Differential Evolution for Optimal Siting and Sizing of Flexible AC Transmission System Devices on the IEEE 30-Bus System with Techno-Economic Assessment

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Abstract

The optimal siting and sizing of Flexible AC Transmission System devices is a non-linear, non-convex optimal power flow problem in which technical benefit must be balanced against high capital cost. This study allocates two static var compensators and two thyristor-controlled series capacitors on the IEEE 30-bus system using Differential Evolution, benchmarked against a Genetic Algorithm and Particle Swarm Optimisation under an identical evaluation budget. Each candidate design is evaluated with a Newton-Raphson power flow written in MATLAB, and a 24-hour Simulink model links the selected designs to energy loss, net present value and payback. Under the standard voltage limits, a design that ignores cost reduced voltage deviation by 56 percent but reduced loss by only 0.20 percent at a cost of about 6.4 million dollars, whereas a cost-aware design cost about 1.0 million dollars and had a negative net present value because the base case already exceeds the upper voltage limit at two buses. With the upper limit relaxed slightly, the cost-aware solution was a series-compensator-only design costing about 135,000 dollars, with 0.30 percent loss reduction and a payback of 6.4 years. Differential Evolution matched or beat the other algorithms in every case and was significantly better than Particle Swarm Optimisation in all three. When generator voltages and active power were also optimised, loss fell by 72 percent and no compensator was selected, so most of the achievable loss reduction in this model comes from generator re-dispatch rather than from the compensators.

Keywords—differential evolution; flexible AC transmission systems; optimal power flow; static var compensator; thyristor-controlled series capacitor; IEEE 30-bus system; techno-economic analysis

I. INTRODUCTION

Rising electricity demand pushes transmission networks closer to their thermal and voltage limits, which increases active power loss and can degrade voltage profiles. Building new lines is often constrained by cost, right-of-way and environmental considerations, so power-electronic controllers known as Flexible AC Transmission System (FACTS) devices, such as the static var compensator (SVC) and the thyristor-controlled series capacitor (TCSC), are widely considered as an alternative for controlling power flow and voltage on existing corridors [1]. Their capital cost is high, however, so the location and rating of each device determine whether the investment is worthwhile.

Allocating FACTS devices is an optimal power flow (OPF) problem with discrete location variables, continuous rating variables and many non-linear constraints [2], and the OPF literature has been surveyed extensively [3]–[8]. FACTS devices have been incorporated into power flow and OPF formulations [9]–[11]. Gradient-based methods can stall in local minima on such problems, and population-based heuristics such as the Genetic Algorithm (GA) [12] and Particle Swarm Optimisation (PSO) [13], [14] have been applied widely. Differential Evolution (DE) [15] uses scaled differences between population members to generate trial vectors and requires few control parameters, which makes it a natural candidate for this problem. It has been surveyed in detail [16]–[18] and applied to OPF [19] and to OPF with FACTS devices on modified IEEE 30-bus systems, including TCSC and thyristor-controlled phase shifters [20] and multi-objective formulations [21]. A recent review compiled published benchmark results for DE-based FACTS allocation, including loss reductions of about 29 percent and payback periods of 2.5 to 3.8 years [22]. Those figures were synthesised from the literature and were not reproduced on a common, fully specified model.

This paper therefore builds a transparent, matrix-based simulation of the allocation problem and tests those claims directly. The contributions are:

- A from-scratch MATLAB implementation of the Newton-Raphson AC power flow with SVC and TCSC models, validated against the IEEE 30-bus base-case loss of 17.56 MW.
- A like-for-like comparison of DE, GA and PSO on the same fitness function, with identical population size, generation count and ten independent runs per algorithm.
- A techno-economic evaluation that includes device cost curves, a cost-weight sweep, energy-loss savings, payback and net present value (NPV).
- A 24-hour Simulink model that evaluates the base case and the DE-optimised design over a daily load profile.

- A generator voltage and dispatch co-optimisation that separates the loss reduction obtainable from re-dispatch from that obtainable from FACTS.
- An explicit finding that, with generator voltages and dispatch fixed, FACTS-only allocation yields small loss reductions on this system, and that the base case itself violates the upper voltage limit at two buses.

II. Problem Formulation

A. Decision Variables

Each candidate solution encodes two SVCs and two TCSCs as an eight-element vector: the location index and rating of each SVC, and the line index and compensation factor of each TCSC. Location indices are continuous in the search space and rounded to the nearest valid index during evaluation. SVCs may be installed only at load (PQ) buses, and TCSCs only on plain lines (transformer branches are excluded). The SVC is modelled as a shunt susceptance Q_{SVC}/S_{base} added at the bus, with negative values representing reactive-power absorption (the variable-susceptance concept of [9]). The TCSC modifies the line reactance as $X_{eff} = X_{line}(1 + k)$, where k is negative for capacitive compensation; this is the usual steady-state representation of FACTS devices in power flow studies [11]. A device whose size falls below a dead-band ($|Q| < 1$ MVAr or $|k| < 0.02$) is treated as not installed.

B. Objective Function

The optimiser minimises a weighted, normalised objective with penalty terms:

$$F = w_1(P_{loss}/P_{loss,0}) + w_2(\mathrm{VD}/\mathrm{VD}_0) + w_C(C_{inv}/C_{ref}) + \text{penalties} \quad (1)$$

where P_{loss} is the total active power loss, $\mathrm{VD} = \Sigma|V_i - 1|$ over load buses is the voltage deviation, C_{inv} is the investment cost, and the subscript 0 denotes the base case. The weights were $w_1 = 1$, $w_2 = 0.1$ and $C_{ref} = 5$ million dollars; the cost weight w_C differs between cases (Table II). Active power loss is computed from the branch flows of the converged power flow. Quadratic penalties (multiplier 10^5) are added for load-bus voltages outside their limits, line flows above the thermal rating, and generator reactive power outside its limits. A candidate whose power flow does not converge receives a very large fitness.

C. Constraints

Nodal power balance is satisfied by the power flow itself. Load-bus voltages are limited to 0.95 to V_{max} per unit (p.u.), where V_{max} is 1.05 p.u. in Cases A and B and 1.06 p.u. in Case C. Generator buses hold their voltage set-points. Generator reactive outputs must stay within their limits. Line apparent power must not exceed the rating $S_{max} = \max(1.15 \times$ base-case flow at the design load, 30 MVA); because the standard test data contain no ratings, this is an explicit assumption.

D. Cost Model and Economics

Device investment follows the quadratic cost curves of [12], in US dollars per kVAr with S in MVAr:

$$C_{SVC} = (0.0003\,S^2 - 0.3051\,S + 127.38)\,S \times 1000 \quad (2)$$

$$C_{TCSC} = (0.0015\,S^2 - 0.7130\,S + 153.75)\,S \times 1000 \quad (3)$$

For a TCSC, S is the absolute change in reactive flow through the compensated line relative to the base case. Annual saving is the daily energy-loss reduction over the load profile multiplied by 365 days and an energy price of 50 dollars per MWh. NPV uses a 20-year life and an 8 percent discount rate, and simple payback is investment divided by annual saving.

III. Methodology

A. Power Flow

For every candidate, the bus admittance matrix is rebuilt with the modified line reactances and shunt susceptances, and a Newton-Raphson AC power flow with an analytic Jacobian is solved with a mismatch tolerance of 10^{-8} p.u. The data are the IEEE 30-bus system [2]: six generators, 24 load buses, 41 branches and 283.4 MW of load on a 100 MVA base. With the generator set-points of Table I the base-case loss is 17.556 MW.

B. Differential Evolution and Benchmark Algorithms

DE follows the DE/rand/1/bin scheme [15]. For each target vector, a donor is formed from three distinct random members, $V = X_{r1} + F(X_{r2} - X_{r3})$; binomial crossover with probability CR produces a trial vector that is guaranteed at least one donor component; and greedy selection keeps the better of target and trial. Components leaving their bounds are re-initialised randomly. The GA is real-coded with tournament selection (size 3), BLX-0.5 crossover, Gaussian mutation and two elite individuals (cf. [12]). PSO [14] uses a linearly decreasing inertia weight (0.9 to 0.4), acceleration coefficients of 2 and velocity clamping at 20 percent of each variable range. All three algorithms use a population of 50 for 300 generations, and each is run ten times from different random seeds. Differences between algorithms were tested with the two-sided Mann-Whitney U test [23] (see [24] for the use of non-parametric tests to compare evolutionary algorithms; normal approximation with tie and continuity corrections, significance level 0.05) on the final fitness of the ten runs.

C. 24-Hour Simulink Model

A Simulink model evaluates two parallel cases, the base network and the DE-optimised design, over 24 one-hour steps. A lookup table supplies the hourly load factor (0.55 to 1.30, peaking at hour 18), and each case calls the same power-flow routine through an Interpreted MATLAB Function block. The model outputs hourly active loss, minimum voltage and maximum line loading, integrates energy loss in MWh, and computes annual saving and payback (Fig. 1). The Simulink model reuses the MATLAB solver, so it is an operating-study wrapper rather than a physical-component (Simscape) network model.

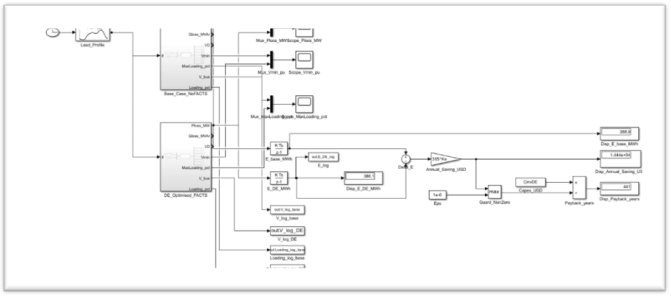

Fig. 1. Simulink model for the 24-hour evaluation of the base case and the DE-optimised FACTS design.

D. Generator Co-optimisation

To separate the contribution of FACTS from that of conventional generator control, the decision vector is extended with the six generator terminal voltages (0.95 to 1.10 p.u.) and the active power of the five non-slack generators (limits 20-80, 15-50, 10-35, 10-30 and 12-40 MW at buses 2, 5, 8, 11 and 13); the slack generator is limited to 50-200 MW and supplies the balance. Three scenarios are solved with DE using the settings of Table I except that 100 generations are used (five runs each) and the same objective, with $w_C = 0.1$ and $V_{max} = 1.05$ p.u.: generator controls only (a classical loss-minimising OPF without FACTS), FACTS only with generators at the data-file set-points, and both together. The combined scenario is seeded with the generator-only solution, so it cannot score worse than it. For the daily profile, the generator controls are re-optimised every hour with a warm-started DE (population 40, 150 generations), with any selected FACTS design held fixed.

IV. Simulation Setup

Table I lists the settings common to all cases and Table II defines the three scenarios. All results are for a design load factor of 1.0; the 24-hour study uses the load profile in Table I.

TABLE I. Simulation Settings Common to All Cases

Item	Value
Test system	IEEE 30-bus; 6 generators, 24 load buses, 41 branches; 283.4 MW; 100 MVA base
Generator set-points (p.u.)	Buses 1, 2, 5, 8, 11, 13: 1.060, 1.043, 1.010, 1.010, 1.082, 1.071; bus 2 at 40 MW, slack at bus 1
FACTS devices	2 SVC (load buses), 2 TCSC (plain lines)
SVC range	−30 to +30 MVAr (negative = absorbing)
TCSC factor k	−0.8 to +0.2 ($X_{eff} = X_{line}(1 + k)$)
Dead-bands	1 MVAr (SVC), 0.02 (TCSC)
Thermal rating (assumed)	max(1.15 × base-case flow at design load, 30 MVA)
Objective weights	$w_1 = 1$, $w_2 = 0.1$, $C_{ref} = 5$ million dollars; penalty multipliers 10^5
DE	$NP = 50$, $G = 300$, $F = 0.6$, $CR = 0.9$, DE/rand/1/bin
GA / PSO	$NP = 50$, $G = 300$; GA: tournament 3, BLX-0.5, mutation rate 0.15; PSO: inertia 0.9 to 0.4, $c_1 = c_2 = 2$
Runs	10 independent runs per algorithm
Economics	50 dollars per MWh, 8 percent discount rate, 20-year life
Hourly load factors (hours 0-23)	0.62, 0.58, 0.56, 0.55, 0.57, 0.65, 0.78, 0.90, 1.00, 1.05, 1.08, 1.10, 1.08, 1.05, 1.03, 1.05, 1.12, 1.25, 1.30, 1.25, 1.15, 1.00, 0.82, 0.68

TABLE II. Definition of the Three Scenarios

Case	Cost weight w_C	Upper voltage limit	Purpose
A	0	1.05 p.u.	Technical optimum, cost ignored
B	0.2	1.05 p.u.	Cost-aware design under strict limits
C	0.1	1.06 p.u.	Cost-aware design, relaxed upper limit

V. Results and Discussion

A. Base Case

At the design load the base case converges with a loss of 17.556 MW, a reactive loss of 33.04 MVAr, a minimum voltage of 0.9919 p.u. at bus 30 and VD = 0.6190, with no line above its assumed rating. The loss agrees with the base-case value of about 17.5 MW compiled in [22]. Although every load-bus voltage is above 0.95 p.u., buses 9 and 12 sit at about 1.051 and 1.057 p.u., which exceeds a 1.05 p.u. upper limit. This has a strong effect on the results below. The generator buses 11 and 13 hold their set-points of 1.082 and 1.071 p.u.

B. Algorithm Comparison

Table III summarises the ten runs of each algorithm in each case and Table IV gives the pairwise Mann-Whitney tests. In Case A, DE and GA reached the same best fitness (1.04191), but DE had a mean of 1.04276 and a standard deviation of 0.00081, against 1.04751 and 0.00422 for GA and 1.04989 and 0.00205 for PSO; PSO never reached the best design (Fig. 2). The median fitness of DE was significantly lower than that of PSO ($p = 0.0002$) and lower than that of GA at a borderline level ($p = 0.070$). In Case B, DE obtained the lowest best fitness (1.13093) and a significantly lower median than both GA ($p = 0.006$) and PSO ($p = 0.013$), although the absolute differences are very small (about 0.0015 in fitness) and the spreads are similar. In Case C, DE and GA tied ($p = 0.27$) and both were significantly better than PSO ($p = 0.0005$ and 0.002), with PSO converging to a different, cheaper and slightly worse design. DE was therefore never significantly worse than the alternatives, was significantly better than PSO in every case and than GA in Case B, and was clearly the most repeatable in Case A. Because the samples are small and contain many tied values, the normal-approximation p-values are approximate, and the practical differences between the algorithms are small.

TABLE III. Best, Mean, Worst and Standard Deviation of the Final Fitness over Ten Runs

Case	Algorithm	Best F	Mean F	Worst F	SD
A	GA	1.04191	1.04751	1.05121	0.00422
A	PSO	1.04502	1.04989	1.05195	0.00205
A	DE	1.04191	1.04276	1.04452	0.00081
B	GA	1.13125	1.13292	1.13352	0.00070
B	PSO	1.13131	1.13290	1.13353	0.00077
B	DE	1.13093	1.13167	1.13337	0.00077
C	GA	1.09860	1.09870	1.09878	0.00008
C	PSO	1.09874	1.09882	1.09908	0.00010
C	DE	1.09860	1.09866	1.09878	0.00008

TABLE IV. Pairwise Mann-Whitney U Tests on the Final Fitness of Ten Runs (Two-Sided; Smaller Fitness Is Better)

Case	Comparison	Median F (first)	Median F (second)	U	p-value	Result
A	DE vs GA	1.04265	1.04982	25.5	0.0695	not significant (borderline)
A	DE vs PSO	1.04265	1.04980	0.0	0.0002	DE better
A	GA vs PSO	1.04982	1.04980	35.5	0.2896	not significant
B	DE vs GA	1.13149	1.13306	13.5	0.0063	DE better
B	DE vs PSO	1.13149	1.13315	17.0	0.0134	DE better
B	GA vs PSO	1.13306	1.13315	43.0	0.6174	not significant
C	DE vs GA	1.09860	1.09874	36.0	0.2724	not significant
C	DE vs PSO	1.09860	1.09878	6.0	0.0005	DE better

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C	GA vs PSO	1.09874	1.09878	11.0	0.0021	GA better

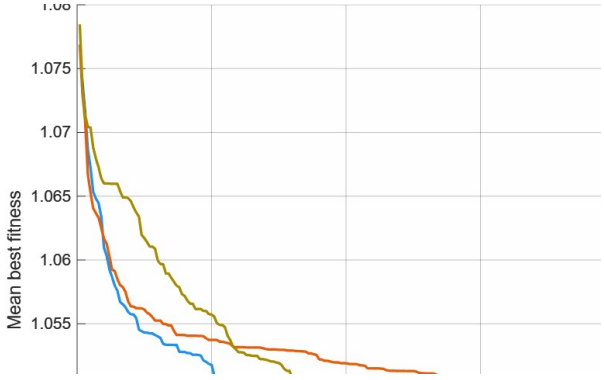

Fig. 2. Convergence of GA, PSO and DE in Case A (mean best fitness over ten runs). DE converges more slowly at first but reaches the lowest mean fitness after about 100 generations and is still improving at generation 300.

C. *Case A: Technical Optimum*

When cost is ignored, DE places two absorbing SVCs at buses 10 (−14.4 MVAr) and 12 (−25.3 MVAr) together with TCSCs on lines 1-2 (k = +0.200) and 2-5 (k = −0.271). Voltage deviation falls from 0.619 to 0.2715 (−56 percent), buses 9 and 12 drop below 1.05 p.u. (to about 1.038 and 1.032 p.u.), and most load-bus voltages move towards 1.00 to 1.02 p.u. (Fig. 3). The minimum voltage falls from 0.9919 to 0.9804 p.u. because the SVCs absorb reactive power. Active loss decreases only from 17.556 to 17.521 MW (0.20 percent), and the design costs about 6.37 million dollars, with a payback of 441 years. Lines 9-10 and 12-13 reach about 100 percent of their rating (Fig. 4), so the thermal constraint becomes active as the SVCs draw reactive power through those lines. This design buys voltage quality, not loss reduction.

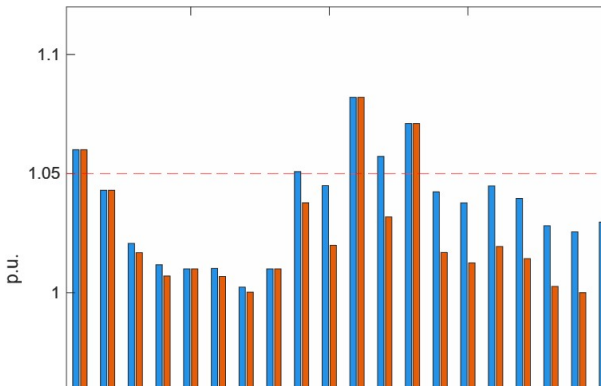

Fig. 3. Load-bus voltage profile in Case A at the design load (load factor 1.0): base case versus DE-optimised design. The dashed lines mark 0.95 and 1.05 p.u.

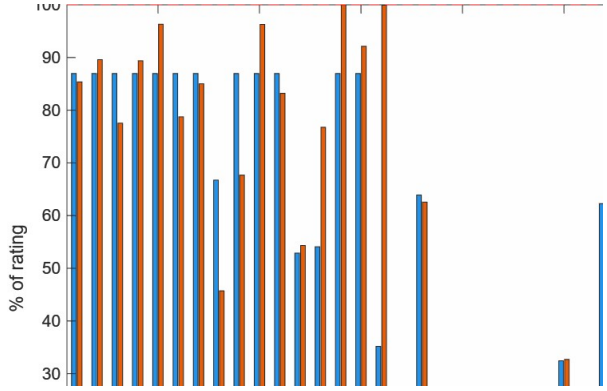

Fig. 4. Line loading as a percentage of the assumed thermal rating in Case A at the design load. Lines 14 (9-10) and 16 (12-13) approach 100 percent in the optimised design.

D. *Case B: Cost-Aware Design under Strict Limits*

With a cost weight of 0.2 and the same 1.05 p.u. limit, DE selects one absorbing SVC of 8.2 MVAr at bus 12 and TCSCs on lines 24-25 (k = −0.516) and 9-11 (k = +0.087), costing about 1.03 million dollars. The design brings bus 12 down to about 1.05 p.u. (Fig. 5), so it is essentially the cheapest way to satisfy the upper voltage limit. It does not reduce losses: loss rises slightly to 17.592 MW (−0.21 percent), the 24-hour energy loss increases by 0.83 MWh per day, payback is not achieved and NPV is −1.18 million dollars. The cost sweep below shows the same pattern for all cost weights from 0.1 to 5 under this limit.

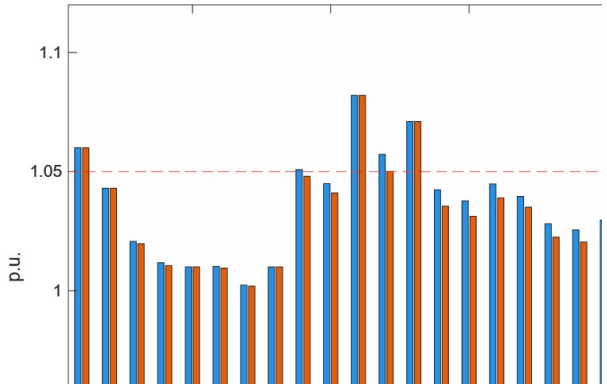

Fig. 5. Load-bus voltage profile in Case B at the design load. Bus 12 is brought down from about 1.057 to about 1.05 p.u.

E. *Case C: Cost-Aware Design with a Relaxed Upper Limit*

When the upper limit is relaxed to 1.06 p.u., the base case is feasible and no SVC is needed. DE and GA both select a TCSC-only design: line 2-5 with k = −0.066 and line 9-10 with k = +0.200, which is at the upper bound of the allowed range. The investment is about 134,700 dollars. Loss falls from 17.556 to 17.502 MW (0.30 percent), the daily energy saving is 1.15 MWh, the annual saving is about 21,000 dollars, the simple payback is 6.4 years and the 20-year NPV is about +71,500 dollars. Voltage deviation changes little (0.619 to 0.6125) and the line loading is almost unchanged (Fig. 7), with line 9-10 falling from about 87 to 84 percent and line 2-5 rising from 87 to 89 percent. This is the only configuration in this study with a positive NPV, but the margin is small and depends on the assumed energy price, discount rate and cost curve. PSO

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converged to a cheaper design (about 25,000 dollars) with no net loss reduction (Fig. 6, Table V).



Fig. 6. Convergence of GA, PSO and DE in Case C. The three algorithms reach practically the same fitness (about 1.0986).

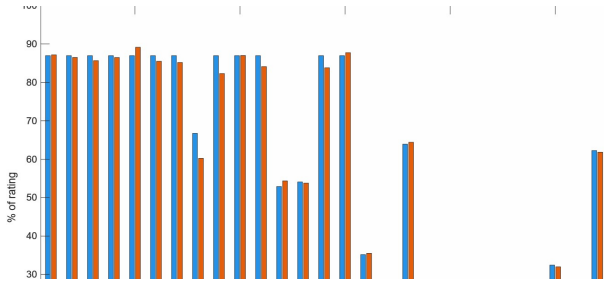

Fig. 7. Line loading as a percentage of the assumed thermal rating in Case C at the design load: base case versus TCSC-only DE design.

TABLE V. BEST DE DESIGNS AND PERFORMANCE AT THE DESIGN LOAD (LOAD FACTOR 1.0)

Item	Base	Case A	Case B	Case C
Cost weight / V_{max}	–	0 / 1.05	0.2 / 1.05	0.1 / 1.06
SVC (bus: MVAr)	–	10: −14.4; 12: −25.3	12: −8.2	none
TCSC (line: k)	–	1-2: +0.200; 2-5: −0.271	24-25: −0.516; 9-11: +0.087	2-5: −0.066; 9-10: +0.200
P_{loss} (MW)	17.556	17.521	17.592	17.502
Loss reduction (%)	–	0.20	−0.21	0.30
V_{min} (p.u.)	0.9919	0.9804	0.9911	0.9919
Voltage deviation VD	0.6190	0.2715	0.5425	0.6125
Capex (dollars)	–	6,368,094	1,029,484	134,671
Energy saving (MWh/day)	–	0.79	−0.83	1.15
Annual saving (dollars)	–	14,440	−15,089	21,004
Simple payback (years)	–	441.0	none	6.4
NPV, 20 years, 8% (dollars)	–	−6,226,320	−1,177,632	71,546

F. Cost-Weight Sweep

To separate the effect of cost from the effect of the voltage limit, DE was run for seven cost weights (five runs each, with the no-FACTS design seeded in the initial population) under both limits (Table VI, Fig. 8). Under the 1.05 p.u. limit, the capital cost never falls below about 0.94 million dollars, because every feasible design must remove the over-voltage at buses 9 and 12, and the loss reduction is zero or negative for cost weights of 0.1 and above. Under the 1.06 p.u. limit, a cost weight of 0.1 gives the 135,000-dollar TCSC design of Case C, and cost weights of 1 and above correctly give no devices. Capital cost therefore has to be weighed explicitly: with the cost term negligible, the optimiser installs 5 to 6 million dollars of devices for a loss reduction of 0.1 to 0.2 percent.

TABLE VI. COST-WEIGHT SWEEP OF THE DE DESIGN UNDER TWO UPPER VOLTAGE LIMITS

w_C	Capex 1.05 (M$)	ΔP 1.05 (%)	NPV 1.05 (M$)	Capex 1.06 (M$)	ΔP 1.06 (%)	NPV 1.06 (M$)
0	6.37	0.20	−6.23	6.17	0.16	−6.05
0.02	5.35	0.09	−5.31	5.35	0.10	−5.30
0.1	1.05	−0.07	−1.10	0.135	0.30	0.07
0.5	1.05	−0.06	−1.09	0.006	−0.01	−0.02
1	1.03	−0.17	−1.15	<0.001	0.00	0.00
2	1.02	−0.20	−1.16	0	0.00	0.00
5	0.94	−0.19	−1.07	0	0.00	0.00

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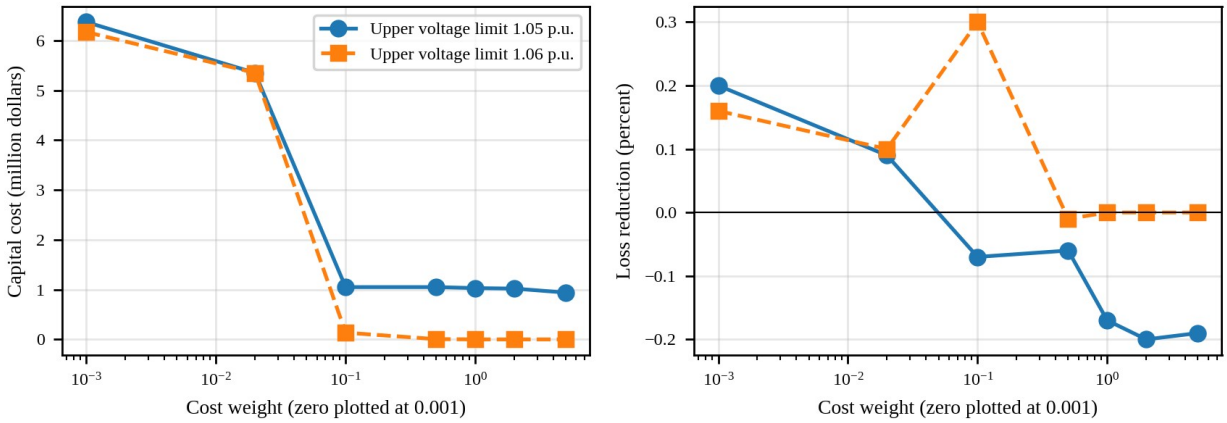

Fig. 8. Capital cost (left) and active-power loss reduction (right) of the DE design as the cost weight increases, for upper voltage limits of 1.05 and 1.06 p.u.

G. 24-Hour Operation

Over the daily load profile, the base and Case C loss curves are visually almost identical (Fig. 9), consistent with a daily energy-loss saving of only 1.15 MWh (about 0.3 percent). The Simulink maximum-line-loading signal (Fig. 10) shows a further limitation: because the ratings are defined at the design load, both the base case and the optimised design exceed 100 percent of rating in the evening peak (and marginally around hour 11), reaching about 134 percent at hour 18 (load factor 1.30). The designs in this study were optimised at a single load level, so they do not address peak-hour congestion; a multi-period formulation would be needed for that purpose.

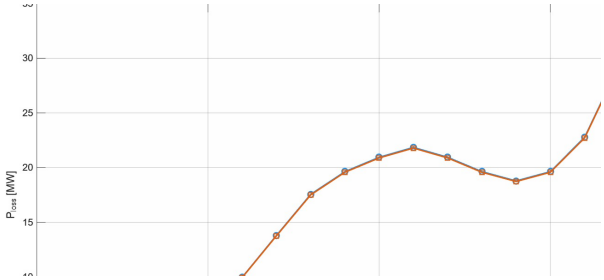

Fig. 9. Active power loss over 24 hours in Case C: base case versus DE-optimised design.

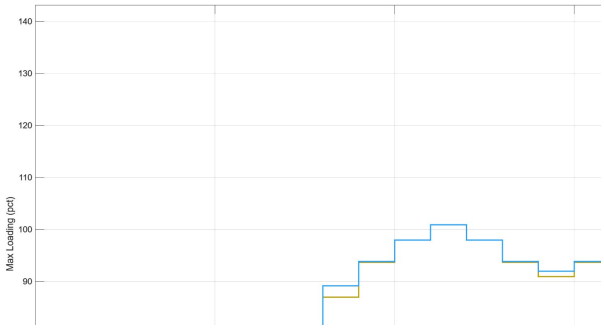

Fig. 10. Simulink scope of maximum line loading (percent of assumed rating) in Case C over 24 hours (yellow: base case; blue: DE-optimised design).

H. Comparison with Published Benchmark Claims

The review in [22] compiled loss reductions of about 29 percent and paybacks of 2.5 to 3.8 years for DE-based FACTS allocation. The present simulation does not reproduce them: the best loss reduction was 0.30 percent and the best payback 6.4 years, with generator voltages and dispatch fixed and a standard data set. The difference can plausibly arise from (i) additional control variables such as generator voltages and dispatch, which usually dominate loss reduction in OPF studies, (ii) different or stressed test networks and loading, (iii) different cost and tariff assumptions, and (iv) differences in how the base case is defined. Explanation (i) is supported by the generator co-optimisation below, where generator controls alone reduced the loss by 72 percent; the other explanations were not tested here and should be treated as hypotheses.

I. Sensitivity to the Energy Price

The energy price enters only the economic evaluation, so the NPV, payback and break-even price of each selected design can be recomputed directly from its capital cost and daily energy saving (Table VII, Fig. 11). The Case C design breaks even at about 33 dollars per MWh; at 100 dollars per MWh its payback falls to 3.2 years (NPV about +0.28 million dollars) and at 150 dollars per MWh to 2.1 years (NPV about +0.48 million dollars), which is of the same order as the 2.5 to 3.8 years quoted in [22]. That short payback, however, belongs to a very small investment that reduces losses by only 0.3 percent, so a short payback should not be read as a large technical benefit. The Case A design would need an energy price of roughly 2,250 dollars per MWh to break even, and Case B never pays back because it slightly increases losses. The designs were not re-optimised for each price.

TABLE VII. BREAK-EVEN ENERGY PRICE, PAYBACK AND NPV OF THE SELECTED DESIGNS (20 YEARS, 8 PERCENT; COMPUTED FROM THE ROUNDED DAILY SAVINGS)

Case	Break-even K_e ($/MWh)	Payback at $50 (y)	Payback at $100 (y)	Payback at $150 (y)	NPV at $100 / $150 (M$)
A	≈ 2,250	442	221	147	−6.08 / −5.94
B	never (loss increases)	none	none	none	−1.33 / −1.48

C	≈ 33	6.4	3.2	2.1	+0.28 / +0.48

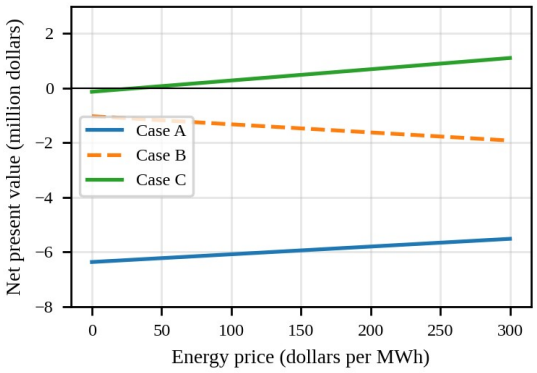

Fig. 11. Net present value of the three selected designs as a function of the energy price.

J. Generator Co-optimisation

Table VIII compares the scenarios at the design load. With generator controls alone, DE reduces the loss from 17.556 to 4.903 MW (72.1 percent) and the voltage deviation from 0.619 to 0.226, while every line stays below its assumed rating (maximum loading 97.7 percent) and all load-bus voltages remain within 0.95 to 1.05 p.u. The optimum moves generation away from the slack generator (261.0 MW in the data-file dispatch, 91.8 MW in the optimum) towards the other generators (72.0, 48.9, 25.9, 21.9 and 27.8 MW at buses 2, 5, 8, 11 and 13) and lowers the generator voltages to 1.004 to 1.038 p.u. When generator controls are available, the combined scenario installs no FACTS device: all five runs returned the generator-only solution, so at a cost weight of 0.1 FACTS provide no benefit on top of re-dispatch. The over-voltage at buses 9 and 12, which required about 1.0 million dollars of FACTS in the strict-limit FACTS-only design, is removed at no cost by lowering the generator voltages. The 11-variable generator-only problem was harder for DE than the FACTS-only problem: the best fitness over five runs ranged from 0.3158 to 0.3273, so with 100 generations the reported optimum is not fully converged and the attainable loss reduction is slightly higher.

TABLE VIII. GENERATOR CO-OPTIMISATION AT THE DESIGN LOAD (LOAD FACTOR 1.0, UPPER VOLTAGE LIMIT 1.05 P.U., COST WEIGHT 0.1)

Item	Reference	FACTS only	Generator OPF only	FACTS + generator OPF
P_{loss} (MW)	17.556	17.585	4.903	4.903
Loss reduction (%)	–	−0.16	72.07	72.07
V_{min} (p.u.)	0.9919	0.9902	0.9720	0.9720
Voltage deviation VD	0.6190	0.5478	0.2261	0.2261
Slack generation (MW)	261.0	261.0	91.8	91.8
Maximum line loading (%)	87.0	88.5	97.7	97.7
FACTS capex (dollars)	–	1,013,350	0	0 (none selected)
Best fitness (5 runs)	–	1.1106	0.3158	0.3158

Over the 24-hour profile, hourly re-dispatch reduced the daily energy loss from 388.9 MWh to 119.7 MWh, a reduction of 269.2 MWh per day (69 percent), worth about 4.9 million dollars per year at 50 dollars per MWh with no capital cost; because no FACTS device is selected, the OPF and OPF-with-FACTS results coincide in every hour. The hourly optimisation reached losses of 4.54 to 4.56 MW at load factor 1.0, which is below the 4.903 MW of the design-load scenario, so the design-load runs (100 generations) were not fully converged and the 72 percent loss reduction in Table VIII is slightly conservative (about 74 percent for 4.54 MW).

These savings must be read with care. The reference is the data-file snapshot, in which the slack generator supplies 261 MW (above its 200 MW limit); the objective minimises loss only and ignores fuel cost, ramp limits and security; and moving output away from the slack generator may raise fuel cost. The result therefore shows that, in this model, generator dispatch has a far larger effect on loss than FACTS do, not that a utility would realise a 4.9 million dollar saving.

VI. LIMITATIONS AND FUTURE WORK

- In Cases A to C the generator voltages and active dispatch were fixed to isolate the FACTS-only benefit; the generator co-optimisation was done only at the design load, with five DE runs per scenario.
- The generator co-optimisation ignores fuel cost, ramp limits and security constraints, and its reference is the data-file dispatch (slack output 261 MW, above the 200 MW limit); the quantified savings indicate the relative size of the effect and are not a realisable economic benefit.
- Line thermal ratings were assumed (1.15 times the base-case flow), because the standard data contain none, and Cases A to C use a single design load of 1.0.
- SVCs and TCSCs were fixed-size across the daily profile, and no controller dynamics, N-1 contingencies or stochastic renewable generation were modelled.
- The objective is a weighted sum; a true multi-objective formulation would produce a proper Pareto front of loss, voltage and cost.
- Ten runs per algorithm were used; the Mann-Whitney p-values rely on a normal approximation with many tied values, and the absolute fitness differences between algorithms are small.
- Economic results depend on the cost curves, the energy price and the discount rate; the energy-price sensitivity evaluates fixed designs and does not re-optimise them for each price.

VII. CONCLUSION

This study implemented a matrix-based Newton-Raphson power flow with SVC and TCSC models on the IEEE 30-bus system and used DE, GA and PSO to allocate two SVCs and two TCSCs, together with a 24-hour Simulink evaluation and a techno-economic analysis. The main findings are as follows.

- The base-case loss of 17.556 MW was reproduced, and the base case already exceeds a 1.05 p.u. upper voltage limit at buses 9 and 12.
- Ignoring cost, the DE design cut voltage deviation by 56 percent but reduced losses by 0.20 percent for about 6.4 million dollars.
- Under strict limits, the cheapest feasible design (about 1.0 million dollars) mainly corrects over-voltage and has a negative NPV; with the upper limit relaxed to 1.06 p.u., the cost-aware optimum is a TCSC-only design of about 135,000 dollars with 0.30 percent loss reduction, a 6.4-year payback at 50 dollars per MWh (break-even about 33 dollars per MWh) and a small positive NPV.
- DE matched or beat GA and PSO in best fitness in every case, was significantly better than PSO in all cases and than GA in Case B (Mann-Whitney), and was clearly more repeatable in Case A; the absolute differences between the algorithms were small.
- When generator voltages and active power were also optimised, loss fell by 72 percent at the design load (17.56 to 4.90 MW) and no FACTS device was selected at a cost weight of 0.1, so in this model most of the achievable loss reduction comes from generator re-dispatch and not from FACTS.
- The loss reductions and paybacks reported in earlier compilations were not reproduced with generator settings fixed, which suggests that the FACTS-only contribution on this system is modest.

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