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FUZZY MEMBERSHIP FUNCTION DESIGN FOR EFFECTIVE GENERATOR REACTIVE POWER RESERVE MANAGEMENT

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ABSTRACT

The power system has to be operated within acceptable scope of voltage stability by properly setting up reactive power sources and voltage profile. Besides the system guides to the in stability of voltage and requires proper control. The measures against voltage unsteadiness are protective and corrective controls. The proposed work gives a methodical approach to enhance the voltage stability of a test system. So a preventive counteract measure is proposed for voltage and reactive power management initial at generator's approach to maximize the Effective Generator Reactive Power Reserve (EGRPR). An proficient process to maximize EGRPR is formulated as a Fuzzy controlled optimization problem where P-delta loop and Q-V loop is updated for iteration. For wide range of loading conditions the Fuzzy membership functions are generated from unsupervised learning using Self Organizing Featured Maps (SOFM). A simple SOFM Fuzzy constrained OPF and Bender's decomposition methods are used to maximize the EGRPR and proposed method is tested on 6- bus structure.

KEYWORDS: SOM, Voltage Stability, Reactive Power, Fuzzy Logic

I. INTRODUCTION

Power system operator is liable for voltage and reactive power management in a restructured network, where its operation is constrained by firm economic constraints. This leads power system to fall under stress and operate around operating limits that in turn lead to blackout with insufficient voltage and reactive power reserve [1, 2]. In such electricity markets, the voltage and reactive power control services are the critical additional services that are continuously supply consistent for operation. Sufficient control actions are to be initiated for safekeeping of bulk power system against the small and long-standing unsteadiness. These actions comprises of Reactive Power Reserves (RPR) and disaster counter measures that can be measured as the protective and remedial controls. The main precautionary actions aligned with power system voltage instability are management of reactive power reserves through load tap changing, capacitor switching and execution of hierarchical voltage and reactive power control schemes [2]. In cooperation reactive power generation and reserve should be considered for acquiring and setting up of reactive power resources. Such reactive power management will increase the voltage stability margin. It must be noted that RPR can be viewed from load and generator side approach. Literature paid more attention on load approach rather than generator approach. The generator reactive power reserve (GRPR) is classified into Technical generator reactive power reserve (TGRPR) and effective generator reactive power reserve (EGRPR). Many studies utilize TGRPR rather than EGRPR, since it can be easily calculated [27, 28]. In [15] it is shown that effectual RPR not only depend on generator capability curve but also depend on the transmission network characteristics. In [15] the author implements the two level benders decomposition, including a base case and stressed cases, based on OPF for the improvement of voltage stability. The effectual RPR for a bus or an area is found in [16] as the biased sum of the individual RPRs of generators at the minimum of VQ curve. In [16] author uses two level Benders' decomposition method as preventive control action against voltage instability.

Load flow analysis plays an important role in power system studies. Literature proposes a number of conventional power flow methods [14-19]. In stability studies, the solution of load flow problem is obtained when a power system is operated at load ability limit. Maximum load ability margin is the amount of load demand that a power system can support before voltage collapse [20-26]. The load ability margin is a function of reactive power reserve in the network and the relationship between voltages and network load ability is

nonlinear. To determine the maximum load ability limit of power system continuous power flow (CPF) technique and OPF methods (OPF) or mathematical optimization techniques are widely used. The fundamental approaches to determine reactive power reserve range from the linear programming techniques to nonlinear programming [7-13]. Due to the power flow derivatives, the conventional methods face jacobian singularity and fail to give solution at those situations. And repetitive solution of these methods requires large amount of memory. To overcome these limitations a number of evolutionary optimization methods like Evolutionary Algorithms, Swarm Optimization, and Cultural Algorithms and Fuzzy Logic (FL) and Artificial Intelligence have been proposed [4-6]. These approaches are not based on the power flow derivatives, hence, do not face problem of singularity at maximum loading conditions. In [4] author proposes fuzzy logic controller to update the power variables. The present work is to propose an effective procedure to maximize EGRPR by formulating as a Fuzzy constrained optimization problem where P-δ loop and Q-V loop is updated in every iteration. For wide range of loading conditions the fuzzy mfs are found to be in-adaptive. Researchers addressed the problem of fuzzy membership function production in many ways. A critical part in fuzzy set theory is to properly design fuzzy membership function. Many methods can be adapted to generate membership from chosen data. These methods include based on possibility theory (Zadeh, 1978), and methods based on clustering. Procedures based on clustering followed by generation of status of membership functions using parameters determined from the clusters and to tune fuzzy mf during the clustering process is a prime interest in this present work. The tools of neural network can be used to generate membership functions from the attained training data with labeling. The number of neurons used in the input and output layers are the measurement of input features and the number of class labels, respectively. The training process come together with a supervised training algorithm in the learning phase, thus neural network provides for generation of membership network in the retrieving phase.
Non-recurrent and recurrent neural networks in combination with a fuzzy neural network training process had been used for classifying patterns in feature space. These networks have the capability of differentiating among the patterns close up to the limits resulting from the partitioning of the feature space. The topology of the Self Organized maps provides for forward and feedback components that can be employed to tune graded fuzzy membership for the duration of clustering process as a one-step process. The self-Organizing Map (SOFM) [33-35] affects unsupervised learning, is measured to be a clustering technique. It is yet possible for tuning the fuzzy membership function (mf) for the duration of the training and retrieving phases of SOFM. The proposed method achieves a self tuned adaptive mfs from SOFM clustering technique. The SOM clustering technique modifies the Fuzzy Optimal Power Flow to properly choose the range of input variables such that they become adaptive to calculated correction vectors of power system variables.

II. REACTIVE POWER RESERVE MANAGEMENT

The RPR is standby reactive power available in the system for aiding the voltage control, respond to unexpected events which leads to a sudden change of reactive power requirement. Thus, the generators are the main sources of reactive power reserve. The RPR can be viewed from load's and generator'approach. A generator and load is connected between two buses, the QV-curve method [14] is used to get the reactive power scope to voltage crumple point. To achieve this fictitious reactive power supports Q_f's are connected for identified voltage sensitivity nodes ie., pilot nodes. The QV-curve [14] shows the link between reactive power support (Q_f) at a given bus and total amount of voltage at that bus (V) [1-3]. The minimum of QV-curve shows the reactive power margin to drop the operating point this point is called collapse point and the operating point is at which ($Q_f=0$). Present work uses optimal power flow (OPF) method to compute the reactive power margin to the voltage collapse point [15, 16].

The Load RPR (LRPR) is the smallest amount of the reactive load increase for which the system losses its operation capability [1-3, 16]. The GRPR focus on the rate of RPR provided by each generator. TGRPR is the difference between the maximum reactive power capacity of the generator and its reactive power production at the current working point. However, this measure cannot be represented as the valuable amount of the RPR since at the collapse point all the quantity of the TGRPR cannot be used. EGRPR, is a more exact representative of the GRPR, is the difference between the generator's reactive power output at the voltage collapse point and the generator's reactive power output at the present operating point. The TGRPR is an upper bound for the EGRPR. LRPR, TGRPR, and EGRPR [3, 16,36].

This paper deals with maximization of GRPR especially on EGRPR as main protective act to improve the voltage stability margin. An optimization problem is decomposed into two level optimization using Bender's decomposition method based on the participated optimized variables and is further solved with optimal SOM

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Fuzzy- interior point algorithm. Optimization is carried out for given active power operating point whose act is compared with conventional method [16].

III. FUZZY MEMBERSHIP FUNCTION DESIGN USING SOM

1. Self Organizing Maps (SOM) :

The SOFM is, a two-layered network where the neurons in the output layer are organized into a one or two-dimensional lattice formation where the number of neurons in the input layer is the dimension *d* of input characteristic vector. The synaptic weight vector at neuron j in the output layer is denoted by $w_j = \left[w_{j1}\, w_{j2}\, w_{j3} \ldots w_{jd} \right]'$, j =1,2,..., J, where J is the total number of neurons in the output layer and w_{jk} =1,2,..., d, is the linking weight from the jth neuron in the output layer to the k^{th} neuron in the input layer. In the phase of leaming, the first step, with x_n as the input vector, to get the best matching neuron from

$$q(x_n) = \min_{\forall j} \left\| x_n - w_j \right\| \tag{1}$$

where, for input vector x_n, q(x) is the index label of the winning neuron q2{1, ..., J}, in the output layer and ||.|| is a distance measure (usually the Euclidean norm). The next step is to update the weight vectors associated with the label $q(x_n)$. The rule of leaming for neuron $j \in N_q$, where N_q is the selected neighbourhood of captivating neuron q for input vector x_n, is given by (1)

$$w_j[t+1] = w_j[t] + n_{qj}[t]\left(x_n[t] - w_j[t]\right) \tag{2}$$

Where

$$n_{qj}[t] = \begin{cases} \mu[t] & if \;\; j \in N_q, \\ 0 & if \;\; j \notin N_q. \end{cases}$$

Here, l[t] is the rate of leaming, 0 < l[t] < 1, at time index t. In the phase of retrieving, when x is the input vector, only the winning neuron, after junction, will have positive response. Two different information could be retrieved from the winning neuron q, namely its index label $q(x_n)$ and its allied weight vector w_q.

2. Extracting Membership Functions using SOM :

A SOM is an extreme derivative of the more traditional neural networks such as a back propagating network. While traditional neural networks require training data to contain complete information about the inputs, its characteristics, and desired outputs, SOMs only necessitate input. Hence, a SOM unlike its predecessor is an algorithm for unsupervised learning; SOM has the ability to learn based on the similarities, or dissimilarities, of the set data. This inherent learning feature of the SOM is called clustering [32-35]. Clustering in terms of SOMs, involves categorization of data based on the similarities of the input. Generalized SOM, have two layers: an input layer of nodes and a classification layer of nodes, or lattice layer.

As depicted by the Fig 1, each input node in the input layer is connected to each node in the output lattice; so, the node is deemed fully connected. Much like a traditional neural network, each connection, or edge, has a weight associated between the two entities. SOMs are feed forward neural networks in that information is "fed" into the input nodes as these nodes further cascade information to other layers. As SOMs have two layers, the input nodes flow into the classification lattice. It has to reduce the dimensions of the input vectors; is called vector quantization [35]. Present work uses SOM clustering technique to develop adaptive fuzzy mfs for wide range of loading conditions. A data set of power system parameters ('ΔP' and ' ΔQ') at different loading conditions are clustered considering similarities and adaptive fuzzy triangular mfs are developed from obtained clusters is discussed in section 4.

IV. PROPOSED METHODOLOGY

To make sure the voltage stability of a system, managing of reactive power generation and its preserve is a interconnected task which strongly depends on the generator and transmission system capabilities. For a given real power output, the reactive power generation is restricted by both field and armature current restriction. The

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maximum produced reactive powers concerning these two limitations are given by (2) and (3). The minor of the two values is selected as utmost reactive power output (Q_k^{max}).

$$Q_{rk} = -\frac{V_k^2}{X_{sk}} + \sqrt{\frac{V_k^2 I_{kf}^2}{X_k^2} - P_k^2} \tag{2}$$

$$Q_{ak} = \sqrt{V_k^2 I_{ak}^2 - P_k^2} \tag{3}$$

where k is index of generators, V_k is generator terminal voltage, P_k is generator active power output, I_{kf} is maximum field current, I_{ak} is the maximum armature current, and X_{sk} is the synchronous reactance.
For the k^{th}- generator, *TGRPR* and *EGRPR* are defined by the following equations [23].

$$TGRPR = Q_k^{\max} - Q_k \tag{4}$$

$$EGRPR = QC_k - Q_k \tag{5}$$

where Q_k is the generator reactive power output at current operating point, Q_{Ck} is the generator reactive power output at voltage collapse point and Q_k^{max} is maximum reactive power output obtained from (2) and (3). To maximize EGRPR and as result to get better voltage stability scope the objective function can be formulated as

$$\max EGRPR = \max \sum_{i\in NG} QC_k - Q_k \;\Box\; \min \sum_{i\in NG} Q_k - QC_k \tag{6}$$

The hierarchical connection between operating and collapse point in (6) is achieved by decaying the objective function. The problem is decomposed into two parts, a master-problem, and a sub-problem and is solved by the Bender's decomposition method in an iterative way [15, 16] in view of optimization variables. To compare master- problem and sub-problem a Benders' cut is added to master problem. The proposed two level Benders' decomposition is shown in the Fig. 2.

a. Master Problem

The main objective function in (5) is formulated as the master-problem

$$\min_{u,\alpha} f(x,u) + \alpha \tag{7}$$

$$\text{subject to: } h(x,u) = 0 \tag{8}$$

$$g(x,u) \le 0 \tag{9}$$

$$\alpha_{down} \le \alpha \tag{10}$$

$$BC_k^{(i)} \le \alpha_k \qquad i = 1....v, \;\; to\ NG \tag{11}$$

where $f(x,y)$ is reactive power output optimization minimization of generators $(\sum Q_k)$. u is the vector of control variables including voltage of *PV* generators and reactive power output of *PQ* generators. x indicates the vector of the state variables. α is optimal objective function vector of sub-problem for master problem. *h(x,u)* are equality constraints like load flow equations is given by (12-13). *g(x,u)* represents inequality constraints like transmission power flow limit given by (14). Limits on reactive power and voltage magnitude are given by (15, 16). The constraint given in equation (11) represents Benders' cut added to the master problem. Here, i denote the number of iterations and v represents number of cuts added to master problem.

$$P_{kn} - P_{dn} - \sum_{m\in NB} V_n V_m (G_{nm}\cos\theta_{nm} + B_{nm}\sin\theta_{nm}) = 0 \qquad n \in NB \tag{12}$$

$$Q_{kn} - Q_{dn} - \sum_{m\in NB} V_n V_m (G_{nm}\sin\theta_{nm} - B_{nm}\cos\theta_{nm}) = 0 \qquad n \in NB \tag{13}$$

$$(G_{nm}^2 + B_{nm}^2).(V_n^2 + V_m^2 - 2V_n V_m \cos\theta_{nm}) \le (T_l^{\max})^2 \qquad \{n,m\} \in l, l \in NL \tag{14}$$

$$Q_k^{\min} \le Q_k \le Q_k^{\max} \qquad k \in NG \tag{15}$$

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$$V_k^{\min} \le V_k \le V_k^{\max} \qquad k \in NB \qquad (16)$$

$$-QC_k^{(i)} + \lambda_{k-pv}^{(i)}.(V_k - V_k^{(i)}) \le \alpha_k \qquad i = 1........v, (k \in NG : PVnodes) \qquad (17)$$

$$-QC_k^{(i)} + \lambda_{k-pq}^{(i)}.(Q_k - Q_k^{(i)}) \le \alpha_k \qquad i = 1........v, (k \in NG : PQnodes) \qquad (18)$$

The control variables taken from the master- problem u^* are used as input to the sub-problem Fig. 3 and determines the generator's reactive power output at voltage collapse point. Obviously the results of master-problem and sub-problem are dependent to each other. The reactive power output of generators at voltage collapse point is evaluated by following optimization.

b. Sub Problem

The objective function of sub-problem is formulated as follows.

$$\max_p e(x, u^*, p) \qquad (19)$$

$$subject\,to : h(x, u^*, p) = 0 \qquad (20)$$

$$g(x, u^*) \le 0 \qquad (21)$$

$$u_k = u_k^* \; : \lambda; \; k = 1...NG \qquad (22)$$

$e(x,u^*,p)$ summation of reactive power output of generators at voltage collapse point $\sum_{k \in NG} QC_k$.

It should be noted that maximization of reactive power output at voltage collapse point is the same as maximization of fictitious reactive power injection at pilot nodes $\sum_{k \in NP} Q_{fp}$, where the index p represents pilot nodes and NP is number of pilot nodes. Q_{fp} is fictitious reactive power injection at pilot nodes at bus p. Positive and negative values of Q_{fp} , are devoted for reactive power consumption and generation. Where $h(x,u^*,p)$ and $g(x,u^*)$ are the equality and inequality constraints as like master-problem given by (24, 25).All the constraints are same as the master problem, except reactive power balance equation (25) is different with (13). In (25) the term Q_{fp} is added it indicates reactive power insertion at pilot nodes. p is the fictitious injected reactive power at the voltage collapse points for each voltage pilot nodes. λ_k is the lagrangian multipliers obtained by solving the sub-problem [30-32]. These multipliers are calculated for all PV nodes (λ_{k-pv}) PQ nodes (λ_{k-pq}) . By using the twin variables obtained from sub-problem Bender's cut is added to master-problem as like (11) shown in (17-18).

$$BC_k^{(i)} = -e(x, u_k^{(i)}, p) + \lambda_k^{(i)}.(u_k - u_k^{(i)}) \qquad (23)$$

Constraints of sub-problem:

$$P_{kn} - P_{dn} - \sum_{m \in NB} V_n V_m (G_{nm} \cos\theta_{nm} + B_{nm} \sin\theta_{nm}) = 0 \qquad n \in NB \qquad (24)$$

$$Q_{kn} - Q_{dn} - Q_{fp} - \sum_{m \in NB} V_n V_m (G_{nm} \sin\theta_{nm} - B_{nm} \cos\theta_{nm}) = 0 \qquad n \in NB \qquad (25)$$

$$(G_{nm}^2 + B_{nm}^2).(V_n^2 + V_m^2 - 2V_n V_m \cos\theta_{nm}) \le (T_l^{\max})^2 \qquad \{n, m\} \in l, l \in NL \qquad (26)$$

$$Q_k^{\min} \le Q_k \le Q_k^{\max} \qquad k \in NG \qquad (27)$$

$$V_k^{\min} \le V_k \le V_k^{\max} \qquad k \in NB \qquad (28)$$

c. SOM Fuzzy Constrained Optimal Power Flow

In the conventional load flow problems like, Fast Decoupled Load Flow method (FDLF) the repetitive solution is obtained by considering equation (28) and (29).

$$\left[\frac{\Delta P}{V}\right] = [B'][\Delta\delta] \qquad (29)$$

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$$\left[\frac{\Delta Q}{V}\right]=[B''][\Delta V] \tag{30}$$

The above equation (28) & (29) can be expressed as

$$\Delta Y = J.\Delta X \tag{31}$$

where ΔY , real and reactive power mismatch vector , ΔX , correction vector (voltage magnitude or voltage angles). The above equation shows that the correction of state vector, ΔX at each node of the network is directly proportional to vector ΔY . The SOM fuzzy load flow algorithm is based on previous fast decoupled load flow equations (29) & (30) but updating of correction vector of the power system will performed via fuzzy logic controller [4,5].

$$\Delta X = fuz(\Delta Y) \tag{32}$$

Where, *fuz* represent a fuzzy logic function

In SOM Fuzzy Power flow algorithm, both power mismatch and summation of power mismatch are taken as two crisp input signals for SOM Fuzzy logic controller at each node of the system. Considering the magnitude of power mismatch and sign of power mismatch, 25 fuzzy rules are considered from two set of input signals. Two separate *p*-δ and *q*-*v* loops are used to update the power flow variables [4-6]. The two separate loops contain five triangular mfs which are developed from SOM clustering technique.

1. **Unsupervised Design of Fuzzy Input Variables using SOM:**

The maximum ranges for input variables can be evaluated as follows [33]

1. Collect Power system variables ('*ΔP' and 'ΔQ*') at different loading conditions.
2. Cluster the collected power system variables data into 5 clusters according to similarities. The Fig.4(a). shows the SOM sample hits for clustered data for two input samples.
3. Calculate centers of obtained clusters by using mean average method shown in Table.1. These centers are chosen as centers of triangular membership functions.
4. The left and right vertex of each of the triangular fuzzy mf is calculated as follows.
    - Find maximum and minimum data value of each cluster formed from weight vectors.
    - Approximated the maximum by 10% increase to form right vertex of the mf and minimum by 10% decrease to form the left vertex of the membership function, this is done for overlapping the membership functions.

The Fig.3(a) shows the SOM weight positions for the input vector. The obtained triangular mfs for two inputs loops *p*-*δ* and *q*-*v* are shown in Fig.4(a) and Fig.4(b) and the output is shown in Fig.4(c).

2. **Unsupervised Design of Fuzzy Output variable using SOM:**

The maximum range of output variables evaluated as follows

P-δ loop:

$$\Delta\delta_{\max} = [B']^{-1}\left[\frac{\Delta P_{\max}}{V_m}\right] \tag{33}$$

Q-V loop:

$$\Delta V_{\max} = [B'']^{-1}\left[\frac{\Delta Q_{\max}}{V_m}\right] \tag{34}$$

where, $\Delta P_{\max}$ is maximum real power mismatch at mth bus & $\Delta Q_{\max}$ is maximum reactive power mismatch at mth bus. *B' & B''* are admittance matrices, *n* is number of buses & *m* is *PQ* buses

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SOM cluster centers for real and reactive power data

Table.1 SOM cluster centers for real and reactive power data

	Cluster-1	Cluster-2	Cluster-3	Cluster-4	Cluster-5
Input-1	-0.8905	-0.3384	0.094	0.6080	0.8404
Input-2	-1.076	-0.6074	-0.0020	0.3398	0.9746

3. Membership Function for Input and Output Variables:

The two crisp input signals are fuzzified with five linguistic variables; negative Large (NL), negative (N), zero (Z), positive (P), positive Large (PL). The fuzzy crisp input signals are sent to process logic, which generates a fuzzy output signal. The fuzzy output signal then sent defuzzification interface having five linguistic variables similar as input linguistic variables. The centroid of area (COA) strategy is employed for defuzzification of fuzzy output signal. For two inputs similar type of mfs are considered to generate the rule base with 25 rules is as shown in Table 2. The correction vectors calculated from two SOM Fuzzy control loops and the power variables are updated in every iteration for each node of the system. The complete process of unsupervised fuzzy mf design using SOM is shown in the Fig 5. Fig.6 shows the flow chart for unsupervised fuzzy mf design and OPF to minimize Effective Generator Reactive Power Reserve.

V. CASE STUDY

The proposed method i.e. maximization of *EGRPR* is a non-linear OPF model and has been tested on 6-bus scheme shown in Fig. 7 for different loading conditions. The test system [37] has 3 loads, 3 generators, and 11 transmission lines. Bus-5 is chosen as voltage sensitivity node (pilot node) since it is directly connected to all generators. The simulation is carried out with 3 PV generators. The ability curves [37] are considered for all 3 PV generators and the parameters of (1) and (2) are equal to $I_f=2pu$, $I_a=1.5pu$, $X_s=1pu$. The voltage deviation of all the buses is suitable within $\pm 5\%$ of nominal voltage value. The optimization stops at the k^{th} iteration where $EGRPR^k$ becomes lower than $EGRPR^{(k-1)}$.

$$EGRPR^k - EGRPR^{(k-1)} < 0 \qquad (35)$$

VI. RESULTS AND ANALYSIS

The proposed method is tested on 6-bus system shown in Fig 7, and the algorithm converges in 12 iterations to satisfy the defined optimization criteria in (35) and Table.3 show the comparative analysis of e [16] and proposed method at different loading conditions. Fig.8 shows the generators reactive power output at the present operating point (Q_k) and at collapse operating point (Q_{Ck}) where $k=1,2,3$. Fig.9 shows increase in *EGPRP versus* number of iterations for 100% loading condition. The efficiency of the proposed method is also tested for 90% loading condition and 105% loading condition. The load demand D_1,D_2,D_3 are reduced by 10% and increased by 5% and the algorithm converges to satisfy the defined optimization criteria in (34) there is an increase in *EGPRP versus* number of iterations.

VII. CONCLUSION

This paper presents the Unsupervised Fuzzy Mf Design and OPF for Effective Generator Reactive Power Reserve management for increasing voltage stability margin. The proposed methodology is based on optimal SOM Fuzzy power flow method. In the proposed SOM Fuzzy constrained method the fuzzy mfs are developed using unsupervised clustering for wide range of loading conditions. The proposed SOM Fuzzy constrained OPF method converges for more number of iterations than the conventional load flow methods. But the proposed method does not require any factorization and computation of Jacobian matrix at every iteration. In the proposed method the OPF problem is decaying into a master-problem and a sub-problem through bender decomposition method, optimal SOM Fuzzy constrained power flow method is used to solve master and sub problems. The results prove that EGRPR is increased at end of optimization. The method ensures the maximum possible preventive voltage margin from the available voltage and reactive power control resources.

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