

Optimal Placement of Facts Devices Using Particle Swarm Optimization Technique for the Increased Loadability of a Power System

D.Venugopal¹, Dr. A. Jayalaxmi²

¹(Associate Professor, Electrical and Electronics Engineering Department,
Kamala Institute of Technology and Science, Singapur, Karimnagar, Telangana State, India)

²(Professor, Electrical and Electronics Engineering Department,
Jawaharlal Nehru Technological University College of Engineering, Kukatpally, Hyderabad,
Telangana State, India)

Abstract: This paper deals with the optimal location and parameters of TCSC and SVC in electrical power systems, using Particle Swarm Optimization technique (PSO). The objective is to maximize the transmission system loadability subjected to the transmission line capacity limits and specified bus voltage levels. Using the proposed method, the location of SVC and TCSC and their parameters are optimized simultaneously for IEEE 30 bus system. PSO is used to solve the above non linear programming problem for better accuracy.

Keywords: Thyristor Controlled Series Capacitor, Static Var Compensator, Particle Swarm Optimization, Evolutionary Computation, Power flow.

I. Introduction

Recently FACTS technology has become a very effective means to enhance the capacity of existing power transmission networks to their limits without the necessity of adding new transmission lines. Better utilization of existing power system capacities is possible by connecting FACTS devices in the transmission network. By introduction of FACTS devices, flexible power flow control is possible. It is known that the power flow through an ac transmission line is a function of line impedance, the magnitude and the phase angle between the sending end and the receiving end voltages. By proper utilization of Thyristor controlled series capacitor, Static Var Compensator in the power system network, both the active and reactive power flow in the lines can be controlled. The additional flexibility of power flow using FACTS devices must lead to a net economic gain despite the high cost of FACTS devices.

The modeling and selection of possible locations for the installation of FACTS devices have been discussed in [6]. In a congested power system, first the locations of the FACTS devices are decided based on the sensitivity factors and then dispatch problem is solved in [10]. Genetic algorithm based separate and simultaneous use of TCSC, UPFC, TCVR, SVC were studied in [3] for increased power flow. The objective of this present work is the optimal allocation of FACTS devices in the transmission network so the transmission loss gets minimized and also simultaneously increases the power transfer capacity of the transmission network.

Minimization of transmission loss is a problem of reactive power optimization and it can be done by controlling reactive generation of the generators, controlling transformer tap positions and adding shunt capacitors in the weak buses [16] but the active power flow pattern cannot be controlled. In the proposed work, first the location of the FACTS devices are identified by calculating different line flows. Voltage magnitude and the phase angle of the sending end buses of the lines where major active power flow takes place are controlled by UPFC. TCSC's are placed in the lines where reactive power flows are very high and the SVC's are connected at the receiving end buses of the other lines where major reactive power takes place. Particle Swarm Optimization based approach considering the simultaneous effect of the two types of the FACTS devices are presented and the effectiveness of this technique is clearly evident from the results shown.

II. Facts Devices

Mathematical modeling of FACTS devices is required for the steady state analysis. Here the FACTS devices used in the transmission network are TCSC, SVC.

2.1 TCSC

By modifying the line reactance, TCSC acts either as inductive or capacitive compensator. The maximum value of the capacitance and inductance are fixed at $-0.8X_L$ and $0.2X_L$ respectively, Where X_L is the line reactance.

2.2 SVC

SVC can be operated either as inductive or capacitive compensator. It can be modeled with two ideal switched elements in parallel: a capacitor and an inductor. So the function of the SVC is either to inject reactive power to bus or to absorb reactive power from the bus where it is connected.

2.3 Optimal Siting Of Facts Devices

The decision where to place a FACTS device is largely dependent on the desired effect and the characteristics of the specific system. Static Var Compensators (SVC) are mostly suitable when reactive power flow or voltage support is necessary. TCSC devices are not suitable in the lines with high reactive power flow. Also the costs of the devices play an important role for the choice of a FACTS device. Having made the decision to install a FACTS device in the system, there are three main issues to be considered: Type of device, capacity and location.

There are two distinct means of placing a FACTS device in the system for the purpose of increasing the system ability to transmit power, thereby allowing for the use of more economic generating units. That is why FACTS devices are placed in the more heavily loaded lines to limit the power flows in that line. This causes more power to be sent through the remaining portions of the system while protecting the line with the device for being overloaded. This method which sites the devices in the heavily loaded line is the most effective. If the reactive power flow is a significant portion of the total power flow on the limiting transmission line, either a TCSC device in the line or a SVC device located at the end of the line that receives the reactive power, may be used to reduce the reactive power flow, thereby increasing the active power flow capacity.

III. Particle Swarm Optimization (PSO)

3.1 PSO Operation:

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO is inspired by social system, more specifically, the collective behaviors of simple individuals interacting with their environment and each other. PSO simulates the behaviors of bird flocking [13]. Assume 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. The effective one is to follow the bird, which is nearest to the food. PSO learned from 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 then searches for optima by updating generations, the particles are "flown" through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called pbest (particle best). Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called gbest (global best). The basic concept behind the PSO technique consists of changing the velocity (or accelerating) of each particle toward its pbest and the gbest positions at each time step. This means that each particle tries to modify its current position and velocity according to the distance between its current position and pbest, and the distance between its current position and gbest.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, the PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods.

Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. One version, with slight variations, works well in wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement. PSO has been successfully applied in areas like, function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.

3.2. Optimization Process

3.2.1. Initialization

Generate particles & their velocities randomly with uniform probability over the optimized parameter search space i.e. within its minimum & maximum values.

Optimization process is tested for its robustness on a standard IEEE 30 bus system. The network consists of 6 Generator buses, 21 load buses & 41 lines, of which 4 lines are due to tap setting transformers. Buses 10, 12, 15, 17, 20, 21, 23, 24 & 29 have been selected as shunt compensation buses. It contains 24 control variables. In this case each particle would include all control variables, i.e. 5 active powers of generators, 6 generator voltages, 4 transformer taps & 9 shunt locations.

3.2.2. Evaluation of Objective function

Each particle offers data related to PG & V of generators except slack bus, tap settings & shunt admittance values. Using this data, the base case data is updated using the equations run the load flow is run to evaluate the corresponding objective functions. As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time upto the current time. The best position that is associated with the best fitness encountered so far is called the individual best i.e. pbest. Global Best is the best position among all individual best positions achieved so far.

3.2.3. Updation

$$V_i^{k+1} = V_i^k + C_1 \times \text{rand1} \times (pbest_i - S_i^k) + C_2 \times \text{rand2} \times (gbest - S_i^k) \tag{1}$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{2}$$

Where

V_i^{k+1} = Velocity of particle i at iteration k+1

V_i^k = Velocity of particle i at iteration k

S_i^{k+1} = position of particle i at iteration k+1

S_i^k = position of particle i at iteration k

C_1 = Constant weighing factor related to pbest

C_2 = Constant weighing factor related to gbest

rand1, rand2: Random numbers between 0 and 1

$pbest_i$ = pbest Position of particle i

gbest: gbest Position of the swarm

Expressions (1) and (2) describe the velocity and position update, respectively. Expression (1) calculates a new velocity for each particle based on the particle's previous velocity, the particle's location at which the best fitness has been achieved so far, and the population global location at which the best fitness has been achieved so far.

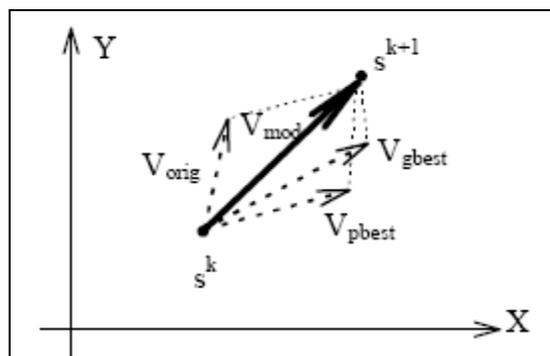


Figure 1. Concept of modification of a searching point.

- S^k Current Position
- S^{k+1} Modified Position
- V_{orig} Current Velocity
- V_{mod} Modified Velocity

V_{pbest} Velocity base on $pbest$

V_{gbest} Velocity based on $gbest$

As explained earlier, PSO simulates the behaviors' of bird flocking. Suppose 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 is initialized with a group of random particles (solutions) and then searches for optima by updating generations. 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 $pbest$. 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 $gbest$. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called $lbest$.

3.2.4 Construction of Particle

The goal of the present optimization is to find the best location of a given number of FACTS devices in accordance with a defined objective function within the equality and inequality constraints [13]. The configuration of FACTS devices is encoded by three parameters: the location, type and its rating. Each individual is represented by n_{FAC} number of strings, where n_{FAC} is the number of FACTS devices to be optimally located in the power system [3], as shown in fig.2.

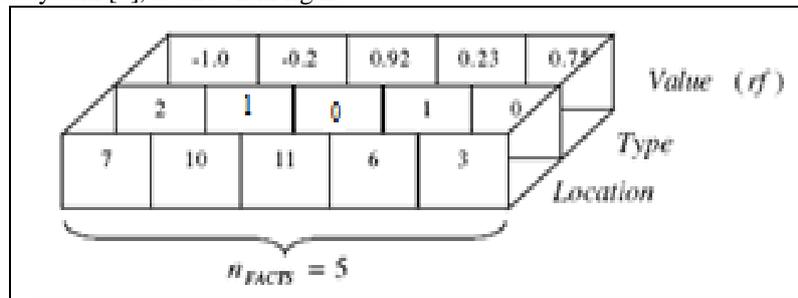


Figure2. Individual configuration of FACTS devices.

The first value of each string corresponds to the location information. It must be ensured that on one transmission line there is only one FACTS device. The second value represents the types of FACTS device (n_{ty}). The values assigned to FACTS devices are: "1" for SVC located at a bus; "2" for TCSC located in a line, "0" for no FACTS device. The last value rf represents the rating of each FACTS device. This value varies continuously between -1 and $+1$. If the selected FACTS device is TCSC, then the rated value generated lies between $-0.8X_l$ to $0.2X_l$. If it is SVC, the rated value is SVC susceptance (Bsvc) and this value generated lies between -0.45 p.u to and 0.45 p.u.

To obtain PSO Particles, the above operations are repeated n_{Ind} times, where n_{Ind} is number of individuals of the population. The objective function is computed for every individual of the particle and its fitness. In this paper, the objective function is defined in order to quantify the impact of the FACTS devices on the state of the power system and is presented in the next section.

IV. Objectives Of The Optimization

The three objectives considered here are Branch Loading (BL) maximization, Voltage Stability (VS) maximization and Loss Minimization (LM).

4.1 Branch Loading (BL) maximization

The first objective is related to the branch loading and penalizes overloads in the lines [13]. This term, called BL, is computed for every line of the network. When the branch loading is less than 100%, its value is equal to 1; then it decreases exponentially with the load [6].

$$BL = \prod_{line} J_{line} \quad (3)$$

$$J_{line} = \begin{cases} 1 & ; \text{if } S_{pq}^{max} \geq S_{pq} \\ e^{\left[\lambda \left(1 - \frac{S_{pq}}{S_{pq}^{max}} \right) \right]} & ; \text{if } S_{pq} > S_{pq}^{max} \end{cases}$$

Where, BL is Branch Loading factor, S_{pq} and S_{pq}^{max} are MVA flow and thermal limit of the line between buses p and q. λ is a small positive constant equal to 0.1.

4.2 Voltage Stability (VS) maximization

The second objective function is concerned with voltage levels. It favors bus voltages which are close to 1 p.u. The function is calculated for all buses of the power system. For voltage levels comprised between 0.95 p.u. and 1.05 p.u., the value of the objective function VS is equal to 1. Outside this range, the value decreases exponentially with the voltage deviation [13].

$$VS = \prod_{BUS} J_2 \tag{4}$$

$$J_2 = \begin{cases} 1 & ; \text{if } 1.05 \geq V_b \geq 0.95 \\ e^{-[\mu(1-V_b)]} & ; \text{otherwise} \end{cases}$$

Where, V_b is Voltage at bus b and μ is a small positive constant equal to 0.1.

4.3 Loss Minimization (LM) minimization

For reactive power optimization, system transmission loss minimization is considered as the objective function. The converged load flow solution gives the bus voltage magnitudes and phase angles. Using these, active power flow through the lines can be evaluated. Net system power loss is the sum of power loss in each line

$$J_3 = \sum_{i=1}^{NL} LOSS_i = LM \tag{5}$$

Where, NL is the number of transmission lines in a power system.

In most of the optimization problems, the constraints are considered by using penalty terms in the objective function. In this paper also, the objective function used, penalizes the configurations of FACTS devices which cause overloaded transmission lines and over or under voltages of buses [3]. Branch loading penalizes overloads in the lines and voltage stability penalizes for bus voltages which are not between 0.9 and 1.1 p.u.

4.4 Methodology

The step by step algorithm for solving the proposed optimization problem is given below.

Step 1: The number of FACTS (TCSC&SVC) devices to be placed and the initial load factor are declared.

Step2: The initial population of individuals is created satisfying the TCSC &SVC constraints and also it is verified that only one device is placed in each line.

Step 3: For each individual in the population the fitness function given by the equation

$$\text{Minimize } F = \prod_{lines} J_{lines} + \prod_{BUS} J_2$$

Is evaluated after running the load flow.

Step 4: Velocity is updated by equation 1 and the new population is created by equation 2.

Step 5: Step 3 and 4 are repeated till maximum number of iterations is reached.

Step 6: If the final best individual obtained satisfies all the constraints in the problem, then increment the load factor and go to step2 else go to next step.

Step7: Print the previous best individual which contains location and parameters of TCSC & SVC with the corresponding load factor.

Step 8: Stop the procedure.

In this paper, all the loads are increased in the same proportion and it is assumed that the increase in real power generation due to this increase in load is met by the generator connected to the slack bus. The optimization strategy has been adopted in this paper reduces the computational time which is significant especially in large systems.

V. Results And Discussions

To verify the effectiveness and efficiency of the proposed PSO based loadability maximization approach, the IEEE-30 bus system is used as the test system. The numerical data for IEEE-30 bus system is taken from [18].The simulation studies are carried out on Intel core2Duo, 2.8 GHz system in MATLAB environment.For the given optimization problem, it is found that, by setting the acceleration coefficients C_1 and C_2 both equal to 2.5., better solutions are obtained in a reasonable time. Although PSO is sensitive to the tuning of parameters, this paper has proved its potential in solving complex power system problems. It has been found from results that, PSO quickly finds the high quality optimal solution.

5.1 IEEE 30-Bus Test System

The parameters of PSO chosen for IEEE -30 Bus system are

Number of iterations=50
 Number of particles=20

Figure 3 shows the maximum possible loadability with the given number of FACTS (TCSC&SVC) devices for IEEE-30 bus test system. It is observed that the optimal location and parameters of FACTS devices increase the system loadability.

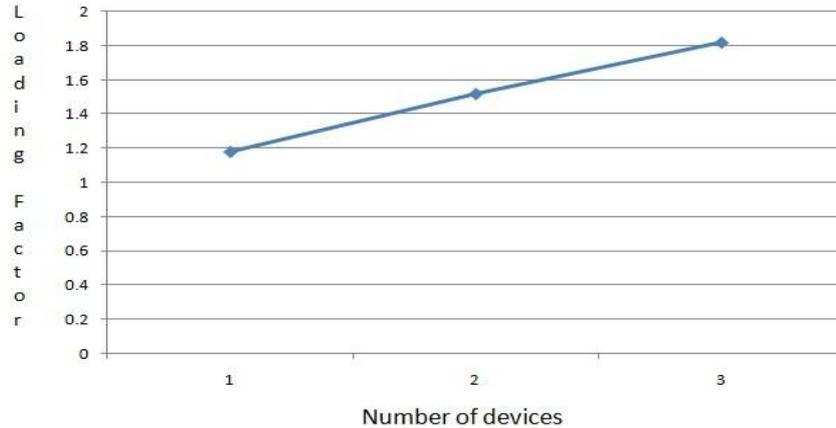


Figure 3. Maximum loading factor with respect to given number of FACTS Devices for IEEE 30- bus system

Table I: Optimal location and parameters of FACTS devices for different load factors for IEEE-30 bus system

Number of Devices	Type of Device	Loading Factor	Branches embedded with FACTS Devices (Line/Bus)	FACTS Devices Parameters
1	One Series Device (TCSC)	1.18	4-6 (line7)	-0.1535
2	Two Shunt Devices (SVC)	1.52	Bus 10 Bus 24	14.4510 13.4761
3	One Series (TCSC) & Two Shunt Devices (SVC)	1.82	15-18 (Line 22) Bus 10 Bus 24	-0.2988 8.32050 18.6102

The results obtained using the proposed method for IEEE 30 bus system is summarized in Table I. Table I gives the optimal location and parameters of FACTS devices for different load factors for IEEE 30 bus system. From the results, it is observed that the loadability has been increased to 118% by installing a TCSC in line 7 which connects buses 4 and 6. The maximum loadability with two SVC's without violating thermal and voltage constraint is 152%. For this load factor, the SVC's are placed at buses 10 and 24. From figure, it is clearly evident that there is maximum number of devices beyond which the efficiency of the network cannot be further improved.

According to the used optimization criterion for IEEE-30 bus system, the maximum number of FACTS devices (TCSC&SVC) beyond which the loadability cannot be increased is 3.

Table II: Comparison of simulation results of IEEE 30 bus system

Compared Item	EP Based Method	PSO Based Method
Maximum possible loadability	1.7959	1.82
Number of FACTS Devices required for obtaining the maximum load ability	4	3
Total number of generations	100	50
Population size	300	20

To demonstrate the superiority of the proposed PSO based approach, simulation results have been compared with the results available in literature using evolutionary programming (EP) method presented [9]. In [9], a deterministic based method has been applied to evaluate the network losses. The network losses are set to 10% of the total losses. The objective function formed in [9] includes the loadability term which is slightly different from the objective function used in this paper. In this paper losses are calculated by conducting Fast decoupled Load Flow solution method.

Table II summarizes the results as obtained by the two methods for the IEEE-30 bus system. Using the proposed methodologies, the results show that the optimal solutions determined by PSO lead to increased loadability of the lines with less number of FACTS devices, which confirms that PSO based present approach is capable of determining global optimal or near global optimal solution.

Table II also shows that PSO is faster than EP in speed because of less number of generations or iterations and smaller population size used by PSO to obtain the optimal solution.

VI. Conclusion

This paper investigates two promising FACTS devices, namely TCSC and SVC as control agents in a power system. Particle Swarm Optimization technique is used to determine the optimal location and parameters of TCSC and SVCs. The system loadability was employed as a measure of power system performance. Simulation results validate the efficiency of this new approach in maximizing the loadability of the system. Even though the number of FACTS devices is increased, the system loadability increases only upto a limit. The performance of the method demonstrate through its evaluation of the IEEE 30 bus power system, shows that PSO is able to undertake global search with a fast convergence rate and a feature of robust computation. The proposed algorithm is an effective method for the allocation of FACTS devices in large power systems.

References

- [1] N. G. Hingorani and L. Gyugyi, "Understanding FACTS Concepts and Technology of Flexible AC Transmission Systems". (Piscataway: IEEE Press, 1999).
- [2] F. D. Galiana, K. Almeida, M. Toussaint, J. Griffin, and D. Atanackovic, "Assessment and control of the impact of FACTS devices on power system performance," IEEE Trans. Power Systems, Vol. 11, No. 4, Nov. 1996.
- [3] S. Gerbex, R. Cherkaoui, and A. J. Germond, "Optimal location of multi type FACTS devices in a power system by means of genetic algorithms," IEEE Trans. Power Systems, Vol. 16, pp. 537-544, 2001.
- [4] S.N.Singh and A.K.David, "Congestion Management by optimizing FACTS devices location", IEEE Power Engineering Review, September 2000, pp.58-60.
- [5] Keshi Reddy Saidi Reddy, Narayana Prasad Padhy, and R.N.Patel, "Congestion Management in Deregulated Power System using FACTS devices" IEEE 2006.
- [6] D.J.Gotham and G.T. Heydt, "Power Flow Control and Power Flow Studies for system with FACTS Devices," IEEE Trans on Power System, Vol 13, No 1, February 1998.
- [7] B.Battaacharya, B.S.K.Goswami, "Optimal Placement of FACTS Devices using Genetic Algorithm for the increased loadability of a power system", World Academy Of Science and Technology, 2011.
- [8] R.M.Mathur, R.K. Varma, "Thyristor Based FACTS Controllers for Electrical Transmission Systems", (John Wiley & Sons Inc., 2002).
- [9] J.Hao, L.B.Shi and Ch.Chen, "Optimising location of unified power flow controllers by means of improved evolutionary Programming", IEE Proc. Gener. Transm. Distrib., Vol. 151, No. 6, PP 705-712, November 2004.
- [10] S.N. Singh and A.K.david, "Optimal location of FACTS devices for congestion management" Electric power system research, Vol 58, pp 71-79, 2001.
- [11] H.Ambriz-perez, E.Acha and C.R. Fuerte-Esquivel, "Advanced SVC models for Newton-Raphson load flow and Newton Optimal Power flow studies", IEEE.
- [12] L.J.Cay, I.Erlich, "Optimal choice and allocation of FACTS devices using Genetic Algorithms", 2004.
- [13] M.Saravanam, S.MaryRajaSlochanal, P.V.Venkatesh, Prince Stephen Abraham, J, "Application of PSO technique for optimal location of FACTS devices considering system loadability and cost of installation" In: Power Engineering Conference, 716-721.
- [14] J.G.Singh, S.N.Singh and S.C.Srivastava, "Placement of FACTS controllers for enhancing FACTS controllers", IEEE 2006.
- [15] James A.Momoh, M.E.El-Hawary, Rambabu Adapa, "A Review of Selected Optimal Power Flow Literature to 1993 Part-I: Non-linear and Quadratic Programming approaches", IEEE Transactions on Power Systems, Vol. 14, No.1, February 1999, pp. 96-104.
- [16] B.Battacharya, S.K.Goswami, R.C.Bansal, "Sensitivity approach in evolutionary Algorithm for reactive power planning", International Journal of electric power components and system, Taylor and Francis group, Vol 37, Issue 3, pp 287-299, 2009.
- [17] D.Venugopal, Dr.A.Jayalaxmi "Congestion Management by Optimal Choice and allocation of FACTS Controllers using Genetic Algorithm" International Journal of Soft Computing and Engineering (IJSCE), July-2014, ISSN:2231-2307, Vol.4, Issue3, PP.72-76.
- [18] The university of wasihngton archive, <http://www.ee.washington.edu/research/pstca>