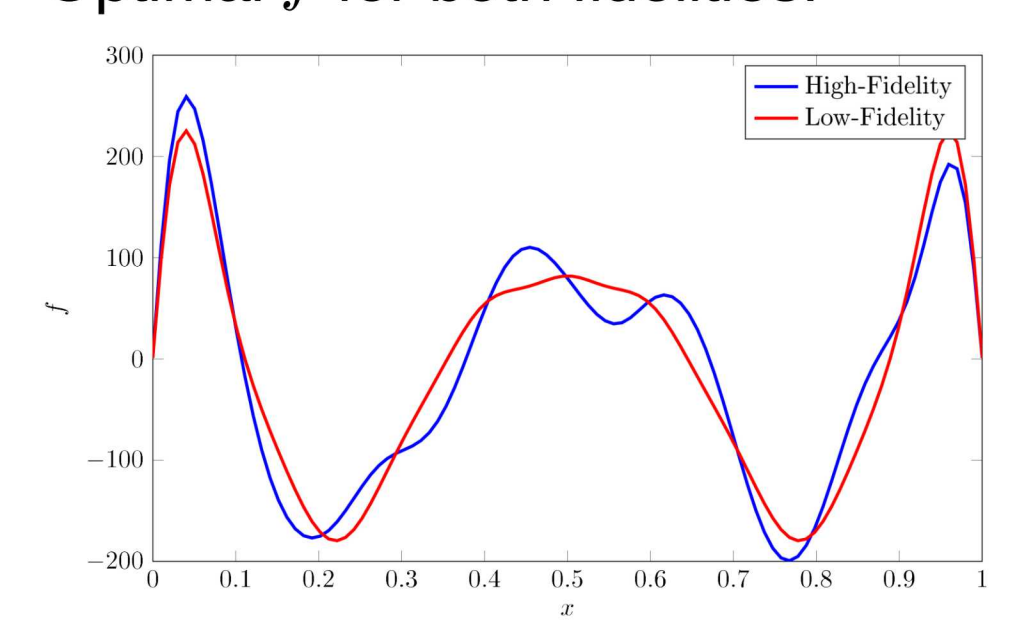
  

2 fidelities and 2 levels		Fine	Coarse
High-Fidelity	65	82	
Low-Fidelity	26	29	

ODE solution at initial guess:



Optimal  $f$  for both fidelities:



### Transonic Airfoil Problem: (Calculations performed using SU2)

Baseline airfoil: NACA 0012,  $M_\infty = 0.8$ ,  $AoA = 1^\circ$

Optimization problem:

( $x$  parameterizes 38 Hicks-Henne bump functions)

$$\text{minimize}_x C_D(u(x))$$

$$\text{subject to } c(x, u(x)) = 0$$

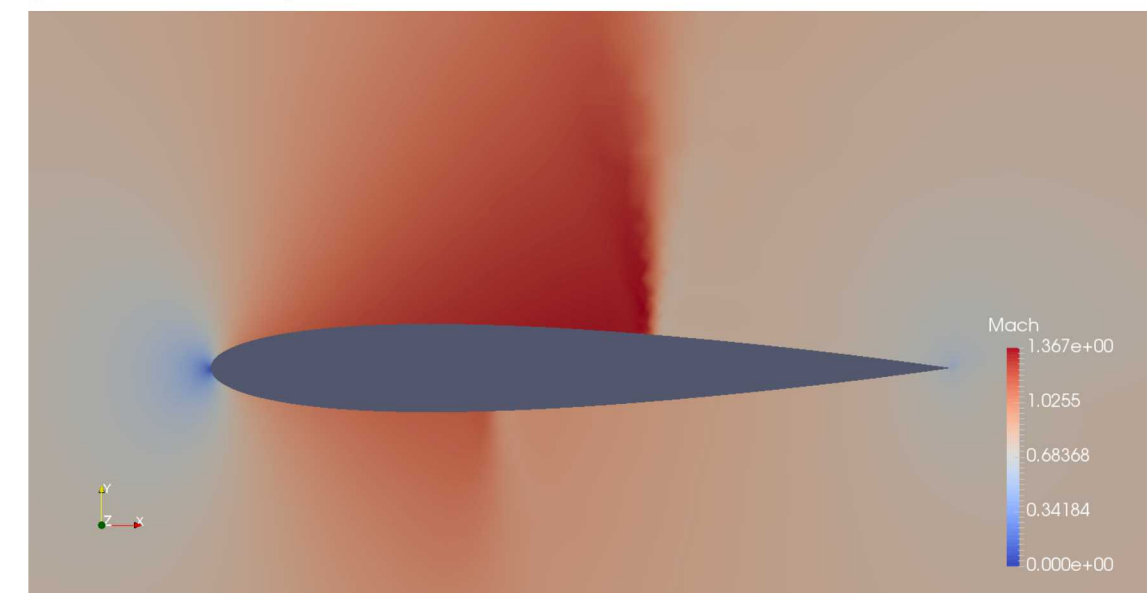
High-fidelity: RANS-SA

- Fine-grid: 319,859 cells (C-grid)
- Coarse-grid: 140,768 cells (C-grid)

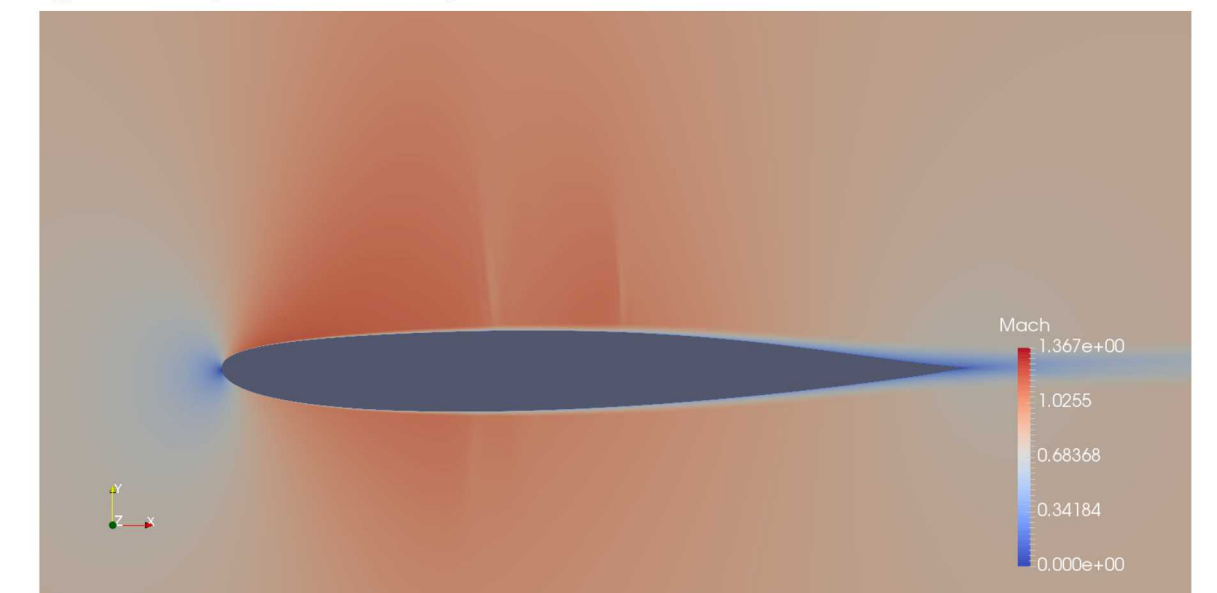
Low-fidelity: Euler

- Fine-grid: 32,626 cells (unstructured grid)
- Coarse-grid: 6,131 cells (unstructured grid)

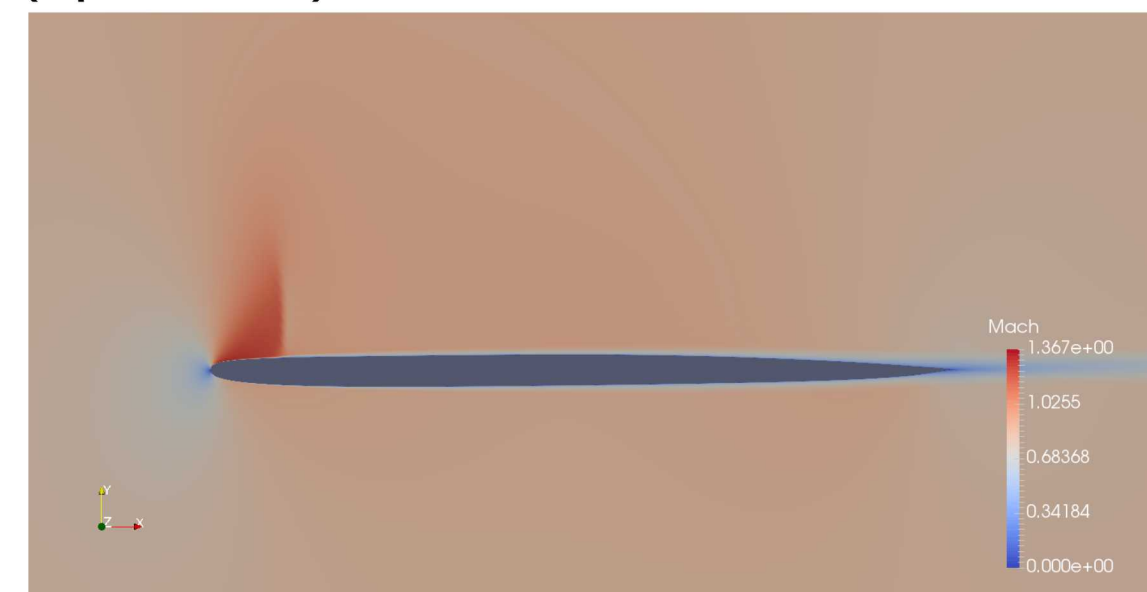
Euler, fine grid,  $C_D = 0.0168$   
(Baseline)



RANS-SA, coarse grid,  $C_D = 0.0127$   
(pre-optimized)



RANS-SA, coarse grid,  $C_D = 0.0111$   
(optimized)



Function evaluations		
	Fine	Coarse
High-Fidelity	-	11
Low-Fidelity	23	-

## Conclusions & Future Work

An up to second-order consistent multilevel-multifidelity optimization scheme was presented. This optimization scheme was applied to a 1D diffusion problem and transonic airfoil optimization. Both problems converged leveraging lower-fidelity and/or coarser discretization models.

Future work will compare trust regions to line searches and incorporate general constraints.

### References:

- Lewis, Robert Michael, and Stephen G. Nash. "Model problems for the multigrid optimization of systems governed by differential equations." SIAM Journal on Scientific Computing 26.6 (2005): 1811-1837.
- Eldred, M. S., et al. "Second-order corrections for surrogate-based optimization with model hierarchies." Proceedings of the 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Albany, NY, Aug. 2004.