OPTIMIZATION OF PLACEMENT OF FLEXIBLE AC TRANSMISSION SYSTEMS USING EVOLUTIONARY ALGORITHMS

CS 448 Project First Draft

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ABSTRACT

The crucial factor affecting the modern power systems today is power flow control. The Unified Power Flow Controller (UPFC) provides an effective means for controlling the power flow and improving the stability in a power network. For maximum positive impact of this device on the power grid this device should be installed in a correct location with its best control settings. The first objective of this project is to find the best placement and control settings of the FACTS device by using an Evolutionary Algorithm and Sequential Quadratic Programming (EASQP) respectively. Previous research shows that an algorithm which considers both optimizing the control settings and placement is the one with Max Flow control settings and a Heuristic for placement (MFH). Therefore the second objective of this project is to compare the performance of the proposed algorithm (EASQP) with MFH. Experiments for the EASQP are performed in MATLAB 7.0 environment on the IEEE 118 data bus system. Due to computational intensity the algorithms are tested for two FACTS devices only.
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1. INTRODUCTION & MOTIVATION

With the ever increasing complexities in power systems across the globe and the growing need to provide stable, secure, controlled, economic, and high-quality electric power – especially in today’s deregulated environment – it is envisaged that Flexible AC Transmission System (FACTS) devices are going to play a critical role in power transmission systems [1]. Transmission congestion results when there is insufficient capacity to transmit power over existing lines and maintain the required safety margins for reliability. FACTS devices enhance the stability of the power system both with its fast control characteristics and continuous compensating capability. The two main objectives of FACTS technology are to control power flow and increase the transmission capacity over an existing transmission corridor by placing the device at an optimal location.

To solve above problem, heuristic methods can be used. The heuristic algorithms search for a solution inside a subspace of the total search space. Thus, they are able to give a good solution of a certain problem in a reasonable computation time, but they do not assure to reach the global optimum. The most important advantage of heuristic lies in the fact that they do not have limits by restrictive assumptions about the search space like continuity, existence of derivative of objective function, etc. There are many heuristic algorithms such as simulation annealing, evolutionary algorithms (EA) etc. Among these an EA is a good fit to solve this optimization problem as it can deal with nonsmooth, discontinuous and non-differentiable functions which are confronted in power flow control with FACTS devices. In the past EAs proved to be successful at searching such complicated and uncertain regions to converge at near optimal/optimal solution. Considering the facts above an EA can be used for determining the location of FACTS devices.

While determining the placement it is crucial to have optimal control setting for the FACTS device for its best usage. Previously techniques such as Max-flow and SQP have been used for this optimization, of these SQP technique proved to be better. Henceforth the main goal of this project is to find a placement for one of the most costly
and powerful FACTS device UPFC, using an EA while the control settings are
determined by SQP.

In this first draft, of the project report, Section 2 puts forth the problem that has to
be solved by using the proposed algorithm (EASQP). Section 3 gives a brief overview of
the previous research and their short comes which are solved by the proposed algorithm.
Section 4 describes the experimental setup of IEEE 118 bus test system and FACTS
device model used in this project. Section 5 gives an introduction to the parameters that
may be used for conducting the experiments on the proposed algorithm. Section 6 shows
the experiments conducted on the test system and relevant statistical analysis. Section 7
gives the conclusion and future work for the project.

2. PROBLEM STATEMENT

Due to ever increasing load demand and reduced rights of way, modern power
transmission systems are forced to carry increasingly more power over long distances.
Consequently, the transmission system becomes more stressed, which, in turn, makes the
system more vulnerable to stability and security problems. In such a condition, a few
failures (contingencies) in the system can cause excessive burden on the remaining
components and eventually lead to cascading failures similar to the 2003 blackout that
affected a large portion of the northeastern U.S. and parts of Canada.

The need of the hour is, therefore, to operate the high power transmission grid in a
way that it is able to carry more power (ideally close to its thermal limit) over long
distance without sacrificing its stability and security margins. The above task can only be
accomplished when there is a proposed fast control, over power flow in a transmission
system. With the emergence of high power semiconductor switches, a number of control
devices under the generic name of FACTS have come under active consideration to
achieve the above objective.

FACTS devices, by virtue of their fast controllability, are expected to maintain the
stability and security margin of highly stressed power systems. However, to achieve the
good performance of these controllers, proper placement of the controlling devices in the grid is as important as an effective control strategy. Hence, it is imperative that proper placement strategy must precede the installation of any such device. There are several indices/methods proposed in literature for placement of FACTS devices. In this project one of such indices called Modified Performance Index* (MPI) is used to qualify the impact on the power system. This index minimizes the overloads as higher overloads incur heavier penalties than lower overloads and power flow imbalances because any imbalance is penalized, resulting in less line losses. The equation for the MPI is as shown below by Eq (1)

$$MPI = \sum_{SLCs} P_c \left( \sum_{LineL} \omega_L \left( \frac{S_L}{S_{L\text{max}}} \right)^n \right)^m$$

(1)

where $P_c$ = Probability of the contingency to occur

$\omega_L$ = Line Importance

$S_L$ = Apparent power flow on the line during an SLC

$S_{L\text{max}}$ = Maximum apparent power flow on the line

and $n$ and $m$ are the constants which are greater than 1 to decrease the masking effect. For this project the values will be $P_c = 1$, $\omega_L = 1$, $n = 2$, $m = 1$ which renders the Eq (2) from Eq (1)

$$MPI = \sum_{SLCs} \sum_{all\ Lines} \left( \frac{S_i}{S_{i\text{max}}} \right)^2$$

(2)

The problem of this project is to find a vital location for a given number of FACTS devices in a power system (118 bus) in order to decrease the over loads in the system during a single line contingency. The goal is to maintain the steady state power flow of the system using a FACTS device such that it impacts the system the best to retain its stability. This can be mathematically stated as – given a power system with $M$ buses, $N$ lines and $K$ FACTS devices, find a set of $K$ lines where the FACTS can be placed, such that the overloaded power of the system is minimized over all the single line contingencies (SLCs) while optimizing the control settings at that particular location.
(using SQP). The second objective of this problem is to compare these results with MFH which has shown best results so far in optimizing the control settings and placement.

3. PREVIOUS RESEARCH

For last two decades researchers developed new algorithms and models for power flow and optimal power flow incorporating FACTS devices, so that cheap power can be made available to the customers without violating system constraints. Still research is in progress to meet the present day congestion management problem with the help of FACTS devices, but no solution is yet reached. Previously different algorithms have been proposed to solve power flow and optimal power flow for power system equipments with first (TCSC, SVC) and second generation (STATCOM, SSSC) FACTS devices, but not many researchers solved the power flow problem involving UPFC. Few researchers [2, 3] have worked on the installation of UPFC from an economic perspective rather than security perspective. This research did not consider the contingency analysis or fault criterion for optimizing the control settings and placement of the FACTS devices. Research made by Armbruster. A et al [4] tried to improve the security of the power system by using Max Flow Algorithm.

Armbruster. A et al proposed a graph theory based Max Flow algorithm for UPFC control setting and a heuristic for placement which aimed at decreasing the system overloading by minimizing the Number of Overloads (NOL). In Max Flow algorithm, the power network is modeled as a directed graph G(N,A) where power flow is represented as flow in graph. The set of nodes, N, corresponds to the buses of the power network. The power line between buses \( n_i, n_j \in N \) is represented by an arc \( a_{ij} \in A \). Each arc is assigned a tuple of the amount of remaining flow and the maximum flow \( u_{ij} \), for that particular line. For the basic max-flow algorithm there are two special nodes, the virtual source(s) and the virtual sink (t), representing the combination of the generator(s) and load(s), respectively. Each line out of the virtual source has a maximum flow that matches the generation of the connected node, and each line into the virtual sink represents the load
demanded by the connected node. Figures 1 and 2 show an example power system with 5 buses and its corresponding directed flow graph respectively.

Fig. 1 Example power system with buses A, B, C, D and E.

Fig. 2 Power Network in Fig 1 shown as a directed flow graph with virtual nodes s and t
Initially the arc capacities are set to the steady state power flow values. By starting from the steady state values, the Max Flow algorithm attempts to keep the network in a physically feasible configuration. If the Max Flow cannot satisfy these settings, changes are made to try to satisfy the load. First, all of the settings are increased to the corresponding line capacities. The Max Flow algorithm is then restarted with the unsatisfied sink nodes as source nodes and source nodes as sink nodes. This algorithm changes slightly to compensate for the change in source and sink nodes. When the arc flows are modified, the negative value of the \( \Delta \) is added to or subtracted from the arc flow. The final change to the algorithm is in the calculation of the \( \Delta \) values to be \( \Delta_{ij} \leftarrow u_{ij} - f_{ij} \). The resulting flow is a solution that satisfies all loads and line capacities, if one exists. The lines to which the UPFCs are attached are set to the Max flow settings to control power flow in UPFCs. An algorithm for the Max Flow and a heuristic for the placement are given in the paper by Armbruster A et al [4].

In this project a SQP method is proposed to find the control settings of the UPFC based on MPI metric search space. To find the nature of the search space two UPFCs are located at two random positions and a plot of the objective function was generated for all combinations of UPFC control settings. These control settings are in the range of (Steady state value \( \pm 20\% \) of \( P_{\text{max}} \) value) of the line on which the UPFCs are installed. Figure 3 shows the concave smooth surface of the MPI metric over the control settings. For this surface techniques such as SQP can be used. Although the search space seems to be smooth there may be local minima. To ensure the existence of local minima a sampling test is done starting with various random points. In this test multiple UPFCs (ranging from 2 to 10) are randomly placed in the system and the SQP optimization is performed using randomly chosen start points. If any local minimum is present the algorithm should converge at different points. But the algorithm converged always to the same point as shown in Fig 3. Therefore SQP in conjunction with EA is used to find the optimal control settings and relevant placement of the FACTS devices.
4. IMPLEMENTATION OF EA

Evolutionary algorithms are robust search and optimization algorithms based on natural selection in environments and natural genetics in biology. They are based on the natural evolution according to the principle of survival of the fittest. The placement of FACTS devices is a computationally intensive problem, and also the non linear dependencies among the devices can cause complex local optima in the search space. To solve such kind of problem, heuristic methods can be used. Among these EA is the best to solve this problem.

4.1 Representation - The population of EA is a set of integers which indicate the branches on which the FACTS devices have to be placed. The length of each individual (solution) is fixed to $N_{\text{Facts}}$, where $N_{\text{Facts}}$ are the number of FACTS devices that have
to be installed in the IEEE 118 bus power system for decreasing the loadability of the system. Each gene of the individual represents a line number where FACTS device has to be installed. For example, for a placement with N\text{Facts} = 4, a single individual in the population might be as shown below, in Fig. 4.

| 10 | 27 | 50 | 117 |

*Fig. 4 Example Placement*

In the individual shown above gene 10 - represents a line connected between buses (5, 11), gene 27 – represents a line connected between buses (17, 18), gene 50 – represents a line between buses (30, 38) and gene 117 – represents a line connected between (69, 70).

**4.2 Fitness Function** – The objective of the optimization problem here is to minimize the overloading of the system by optimal placement of more than one FACTS device. For this EA the fitness is the MPI value which is obtained by running the SQP over all Single Line Contingencies (SLCs) to obtain the best control settings. As the fitness should always be maximized the fitness function is negative of the MPI value obtained from SQP, as shown by Eq (3).

\[
\text{Fitness Function} = -\text{MPI} = - \sum_{\text{SLCs}} \sum_{\text{Lines}} \left( \frac{S_i}{S_{i\text{max}}} \right)^2
\]

The time taken for the computation of the one MPI value is 108 sec on Pentium VI machines in Matlab 7.0 environment.

**4.3 CACHE:** As (mention earlier) the computational intensity of SQP is pretty high a CACHE is designed to decrease the computational time by decreasing the number of calls for the calculating the fitness value. The design of the CACHE is as shown in Fig. 5. Whenever the calculation of fitness is called for, the CACHE is looked up for the given placement. If the placement exists in the CACHE, the flag is set to 1 and CACHE hit is counted. The value of the fitness is assigned to the value from CACHE. If it is a miss then the flag is set to 0 and the blackbox is called for calculating the fitness value. Once
the fitness is calculated it is logged into the CACHE at the next index position. The variable, index points to the last placement in the stack of the CACHE.

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**Fig. 5 Design and implementation of CACHE**

The design of CACHE and its implementation has expedited the algorithm by 10 times. A detailed statistical analysis of the CACHE will be explained in Section 6. The advantages of implementing CACHE are

- It decreased the computational intensity of the algorithm
- It helped to retrieve the data very easily in case of sudden shut down of the experiments. Usage of the same seed for the random number generator helped to calculate all the data back easily.
- The total time for running 60 generations decreased substantially if the initial population is assigned from CACHE.
4.4 Initialization - A random population (population size -1) is generated where the number of individuals in the population is specified by the parameter population size. The length of each individual is equal to number of FACTS devices which is specified by parameter N Facts. The population is initialized such that the genes reflect the lines. The last individual in the population is the best placement obtained from MFH. This is done to test if the best individual which survives in the EA is the best placement of MFH. This did not happen; the EA could find a better individual which replaced the MFH placement.

Table 1. Specifications of EA for placement problem

<table>
<thead>
<tr>
<th>Representation</th>
<th>Fixed length integer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initialization</td>
<td>Customized (Section 3.4)</td>
</tr>
<tr>
<td>Parent Selection</td>
<td>Tournament Selection with variable length of offspring and parents</td>
</tr>
<tr>
<td>Recombination</td>
<td>One point crossover</td>
</tr>
<tr>
<td>Mutation</td>
<td>Customized (Section 3.6)</td>
</tr>
<tr>
<td>Survivor Selection</td>
<td>Rank Based for Steady State (μ + λ)</td>
</tr>
<tr>
<td>Termination</td>
<td>Number of Generations</td>
</tr>
</tbody>
</table>

4.5 Parent Selection – A set of individuals are selected from the population to conduct tournament for the fittest individuals. The number of parents in the tournament is specified by the parameter NParents. The output of the tournament gives two parents which are used to generate new offspring by doing recombination of the fittest parents.

4.6 Recombination – The number of offspring that can be generated by recombination is specified by the parameter Noffspring. Once the parents for the recombination are selected the mating of these parents depends on the recombination parameter called CrossOverRate. If a random number generated is less than the CrossOverRate an offspring is generated by implementing one point crossover else the same individual is retained for the next generation. In this way Noffspring are generated.

4.7 Mutation – Each offspring generated by recombination are mutated depending on a mutation probability called MutationRate. Mutation here reflects the movement of the
FACTS device to its neighboring lines. This movement is performed based on system topology. A gene in a placement will be mutated to its neighbor. A line is a neighbor to another line if it has a common bus. Therefore a FACTS device, when chosen for mutation depending on the *MutationRate*, is moved from the present line to its neighboring lines. This helps in identifying a line which actually affects the power system by decreasing the overloaded power.

Figures 6a and 6b shown below show a small network with lines 20, 21, 22, 23, 24 and 28 connected to each other. All these lines will be prone to mutation as the FACTS device is installed on line 20 initially. It shares a common bus with all the remaining lines. By mutation operation mentioned above, the FACTS device is moved to neighboring line of 20 which is 21. This example consolidates the mutation operation for this placement algorithm [5].

### 4.8 Validation

Validation is an extra stage in the EA to check if any of the line numbers are duplicated in the placement which is an invalid condition in real time power system. An example for an invalid placement is as shown below in Fig. 7.

<table>
<thead>
<tr>
<th>10</th>
<th>50</th>
<th>50</th>
<th>117</th>
</tr>
</thead>
</table>

*Fig. 7 Invalid Placement*
In this placement two FACTS devices are placed on the same line 50. This can be corrected by checking the placement right after the offspring is generated and moving the device to lines away from the present installation 50. By implementing validation every placement is ensured to be unique before it is evaluated for its MPI value.

4.9 Survivor Selection – A steady state EA with rank based selection is used for survival selection. This type refers to \((\mu + \lambda)\) strategy where the population size is always fixed to the value of \(\mu\), population size. Population size remains constant from one generation to the next. Thus, after the specified number of offspring has been created, the exact same number of individuals must be removed. This is done by removing the \(\lambda\) least fit individuals from the total population of \((\mu + \lambda)\). The total population is sorted according to fitness, and the best \(\mu\) of them are selected to survive. This deterministic approach is chosen over stochastic for faster convergences as the given fitness function is computationally intensive.

4.10 Termination Condition – Considering the computational constraints and the unavailability of near optimal/optimal solution, the termination condition is confined to number of generations.
5. EXPERIMENTAL SETUP

5.1 Dataset: The data for the placement algorithm is the IEEE 118 bus power system. This dataset represents a power network with 118 buses, 186 lines and 20 generators in the power system. The one line diagram of the network is as shown in Fig. 8. For implementation in MATLAB 7.0.0 the data is provided in a script file.

![Fig. 8 IEEE 118 bus Power System](image)

The inputs to the SQP algorithm are the set of line numbers where the FACTS devices have to be placed. The output of the SQP is the MPI value calculated over all SLC’s using SQP optimization.

5.2. FACTS Model: Two FACTS devices are installed in the test system mentioned above. For representing installation of the UPFC in the power system a particular power flow model of the FACTS device is needed. The function of the UPFC in the network is to act as a means of forcing a specific amount of real power to flow through a line. By forcing power through a line, the remaining lines in the system adjust their power flow according to the physics of the system. The UPFC is modeled as a
device which delivers real power to one of the buses of \( \text{Line}_{ij} \) (shown in Fig 9a) and draws a corresponding amount of real power from the other bus of the same line. Figure 9a shows the original configuration of \( \text{Line}_{ij} \) on which the UPFC is installed. Figure 9b shows the configuration of the same line after UPFC is installed. It is assumed that the installation of UPFC will increase or decrease the real power flow through \( \text{Line}_{ij} \) by \( \pm 20\% \) of the line capacity, \( P_{\text{max}} \). The experimental set up of the IEEE 118 bus power system along with the UPFC installation as explained above will be utilized for the simulation results.

![Fig. 9a Original configuration of Line\(_{ij}\)](image)

![Fig. 9b UPFC installed Line\(_{ij}\)](image)

### 6. SIMULATION RESULTS

The experimental setup described above is used for testing the proposed EA. An EA can be tuned for better results by varying various parameters. These parameters are described in the section above. Three parameter sets have been tested on the proposed algorithm to find the best placement. These parameter sets are shown in Table 2. Each parameter set is run for 60 generations. Table 3 shows the mean and standard deviation of the highest fitness (\( H_{\text{fit}} \)) of three parameter sets over 5 runs.

As the computation of MPI index (fitness) takes 108 sec for each individual (on an average) in the population, the algorithm is run for 5 runs only for statistical analysis. A test which can be used for few runs (less than 30) is Wilcoxon Rank Sum Test (WRST). The three parameter sets are tested for variances by using WRST in MATLAB 7.0 statistical tool box. WRST performs a two-sided rank sum test of the hypothesis on two independent samples, coming from distributions with equal medians, and returns the probability value (P) from the test. P is the probability of observing the given result, by
chance if the null hypothesis is true, the medians are equal. Small values of P cast doubt on the validity of the null hypothesis [6].

Experiment I performs the WRST on Hfit values of parameter set 1 and parameter set 2 for 5 runs. These Hfit values are logged in the 60th generation (final generation) of each run. The mean of the Hfit for parameter set 1 is -50.9945 and for parameter set 2 is -51.0253. Performing the WRST on these sets gave a P-value which is greater than $\alpha = 0.05$, i.e, P=0.7222. Also the hypothesis value $H = 0$. Therefore these two sets have equal variances and the null hypothesis of equal variances is accepted. Similar experiments are performed for every combination of the three parameter sets as shown in Table 4. The concerned P-values and the output of the hypothesis are tabulated in the same table.

Table 2 Parameter sets which are used to test the EA for placement

<table>
<thead>
<tr>
<th>Parameters Compared</th>
<th>Population Size</th>
<th>Number of Parents involved in Tournament</th>
<th>Number of Offspring Generated</th>
<th>Cross Over Rate</th>
<th>Mutation Rate (1/n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSet1</td>
<td>50</td>
<td>10</td>
<td>5</td>
<td>0.8</td>
<td>0.01</td>
</tr>
<tr>
<td>PSet2</td>
<td>25</td>
<td>3</td>
<td>5</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>PSet3</td>
<td>100</td>
<td>10</td>
<td>10</td>
<td>0.8</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Table 3. Mean and STD of the Highest Fitness for 5 runs and 3 parameter sets

<table>
<thead>
<tr>
<th>Parameter Sets</th>
<th>Mean of Highest Fitness over 5 runs</th>
<th>Standard Deviation of Highest Fitness over 5 runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSet1</td>
<td>-50.9945</td>
<td>0.2389</td>
</tr>
<tr>
<td>PSet2</td>
<td>-51.0253</td>
<td>0.3124</td>
</tr>
<tr>
<td>PSet3</td>
<td>-50.5227</td>
<td>0.3594</td>
</tr>
</tbody>
</table>

Depending on the mean of Hfit (shown in Table 3) parameter set 3 has highest mean fitness over all runs. The next highest average Hfit value is a result of parameter set 1. Performing WRST on these parameter sets gave a P value equal to 0.0317 and $H = 1$. 
As the probability is less than the alpha value and hypothesis is 1 this proves that both the sets have unequal variances and the null hypothesis of equal variances is rejected. Parameter set 3 has the highest mean value of $H_{fit}$ therefore this is chosen over the other sets as the best for the optimal solution of the placement for this report. Figures 10a and 10b show the highest and average fitness values for this set over 60 generations.

![Fig. 10a Average fitness of parameter set 3](image1)

![Fig. 10b Highest fitness of parameter set 3](image2)

<table>
<thead>
<tr>
<th>Experiment Number</th>
<th>Parameter Sets Compared</th>
<th>$\alpha$ Value</th>
<th>$P$ Value from WRST</th>
<th>$H$ Value from WRST</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 – 2</td>
<td>0.05</td>
<td>0.7222</td>
<td>0</td>
<td>Accept Null Hypothesis</td>
</tr>
<tr>
<td>2</td>
<td>1 – 3</td>
<td>0.05</td>
<td>0.0317</td>
<td>1</td>
<td>Reject Null Hypothesis</td>
</tr>
<tr>
<td>3</td>
<td>2 – 3</td>
<td>0.05</td>
<td>0.0215</td>
<td>1</td>
<td>Reject Null Hypothesis</td>
</tr>
</tbody>
</table>

The best placement obtained using EASQP for two FACTS devices is on lines 69 and 158. A pictorial representation of this is show in Fig. 11. The best placement obtained by using MFH for two FACTS devices is on lines 42 and 170. These two placements and settings are compared for their performance as shown in Table 5. It can
be seen from the table that the performance of EASQP is better than the MFH. The MPI value obtained from EASQP is far lesser than the MFH also the number of overloads are less. The only constraint that can be seen using the EASQP is the time, which will be dealt with in future research (by author).

![Diagram](image)

**Fig. 11 Best Placement of EASQP on lines 69 and 158**

<table>
<thead>
<tr>
<th>Comparison</th>
<th>EASQP</th>
<th>MFH</th>
<th>MF with EA Placement</th>
<th>SQP with Brute Force (Heuristic) Placement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Placement</td>
<td>[69, 158]</td>
<td>[42,170]</td>
<td>[69, 158]</td>
<td>[42,170]</td>
</tr>
<tr>
<td>MPI</td>
<td>9275</td>
<td>14643</td>
<td>9317.1</td>
<td>10925</td>
</tr>
<tr>
<td>Number of Overloads</td>
<td>100</td>
<td>102</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Time</td>
<td>108 sec</td>
<td>51 sec</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
A statistical analysis of the CACHE for the three parameter sets is conducted which is shown in the Table 6 below. During the runs of the EA it is observed that the number of hits for each run increases as the generations’ progress (shown in Fig. 12). Similar trend is observed on all the parameter sets. A statistical analysis is performed on the highest number of hits for each parameter set, for the five runs. The results are enclosed in Table 6 as shown. The results seem substantial, as the CACHE built over different parameter sets the number of hits increased further increasing the mean and the standard deviation. Also for parameter set 3 the population is larger than the population of previous parameter sets therefore the mean and standard deviation for this set is quite high.

![Graph showing the number of CACHE hits over 60 generations](image)

*Fig. 12 Number of CACHE Hits for one run over 60 Generations*

<table>
<thead>
<tr>
<th>Parameter Sets</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSet1</td>
<td>188.8</td>
<td>5.4955</td>
</tr>
<tr>
<td>PSet2</td>
<td>190.4</td>
<td>8.5029</td>
</tr>
<tr>
<td>PSet3</td>
<td>361.4</td>
<td>41.6029</td>
</tr>
</tbody>
</table>
Another interesting criterion that can be compared is the effect of number of FACTS devices. This can be analyzed by comparing the highest fitness values for single placement obtained by brute force using SQP (BFSQP) to the highest fitness value which is obtained by using EASQP. The best placement for a single FACTS device using BFSQP is line 69. This is one of the best placements for two FACTS devices. This further fortifies the results obtained by EASQP. The result of the comparison of BFSWP with EASQP with $N_{\text{Facts}}$ equal to 2 is shown in Fig. 13. The graph shows that as the number of FACTS increases the MPI value decreases indicating that the overloaded power of the system has decreased.

![Fig. 13 Comparison of MPI values for placement with one FACTS device and 2 FACTS devices](image-url)
7. CONCLUSION

This project successfully designed an EASQP for the placement of 2 FACTS devices in IEEE 118 bus system and compared the performance of EASQP with MFH. The main conclusion of this project is that the proposed EASQP outperformed MFH. The placement and settings obtained from EASQP render lesser overloaded power and number of overloads. The only constraint of EASQP algorithm is the time, this will be dealt in future by optimizing the load flow and the SQP algorithms.

Future work includes testing the algorithm for larger number of FACTS devices, perform Brute Force with SQP settings for more than one FACTS device to compare with EASQP and look into stability issues of the EASQP placements.

8. BIBLIOGRAPHY


A. APPENDIX

SOLUTION
Results of EA with Best parameter set 4

Parameters
Population size = 100
Parents in tournament = 10
Crossover Rate = 0.8
Mutation Rate = 0.8
Number of Offspring = 10
Number of Generations = 60

Results
Highest Fitness = -50.6618
Average Fitness = -5.1953
Placement lines = (69, 158)
Placement Buses = [(42, 49); (92, 94)]
B. APPENDIX

USER MANUAL

1. Unzip the contents of the file into a directory.
2. For running the placement algorithm open MATLAB command window. Change to the directory where you stored files. At the command window prompt type >> Run MAIN placement. This will invoke the main file of the program. The outputs will be seen on the command window.
3. To change the parameters of the algorithm open the script file Parameters_direct.m. The parameters, the data types of the parameters and boundaries on the parameters are as shown in the table below.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variable Type</th>
<th>Default Value</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Popsize</td>
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<td>100</td>
<td>1</td>
<td>10000</td>
</tr>
<tr>
<td>CrossOverRate</td>
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<td>1</td>
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<tr>
<td>MutationRate</td>
<td>Float</td>
<td>0.8</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>NParents</td>
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<td>10</td>
<td>1</td>
<td>Popsize</td>
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<tr>
<td>NGenerations</td>
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<td>none</td>
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<td>3</td>
</tr>
</tbody>
</table>

4. To assign values to these parameters just type in the parameter file. Make sure to save the parameter file before running the Main file.
5. To see the log file over all runs and generations, open the “XXX.xls” file. The XXX is the name of the log file printed in the command window while executing the file.