1 Introduction

Clean energies are going to be important by considering recently environmental limitations as greenhouse gases and earth warming problem. Offgrid renewable energies such as solar energy, wind power energy, hydrenegy, and biomass energy are the main alternative to overcome the mentioned problems. Unfortunately, renewable energies are not always economical in comparison with the conventional energies. Therefore, designing the low-cost machines with higher efficiencies is a hot topic for researchers and engineers [1–3].

Small hydropower stations became attractive after the oil price crisis of the 1970s and again in recent years. However, the cost per-kW of the energy produced by these stations is higher than the large hydroelectric power stations [4].

In recent years, numerous publications emphasized the importance of using simple turbines to reduce the cost of generated energy. Using centrifugal pump as turbine (PAT) is an attractive and significant alternative. Centrifugal pumps are relatively simple machines with no special designing and are readily available in most developing countries. Besides, their installation, commissioning, and maintenance are easy and cheap. Some researchers have developed application of centrifugal pumps as turbines for high/medium-head micro hydropower stations (MHS). Nautical and Kumar have reviewed analytical, experimental, and numerical studies done on reverse running of centrifugal pumps [5].

Because low-head hydropotentials are usually available in all regions, e.g., small rivers, aquacultures, and farms, developing the low-cost machines are very interesting. A good method in which the optimal arrangement of the hydropower stations has been determined by a computational operation using discrete data at points along the river such as the drainage area, altitude, and distance along the river channel as obtained from topographical maps instead of drawing on engineers’ experiences and the intuitions of experts by Hayash et al. [6].

In the present work, a simple machine has been introduced instead of conventional propeller turbines. The key is using axial pump as propeller turbine. Researches in this field are limited to the works of Gantar [7], Joshi et al. [8], Nurbakhsh et al. [9], and Bozorgi et al. [10]. They have investigated analytically, numerically, and experimentally some propeller pumps rotating as turbines.

Recently optimization toolbox have been applied for small hydraulic turbine performance improving. Genetic algorithms coupling with artificial neural network as a approximate model, joined with computational fluid dynamics have been applied by Derakhshan et al. [11] for centrifugal reverse pumps, Kueny et al. [12] for axial small hydraulic turbine, Derakhshan and Mostafavi [13] for small Francis turbine. Also, similar research work done in the field of optimization of energy resources in optimization of power absorption from sea waves that this project presents a generalized procedure for selecting rationally the design parameters of a simple wave power absorption system [14].

In this study, using commercial flow solver, all geometries of pump including inlet, impeller, and outlet have been simulated in the modes of direct and reverse operation. To verify the numerical results, a complete micro hydropower test ring was established at laboratory and was used for experimental verification of
numerical results. The simulated propeller pump was tested as turbine using this test ring. All required parameters were measured for obtaining complete characteristic curves of the PAT. Finally, all numerical and experimental results were compared and discussed. The results showed that a propeller pump could be easily run as a low-head turbine.

In the next step, paper focused on the optimization with simple design and good performance and low price using genetic algorithms and artificial neural networks coupling by computational fluid dynamics. The goal was to optimize the geometry of the blades of propeller pump as turbine runner which leads to maximum hydraulic efficiency. The results showed that the efficiency has improved more than 14%, and indeed the geometry has better performance in cavitation.

2 Propeller Pumps as Turbines

One way to overcome the high-cost capital price of the MHS is using simple machines instead of conventional machines. Previous experiences have shown that industrial pumps can be property operated as turbines [15]. Figure 1 shows different pumps as turbines. Centrifugal pumps can be rotated as turbines in heads ranged 15–100 m and flow rates ranged 5–50 l/s. These ranges for mixed flow PATs is 5–15 m and 50–150 l/s for heads and flow rates, respectively. For heads, ranged 15–100 m and flow rate ranged 50–1000 l/s, the double suction pumps or parallel centrifugal pumps are suitable. Pump manufacturers usually produce centrifugal and mixed pumps in mass production. Therefore, these types are easily available in the market with a low price.

For heads ranged between 1 and 5 m and flow rates ranged between 50 and 1000 l/s, propeller pumps can be used as turbines. However, these types of pumps are not usually found in the market. Because pumps manufactures supply them in customized way, therefore their prices are not low.

3 Case Study

A propeller pump with a rotational speed of 1000 rpm with fixed blades was used. The impeller diameter is 300 mm and its blade numbers are four. Figure 2 depicts the pump impeller.

4 Numerical Investigation

Flow simulations were entirely performed by means of a commercial 3D Navier–Stokes CFD code which uses the finite element-based finite volume discretization method. It is a fully implicit solver, thus creates no time step limitation and is considered more flexible to implement. A coupled method was exploited to solve the governing equations, meaning that the equations of momentum and continuity were solved simultaneously. This approach reduces the number of iterations required to obtain convergence and no pressure correction term is required to retain mass conversion, leading to a more robust and accurate solver. The governing equations for the steady incompressible turbulent flow are the continuity (Eq. (1)) and the Reynolds average Navier–Stokes (Eq. (2)) equations.

\[
\frac{\partial u_i}{\partial x_i} = 0 \quad (1)
\]

\[
\frac{\partial}{\partial x_j} \left( \rho u_i u_j \right) = \frac{\partial P}{\partial x_j} + \mu \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) + \rho F_i \quad (2)
\]

where \( u_i \) is the averaged velocity component in the \( i \) direction, \( \rho u_i u_j \) is the Reynolds stress, \( P \) is the averaged pressure, \( \mu \) is the viscosity, and \( F_i \) is the averaged external force component. To consider turbulence, the Reynolds stresses are modeled with Boussinesq approximation. The Boussinesq approximation causes to use an eddy viscosity \( \mu_t \) to model the turbulence Reynolds stresses,

\[
- \rho u_i u_j = \mu_t \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) + \frac{2}{3} \delta_{ij} \left( \rho k + \frac{\partial u_i}{\partial x_j} \right) \quad (3)
\]

where \( k \) is the turbulent kinetic energy which can be defined as

\[
k = \frac{1}{2} \left( \rho u_i u_j \right) \quad (4)
\]

4.1 Solution Parameters. To calculate \( \mu_t \), the RNG \( k-\varepsilon \) turbulence model, which is based on renormalization analysis of Navier–Stokes equations, was employed [16]. The rapidly straining flow and high streamline curvatures, which are present in this case study, necessitate the use of RNG \( k-\varepsilon \) turbulence model [17].

A convergence criteria, the computations were continued until the global residuals decreased to less than \( 10^{-6} \) for discretized equations. In the numerical simulation process, the mechanical loss resulting from seals and bearings are calculated according to Ref. [18]. Thus, the obtained efficiency includes the mechanical loss caused by friction and bearings and the volumetric loss through the wear ring [19]. As the boundary condition, mass flow rate, flow angles, and averaged static pressure were imposed for the outlet and average static pressure was set for inlet, this setup was shown to have better convergence behavior [20]. No-slip condition with 50 \( \mu \) sand grain roughness was assumed for each wall exposed to fluid flow.

4.2 Grid Generation. The fluid was split into three component parts: they were pump inlet pipe, impeller, and outlet. This separation allows each mesh to be generated individually and tailored to the flow requirements in that particular component. To get a relatively stable inlet and outlet flow, four times of pipe diameter have been extended in the PAT inlet and outlet section. The numerical model is shown in Fig. 3.
The $y^+$ near the boundary wall was around 40. Due to the complexity of generating a structured mesh based on geometry, great efforts had been taken in the mesh generation of volute. Figures 4 and 5 give a general view of 3D of complete domain and blade grid, respectively.

The independence of turbine mode’s hydraulic efficiency from grid number was performed as depicted in Fig. 6. In each step, the grid size, especially near the wall boundaries and in the blade tip, was investigated so that the velocity gradient could be calculated more precisely. It was observed that the efficiency varies by less than 0.5% when the grid numbers are more than approximately $1 \times 10^6$. Table 1 lists the selected grid numbers of each component.

### 5 Experimental Setup

A complete PAT open-circuit test ring was built and utilized in this study. A schematic of all components of the setup is depicted in Fig. 7.

The setup is composed of an axial PAT, generator, torque meter, feed pump, electric motor, venture, butterfly valve, pressure gauges, several pipes, and connections that are installed on the reservoir.

In this setup, a conventional synchronous generator was applied. The rotational speed ($N$) was checked by an optical rotor meter.

Some dummy loads were used as the energy consumer. In addition, the generator was changed to suspend state and the torque was measured by a scaled arm and several weights (Fig. 8). The needed flow rate and head of the PAT were supplied by the feed pump. The feed pump was used and could prepare a sufficient range of operation for the axial PAT.

To obtain the characteristic curves of the PAT, the flow rate was changed by the butterfly valve.

In each test, the flow rate was measured by a venture based on the standards presented in Ref. [21] and the pressures were measured by some barometers. After measuring all the parameters, the flow rate, head, output net power, and efficiency have been determined. A first-order uncertainty analysis was done using constant odds combination method, based on a 95% confidence level as explained by Moffat [22]. The uncertainties for the head, flow rate, and power measurements were $\pm 4.5\%$, $\pm 5.8\%$, and $\pm 5.2\%$, respectively.

### 6 Optimization

The goal of the optimization is to find the minimum of the objective function using the simplified analysis model. The optimization problems associated to turbomachinery design often involve many constraints and large set of parameters, which in general leads to objective functions presenting many extremes. It is well-known that optimization methods based on gradient
techniques are efficient in terms of convergence rate, but do not guarantee to produce the global optimum \cite{23}. On the other hand, stochastic techniques such as the genetic algorithms offer the advantage of enhancing the probability of reaching the global optimum, but may require a large number of iterations \cite{24}.

6.1 Artificial Neural Network (ANN). In the current study where the calculation of objective function is considered a time-consuming and formidable task, the use of stochastic optimization techniques may be impossible, for they require the calculation of objective function in the population in each iteration. To reduce the computational cost, an ANN could be utilized.

A generalized regression neural network (GRNN) was used. GRNN is often used for function approximation and it can be designed very quickly.

In the presented method, the network is initially trained with a small number of samples. Starting with the optimization process, in each iteration, the optimal point is added to the sample data. Thus, the accuracy of networks increases in each iteration. At the end of each iteration, the obtained value of objective function from ANN is compared with that of CFD, and the error is considered as a stoppage criterion of overall optimization process. This method has been proved to be very efficient in terms of accuracy and computational cost \cite{25}.

6.2 Genetic Algorithm. Genetic algorithm was first proposed in 1970s by Holland, and further improved by Goldberg \cite{21}. The first step in this algorithm is to generate a random population of data in the whole scope of design parameters. Through some procedures, the algorithm generates new populations which contain better individuals. Then the fitness of each individual is calculated and the elitism is applied in order to keep the best elements and eliminate the others. Then the combination and mutation processes are applied. Pairs of individuals are selected from, based on their objective function values, and each pair undergoes a reproduction mechanism to generate a new population in such a way that fitter individuals will spread their genes with higher probability. The children replace their parents. As this proceeds, inferior traits in the pool die out due to lack of reproduction. At the same time, strong traits tend to combine with other strong traits to produce children who perform better.

6.3 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. End walls can be parameterized by making use of Bezier or B-spline curves. 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 29 (five control points on each section and four control point for tangential law).

6.4 Objective Function. The goal of the optimization process is to increase hydraulic efficiency in a constant operating point. Thus, the objective function contains a penalty term which penalizes the function value when the deviation from the imposed operating head is increased.

The efficiency term of the objective function is defined in terms of torque, instead of efficiency itself, which has been proven to lead to more robust solution, for its independence from the pressure difference. The objective function which is the sum of efficiency and penalty term is defined as

\[ \text{OF} = m \left( \frac{T_{\text{target}} - T}{T_{\text{target}}} \right)^2 + n \left( \frac{\Delta p_0 - \Delta p}{\Delta p_0} \right)^2, \quad \frac{m}{n} = k \] (5)

\[ \text{Fig. 7} \quad \text{Low-head micro turbine test rig established in laboratory} \]

\[ \text{Fig. 8} \quad \text{Method of measuring the shaft torque of PAT} \]
whereby increasing torque ($T$) in constant pressure difference ($Dp$) and flow rate ($Q$), efficiency will be improved ($\eta = T/(QDp)$). Figure 9 shows the optimization algorithm used in this study.

7 Results and Discussion

To validate the accuracy of CFD results, comparison between pump two modes’ experimental results and CFD results are presented. The investigated pump mode’s performance data are presented in Figs. 10–12, which illustrate hydraulic head, efficiency, and shaft power, respectively. Table 1 lists pump’s experimental and numerical results for best efficiency point (BEP). Figures 10–12 indicate that the numerically predicted pump’s performance curves are in accordance with those of experimental data. The difference between the numerical and experimental results is mainly due to the volumetric loss from the mechanical seals and the cavitation phenomena which was not taken into account in the simulation. As illustrated in Fig. 12, the deviation from experimental efficiency is increased in the higher mass flow rates. This difference can be attributed to cavitation which decreases the hydraulic efficiency. Table 1 indicates that relative error of predicted head, shaft power, and efficiency to experimental data at BEP is 4.8%, 3.8%, and 1.3%, respectively. This demonstrates that CFD could predict pump performance with an acceptable accuracy, especially at the BEP.

The turbine mode’s performance data are presented in Figs. 13–15. Table 2 lists its experimental and numerical results. As illustrated in Figs. 13–15, PAT’s numerical predicted performance curves are with an acceptable accuracy, compared with the experimental data. Table 2 indicates that the relative error of predicted
head, shaft power, and efficiency to experimental data at BEP is 4.1%, 9.1%, 22.0%, and 9.5%, respectively. Numerical predicted efficiency, pressure head, and shaft power are higher than that of experimental results. This overpredict of efficiency, pressure head, and shaft power may attribute to the neglecting of leakage loss through balancing holes and the volumetric loss caused by mechanical seal and bearings.

Dimensionless parameters $h$ and $q$, head and flow rate ratios, respectively, which were also used by other researchers [15,19] are

$$h = \frac{H}{H_{pb}}, \quad q = \frac{Q}{Q_{pb}}$$  \hspace{1cm} (6)

Experimental results show that $h$ is 1.57 and $q$ is close to 1.92. Pump worked in higher flow rates and lower heads in turbine mode.

When a pump rotates as a turbine, the efficiency of turbine mode is usually close to pump efficiency. Our results showed lower efficiency in turbine modes. These unexpected results can be occurred by the influence of various subjects. For example, there may be happened cavitition phenomena in turbine blades, because there was not any control or visualization device for cavi- tation detection. In reverse running of a propeller pump, the main problematic element is the suction bell-mouth. So, at the impeller discharge in turbine mode, the kinetic energy can be utilized by replacing the bell-mouth with carefully designed concentric dif- fuser or with a diffuser combined with a bend. Diffuser is impor- tant in high specific speed pumps because at impeller discharge, the part of kinetic energy in total energy is large. Our tests have been done without diffuser.

This turbine coupled with a synchronized generator and an electronic load controller was installed in a remote area with head 6 m and flow rate 200 l/s. The output power of micro hydropower is almost 5 kW.

The convergence history of the optimization procedure has been shown in Fig. 16. One can be observed that the error between the neural network predictions and the CFD results decrease, both curves finally converging after some 18 iterations.

The optimization, numerical and experimental curves are shown in Fig. 17. These curves show that the optimization modified the efficiency more than 14%.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>PAT experimental and numerical data for BEP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error (%)</td>
<td>CFD</td>
</tr>
<tr>
<td>+9.1</td>
<td>6.0</td>
</tr>
<tr>
<td>+22</td>
<td>8.3</td>
</tr>
<tr>
<td>+9.5</td>
<td>69</td>
</tr>
</tbody>
</table>

Fig. 13 Comparison between PAT head experimental and numerical results

Fig. 14 Comparison between PAT efficiency experimental and numerical results

Fig. 15 Comparison between PAT power experimental and numerical results

Fig. 16 Evolution of objective function during optimization

Fig. 17 Comparison between PAT power experimental and numerical results

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8 Conclusions

Numerical and experimental investigation into prediction methods of propeller pump as turbine performance was carried out. A propeller pump was simulated using CFD in direct and reverse modes. In the process of numerical simulation, all domains except the mechanical seals are included. To verify the numerical results, the simulated PAT was made and tested at the established test ring. CFD results were in good coincidence with the experimental data for pump and turbine mode especially at BEP.

Results show that head is 1.57 m and mass flow is close to 1.92 l/s. Pump worked in higher flow rates and lower heads in turbine mode. The efficiency of turbine mode was lower than pump mode. These unexpected results can be happened by the influence of cavitation, because there was not any control or visualization device for cavitation detection. In addition, diffuser is important part of kinetic energy in total energy.

To verify the numerical results, the simulated PAT was made and tested at the established test ring. CFD results were in good coincidence with the experimental data for pump and turbine mode especially at BEP.

Fig. 17 Comparison between PAT efficiency experimental, numerical, and optimization results

References


Nomenclature

ANN = artificial neural network
BEP = best efficiency point
H = head (m)
H = head ratio
k = turbulent kinetic energy
N = rotational speed (rpm)
P = power (W)
P = pressure (bar)
Q = volumetric flow rate (l/s)
Q = volumetric flow rate ratio
T = torque (Nm)
η = efficiency
μ = eddy viscosity
ρ = fluid density (kg/m³)