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Enhanced Computational Performance and Stability & Control Prediction for NATO Military Vehicles

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Numerical simulations are a principal tool across the lifecycle of NATO military air and sea vehicles. Traditional low-fidelity methods such as potential flow or Euler codes are often used in the early stages of the design cycle due to their lower computational cost and time requirements. However, these methods may lack the required accuracy for certain design scenarios, and the use of higher-fidelity methods such as computational fluid dynamics and experiments is often limited by the tremendous cost and timescales necessary for providing comprehensive data sets. A feasible means to overcome these limitations is reduced-order modeling. Over a four-year period the NATO Science & Technology Organization Research Task Group 351 of the Applied Vehicle Technology panel developed various data-driven reduced-order models. Those were applied on four different air and sea vehicle use cases, which demonstrated nearly real-time data set population and maneuver or course-keeping prediction capabilities. A summary of the Research Task Group is presented in terms of the air and sea use cases, methods, and results. Additional work is required to understand the real extent of cost reduction achievable with these approaches. Open questions remain on combining data sets with different fidelity levels or quantifying uncertainty in models.

I. Introduction

COMPUTATIONAL prediction capabilities of ship and aircraft performance as well as maneuvering or stability and control (S&C) characteristics are essential for the design and analysis of modern military vehicles. Nowadays, numerical simulations have become a principal element in the design process because of their flexibility in evaluating multiple, alternate designs [1] at a lower cost compared to physical experiments. However, during early phases of a design cycle, the representation fidelity of the future vehicle was—and often still is—restricted to the use of lower-fidelity methods such as strip theory approaches, panel codes, or Euler codes to predict flight and seakeeping performance or the determination of loads [1,2] due to computational cost and time requirements imposed by higher-fidelity methods. Hence, either physical model testing or numerical tools of higher fidelity at later stages within the design cycle have to confirm design decisions and to improve the accuracy of performance and S&C data sets. This comes along with significantly increased cost if retroactive design modifications become necessary. An early integration into the design cycle would improve the flexibility within the design process itself while identifying future cost drivers as early as possible. However, this represents a key challenge insofar as flow phenomena, such as vortex-dominated and highly separated flows at a minimum, must incorporate Reynolds-averaged Navier–Stokes (RANS) modeling, if not beyond, to overcome current limitations in simulating these phenomena through the use of hybrid RANS/large-eddy simulation (LES) [3,4].

In view of this, computational fluid dynamics (CFD), along with its validation, is one of the key enabling technologies for digital engineering [5]. In addition to the need to strengthen confidence in CFD results by determining their uncertainty, high computational cost limits the use of CFD for data set generation in early design stages. Here, a second key enabling technology, which addresses real-time requirements on data set generation as defined in [5], might be reduced-order modeling. Reduced-order modeling allows for an efficient usage of CFD within product design cycles by leveraging high-fidelity CFD data to provide estimates of vehicle performance and S&C characteristics at untried conditions in real-time.

A reduced-order model (ROM) is usually defined as a computationally inexpensive mathematical approximation model of the full-order simulation model. In general, such mathematical approximation models could be categorized either into model order reduction techniques, aiming for lower computational complexity, or simplified mathematical models, representing input and output relations called metamodels or surrogate models. In recent years, ROMs have received much attention in leveraging high-fidelity CFD to improve representation fidelity of the future vehicle. For instance, low-fidelity methods were extended with data-driven approaches to improve their fidelity and accuracy both during design and sustainment phases of the sea platform lifecycle [6–8]. Approximation models for expensive computer simulations often include statistical techniques such as regression techniques, e.g., radial basis function (RBF) [9,10] and Gaussian process regression (GPR) [11,12], and have been the subject of research for a long time. Various single- and multi-fidelity regression techniques [13–17], coefficient-based system identification (SID) models [18–20], and neural network (NN) architectures to model global coefficients directly [21] have been applied to approximate high-fidelity simulations with a demonstration for military vehicles. These methods were also used in conjunction with model order reduction approaches, such as auto-encoders/decoders (AE) [22,23], dynamic mode decomposition (DMD) [24,25], or proper-orthogonal decomposition (POD)

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[26–28]. Other approaches used indicial response function modeling [29–31], based on nonlinear system theory, i.e., Volterra series [32,33]. All of the preceding methods aimed to reduce large turnaround times of computational full-order model evaluations by providing data in a fraction of the time. ROM predictions based on few CFD simulations are affordable at early design stages or generic CFD-based training maneuvers could meet the requirements of high throughput and fast turnaround time [34,35].

The authors provided a comprehensive summary of preceding and related activities under the North Atlantic Treaty Organization/Science and Technology Organization (NATO/STO) Applied Vehicle Technology (AVT) panel that led to the Research Task Group (RTG) AVT-351 [36]. Multiple activities focused on the validation of CFD methods and their applicability during early and advanced design stages and showed consistent results compared to experiments in many operational conditions. However, much effort is needed to provide comprehensive high-fidelity CFD-based data sets, both for capturing the nonlinear flow regime and for evaluating dynamic motions of the vehicle. AVT-351 investigated computational methods such as ROMs in their capability and applicability to efficiently predict the extensive amount of data needed for design evaluations of different air and sea vehicles.

This article summarizes individual contributions to the AVT-351 RTG. First, the scientific objectives, structure of the RTG, and brief descriptions of the air and sea domain use cases together with numerical experimental data sets are presented (see Sec. II), followed by an overview and categorization of reduced-order modeling techniques that are developed and applied within this RTG (see Sec. III). Results for each of the four use cases are summarized in Sec. IV. The final section presents conclusions drawn for both air and sea domains and provides an outlook on investigations that are recommended to be conducted in the future.

II. Research Task Group

The main objective of AVT-351 was to investigate ROM techniques to overcome current limitations of CFD in terms of providing comprehensive data sets, especially with respect to turnaround times. This included three scientific objectives to be addressed: first, the development and validation of ROMs; second, the definition of optimal input signals for ROM generation; and third, the application of ROMs on subsequent disciplines to evaluate the effect of the ROM accuracy and its capabilities on vehicle design tasks. The first two objectives addressed the generation of various types of ROM methods enabling efficient usage of limited high-fidelity numerical or experimental data in early design phases. Part of the development was an assessment of input signals to determine whether they were able to cover the vehicle design space in an efficient manner. Investigation of the applicability of the aforementioned methods was addressed by the third objective, which included the employment of ROMs in maneuvering simulations and flight dynamic modeling (FDM) for control system design.

A broad community from academia, (government) research facilities, and industry represented the air and sea domain in AVT-351. Table 1 in the Appendix lists all involved organizations, nations, and use cases they were involved in and the contributions they made. This wide range of experts highlighted the importance of ROM development for the participating nations. The field of ROM development was accompanied by related activities to generate and utilize numerical and experimental data sets, as well as investigate the applicability and impact of an ROM and its prediction accuracy on a subsequent discipline in a vehicle's design cycle, such as FDM. Great emphasis was placed on cross-domain knowledge transfer during the four-year working period of the RTG. Multiple subgroups were established dealing with the individual use cases. All subgroups organized regular virtual meetings to keep track of recent progress in addition to the biannual AVT Panel Business Meeting weeks. These regular technical meetings and discussions, which were also attended by additional observers and technical advisors, helped to draw up roadmaps, carry out continuous evaluation, and foster cross-domain exchange. Over 7000 person hours and 11 million High Performance Cluster (HPC) core hours were dedicated to AVT-351, which testifies to the collaborative research model of NATO/STO. The person-hours were applied toward model design, wind tunnel model manufacturing and wind tunnel testing, CFD modeling and computation setup, data analysis, and ROM generation. Note that wind tunnel use and associated costs are not included here.

With the very diverse composition of the RTG, many different potential applications and development objectives were put forward. The overall scope was massive and could not be addressed in full by this RTG. A framework needed to be created to guide ROM development for selected applications, not just in this RTG but also in follow-on activities. AVT-351 focused on defining the use cases along with the ROM development roadmaps [36], generation of the data required to develop the ROMs, and primarily demonstrating their applicability toward a use case. An optimization and evaluation of input signals, which are of great importance to the accuracy and the computational cost of an ROM, were not addressed. Other topics related to ROM development, such as uncertainty quantification in

Table 1 Composition of the Research Task Group

Organization	Nation	Use case	Database[a]	Experiments	Computations	ROM	FDM
BAE Systems	GBR	FFD		X	X		
CNR-INM	ITA	5415M	X			X	
DLR	DEU	FFD	X		X	X	
DRDC	CAN	BB2, 5415M			X	X	
DSTL	GBR	FFD, Diana2			X		
FOI	SWE	FFD, Diana2			X	X	X
ITU	TUR	FFD, Diana2			X		
MARIN[b]	NLD	BB2, 5415M	X				
Nangia	GBR	FFD, Diana2			X		
NLDA	NLD	FFD, Diana2					X
NLR	NLD	FFD, Diana2			X	X	
NSWCCD	USA	BB2, 5415M			X	X	
ONERA	FRA	FFD		X	X		
ONR[b]	USA						
QinetiQ[b]	GBR						
SOTON	GBR	FFD				X	
UDC	ESP	Diana2			X		
UIOWA	USA	BB2			X		
UNB	CAN	BB2				X	
USAFA	USA	FFD			X	X	
ZHAW[b]	CHE						

[a]Existing numerical or experimental data sets provided to the RTG.

[b]Observer or technical advisor within the RTG.

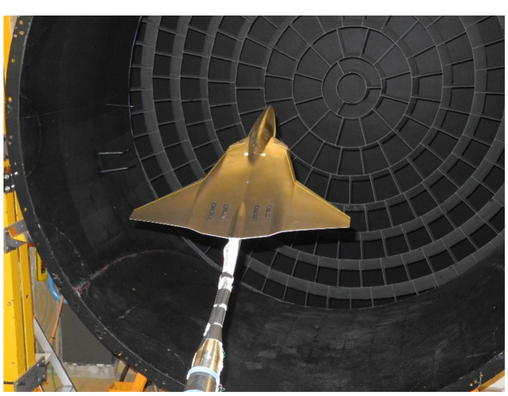
models across all fidelity levels and its propagation within multi-fidelity frameworks, a quantitative comparison of ROM approaches, investigation of data fusion approaches to combine various different data sets from multiple numerical and experimental sources, or how an existing ROM could be expanded, e.g., when a minor design change is adopted, a store is added, or the design space is altered, were not pursued within AVT-351.

In total, four use cases from the air and sea domain featuring specific challenges for aerodynamic and hydrodynamic modeling were selected. The first use case from the air domain, a wind tunnel model, represented a Future Fighter Demonstrator (FFD). This generic triple delta wing configuration is based on the baseline DLR-F22 wind tunnel model [37,38] as part of a multi-disciplinary technology assessment program at the German Aerospace Center (DLR) addressing design capabilities of an FFD [39]. The RTG was able to leverage existing datasets for initial CFD validation studies from DLR wind tunnel experiments. A revision of the wing design of the DLR-F22 model by ONERA led to the ONERA_DLR_M421 wind tunnel model [40], as shown in Fig. 1a. In comparison with the baseline DLR-F22 model, the ONERA_DLR_M421 wind tunnel model features a moderate thickness, positive camber, and twist distribution. This model design was utilized to investigate flight dynamic characteristics in multiple static and dynamic wind tunnel experiments at ONERA and BAE Systems to validate CFD simulations of RTG participants and for ROM development within the AVT-351. ROM techniques ranging from SID over regression and NN models to model order reduction techniques were employed for this use case.

A remotely piloted 1:3 scaled model of the Diana2 glider serves as a second air domain use case. The Diana2 model in Fig. 1b was acquired to serve as a test platform for aeroservoelastic flight testing in order to develop and evaluate SID approaches for highly flexible aircraft that manifest a strong interaction between aircraft rigid-body responses and aeroelastic effects [41–43]. It is manufactured by Baudismodel [44]. A CFD model was created from a 3D structured light scan. A structural model was also created using ground vibration test results as part of the aeroservoelastic research [42] and made available to the RTG. The Diana2 model was selected as a platform for rigid and aeroelastic ROM development. However, Diana2 studies in AVT-351 have been limited to the rigid model, with aeroelastic research to follow. Within AVT-351, a POD-based dimensionality reduction technique combined with an NN modeling approach as well as a quasi-steady regression and direct NN modeling technique has been investigated to predict distributed surface pressures.

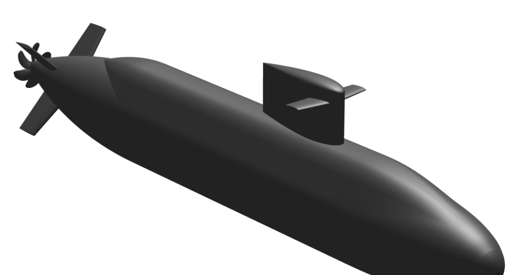
The first use case of the sea domain represented a modern generic subsurface hunter-killer (SSK)-class submarine geometry developed by AUS and NLD to help foster international collaboration on hydrodynamics. The original Joubert hull form [45,46], on which the BB2 was based, did not include appendages or a realistic sail cross-section, so a number of modifications were developed to create a directionally stable submarine [47,48]. The BB2 geometry is shown in Fig. 1c, which was previously used and investigated, e.g., in AVT-301 [49]. The RTG leveraged a database of CFD and model-scale maneuvering data previously generated by the Maritime Research Institute Netherlands (MARIN) and extended this by additional static and dynamic high-fidelity CFD simulations by the University of Iowa (UIOWA). ROM development focused on augmenting semi-empirical maneuvering models for maneuvering and control simulations with indicial response modeling and NN approaches.

The second sea domain use case was a surface ship geometry, 5415M, representative of a naval combatant. The 5415M model in Fig. 1d is a geosim of the DTMB 5415 and 5514 models, but with modified appendages and skeg. Specifics can be found in [50]. In contrast to all other use cases, a stochastic ocean wave environment was taken into account and was composed of many parameters (ship heading, ship speed, wave height, wave direction, and wave period), which added complexity to an already computationally difficult problem. In this RTG, CFD was used to derive model coefficients to tune nonlinear potential flow simulations. These run closer to real-time, and generated data was used to build data-driven models and alleviate part of the data generation problem. Performance was

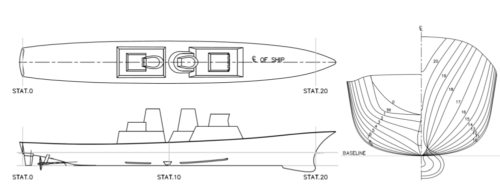


a) FFD: ONERA_DLR_M421 model on the forced oscillation test rig in the ONERA-L1 wind tunnel

b) High-aspect ratio glider: Diana2 model



c) Generic SSK class submarine: BB2



d) Naval combatant: 5415M surface ship model. Reprinted with permission from Toxopeus, S. L., van Walree, F., and Hallmann, R., "Manoeuvring and Seakeeping Tests for 5415M" [50]. Copyright 2011 by MARIN

Fig. 1 AVT-351 air and sea domain use cases.

evaluated using data from held-back nonlinear potential flow models as well as CFD and model-scale data, the latter kindly provided to our RTG and AVT-280 [51] by MARIN [52]. Reduced-order modeling approaches covered semi-empirical, NN, and model order reduction techniques or combinations thereof.

III. Reduced-Order Modeling

Various reduced-order modeling techniques were investigated within this RTG. Those were primarily all data-driven and belong either to the class of surrogate modeling or model order reduction approaches. The former, surrogate models, are further subdivided into three categories (coefficient-based and hybrid models, regression models, and NN models), whereas the latter employs a dimensionality reduction technique to compute a low-dimensional subspace, which is usually combined with a surrogate model to obtain a predictive model. In the following, a ROM description is introduced.

A. Coefficient-Based and Hybrid Models

Coefficient-based models relate independent input variables $\boldsymbol{x}$ to a dependent output variable y. A generalized form is given by a linear regression model that is obtained by taking linear combinations of parameters (coefficients) and independent variables:

$$y(\boldsymbol{x}) = \boldsymbol{x}^\top \beta + \varepsilon \tag{1}$$

The model is linear in the parameters β but employs linear or nonlinear functions for the input variables $\boldsymbol{x}$. The quantity ε is the measurement error term. Coefficient-based models require a priori knowledge about the system dynamics for model postulation. That is, the model class is predefined, from which a specific form will be selected. An example of a classical, linear-coefficient-based model based on stability derivatives for the pitching moment coefficient C_m is given as

$$C_m = C_{m_0} + C_{m_\alpha}\alpha + C_{m_q} q + C_{m_{\dot\alpha}}\dot\alpha \tag{2}$$

The model parameters, e.g., stability derivatives, and (eventually) the specific form of the model are usually determined by SID techniques [20,53], semi-empirical approaches, e.g., standard equations of motion for sea vehicles [54–57], or from experimental and CFD data for the identified model structure. A formulation of unsteady dynamics (as well as determination of unsteady dynamic stability derivatives) is obtained in terms of indicial response functions [13,30,31,58–61] or based on nonlinear system theory using Volterra series [32,33,62,63]. When augmenting the model parameters by using additional data-driven surrogate modeling techniques such as NN to account for different data sources, such an approach is referred to as a hybrid model.

B. Regression Models

Regression models are again obtained by taking linear combinations of parameters and fixed basis functions. In fact, now linear combinations of the training set output variables are taken. In consequence, the model parameters β are now determined for the N observations with the corresponding training set outputs by, e.g., maximum likelihood or least squares:

$$y(\boldsymbol{x}) = \boldsymbol{\Phi}^\top \beta + \varepsilon \tag{3}$$

with the input matrix $\boldsymbol{\Phi}$ given by the basis functions. In contrast to coefficient-based models, here the a priori model postulation and model structure determination are not necessary, but the fixed basis functions need to be specified that usually include a nonlinear feature space mapping $\Phi(\boldsymbol{x})$. An equivalent representation is a linear combination of a kernel function evaluated at the training set data points $k(\boldsymbol{x}, \boldsymbol{x}') = \Phi(\boldsymbol{x})^\top \Phi(\boldsymbol{x})$. For example, RBF or GPR models belong to this model category [11,12,64]. For unsteady applications, one could refer to a surrogate-based recurrent framework (SBRF) [65–68] as one option to include transient effects into model generation.

C. Neural Network Models

Neural networks introduce a nonlinear relationship between input and output variables. Taking the linear regression model in Eq. (3), for a NN the basis functions depend on parameters that are adapted along with the coefficients during training of the NN to data, resulting in parametric forms for the basis functions. Each basis function is itself a nonlinear function of a linear combination of the inputs known as activations. Differentiable, nonlinear activation functions are used to transform the activations to be used in a series of functional transformations, i.e., linear combinations. The transformed quantities are called hidden units that usually form multiple hidden layers. Examples of different NN architectures are multilayer perceptron (MLP) and recurrent-type NNs, such as recurrent neural network (RNN), gated recurrent unit (GRU), and long short-term memory (LSTM) networks that are usually applied for time-series prediction tasks. For more details on the application of NNs, including MLP, RNN, GRU, and LSTM, see, e.g., [22,64,69–72]. Another deep learning approach is called geometric deep learning (GDL) [73–75], which involves encoding of geometric understanding of the data structure.

D. Model Order Reduction

The class of model order reduction models features a lower-dimensional representation of the full-order model. Popular methods include POD [76,77], DMD [78,79], and AE [80,81]. In combination with regression or NN surrogate modeling techniques that are applied on the low-dimensional subspace, the model order reduction methods provide predictive capabilities, including a reconstruction of the high-dimensional solution. Another approach, labeled here as the model order reduction approach, is the intrusive physics-based linear frequency domain (LFD) method [82,83] used in this RTG to determine stability coefficients.

E. Reduced-Order Models Applied in AVT-351

An overview of all reduced-order modeling approaches that were developed and applied to one of the four use cases is given in Table 2 in the Appendix. Hybrid approaches that combine semi-empirical modeling with NN on the one hand and indicial response

Table 2 Reduced-order modeling approaches applied within AVT-351 on air and sea domain use cases

Organization	Use case	Coefficient-based / hybrid	Regression	Neural network	Model order reduction
CNR-INM	5415M			LSTM / GRU [72], RNN [90]	DMD [24,25,88,101] DMD + NN [90]
DLR	FFD		SBRF [68,91]		LFD [94]
DRDC	5415M	Semi-empirical [56,57,88]			
DRDC, UNB	BB2	Semi-emp. + Indicial resp. [55,85–87]			
FOI	FFD, Diana2		RBF [93]	LSTM [93]	
NLR	FFD, Diana2				POD + LSTM [27,28,91,92]
NSWCCD	5415M	Time-domain potential flow [89]			POD + MLP [88]
NSWCCD	BB2	Semi-empirical + MLP [84]			
SOTON	FFD			GDL + AE + GRU [96]	
USAFA	FFD	SID [91,95], Indicial resp. [95]		FFNN [95]	

modeling on the other hand were applied on the BB2 use case by Naval Surface Warfare Center—Carderock Division (NSWCCD) [84] and a joint effort of Defence Research and Development Canada (DRDC) and University of New Brunswick (UNB) [85–87], respectively. Two additional semi-empirical models, both developed for surface ship modeling, were employed on the 5415M hull form by DRDC [88] and NSWCCD [89], respectively. Developments at the National Research Council-Institute of Marine Engineering (CNR-INM) for the same use case focused on NN [72,90] and model order reduction techniques [24,25,88].

A similar approach belonging to the model order reduction category was followed by the Royal Netherlands Aerospace Centre (NLR) with the combination of POD with an NN model for the prediction of wing surface pressure distribution [27,28]. This technique was applied on both air domain use cases, the Diana2 and FFD models. By introducing enrichment functions, an improved modeling of discontinuities such as shocks was achieved, as demonstrated on the FFD model [91,92]. Another application of those two use cases from the Swedish Defence Research Agency (FOI) was based on the one hand on the family of RBF regression models and on the other hand on LSTM models [93]. Contributions from all four categories were received for the FFD use case, in addition to the NLR and FOI contributions. Here, DLR applied a physics-based technique [94] and an unsteady regression model [68,91]; the United States Air Force Academy (USAFA) used two coefficient-based [91,95] and a feed-forward neural network (FFNN) [95] modeling approach; and finally the University of Southampton (SOTON) developed a recurrent GDL model [96] in combination with GRU and AE techniques belonging to the NN category.

IV. Summary of Results

AVT-351 worked on the development of enhanced numerical methods based on computational fluid dynamics and experiments to efficiently generate comprehensive performance as well as stability and control data sets at a feasible cost for air and sea vehicles. Results for each of the four use cases from air and sea were obtained. This section highlights a subset of results across both domains, while individual publications of the participating organizations, referenced in this paper, contain a more detailed discussion of results and findings.

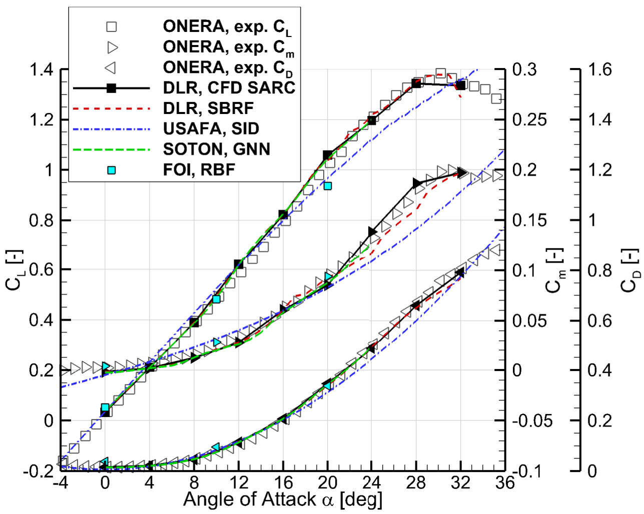
A. Generic Fighter Aircraft: FFD

Various aspects of the aerodynamic modeling, data set generation, and their application for the FFD use case were considered by a total of 11 organizations. After an initial validation of CFD, the baseline generic triple-delta wing configuration was adapted in order to feature more application-oriented aerodynamic characteristics relevant for flight dynamics investigations. Static and dynamic CFD simulations by multiple organizations were conducted to replicate, on the one hand, ONERA's experiments [40], and on the other hand, to extend the numerical database toward transonic flow conditions as well as to provide generic maneuvers as input and reference data for the ROM development [68,91,93,95]. The dynamic reference conditions chosen for the subsonic wind tunnel experiments comprise variations of angle of attack and pitch rate for longitudinal performance assessment by means of forced oscillation tests in ONERA Low Speed Wind Tunnel L1 (ONERA-L1), but also lateral and longitudinal effects due to rotation about the velocity vector, which are important for the assessment of lateral stability and capacity of entering roll maneuvers, through a rotary test program in the ONERA Vertical Wind Tunnel SV4 (ONERA-SV4) [40]. As part of a second wind tunnel test program, BAE Systems investigated the capability of a five-degree-of-freedom maneuver rig platform. The rig allows for a model to be assessed in up to five degrees of freedom, which enables assessment of nonlinear aircraft behavior and the generation of both static and dynamic stability derivatives. Additionally, efforts relying on low-fidelity aerodynamic modeling of control surface effects to enable FDM analysis were undertaken by Istanbul Technical University (ITU) and Netherlands Defence Academy (NLDA). NLDA further developed a nonlinear flight dynamics model to perform trim analysis, assess agility metrics considering large amplitude maneuvers, and evaluate handling qualities of the FFD model. The potential of machine learning methods to build accurate models of time-dependent, aerodynamic force and moment responses when used in flight dynamic analysis for control system design was evaluated by FOI. Different aerodynamic models in open- and closed-loop stability analysis in trim conditions were compared, where the unsteady LSTM model outperformed a quasi-steady regression model [93].

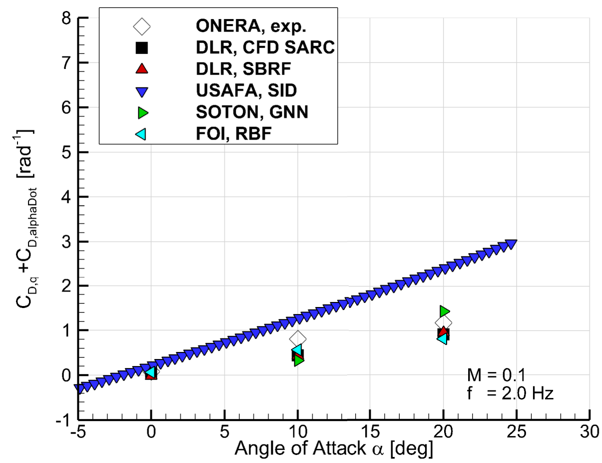
Figure 2 shows ROM predictions in comparison with a numerical CFD benchmark data set computed by DLR [68], which was validated with experimental data from ONERA [40]. Static predictions at a subsonic Mach number equal to 0.1 showed an excellent agreement with the CFD reference data over a wide angle of attack range (Fig. 2a). Estimates of the lumped stability derivatives that consist of a rotary and a translation acceleration component indicated by the subscripts q and $\dot{\alpha}$ are computed from predicted sinusoidal pitch motions for multiple mean angles of attack. These damping derivatives are shown for a constant frequency of 2 Hz in Figs. 2b–2d for the drag, lift, and pitching moment, respectively ($C_{D,q} + C_{D,\dot{\alpha}}$, $C_{D,q} + C_{L,\dot{\alpha}}$, and $C_{m,q} + C_{m,\dot{\alpha}}$). Overall, a good agreement between experiment, CFD, and ROMs was obtained. This agreement is notable considering that different models and input data were used. ROMs by DLR and SOTON are based on time-accurate forced motion CFD simulations generated by DLR [68]. These include a Schroeder multisine signal with varying mean angle of attack (Fig. 3) and a series of DCChirp signals covering high-incidence conditions, in addition to the sinusoidal pitch oscillation reference cases. Even though SOTON applied a coarsening approach to the CFD surface mesh to reduce the total number of grid points and computational cost, the reconstructed integral force and moment coefficients from predicted surface pressure and skin friction distributions by the GDL ROM match the reference data accurately [96]. An example of a prediction of the surface pressure coefficient c_p at one time instance of a sinusoidal motion in Fig. 4 shows that the GDL ROM is capable of reproducing the vortex topology of the triple-delta wing quite well. Similar to SOTON, DLR chose an autoregressive model, but modeled the force and moment coefficients directly with the unsteady SBRF. A high sensitivity to the time-delayed input and output quantities was found, but nevertheless accurate predictions for multiple flow conditions were reported [68,91].

It was shown that for flight conditions at rather moderate reduced frequencies ($k = (\omega c/2U_\infty)$) in the range of 0.025–0.075, the application of quasi-steady modeling techniques by FOI and USAFA led to similar results in comparison with the unsteady models. Differences in the ROM predictions are most likely due to different CFD codes and signal types used to train the ROMs. FOI generated input data in the form of sinusoidal pitch motions at multiple Mach numbers and trained their quasi-steady RBF model using this training set. Comparable results are obtained when employing an LSTM model [93]. USAFA worked on an efficient and effective input signal design and assessed the applicability of different training maneuvers for their quasi-steady SID technique. The SID predictions shown are based on a modified pseudo-random binary sequence (PRBS) training maneuver with a varying Mach number from 0.1 to 0.9 (Fig. 5) [91]. Even though the training signal covers a large Mach number range, the overall trend at $M = 0.1$, with some differences in magnitude, is captured by the SID model when compared with the other numerical and experimental data sources.

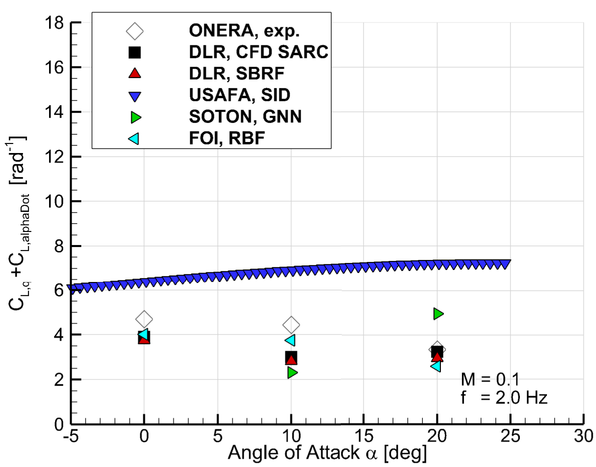
An enriched POD-LSTM method was developed by NLR in collaboration with Delft Technical University (TUD) and applied to the prediction of sectional wing pressure distributions at a transonic Mach number equal to 0.85 [91]. This method proved very successful in predicting the shock location and strength using a limited number of parameters consisting of 8 enrichment parameters and 10 standard POD modes for a total of 18. An example of the results is shown in Fig. 6. The ePOD prediction is compared to CFD and predictions by the standard POD-LSTM approach using 10 and 18 modes and shows much improved prediction of both shock location and strength.



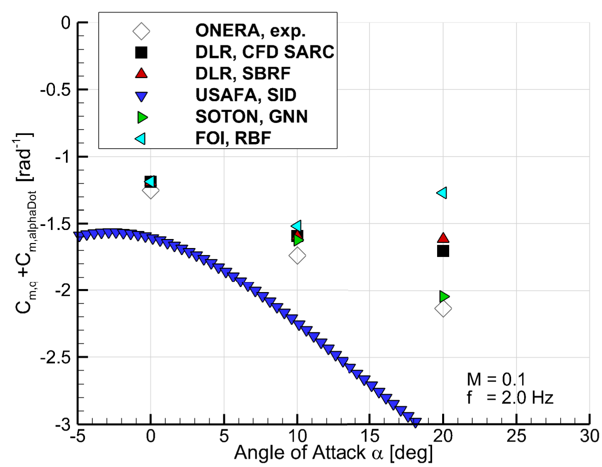
a) Static force and moment coefficients



b) Quasi-steady damping derivative $C_{D,q}$

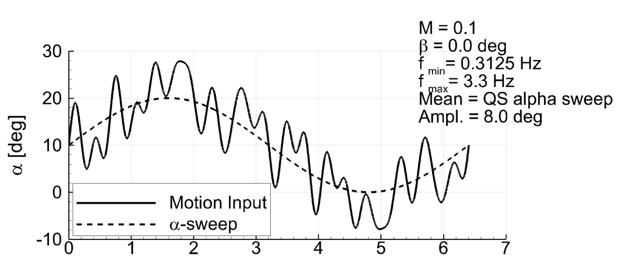


c) Quasi-steady damping derivative $C_{L,q}$

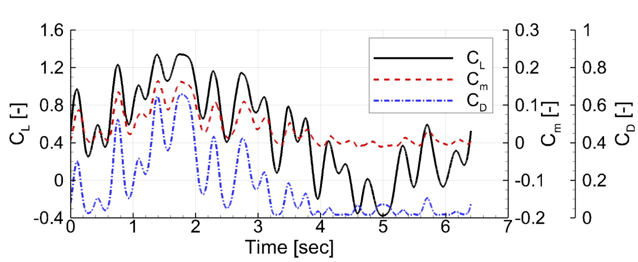


d) Quasi-steady damping derivative $C_{m,q}$

Fig. 2 Comparison of multiple ROM predictions at $M = 0.1$ with CFD simulations of the DLR TAU-Code and static and dynamic experimental data from ONERA.



a) Forced motion input



b) CFD response

Fig. 3 Schroeder multi-sine CFD training maneuver with varying mean angle of attack.

B. High-Aspect Ratio Aircraft: Diana2

A CFD data set was generated by NLR consisting of different types of training and reference maneuvers, all for a rigid half-body model. The reference maneuvers, a pull-up and dive-and-climb maneuver, were created with a simplified flight dynamics model based on steady-state CFD results. Flight paths were constructed from pitch rates specified at selected times. The training maneuvers include a modulated alpha-chirp in which an angle-of-attack oscillation increased in both amplitude and frequency with pitch rate $q = 0°/\mathrm{s}$, an identical signal but with varying pitch instead of angle of attack, and a Schroeder signal. The alpha-chirp signal is shown in Fig. 7. All maneuvers were at a constant Mach number equal to 0.10.

The pressure distributions of the wing's upper surface were extracted from the CFD results of the three training maneuvers, as well as the two reference maneuvers for comparison with ROM predictions. For each of the training signals, a POD basis was calculated from the pressure distributions, i.e., C_p weighted by cell area. The POD basis consists of the POD modes $\boldsymbol{\Phi}_n(\boldsymbol{x})$ and the associated time coefficients $\boldsymbol{a}_{n,m}$. These were used to train an LSTM-type NN, with training parameters being time step, angle of attack α and its first time derivative $\dot{\alpha}$, and pitch rate q and its first time derivative $\dot{q}$. Note that $q = \dot{q} = 0$ for the alpha-chirp signal. Training was performed separately for 5, 10, and 20 modes and both a small network containing a single LSTM layer of 64 units and a large network containing 2 LSTM layers of 1024 units. Both used

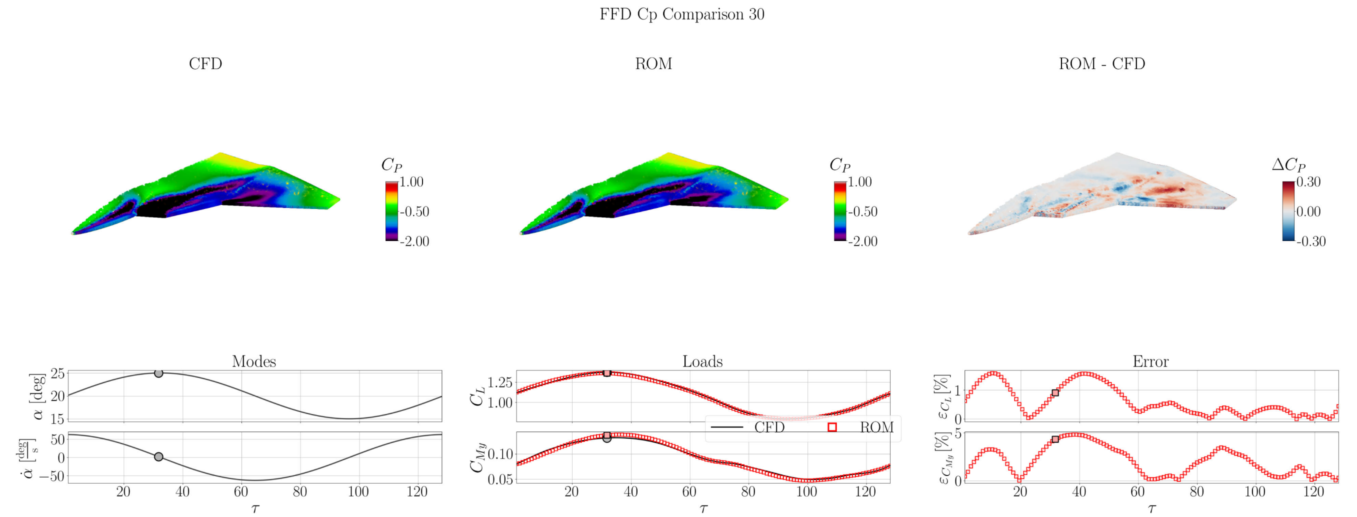
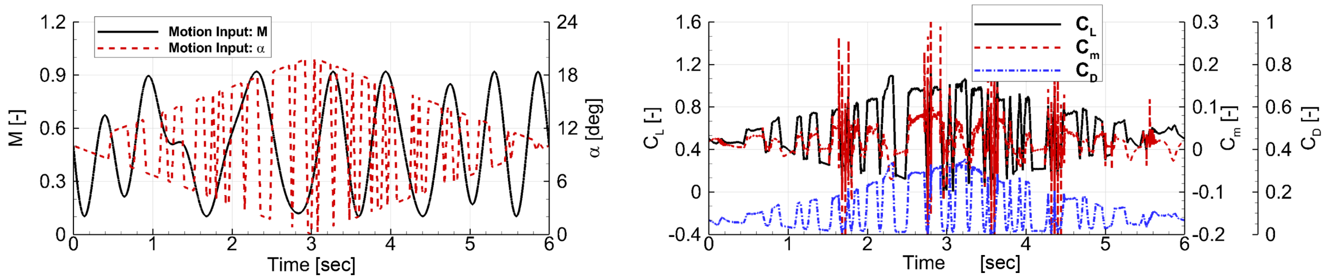


Fig. 4 Time instance of pressure coefficient c_p prediction in comparison with CFD results based on a coarsened CFD mesh.



a) Forced motion input

b) CFD response

Fig. 5 Pseudo-random binary sequence CFD training maneuver with varying Mach number.

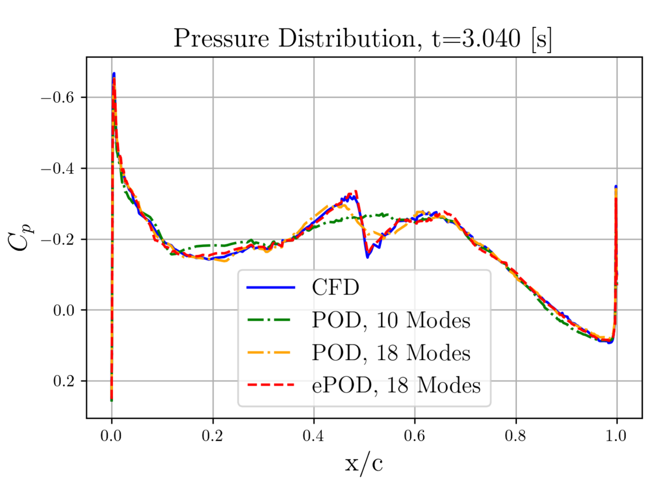


Fig. 6 Sectional c_p predictions with ePOD-LSTM and POD-LSTM compared to CFD. Reprinted with permission from Ghoreyshi et al. [91]. Copyright 2025 by the American Institute of Aeronautics and Astronautics, Inc.

10 previous time steps. The trained NNs were then applied toward predicting pressure distributions for the two reference maneuvers. Prediction times were very fast, with the large network taking approximately 2.5 s. No discernible influence of mode count on prediction times was observed.

An illustration of the results for the pull-up maneuver is provided in Figs. 8 and 9. Figure 8 compares the various errors associated with the predictions by the networks trained using the alpha-chirp signal in terms of the area-weighted RMS error of the pressure distribution for each time step of the maneuver. The POD projection error is the difference between direct projection of the POD basis and the CFD result, the network error is the difference between the predicted pressure distribution and the POD projection, and the prediction error is the difference between the predicted pressure distribution and the CFD result. The projection error decreases with mode count for most of the maneuver, except when high angles of attack are achieved and the flow separates. For these same regions of the maneuver, the network trained with 5 modes has the lowest network error, while 10 modes give the lowest network error for moderate angles of attack. The prediction error has a trend similar to the projection error. Furthermore, the small network results are comparable to those of the large network. Increasing the number of POD modes does not necessarily result in improved network prediction accuracy. This is because the greater complexity of time signals associated with higher-order modes makes them more difficult to predict. With the POD approach, both the number of modes used and the complexity of their time coefficient signals (for the training and validation signals) are known before network training starts. This knowledge might be used for the selection and design of an appropriate neural network.

Pressure distributions for two time instances with severe flow separation are shown in Fig. 9. The results here are produced with the large network variants utilizing 20 POD modes. The results of the CFD calculation, the POD projection, and the network prediction are shown together with the various errors. As observed in the validation, the largest errors are located at the leading edge near the separation zones. Similar observations were made for the results for the dive-climb maneuver predictions, which are not shown here. Since the direct POD projections represent the results an optimal neural network would achieve, it can be concluded that the network predictions may be improved by optimizing the LSTM network and possibly the training signal, neither of which was attempted within this task group.

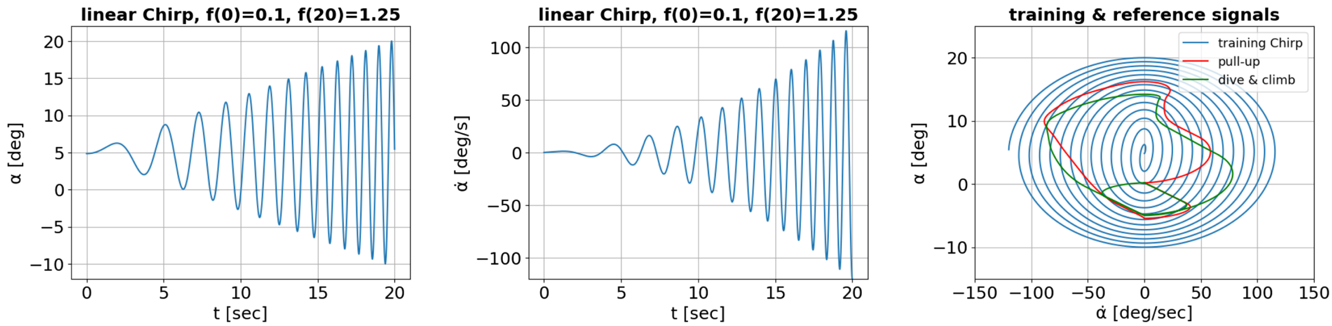


Fig. 7 The alpha-chirp training signal: α (left) and time-derivative $\dot{\alpha}$ (middle) as function of time, and α vs $\dot{\alpha}$ compared to reference maneuvers (right).

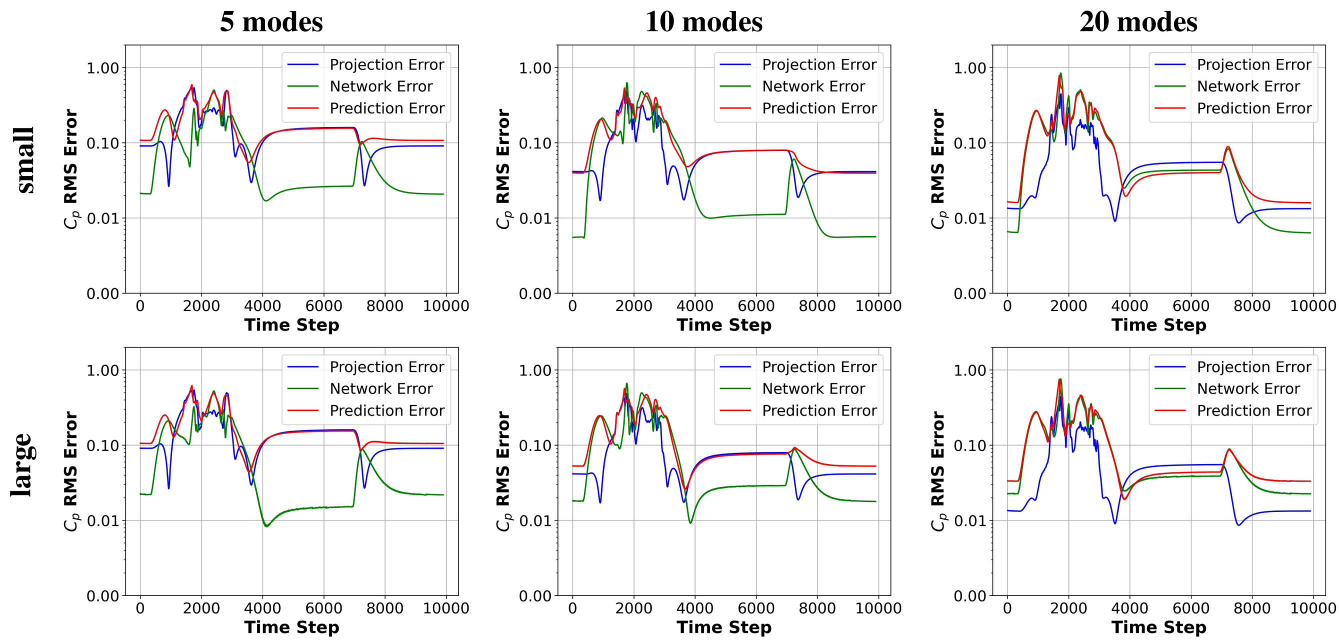


Fig. 8 Pull-up maneuver prediction: projection, network, and prediction errors for different mode counts and network sizes. Network trained with alpha-chirp signal.

A combination of data dimensionality reduction through POD and LSTM neural networks was used to predict surface pressure distributions. This approach enables very fast ROMs that deliver predictions with good to reasonable accuracy for the test maneuvers. Improvements are possible by application of clustered PODs and improved training signal design and network design. The developed approach offers several advantages:

1) The number of POD modes required for a desired level of accuracy in the reconstructed pressure distribution can be determined from the training and validation signals.

2) The number of parameters is greatly reduced, thereby also reducing the complexity of the neural network, the network training time, and the network prediction time.

3) A distinction can be made between POD projection error and network error.

4) Network design is informed by the number of selected POD modes and the complexity of the corresponding time signals in the training and validation signals.

Aeroelastic effects will be included in future work. The structural model is available, and initial steady-state CFD calculations have already been performed.

Additional studies were performed at FOI on the design of efficient training signals for the development of time-dependent aerodynamic models using FDM and LSTM neural networks. A quasi-steady FDM was used to evaluate training signals, illustrating that including the FDM in the design of training signals could lead to very different signals from the ones currently used (alpha-chirp, theta-chirp, and Schroeder) for developing more accurate aerodynamic response models aimed at control system design.

C. Generic SSK Class Submarine: BB2

A joint effort between DRDC and UNB for the BB2 use case was an indicial ROM, which combined a quasi-steady (QS) coefficient model with an indicial response model, designed to capture motion history effects. The QS model is trained from the database of static CFD simulations provided by MARIN, while the indicial ROM is trained from CFD simulations of impulsive accelerations conducted by UNB. Sample indicial response functions are shown in Fig. 10a. This model was compared and contrasted with DSSP, a semi-empirical submarine simulator developed over several decades by DRDC using experimental data. Full details on the QS model are presented in [55,97,98], the indicial model formulation is available in [85,87,99], and DSSP is described in [55].

The indicial ROM combines the advantages of CFD training data with the ability to model motion history effects on vehicle forces. Comparisons were made across two sets of reference data. The first was unsteady sinusoidal oscillations, simulated by UNB, which were intended to improve the understanding of unsteady flow physics for submarines.

These oscillations were chosen with realistic operating frequencies based on an analysis of horizontal (HZZ) and vertical plane zigzags (VZZ) but are limited in amplitude so as to avoid stall effects in the stern plane and are more representative of laboratory experiments than operational maneuvers. In these tests, the in-plane

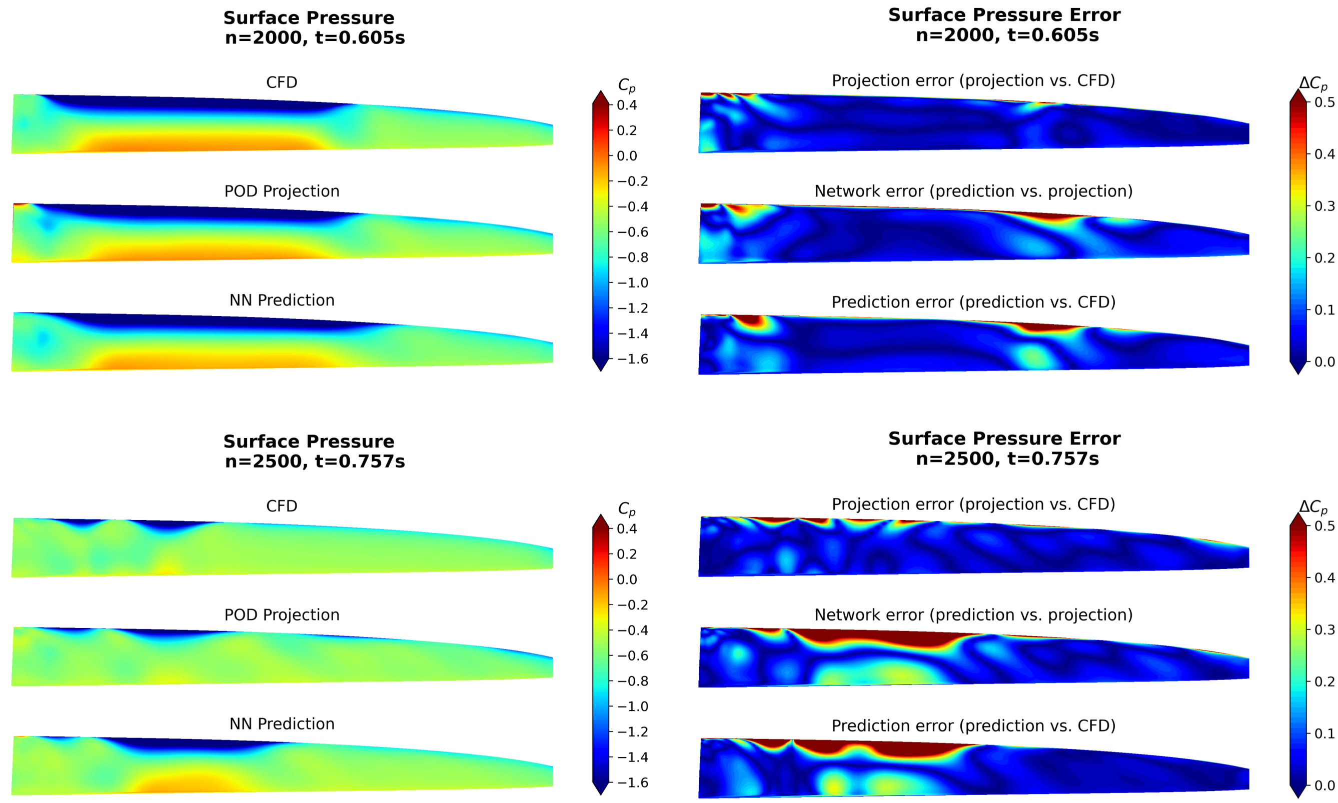
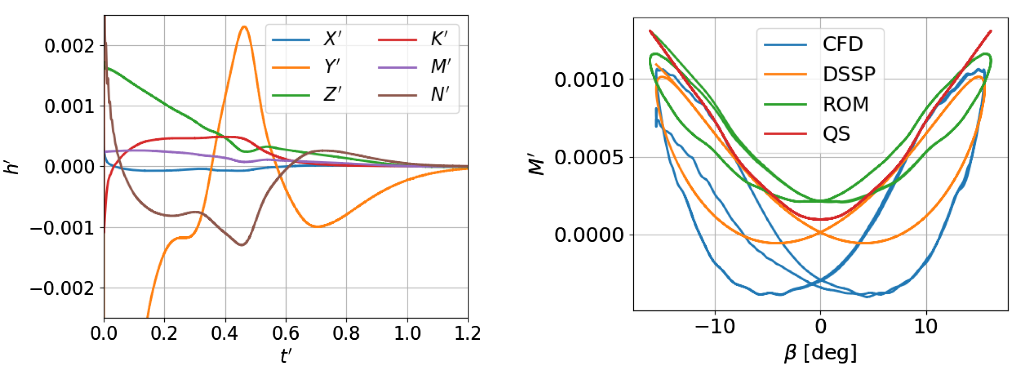


Fig. 9 Pull-up prediction: CFD results, POD projection, and network prediction with errors (right) for two instances with flow separation (large network, 20 modes).



a) Sample response functions from impulsive lateral acceleration with zero initial drift angle

b) Sample pitching moment hysteresis predictions for lateral oscillation at reduced frequency $k = 0.12$

Fig. 10 Sample indicial response functions. Reprinted with permission from Doyle et al. [99]. Copyright 2024 to His Majesty, the King in Right of Canada, Department of National Defence, Canada.

loads (Y & N) were found to have a linear unsteady response without significant unsteady cross-coupling, while the out-of-plane loads (Z & M) were found to have a nonlinear unsteady response with significant cross-coupling effects, with axial loads demonstrating a mixed character between the two.

A sample hysteresis loop demonstrating some model results is shown in Fig. 10b. These results further suggest that there may be an acceleration dependency in the out-of-plane load response, which is counter to previous assumptions in the submarine community; however, further research is required to explore this finding. Full details on this study are presented in [85,87,99].

The second set of reference data was CFD simulations of free submarine maneuvering supplied by the UIOWA, consisting of turning circles and high pitch rate pull-up maneuvers. In these test cases, motion history was found to only be marginally significant to the out-of-plane loads during the transient phase of the maneuver. From these results, it is unlikely that unsteady flow has a significant impact on derived maneuvering quantities such as the tactical diameter or transfer time, although this could not be verified in the present work.

In both comparisons, unsteadiness was significant for the out-of-plane loads and made minor contributions to the axial loads, with the quasi-steady assumption giving relatively good results for the in-plane loads. Comparison with the empirical Feldman integral showed consistent results between the two methods, with marginal gains from the ROM due to the advantages of CFD tuning. The indicial ROM requires a relatively high number of additional unsteady CFD simulations in order to achieve this gain, and so the utility of this method in comparison with the Feldman integral is questionable. Some degree of unsteady modeling is required; however, if accurate prediction of the unsteady out-of-plane loads is of interest, whether with an indicial ROM or some other method. The most likely application areas for this are believed to be in experimental testing, such as with a Planar Motion Mechanism (PMM) or similar; however, there may also be implications for near-surface depth keeping in wavy seas.

As an alternative to the approach utilized by DRDC and UNB, NSWCCD has taken a data-driven machine learning approach to enhance the performance of their in-house simulation tool: Maneuvering and Control Simulation (MCSIM). MCSIM was developed by NSWCCD as the Navy's primary modeling and simulation (M&S) tool that provides physics-based M&S capabilities for predicting the six-degree-of-freedom (6-DOF) trajectories of submarines over the entire range of expected operating conditions. MCSIM has served as a key link within the hydrodynamic characterization process that combines reduced-order modeling, model-scale testing and full-scale sea trial data, and simulation techniques to evaluate maneuvering performance for both design and fleet support. The modeling of hydrodynamic forces and moments in MCSIM utilizes either a coefficient-based or a multivortex-based approach. Both modeling approaches require captive and free-running model (FRM) testing, full-scale trial (FST), and/or computational fluid dynamics (CFD) data in order to empirically tune the model coefficients/parameters and validate model predictions.

The data-driven machine learning (ML) approach undertaken by NSWCCD is one in which feed-forward NNs are combined with MCSIM to compensate for the differences between predictions and the measured maneuvers (FRM, FST, or CFD). Details can be found in [84]. In particular, the ML-enhanced MCSIM aims at improving the prediction of hydrodynamic forces and moments by training the deep learning NN models to correct the baseline MCSIM. The corrections to hydrodynamic forces and moments can be obtained equivalently by computing corrections to the linear and angular accelerations and adding their multiplication with the inertia matrix to the right-hand side of the 6-DOF equations of motion. The input data to the NN models consists of combinations of the state variables of ship motion, control surface deflection angles, and propulsion. The output data of the NN models is simply the correction to linear and angular acceleration predicted by the baseline MCSIM. This ML approach may apply to model- and full-scale output utilizing the FRM and FST data, respectively.

MARIN has provided CFD data for hydrodynamic forces and moments in captive mode and measured FRM test data. The MARIN FRM test consists of three types of maneuvers—HZZ, VZZ, and controlled depth turning circles (CDTC)—with a total number of 17 runs. Separately, UIOWA has conducted 6-DOF CFD simulations of fixed plane turn (FPT), CDTC, and maximum-q (MAX-q) at model scale with a total number of four runs.

The activities conducted by NSWCCD related to the BB2 use case are summarized by Fig. 11. Utilizing the measured maneuvering data of the MARIN BB2 FRM test scaled up to full-scale, NSWCCD has empirically tuned an MCSIM multivortex (MV) model as the baseline and applied the ML-informed approach to BB2 and trained NN models. To evaluate model performance, an average angle measure (AAM) metric, developed by NSWCCD, is used. The AAM represents a mixture of both amplitude and phase errors between two time series; see [100] for details. Here, the AAM shows that the ML-enhanced MCSIM-MV has improved the correlation between the predicted and measured maneuvering data in comparison with the baseline MCSIM-MV. Figure 12 compares predictions from both the baseline and ML-corrected MCSIM-MV with MARIN FRM test data for a vertical overshoot maneuver as a validation. Since MCSIM and MARIN FRM used different controllers for the equivalent rudder angle to maintain heading, one would expect to see differences in out-of-plane motions, such as lateral velocity, roll, roll rate, yaw, and yaw rate. On the other hand, the predictions in the in-plane motions are significantly improved. The magnitude of the out-of-plane motions is much smaller than that of the in-plane motions. The ML-informed approach has also been shown to be stable and has produced reasonable predictions for the generalization test cases. Both the baseline and ML-corrected MCSIM-MV have also been used to predict the four maneuvers of UIOWA CFD for comparison. Overall, the MCSIM prediction agrees reasonably well with the CFD data, despite some discrepancies due to different controllers and approaching conditions. The UIOWA CFD tends to predict higher values in yaw range and angle in turning maneuvers. The ML-corrected MCSIM-MV does not agree, however, with the CFD for the MAX-q maneuver with an equivalent stern plane angle of 30 deg given that the training data from MARIN FRM only has up to 20 deg stern plane angles in the VZZ maneuvers. No attempt is made to augment the UIOWA CFD data with the MARIN FRM test data for another round of ML training due to the discrepancies in yaw rate and angle.

D. Naval Combatant Surface Ship: 5415M

For the surface ship use case, a single approach was taken by CNR-INM. DMD was applied to computational models' diagnostics, forecasting, and SID of the 5415M in beam-quartering Sea State 7 irregular waves, under roll resonance conditions. Computational results include output from an overset block-structured CFD solver designed for ship applications (CFDShip-Iowa) as well as output from two 6-DOF nonlinear potential flow codes: TEMPEST (NSWCCD) and ShipMo3D (DRDC). Benchmark experimental fluid dynamics data are taken from [52]. Full details can be found in [88].

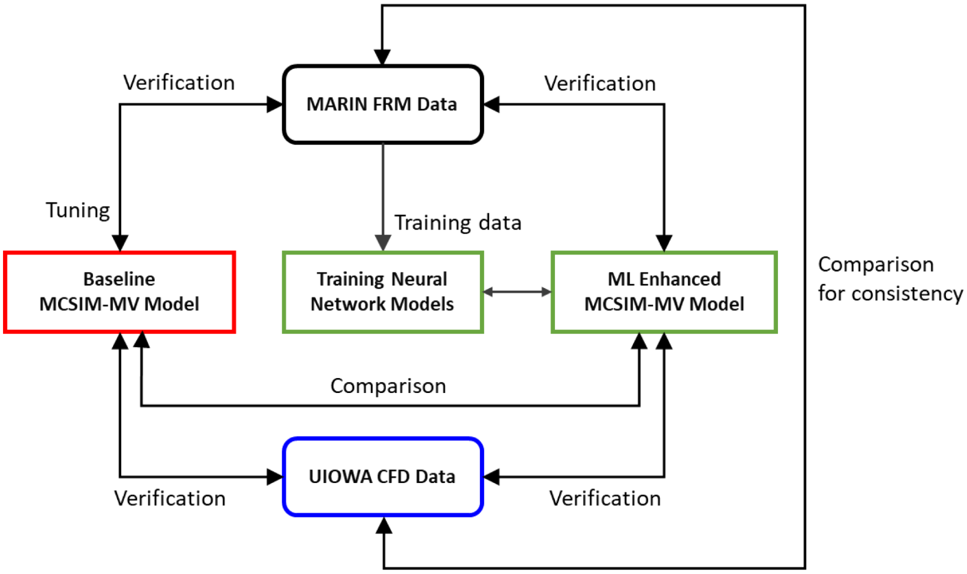


Fig. 11 Process for training, verification, and validation of ML-corrected MCSIM-MV.

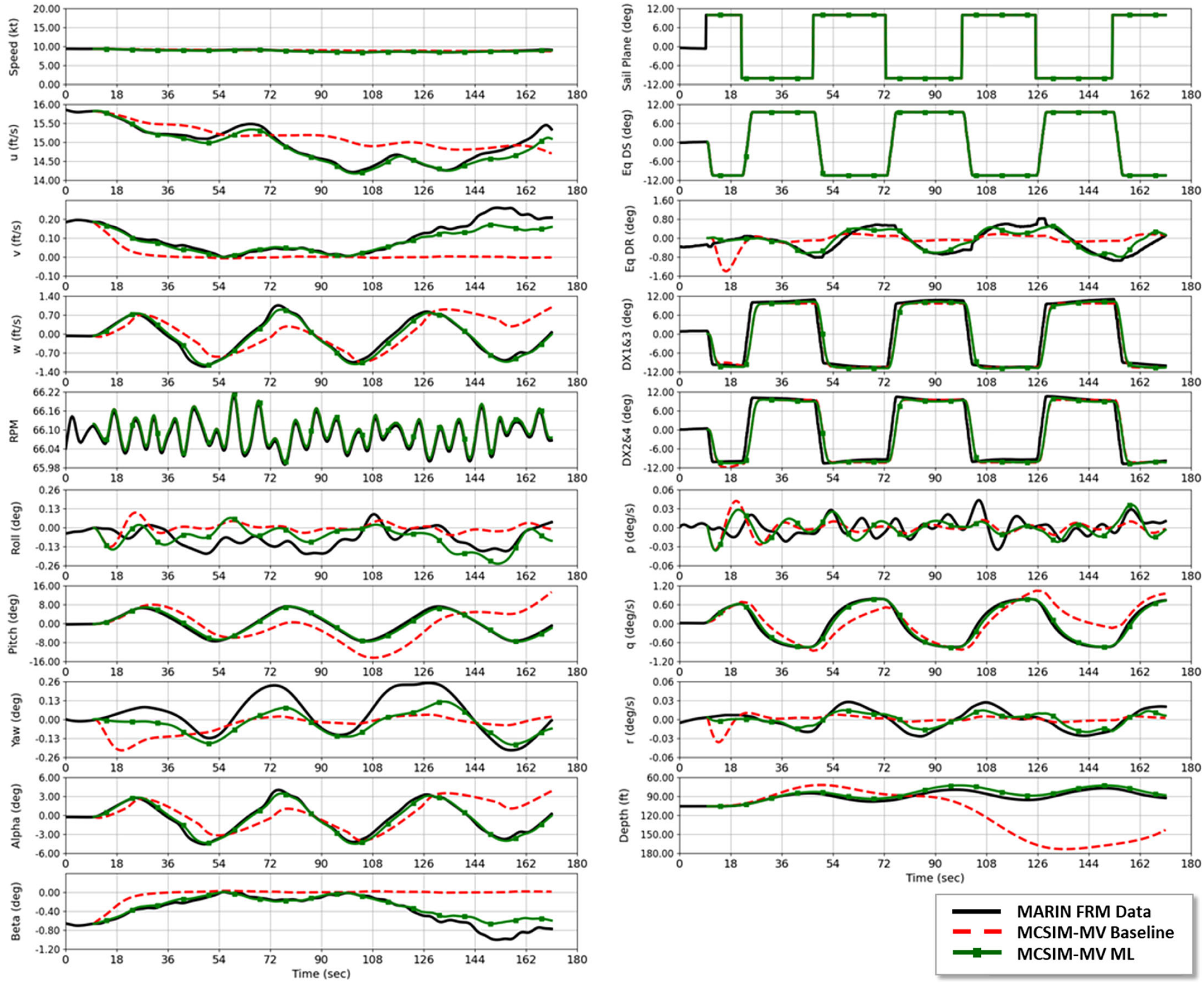


Fig. 12 BB2 vertical overshoot maneuver with ±10 deg sail and equivalent stern plane angle predicted by baseline and ML-enhanced MCSIM-MV in comparison with FRM test data.

Computational models' diagnostics via DMD revealed that all computational models can capture reasonably well the modal participation of the most participated system's modes, both in terms of energy and frequency (Fig. 13). The roll-resonance mode is mostly participated in by heave, roll, pitch, yaw, and rudder angle, which appear all correlated. Surge and sway barely participate in the roll-resonance mode. The correlation between variables is very well captured by all computational models, with small uncertainty, possibly favored by a strong excitation of the roll-resonance mode. The shapes predicted from the various models almost collapse with very limited deviations from the EFD results (Fig. 14a). The slowest mode shows participation mostly by surge and sway and, to a lesser extent, roll, yaw, and surge and sway velocities. In general, larger uncertainties are observed in the mode shape identification by the computational models along with larger differences with the EFD modal shape. It may be noted how ShipMo3D cannot properly identify the surge contribution, underpredicting and falling outside the uncertainty of the experimental data, which may indicate directions for further model developments (Fig. 14b).

Forecasting results are promising and show the beneficial effects of augmenting the data set with time shifted copies of the time-series in a Hankel matrix. Time histories covering four encounter wave periods are used to build the system's matrix, following [24]. The use of delayed states is found beneficial to the forecasting accuracy.

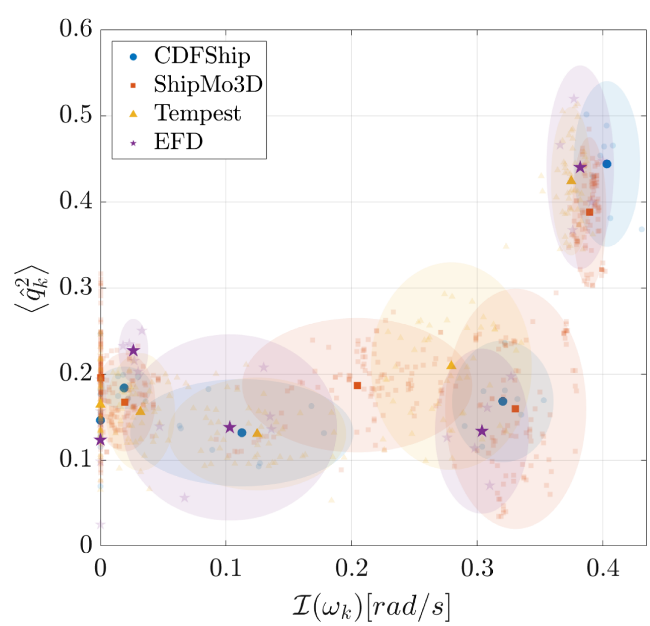
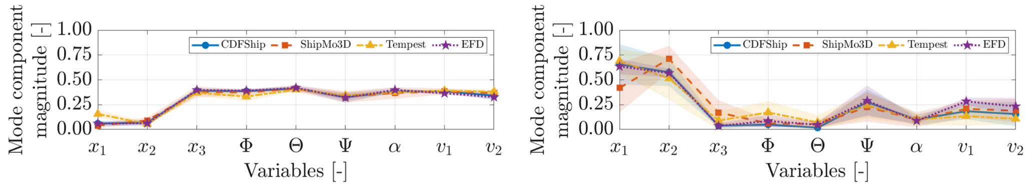


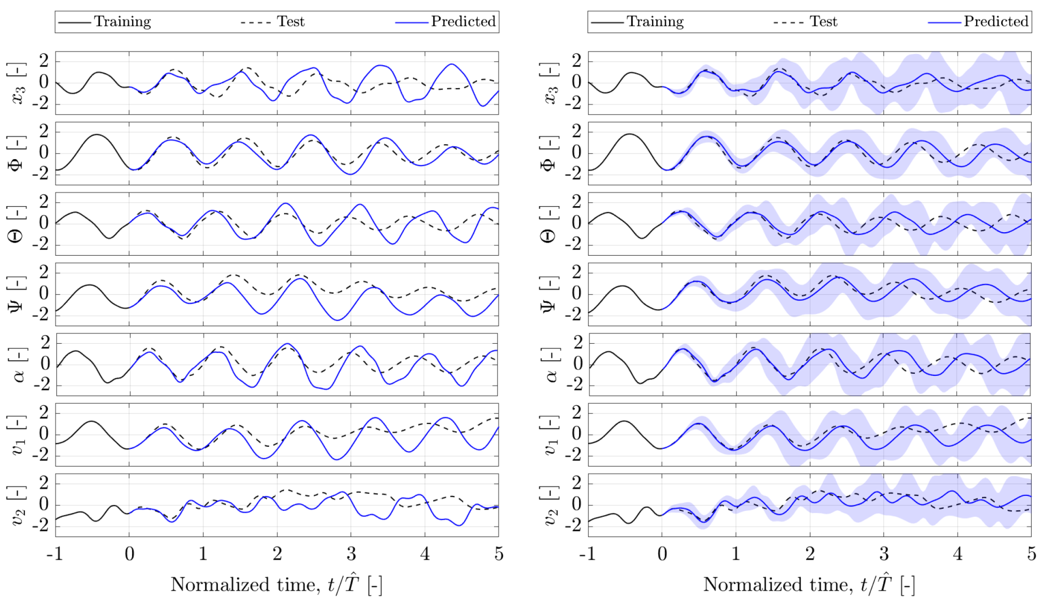
Fig. 13 Standardized modal energy versus full-scale angular frequency obtained by DMD for the 5415M test case.



a) Roll-resonance mode

b) Slow mode

Fig. 14 Standardized mode component magnitude for each variable obtained by DMD for the 5415M test case.



a) Deterministic forecasting

b) Bayesian forecasting

Fig. 15 Deterministic vs Bayesian DMD forecasting prediction for the 5415M test case.

To the team's knowledge, this was the first time that predictions of ship motions were obtained via DMD with system identification. Results look very promising and show how using a large number of incoming waves (up to 200) to build the system's matrices has a beneficial effect on the prediction accuracy. Using multiple wave elevation (virtual) measurements was not found to have evident beneficial effects on the results; however, additional investigations on the topic will be conducted in the future. Finally, a Bayesian extension of DMD was introduced during the RTG activities, providing DMD predictions (for both forecasting and SID) with an uncertainty band. The mean prediction is generally found to be more accurate than its deterministic counterpart, which is an indication of the desired robustness associated with the Bayesian approach (Fig. 15). Details may be found in [88,101].

The work includes a systematic statistical study for the various DMD methods and setups applied, providing prediction errors with mean values and standard deviations that allowed us to draw some general conclusions and best practices. SID has been applied also for test sets with conditions unseen in the training, using time histories obtained with TEMPEST, considering operational and environmental condition perturbations, and addressing variations of speed, relative heading, and significant wave height. It has been found that variations of significant wave height can be successfully addressed without the need for additional training of the DMD model; speed variations are responsible for discrepancies in the frequencies of the predicted and true signals, whereas a modified relative heading introduces significant errors in the prediction, leading to unreliable forecasts. Moreover, extensions to other test cases than course keeping, such as transient maneuvering in waves, will be considered in the future and investigated in collaboration with the new NATO AVT-399 on "Assessment of Experiments and Prediction Methods for Naval Ship Transient Maneuvers in Calm Water and Waves."

V. Conclusions

The NATO Research Task Group AVT-351 on Enhanced Computational Performance and Stability & Control Prediction for NATO Military Vehicles investigated various reduced-order modeling techniques to supplement CFD by providing comprehensive data sets without increasing turnaround times. A wide range of experts from academia, (government) research institutes, and industry were involved, reflecting the interest in and importance of ROM development. Various activities addressed during the four-year working period of AVT-351 include definitions of use cases and ROM development roadmaps, numerical and experimental data generation, and establishing as well as developing different ROM approaches and performance metrics. Part of the ROM development was an assessment of input signals to determine whether they are able to cover the vehicle design space efficiently. Investigation of the applicability of the aforementioned methods was addressed by the employment of ROMs in maneuvering simulations and flight dynamic modeling for control system design. Advantageous for all these activities was the collaborative framework under the NATO umbrella, which allows for and encourages free discussion and sharing of ideas, methods, models, and results. This greatly enhanced and accelerated technology and capability development within the participating organizations.

A subset of results across the air and sea domains is highlighted in this article. Aerodynamic performance and stability and control modeling through the application of various reduced-order modeling techniques demonstrated their applicability toward accurate and nearly real-time data set population. Use of hybrid approaches and model order reduction methods for naval platform performance modeling showed consistent and improved results compared to classical models and illustrated the need to include time-history effects in the models for multiple test scenarios. An enabling key is the efficient generation of computational or experimental input data sets. For this purpose, the task group leveraged a range of existing experimental and computational data and generated additional data sets to complement and validate these. First steps toward an application of models in maneuvering and flight dynamics simulations were accomplished. These steps could enable performance assessment of next-generation military air and sea platforms at reduced cost, but additional work is still required to understand how much of a cost reduction is achieved.

Reduced-order modeling approaches currently in use in the air and sea domain accounted for domain specifics in terms of their underlying design philosophy. Multiple models for naval platform performance prediction combined traditional modeling approaches with advanced numerical methods for model augmentation while incorporating computational data of different fidelity and (existing) experimental data quite effectively. In contrast, in the air domain, most approaches were based on generic, prescribed maneuver simulations obtained from high-fidelity CFD that aim to cover the flight envelope efficiently. Both approaches in the air and sea domains seem to be promising in reducing computational cost. But additional steps to exploit benefits from both approaches, along with a systematic comparison to a classical way of modeling, are needed.

Several related topics to ROM development that could not be addressed within the available timeframe were briefly discussed and indicate possible topics for follow-on activities. Noteworthy, the use cases and ROM development roadmaps were not limited to research pursued in AVT-351 but intended to provide a clear research direction for follow-on activities as well. Thus, future work might focus on an extended analysis of efficient input signal designs and input signal optimization, since apart from the prediction capability of an ROM and its related accuracy, also the computational cost to build the ROM is associated with the ability of the training data to provide an efficient coverage of the design space. A systematic assessment of such generic training signals (i.e., forced motion CFD simulations) and ROM is necessary, also as to whether these are superior to classical design-of-experiment strategies and/or modeling approaches.

Multiple ROM approaches pursued within AVT-351 used data from multiple sources and fidelity levels, such as wind tunnels, towing tanks, CFD, or potential flow codes. From a vehicle design cycle perspective, it would be both efficient and logical to expand and/or improve a ROM that was initially generated in earlier phases, with experimental data becoming available later during vehicle design. Open questions remain on how to combine these different data sets, each with different fidelity levels, error sources, and, in the case of model experiments, also different Reynolds numbers. Further, quantifying uncertainty in models across all fidelity levels and understanding how this uncertainty propagates within a multi-fidelity framework is crucial for building confidence in prediction tools and setting realistic expectations with regard to the accuracy of modeling and simulation tools. Such an assessment of the reliability of model predictions with regard to their usability in vehicle design is required. This includes the impact of the model on S&C data and implications for vehicle design changes.

In addition, an extension of the air domain use cases toward modeling of out-of-plane motions and aeroelastic effects would allow a more comprehensive evaluation of the developed ROMs with regard to the abovementioned issues. In the sea domain, an extension toward additional challenging test cases, e.g., transient maneuvering in waves, and the development and evaluation of efficient training signals in comparison to current state-of-the-art data acquisition approaches are of great interest.

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