Roll Damping Predictions using Physics-based Machine Learning

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Abstract

Computational Fluid Dynamics simulations and Machine Learning models are useful predictions tools that have the potential to work even better when used together. This paper presents a physics-based machine learning approach that supplements standard regression basis functions, such as polynomials, with simple physical models of the system. This mitigates the data dependence of machine learning predictions, and the associated computational cost of generating the training set simulations. We illustrate this method by increasing the accuracy of roll-damping power coefficient predictions by 50 to 200% using O(10) training examples.

1. Introduction

Computational Fluid Dynamics (CFD) is increasingly used to analyse the hydrodynamic response of ship structures, but the cost of such simulations is still too high for iterative design work. Given practical limits on computational time and the large number of adjustable parameters for a given design, only a small number of CFD simulations can be run, making it difficult to obtain a unique global optimum for single objective optimization, and essentially impossible to use in mapping out a complete optimal Pareto front (*Schmitz et al., 2002*).

Machine Learning appears to be the panacea of our time, but it does little on its own to address this issue. The vast majority of state-of-the-art machine learning methods require $O(10^3)$-$O(10^6)$ sets of examples, known as training data, in order to determine the model parameters (*Witten et al., 2016*). In addition, more complex physical systems typically necessitate more elaborate learning models, which must be trained with correspondingly larger sets of examples (*Evgeniou et al., 2000*). Once this learning process is complete, the evaluation of the model to predict new cases is typically negligible, but generating this number of simulated training examples using CFD is completely impractical.

In this work we will examine the utility of including CFD in the process of optimizing roll-damping keels. A roll-damping keel is an ideal candidate system for the inclusion of CFD as viscous effects are dominant. The particular physics of roll damping differ substantially to those of the remaining degrees of freedom of ship motions, where motions such as heave, sway and pitch may be easily and sufficiently accurately obtained from potential flow methods in the form of strip theory. The viscous nature of roll-damping results in substantial non-linearity in roll responses for various hull shapes, ship operational types and requirements, and the intensity of the forced roll responses due to irregular seas (*Ikeda et al., 1978*).

This work focuses on two elements of viscous roll-damping predictions. First, we will investigate the periodic flow past a rolling ship using a novel extension of 2D+T methods (*Fontain and Cointe, 1997, Weymouth 2013*). While many previous investigations of viscous roll-damping such as Jaouen *et al. (2011a, 2011b)* and *Hubbard and Weymouth (2017)* use a rolling body without forward motion, this has the inherent issue that the local vortex flow is not convected down-stream, leading to modelling and accuracy issues. The new 2D+2T approach avoids this issue and is many orders of magnitude faster than 3D unsteady ship simulations enabling the production of a large set of roll-damping simulations.

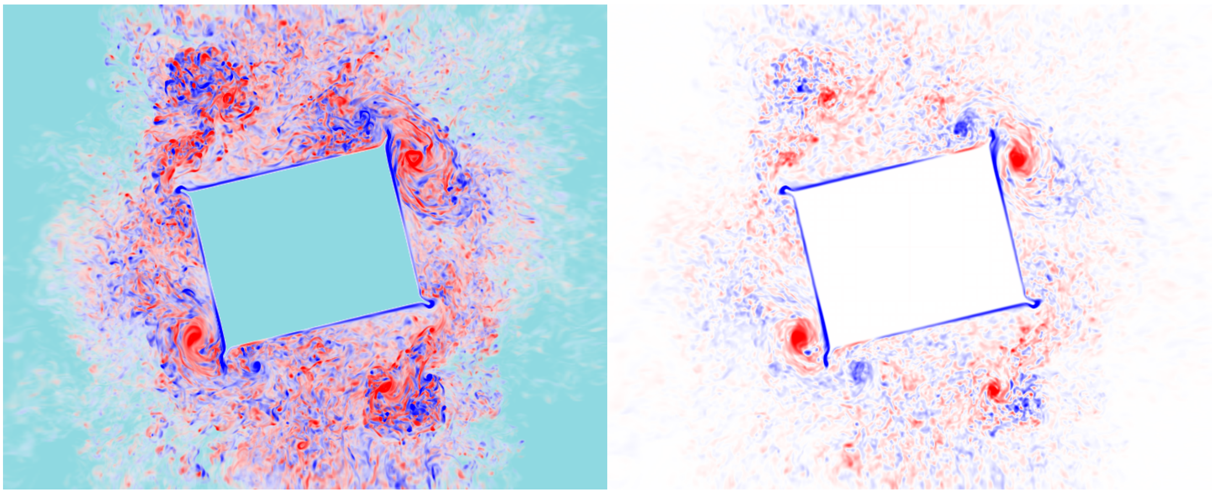

Fig.1: Instantaneous in-plane vorticity (red/blue colouring) due to periodic roll motion of a 3D rectangular cylinder with bilge keels (shown as negative space). The left image is a volume rendering and the right image shows the vorticity averaged longitudinally through the domain. From *Hubbard and Weymouth (2017)*.

Second, we use the mean and amplitude of the unsteady roll-damping power, to investigate the data dependence of machine learning methods on nonlinear fluid dynamics problems such roll-damping using the open source library Scikit-learn (*Pedregosa et al., 2011*). In particular, Physics-based Learning Models (*Weymouth and Yue, 2013*) are shown to greatly mitigate the data dependence of typical machine learning methods. As such, these models enable rapid surrogate model development for global multi-objective design search and optimization.

2. Roll-damping model

Roll damping is one part of the full 6DOF seakeeping problem, but the roll-motion is typically decoupled from the other degrees of freedom in ship dynamics analysis. In addition, because the wave damping caused by roll is linear and fairly simple to determine, viscous roll-damping is often studied in isolation, without a free-surface, by mirroring the geometry across the waterline. Finally, in order to simplify experimental measurements, the effect of ship taper and forward speed is neglected, reducing the problem of viscous roll-damping to a periodically oscillating cylinder in otherwise still water.

As shown in *Hubbard and Weymouth (2017)*, numerical methods can be used to simulate this experimental set-up with a high degree of accuracy. However, that reference shows that this model of roll damping has progressed too far from the original physics in a critical way. Figure 1 shows that as the cylinder is forced to oscillate, it generates more and more vorticity in the near wake, which is only very gradually diffused into the surrounding flow. In contrast, shed vorticity in the real ship flow is immediately swept away by the forward motion of the ship, completely changing the near body flow and strongly impacting the forces.

To avoid this issue while still limiting the computational effort, this works extends the classic 2D+T method to periodic flow cases. As illustrated in Figure 2, the classic 2D+T method transforms a three-dimensional steady state flow into a two-dimensional unsteady flow (thus 2D+T) by restricting the simulation to one plane that the ship passes through as speed U, an approximation that is only valid in the limit of very slender and high speed vessels. As shown in the figure, the cross section geometry changes in time as the ship travels, making Cartesian grid methods ideally suited for these simulations, see *Weymouth et al. (2006)* for an initial 2D+T applications and *Weymouth 2013* for a detailed treatment of the projected time varying hull geometry.

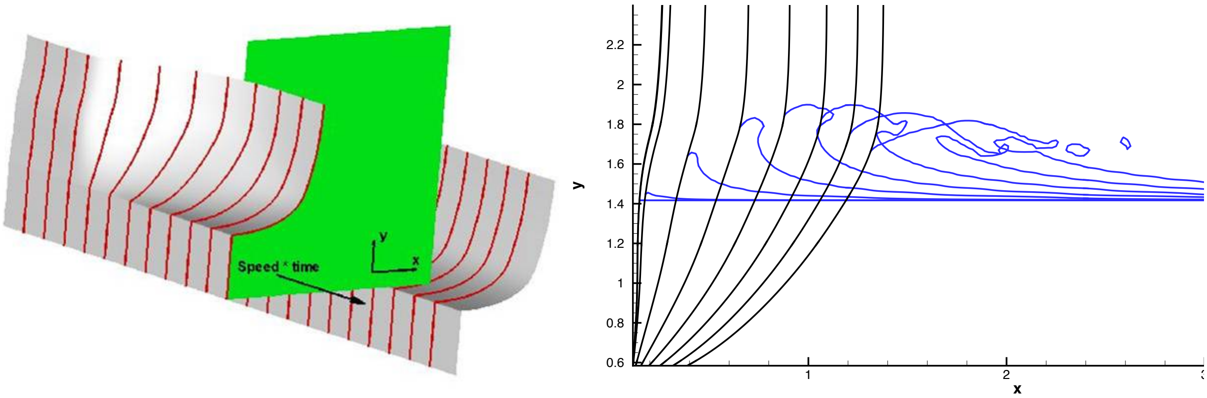

Fig.2: Two-dimensions plus time (2D+T) representation of a ship flow, from *Weymouth et al (2006)*. The left shows a "fish eye view" of the flow as it sweeps past the hull transforming a pseudo-steady 3D plunging ship bow wave into a 2D unsteady plunging wave generate by a 'flexible wave-maker'.

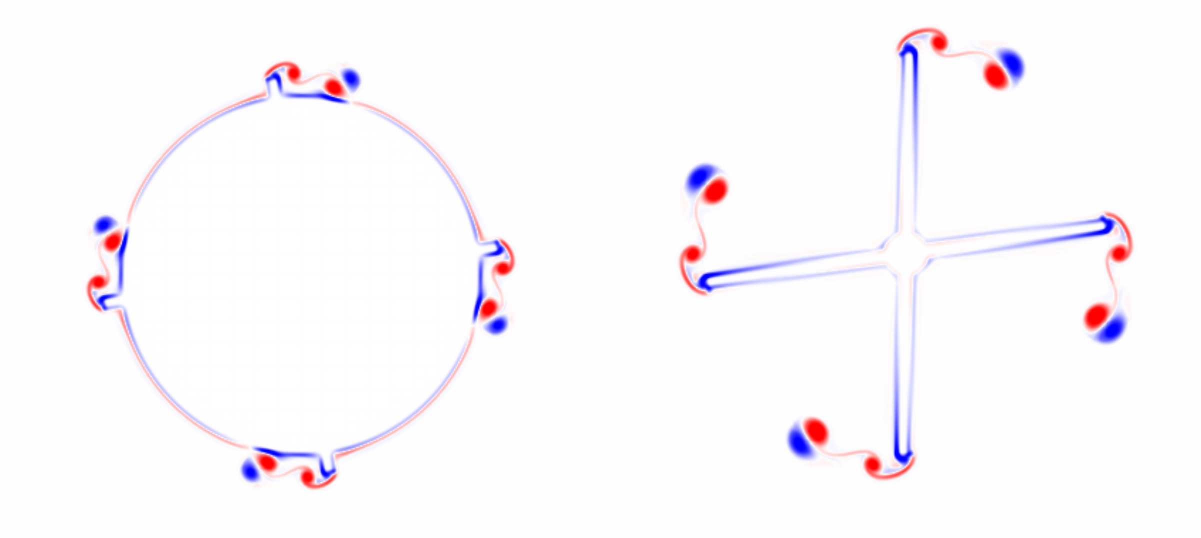

Fig.3: Two of the 2D+T roll-damping cases illustrating two different circle ratios ($r/R = 0.9$ and $r/R = 0.1$) and two different keel angles ($\alpha = 90°$, $\alpha = 72°$) and the same roll magnitude ($\Theta = 8°$). The images show the instantaneous vorticity at the end of the 'body', ie $z = L$.

However, this model of the flow assumes that each stationary plane will see the same flow since the flow is steady state. In the case of a ship in roll, the flow is periodic and different simulations must be run to capture each of these phases of motion. Since the original flow is 3D+T, and we are still mapping $z \rightarrow Ut$, we call this a 2D+2T simulation. Note that each plane is a completely independent simulation, making them trivially parallel, and that only a few such planes are required to determine the low frequency unsteady behaviour.

3. Canonical roll-damping case

While the 2D+2T model described above could be applied to realistic hull geometries, the focus of the current paper is the integration of machine learning methods. Therefore a simple canonical test case of a circular cylinder geometry with four bilge keels is developed to highlight issues with machine learning methods for nonlinear viscous flows, Figure 3. Two geometric features are studied in this work; the angle between adjacent keels α and $\pi - \alpha$, and the relative size of the keels measured by the ratio r/R where r is the circle radius, and R the distance from the keel tip to the center of the circle. Figure 3 shows two configurations of this test case.

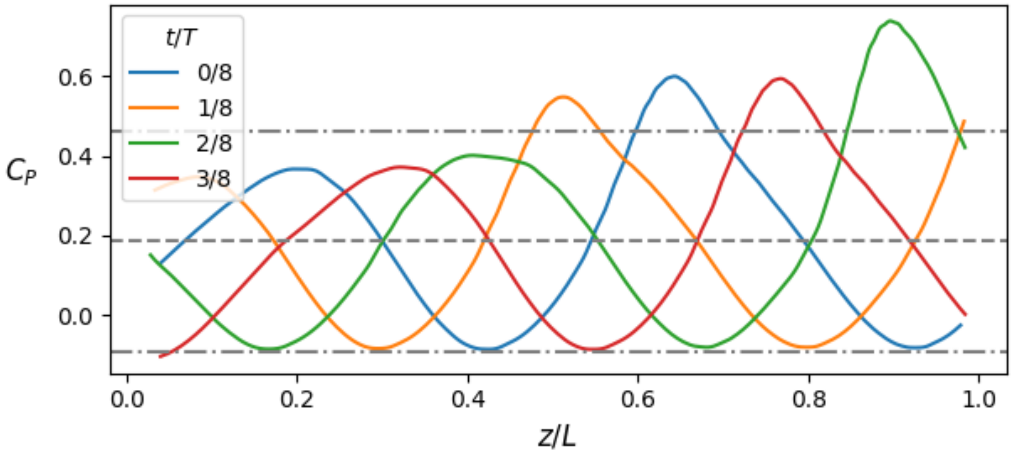

Fig.4: Roll-damping power coefficient for the Fig 3 (left) case at four different phases of the motion period T. Note the power itself has period $0.5T$. The dashed line is the mean power coefficient, and the dash-dot lines indicate mean-absolute-deviation.

The geometry was prescribed to roll harmonically via the simple equation $\theta(t) = \Theta \sin \omega t$. The roll amplitude Θ is proportional to the Keulegan-Carpenter number, and was studied as an additional variable to the two geometric variables. The frequency ω sets Sarpkaya's beta

$$\beta = \frac{\omega R^2}{\nu}$$

where ν is the fluid kinematic viscosity. In this work we use a constant $\beta = 10^5$. The use of 2D+2T means we cannot define a forward speed or boat length independently, only their time scale ratio $T = L/U$ which is set equal to the period of motion $T = 2\pi/\omega$.

This geometry and motion was simulated using LilyPad, an open source Navier-Stokes solver that has been heavily validated for unsteady fluid dynamics simulations, *Weymouth (2015)*. The same grid was used for all cases, with domain $x, y = -10R$ to $10R$ and grid size $h = R/140$. Twelve slices over $0.5T$ were used to discretize the roll period. Each parameter was varied over 10 values, leading to 1000 independent roll-damping cases, two of which are shown in Figure 3. The total computational time for the simulations on a 12-core workstation was around 6 hours.

The performance of each case was measured using the power P required to roll the body through the fluid, characterized by the power coefficient

$$C_P = \frac{P}{\rho \Omega^3 R^4}$$

where $\Omega = |\dot{\theta}| = \omega\Theta$ is the amplitude of the rotation velocity. Figure 4 shows the results for a representative case. Note that the power required increases as the flow develops along the 2D+T 'hull'. There are periods of negative powering where the fluid is transferring energy into the body motion, but the positive values are much larger.

Figure 5 shows the simulated mean power coefficient $\overline{C_P}$ and amplitude $|C_P|$ for all 1000 cases. Note that even after dimensionally scaling the power (and adjusting the amplitude to be scaled by acceleration instead of velocity squared, ie $\dot{\Omega}\Omega = \omega^3\Theta^2 = \Omega^3/\Theta$) the results depend nonlinearly on all three input variables.

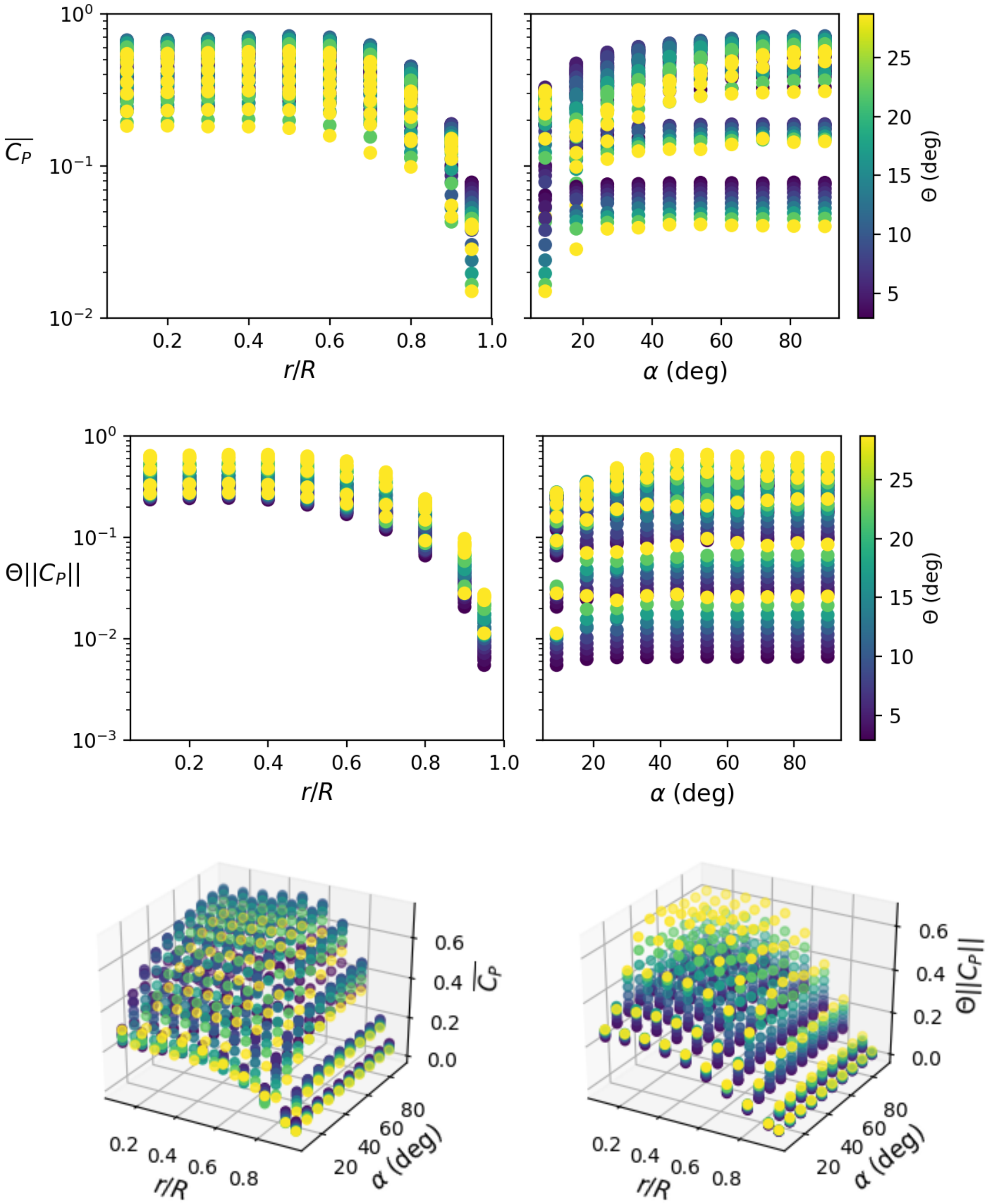

Fig.5: Mean and amplitude of the roll-damping power coefficient for all 1000 cases. Note the amplitude of the power coefficient is scaled by Θ and the top two plots have a logarithmic y-scale.

4. Machine Learning predictions

The data in Figure 5 was next used to study the data dependence of machine learning methods in nonlinear fluid dynamics flows. While Deep Neural Nets are all the rage these days because of their universal description and automatic feature selection capabilities, the data in Figure 5 is not nearly plentiful enough to train such a method. Instead this worked uses a simple linear Ridge-Regression model, otherwise known as Tikhonov regularization (*Evgeniou et al., 2000*).

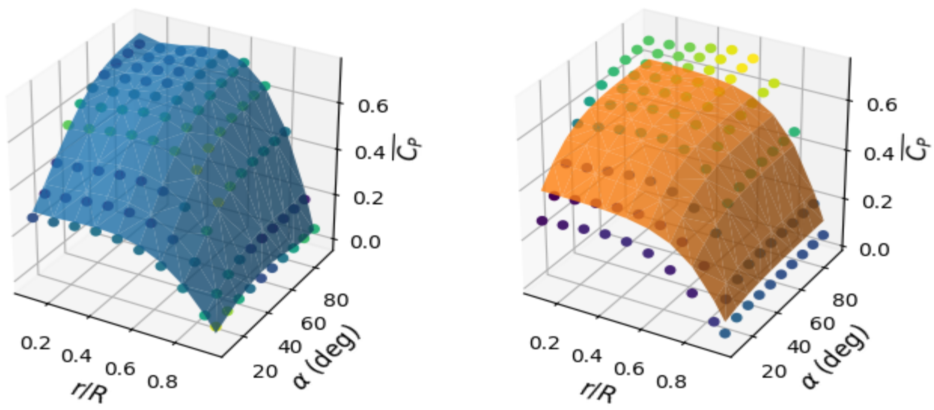

Fig.6: Ridge-Regression surface of the mean power coefficient trained using all 1000 cases (left) and the intermediate model surface (right). The points are a slice of the data for $\Theta = 8°$ and are coloured by the error of the fit at each point.

In Ridge-Regression, a linear least-squares error function is supplemented by a regularization term proportional to the model's second derivative and so increasing the regularization strength decreases the variance in the model, improving its generalization. The class of regression can be used with any basis functions, but this work uses a simple polynomial kernel of the input variables, ie

$$X = \left[\Theta, \alpha, \frac{r}{R}, \Theta^2, \Theta\alpha, \frac{\Theta r}{R}, \alpha^2, \frac{\alpha r}{R}, \left(\frac{r}{R}\right)^2, \cdots\right], \qquad y = [\overline{C_P}]$$

and the mean pressure coefficient was used as the target function. The method was implemented in Scikit-learn, with a polynomial kernel up to 4th order terms and 10-fold cross validation was used to determine the regularization strength.

When trained using all 1000 cases, the learning model captures 97.6% of the variation in the data. Figure 6 left shows the Ridge-Regression model applied to a slice of the input data where $\Theta = 8°$, which shows an excellent fit and little to no spurious variance in the model.

However, no practising engineer has time to run 1000 full 3D unsteady CFD simulations. It is much more relevant to ship science and other engineering domains to train the learning model with only a handful of cases. Figure 7 (blue dots and line) shows that as the number of samples in the training set is reduced, the accuracy drops drastically, and the variability of the model increases dramatically. For example, with 100 simulations you have between an 80% and 95% accurate model, and this difference depends entirely on which points you happen to simulate ahead of time. Drop the training set size to 30 and the model is between 10% and 70% accurate, and below that even the median model of this class of machine learning methods drops to below 50% accuracy.

5. Physics-based Machine Learning

The method of Physics-based modelling introduced in *Weymouth and Yue (2013)* limits the dependence of the learning model on the specifics of the data set by including additional physics-based information about the system. In particular, the method uses a set of intermediate system models to supplement the (generic) polynomial basis. As long as this intermediate model is functionally similar to the target function, the resulting learning model is much more robust.

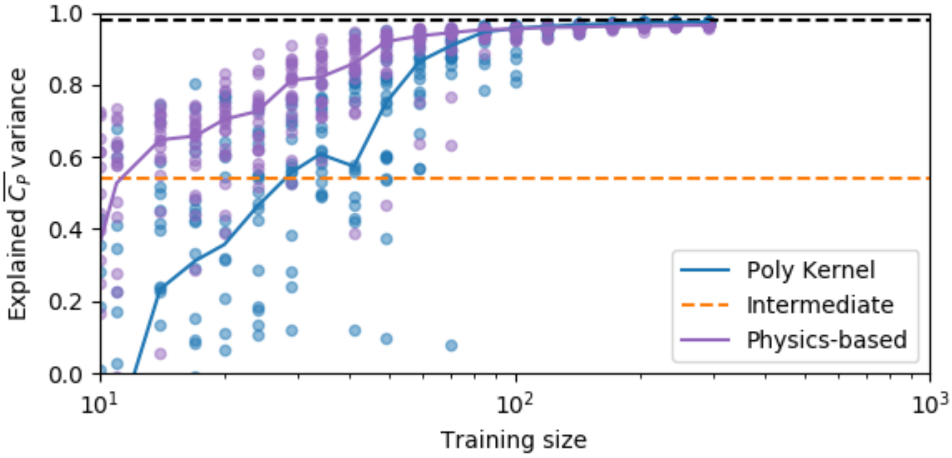

Fig.7: Prediction accuracy of the mean power coefficient as the training set size is varied. Each training size was tested with 20 different random selections of training sets with the accuracy of each model marked by a dot. The solid lines indicate the median accuracy at a given training set size.

In this case, there is no obvious pre-existing intermediate model as the test case is such a departure from typical ship sections. The simplest model is to assume that each variable acts independently

$$f_{IM}\left(\Theta, \alpha, \frac{r}{R}\right) = f_\Theta(\Theta) f_\alpha(\alpha) f_{r/R}\left(\frac{r}{R}\right)$$

Comparing the two cases in Figure 3, we know physically that the power will not depend strongly on $\alpha > \pi/4$ since the keels would all be too far apart to interact, while $\alpha \sim 0$ will have two keels so close that they act as one. As such, $f_\alpha = 1 + \tanh 2\alpha$ is reasonable. Similarly, the power should scale with the keel length when $r/R \sim 1$, but for $r/R < 2/3$ the circle is too far from the keel tip to influence the development of the vortex. Therefore, $f_{r/R} = \tanh[4(1 - r/R)]$ is reasonable. Finally, we have already scaled $\overline{C_P}$ using cubic power scaling, meaning f_Θ is assumed constant.

Figure 6 shows the intermediate model prediction on the same slice of data using a coefficient of $f_\Theta = 0.3$ and a resulting explained-variance of 54%. However, the intermediate model's role as a basis function makes this coefficient unimportant, we are only interested in the shape. Figure 7 (purple dots and line) shows that adding this model to the basis function of the same Ridge-Regression model roughly doubles the median accuracy of the resulting model and reduces the model variation by a factor of 4 for $O(10)$ training set sizes.

6. Conclusions

In this work, a novel 2D+2T concept was developed to model periodic ship flows. This model has more physical realism than neglecting the forward motion of the hull, is simple to compute using Cartesian-grid methods, and is easily extended to realistic hull geometries and even including the effects of the free surface.

This concept was used to generate a large 1000 case canonical data-set of roll-damping power coefficients with two geometric and one kinematic independent variables. Using this data, a broad study was carried out on the impact of training set size on machine learning accuracy for nonlinear fluid dynamic problems. While typical machine learning approaches, such as Ridge-Regression with polynomial basis functions, quickly loose accuracy and consistency as the amount of training data is reduced, Physics-based learning methods offer a fairly turn-key method to introduce simple physical insights into the learning process, greatly improving model predictions in the limit of few examples. In this future, we plan to combine these two approaches to model full 3D ship roll-damping characteristics with only a few example points using 2D+2T as the simplified model.

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