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RANS Turbulence Model Optimisation based on Surrogate Management Framework

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Abstract

In this study, the accuracy of k-ω turbulence model was improved for hydrodynamics predictions of underwater vehicles. The closure coefficients were optimised by applying an algorithm called Surrogate Management Framework [1, 2] and comparing with the experimental data of SUBOFF submarine model. The outcome revealed the sensitivity of RANS accuracy with respect to various closure coefficients, and highlighted the improvements achieved from using the optimised coefficients.

Introduction

Computational Fluid Dynamics (CFD) is developing into an important tool for evaluating the stability and manoeuvrability of an underwater vehicle. Reynolds Averaged Navier-Stokes (RANS) equations are commonly solved to predict the pressure and friction forces around the vehicle. Investigations carried out by [3] had shown that the accuracy of RANS predictions was strongly dependent on the turbulence model employed in the calculation, and that some differences existed in the hydrodynamic predictions of underwater vehicle.

One approach to improve the accuracy of RANS predictions is to optimise the closure coefficients in the RANS turbulence model. These coefficients by nature are arbitrary. Their values have been derived from generic flow cases, such as homogeneous isotropic turbulence, turbulent mixing layer flows, etc. As a result, it is likely that the existing coefficients may not be optimal for accurate modelling of underwater hydrodynamics.

In this paper, a study was undertaken to optimise the closure coefficients of the standard Wilcox k-ω turbulence model [4]. The optimisation was carried out based on the case of the flow over a SUBOFF bare hull at static drift incidence of 10°. The optimisation algorithm called Surrogate Management Framework (SMF) was utilised to ensure a convergence to the global optimum solution.

SMF Optimisation Algorithm

The SMF is an optimisation algorithm that uses a surrogate surface to represent the objective function in a given design space. As outlined in [2], the surrogate-based algorithm possesses several advantages over other algorithms. First, the surrogate surface provides a visual aid in understanding the input and output relationship. This feature is particularly useful in making trade-offs among competing objectives. Second, the surrogate surface in some cases can indicate the probable locations of global optimum solution. Therefore, the optimisation attempt can be focused on those specific regions.

Third, the surrogate-based algorithm allows for multiple data acquisitions prior to and during the optimisation process. This flexibility allows for a significant enhancement in the convergence rate. Lastly, a speed-up in the optimisation process can also be gained by re-using the data points for optimising different objective functions.

References [1] and [2] recommended using Kriging interpolation function to generate the surrogate surfaces. A Kriging function uses a statistical interpretation of data points to construct surfaces. The values of surrogate surfaces are exact at the location of data points and are least accurate in-between data points. The Kriging function also provides a statistical error estimate that can be utilised to improve the robustness and convergence rate of the SMF algorithm.

The present SMF algorithm uses the same formulation as that in [1]. Data points are forced to lie on a fictional mesh with uniform spacings. The optimisation cycle consists of two steps – SEARCH step and POLL step. In the SEARCH step, a surrogate surface is fitted onto the data points, and the resulting surrogate function is evaluated at all mesh points. The SEARCH algorithm subsequently looks for a surrogate value that improves the current-best optimal point. If this is successful, the objective function (i.e. CFD calculation) is evaluated at that mesh point. The new data point is added to the data set and the SEARCH step is repeated.

When the SEARCH algorithm fails to find a better surrogate value, the SEARCH process is terminated and the POLL step begins. The aim of POLL step is to examine the convergence of current-best optimal point. This is done by evaluating the objective function at mesh points neighbouring the optimal point. These neighbouring points are called POLL points, and are selected in a positive spanning set of directions (see [1]).

The POLL step is successful if one of the POLL points improves the current-best optimal point. The new point is added to the data set, and the optimisation process returns to the SEARCH step. If the POLL step is unsuccessful, the mesh spacing is halved and the process returns to the SEARCH step as well. The optimisation cycle is terminated by a convergence criteria applied at the end of POLL step.

1D Test Case

To illustrate the optimisation process, the SMF algorithm was used to locate the global minimum in the following objective function

$$f(x) = e^{-2x} \cos(5\pi x) \quad (1)$$

where $x \in [0, 1]$. This objective function represents a damped oscillation problem where multiple minima exist in the design space. The exact location of global minimum is at $x = 0.192$ and $f(x) = -0.6758$. Figure 1 shows the profile of the objective function.

The optimisation process was started using three initial data points (see Fig. 1). After three cycles, it returned a current-best optimal point at $x = 0.19$ and $f(x) = -0.6754$. This prediction was fairly accurate already with a maximum error of 1.04%. The optimisation was considered converged after six cycles where the errors had dropped to below 0.1%.

Figure 2 shows the evolution of surrogate function in the first three cycles. The initial and 1st-cycle surrogate functions clearly showed poor representations of the objective function. However as the optimisation was iterated, the representation was improved, especially in the vicinity of global minimum where ample data points were collected. It should be noted that an exact representation of the objective function is not the goal of SMF as it requires an excessive number data points.

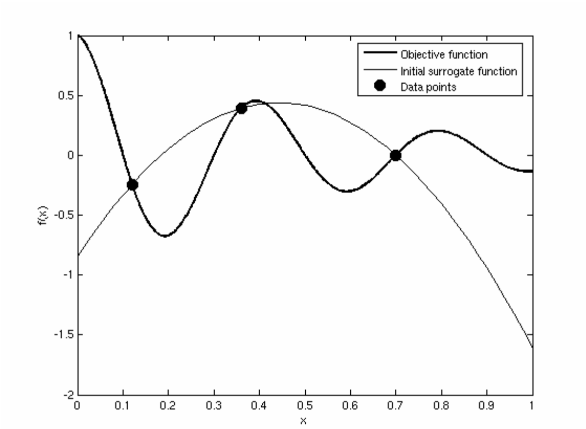

Figure 1: One-dimensional objective function along with the initial data points and initial surrogate function.

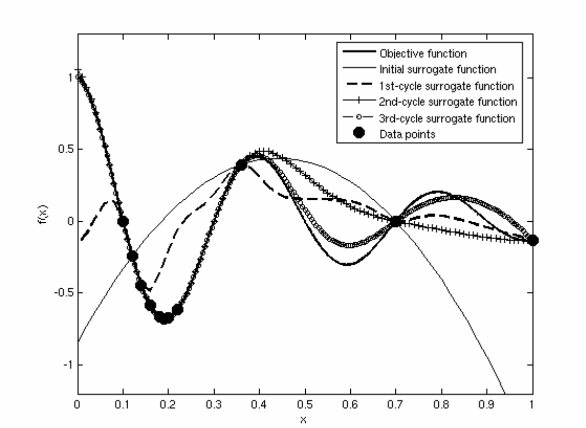

Figure 2: Evolution of surrogate function in the first three optimisation cycles.

SUBOFF CFD Set Up

The turbulence model optimisation was conducted on the benchmark case of the flow over SUBOFF model. The SUBOFF model is a generic submarine model that has been extensively studied in both experimental and computational researches. It was originally designed by David Taylor Research Center [5, 6] in 1989 to evaluate the accuracy of CFD tools available at that time. The validation data were provided by Roddy [7] and Huang et al. [8] using towing tank and wind tunnel measurements.

The present CFD set-up was identical to that in [3]. The SUBOFF bare hull model was set at a static drift incidence of 10°. The hull has a length of $L = 4.356$ m and a maximum diameter of $D = 0.508$ m. It was embedded inside a computational box of size $6L \times 4L \times 2L$. The freestream velocity was set to $U = 3.23$ m/s, giving a Reynolds number of 14 millions.

The mesh was generated using ICEM-CFD software. It consisted of structured Hexahedral elements around the hull and unstructured Tetrahedral elements in the far field (see Figs. 3 and 4). The high quality Hexahedral elements were aimed at providing a good resolution to the important flow structures such as the hull boundary layer, wake field, and off-body vortices. The entire mesh contained 1.4 million Hexahedral elements and 0.6 million Tetrahedral elements.

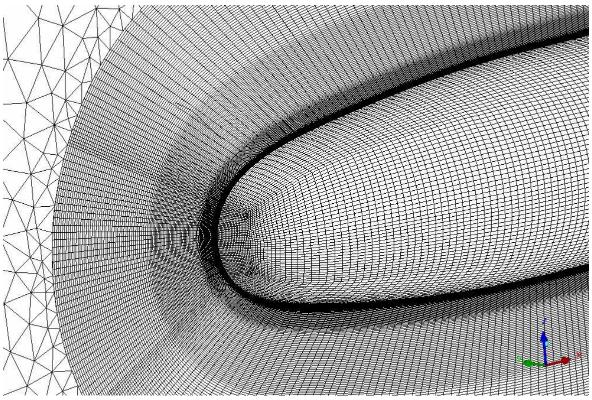

Figure 3: Hexahedral mesh elements in the near field.

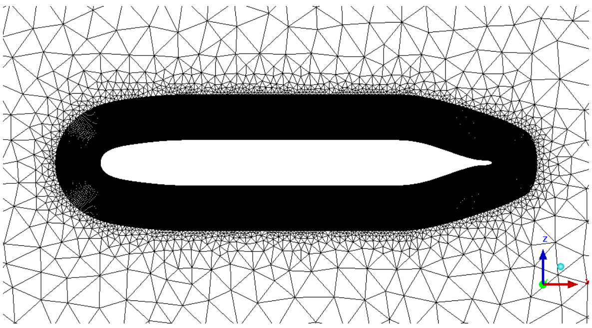

Figure 4: Tetrahedral mesh elements in the far field.

Turbulence Model Optimisation

The RANS calculation employed the standard Wilcox k-ω turbulence model in FLUENT software [9]. Reference [3] reported an average error of 5.1% in the axial force (X), yaw force (Y) and yaw moment (N) predictions using the default closure coefficients. The reference experimental data were $X_{\exp} = 0.001064$, $Y_{\exp} = 0.002394$ and $N_{\exp} = 0.001942$.

In this study, an attempt was made to improve the accuracy of the k-ω model via optimising the closure coefficients α_∞ and β_i. These coefficients are related to the production and dissipation of specific dissipation rate (ω) respectively. The optimisation was performed using the SMF algorithm. The objective function was defined as the average error in the X, Y and N predictions.

To ensure the capturing of global minimum, a large design space of $0.1 \le \alpha_\infty \le 1.6$ and $0.01 \le \beta_i \le 0.2$ was selected. However, it was discovered that the optimisation process would take a considerable amount of time to explore the design space and reach a converged solution. This problem was caused by the manual information passing between the SMF program in MATLAB software and the CFD evaluations in FLUENT software.

In response to the lack of an automatic information passing, an alternative approach was employed where multiple CFD evaluations were performed in parallel to speed up the data acquisition. A surrogate surface was fitted onto the data points and provided an overview of the objective function. Figure 5 shows the contour lines of the surrogate surface. Red and blue contours correspond to regions of high and low magnitudes of the average error respectively.

The surrogate surface demonstrated the highly oscillatory nature of the objective function. It also revealed the probable regions of global minimum (i.e. regions of smallest average error). These regions were marked by dark blue contours that extended diagonally across the design space. Following this finding, a smaller design space was formulated around the dark blue regions, and the SMF optimisation was carried out within this design space.

The distribution of initial data was based on a two-dimensional full factorial sampling with nine levels in α_∞ and five levels in β_i. The optimisation converged to the global minimum after five cycles. The optimum closure coefficients were found to be $\alpha_\infty \approx 0.283$ and $\beta_i \approx 0.0474$. They yielded an average error of 1.55% in the force-moment predictions. This outcome demonstrated a 70% improvement in the k-ω turbulence model. The initial and final surrogate surfaces are given in Figs. 6 and 7 respectively. The contour level has been confined between 0 and 0.2, illustrating the regions of average error up to 20%.

Figure 8 shows the contours of pressure on the hull surface and velocity magnitude at several axial locations. The red pressure contour at the bow marked the location of stagnation point, while the dark blue contour indicated a suction region at the leeward side of the bow. The velocity contours ranged from 2 m/s to 3 m/s. They demonstrated the growth of boundary layer and the shedding of cross-flow vortices in the stern region.

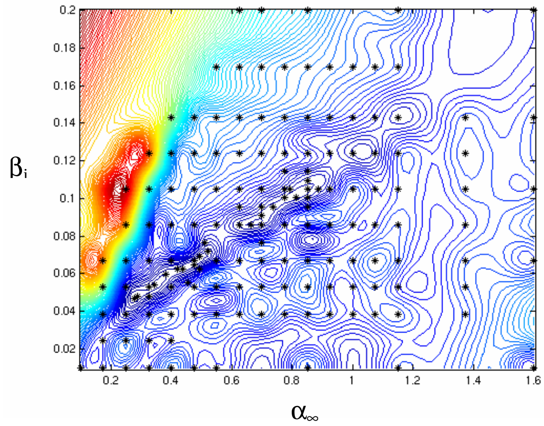

Figure 5: Surrogate surface over discrete data points in the initial design space.

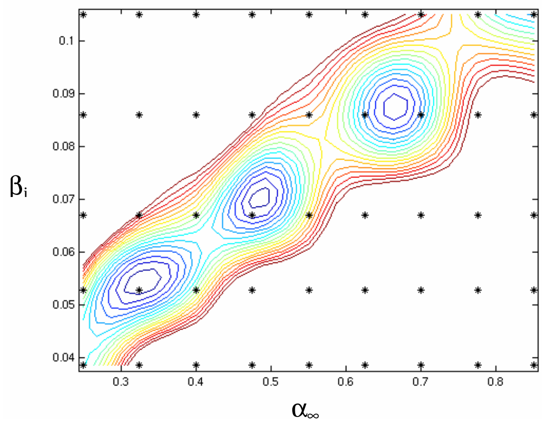

Figure 6: Surrogate surface over initial data points in the reduced design space. Contour level is between 0 and 0.2.

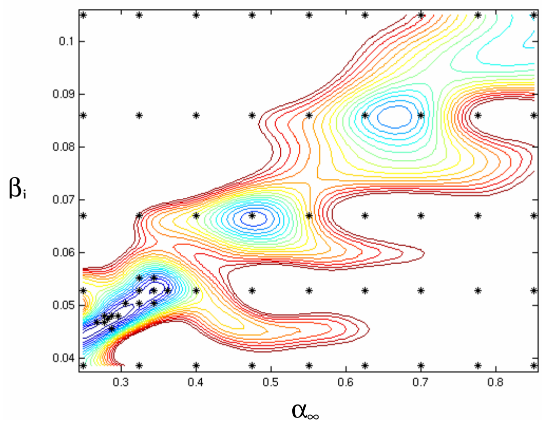

Figure 7: Final surrogate surface after the optimisation converges. Contour level is between 0 and 0.2.

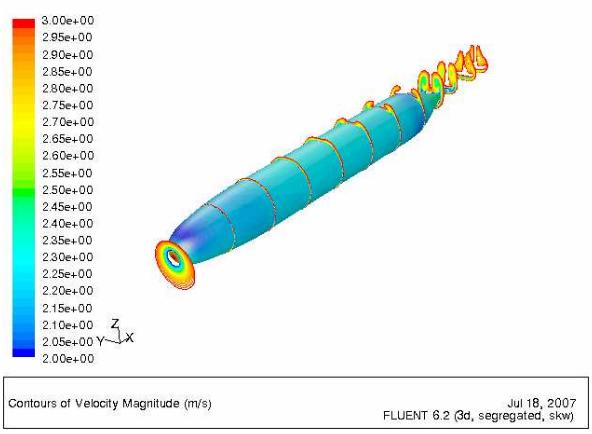

Figure 8: Contours of pressure on SUBOFF hull and velocity magnitude at several axial locations.

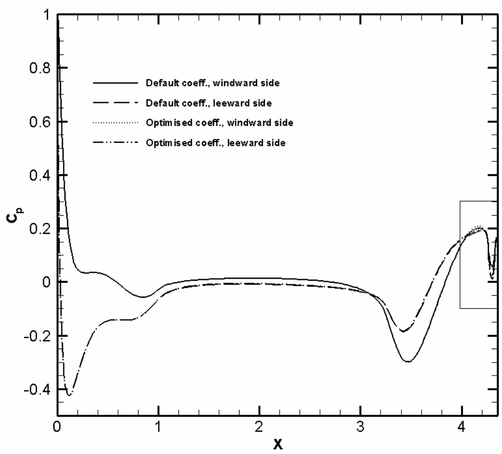

Figure 9: Comparison of predicted axial pressure distributions using the default and optimised coefficients.

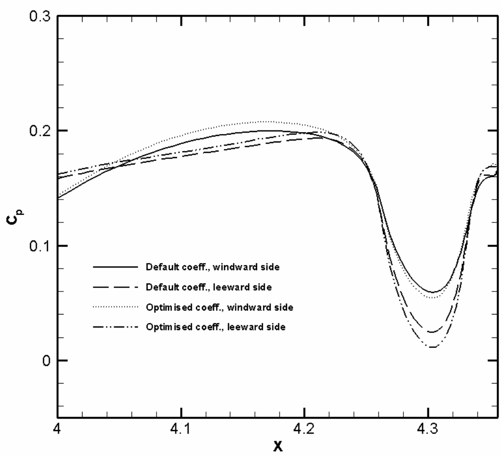

Figure 10: Inset from Fig. 9.

Figure 9 gives the axial pressure distribution on the windward and leeward sides of the hull. The leeward side was shown to have a much lower pressure in the bow region, but the difference diminished in the mid section. At the start of stern region, the pressure on the windward side experienced a large drop in magnitude. However it recovered fairly quickly close to the end cap region.

Predictions using the default coefficients and optimised coefficients were also provided in Fig. 9. They matched well in most parts of the hull, but some differences were observed in the stern region (see Fig. 10). These differences corresponded to the relatively higher rate of turbulence dissipation in the stern region.

As mentioned earlier, the surrogate surface in SMF algorithm can be used to analyse the sensitivity of various parameters. In this case, the impact of varying closure coefficients was examined for each force/moment prediction.

Figures 11 - 13 show the prediction errors of axial force, yaw force and yaw moment respectively. The dark blue regions of low error were consistent in all surrogate surfaces. This implies that there is no conflicting objective in the k-ω model optimisation. Moreover, the linear distribution of dark blue regions suggests that there could be a linear relationship between the coefficients α_∞ and β_i.

Conclusion

In conclusion, the SMF optimisation algorithm has successfully modified the RANS k-ω closure coefficients to improve the agreement between the CFD model and the experimental data. A 70% improvement in the hydrodynamic force-moment predictions was achieved by using the optimised closure coefficients of $\alpha_\infty \approx 0.283$ and $\beta_i \approx 0.0474$. Furthermore, the sensitivity analysis using the surrogate surface suggested that there could be a linear relationship between α_∞ and β_i. This finding is potentially useful in future developments of RANS turbulence model.

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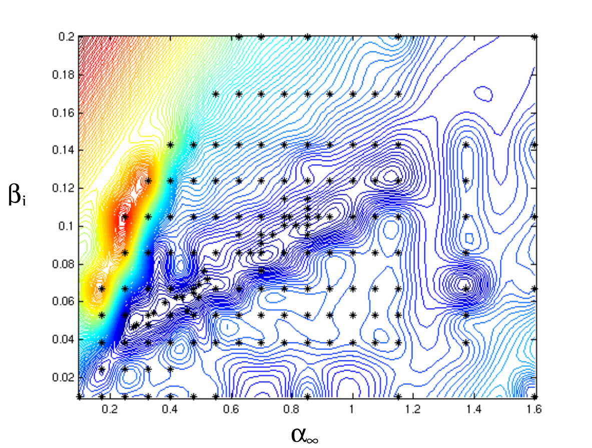

Figure 11: Surrogate surface of the error in axial force prediction.

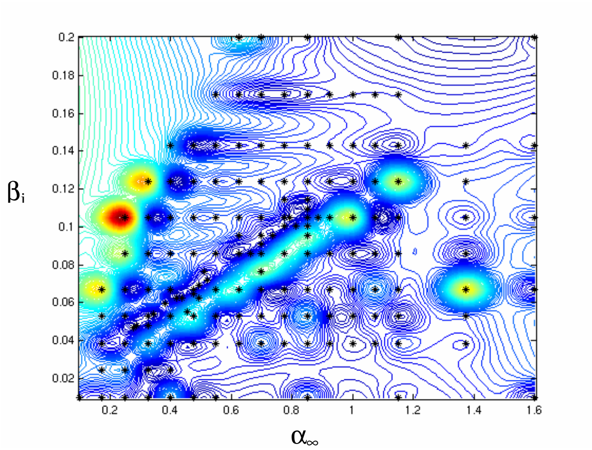

Figure 12: Surrogate surface of the error in yaw force prediction.

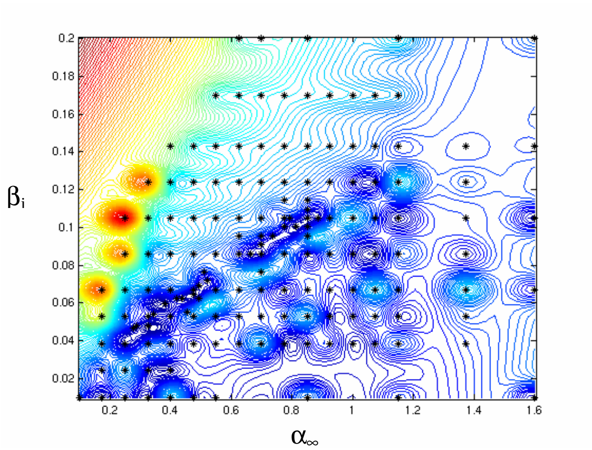

Figure 13: Surrogate surface of the error in yaw moment prediction.

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