Ocean Engineering 167 (2018) 397–404

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Optimization of a marine contra-rotating propellers set

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ARTICLE INFO

Keywords:
Optimization
Genetic algorithm
Contra-rotating propellers
Kriging method
CFD

ABSTRACT

In this research, optimization of a marine contra-rotating propellers (CRP) set is investigated using RANS-based CFD, genetic algorithm and kriging method. The CFD tool is applied for determining the hydrodynamic performance of CRPs. The Kriging algorithm is coupled with the genetic optimization tool in order for performing the optimization process. In this paper, the performed optimization process was an iterative one. It means that, the extracted geometry of the previous step is simulated using CFD tool and the results are added to the initial population used for the next optimization step. In this way, the added points reduce the number of simulations. The obtained results presented an acceptable efficiency for the utilized algorithm as an optimization package for marine propellers.

1. Introduction

The best performance of a marine propeller is occurred in a specific regime of flow. Therefore, an open water standard propeller is not the best solution in all problems and the wake flow behind the body should be considered in the design process, especially a radially variant wake flow.

Schmitz et al. (2002) presented a method for reducing the cost of computational fluid dynamics optimizations by using Neural Networks algorithm. Benini (2003) developed a method for optimizing B-type screw propellers by coupling evolutionary algorithm and regression formula. An optimum composite propeller was designed by Lee and Lin (2004) using genetic algorithm. Calcagni et al. (2010) combined inviscid-flow hydrodynamics modeling, Neural Networks and genetic algorithm for preliminary designing of marine propellers. Zeng and Kuiper (2012) presented a blade section design method by integrating the genetic algorithm with the Eppler-Shen program. Surrogate methods for optimizing propellers were investigated by Vesting and Bensow (2014). They discussed several response surfaces to replace the main computations and concluded that Kriging and iKriging methods showed good prediction capabilities. Mirjalili et al. (2015) optimized the shape of marine propellers using Multi-objective Particle Swarm Optimization (MOPSO) for the first time. The considered objectives were maximizing the efficiency and minimizing cavitation. Gaggero et al. (2016) presented a procedure for optimizing contracted and tip-loaded propellers by coupling Panel Method/Boundary Element Method and genetic algorithm. They resulted once again that BEM method has some limitations in modeling the performance of propellers, especially in the case of endplate contraction. Gaggero et al. (2017) presented a procedure for designing a propeller for a high-speed craft by coupling BEM, a viscous flow solver based on RANSE approximation, a parametric 3D description of the blade and a genetic algorithm. They could improve the propulsive efficiency, maximize the ship speed, reduce the cavitation extension and increase the cavitation inception speed. Jiang et al. (2017) presented a multi-objective optimization method by coupling Non-dominated Sorting Genetic Algorithm-II and Fluid-Solid interaction (FSI) based on Panel Method and Finite Element Method. Using this method, they could maximize the propeller efficiency, minimize the blade mass and minimize the unsteady thrust coefficient.

In this research, optimization of a CRP set was investigated numerically. The objective function was to maximize the hydrodynamic efficiency and the design constraints were: a) keeping the total thrust constant, and b) keeping the difference between forward and afterward propellers torques at a minimum acceptable range. Note that balancing the axial torques could help the body to easily avoid rolling motion during its movement.

According to the literature, Kriging method and genetic algorithm were selected as surrogate method and optimization tool, respectively. The initial population for the optimization problem was gathered from several RANS-based CFD simulations performed on several CRPs in Applied Hydrodynamic Laboratory of Iran University of Science and Technology. After each step of the optimization process, the output geometry was simulated using CFD and then, the obtained result was added to the initial population required for the next iteration. Adding new points iterate by iterate, increases the convergence speed. This

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https://doi.org/10.1016/j.oceaneng.2018.05.067
Received 3 February 2017; Received in revised form 8 April 2018; Accepted 28 May 2018

process was repeated until the convergence reached.

2. Propeller theory

In order to obtain the required results in the design procedure of an optimum propeller for a certain operating condition, utilizing the propeller theories is inevitable. These theories contain Ghose, 2004:

1 Momentum theory: This theory assumes the propeller an actuator disk which increases the pressure of the passing flow. This theory gives no detail about the geometry of the propeller.
2 Blade element theory: This theory explains the effect of propellers radial sections on its performance. The weakness of this theory is the incorrect result about the hydrodynamic efficiency of the propeller which is 100 percent.
3 Circulation theory (Vortex theory): This theory explains the performance of propellers more satisfactory than two previous methods. In this theory, the thrust produced by the propeller is explained in terms of circulations around its radial sections. This theory contains lifting line, lifting surface and surface panel methods.
4 Numerical solution of Navier Stokes equations: This method could handle the effects of viscous fluid flow over the propeller performance. RANS[1] based solvers belong to this group. These solvers evaluate the performance of the propellers better than panel methods because of the ability of more precise calculation of the wake flow and turbulence effects.

3. Optimization

Most optimization problems include several targets and classified as multi-objective and multi-variant ones. In order to solve these problems, some multi-objective evolutionary algorithms have been proposed since 1985. Such algorithms are able to search multiple solutions in a single run Zitzler and Thiele, 1999.

Genetic algorithm, which is used in this study, is one of the common evolutionary algorithms that uses biologic properties, such as inheritance and mutation and is one of the random search-based algorithms inspired from the nature. Genetic algorithm is a useful tool in optimization problems with linear, nonlinear, and multiobjective functions.

4. Surrogate method

In this research, the applied surrogate method was the Kriging algorithm. In the other words, the kriging method was used as a tool for parabolic interpolation of existing data in order to provide a continuous search space for the genetic algorithm. The general form of kriging estimator is as follows Bohling, 2005:

$$Z^*(u) - m(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha [(Z(u_\alpha) - m(u_\alpha)] \tag{1}$$

which $Z^*(u)$ is the estimator, u is the location vector of the estimation point, u_α is the location vector of a neighboring point, $Z(u_\alpha)$ is the value of the function at the neighboring point, n(u) is the number of neighboring points which are used for estimation, m(u) and $m(u_\alpha)$ are the expected values (means) for Z(u) and $Z(u_\alpha)$, and λ_α is the kriging weight assigned for $Z(u_\alpha)$ in order to perform the estimation in location u. Z(u) is treated as a random field function which is decomposed into residual (R(u)) and trend components m(u), Z(u) = R(u)+m(u). R(u) is treated as a random field with a stationary mean of 0 and a stationary and isotropic covariance function of Cov{R(u), R (u + h)} = E{R(u). R (u + h)} = C_R(h), where h is a lag. The residual covariance is derived from the input semivariogram model, C_R(h) = C_R (0)-γ(h), where γ is the semivariogram. Kriging weights (λ_α) are derived from the input variogram. The variogram of Z(x) is obtained using the function of 2γ(h) = Variance (Z (x + h)-Z(x)). The variogram is a function that relates the dissimilarity between data to the distance (h). The goal in this problem is to find the Lambda coefficient (coefficients matrix of kriging), so that the amount of the following variance is minimized:

$$\sigma^2(u) = \mathrm{var}(Z^*(u) - Z(u)) \tag{2}$$

which is performed by satisfying the following constraint for the expectation function:

$$E(Z^*(u) - Z(u)) = 0 \tag{3}$$

Kriging algorithm is decomposed into simple, universal and ordinary ones. These different types differ each other in their treatments of the trend component, m(u). For example, simple Kriging assumes that the trend component is a known component, m(u) = m. In this research, the simple kriging was used because of the studied literature Vesting and Bensow, 2014.

5. Case study

A CRP contains two coaxial propellers rotating in opposite directions. These systems display higher efficiencies compared to single propellers because of reducing the rotational energy of the passing flow behind the propulsion unit. Furthermore, two counter rotating coaxial propellers could prevent the cavitation occurrence and are able to eliminate each other axial torque which could help the body to move smoothly through the water.

Several parameters including diameter, blades number, pitch ratio, camber ratio, chord length, rotational speed and etc., affect the geometry of marine propellers. In this research, pitch and camber ratios were selected as optimization parameters according to their strong and complicated influence on the propellers performance, which would change the main effective angles between the flow and blades radial sections. Note that, other main parameters such as chord length, thickness distribution, rotational speed, diameter and number of blades are selected according to the operational condition, cavitation and structural stiffness. Secondary parameters such as rake and skew do not strongly affect the propellers performance and were neglected in the optimization process.

The initial population for the optimization process was obtained from several simulations performed over CRP propulsion units in Applied Hydrodynamic laboratory of Iran University of Science and Technology. The initial population contained 100 different CRP sets with constant geometrical parameters except for the camber and pitch ratios distributions. The maximum efficiency between the selected data was about 85 percent. For the initial population, the applied radial distributions of pitch ratios were selected between 1.6 and 2.8 and the radial distributions of camber ratios were selected between 1.5% and 3%. In this research, the goal was to maximize the hydrodynamic efficiency with regard to time and cost limitations.

6. Computational fluid dynamics

In order to solve the flow field around CRPs, mass conservation and Navier-Stokes equations should be solved. Using Reynolds decomposition technique, these equations are as follows:

$$\frac{\partial \bar{\rho}}{\partial t} + \frac{\partial}{\partial x_i}(\bar{\rho}\,\overline{u_i}) = 0$$
$$\bar{\rho}\frac{\partial(\overline{u_i})}{\partial t} + \bar{\rho}\,\overline{u_j}\frac{\partial}{\partial x_j}(\overline{u_i}) = -\frac{\partial(\bar{p})}{\partial x_i} + \mu\frac{\partial^2 \overline{u_i}}{\partial x_j^2} + \frac{\mu}{3}\frac{\partial}{\partial x_i}\left(\frac{\partial \overline{u_j}}{\partial x_j}\right) - \bar{\rho}\frac{\partial}{\partial x_j}(\overline{u'_i u'_j}) \tag{4}$$

where u is the velocity vector, P is the static pressure, $\bar{u}$ and u' are time averaged and fluctuating terms, respectively. In order to compute the

[1] Reynolds Averaged Navier Stokes.