# **CHAPTER 4**

# **OPTIMIZATION AND DESIGN**

## Introduction

In the previous chapter, electrical and mechanical design parameters of the selected axial flux permanent magnet generator are presented. In order to do that, mathematical design equations and related drawings are represented. These equations are important for this thesis work, as they are used in the main design algorithm code, which is written in MATLAB. Also in the previous chapter, verification of the analytical equations of the some important design parameters is given by means of finite element analysis for a sample design. For this purpose, comparison of the design equations and the finite element analysis is made in terms of airgap flux density and induced emf. It’s concluded that the results show good agreement. Therefore, these equations can be used in the optimization algorithm with high accuracy. In this chapter, optimization process of the given design will be summarized and the optimum design parameters of the proposed 5 MW AFPM generator will be determined. Firstly, evolutionary algorithms (EA) will be reviewed including the chosen genetic algorithm (GA). Then, process of the genetic algorithm based optimization method, which is used in this thesis study, will be explained in detail. Optimization of the proposed generator is constructed with MATLAB optimization toolbox. Also in this chapter, a brief information of this toolbox and used parameters in the optimization algorithm will be covered. Finally, optimum design parameters of the proposed 5 MW 12 rpm AFPM generator will be presented. These design parameters will be used in the finite element modelling and analysis in the next chapter.

## Evolutionary Algorithms (EA) and Genetic Algorithm (GA)

There exist different mathematical search algorithms and conventional methods for modern world engineering problems. However, multi-variable nonlinear problems require new methods to avoid from getting stuck into local minimums during the optimization process [1]. The main motivation of the Evolutionary Algorithms (EA) is to mimic the nature to find the optimum solutions to these problems. EA can be evaluated as a direct, stochastic and population-based search algorithm. There are three main rules of biological processes which inspire the EA based search algorithms. These processes can be summarized as follows;

* **Continuous evolution process** which occurs at the most basic level of “source-code” of living beings, i.e. chromosomes
* **Natural Selection mechanism** in which the fittest individuals in a society can have more chance to survive and have more robust offspring than those who are not fit at all.
* **Evolutionary process at reproduction** which is done by the reproduction operators such as cross-over and mutation.

EA mimics the natural selection of living beings. Fittest one in the group has more chance to survive and to breed. Individuals correspond to encoded solutions of the given problem. Every individual has a fitness value which is calculated by the objective function of the problem. Algorithm itself evaluates the “adaptive skills” of every individual according to its fitness value. Least “fit” individuals are eliminated from the population, hence more adapted and robust individuals replace the old generations. Fitness value is the only required quantitative information about the individual in EAs, contrary to other search techniques such as gradient based optimization methods, in which derivative information is needed [2], [3]. Another advantage of evolutionary search algorithm is the population based evaluation, which is a big computational advantage over the conventional search algorithms which sample one individual at a time. This population leveled optimization is more advantageous especially when working with large search spaces [4], [5]. In Fig. 4-1, a classification table of the search techniques is given.



Fig. 4-1. Classification of the search techniques[1], [5], [6]

The most popular search technique among other techniques in the EA family is the genetic algorithm (GA). In this algorithm, individuals are generally represented as fixed-length bit strings as shown in Fig. 4-2 and Fig. 4-3 . Different cell positions in these strings contains information which corresponds to different properties of the individual they represent [5]. Two frequently used operators during the reproduction stage of GA are cross-over and mutation operators. Various “individuals” or various “solutions” can be obtained during the optimization process by using these two operators. Working principles of cross-over and mutation operators are depicted in Fig. 4-2 and Fig. 4-3, respectively. In cross-over, data interchanges between parents around the crossover point which determined in the reproduction stage. However, in mutation, random new data is written to randomly selected locus on the selected “chromosome” or “individual”.



Fig. 4-2. Bit string cross-over operation between parent individuals [5]



Fig. 4-3. Bit string mutation operation [5]

Evolutionary algorithms start with the initial population where values of the initial variables are selected randomly by selection operators based on stochastic methods. Successive generations are created based on the selection and the reproduction principles. Population size is preserved throughout the generations. Algorithm stops when termination criteria are satisfied [4], [5]. These criteria can be different conditions such as predetermined fitness value, predetermined number of successive generation or limited time.

Every problem can be solved by using EA as long as it is expressed with a proper fitness function. User should define a fitness function such that generations could converge to optimal solution. Therefore, every constraint parameter and penalty coefficient corresponding to it should exist in the fitness function maybe not equally but in a weighted form [2]. Penalty coefficients and related definitions will be covered in the following sections. Another advantage of EAs is that it can be combined with other conventional search techniques. EAs can be utilized in a parallel fashion in order to evaluate the fitness among the candidate solutions, as mentioned before. Possibility of converging local minimum is decreased due to this parallel process. Because of the high computational burden related to larger search spaces and hybridization processes, optimization techniques by using distributed computing gaining attention [5]. Also, evolutionary algorithms can easily adapt to changing environmental conditions. Therefore, it’s not necessary to restart the algorithm in case of sudden changes, contrary to as it was in the conventional search methods[1].

To sum up, evolutionary algorithms gaining popularity especially in the last two decades due to advantages aforementioned above although first attempts to use evolutionary techniques in optimization problems were made in nearly 60 years ago [4], [5]. There are two biggest key aspects of this search technique. One of is that the similarity between the nature during selection and variation stages. The other one is that it is not necessary to provide mathematical information except fitness function in order to evaluate generations of individuals [7]. Additionally, there exist a large application area of this algorithm from medical treatments to advanced engineering problems [8]. This application area seems to enlarge due to new explorations of evolutionary genetics science in biology and increased computer capacities.

## Genetic algorithms based optimization

Genetic algorithms (GA) are stochastic search techniques and exist on the subgroup of evolutionary algorithms. GA was first proposed by John Holland in 1975 with the aim of investigating the usage of natural evolutions for optimization principles [4]. The most salient feature of the GA among the other search techniques is that it doesn’t need derivative information of related search space. This feature helps GA to avoid trapping at local minimums [8], [9]. Algorithm itself based on the three operators namely selection, crossover and mutation [4], [10]. As it was in the evolutionary algorithm case, GAs can also explore the search space in a parallel fashion. Another advantage of GA is that optimization procedure can converge to global minimum solution regardless of the starting point. Crossover and mutation definitions are same for the GA, as it was mentioned in the previous section. For an effective optimization, options of the GA such as population size, cross-over and mutation possibilities and termination criteria, should be suitably configured [11].

General flowchart of a GA is given in Fig. 4-4. However, it is useful to describe some of the technical terms about GA before continue with the flowchart.

* *Gene* is a parameter which defines the specific trait of the considered solution such as stator outer diameter, axial length or airgap flux density. This parameter is encoded in the related locus of fixed-length chromosome.
* *Chromosome* is the combined form of genes, thus representing a complete “individual”.
* *Locus* is the specific position of encoded data exist in each string of individual or solution.
* *Fitness* is the measure of suitability of a generated solution for the given optimization problem. This numeric value is used by the GA when evaluating and selecting the best individual from the candidate solutions. Because of this reason GA optimizations are usually mentioned with the term “survival of the fittest”. Fitness function of the optimization problem should be constructed carefully in order to achieve the optimum design parameters of the selected AFPM topology.
* *Selection* used in GA is mainly based on stochastic processes and natural similarities. However, there are different selection methods for application such as roulette wheel selection and tournament selection [3], [5].
* *Population* can be considered as a group of individuals in one generation. Large sizes of population leads to longer solution times but larger search spaces.
* *Generation* is the set of individuals employed in one cycle of optimization. As the evaluated number of generations are increased, more fit solution candidates will be created by the GA.
* *Elitism* is related to best individuals which are preserved and directly pass to next generation without any manipulation. If number of elite is too much generations don’t change much and diversity decreases. If number of elites is low then optimization lasts longer to converge to global minimum because of large diversity.
* *Independent variable* is an optimization parameter which is changed by the GA at every iteration. For example in this thesis work, there are 15 different independent variables in the optimization process of the proposed AFPM.
* *Penalty function* is a concept that is used to convert a constrained optimization to an unconstrained optimization problem. Main idea in this concept is that to “penalize” the individuals with additional higher fitness values, whose solution parameters violate the limits of predetermined constraints.



Fig. 4-4. General flowchart of a GA optimization [11]

## MATLAB GA Toolbox Implementation

## MATLAB Toolbox and Configurations

In this thesis, optimization procedure is implemented by MATLAB optimization toolbox. For this purpose, three different codes, which include the necessary design equations described in the previous chapter, are written and tested in the MATLAB environment. These codes are mainly performs following actions;

* Optimization main handling and saving performance parameters
* Iterative loop for required multi-speed operation calculation
* Main design calculation of the generator for a given set of variables

In our design, objective function is constructed based on the cost of the proposed generator. Therefore, GA tries to minimize the total cost of the generator by using different mass combinations of different materials used in the generator. Details of the objective function and constants will be given in the following subsections. In this subsection, details and the configurations of optimization procedure will be described. Configuration parameters used in the optimization process are given in Table 4-1.

Table 4-1. Configuration parameters of the MATLAB optimization toolbox

|  |  |
| --- | --- |
| Solver | Genetic Algorithm-ga |
| Number of variables | 15 |
| Population Size | 100 |
| Fitness Scaling | Rank |
| Selection Function | Stochastic Uniform |
| Elite Count | 15 |
| Crossover Fraction | 0.9 |
| Mutation | Gaussian with Scale/Shrink |
| Crossover Function | Scattered |
| Number of Generation | 200 |
| Stall Generations | 50 |
| Stall tolerance | 1x10-6 |

As seen from Table 4-1, there are 15 different independent variables used in our design optimization. These variables can be seen in Table 4-2. Selection is realized via stochastic uniform function based on the fitness value. In this function, individuals have probability to be selected by the GA inversely proportional to their rank value. Therefore, individuals with lower rank value have more chance to be selected. Cross-over fraction determines the rate of the individual in a population (except the elite ones) which are subjected to cross-over operation during the reproduction stage. Higher rates of this parameters results in higher diversity despite longer solution times. Cross-over is realized via scattered function. In this function first a random vector, which consists of random binary numbers, is created. Then this random vector is compared with the selected parent vectors in bit-wise. Variables of the offspring individual created according to this comparison. If binary number is 1 then “gene” is taken from first parent otherwise second parent gives the related gene from its corresponding locus [12].

Table 4-2. Independent variables of the optimization

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable Vector-x** | **Variable Definition** | **Variable Vector-x** | **Variable Definition** |
| x(1) | Mean radius | x(9) | Number of poles *Np* |
| x(2) | Airgap *g* | x(10) | Number of branches |
| x(3) | Current Density *J* | x(11) | Height of the winding |
| x(4) | Outer limb thickness | x(12) | Pitch ratio |
| x(5) | Inner limb thickness | x(13) | Fill factor *kfill* |
| x(6) | Steel web thickness *lc* | x(14) | Height of the magnet *hm* |
| x(7) | Magnet/steel width ratio | x(15) | Length of the magnet *l*m |
| x(8) | Number of turns *Nt* | x(16) | Number of parallel stacks |

In our optimization process two different termination criterions are defined as it can be seen on Table 4-1. Optimization process will stop either when the total number of generation is equal to 200 or when 50 successive generations occur with average change in fitness function is less than “Stall tolerance”. GA algorithm in MATLAB searches for the optimum set of parameters in the predetermined lower and upper boundaries. These boundaries of the optimization is given in Table 4-3 with respective units.

Table 4-3. Lower and upper boundaries of the independent variables

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable name** | **Lower boundary** | **Upper boundary** | **Unit** |
|  | 4 | 8 | m |
| *J* | 5 | 7 | A/mm2 |
|  | 0.03 | 0.045 | m |
|  | 0.02 | 0.03 | m |
| *lc* | 0.02 | 0.03 | m |
|  | 0.7 | 0.8 | - |
| *Nt* | 50 | 90 | Turn |
| *Np* | 200 | 260 | Pole |
|  | 4 | 6 | Branch |
|  | 0.03 | 0.045 | m |
|  | 0.3 | 0.4 | - |
| *kfill* | 0.7 | 0.8 | - |
| *hm* | 0.01 | 0.02 | m |
| *l*m | 0.25 | 0.3 | m |
|  | 3 | 6 | - |

As mentioned earlier, airgap clearance *g* is segregated from this table because it is taken as constant. Constant value of this parameters is taken as 7 mm for our proposed generator.

## Constants and Constraints

## Constants

Although there are 16 independent variables in our optimization, some other variables and parameters can be taken as constant based on the assumptions and experiences in order to simplify the optimization handling and to avoid large and complex search spaces. Conceptual constants aforementioned above are given in Table 4-4 for our proposed AFPM.

Table 4-4. Conceptual optimization constants of the proposed AFPM

|  |  |
| --- | --- |
| **Constant** | **Value** |
| Efficiency of the gearbox | 1 |
| Gear ratio | 1 |
| Airgap clearance | 7 mm |
| Groove | 0 mm |
| Spacer gap | 0 mm |
| Number of phases | 3 |
| Ambient temperature | 20o C |
| Current Density | Forced air cooling with 7 A/mm2 @100oC |
| Power factor angle | 0o (cosφ=1) |
| Coil pitch/Pole pitch | 4/3 |

Efficiency and gearbox ratio values are taken as unity due to selected direct drive concept. Airgap clearance value is determined based on the cost comparison of designs with different airgap values. Besides, selected 7 mm of airgap clearance value is consistent with the assumption of “airgap clearance could be nearly 1/1000 of the bore diameter” principle of electrical machine design. Negligible small groove and spacer gap distance values can be ignored by the optimization in order to achieve smoother surface mount of permanent magnets on the steel core limbs, as mentioned in the previous chapter. Current density is optimized during the optimization process with other independent variables. However, final value of this variable is determined by the iterative design loops in the multi-speed code, instead of random number assigned by the GA. To do this, predetermined current density value (7 A/mm2 for this design) is assumed for reference operational temperature at 100o C. Operating temperature and final value of the current density are calculated according to this current density reference-based iterative loops in the design code. Detailed explanations will be given in the flowchart subsection. Power factor is assumed as unity in our design. This assumption is based on a full scale vector controlled power electronic converter which connects the proposed AFPM generator to grid [13]. Ratio of “4/3” between the coil pitch and the pole pitch is natural result of the proposed AFPM generator topology.

In addition to conceptual constants described above, there are number of constants related to material characteristics such as mass density and remanence flux density. These constants used in the optimization are given in Table 4-5.

Table 4-5. Material constants of the proposed AFPM

|  |  |  |  |
| --- | --- | --- | --- |
| **Constant** | **Value** | **Constant** | **Value** |
|  | 3.9x10-3 |  | 0.95 |
|  | 1.7x10-8 |  | 1 |
|  | 0.01 m |  | 1 mm |
|  | 0.04 m |  | 7850 kg/m3 |
|  | 1.257x10-6 H/m |  | 8230 kg/m3 |
|  | 1.4 T (grade N50 permanent magnet) [14] |  | 8400 kg/m3 |
|  | 1.05 |  | 900 kg/m3 |
|  | 750 H/m |  | 6 |
|  | 0.015 m |  | 8 |
|  | 0.3 m |  | 0.1 m |
|  | 3 £/kg |  | 8 £/kg |
|  | 110 £/kg |  | 10 £/kg |

where , ,  and  are unit cost of steel, unit cost of copper, unit cost of permanent magnet and unit cost of epoxy resin, respectively.

If a design calculations of a wind turbine generator is only based on the rated speed and power output conditions, probably manufactured design will not be efficient as much as it was in the design stage. This is due to intermittent nature of the wind. Therefore, variable speed operation must be taken into account and different speed distributions of the turbine must be evaluated during the optimization. In this study, design optimization of the proposed AFPM is carried under 9 different wind speed conditions with respect to given time probabilistic densities. Different properties of the wind speed distribution and “reference” wind turbine characteristics under these wind conditions, which are desired to be reached by the optimized AFPM of this study, are tabulated in Table 4-6.

Table 4-6. Wind speed distributions and reference generator ratings

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Wind Speed | Average Speed (rpm) | Average Torque (kNm) | Average Power (W) | Time Probability | Energy Ratio |
| 4 m/s | 1 | 6 | 600 | 9.00 % | 0.00 % |
| 5 m/s | 1 | 6 | 600 | 9.00 % | 0.00 % |
| 6 m/s | 2.9 | 55 | 16.500 | 15.00 % | 0.21 % |
| 7 m/s | 4.8 | 152 | 76.200 | 12.00 % | 0.77 % |
| 8 m/s | 6.7 | 299 | 209.000 | 9.00 % | 1.58 % |
| 9 m/s | 8.6 | 494 | 444.000 | 9.00 % | 3.36 % |
| 10 m/s | 10.5 | 738 | 811.000 | 9.00 % | 6.14 % |
| 11 m/s | 12 | 846 | 1.063.000 | 9.00 % | 8.05 % |
| 12 m/s (Rated) | 12 | 3981 | 5.000.000 | 19.00 % | 79.89 % |
| Weighted Average (time) | 6.8 | 997.9 | 1189157 | 100.00 % | 100.00 % |

## Constraints

Constraint in an optimization problem mainly defines the condition which are not supposed to be violated. This necessity can be due physical properties of the materials or due to designer priorities. In this study, independent variables are allowed to vary between lower and upper bounds of the predetermined search space. However, sometimes selection of these variables by GA can result in improper consequences. Therefore this kind of faulty selections must be corrected by the optimization programming [9]. For example in this study; airgap clearance, number of turns, number of poles, number of parallel branches and number of stacks are selected as integer variables. In addition to that, number of poles are rounded nearest integer which is multiple of four, in order to get a suitable number of series connected coils. Winding thickness/coil pitch ratio is also controlled in case any improper former dimensions. Outer core limbs must be always thicker than inner core limbs in order to withstand single-sided magnetic forces. Magnet/steel width ratio should be selected in proper limits in order utilize the magnets efficiently. In our design this value is allowed to vary between 0.7 and 0.8. Fill factor should be selected high due to concentrated windings and slotless topology of the generator. In this study fill factor is optimized between 0.7 and 0.8. These corrections occur at every loop of design calculation of generator.

Controls described until here were generally related to geometrical design parameters of the proposed generator and can be corrected via adjusting limits of the search space. Hence these can be categorized as search space manipulations. Other than these corrections, there are some other parameters which should be checked if any resulting parameter value of the designed generator violates the safety/necessity margins or not. These kind of parameters are generally named as “constraint” in the optimization process. User/designer can keep this kind of parameters under control by using penalty functions. As described before, penalty functions are used to convert constrained functions to unconstrained functions by assigning additional penalty values, which are relatively large with respect to normal fitness values, to related objective function in the optimization. Hence individuals which are penalized with these penalty functions have large fitness values and then finally eliminated from successive generations. By this way, optimization changes the search direction to where individuals satisfy all the constraints[9], [11], [15]. Details of the objective function and penalty coefficients will be given in the following subsection.

In our design optimization, various constraints are used with proper penalty functions. Efficiency is controlled at every design loops and individuals with efficiency values lower than 95% , are penalized. Another constraint is related C-core deflection. Due to magnetic attraction forces between magnets, C shaped cores are inclined to be deflected and close the airgap. If this deflection rate with respect to airgap clearance excess 10%, individual, which has this much deflected core, is penalized. Another constraint is related to axial length and it’s very important. Because one of the salient advantages of proposed AFPM is shorter axial length. For this purpose, individuals who has axial length higher than 5 meters, are penalized.

Stator outer diameter is another important parameter of the generator, especially when nacelle volume is limited. Therefore individuals with stator outer diameters above 10 meter, are also penalized. Operating temperature is another important design parameter related to efficiency. In this design optimization, individuals which has operating temperature higher than 100o C , are penalized. In addition to temperature constraint, efficiency constraint also guarantees the temperature rise by enforcing high efficiency penalty to candidate individuals with high copper losses. As mentioned before, in every optimization loop GA algorithm tries to determine the design parameters of the AFPM which gives output power of 5MW at 12 rpm rated speed. For this purpose, designed machine is operated at every speed interval which defined earlier in Table 4-6 and tries to match the output power of every specific interval. Individual which misses this speed interval, is penalized with a penalty function.

Final constraint employed in this optimization work is related to electrical rating of the proposed generator. Rms value of the voltage per phase () is kept under controlled via suitable penalty function such that line-to-line rms voltage level can’t excess the 690 V, which is a common voltage level among commercial wind turbine generators[16], [17]. Proper voltage level selection is important since output voltage level which is too high or too low can cause higher power electronic converter costs.

## Flowchart and Objective function

In this thesis work, considered AFPM design problem can be described as a non-linear optimization problem. Nonlinear constrained optimization problems are generally expressed as follows [9], [15],

Minimize *F(x)* (4-1)

  (4-2)

  (4-3)

 (4-4)

where *F(x)* corresponds to objective function and *x* represents the set of the independent variables. Conditions given in the Eq. (4-2) and Eq. (4-3) are defined as inequality constraints and equality constraints to which objective function is subjected. As mentioned before, variable set is chosen between lower and upper bound interval which predetermined before GA optimization process. These boundaries are shown in Eq. (4-4). In this study, main objective function is constructed based on the cost of the designed generator and can be expressed as follows,

 (4-5)

where  , ,  and  are cost of steel, cost of copper, cost of permanent magnet and cost of structure, respectively. Coefficient of “1.2” is multiplied by the total material cost due to add the approximate labor cost effect to the main cost function. Cost components of the main objective function given in Eq. (4-5), can be calculated as follows,

 (4-6)

 (4-7)

 (4-8)

 (4-9)

Penalty functions are defined and used in order to convert our constrained optimization problem to an unconstrained optimization problem. Therefore, it is not necessary to define equality and inequality constraints in MATLAB optimization toolbox. Penalty functions are used such that an additional value, which is to be added to original objective function, is calculated proportional to measure of violation of a constraint [5], [9]. In this study, seven different constraints are added in a form of penalty functions to the main objective function. Details of the penalty functions were given in the previous subsection. Resulting objective function in which the penalty functions added form is given as follows,

 (4-10)

where  and  are the penalty function for ith constraint and penalty coefficient for ith penalty function. Order of these seven penalty functions and related penalty coefficients are given in Table 4-7.

Table 4-7. Objective function Penalty Table

|  |  |  |  |
| --- | --- | --- | --- |
| Penalty Function | Constraint | Penalty Coefficient | Coefficient Value |
|  | Efficiency |  | =5x109  =3x109 |
|  | Deflection |  | 105 |
|  | Axial length |  | 105 |
|  | Outer diameter |  | 108 |
|  | Temperature |  | 105 |
|  | Power |  | =1  =10 |
|  | Voltage |  | 106 |

These penalty functions are calculated as follows,

 (4-11)

 (4-12)

 (4-13)

 (4-14)

 (4-15)

 (4-16)

 (4-17)

As it can be seen from calculations, response of the penalty functions can be adjusted via penalty coefficients at different order of magnitude and via different measure of violation calculations such as absolute difference or square of the absolute difference. Hence optimization will converge to an area of search space such that chosen set of independent variables don’t violate the constraints. As a result, penalty coefficients are chosen very large to satisfy all the constraints strictly. Therefore, a small violence of any constraint will be penalized with a large fitness [9]. Flowchart of the used optimization algorithm in this study is given in Fig.4-6.



Fig. 4-6. Optimization flowchart

First, an initial population is created by the MATLAB optimization tool based on the configurations given in Table 4-1. Then, reference wind speed data is taken from Table 4-6. Current density is initially assigned as the half of the upper limit of the current density, namely Jmax/2 . Then this current density value, rpm value and demanded power are used together with the random independent variables in order to calculate the design parameters of the generator. Demanded power for one stack of generator is calculated by dividing the power level for each speed interval given in reference table by the number of parallel stacked machines. After the first design calculation, current density value is adjusted according to efficiency of the design and reference current density values calculated for initial and short circuit conditions. Then a final design calculation is made for the current rpm interval. This calculations are repeated for all 9 speed intervals for the same generator design to see the performance ratings at different speeds. Cost function is calculated according to objective function defined in Eq. (4-10) by considering the energy ratios of the different wind speed intervals given in the reference table. After this process, performance and design parameters are saved in a file and exported. Then, termination criteria are checked in order to stop the optimization process. This procedures are repeated until termination criteria are satisfied and the optimal design is achieved.

## 5MW AFPM generator with optimized design parameters

Cost optimization is made with MATLAB toolbox based on the configurations given in Table 4-1 and Table 4-3. Optimized independent variables of the proposed AFPM generator at rated conditions of 12 rpm/5 MW, are reported in Table 4-8.

Table 4-8. Optimized generator independent variables at 12 rpm/5MW

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| Mean radius- | 4.57 m |
| Airgap-*g* | 7 mm |
| Speed | 12 rpm |
| Current density-*J* | 2.70 A/mm2 |
| Outer limb thickness- | 30 mm |
| Inner limb thickness- | 20 mm |
| Steel web thickness-*lc* | 21.5 mm |
| Number of turns- *Nt* | 50 |
| Number of poles- *Np* | 216 |
| Number of branch- | 6 |
| Height of the winding- *hw* | 40.6 mm |
| Winding thickness/Coil pitch ratio | 0.382 |
| Magnet/Steel width ratio- | 0.737 |
| Fill factor-*kfill* | 0.799 |
| Height of the magnet-*h*m | 17.1 mm |
| Length of the magnet- *l*m | 261 mm |
| Number of parallel stacks- | 6 |

Other design parameters of the optimized AFPM generator can be calculated by using the design equations given in Chapter-3. Performance ratings of the optimized generator at different wind speed conditions are given in Table 4-9.

Table 4-9. Optimized generator performance ratings

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Wind Speed | Rpm | *J*  *A/mm2* | *V* |  | Average Power  W | Total Power  W | Efficiency | Net Power  W |
| 4 m/s | 1 | 0.0035 | 33.66 | 0.94 | 600 | 600 | 0.954 | 572.95 |
| 5 m/s | 1 | 0.0035 | 33.66 | 0.94 | 600 | 600 | 0.954 | 572.95 |
| 6 m/s | 2.9 | 0.034 | 97.44 | 9.25 | 16500 | 16500 | 0.983 | 16235.71 |
| 7 m/s | 4.8 | 0.098 | 161.01 | 25.96 | 76200 | 76200 | 0.987 | 75268.89 |
| 8 m/s | 6.7 | 0.193 | 224.33 | 51.15 | 209000 | 209000 | 0.988 | 206572.5 |
| 9 m/s | 8.6 | 0.32 | 287.36 | 84.80 | 444000 | 444000 | 0.987 | 438644 |
| 10 m/s | 10.5 | 0.47 | 349.99 | 127.05 | 811000 | 811000 | 0.987 | 800457.7 |
| 11 m/s | 12 | 0.55 | 399.80 | 145.77 | 1063000 | 1063000 | 0.986 | 1049058 |
| 12 m/s | 12 | 2.70 | 367.79 | 717.48 | 5000000 | 4999999 | 0.950 | 4750003 |

Best and mean values of the optimization process through the 200 generations are plotted in the graph given in Fig. 4-7. As it can be seen from this figure, best fitness value of the optimization converged to 1.69x106.

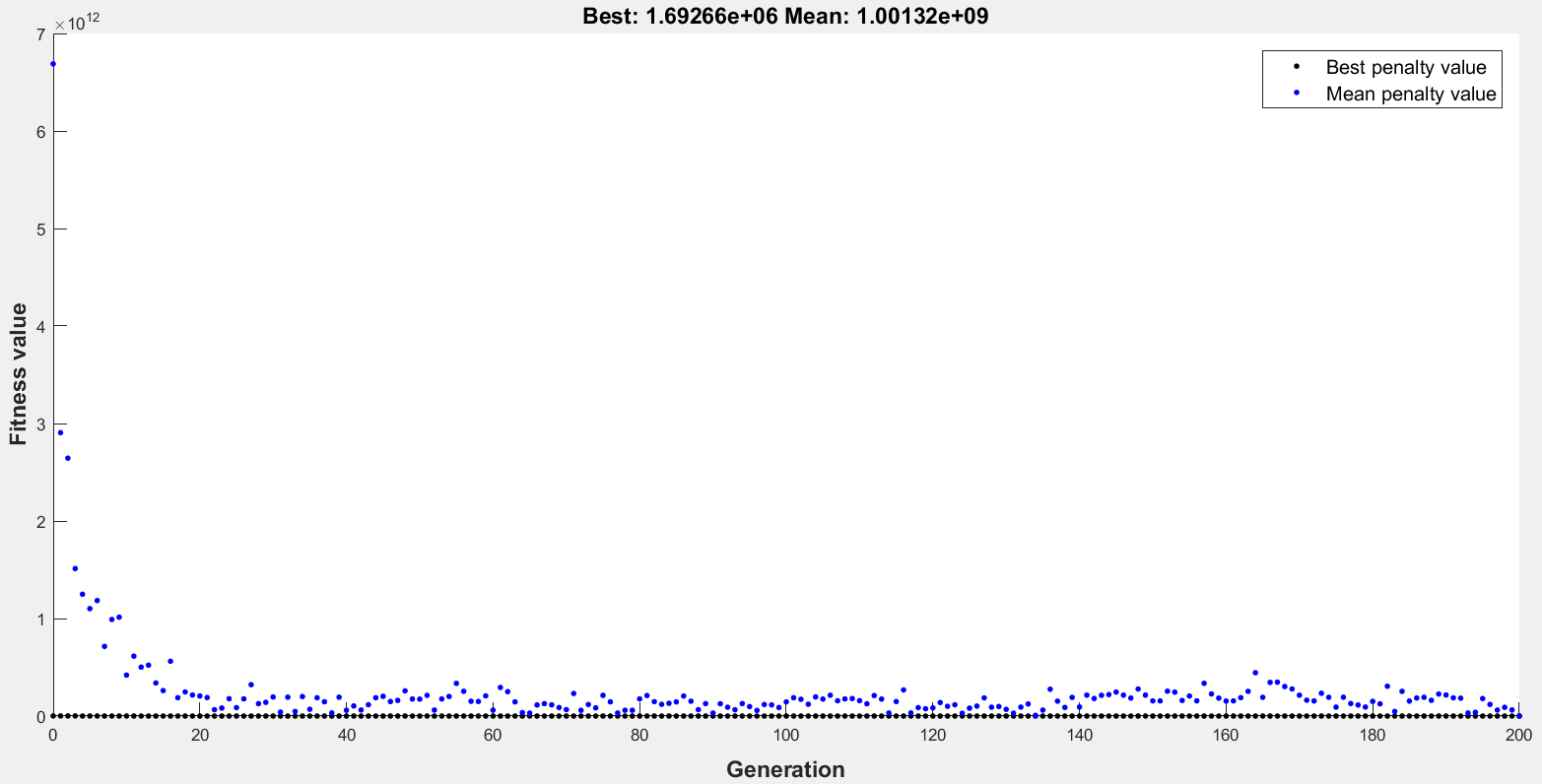


Fig. 4-7. Best and mean values of the optimization

Components of the objective function, which was given in Eq. (4-10), are tabulated for the optimized design in Table 4-10 . As in an ideal optimization procedure, all the penalty values are zero except  which is negligible small with respect to material cost function. Therefore it can be said that, variation of the objective function can be directly considered as variation of the cost of the proposed AFPM.

Table 4-10. Fitness and penalty values of the optimized design

|  |  |
| --- | --- |
| Fitness value | 1.69266x106 |
| Material cost (£) | 1.69266x106 |
|  | 0 |
|  | 0 |
|  | 0 |
|  | 0 |
|  | 0 |
|  | 0.044 |
|  | 0 |

Fitness values of all individuals regardless of mean values, are depicted in Fig. 4-8. As it can be seen from this figure, cost of the considered generator showing a decreasing trend as the optimization procedure continues.

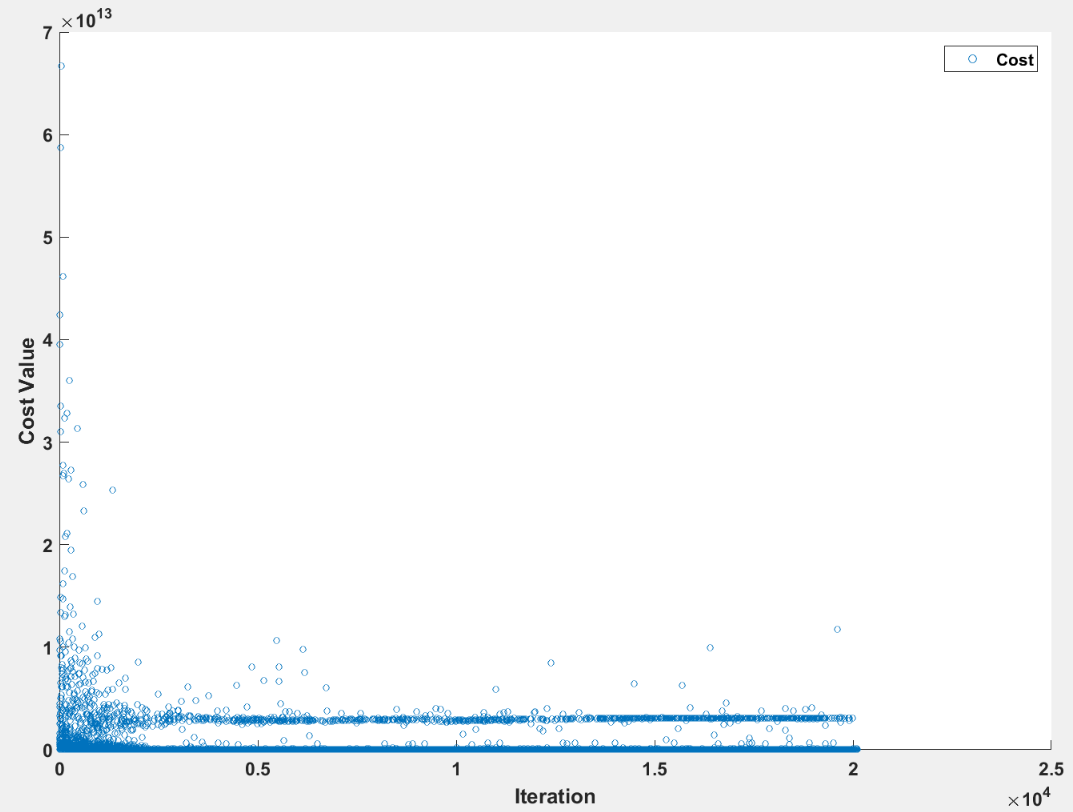


Fig. 4-8. Cost distribution of the optimization according to iterations

## Conclusion

This chapter mainly focused on the optimization procedure and its results. First, general overview of the EA is given including the selected GA optimization. This algorithm is chosen in this thesis work because of its derivative-free approach and application simplicity. GA is the most prominent algorithm in the EA family. GA mimics the nature when reproducing and evaluating the candidate individuals for the proposed AFPM. This algorithm is applied by using MATLAB genetic algorithm optimization toolbox. For this purpose, few scripts are written which includes the necessary design equations of the selected AFPM and other optimization handling algorithm. Details of the MATLAB optimization toolbox configurations and used algorithm flowcharts are given in the related subsections. Seven different penalty functions are used in order to convert our constrained optimization problem to an unconstrained problem. 16 different independent variables are used in the optimization problem. Details of the constants, independent variables, objective function and penalty functions are given in the related subsections. In this study objective function is constructed based on the cost of the proposed AFPM generator. Therefore, evaluated fitness values can be considered as the cost of the design. Also in this study, proposed AFPM generator is optimized according to different wind speed conditions and different energy ratios. These sample values are taken from a reference wind speed characteristics table. Details of the reference wind speed table and performance parameters of the optimized generator under these wind conditions are given in related subsection. Finally, optimized parameters of the proposed 5MW/12 rpm AFPM design and fitness evolution tables are given and discussed. These optimized parameters are very important because they will be used in the finite element modelling and verification of the proposed generator in the next chapter.

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