Fine-Tuning the Parameters for Solving the Multi-Objective D-FACTS Optimal Allocation Problem

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Abstract

Distributed Flexible AC Transmission Systems (D-FACTS) and D-FACTS allocation are new topics that are gaining traction in the field of power systems. The reason for this is that they are a simple yet effective tool for improving power flow control, power system flexibility, and reducing overall power systems cost by manipulating some properties of the transmission lines on which they are installed. So far, most research has focused on improving the algorithms used to optimally allocate the D-FACTS along existing networks in order to maximize or minimize a certain objective. However, much of this research has been based on the assumption that all the parameters are pre-defined and immutable. The key objective of this study is thus to study how the changing of different parameters may affect the final solutions found by the optimization algorithm. The key parameters studied are the line reactance adjustment limit, the number of lines on which D-FACTS are allowed, and the investment cost limit. Results show that all these parameters have an effect on the final solution set, and decisions need to be made by carefully weighing the available resources, convenience for deployment, and the potential benefits that could be brought by utilizing D-FACTS devices.

Keywords
Power Systems, D-FACTS, Optimization, Multi-Objective Optimization and Sensitivity Analysis.

1. Introduction

American electric grids are facing an increasing number of issues, some of which are related to an ever-increasing changing climate; from the now yearly phenomenon of wildfires caused by fallen PG&E lines in California to the weeks-long outages in Texas in early 2021 due to freezing temperatures. While some of the issues may be weather-related and harder to control or prepare for, many issues stem from increased demand, such as congestion and line overloading. Congestion is such a major issue in U.S. power grids that $40 billion were spent on congestion reduction projects in 2018 alone, and yet congestion costs are still measured in the billions of dollars per year (US DOE, 2020). In order to help mitigate this problem, we propose the use of variable-impedance series flexible AC transmission systems (FACTS), which help provide effective power flow control as part of smart transmission systems (Li, *et al*, 2010). FACTS, as well as Distributed FACTS (D-FACTS), can help improve the utilization of an existing network and provide a more reliable and sustainable power delivery network (Gotham and Heydt, 1998).

As an extension of FACTS technology, D-FACTS are a lightweight version of traditional FACTS. These have the associated benefits of reduced cost and spatial footprint, as well as a capacity for being re-deployed based on shifting power needs. Traditional FACTS require large spaces for installation next to buses in the system, but D-FACTS can be installed along existing transmission lines or towers in a modular fashion (Sang and Sahraei-Ardakani, 2019). That is why D-FACTS devices have become more popular and are being implemented in various electric grid improvement projects throughout the country, and their benefits in the integration of renewable energies into new grids has been previously demonstrated by Gandoman et al (2018). However, D-FACTS allocation is still a new field and has not been studied in full detail. The expectations and some preliminary studies indicate that they will be similarly useful in the integration of renewable energy into existing and established grids, but more research is needed to see to what extent this will be possible and under what conditions and parameters they would be able to do so.

Although arguably more versatile and effective, the allocation of D-FACTS modules rather than traditional FACTS devices introduces nonlinearities to the optimal allocation model which can be computationally exhausting to solve (Sang & Sahraei-Ardakani, 2018). For some time, the challenge was then to improve on the computational complexity of the algorithms in order to solve the allocation problem. Castillo Fatule (2021) proposed a new formulation and algorithm to eliminate the nonlinearities by the use of metaheuristic optimization and greatly reducing the computational time for this problem.

Since the benefits of incorporating D-FACTS devices into a network have been thoroughly studied and demonstrated, and progress has been made into improving the optimization process, the main objective in this research is now to estimate under which parameters the D-FACTS devices will be able to perform best to improve upon the objectives being studied.

The main objectives considered for the optimization process are the total expected system costs, the total expected Global Warming Potential (GWP), and Line Utilization Factor (LUF). These three objectives are to be minimized simultaneously, but they are conflicting with each other, thus a multi-objective optimization process is utilized to obtain a set of non-dominated Pareto-optimal solutions. The optimization algorithm will be then executed repeatedly while varying the parameters being studied in order to perform a sensitivity analysis of the parameters.

The key objective of this study is thus to use Design of Experiments tools to study the change of the objective function values in the Pareto sets and analyze the impact of each of the parameters being modified.

This research aims to fill gaps in the research by providing the following contributions: (1), A computationally efficient algorithm is proposed to optimally allocate D-FACTS devices in power systems considering operational constraints and stochastic scenarios. (2), an analysis of the operating conditions of these devices is performed to estimate how these parameters can be altered to improve the operating conditions of the power system. (3), The relations between each of the proposed adjustable parameters and the objective functions is analyzed; and (4), statistical and regression analysis techniques are used to create predictors for the objective functions based on the state of the parameters.

2. Literature Review

FACTS and D-FACTS are thyristor-based controllers designed to manage series impedance, shunt impedance, phase angle, or some other parameter in electric transmission systems (Hingorani, 1993). Some of the most common types of FACTS are Static Series Var Compensator (SSVC), used to control voltage, Thyristor Controlled Series Capacitor (TCSC) used to increase transfer capability and stability, Static synchronous series Compensator (SSSC) used for power transmission series compensation with synchronous voltage, and Unified Power Flow Controller (UPFC) for enhancing steady state, dynamic, and transient stability (Murali *et al*, 2010). Similarly, there is a distributed version for most of these types of devices.

Previous research such as Habur and O'Leary's (2004) has shown that the installation of FACTS devices can not only improve the stability of transmission networks, but also reduce operational costs and open the possibility for increased sales by utility companies. Others such as Wibowo et al (2011) and Torino et al (2003) have used FACTS to reduce congestion, stabilize voltage, integrate new energy sources into the grid and improve network security. In addition, it is by design that all the applications for which traditional FACTS can be used are also applicable for D-FACTS devices.

The allocation of FACTS devices has been a relatively established research field for some time now. Jordehi (2015) shows various uses Particle Swarm Optimization (PSO) algorithms for determining optimal location and size of STATCOM-type FACTS devices in power systems, optimal type and location of multi-type FACTS devices including TCSC, SVC, and UPFC to maximize voltage stability, optimal FACTS settings to optimize system loadability and installation costs, minimization of copper losses, etc. In fact, various authors have implemented different methods for optimizing the allocation of FACTS and D-FACTS devices around a specific parameter in the power system, including optimizing voltage stability during outages as a Line Stability Index (LSI) using a modified PSO algorithm (Srivastava et al, 2014); minimizing total operation and installation costs (Mohamed et al, 2010); optimization of system security and installation costs using Genetic Algorithms (GA) (Radu and Besanger, 2006); as well as various other parameters by the use of less commonly used optimization algorithms.

Similarly, the allocation of D-FACTS devices has also been a popular field in recent years since D-FACTS were first proposed by Divan and Johal in 2005, emphasizing their added benefits of a reduced investment cost, space requirements, system stress, and reliability requirements. In addition to these benefits, it has been studied that the potential economic benefits of D-FACTS devices outperform those of FACTS devices (Sang and Sahraei-Ardakani, 2018). This is not considering the long-term benefit of re-deployability that D-FACTS have, which have yet to be studied given the additional complexity for the problem, but that promises further reduced costs if a situation arises in which the network configuration changes and re-allocation becomes necessary.

D-FACTS also help integrate new renewable energy sources into the grid. An analysis performed by Suresh and Sreejith (2017) showed that the use of D-FACTS can improve the voltage profile and reduce line power loss when integrating new power sources to the grid. It is estimated that by 2050 at least 20% of energy in global grids will come from renewable sources (Jha et al, 2017). As it stands, power flow control devices will become more relevant in managing distribution networks and grid congestion. Also, more than FACTS, D-FACTS are more attractive control devices for the dynamic management of voltage, reactive power, and power quality, since they can provide more precise and dynamic management of microgrids to mitigate the uncertainty associated with the incorporation of renewable energies (Gupta and Kumar, 2016; Gaigowal and Renge, 2016).

The problem of allocating D-FACTS has been studied through various algorithms and mathematical models. One very common optimization method is Linear Programming (LP), formulated in 1947. However, the allocation of D-FACTS created non-linearities in the equations used to model the problem, not to mention that for problems that are NP-hard or NP-complete, a pure LP approach is computationally expensive. A better approach to avoid excessive computational burdens is the use of a metaheuristic algorithm. Metaheuristic algorithms are advanced search algorithms designed to search for an optimal solution by testing possible solutions around the search space, testing their objective functions, and adjusting the solutions further until convergence around an optimum or some other condition occurs. For the purpose of this study, a genetic algorithm will be used to search the solution space by testing possible combination of D-FACTS allocated along the power network and using these combinations to eliminate the nonlinearities in the mathematical model to solve the reduced problem using a LP approach. GAs were first proposed by Holland in 1975 around the idea of mimicking natural evolution processes. Their basic procedure is to initialize a population or set of possible solutions, evaluate them, and, while the termination criteria is not reached, select solutions for the next population and perform crossover and mutation before evaluating this new population (Srinivas and Patnaik, 1994). Although not as much as PSO methods, GAs have been also used to allocate FACTS and D-FACTS devices such as the allocation of multi-type FACTS for improving voltage stability by Baghaee et al (2008), among others.

Multi-Objective optimization is an optimization procedure used to optimize more than one conflicting objective function simultaneously. While some approaches attempt to use linear functions to combine the objectives into a single aggregated objective, the approach we take in this study is instead to store all the solutions that can be objectively be considered “not worse” than any others by not being worse in all objectives compared to the rest. This is usually called a non-dominated set of solutions or a Pareto set. This concept implies that there will be no other solution in the feasible region which is quantifiably better in all objectives than the Pareto-Optimal set, and allows for trade-offs to be made from the decision-maker’s point of view (Zitzler et al, 2002). Because of the nature of a Pareto-optimal set, the decision maker must have some expertise in the field for which the problem is solved, as well as knowledge on the resulting set of solutions, in order to make an educated choice as to which solution would be best, as well as to give weights to the objectives being evaluated. The Pareto-optimal set can help reduce the design alternatives from a feasible region into optimal trade-offs (Yancang et al, 2010).

In this study, the multi-objective algorithm used is one similar to the Non-Dominated Sorting Genetic Algorithm (NSGA), an approach in which all non-dominated solutions are classified into a separate category and assigned a fitness value based around population size, but a different fitness assigning metric, as proposed by Taboada *et al* (2017). This metric is based on both inter-solution distance and dominance, and is based around attempting to increase the spread of solutions over the Pareto set as well as improve proximity to the true Pareto frontier. This method has been proven useful in D-FACTS allocation with the dual objectives of minimizing total system costs and renewable energy curtailment (Castillo Fatule et al, 2021), as well as in solving various other engineering problems including some in the areas of logistics and biofuel production.

As shown in the literature, D-FACTS optimization is an active research topic in the area of power systems and transmission system optimization, but there is still much to study in the field. Very few studies consider quantified environmental impact metrics as an objective to optimize, which becomes a more significant topic as climate change effects worsen. Additionally, while some studies such as Sang and Sahraei-Ardakani (2019) have considered varying load scenarios, none have accounted for generator or line failures, opting for less computationally-burdensome deterministic approaches, considering only the most likely scenario of optimal operating conditions. Also, sensitivity analysis of the operating parameters for the D-FACTS devices has not been a focus on any research in the found literature. As such, the present research will use some previously-developed multi-objective optimization algorithms in order to analyze the effects of adjusting some of the parameters of D-FACTS allocation.

3. Methods

In order to solve the D-FACTS allocation algorithm, the following mathematical model was created based on Sang and Sahraei-Ardakani's (2019) model. This model was created not only to address the nonlinearities created by the incorporation of the D-FACTS devices but also to account for the calculations of environmental impacts, and combine some constraints that become redundant after addressing the nonlinearities in the previous models. The full model is described below. In addition, the flow direction of power lines is relevant when adjusting impedance, so the following DC power flow constraints are applicable:

$$If\ \theta_{fr,k,s} - \theta_{to,k,s} \geq 0, \left(\theta_{fr,k,s} - \theta_{to,k,s}\right)/X_k^{\max} \leq F_{k,s} \leq \left(\theta_{fr,k,s} - \theta_{to,k,s}\right)/X_k^{\min}$$

$$If\ \theta_{fr,k,s} - \theta_{to,k,s} \leq 0, \left(\theta_{fr,k,s} - \theta_{to,k,s}\right)/X_k^{\min} \leq F_{k,s} \leq (\theta_{fr,k,s} - \theta_{to,k,s})/X_k^{max}$$

Having considered flow constraints, the objective functions for the model are as follows:

$$\min OF_1 = \sum_{s=1}^{N_s} P_s \left(\sum_{g=1}^{N_g} \left(\sum_{seg=1}^{N_{seg}} C_{g,seg}^{linear} P_{g,s}^{seg} + C_g^U R_{g,s}^U + C_g^D R_{g,s}^D + C_g^{NL} \right) + \sum_{r=1}^{N_r} c_r P_{r,s}^C \right) + C_{inv}^D \tag{1}$$

$$\min OF_2 = \sum_{s=1}^{N_s} P_s \left(\sum_{g=1}^{N_g} \sum_{c=1}^{N_c} GWP_{g,c,s} \right) \tag{2}$$

$$\min OF_3 = \frac{1}{N_k} \sum_{s=1}^{N_s} \sum_{k=1}^{N_k} P_s \left(\frac{F_{k,s}}{F_k^{\max}} \right)^{100} \tag{3}$$

These objective functions correspond with the three key objectives considered in this study which are (1) minimize total system operational costs, including a transformed investment cost, (2) minimize the total environmental impacts expressed in terms of Global Warming Potential (100kg CO_2 equivalent), and (3) minimize the line utilization factor, a measure of congestion proposed by Das *et al* (2009). The model constraints are below:

$$P_{g,s} = \sum_{seg=1}^{N_{seg}} P_{g,s}^{seg} \tag{4}$$

$$P_g^{min} \leq P_{g,s} \leq P_g^{max} \tag{5}$$

$$-F_k^{max} \leq F_{k,s} \leq F_k^{max} \tag{6}$$

$$\sum_{k\in\sigma^+(n)} F_{k,s} - \sum_{k\in\sigma^-(n)} F_{k,s} + \sum_{g\in g(n)} P_{g,s} + \sum_{r\in r(n)} \left(P_{r,s} - P_{r,s}^C\right) = L_{n,s} \tag{7}$$

$$\sum_{g=1}^{N_g} R_{g,s}^U \geq S^U \tag{8}$$

$$\sum_{g=1}^{N_g} R_{g,s}^D \geq S^D \tag{9}$$

$$R_{g,s}^U \leq P_g^{max} - P_{g,s} \tag{10}$$

$$R_{g,s}^D \leq P_{g,s} - P_g^{min} \tag{11}$$

$$R_{g,s}^U, R_{g,s}^D \geq 0 \tag{12}$$

$$\Delta\theta_k^{min} \leq \theta_{fr,k,s} - \theta_{to,k,s} \leq \Delta\theta_k^{max} \tag{13}$$

$$\theta_{1,s} = 0 \tag{14}$$

$$f_{k,s}\left(1 + \frac{x_k^D}{l_k}\eta_L\right)X_k F_{k,s} \geq f_{k,s}\left(\theta_{fr,k,s} - \theta_{to,k,s}\right) \tag{15}$$

$$f_{k,s}\left(1 + \frac{x_k^D}{l_k}\eta_C\right)X_k F_{k,s} \leq f_{k,s}\left(\theta_{fr,k,s} - \theta_{to,k,s}\right) \tag{16}$$

$$0 \leq x_k^D \leq i_k^{max} \tag{17}$$

$$\sum_{k=1}^{N_k} \frac{x_k^D}{\max(x_k^D, 1)} \leq l_{max}^{alloc} \tag{18}$$

$$GWP_{g,c,s} = \sum_{seg}^{N_{seg}} H_{g,seg}^{linear} P_{g,s}^{seg} G_{g,s} W_c \tag{19}$$

$$C_{inv}^D = \sum_{k=1}^{N_k} 3x_k^D C_{sh}^D \tag{20}$$

$$C_{inv}^D \leq C_{inv}^{max} \tag{21}$$

$$C_{sh}^D = C_{single}^D \frac{I(1+I)^N}{8760((1+I)^N - 1)} \tag{22}$$

$$0 \leq P_{r,s}^C \leq P_{r,s} \tag{23}$$

$$f_{k,s} = \frac{F_{k,s}}{\left|F_{k,s}\right|} \tag{24}$$

Equation (4) segmentizes the power generation at each generator in order to match with the segments of the linearized cost functions. Eq. (5) defines the minimum and maximum generation level for each generator. Eq. (6) defines the maximum flow capacity for each line, in either positive or negative direction. Eq (7) defines the load at each bus as the sum of all incoming energy flows minus the sum of all outgoing flows, plus the sum of all power generated at this bus via traditional generators and the sum of all non-curtailed renewable energy attached to this bus. Equations (8-9) define the up and down reserve requirements for the system, with eqs. (10-12) defining the reserves at each generator. Eq. (13) defines the voltage angle stability limits at each bus and eq. (14) defines the angle at bus 1 to be 0 as a reference point.

Eqs. (15-16) are the DC power flow equations considering the reactance adjustment effect of the D-FACTS devices in both inductive and capacitive modes, and the flow directions. Eq. (17) serves to define the number of D-FACTS that can be installed at each line, with eq. (18) limiting the number of lines in which the devices may be installed. Eq. (19) serves to define the Global Warming Potential of the generator configurations. Eq. (20) defines the D-FACTS investment cost, which is then limited by eq. (21). Eq. (22) converts the cost of the devices into an hourly value via a compound interest function in order to have the same units as the rest of the data, and finally eq. (23) defines the

curtailment of renewable energy as no more than the amount produced. Eq. (24) is not part of the optimization model, but is used as an intermediate step in order to obtain the power flow directions required in other equations.
In addition, the following equations describe the Pareto dominance criteria:

$$If\ OF_{obj,a} \leq OF_{obj,b}\ \forall obj;\ \ D_{a,b} = 1;\ else, D_{a,b} = 0 \tag{25}$$

$$\sum_{a=1}^{N_{pop}} D_{a,b} = 0 \tag{26}$$

Where a solution is non-dominated if it meets equation 26
The fitness metrics used in the algorithm for parent selection are:

$$FM_{1,a} = \sum_{b=1}^{N_{pop}} \sqrt{\sum_{i=1}^{N_{obj}} \left(OF_{i,a} - OF_{i,b}\right)^2} \tag{27}$$

$$FM_{2,a} = \sum_{b=1}^{N_{pop}} D_{a,b} \tag{28}$$

And an aggregated fitness metric is obtained by normalizing both these values and adding them together.

For solving the problem associated to this model, a modified multi-objective evolutionary algorithm is proposed. This algorithm follows the following steps:

0. START
1. Using a reduced model consisting of Eqns. (1), (4-9), (13-17), and (23), with $x_k^D = 0\ and\ f_{k,s} = 1$ solve the linear problem to obtain the values of $F_{k,s}$.
2. Obtain the values of $f_{k,s}$ via equation (24).
3. Generate an initial population using the parameters i_k^{max} and l_{max}^{alloc} defined in equations (17) and (18).
4. For each chromosome, solve the linear problem consisting of equations (1), (4-7), (13-17), and (20-23).
5. Using the outputs from each linear problem, use a greedy algorithm to allocate the up and down spinning reserves as defined in Eqns. (10-14).
6. From this information, calculate the values for the objective functions in (2, 3).
7. Use the Pareto Dominance criteria in Eqns. (25-26) on all solutions and store the non-dominated ones.
8. IF the stopping criteria have been met, go to step (13). Otherwise, go to step 9.
9. Obtain the Fitness Metrics and calculate the Aggregated Fitness Metric.
10. Rank solutions according to the Aggregated Fitness Metric obtained in step 9.
11. Select Parents from the current population.
12. Generate a new population and return to step 4.
13. Retrieve the stored solutions and re-check for dominance to obtain the Pareto-Optimal set
14. END

This process is summarized below in fig. 1:

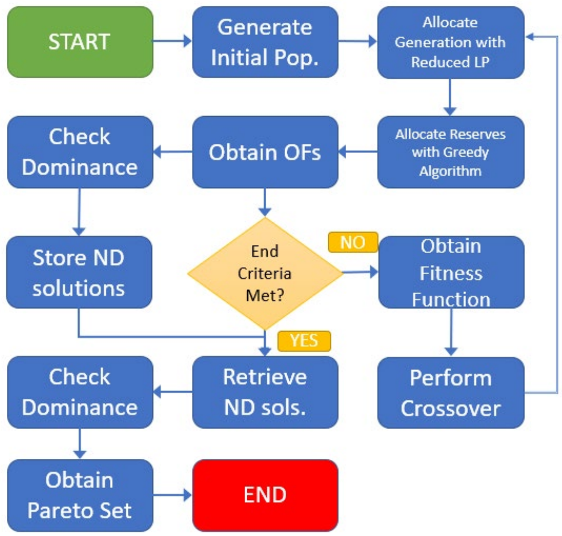

Figure 1. Evolutionary Algorithm Flowchart

Tournament selection for the parents and single-point crossover method are used in the algorithm for creating a new population.

4. Data Collection

As the base of analyzing electrical grids, a modified version of the IEEE 1996 Reliability Test System was used. The modifications are described in Sang and Sahraei-Ardakani's (2017) study. These modifications consist mainly of modifying load and generation capacities in order to produce additional congestion in the system.

In summary, the IEEE RTS-96 is a fairly simple network consisting of 24 buses, 38 transmission lines, 32 traditional generators, and 2 renewable energy sources. It was originally proposed by Cliff Grigg in the 1996 IEEE Winter Power meeting. While there are extensions to increase the system to three areas, only a single area is used for this study.
In addition, the base case used as reference for this study is the one described by Castillo Fatule (2021), with the following parameters for the D-FACTS allocation. The number of lines in which devices may be installed is limited to 5 lines for feasibility in installation (corresponding to eq. 18), the maximum change in reactance is 20% of the line's current reactance for stability purposes (reflected in eq. 17), and the hourly investment limit has been set to $25/hr (corresponding to eq. 21).

These are the three key parameters that will be modified for the sensitivity analysis. In addition, the other parameters used in the algorithm which will not be studied are the following:

- Number of generations used in the MOEA: 100
- Number of Individuals in each generation: 100
- Mutation Factor: 5%
- Elitism: 10%
- Reactance change in inductive and capacitive mode per device: 2.5% per phase per mile
- Life Expectancy of the devices: 10 years
- Interest rate on the devices: 6%

For reference, the results from the original study are summarized below in figure 2:

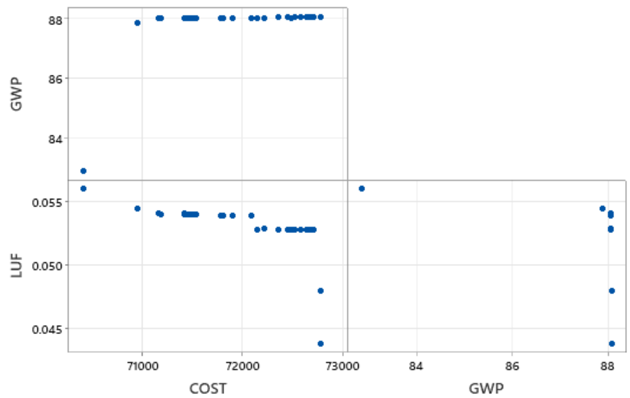

Figure 2. Matrix scatterplot for Cost, GWP, and LUF for original optimization problem without sensitivity analysis

Results and analysis from the sensitivity analysis are presented in section 5 below.

5. Results and Discussion

5.1 Numerical Results

The sensitivity analysis involved changing three factors in the D-FACTS parameters in order to study their effects on the non-dominated Pareto set. These factors and their levels are summarized below in Table 1.

Table 1. Sensitivity Analysis Factors

Factor	Reference Level	Test Levels
Ch_{lim}	20%	15%, 25%
n_{lines}	5	10
C_{max}^{D}	\$25	\$20, \$30, \$35

The twenty-four experiments were carried out using the algorithm described in section 3 on a Dell Computer with an Intel® Xeon ® W-2195 CPU and 256GB of RAM, with an average computing time of 19s.

The results of the tests are summarized below in Table 2. The objectives in the Pareto Front are summarized as Best value, Worst value, and Average value for each of the objectives being considered. The number of non-dominated solutions are also recorded under NOBS in the table. For the purpose of simplicity, these values will also be used in the sensitivity analysis.

In Addition, Table 3 will show the p-values for the ANOVA analysis of each of the below columns against the factors being studied, including an interaction between the maximum investment limit and the line limit, which was found to be significant in some cases. In Table 3, an asterisk will be used to indicate factors that have a small but significant effect at a 10% significance level, two asterisks for a moderately significant effect on the response variable at significance level of 5% is used for the statistical analysis, and three asterisks will be shown on highly significant effects with a significance level of 1%. Interestingly, the reactance change limit is not a very significant factor (marked with ** or *** in table 3) in any of the responses except in the worst-case LUF. Additionally, the worst-case responses for both cost and GWP are seemingly independent from all the factors with a slightly significant effect from the reactance change limit in the worst-case cost response). However, worst-case responses in one objective function usually correspond with best-case responses in a different objective function, and thus we cannot automatically assume that there is no benefit from studying these responses.

Table 2. Summarized Experiment Data

EXP	BCOST	BGWP	BLUF	WCOST	WGWP	WLUF	ACOST	AGWP	ALUF	NOBS	CHLIM	NLINES	CDMAX
1	71011.2	88.025	0.050	72925.0	88.054	0.054	72220.9	88.042	0.053	24	0.2	5	20
2	70406.0	82.874	0.044	72778.5	88.051	0.056	71947.5	87.848	0.053	28	0.2	5	25

3	70446.2	83.556	0.044	72786.2	88.050	0.055	71696.7	87.696	0.053	24	0.2	5	30
4	69651.6	75.957	0.043	72777.2	88.050	0.060	71135.9	85.530	0.054	14	0.2	5	35
5	71214.4	88.026	0.048	72899.3	88.053	0.054	72124.5	88.041	0.053	20	0.15	5	20
6	70847.7	87.041	0.048	72561.8	88.045	0.055	71721.4	87.952	0.053	12	0.15	5	25
7	70903.5	86.792	0.047	72889.6	88.053	0.058	72107.6	87.944	0.053	17	0.15	5	30
8	70342.6	78.277	0.046	72869.9	88.052	0.060	71536.2	87.005	0.054	23	0.15	5	35
9	71045.5	88.023	0.053	72779.9	88.051	0.054	71955.9	88.038	0.054	23	0.25	5	20
10	71045.5	88.023	0.053	72779.9	88.051	0.054	71955.9	88.038	0.054	23	0.25	5	25
11	70410.0	83.209	0.043	72790.4	88.051	0.055	71623.1	87.544	0.053	23	0.25	5	30
12	70402.9	83.299	0.043	72737.3	88.050	0.055	71529.9	87.628	0.052	23	0.25	5	35
13	71671.0	88.034	0.051	72847.7	88.052	0.054	72481.0	88.046	0.053	22	0.2	10	20
14	71389.1	88.028	0.046	72810.9	88.051	0.054	72207.1	88.041	0.053	20	0.2	10	25
15	71210.1	88.018	0.045	72717.3	88.049	0.055	71893.1	88.036	0.053	27	0.2	10	30
16	70701.2	86.089	0.049	72597.9	88.048	0.057	71941.9	87.939	0.053	23	0.2	10	35
17	71863.9	88.036	0.052	72880.6	88.053	0.054	72416.1	88.045	0.053	28	0.15	10	20
18	71459.9	88.028	0.049	72880.2	88.053	0.054	72321.6	88.043	0.053	20	0.15	10	25
19	70915.4	88.019	0.047	72899.6	88.053	0.056	72269.9	88.042	0.053	34	0.15	10	30
20	70673.6	86.474	0.045	72868.8	88.052	0.055	71952.9	87.988	0.053	32	0.15	10	35
21	71846.4	88.034	0.050	72882.8	88.053	0.054	72442.6	88.046	0.053	28	0.25	10	20
22	71397.3	88.026	0.053	72765.2	88.050	0.054	72301.8	88.043	0.053	29	0.25	10	25
23	71089.8	88.022	0.044	72743.2	88.050	0.054	72068.8	88.039	0.052	20	0.25	10	30
24	70745.3	83.447	0.053	71670.8	87.833	0.054	72575.2	88.047	0.060	23	0.25	10	35

Table 3. ANOVA p-values

Response Var	Ch lim p-value	N lines p-value	CDmax p-value	Nlines*CDmax
Best Cost	0.778	0.000***	0.000***	0.473
Average Cost	0.997	0.000***	0.000***	0.144
Worst Cost	0.092*	0.372	0.065*	0.107
Best GWP	0.947	0.005*	0.000*	0.010***
Average GWP	0.848	0.038**	0.019**	0.012**
Worst GWP	0.202	0.315	0.160	0.170
Best LUF	0.437	0.148	0.010***	0.255
Average LUF	0.314	0.596	0.192	0.300
Worst LUF	0.034**	0.017**	0.001***	0.045**

After removing the non-significant factors for each response column, the following regression equations were obtained. Only responses with at least one significant factor at a 5% significance level were considered:

$$BestCost = 71872 + 120.6 * N_{lines} - 66.59 * C_{max}^{D}$$

$$AvgCost = 72243 + 88.6 * N_{lines} - 32.34 * C_{max}^{D}$$

$$BestGWP = 107.84 - 1.603 * N_{lines} - 0.958 * C_{max}^{D} + 0.0796 * N_{lines} * C_{max}^{D}$$

$$AvgGWP = 91.69 + 0.357 * N_{lines} - 0.1637 * C_{max}^{D} + 0.01604 * N_{lines} * C_{max}^{D}$$

$$BestLUF = 0.05618 - 0.00031 * C_{max}^{D}$$

$$WorstLUF = 0.04734 - 0.01525 * Ch_{lim} - 0.000779 * N_{lines} + 0.000474 * C_{max}^{D} - 0.000039 * N_{lines} * C_{max}^{D}$$

Based on these equations we can perform some analyses on the effects on the significant variables on the Pareto front. First, increasing the number of lines over which the D-FACTS may be allocated actually increases both the total costs and GWP of the system, but it decreases the LUF. A reasoning for this is that it can reduce strain on more lines as the devices are allocated throughout the system, but by not focusing improving the transmission around more cost-efficient and environmentally friendly generators, it forces the system to rely on more expensive and/or more polluting generators which are more distributed throughout the system.

Another interesting observation is the effect of increasing the investment limit over the objectives. While it reduces both the cost objective and the Global Warming Potential throughout the system, as is expected for an improved network with improved transmission capacity from more efficient generators, it actually has an undesirable effect (at least linearly) on the worst-case of line utilization. This can also be attributed once again to the increased transfer capability from the generator nodes and into the rest of the network, with those specific lines being utilized more heavily, but it still has a desirable effect on the best-case LUF, possibly due to an overall network health improvement.

Further, the effect of the number of lines in which D-FACTS may be installed actually has different effects on the best-case and the average-case for the GWP. While part of this result can be explained by the interaction effect with the investment limit, it is hard to fully understand this difference, especially when considering that these results come from a metaheuristic algorithm, and so we not only not have a full representation of the Pareto frontier, but also we may be looking at a local optimal set rather than the true optimal set.

Overall, however, increasing the investment limit on the DFACTS devices in order to install more of them seems to have, overall, a positive effect on the objective functions being studied. Section 5.2 below has some illustrative graphs to help further the analysis.

5.2 Graphical Results

Below, Figure 3 is a scatterplot with trend line of the cost vs investment limit, for both 5 lines and 10 lines max. allocation and with both the best and average cases for the objective. Figure 4 is a scatterplot with trend line of the average cases for GWP. Only the average cases were used here since the range of the best cases is very wide and there are outliers in the data which impair visualization by over-expanding the axis range. Finally, Figure 5 shows the LUF values against the investment limit in all three cases.

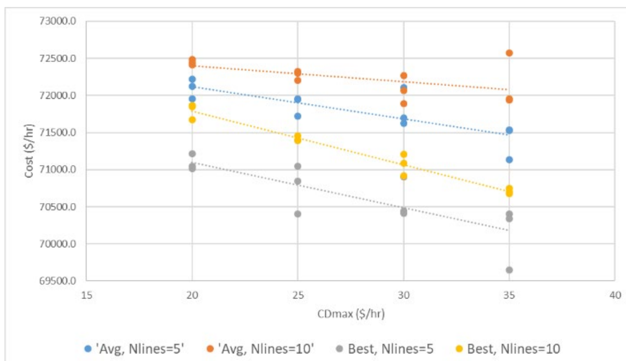

Figure 3. Expected Cost vs. Investment limit

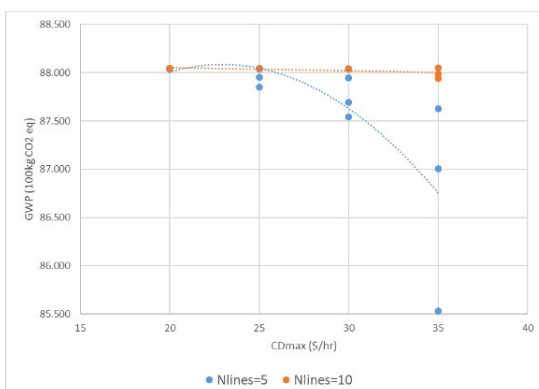

Figure 4. Average-case Global Warming Potential vs. Investment limit

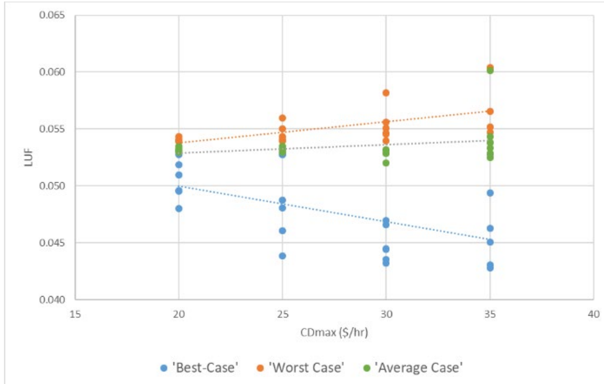

Figure 5. Line Utilization Factor vs. Investment limit

Overall, as described in the analysis in section 5.1, it's very apparent that both the Cost and Global Warming Potential appear to go down as the investment limit increases. Although there will be a limit to how much this limit can increase before the objectives stop improving, this value is larger than the scope of this sensitivity analysis.

Furthermore, in the LUF, while the worst and average case do slightly increase with the investment limit, the best case does have a downward trend, although it has very high variability which is attributed to noise, as it was found that none of the other factors have a significant enough effect on this variable.

In addition, as reflected in figure 3, an increased number of lines in which installation of D-FACTS devices does not improve the overall system costs or environmental impacts. In Figure 3, the trends of the best and average cases have very similar slopes despite the number of lines, but the intercepts are different based on whether we look at the cases with 5 lines max. or with 10 lines max. In Figure 4, the effect is even more pronounced. The trend for the case with 5 lines max appears to decrease almost quadratically as the investment limit increases (although this may be caused by to outliers in the data, since the regression equations do not have any significant quadratic terms), while the case with 10 lines decreases linearly and at a much slower rate.

6. Conclusion

This study performed a sensitivity analysis of the D-FACTS allocation problem taking into account three key parameters relevant to network properties rather than the optimization algorithm. These parameters were the amount of reactance change allowed on transmission lines, which affects voltage stability and total transfer along the line; the maximum number of lines over which D-FACTS may be installed, which affects how many lines will receive the devices and the feasibility of having the resources to perform the installation; and finally the monetary investment limit, which affects the amount of devices which will be installed throughout the system. The effects of these parameters are measured based on the resulting changes in the objective functions of the solutions remaining in the Pareto-optimal set after running the optimization algorithm, which are summarized into best-case, average-case, and worst-case for total expected operating costs, expected Global Warming Potential, and Line Utilization Factors, which correspond to economic, environmental, and sustainable effects.

The sensitivity analysis was performed mainly by the use of statistical regression analysis, with a significance level of 5% as a standard. These calculations were assisted by the use of Minitab ® software. Statistical analysis found that the reactance change limit has little impact on most of the objectives and that it is not a very significant parameter in the optimization process. On the other hand, number of lines and investment limit have a much more significant effect, with number of lines having an apparent inverse relation with most objectives, while the investment limit has a direct relation with improving the objective function values. The main drawback, however, is that investors and decision-makers may oppose increasing their investments despite obvious long-term benefits. Since each D-FACTS device has an estimated cost of $3000, and the hourly cost is calculated to be approximately 2.5 cents, an increase of $5/hr to the investment limit translates to approximately $600,000 in initial investment, which would discourage change and risk-averse executives, even despite previous studies estimating hourly savings in the tens of thousands of dollars.

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