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Numerical shape optimization of a centrifugal pump impeller using artificial bee colony algorithm

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ABSTRACT

Centrifugal pumps consume huge amounts of energy in various industrial applications. Therefore for these pumps, the improvement of machine efficiency has become a major challenge. Since the hydraulic performance of a centrifugal pump strictly depends on its impeller shape, in the present work, an efficient and original approach has been developed and applied to the design of centrifugal pump impellers in order to achieve a higher efficiency. A global optimization method based on the Artificial Neural Networks (ANNs) and Artificial Bee Colony (ABC) algorithm has been used along with a validated 3D Navier–Stokes flow solver to redesign the impeller geometry and improve the performance of a Berkeh 32-160 pump as a case study. In the next step, to verify the optimization results, all the domains within the centrifugal pump were simulated using the CFD method. The complete numerical characteristic curves of the pump with the optimized impeller were compared to the validated (using the available experimental data) numerical characteristic curves of the initial pump. The numerical results show an efficiency improvement of 3.59% at only 6.89 m increase of total pressure difference for the Berkeh 32-160 centrifugal pump. The new impeller geometry presents much more changes in the meridional channel and blade profile. The results indicate a reasonable improvement in the optimal design of pump impeller and a higher performance using the ABC algorithm.

1. Introduction

Centrifugal pumps are huge consumers of energy in various industries. So, it is essential to improve the efficiency of such equipment through design optimization. The optimum configuration of a centrifugal pump is a compromise between reliability, manufacturing cost and efficiency [1]. The hydraulic performance of a centrifugal pump strictly depends on the shape of its impeller blades. Hydrodynamic shape optimization has become one of the most popular issues in hydrodynamic design process in recent decades. Gradient-based and evolutionary optimization algorithms have been widely used in pump impeller design to achieve higher performance [2–4]. Nowadays; the exponential increase of computation power has allowed the development of approaches based on the automation of the conventional design process by coupling the optimization method with computational fluid dynamics. These methods lead to a design process that relies more on a systematic methodology than on experience. They are less time-consuming than traditional approaches, which require a continuous refinement of component geometry.

The artificial bee colony algorithm has been proposed by Karaboga for the optimization of real parameters. This algorithm is based on the foraging behavior of a bee colony [5], and can be applied in multi-objective [6], combinatorial [7], unconstrained and constrained [8,9] optimization problems. Rao et al., Kang et al., Singh and Yildiz have expressed the ABC algorithm as a quite simple, flexible and robust method [10–13].

The core of the shape optimal design system in fluids mechanics is a database containing the results of all the computational fluids dynamics (CFDs) computations performed during the previous and present design processes. For each sample, the inputs are the geometrical parameters, fluid properties and the flow-field boundary conditions used by the 3D flow solver. The outputs are the efficiency and total pressure rise, which characterize the hydrodynamic performance.

In this design process, an iterative procedure is used. The first step is a "learning process" which is used to build an Artificial Neural Networks (ANNs) model based on the examples stored in the database. The learning process is accomplished by a generalized regression neural network. After this process, the ANN is able to predict the hydrodynamic performance of blade geometries under the boundary conditions not previously included in the database.

The next step consists of finding a new design using an optimization procedure presented by the ABC algorithm, which is based on the hydrodynamic performances provided by the trained ANN instead of the flow solver. The global impeller performance is

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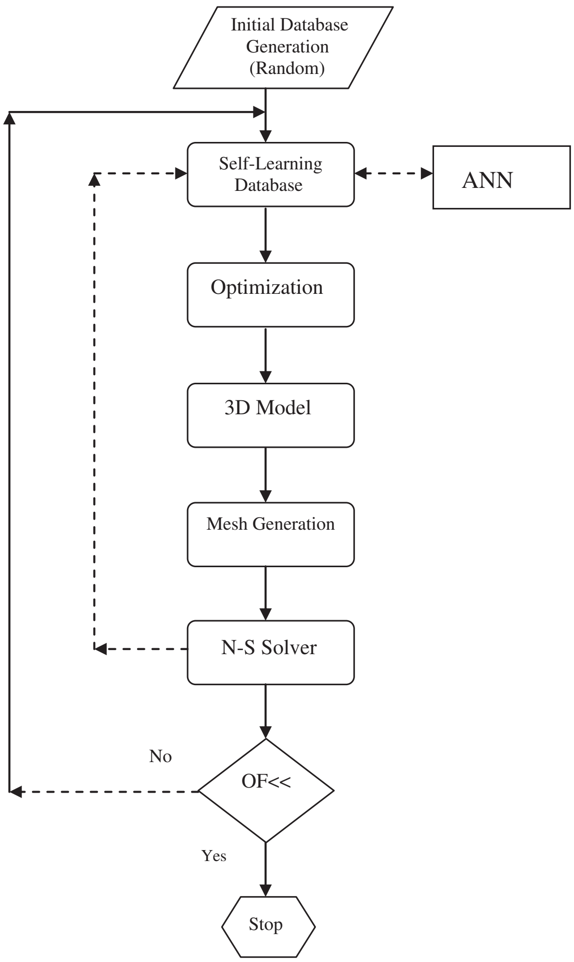

Fig. 1. Presented optimization technique.

determined through an objective function, which translates all the user-imposed constraints into a single number. The outcome of this optimization is a point in the design space, which is expected to be the optimum solution of the real problem. The new geometry provided by the optimization is then evaluated by the CFD solver. This new sample is also added to the database. By comparing the impeller performance obtained by CFD to the one predicted by ANN, the accuracy of the trained ANN can be evaluated. The obtained performance is also compared to the initial one. If the target performance has not been achieved, the next iteration is started, and the same process is repeated until the optimum blade is obtained (Fig. 1). Each design iteration starts with ANN training. As the optimization proceeds, the database grows, leading to the improvement of the approximate relation and therefore to a better localization of the real optimum.

In this research, a numerical optimal design package including the modules of parameterization, CFD, Artificial Neural Networks (ANNs) and Artificial Bee Colony (ABC) algorithm has been developed for the geometrical optimization of a centrifugal pump impeller. In advance, to validate the CFD code, the complete geometry of the initial pump including the inlet, impeller, chambers and the volute was simulated. The obtained characteristic curves were compared with the available experimental data. After the optimization process, the characteristic curves of the pump with new impeller were compared to the characteristic curves of the pump with initial impeller. Finally, all the results were compared and discussed.

2. Optimal design of centrifugal pump impeller

Fig. 1 shows the developed numerical optimal design package including the parameterization, CFD, ANN and ABC modules for the geometrical optimization of an initial centrifugal pump impeller. The details of the developed package are described in the following sections.

2.1. Design parameters

Arbitrary design parameters can be used as input data for an in-house pump design software program in order to generate the impeller geometry. The performance of an impeller depends on various parameters. However, the main parameters are [14]: Hub diameter (d_H), suction diameter (d_S), impeller diameter (d_2),

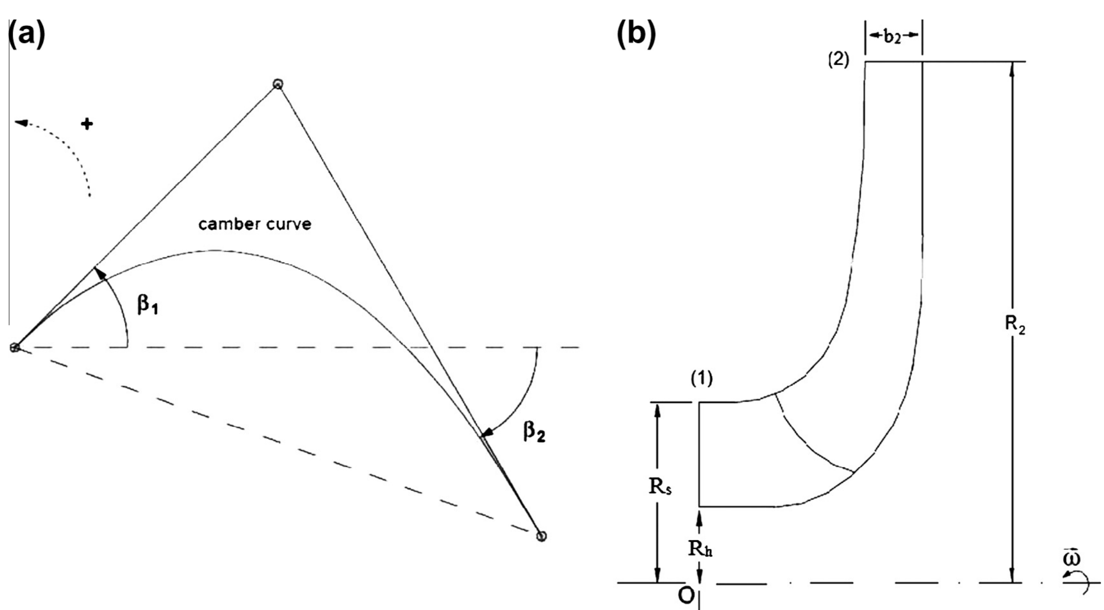

Fig. 2. Design parameters of impeller.

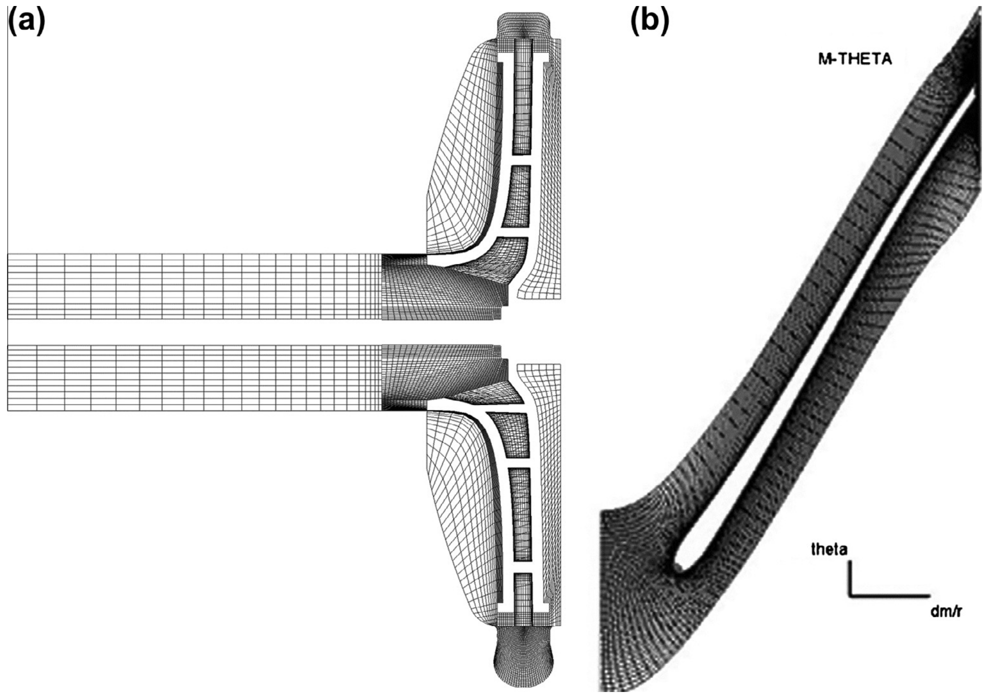

Fig. 3. Generated mesh for (a) complete computational domain, and (b)single blade.

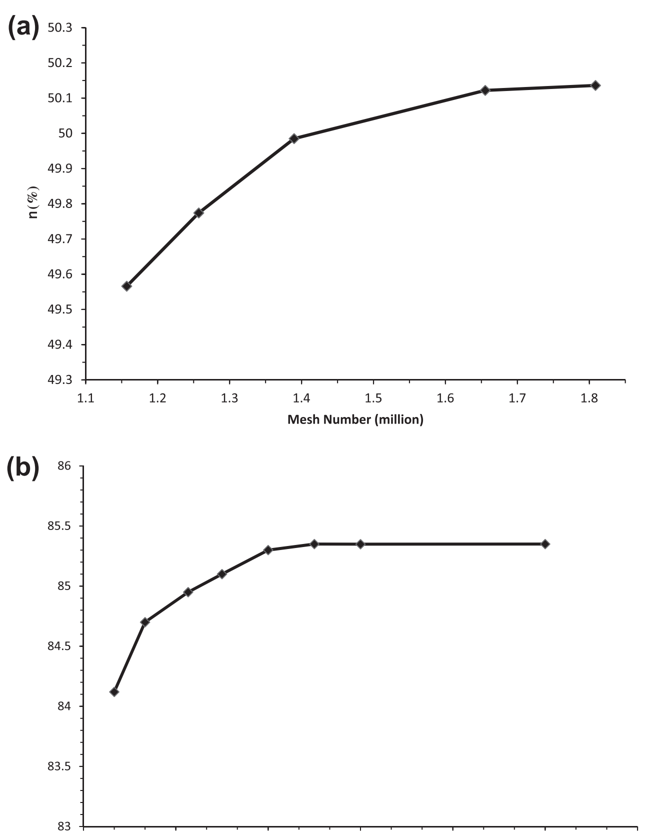

Fig. 4. Efficiency versus mesh number for (a) complete computational domain, and (b) single blade.

impeller width (b_2) and inlet and outlet blade angles (β_1 and β_2), according to Fig. 2. Using the Bezier curves, the shape of the impeller can be obtained by means of β_1 and β_2. The optimization

Table 1
Grid properties for each component.

Simulation	Component	Number of nodes
Complete geometry	Inlet	353,244
	Volute	574,334
	Impeller	907,025
	Front case	41,664
	Rear case	149,884
	Total	2,026,151
Single passage	Single passage	232,653

problem can be formulated as: Objective function = $f(d_H, d_S, d_2, b_2, \beta_1, \beta_2)$. The effect of other global variables such as number of blades have been investigated by one of the authors in [15].

2.2. 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. A coupled method was exploited to solve the governing equations, meaning that the equations of momentum and continuity were solved simultaneously. As a convergence criterion, the computations were continued until the global residuals decreased to less than 10^{-6} for discretized equations.

2.2.1. Solution parameters

In order to achieve more accurate and robust results, the RNG k–ε 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 the RNG k–ε turbulence model [17]. In the numerical simulation process, the volumetric loss caused by balancing holes is neglected. The mechanical loss resulting from seals and bearings are calculated according to [18]; so, the

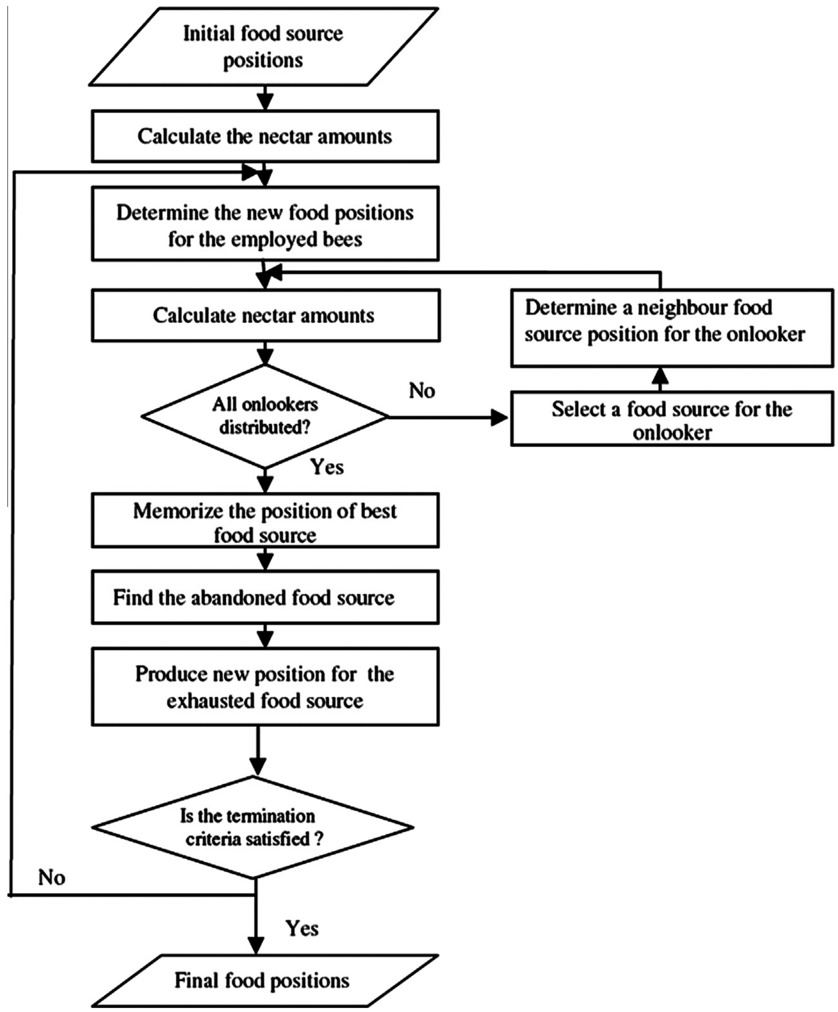

Fig. 5. Basic flowchart of the ABC algorithm.

Fig. 6. Impeller of Berkeh 32-160 pump.

obtained efficiency includes the volumetric loss through the wear ring and the mechanical loss caused by disc friction and bearings [19].

Values of mass flow rate, flow angles and averaged static pressure were imposed for both the inlet and outlet. No-slip condition with 400 μm sand grain roughness was assumed for each wall exposed to fluid flow.

2.2.2. Grid generation

With the aim of generating a structured hexahedral grid, the solution domain was divided into five component parts: Pump inlet, front and rear chambers, impeller and volute (Fig. 3). Because of the computation limit, a single impeller was used in the optimization process. The independence of pump's hydraulic efficiency from grid number was checked for both the single blade and complete geometry simulations, as depicted in Fig. 4. It was found that efficiency varies by less than 0.5% for both the single blade and complete geometry when grid numbers are more than 0.2 million and 1.6 million respectively. Table 1 lists the final grid numbers of each component.

2.3. Artificial neural networks

The optimization method is based on the use of Artificial Neural Networks (ANNs). ANNs are used for the construction of meta-models of each constraint or objective function within an optimization. They are chosen mainly for one reason: the use of a meta-model allows the calculations to be performed in parallel, with a consequential reduction of the overall timescale of the

Table 2
Optimization results for various $K_e = \frac{m}{n}$.

	Efficiency (%)	Total pressure difference (Pa)	Torque	Power (W)
Initial pump	85.36	387,600	7.7696	−2359.5
$K_e = 100$	90.27 (+%5.75)	416,760 (+%6.99)	8.4245 (+%8.42)	−2558.4 (+%8.42)
$K_e = 10$	90.551 (+%6.08)	417,440 (+%7.69)	8.4121 (+%8.26)	−2554.6 (+%8.26)
$K_e = 0.1$	90.95 (+%6.54)	424,680 (+%9.56)	8.5197 (+%9.65)	−2587.3 (+%8.804)

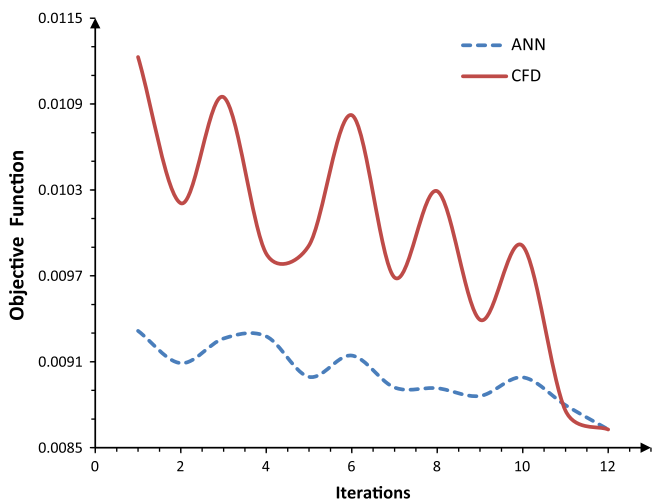

Fig. 7. Evaluation of objective function during optimization.

Table 3
Time spent for one design.

Step	Time (min)
ANN	7
ABC	11
Mesh generation	3
CFD	8
One design iteration	29

Table 4
Control parameters of ABC.

Population size	Parameter count
Number of generations/cycles	500
Limit (ABC)	80

activity. A generalized regression neural network (GRNN) was used. GRNN is often used for function approximation and it can be designed very quickly. It has a radial basis function called 'spread'. Details can be found in [20].

2.4. Artificial bee colony algorithm

The artificial bee colony algorithm is a heuristic optimization algorithm proposed by Karaboga [5]. The ABC algorithm has been inspired by honeybees' intelligent foraging behavior. In the ABC model, the colony consists of three different bee groups, namely worker bees, onlooker bees and scout bees. To explore each food source, only one worker bee is employed. So, the number of worker bees indicates the number of food sources. Honeybees' intelligent foraging behavior can be explained as follows. Each worker bee flies to a food source. After determining the nectar amount of that food source, it explores new neighboring food sources. Then, the bee comes back and dances around the hive. The onlooker bees that are watching the dances of the worker bees choose a food source based on the worker bees' dances. The Probability of choosing a food source is related to the quality of food nectar and the leftover amount of food. If a food source cannot be exploited further through a predefined number of cycles, then the source is abandoned. Subsequently, the scout bees replace the abandoned food sources with randomly found new sources. The best food source is determined and the position of that food source is memorized. This cycle is repeated until the requirements are met. The basic flowchart of the ABC algorithm is illustrated in Fig. 5.

In the ABC algorithm, a food source indicates a possible solution of the optimization problem, and the nectar amount of the food source indicates the fitness value of that food source. The number of worker bees corresponds to possible solutions. Initially, a randomly distributed population is generated. After the initialization, a search cycle involving the worker, onlooker and scout bees in the population is repeated in sequence. A worker bee examines the existing food source and also discovers a new food source. If the nectar amount of the new source is more than the old one, the worker bee learns the new address and discards the old one; otherwise, it keeps the old location. After all the worker bees have completed the search process, they convey the location information to the onlooker bees. The onlooker bees evaluate the nectar amounts and choose a food source. The probability value of a food source is calculated by:

$$P_i = \frac{f_i t_i}{\sum_{m=1}^{SN} f_i t_n} \tag{1}$$

where P_i is the probability value of the source i, f_i is the fitness value of solution i (proportional to the nectar amount), and SN is the number of food sources or worker bees.

The ABC algorithm uses Eq. (2) to obtain a new food location from the old location saved in the memory:

$$X_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

In the above equation, $j \in \{1, 2, \ldots, SN\}$ and $i \in \{1, 2, \ldots, D\}$ are randomly selected indices, and j must be different from i. D indicates the number of parameters to be optimized, φ_{ij} is a random number between $[-1, 1]$ and this number controls the production

Table 5
Results of optimization.

	d_N	d_S	d_2	b_2	B_1	B_2	η	Torque	ΔP	Power
Initial	30	40.5	169	5	36.8	26.8	85.36	7.7696	387600	−2359.5
Optimized	28	43.7	167.5	7	38.596	20	91.048	8.4453	421390	−2564.7

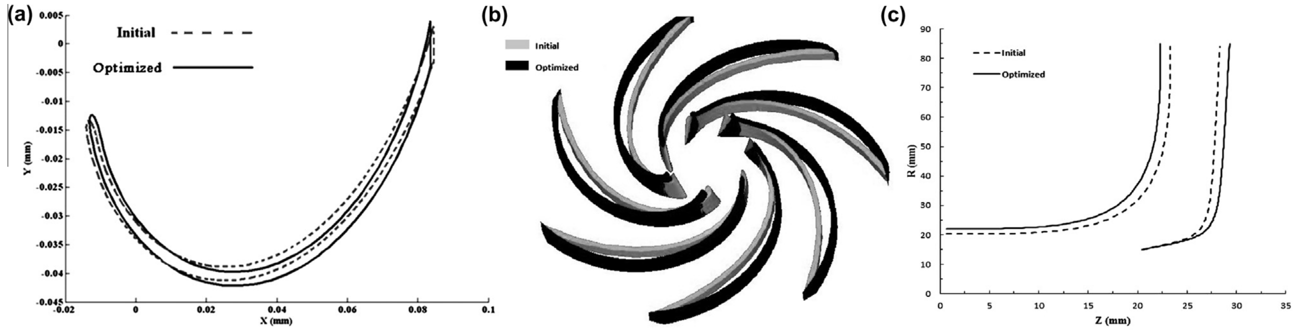

Fig. 8. Initial and optimized geometries: (a) Blade profile, (b) 3D view, and (c) meridional view.

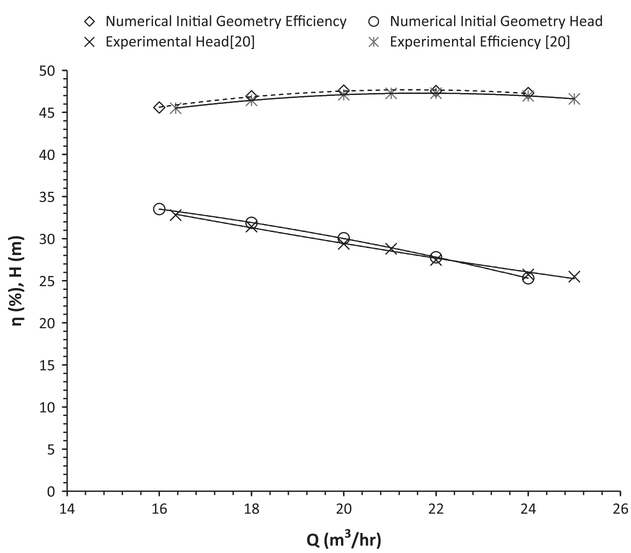

Fig. 9. Comparison between experimental and numerical results of the initial pump.

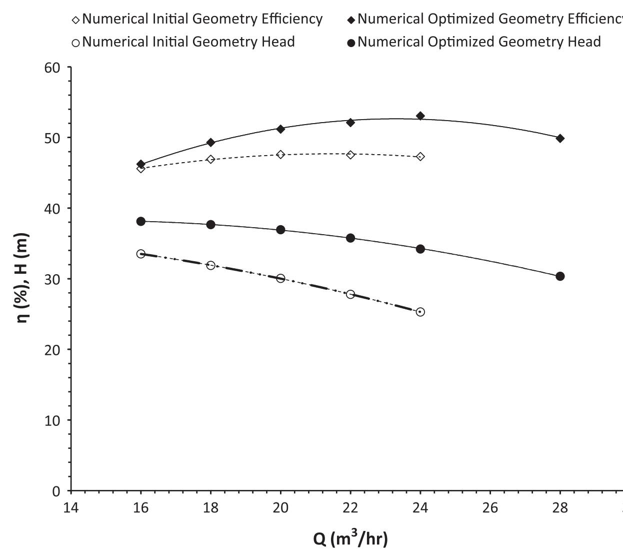

Fig. 10. Comparison between numerical results of pumps with initial and optimized impellers.

of food sources around X_{ij}. As can be seen from Eq. (2), if the difference between X_{ij} and X_{ik} decreases, the step size diminishes accordingly. Therefore, the step size is adaptively modified while the algorithm reaches the optimal solution in the search area. The food source that does not improve in a certain number of cycles is abandoned. This cycle number (called a 'limit') is very important for the ABC algorithm. The control parameters of the ABC algorithm include the number of sources (*SN*), limit parameter and the number of maximum cycles [20].

2.5. Objective function

The multi-objective optimization was based on a constant operating point, which was to be simultaneously optimized with respect to design parameters. The optimization objective function was imposed on the operating point to increase the efficiency at a constant total pressure difference. This objective function is expressed as:

$$OF = m\left[\frac{E_t - E}{E_t}\right]^2 + n\left[\frac{\Delta p_0 - \Delta p}{\Delta p_0}\right]^2 \quad (3)$$

where $E_t = 1.0$ is the target efficiency, and Δp_0 is the initial total pressure difference.

3. Case study

The case study involves a Berkeh type 32-160 pump (Fig. 6). The pump has seven impeller blades. Its hub diameter is $d_H = 0.3$ m, suction diameter is $d_S = 0.405$ m, impeller diameter is $d_2 = 0.169$ m and impeller width is $b_2 = 0.05$ m. The blade angles are $\beta_{b1} = 36.8°$ and $\beta_{b2} = 26.8°$. The rotational speed, flow rate, head and specific speed (rpm, m^3/s, m) of this pump are 2900 rpm, 20 m^3/h, 35 m and 15 respectively. In the optimization process, a maximum variation of 10% is assumed for the design parameters.

4. Optimization results

The optimization results of Berkeh 32-160 pump have been shown in Table 2 for the initial and final impellers. By increasing the $K_e = \frac{m}{n}$, the discrepancy with the design point increases as well; because with the increase of this parameter, the effect of the restriction applied by the head penalty to limit the optimization to the constant design point diminishes. The best result is obtained at $K_e = 0.1$, where the efficiency improves 6.54% by increasing the total pressure difference by 9.56%.

The convergence histories of the optimization procedure which is the measure of ANN's local precision have been shown in Fig. 7. In each iteration the database has been developed locally around the output point of the optimization, and it can be observed that with the increase of iterations, the error between the artificial neural network predictions and the CFD results diminishes, and that both curves converge after 12 iterations.

The approximate time required for one design iteration has been presented in Table 3. The corresponding computation time was 5.8 h for the optimization process when using a PC with Intel Core i5 chip, 2.4 GHz of speed and 4 GB of RAM memory.

Table 4 shows the population size and number of cycles generated by the ABC as 500 and 80, respectively. Using these parameters, the final geometry is obtained. In Table 5, the optimized impeller parameters have been compared with the initial ones. It can be observed that some parameters increase and some others decrease in value. New and initial impellers have been compared in Fig. 8. There are differences in meridian plane and blade profile between the initial and optimized impellers.

5. Verification of optimization results

Since the optimized results by CFD were only evaluated for the impeller, the pump's total performance including its other elements (pump inlet, front and rear chambers and volute) needs to be evaluated as well. Fig 10 shows the comparison between characteristic curves extracted from numerical simulations for the Berkeh 32-160 pump with initial impeller (validated by available experimental data from [21] in Fig. 9 and with optimized impeller. In Fig. 9, the maximum difference in hydraulic head and efficiency, within the scope of 0.8–1.2 Q_{BEP}, are 1.25 m and 4.18%, respectively. In addition, the errors between predicted hydraulic head and efficiency and experimental values at BEP are 0.72 m and 0.50%, respectively. This demonstrates that CFD could be used to predict pump performance with an acceptable accuracy.

As is indicated in Fig. 10, the head and efficiency at BEP of pump with new impeller have risen from 30.05 m to 36.94 m and from 47.59% to 51.18%, respectively.

The results indicate reasonable improvement in the optimal design of pump impeller and the achievement of a higher performance using the ABC algorithm. The optimization by ABC could be exploited as a beneficial approach in the optimal design of pumps.

6. Conclusions

An efficient and original approach was developed and applied to the design of centrifugal pump impellers. This method makes use of an Artificial Neural Network (ANN) during the optimization phase, which allows for the application of Artificial Bee Colony (ABC) algorithms in an efficient way. The selected multi-objective optimization process guaranties that efficiency improves over the best efficiency operating point. The pump with optimized impeller was simulated completely by means of a validated (using available experimental data for initial pump) 3D Navier–Stokes flow solver. Numerical results showed efficiency improvement of 3.59% at only 6.89 m increase of total pressure difference for the centrifugal Berkeh 32-160 pump. The new impeller geometry presents much more changes in the meridian channel and blade profile. The results indicate reasonable improvement in the optimal design of pump impellers and a higher pump performance when using the ABC algorithms. The optimization by ABC algorithms could be exploited as a beneficial approach in the optimal design of pumps.

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