Optimal Design of Three-Phase Induction Motor Using Particle Swarm Optimization

R. Kannan, R. Bhuvaneswari, and S. Subramanian

Abstract—In this paper, an efficient and reliable Particle Swarm based approach to Optimal Design of three-phase Induction Motor (ODIM) is proposed. The proposed approach employs a particle-swarm-optimization (PSO) technique to search for optimal values induction motor design parameters. The proposed approach has been examined and tested on two sample motors with different objectives that reflect the motor’s efficiency, active material cost, and performance under starting and full load conditions. The proposed approach results have been compared to those reported in the literature. The results are promising and show the effectiveness and robustness of the proposed approach.

Index Terms—Optimal design, three-phase induction motor, particle swarm optimization, active material cost, starting and running performance.

I. INTRODUCTION

INTEREST in means of optimization of electric machine design is high because of increased cost of electrical energy and pressures for its conservation, plus the increased competition in world markets. The objective of the optimization process is usually to minimize the cost of the machine or to maximize the efficiency of the machine. This paper is concerned with the optimization of four different objective functions namely efficiency, active material cost, starting torque to full load torque ratio (Tst / Tfl) and temperature rise.

The design of a machine can be described by a vector \( X \) of \( n \) variables stating dimensions or dimension ratios, current densities, flux densities etc. The design is subject to a set of \( m \) constraints which may include specifications arising from thermal, mechanical, manufacturing or standards limits. The goal of design optimization is to make a chosen objective function \( F(X) \) reach its optimum value while keeping other technical indices within acceptable ranges. Typically for an electric motor the objective function might be its efficiency or cost or starting torque or temperature rise. The complexity of electric machine design is such that explicit methods of optimization such as those dependent on making certain derivatives equal to zero are not feasible. Thus most practical optimization employs nonlinear programming methods. The available literature in this regard is as follows.

A computer aided design optimization procedure for a three-phase squirrel cage induction motor using modified Hooke-Jeeves method was presented in [1]. A method adopted by [2] performed synthesis followed by an optimization procedure for ODIM. In [3] Augmented Lagrangian multiplier method was implemented for ODIM and the results were compared with the exterior penalty function method. Several optimization techniques viz., gradient techniques, dynamic programming and Monte-Carlo method were applied to solve the design problem [4]. Artificial Neural network was used for optimal design of electromagnetic devices in a design environment which consisted of numerical computations and experts input for generating a variety of ANN training data [5]. A computer aided design assistant was built for the synthesis, analysis and optimization of a three-phase squirrel cage induction motor [6]. Minimization of noise created by an induction motor was minimized by formulating it as a nonlinear programming problem with eight independent variables [7]. Genetic Algorithm was applied for design optimization of a magnetizer by optimizing its pole face to obtain the desired flux density distribution [8]. Optimal lamination approach was proposed for global optimization of induction motor design [9]. Evolutionary Algorithm, Simple Genetic Algorithm and Simulated Annealing were used for optimization of design of induction motor [10], [11]. A method to estimate flux linkages and parameters of induction motor using a finite element model was discussed [12]. Simulated Annealing algorithm was applied to solve the problem of ODIM for three different objective functions [13].

Recently a new evolutionary computation technique called Particle Swarm optimization has been proposed and introduced. PSO is based on the analogy of swarm of bird and school of fish [14]. PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. In PSO, each individual makes his decision using his own experience together with other individuals’ experiences [15]. The algorithm, which is based on metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multi dimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors [16]. The main advantages of PSO algorithm are summarized as simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques. Unlike the other heuristic techniques, PSO has a flexible and well balanced mechanism to enhance and adapt to the global and local exploration abilities.

The proposed approach has been examined and tested on two sample motors whose details are given in Appendix. The potential and effectiveness of the proposed approach...
are demonstrated. Additionally the results are compared to those reported in the literature.

II. OPTIMIZATION OF THREE-PHASE INDUCTION MOTOR DESIGN-PROBLEM FORMULATION

A general nonlinear programming problem can be stated in mathematical terms as follows:

\[ F(X) = \text{function to be optimized} \]

\[ \text{subject to: } g_i(X) \leq 0, \quad i = 1, 2, \ldots, m \]

Such that \( F(X) \) is a maximum or minimum and \( g_i(X) \) are the constraint functions. It is to be noted that the constraints are all of inequality type. The following constraints are imposed in an induction motor design.

\[ \text{Motor1} \quad F(X) \quad \geq \quad 0.07 \, \text{Motor2} \]

\[ \text{Full load slip} \leq 0.07 \]

\[ \text{Full load power factor} \geq 0.75 \]

Apart from these constraints, mechanical considerations introduce a constraint namely the shaft diameter being above a particular value. This value is taken from standard requirement. To limit saturation in the machine, it is imperative to put an upper bound on the operating flux densities. Hence the maximum tooth flux density becomes a constraint. Thus in all there are five constraints besides the physical realizability criterion that all the variables in \( X \) should be greater than zero. A very important problem is to select the independent variables in an induction motor. In the design synthesis of a motor, if large number of variables is selected, the problem will become very complicated. Variables like slot opening, lip height, wedge height etc have only a small influence on the performance of the motor. All but a few of the variables can either be treated as being fixed for a particular motor or expressed in terms of other variables. Thus the following eleven variables which govern the objective functions and constraints critically were selected [13].

- Length of stator stack (m) \( x_1 \)
- Width of stator slot (m) \( x_2 \)
- Depth of stator slot (m) \( x_3 \)
- Depth of end ring (m) \( x_4 \)
- Width of rotor slot (m) \( x_5 \)
- Depth of rotor slot (m) \( x_6 \)
- Air gap flux density (Weber per sq m) \( x_7 \)
- Air gap length (m) \( x_8 \)
- Width of end ring (m) \( x_9 \)
- Internal dia. of stator (m) \( x_{10} \)
- External dia. of stator (m) \( x_{11} \)

The constraint functions are expressed in terms of the independent variables. In the present case, four objective functions have been considered.

1. The first objective function is taken as the efficiency of induction motor. An improvement in efficiency would have a significant impact on energy conservation in the global arena.

2. The second objective function is the active material cost of the induction motor which includes the cost of iron stampings and cost of copper in stator and rotor. The design corresponding to this objective will result in a motor that is cheap compared to that obtained from other objectives.

3. The third objective function is the ratio between starting torque and full load torque. The design corresponding to this objective is expected to result in a motor with improved starting performance.

4. The fourth objective function is the temperature rise of induction motor. This is considered to design the motor for effective cooling and dissipation of heat by minimizing the temperature rise.

III. PARTICLE SWARM OPTIMIZATION

A. Overview

Similar to evolutionary algorithms, the PSO technique conducts searches using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO system, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. In social science context, a PSO system combines a social-only model and a cognition-only model [14]. The social-only component suggests that individuals ignore their own experience and adjust their behavior according to the successful beliefs of individuals in the neighborhood. On the other hand, the cognition-only component treats individuals as isolated beings. A particle changes its position using these models. The advantages of PSO over other traditional optimization techniques can be summarized as follows [17].

a. PSO is a population-based search algorithm (i.e., PSO has implicit parallelism). This property ensures PSO to be less susceptible to getting trapped on local minima.
b. PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, PSO can easily deal with non-differentiable objective functions. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization methods.
c. PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO more flexible and robust than conventional methods.
d. Unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of PSO overcomes the premature convergence problem and enhances the search capability.
e. Unlike the traditional methods, the solution quality of the proposed approach does not rely on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution.

B. PSO Algorithm

The basic elements of PSO technique are briefly stated and defined as follows

- **Particle \( X(t) \):** It is a candidate solution represented by an \( m \)-dimensional real-valued vector, where \( m \) is
the number of optimized parameters. At time \( t \) the \( j \) th particle can be described as \( X_j(t) = [x_{j,1}(t), x_{j,2}(t), \ldots, x_{j,m}(t)] \) where \( 'x' \) are the optimized parameters, and \( x_{j,k}(t) \) is the position of the particle with respect to the \( k \) th dimension (i.e., the value of the \( k \) th optimized parameter in the \( j \) th candidate solution).

- **Population pop(t):** It is a set of \( n \) particles at time \( t \) (i.e., \( \text{pop}(t)=[X_1(t), X_2(t), \ldots, X_n(t)] \)).
- **Swarm:** It is an apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction [18].
- **Particle Velocity \( V(t) \):** It is the velocity of the moving particles represented by an \( m \) dimensional real-valued vector. At time \( t \), the \( j \) th particle velocity \( V_j(t) \) can be described as, \( V_j(t) = [v_{j,1}(t), v_{j,2}(t), \ldots, v_{j,m}(t)] \) where \( v_{j,k}(t) \) is the velocity component of the \( j \) th particle with respect to the \( k \) th dimension.
- **Weighting Function \( w(t) \):** It is a control parameter that is used to control the impact of the previous velocities on the current velocity. Hence, it influences the tradeoff between the global and local exploration abilities of the particles [18]. For initial stages of the search process, large weight to enhance the global exploration is recommended while, for last stages, the weight is reduced for better local exploration. The weighting function is defined as \( w = w_{\text{max}} - \left((w_{\text{max}} - w_{\text{min}}) \times \frac{\text{Iter}}{\text{Iter}_{\text{max}}}) \right) \) where \( w_{\text{max}} \) and \( w_{\text{min}} \) are initial and final weights, \( \text{Iter}_{\text{max}} \) maximum iteration number and \( \text{Iter} \) current iteration number.
- **Individual Best \( X^*(t) \):** As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best \( X^*(t) \). For each particle in the swarm, \( X^*(t) \) can be determined and updated during the search. In a minimization problem with objective function \( J \), the individual best of the \( j \) th particle \( X_j^*(t) \) is determined so that \( J(X_j^*(t)) \leq J(X_j(t)) \), \( \forall j \). For simplicity, assume that \( J_\text{best} = J(X_j^*(t)) \). For the \( j \) th particle, individual best can be expressed as \( X_j^*(t) = [x_{j,1}^*(t), x_{j,2}^*(t), \ldots, x_{j,m}^*(t)] \).
- **Global Best \( X^{**}(t) \):** It is the best position among all of the individual best positions achieved so far. Hence, the global best can be determined such that \( J(X^{**}(t)) \leq J(X_j^*(t)) \), \( j=1, 2, \ldots, n \). For simplicity, assume that \( J^{**} = J(X^{**}(t)) \).
- **Stopping Criteria:** These are the conditions under which the search process will terminate. In this study, the search will terminate if the number of iterations reaches the maximum allowable number.

The particle velocity in the \( k \) th dimension is limited by some maximum value, \( v_{\text{max}} \). This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning [14]. The maximum velocity in the \( k \) th dimension is characterized by the range of the \( k \) th optimized parameter and given by \( v_{k,\text{max}} = (x_{k,\text{max}} - x_{k,\text{min}})/N \), where \( N \) is the number of intervals in the \( k \) th dimension. In a PSO algorithm, the population has \( n \) particles that represent \( m \) candidate solutions. Each particle is an \( m \) dimensional real-valued vector, where \( m \) is the number of optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space. The PSO technique can be described in the following steps.

**Step 1) Initialization:** Set the time counter \( t = 0 \) and generate \( n \) random particles, \( \{X_j(0), j=1,2,\ldots,n\} \), where \( X_j(0) = [x_{j,1}(0), x_{j,2}(0), \ldots, x_{j,m}(0)] \). \( X_j(0) \) is generated by randomly selecting a value with uniform probability over the \( k \) th optimized parameter search space \( [x_{k,\text{min}}, x_{k,\text{max}}] \). Similarly, generate randomly initial velocities of all particles, \( \{V_j(0), j=1,2,\ldots,n\} \), where \( V_j(0) = [v_{j,1}(0), v_{j,2}(0), \ldots, v_{j,m}(0)] \). \( v_{j,k}(0) \) is generated by randomly selecting a value with uniform probability over the \( k \) th dimension \( [v_{k,\text{min}}, v_{k,\text{max}}] \). Each particle in the initial population is evaluated using the objective function, \( J \). For each particle, set \( X_j^*(0) = X_j(0) \) and \( J_j^* = J_{\text{best}} \). Set the initial value of the weight parameter \( w_{\text{min}} \) and \( w_{\text{max}} \).

**Step 2) Time Updating:** Update the time counter \( t = t + 1 \).

**Step 3) Weight Updating:** Update the weight parameter \( w(t) = w_{\text{max}} - ((w_{\text{max}} - w_{\text{min}}) \times \frac{\text{Iter}}{\text{Iter}_{\text{max}}}) \).

**Step 4) Velocity Updating:** Using the global best and individual best, the \( j \) th particle velocity in the \( k \) th dimension is updated according to the following equation:

\[
v_{j,k}(t) = w(t)v_{j,k}(t-1) + c_1r_1(x_{j,k}^*(t-1) - x_{j,k}(t-1)) + c_2r_2(x_{j,k}^{**}(t-1) - x_{j,k}(t-1))
\]

where \( c_1 \) and \( c_2 \) are positive constants and \( r_1 \) and \( r_2 \) are uniformly distributed random numbers in \([0,1]\). Check the velocity limits. If the velocity violated its limit, set it at its proper limit. It is worth mentioning that the second term represents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

**Step 5) Position Updating:** Based on the updated velocities, each particle changes its position according to the following equation: \( x_{j,k}(t) = x_{j,k}(t-1) + v_{j,k}(t-1) \). The resulting position of each particle in not always guaranteed to satisfy the inequality constraints due to over/under velocity. If any particle violates its inequality constraint due to over/under speed, then the position of the particle is fixed at its maximum/minimum operating point. Therefore this can be formulated as [19]
The following steps were followed in the implementation of PSO to ODIM:

1. Choose the population size & number of iterations.
2. Specify the minimum limits and maximum limits values of independent variables.
3. Set the time counter $t = 0$ and generate randomly $n$ particles $\{X_i = 0, i = 1, 2, ..., n\}$ where $X_i$ is the initial value for $i$th independent variable and is generated by random selecting a values with uniform probability over the $k$ optimized parameter search space $[X_{min}, X_{max}]$. Similarly generate randomly initial velocities of all particles $\{V_i = 0, i = 1, 2, ..., n\}$, where $V_i$ is randomly generated by randomly selecting a value with uniform probability over the $k$th dimension $[-V_{i, max}, V_{i, max}]$ evaluate objective function (Efficiency, $\eta$, $\tau$, $T_{st}$, $T_{fl}$, Stator temperature rise, Active material cost) for each particle. Maximum velocity of a particular dimension is given by $V_{max} = \left[\frac{X_{max} - X_{min}}{Na}\right]$ where $Na$ = No of intervals.
4. Evaluate the fitness for each particle according to the objective function. (Including penalty functions)
5. Set Gbest_counter = 1.
6. For each particle, as its best position, say it as Pbest and assign Gbest that corresponds to the $X_i(0)$=$X_{i,0}$, $X_{i,0}$, $X_{i,0}$, $X_{i,0}$ particle shown by Gbest_counter from Pbest.
7. Update the time counter $t = t + 1$.
8. Using the global best the individual best of each particle, the $i$th particle velocity in the dimension is updated. It is worth mentioning that the second term represents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptive of knowledge. If a particle violates the velocity limits, set its velocity equal to the limit.
9. Based on the updated velocities, each particle changes its position. If a particle violates the position limits in any dimension, set its position at the proper limit.
10. Personal best positions are updated.
11. After first iteration the Gbest_counter Update itself according to the minimum value of the fitness function from the Pbest set.
12. When the stopping criteria reaches 50 (number of iteration), the procedure comes to end, else go to Step 7.

The above mentioned approach has been implemented on two sample three-phase induction motors [20], [21] (Appendix). Where the particles are equivalent to independent variables in the optimization process $(X_1, ..., X_11)$. Practically, it is seen that the most effective parameters on PSO performance are the weight parameters and the maximum allowable velocity. Initially, several runs have been done with different values of these two parameters. The results are tabulated in Tables I-III. These programs were implemented using MATLAB 6.5® on a PC with configuration as P-IV, 1.9 GHz; the computation time taken by the computer is shown in table II, IV.

V. RESULTS AND DISCUSSION

The results show better performance with weight parameters in the range $[0.4, 1]$ and number of intervals $N \in [5, 10]$. It is worth mentioning that these parameters should be selected carefully for efficient performance of PSO. In our implementation, the weight parameters $w_{min}$, $w_{max}$ and the number of intervals $N$ in each space dimension are selected as 0.4, 0.8 and 10, respectively. It was observed that these values work satisfactorily in all simulation results of this work. Other parameters were set as number of particles $n = 25$, $c_1 = c_2$ = random numbers in the range 0 to 1, and the search will be terminated if the number of iterations reaches 50.

In order to demonstrate the effectiveness and robustness of the technique, several cases with different objectives to maximize the efficiency, improve the starting performance, to minimize active material cost and to enhance the heat dissipation in the motor have been considered as follows.

Case I- Maximization of efficiency

In this case the objective function $F$ is considered as the induction motors’ efficiency. The variation of efficiency of sample motors 1 and 2 with iterations is shown in Fig. 1.

Initially the efficiency is 72.91 % and 75.02 % respectively for motors 1 and 2. The efficiency obtained by the proposed technique is 85.4 % and 88.5 %, respectively.

It is clear that the efficiency is greatly increased (13% increase).

The main dimensions of the motor have reduced significantly thereby resulting in a huge saving in material and hence cost of the motor. With increase in efficiency, temperature rise has decreased. Power factor and starting torque to full load torque ratio has increased. Thus optimization of motor efficiency using PSO results in a motor whose operating performance is improved along
with a considerable reduction in main dimensions and hence active material cost.

Case-2 Minimization of active material cost

Here the objective function is the active material cost which includes the cost of iron stampings and cost of copper in stator and rotor. The variation in cost is shown in Fig. 2.

The initial cost is Rs.3010.9 and Rs 5221.4 respectively. The proposed approach results in a final cost of Rs 2175.3 and Rs 4379.6. There is a considerable reduction in active material cost (28% and 16% for motors 1 and 2). However the efficiency, full load slip and torque ratio have reduced compared to that of case 1. Thus PSO results in a cheaper motor whose performance is slightly deteriorated compared to that of case 1.

Case-3 Enhancement of starting performance

The objective function considered here is the ratio between starting and full load torque which plays a vital role in deciding the starting performance of the motor. The variation in torque ratio is depicted in Fig. 3.

The initial ratio is 0.91 and 0.83 respectively for motors 1 and 2. The PSO based approach results in 1.88 and 1.42 for the same. There is a substantial increase in torque ratio which is desirable. However, the cost of the motor has increased and efficiency has decreased with increase in torque ratio. Thus PSO applied to maximize starting torque results in a costlier and less efficient motor.

Case-4 Improvement of heat dissipation in the motor

The minimization of temperature rise in a motor plays an important role in limiting the losses in a motor which in turn results in an increase in efficiency of the motor. The initial value of temperature rise in the stator of motor is 50.7 and 47.02 degree centigrade respectively for motors 1 and 2 (Fig. 4).

The PSO based minimization of temperature rise procedure results in final value of 32.08 and 26.76 degree centigrade. There is a considerable reduction in temperature rise in the motor which reduces the losses taking place and increases the efficiency of the motor. Thus by reducing the temperature rise, the heat dissipation property of the motor is improved.

From the above discussion, the following salient points were observed.

1. Considering the efficiency as an objective function the overall performance of motor has increased along with the air gap flux density and temperature of stator.
2. Material cost as an objective function, the stator stack length and temperature in the case of stator has reduced when compared with other methods.
3. Tst/Tfl as an objective function the overall dimension has increased thereby increasing the material cost of the motor. The performance of the motor has deteriorated.
4. Temperature rise as an objective function the overall main dimension of the motor has increased. Increase in the main dimension leads to improved heat dissipation property of the motor.
Fig. 3. Variation of torque ratio for sample motors 1 and 2.

Fig. 4. Variation of temperature rise for sample motors 1 and 2.

TABLE III
RESULTS FOR SAMPLE MOTOR-2

<table>
<thead>
<tr>
<th>Variables</th>
<th>Conventional design</th>
<th>Objective function</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Efficiency</td>
<td>Active material cost</td>
</tr>
<tr>
<td>Length of stator stack (m)</td>
<td>0.09</td>
<td>0.1195</td>
</tr>
<tr>
<td>Width of stator slot (m)</td>
<td>0.0076</td>
<td>0.0082</td>
</tr>
<tr>
<td>Depth of stator slot (m)</td>
<td>0.024</td>
<td>0.0104</td>
</tr>
<tr>
<td>Depth of end ring (m)</td>
<td>0.012</td>
<td>0.0091</td>
</tr>
<tr>
<td>Width of rotor slot (m)</td>
<td>0.0065</td>
<td>0.0046</td>
</tr>
<tr>
<td>Depth of rotor slot (m)</td>
<td>0.0105</td>
<td>0.0091</td>
</tr>
<tr>
<td>Air gap flux density (wbl/m²)</td>
<td>0.63</td>
<td>0.62</td>
</tr>
<tr>
<td>Air gap length (m)</td>
<td>0.0004</td>
<td>0.0004</td>
</tr>
<tr>
<td>Width of end ring (m)</td>
<td>0.015</td>
<td>0.0148</td>
</tr>
<tr>
<td>Internal dia. of stator (m)</td>
<td>0.15</td>
<td>0.1273</td>
</tr>
<tr>
<td>External dia. of stator (m)</td>
<td>0.24</td>
<td>0.207</td>
</tr>
<tr>
<td>Efficiency (%)</td>
<td>83.0%</td>
<td>88.5005</td>
</tr>
<tr>
<td>Active material cost (Rs)</td>
<td>5391.28</td>
<td>5252.681</td>
</tr>
<tr>
<td>Tst/Tfl</td>
<td>31.1539</td>
<td>30.0825</td>
</tr>
<tr>
<td>Temperature rise of stator (°C)</td>
<td>0.8444</td>
<td>0.8461</td>
</tr>
<tr>
<td>Full load power factor</td>
<td>0.7731</td>
<td>0.8405</td>
</tr>
</tbody>
</table>

TABLE IV
COMPUTATION TIME TAKEN BY PSO FOR SAMPLE MOTOR 2

<table>
<thead>
<tr>
<th>Objective function</th>
<th>Time taken (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>4.985</td>
</tr>
<tr>
<td>Active material cost</td>
<td>3.563</td>
</tr>
<tr>
<td>Tst/Tfl</td>
<td>5.875</td>
</tr>
<tr>
<td>Temperature rise</td>
<td>6.625</td>
</tr>
</tbody>
</table>

dissipation and hence temperature rise of the motor is reduced. The area of the end ring has reduced.

VI. CONCLUSIONS

In this paper, a novel PSO based approach to ODIM is presented. The proposed approach utilizes the local and global exploration capabilities of PSO to search for optimal dimensions of the motor. Different objective functions have been considered to maximize efficiency, starting torque to full load torque ratio, minimize cost of active material and minimize temperature rise in the motor. The proposed approach has been tested and examined with different objectives to demonstrate its effectiveness and robustness. The results using the proposed approach were compared to those from conventional method. The results confirm the potential of the proposed approach and show its effectiveness and superiority over the conventional techniques.

ACKNOWLEDGEMENT

The authors express their gratitude to the authorities of Annamalai University, Chidambaram, for permitting to do this work and for providing all the facilities.

APPENDIX I

Sample Motor 1 [20]
Capacity : 3 hp
Voltage per phase: 400volts
Frequency : 50 Hz
Number of poles: 4
Number of stator slots: 36
Number of rotor slots: 44

Sample Motor 2 [21]
Capacity : 5 hp
Voltage per phase: 400volts
Frequency: 50 Hz
Number of poles: 6
Number of stator slots: 36
Number of rotor slots: 30

REFERENCES


R. Kannan received his B.E. degree in Electrical Engineering from Annamalai University in 2000 and M.E. degree in Power System Engineering in 2005 from the same University. He is working as a Lecturer in the Department of Electrical Engineering, Annamalai University. His areas of interest are electrical machine design, power system optimization.

R. Bhuvaneswari received B.E. degree in Electrical Engineering from Annamalai University in 1992 and M.E. degree in Power System Engineering in 2002 from the same University. At present she is working as a Selection Grade Lecturer in the Department of Electrical Engineering, Annamalai University. Her areas of interest are electrical machines and power systems.

S. Subramanian is a Professor in Electrical Engineering, Annamalai University. He obtained his B.E. (Electrical) and M.E. (Power Systems) from Madurai Kamaraj University and PhD in Power system Economics from Annamalai University in the year 1989, 1990 and 2001 respectively. His research interest includes power system economics, electrical machine design and voltage stability studies. He is a member of Institution of Engineers, Indian Society for Technical Education and Systems Society of India.