Gaussian Mutation Strategy based self-adaptive Evolutionary programming to optimize the PMSG geometrical parameters.

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Abstract: In this paper, novel hybrid intelligent methods based on combined RBF neural network and Dynamic PSO (DYPSO-RBFNN), RBF neural network and Gaussian Mutation Strategy based self-adaptive Evolutionary programming(GMEP-RBFNN) have been developed and applied separately to optimize permanent magnet length bm and rotor slot opening bo simultaneously to maximize the linkage and mutual flux components and minimize the leakage flux component of PMSG. The use of self adaptive Gaussian mutation strategy has been applied to make the solution free from manual tuning of strategy parameters. The simultaneous estimation of permanent magnet length and rotor slot opening parameters provides the comfort in design process as well saving in the computation cost. The performance of GMEP has been compared with dynamic PSO to understand the relative benefits. It is observed that GMEP outperforms DYPSO in terms of maximizing the linkage and mutual flux components and minimizing the leakage flux component of PMSG. In terms of algorithm characteristics GMEP is having better and consistent convergence in compared to DYPSO.

Keywords: Permanent magnet synchronous generators (PMSG),Dynamic Particle Swarm Optimization (DYPSO), Gaussian Mutation Strategy based self-adaptive Evolutionary programming (GMEP)

1. INTRODUCTION

Wind energy is renewable, clean and is an emerging resource for the power generation. A recently published report [1] reports a phenomenal wind power generation growth of 17% in 2015 when compared to 2014. Total of 433 GW power was generated from wind farm installations in 2015 globally. A rapid growth and additional power generation estimates till 2050 is also mentioned in the report. Conversion efficiency improvement and cost reduction of wind turbines play a vital role in the growth reported [1].The wind turbines (WT) convert kinetic energy of the wind into mechanical power. The mechanical power is converted to electrical power later by using a gearbox and generator assembly. The two types of Wind Turbines commonly used are: vertical-axis wind turbine and horizontal-axis wind turbine. Horizontal-axis wind turbine is the most commonly used one in which rotating blades are situated on parallel-axis to the land. The gearbox used in Wind Turbine Generator machine for transferring power from turbines blades to generator are of three types Single-Stage, Multi-Stage and Direct-drive. Researchers have proved that a direct drive wind turbines perform better than its geared counterparts [2, 3, and 4]. Research work presented in [4, 5, 6 and 7] prove that permanent magnet generators in Wind Turbine Generators are preferred and most widely accepted in wind farm installations. A permanent magnet generator with direct drive configuration is most suitable due to its low manufacturing cost, low maintenance cost, high availability and high efficiency. Improving efficiency to maximize electrical power generation is always a desired feature of Wind Turbine Generator designers. To improve efficiency of Wind Turbine Generator, numerous optimization techniques are incorporated at various levels of design and manufacturing. In this present work, we use novel hybrid intelligent methods based on combined RBF neural network and PSO (PSO-RBFNN), RBF neural network and Gaussian Mutation Strategy based self-adaptive Evolutionary programming separately to optimize permanent magnet length bm and rotor slot opening bo simultaneously to maximize the linkage and mutual flux components and minimize the leakage flux component of PMSG.

Paper organization is as follows. Literature review is presented in section 2. The PMSG transverse section geometry is presented in section 3. The basic concepts concerning RBFNN, the dynamic PSO and Evolutionary programming are presented in sections 4, 5 and 6 respectively. The methodology proposed is described in section 7. The experimental results and comparisons are described in section8. In section 9 conclusions of this research work are given finally.

2. LITERATURE SURVEY

Permanent magnet synchronous generator (PMSG) is eventually making a serious impact on to the direct drive wind power application. In [8], a 2D finite element method has been proposed for optimization of transverse geometry of permanent magnet synchronous generator (PMSG) used for generating wind power. The magnetic flux of the generator is maximized by varying the permanent magnet length and rotoric slot opening dimensions by keeping the same diameter of the rotor. In [9] various wind generator systems are evaluated by optimization designs and comparisons. In [10], the electrical parameters of a PMSG namely the phase resistance, the phase inductance and the linkage flux of the rotor permanent magnet were identified by using particle swarm optimization (PSO) algorithm based on experimental tests. An investigation is carried out for optimization of radial surface permanent-magnet generator (PMSG) with an outer rotor used for wind power applications in [11]. An optimization strategy has been proposed in [12] that take into consideration the annual wind profile of a wind turbine to design a high-efficiency permanent magnet synchronous generator. An analysis of a permanent magnet synchronous generator is proposed in [13] based on the reduction of cogging torque by skewing slots and simultaneously the decent output performance. A design procedure is adopted for the analysis of a radial flux surface mounted PMSG in [14]. The authors have applied ∈-constrained differential evolution with gradient based mutation optimization technique in order to optimize the weight and losses of the PMSG. In [15] the multidisciplinary design optimization (MDO) of a permanent magnet synchronous generator (PMSG) employed for Wind Energy Conversion Systems (WECS) has been proposed. The objective function of the MDO is the cost minimization of a medium power Wind Energy Conversion Systems having power rating 55 kW. In addition to the model of the PMSG, the WECS model includes power loss and cost models of the power electronic converter. An optimal design of a permanent magnet synchronous generator based on metaphysics is presented in [16]. The metaphysics model of the generator and the power loss and cost models of the static power electronic converters connected to the grid are included in the design. In [17], permanent magnet length bm and rotor slot opening bo of PMSG have been optimized separately and independently to maximize the linkage flux and mutual flux components and minimize the leakage flux component. Therefore the computational cost involved is more. In order to improve the performance of optimization strategy and optimization algorithm, permanent magnet length bm and rotor slot opening bo of PMSG have been optimized simultaneously to maximize the linkage flux and mutual flux components and minimize the leakage flux component, Gaussian Mutation Strategy based self-adaptive Evolutionary programming and dynamic PSO algorithms.

3. TRANSVERSE SECTION GEOMETRY OF PMSG GENERATOR

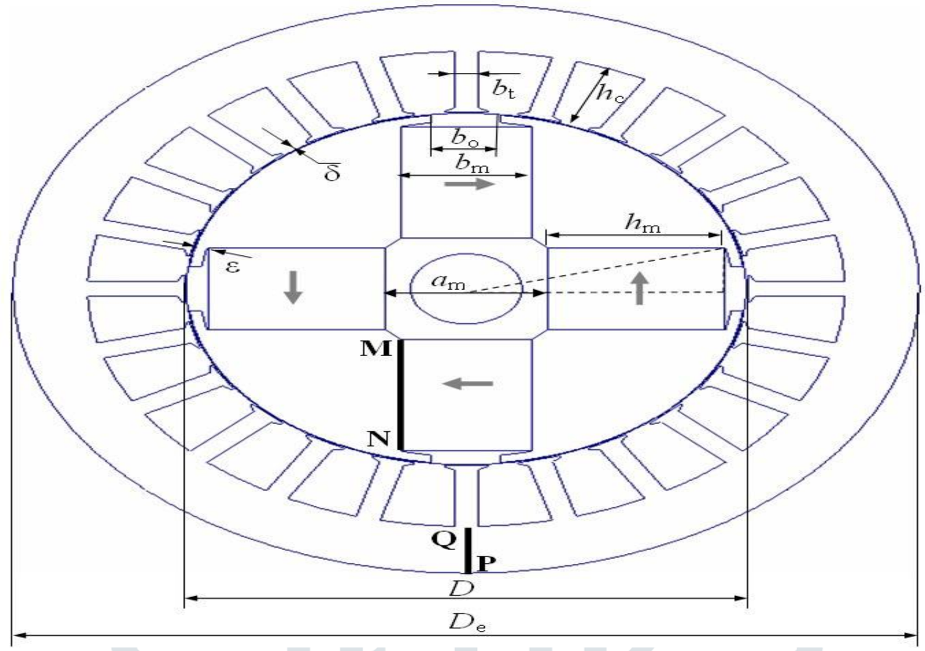

Figure 1: Transverse Section of PMSG

The PMSG machine considered in this present research work consists of four poles. In figure 1.the transverse section of the PMSG machine is shown. The permanent magnets of the PMSG machine are placed over a parallel piped iron stump. The steel parts with special shape that provide a closed path for the magnetic flux lines are used to fill the spaces between the magnets (rotor slot opening). The magnetization direction of the permanent magnets are represented by the arrows that are placed inside the permanent magnets in Figure1 represent The geometrical parameters and magnetic characteristics of the PMSG machine considered is shown in Table1. The useful magnetic flux is the average inductor magnetic flux passing through a stator tooth of the PMSG machine. The geometrical cross-section and the material characteristics of the magnetic cores of the PMSG determine the useful magnetic flux of PMSG.

Table 1**.** The permanent magnets of the PMSG machine are made up of NdFeB alloy and the geometrical and magnetic characteristics are as follows

Geometrical Parameters	**Magnet characteristics**
bt(tooth width) = 5mm, am = 38mm, ε = 3mm, δ= 0.5mm	The coercivity Hc = 979000A/m
hc(Stator Slot height)=20mm	Relative permeability of permanent magnets μ_r = 1.049
Diameter of the Rotor D = 120mm	Maximum magnetic energy of permanent magnets B.Hmax = 40 MGOe
Outer of Stator Diameter De=195mm	Electrical conductivity σ = 0.667 MS/m

The generator shaft is made up of stainless steel and it has the following properties: the relative permeability μ_r = 1 and electrical conductivity σ= 1.35 MS/m.

4. RADIAL BASIS FUNCTION (RBF) NEURAL NETWORK

Radial basis function neural networks are widely used in many engineering applications because of their fast convergence, small extrapolation errors and high reliability compared to traditional multilayer perceptrons. Because of these benefits, in this research work to estimate the magnetic flux from the finite element method, a novel method of nonlinear system identification based on constructing Radial basis function neural network has been employed. The neural network algorithm based on supervised learning is often thought-about because of the curve fitting method. The training pairs are given to the neural network. Every training pair consists of a vector from associate input house in conjunction with a desired network response. The network uses an outlined learning formula for implementing the changes of its weights, in order to reduce the error between particular and desired response relative to some optimization criteria. After the accomplishment of network training, this neural network executes the interpolation within the output vector house. The achievement of nonlinear Mapping between the input and the output vector areas are often with radial basis function. The design of the RBF NN consists of 3 layers as shown in Fig2: associate input layer, one layer of nonlinear process neurons referred to as hidden layer and the output layer. Equation (1) is used to calculate output of RBFNN which is given as follows.

$$y_i = f_i(x) = \sum_{k=1}^{N} W_{ik} \Phi_k(x, c_k) = \sum_{k=1}^{N} W_{ik} \Phi_k(\|x - c_k\|_2) \quad (1)$$

where i=1, 2,....m

Where $x \in \Re^{n \times 1}$ represents an input vector, $\phi_k(.)$ represents a function from $\Re^+$ to $\Re$, the Euclidean norm is denoted by $\|.\|_2$, W_{ik} represents the weights in the output layer, N represents the number of neurons in the hidden layer, and $c_k \in \Re^{n \times 1}$ represents the centers of RBF in the output space. For every neuron in the hidden layer, the Euclidean distance between the input to the network and weights present in the output layer is determined. The output of the hidden layer is a nonlinear function of the distance of the neural network. Henceforth the neural network's output is computed as a weighted sum of the outputs in the hidden layer. The functional form of $\phi_k(.)$ is assumed to be given and is mostly Gaussian function as given by Equation (2).

$$\Phi(x) = \exp(-x^2/\sigma^2) \quad (2)$$

where σ represents the spread parameter and it controls the "width" of RBF. The adequate sampling of the input vector space is performed by defining the centers as the defined points and they are commonly chosen as a subset of the input data. In the case of the Gaussian RBF, the spread parameter σ is normally set according to the heuristic relationship which is gives as follows

$$\sigma = \frac{d_{max}}{\sqrt{k}} \quad (3)$$

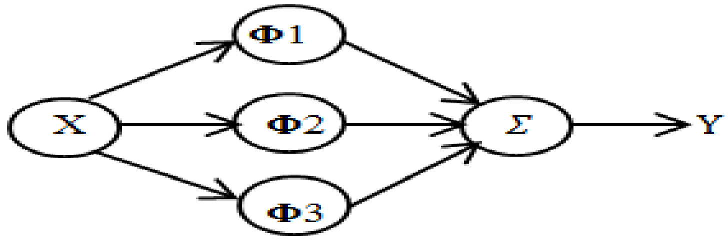

Figure 2. RBF Architecture

The centre and the width of radial basis function of the hidden layer and the weight values of the output layer mainly decide the performance of the RBF neural network. The neural network learning strategy of the traditional RBF has major drawbacks, and only finds the optimal solution in local space to determine parameters of the network structure. If the setting of these parameters is incorrect, it would cause decline in the approaching accuracy and leads to divergence of the network.

4.1. Training data

Training data as shown in Table 2 has been taken from [8]. For five different values of permanent magnet length bm, linkage flux, mutual flux and leakage flux are available. The rotor slot opening bo for this case is fixed and its value is bo=15mm. Choosing an appropriate algorithm for training a neural network is very important. To estimate the magnetic flux from the finite element method, system identification based on Radial basis function neural network has been employed in this research work. Three different RBFNN systems have been developed for the estimation of mutual flux, Linkage flux and leakage flux respectively by using the training data shown in Table 2. Pre-processing of data has been applied in terms of removal of the mean value and then the remaining data is normalized so that neural network could get better learning. The performance of training is shown in Table 3. Training data estimated by finite element method in [8] and those obtained from system identification are compared critically. It can be observed from Table 3 that there is nearly zero error in learning. Results indicate that the input-output relationships of the FEM model are more accurately mapped by RBFNN systems.

Case1: Rotor slot opening bo is fixed at 15mm and permanent magnet length bm is varied

Table.2. Training data of permanent magnet length bm for RBFNN

Magnetic length bm(mm)	**Linkage flux** ϕ_t(Wb)	**Mutual flux** ϕ_u(Wb)	**Leakage flux** ϕ_σ(Wb)
1.800e+001	1.4150e-003	1.3120e-003	1.031e-004
2.3000e+001	1.4450e-003	1.3260e-003	1.181e-004
2.800e+001	1.4570e-003	1.3290e-003	1.274e-004
3.300e+001	1.4590e-003	1.3260e-003	1.333e-004
3.800e+001	1.4330e-003	1.301e-003	1.317e-004

Table.3. RBFNN performance in training

Magnetic length bm(mm)	**Linkage flux** ϕ_t(Wb)	**Mutual flux** ϕ_u(Wb)	**Leakage flux** ϕ_σ(Wb)
1.800e+001	1.414999999999946e-03	1.311999999999957e-03	1.030999999999871e-04
2.3000e+001	1.444999999999992e-03	1.325999999999999e-03	1.180999999999922e-04
2.800e+001	1.456999999999994e-03	1.329000000000006e-03	1.273999999999893e-04
3.300e+001	1.459000000000017e-03	1.325999999999973e-03	1.332999999999944e-04
3.800e+001	1.433000000000016e-03	1.300999999999974e-03	1.317000000000025e-04

Case2: Permanent magnet length bm is fixed at 28mm and rotoric slot opening bo is varied

Training data as shown in Table 4 has been taken from [8]. For four different values of rotoric slot opening bo, training over linkage flux, mutual flux and leakage flux has been given. The performance of training is shown in Table 5. Again as in the case of ‘bm’, nearly absolute training has taken place.

Table.4. Training data of rotoric slot opening for RBFNN

Rotoric Slot opening bo(mm)	**Linkage flux** ϕ_t(Wb)	**Mutual flux** ϕ_u(Wb)	**Leakage flux** ϕ_σ(Wb)
5.000e+000	1.4679e-003	1.1902e-003	2.7770e-004
1.000e+001	1.4586e-003	1.2905e-003	1.6806e-004
1.500e+001	1.4532e-003	1.3283e-003	1.2489e-004
2.000e+001	1.4474e-003	1.3468e-003	1.0059e-004

Table.5. RBFNN performance in training

Rotoric Slot Opening bo(mm)	**Linkage flux** ϕ_t(Wb)	**Mutual flux** ϕ_u(Wb)	**Leakage flux** ϕ_σ(Wb)
5.000e+000	1.467900000000005e-03	1.190199999999931e-03	2.777000000000303e-04
1.000e+001	1.458600000000001e-03	1.290499999999974e-03	1.680600000000083e-04
1.500e+001	1.453200000000003e-03	1.328299999999976e-03	1.248900000000013e-04
2.000e+001	1.447400000000001e-03	1.346799999999964e-03	1.005900000000063e-04

5. DYNAMIC PARTICLE SWARM OPTIMIZATION (DYPSO) ALGORITHM

Dynamic particle swarm optimization (DYPSO) was originally proposed by Shi and Eberhart in which they introduced a linearly decreasing inertia weight factor into the velocity of the updated equation from the original PSO. Inertia weight factor w plays the central role in the convergence characteristics of PSO. High value of w makes PSO under the exploration stage. Low value will make the move towards the exploitation. It is very logical that at the beginning of iteration there is need of high level of exploration and as the iterations are increasing, level of exploration has to reduce. Mathematically in this work, this has been achieved by providing a reduced value of inertia weight w as a function of iterations as given by Equation (4).

The DYPSO balances out the global and local search abilities of the swarm effectively and therefore an improvement in the performance can be expected from DYPSO compared to the original version of PSO. In DYPSO, the inertia weight ‘w’ is linearly decreased from 1.2 to 0.1 through the search process with iterations

$$w = w_{max} - \frac{(w_{max} - w_{min})}{iter_{max}} \times iter \qquad (4)$$

Where w_{max}: initial weight. wmin: final weight. itermax : maximum iteration number. iter: current iteration number.

6. EVOLUTIONARY PROGRAMMING

Evolutionary computation uses computational models of evolutionary processes as key elements in the design and implementation of computer-based problem solving systems. There are a variety of evolutionary computational models that have been proposed and studied which we will refer to as evolutionary algorithms. They share a common conceptual base of simulating the evolution of individual structures via processes of selection and reproduction. These processes depend on the perceived performance (fitness) of the individual structures as defined by an environment. More precisely, evolutionary algorithms maintain a population of structures that evolve according to rules of selection and other operators, such as recombination and mutation. Each individual in the population receives a measure of its fitness in the environment. Selection focuses attention on high fitness individuals, thus exploiting the available fitness information. Recombination and mutation perturb those individuals, providing general heuristics for exploration.

In the most elementary of models, it may be summarized as a difference equation given by equation (5):

$$x\,[\mathrm{t}+1] = s\,(\mathrm{V}(x[\mathrm{t}])) \qquad (5)$$

where the population at time, t, denoted as *x[t]*, is operated on by random variation, v, and selection, *s*, to give rise to a new population *x[t* + 1]. Natural evolution does not occur in discontinuous time intervals, but the use of a digital computer requires discrete events. Over successive iterations of variation and selection, an evolutionary algorithm can drive a population toward particular optima on a response surface that represents the measurable worth of each possible individual that might reside in a population. *Evolutionary computation* is the field that studies the properties of these algorithms and similar procedures for simulating evolution on a computer. it can be seen that evolutionary algorithms differ substantially from more traditional search and optimization methods. The most significant differences are:

- Evolutionary algorithms search a population of points in parallel, not just a single point.
- Evolutionary algorithms do not require derivative information or other auxiliary knowledge; only the objective function and corresponding fitness levels influence the directions of search.
- Evolutionary algorithms use probabilistic transition rules, not deterministic ones.
- Evolutionary algorithms are generally more straightforward to apply, because no restrictions for the definition of the objective function exist.

Evolutionary algorithms can provide a number of potential solutions to a given problem. EP is often used as an optimizer.

After initialization, all *N* individuals are selected to be parents, and then are mutated, producing *N* children. These children are evaluated and *N* survivors are chosen from the 2*N* individuals, using a probabilistic function based on fitness. In other words, individuals with a greater fitness have a higher chance of survival. The form of mutation is based on the representation used, and is often adaptive. For example, when using a real-valued vector, each variable within an individual may have an adaptive mutation rate that is normally distributed with a zero expectation. Recombination is not generally performed since the forms of mutation used are quite flexible and can produce perturbations similar to recombination, if desired. One of the interesting and open issues is the extent to which an EA is affected by its choice of the operators used to produce variability and novelty in evolving populations. The function form of EP has shown in Figure 3.

```
procedure EP; {
t = 0;
initialize population P(t);
evaluate P(t);
 until (done) {
          t = t + 1;
          parent_selection P(t);
            mutate P(t);
            evaluate P(t);
            survive P(t);
           }   }
```

Figure 3. The functional form of evolutionary programming algorithm.

7. PROPOSED SOLUTION

The flow chart for RBFNN learning algorithm is shown in Figure 4. The major objective of this research work is to find the optimum values of geometrical parameters namely, length of permanent magnet bm and slot opening of rotor bo simultaneously to maximize the linkage flux and mutual flux components and minimize the leakage flux component of permanent magnet synchronous generator (PMSG) used for Wind Energy Conversion Systems (WECS).

The novel hybrid intelligent algorithms method based on combination of RBF neural network and dynamic PSO (DYPSO-RBFNN), RBF neural network and Gaussian Mutation Strategy based self-adaptive Evolutionary programming (GMEP-RBFNN) are adapted separately to optimize bm and bo of PMSG simultaneously. For different values of bm/bo through finite element method, the different magnetic fluxes (linkage flux, mutual flux and leakage flux) have been estimated and stored as a data set in [8]. This data set has been taken to train three radial basis function neural networks (RBFNN). Linkage flux is estimated by first RBFNN, the second RBFNN is used to estimate Mutual flux and the third one is used to estimate the leakage flux instantaneously for any value of bm/bo as an input.

Gaussian Mutation strategy based self –Adaptive Evolutionary Programming and dynamic PSO have been applied separately and independently to find the optimal value of bm/bo simultaneously by estimating the fitness of the solution with help of obtained corresponding magnetic fluxes from RBFNN. The GMEP and DYPSO algorithms are utilized to perform a 2-D search in the solution space to determine optimal value of bm and bo is simultaneously.

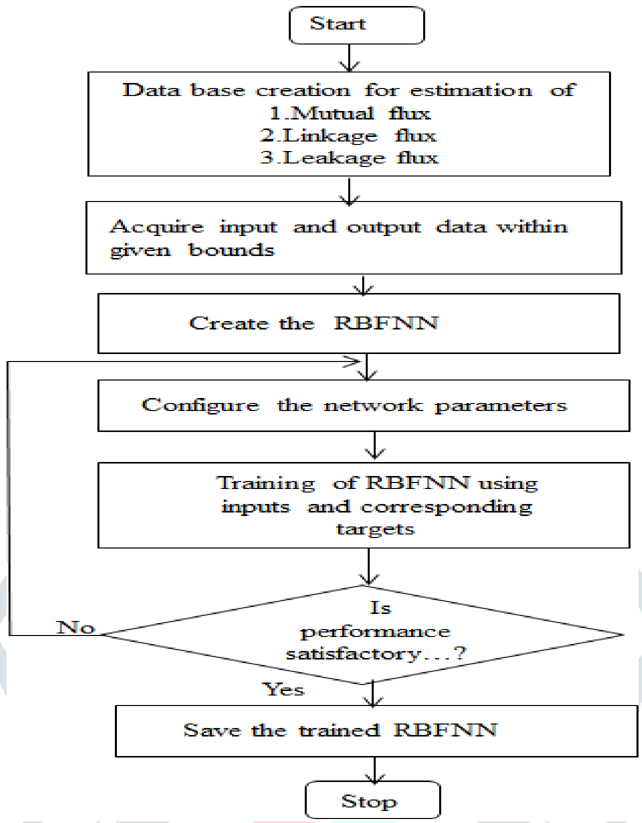

Figure 4. Flow chart of RBFF learning algorithm

Algorithmic steps in Gaussian Mutation strategy based self –Adaptive Evolutionary Programming in flux maximization:

1. A population of N trail solution initialized. Each solution taken as a pair of two real valued vector (x_i, σ_i), for all i Є {1, 2,…….N}.

   The initial components of each x_i, for all i Є {1, 2,……N} were selected in accordance with a uniform distribution ranging over a presumed solution space.

   The values of σ_i, for all i Є {1 . . . . N}, the so called strategy parameters were initially set to some value.

2. The fitness score of each solution x_i evaluated in light of an objective function Φ (x_i).

$$\Phi\ (xi) = \frac{(TMF_{bm} + TMF_{bo})}{2} \quad ; \qquad (6)$$

Where $TMFbm$ and $TMFbo$ are the total magnetic flux achieved with the corresponding bm and bo values.

$$TMF = linkage\ flux + mutual\ flux - leakage\ flux \qquad (7)$$

3. One offspring (x'_i, σ'_i) generated from each parent (x_i, σ_i) by self adaptive Gaussian mutation strategy.

$$x'i\,(j) = xi\,(j) + \sigma i\,(j).N(0,1) \qquad (8)$$

$$\sigma' i\ (j) = \sigma i\ (j)\, exp(\tau'\, N(0,1) + \tau\, Nj(0,1)) \qquad (9)$$

$$for\ all\ j \in \{1, \ldots .n\}$$

where

$xi\,(j),\ x'i\,(j),\ \sigma i\ (j),\ \sigma i\ (j)$ denote the jth component of the vectors $xi\,,\ x'i\,,\ \sigma i\,,\ \sigma' i$ respectively.

$N(0,1)$ → a realization of standard Gaussian random variable.

$Nj(0,1)$ → a random variable is sampled a new for each value of the j.

τ and τ' are the constant and dimensional dependent as given below

$$\tau = \left[\sqrt{2\sqrt{n}}\right]^{-1} \qquad (10)$$

$$\tau' = \left[\sqrt{2n}\right]^{-1} \qquad (11)$$

Where n is the dimension of problem and here it is equal to 2.

4. The fitness score of each offspring Φ (x_i) is determined.
5. Pair wise comparisons over all the 2N solution, x_i and x'_i conducted. For each solution, 10% of 2N opponents were chosen from among all parents and offspring with equal probability. In each comparison if the conditioned solution offers at least as good performance as the randomly selected opponent, it receives a 'win' tag.
6. The N best solutions out of 2N based on the number of wins received were selected to be the parents for the subsequent generation.
7. The algorithm proceeded to step 3 unless available execution time exhausted or accepted solution has been discovered.

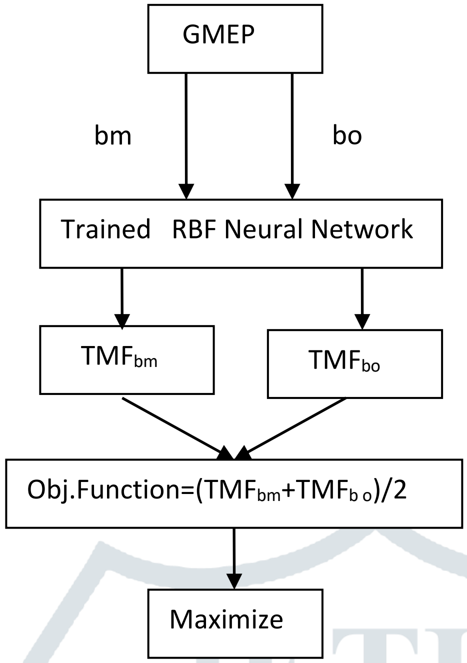

Figure 5. GMEP in PMSG parameter optimization

Gaussian mutation strategy based evolutionary programming has been applied to optimize the both parameter magnetic length and slot opening simultaneously with help of trained RBF .Two parameters bm and *bo* have explored by GMEP have passed to trained RBF to obtained the corresponding magnetic flux TMF .The mean value corresponding to TMFbm and TMFbo has considered as objective function which has to maximize as shown in Figure 5.

Both parameters were optimized using dynamic PSO (DYPSO) and Gaussian mutation strategy based EP (GMEP). The initialization of population have defined under U[0.2 1].The population size for both algorithms have been considered as 10 and allowed number of generations as 100. To understand the temporal characteristics of both algorithms 10 independent trails have been applied. In GMEP the initial value of standard deviation for Gaussian mutation has been considered as 0.01. The obtained performances for both alorithms under 10 independent trials have shown in Figure.6 and Figure.7. It is clear that in DYPSO there is slower convergence as well as issue of consistency. Performance of GMEP is not only better than DYPSO but also there is high level of consistency which is very important for practical point of view. The mean convergence characteristics for the comparison purpose have been shown in Figure.8. The obtained optimal parameters along with the corresponding magnetic fluxes have been shown in Table 6 and Table 7. It can be observed that the linkage and mutual flux components are more and value of leakage flux component is less with the parameters which have been delivered by GMEP.

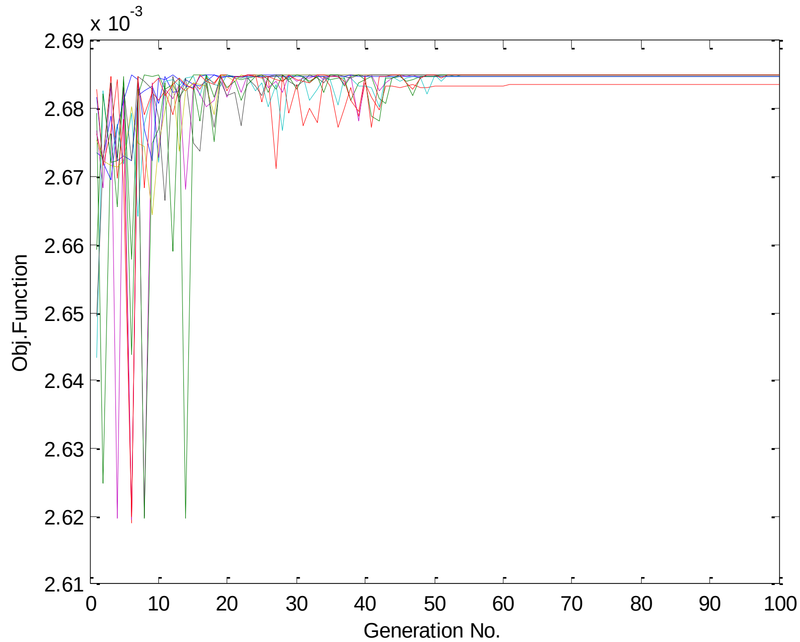

Figure 6. Convergence characteristics of DYPSO under 10 independent trials

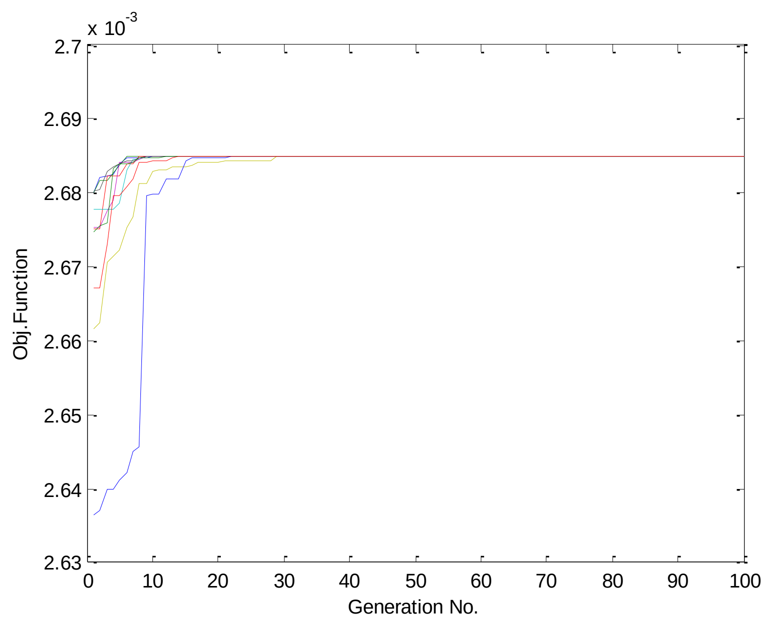

Figure 7. Convergence characteristics of GMEP under 10 independent trials

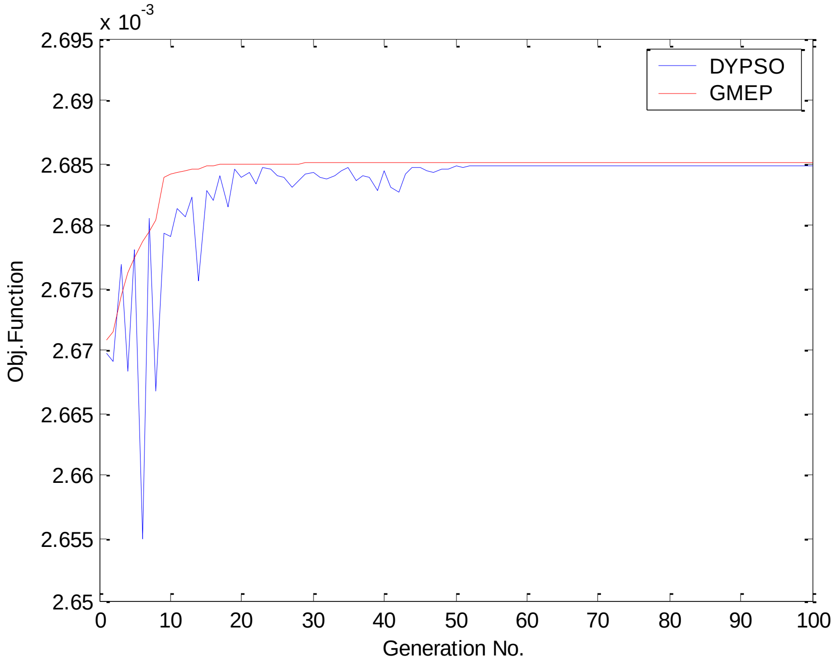

Figure 8. Mean Convergence characteristics of DYPSO & GMEP under 10 independent trials

Table.6. Performance comparison of DYPSO and GMEP for magnet length

permanent magnetic length	DYPSO	GMEP
Optimal *bm*	2.820364949491218e+001	2.855246674196535e+001
Obj.Fun val	2.685017041708837e-003	**2.685029401977366e-003**
Linkage flux	1.457314115417364e-003	1.457821033036996e-003
Mutual flux	1.329035602284756e-003	1.329079156946245e-003
Leakage flux	1.277134898846693e-004	1.282392415154010e-004

Table.7. Performance comparison of DYPSO and GMEP for slot opening

6.

Rotoric Slot pening	DYPSO	GMEP
Optimal *bo*	1.858762165937329e+001	1.858774460009358e+001
Obj.Fun. val	2.685017041708837e-003	**2.685029401977366e-003**
Linkage flux	1.447741741996738e-003	1.447741636135700e-003
Mutual flux	1.355684990771695e-003	1.355684990930294e-003
Leakage flux	9.202887716820817e-005	9.202877157911007e-005

CONCLUSION

Simulation results show the efficiency of the proposed method of self-adapting the mutation strategy in the evolutionary programming. Gaussian Mutation Strategy based self-adaptive Evolutionary programming is more efficient in maximizing the linkage flux and mutual flux components and minimizing the leakage flux component compared to DYPSO. Performance of GMEP is not only better than DYPSO but also there is high level of consistency exist which is very important for practical point of view. Hence GMEP can be used as an effective and efficient evolutionary algorithm for design optimization of wind turbine PMSG.

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