



Stochastic reduced order model for real-time unsteady flow estimation

Valentin Resseguier, Matheus Ladvig, Agustin M Picard, Etienne Mémin,
Reda Bouaida, Bertrand Chapron

► To cite this version:

Valentin Resseguier, Matheus Ladvig, Agustin M Picard, Etienne Mémin, Reda Bouaida, et al.. Stochastic reduced order model for real-time unsteady flow estimation. WESC 2019 - Web Wind Energy Science Conference, Jun 2019, Cork, Ireland. pp.1-23. hal-02160160

HAL Id: hal-02160160

<https://hal.science/hal-02160160>

Submitted on 19 Jun 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

STOCHASTIC REDUCED ORDER MODEL FOR REAL-TIME UNSTEADY FLOW ESTIMATION

Valentin Resseguier,

Matheus Ladvig, Agustin M Picard

Etienne Mémin, Reda Bouaida, Bertrand Chapron

@Scalian 2019. All rights reserved.

CONTENT

1. Context
2. Physics + data = reduced order model (ROM)
3. Simulation + measurements = data assimilation
4. Results

The background is a deep blue-purple gradient. On the right side, there is a large, complex, low-poly wireframe structure that resembles a brain or a futuristic helmet, composed of many interconnected triangles and lines. On the left side, a human hand is visible, with fingers slightly curled as if reaching out or interacting with the digital space. Faint, glowing white dots are connected by thin lines, suggesting a network or data flow across the entire scene.

PART I

CONTEXT

@Scalian 2019. All rights reserved.

Lab (~ 15 peoples)

Research, R&T, R&D

Expertise:

- Geophysical fluid dyn.
- Signal, data assimilation
- Machine Learning
- Multi-agents systems
- Drones

CEN « Simulation » (~ 70 people)

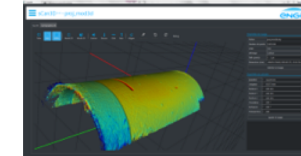
R&D and engineering

Expertise:

- Radar, optronics, sonar
- Geophysical fluid dyn.
- Mechanical and thermal

Business:

- Scientific softwares
- Simulations, HPC
- VR & AR

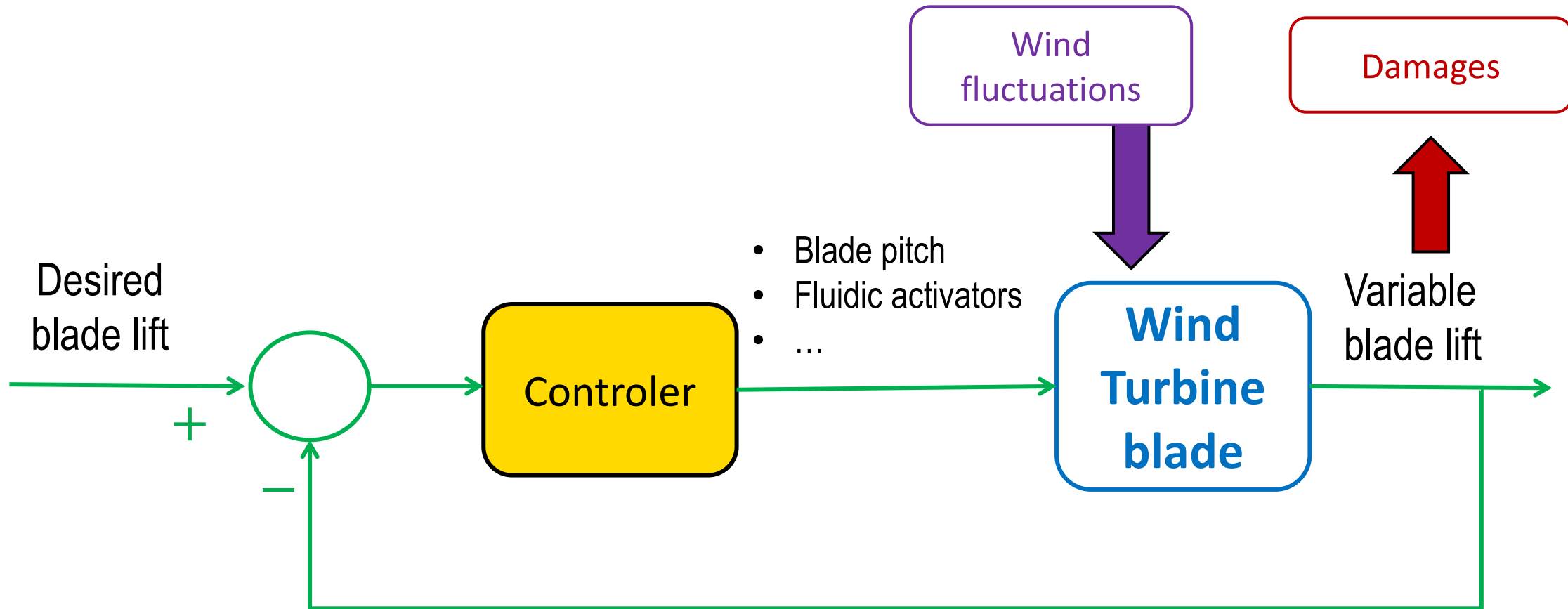


Other Business Units

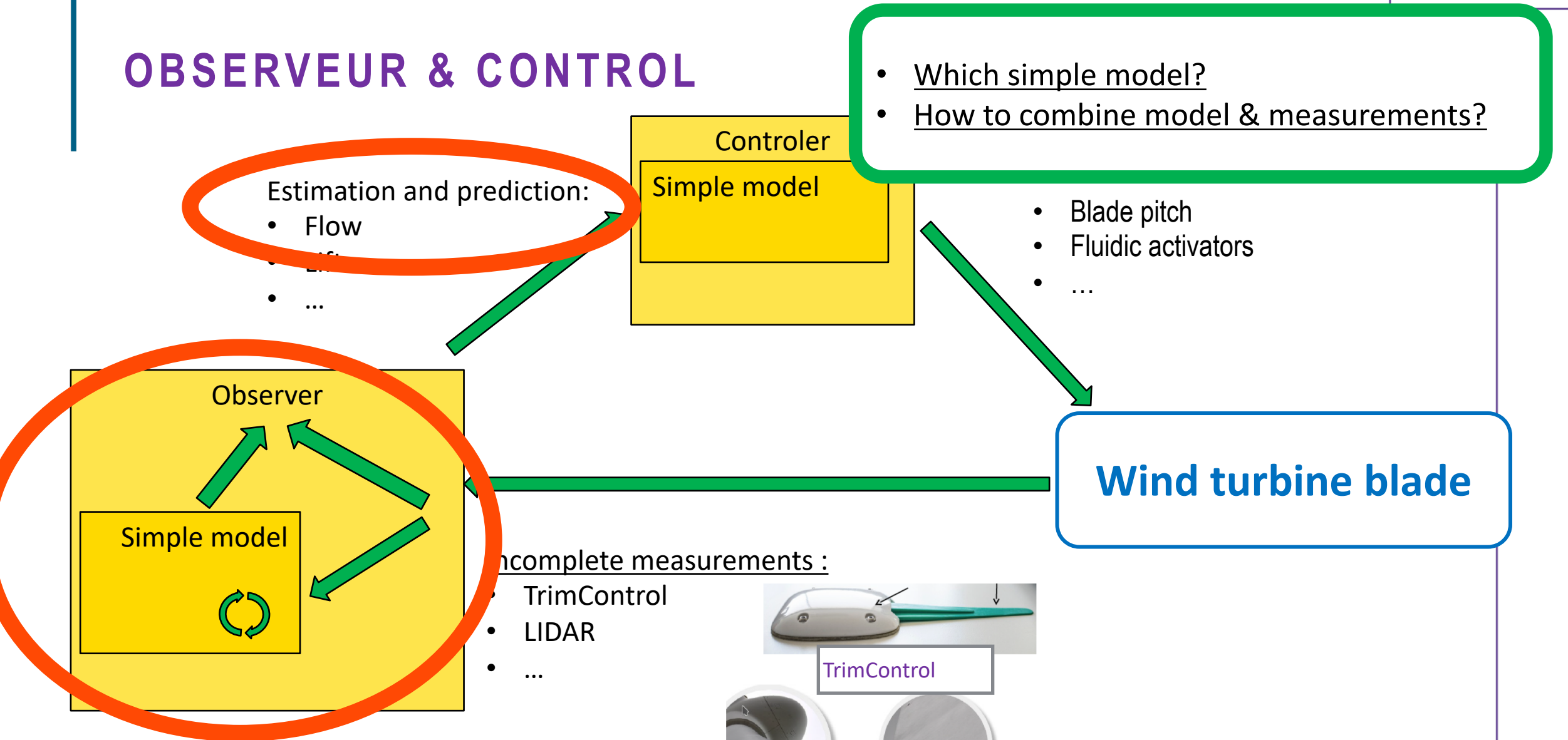
~ 2400 people



BLADE LIFT CONTROL



OBSERVEUR & CONTROL



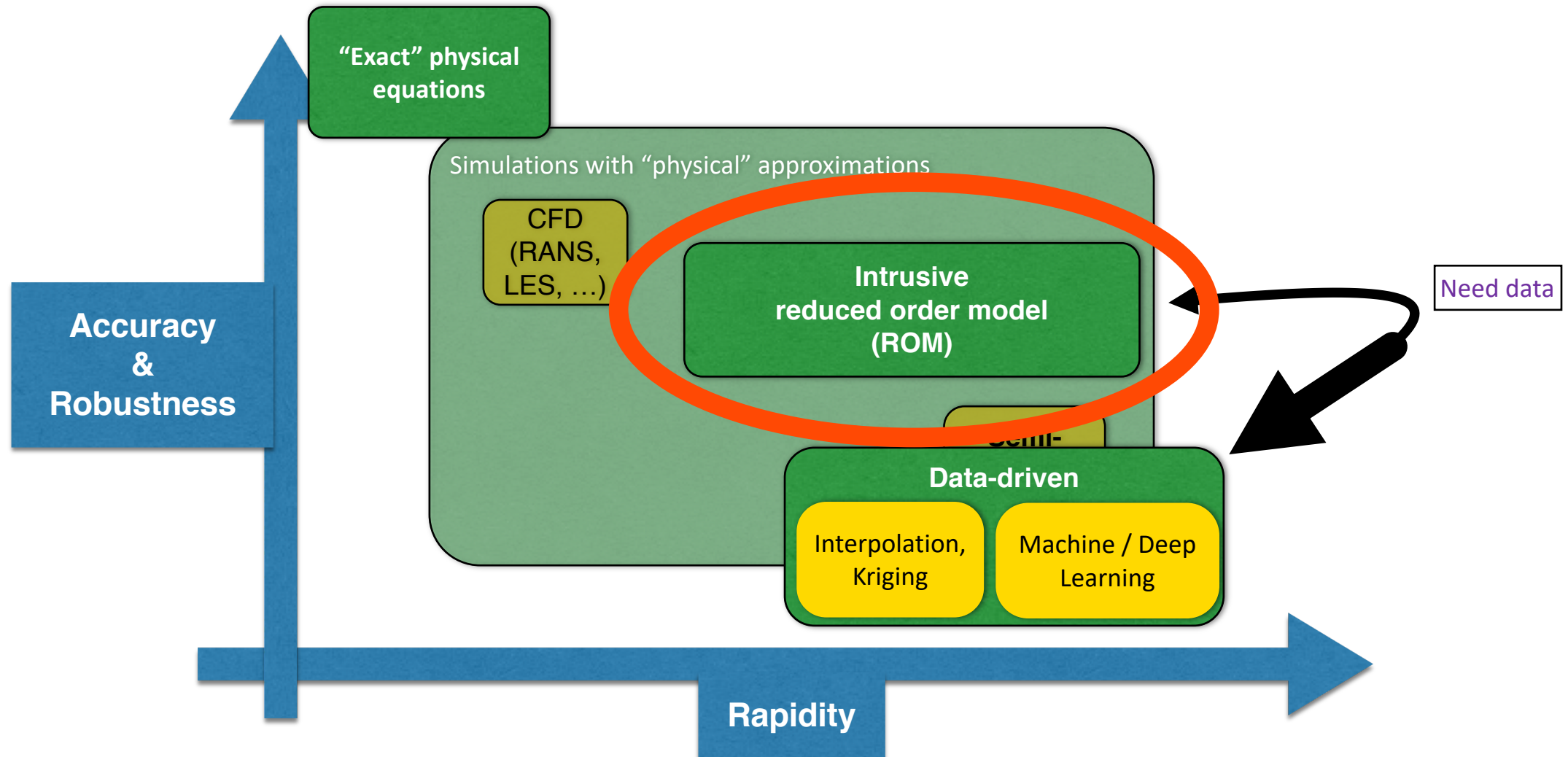
PART II

PHYSICS + DATA

= REDUCED ORDER MODEL

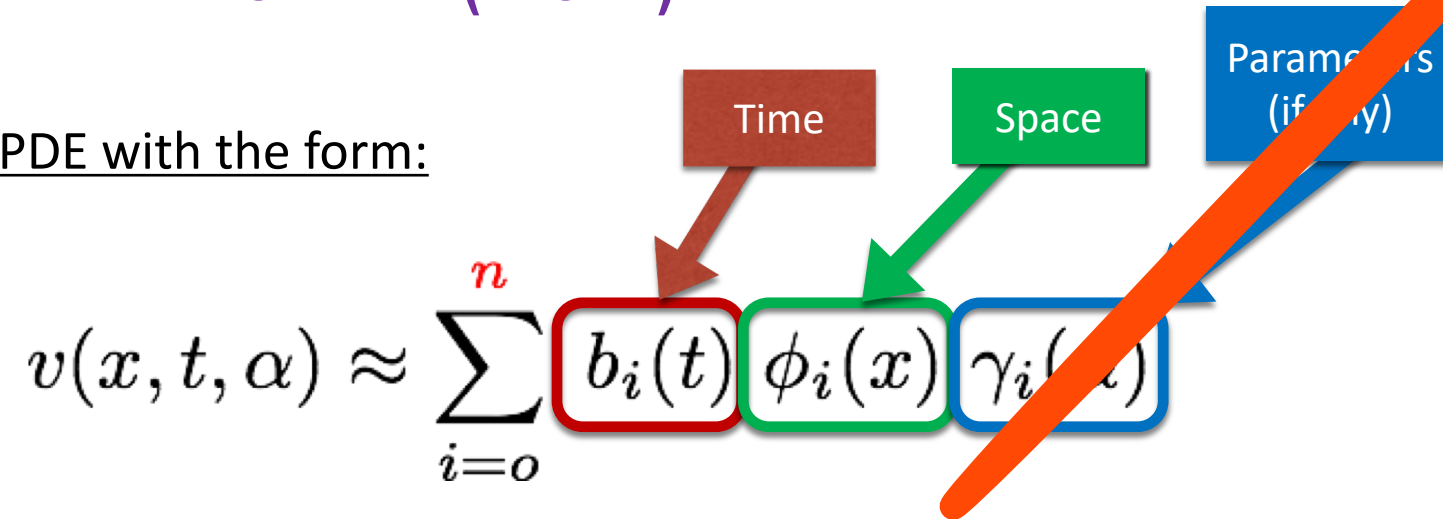
@Scalian 2019. All rights reserved.

TRADEOFF ACCURACY / RAPIDITY



REDUCED ORDER MODEL (ROM)

Solution of an PDE with the form:

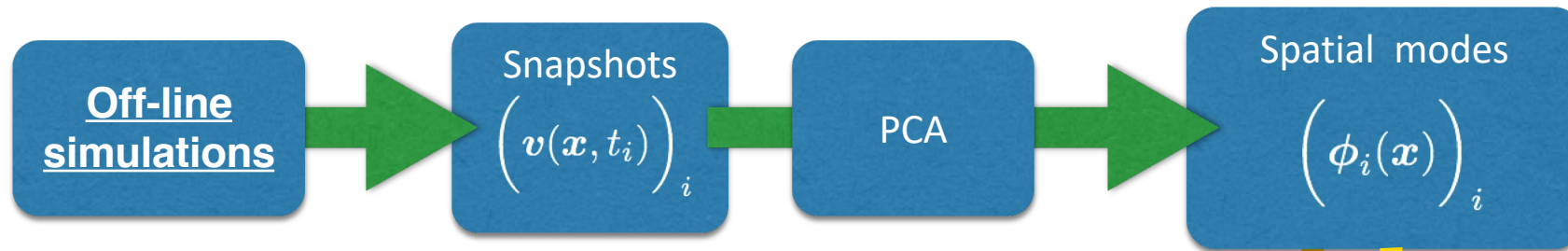
$$v(x, t, \alpha) \approx \sum_{i=0}^n \boxed{b_i(t)} \boxed{\phi_i(x)} \boxed{\gamma_i(\alpha)}$$


Order of
magnitude
examples in CFD

	Full space	Reduced space
Solution coordinates	$v_q(x_i, t))_{qi}$	$(b_i(t))_i$
Dimension	$M \times d \sim 10^7$	$n \sim 10 - 100$

POD (PROPER ORTHOGONAL DECOMPOSITION)

- Principal Component Analysis (PCA) on a *dataset* to reduce the dimensionality:



- Approximation:

$$v(x, t) \approx \sum_{i=0}^n b_i(t) \phi_i(x)$$

Resolved modes

- Projection of the “physics” onto the spatial modes :

$$\int_{\Omega} dx \phi_i(x) \cdot (\text{Physical equation (e.g. Navier-Stokes)})$$

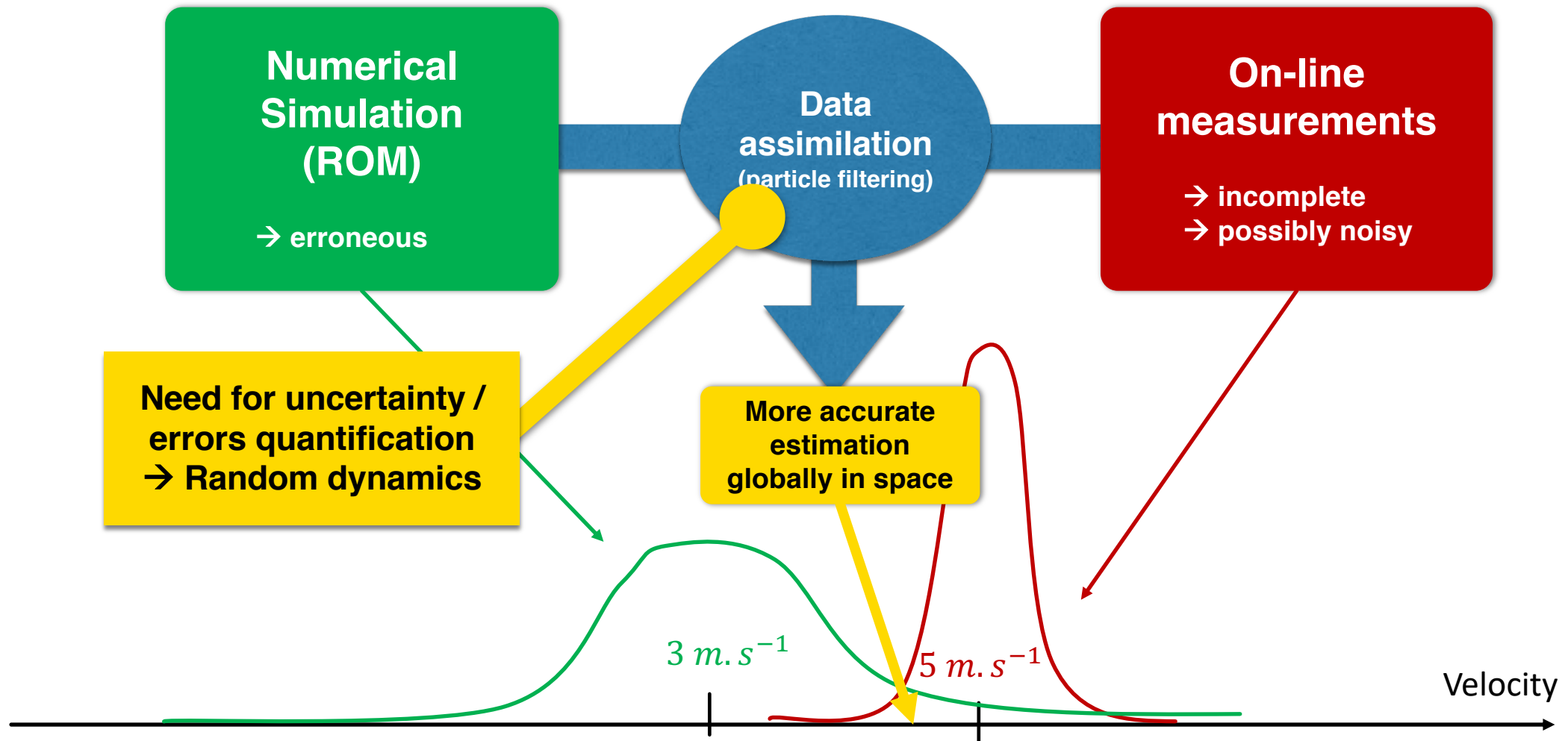
→ ROM for very fast simulation of temporal modes

PART III

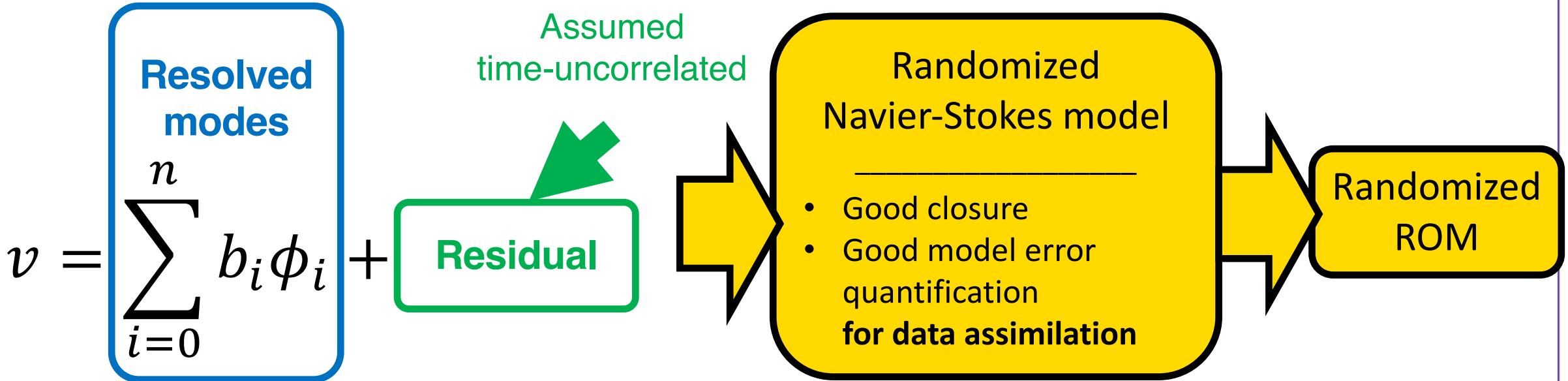
SIMULATION + MEASUREMENTS
= DATA ASSIMILATION

@Scalian 2019. All rights reserved.

COMBINING SIMULATIONS AND MEASUREMENTS



LOCATION UNCERTAINTY MODELS (LUM)



References :

Mikulevicius &
Rozovskii, 2004
Flandoli, 2011

LUM

Memin, 2014
Resseguier et al. 2017 a, b, c, d
Cai et al. 2017
Chapron et al. 2018
Yang & Memin 2019

SALT

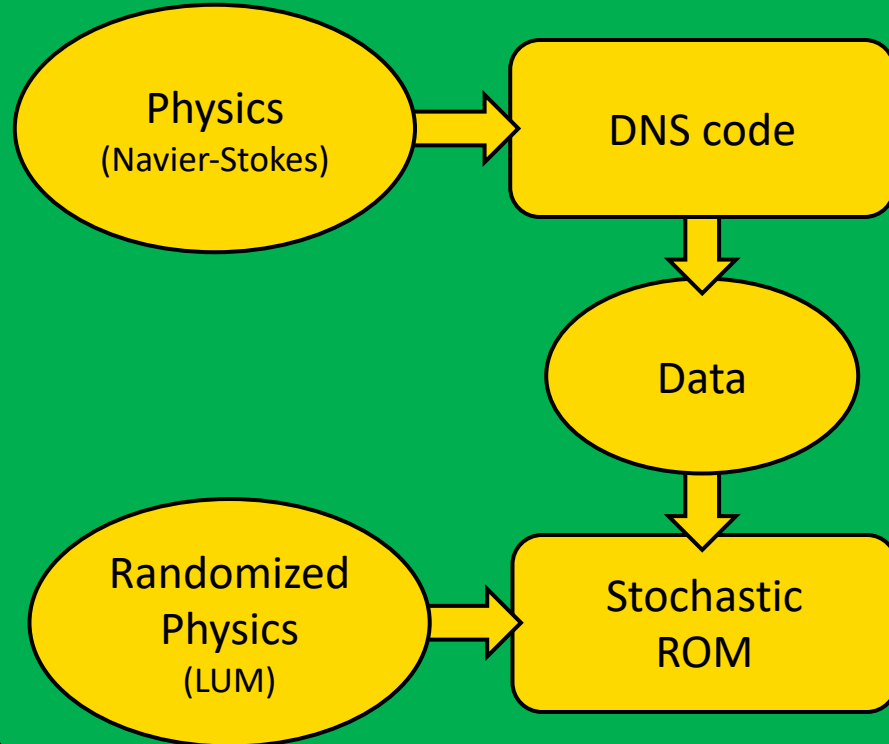
Holm, 2015
Holm and
Tyranowski, 2016
Arnaudon et al. 2017

Crisan et al., 2017
Gay-Balmaz & Holm 2017
Cotter and al. 2018 a, b
Cotter and al. 2019

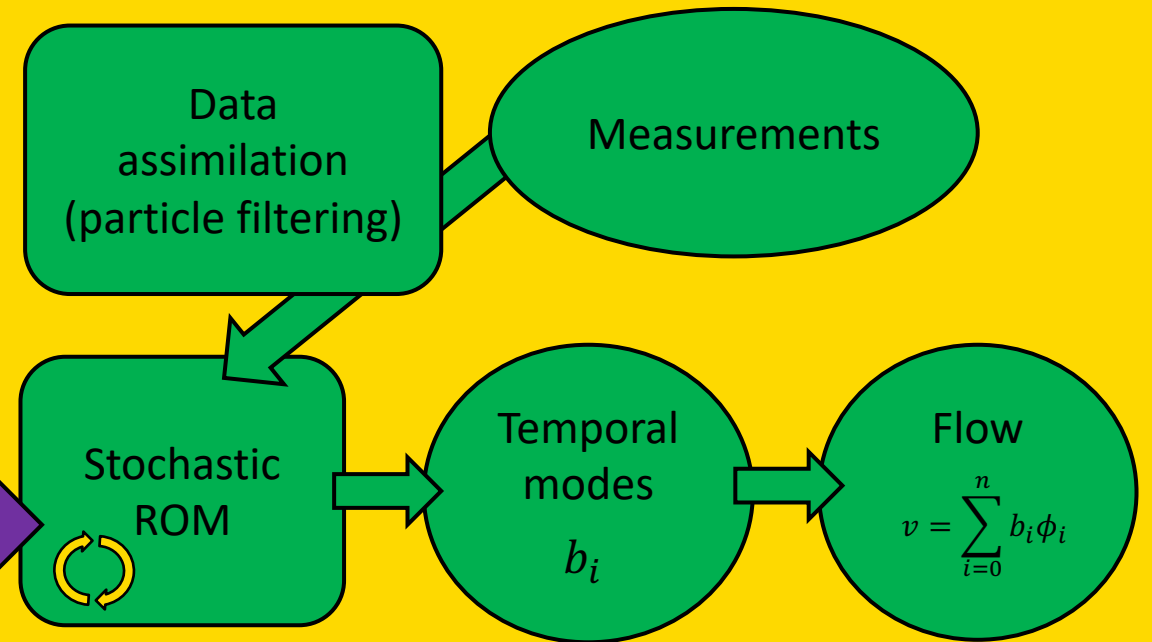
Cotter and al. 2017 Resseguier et al. 2019 a, b

SUMMARY

Off-line : Building ROM



On-line : Simulation & data assimilation

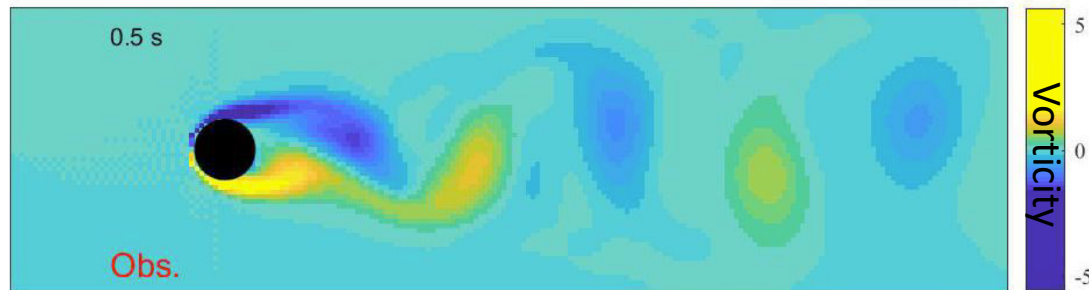
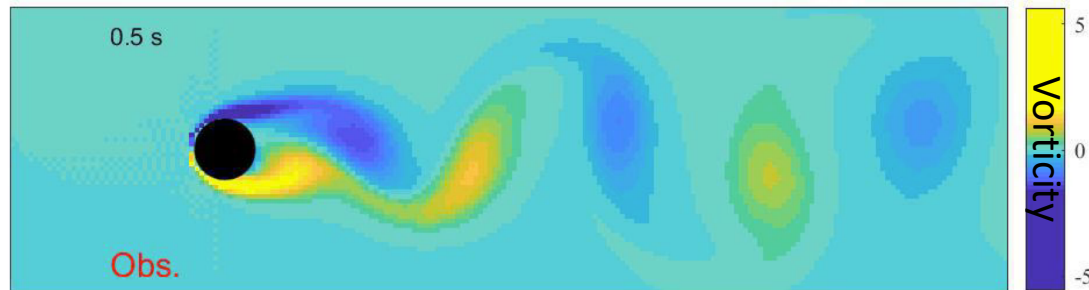


PART IV
RESULTS :
FAST OBSERVER OF THE FLOW

@Scalian 2019. All rights reserved.

1ST RESULTS: WAKE AT RE 100

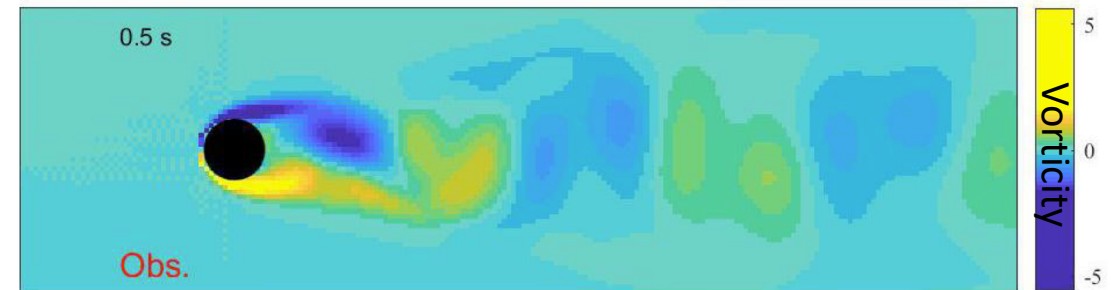
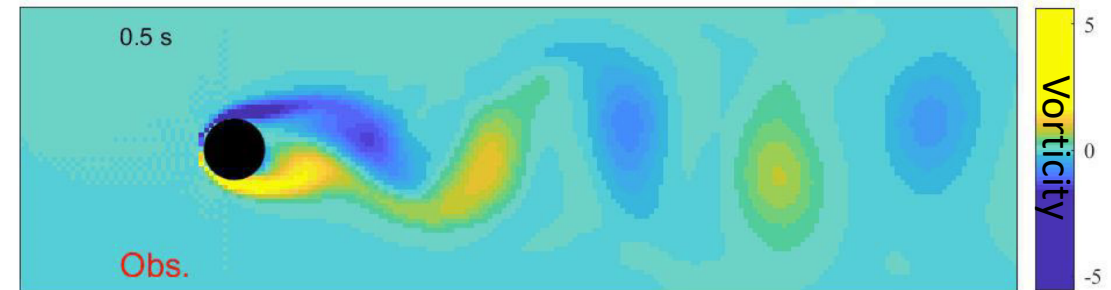
Reference
(DNS)
 10^4 degrees of freedom



Our method
(Red-LUM-based data-assimilation)
6 degrees of freedom

Reduced order models with $n = 6$
and 2dB-SNR obs. assimilated every 5 sec

Theoretical bound
(Optimal from 6-d.o.f. linear decomposition)
6 degrees of freedom

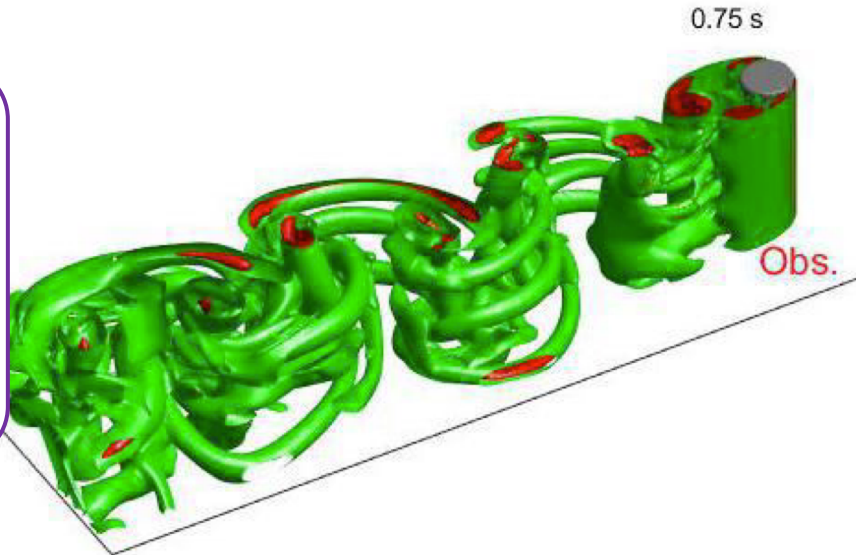


Benchmark
(POD-ROM (with eddy viscosity) + init. by obs.)
6 degrees of freedom

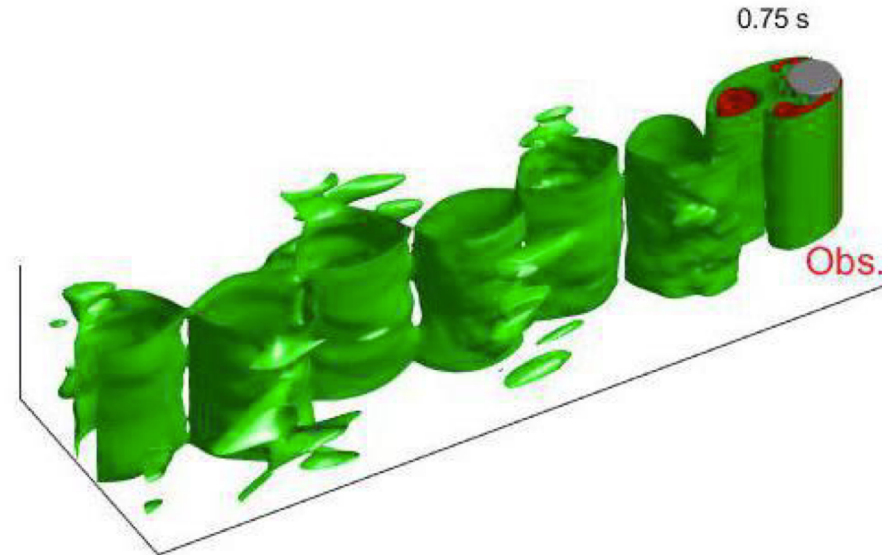
1ST RESULTS: WAKE AT RE 300

Reduced order models with $n = 6$
and 2dB-SNR obs. assimilated every 5 sec

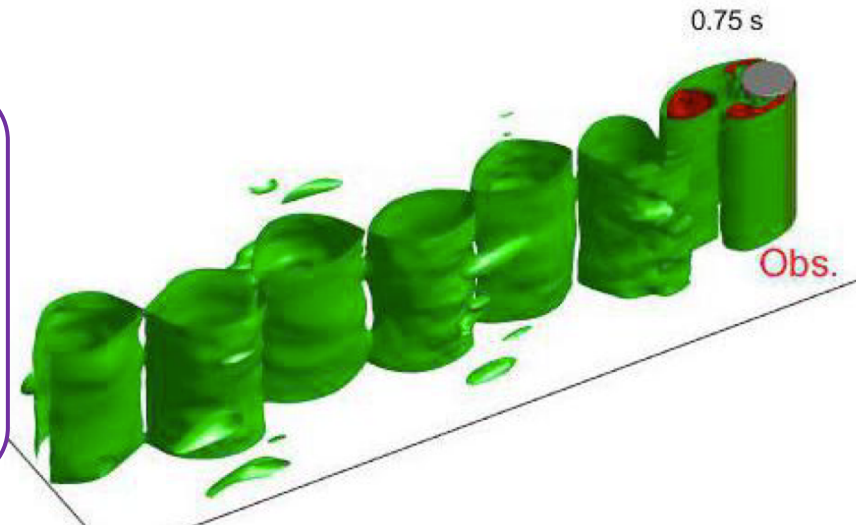
Reference
(DNS)
 10^7 degrees of
freedom



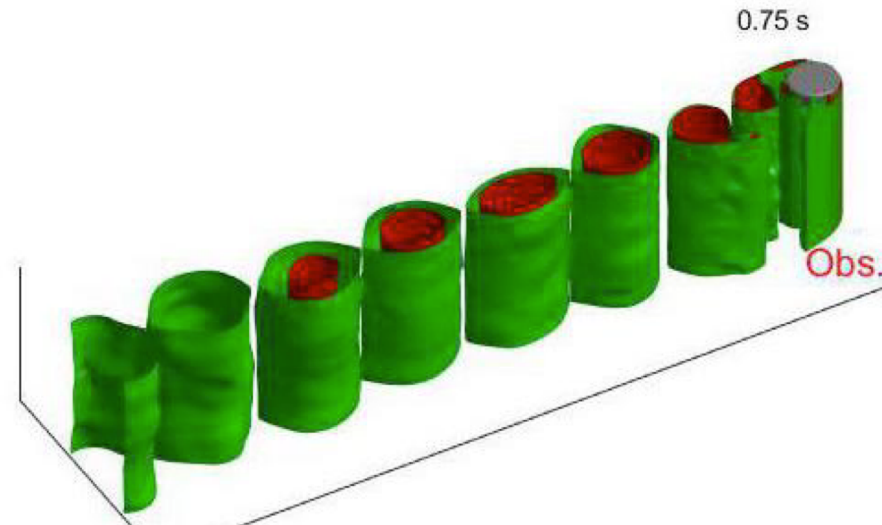
Theoretical
bound
(optimal from
6-d.o.f. linear
decomposition)
6 degrees of
freedom



Our method
(Red-LUM-
based data-
assimilation)
6 degrees of
freedom



Benchmark
(POD-ROM
(with eddy
viscosity) +
init. by obs.)
6 degrees of
freedom





CONCLUSION

@Scalian 2019. All rights reserved.

CONCLUSION

- ▶ Reduced order model (ROM) : for very fast and robust CFD ($10^7 \rightarrow 6$ degrees of freedom.)
 - Combine data & physics (built off-line)
 - Closure problem handled by LUM
- ▶ Data assimilation : to correct the fast simulation on-line by incomplete/noisy measurements
 - Model error quantification handled by LUM
- ▶ First results
 - Optimal unsteady flow estimation/prediction in the whole spatial domain (large-scale structures)
 - Robust far outside the learning period

NEXT STEPS

- ▶ Real measurements (PIV, TrimControl, ...)
- ▶ Increasing the degrees of freedom (n)
- ▶ Increasing Reynolds (reduced DNS $\rightarrow$ reduced LES)
- ▶ Blade geometry



BONUS SLIDES

@Scalian 2019. All rights reserved.

LUM: ADVECTION OF TRACER Θ

The diagram illustrates the LUM (Langevin Unbiased Method) equation for the advection of a tracer Θ . The equation is presented as:

$$\partial_t \Theta + \underbrace{(w^* \cdot \nabla \Theta + \sigma \dot{B} \cdot \nabla \Theta)}_{D_t} = \underbrace{\nabla \cdot \left(\frac{1}{2} a \nabla \Theta \right)}_{\text{Diffusion}}$$

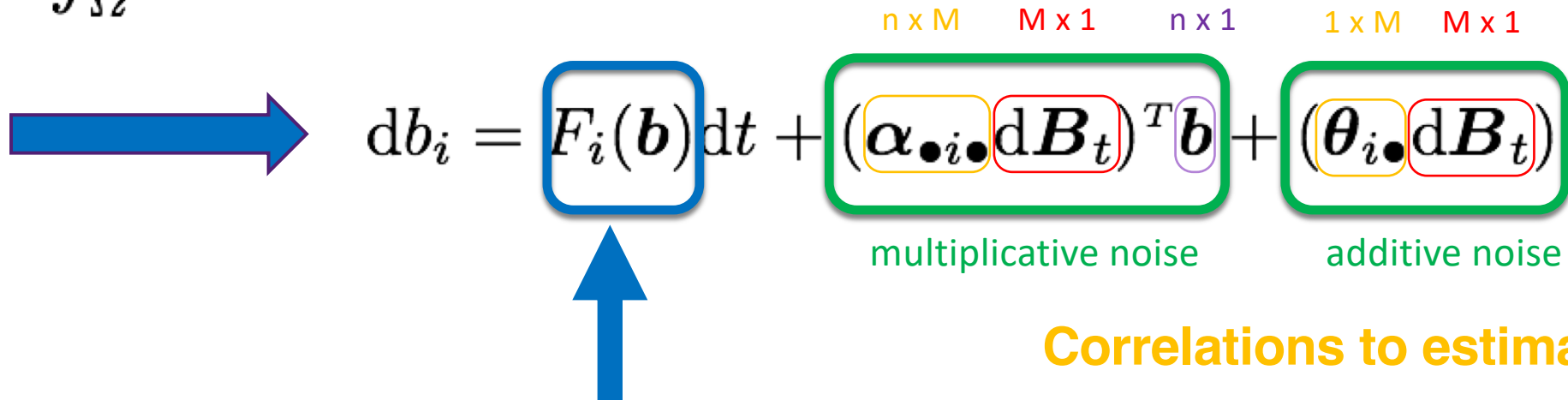
Annotations and components:

- Drift correction:** An orange arrow points to the w^* term in the advection part of the equation.
- Multiplicative random forcing:** A purple arrow points to the $\sigma \dot{B} \cdot \nabla \Theta$ term in the advection part.
- Balanced energy exchanges:** A green arrow points from the diffusion term to the advection term, indicating a balance.
- Advection:** The entire left-hand side of the equation is enclosed in a light blue box labeled "Advection".
- Diffusion:** The right-hand side of the equation is enclosed in a light green box labeled "Diffusion".
- D_t :** A purple arrow points to the underlined advection term, which is labeled D_t .

$$v = w + \sigma \dot{B}$$

GALERKIN PROJECTION GIVES SDES FOR RESOLVED MODES

$$\int_{\Omega} \phi_i \cdot (\text{stochastic Navier-Stokes})$$



$$db_i = F_i(\mathbf{b})dt + (\alpha_{\bullet i \bullet} d\mathbf{B}_t)^T \mathbf{b} + (\theta_{i \bullet} d\mathbf{B}_t)$$

multiplicative noise additive noise

Correlations to estimate

2nd order polynomial:
coefficients given by physics,

and $(\phi_j)_j$ $a(\mathbf{x}, \mathbf{x}) = \frac{1}{t} \langle (\sigma(\mathbf{x})\mathbf{B})_{obs}, (\sigma(\mathbf{x})\mathbf{B})_{obs}^T \rangle_t$