OPTIMAL STEADY STATE OPERATION OF UNIFIED POWER QUALITY CONDITIONNER FOR POWER LOSSES REDUCTION AND VOLTAGE REGULATION IMPROVEMENT

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Abstract: A new optimization paradigm based on hybrid differential evolution is developed to solve the challenging problem of optimal steady state operation of unified power quality conditioner in a primary electric power distribution system. The objective is to minimize the power losses and improve voltage profile to determine the best location and the size of unified power quality conditioner (UPQC) while the load constraints, network constraints and operational constraints are satisfied. The voltage compensation can be done by using active power as well as reactive power. The problem is formulated as a nonlinear multi-objective that cannot be efficiently solved by conventional optimization techniques. To illustrate the effectiveness of the proposed paradigm, simulation studies have been carried out on a 69 bus radial distribution system to define the number, optimal location and sizing of UPQC devices to be installed.

Key words: differential evolution optimization, distribution systems, load compensation, power quality, UPQC, voltage sag mitigation.

1. INTRODUCTION

Power quality is became an important aspect for utility distribution networks and sensitive industrial loads such as automated production processes and modern data processing equipment. Outages and service interruptions can cost significant financial loss per incident based on process down time, lost production, and other factors. In order to avoid uneconomic losses, some compensation methods are used for mitigating voltage sags and minimizing losses. The conventional solutions include network reconfiguration, fixed and/or variable capacitors banks, step voltage regulators and transformers with on-load tap changers.

With the development of low-cost, fast-controlled force-commutated power electronics, some new compensation methods are developed to

achieve power quality requirement. Recently, new technologies like custom power devices based on power electronic concepts have been developed to provide mitigation against power quality problems [1]. Generally, custom power devices are divided three categories such as static compensator like the dynamic voltage restorer (DVR) or the interline dynamic voltage restorer (IDVR), static shunt compensator like distribution static compensator (D-STATCOM), and static series and shunt compensator like Unified Power Quality Conditioner (UPOC). These new **D-FACTS** (Distribution Flexible Alternating Current Systems) devices have been emerged using fast power electronics components to enhance voltage sag with or without injecting active power into the distribution systems. The main objectives of D-STATCOM are to compensate for reactive power demanded by the load, to eliminate the harmonic from the supply current, and to regulate the DC link voltage [2]. The DVR injects a voltage in advance to the supply such that the load end voltage is always maintained at the desired level magnitude [3]. The main purpose of a UPQC is to compensate for supply voltage power quality issues, such as, sags, swells, unbalance, flicker, harmonics and for load current power quality problems, such as, harmonics, unbalance, reactive current. The voltage compensation can be done by using active power as well as reactive. When significant voltage sag is to be compensated, active power is needed in addition to reactive power [4-6].

To meet the objective function under various constraints, several researchers have employed evolutionary computation techniques to solve hard problems that are not easily solved by conventional methods [7-10]. Among these paradigms, differential evolution (DE) [10-12] and particle swarm

optimization (PSO) [7, 13] are shown a great promise in system optimization problems.

In this paper, an optimization technique based on a combination of differential evolution and PSO is used for the determination of optimal sizing and sitting of UPQC devices in radial distribution systems.

The rest of paper is organized as follows: Section II is devoted to the problem formulation. The unified power quality conditioner modelling is introduced in section III. The differential evolution optimization method with a particle swarm optimization-based mutation scheme, which is used to solve the optimization problem, is introduced in section IV. In section V, a 69-bus radial distribution network case study with 69 buses and 7 laterals is presented for studying.

2. PROBLEM FORMULATION

This paper considers a general distribution network with N_d possible locations for UPQC with different loading conditions. The optimization problem consists to minimize the total power losses and the deviation of bus voltage subject to some equality and inequality constraints.

2.1. Objective function

In this work we have used the normalized weighting method to generate a single-objective optimization problem from two objective functions, one representing power losses reduction and the other one representing minimization of voltage deviations. We formulate the optimization problem by minimizing the weighted function given by equation (1).

$$F = wF_1 + (1 - w)F_2 \tag{1}$$

w is the weighting factor within [0,1]. The normalized power losses are given by:

$$F_{1} = \frac{1}{P_{loss}^{\text{max}}} \sum_{i=1}^{N_{L}} R_{j} I_{j}^{2}$$
 (2)

And the normalized voltage deviations by:

$$F_2 = \frac{1}{V_D^{\text{max}}} \left(\sum_{i=1}^{N_B} (V_i - V_0)^2 \right)^{1/2}$$
 (3)

Where P_{loss}^{\max} and V_D^{\max} are the maximal power losses and voltage deviations for the initial non-optimized system, respectively. N_L and N_B are total lines and number of buses.

2.2. Equality constraints

The equality constraints are represented by the load-flow equations which are solved using the backward/forward sweep algorithm in two sweeps. Branch currents are updated during the backward sweep and bus voltages are updated during the forward sweep. The process is repeated until convergence is achieved within a given tolerance.

2.3. Inequality constraints

The voltage magnitude at each bus must be maintained within limits and the current branch must satisfy the branch's capacity:

$$V_{\min} \le |V_i| \le V_{\max} \tag{4}$$

$$\left|I_{i}\right| \leq I_{i}^{\max} \tag{5}$$

Where $|V_i|$ is voltage magnitude at bus i, V_{\min} and V_{\max} are minimum and maximum bus voltage limits, respectively. $|I_i|$ is current magnitude and I_i^{\max} is maximum current limit of branch i.

The reactive power injected by the shunt compensator and series injected voltage are bounded:

$$V_{SVR} \le V_{SVR}^{\text{max}} \tag{6}$$

$$Q_{SC} \le Q_{SC}^{\max} \tag{7}$$

Where V_{SVR}^{\max} and Q_{SC}^{\max} are injected voltage of series voltage regulator and reactive power of shunt compensator maximal ratings, respectively.

3. UPQC STEADY STATE OPERATION

The unified power quality conditioner (UPQC) consists of two voltage source converters (VSCs) that are connected to common dc storage. One of the VSCs is connected in series with a distribution feeder, while the other one is connected in shunt with the same feeder. The dc links of both VSCs are connected to a common dc capacitor. A typical three-phase line diagram of a UPQC compensated distribution system is shown in Fig. 1. The main purpose of a UPQC is for simultaneous voltage

regulation and current compensation in several situations: voltage sag/swell, presence of unbalance and harmonics in both load currents and source voltages. The voltage compensation can be done by using active power as well as reactive power. When UPQC is used to compensate voltage sag by reactive power, it is termed as UPQC-Q [5]. When UPQC is used to compensate significant voltage sag, active power is needed in addition to reactive power [6].

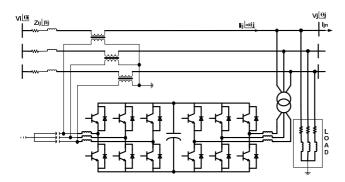


Fig. 1- UPQC configuration

In the case of lower voltage sags, the load voltage magnitude can be corrected by injecting only reactive power into the system: this is called zero active power injection (ZAPI) mode. In other hand, for higher voltage sags, injection of active power, in addition to reactive power, is essential to correct the voltage magnitude: this is called minimum apparent power injection (MAPI) mode [2]. In this work we need to integrate the two control modes in a radial distribution power flow. Following the notation used in Fig. 2, the series injected voltage regulator (SVR) can be written as:

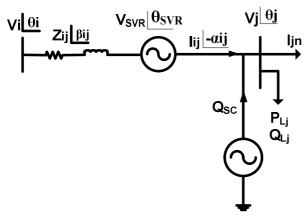


Fig. 2 - Single line diagram for UPQC

$$V_{svr} = V_j + Z_{ij}I_{ij} - V_i$$
 (8)

Where Z_{ij} and I_{ij} are given by

$$Z_{ij} \left| \beta_{ij} = Z_{SVR} + Z_{Lij} \right| \tag{9}$$

$$I_{ij} \left| -\alpha_{ij} \right| = \left(\frac{P_{Lj} + j \left(Q_{Lj} - Q_{SCj} \right)}{V_j} \right)^* + I_{jn}$$
 (10)

3.1. Zero active power injection control mode

In this mode, no active power injection into the system is required to correct the voltage sag. In this case, the angle θ_{svr} of the series injected voltage V_{svr} can be written as

$$\Theta_{svr} = \frac{\pi}{2} - \alpha_{ij} \tag{11}$$

The angle θ_{svr} can also be expressed as

$$\Theta_{ssr} = \tan^{-1} \left(\frac{V_j \sin\Theta_i + Z_{ij} I_{ij} \sin(\beta_{ij} - \alpha_{ij}) - V_i \sin\Theta_i}{V_j \cos\Theta_j + Z_{ij} I_{ij} \cos(\beta_{ij} - \alpha_{ij}) - V_i \cos\Theta_i} \right)$$
(12)

It is assumed that the receiving end voltage magnitude, V_j , is to be maintained at a specified value during the voltage sag conditions.

The phase angle of the receiving end voltage can be expressed as

$$\Theta_{j} = \cos^{-1} \left(\frac{c_{1} - c_{2}}{\sqrt{c_{3}^{2} + c_{4}^{2}}} \right) - \alpha_{ij}$$
 (13)

Where:

$$\begin{aligned} c_1 &= Z_{ij} I_{ij} \cos \left(\beta_{ij} - \alpha_{ij}\right) - V_i \cos \Theta_i \\ c_2 &= tg \alpha_{ij} \left(Z_{ij} I_{ij} \sin \left(\beta_{ij} - \alpha_{ij}\right) - V_i \sin \Theta_i\right) \\ c_3 &= V_i \cos \alpha_{ij} \\ c_4 &= V_i \sin \alpha_{ij} \end{aligned}$$

The condition that must be satisfied to ensure a feasible solution can be written as.

$$V_{i} \ge \left(V_{j} \cos \alpha_{ij} + Z_{ij} I_{ij} \cos \beta_{ij}\right) \tag{14}$$

If the above condition is not satisfied, the control voltage of the receiving end cannot be maintained without injecting active power into the system. With no active power injection, the receiving end voltage control mode is release and is expressed as

$$V_{j} = \frac{V_{i} \cos(\Theta_{i} + \alpha_{ij}) - Z_{ij} I_{ij} \cos(\beta_{ij})}{\cos(\Theta_{j} + \alpha_{ij})}$$
(15)

$$\Theta_i = -\alpha_{ii} \tag{16}$$

3.2. Minimum apparent power injection control mode

In some cases we need to inject active power into the system to achieve the desired voltage correction. To operate the DVR device in an optimal mode, it is hopeful to inject a minimum apparent power. The condition to be satisfied is written as Eq. (17).

$$\frac{\partial V_{svr}^{2}}{\partial \Theta_{j}} = 0$$

$$V_{svr}^{2} = V_{j}^{2} + V_{i}^{2} + Z_{ij}^{2} I_{ij}^{2} + 2V_{j} Z_{ij} I_{ij} \cos(\beta_{ij} - \alpha_{ij} - \Theta_{j})$$

$$- 2V_{i} Z_{ij} I_{ij} \cos(\beta_{ij} - \alpha_{ij} - \Theta_{i})$$

$$- 2V_{i} V_{j} \cos(\Theta_{i} - \Theta_{j})$$
(18)

$$\Theta_{j} = \tan^{-1} \left(\frac{Z_{ij} I_{ij} \sin(\beta_{ij} - \alpha_{ij}) - V_{i} \sin(\Theta_{i})}{Z_{ij} I_{ij} \cos(\beta_{ij} - \alpha_{ij}) - V_{i} \cos(\Theta_{i})} \right)$$
(19)

4. DIFFERENTIAL EVOLUTION OPTIMIZATION ALGORITHM

The differential evolution (DE) is a population-based search algorithm originally proposed by Price and Storn ([11],[12]) for optimization problem over continuous domain. It performs a global exploratory search during the early stages of the evolutionary process and local exploration during the mature stage of the search. It employs three basic search operators: mutation, crossover and selection. The main strategy is to generate a new position for an individual by calculating weighted vector differences between other randomly selected members of the population. The following are the outline of the differential evolution algorithm.

Step 1: Initialization: Create an initial population of candidate solutions by assigning random

values to each decision parameter of each individual of the population. Such values must lie inside the feasible bounds of the decision variables and can be generated by equation

$$X_{ij}^{0} = L_{j} + R_{j} \left(U_{j} - L_{j} \right)$$

$$i = 1, N_{p}$$

$$j = 1, D$$

$$(20)$$

Where L and U are, respectively, the lower and upper bounds of the decision variables and, R, is a uniformly distributed random number within [0,1] generated for each variable. Np is the number of individuals in each population. D is the number of the decision variables.

- **Step 2:** Repeat steps 3 to 7 until termination criteria: Termination criteria: the maximum generation or the desired fitness functions.
- **Step 3:** Fitness function evaluation: Evaluate the objective function given by Eq. (1).
- **Step 4:** Mutation: For each target (or parent) vector, a mutant vector (M) is produced by perturbing a randomly selected vector (X_a) with the difference of two, three or four others randomly selected vectors (X_b, X_c, X_d and X_e). The classical DE algorithm contains different mutation strategies. All of them focus on the differences between two different individuals in population. On the basis of these mutation strategies, different mutation strategies have been proposed to improve the performance of DE. The following is the strategy commonly used

$$M_i^G = X_i^G + F(X_a^G - X_b^G) + K(X_c^G - X_d^G)$$
 (21)

Where a, b, c, d and e are chosen randomly from the interval [1,Np] and must be different from each other's and from the running index i. Scalar factors F and K are introduced and lie inside the interval [0,1.2].

A new mutation scheme is introduced in [13] based on a best mutation operation from the idea of particle swarm optimization. This idea is used in the present work and the following is the detailed denotation:

$$M_{i}^{G} = X_{\text{obest,i}}^{G} + c_{1}R_{1} \left[X_{\text{obest,i}}^{G} - X_{i}^{G} \right] + c_{2}R_{2} \left[X_{\text{obest,i}}^{G} - X_{i}^{G} \right]$$
 (22)

Where X_{gbest} represents the best solution called the global extreme value for individuals in the population, X_{pbest} denotes the best solution of the ith individual who can explore. c_1 and c_2 are scaling factors, R_1 and R_2 are random numbers within [0,1]. The second sector in Eq. (22) represents self-controlling of the individual. The third sector in Eq. (22) denotes sharing information and cooperating with each other in population. This mutation makes the best of exchanging action and congregating effect which has quick convergent speed [13]. Each control variable is set to its nearest boundary when boundary constraints (lower or upper) are exceeded.

To expand DE into the discrete optimization field, a binary-coding DE was proposed to overcome the problem using:

$$M_i^G = E(M_i^G) + f(M_i^G) \tag{23}$$

Where E(x) is the integer part function and f(x) is a sigmoid function defined by:

$$f\left(x\right) = \frac{1}{1+e^{-x}}\tag{24}$$

Step 5: Crossover/recombination: The parent (X) and the mutant (M) vectors are mixed to yield the trial vector (T) using a crossover operation.

$$T_{ij} = \begin{cases} X_{ij}^G & \text{if } R_j > C_R \text{ or } rand() = j \\ M_{ij}^G & \text{otherwise} \end{cases}$$
 (25)

 R_j is a uniformly distributed random number within [0,1] generated anew for each value of j. C_R lies inside [0,1] is the crossover probability and constitutes a control variable for the DE algorithm.

Step 6: Selection: The performance of the offspring (trial) vector and its parent is compared and the better one is selected. If f() denotes the fitness function under minimization problem, then:

$$X_{i}^{G+1} = \begin{cases} T_{i}^{G} & \text{If } f\left(T_{i}^{G}\right) \leq f\left(X_{i}^{G}\right) \\ X_{i}^{G} & \text{Otherwise} \end{cases}$$
 (26)

Step 7: Migrating operation if necessary: A migration operation is introduced to regenerate a new diverse population in order to enhance the investigation to the search

spaces. The hth gene of the ith individual is as follows:

$$X_{h}^{G+1} = \begin{cases} X_{h \text{test}}^{G+1} + \rho \left(X_{h \text{min}} - X_{h \text{test}}^{G+1} \right), & \text{if } \rho_{2} < \frac{X_{h}^{G+1} - X_{h \text{min}}}{X_{h \text{max}} - X_{h \text{max}}} \\ X_{h \text{test}}^{G+1} + \rho \left(X_{h \text{max}} - X_{h \text{test}}^{G+1} \right), & \text{Otherwise} \end{cases}$$
(27)

Where ρ_1 and ρ_2 are randomly generated in the range of [0,1]. The migration is executed only if the following measure fails to match the desired tolerance of population diversity

$$\rho = \sum_{\substack{i=1\\i\neq b}}^{N_p} \sum_{j=1}^{N_c} \frac{\chi_{ji}}{N_c(N_p - 1)} < \varepsilon_1$$
(28)

Where

$$\chi_{ji} = \begin{cases} 1, & \text{if } \left| \frac{X_{ji}^{G+1} - X_{jbest}^{G+1}}{X_{jbest}^{G+1}} \right| > \varepsilon_2 \\ 0, & \text{Otherwise} \end{cases}$$
 (29)

The parameters ε_1 and ε_2 are, respectively, the tolerance for the population diversity and gene diversity.

5. APPLICATIONS

The proposed PSO-based hybrid differential evolution (PSO-HDE) paradigm for losses reduction and voltage deviations minimization has been evaluated using the 69-bus radial distribution network. The simulated distribution system is a 12.66 kV system with 69 buses and 7 laterals. The load data and transmission line details are presented in [14]. The parameters used to simulate this test system for the PSO-HDE paradigm are shown in Table 1.

Table 1 - Random parameters of PSO-HDE paradigm

Parameters	Value
Ng (generation size)	30
Np (population size)	10
c ₁ (self-controlling parameter)	1.0
c ₂ (sharing information parameter)	1.0
C _R (crossover probability)	0.5
ε_1 (tolerance for the population diversity)	0.1
ε_2 (tolerance for the gene diversity)	0.1

Without using compensation devices, maximal power losses = 225 kW and maximal squared sum of voltage deviations = 0.0992. Three cases are investigated using different values for the normalized weighting factor.

case 1: Only power losses minimization is considered (w=1).

case 2: Equally consideration of power losses and voltage deviations minimization (w=0.5).

case 3: Only the voltage deviations index is considered (w=0).

The results of optimal sitting, reactive power shunt compensation, and the series voltage injected for one, two and three UPQCs installed are shown in tables 2 and 3 under ZAPI and MAPI control modes, respectively. The desired voltage is set to 1.0 pu and the maximum series voltage regulator is set to 0.2 pu.

Table 2- Optimal location and sizing of UPQC using ZAPI control mode

UPQC		Case 1 Case 2		Case 3
No.				
	Line	60-61	7-8	58-59
1	Qshunt (MVAr)	0.998	0.6896	0.392
	Vsvr (pu)	0.20	0.0491	0.1863
	Qsvr (pu)	0.0338	0.0149	0.0348
	Lines	28-29	19-20	8-9
		61-62	6-7	56-57
	Qshunt	1.752	0.0708	0.0504
2	(MVAr)	0.885	0.515	0.5502
	Vsvr (pu)	0.2	0.1825	0.0565
		0.2	0.200	0.1002
	Qsvr(pu)	0.0425	0.034	0.016
		0.0196	0.034	0.0184
	Lines	36-37	42-43	57-58
		47-48	43-44	64-65
		60-61	3-4	51-52
	Qshunt	3.32	5.29	2.471
	(MVAr)	1.04	0.041	7.840
		1.39	2.30	0.040
3	Vsvr (pu)	0.20	0.2	0.2
		0.20	0.2	0.2
		0.20	0.2	0.2
	Qsvr (pu)	0.080	0.1232	0.3323
		0.021	0.0018	0.2950
		0.036	-0.0001	0.0010

Table 3 - Optimal location and sizing of UPQC using MAPI control mode

MAPI control mode							
UPQC		Case 1	Case 2	Case 3			
	Line	57-58	57-58	57-58			
	(From-To)						
	Vsvr (pu)	0.0591	0.0590	0.0591			
	D	0.0100	0.0100	0.0100			
1	Psvr (pu)	0.0100	0.0100	0.0100			
	Qsvr	0.0032	0.0032	0.0033			
	(pu)	0.0032	0.0032	0.0055			
	Oshunt	0.6502	0.6539	0.6456			
	(MVAr)	0.0302	0.0337	0.0430			
	Lines	60-61	57-58	7-8			
	(From-To)	57-58	10-11	57-58			
	Vsvr (pu)	0.0135	0.0595	0.0182			
		0.0532	0.0226	0.0438			
2	Psvr	0.0021	0.0101	0.0049			
	(pu)	0.0088	0.0017	0.0074			
	Qsvr	0.0007	0.0046	0.0021			
	(pu)	0.0004	0.0003	0.0041			
	Qshnut	0.5951	0.4192	0.4549			
	(MVAr)	0.5189	0.6615	0.2552			
	Lines	66-67	57-58	58-59			
	(From-To)	56-57	6-7	12-13			
3		59-60	9-53	7-8			
	Vsvr (pu)	0.0222	0.0381	0.0455			
		0.0433	0.0139	0.0128			
		0.0168	0.0046	0.0174			
	Psvr	0.0000	0.0064	0.0077			
	(pu)	0.0073	0.0038	0.0005			
		0.0027	0.0008	0.0046			
	Qsvr	-0.0006	0.0025	0.0033			
	(pu)	-0.0020	0.0004	0.0003			
		0.0008	0.0001	0.0016			
	Qshunt	0.2748	0.5542	0.4733			
	(MVAr)	0.6184	0.5002	0.0010			
		0.6171	0.5707	0.4783			
1	1	1	1	1			

An investigation has been carried out to study the impacts of weighting factor on the maximum voltage deviation and power losses at all nodes considering the two control modes presented earlier. A comparison results shown in Table 4 indicate that the UPQC is a versatile device to mitigate voltage drop and reduce power losses taking into account for minimization of apparent power requirement of UPQC. The best choice for a maximum power losses reduction is obtained by using three UPQCs between lines 66-67, 56-57 and 59-60 under MAPI control mode.

Comparative voltages variation at different nodes is shown in Figs.3-8 when using one, two and three UPQCs under ZAPI and MAPI control modes. The results indicate a voltage regulation improvement in all cases.

Table 4 -: Comparison results with UPQC using different weighting factors

different weighting factors						
Control		No.	Weighting factor			
Mode		UPQC	1.0	0.5	0.0	
	Max. ΔV	1	4.71	4.39	4.62	
	(%)	2	4.73	3.33	3.28	
		3	2.31	4.10	5.10	
	Losses	1	28.4	29.9	28.9	
ZAPI	reduction	2	34.9	23.2	15.8	
	(%)	3	36.6	29.3	22.5	
	Objective	1	71.60	80.87	79.98	
	function	2	75.01	55.52	27.46	
	(%)	3	71.83	62.55	24.41	
MAPI	Max. ΔV	1	5.00	5.00	5.00	
	(%)	2	4.71	5.0	3.40	
		3	3.71	2.88	4.18	
	Losses	1	27.5	27.6	27.6	
	reduction	2	35.2	28.3	22.8	
	(%)	3	36.8	30.8	29.0	
	Objective	1	80.66	84.11	87.77	
	function	2	70.81	53.46	23.98	
	(%)	3	68.74	59.97	47.78	

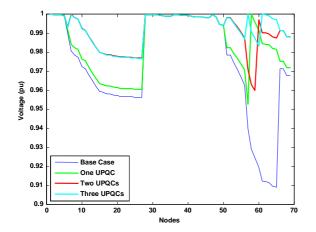


Fig. 3 - Nodes voltage variation under ZAPI for case 1

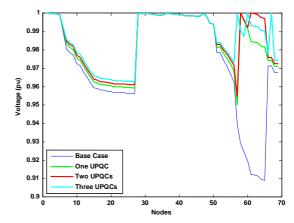


Fig. 4 -Nodes voltage variation under MAPI for case 1

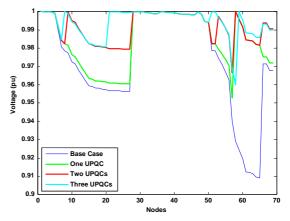


Fig. 5- Nodes voltage variation under ZAPI for case 2

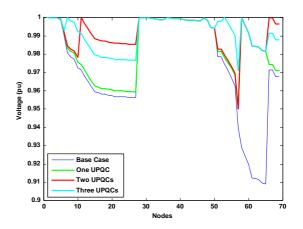


Fig. 6-Nodes voltage variation under MAPI for case 2

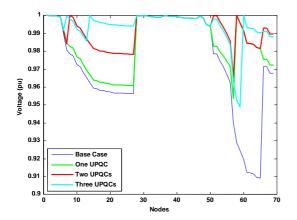


Fig. 7-Nodes voltage variation under ZAPI for case 3

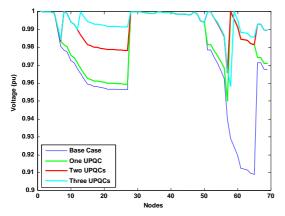


Fig. 8-Nodes voltage variation under MAPI for case 3

6. CONCLUSION

The problem of the sitting and sizing of unified power quality conditioner in radial distribution systems is considered. This problem has been modelled as a nonlinear multi-objective optimization problem and solved using a particle swarm optimization-based hybrid differential evolution paradigm. The results indicate that the UPQC is a versatile device to mitigate voltage drop and reduce power losses taking into account for minimization of apparent power requirement.

The proposed method has been tested on a 12.66 kV radial distribution systems for various cases. The impact of weighting factor has been investigated to show the effectiveness the proposed optimization paradigm.

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