INTERNATIONAL JOURNAL FOR NUMERICAL METHODS IN FLUIDS
Int. J. Numer. Meth. Fluids 2016; **00**:1–7
Published online in Wiley Online Library (www.onlinelibrary.wiley.com). DOI: 10.1002/fld.4290

Editorial

Model Reduction and Inverse Problems and Data Assimilation with Geophysical Applications
A special issue in honor of I. Michael Navon's 75th birthday

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Received . . .

Professor Ionel Michael Navon retired in September 2014 from the Scientific Computing Department, Florida State University, Tallahassee Florida after a brilliant academic career. Since 1997, he is a fellow of American Meteorological Society and recently he became an honorary member of Academy of Romanian Scientists. His distinguished pioneering achievements in the domains of data assimilation, inverse problems and reduced order modeling during the last few decades have greatly contributed to the establishment and development of these aforementioned fields. In particular, his rich interdisciplinary expertise allowed him to advance the science reduced order modeling and inverse modeling as core techniques for data-driven modeling. He generalized predictive computational modeling leading to fast novel solution approaches for real-world inverse problems of oceanography and weather forecast. At the same time, Professor Ionel Michael Navon has been an outstanding mentor, advisor, role model and friend to his 9 PhD students and 11 postdoctoral scholars, with the large majority of them pursuing successful academic, scientific, and industry careers.

This year Professor Ionel Michael Navon celebrates his 75th anniversary and this special issue recognizes his accomplishments. The contributors to this special issue are former students, postdoctoral scholars, colleagues, close collaborators, and friends of Professor Ionel Michael Navon. The next three paragraphs describe his most important contributions to data assimilation and reduced order modeling fields in the last 10 years while the last part of the editorial focuses on the special issue's contributions.

Professor Navon's work addressed fundamental issues in both variational and statistical data assimilation with applications in fluid dynamics and atmospheric flows. Professor Navon extended

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and proposed frameworks to tackle non-differentiability in models and objective functions. For example, he formulated the Maximum Likelihood Ensemble Filter (MLEF) equations without the differentiability requirement for the prediction model and for the observation operators 1] and measured the impact of non-smooth observation operators on variational and sequential data assimilation 2]. Other efforts include coupling a Gaussian resampling method to generate more effective and efficient Particle Filter posterior analysis ensembles 3], improvement on the ensemble Kalman filters 4–7] and MLEF 8]. Professor Navon is also the co-author of a recent book 9] and several book chapters 10–13] describing the recent advancements and methodologies in variational data assimilation and non-linear sensitivity analysis. Goal-oriented adjoint sensitivity methods were proposed to guide to the adaptivity of finite element meshes 14, 15]. Moreover, he developed different approaches to model error formulation 16] and identify targeted observations 17] in 4D-Var, and formulated several 4D-Var lighting data assimilation schemes 18] for Weather Research and Forecasting model. He is also the co-author of the recently proposed independent set perturbation adjoint method 19] that facilitates the differentiating of the mesh based fluids models.

Professor Navon is also among the pioneers of coupled reduced order modeling and 4D-Var methods with applications in oceanography 20] and atmospheric flows 21]. In the latter, a Hessian-free truncated-Newton (HFTN) minimization algorithm in the Proper Orthogonal Decomposition (POD)-based space was developed based on a reduced second-order adjoint model. Adaptivity of the POD basis was employed as minimization advances in a proposed reduced order 4D-Var system using the Imperial College Ocean Model 22]. Trust-region methods were subsequently used to guide the adaptivity of the reduced order model during the optimization process 23, 24]. Dual weighted methods based on sensitivity analysis 25, 26] were pioneered by his group to enrich the reduced order bases and increase the accuracy of the reduced order 4D-Var analyses. Reduced-order observation sensitivity was also formulated 27]. Recently, it was shown that accurate reduced order Karush-Kuhn-Tucker conditions with respect to their full order counterparts represent a fundamental requirement for an accurate reduced order optimization solution 28].

Professor Navon's research work in the field of reduced order modeling is extremely rich. Together with his collaborators he developed POD-Galerkin and reduced order models and associated error estimates for various discrete high-fidelity flow models such as the Upper Tropical Pacific Ocean Model 29] based on finite difference 30–32], finite element 33, 34], finite volume 35] and unstructured meshes 36–40]. Petrov-Galerkin projections were also employed in the context of finite element models 41–43]. Efficient POD reduced order models were constructed for other type of models such as the chemical vapor deposit equations 44], nuclear radiation transport models 45, 46], prey-predator systems 47], borehole induction systems 48] and fluid-structure interactions models 49]. A particular attention was given to reducing the computational complexity of the non-linear reduced order models using Discrete Empirical Interpolation Method 50–52], tensorial POD 53] and non-intrusive methods 54, 55]. Very important studies on the practical and theoretical aspects of dynamic mode decomposition have been recently published 56, 57].

The special issue contains 18 original papers including those presented at the mini-symposium dedicated to "Inverse Problems and Data Assimilation", at the SIAM Conference on Computational Science and Engineering, Salt Lake City, Utah, USA, March 14-18, 2015. The aim of this special issue is to document recent mathematical developments in the field of reduced order modeling and inverse problems based on theoretical and numerical grounds that are relevant for various scientific and real life applications. The main topics consist in reduced order modeling framework (6 manuscripts), deterministic and statistical approaches to inverse problems and data assimilation (9 manuscripts) and sensitivity analysis (3 manuscripts).

While still in its infancy, the field of reduced order modeling is becoming attractive especially for the potential of drastically reducing the computational complexity of problems in data assimilation, inverse problems, uncertainty quantification, etc. Six intrusive and non-intrusive reduced order modeling studies for simulations of swirling and multiphase porous media flows, shallow water equations model, fluid-structure interaction problems with prescribed boundary motion and heat equation are proposed.

58] investigate the potential of POD reduced order models to accurately approximate the solutions of nonlocal diffusion equations. 59] make use of POD-Galerkin and reduced basis methods to develop a novel reduced order modelling framework for fluid-structure interaction problems with prescribed boundary motion using efficient geometrical techniques. 60] propose a sparse matrix discrete interpolation method to efficiently compute matrix approximations in the reduced order modeling framework. 61] focus on a difficult task in hydrodynamic stability analysis by modeling the dynamics of swirl intense flows. A linear stability analysis is elaborated, and a Dynamic Mode Decomposition (DMD) is carried out yielding an excellent prediction of the instability frequency and identifying the coherent structures of dynamic modes. 62] describe the first time application of non-intrusive Proper Orthogonal Decomposition (POD) reduced order modeling based on Smolyak sparse grids to porous media multiphase flows. A set of interpolation functions (hyper-surface) is constructed to represent the reduced unsteady dynamical system and its solution at the current time step is calculated by inputting the previous time steps solutions. 63] introduce another non-intrusive POD method by coupling a least squares fitting method and Smolyak sparse grid collocation procedure which performed well for two computational fluid dynamics models.

Theoretical and practical aspects involving inverse problems framework have been considered. Let us evoke the development of a novel variational data assimilation smoother together with its practical version relying on projected reduced order models with applications on a Shallow Water Equations model. Ensemble based data assimilation is well represented by three studies involving an unstructured adaptive mesh ocean model, a novel method for creating static reduced rank error covariance matrix and a new version of Kalman filter suitable for parallel implementation. A hybrid variational ensemble study is also available. Uncertainty quantification for strong and weak constraint variational data assimilation problems is addressed with a study on the influence of the model errors on the analysis error covariance. An adaptive observation study based on reduced order adjoint models is also present. Finally, solutions to accommodate a wide range of temporal and spatial scales in atmospheric and oceanic data assimilation problems are elaborated. 64] construct an ensemble-based sampling smoother for four-dimensional data assimilation using a Hybrid/Hamiltonian Monte-Carlo (HMC) approach. Unlike the well-known ensemble Kalman smoother, which is optimal only in the linear Gaussian case, the proposed methodology naturally accommodates non-Gaussian errors and non-linear model dynamics and observation operators. 65] explore the applications of projected reduced order models based on POD and Discrete Empirical Interpolation Method (DEIM) to develop economical versions of the HMC sampling smoother. Projection of the posterior distribution in the linear case is theoretical analyzed. Using block circulant matrices, 66] creates a high-dimensional global covariance matrix from a low-dimensional local sub-matrix for potential use in hybrid variational-ensemble data assimilation. 67] make the first attempt to construct an Ensemble Kalman Filter method to accommodate an unstructured adaptive mesh ocean model. 68] propose a Quasi-Newton approximation for the covariance matrix employed by the Kalman filter algorithm and derive parallel formulation of the filtering task. 69] use the variational Ensemble Kalman Filter and the Coupled-Hydrodynamical-Ecological Model for Regional and Shelf Seas to assimilate high resolution satellite images of turbidity and chlorophyll-a with application in ecology. An uncertainty quantification research proposed by 70] focuses on evaluating the analysis error covariance matrix for weak constraint variational data assimilation problems. Besides the inverse Hessian of an associated objective function, the analysis error includes an additional component associated to the model error. 71] use an adjoint sensitivity technique based on reduced order models to identify the impact of observations on the predictive accuracy of a quantity of interest, and to guide placing the sensors at the locations with high impacts. For atmospheric and oceanic fine resolution data assimilation problems, 72] revealed that the use of a various temporal and spatial resolutions having different dynamical and statistical properties imposes fundamental difficulties. Their research shows a set of theoretical and numerical analyses to highlight these shortcomings and suggests possible solutions.

Three sensitivity analyses studies complete the current list of the manuscripts. Advances to the current sensitivity analyses methods are proposed and their applications include: the construction of a quantitative risk assessment for design and development of a renewable energy system to support decision-making among design alternatives - 73], implementation of computationally efficient operator-type response sensitivities for uncertainty quantification and predictive modeling - 74] and the development of a second order adjoint model to better understand the impact of the changes in pollutant emission onto a target region 75].

As a researcher, Professor Navon excels in multiple disciplines. His significant research achievements are closely related to the topics of inverse problems, data assimilation and reduced order modeling. This special issue celebrates the enduring legacy of Professor Navon's work.

The papers featured here will be collected together as a 'virtual' special issue at the IJNMF homepage and can be accessed directly at the following link: `http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1097-0363/homepage/virtual_issues.html`.

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