Ocean Engineering 92 (2014) 55–63

Contents lists available at ScienceDirect

Ocean Engineering

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

Heuristic optimization of submerged hydrofoil using ANFIS–PSO

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ARTICLE INFO

Article history:
Received 2 March 2013
Accepted 27 September 2014

Keywords:
Optimization
Hydrofoil
PSO
ANFIS
Heuristic
Submerge

ABSTRACT

In this research, optimization of shape and operating conditions of a submerged hydrofoil is investigated by a heuristic optimization approach, been a combination of an adaptive network based fuzzy inference system model (ANFIS) and particle swarm optimization (PSO). The constrained discrete variables such as the thickness and camber of hydrofoil, angle of attack and submerge distance are clearly defined as design variables and the lift to drag ratio is selected as a nonlinear objective function, which is extracted from an accurate numerical procedure. The Navier–Stocks equation is numerically solved, and volume of fluid (VOF) method has been utilized to simulate two-phase fluid (water and air). The results demonstrate that the resulted body of the hydrofoil in the optimum operating conditions should reach a maximum value of lift to drag ratio.

1. Introduction

Hydrofoils play a significant role in the design of hydrofoil-boats, which move on the water surface and applied the hydrofoil to reduce drag force. Hydrofoils are installed under boat's hull and have moved underwater, near the free surface of water. Therefore, generated water wave, which is created by boat movement, can influence in the hydrofoil performance and the boat revenue, consequently. There is a great volume of published work dealing with the hydrofoil performances, (De Blasi et al., 2000; Daskovsky, 2000; Filippov, 2001; Kouh et al., 2002; Bourgoyne, 2003; Chen and Liu, 2005; Hay and Visonneau, 2005; Carcaterraa et al., 2005; Xie and Vassalos, 2007; Sadathosseini et al., 2008; Ducoin et al., 2009; Münch et al., 2010; Zanette et al., 2010; Kim and Yamato, 2005). The ultimate goal is to develop knowledge that helps hydrofoil design and services more effectively and efficiently. As a result, several numerical simulation and optimization methods have been widely applied in hydrodynamics. Traditional methods that need to calculate and analyze for modification of the model frequently, had wasted time and had not been in suitable accuracy. On the other hand, the visualization of flow based on *CFD* has well established, and quite accurate and robust approximate models and optimization algorithms have innovated for the last decade, too. Today, several new techniques are widely applied to optimize some equipment (Hwang et al., 2009; Shafaghat et al., 2008; Schmitz et al., 2004; Hsin et al., 2006; Spogis and Nunhez, 2009). Furthermore, deterministic optimization process such as first order gradient techniques had been applied to reach the maximum value of drag to lift ratio (Tozzi, 2004). Heuristic method such as genetic algorithm is used to optimize hydrofoil in many researches, too (Ouyang et al., 2006; Wang et al., 2012; Yang et al., 2012, 2009; Yang and Shu, 2012; Frunz et al., 2010; Guo et al., 2009; Cocke, 2012).

In the previous studies, neither high accuracy numerical methods, nor robust optimization algorithms, which can simultaneously optimize the operating conditions, are used. On the other words, almost all of them have focused to find optimum configurations of hydrofoil with the negligence of the operating conditions. Furthermore, design variables in most of them have been continuous ones and additionally, these methods would be very expensive and time consuming.

In this study, a robust method is designed for optimization of hydrofoil, moving near the free surface of water. This algorithm combines ANFIS method and PSO algorithm. Thickness and camber of hydrofoil, angle of attack and submerge distance are considered as constrained design variables and value of lift to drag ratio is defined as the objective function, which has a nonlinear behavior. The objective function is obtained by numerical simulation. On the other hand, the design variables are discrete ones and ANFIS is estimated the variable performance and an accurate continuous search space is generated. Finally, PSO algorithm, which is simple, fast, more efficient, and useful for complex and nonlinear problem, is obtained the best configuration of hydrofoil and optimum operating conditions.

2. Governing equations

The basic equations, which describe the conservation of mass, momentum, and scalar quantities can be expressed in the following

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http://dx.doi.org/10.1016/j.oceaneng.2014.09.033
0029-8018/

Nomenclature

A	cell face area
AOA	angle of attack
BP	back propagation algorithm
c	cord length
Ca	camber of hydrofoil
CFD	computational fluid dynamic
CL	lift coefficient
CD	drag coefficient
2D	two dimension
F	mass flux
Fr	Froude number according cord length
G	generation term
g	gravity acceleration
GA	genetic algorithm
H	water depth
h	submerge distance
I^c	convection flux
I^D	diffusion flux
k	turbulence model parameter
LS	least square method
$\dot{m}$	mass transfer
P	pressure
PSO	particle swarm optimization
$\vec{q}$	scalar flux vector
Re	Reynolds number
$\vec{S}$	source term
t	time
$\vec{T}$	stress tensor
th	thickness of hydrofoil
ν_i	normalized ring strengths
V_i	current position due to new velocity of every particle
$\vec{V}$	velocity vector
VOF	volume of fraction
X	horizontal Cartesian coordinate
Y	vertical Cartesian coordinate
θ	angle (°)
ε	turbulence model parameter
$\delta\nu$	cell volume
ρ	density
α	volume fraction
ϕ	scalar quantity
ϖ_i	normalized ring strengths
Γ	diffusivity coefficient
μ	dynamic viscosity

vector form, which is independent of the coordinate system.

$$\frac{\partial\rho}{\partial t}+div\left(\rho\vec{V}\right)=S_m \tag{1}$$

$$\frac{\partial(\rho\vec{V})}{\partial t}+div\left(\rho\vec{V}\otimes\vec{V}-\vec{T}\right)=\vec{S}_v \tag{2}$$

$$\frac{\partial(\rho\phi)}{\partial t}+div\left(\rho\vec{V}\phi-\vec{q}\right)=\vec{S}_\phi \tag{3}$$

The stress tensor for a Newtonian fluid is:

$$\vec{T}=-P\vec{I} \tag{4}$$

In addition, the Fourier-type law usually gives the scalar flux vector:

$$\vec{q}=\Gamma_\phi grad\phi \tag{5}$$

In this study, the $k-\varepsilon$ model has been chosen because of being a public turbulent model. The comparison of experimental and numerical data shows that the $k-\varepsilon$ model is suitable, too. Furthermore, the turbulent intensity is equal to 5% (Yue et al., 2003', 2005).

$$\frac{\partial}{\partial t}(\rho k)+\frac{\partial}{\partial x_j}\left(\rho u_j k-\Gamma_k\frac{\partial k}{\partial x_j}\right)=G-\rho\varepsilon \tag{6}$$

$$\frac{\partial}{\partial t}(\rho\varepsilon)+\frac{\partial}{\partial x_j}\left(\rho u_j\varepsilon-\Gamma_\varepsilon\frac{\partial\varepsilon}{\partial x_j}\right)=C_1\frac{\varepsilon}{k}G-C_2\rho\frac{\varepsilon^2}{k} \tag{7}$$

The turbulent viscosity and diffusivity coefficients are defined as:

$$\mu_t=C_\mu\rho\frac{k^2}{\varepsilon} \tag{8}$$

$$\Gamma_\phi^t=\left(\frac{\mu_t}{\sigma_\phi^t}\right) \tag{9}$$

Moreover, the generation term G in Eqs. (6) and (7) is defined as:

$$G=\mu_t\left[\left(\frac{\partial u_i}{\partial x_j}+\frac{\partial u_j}{\partial x_i}\right)\frac{\partial u_i}{\partial x_j}\right] \tag{10}$$

The discretization of the above differential equations is carried out by applying a finite-volume approach. First, the solution domain is divided into a finite number of discrete volumes or cells, where all variables are stored at their geometric centers (see e.g., Fig. 1).

The equations are then integrated over all the control volumes by utilizing the Gaussian theorem. The discrete expressions are presented to refer only one face of the control volume, e, for the sake of brevity. For every variable ϕ (which may also stand for the velocity components), the result of the integration yields:

$$\frac{\partial\nu}{\partial t}\left[(\rho\phi)_p^{n+1}-(\rho\phi)_p^n\right]+I_e-I_w+I_n-I_s=S_\phi\delta\nu \tag{11}$$

where I's are the combined cell-face convection I^c and diffusion I^D fluxes. The diffusion flux is approximated by central difference. The discretization of the convective flux requires special attention and it causes to develop the various schemes. A representation of the convective flux for cell-face (e) is:

$$I_e^c=(\rho\times V\times A)_e\phi_e=F_e\phi_e \tag{12}$$

The value of ϕ_e is not known and should be estimated from the values of neighboring grid points by interpolation. The expression for the ϕ_e is determined by Second order Upwind scheme. The final form of the discretized equation from each approximation is given as:

$$A_p\times\phi_p=\sum_{m=E,W,N,S}A_m\times\phi_m+S'_\phi \tag{13}$$

where A's are the convection-diffusion coefficients. The term S'_ϕ in Eq. (13) contains quantities arising from non-orthogonality, numerical dissipation terms and external sources. For the momentum equations, it is easy to separate out the pressure-gradient source from the convection momentum fluxes.

VOF ideas have been used to simulate two-phase fluid (water and air). The VOF model can model two or more immiscible fluids by solving a single set of momentum equations and tracking the