A reduced order Kalman filter for CFD applications

Carolina Introini, Stefano Lorenzi, Antonio Cammi, Davide Baroli

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Issue: improve the plant availability and the ability to follow grid demands by enhancing the performance of Nuclear Power Plants

Real-time control of the nuclear reactor plays a fundamental role

1D Modelling (lumped parameter approach)	3D Modelling (CFD simulations)
Control-oriented	Design-oriented
Main feature: simplicity	**Main feature:** detail
Fast-running	High-detailed
ODE based	PDE based
Integral information	Spatial information
Lacks predictive capabilities	Too expensive for most available analysis tools

SOLUTION

Question: it is possible to provide the control simulation tools with relevant spatial information capabilities, enhancing the level of detail without a strong computational burden?

Reduced Order Models (ROM)

- Replace the high-fidelity (accurate) problem by one featuring much lower complexity
- Input-output relationships have to be preserved
- Must be stable, sufficiently accurate and within scope of the analysis and design tools
- Computationally efficient

Data-driven algorithms (DDA)

- Real-time integration of experimental data within the numerical model, thus improving the efficiency of the latter
- Observations offers a local (spatial) but accurate information
- Feedback on the accuracy of both the model prediction and the experimental data itself

SOLUTION

Question: it is possible to provide the control simulation tools with relevant **spatial information capabilities**, enhancing the level of detail without a strong computational burden?

Reduced Order Models (ROM)

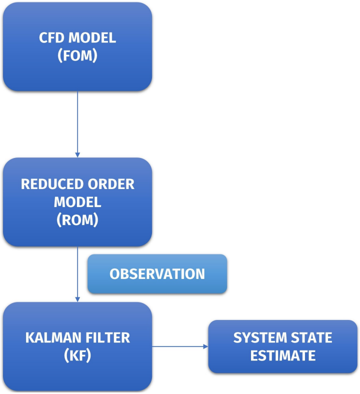
- **Offline**: collect few high fidelity solutions
- **Offline**: calculate the basis where to project the governing equations
- **Online**: Galerkin projection of the variable of interest (reduced Navier-Stokes equation)
- **Online**: field reconstruction

Data-driven algorithm (Kalman filter)

- **Prediction step**
  1. State prediction (numerical model)
  2. A priori error covariance
- **Corrector step** (if observation is present)
  1. Kalman gain evaluation
  2. Augmented prediction
  3. A posteriori error covariance

SOLUTION - ROM + KF (STATE OF THE ART)

Solution: combine the reduced order model and the data-driven algorithm in order to develop an online control system with feedback from real-time experimental data

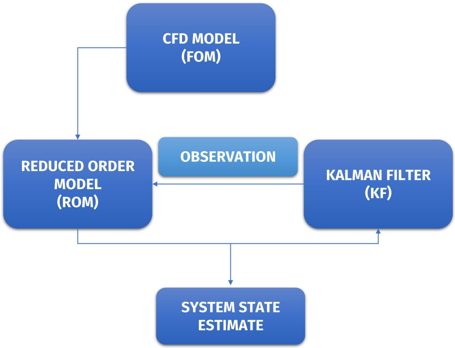


STATE OF THE ART

- ”Serial” approach
- The filter acts on the reconstructed variable obtained from the reduced order model
- BOTTLENECK: size of the covariance matrix P = number of elements of the numerical mesh (full order)
- No sensible time saving with respect to the FOM

SOLUTION - ROM + KF (NOVEL APPROACH)

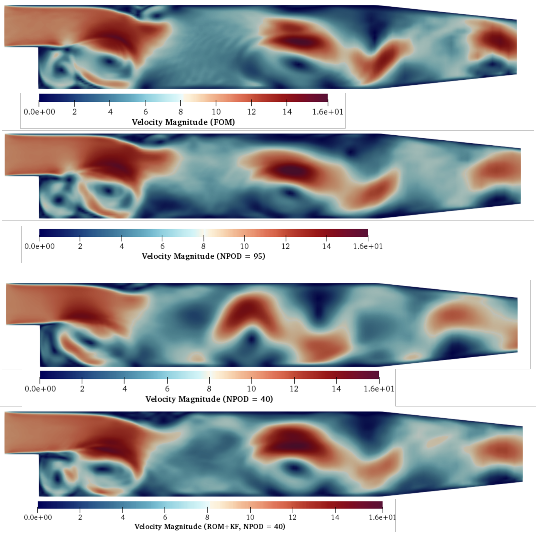
Solution: combine the reduced order model and the data-driven algorithm in order to develop an online control system with feedback from real-time experimental data



NOVEL APPROACH

- ”Parallel” approach
- The filter acts on the reduced variable (POD coefficients)
- Size of the covariance matrix P = number of reduced basis $\ll$ number of elements of the numerical mesh
- Sensible saving with respect to the FOM and the serial approach is expected

TEST CASE - BACKWARD FACING STEP



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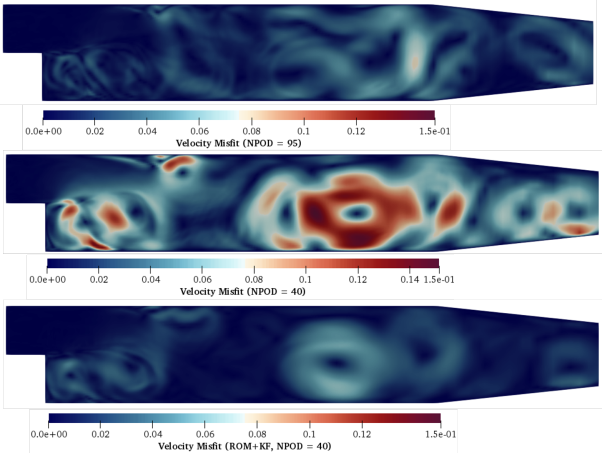

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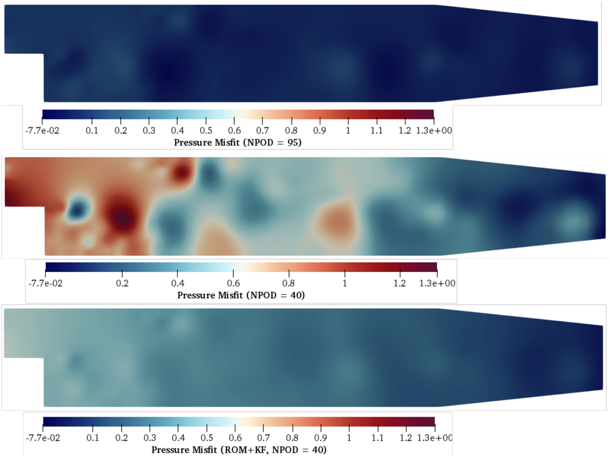

CONCLUSIONS

	FOM	ROM ($N_{POD} = 95$)	ROM ($N_{POD} = 40$)	ROM+KF ($N_{POD} = 40$)	Serial ($N_{POD} = 40$)
Offline	1260 s				
Online		428.57 s	75 s	230.77 s	535.62 s

Table: Computational times for the various cases

- Given the same accuracy of the reconstruction (i.e. the same number of basis), the parallel integration of ROM and Kalman filter allows for better results, comparable to those obtained by a ROM with greater accuracy (greater number of basis)
- The increase of computational time due to the Kalman filter is not negligible, however it remains lower than both the serial case, and the more accurate ROM