TuEngr Group

International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

http://TuEngr.com

MODELING AND OPTIMIZATION OF CENTRIFUGAL PUMPS USING ANSYS FLUENT® AND GENETIC ALGORITHM ANALYSIS

Pouria Hemmati [a], Shahriyar Mirhakimi [a*]

[a] *Department of Chemical Engineering, Faculty of Engineering, Islamic Azad University Arak, IRAN.*

ARTICLEINFO

Article history:
Received 14 March 2019
Received in revised form 27 May 2019
Accepted 03 June 2019
Available online 06 June 2019

Keywords:
Net positive suction head (NPSH); Computational Fluid Dynamics (CFD); SIMPLEC algorithm; Multiobjective Pareto optimization; Pareto Front; Epsilon Removal Algorithm, GA analysis.

ABSTRACT

In this research, optimization and design of fluid flow in a centrifugal pump is investigated and modeled using numerical analysis of computational fluid dynamics (CFD) and FLUID. First, geometry simulation is done using Gambit program and developing the geometry of the pump considered. After meshing fluid volume for mathematical analysis and then defining the volume of control in accordance with conditions, the simulated pump is ready to be implemented in ANSYS FLUENT®. Then, the results obtained from FLUENT are investigated to optimize the pump performance in group inference using GMDH neural network model (Group Method of Data Handling). Finally, using polynomials related to efficiency and net positive suction head (NPSH) associated to geometric variables by parametric functions that are introduced as neural networks, multi-objective genetic algorithm is used to optimize centrifugal pump based on two objectives of increasing pump efficiency and decreasing NPSH, which according to Pareto Front, as one of the best approximations, will result in optimal design of the pump.

1 INTRODUCTION

The human needs primarily water and other fluids that help him produce, move and survive. The transfer of fluids may be required. When moving fluids from a lower level to a higher level or from a low-pressure environment to a high-pressure one, a pump is necessary. This massive demand has led to the expansion of varieties of pumps whether in terms of performance or volume of fluid which can be transferred. Pumps as rotating equipment are often exposed to erosion, corrosion, cavitation, and leakage. On the other hand, most of the pumps' problems are caused by the wrong choice of the pump in terms of volume of discharge (debit) and selective head and finally inappropriate pump performance. In general, the most common problems of pumps are as follows: issues such as pump leakage, fouling, shaft non-alignment of pump and electromotor, crack at the connection point of pump body with tube (flange and anti-vibrator) and finally leakage and other

*Corresponding author (S.Mirhakimi) E-mail: sh-mirhakimi@iau-arak.ac.ir

problems.

Multi-objective Pareto optimization of the centrifugal pump using genetic algorithm was conducted by Narimanzadeh and Amanifard (2007), by investigating optimization and objectives such as general head, input power and hydraulic efficiency using input parameters as debit and impeller outer radius. The multi-objective method offers a set of positive answers and provides optimal choices for the designer. Safikhani et al. (2010) investigated multi-objective Pareto optimization of the centrifugal pump using CFD, neural networks and genetic algorithm. In this research, the multi-objective optimization of the centrifugal pump is done in three stages. In the first stage, modeling is done using Nomka program. The second stage is modeling of target functions according to variables of geometry designed. In the last stage, using the polynomials of neural networks achieved, a multi-objective genetic algorithm is conducted for Pareto optimization (Narimanzadeh, & Amanifard, 2007).

Nagahara et al. (2012) investigated pumps using computational fluid dynamics and optimization technique, and measured sensitivity of each parameter to achieve optimal state by design of experiments (DOE).

This research aims to optimize the design of fluid flow in a centrifugal pump, which consists of a pump casing, suction valve, impeller (rotor), diffuser, pump main shaft and output channel. Basically, this research is investigated using numerical analysis of computational fluid dynamics (CFD) and FLUENT for modeling and numerical analysis. It is used as an applied tool in this research. In the present study, due to categories which can be investigated in the optimization of pump modeling, categories such as cavitation, internal rotation of fluid, optimization of NPSH, improving the best point of efficiency to increase the performance of centrifugal pump are also studied.

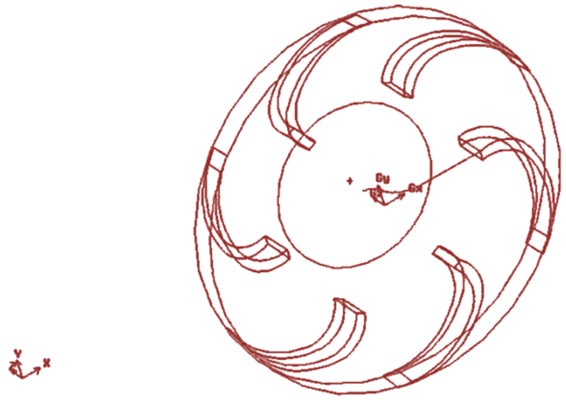

Figure 1: Impeller geometry formed using Gambit program.

2 MATERIALS AND METHODS

This research carried out in three stages. In the first stage, FLUENT provides the results through analysis of continuity equations, momentum, and energy as numerical analysis and three-dimensional simulation of flow in the desired control volume. In the second stage, efficiency modeling and NPSH are carried out according to variables of geometric design. In the third stage, polynomial neural networks obtained from the multi-objective genetic algorithm are used for Pareto optimization of a centrifugal pump.

2.1 FORM GEOMETRY

In order to analyze the fluid flow and subsequently to adjust geometric parameters to achieve higher efficiency, the geometry of centrifugal pump is firstly constructed according to ETANORM 60-65 model using Gambit program, as shown in Figure 1. Dimensions calculated in impeller geometry are applied according to Table 3.

Table 1: Parameters used in forming pump geometry.

Parameter	Size
Suction pipe diameter	Ds= 142.4 mm
Impeller diameters	D1= 157 mm, D2=274mm
Impeller widths	b1=31 mm, b2=20.8 mm
Impeller angles	$\beta_1 = 10^o$, $\beta_2 = 30^o$
Number of blades	6

After forming impeller, pump casing is achieved which is considered as one of the complex geometries in design due to its spiral and asymmetrical structure, Figure 2. This volute casing is as a diffuser which results in an increase in the pressure of the fluid flow.

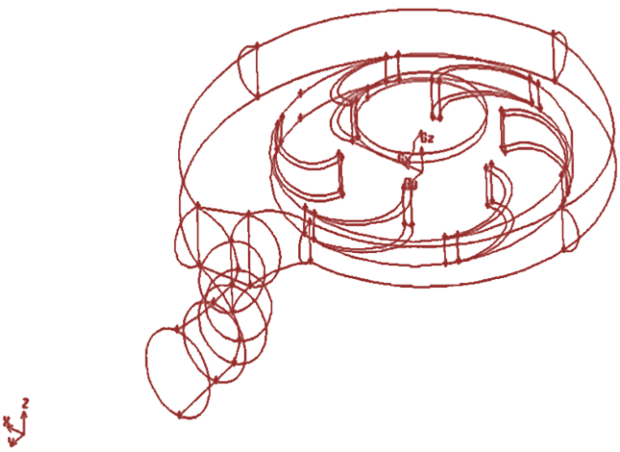

Figure 2: Geometry of pump casing and impeller in three-dimensional volumetric model.

2.2 MESH

Due to the formation of impeller and volute casting, at the meshing stage, two volumes with hexagonal and hybrid meshes are tested and after several stages of trial and error, finally, in the periodic counting mode, 100 meshing was completed as shown in Figure 3.

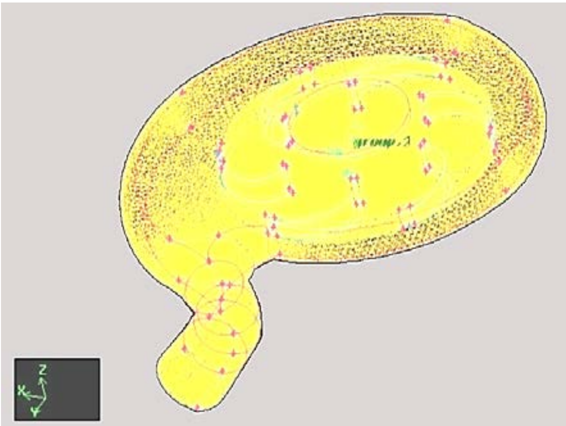

Figure 3. The geometry of casting and impeller in meshing mode

Finishing meshing with 29417 nodes and 124053 meshes for volute casing, 59190 nodes and 242031 meshes for impeller and a total of 88607 nodes and 366084 meshes, conditions and type of continuous environments as inner fluid (inside impeller) and outer (inside casing) were considered and provided as described previously and data were studied using FLUENT.

2.3 SIMULATION FLOW REGIME AND PERFORMANCE OF FLUID IN THE PUMP USING FLUENT

In order to achieve the ultimate objective, namely the highest efficiency and to predict a lower NPSH curve to optimize the centrifugal pump, ANSYS FLUENT® was applied. In this way, three-dimensional Navier Stokes equations, unstable and incompressible mode for analysis of continuity and momentum equation during the problem-solving process are solved after arranging a series of input data.

2.4 MULTI-OBJECTIVE GENETIC ALGORITHM

Due to the basic problems in gradient methods, such as their strong dependence to initial guess, other optimization methods were discovered in the last decade; the genetic algorithm method is the most important one. In this research, target functions for optimization are the determination of the efficiency of centrifugal pump and optimum NPSH; it results in opposite parameters so that the optimal result of this analysis is the optimal response of Pareto. In this research, NPSH is calculated using Equation (1).

$$NPSH = \frac{P_{In} - P_{min}}{\gamma \frac{V_{in}^2}{2g}} \quad (1).$$

P_{In} is input power, P_{min} is minimum pressure of impeller obtained from FLUENT, γ is a specific weight of fluid and V_{in} is fluid inlet velocity. Design variables β_1 are leading angel (angle of attack), β_2 trailing edge angle and γ angle. Two parts of shroud and hub are considered which are regarded to be the same in two sides; it is shown in mathematical form as

$$\beta_{2Hub} = \beta_{2Shroud} \quad (2).$$

Therefore, there are four variables of $\gamma, \beta_{1Hub}, \beta_{1Shroud}, \beta_2$ which are investigated. The design variables selected for modeling and their variance range are listed in Table 2.

Table 2. Design variables with values selected and range of variance

No.	Design variable	From	To	Values selected for modeling
1	γ	110	190	110, 130, 150, 170, 190
2	β_{1Hub}	60	80	60, 70, 80
3	$\beta_{1Shroud}$	45	75	45, 60, 75
4	β_2	55	70	55, 63, 70

By changing non-geometric parameters according to Table 2, the various design will be achieved and assessed using CFD and FLUENT. As a result, several meta-models will be optimally formed using GMDH neural networks. GMDH neural networks which will be later applied to design multi-objective Pareto of a centrifugal pump. In this way, 80 different analyzes of CFD are achieved using FLUENT related to different design geometries. SIMPLEC algorithm and 2nd Order Upwind condition are used for faster convergence of response as well as for discretization in continuity and momentum equations.

2.5 EFFICIENCY AND NPSH MODELING USING GMDH NEURAL NETWORK

There are two general concepts in the design of neural networks, specifically known as parametric issues and structural identity. Therefore, researchers presented a hybrid genetic algorithm and a singular values decomposition method for the optimal design of a polynomial neural network (Atashkari, et al., 2005). Models derived from GMDH polynomial have optimal ability to estimate unseen data pairs in the process. It includes four variables as inputs (four geometric parameters of the pump) and outputs that are efficiency and NPSH. The practice mode includes 60 out of 80 input and output data pairs which were considered for efficiency and NPSH. The test mode consists of 20 samples of input-output data for η and NPSH, which were applied to estimate GMDH neural networks during practice process. GMDH neural network is used to find NPSH and η polynomials based on their effective input parameters (Oyama & Liou, 2001; Safikhani et al., 2010).

2.6 MULTI-OBJECTIVE OPTIMIZATION OF CENTRIFUGAL PUMP USING POLYNOMIAL NEURAL NETWORK MODELS

Investigation on performance of the centrifugal pump, polynomial neural networks models were used in multi-objective optimization method. Multi-objective optimization is presented as follows:

$$\uparrow \eta = f_1(g, b_{1Hub}, b_{1Shroud}, b_2)$$
$$\downarrow NPSH = f_2(g, b_{1Hub}, b_{1Shroud}, b_2)$$
$$110^0 \leq g \leq 190^0$$
$$60^0 \leq b_{1Hub} \leq 80^0$$
$$45 \leq b_{1Shroud} \leq 75$$
$$55 \leq b_2 \leq 70$$

Multi-objective Pareto optimization is performed using the NSGA II algorithm called generic epsilon removal algorithm in which the population size was 60 for all processes with a cross probability of 0.7, and the transformation probability of 0.07.

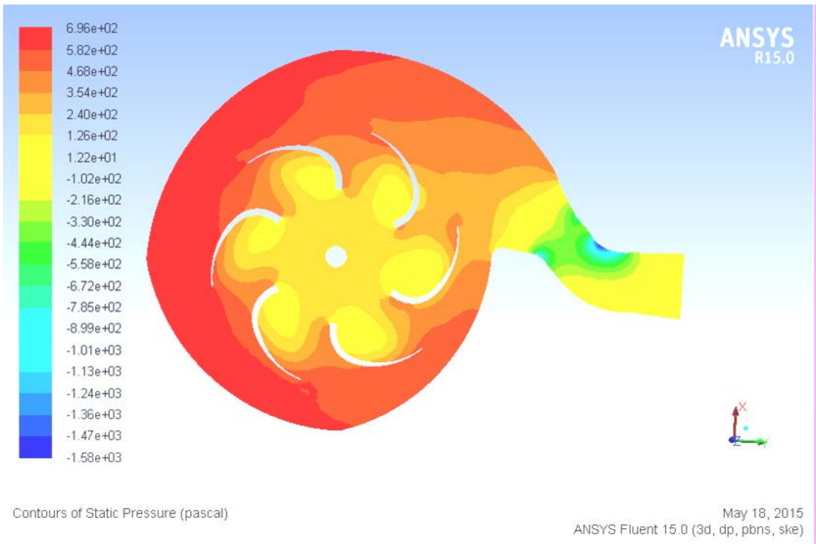

Figure 4: Static pressure contour in the central plate.

3 RESULTS

3.1 PRESSURE CONTOUR

Due to the importance of pressure variations in the pump, the rate of changes in static pressure with the impeller movement inside the volute casing is shown based on the figure presented pressure mode. For a better view of contours, a plate is defined in the central part of the casing volute that is called central plate; it is shown as pressure contour in Figure 4.

3.2 ANALYSIS RESULTS FROM FLUENT

Due to the importance of examining two factors of high-efficiency output and lower NPSH, and more specifically that in this research, other factors such as input and output power, head or head loss due to friction are used in an independent system, the results were tested using three types of meshing. It was finally concluded that output parameters acted as independent variables and numerical analysis of geometry was independent of meshing. As a result, regarding meshes in terms of accuracy, the best meshing mode was selected mode A with 124053 meshes to solve the problem.

3.3 ANALYSIS RESULTS FROM GENETIC ALGORITHM METHOD AND GMDH

The genetic algorithm was used for the optimal design of GMDH neural network models in regard to efficiency and NPSH of centrifugal pumps as well as for multi-objective Pareto optimization similar to Fonseca and Fleming studies. Two different polynomial relations in regard to efficiency and NPSH were found by GMDH neural network using output data of FLUENT modeling and output and input data of pumps. The data obtained were divided into two practice and test modes. Practice mode includes 60 out of 80 input and output data pairs which were considered for efficiency and NPSH. The test mode consists of 20 samples of input-output data for η and NPSH, which were applied to estimate GMDH neural networks during practice process.

In this research, premature multi-objective Pareto convergence was prevented, and answers were distributed and led to correct Pareto Front using an extended algorithm called the Epsilon Removal Algorithm. According to Table 3, it is clear that the model investigated using GMDH method is well suited to the FLUENT analysis model.

Table 3: Statistical values of absolute difference, R^2 (r-squared), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Parameter	Efficiency		NPSH	
	Practice	Test	Practice	Test
RMSE	1.342	1.819	0.05132	0.05088
R^2	0.912	0.936	0.99066	0.99334
MAPE	0.118	0.112	0.01066	0.01150

Then, the polynomial models were used in multi-objective Pareto optimization process by which the optimal design of pumps was achieved with respect to the pump control variables, such as geometric parameters of $\gamma, \beta_{1Shroud}, \beta_{1Hub}, \beta_2$, which are very close and even slightly higher than results and analysis obtained by Safikhani et al. (2010). Based on these values, the equilibrium point simply contains the sum of those values by which design point of C is achieved using the mapping method.

As a result, important equations have been achieved in the optimal design of centrifugal pump based on Pareto Front of two conflicting objective functions. As shown in Figure 5, all optimum design points in the Pareto Front are non-dominated and can be selected as an optimal pump by the designer.

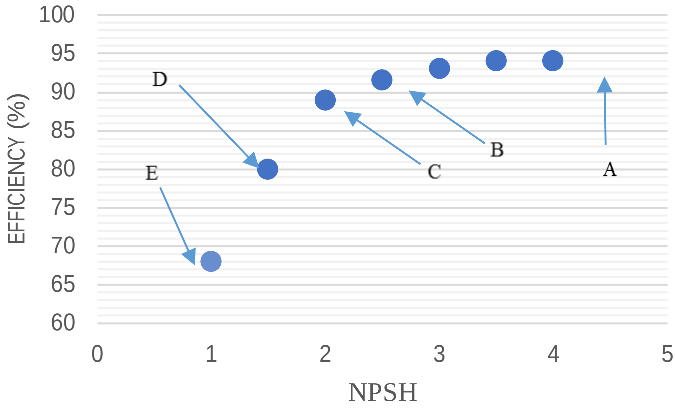

Figure 5: Comparing Pareto Front efficiency and NPSH.

Pareto Front (Figure 5) obtained from the present research was compared with results of FLUENT calculations (Figure 6). As shown in 6, Pareto Front obtained is at the best mode in proportion to target values obtained from FLUENT calculations.

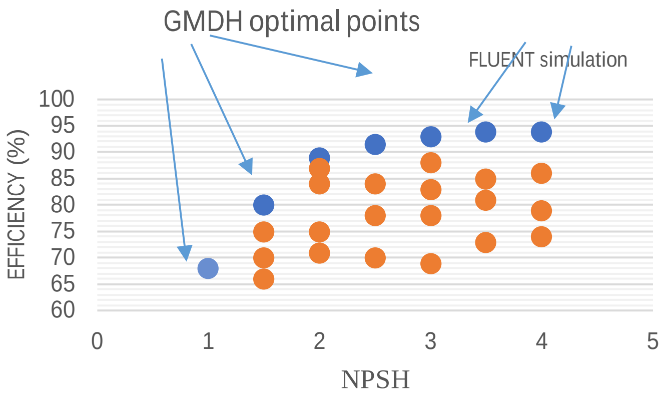

Figure 6: Comparing efficiency and NPSH in Pareto Front and FLUENT

This hybrid application, GMDH neural network modeling for input-output data and the resulting non-dominated Pareto optimization process can be very promising in discovering interesting and useful relationships.

Table 4: Comparing results obtained from the present research with results obtained by others (results of GMDH method)

Point	η		NPSH	
	This research	Safikhani et al. (2010)	This research	Safikhani et al. (2010)
A	94.8	94.8	4.1	6.084
B	91.5	91.5	2.52	5.034
C	88.9	88.9	2.069	4.196
D	80.3	80.3	1.63	3.8
E	68	68	1.059	3.5

Table 4, results obtained from the present research were compared to the results obtained by Safikhani et al. (2010). The values obtained in this research are somewhat better than other values; this approves research method and illustrates the main objective of the study that is to improve and optimize those values.

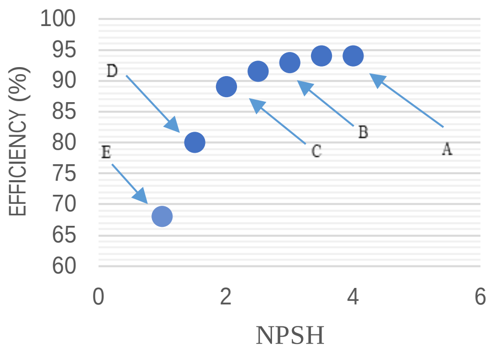

Figure 7: Comparing Pareto Front efficiency and NPSH

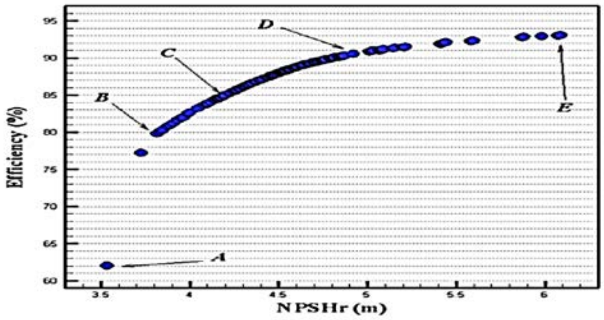

Figure 8. Comparing Pareto Front efficiency and NPSH by Safikhani et al. (2010).

In Figure 7, finally, point C was achieved as the optimal design point both in terms of efficiency and NPSH using mapping method. Figure 8 is presented as an example of the research by Safikhani et al. (2010) which is shown as follows. In this Figure, the C point, similar to Figure 7, is selected as the optimal design point in terms of efficiency and NPSH. As shown, although number of points on this graph is very high, and points A to E are considered as samples, by comparing C points in both 7 and 8 graphs that have same conditions, it can be concluded that efficiency and NPSH of C point in Figure 7 are respectively 88.9 and 2.069, and in Figure 8, they are respectively 85.02 and 4.96.

Considering the analysis of genetic algorithm in this research and regarding the independence of problem-solving from other factors, it can be said that this type of algorithm is very efficient and significant in many engineering issues and can be used extensively in this area. Finally, responses obtained from the present analysis present important objective functions that pump designer can simply use those responses among other answers.

4 CONCLUSION

Optimization and design of fluid flow in the centrifugal pump has been investigated and modeled using numerical analysis of computational fluid dynamics (CFD) and FLUID. Simulation geometry of the pump is built via Gambit software. After meshing fluid volume for mathematical analysis and then defining the volume of control, the simulated pump is analyzed using ANSYS FLUENT® as a research tool. Then, the results are then investigated to optimize the pump performance in group inference using GMDH neural network model (Group Method of Data Handling). Finally, using polynomials related to efficiency and net positive suction head (NPSH) associated to geometric variables by parametric functions that are introduced as neural networks, multi-objective genetic algorithm is used to optimize centrifugal pump based on two objectives of increasing pump efficiency and decreasing NPSH, which according to Pareto Front, as one of the best approximations, gives optimal design of the pump. The simulation of the centrifugal pump by FLUENT is considered as a more efficient and accurate method than other methods with regard to other computational fluid dynamics, investigated by other researchers, including Safikhani, et al. (2010), Narimanzadeh and Amanifard (2007), Oyama and Liou (2001).

5 DATA AVAILABILITY STATEMENT

The used or generated data and the result of this study are available upon request to the corresponding author.

6 REFERENCES

Narimanzadeh, N. & Amanifard, N. (2007). Multi-Objective Pareto Optimization of Centrifugal Pump Using Genetic Algorithms. *11th WSEAS International Conference on COMPUTERS*, Agios Nikolaos, Crete Island, Greece, July 26-28, 2007

Oyama, A. & Liou, M.S. (2001). Multi-objective Optimization of Rocket Engine Pumps Using Evolutionary Algorithm. AIAA Paper 2002581, *15th AIAA Computational Fluid Dynamics Conference*, Anaheim, California, June 2001.

Atashkari, K., Narimanzadeh, N., Pilechi, A., Jamali, A. and Yao, X. (2005). Thermodynamic Pareto Optimization of Turbojet Engines Using Multi-objective Genetic Algorithms. *International Journal of Thermal Sciences*, Vol.44, No.11, 2005, pp.1061071

Safikhani, H., Nourbakhsh, A., Khalkhali, A. & Narimanzadeh, N. (2010). Modeling and Multi-Objective Optimization of Centrifugal Pumps Using CFD and Neural Networks. *2nd International Conference on Engineering Optimization*. September 6 - 9, 2010, Lisbon, Portugal

Nagahara, T., Okihara, T., & Torii, D. (2012). Investigation of the hydraulic design for a high-performance centrifugal pump. In *IOP Conference Series: Earth and Environmental Science* (Vol. 15, No. 3, p. 032028). IOP Publishing.

Pouria Hemmati is associated with Department of Chemical Engineering, Faculty of Engineering, Islamic Azad University Arak, IRAN.

Shahriyar Mirhakimi is a Lecturer at Department of Chemical Engineering, Faculty of Engineering, Islamic Azad University Arak, IRAN.