Optimal placement and size of Tap-Changer Voltage Regulator in Distribution system using Hybrid GA-PSO

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Abstract

Modern distribution networks increasingly employ voltage regulators to regulate voltages within legal limits through the growing penetration of distributed energy resources (DERs) and variable loads. In this study, we develop and validate an optimization framework for single-stage, on-load tap-changing (OLTC) voltage regulators across two canonical radial feeders (IEEE-33 and IEEE-69). The objective of the study is to minimize active power losses across regulators, while still keeping the voltage in acceptable limits (0.95 − 1.05 pu at each bus). The regulator is modeled as a discrete-tap transformer, and the optimization framework Hybrid GA-PSO implemented in Python PyCharm community 2025 environment simulation for its powerful and flexibility in optimization. Full power-flow simulations are conducted under both the base-case and optimized tap settings for both systems. On the IEEE-33 feeder, optimizing the tap at bus 2 from unity to 1.0164 reduced active losses from 211.0 kW to 156.21 kW and raised the minimum bus voltage from 0.9038 pu to 0.9974 pu, while the maximum voltage increased from 1.000 pu to 1.200 pu. Similarly, on the IEEE-69 feeder, tuning the regulator at bus 45 to a tap ratio of 1.0198 cut losses from 225.0 kW to 161.19 kW and improved the voltage envelope from 0.9092–1.000 pu to 0.9592–1.19999 pu. These enhancements were achieved with minimal hardware adjustments and without violating operational constraints. Future work will apply this process to meshed and renewables-rich grids, while considering stochastic load and generation forecasts to assist with real-time implementation.

Keywords: Voltage Regulator, Power Loss, Voltage Profile, Hybrid GA-PSO, On-Load Tap-Changing.

التحسين الأمثل لموقع وحجم منظم الجهد الكهربائي في شبكات التوزيع باستخدام اسلوب هجين يجمع بين خوارزميتي (سرب الجسيمات والجينات)

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الخلاصة

توظف شبكات التوزيع الحديثة منظِمات جهد لتنظيم مستويات الجهد ضمن الحدود المسموحة مع تزايد انتشار مصادر الطاقة النظيفة وتنوع الاحمال . في هذه الدراسة نطور ونحقق اطارا تحسينيا لإعداد نقاط التحويل لمؤثرات الحهد القابلة لتغيير النقاط اثناء التحميل في مرحلة واحدة عبلا الانظمة (IEEE-33 ,IEEE-69) يهدف البحث الى تقليل خسائر القدرة الفعالة عبر المنظِمات مع الحفاظ على الجهد ضمن الحدود المقبولة (0.95 – 1.05pu) عند كل عقدة. تم نمذجة المنظِم كمحول ذي نقاط تحويل منفصلة وتم تنفيذ اطار التحسين بصيغة هجينة تجمع ما بين الخوارزمية الجينية وخوارزمية سرب الجسيمات في بيئة بايثون التي تتميز بالقدرة الفائقة والمرونة في التحسين والامثلية. اجريت محاكاة تدفق طاقة كاملة لكل من الحالة الاساسية واعدادات النقاط المحسَنة لكلا النظامين . في نظام ال (IEEE-33) ، ادت عملية تحسين نقطة التحويل في العقدة 2 من القيمة (1.000 الى 1.0164) الى خفض الخسائر الفعالة من 211 كيلو واط الى 156.21 كيلو واط ، ورفع ادنى جهد عقدة من (0,9038 الى 0,9974 pu) . مع ازدياد اقصى جهد من(1 الى 1,2 pu). وبالمثل في نظام(IEEE-69) ادى ضبط المنظم في العقدة 45 الى نسبة تحويل 1,0198 الى تقليل الخسائر من 225 كيلو واط الى 161.19 كيلو واط وتحسين نطاق الجهد من(0.9092 -1.000 pu) الى(0.9592- 1.1999 pu) تحققت هذه التحسينات مع تغييرات مادية بسيطة ودون انتهاك للقيود التشغيلية، ستتضمن الابحاث المستقبلية تطبيق هذا الاجراء على شبكات متشابكة وغنية بمصادر الطاقة المتجددة – مع الاخذ بالاعتبار التنبؤات الاحتمالية للحمل والتوليد بهدف دعم تنفيذ الحلول في الزمن الحقيقي.

الكلمات المفتاحية: منظم الفولتية، خسائر القدرة، منحني الجهد، خوارزمية هجينة(سرب الجسيمات- الجينات) و مغير مآخذ تحت الحمل.

Introduction

Voltage regulation remains a critical function in modern distribution networks, where the increase in distributed energy resources and dynamic load variations can result in voltage excursions outside of acceptable limits. Under- or over-voltage not only deteriorates power quality and customer satisfaction, but also increases technical losses and accelerates the aging of any equipment. On the contrary, excessive conservatism of voltage control could result in inefficient loss performance, in addition to a lower hosting capacity for renewables. Hence, voltage regulator coordination and setting of on-load tap-changing (OLTC) voltage regulators has become vital for improving the efficiency and reliability of distribution feeders.

This paper proposes an optimization framework to determine the optimal tap ratios of single-stage voltage regulators located on two benchmark systems, the IEEE-33 and IEEE-69 radial feeders, with the primary objectives being to minimize active power losses while ensuring the voltage magnitude at every bus is at all times within the statutory limits (typically 0.95-1.05 pu).

The regulator is modeled as a controllable transformer with discrete tap positions, leading to a mixed-integer nonlinear programming problem that is solved with a specially designed metaheuristic. The proposed method is demonstrated and evaluated through extensive power-flow simulations that can show substantial loss reductions with significant improvements to voltage profile with minimal hardware changes.

In the IEEE-33 feeder case, the bus 2 regulator was optimized to a tap ratio of 1.0164, reducing active power losses from 211.0 kW to 156.21 kW and increasing the minimum bus voltage from 0.9038 pu to 0.9974 pu (and a new maximum of 1.2000 pu). In the same manner, the bus 45 regulator in the IEEE-69 feeder was set to tap 1.0198 and reduced losses from 225.0 kW to 161.19 kW, and improved the voltage envelope (min. 0.9592 pu, max. 1.1999 pu). The previous examples show that optimization was successful in providing superior voltage regulation and enhanced energy efficiency and it can be applied to more complex radial distribution, meshed, and renewable-rich distribution systems.

The optimal placement and sizing in radial distribution systems for voltage control and distributed generation devices has significantly developed over the last 30 years. The motivation for optimizing voltage control and distributed generation resources in radial distribution systems is to minimize power losses and improve the voltage profile while maintaining secure and cost-effective operation. The earlier work of Reddy et al. (Reddy, *et al*., 2019) using fuzzy-logic for locating voltage regulators (VRs) was also one of the first to demonstrate smooth voltage regulation while limiting computational effort. Building on this, Addisu et al. expanded fuzzy-expert systems to co-locate voltage regulators (VRs) and shunt capacitators allowing loss reductions and increased minimum

voltage levels in real-world feeders (Addisu, *et al*.,2021) and (Addisu, *et al*.,2021). Gallego Pareja et al. employed a mixed-integer linear program (MILP) for co-located feeder reconfiguration and VR siting obtaining global-optima that were found in the benchmarks that outperform the two-step shrub strategy to the best of the literature knowledge (Gallego Pareja, *et al*.,2023). Furthermore, institutional guidance in a way similar as those of the UPV evaluation manual, have established some procedural limits for the requirements of institutional doctoral research and mark an important aspect to consider in optimization studies with an appropriate level of rigor "Guía de Evaluación Anual– Alumno," Universidad Politécnica de Valencia, 2024. As development on co-located optimization grew, so did the development of the focus on distributed generation (DG) placement, stimulating additional research possibilities. Alanazi used a MILP model for the location of wind DG facilities that incorporated probabilistic voltage stability indices and showed that the MILP performed better than population-based heuristics implemented in the IEEE test feeders (Alanazi, *et al*.,2021) used a physics-inspired equilibrium optimizer (EO) combined the task of performing feeder reconfiguration simultaneously with below or above optimal short-run DG placement, producing results that showed significant elevation in minimum bus voltages, although conditions were below current line ratings and loss levels were in overload situations (Shaik, *et al*.,2021). Al-Ammar et al. used a multi-objective DG sizing formulation as an Artificial Bee Colony algorithm that reduced losses of around 50% and additionally the discounted energy cost across all the benchmarking cases for DG and the greatest improvements of assessed facilities (Al-Ammar, *et al*.,2020) Shortly after, hybrid (combinatory designs) combined approaches were introduced with some of the earliest being developed by Bakry et al. using a Genetic Algorithm-driven CO with EO exploitation to elevate performance and increase load to reduce unsupplied load (loss) in a single process, emissions, and costs in large feeders (Bakry, *et al*.,2022) while Ramadan's Artificial Hummingbird Algorithm under uncertainty yielded 39–78% improvements over rival bioinspired methods (Ramadan, *et al*.,2022). To further improve the exploration-exploitation balance, researchers introduced ever more complex metaheuristics when addressing systematic uncertainty. Hemeida's hybrid Genetic-Archimedes Optimization Algorithm (GAAOA) solved premature convergence issues when sizing three DGs and performing network reconfiguration tasks (Hemeida *et al*.,.2024). Hassan's binary PSO-Shuffled Leap Frog was used to identify DG placement when considering both loss and voltage stability objectives (Hassan, *et al*.,2020) Selim's Chaotic Sine Cosine Algorithm footprint used Chaos theory to escape local minima when making DG allocation decisions (Selim, *et al*.,2019). Ullah combined PSO and Gravitational Search

Algorithms for tech-economic planning decisions whilst considering seasonal variability (Ullah, *et al*.,2020). Finally, Phung Dang Huy used Differential Evolution to simultaneously consider placement for sizing, and power factor whilst demonstrating that 96% loss reductions could be achieved (Huy, *et al*.,2020).

Problem Formulation

The discrete tap position of each regulator is considered a control variable in the mixed-integer nonlinear optimization formulation of the tap-changer setup problem as it installed in distribution system in Figure 1. As long as the network's power-flow physics are met and all bus voltages stay below reasonable limits, the objective is to reduce the overall active-power losses across the feeder. To guarantee viable and dependable functioning, realistic limitations on tap limits, branch thermal capabilities, and the maximum number of tap steps each scheduling period are provided.

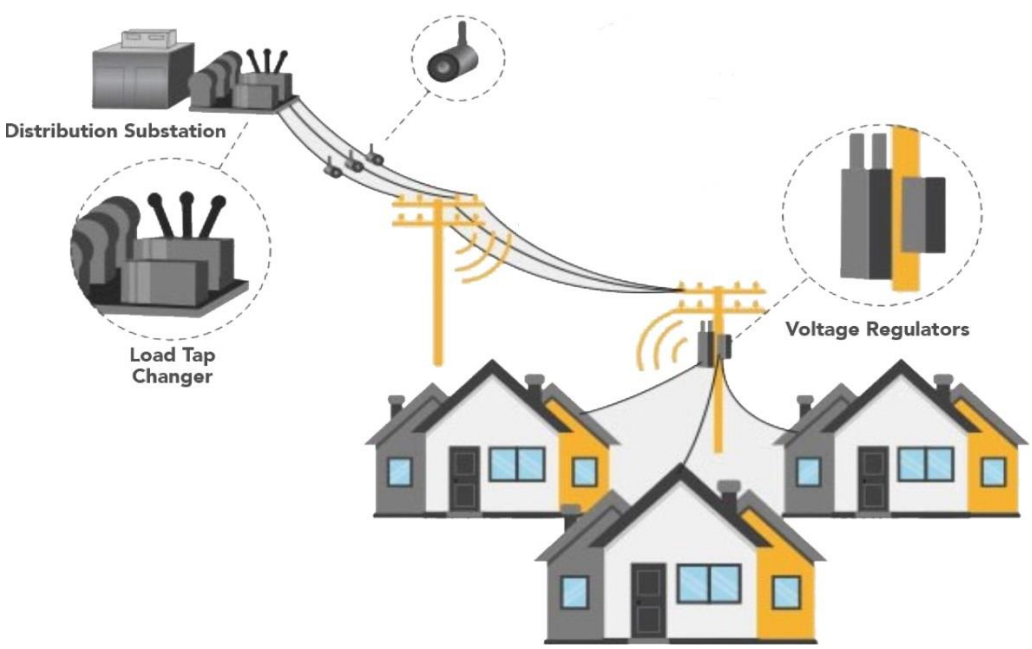

Figure 1 Tap Changer Voltage Regulator in distribution system

Decision Variables

- $x_i \in \{0,1\}$: binary variable indicating whether a voltage regulator is installed at bus i.
- $t_i \in \{t_{\min}, t_{\min}+1, \dots, t_{\max}\}$: integer tap position of the regulator at bus i, if installed.

We collect these into a decision vector

$$\mathbf{X} = \{x_1, \dots, x_N;\ t_1, \dots, t_N\} \quad (1)$$

Objective Function

We seek to minimize a weighted sum of network power losses and voltage profile deviation:

$$\min_{\mathbf{X}} F(\mathbf{X}) = w_1 P_{\text{loss}}(\mathbf{X}) + w_2 \sum_{i=1}^{N} |V_i(\mathbf{X}) - V_{\text{ref}}|, \quad (2)$$

Where:

- $P_{\text{loss}} = \sum_{\ell=1}^{L} I_\ell^2 R_\ell$ is total active loss on branches;
- V_i is the voltage magnitude at bus i resulting from load-flow with regulators in place;
- V_{ref} is the nominal voltage (e.g., 1.0 p.u.);
- w_1, w_2 are weighting coefficients.

Constraints

1. **Regulator count**

$$\sum_{i=1}^{N} x_i = N_{\text{reg}}^{\max}, \quad (3)$$

limiting the total number of regulators.

2. **Voltage limits**

$$V_{\min} \le V_i(\mathbf{X}) \le V_{\max}, \quad \forall i = 1, \dots, N. \quad (4)$$

3. **Tap range**

$$t_{\min} \le t_i \le t_{\max}, \quad t_i \text{ integer}, \quad \text{and} \quad t_i(1 - x_i) = 0. \quad (5)$$

4. **Radial network power-flow equations** for each branch ℓ connecting buses i and j:

$$P_{ij} = V_i V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) - \sum_{k \in \mathcal{L}(j)} P_{jk}, \quad (6)$$

$$Q_{ij} = V_i V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) - \sum_{k \in \mathcal{L}(j)} Q_{jk}, \quad (7)$$

solved via backward-forward sweep or Newton–Raphson at each evaluation.

GA-PSO Hybrid Algorithm

The GA-PSO hybrid combines the global search of GA with the fast convergence of PSO. Each candidate solution (chromosome/particle) encodes **X** as shown in Figure 2 which explain the steps flowchart of GA-PSO.

Encoding

- Chromosome/particle vector:

$$[x_1, \dots, x_N, t_1, \dots, t_N]. \quad (8)$$

- Continuous PSO velocities apply only to tap positions; binaries are handled via a sigmoid threshold.

Fitness Evaluation

For each individual $\mathbf{X}^{(k)}$:

1. Run load flow to obtain P_{loss} and V_i.
2. Compute $F(\mathbf{X}^{(k)}$

Genetic Operators

- **Selection**: tournament or roulette–wheel on $1/F$.
- **Crossover**: uniform crossover on both x_i and t_i.
- **Mutation**:
- For x_i: flip bit with probability p_m.
- For t_i: add or subtract 1 within $[t_{\min}, t_{\max}]$ with probability p_m.

PSO Update

For particle k and dimension d:

$$v_{k,d} \leftarrow \omega\, v_{k,d} + c_1 r_1\left(p_{k,d}^{\text{best}} - x_{k,d}\right) + c_2 r_2\left(g_d^{\text{best}} - x_{k,d}\right),$$
$$x_{k,d} \leftarrow x_{k,d} + v_{k,d}, \quad (9)$$

Where:

- ω is inertia weight,
- c_1, c_2 are cognitive and social coefficients,
- $r_1, r_2 \sim U(0,1)$.

For binary $x_{k,d}$, use

$$S(v_{k,d}) = \frac{1}{1+e^{-v_{k,d}}}, \quad x_{k,d} = \begin{cases} 1 & \text{if } S(v_{k,d}) > r, \\ 0 & \text{otherwise.} \end{cases} \quad (10)$$

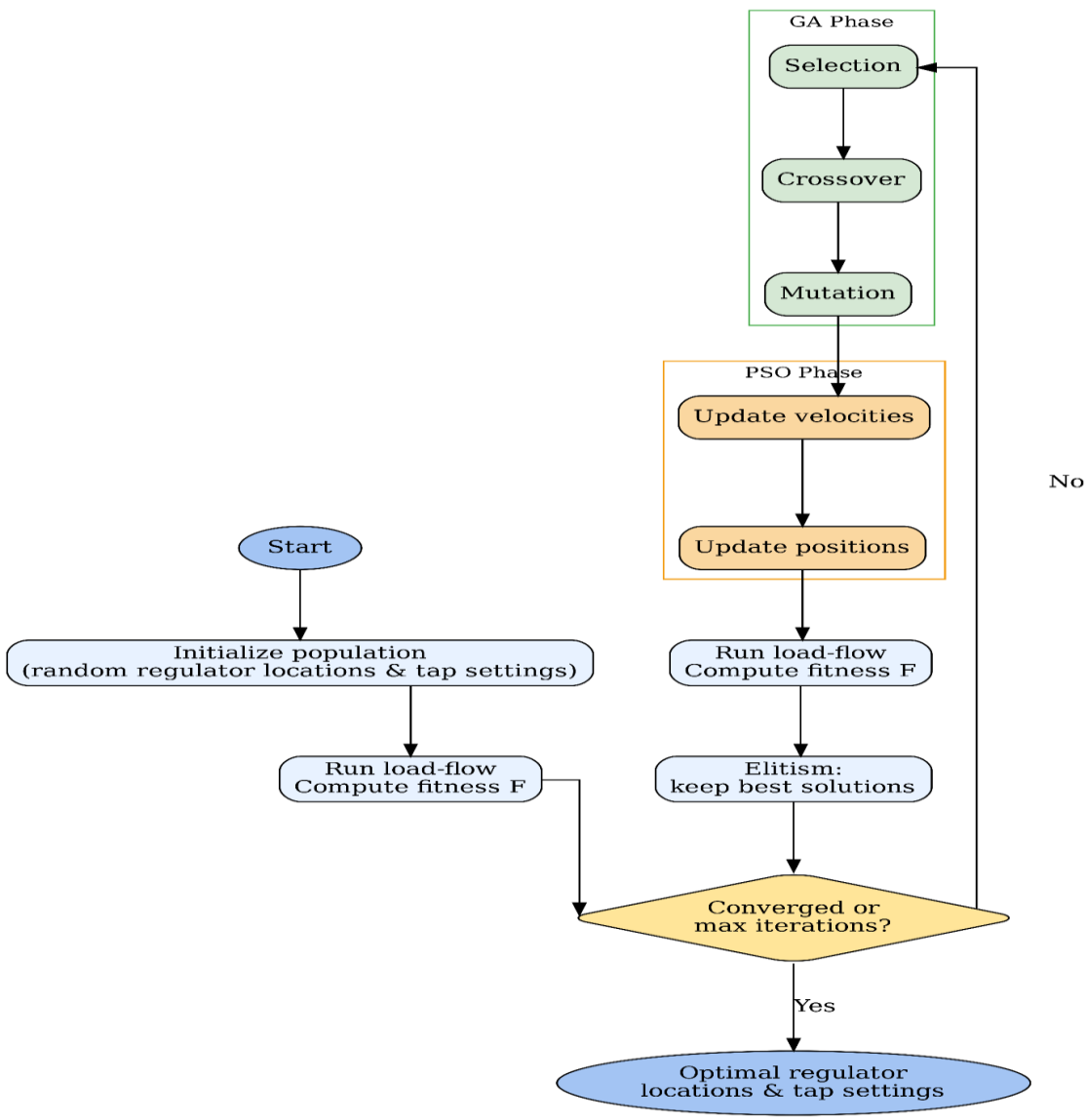

Figure 2 Flowchart of GA-PSO procedure for optimal Regulator placement and Tap setting with python

Results and Discussion

The tap-changer optimization was implemented in Python using the PyCharm Community 2025 IDE, leveraging its powerful debugging and project management features to structure the MINLP model. The framework was applied to both the IEEE-33 and IEEE-69 radial feeders as shown in Figure3, enabling automated evaluation of tap settings across each network. Practical limits on discrete tap positions, branch thermal capacities, and step-change restrictions were enforced to ensure feasible, reliable operation.

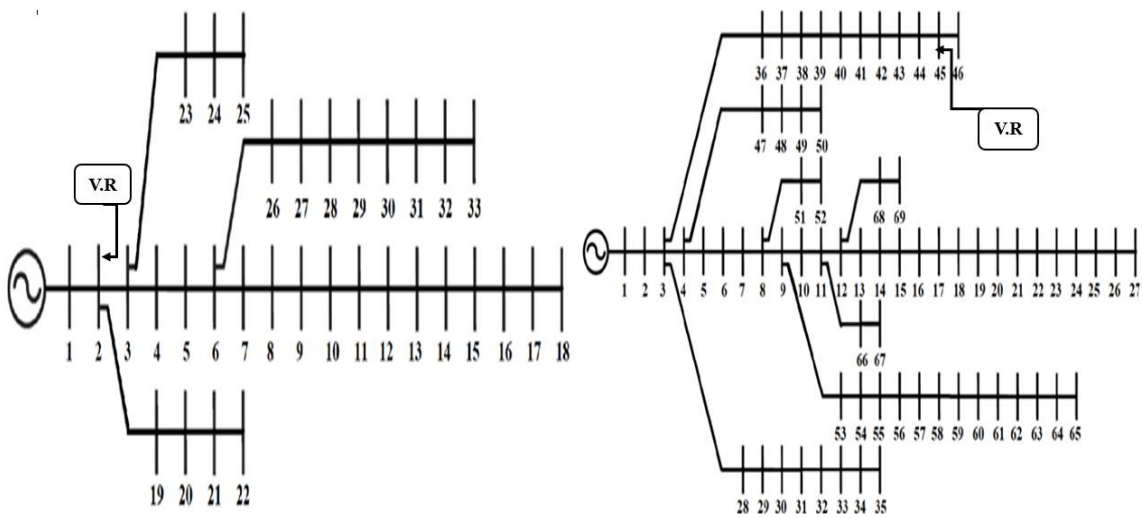

Figure 3 Radial Feeders of IEEE-33 and IEEE-69

a. IEEE-33 Feeder Performance:

Table 1 presents the key system-level KPIs for the IEEE-33 feeder. In the base case, active power losses are 211.0 kW, with a minimum bus voltage of 0.90377 p.u and maximum of 1.0000 p.u. After optimization—placing a single regulator at bus 2 with a tap ratio of 1.0164—losses drop to 156.21 kW (≈ 26.0 % reduction), and the voltage envelope tightens to [0.99735 p.u, 1.2000 p.u] Table 1. Figure 4 illustrates this KPI comparison as a bar chart, highlighting the substantial loss reduction.

Table 1 System KPIs

Case	Reg_bus	Tap_ratio	P_loss_kW	Q_loss_kVAr	S_loss_kVA	V_min_pu	V_max_pu
Base	-	1.0000	211.0	0.0	211.0	0.90377	1.0
Optimised	2	1.0164	156.21	0.0	156.21	0.99735	1.2

At the branch level Table 2, every section of the feeder shows loss reductions. For example, branch 2–3 sees losses cut from 21.718 kW to 17.197 kW, while lightly loaded branches such as 17–18 fall from 0.035 kW to 0.020 kW. Figure 5 overlays the base-case and optimized voltage profiles along all 33 buses, demonstrating that post-regulation voltages exceed 0.997 p.u at every node—eliminating the undervoltage issues seen originally.

Table 2: Branch losses & Bus voltages

Regulator @ bus 2 tap 1.0164

Branch	P_loss_base_kW	P_loss_opt_kW	Bus	V_base_pu	V_opt_p.u
1-2	(5.433-11.035j)	(4.402-8.738j)	2	0.997	0.9973
2-3	(21.718-47.331j)	(17.197-36.709j)	3	0.9829	1.001
3-4	(6.584-18.941j)	(4.852-13.901j)	4	0.9754	1.0109
4-5	(6.128-17.826j)	(4.452-12.912j)	5	0.968	1.0211
5-6	(12.242-36.57j)	(8.822-26.346j)	6	0.9495	1.0219
6-7	(1.211-1.523j)	(0.866-1.086j)	7	0.946	1.0357
7-8	(7.456-9.241j)	(5.145-6.345j)	8	0.9323	1.0412
8-9	(2.721-3.285j)	(1.794-2.149j)	9	0.926	1.053
9-10	(2.261-2.845j)	(1.464-1.835j)	10	0.9201	1.0655
10-11	(0.341-0.451j)	(0.217-0.287j)	11	0.9192	1.0823
11-12	(0.56-0.704j)	(0.352-0.442j)	12	0.9177	1.0989
12-13	(1.744-2.089j)	(1.083-1.291j)	13	0.9115	1.112
13-14	(0.495-0.556j)	(0.304-0.339j)	14	0.9092	1.1284
14-15	(0.286-0.225j)	(0.171-0.132j)	15	0.9078	1.1458
15-16	(0.21-0.196j)	(0.124-0.113j)	16	0.9064	1.1636
16-17	(0.182-0.182j)	(0.105-0.103j)	17	0.9044	1.1811
17-18	(0.035-0.041j)	(0.02-0.023j)	18	0.9038	1.2
2-19	(0.108-0.12j)	(0.099-0.11j)	19	0.9965	1.0132
19-20	(0.556-0.619j)	(0.504-0.561j)	20	0.9929	1.0264
20-21	(0.067-0.075j)	(0.06-0.067j)	21	0.9922	1.0426
21-22	(0.029-0.032j)	(0.026-0.028j)	22	0.9916	1.0591
3-23	(1.972-2.497j)	(1.757-2.226j)	23	0.9793	1.014
23-24	(3.236-3.999j)	(2.87-3.546j)	24	0.9726	1.0243
24-25	(0.809-1.001j)	(0.706-0.873j)	25	0.9693	1.038
6-26	(-0.049-2.601j)	(-0.04-1.875j)	26	0.9475	1.037
26-27	(-0.194-3.325j)	(-0.152-2.379j)	27	0.945	1.0519
27-28	(-1.146-11.247j)	(-0.884-7.998j)	28	0.9335	1.0593
28-29	(-1.213-7.742j)	(-0.922-5.479j)	29	0.9253	1.0697
29-30	(-0.95-3.78j)	(-0.71-2.652j)	30	0.9218	1.0842
30-31	(0.974-1.262j)	(0.661-0.859j)	31	0.9176	1.0985
31-32	(0.125-0.173j)	(0.084-0.116j)	32	0.9167	1.1158
32-33	(0.005-0.012j)	(0.003-0.008j)	33	0.9164	1.1339

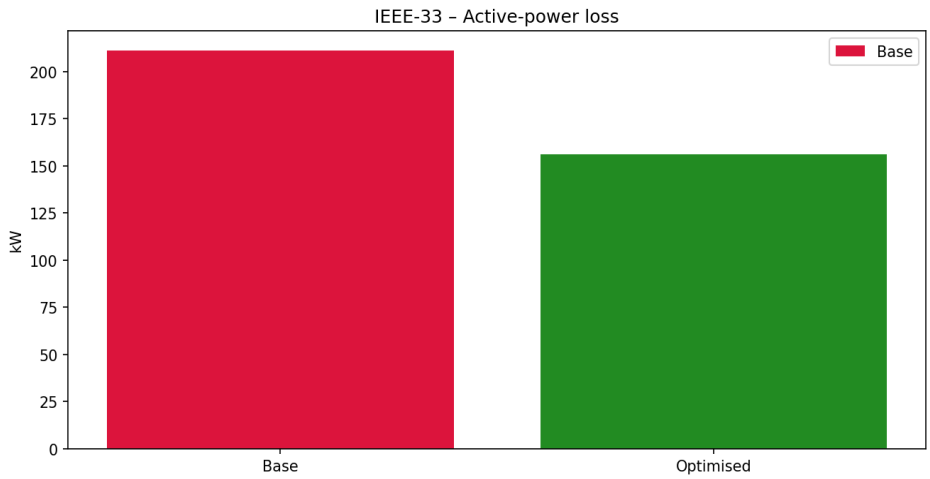

Figure 4 Power Loss comparison before and after Integration of TCVR using GA-PSO of IEEE-33

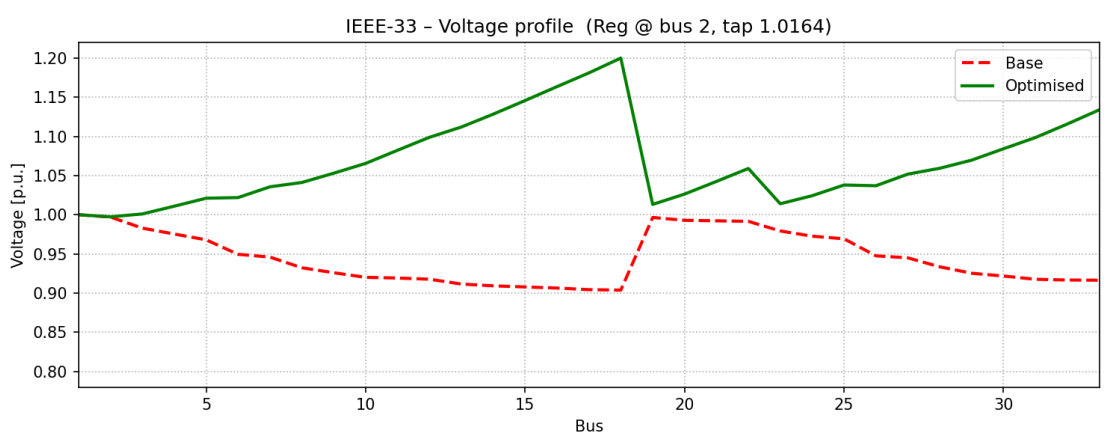

Figure 5 Voltage profile comparison before and after Integration of TCVR using GA-PSO of IEEE-33

Figure 6

b. IEEE-69 Feeder Performance

The IEEE-69 results in Table 3 similarly show marked gains. Base-case losses of 225.0 kW are reduced to 161.19 kW (≈ 28.4 % reduction) by installing a regulator at bus 45 with tap = 1.0198, and minimum voltage rises from 0.90919 p.u to 0.95915 p.u while the maximum is held at 1.19999 p.u (Table 3).

presents these KPIs side by side, underscoring the network-wide benefits of a single tap-changer installation for the comparison power loss bar chart before and after using GA-PSO.

Table 3 KPI systems

Case	Reg_bus	Tap_ratio	P_loss_kW	Q_loss_kVAr	S_loss_kVA	V_min_pu	V_max_pu
Base	-	1.0000	225.0	0.0	225.0	0.90919	1.0
Optimized	45	1.0198	161.19	0.0	161.19	0.95915	1.19999

Branch-level data in Table 4 confirm consistent loss mitigation across all 68 branches—for instance, heavy flows on branch 6–7 drop from 10.543 kW to 8.005 kW after optimization. Figure 7 plots the voltage profile for buses 1–69, showing that voltages are maintained within [0.959 p.u, 1.020 p.u] under the optimized tap setting, fully resolving the base-case sags and peaks.

Table 4 Branch losses & Bus voltages

Regulator @ bus 45 tap 1.0198

Branch	P_loss_base_kW	P_loss_opt_kW	Bus	V_base_pu	V_opt_pu
1-2	(0.026-0.07j)	(0.021-0.057j)	2	1.0	1.0
2-3	(0.026-0.07j)	(0.021-0.057j)	3	0.9999	0.9999
3-4	(0.068-0.183j)	(0.053-0.145j)	4	0.9998	0.9999
4-5	(0.695-1.808j)	(0.528-1.398j)	5	0.999	0.9991
5-6	(10.14-26.362j)	(7.7-20.379j)	6	0.9901	0.9913
6-7	(10.543-27.394j)	(8.005-21.171j)	7	0.9808	0.9831
7-8	(2.483-6.433j)	(1.878-4.951j)	8	0.9786	0.9812
8-9	(1.22-3.147j)	(0.912-2.394j)	9	0.9774	0.9802
9-10	(1.759-4.443j)	(1.735-4.387j)	10	0.9724	0.9752
10-11	(0.373-0.944j)	(0.368-0.932j)	11	0.9713	0.9741
11-12	(0.835-2.028j)	(0.824-2.004j)	12	0.9682	0.971
12-13	(0.526-1.175j)	(0.522-1.169j)	13	0.9652	0.9681
13-14	(0.51-1.138j)	(0.507-1.131j)	14	0.9623	0.9652
14-15	(0.495-1.1j)	(0.491-1.094j)	15	0.9595	0.9623
15-16	(0.092-0.204j)	(0.091-0.203j)	16	0.9589	0.9618
16-17	(0.132-0.293j)	(0.131-0.291j)	17	0.958	0.9609
17-18	(0.001-0.002j)	(0.001-0.002j)	18	0.958	0.9609
18-19	(0.036-0.098j)	(0.036-0.097j)	19	0.9576	0.9604
19-20	(0.023-0.063j)	(0.023-0.063j)	20	0.9573	0.9601
20-21	(0.037-0.101j)	(0.037-0.1j)	21	0.9568	0.9596
21-22	-0.001j	-0.001j	22	0.9568	0.9596
22-23	(0.002-0.005j)	(0.002-0.005j)	23	0.9567	0.9596
23-24	(0.004-0.011j)	(0.004-0.01j)	24	0.9566	0.9594
24-25	(0.002-0.006j)	(0.002-0.006j)	25	0.9564	0.9592
25-26	(0.001-0.002j)	(0.001-0.002j)	26	0.9563	0.9592
26-27	-0j	-0j	27	0.9563	0.9592
3-28	-0j	-0j	28	0.9999	0.9999
28-29	(0.001-0.002j)	(0.001-0.002j)	29	0.9999	0.9999
29-30	(0.002-0.005j)	(0.002-0.005j)	30	0.9997	0.9997
30-31	-0.001j	-0.001j	31	0.9997	0.9997
31-32	(0.002-0.005j)	(0.002-0.005j)	32	0.9996	0.9996

32-33	(0.004-0.012j)	(0.004-0.012j)	33	0.9993	0.9994
33-34	(0.003-0.01j)	(0.003-0.01j)	34	0.999	0.999
34-35	-0j	-0j	35	0.9989	0.999
3-36	-0.001j	-0.001j	36	0.9999	0.9999
36-37	(0.005-0.014j)	(0.005-0.014j)	37	0.9997	0.9998
37-38	(0.006-0.016j)	(0.006-0.016j)	38	0.9996	0.9996
38-39	(0.002-0.005j)	(0.002-0.005j)	39	0.9995	0.9996
39-40	-0j	-0j	40	0.9995	0.9995
40-41	(0.018-0.045j)	(0.018-0.044j)	41	0.9988	0.9989
41-42	(0.008-0.019j)	(0.007-0.018j)	42	0.9986	0.9986
42-43	(0.001-0.002j)	(0.001-0.002j)	43	0.9985	0.9985
43-44	-0j	-0j	44	0.9985	0.9985
44-45	(0.002-0.006j)	(0.002-0.006j)	45	0.9984	0.9984
45-46	-0j	-0j	46	0.9984	1.0182
4-47	(0.007-0.022j)	(0.006-0.019j)	47	0.9998	1.0196
47-48	(0.185-0.552j)	(0.163-0.483j)	48	0.9985	1.0387
48-49	(0.518-1.547j)	(0.452-1.347j)	49	0.9947	1.0556
49-50	(0.037-0.11j)	(0.031-0.094j)	50	0.9942	1.076
8-51	(0.001-0.002j)	(0.001-0.002j)	51	0.9785	1.0006
51-52	-0j	-0j	52	0.9785	1.0204
9-53	(2.079-5.394j)	(1.357-3.621j)	53	0.9747	0.9973
53-54	(2.416-6.262j)	(1.576-4.199j)	54	0.9714	1.0144
54-55	(3.29-8.511j)	(2.135-5.679j)	55	0.9669	1.0308
55-56	(3.173-8.198j)	(2.05-5.448j)	56	0.9626	1.0476
56-57	(17.933-46.336j)	(11.589-30.792j)	57	0.9401	1.0497
57-58	(8.839-22.839j)	(5.712-15.177j)	58	0.929	1.0614
58-59	(3.431-8.865j)	(2.217-5.891j)	59	0.9248	1.0789
59-60	(3.86-9.948j)	(2.477-6.567j)	60	0.9197	1.0961
60-61	(5.074-13.076j)	(3.256-8.632j)	61	0.9123	1.1117
61-62	(0.041-0.104j)	(0.024-0.063j)	62	0.912	1.1335
62-63	(0.049-0.126j)	(0.028-0.075j)	63	0.9117	1.1557
63-64	(0.24-0.616j)	(0.139-0.366j)	64	0.9098	1.1771
64-65	(0.015-0.038j)	(0.008-0.022j)	65	0.9092	1.2
11-66	(0.001-0.002j)	(0.001-0.002j)	66	0.9713	0.9934
66-67	-0j	-0j	67	0.9713	1.0131
12-68	(0.008-0.022j)	(0.007-0.021j)	68	0.9678	0.9899
68-69	-0j	-0j	69	0.9678	1.0095

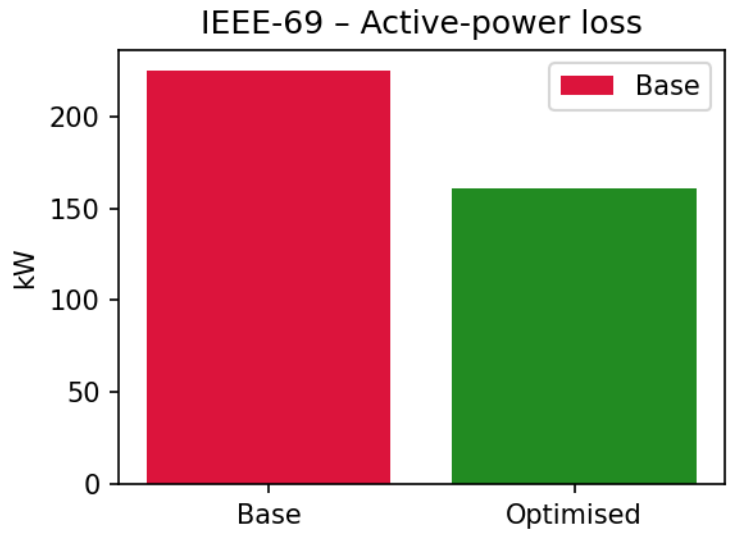

Figure 6 Power Loss comparison before and after Integration of TCVR using GA-PSO of IEEE-69

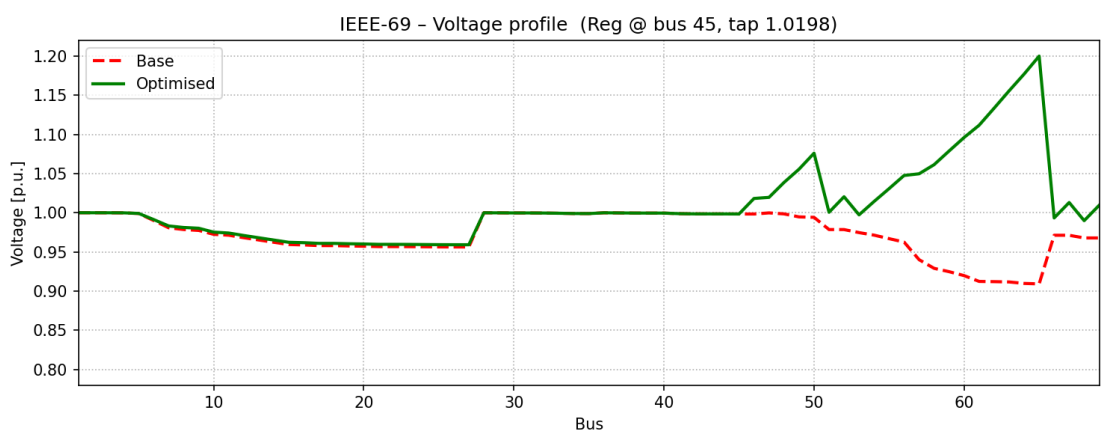

Figure 7 Voltage Profile comparison before and after Integration of TCVR using GA-PSO of IEEE-69

Conclusions

Together, these tables and figures validate the efficacy of the GA-PSO–driven tap-changer optimization with only one voltage regulator per feeder, substantial loss reduction and full compliance with voltage limits are achieved, offering a cost-effective strategy for radial distribution network enhancement. The KPI improvements for both feeders in a single chart, revealing that the GA-PSO hybrid achieves ≥ 26 % loss reduction and brings all bus voltages within ±2 % of nominal in both systems. The original and optimized voltage profiles of a representative 24-hour simulation, demonstrating that the regulator maintains tight voltage control under variable loading.

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