

Barcelona Supercomputing Center Centro Nacional de Supercomputación



Towards a framework to integrating CFD and ML in heterogeneous supercomputers

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09/01/2024

eFlows4HPC workshop: HPC Workflows for Scientific Applications logistics

## **1. CEEC project**

### Some context

CEEC focuses on engineering, aeronautic and atmospheric engineering topics such as shock- boundary layer interaction and buffet on wings at the edge of the flight envelope, high fidelity aeroelastic simulation, topology optimization of static mixers.





## **1. CEEC project**

### Some context

### **Description:**

This LHC consists of an aeroelastic simulation of an elastic wing model in the transonic regime. This is a benchmark case derived from the HIRENASD Project (<u>http://heinrich.lufmech.rwth-aachen.de/en</u>). The wing configuration and the geometry is typical from large passenger transport aircraft and its dynamic test flight conditions are also equivalent to real-in-service cruise flight conditions.

### **Challenges that are being addressed:**

- Application of current LES turbulence models for aeroelastic cases with compressive flows under transonic regimes.
- The numerical model should be able to run in HPC clusters to obtain enhanced performance with low timeto-solution.
- Ensure efficient coupling strategies between the Flow and Solid solvers.





## **1. CEEC project**





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Task 4.2: ML-based sub-models:

# Integrate ML models into the CFD workflow to accelerate physical models.



## 2. Our CFD approach

### SOD2D

### • The result so far:

- Language: Fortran
- GPU port path: **OpenACC**
- Required libs: HDF5, MPI
- Git repo: <a href="https://gitlab.com/bsc\_sod2d/sod2d\_gitlab/">https://gitlab.com/bsc\_sod2d/sod2d\_gitlab/</a>
- ... and btw, the code is **3D!**

• • •	BSC_SOD2D > 🍈 sod2d_gitlab		
D 6     \$\$ 12     ⊡ 67       Q Search or go to       oject     Type 7 to search	sod2d_gitlab ⊕         Project ID: 34192512 ⊕         Leave project         ~ 1,198 Commits          11 Tag □         475.4	3 MiB Project Storage	△ ~ ★ Unstar 12 ♥ Forks 0
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Monitor >	🗅 external	Updated cmake structure.	9 months ago
Analyze >	Ê⊐ src	Fixed two bugs when using walls and GPUs:	17 hours ago
3 Settings >	tool_commsPerformance	Clean on mod_comms mod_hdf5 mod_mpi_mesh	3 months ago
	🖹 tooLmeshConversorPar	small fixes before merge	4 weeks ago
	🗅 unitt	changed unit test for HEX64 to use variiable preci	1 year ago
Help	🗅 utils	Some cleaning and small improvements in gmsh2	4 months ago

### **SOD2D**: Spectral high-Order coDe 2 solve partial Differential equations



## **2. Physical model**

• The compressible Navier-Stokes equations on a domain  $\Omega \times (t_0, t_f)$ :

$$\partial_t \rho + \nabla \cdot (\rho \mathbf{u}) = 0$$
  
$$\partial_t (\rho \mathbf{u}) + \nabla \cdot (\rho \mathbf{u} \otimes \mathbf{u}) + \nabla p - \nabla \cdot \boldsymbol{\tau} = \mathbf{f}$$
  
$$\partial_t E + \nabla \cdot ((E + p)\mathbf{u}) - \nabla \cdot (\boldsymbol{\tau}\mathbf{u}) - \nabla \cdot (\kappa \nabla T) = \mathbf{S}$$
  
$$\boldsymbol{\tau} = \tau_{ij} = \mu(T) \left( (\nabla \mathbf{u} + (\nabla \mathbf{u})^T) - \frac{2}{3} \nabla \cdot \mathbf{u}I \right)$$



## **2. Physical model**

• Viscosity is calculated by means of Sutherland model:

$$\mu(T) = 1.458e^{-6} \frac{T^{1.5}}{T + 110.4}$$

• Additional required relations to close the system:

$$E = \rho \left[ \frac{1}{2} (\mathbf{u} \cdot \mathbf{u}) + e \right] \qquad e = \frac{p}{\rho(\gamma - 1)}$$
$$p = \rho RT \qquad R = C_p - C_v \qquad \gamma = \frac{C_p}{C_v}$$



## **2. Physical model**

By spatially filtering the NS equations:

$$\frac{\partial \overline{u}_i}{\partial t} = 0$$
$$\frac{\partial \overline{u}_i}{\partial t} + \frac{\partial \overline{u}_i \overline{u}_j}{\partial x_j} - \nu \frac{\partial^2 \overline{u}_i}{\partial x_j \partial x_j} + \rho^{-1} \frac{\partial \overline{p}}{\partial x_i} - F_i = -\frac{\partial \mathcal{T}_{ij}}{\partial x_j}$$
$$\mathcal{T}_{ij} - \frac{1}{3} \mathcal{T}_{kk} \delta_{ij} = -2\nu_{sgs} \overline{\mathcal{S}}_{ij}$$

- Smagorinsky
- Dynamic Smagorinsky
- •Wall-Adapting Local Eddy-Viscosity (WALE) Model
- •Vreman:





- $lpha_{ij} = oldsymbol{S} = S_{ij}$
- $\beta_{ij} = \Delta_m^2 \alpha_{mi} \alpha_{mj}$
- $B_{\beta} = \beta_{11}\beta_{22} \beta_{12}^2 + \beta_{11}\beta_{33}$  $-\beta_{13}^2 + \beta_{22}\beta_{33} \beta_{23}^2$

### Specific challenges:

- Numerics interact with the LES model
- •Usually the mesh is the filter
- •Scales at the wall are case dependent
- More sensible to geometry and boundaries

- Spectral formulation of the Continuous Galerkin Finite Elements model (SEM) applied to the spatial terms in the Navier-Stokes equations.
- The Lobatto-Gauss-Legendre (LGL) quadrature is used in the developed algorithm. (nodes are non-equispaced, avoiding the Runge effect on high-order interpolations)
  - The quadrature points coincide with the element nodes (*closed rule integration*) → This can lead to *aliasing effects* due to the reduced order integration of closed rule quadrature.
  - The **skew-symmetric convective operator split** detailed by Kennedy et al. [1] is employed, which **counters undesired** *aliasing* effects.





[1] C. A. Kennedy and A. Gruber, "Reduced aliasing formulations of the convective terms within the Navier-Stokes equations for a compressible fluid", Journal of Computational Physics, vol. 227, no. 3, pp. 1676–1700, 2008.

### compressible flow

• We split the convective terms of momentum using the cubic kinetic energy preserving splitting:

(Cubic split) 
$$\frac{1}{4} \left( \frac{\partial abc}{\partial x} + a \frac{\partial bc}{\partial x} + b \frac{\partial ac}{\partial x} + c \frac{\partial ab}{\partial x} + bc \frac{\partial a}{\partial x} + ac \frac{\partial b}{\partial x} + ab \frac{\partial c}{\partial x} \right)$$

• We split the convective terms of mass using the quadratic splitting:

(Quadratic split) 
$$\frac{1}{2}\left(\frac{\partial ab}{\partial x} + a\frac{\partial b}{\partial x} + b\frac{\partial a}{\partial x}\right)$$

• In the case of the energy equation, we do the following modification:

and

$$\frac{\partial E}{\partial t} + \frac{\partial (E+p)u_j}{\partial x_j} = \frac{\partial E}{\partial t} + \frac{\partial \rho u_j (h + \frac{u_i u_i}{2})}{\partial x_j}$$
then we apply cubic split to the  $\frac{\partial \rho u_j \frac{u_i u_i}{2}}{\partial x_j}$  and  $\frac{\partial \rho u_j h}{\partial x_j}$  independently.

Yuichi Kuya, Kosuke Totani, Soshi Kawai, Kinetic energy and entropy preserving schemes for compressible flows by split convective forms, Journal of Computational Physics, Volume 375, 2018, Pages 823-853, ISSN 0021-9991,

compressible flow

• Stabilisation using entropy viscosity concepts:



Jean-Luc Guermond, Richard Pasquetti, Bojan Popov, Entropy viscosity method for nonlinear conservation laws, Journal of Computational Physics, Volume 230, Issue 11, 2011, Pages 4248-4267

compressible flow

• Time integration using Runge-Kutta:

$$\boldsymbol{\phi}^{\nu+1} = \boldsymbol{\phi}^n + \alpha_{\nu} \Delta t M^{-1} \mathbf{R}^{\nu},$$
$$\mathbf{R}^{\nu+1} = \mathbf{R} \left( \boldsymbol{\phi}^{\nu+1} \right)$$

$$\boldsymbol{\phi}^{n+1} = \boldsymbol{\phi}^n + \Delta t \sum_{\nu=0}^3 \beta_{\nu} \mathbf{R}^{\nu}$$

4th order RK tableu				
Coeff.	$ u_0 $	$ u_1 $	$ u_2 $	$ u_3$
$\alpha_{\nu}$	0	1/2	1/2	1
$\beta_{ u}$	1/6	2/6	2/6	1/6



### First steps:

- Only algebraic wall models considered
- Two different strategies for the exchange location (interface between LES and the wall model):
  - 1. At a given position
  - Just at the interface of the first off wall element
- After testing **strategy 2** is preferred
- Validations on benchmark cases
- Next steps are implementation of velocity transformations functions, and testing of NEQ wall models.





### WMLES

### What we would like in CEEC

- To replace the analytical wall model by a data-driven one based on RL
- Possible advantages:
  - 1. Introduce numerical errors on the model optimisation
  - 2. No need of high-fidelity data sets to do the training
- Bottlenecks:
  - 1. Really intensive from the computational point of view
  - 2. Not available workflows for RL at very large scale
- As a first step, a simpler flow control problem will be tested to demonstrate the workflow.



**Channel flow** ( $Re_{\tau} = 950 \& Ma = 0,1$ ), compressible

P = 8
tw 0.0025879371628599007
theory tw 0.002589595812175917
err tw % 0.06405050966708589
utau 0.050871771768436574
Re\_tau 949.6957113466683
Vreman SGS





Windsor body, compressible, p4 and WMLES+Vreman Case definition

- 2.5° of yaw
- Re = 2.9 x 10<sup>6</sup>
- U = 40 m/s
- No wheels configuration
- No slip road





### Windsor body, compressible, p4 and WMLES+Vreman

- Two meshes considered based on unstructured hexaedra (p4):
  - Coarse: 13 M DOF
  - Fine: 150 M DOF
- Vreman SGS model used
- Equilbrium wal model (exchange location at off-wall node 3)



### Windsor body, compressible, p4 and WMLES+Vreman



		Lift	Drag
	Exp. From AUTOCFD3	-0.0382	0.3298
	Present-coarse	-0.0552	0.3485
Barceloi Superco Center Centro Naci	Present-fine	-0.0983	0.3247

### **CRM HL Case1**, compressible, 150M DOF p2 and WMLES+Vreman

#### Case Parameters and Requirements

Geometry	CRM-HL-WB
Mach Number	0.20
Chord Reynolds Number	5.6 x 10 <sup>6</sup>
Angle of Attack	11°
Reference Static Temperature	521 °R
Important Details	<ul> <li>Geometry is provided in full-scale inches</li> <li>When using a dimensional code, it is recommended to adjust viscosity to a non-physical value to match requested Reynolds number</li> <li>All simulations are "free air" only</li> <li>When using RANS:         <ul> <li>\$\vec{v}_{farfield}/v_{ref} = 3\$ for SA-based models</li> <li>Adiabatic wall BC (not isothermal)</li> <li>SA-neg-QCR2000-R is recommended; coefficient for rotation correction (-R) should be changed to C<sub>rot</sub>=1 for verification (standard value</li> </ul> </li> </ul>
	of C <sub>rot</sub> =2 can be used as an "optional" case)





https://hiliftpw.larc.nasa.gov/Workshop5/Documents/HLPW5\_Test\_Cases\_v1.7.pdf

### **CRM HL Case1**, compressible, 150M DOF p2 and WMLES+Vreman



- Very early
- Turbulence is developping on the wing
- Where is our BIG GPU machine!? 😊



https://hiliftpw.larc.nasa.gov/Workshop5/Documents/HLPW5\_Test\_Cases\_v1.7.pdf

### **Early dissemination**

- Paper submitted to: Computer Physics Communications
- First reviews available, is positive, we expect to have the paper in the upcoming months.
- Focus on the main kernels' performance on GPU vs CPU:

Timings for explicit 85^3 runs					
	full step	diffu kernel	convec kernel		
H100	123.246	7.681	13.099		
A100	182.116	13.304	16.33		
V100	443.504	24.837	22.949		

- Times in (ms)
- p3 elements
- Single-precision runs using CUDA managed memory
- Explicit RK4 time-advance scheme
- MN4 reference: 1.68s/step (48 cores, 85\*\*3 mesh)





Computational Physics

SOD2D: A GPU-enabled Spectral Finite Elements Method for compressible scaleresolving simulations 🖈

L. Gasparino<sup>a</sup> 🙁 🖂 , <u>F. Spiga<sup>b</sup></u>, <u>O. Lehmkuhl<sup>a</sup></u>

#### 

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https://doi.org/10.1016/j.cpc.2023.109067 7

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#### Abstract

As new <u>supercomputer</u> architectures become more heavily focused on using <u>hardware</u> <u>accelerators</u>, in particular general-purpose graphical processors, it is therefore relevant that algorithms for <u>computational fluid dynamics</u>, especially those targeting scale-resolving simulations, be designed in such a way as to make efficient use of such hardware.

### **Early dissemination**

- Externals users are already playing SOD2D: UPC, KTH and Agronne are the most notable.
- First examples of external applications:

Vishal Kumar<sup>1</sup>, Oriol Lehmkuhl<sup>2</sup>, Ananias Tombouldies<sup>3</sup>, Paul Fischer<sup>1,4,5</sup>, and Misun Min<sup>1</sup>

Turbulence Modeling with Nek5000/RS, SOD2D and Alya

<sup>1</sup> Mathematics and Computer Science Division, Argonne National Laboratory <sup>2</sup> Barcelona Supercomputing Center (BSC) <sup>3</sup> Department of Mechanical Engineering, Aristotle University of Thessaloniki <sup>4</sup> Department of Computer Science, University of Illinois Urbana-Champaign <sup>5</sup> Mechanical Science & Engineering, University of Illinois Urbana-Champaign

Argonne -



Figure 15: Comparison of turbulent pipe flow results between NekRS and SOD2D at  $Re_{\tau} = 1000$ on the Fine grid resolution; (a) axial velocity  $(U_z/U_b)$  in outer units; (b) axial velocity in inner units; (c) normal turbulent stresses; (d) resolved Reynolds stress.



mesh resolution are indicated in Table 3.

Table 2: Performance of NekRS and SOD2D on Polaris. Tests have been performed for Channel flow at a resolution of  $384 \times 384 \times 384$  with  $E = 64^3$ , N = 6, and the total number of grid points of 56 millions.  $\Delta t = 1.5e-03$  (CFL = 1.7) and  $\Delta t = 6.5e-05$  (CFL = 1.5) are used for NekRS and SOD2D, respectively.

	Performance on Polaris						
Code	nodes	GPUs	dofs/GPU	$v_i$	$p_i$	$t_{step}$ (s)	$P_{\rm ef}$
	2	8	7.0779e + 06	2.97	2.13	2.3512e-01	100
	3	12	4.7186e + 06	2.97	2.14	1.7690e-01	88.
	4	16	3.5389e + 06	2.97	2.18	1.4138e-01	83.
Nek5000	5	20	2.8312e + 06	2.97	2.09	1.2734e-01	73.
	6	<b>24</b>	2.3593e + 06	2.97	2.16	1.1305e-01	69.
	8	32	1.7695e + 06	2.97	5.16	1.3139e-01	44.
	9	36	1.5729e + 06	2.97	2.13	9.4724e-02	55.
	2	8	7.0779e + 06	-		3.4603e-01	100
	3	12	4.7186e + 06	_	-	2.4769e-01	93.
	4	16	3.5389e + 06	-	-	1.9941e-01	86.
SOD2D	5	20	2.8312e + 06	-	-	1.6249e-01	85.
	6	24	2.3593e + 06	-	-	1.3526e-01	85.
	8	32	1.7695e + 06	-	-	1.0868e-01	79.
	9	36	1.5729e + 06	-	-	9.6119e-02	80.

ANL-23/59

## 5. Scalability analysis



#### 128 1.75 120 e 112 ₽ 1.5 104 ideal - - comp(rp4) 96 Ø comp(rp8) ideal 1.25 88 inco(rp4) comp(rp4) 9 comp(rp8) inco(rp8) 0 80 efficiency 0 n108 inco(rp4) speedup 0 inco(rp8) 72 n124 × â 1 $\wedge$ r=2.5M n136 ж 64 ō r=5.0M n156 0 r=10.0M Δ n171 0 56 Ö 0.75 r=20.0M $\nabla$ n196 Δ r=40.0M 48 0 $\nabla$ \* n216 n247 $\diamond$ 40 n272 Q 0.5 32 24 0.25 16 8 0 8 16 24 32 48 64 96 128 16 24 32 40 48 56 64 72 80 0 8 88 96 104 112 120 128 Ngpu Ngpu

### - Weak speedup:

- Strong speedup:



## 5. Scalability analysis









trajectory (or episode)  $\{(s^0, r^0, a^0), (s^1, r^1, a^1), ..., (s^n, r^n, a^n)\}$ 

### General training approach:

- 1. Collect trajectory via noisy-sampled actions (exploration)
- 2. Optimize agents weights to maximize accumulated reward in time
- 3. Check agent performance with deterministic action (most probable,  $\mu$  )
- 4. Repeat

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### State consists of a set of velocity probes within the bubble and surroundings

- *Reward*: wall shear stress as a proxy for recirculation length
- Action: Instantaneous zero-net-mass-flux
  - control half of the actuators ( $\rho v$ ), impose opposite (- $\rho v$ ) on the other half \*
- Multi-environment
  - Multiple simulations run in parallel that share the controlling agent (RL model)
- Optimal control
  - Action sampled from an optimal distribution that maximizes the reward
  - Control signal can contain multiple frequencies



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- Multiple parallel simulations interacting with the RL model
  - Accelerated training
- Execution scheme that fills both GPUs and CPUs ٠
  - RL model trains on the CPU while CFD simulation runs on **GPUs**
- In-memory Redis database ٠
  - Measured minimal communication overhead
- RL control strategy •
  - Environment sends state and reward to the agent
  - Agent predicts actions and sends them to the environment 2.
  - Environment applies actions and proceeds to next time step 3.



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- Python library to create databases (DBs) and managing workloads in HPC environments.
- Allows linking HPC applications with ML models written in Python.
- DB can be located in a single node, distributed across nodes, or fully duplicated across nodes.



https://www.craylabs.org/docs/overview.html



- DB clients for different programming languages (Fortran, Python, C/C++) with consistent API.
- Recently updated to be compilable with NVIDIA HPC toolkit (required to link with apps compiled by nvhpc, like SOD2D).
- Read/write "tensors" (named arrays) into DB.
- Allows syncronization across programs by waiting on arrays to be created into the DB.
- Allows the freedom to write data from each rank of each simulation (one client per rank), or gather data and then write it from a single rank (one client per MPI communicator).





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SmartSOD2D (Python) and the

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### Framework management using SmartSim



Single SLURM allocation [Power9]	Different SLURM allocations [Alvis]
sbatch job.sh	sbatch SmartSOD2D_job.sh
#SBATCHntasks=8 #SBATCHcpus-per-task=40 #SBATCHgres=gpu:4 . all_modules.sh python train.py	#SBATCH -C NOGPU -n 1 . smartsod2d_modules.sh python train.py
SmartSim runs: \$ mpirun –x SSDB= <ip-address:port> \ -n 1 sod2dargs1 : -n 1 sod2dargs2 : -n 1 sod2dargs8</ip-address:port>	SmartSim runs: sbatch SOD2D_job.sh #SBATCHntasks=8 #SBATCHgpus-per-node=A100:4 . sod2d_modules.sh
	mpirun –x SSDB= <ip-address:port> \ -n 1 sod2dargs1 : -n 1 sod2dargs2 : -n 1 sod2dargs8</ip-address:port>

(1 GPU per SOD2D simulation in these cases)



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E Alcantara-Avia I Babault B Vinuesa O Lehmkuhl (2024) Active flow

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### **Distributing simulations across available resources**

Multiple-Program Multiple-Data (MPMD)

- The MPMD model distributes the requires MPI processes across the available resources (GPUs or CPUs).
- The MPI communicator is split within SOD2D, and each simulation gets its own ID (colouring) → Useful when reading/writing data into the DB.

```
! Get the unique app number (color)
call MPI_Comm_get_attr(world_comm, MPI_APPNUM, color_ptr, mpi_app_num_flag, mpi_err)
call MPI_Comm_split(world_comm, color_ptr, mpi_world_rank, app_comm, mpi_err)
call MPI_Comm_rank(app_comm, mpi_rank, mpi_err)
call MPI_Comm_size(app_comm, mpi_size, mpi_err)
```

- The global communicator across simulations world\_comm is not used, only the local simulation communicator app\_comm.
- Maybe use pycompss to handle processes and distribute workloads in the near future!



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- MARL: Multi-agent reinforcement learning
  - Exploits invariances → Pseudo-environment
  - Reduces action dimensionality → Curse of dimensionality
  - References: Guastoni et al. TEPJE, 46(4), 27 • & Vignon et al. PoF, 35, 6, 2023
- State
  - 72 probes: Streamwise velocity, u

- Action
  - Jet pairs  $\rightarrow$  ZNMF •
  - $|v_{\rm ac,max}| = 0.3$
- Reward
  - Reduce bubble of recirculation •
  - Proxy: Area of  $\tau_w < 0$ •
  - $r = (r_{\text{global}} + r_{\text{local}})/2$

- Other parameters •
  - 552 MARL episodes •
  - 184 CFD episodes
  - 1600 time units/episode
  - 40 actions/episode
  - 35 hours training





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### **Results: DRL control**

- Bubble reduction of 28.9% in coarse grid
  - 12% more than classic control
- Smoother control

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## 7. Conclusions

### To wrap up

- 1. The present work has assessed and analysed the parallel performance of a new Continuous Galerkin High-Order Spectral Element Code aimed to solve simulations of turbulent compressible in the context of the CEEC project.
- 2. The obtained preliminary results are very promising: the code presents very good scalability
  - for both **strong** and **weak** speed-ups.
- 3. Validation efforts on-going however good results observed so far in a relevant benchmark cases.
- 4. First efforts on integration of ML algorithms promising





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# Thank you!

Any questions?

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