Journal of Applied Fluid Mechanics, Vol. 15, No. 4, pp. 1269-1280, 2022.
Available online at www.jafmonline.net, ISSN 1735-3572, EISSN 1735-3645.
https://doi.org/10.47176/jafm.15.04.33040

Multiple Performance Optimization of a Single Stage Centrifugal Pump using an Intelligent System Approach

H. Sevil Ergur†

Eskisehir Osmangazi University, Faculty of Engineering and Architecture, Mechanical Engineering Department), Batı Meşelik, 26480, Eskisehir, Turkey

†*Corresponding Author Email: hsergur@ogu.edu.tr*

(Received May 24, 2021; accepted April 3, 2022)

ABSTRACT

This study aims the use of an intelligent system to analyze and enhance the performance of a single stage centrifugal pump (SSCP) with respect to the blade number of impeller, which is crucial for the centrifugal pump design. In general, maximizing the efficiency (η) is the most common performance cost. Moreover, maximizing the pump head (H) and minimizing the power (P) are the other important criteria that should be considered for the optimal blade number. These goals are not simultaneously considered usually in the studies on this topic. The motivation of this study is to expand the system management perspective by evaluating the performance of the system with these multiple criteria. The centrifugal pump design is a typical Multi-Objective Optimization (MOO) problem. The MOO approach consists of five decision variables and three objective functions with different blade numbers for impellers. To determine the optimal solution of this MOO problem, the experimental data is initially expanded using a learning by examples methods based on an intelligent network model training. Then, extended data is used for calculating performance measures at each input-output pairs. In order to evaluate the results of the proposed approach on a real-time system, B50−200/100 type model pump with the speed of 2950 rpm and an outlet angle of 22.15^0 was tested at State Sugar Machine Plant, Eskisehir (Turkey). Since the main purpose is to determine the optimal blade number, different blade numbers has been used while other geometric parameters were kept constant. To determine the optimal solution, experimental data has used to train a selected soft computing model known as FWNN model. This model has advanced to express the relationship between the inlet and outlet values of the centrifugal pump. FWNN model achieves the general characteristics of the performance measure. The analysis with the use of FWNN model shows that, the optimum number of blades by considering the specified performance parameters for the centrifugal pump design is seven. Comparing with pump impeller with number of blades 5, 6, 8 and 9 increases in efficiency rates are 0.4%, 2.57%, 6.4% and 7.2%, respectively. The FWNN model over the performance analysis algorithm completes the missing data if exists and indicates the best performance solution as given.

Keywords: Centrifugal pump; Impeller blade; Blade number; Optimization; FWNN model.

NOMENCLATURE

BEPs	Best Efficiency Points	Z	number of blades
D_1	impeller inlet diameter	β_m	average value of inlet angle and exit angle
D_2	Impeller outlet diameter	η	efficiency
DFP	Davidon-Fletcher-Powell	k	performance index
FWNN	Fuzzy Wavelet Neural Network		
H	pımp head		
MOO	Multi-Objective Optimization		
SSCP	Single Stage Centrifugal Pump		

1. INTRODUCTION

Centrifugal pumps, which play an important role in most industrial facilities, are used in many different applications such as petroleum, irrigation, water supply, chemical industry, power plants, defense and aviation. Pump manufacturers have been focused on developing low-cost, high-performance and superior quality centrifugal pumps to offer customers, in recent years. (Wang *et al.* 2019a). Moreover, many researches are ongoing to increase the performance and reduce losses such as turbulence, shock, blade friction, etc. for centrifugal pumps. In the world industry market, even a one percent increase in efficiency is important for highly demanded pumps (Gülich 2010). Thus, appropriate design parameters and selection of operating ranges are essential for effective optimization methods on maximizing the head and efficiency, and minimizing the consumed power, which constitutes 10% of global power consumption (Bellary *et al*. 2018). In improving head, efficiency and shaft power, large number of variables such as number of blades, inlet-outlet blade angles, inlet-outlet widths and blade profile are effective (Siddique *et al*. 2018). However, the centrifugal pump design and performance analysis that considers such many parameters is a very long and difficult process. Hence, evaluation of these factors and setting up the corresponding values are important.

The studies in the literature highlights, some of the pump parameters such as impeller exit diameter, blade angle and blade number that directly affect the pump design and performance. It is also stated that the most important performance parameter in centrifugal pump design is the blade number and hence the impeller design geometry. For instance, Matlakala *et al.* (2019) show that design parameters such as the diameter of the impeller, blade angles, and number of blades, suction diameter and discharge diameter can have considerable influence on the performance of the centrifugal pumps. Many researchers studied the effect of blade number on the performance of centrifugal pump and found that head and efficiency increase with the blade number, providing the casing and other geometrical dimensions remain constant. In addition to the number of blades, blade exit angle is another important parameter that is effective in increasing efficiency. Ding *et al*. (2019) showed that when the flow rate gradually increases, the impeller hydraulic loss gets larger with increasing the blade exit angle, and the blade exit angle has a significant effect on the efficiency of the centrifugal pump at high flow.

Besides the investigation of centrifugal pump parameters, previous studies in the literature also shows that, the pump design and optimization have carried out based on the trial and error approach applying on the tested model pumps Elyamin *et al.* (2019), Matlakala *et al*. (2019), Bozorgasareh *et al.* (2021). Concordantly, the computational technology is becoming widespread in predicting pump performance on reducing costs with energy savings and shortening the development process. For instance, high accuracy and efficiency in calculation have obtained with different response surface models created for design parameters and performance functions at the study of Škerlavaj *et al* (2017). Fu and Hong (2016), has also stated a mathematical optimization model that achieves the highest efficiency and maximum theoretical head, and Haifeng *et al*. (2001) examine the model and hydraulic properties with numerical simulation and performance tests, for a low specific speed centrifugal pump.

Herein, the optimization is not only dependent on the designer's experience, as engineers have defined the methods with numerical simulations. Experiments or CFD simulations usually achieve performance goals; do not have to be repeated for performance optimization unless appropriate models have been adopted between objective functions related to decision variables. Therefore, an effective and powerful multi-objective optimization with the use of numerical simulations and experimental verification methods is necessary for optimum solutions.

There is a motivation to evaluate the remarkable results from previous studies and to extend, and solve the mentioned optimization problem. For this purpose, it is aimed to use soft computing techniques. These techniques resemble the learning and inference mechanisms of the human brain and are effective for making judgements about the prediction of missing or unlearned part of a handled function space. According to the literature, there is no significant study on the performance evaluation of the SSCP system of soft computing techniques. There are only some studies for centrifugal pump impeller optimization, which engages mathematical models such as artificial neural networks, artificial bee colony algorithms, fuzzy logic rules, etc. For instance, Šakthivel *et al*. (2012) presented the use of rough sets to generate the rules from statistical features extracted from vibration signals under good and faulty conditions of a centrifugal pump. They proposed a method based on a soft computing technique as an approach to fault diagnosis of centrifugal pump. Papierski and Blaszczyk (2011) individually considered the MOO and design problem of the centrifugal pump for maximum efficiency. As a different work in literature, Derakhshan *et al*. (2013) optimized the shape of the centrifugal pump impeller with the artificial neural network and artificial bee colony algorithm. As another study, Wang *et al*. (2019b) proposed a neural network algorithm adopted for higher order nonlinear problems by comparing various models, including estimation accuracy, efficiency and robustness, according to many defined criteria . Moreover, Duan *et al*. (2015) combined the progressed back-propagation neural network with the non-dominated by genetic algorithm to improve the efficiency and head of a mini pump at the design point. Similarly, Safikhani *et al*. (2011) developed a unique MOO for centrifugal pumps with a genetic algorithm based on neural network meta models for multipurpose optimization method.

On the lights of the studies in the literature, one can state that optimization of the impeller design with respect to the blade number and blade design with an innovative approach using a multi-objective analysis model is highly required for better performance in centrifugal pumps. This present paper utilizes the Multi-Objective Analysis (MOO) model, which investigates the performance effects over specified variables on the centrifugal pump. This study is carried out to improve the selected performance parameters and defined the pump characteristics with an optimized blade number over an adopted MOO model. Hence, the aim of this study is to improve the process on pump design without any significant loss in performance to access the best efficiency point by engaging a powerful MOO algorithm.

The present study aims to use a soft computing model to investigate the performance effects on the centrifugal pump. It is obvious that this paper will be beneficial on the usage of soft computing techniques for the optimal design of centrifugal pump impellers, since there are few numbers of studies. In general, maximum efficiency is the major criteria for number of blade selection in the literature. Besides, the other performance criteria, which are need to be satisfied, are the maximum pump head and the minimum power. This study focuses on satisfying these multi criteria simultaneously. A study has been carried out to improve the performance parameters and defines the pump characteristics with an optimized blade number. The most important limitation encountered in this study and similar studies is the insufficient number of data. In other words, the experimental data do not have enough input-output pairs to realize the entire system, and also show very rapid changes compared to the previous value. Firstly, these missing parts of the data should be fulfilled by a soft computing method. To correct these missing parts of the data, this article proposes a soft computation algorithm. Then, a performance criteria calculations determined for the multiple optimization of the SSCP system discussed are made for the expanded data. The next step is to identify the input-output pair that minimizes this performance cost. In the soft computation algorithm, the wavelet neural network (WNN) model has been used as the intelligent system model. Due to the time-frequency localization of the wavelets, the fast convergence feature is utilized as a main tool that provides high accuracy and handles rapid changes in existing data. On the other hand, to make new judgments about missing parts of centrifugal pump data, fuzzy neural network representing the inference mechanism of the human brain should be used. In summary, the fuzzy-wavelet-neural network is the most fundamental component of the proposed algorithm. One of the popular fuzzy wavelet neural network (FWNN) models will be successfully applied in the prediction and description of nonlinear dynamic systems (Yılmaz and Oysal 2010). This model will express the relationship between the performance of the centrifugal pump and the number of blades. In this study, a FWNN model will also obtain the general properties of the performance measure and will be used to find the optimum number of blades that meet these three criteria simultaneously.

Unlike other optimization methods applied to the centrifugal pump system, the proposed soft calculation method offers two solutions at the same time. The first one is the realistic prediction of missing data information, which is expensive to obtain experimentally. The other one is to offer an optimal solution proposal about the system by learning.

This study is mainly organized with seven sections. In the first section, the experimental set-up with the selection of based impeller, which is comprised of design and performance evaluation. Section 2 explains the embodiments of the optimized impeller. In Section 3, the steps of the proposed algorithm based on an intelligent system approach for analyzing the pump performance is given The evaluation of the test results on the pump performance takes part in Section 4. Finally, a brief conclusion is mentioned in Section 5.

2. MATERIALS AND METHOD

2.1 Experimental Setup and Test Facility

The experimental setup shown in Fig. 1 assembled and the related experiments performed in accordance with the TS EN ISO 9906 and TS EN 837 standards. The experiments were conducted in an open test rig, which consists of a computer-aided measurement gauges. An ONO SOKKI HT-6200 tachometer (accuracy ±0.02%) measured the rotation speed. A ModMAG M100 uni-directional flowmeter (accuracy ±0.50%), and a Hart ABB Series 2600T-261 GX pressure transmitter (accuracy ±0.15%) were used to measure the flowrate and the discharge pressure, respectively.

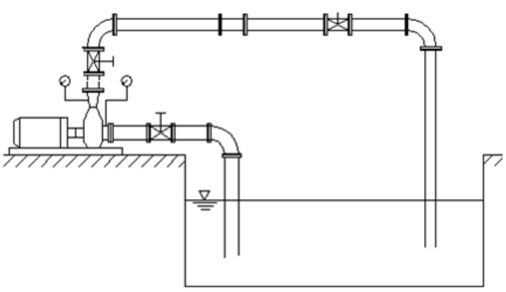


Fig. 1. Experimental test rig.

A Triad Enerdis T 010 and IEC60688 T82N power meter (accuracy ±0.50%) automatically revealed the power consumption. The pumps were driven by a three-phase AC electric motor (Gamak, Model GM 132 S6) and their rated power were 15 kW. Each testing device was calibrated in an accredited laboratory prior to the experiments. The experiments were performed in accordance with the TS EN ISO 9906-class 1 standard, which allows an uncertainty limit of 1.5% for head and power measurements and 2% for flowrate determination.

2.2 Embodiments of the Optimized Impeller with respect to Blade Design

As a well-known fact, the relative velocity in the impeller decreases with the increase in number of blades. The "jet-wake" occurs with less number of blades, which affects the flow transition and becomes more evident over time as the number of blades increases (Li *et al*. 2002). Therefore, the impeller design process shall be handled with the optimum number of blades to minimize this damaging effect and reduce losses. Öztekin *et al.* (2002) also demonstrated that the proportionate number of blades should be in the range of 5 to 7. The impeller design with more blades shows stable behavior, while less blades at low flow rates access unstable characteristics. Since the static pressure at the volute outlet increases continuously with the number of blades (Heinz *et al*. 2006), the uniformity in pressure distribution is disturbed. In this aspect, Singh *et al.* (2017) claimed the low-pressure area at the entrance of the impellers with multiple blades would result as an increase in the blade number. Hence, the choice of blade number depends on the efficient flow in the blade passages as well as the interaction of flow and pressure fields. Moreover, Houlin *et al*. (2010) stated that the number of blades has a significant effect on the low-pressure zone formed behind the impeller inlet and the jet wake. Chakraborty and Pandey (2011) and Jafarzadeh *et al.* (2011) declared that despite variable efficiency, the head and pressure of the pump increase with the number of blades where there shall be an optimum value for each number of blades, providing the casing and other geometrical dimensions remain constant. Elyamin *et al*. (2019) tested numerically by three different impellers with 5, 7 and 9 blades at a rotational speed of 2800 rpm. The researchers claimed that the head and efficiency for the 7-bladed impeller are higher than the other blade numbers. Best efficiency is achieved for this case by number of blades 5–8. Moreover, if the number of blade is below 4, instability of the pump characteristics increases and the efficiency decreases.

Besides, the effect of outlet diameter on pump performance has been investigated in various studies at literature and it is claimed that the discharge head increases and the slope of the curve decreases as the outlet diameter increases. Contrary to this, efficiency decreases as the outlet diameter increases. Chakraborty and Pandey (2011) evaluated the centrifugal pump performance of impellers with different blade numbers (4 to 12) of the same outlet diameter, which has designed to operate at a rotational speed of 4000 rpm. Namazizadeh *et al.* (2020) examined the impeller of a centrifugal pump by optimizing with adding the splitter blades and modifying their geometry. Yuan *et al.* (1993) revealed the effect of geometric parameters on performance with priority order as shown in Table 1. Priority order is a ranking that shows which parameter is more efficient and effective. Thus, if a parameter is the first in the priority list, then it is the most important one you have to deal with.

Furthermore, the calculation of centrifugal pumps' impeller blade numbers shows explicit differences among the researchers. According to Stephanoff (1986), the blade number can be predicted simply by dividing the blade outlet angle by 3, whereas in the study of Karassik *et al.* (2001), the numerical expression

$$Z = 6.5\left[(D_2 + D_1)/(D_2 - D_1)\right]\sin\beta_m \qquad (1)$$

will be more satisfactory in predicting the blade number, where $\beta_m = (\beta_{b1} + \beta_{b2})/2$ as given in Table 2. In equation (1), the blade number is shown as Z, while (β_{b1}) and (β_{b2}) represents inlet and outlet blade angles and D_1 and D_2 are the inlet and outlet diameters of impellers, respectively. For the further investigation of this expression, the pump head can be reduced by decreasing the outlet blade angle. However, if the outlet angle increases, absolute velocity at outlet will also increase. As a result, the losses in the centrifugal pump system rise while the overall pump efficiency decreases. If the geometric parameters are chosen properly and tests are done accurately, the characteristic curve shows a stable behavior when the outlet angle is below 25^0.

Table 1 Priority order for pump performance with geometric parameters

Priority					
Q	β_2	Z	b_2	D_2	D_1
η (%)	β_2	Z	D_1	D_2	b_2
H (m)	β_2	D_2	D_1	b_2	Z
P_{pump} (kW)	β_2	Z	D_2	D_1	b_2

Table 2 Design specifications of single stage centrifugal pump

Parameter	Value
Design flow rate, Q	20 l/s
Design Head, H	50 m
Rotational speed, n	2950 rpm
Outlet diameter of impeller, D_2	200 mm
Inlet diameter of impeller, D_1	70 mm
Impeller blades number, Z	7
Outlet blade angle, β_{b2}	22.15^0
Inlet blade angle, β_{b1}	31.35^0
Outlet blade width, b_2	20 mm
Inlet blade width, b_1	28 mm
Impeller blade thickness, s	4 mm

In our work, the design specifications for model of a single stage centrifugal pump is given in Table 2. Impeller models with 5, 6, 7, 8 and 9 number of blades are given in Fig. 2. The main geometric dimensions of the pump impellers tested are the same as those for the 6-bladed impeller in Fig. 3. In this study, as a base impeller B50–200/100 type model pump with the speed of 2950 rpm and an outlet angle of 22.15^0 was tested at State Sugar Machine Factory, Eskisehir, Turkey. The geometrical parameters such as casing and stuffing box, blade angles and impeller outlet diameter were remained unchanged.

The recorded inlet-outlet data gathered from test experiments is considered for further analysis. Because of the experimental limitations, i.e.

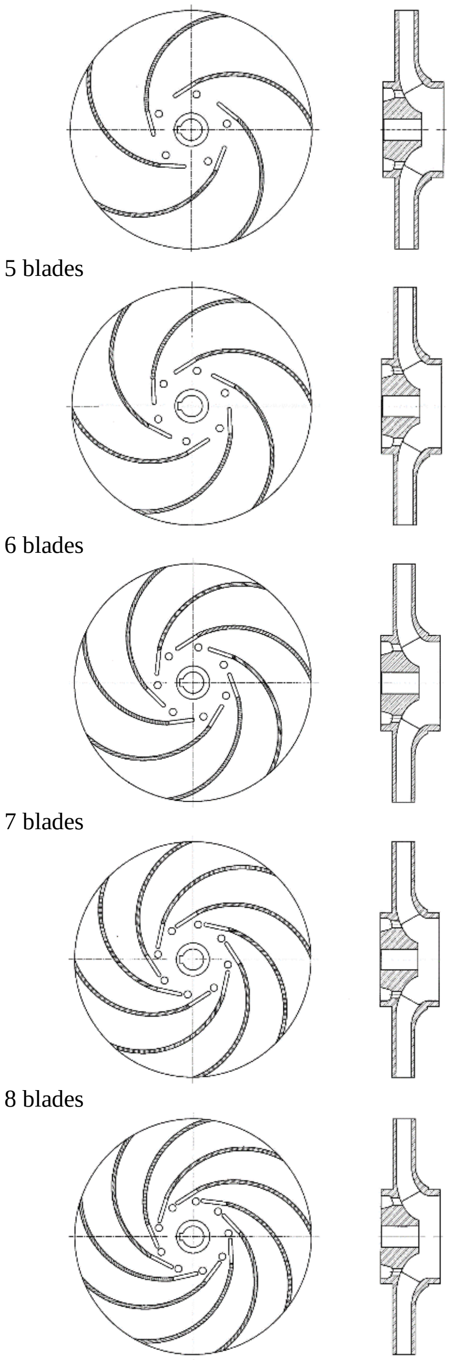


Fig. 2. Model impellers.

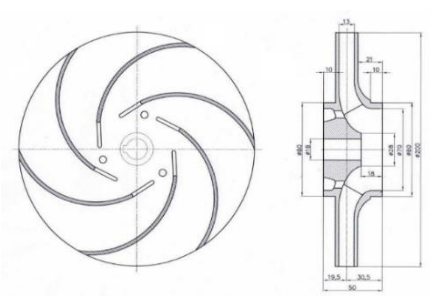


Fig. 3. Geometrical dimensions of model impellers (6-bladed).

sensitivity of parameter changes, the gathered data contains restricted number of input-output pairs. The size of the experimental data does not always provide the opportunity to use the formulas specified in the literature and to benefit from scientific results about the system under consideration. Therefore, this data should be extended numerically by an acceptable method. In order to fulfill the missing parts of the data, a well-known mathematical model has needed. This study offers an intelligent system to encapsulate these situations, i.e. an intelligent system will realize the mathematical model and will provide the missing information for the impellers with number of 5, 6, 7, 8 and 9 blades.

To sum up, all of the above research results in the literature deal with maximizing the efficiency as performance goal. Moreover, considering to maximize the pump head (H) and minimize the power (P) parameters are inevitable performance criteria. In this study, in order to determine the optimal parameter values of the centrifuge system that meets these three criteria at the same time, firstly a performance index has been defined. Then, the extended performance index will be satisfied with a proposed intelligent algorithm that uses the mentioned intelligent mathematical model. In section 3, this algorithm will be introduced in details.

3. THE MOTIVATIONS

There are few studies on the use of soft computing techniques for the centrifugal pump impellers in the literature. In Gölcü (2006), an artificial neural network (ANN) was used to model the performance of the deep well pumps to investigate the effects of the splitter blade length on different blade numbers. In another study, a global optimization method, based on Artificial Neural Networks (ANN) and Artificial Bee Colony (ABC) algorithm was utilized to achieve high efficiency in the design of centrifugal pump impellers (Derakhshan *et al*. 2013). In Wu *et al*. (2016), a new estimation method based on the double neural network architecture was proposed and trained to determine the condition of the pump driver. Later a complex flow pump with guide vanes has been selected as a research model and eight parameters of the impeller has accepted as optimization variables (Wu *et al*. 2020). In determining the performance prediction model as objective function, the neural network with Radial Based Function (RBF) has adopted. Han *et al*. (2019) proposed a prediction method based on the combination of Levenberg-Marquardt (LM) training algorithm and double hidden layer Back Propagation (BP) neural network for centrifugal pump performance.

In general, maximum efficiency is the main criterion for blade selection. However, maximum pump head and minimum power are other performance criteria that should be met. The performance index chosen to meet these three criteria at the same time is as follows:

$$k = (H.\eta)/P \qquad (2)$$

As can be seen, this index takes its maximum value when these three criteria are met. It is not sufficient to calculate this criterion for experimentally obtained data. Missing data values should be estimated and considered to determine the optimal operating point. Therefore, the main motivation of this study is to evaluate the performance of the system with more than one criterion and to find the optimum number of blades that meet these three performance criteria simultaneously by expanding the system management perspective. The steps of the proposed soft computing algorithm to find a solution to optimize the performance of the SSCP system by maximizing this criterion are as follows:

1. Normalize all experimental data values of SSCP system. In the normalization process, first of all, the minimum value of each data set is subtracted from the corresponding data set values. The minimum value is deducted from the maximum value and the resulting value divides the respective data set.
2. Select an intelligent system model with its layer-by-layer structure. The number of parameters of the selected structure should be sufficient to enable learning.
3. Initialize the selected intelligent system (network) model parameters in between 0 and 1 randomly.
4. Apply a learning (training) algorithm to minimize the mean square errors (MSE) in between the desired actual outputs with the estimated outputs of the intelligent system model. Use the 80 percent of randomly selected data pairs for training.
5. If desired stopping criteria (minimum MSE value to be determined) is not satisfied then go to step 3.
6. Use the remaining data for model verification. If MSE is not acceptable, go to step 2 and change the model structure.
7. Apply the extended input values to the intelligent system model to produce the extended version of the output variables.
8. Calculate the standard deviation of the extended data. If this value is larger than a pre-determined acceptable interval, go to step 2 and change the model structure.
9. Otherwise, use this new data to calculate the performance index , which is maximum when H and η values are both big and P is small. Thus, finding the maximum k value stands for finding the optimal solution that satisfies these three performance criteria at the same time.
10. Obtain the optimal corresponding blade number of the maximum k value of step 9.

According to the flow analysis, distinctive results have observed by experimental data. This data composed of 90 inlet-outlet values. As stated above, some values cannot be obtained because of the experimental hardware restrictions. As seen this algorithm uses an intelligent system model to fulfill (predict) the missing part of the data obtained experimentally for some operating conditions. Once the missing parts has been completed then for each input-output pairs of data, these index values have been calculated and then the minimum one is chosen as the winner as the optimal one.

The major motivation of this research study is to specify and obtain a realistic intelligent system model through the existing experimental data in order to find the optimal blade number, which is the main aim of this work. The data seems to be changing because of the experimental limitations that cause some missing parts of data. Therefore, in the second step of the proposed intelligent algorithm, it has been decided to use a fuzzy wavelet neural network (FWNN) model, which provides high accuracy due to the time-frequency localization of the wavelets. In addition, this soft computing model can easily be trained with fast convergence feature.

The FWNN model is a neural network model that incorporates a “Sugeno Fuzzy” system with wavelet functions. The input space has divided into fuzzy regions and the output space has represented by the linear wavelet functions of inputs through this model. Inclusion of wavelet functions is utilized to increase computational power of neuro-fuzzy systems in many applications (Yilmaz and Oysal 2010). Multi resolution property of wavelets is very effective in approximation of these type of problems. The wavelets can determine global (low frequency) and local (high frequency) behavior of any function easily. This characteristic gives the FWNN model fast convergence, easy training and high accuracy abilities. The six-layer structure of the FWNN models are in Fig. 4.

• The first layer is the input layer of the crisp input signals: $x_1, x_2, \ldots, x_n$

• The second layer contains neurons that represents fuzzy sets of the antecedent parts of the fuzzy rules. The outputs of this layer are the membership values of each input signals. There are total $l_1$membership functions for the first input,l_2 for the second input and so on. Following equation shows i_{th}, Gaussian membership function for j_{th} input variable.

$$A_j^{i_j} = exp\left(-\frac{1}{2}\left(\frac{x_j-\mu_{i_j}}{\sigma_{i_j}}\right)^2\right)$$

$$j = 1, 2, \ldots, n \quad \text{and} \quad i_j = 1, 2, \ldots, l_j \tag{3}$$

Here $A_j^{i_j}$is the i_{jth} Gaussian type of the membership function for the j_{th} input where μ is the center and σ is the spread (standard deviation) parameters of the Gaussian function.

• The third layer is the fuzzy rule layer. Each node in this layer calculates the firing strength of the corresponding rule by using multiplication operator for AND connections. Therefore, the output of the l_{th} node in this layer is depicted as shown below:

$$\eta_l = \prod_{j=1}^{n} A_j^{i_j}(x_j) \quad (l = i_1 i_2 \ldots . i_n) \tag{4}$$

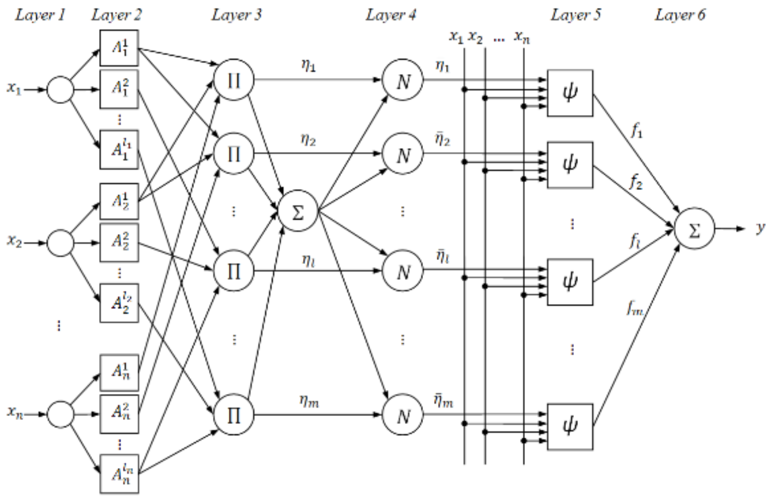


Fig. 4. Structure of fuzzy wavelet neural network.

• The fourth layer represents the contribution of a given rule combination to the result. This layer calculates the normalized activation strengths of l_{th} rule by:

$$\bar{\eta}_l = \frac{\eta_l}{\sum_{i=1}^{m} \eta_i} \qquad (l = 1, 2, \ldots, m) \tag{5}$$

• The fifth layer calculates the weighted consequent value of a given rule as follows for $l = 1, \ldots, m$:

$$f_l = \bar{\eta}_l \emptyset_l \tag{6}$$

$$\emptyset_l = w_i \prod_{i=1}^{n} \left(1 - \left(\frac{x_i - b_{il}}{c_{il}}\right)^2\right) exp\left(-\frac{1}{2}\left(\frac{x_i - b_{il}}{c_{il}}\right)^2\right) + p_l \tag{7}$$

Here $\emptyset\left(\frac{x-b_i}{c_i}\right) = \left(1 - \left(\frac{x-b_i}{c_i}\right)^2\right) exp\left(-\frac{1}{2}\left(\frac{x-b_i}{c_i}\right)^2\right)$

is the Mexican Hat wavelet function in which b_i and c_i are translation and dilation parameters.

• The sixth layer contains only a single node and it computes the overall output as the summation of all incoming signals, which is given by:

$$y = \sum_{l=1}^{m} f_l \tag{8}$$

This FWNN model was applied successfully for prediction and identification of nonlinear dynamical systems before (Yılmaz and Oysal 2010). Therefore, this model has been chosen to express the relationship perfectly between the performance and the blade numbers of the centrifugal pump. It has been claimed that the FWNN model can achieve the general characteristics of the selected performance measure.

In FWNN learning process, flow discharge (Q), revolution per minute (n) and blade numbers (Z) shall be the input signals while the pump head (H), efficiency (η) and power (P) shall be the output signals as seen in Fig. 5. Furthermore, network parameters are set by FWNN training in order to accomplish given function or input-output pairs. In this paper, unknown parameters of the FWNN model are adjusted by using a gradient method. The parameters in the preceding part of the FWNN model's fuzzy rules given by equations (3) and (4) are the central parameters (μ) and scaling parameters (σ) of the Gauss membership function. Similarly, the consequent part of the fuzzy rules given by (7) consist of the translation (b) and dilation (c) parameters of wavelet function considering the weight (w) and bias (p) parameters. The initial values that are set to 1 for the scaling parameters of the Gauss membership functions and the dilation parameters of the wavelet functions are randomly generated from 0 to 1 for other parameters.

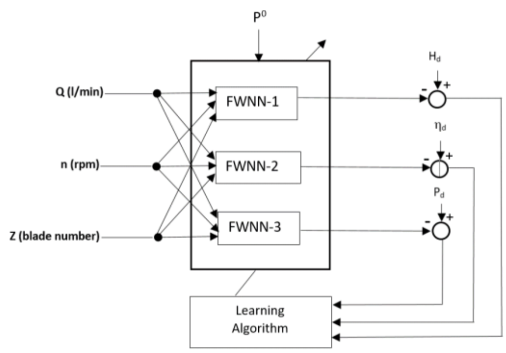


Fig. 5. Training of FWNNs for a single stage centrifugal pump process.

After the learning process of FWNN model through the parameters stated above, a realistic FWNN model will produce the missing parts of the experimental data. These filled parts will also be used to command on the performance of the single stage centrifugal pump (SSCP) system with respect to input variables.

4. RESULTS AND DISCUSSIONS

This study proposes the use of a popular fuzzy wavelet neural network model that combines the learning mechanism of human neurons with time-frequency localization of wavelets and inferencing ability of fuzzy systems. The learning method is only a tool to obtain the optimal parameters of the FWNN model.

Various number of learning algorithms or methods can be used to train a FWNN model to get the optimal solutions of the desired performance goals. For instance, “quasi-Newton” method known as Davidon–Fletcher–Powell (DFP) algorithm is one of the best and well-known method to get the optimal FWNN model that fits over the actual 90 inlet-outlet values. This method uses the gradient information to update the FWNN parameter values. Although the optimization method seems to be old, it is based on the inverse of Hessian matrix that provides the history parameter and gradient changes yielding approximate second order information. This factor means faster convergence to the local minimum of the performance index. Consequently, it can be claimed that the DFP algorithm with line search as performed in this study is exactly robust and its rate of convergence is super linear, which is fast enough for most practical purposes. Besides, a more important advantage for DFP can be stated as; it does not require any calculation of second derivatives. Table 3 shows the final internal parameters of the FWNN models after the learning stage.

DFP method captures the desired (actual) outlet values by minimizing the mean square error as seen in Fig. 6, Fig. 7 and Fig 8, respectively. These acceptable results require a large number of simulations. Nevertheless, there is no deterministic method for deciding the optimal number of fuzzy rules or parameters in the FWNN models. “More unknown parameters” means large number of local minimums exist and only one of them is the global one. Thus, initialization method is important to reach an optimal solution. Hence, this study considers only the learning criteria of FWNN model for the centrifugal pumps' performance measures, i.e. minimum mean square errors. This learning algorithm presents a well-designed FWNN model to constitute the desired performance criteria for centrifugal pumps.

Table 3 Optimal FWNN parameters with 8 rules after training

FWNN-1 Parameters

Center (µ)	Scaling (σ)	Translation (b)	Dilation (c)
0.3324 1.9050	0.2088 0.4195	-0.2932 0.9917 1.6456	1.3779 1.3131 1.0505
-0.2949 1.0000	0.9497 1.0000	0.7472 0.9979 0.3462	2.1544 1.0091 0.9582
0.6016 1.7364	0.3872 1.2015	0.4819 -0.1026 0.3904	0.4461 0.6370 1.0164
		0.3765 0.5479 0.1276	0.3170 1.2672 1.2175
		0.8986 -0.3162 -0.0549	1.0390 0.2530 0.6945
		0.7506 0.9901 2.1643	0.0813 1.0335 1.0598
		0.6723 0.9999 0.7366	0.4696 1.0759 0.0466
		0.9078 -0.3390 0.5383	1.0865 0.2732 0.9893

Weights (w)	Bias Terms (b)
1.8787	0.7313
1.5698	0.8307
1.1701	0.8508
0.8162	0.5166
0.8538	1.3066
5.1807	-0.7649
6.9807	1.1172
0.9491	-1.4115

FWNN-2 Parameters

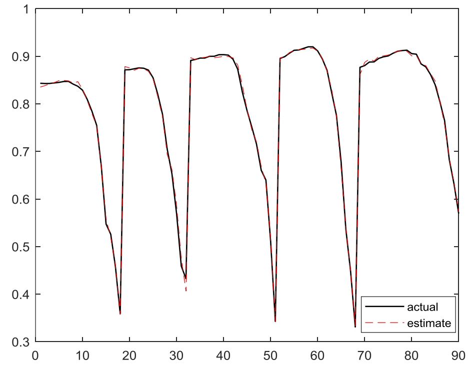
Center (µ)	Scaling (σ)	Translation (b)	Dilation (c)
-1.5228 0.2139	0.4948 0.1202	0.8140 1.0001 0.1016	0.3224 1.1584 1.6977
0.9751 1.0000	1.7218 1.0000	0.7937 1.0003 0.7852	0.4519 1.6857 0.0821
0.7740 0.8864	1.8135 0.1415	0.8057 1.0007 0.9370	0.1734 1.1557 0.1384
		-0.4678 0.6088 -1.0500	0.8166 1.0475 0.4250
		-0.3444 1.0002 2.9944	0.3039 1.2053 1.2343
		0.2253 -0.2382 0.4912	1.1246 0.7156 0.4487
		0.8407 1.0022 0.7550	0.9205 1.3347 0.6981
		-0.1259 0.9989 1.1947	0.4555 1.0081 0.8385

Weights (w)	Bias Terms (b)
3.7710	-0.5582
3.0514	-0.3422
2.6603	-0.4924
0.7281	-0.4248
2.9675	-0.4418
1.5198	0.7763
2.8162	0.0316
-1.7091	0.5836

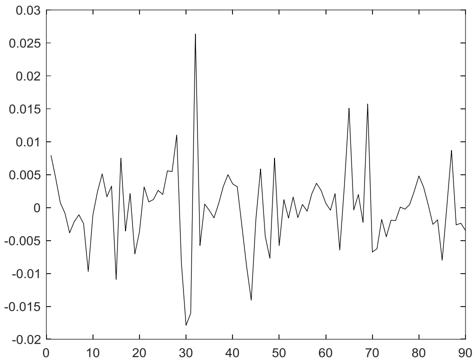
FWNN-3 Parameters

Center (µ)	Scaling (σ)	Translation (b)	Dilation (c)
0.3038 1.8860	0.1647 0.6519	-1.3429 0.8515 0.8706	2.1109 0.9985 0.1715
0.2555 1.0000	1.3279 1.0000	0.7118 0.9997 1.2359	0.9724 1.0218 2.6880
0.1428 -0.1264	1.4129 1.3181	1.9623 0.6770 0.0591	1.5283 0.9552 1.7557
		0.6409 0.0592 0.3879	1.1279 0.5470 0.8980
		1.0689 -0.1283 0.4240	1.5916 0.2626 1.3585
		0.6054 -0.3329 0.6594	0.2086 0.7702 0.1682
		2.0357 0.9945 1.0579	1.2890 1.4013 0.2331
		-0.0063 1.0007 0.6549	0.7706 1.0200 0.0841

Weights (w)	Bias Terms (b)
0.5389	-0.0712
3.1509	0.9663
0.3926	-0.1781
0.7700	0.2127
0.2015	0.5030
1.5568	1.2431
2.3082	0.8509
2.7897	1.0570

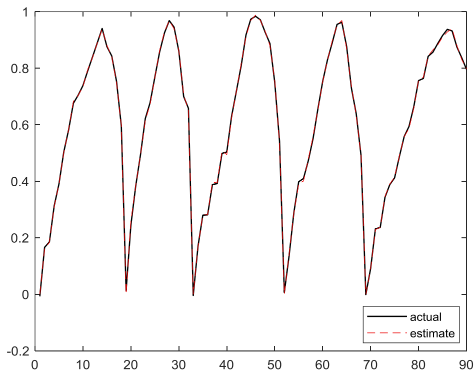


(a)

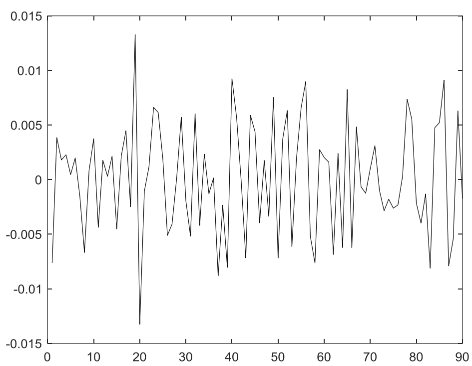


(b)

Fig. 6. (a) Estimation of H values by the FWNN-1 model, (b) Estimation errors for H.

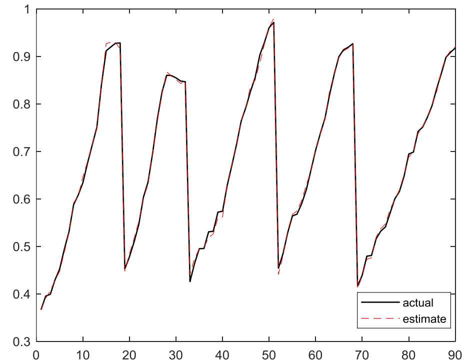


(a)

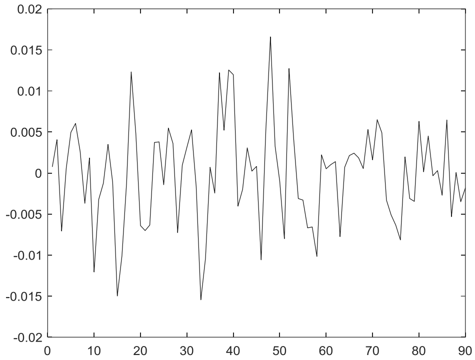


(b)

Fig. 7. (a) Estimation of η values by the FWNN-2 model, (b) Estimation errors for η.



(a)



(b)

Fig. 8. a) Estimation of P values by the FWNN-3 model, b) Estimation Errrors for P.

As a result, this study focused on Fuzzy Wavelet Neural Network (FWNN) estimations and experimental verification to investigate the effects of blade number on performance of a centrifugal pump. Besides, the variations in head as well as efficiencies with the increase of blade number were examined. This scientific work also states that the maximum value was achieved with a 7-blade impeller for only the best efficiency point by employing FWNN model through real-time experimental data as shown in Table 4.

Table 4 Experimental data and FWNN estimations at best efficiency points

Experimental Data			
Blade number (Z)	Head (m)	Power (kW)	Efficiency (%)
5	39.86	12.64	65.69
6	41.65	13.01	67.78
7	44.72	12.32	69.15
8	46.35	12.93	67.83
9	45.38	13.04	65.79
FWNN Estimations			
Blade number (Z)	Head (m)	Power (kW)	Efficiency (%)
5	40.06	12.63	65.83
6	42.31	12.90	67.78
7	45.08	12.39	68.86
8	46.55	12.94	67.38
9	45.90	12.96	65.23

Rababa (2011) and Singh *et al*. (2017) performed experiments and simulations on a centrifugal pump with different number of blades to investigate the flow area and found that the increase on the number of blades increased the head, as well. This statement is consistent with the results in Table 4 and Table 5 in which shows the FWNN estimations at best efficiency points. The effects of H, P and η were defined by the performance index (2). After applying the whole inlet values to the FWNN model, the extended version of the outlet values is obtained. Moreover, for each inlet-outlet pairs, the performance index (k) is also calculated exactly. Table 6 lists the best k values of each blade numbers with the best efficiency points. The optimal value (k = 2,83) is reached when the blade number is 8. Accordingly, the number of blades providing the highest performance index was found to be 8. However, only considering the efficiency criteria as in the literature, higher efficiency is obtained with the number of 7-blade impeller shown in Table 5.

Table 5 The effect of blade numbers to *k* with pump performance by FWNN for BEPs

Z	k	Q/Q_{design}	H (m)	η (%)	P (kW)
5	2.45	1.195	44.22	64.34	11.62
6	2.33	1.065	44.29	67.34	12.80
7	2.73	1.152	47.62	67.47	11.77
8	2.58	1.061	48.08	67.60	12.61
9	2.52	1.077	48.06	65.67	12.53

Table 6 Best performance index (*k*) values of the FWNN models' estimations.

Inlet Values			Outlet Values			*k*
Q (l/min)	N (rpm)	Z	H(m)	η (%)	P(kw)	
545	2950	5	50.26	49.07	9.08	2.71
1180	2950	5	41.75	66.08	12.34	2.23
595	2950	6	51.56	52.58	10.27	2.64
1085	2950	6	42.70	67.81	12.89	2.25
810	2950	7	50.91	60.95	11.15	2.78
1165	2950	7	45.55	68.92	12.28	2.56
765	2950	8	52.91	60.59	11.33	2.83
1050	2950	8	47.63	67.65	12.72	2.53
740	2950	9	53.20	58.41	11.06	2.81
1050	2950	9	47.57	65.71	12.64	2.47

Comparing with pump impeller with number of blades 5, 6, 8 and 9 increases in efficiency rates are 0.4%, 2.57%, 6.4% and 7.2%, respectively. These rates show that as the number of blades increases, the efficiency decreases. This is a result consistent with previous scientific studies. In simple terms, the experiments showed that the number of blades effect the performance of the pump considerably and the design with higher blade numbers has a strong influence on the pump's performance. Nevertheless, the experiment results also showed that the design with lower number of blades has an insignificant effect on the pump performance. Thus, an impeller with optimum blade number should be chosen for centrifugal pump and this optimal blade number can be specified through engaging a powerful FWNN model with respect to other determined parameters.

This study also shows that, the FWNN models allow us to produce new data that cannot be experimentally obtained from the test rig and this new extended data can be considered as a look up table for the application of SSCP system with the desired operating conditions. Here, this work offers a performance criterion satisfying three goals at the same time. Moreover, as a future work one can investigate other optimization or performance criteria through using any combination of these selected goals. Additionally, experimental limitations can be included mathematically to the selected performance criteria.

On the other hand, number of blades should not exceed the optimum value otherwise unnecessary skin friction drag will occur which causes reduction in efficiency. It is also important to ensure the minimum energy consumption in this case. However, as the number of blade increases, the head value rises very clearly that results in high power consumption. As the blade number increases, the hydraulic loss within the pump increases too under the same flow conditions. In this study, the efficiency for the impeller design with 7 blades is higher than the impeller design with 8 and 9 number of blades. As oppose to this finding, it is also determined that, the head value is higher for the impeller design with 8 and 9 blades than the design with 7 blades. The respective findings are also given in Table 4. These results imply that the influence of the number of blades on the head can be fortified to some extent, as the blade number increases.

5. CONCLUSION

The predicted results for the head, efficiency and power developed in the impeller have presented over the entire flow range. In order to reveal the effect of the number of blades on the efficiency clearly, by keeping constant the geometrical dimensions of the pump, and experiments have been carried out with 5, 6, 7, 8 and 9 blades. The comparison between prediction values and experimental results indicates that, the results of FWNN are satisfactory.

In this work, an optimization design method was selected for a single stage centrifugal pump, and it was proved to be effective on improving pump performance at a minimum cost. The models for performance parameters were established, and the optimal solutions have obtained using the optimization method of FWNN, which revealed the objective functions of head, efficiency, and power on different number of blades. This software agreed with the experimental data well at the test points, and solution results showed the significant influence of decision variables on the centrifugal pump in terms of performance index (k). A tradeoff point has selected from the optimal set using a robust design method based on FWNN.

The investigations on the effect of the number of blades with the experimental data gathering from a pump type B50−200/100 and employing this data through a FWNN model presents a number of conclusions, as stated below:

1. The number of blades has a strong influence on the performance of centrifugal pumps when the blade number increases, the limitation between blade and flow stream gets more obvious, so the increase in the blade number is useful to reduce the mixture loss of “jet” and “wake” for centrifugal pumps.
2. The analysis with the use of FWNN model shows that, the optimum number of blades by considering the specified performance parameters for the centrifugal pump design is seven. Comparing with pump impeller with number of blades 5, 6, 8 and 9 increases in efficiency rates are 0.4%, 2.57%, 6.4% and 7.2%, respectively.
3. The variation regulations on efficiency are complex due to the increases in pump head value with the increase in the number of blades. However, there is an optimum value for the best efficiency and this optimum blade number is 7 when the others parameters kept constant.
4. The FWNN model over the performance analysis algorithm completes the missing data if exists and indicates the best performance solution as given in Table 5.

ACKNOWLEDGEMENTS

This work assisted by Turkey State Eskisehir Sugar Machinery Plant located in Eskisehir (Turkey Sugar Factories Inc.). The experimental assembled and the related experiments performed in accordance with the TS EN ISO 9906 and TS EN 837 standards:

TS EN 837 (1997) Selection and installation recommendations for pressure gauges: Turkish Standards

TS EN ISO 9906 (2012) Rotodynamic pumps-hydraulic performance acceptance tests-grades 1, 2 and 3.

The author would like to thank all the members of the establishment for their cooperation.

REFERENCES

Bellary S., A. Husain, A. Samad and R. A. Kanai (2018). Performance optimization of centrifugal pump for crude oil delivery. *Journal of Engineering Research* 15(1), 88-101.

Bozorgasareh, H., J. Khalesi, M. Jafari and H. O. Gazori (2021). Performance improvement of mixed-flow centrifugal pumps with new impeller shrouds: Numerical and experimental investigations. *Renewable Energy* 163, 635-648.

Chakraborty, S. and K. M. Pandey (2011). Numerical studies on effects of blade number variations on performance of centrifugal pumps at 4000 rpm. *International Journal of Engineering and Technology (IACSIT)* 3(4), 410-416.

Derakhshan, S., M. Pourmahdavi, E. Abdolahnejad, A. Reihani and A. Ojaghi (2013). Numerical shape optimization of a centrifugal pump impeller using artificial bee colony algorithm. *Computers and Fluids* 81(9), 145-151.

Ding, H., Z. Li, X. Gong and M. Li (2019). The influence of blade outlet angle on the performance of centrifugal pump with high specific speed. *Vacuum* 159, 239-246.

Duan, B., M. Luo, C. Yuan and X. Luo (2015). Multi-objective hydraulic optimization and analysis in a minipump. *Science Bulletin* 17, 1517-1526.

Elyamin, A. G. R. H., M. A. Bassily, K. Y. Khalil and M. S. H. Gomaa (2019). Effect of impeller blades number on the performance of a centrifugal pump. *Alexandria Engineering Journal* 58(1), 39-48.

Fu, L. and Z. Hong (2016). Optimization design of lower speed pump based on genetic algorithm. *Journal of Chinese Agricultural Mechanization* 37(2), 233-236.

Gölcü, M. (2006). Artificial neural network based modeling of performance characteristics of deep well pumps with splitter blade. *Energy Conversion and Management* 47(18), 3333-3343.

Gülich, J. F. (2010). *Centrifugal Pumps*. New York: Springer, 2nd Ed.

Haifeng, L., W. Yulin and Z. Zhimei (2001). The determination of centrifugal pump impeller’s design with three-dimensional turbulent flow simulation. *Fluidmachinery* 29(9), 18-21.

Han, W., L. Nan, M. Su, Y. Chen, R. Li and X. Zhang (2019). Research on the prediction method of centrifugal pump performance based on a double hidden layer BP neural network. *Energies (MPDI)* 12(14), 1-14.

Heinz, B., P. Bloch and R. A. Budris (2006). *Pump users’ handbook Lilburn*, The Fairmont Press Inc.

Houlin, L., W. Yong, Y. Shouqi, T. Minggao and W. Kai (2010). Effects of blade number on characteristics of centrifugal pumps. *Chinese Journal of Mechanical Engineering* 23(06), 742-747.

Jafarzadeh, B., A. Hajari, M. M. Alishahi and M. H. Akbari (2011). The flow simulation of a low-specific-speed high-speed centrifugal pump. *Applied Mathematical Modelling* 35(1), 242–249.

Karassik, I. J., J. P. Messina, P. Cooper and C. C. Heald (2001). *Pump handbook*. New York, McGraw-Hill.

Li, W. G., F. Z. Su and C. Xiao (2002). Influence of the number of impeller blades on the performance of centrifugal oil pumps. *World Pumps* 427, 32-35.

Matlaka, M. E., D. V. V. Kallon., S. P. Simelane and P. M. Mashinini (2019). Impact of Design Parameters on the Performance of Centrifugal Pumps. *Procedia Manufacturing* 35, 197-206.

Namazizadeh, M., M. T. Gevari, M. Mojaddam and M. Vajdi (2020). Optimization of the splitter blade configuration and geometry of a centrifugal pump impeller using design of experiment. *Journal of Applied Fluid Mechanics* 13, 89-101.

Öztekin, A., B. R. Seymour and E. Varley (2002). Unsteady stratified swirling shear flows. *Mathematical and Computer Modeling* 36(3), 321-337.

Papierski, A. and A. Błaszczyk (2011). Multiobjective optimization of the semi-open impeller in a centrifugal pump by a multilevel method. *Journal of Theoretical and Applied Mechanics* 49(2), 327–341.

Rababa, K. S. (2011). The effect of blades number and shape on the operating characteristics of groundwater centrifugal pumps. *European Journal of Scientific Research* 52(2), 243-251.

Safikhani, H., A. Khalkhali and M. Farajpoor (2011). Pareto based multi-objective optimization of centrifugal pumps using CFD, neural networks and genetic algorithms *Engineering Applications of Computational Fluid Mechanics* 5(1), 37-48.

Sakthivel, N. R., V. Sugumaran and B. B. Nair (2012). Automatic rule learning using roughset for fuzzy classifier in fault categorization of mono-block centrifugal pump. *Applied Soft Computing* 12(1), 196-203.

Siddique, M. H., A. Afzal and A. Samad (2018). Design optimization of the centrifugal pumps via low fidelity models. *Mathematical Problems in Engineering* ID (3987594), 1-14.

Singh V. R., M. J. Zinzuwadia, S. Sheth and R. J. Desai (2017). Parametric study and design optimization of centrifugal pump impeller. International Conference on Research and Innovations in Science, Engineering &Technology (ICRISET) 1, 507-515

Škerlavaj, A., M. Morgut, D. Jošt and E. Nobile (2017). Optimization of a single- stage double- suction centrifugal pump. In: IOP Conf. Series: *Journal of Physics Conference* 796(1), 1-11.

Stephanoff, A. J. (1986). *Centrifugal and axial flow pumps: theory, design, and application.* New York, Amazon Company

Wang, W., M. K. Osman, J. Pei, X. Gan and T. Yin (2019a). Artificial neural networks approach for a multi-objective cavitation optimization design in a double-suction centrifugal pump. *Processes (MDPI)* 246 (7), 1-23.

Wang, W., J. Pei, S. Yuan, X. Gan and T. Yin (2019b). Artificial neural network for the performance improvement of a centrifugal pump. *IOP Conf. Series: Earth and Environmental Science* 240(3), 1-11.

Wu, Q., Q. Shen, X. Wang and Y. Yang (2016). Estimation of centrifugal pump operational state with dual neural network architecture based model. *Neurocomputing* 216, 102-108.

Wu, X. F., X. Tian, M. G. Tan and H. L. Liu (2020). Multi-parameter optimization and analysis on performance of a mixed flow pump. *Journal of Applied Fluid Mechanics* 13(1), 199-209.

Yilmaz, S. and Y. Oysal (2010). Fuzzy wavelet neural network models for prediction and identification of dynamical systems. *IEEE Transactions on Neural Networks* 21(10), 1599-1609.

Yuan, S. Q., C. Q. Chen and W. Cao (1993). Design method of obtaining stable head-flow curves of centrifugal pumps. In: *ASME Pumping Machinery Meeting FED* 154, 171-175.