Automated Marine Propeller Design
Combining Hydrodynamics Models and Neural Networks

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Abstract—An automated computational methodology for the preliminary design of marine propellers is presented. A Neural Network architecture is developed to describe the performance of propeller models from a virtually-generated systematic series. Propeller performance predictions are based on a propeller hydrodynamics model based on an inviscid-flow model. Next, propeller geometry optimization is investigated through a Genetic Algorithm formulation. The structure of the resulting propeller design environment is illustrated and Neural Network, optimization models are validated through comparisons with existing experimental data and results from alternative approaches. Numerical applications to a notional design excercise addressing a propeller retrofit study for an aged fishing vessel are also presented.

Marine Propulsion; Ducted Propellers; Neural Networks; Numerical Optimization (key words)

1. INTRODUCTION

The quest for reducing operating costs and the increasing awareness of environmental issues related to fuel consumption and NOx emissions raise pressing demands to improve the energetic efficiency of vessels. The propulsion system is among the most important factors contributing to determine vessel performance, and hence consistent efficiency improvements are expected from a successful design of propulsion components.

Dealing with large transport ships, enhanced design techniques taking advantage of state-of-the-art experimental and computational techniques can be applied in view of the large investments shipowners can afford for that kind of vessels. This is not the case with smaller vessels like fishing boats where budget available for design is typically very limited and standard, sometimes obsolete, analysis and prediction approaches are used.

A viable strategy to achieve efficiency improvements for fishing boats is to develop fast and automated modelling techniques to rapidly explore propulsion retrofitting solutions as well as to design new vessels compliant to more and more stringent regulations.

In the present paper, a propeller design environment combining multi-disciplinary models is described. Specifically, three different tools are integrated: (i) propeller hydrodynamics modelling through robust techniques, (ii) virtually-generated systematic propeller series processing, and (iii) automated ‘optimal’ geometry refinement. Proposed modelling and analysis tools are described in the following sections and applications to sample design problems are presented.

Computational hydrodynamics modelling is based on an inviscid flow approach developed over the last decade and extensively validated for marine propeller flow studies. This approach provides fast and robust performance predictions once propeller geometry and operating conditions are defined. Applications of this methodology to both open and ducted propellers are presented.

Next, a procedure to identify general relationships between propeller performances and geometry/operating conditions is developed by using an Artificial Neural Network (ANN) model. Combining computational hydrodynamics and ANN models, a virtual systematic propeller series is created and new design configurations are found through fast automated procedures. The capability of the proposed ANN model to describe a whole propeller series is demonstrated by considering the Wageningen B-Series for open propellers as a reference case. Finally, an optimal propeller design exercise is proposed, in which the computational hydrodynamics/ANN model is interfaced to a numerical optimization code based on a Genetic Algorithm methodology.

The capabilities of the resulting design environment are described and evaluated through a notional design exercise addressing a propeller retrofit study for an aged fishing vessel.
II. COMPUTATIONAL MODELS

Core of the present automated design technique is the computational hydrodynamics model used to predict propeller performance under given operating conditions. In view of the application to fishing vessels, emphasis is given here to numerical models capable to describe ducted propellers. With respect to conventional open screw propellers, ducted propellers have the advantage of increasing thrust and efficiency at low speed when an accelerating duct is used, whereas the risk of blade cavitation is reduced by mounting decelerating ducts. The hydrodynamic interaction between propeller and duct is very complex and is characterized by viscosity driven phenomena such as blade tips immersed into the inner duct boundary layer, flow separation on outer duct surface and thick viscous wakes downstream blunt duct trailing edges. Nevertheless, an inviscid-flow approach is capable of capturing global interactional phenomena related mainly to thrust-induced vorticity and three-dimensional unsteady flow effects.

Current approaches for the computational analysis of ducted propellers include both inviscid (potential) and viscous flow solvers. Inviscid methods are widely used because of their robustness and limited computational effort required. Examples of these type of models are described in [1], [2], and in recent work as [3].

Major drawbacks of inviscid-flow approaches are that flow details where viscosity effects are dominant are neglected. This may traduce into unreliable predictions of propeller performance of screw operating in off-design conditions. The exact description of viscous phenomena characterizing duct/blade interaction requires viscous flow models based on the solution of Navier-Stokes equations. An example of RANS flow field calculations on a complete ducted propulsor is reported in [4]. Of course, sophisticated flow modelling and highly-accurate results are obtained at computational costs that are typically unaffordable for design procedures where several candidate configurations are evaluated and compared to determine the best one.

A. Propeller Hydrodynamics Model

In view of the analysis above, a computational approach suitable for design scopes and based on inviscid-flow modelling is proposed here and referred to as BEM hydrodynamics model. Limitations typical for these type of methods are minimized by using a general formulation in which blade trailing vorticity dynamics, boundary layer flow and cavitation are described. Specifically, an approach for open screw propellers developed and validated over the last decade (see [5] and [6]) has been extended to analyse ducted propulsors [7]. Description of blade/duct interaction is enhanced through trailing vortices alignment [8] and gap-flow modelling proposed in [9].

By discretization, the problem is recast as the solution of a linear system of equations. Once the perturbation potential \( \varphi \) is determined, the total velocity field follows as \( \mathbf{q} = \mathbf{v}_t + \nabla \varphi \), where \( \mathbf{v}_t \) has different expressions to describe the incoming flow to each propulsor component (screw and duct). Velocity and pressure fields are related through Bernoulli’s theorem

\[
\frac{\partial \varphi}{\partial t} + \frac{1}{2} \mathbf{v}_t^2 + \frac{p}{\rho} + g z_0 = \frac{1}{2} \mathbf{q}^2 + \frac{p_0}{\rho},
\]

where \( p \) is the pressure, \( q = ||\mathbf{q}|| \), \( v_t = ||\mathbf{v}_t|| \), and \( g z_0 \) is the hydrostatic head.
As a result of the hydrodynamic analysis, open propeller thrust $T_p$ and torque $Q_p$ are calculated by integrating pressure $p$ and viscous friction $\tau$ over the propeller surface $S_p$:

$$ T_p = -\oint_{S_p} p\,n_x\,dS + \oint_{S_p} \tau\,t_x\,dS \quad (2) $$

$$ Q_p = -\oint_{S_p} p(r \times n)_x\,dS + \oint_{S_p} \tau(r \times t)_x\,dS $$

where $n$ and $t$ are respectively unit normal and tangent to $S_p$, and subscript $x$ denotes vector projection along the propeller axis direction. In (2) above, the pressure is estimated by coupling BEM and boundary-layer models or simply from semi-empirical formulas for a flat plate in turbulent flow, [10].

Replacing propeller surface with duct surface, similar expressions determine duct thrust $T_D$.

$$ T_D = T_p + T_D $$

whereas the thrust coefficient is $K_{p,T} = T_p/\frac{1}{2} \rho n^2 D_p^4$, with $n$ and $D$ respectively propeller rotational speed (rps) and diameter. Similarly, ducted propeller torque coefficient is $K_{q,D} = Q_D/\frac{1}{2} \rho n^2 D_p^4$. Figure 1 shows a BEM model computational grid describing a ducted propeller and vortical wakes emanated by blades and by the duct trailing edge.

### B. Neural Network Model

BEM hydrodynamics modelling can be used to evaluate the performance of a given propeller once geometry and operating conditions are assigned. Dealing with design, it is also important to develop procedures to find general relationships between propeller performances and geometry/operating conditions. To achieve this, BEM hydrodynamics model is combined with an Artificial Neural Network (ANN) model.

Neural Networks denote a general approach to describe a complex system through the relationships among $N_{in}$ input and $N_{out}$ output variables without any explicit mathematical input/output model, but simply through a learning process. Developed over the last five decades, today ANNs are widely used in many disciplines, and applied with different aims such that of function approximation, classification and data processing [20].

ANN architectures try to mimic biological systems: multiple layers of neurons are linked each other through synapses that transfer information from the input layer to the output layer. A feed-forward architecture implies that information flux is mono-directional. Each neuron receives and processes information from all neurons of the preceding layer through the following steps (see Fig. 2):

1. information incoming to a neuron from all neurons of the preceeding layer is summed and biased in order to allow/disable activation of the neuron itself;
2. a proper transfer function modifies the input signal, generating the output signal of the neuron;
3. the output signal is sent, through synapses, to all the neurons in the following layer.

The output $Y_{i(l)}$ of a single neuron may be expressed as

$$ Y_{i(l)} = F(a_{i(l)}) = F\left(\sum_{j=1}^{N_{out}} w_{i(l)}^j X^j + w_{i(l)}^0 X^0\right) $$

$$ 0 \leq l \leq L_{layer}; Y_{i(0)} = X^1; X^0 = -1 $$

where $a_{i(l)}$ represents the activation function, $X^j$ the input data to neurons weighted by quantity $w_{i(l)}^j$, related to the connection between neurons. Quantity $F$ is a monotone, continuous and differentiable transfer function. A sigmoid function is used here, see right Fig. 2.

In order to reproduce the input/output structure characterizing a given system, ANNs require suitable training. The problem of training a neural network consists in determining the optimal set of weights $w$ that allows to describe a response surface over the entire domain of the independent variables with a minimum error; they are updated through a recursive procedure that ends when neural numerical and desired outputs differ less than a prescribed threshold. Specifically, a ‘Levenberg-Marquardt’ algorithm, based on a gradient search direction calculated via a back-propagation of the error, is here used [12].

Once training is completed, the ANN is ready to simulate and predict the behaviour of any configuration described as arbitrary combination of input variables. The only requirement is that queried input variables do not take values that are significantly outside the range of variation of input variables used in the training phase. A major advantage of using trained ANNs is that computational time required to predict system output is negligible. Thus, this technique is appealing when combined with design and optimization procedures where recursive calculations are necessary.

### C. Numerical Optimization Model

In the design process of a marine propeller, one of the main goals is the definition of the optimal combination of the design parameters, defining screw geometry and operating conditions, in accordance to required performances. To have a fast and automated design tool, an optimization procedure based on trained ANNs to describe the physical behaviour of the system is here proposed.
Numerical optimization applied to propeller design typically implies that propeller performance figures (objective functions) have to be maximized (or minimized) through variation of a given set of parameters defining propeller geometry and operating conditions (design parameters). Physical or practical limitations to values that variables assume during the optimization procedure are called constraints. In the following sections, examples of design parameters, objective functions and constraints are given.

In the present work, a numerical optimization procedure based on genetic Algorithms (GAs) is considered. Basic features of the methodology are given here, whereas details can be found e.g. in [13], [14] and [15]. The underlying idea of GAs is to mimic natural selection in the process of finding the optimal solution. Candidate solutions during the optimization procedures are called individuals and the whole set of individuals is a population. Here, since binary-based GAs are used, each individual is associated to a string of binary digits (genes) ordered in a given sequence (chromosome).

At each step of the process, solutions corresponding to all individuals are evaluated in terms of the objective functions. A penalty-function technique [16] is used to include the constraints in the optimization process. A selection of the best individuals, based on a fitness measure calculated from the objective function and constraints, is done and chromosome strings are saved to build a new generation. New offsprings starting from the actual population are generated through chromosome string manipulations (crossover). A mutation operator is also applied to avoid premature convergence to local optima, instead of global ones. The amount of chromosome variations during the evolutionary process is controlled in order to reduce the impact of random mutations as the solution converges to an optimum. Furthermore, an elite selection strategy is used to prevent new generations producing worse results than elder ones. The optimization procedure is iterated until the chromosomes similarity (bit-string affinity) reaches a given value [13].

D. Parametric Search

An alternative approach to find the optimum inside a population is represented by parametric search. Specifically, the optimum is searched by investigating the region of design variables space where all constraints are satisfied [17]. In this case the search procedure is simply based on parametric variation of all design variables in order to span all the domain of interest. The optimum is found by comparing objective function values in all tested design variables space points. Because of the dummy search technique, such a procedure typically requires to test a larger number of conditions than those investigated by numerical optimization algorithms and hence it tends to be computationally inefficient, especially when the number of design variables growths. In the present work parametric search is used to compare results from optimization via GAs.

III. VALIDATION OF NEURAL NETWORK MODEL

A necessary step before application of ANNs to optimal design consists in assessing the capability of the proposed Neural Network Model to simulate performances of a general class of propellers [18]. As an example of training dataset, the Wageningen B-Series open propellers [19] are considered here. Specifically, available experimental data for the Wageningen B-Series allow to build an extensive dataset of 230
propeller models obtained from different combinations of geometry parameters as number of blades $Z$, pitch/diameter ratio $P/D$, expanded area ratio $EAR$. Each model is tested at advance ratio $Ja = VA/nD_p$ from zero (bollard pull) to zero thrust. Input/output relationship are sketched in Fig. 3. A total of $\approx 4000$ combinations of geometry and operational conditions is then considered, for which measured propeller $K_T$, $K_Q$ and efficiency $\eta = (J_a/2\pi)K_T/K_Q$ are known.

Two cases are considered:

(a) training dataset based on experimental data from the original Wageningen series [19];

(b) training dataset for the same propeller series, with experimental data replaced by computational results from BEM hydrodynamic model.

In order to perform Neural Network training first and validation then, the whole dataset is splitted into two subsets. The subset used in the training phase (training dataset) is obtained from the whole dataset by considering only dataset entries at even values of $J_a$, whereas dataset entries at odd $J_a$ values form the subset used for ANN results validation. Results by the ANN architecture developed in the present work are compared to those obtained using software NeuroSolutions$^{TM}$ [21]. In order to make the two ANN models comparable, input data arrangement and neurons transfer function used are the same, and both models use a Levenberg-Marquardt procedure for the gradient search in the back propagation step [20]. Moreover, a check on the correctness of the hidden layer compositions in terms of number of neurons has been made, by adopting a genetic algorithm scheme in the determination of the optimal layers dimension [15]. This form of optimization requires that the network be trained several times in order to find the combination of inputs that produces the lowest error.

The comparison between original Wageningen B-Series open propeller data and those obtained from Neural Network test simulations is described in Figs. 4, 5. Figures 4 depict error maps of calculated propeller $K_T$ versus original data [19] in particular, the figure shows the influence of two input variables, $J$ and $P/D$, for given value of other ones, $Z = 4$ and $A_e/A_0 = 0.85$. ANN prediction error is below 4% over a wide range of input variables $P/D, J$. Only exception is 10% error peaks in the boundary region with lowest $P/D$ and highest $J$ values (thrust close to zero). Results by the two ANN models are in good agreement. Similar results are obtained for other output variables $K_Q$ and $\eta$.

The quantitative comparison of original vs. ANN-predicted data is confirmed by Figure 5, where actual $K_T$ results are shown for three different values of $P/D$. B-Series experimental data [19] and ANN results are within plotting accuracy. In particular, results by the present ANN model and those from commercial software NeuroSolutions$^{TM}$ software [21] are in excellent agreement.

IV. AUTOMATED DESIGN: CASE STUDY

The integrated ‘BEM hydrodynamics-Neural Networks model’ is coupled to numerical optimization via Genetic Algorithms and applied to a propeller design exercise. Akin to classical propeller series like the Wageningen B-Series, a basic assumption here is that a propeller series may be built by considering only four design parameters:

- the propeller diameter $D_p$
- the number of blades, $Z$
- the expanded area ratio, $EAR$
- pitch to diameter ratio, $P/D$
Other blade geometry details including radial distributions of chord, pitch, skew, sectional profile thickness and camber are implicitly defined through combinations of the four design variables above.

The design objective is to maximize hydrodynamic efficiency $\eta$ while keeping fixed delivered torque $Q_d$ (and power $P_d$, with $n$ also kept constant).

Then, design constraints are imposed as follows:

1. torque absorbed by propeller at given rps matches delivered torque within a 2.5% allowed deviation: $| (Q - Q_d) / Q_d | \leq 0.025$;
2. propeller thrust at given ship speed matches hull resistance within a 2.5% deviation: $| (T - R) / R | \leq 0.025$;
3. propeller diameter is limited to fit into an existing afterbody layout: $D_P \leq D_{max}$;
4. cavitation condition based on ’Keller’s Formula’: $EAR \geq EAR_{min}$, with [19]:
   \[
   EAR_{min} = \frac{(1.3 + 0.3Z)T}{(p_0 - p_v)D_P^2} + k
   \]  
   where $k = 0.2$ is used for single-screw vessels.

Constraint no. 2 implies that vessel speed cannot be lower than reference speed $V_S$. Then, hydrodynamic efficiency optimization means that thrust (and vessel speed) is increased. A real-life case study is derived from existing vessel data analysed during the EU-FP6 research project 'SUPER-PROP', [7]. Aim of the project (2005-2008) was to analyse tecno-economical aspects related to retrofitting propellers of aged boats like trawlers and tugs.

The reference configuration chosen here reflects the propeller of a fishing vessel of about 1400 T gross weight, 70 m length, 2000 kW/375 RPM engine power at MCR. Considering freerunning conditions, design parameters for this reference configuration are:

- reference ship speed, $V_S = 7.31$ m/s
- delivered power, $P_d = 1714$ KW
- engine rotational speed, $n = 4.17$ rps
- maximum diameter allowed, $D_P = 2.7$ m

Combining model test and sea-trials data from the project above, hull resistance curve $R = R(V_S)$, wake fraction $(1 - w_t)$ and thrust deduction $(1 - t)$ factors are known for this reference configuration.

The optimum search is based on numerical optimization via genetic algorithms and results are compared to those obtained by the parametric search approach. In particular, the parametric search procedure can be summarized as sketched in Fig. 6: (i) determine the condition for $D_p$ satisfying the $K_Q$-constraint; (ii) determine the condition for $V_S$ satisfying the $K_T$-constraint; (iii) check other constraints affecting $EAR$ in combination to $D_p$, $V_S$.

Considering alternative optimum search techniques (parametric search Vs. numerical optimization) and NN training dataset (experimental Vs. BEM hydrodynamics), four different combinations are obtained and addressed here below.

With respect to design variables, a set of optimal conditions, for which the choice of the best is made only by comparison of the chosen objective function, is shown in Figs. 8 to 10.
V. EXTENSION TO DUCTED PROPELLERS

The propeller design exercise described above refers to open screw configurations. In view of application of the proposed methodology to working boats like fishing and supply vessels, the extension to include ducted propeller modelling capabilities is necessary.

To this aim, the integrated BEM hydrodynamics/Neural-Networks/numerical optimization tool described above is easily generalized once open propeller hydrodynamics by BEM is extended to ducted propellers. Work underway in this area is described in the present section.

In order to assess the proposed methodology, the present numerical model has been used to predict global performances of the original propeller mounted on the fishing vessel taken as the reference case. Its model propeller is denoted ‘E1622’ in the INSEAN nomenclature and is characterized by a pitch to diameter ratio, $P/D$, equal to 1.0 and an expanded area ratio $A_e/A_0 \approx 0.85$. Experimental data are available for the propeller working in ducted as well as in unducted configuration.

In Fig.11 predicted thrust and torque are compared to experimental data for the INSEAN E1622 isolated propeller case. A good agreement is shown for all values of the advance coefficient. Propeller thrust coefficient $K_T$ is slightly underpredicted at high values of $J$. Next, in Fig.12 the ducted propeller configuration is considered and results obtained by using different trailing wake models are compared. Specifically, results are labelled respectively as $PW$ and $FW$, where $PW$ stands for numerical calculations considering a prescribed helicoidal wake shape, whereas the notation $FW$
VI. CONCLUDING REMARKS

An automated computational methodology for the preliminary design of marine propellers has been described. The methodology combines inviscid-flow hydrodynamics modelling, Neural Networks and numerical optimization via Genetic Algorithm into a fast and robust tool that can be used at reduced computational costs. In the paper, the computational methodology has been outlined and ongoing development and validation work has been presented.
In particular, simple numerical applications have been presented to assess the capability of the whole methodology to correctly predict optimal configurations for given operating conditions and other design constraints. Although the notional nature of the design excercise addressed, model capabilities are demonstrated and the following conclusions can be drawn.

- The computational hydrodynamics model based on BEM provides reliable predictions of propeller performances over a wide range of operating conditions. Ducted propeller modelling reveals critical aspects at low advance ratio that require further investigations.

- The proposed Neural Network model provides a powerful tool to predict input/output relationships to describe a virtual systematic propeller series built on user-defined characteristics.

- Applications of the Neural Network/BEM hydrodynamics model to simulate experimental results for the Wageningen B-series demonstrate virtually-generated propeller series can be easily built.

- The proposed automated technique is able to determine the optimal configuration given operating conditions and design constraints.

Future work will focus on improving BEM hydrodynamics modelling of ducted propeller configurations and creating virtual ducted propeller systematic series by using the proposed Neural Network strategy.

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Figure 12: INSEAN E1622 ducted propeller open water performance. Comparison between BEM results and experimental data. Top: screw and duct thrust. Bottom: total thrust and torque.

References


