

GA Optimisation of CFD Models and Meshes

Open Source CFD International Conference

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Remit; to advance methodology and application of CFD – particularly

- Turbulence (+ other physical modelling) + optimisation
- Biomedical (blood, lymph, IBM)
- Industrial – SUDS, packed beds, tidal turbines

Group consists of 3+2 PhD Students, 2 PDRA, 1 PGRA

Facilities : 64 core 256GB cluster; workroom with 4 high performance workstations. Also access to ALM, micro-CT facilities

Substantial investment in OpenFOAM; also Fluent, Pointwise.

GA Optimisation of Turbulence Models

PhD project (Bjoern Fabritius) to investigate optimisation of turbulence models.

Rationale :

- Turbulence models complex, typically include several parameters (standard $k - \epsilon$ contains 5)
- Parameters often taken to be universal constants – are they?
- Attempts made to provide justification for values; more often just parameter-fit to data.
- Fine tuning accepted for certain canonical flows (eg. circular impinging jet)

Application to turbulence modelling

Aim to explore parameter space for particular turbulence models + demonstrate optimisation process for complex physical model.

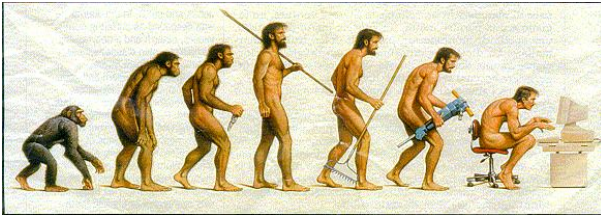
Questions to answer;

- Are the standard parameters optimal for particular canonical flow problems (eg. BFS)?
- What are the tradeoffs between parameters for different flow problems (multi-objective optimisation)?
- Could we create a complete new model from scratch?

Also apply to meshing issues.

Outline of talk

- 1 Basics of GA and integration with OF
- 2 Optimisation of turbulence models
- 3 Optimisation of meshing with `snappyHexMesh`
- 4 Future directions



What are GA's?

Genetic Algorithms – attempt to use Natural Selection techniques to “evolve” an optimal solution to a complex problem.

Methodology :

- ① Develop coding for parameters of project (a genome)
- ② Create a population of individuals with varying genomes
- ③ Evaluate fitness of individuals (run CFD code)
- ④ Eliminate “un-fit” individuals from gene pool
- ⑤ Create new population from retained individuals by
 - Exchanging genetic info (sex)
 - Random mutation
- ⑥ Repeat until convergence

Details

Various options possible (*artificial* process – not restricted)

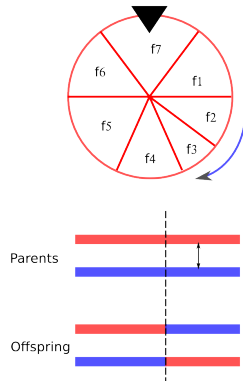
1 Selection

- roulette-wheel selection
- tournament selection
- best fitness selection

2 Cross-over (probability $P(C)$)

- single-point crossover
- multi-point crossover
- uniform crossover

3 Mutation (probability $P(M)$)



Coding

- Use Python and MPI as technological basis
- pyFoam framework :
 - CloneCase – generate new individual
 - ParsedParameterFile – change model coefficients, write RASProperties dictionary
 - BasicRunner – execute solver/sample results
- Parallel evaluation of fitness function possible
- Used the 'strategy' design pattern → selection, fitness function, crossover methods interchangeable
- Toolkit extended to multi-objective optimisation

Coding (cont)

Master node

```
identify all available nodes
create population
while not terminal cond.
    send individual to free node
    receive fitness
until all individuals are evaluated
population.evolve
```

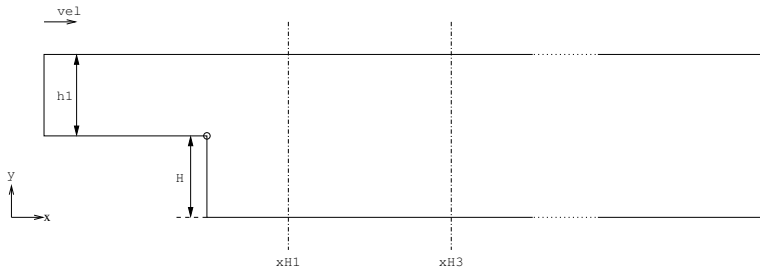
Slave nodes

```
receive individual
run solver / sample
compute fitness
send fitness to master
```

Run parameters can be controlled via gaDict
– model coefficients and limits can be specified

Typical results

Specific flow problems; backward facing step (Pitz-Daily case)



Model equations

Transport equations for k and ε

$$\frac{\partial(\rho k)}{\partial t} + \text{div}(\rho k u) = \text{div} \left[\frac{\mu_t}{\sigma_k} \text{grad } k \right] + 2\mu_t S_{ij} \cdot S_{ij} - \rho \varepsilon$$

$$\frac{\partial(\rho \varepsilon)}{\partial t} + \text{div}(\rho \varepsilon u) = \text{div} \left[\frac{\mu_t}{\sigma_\varepsilon} \text{grad } \varepsilon \right] + C_1 \frac{\varepsilon}{k} 2\mu_t S_{ij} \cdot S_{ij} - C_2 \rho \frac{\varepsilon^2}{k}$$

$$\mu_t = \rho C_\mu k^2 / \varepsilon$$

C_1, C_2 most significant parameters

Pitz-Daily Optimisation: $k - \epsilon$

- 50 individuals, 30 generations
- tournament selection, single point crossover
- $k-\epsilon$ model, $Re=64,000$
- simpleFoam on 10 cores, runtime approx. 2.5h

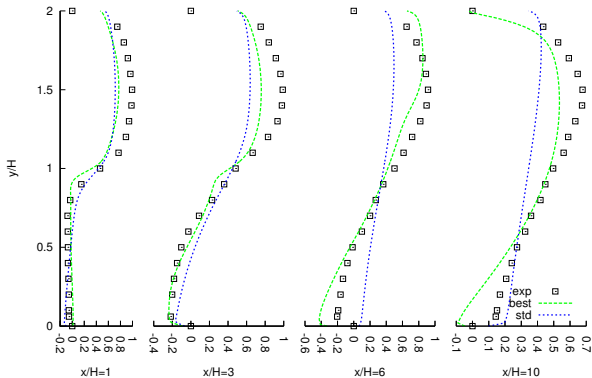
	C_1	C_2
Standard	1.44	1.92
Best Indiv.	1.91	1.86
$\Delta/\%$	32.6	-3.1

Pitz-Daily Optimisation: $k - \omega$

- GA setup as above
- $k-\omega$ model, $Re=64,000$
- simpleFoam on 10 cores, runtime approx. 3.0h

	γ_1	γ_2	β_1	β_2	β^*
Standard	0.553	0.440	0.075	0.083	0.09
Best Indiv.	0.606	0.510	0.053	0.076	0.095
$\Delta/\%$	9.5	15.9	-30.0	-8.4	5.5

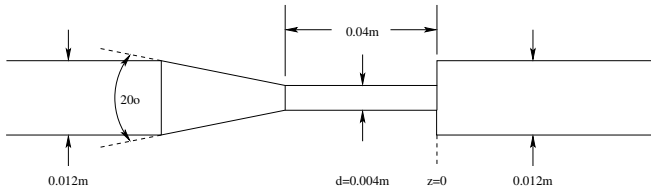
Pitz-Daily Optimisation: Velocity Profiles



$Re=64,000$; $k - \varepsilon$ model

FDA test case

Conical concentrator and sudden expansion

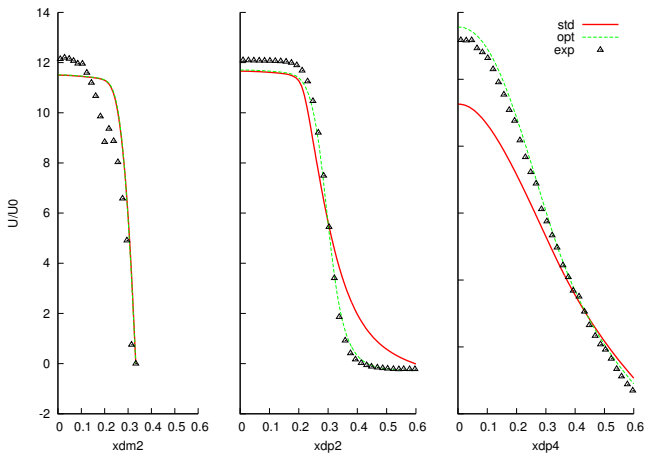


FDA test case – Spalart-Allmaras

- 50 individuals, 30 generations
- tournament selection, single point crossover, elitist
- Spalart-Allmaras model, $Re=5,000$ (throat)
- simpleFoam on 10 cores \Rightarrow runtime approx. 36h

	C_{b1}	C_{v1}	s	κ
Standard	0.1355	7.1	0.666	0.41
Best Indiv.	0.172	9.187	0.447	0.274
$\Delta/\%$	26.9	38.3	-32.9	-33.2

FDA test case



snappyHexMesh

OpenFOAM provides automated mesh generator `snappyHexMesh`. Its behaviour can be prescribed by setting parameters to control for example :

- total number of mesh cells
- thickness of boundary layers
- cell quality w.r.t.
 - cell skewness
 - mesh orthogonality
 - cell volume and face area

Finding the best setting for these parameters to create a high quality mesh is a good candidate for genetic optimisation.

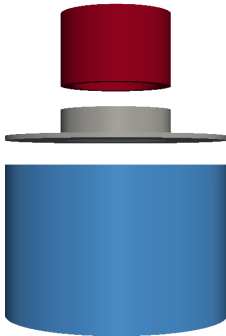
snappyHexMesh Functionality

snappyHexMesh algorithm takes these steps:

- create a base mesh that envelopes the target geometry completely
- load the geometry (STL format)
- castellate by identifying intersection between geometry and base mesh
- discard cells outside of target geometry
- snap boundary cells to target surfaces
- refine cells until requested quality is reached

snappyHexMesh Test Case

Bearing problem : 2 pipes + connector :



- small radii
- mesh inside the pipes
- round surfaces
- sharp corners

Optimisation Objectives

Aim of the optimisation was the minimisation of grid cells with a maximisation of cell quality. The result of this multi-objective problem is a trade-off between these two targets:

Quality Measure	target	bad individual	good individual
Skewness	low	3.759	1.372
Non-Orthogonality	low	86.2384	63.9662
Max aspect ratio	low	44.5033	37.1293
Grid size	low	42,574	60,972

(Higher fitness is highlighted.)

Results

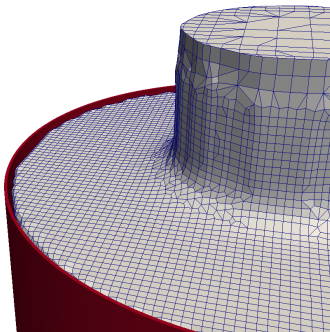


Figure: Bad Mesh Quality

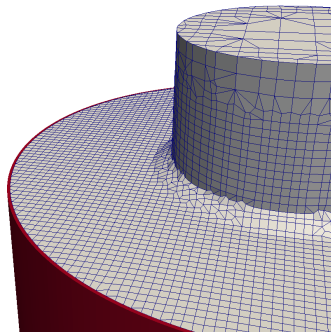


Figure: Optimised Mesh Quality

Conclusions

- We have developed a multi-objective GA framework for optimisation problems on top of OpenFOAM. OF provides excellent framework for these developments.
- Turbulence modelling can be considered a multi-parameter optimisation problem. Previously optimisation carried out 'by hand' – automated optimisation techniques preferable.
- Meshing can also be seen as multi-parameter optimisation process – have demonstrated potential here.

Future Work

- Multi-objective optimisation for turbulence models – examine tradeoffs between different canonical flows.
- Application to other canonical flows (have already examined impinging jet case).
- Application of meshing techniques to more complex cases (Ahmed body, concept car).
- GA optimisation of flow cases, automated surrogate modelling (recent blood flow project).

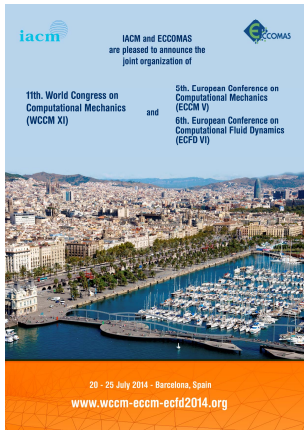
Acknowledgements

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“Use of Evolutionary Algorithms in the Analysis and Optimisation of Turbulence Models”, B.Fabritius, G.Tabor. *Seventh International Conference on Computational Fluid Dynamics (ICCFD7)* Hawaii (2012)

Submitted paper on GA optimisation of turbulence models to *Computers and Fluids*.

Shameless plug



IACM/ECCOMAS Conference
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Minisymposium: CCM with
OpenFOAMTM

Please Contribute!
(Abstract submission 29th Nov)