Optimal design of axial hydro turbine for micro hydropower plants

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Optimal design of axial hydro turbine for micro hydropower plants

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Abstract. In our country we have enormous low head potation flows in agricultures and aquacultures with almost fix flow rates that can be used as micro hydro power plants for producing energy. But the main problem is the high capital price per kW. Therefore there is needed to design a simple machine with a good runner for covering the various potential flows. In this paper an axial hydro turbine has designed for some low heads micro potential flow with flow rates ranged from 50 lit/sec to 150 lit/sec and heads ranged from 1 m to 5 m. The initial runner designed using classical methods and then the runner geometry has been optimized by evolutionary optimization algorithms. The final design has been simulated by a commercial flow solver in a various blade positions. The results showed a wide range characteristic curve with a wide range high efficiency.

1. Introduction
Turbomachinery blades design is a complex task involving many different objectives and constraints coming from various disciplines. Further improvement of this design cycle is probably one of the main challenges of the next decade in the turbomachinery community. Major improvements are expected in terms of reduced design time, reduced engineering time, better performance and increased design complexity. This challenge can only be tackled by selecting and further developing general and efficient design algorithms integrated into software dedicated to this specific design task [1].

In order to help the designer in this complex task, various complex codes are now available to define complex blade geometries (CAD system), compute the flow field inside the blade channel (CFD codes) and the mechanical stresses inside the blade metal (structural codes). Although the CFD softwares are getting more accurate, fast and user-friendly they do not provide algorithms able to automatically optimize the performance of a geometry. However, the very short design time schedule, often imposed by the market, do not allow the designers to test many modifications and therefore cannot take full advantage of the huge potential and huge amount of information provided by the CAD, CFD and structural codes [2].

Today, several other design methods are available such as gradient methods based on finite difference [3] or more recently based on the sensitivity and the adjoint equation [4], genetic algorithm [5], simulated annealing, response surface methods, inverse design [6] or expert systems [7]. All these methods have advantages and disadvantages and cannot cover the whole field of design problems.
A design method has been developed that is based on the concept of function approximation and that combines other very popular techniques such as artificial neural networks, genetic algorithm, database and CFD analysis tools [8] and [9].

A completely new commercial package (FINETM/Design3D) has been developed at NUMECA International that offers more flexibility, improved performance, graphical-user interface (GUI) and full automatization of the design cycle. This new software incorporates various very popular and efficient techniques such as artificial neural networks, genetic algorithms, databases and CFD analysis tools [2].

FINETM/Design3D offers a fully automatic coupling to the NUMECA fast and high fidelity CFD simulator FINE™/Turbo that contains a mesh generator IGG™/Autogrid, a flow solver EURANUS and a post processor CFView™. EURANUS [8] is a finite volume discretization code based on explicit time marching algorithms. The explicit Runge-Kutta time stepping procedure is used to advance the solution to steady state. A centered space discretization is applied and scalar local time stepping is used to advance the solution in time. Acceleration techniques such as implicit residual smoothing and multigrid are used systematically [2].

2. Initial runner design
In this research, design and optimization of blades shape of an axial flow turbine runner has been considered to maximize its total efficiency at the best efficiency point of the turbine via a numerical optimization package including parameterization, CFD, artificial neural networks and genetic algorithms modules. The goal was to optimize the geometry of the blades of axial turbine runner which leads to maximum total efficiency by changing the design parameters of camber line in at least 3 sections of a blade. The turbine is designed according to the method of Arthur Williams for the three meters head and 75 liters per second mass flow [10]. The number of blades is 6. The outer diameter is 214mm. A view of initial runner blade has been shown in Figure1.

![Figure 1. A view of initial runner blade](image)

3. Simulation in NUMEA
Using IGG AUTOGRID/NUMECA robust and high quality meshing software for turbomachinery configuration, good quality meshes are obtained for all possible parameters value.

In the second step Geometric model of the axial turbine has generated in AUTOGRID5 and the mesh settings performed as follows:
Table 1. The specification of mesh setting

<table>
<thead>
<tr>
<th>Type</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>The number of grid(medium)</td>
<td>463518</td>
</tr>
<tr>
<td>The number of flow path</td>
<td>57</td>
</tr>
<tr>
<td>Cell width</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The mesh template file must be defined to be as robust as possible with respect to the blade geometry modification. For the near wall treatment, the first cell widths were assumed to be 0.01, runner blades by assuming $y^+ = 3.0$. A blade to blade mesh view of initial runner blade has been shown in Figure 2.

![Blade to blade mesh view at section 4 of an initial runner blade](image)

Figure 2. Blade to blade mesh view at section 4 of an initial runner blade

Then we simulate the Lattice geometry with the following settings in FINETM/Turbo:

FINE™/Turbo developed by Numeca, is integrated software based on finite volume discretization for multi-block structured grids. To simulate the turbulent quantities with also a good rate of convergence the Spalart-Allmaras model was preferred (with turbulent viscosity, $\nu_t = 1.1 \times 10^{-6}$). The flow conditions for each calculus are imposed at boundaries related to Mass Flow at inlet and Averaged Static Pressure at the outlet. To confirm the grid independency of the present simulations, three grid sizes (340527, 463518 and 889533 grid points) for initial turbine included of runner blades was used. The computed efficiencies were 78.9%, 79.87% and 79.87% respectively, so medium grid level was selected. As a convergence criterion, the computations were continued until the global residual decreased to less than 10-6 for discretized equations. A convergence diagram of an initial runner blade has been shown in Figure 3.

![A convergence diagram of an initial runner blade](image)

Figure 3. A convergence diagram of an initial runner blade

4. Optimization
The optimization problems associated to turbo machinery design often involve many constraints and large sets of parameters, which in general leads to objective functions presenting many extremes. It is well known that optimization methods based on gradients techniques are efficient in terms of convergence rate, but do not guarantee to produce the global optimum [4]. On the other hand, genetic algorithms offer the advantage of enhancing the probability of reaching the global optimum, but may require thousands of iterations [11]. Their coupling with a three-dimensional Navier-Stokes solver cannot be considered under the framework of an industrial design process. The major idea of the optimization system contained in FINETM/Design3D is that the evaluation of the successive designs is performed using an artificial neural network instead of a flow solver, which permits to use the genetic algorithms in an efficient way. The accuracy of the optimization depends on the knowledge of the neural network, which is fed by design examples stored in a database.

For artificial neural networks, the first step is a "learning process" is used to build the neural network on basis of all the examples stored in the database. Learning process is performed by back-propagation of the errors. After this process, the neural network is able to predict the aerodynamic performance of blade geometries under given boundary conditions that are not inside the database.

The next step consists of finding a new design using an optimization procedure formed by a genetic algorithm, the aerodynamic performance being evaluated by means of the trained neural network instead of Navier-Stokes solver. The global blade performance is evaluated through an objective function, which translates all the user imposed constraints into a single number. The result of this optimization is a point in the design space that is expected to be the optimum of the real problem. The new geometry provided by the optimization is then evaluated by means of the 3D Navier-Stokes flow solver and this new sample is added to the database. The comparison of the obtained performance with the one predicted by the neural network permits to evaluate the accuracy of the network. The obtained performance is also compared to the imposed one. If the target performance has not been achieved other iteration is started, and the same process is repeated until the optimum blade is obtained (Figure 4). Each design iteration starts with the neural network learning. As the design proceeds, the database grows, leading to improvements of the approximate relation and therefore to a better localization of the real optimum [11].

![Figure 4. Schematic view of optimization technique](image)

4.1. Geometry parameterization
The geometry parameterization is a critical element in the success of any shape optimization method. Ideally, the parameterization of the geometry should be able to generate a large variety of physically realistic shapes with as few design variables as possible. Turbo-machinery designers are accustomed to work with two-dimensional sections that are then stacked to the three-dimensional blade geometry. One method in blade construction defines a camber line and adds thickness distributions to obtain the suction and the pressure sides. The advantage of this method is that the blade thickness can be easily maintained during the optimization, by freezing the associated parameters. Endwalls can be parameterized by making use of Bezier or B-spline curves.

In this paper, the parametric model that has been adopted in Autoblade™ consists of 3 sections at hub, shroud and one section in mid (Figure 5), defined by a camber line and symmetric thickness distributions. Each camber line is a B-spline curve which was defined with 5 parameters (Figure 6 a). Bezier curve with 5 parameters was used to represent the symmetric blade thickness at each section that they were fixed via optimization process (Figure 6 b).

![Figure 5. Meridional view of axial runner turbine](image)

The meridional location of each leading and trailing edges traces were imposed using a B-spline with 5 parameters which parameters were fixed via optimization process.

![Figure 6. a) B-spline curve with 5 parameters for each section, b) Bezier curve with 5 parameters for thickness distribution at each section.](image)

The tangential location law for the leading edge was defined using a lean law B-spline curve with 4 parameters. The meridional location of each hub and shroud endwall was defined by B-spline curve with 7 parameters which parameters were fixed via optimization process.

Finally, in optimization process, we allowed only variation of cord lines and leading edge stacking curve. Therefore the number of design parameters were limited to 19 (5 control points on each section and 4 control point for tangential law).
Next we need to generate the database of 60 geometries that the parameters of them being varied in a random way. After the generating of database the last level is optimize the geometry. The optimization objective has imposed to the operating point to increase the efficiency in constant head. The objective function use for this paper is defined as:

\[
OF = m(\frac{eff_{imp} - eff_{ref}}{eff_{ref}})^2 + n(\frac{Pres_{imp} - Pres_{ref}}{Pres_{ref}})^2, \quad m = k
\]

where \( eff_{imp} = eff_{ref} = 1 \) and \( Pres_{imp} = Pres_{ref} = -34600 \text{Pa} \).

5. Result
The convergence history of the optimization procedure has been shown in Fig.7. One can be observed that the error between the neural network predictions and the CFD results decrease, both curves finally converging after some 15 iterations.

![Figure 7. Evolution of objective function during optimization](image)

The results of optimization have been shown in table.2.

<table>
<thead>
<tr>
<th></th>
<th>efficiency</th>
<th>Q(kg/s)</th>
<th>H(m)</th>
<th>Torque(N.M)</th>
<th>Pressure Loss(Pa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>79.89</td>
<td>75</td>
<td>3</td>
<td>20.34</td>
<td>0.9628</td>
</tr>
<tr>
<td>Optimized</td>
<td>83.556</td>
<td>75</td>
<td>3</td>
<td>21.1</td>
<td>0.9026</td>
</tr>
</tbody>
</table>

A 3D view of the initial and optimized blade has been shown in Figure 8 and Figure 9 and 10 presents the total and static pressure distributions along the runner blade and hub.

![Figure 8. 3D View of initial and optimized geometry](image)
6. Conclusions

Optimization is a profitable industry in all of parts of our lives but in small and large hydro power plants can be very economic. In the present study, an improvement in the turbine efficiency has been obtained by optimization of turbine blade. Then we could find out that the optimization can be a good idea for small hydro power. The new optimized runner blade induced an important minimum static pressure increase. We noticed a little torque improvement and pressure loss reduction in the optimization procedure. Multi-objective optimization guaranties that the efficiency improvements were obtained over a best efficiency operating point (BEP), which essential in case of a turbine design. More than 3.5% improvements have been obtained in terms of efficiency for axial flow turbine.

References


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