Optimal Capacitance Integration in Self Excited Induction Generator for Supplying Reactive Power using Genetic Algorithm for Efficient Performance

[1]Mohammad Isharat Khan,[2] Shipli Sisodiya

[1]Research Scholar, EED, CP University, Kota, Rajasthan, [2]Assistant Professor (EEXD), MPCT, Gwalior-MP

Abstract — The research article discuss the approach to find the best possible value of the series and shunt capacitance to be connected in order to get the best possible voltage profile with the available arrangement using genetic algorithm. A Meta heuristic approach is used for the selection strategy of the series and shunt capacitors to get optimum voltage regulation. The connection scheme taken is the short shunt scheme as it has performance superiorities as compared to long shunt connections. The two unknowns Xm and f have been found out using the conventional MATLAB routine, these values are used for the further calculations to find out the optimum set of the series and shunt capacitance values for SEIG to give best voltage regulation. This requires evaluating the generator characteristics under constant voltage operation. The technique employed in the article is Genetic Algorithm based Optimization Method which has a population of random solutions and here the series and shunt capacitances have been kept as the random values. The idea behind using this method is that the method is more effective and is not complex and more accurate results are obtained using this method as the other method doe not converge to the expectation.

Indexed Terms **— SEIG, Capacitance Integration, Genetic Algorithm, Reactive Power**

I. INTRODUCTION

Optimization Techniques are method to obtain optimal values of the parameter under consideration. When we encounter with a mathematical equation in which the parameter in the expression do have dependence on different types of the other parameter or if they do have interdependence behavior then we will uses optimization technique to solve the problem. Number of optimization technique are suggested by research scholar to solve a particular problem like (1) Artificial bee colony algorithm (2) Criss-cross algorithm (3) Derivative-free optimization (4) Differential Evolutionary algorithm (5) Genetic algorithm (6) Multi-swarm optimization (7) Particle swarm optimization Swarm (8) Intelligence Tabu search.

In this research dissertation we had implemented Genetic Algorithms to find the optimal solution of the Objective Problem. Holland (1975) has introduced the concept of Genetic Algorithms (GA) first time, later it was proposed and described by Goldbery (1989). Genetic Algorithms is fundamentally heuristic search techniques. Different from traditional optimization techniques, a Genetic Algorithms seeks an optimal solution through the mechanism of natural selection. In Genetic Algorithms, each candidate solution is coded as a chromosome string and the search process starts from a group of these chromosomes referred to as populations. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated using some measures of fitness. In order to generate new solutions which are known as offspring in the next generation, the most popular Genetic Algorithms operators, crossover and mutation, are used. The crossover operation exchanges some genes in the identical positions from two chromosomes in the current generation. The mutation operation modifies the gene in a chromosome from the current generation.

II. GENETIC ALGORITHM

In the power system computer programming field of artificial intelligence, a genetic algorithm (GA) is a heuristic search that mimics the process of natural selection. This heuristic also sometimes notated as meta-heuristic, is a routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. Genetic algorithms find application in bioinformatics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics fields.

Figure shows the Flowchart of Genetic Algorithm Method. Genetic Algorithms work well in complex and non-linear domains since they preserve the common sections of the chromosomes that have high fitness values, discard poor solutions, and evaluate more and more of the better solutions. However, there are no generic genetic algorithms that can be used in all Genetic Algorithms applications, so users have to custom design the algorithm for their problem individually.

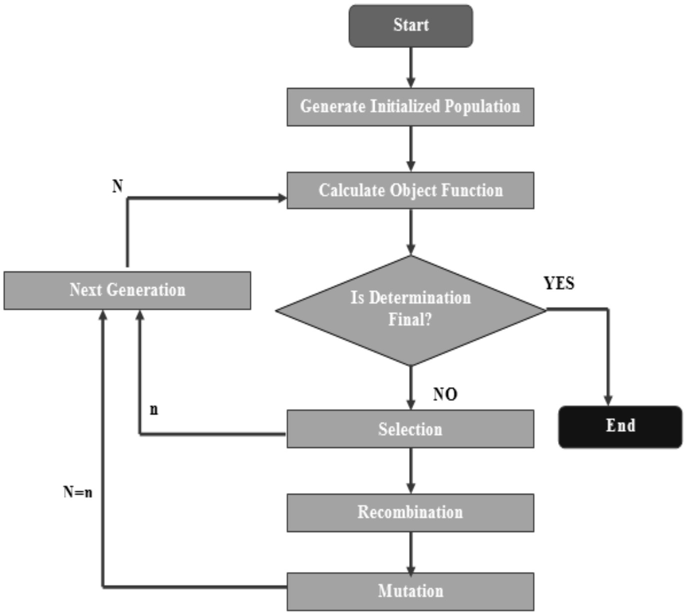

Figure-1. Flowchart of the Genetic Algorithm Method

Application of a Genetic Algorithms to a specific problem requires the development of a fitness function and the representation, or encoding, of a candidate solution in a chromosome string. MATLAB provides a genetic algorithm toolbox for solving optimization problems. Many build-in functions can be used for generating initial population, fitness scaling, selection, reproduction, mutation, and crossover. For particular optimization problems, users can customize their own genetic algorithm process functions. In this thesis, a custom genetic algorithm is developed in MATLAB. The Genetic Algorithms do have different ingredient, the main components of genetic algorithm are discussed.

In a genetic algorithm, a population of candidate solutions to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered, traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals, and is an iterative process. In each generation, the fitness of every individual in the population is evaluated, the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. A typical genetic algorithm requires:

1. A genetic representation of the solution domain
2. A fitness function to evaluate the solution domain

A standard representation of each candidate solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming, a mix of both linear chromosomes and trees is explored in gene expression programming. Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.

III. BUILDING BLOCK HYPOTHESIS

Genetic algorithms are simple to implement, but their behavior is difficult to understand. In particular it is difficult to understand why these algorithms frequently succeed at generating solutions of high fitness when applied to practical problems. The building block hypothesis (BBH) consists of a description of a heuristic that performs adaptation by identifying and recombining "building blocks", Goldberg describes the heuristic as follows:

"Short, low order, and highly fit schemata are sampled, recombined that is crossed over, and re-sampled to form strings of potentially higher fitness. In a way, by working with these particular schemata, We have reduced the complexity of our problem, instead of building high-performance strings by trying every conceivable combination, we construct better and better strings from the best partial solutions of past samplings. "Because highly fit schemata of low defining length and low order play such an important role in the action of genetic algorithms, we have already given them a special name: building blocks. Just as a child creates magnificent fortresses through the arrangement of simple blocks of wood, so does a genetic algorithm seek near optimal performance through the juxtaposition of short, low-order, high-performance schemata, or building blocks.

The encoding of a solution is a critical issue, since a poor initial choice will surely result in a poor algorithm regardless of any significant other features. This issue has been investigated from different aspects. Gen and Cheng (2000) classified the encoding schemes into: (1) Binary encoding, (2) Real Number Encoding, (3) Integer or Literal Permutation Encoding, and (4) General Data structure Encoding.

A string of bits is used to represent a solution of the problem in the binary encoding scheme. It is preferred by the majority of researchers, however, binary encoding for function optimization problems has severe drawbacks limiting the applications of binary representation. It has been demonstrated that real number encoding results in better performance than binary encoding for function optimization and constrained optimization whereas integer or literal permutation is best suited for combinatorial optimization problems since combinatorial optimization problems search for a best permutation or combination of elements subject to constraints.

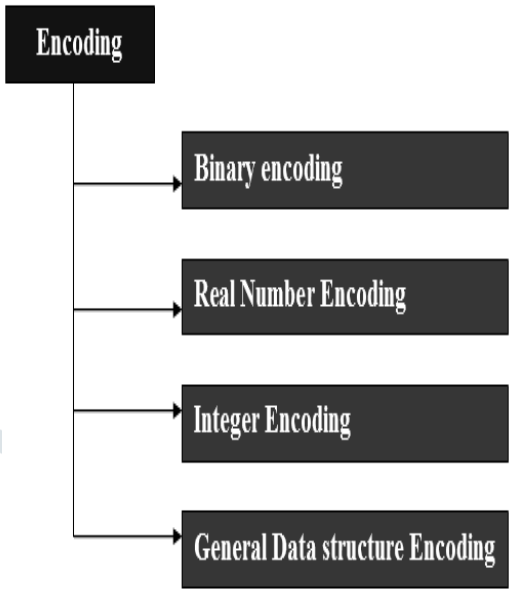

Figure.2- Types of Encoding in Genetic Algorithm

IV. STEPS FOR GENETIC ALGORITHM

Optimization is the process of finding the best solution or achieving the best outcome in a given situation. It involves maximizing or minimizing a particular function or objective subject to certain constraints. Optimization is widely used in various fields, including mathematics, engineering, economics, finance, and computer science. It can be applied to a wide range of problems, such as finding the shortest route between two points, maximizing profit in a business, minimizing waste in a manufacturing process, or finding the best parameters for a machine learning model. Optimization algorithms can be categorized into two types: deterministic and stochastic. Deterministic algorithms, such as gradient descent and Newton's method, use a fixed set of rules to find the optimal solution. Stochastic algorithms, such as simulated annealing and genetic algorithms use a probabilistic approach to explore the solution space and find the optimal solution. Optimization is an important tool for decision-making and problem-solving in many fields. It can help to improve efficiency, reduce costs, and increase productivity.
In order to determine the best possible optimization solution Genetic Algorithm follows a systematic scheme which is as explained below:

1. Initialize the decision variables of GA
2. Creating an initial population by randomly generating a set of feasible solutions.
3. Evaluating each set of solution
4. Find the fitness function corresponding to each solution in the population
5. Applying GA operators to generate new solution (population).
6. Apply the crossover operator to complete the members of the new population.
7. Apply the mutation operator to the new population.
8. Let the current population be the new population.
9. If the convergence criterion is satisfied, stop. Otherwise go to step 3

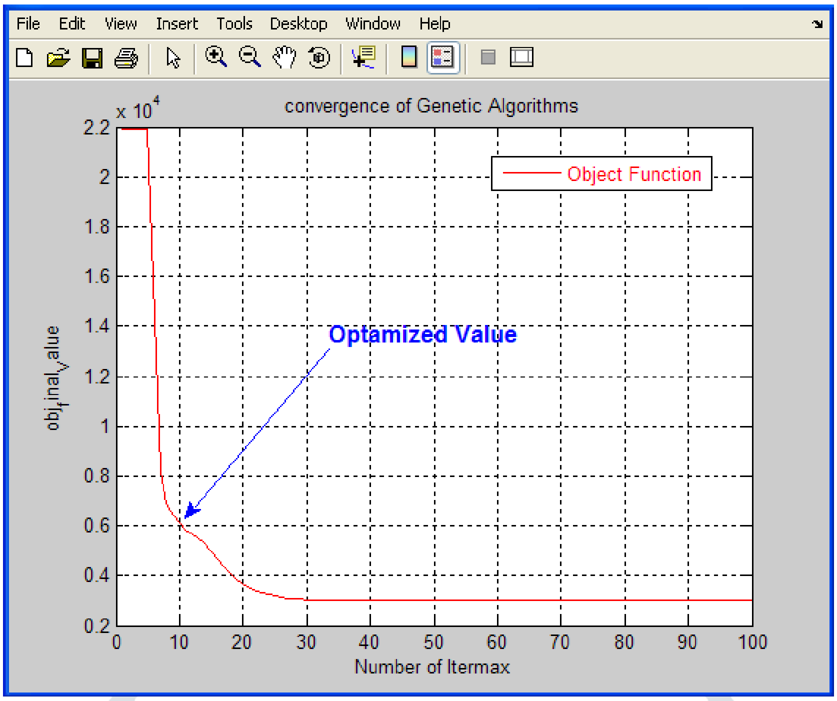

Figure.3- Optimization of Genetic Algorithm

V. PROBLEM FORMULATIONS

The steady-state performance of an induction generator is usually determined from its equivalent circuit. In order to simplify the analysis, the circuit of figure 5.1 is represented by three series impedances as shown in figure.

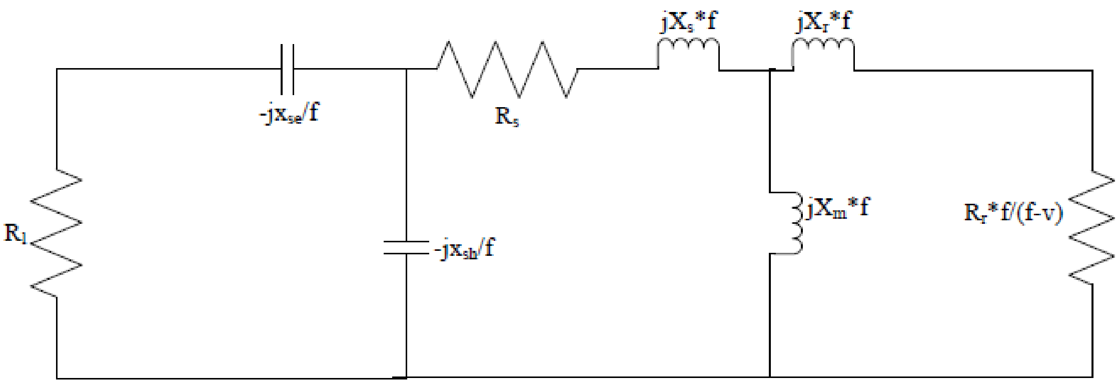

Figure.4- Equivalent circuit of short shunt SEIG

This is the per-phase equivalent circuit of a three-phase short-shunt induction generator with its excitation capacitors and an R load is shown in the figure, here the RS, XS, RR, XR and XM shows the (1) stator resistance (2) stator leakage reactance (3) rotor resistance, rotor leakage reactance and (4) magnetizing reactance, Notation f and V represent per unit frequency and speed respectively. The simplified representation of the equivalent circuit can be seen in figure 5.2 which comprises of three impedances whose formulations are given below in the following equations. The parameter of the above figure may be expressed as shown below:

$$Z_1 = R_s + (j*X_s*f)$$

$$Z_1 = (j*f*X_m)*\left\{R_r*\frac{f}{(f-v)}\right\}+\left[\frac{(j*X_r*f)}{(R_r*\frac{f}{(f-v)})}\right]+(j*f(X_m+X_r))\cdots(1)$$

VI. OBJECTIVE FUNCTION

The above calculation has completed parameter of the mathematical model of the Self Excited Induction Generator. Now the main objective comes into the Picture that is calculation of the series capacitance and shunt capacitance for the schema. Now we are required to implement Genetic Algorithm to calculate the optimal value of Capacitances. To optimize capacitance values we need to specifies the objective function with limit and constrain as written below:

$$Minimize \quad Vd = \sum_{i=0.1}^{Pout} \left\{ \frac{V_1 - V_{Lsp}}{V_t} \right\}^2$$

In the above equation Vd is objective function which is to be optimized, VL load voltage and VLsp is specific value of the load and will be kept at a specific constant value in our case the value is 1.00 pu. The velocity will be change during the operation. In the above expression w(t) is the inertia weight which is in the range of 0.9 to 0.4, C1 and C2 are accelerator coefficient of the objective function respectively.

VII. ALGORITHM

Following are the steps for exciting the algorithm:

1. Read the machine data. Assume initial values of Xm and f.
2. Initialize particles for series and shunt capacitance. Generate velocities for the same.
3. For the power counter, evaluate Xm and f and hence evaluate the load voltage using the equations, the value of pre specified load voltage already been given.
4. In first iteration of the generation, calculate fitness function as per the equation in the current population.
5. Calculate the local best and compare the particles' fitness evaluation with the local best. Hence the local best is set to current value and location or dimension equal to the current location.
6. Calculate the particles' global best and compare best current fitness with global best, if current value is better than global best, then reset global best to current best position. Update velocities and positions.
7. Repeat steps -9 until a best solution is reached until a maximum number of iterations.
8. Record the global best results and then Stop the iteration process.

VIII. RESULT AND DISCUSSION

The proposed algorithm has been tested at different capacitor values at various power factors. First the simulation results for the resistive load are emphasized. The graphs for resistive loading have been shown in for various machine parameters:

1. Variation of the load voltage and the load power.
2. Variation of the terminal voltage of SEIG and the load power.
3. Variation of stator current and load power

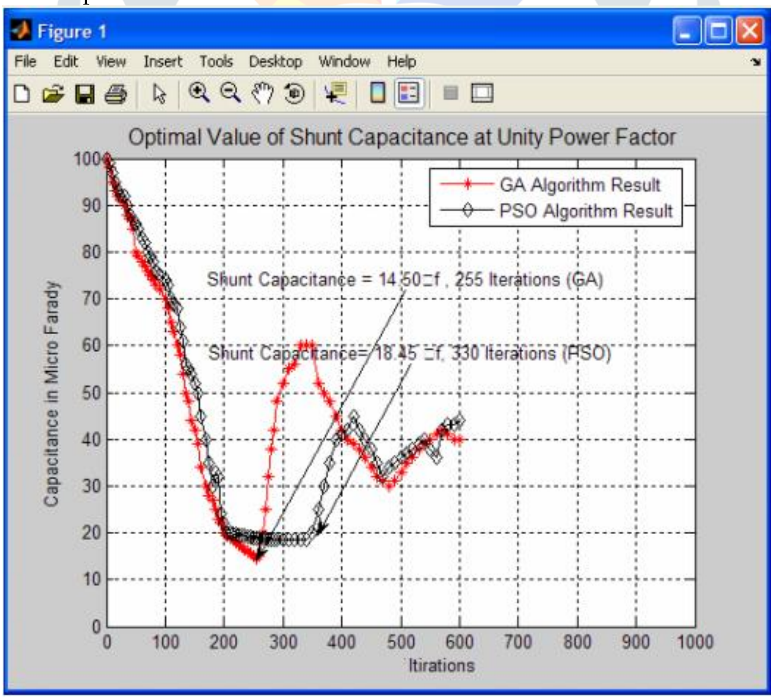

Figure.5- Plot of Convergence of GA and PSO for Optimal Shunt Capacitance for Unit PF

Table-1. Selection of Capacitor pair Values at unity p.f. load

Method	Shunt Capacitance	Series Capacitance
PSO	18.45 μf (330 Iterations)	165.5 μf
GA	14.50 μf (255 Iterations)	143.5 μf

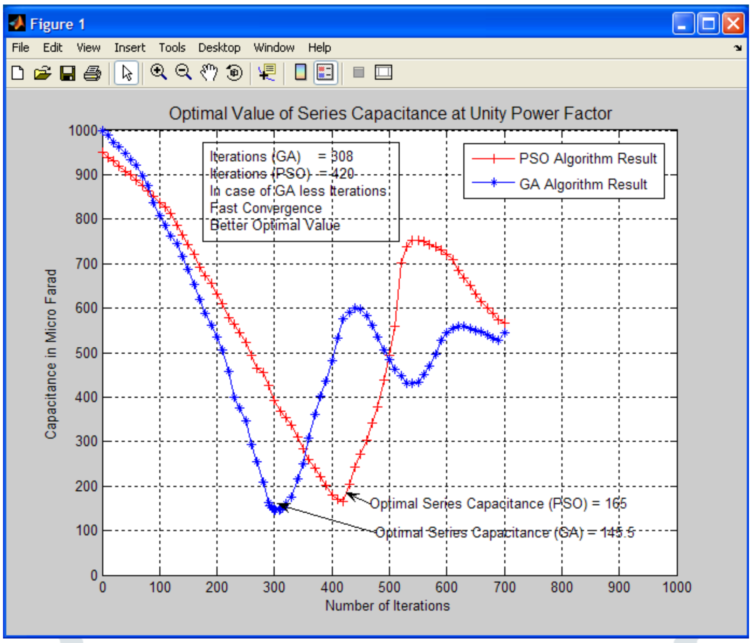

Figure.6- Plot of Convergence of GA and PSO for Optimal Series Capacitance for Unit PF

In the figure above the plot of the GA and PSO optimization technique has been implemented. The graph 5.4 shows the optimal value for shunt capacitance to be connected in the stator circuit of the SEIG for optimal performance. The graph also show the comparison between GA and PSO techniques. In case of GA optimization reaches the optimal value faster then PSO with better performance. Similarly figure 5.5 shows the graph of the GA and PSO for optimal series capacitance evaluation. Graph shows that we get fast and better result as compared to PSO. The above graph shows evaluating the series and shunt capacitance values GA is far better than the PSO. Fast convergence, better value, higher reliability and better performance is the characteristics of the GA and these quality of the GA makes it better choice than the PSO. The graph of the figure 5.6 shows convergence of PSO and GA at 0.98 power factor. Red color graph shows the PSO convergence while blue color shows the GA convergence. The number of the iteration in the case of PSO is about 325 while in the case of GA is 210 only.

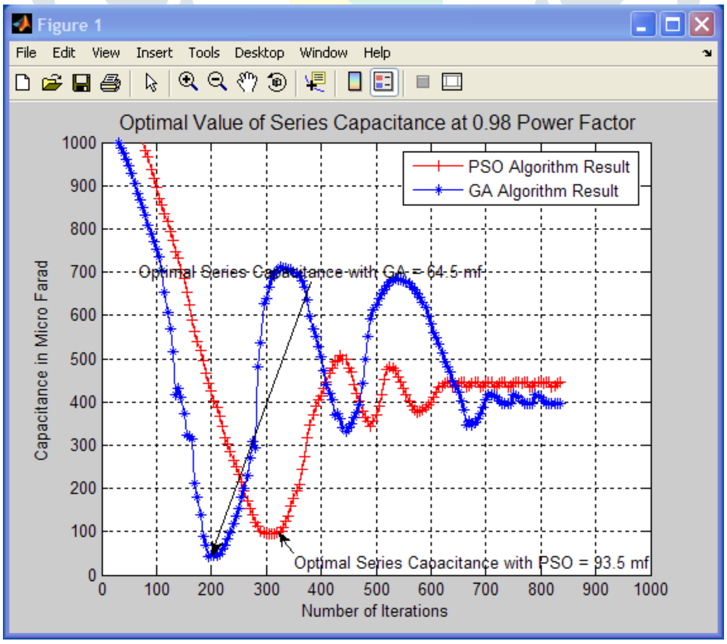

Figure.7- Plot of Convergence of GA and PSO for Optimal Series Capacitance for 0.98 PF

The value of the optimal Series capacitance is also 93.5 micro farad in case of PSO while the same is only 64.5 micro farad in case of GA.

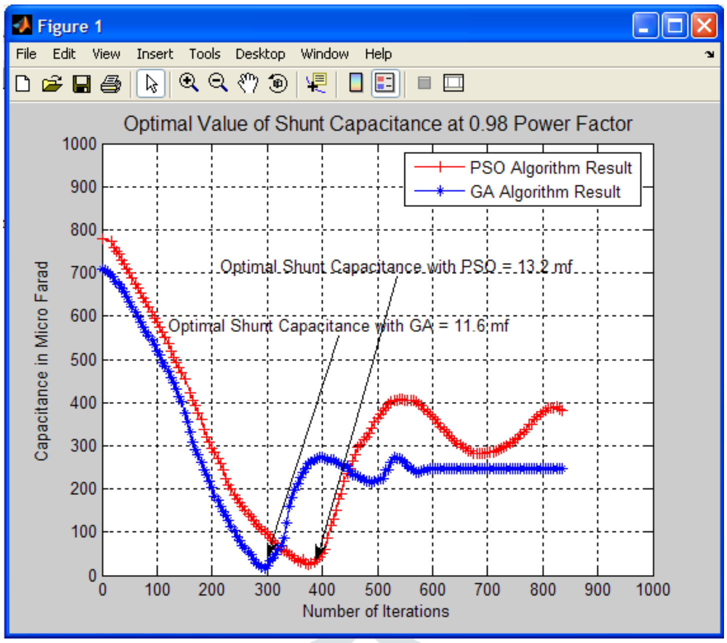

Figure.8- Plot of Convergence of GA and PSO for Optimal shunt Capacitance for 0.98 PF

Table-2. Selection of Capacitor pair Values at 0.98 p.f. load

Method	Shunt Capacitance	Series Capacitance
PSO	13.2 µf	93.5 µf
GA	11.6 µf	64.2 µf

Figure 7& 8, above depicts the convergence of PSO and GA at 0.98 power factor. Clearly the number of the Iteration required in the case of the GA is lower as compare to the PSO. This means that we can achieve faster convergence in case of the GA as compare to that of the PSO. Also the value of the optimal capacitance is lower in case of the GA than that of the PSO. As the value of the optimal capacitance is fewer that that of the PSO the voltage regulation and hence the voltage profile of the system is also enhanced in case of GA than that of the PSO.

IX. CONCLUSION

The performance of short shunt SEIG has been studied in detail and the results with PSO have been compared with the GA results and the results have been simulated for different values of power factors for resistive and reactive loading. It is seen that the combination of shunt and series capacitor affects the generator performance greatly, the invigoration of the optimum value of the series and shunt capacitors has been done to maintain almost constant load voltage using the two simple techniques. It is observed that a voltage regulation within reasonable limits is possible by selecting suitable values of series and shunt capacitors by the proposed methodology that is GA Optimization. Added Advantage of Genetic Algorithm Application in comparison of PSO can be summarizing as below:

1. Voltage Stability has been Improved in Case of GA which can be observed from the Graph in comparison of PSO
2. Frequency Sustainability has been Improved with the application of GA instead of PSO
3. Overall Voltage Regulation has been Improved
4. Voltage Profile has been Improved
5. Fast Convergence can be achieved while implementing GA instead of PSO

X. FUTURE SCOPE

The study of short shunt SEIG for selection of series and shunt capacitors have been presented here. The study can be extended in the following potential areas:

1. The work can be extended to non-linear load like controlled rectifier type of load.
2. The work can be extended to study the load unbalancing.
3. The hardware for STATCOM based voltage regulator can be developed.
4. This study can be extended to long shunt SEIG and a comparison of the two configurations can be established.
5. The work can be extended to variable speed machine where the speed parameter can also be embedded in the objective for further analyses.

References

[1]. L.Shridhar, Bhim singh,C.S.Jha,B.P. singh , S.M. Murthy "Selection of capacitor for the Self regulated short shunt self excited induction generator", IEEE Transactions on Energy conversion,vol. 10, No.1,March 1995

[2]. J.faiz, A.A. Dadagari, S.Horning, A.Keyhani "Design of a Three-phase self-Excited Induction Generator", IEEE transactions on Energy Conversion,Vol.10, No.3, September 1995.

[3]. Cheng-Tsung Liu, Wen-Lin chang " Transient Simulation Technique for studies of Self-excited Generator Systems",Electric power systems research 33 (1995)101-109.

[4]. N.P.A. Smith, "Induction generators for stand-alone micro-hydro systems ", IEEE International conference on Power Electronics Drives and Energy Systems, January 1996,pp.669-673.

[5]. Li wang and Jian-Yi su "Effects Of Long-shunt and Short-shunt connections on voltage variations of a self-excited induction generator", IEEE Transactions on Energy conversions, Vol. 12, No.4 December 1997.

[6]. R.Wamkeue and I.Kamwa "Numerical Modelling and Simulation of Saturated Unbalanced Electromechanical Transients of Self-Excited Induction Generators", 2000 IEEE.

[7]. S.C. Kuo and L.wang ," Analysis of voltage control for a self-excited induction generator using a current-controlled voltage source inverter" IEE Proc.Gener.Trans.Distrib.,Vol 148,No 5, September 2001.

[8]. S.C. Kuo and L.wang ,"Analysis of isolated self-excited induction generator feeding a rectifier load", IEE Proc.-genr.Transmission Distribution Vol.149, No.1, January 2002.

[9]. Paul C. Krause, Oleg Wasynczuk, Scott D. Sudhoff "Analysis of Electric Machinery and Drive system" A Willey interscience publication, 2002 USA.

[10]. S.K.Jain, J.D. Sharma and S.P.singh "Transient performance of three-phase self-excited induction generator during balanced and unbalanced faults", IEE Proceedings Online no.20020007, IEE 2002.

[11]. Tarek Ahmed, Osamu Noro, Eiji Hiraki, Mutsuo Nakaoka, "Terminal voltage Regulation Characteristics by Static VAR Compensator for a three-phase Self-Excited Induction Generator" IEEE Transactions on Industry Applications, Vol.40, No.4, July/August 2004.

[12]. B.singh, S.S.Murthy and S.Gupta " Analysis and design of STATCOM-Based voltage regulator for Self-Excited Induction Generators", IEEE Transactions on Energy conversion, Vol.19, No.4 December 20004.

[13]. P.K. Gayen, D. Chatterji, S. K. Gowami "Stator side active and reactive power control with improved rotor position and speed estimator of a grid connected DFIG(Doubly-fed induction generator)"Energy xxx (2015) 1-12.

[14]. B. Sawetsakulanond, V. Kinnares "Design analysis and construction of a small scale self-excited induction generator for a wind energy application"Energy 35 (2010) 4975-4985.

[15]. Shakuntla Boora, Analysis of self-excited induction generator under balanced or unbalanced conditions, ACEEE

[16]. International Journal on Electrical Power Engineering, Vol. 01, No. 03, December 2010, pp. 59-63.

[17]. A.A. Dadagari, S. Horning, A. Keyhani "Design of a three phase self-excited induction generator," IEEE Trans. on Energy Conversion, Vol.10, No.3, September 1995.

[18]. E. Levi, Y. W. Liao "An Experimental Investigation of Self-Excitation in Capacitor Excited Induction Generators", Electric power research 53(2000) 59-65.

[19]. G. K. Singh "Self-Excited Induction Generator Research-A survey", Electric power systems research 69(2004) 107-114

[20]. N. P. A. Smith "Induction Generators for stand-alone Micro-Hydro systems," IEEE International Conference on Power Electronics Drives and Energy Systems, January 1996, pp.669-673.

[21]. S. P. Singh, S. K. Jain, J. D. Sharma, "Transient performance of three-phase Self-Excited Induction Generator during balanced and unbalanced faults," IEE Proceedings Online no.20020007, IEE 2002.

[22]. S. C. Kuo and L. Wang "Analysis of isolated self-excited Induction Generator feeding a rectifier load," IEE Proc. Genr. Transmission Distribution, Vol.149, No.1, January 2002.

[23]. Roberto Leidhold, Guillermo Garcia, Mariaines Valla "Induction Generator controller based on instantaneous reactive power theory," IEEE Trans. on Energy Conversion Vol.17, No.3, September 2002.

[24]. Bhim Singh, Madhusudhan, A. K. Tondon, "Dynamic Modeling and analysis of Three Phase Self excited Induction Generator using MATLAB," NPSC, 2002.

[25]. Tarek Ahmed, Osamu Noro, Eiji Hiraki, Mutsuo Nakaoka "Terminal Voltage Regulation characteristics by Static VAR Compensator for a three-phase Self-excited Induction Generator," IEEE Trans. on Industry 2005