CHAPTER-4

Optimization of MILO using Particle Swarm Optimization (PSO) Algorithm

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4.1. Introduction

The complete design, simulation of an S-band MILO and its parametric (both electrical and circuit) optimization using 3-D commercial electromagnetic code was discussed at length in Chapter 3. The real performance of the MLIO could be realized under practical condition, i.e., under hot condition (in the presence of the electron beam) using a commercially available advanced 3D PIC codes, like, MAGIC, MAFIA, CST Studio Suite, TWO QUICK, QUICK SILVER, KARAT codes etc. These codes basically provide a deeper understanding of the complex beam-wave interaction process in any vacuum electron devices. In Chapter 3, in order to study the reliability and accuracy of "CST PIC simulation code" and its efficient use in HPM device like MILO using conventional RF interaction circuits, the RF behavior of S-band MILO using a co-axial cylindrical cavity type slow-wave structure (SWS) has been presented. The MAGIC simulation code was also used to investigate the RF behavior of MILO [Cousin (2006)]. However, these commercial 3D electromagnetic simulation codes do not include inbuilt optimization techniques in it algorithm. Therefore, in the present chapter an Artificial Neural Networks (ANN) based optimization technique called "Particle Swarm Optimization" (PSO) is used for optimizing various electrical and circuit parameters of the present S-band MILO to improve its overall efficiency. The parametric optimization of MILO using 3D electromagnetic code, like, MAGIC, CST Particle studio, KARAT code is very complex, computationally expensive and time consuming process. But, the PSO uses simple concept, easily programmable, faster in convergence and mostly provides better solution comparing with the other algorithms, like, Genetic algorithm (GA), etc. Further, the PSO has proved its applicability in the design of microwave devices like antenna, filters, etc., for high power microwave applications [Chengyang, 2015].

This chapter is organized as follows: In section 4.2 different types of Artificial Neural Networks (ANN) techniques for optimization are discussed and in section 4.3, the Fitness Function for PSO of RF interaction structure is discussed. The design optimization of RF interaction structure using PSO algorithm is presented in section 4.4 and the performance evaluation of S-band MILO using particle swarm optimized parameters is described in section 4.5. Finally, the conclusion is drawn in Section 4.6.

4.2. Different Artificial Neural Networks (ANN) Techniques for Optimization

There are different Artificial Neural Networks (ANN) techniques for optimization of problems related to different practical applications namely Genetic Algorithm, Back propagation (BP), Simulated Annealing (SA), Tabu Search (TS) and Particle Swarm Optimization (PSO) and about each algorithm is discussed below.

4.2.1. Genetic Algorithm (GA)

Genetic algorithm is an effective tool for solving non-linear function of both constrained and unconstrained optimization problems [Dorsey *et al*. (1994)] [Dorsey and Mayer, (1995)]. This technique is based on the process which mimics biological evolution. An objective function is evaluated at different candidate points from a set of randomly selected initial population. At each iteration genetic algorithm uses current population as parent and genetic offspring candidate points based probability. The new population is randomly paired for crossover process by randomly selecting a position in the parameter and swapping. This crossover aids in retaining the characteristics from parent points. Each weight is replaced by realistically resulting in the mutation of the point. This helps in tiding over the local optima solution ensuring the robust solution. The population evolves leading to an optimal solution on repeated iterations.

4.2.2. Back-Propagation (BP)

Back-propagation, an abbreviation for "backward propagation of errors", is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respect to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function. Backpropagation requires a known, desired output for each input value in order to calculate the loss function gradient. It is therefore usually considered to be a supervised learning method, although it is also used in some unsupervised networks such as auto encoders. It is a generalization of the delta rule to multi-layered feed forward networks, made possible by using the chain rule to iteratively compute gradients for each layer. Back propagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable. Backpropagation has been designed as gradient search techniques for local search. The best solution has been achieved in the region of their starting point. The starting values of fortuitous choice are significant for obtaining a global solution. The optimal solution is obtained consistently by known global search techniques.

4.2.3. Simulated Annealing (SA)

Simulated annealing is a method of solving both constrained and unconstrained objective function by imitating the physical process of cooling of hot objects. During the annealing process, the physical substances moves from high energy state to low energy state based on the cooling rate. In simulated annealing the probability of transition to higher energy state decreases during the cooling process. In this method, the search states with initial random points and takes step predefined by the user. The user defined parameter T (temperature) and RT (temperature reduction factor) is used initially to decide the probability for higher value objective function. As T increases the probability of accepting the higher value decreases which is similar to annealing process. The probability is determined by metropolis criteria. The number of interactions between the temperature reductions is decided by the preset parameter NT. This helps in escaping the local optima solutions. As the search proceeds, the length of the step reduces leading to a final solution. In simulated annealing, the performance is driven by the user defined parameters in contrast with GA where the parameters are dynamically determined by the algorithm. As the performance is affected by the selection of parameters, a range of parameters are to be used for T, RT and NT.

4.2.4. Tabu Search (TS)

Tabu search (TS), proposed by [Glover and Laguna, (1997)], is a meta-heuristic method that has received widespread attention recently because of its flexible framework and several significant successes in solving NP-hard problems [Sexton *et al*. (1998)]. The method of neighbourhood exploration and the use of short-term and long-term memories distinguish Tabu search from local search and other heuristic search methods, and result in lower computational cost and better space exploration. TS involves a lot of techniques and strategies, such as short-term memories (Tabu list), long-term memories and other prior information about the solution can used to improve the intensification and diversification of the search. It can be confirmed that the strategy of intensification and diversification is very important at most time, therefore, a novel adaptive search strategy of intensification and diversification, proposed in literature [He *et al*. (2004)] was employed to improve the efficiency of TS for neural network optimization.

4.2.5. Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm is the best suited for optimization of RF interaction parameters of MILO due to fast convergence and easy implementation. This algorithm is most effective in cases where the search space and the number of iterations are less. In recent years, swarm intelligence based algorithms such as particle swarm optimization for the optimization of design parameters [Samii and Michielssen, (1999)] [Robinson and Samii, (2004)]. PSO is a population based stochastic optimization technique developed by [Eberhart and Kennedy (1995)], inspired by social behavior of flocking of birds or fish schooling. PSO is another form of evolutionary computation techniques and is stochastic in nature much like genetic algorithm. Comparing with genetic algorithm (GA), the information sharing mechanism in PSO is significantly different. In GA, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only gbest (or lbest) gives out the information to others. It is a one way information sharing mechanism. The evolution only looks for the best solution. Compared with GA, all the particles tend to converge to the best solution quickly even in the local version in most cases.

Let us consider the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food?. The effective one is to follow the bird which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and is an iterative process. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called p-best. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g-best. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called *l*-best.

The key to PSO is the computation of a particle's new velocity. Expressed in mathematical terms, the velocity and position update equations are given by [Eberhart and Kennedy (1995)]:

$$v_i(t+1) = (w^a * v_i(t)) + (c1 * r1 * (p_i(t) - x(t)) + (c2 * r2 * (p_g(t) - x_i(t)) , \tag{4.1}$$

and
$$x_i(t+1) = x_i(t) + v_i(t+1) , \tag{4.2}$$

where i – particle index ; t – discrete time index; $v_i(t)$ – Current velocity of i^{th} particle at time t ; $x_i(t)$– current position of i^{th} particle at time t ; $p_i(t)$ – best position found by i^{th}

particle (personal best) at time t ; $P_g(t)$ – best position found by swarm (global best, best of personal bests) at time t ; $r1$, $r2$ – random numbers on the interval [0,1] applied to ith particle, but strictly less than 1. 'c1' and 'c2' are usually social and cognitive constants respectively, ie., $c1$=$c2$=2. 'w^a' factor is called the inertia weight which is taken from 0.4 to 0.9.

The update process is actually much simpler than these equations suggest. The equation (4.1) updates a particle's velocity. The term $v_i(t+1)$ is the velocity of i^{th} particle at time $t+1$. Notice that v is the velocity which has a vector value and has multiple components rather than being a single scalar value. The new velocity depends on three terms. The $v_i(t)$ is the current velocity at time t.

The second term is $c1 * r1 * (p_i(t) - x_i(t))$. The c1 factor is a constant called the cognitive (or personal or local) weight. The third term in the velocity update equation is $(c2 * r2 * (p_g(t) - x_i(t))$. The $c2$ factor is a constant called the social, or global, weight. Once the new velocity, $v_i(t+1)$ has been determined, it is used to compute the new particle position $x_i(t+1)$.

4.2.6. PSO parameters control

From the above case, we can learn that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the advantages of PSO is that PSO take real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. There are not many parameter need to be tuned in PSO. Here is a list of the parameters and their typical values [Kayarvizhi *et al*. (2013)].

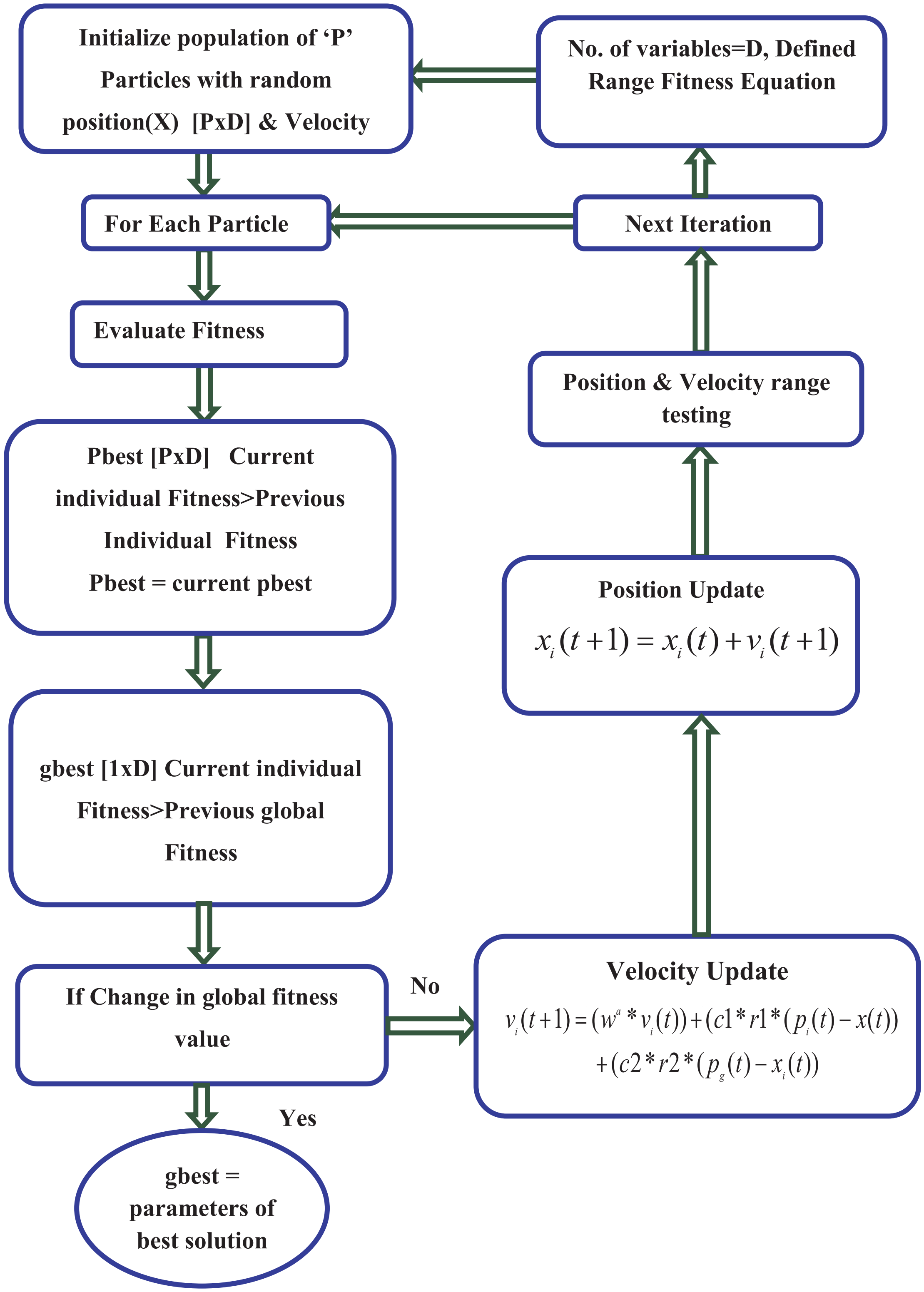
Number of Particles (N): The number of particles: the typical range is 20–50 but less than 50. Large population causes more computational efforts, so the population size is kept below 50. Generally between 20 to 50 particle population is preferred. Actually for most of the problems 10 particles is large enough to get good results. For some difficult or special problems, one can try 100 or 200 particles as well.

Dimension of particles (D): It is determined by the problem to be optimized. **Range of particles**: It is also determined by the problem to be optimized, you can specify different ranges for different dimension of particles.

Learning factors: *c1* and *c2* usually equal to 2. However, other settings were also used in different papers. But usually *c1* equals to *c2* and ranges from [0, 4]. **The stop condition:** The maximum number of iterations the PSO execute and the minimum error requirement.

Inertia weight: w_{max}^{a} is the Inertia weight which is generally taken from 0.4 to 0.9.

4.2.7. Flow Chart of PSO Algorithm



4.3. Fitness Function for PSO of RF interaction structure

In the present work, a co-axial vane loaded conventional MILO structure is considered. The cylindrical coaxial waveguide structure comprising axial periodic metal vanes of finite thickness projecting radially inward as shown in Fig. 4.1, was already field analyzed [Dwivedi and Jain, (2012)]. In the analysis, it was assumed that the space harmonics of the travelling-wave being generated due to the axial periodicity of the structure and the modal harmonics of standing wave caused due to the reflections of electromagnetic waves from the metal discs. Therefore, travelling waves are present in the structure vane-free region (region I), between the central conductor and the metal vanes, and the standing waves in the vane-occupied region (region II) of each unit cell, considered between two consecutive vanes of the cylindrical coaxial waveguiding structure [Dwivedi and Jain, (2012)]. In this structure as shown in Fig. 4.1, region I occupies the space $r_c \leq r \leq r_i$, $0 \leq z \leq \infty$ and region II occupies $r_i \leq r \leq r_o$, $0 \leq z \leq (s\text{-}w)$. Here, r_c is the cathode radius, r_i is the inner radius of SWS vane, w is the thickness of SWS vane, s is the circuit periodicity, and r_o is the outer radius of SWS vane.

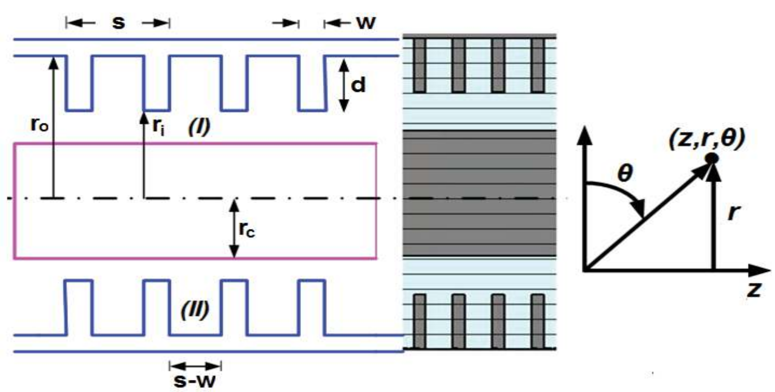


Fig. 4.1: Schematic of RF interaction structure of MILO

The fitness function (F) (ie., the power transmitted through structure as shown in Fig. 4.1) is given by [Dwivedi and Jain (2015)] in terms of s, r_c, r_i, r_o and w :

$$P_t = \sum_{n=-\infty}^{\infty} P_n^I = \pi\omega\varepsilon \sum_{n=-\infty}^{n=\infty} \frac{\beta_n^I}{\gamma_n^{I\,4}} \left[Y_n\{\gamma_n^I r_c\} \left(\frac{r_i^2}{2} (J_n^{'2}\{\gamma_n^I r_i\} + J_n^{\,2}\{\gamma_n^I r_i\}) \right) \right.$$

$$\left. - J_n\{\gamma_n^I r_c\} \left(\frac{r_c^{\,2}}{2} (J_n^{'2}\{\gamma_n^I r_c\} + J_n^{\,2}\{\gamma_n^I r_c\}) \right) \right] A_n^{I\,2} \quad . \quad (4.3)$$

Now, the final expression for the field constant A_n^I,

$$A_n^I = \frac{1}{\pi \left(\sum_{n=-\infty}^{n=\infty} D_{nm} + 2 (\sum_{m=1}^{m=\infty} M_{n,m}{}^2 Q_{nm}) \right)^{1/2}} \quad , \quad (4.4)$$

where, D_{nm} is dimensionless function involving propagation constants and structure parameters and Q_{nm} is dimensionless function involving propagation constants and structure parameters.

$Q_{nm} = (U_m)\sin^2(\beta_m^{II} z)$ and $U_m = (S_{1m} \cdot U_{1m} + S_{2m} \cdot U_{2m} + S_{3m} \cdot U_{3m})$

where,

$$U_{1m} = S_{1m} \left[r_o^2 \left(J_0^{'2}\{\gamma_m^{II} r_o\} + \left(1 - \frac{1}{(\gamma_m^{II} r_o)^2}\right) J_0^2\{\gamma_m^{II} r_o\} \right) - r_i^2 \left(J_0^{'2}\{\gamma_m^{II} r_i\} + \left(1 - \frac{1}{(\gamma_m^{II} r_i)^2}\right) J_0^2\{\gamma_m^{II} r_i\} \right) \right], \quad (4.5)$$

$$U_{2m} = \frac{S_{2m}}{4} \left[r_o^2 (2J_1\{\gamma_m^{II} r_o\} Y_1\{\gamma_m^{II} r_o\} - J_0\{\gamma_m^{II} r_o\} Y_2\{\gamma_m^{II} r_o\} - J_2\{\gamma_m^{II} r_o\} Y_0\{\gamma_m^{II} r_o\}) \right.$$

$$\left. - r_i^2 (2J_1\{\gamma_m^{II} r_i\} Y_1\{\gamma_m^{II} r_i\} - J_0\{\gamma_m^{II} r_i\} Y_2\{\gamma_m^{II} r_i\} - J_2\{\gamma_m^{II} r_i\} Y_0\{\gamma_m^{II} r_i\}) \right], \quad (4.6)$$

$$U_{3m} = S_{3m} \left[r_o^2 \left(Y_0^{'2}\{\gamma_m^{II} r_o\} + \left(1 - \frac{1}{(\gamma_m^{II} r_o)^2}\right) Y_0^2\{\gamma_m^{II} r_o\} \right) - r_i^2 \left(Y_0^{'2}\{\gamma_m^{II} r_i\} + \left(1 - \frac{1}{(\gamma_m^{II} r_i)^2}\right) Y_0^2\{\gamma_m^{II} r_i\} \right) \right], \quad (4.7)$$

and $S_{1m} = Y_0^2\{\gamma_m^{II} r_o\}$, $S_{2m} = J_0\{\gamma_m^{II} r_o\} Y_0\{\gamma_m^{II} r_o\}$, $S_{3m} = J_0^2\{\gamma_m^{II} r_o\}$

$$D_{nm} = \left[r_i^2 \left(J_0^{'2}\{\gamma_n^I r_i\} + \left(1 - \frac{n^2}{(\gamma_n^I r_i)^2}\right) J_0^2\{\gamma_n^I r_i\} \right) - r_c^2 \left(J_0^{'2}\{\gamma_n^I r_c\} + \left(1 - \frac{n^2}{(\gamma_n^I r_c)^2}\right) J_0^2\{\gamma_n^I r_c\} \right) \right], \quad (4.8)$$

$$M_{n,m} = \left(\frac{2\beta_m^{II}}{s - w} \right) \left(\frac{(-1)^m \exp(j\beta_n^I (s - w)) - 1}{\beta_m^{II^2} - \beta_n^{I^2}} \right) \left(\frac{X_0\{\gamma_m^{II} r\}}{Z_0\{\gamma_n^I r\}} \right) .$$

4.4. Design Optimization of RF interaction Structure using PSO Algorithm

The PSO algorithm has been used almost in all areas of research. In the present work, the structural parameters of the RF interaction circuit for an S-band MILO has been optimized. A detailed analytical method for computing the design parameters, including cathode radius, SWS vane inner radius, circuit periodicity and thickness of SWS vane of RF interaction structure of S-band conventional MILO was discussed in Chapter 3. Based on that the design parameters of a conventional MILO are shown in Table 4.1, and the same has been modeled in CST 3D Particle-in-Cell Studio.

Table-4.1: Design Parameters of conventional MILO.

Parameter	Specifications
Frequency (f)	3.1 GHz
Beam voltage (V)	500 kV
Total anode current (I_t)	47.5 kA
Anode Radius(r_o)	61.4 mm
Choke vane Radius(r_{ch})	34 mm
SWS vane inner radius(r_i)	39 mm
Extractor vane radius(r_{ex})	49 mm
Period between cavities(s)	13 mm
Thickness of vanes(w)	4 mm
Collector inner radius	40 mm
Collector outer radius	44 mm
Beam dump length	80.5 mm

The simulation predicted an RF peak power of ~ 6 GW at ~ 3.1GHz for the beam voltage of 500kV and current of 47.5kA with a power conversion efficiency of ~ 25%. In order to improve the performance of this particular design, the PSO algorithm has been used. In this PSO algorithm, the control parameters are *c1*, *c2* and w^a are selected appropriately from the literatures as shown in Table 4.2 that plays vital role in convergence, otherwise functional evaluation would become complex and time consuming process. Accordingly, the control parameters have been chosen as, N=10; *c1*=*c2*=1.4, $w^a_{\max} = 0.9$ and $w^a_{\min} = 0.4$, and which were used in the evaluation of fitness function linking PSO algorithm for optimizing the structural parameters of the RF interaction circuit of S-band MILO.

Table 4.2: Control parameters of PSO for Design Optimization.

Parameters	Size
No . of swarms (*N*)	10
c_1 , c_2	1.4
Inertia factor (w^a)	$w^a_{\max} = 0.9$; $w^a_{\min} = 0.4$
No. of Iterations	10

4.4.1 Parameters Selection for Design Optimization of RF interaction structure

In this context, we have considered four nominal parameters of RF interaction structure including cathode radius (r_c), SWS vane inner radius (r_i), circuit periodicity (s) and thickness of SWS vane (w) that play vital role in S-band MILO for generating maximum RF output power. The range of design parameters considered for the optimization are summarized in Table 4.3. The algorithm was coded in MATLAB by linking the fitness function as given through equation (4.3) – (4.9). In PSO algorithm, the particles are flown in multi-dimensional search space (range) as shown in Table 4.3, to get the best solution. The algorithm was executed with swarm size of 10 for about 25 iterations in each case. The iterations considered for the design were sufficient for the convergence of the swarm.

Table 4.3: Design parameters and ranges for design optimization.

Parameters	Ranges
Cathode radius(r_c)	20 to 27 mm
SWS vane inner radius (r_i)	39 to 41mm
Circuit Periodicity (s)	12 to 15 mm
Thickness of SWS vane (w)	2 to 6 mm

4.4.2 Effect of Parameter Variation

After selecting the parameters range as given in Table 4.3, the effects of variation of these parameters on the performance of RF interaction of S-band MILO have been investigated. The PSO algorithm solves fitness function, representing the power transmission through the RF interaction circuit of MILO, for maximum convergence. The power transmission through the structure depends on four significant parameters including cathode radius (r_c), SWS vane inner radius (r_i), thickness of the SWS vane (w) and the periodicity (s) of the circuit. Therefore, the fitness function is solved for maximum convergence by varying one design parameter at a time and keeping other parameters remains constant to maximize the power output.

Figure 4.2 shows the optimization of cathode radius (r_c) for the maximum power output of S-band MILO using PSO technique. The PSO algorithm searches the best solution (maximum power output) in the range of cathode radius from 20 mm to 27 mm, while keeping other three parameters are constant as per the design value. The search in the given range converged at the cathode radius of 26.85mm; hence the maximum RF power output was obtained as ~ 4.6 GW as shown in Fig 4.2. Similarly, Fig. 4.3 shows the optimization of SWS vane inner radius (r_i) for maximum power output of S-band MILO. In this case, the SWS inner radius ranged from 39 mm to 41 mm and the convergence was observed while keeping other three parameters remains constant. The maximum RF power output has been obtained ~ 6.92 GW for the converged SWS vane inner radius of 40.94 mm as shown in Fig. 4.3. .

Further, the same technique was adopted for maximizing the RF output power by varying the thickness (w) of SWS vanes. The range of the vane thickness chosen from 2 mm to 6 mm and obtained the maximum power as ~ 2.44 GW for the converged vane thickness of 2.77 mm as shown in Fig. 4.4. The fourth parameter, periodicity of the circuit range defined from 12 mm to 15 mm and the algorithm converged at 12.46 mm for the maximum RF output power of ~ 2.43 GW as shown in Fig. 4.5. The convergence of these four parameter concludes that the RF output power is more sensitive to the cathode radius (r_c) and the SWS vane inner radius (r_i), which are critical in maximizing the power in MILO. The comparison between the designed and particle swarm optimized parameters of the proposed RF interaction structure is shown in Table 4.4.

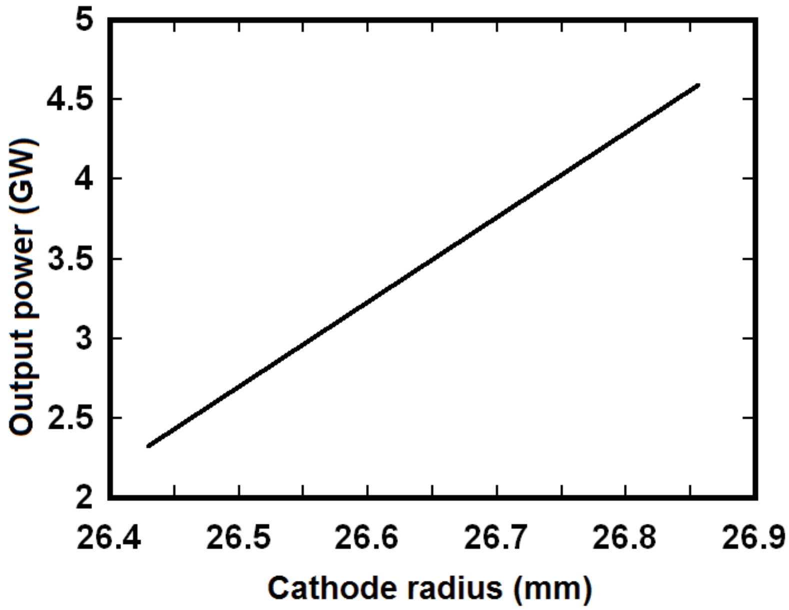


Fig. 4.2: Cathode radius versus output power.

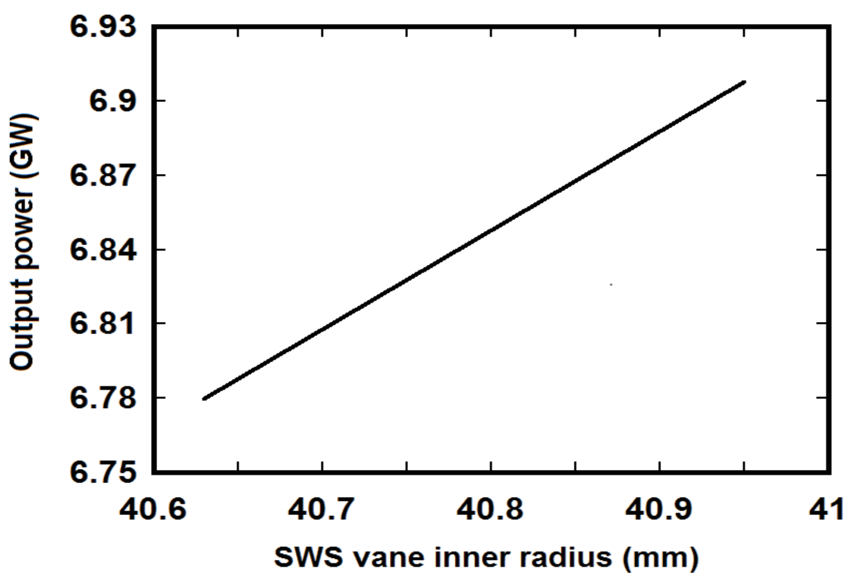


Fig. 4.3: SWS vane inner radius versus output power.

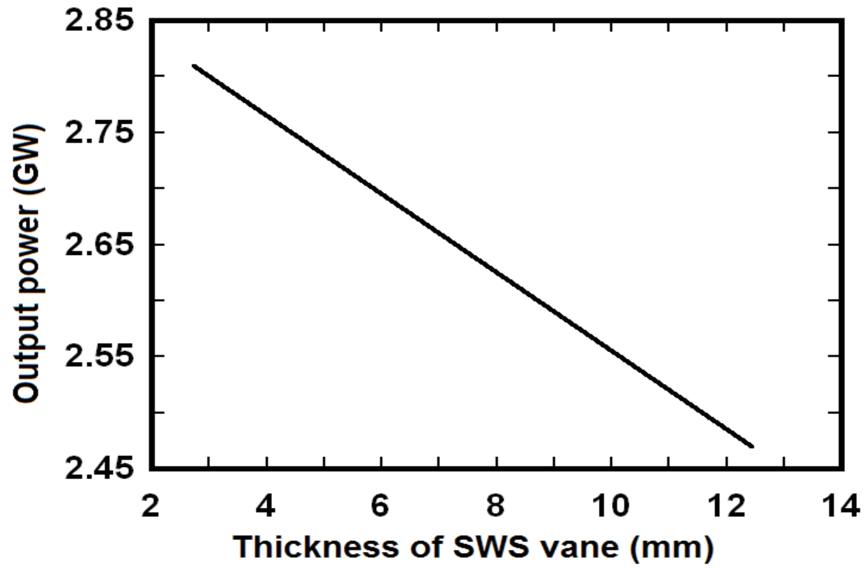


Fig. 4.4: Thickness of SWS vane versus output power.

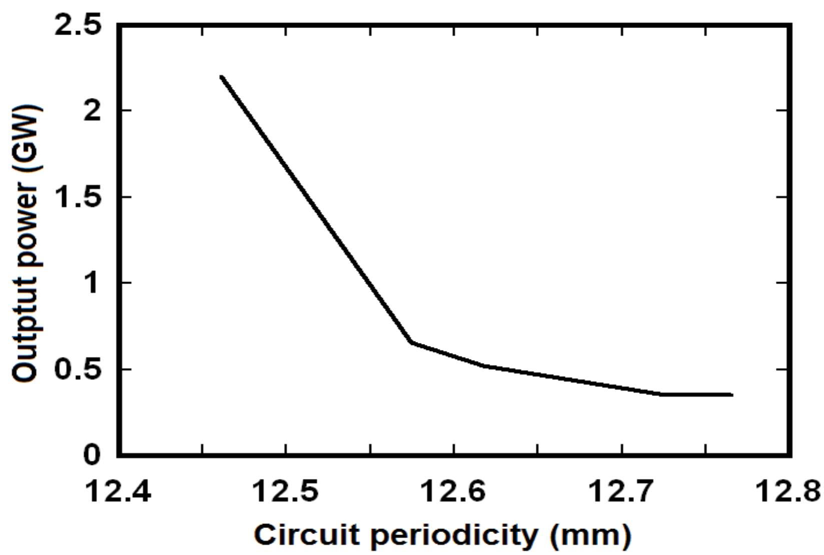


Fig. 4.5: Circuit periodicity versus output power.

Table 4.4: Comparison of optimized parameters of RF interaction structure of S-band MILO using parametric technique and PSO algorithm.

Parameters	Optimized dimensions using Parametric Technique	Optimized dimensions using PSO algorithm
Cathode radius(r_c)	25.0 mm	26.85 mm
Inner radius of the SWS vane (r_i)	39.0 mm	40.94 mm
Circuit periodicity (s)	13.0 mm	12.46 mm
Thickness of the SWS vane (w)	4.0 mm	2.77mm

4.5. Performance Evaluation of S-band MILO using Particle Swarm Optimized Parameters

Device structure modelling and beam-wave interaction study of a conventional S-band MILO uisng "CST Particle Studio" was explained in detail in the previous chapter, Chapter 3. Further, the conventioanl MILO results discussed in the previous Section 4.4 is considered here again for its performnace improvement. The particle swarm optimized parameters shown in Table 4.4 are used to study its beam-wave interaction behaviour of the MILO discussed in section 4.4. The beam voltage of 500kV with the rise time of 1ns as shown Fig. 4.6 was applied between cathode and anode at the input port and hence the current due to electrons emitted by the high explosive emission from the surface of a cylindrical velvet cathode is shown in Fig. 4.7. Due to the self-generated magnetic field, electron beams are confined between the SWS vanes and cathode. The genertaed RF power at the fundamental mode was extracted at the output port. The RF output power (square of the E-field amplitude) of ~7.2 GW as shown in Fig. 4.8 at 3.1 GHz in TM_{01} with a power conversion efficiency of ~29 % have been achieved by employing the beam voltage 500 kV, and the current of 50 kA. The Fourier transform of the *E*-field amplitude shows the desired frequency of operation, i. e., 3.1 GHz as shown in Fig 4.9. Further, Table 4.5 shows comparison of simulated results of optimization using parametric technique and optimization using PSO for the beam voltage of 500kV.

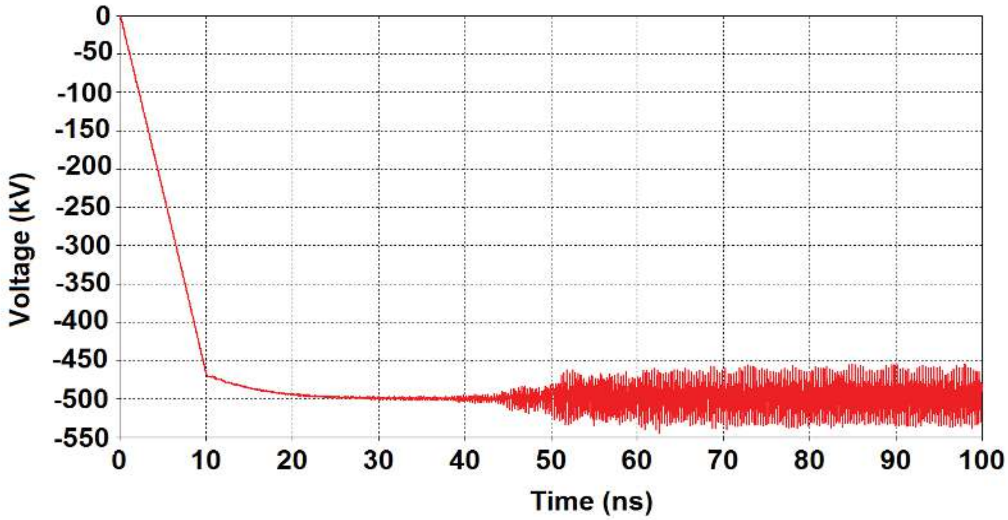


Fig. 4.6: Build-up of voltage with time.

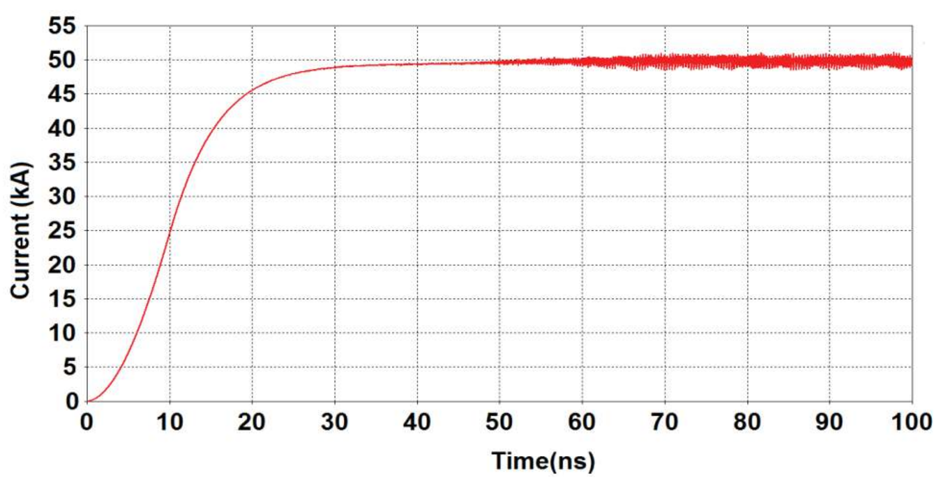


Fig. 4.7: Build-up of current with time.

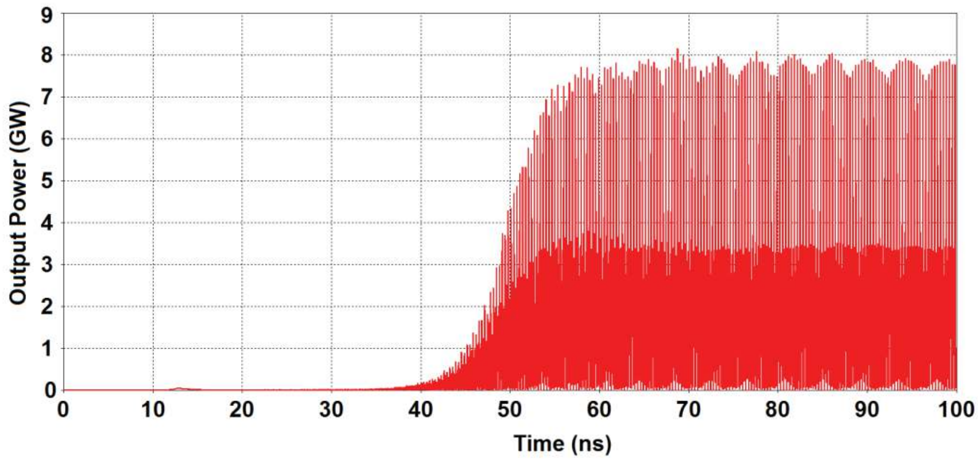


Fig. 4.8: Peak output power of optimized S-band MILO using PSO.

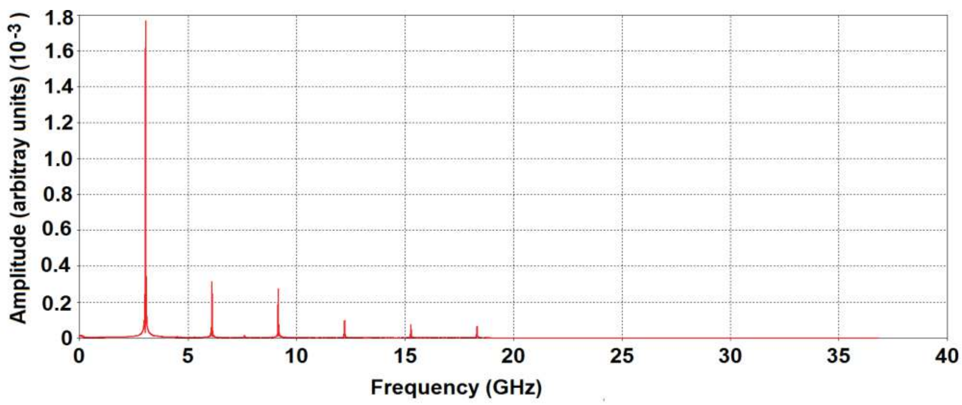


Fig. 4.9 : Fourier transform of the electric field at the output port.

Table 4.5: Comparison of simulated results (S-band MILO) of optimization using Parametric technique and PSO algorithm for the beam voltage of 500kV.

Parameters	Simulated Results	
	Optimization using Parametric technique [Nallasamy *et al*. (2016)]	Optimization using PSO algorithm
RF output power	6.0 GW	7.2 GW
Power conversion efficiency	25.0 %	29.0 %
Frequency	3.1GHz	3.1GHz

4.6. Conclusion

In this chapter, the Particle Swarm Optimization (PSO) technique has been explored for the optimization of structural parameters with an aim of getting maximum output power and power conversion efficiency in fundamental mode of operation of MILO. The effect of various parameters including the inner radius of SWS vane (r_i), cathode radius (r_c), thickness of SWS vane (w) and circuit periodicity (s) have been studied by solving the fitness function using PSO technique. A typical S-band MILO design has been chosen for the optimization purpose and the effect of these parameters on RF output power of MILO has been investigated using PSO. After optimization of structural parameters of RF interaction structure using PSO algorithm, a S-band MILO has been simulated and RF output power of ~ 7.2 GW at 3.1 GHz in fundamental TM_{01} mode with a power conversion efficiency of ~29%, while applying the beam voltage of 500 kV has been obtained. The present simulated results of S-band MILO using PSO optimized parameters have been compared with the results obtained through parametric optimization technique as discussed in Chapter 3 and found both are in close agreement. The efficiency of the device has been enhanced by ~4% through the PSO technique. Because of optimization of design parameters using PSO, the total length of MILO device and the projection of cathode inside beam dump have been reduced significantly. It has also been observed from the literature that increasing the number of swarms more than 50 leads to degradation of the performance and the control parameters namely $c1$, $c2$ and w^a plays vital role for the convergence of the algorithm and have to be chosen very optimistically. All optimizations on fitness function were carried out with the swarm size of 10. Yet, an improved performance can be obtained by using swarm size of greater than 10 , but it would also increase number of fitness function evaluations.