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# Optimal Control and Design of PMBLDC Motor Using NSGA-II Multi-objective Algorithms

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## Abstract

This study presents an optimal design and a control shame for PMBLDC motor based on multi-objective non-dominated sorting genetic algorithms NSGA-II which is able to optimum both volume and cost of constructing of dc motor and tune the PID controller parameters simultaneously in order of trade-off optimal solutions. Single objective population based method such as genetic algorithm or particle swarm optimization have only one solution in single run but multi-objective optimization can find various solutions in a single run. This paper deals with some objective functions. The cost function include of step response characteristic of motor speed, building cost and its volume that should be minimized simultaneously. To reach this goal in this application the NSGA-II and MOPSO are used for the first time. The results of simulations show the validation of this methods.

***Keywords:***Optimal design, Speed control, DC motor, Non-dominated sorting genetic algorithms, Multi objective particle swarm optimization.

## 1. Introduction

Principally speed control of Permanent magnet brushless dc motor, is a multi-objective problem with many variables and constraints.

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The aim of this paper is finding of optimal design for motor in order to minimizing of volume and constructing cost and designing of an appropriate controller for speed control of motor.An appropriate speed controller system is a system that output speed response to reference speed is as fast as possible in the presence of load changes. So the problem of determining the optimal control parameters of DC motor can be considered to be multi-objective problem. This problem has two opposition objectives. The first objective is reducing constructing cost, total volume and another one is tuning of PID parameters that consist of minimizing the maximum overshoot, settling time and rise time.

The main objective of the Multi-Objective (MO) problem is finding the set of acceptable trade-off Optimal solutions. This set of acceptable is called Pareto front. These acceptable trade-off multi level solutions give more ability to the user to make an informed decision by seeing a wide range of near optimal selected solutions that are feasible and acceptable from an "overall" standpoint. Single Objective (SO) optimization may ignore this trade-off viewpoint, which is crucial. Non-dominated sorting genetic algorithm (NSGA-II) was successfully applied to various multi-objective engineering optimization problems [1]. The initial strength of NSGA-II lies in its ease-of use because of its elitism, non-dominated ranking and crowding distance which lead to rapid convergence to very high quality solutions.

Multi objective particle swarm optimization (MOPSO) is also used in this paper. Because MOPSO is much simpler than NSGA-II, and its operation is more convenient, without selection, copy and crossover.

These methods preferred because they have better computational complexity, and has more even individual distribution over the Pareto front. Their advantages to single objective optimization is that they are able to find more optimal solutions in single run and have a good ability in finding global optimum point.

In [2] an optimum design for minimizing of force ripple and maximization of thrust force in linear brushless permanent magnet motor without finite element analysis is represented. In [3] optimal design of brushless dc motor by utilizing novel coefficient modeling for skewed PM and overhang structure is studied. In [4] for the first time, optimal design of these motors with goal of reducing losses, volume and building cost by using of genetic algorithm was presented. In [5,6] the fuzzy PI controller for controlling of BLDC motor was represented. In [7] speed control of DC motor based on fuzzy PI controller was represented. In [8] for better performance of optimization adaptive factor is used in fuzzy PID controller. In [9] the PSO is used for improving in setting of PID controller parameters for speed control of DC motor. In [10], The PID-PSO and the PID-BF controller was compared in speed control of DC motor and the results show that the PSO method is better than BF in terms of settling time, overshoot, rise time and steady state error. In [11] the complete original binary coded GA program in matlab was provided, GA was applied to find optimal solution for the parameters of DC motor with PID controller and indicated that GA is powerful global searching method. In [12] an attempt had been made to review various literatures for the soft computing techniques introduced by the different researchers for tuning of PID controller for speed control of DC motor to optimize the best result.

In [13] the multi-objective bees algorithm to optimal tuning of PID controller for speed control of a DC motor was studied .In [14] the speed control of DC motor is used with NSGA-II based multi objective PID controller tuning. the effectiveness of this approach since it allows the operator to find a near optimal good compromise among its goals which is the best trade-off low cost PID controller design, was showed.

As the above mention the problem of determining the optimal control parameters of PMBLDC motor can be considered to be multi-objective problem. Non-dominated sorting genetic algorithm (NSGA-II) was successfully applied to various multi-objective engineering optimization problems. In [15] NSGA-II based control of switched reluctance motor (SRM) with torque ripple reduction was presented by minimizing the Integral Squared Error (ISE) of speed and torque ripple. The optimum values of proportional and integral gains for both speed and current controller along with the turn on and turn off angles were obtained. The results revealed that NSGA-II based controllers gave better performance in terms of lesser torque ripple and quick settling time.

Adaptive tuning of a PID speed controller for DC motor drives was used by multi-objective particle swarm optimization in [16]. The primary strength of NSGA-II lies in its ease-of-use because of its elitism, non-dominated ranking and crowding distance which lead to rapid convergence to very high quality solutions. The most striking difference between PSO and the other evolutionary algorithms is that PSO chooses the path of cooperation over competition [17]. The other optimization algorithms usually use some form of decimation, survival of the fittest. In contrast, the PSO population is stable and individuals are not destroyed or recreated. Individuals eventually converge on optimal points in the problem domain. So in PSO all the particles tend to converge to the best solution quickly, comparing with GA.

In this paper, a control mechanism for speed control and optimal design of building cost and motor volume is proposed using Pareto-based multi-objective optimizations algorithms NSGA-II and MOPSO. Hence in this work, NSGA-II and MOPSO are utilized to find optimal values for motor parameters and proportional ($K_p$) ,integral ($K_i$) and differential ($K_d$) gains for speed controller. In order to consider minimizing of building cost and total volume of motor as first objective and finding the best step response characterizations as second objective.

The aim of this paper is presenting of appropriate method for optimal design and speed control of PMBLDC motor. In this paper first the motor characteristic in form of mathematical equation is expressed which is obtained from its geometrical structure. Then short definitions about NSGA-II and MOPSO will be expressed. Then the cost function will be explained. After performance evaluation of NSGA-II in compare with MOPSO, the simulation results are finally given to demonstrate the effectiveness of proposed algorithms. The proposed methods have appropriate features in terms of stable convergence and good computational efficiency.

## 2. Materials and Method

### *2.1 Problem formulation*

Figure 1, shows the structure of PMBLDC motor. The motor geometrical parameters are given in table 1.

Table 1: The geometric parameters of motor

| | |
|---|---|
| P | number of poles pairs |
| β | pole-arc per pole-pitch ratio |
| $l_m$ | magnet thickness |
| $l_y$ | stator/rotor core thickness |
| $l_w$ | winding thickness |
| $l_g$ | mechanical air gap |
| $r_r$ | rotor radius |
| $J_{cu}$ | current density |
| $l_s$ | wire gauge and stator/rotor axial length |

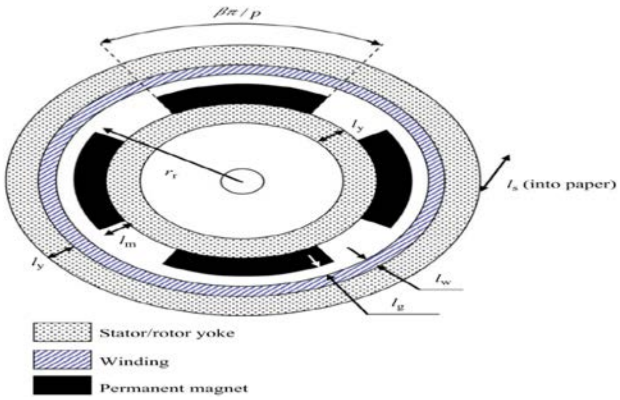


Fig 1: Illustration of the key parameters of the BLDC motor.

### *2.1.1 Motor volume*

The motor total volume is obtained by equation (1).

$$V_t = \pi l_s (r_r + l_g + l_w + l_y)^2 \quad (1)$$

### *2.1.2 Motor building cost*

The cost of building motor includes of consume materials cost used in geometrical parts of motor. Motor constructing cost can be written as follows:

$$C = c_{m1}\rho_m V_m + c_{m2} p + c_w (A_c) k_f \rho_w V_w + c_y \rho_y V_t \quad (2)$$

Where $\rho_m$, $\rho_w$ and $\rho_y$ are the mass density of magnet, winding and stator/rotor core, respectively; $c_{m1}$, $c_w$ and $c_y$ are the cost per unit mass of magnet, wire and core materials, respectively. $V_m$, $V_w$ and $V_t$ illustrate the volumes of the magnet, winding and stator/rotor core, respectively [4].

### *2.1.3 Speed control of DC motor*

At this section the output is speed of motor and reference rate is input. The transfer function of system is expressed in the presence of load torque. This system is controlled with a proportional-Integrator - derivative controller in front of the system's control structure. The speed control's parameter are PID parameters.

Due to advantages of PID controller like simplicity, permanency , reliability and easy tuning of parameters, this controller is used widely in industrial . The standard PID controller computes the difference error between the reference value and real one. Then system of BLDC motor signal is controlled by u(t) and a linear combination of the PID parameters.

The controller u(t) signal is written as follows:

$$u(t) = (K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt}) \tag{3}$$

$K_p, K_i, K_d$ is proportional , integrator and deferential gain respectively.

The transfer function of DC motor in the presence of load torque $T_L(s)$ can be written as follows [8]:

$$\Omega(s) = G_u(s)U_d(s) + G_L(s)T_L(s) = \frac{K_T U_d(s)}{L_a Js^2 + (r_a J + L_a B_v)s + (r_a B_V + k_e K_T)} - \frac{(r_a + L_a s)T_L(s)}{L_a Js^2 + (r_a J + L_a B_v)s + (r_a B_V + k_e K_T)} \tag{4}$$

The diagram of BLDC motor speed controller system is displayed in figure 1.

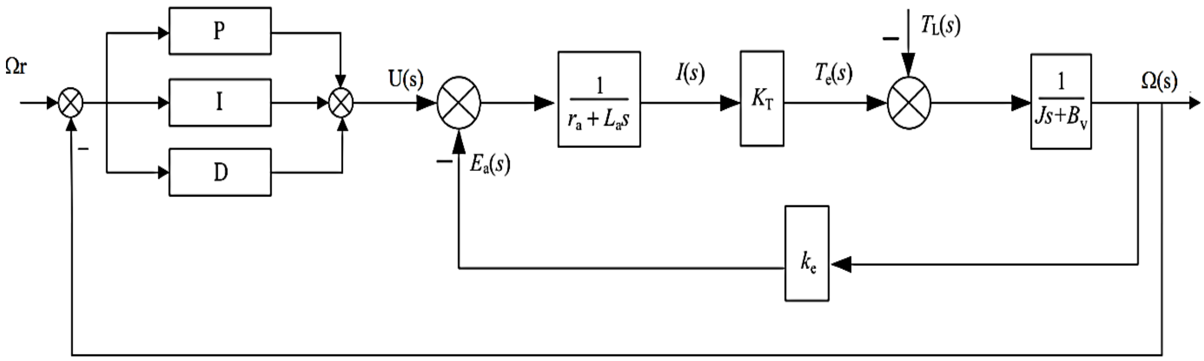


Figure 2: Speed control of DC motor using with PID controller

In this Figure, $\Omega(s)$ is response speed to reference speed.

### *2.2 Multi-objective optimizations*

The following definitions are used in the proposed Multi-Objective Optimization (MO) search algorithm [17]:

**Def. 1** The general MO problem requiring the optimization of N objectives may be formulated as follows:

Minimize $\vec{y} = \vec{F}(\vec{x}) = [\vec{f}_1, \vec{f}_2, ..., \vec{f}_N(\vec{x})]^T$ (5)

j=1,2,...,Msubject $\vec{g}_J(x) \le 0$ (6)

$\Omega \in$where $\vec{x}^* = [\vec{x}_1^*, \vec{x}_2^*, \vec{x}_P^*]$ (7)

$\vec{y}$ is the objective vector, $\vec{g}_J(x)$ represent the constraints and $\vec{x}^*$ is a P-dimensional vector representing the decision variables within a parameter space Ω. The space spanned by the objective vectors is called the objective space. The subspace of the objective vectors satisfying the constraints is called the feasible space.

**Def. 2** A decision vector $\vec{x}_1 \in \Omega$is said to dominate the decision vector $\vec{x}_2 \in \Omega$(denoted by $\vec{x}_1 < \vec{x}_2$), if the decision vector $\vec{x}_1$ is not worse than $\vec{x}_2$in all objectives and strictly better than $\vec{x}_2$in at least one objective.

**Def. 3** A decision vector $\vec{x}_1 \in \Omega$is called Pareto optimal, if there does not exist another $\vec{x}_2 \in \Omega$ that dominates it. An objective vector is called Pareto optimal, if the corresponding decision vector is Pareto optimal.

**Def. 4** The non-dominated set of the entire feasible search space Ω is the Pareto-optimal set. The Pareto optimal set in the objective space is called Pareto optimal front.

#### *2.2.1 Non-dominated Sorting Genetic Algorithm (NSGA):*

Non dominated sorting genetic algorithm (NSGA) is proposed by Srinivas and Deb [18] . The NSGA is based on several layers of classifications of the individuals as propsed by Goldberg [19]. Before selection is performed, the population is ranked on the basis of non-domination: all non-dominated individuals are classified into one category (with a dummy fitness value, which is proportional to the population size, to provide an equal reproductive potential for these individuals). To maintain the diversity of the population, these classified individuals are shared with their dummy fitness values. Then this group of classified individuals is ignored and another layer of non-dominated individuals is considered. The process continues until all individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population. The algorithm of the NSGA is not very efficient, because Pareto ranking has to be repeated over and over again.

*(NSGA-II):* This algorithm is known as Non-dominated Sorting Genetic Algorithm II (NSGA-II) is introduced by Deb and Agarwal in [20] as an improved version of the NSGA [18]. In NSGA-II, for each solution one has to

determine how many solutions dominate it and the set of solutions to which it dominates. The NSGA-II estimates the density of solutions surrounding a particular solution in the population by computing the average distance of two points on either side of this point along each of the objectives of the problem. This value is the so-called crowding distance. During selection, the NSGA-II uses a crowded-comparison operator which takes into consideration both the non-domination rank of an individual in the population and its crowding distance (i.e., non-dominated solutions are preferred over dominated solutions, but between two solutions with the same non-domination rank, the one that resides in the less crowded region is preferred).

The local crowding distance means between every point and another adjacent to it in the same objective space. For example, the crowding distance of point i in objective space is equal to the sum of two side lengths in a rectangular composed of adjacent points i-1 and i+1 as shown in Fig.3. This can be adjusted so that calculation results in the objective space are spread more evenly and with better robustness. The crowding distance of population member for every class is calculated by equations (8,9,10)

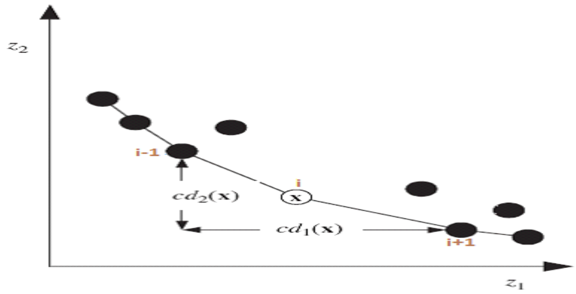


Fig 3. Crowding distance calculation

$$cd_1(x) = \frac{\left|Z_1^{i+1} - Z_1^{i-1}\right|}{Z_1^{\max} - Z_1^{\min}} \quad (8)$$

$$cd_2(x) = \frac{\left|Z_2^{i+1} - Z_2^{i-1}\right|}{Z_2^{\max} - Z_2^{\min}} \quad (9)$$

$$cd(x) = cd_1(x) + cd_2(x) \quad (10)$$

The NSGA-II does not use an external memory. Instead, the elitist mechanism of the NSGA-II consists of combining the best parents with the best offspring obtained. Its mechanism is better. Fig 4 shows the flowchart of NSGA-II.

### *2.2.2 Multi objective particle swarm optimization*

In MOPSO [22,23], a set of particles are initialized in the decision space at random. For each particle i, a position $x_i$ in the decision space and a velocity $v_i$ are assigned. The particles change their positions and move towards the so far best-found solutions. The non-dominated solutions from the last generations are kept in the archive. Moving towards the optima is done by calculation of velocities and positions of particles as follows:

$$V_{id} = \omega \times V_{id} + C_1 \times rand_1(P_{id} - X_{id}) + C_2 \times rand_2(P_{gd} - X_{id}) \qquad (11)$$

$$X_{id} = X_{id} + V_{id} \qquad (12)$$

Where $P_{id}$, $P_{gd}$ are randomly chosen from a single global Pareto archive, $\omega$ is the inertia factor influencing the local and global abilities of the algorithm, $V_{id}$ is the velocity of the particle i in the d_th dimension, $C_1$ and $C_2$ are weights affecting the cognitive and social factors, respectively. According to (12), each particle has to change its position $X_{id}$ towards the position of the two guides $P_{id}$, $P_{gd}$ which must be chosen from the updated set of non-dominated solutions stored in the archive. The particles change their positions during iterations until a termination criterion is met. Finding a relatively large set of Pareto-optimal trade-off solutions is possible by running the MOPSO for many iterations [18]. Fig 5 shows the Flowchart of MOPSO.

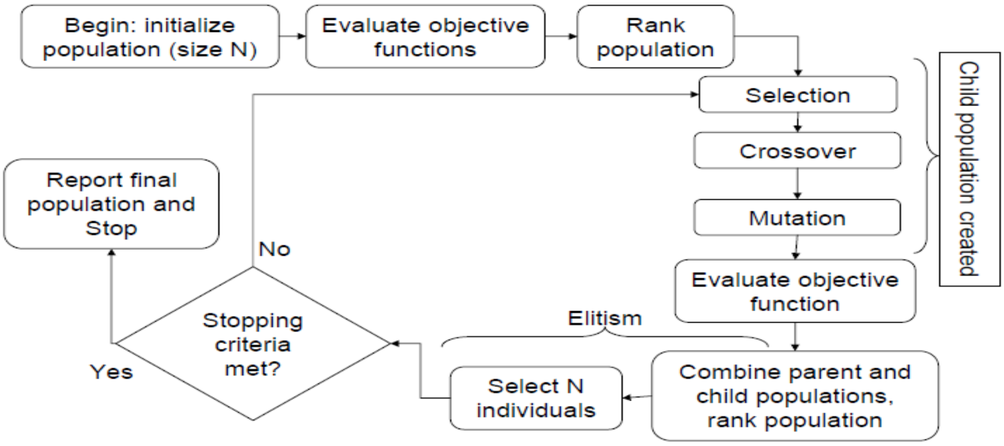


Fig 4. Flowchart of NSGA-II

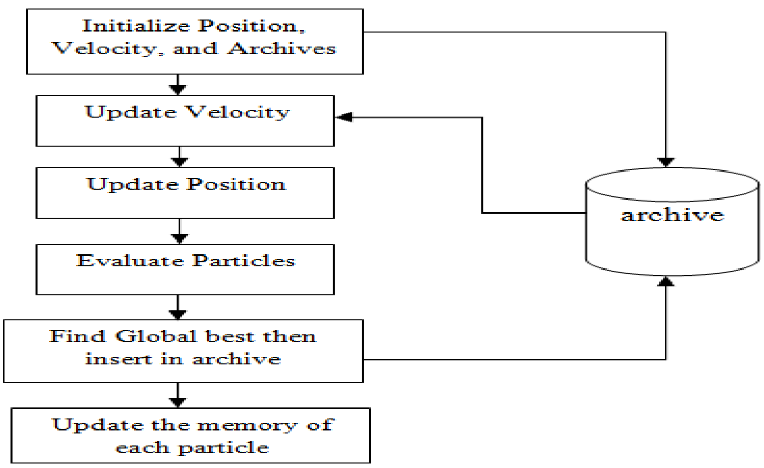


Fig 5. Flow chart of the MOPSO optimization algorithms

**3. Results**

In this paper, the cost function is a combination of optimal design of motor properties and speed control system parameters. The constant parameters of this problem have shown in Table 2.

First the variables of optimization problem are written as follows:

$$X=[P\ \beta\ l_m l_y l_w l_g r_r \lambda\ A_C\ K_P\ K_i\ K_d] \qquad (13)$$

Among which the first 9 parameters are related to the optimal BLDC motor design . While the last 3 ones are related to the PID controller parameters. So, in total, 12 different parameters are given to optimization algorithms.

The cost function will be written as follows:

$$f_1(x) = w_v V_t(X) + w_c C \qquad (14)$$

$$f_2(x) = w_{st} ST(X) + w_{ov} OV(X) + w_{rt} RT(X) + (1/\varepsilon) abs(B_{SY} - B_{SY}^{knee}) \qquad (15)$$

Where, $w_v$,$w_c$are weighting factor of motor total volume and building cost respectively. $w_{st}$ ,$w_{ov}$,$w_{rt}$ are weighting factor of settling time, maximum overshoot and rise time respectively. Also OV(X), RT(X) and ST(X) are the function related to the calculation of the maximum overshoot, rise time and the response settling time for the optimization parameters vector X. They can be obtained by stepinfo command in matlab software. ε is a small constant and is 0.0005. $B_{SY}$ is the stator core maximum flux density due to PM that can be written as follows:

$$B_{SY} = \frac{\pi \beta k_1 B_r l_m}{2 P l_y \ln(\frac{r_r + l_g + l_w}{r_r - l_m})} \qquad (16)$$

$k_1$can be expressed using this equations:

$$k_1 = 1 - \frac{1}{0.9[r_r / (\beta P (l_g + l_w))]^2 + 1} \qquad (17)$$

It should be mentioned that certain relationships related to the speed control system should be changed based on the optimal design values. Changes in the design specifications affects the speed response. So, we will have the equations (18),(19) and (20) .

$$B_V = B_{SY} \qquad (18)$$

$$K_T = K_e = 4PNSB_{sy} \qquad (19)$$

$$S = r_r l_s \qquad (20)$$

Where P is the number of pairs of poles, N is the number of the winding and S is the multiply of rotor radius and effective length of the conductors.

Table 2. The constant parameters and their value

| Parameters | Value | Parameters | Value |
|---|---|---|---|
| $B_{SY}^{knee}(T)$ | 1.5 | $c_{m1}$ | 20 |
| $B_r(T)$ | 1.0 | $c_{m2}$ | 1 |
| $k_f$ | 0.7 | $c_y$ | 3 |
| ε | 0.0005 | $c_1$ | 0.045 |
| $\rho_m$ | 7400 | $c_2$ | 5.42 |
| $\rho_w$ | 8900 | $\rho_y$ | 7700 |

Table (3) illustrates the weighting factor of multi objective cost function that is for reducing motor volume and increasing the rate of speed response. The reference speed and the load torque are 10 RPM and 1 Nm, respectively.

Table 3. The weighting factor for cost function

| weighting factor | Value |
|---|---|
| $w_{vt}$ | 10 |
| $w_c$ | 20 |
| $w_{st}$ | 1 |
| $w_{ov}$ | 70 |
| $w_{rt}$ | 2 |

The maximum and minimum and best parameters obtained by MOPSO and NSGA-II for dc motor have shown in table 4. These are the best optimum parameters obtained by these algorithms in 20 implementations. In the part of implementation of NSGA-II, MOPSO for fairly comparison, the population size and number of iteration of algorithms are the same. In NSGA-II the crossover rate and mutation rate are 0.7 and 0.1 respectively.

Table 4. The maximum, minimum and optimum parameters for DC motor

| Variables | Min | Max | Optimum NSGA-II | Optimum MOPSO |
|---|---|---|---|---|
| P | 1 | 6 | 1.4856 | 1.5852 |
| B | 0.5 | 1 | 0.6518 | 0.9593 |
| $l_m$ | 0.001 | 0.012 | 0.0062 | 0.0047 |
| $l_y$ | 0.002 | 0.01 | 0.0039 | 0.0057 |
| $l_w$ | 0.001 | 0.0055 | 0.0027 | 0.0026 |
| $l_g$ | 0.001 | 0.001 | 0.0033 | 0.0022 |
| $r_r$ | 0.015 | 0.1 | 0.015 | 0.0181 |
| $\lambda$ | 0.3 | 2 | 1.4567 | 1.4947 |
| $A_C$ | 0.1 | 2 | 0.7739 | 1.3781 |
| $k_p$ | 0 | 4000 | 2090 | 2.8316 |
| $k_i$ | 0 | 1500 | 960.8 | 886.5973 |
| $k_d$ | 0 | 500 | 119.36 | 169.9246 |

In this work, 20 independent trails for both algorithms are carried out. The best of motor building cost and its volume that is in first objective are reported. Because in some application this terms are more important that to be minimized. The best and worst results of this terms in 20 trails are showed in Table 5 .Fig 6 and Fig 7 shows the Pareto front of this best solution for NSGA-II and MOSPSO respectively.

Table 5. The best and worst of optimal first objective function design obtained by NSGA-II,MOPSO

| | | Settling time (Sec) | Max.OV (%) | Rise time (sec) | Constructing Cost (£) | Total volume ($m^3$) | Cost2 | Cost1 |
|---|---|---|---|---|---|---|---|---|
| NSGA-II | best | 0.0000801 | 15.6 | 0.0000152 | 4.0512 | 0.0000489 | 1575.3 | 75.5009 |
| | worst | 0.0000842 | 0 | 0.0000395 | 33.549 | 0.0000632 | 3.579 | 670.987 |
| MOPSO | best | 0.0000645 | 14.08 | 0.0000129 | 4.7806 | 0.0000699 | 1310.5 | 95.6135 |
| | worst | 0.0000596 | 0 | 0.0000292 | 32.1135 | 0.0000676 | 23.847 | 642.5151 |

From table 5 it is observed that the total volume and constructing cost obtained by NSGA-II is better than MOPSO but in speed control of motor the step response characteristic obtained by MOPSO is better than NSGA-II. If there is an application that motor should has minimum volume NSGA-II is recommended and if there is an application that motor should has the best speed control MOPSO is better for it.Fig 8 shows the best step response of speed control obtained by MOPSO and NSGA-II.

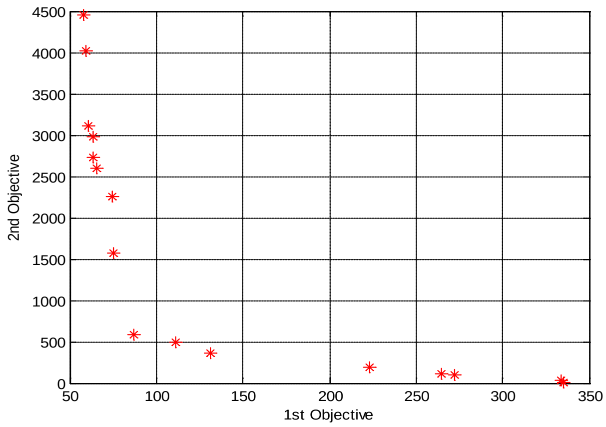


Fig 6. Pareto optimal front using NSGA-II

The optimal solutions obtained by NSGA-II can be seen from Fig 6. From Pareto-front plot can be seen that if the solutions of horizontal line of plot approach to zero then the total volume and building cost of motor will be more minimum than those that have bigger value of 1st value. Similarly if the solutions of vertical line of plot approaches near to zero the step response characteristic of speed control of motor will be more appropriate than those have bigger value of 2st objective cost. Also from Fig 6 it can be observed that NSGA-II obtain good variety of solutions in Pareto optimal front.

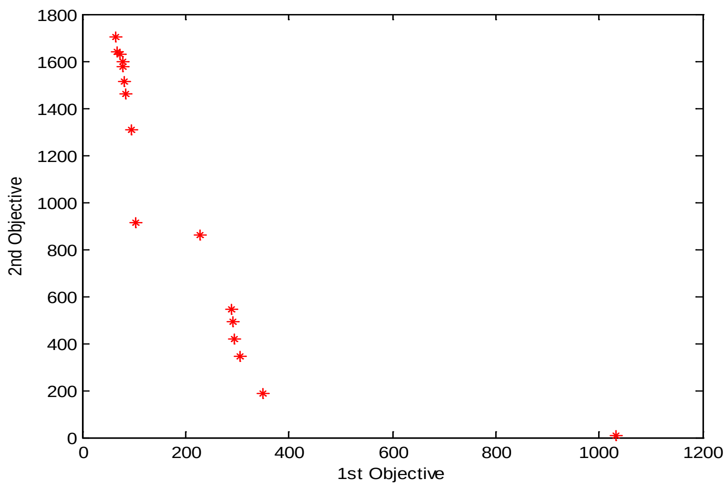


Fig 7. Pareto optimal front obtained by MOPSO

From Figure 7 it can be seen that MOPSO has good ability in finding appropriate solutions of constructing cost and total volume of motor because the most of horizontal solutions are near to optimum. But for NSGA-II the variety of solutions in both objective functions are more than MOPSO.

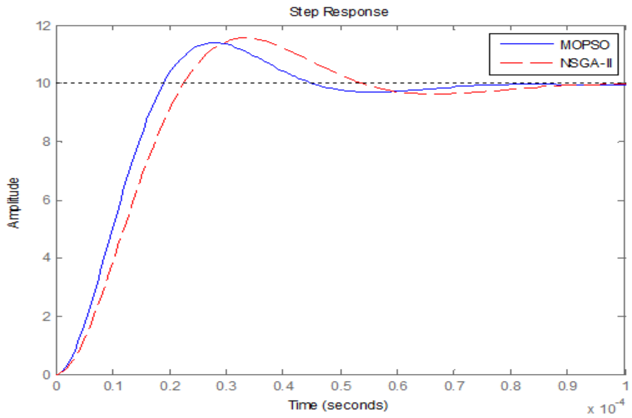


Fig 8. The best response speed obtained by NSGA-II and MOPSO

From Figure 8. it is clearly can seen that MOPSO has better step response than NSGA-II the rise time, settling time and maximum overshoot obtained by MOPSO is less than NSGA-II. We can also observe this results from Table 5 that the step response characteristics obtained by MOPSO is better than NSGA-II but the constructing cost and total volume of motor obtained by NSGA-II is less than MOPSO.

## 4. Conclusions

In, this paper represents optimal design of volume, building cost and speed control of PMBLDC motor using with NSGA-II and MOPSO. Consequently NSGA-II and MOPSO has more solutions in one run than PSO and GA methods. The optimization solution results are a set of near optimal trade-off values which are called the Pareto front or optimality surfaces. Pareto front enables the operator to choose the best compromise or near optimal solution that reflects a trade-off between key objectives. The simulation results show the effectiveness and validity of MOPSO and NSGA-II since it allow the operator to find a near optimal good compromise among the proposed targets, which is the best trade off low cost PID controller and optimal structure design of motor.

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