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Citation for published version:
Gunda, J, Harrison, G & Djokic, S 2018, 'Remedial Actions for Security Constraint Management of Overstressed Power Systems' IEEE Transactions on Power Systems, vol. 33, no. 5, pp. 5183-5193. DOI: 10.1109/TPWRS.2018.2796644

Digital Object Identifier (DOI):
10.1109/TPWRS.2018.2796644

Published In:
IEEE Transactions on Power Systems

Remedial Actions for Security Constraint Management of Overstressed Power Systems

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***Abstract*--Static security constraint management, formulated as security constrained optimal power flow (SCOPF), is one of the critical tasks performed during planning and operation. These constraints at any operating point can be divided into noncritical and critical constraints, where former can be managed with preventive controls, while the latter cannot. The violation of at least one critical constraint indicates that network is overstressed and needs a prompt activation of remedial actions to preserve system integrity. Accordingly, critical constraint violations (CCVs) must be identified by solving related SCOPF problem, as information on their types and locations can help to devise and activate optimal remedial actions. However, when dealing with overstressed systems, conventional SCOPF methods may not be able to identify CCVs due to problem infeasibility and there is no commonly accepted method to find related CCVs. Extending previously developed metaheuristic approach, this paper first identifies the CCVs and then proposes a novel methodology to devise the most effective remedial actions to mitigate overstressed system operating conditions. The practical relevance of the remedial actions is demonstrated using IEEE 30-bus, 39-bus and 57-bus test networks.**

***Index Terms*--Critical and noncritical constraints, constraint management, conventional and metaheuristic optimization, remedial actions, security constrained optimal power flow.**

I. Introduction

MANAGEMENT and control of system security constraints is one of the most important tasks during both planning and operation of power systems. These security limits are typically expressed as bus voltage and branch thermal limits (i.e. steady state security limits), as well as voltage and angle stability limits (i.e. dynamic security limits). The related analysis is commonly denoted as a "security constraint management" (SCM) [1], which essentially has two stages: a) identification of violated security constraints and, b) activation of appropriate corrective actions for resolving violated constraints.

In terms of applied controls, this paper makes distinction between "preventive controls" (e.g. generation rescheduling, re-adjustment of transformer taps, reactive power compensation, etc.), which are generally implemented for balancing power flows during normal and alert operating states, and "emergency controls" (e.g. load shedding, connection of emergency reserves, islanding, etc.), which are activated in case of system inability to balance power flows. Following a disturbance, the readjustment of preventive controls may or may not resolve all resulting constraint violations. The violated constraints that cannot be resolved by adjusting preventive controls are in this paper denoted as "critical constraint violations" (CCVs) and presence of at least one CCV indicates that the corresponding disturbance will develop into overstressed or emergency conditions, typically following a severe contingency [2]. While noncritical constraint violations (NCCVs) can be managed with preventive controls (automatic or operator initiated), CCVs require prompt activation of emergency controls, i.e. remedial actions, to prevent further activation of protection and triggering of cascaded tripping, possibly leading to system blackouts [3].

If the transition from pre-contingency to post-contingency states involves only NCCVs, an experienced operator may successfully select adequate remedial actions to manage all violated constraints. However, if the transition involves CCVs, the most effective remedial actions must be computed algorithmically, as it will be difficult for an operator to select appropriate remedial actions based on previous experience [4].

In that context, this paper discusses how security constrained optimal power flow (SCOPF) can be used by network operators and planners to devise optimal remedial actions for resolving CCVs. SCOPF is a constrained, nonlinear and non-convex optimization problem, which is typically solved by conventional (gradient-based), or metaheuristic (gradient-free) approaches. In case of an overstressed system, featuring one or more CCVs, the conventional SCOPF algorithms may fail to converge due to problem infeasibility or diverge due to the inability to input proper initial values.

The identification of CCVs is essential from both the optimization point of view, as CCVs are the actual cause of convergence problems in conventional algorithms, and from operational point of view, as CCVs indicate where in the network and in relation to which network components optimal remedial actions should be planned (during the planning stage) and activated (during the operational stage). There is currently no commonly accepted method in nonlinear programming for identification and handling of CCVs [5]-[6], although [2] proposes one metaheuristic approach to identify CCVs.

In accordance with the prevailing industrial terminology, SCM can be further divided into congestion management (CM) and volt-var control (VVC). There has been much previous work on CM and VVC based on the use of generation rescheduling and load shedding [7]- [10], distributed generation [11]-[12], FACTS devices [13]-[15], demand side management [16]-[17], energy storage [18], and transmission switching [19]-[21]. Earlier studies were mostly concerned with contingencies that will push the system into an alert state and paid less attention to system emergency state, where, if adequate control actions are not promptly implemented, changes in power flows and energy balance will result in the inability of conventional algorithms to converge. In addition, especially from the context

The authors acknowledge support by the Principal's Career Development and Global Research scholarships from the University of Edinburgh.

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of constraint management, the steady state and dynamic security analysis in most of the earlier works is addressed separately. Neglecting the violation of steady state security constraints and the corresponding protection operations, a system may successfully transit from pre- to post-disturbance state. In this case, the state trajectory or system is dynamically secure, but the post-disturbance state may or may not qualify for the steady state security. If it is not, protection system will trip the overloaded lines which introduce further dynamics and the network may not reach the steady state.

This paper focuses on the following problem: If severe contingency results in emergency conditions, i.e. in overstressed system, what are the most effective remedial actions for returning the system into secure state, in terms of minimizing required system reserves, switching actions and load shedding? In this context, the paper provides the following contributions:

- Presents a novel methodology for selecting optimum remedial actions, using a metaheuristic SCOPF analysis to identify minimum number and extent of CCVs, in which overstressed system state is mapped to the corresponding SCM problem;
- Demonstrates how information on CCVs and injection sensitivity factors can be used to implement selected remedial actions at target network locations, requiring fewer reserves, less switching actions and shedding of minimum, or no load.

This paper is structured as follows: Section II outlines the remedial action framework and describes the implementation of various remedial actions. Simulation results on the test networks are presented in Section III. The main contributions, observations, and limitations of the approach are discussed in Section IV. Section V concludes the paper.

II. Methodology for Selecting Remedial Actions

A. Analytical Framework

As mentioned, (prolonged) operation of the network with CCVs will result in further activation of protection systems, leading to (extreme) emergency conditions and cascade faults. Assuming the operator is responsible for returning the system into a normal or alert state and that active and reactive power reserves are available as the means of remedial actions, operator should select and implement the most effective controls at the best locations. As the network is overstressed, failure to do so might further degrade system security.

Typically, under emergency operating conditions, there will be a (large) number of constraint violations, i.e. line overloading and bus under/over voltage alarms, which operator should immediately address by devising effective remedial actions. These must be computed and implemented in such a way that unnecessary switching and control operations are avoided, not only to minimize the usage of system reserves, but also to prevent the further adverse effect on system dynamics in post-contingency state [22]. For that purpose, this paper presents a novel SCOPF formulation, where one metaheuristic approach is used for identification of the minimum number/extent of CCVs, i.e. to diagnose the overstressed system state and devise most effective remedial action that should be implemented. The methodology is illustrated in Fig. 1 and has the following four main stages:

1. Initiate disturbance and perform analysis of steady state security constraints in post-disturbance state;
2. If any of the constraints is violated, employ conventional SCOPF analysis to re-adjust preventive controls;
3. If the conventional SCOPF method fails to converge, i.e. if there are critical constraints, CCVs, employ metaheuristic approach with suitable penalization to identify CCVs;
4. Classify the SCM problem and employ relevant remedial action(s).

The final stage considers a range of potential solutions for remedial actions, depending on whether the CCVs are related to line loading, or bus voltage constraints. Accordingly, this paper considers: load shedding and demand side management (DSM), distributed generation (DG) dispatch and reactive power control. The stages are explained in the following sections.

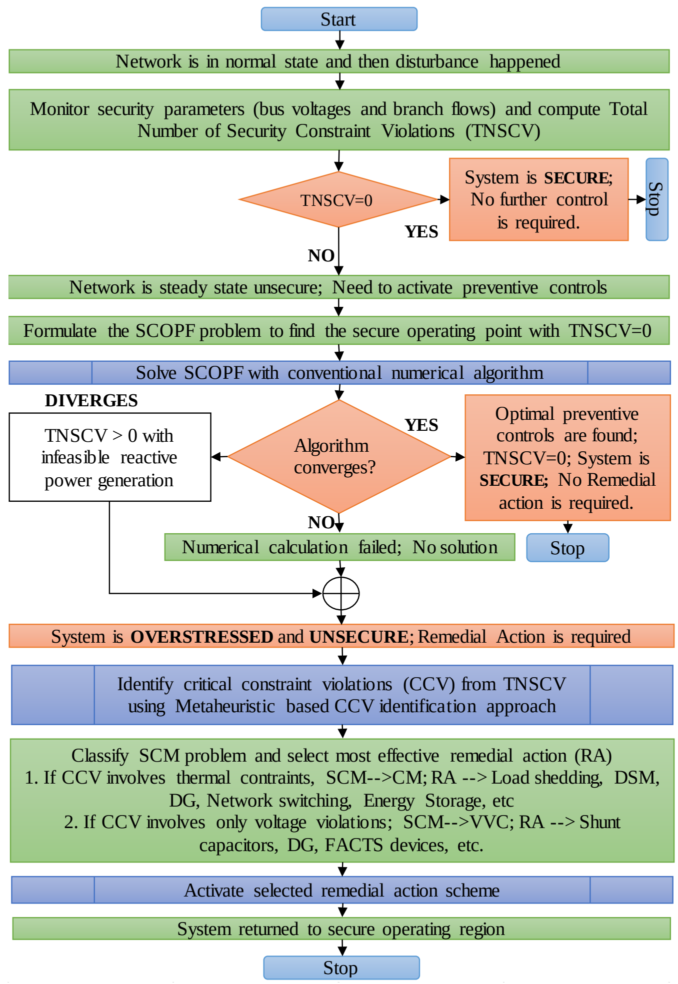


Fig. 1. A general methodology for devising optimal remedial actions.

B. Disturbance Initiation and Analysis of Constraint Violations

The evaluation process starts by initiating a disturbance, e.g. a fault resulting in a contingency, which is in this paper deliberately chosen to lead to an overstressed system and CCVs. After protection clears the fault, the system is analysed immediately after the contingency, before the effect of any automatic or other control. This is carried out by solving an unconstrained power flow with pre-contingency (optimal) control set points applied on a post-contingency configurednetwork. If any of the security constraints is violated, the next step is to try to resolve violated constraints by re-adjusting preventive control settings using SCOPF analysis.

C. Finding Secure and Optimal Operating Point with SCOPF

Conventional SCOPF methods are typically used to identify a feasible/secure operating point with no constraint violation, for which settings of electrical control variables are adjusted, so the stipulated objective function is optimized. Accordingly, the SCOPF problem can be formulated as:

$$min.\quad f(x_0, u_0) \tag{1}$$

$$s.t.\quad g(x_c, u_0) = 0 \tag{2}$$

$$h(x_c, u_0) \leq 0, c \in C = \{0,1,2, \dots N_c\} \tag{3}$$

where: x, u - state and control variables, c - contingency index (zero for base case), g, h - equality and inequality constraints, C - set of credible contingencies, f - objective function (in this paper, fuel cost and active power losses, optimized separately).

An interior point OPF solver from [23] is employed as a conventional method, with all constraints treated as hard, unless stated otherwise [2]. Bus voltage and line loading limits are used as security constraints and loads are represented with constant power model. When related algorithm does not converge, constant current and constant impedance models are also tried. If the conventional algorithm converges, the preventive control settings define a secure system, with no further remedial action required. However, if the conventional method fails to converge, or becomes infeasible, this indicates that the system is overstressed and additional steps are required, notably to identify CCVs using a metaheuristic method.

D. Metaheuristic Approach for Identifying Critical Constraints

From an optimization viewpoint, CCVs can be defined as the minimum set of constraints that cause the search space to be empty or infeasible, and are, therefore, essential for devising remedial actions to resolve overstressed system conditions. However, despite a large body of work on solving (SC)OPF problems using different metaheuristic algorithms aimed at minimizing various objective functions, there is no previous work on resolving infeasible nonlinear optimization problems through the minimization of the number/extent of constraint violations, or to identify CCVs using metaheuristic algorithms.

Most of the conventional and metaheuristic optimization algorithms are developed as unconstrained search methods and their performance when search space is constrained strongly depends on the implemented penalty function (which converts constrained optimization problem into an unconstrained one), as well as on algorithms exploration/exploitation capabilities.

Based on the previous analysis of metaheuristic methods (e.g. [24]-[25]), this paper uses a constriction based particle swarm optimization method (CPSO), as it performs better over the infeasible search spaces than other metaheuristic methods and requires no parameter tuning. While a detailed description of a basic CPSO algorithm is available in [26], two additional techniques are developed and integrated to the basic CPSO in this paper, in order to efficiently guide the search, while maintaining a good level of population diversity: decision variable preconditioning and new "particle best" criteria for updating. Moreover, a new penalty factor updating method is also developed for guiding the particles to minimize the number and extent of constraint violations in final solution.

1) Variable scaling: Values of decision variables are often in quite different ranges, possibly resulting in numerical ill-conditioning (conventional algorithms) or inefficient search (metaheuristic methods), especially if search space is narrow or infeasible. In PSO, for example, the positions and velocities of the particles are updated by inertia, social and cognition coefficients and two random numbers to calculate the next position. As the variables lie in different ranges, the applied updates are non-uniform and particles might hit the boundary in one dimension, but not in the other. To address this issue, all decision variables are transformed into a new space, with same lower and upper limits (0-100 in the paper). This modification resulted in improved computational performance and particle diversity over the iterations [27], Fig. 2.

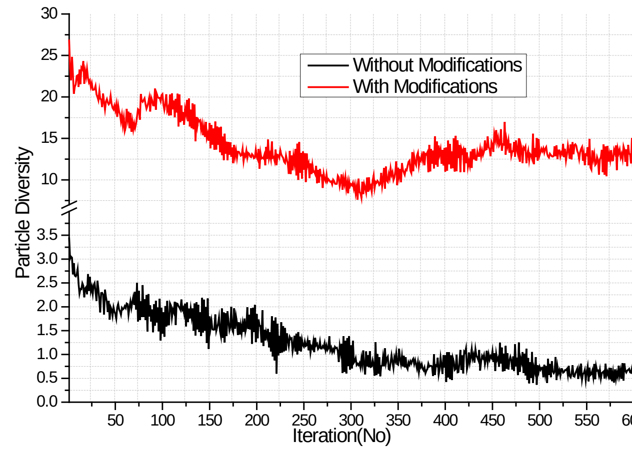


Fig. 2 Particle diversity with proposed modifications to CPSO

2) Modified personal-best updating criteria: The implemented CPSO uses Newton Raphson Power Flow (NRPF) for evaluating solution of each particle. Traditionally, the particle's personal best is updated when it achieves an improvement in the fitness value, but as the algorithm is dealing with infeasible problems, there might be cases when the unconstrained power flow may not converge. These particles may be promoted to next stage if they are not treated properly. To avoid this problem, the modified criteria require each particle to satisfy two conditions: a) new fitness value is better than the old one, and b) the power flow has converged.

3) Modified penalty factor method: While equality (power balance) constraints are automatically taken care of by the NRPF, inequality constraints are linked to objective function using linear penalty functions in (4), resulting in Lagrangian function, or penalized objective function, in (5). Metaheuristic methods need careful tuning of penalty factors, as otherwise search can be driven into an infeasible region. Therefore, a dynamic penalty factor updating method is formulated by (6), as it requires to set only the initial penalty factor values, K_X, and, as the iterations progress, they will be updated automatically based on actual number of constraint violations. Initial penalty factors should be selected based on the priority of the constraints and in this paper the violation of reactive power generation is considered as more severe than violations of voltage and thermal limits. All penalty factor values should be at least in the order 100's, so a change in objective function with respect to a change in constraint can be identified and then used to guide the particles. It is exactly this sensitivity to the constraint violations which is the main parameter helping CPSO to minimize the number of constraint violations.

$$\phi_{LPF} = \begin{cases} K_X^i(Xmin - X) \Big| X < Xmin \\ K_X^i(X - Xmax) \Big| X > Xmax \end{cases} \quad (4)$$

$$L = f(X) + \phi_{LPF}(X, K) \quad (5)$$

$$K_X^i = K_X^{NCV(i)} \quad (6)$$

where: L – the penalized objective function, PFV, f – original objective function, OFV, K - the penalty factor for violating minimum and maximum limits of decision variable set X in i^{th} iteration, NCV - number of constraint violations in the set X in the i^{th} iteration.

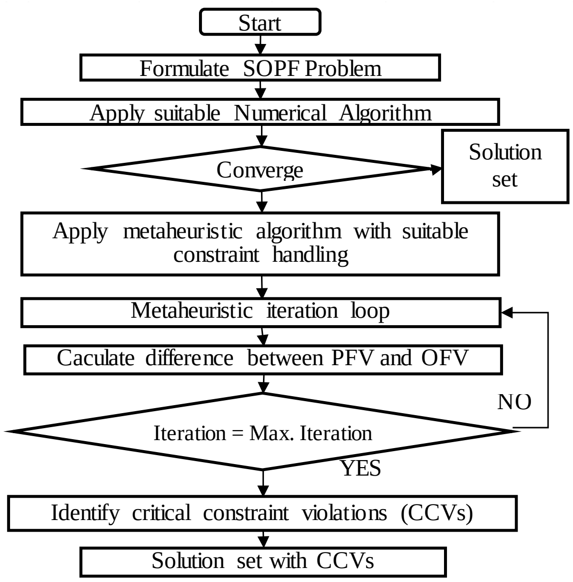


Fig. 3. Metaheuristic approach for identification of critical constraints.

The overall search process is guided by penalized objective function values, rather than gradients of the objective function, as in conventional algorithms. The difference between the penalized function value (PFV) and original function value (OFV) is an indication of the severity of CCVs, i.e. problem infeasibility. As the iterations progress, the guided CPSO search will either lead to a zero measure of violation (i.e. all constraints satisfied), or, if there is no solution satisfying all constraints, the PFV will be used to minimize their number/extent. The remaining constraint violations are the "critical constraints" causing the infeasibility, as they cannot be satisfied with existing preventive control variables, or within their allowed ranges of variations.

The applied CPSO algorithm treats all SCOPF constraints as soft, using exterior penalty functions. The parameter settings of the CPSO and constraint violation penalties are selected to strictly enforce the generation capability limits (Table I).

TABLE I PARAMETERS AND PENALTY SETTINGS FOR APPLIED CPSO

CPSO settings		**Penalty settings**	
Population size	20	Reactive power	500
Maximum number of iterations	600	Slack active power	100
Social and cognition coefficient	1.494	Branch MVA	100
Inertia weight	0.729	Bus voltage	100

E. Selection of the Most Effective Remedial Actions

The final stage is to use information on CCVs to devise the optimal remedial actions for returning the system to secure state. After CCVs are identified, this can be done with either conventional or metaheuristic SCOPF. For that purpose, two factors are calculated [28]: a) active power injection sensitivity factor for line flows (PISF), which captures the sensitivity of the flow through a line between bus i and j with respect to a change in active power injection at bus k, and b) reactive power injection sensitivity factor for bus voltages (QISF), which captures the sensitivity of the voltage at bus i with respect to reactive power injection at bus k (slack bus constraint included).

$$PISF_{ij}^k = \frac{\partial S_{ij}}{\partial P_k} = \frac{\Delta S_{ij}^k}{\Delta P_k} \; ; k \in B \; and \; (ij) \in L \quad (7)$$

$$QISF_i^k = \frac{\partial V_i}{\partial Q_k} = \frac{\Delta V_i^k}{\Delta Q_k} \; ; i \in B \; and \; k \in B \quad (8)$$

where: B - bus index; L - line/branch index; ΔP_k and ΔQ_k - the changes in active and reactive power injection at bus k; ΔS_{ij}^k - the change in apparent power flow in a branch (i, j) due to ΔP_k; ΔV_i^k - the change in voltage at bus i due to ΔQ_k.

If CCVs involve only bus voltage limit violations, the corresponding SCM is a VVC problem and the effective remedial actions should control reactive power injections at target buses. If CCVs involve a mixture of bus voltage and line loading limit violations, or only line limit violations, the corresponding SCM is a CM problem and the effective remedial actions should control both active and reactive power injections. The general steps are:

1. Calculate PISFs and/or QISF for all buses with respect to the critically overloaded lines or undervoltage buses;
2. Select the buses with the highest absolute PISF or QISF values as target buses for implementing selected remedial action and input corresponding parameters (e.g. load or generation at these buses) as new variables in the SCOPF;
3. Solve the modified SCOPF employing relevant objective functions corresponding to the intervention considered.

1) Optimal Control of Distributed Generation (DG): In the context of smart grid functionalities, the control of DG is approached as a practical option for system support services. In this paper, dispatching of DG active power is considered to relieve both line loading and bus voltage congestion and modified SCOPF problem considers DG active production as a control variable in two objective functions: minimizing of the overall fuel cost ("OFC", including DG fuel cost) and active power losses ("L") to optimally dispatch DG in addition to large system generation to resolve CCVs.

2) *Optimal Control of Reactive Power Injection:* An effective approach for resolving bus voltage CCVs due to reactive power imbalance is to install controllable reactive power reserves at specific buses. In this paper, optimal placement and control of shunt capacitors as VVC is employed at buses where undervoltage-CCVs occur. The target buses, with the highest QISFs with respect to the voltages at critical buses, are equipped with shunt capacitors which are considered as a (continuous) control variable in the SCOPF. The SCOPF is

then solved separately for three objective functions: minimize fuel cost (“F”), losses (“L”), and shunt capacitor use (“S”).

3) Optimal Load Shedding and DSM Control

A “last resort” emergency remedial actions available to network operator to resolve CCVs is load shedding. There are a number of potential approaches: (i) hard load shedding (HLS), (ii) optimal load shedding (OLS) and (iii) selective optimal load shedding (SOLS). These differ in terms of selected target buses and the proportion of load available to shed.

In conventional approaches, the target buses for both HLS and OLS are typically associated with buses where immediate post-contingency constraint violations occur. While the HLS approach disconnects all load at target buses (100% load shedding), OLS defines loads at the target buses as control variables to be optimized by the SCOPF (0%-100% load shedding). In contrast, SOLS targets only a small number of buses with the highest PISFs/QISFs with respect to the critically overloaded lines, or critical bus voltages. Only loads at these buses are considered as a control variable and then required amount of disconnected load is minimized (0%-100% load shedding). The related SCOPF problem is then solved with three objective functions: minimizing fuel cost (“F”), losses (“L”) and disconnected load (“DL”), in order to provide the optimal operating point with zero security constraint violations.

Similarly to load shedding, network operator may activate DSM at all, or some of the buses, based on the availability, priority and size of DSM-loads. In general, major electricity consumers will distribute their load into “critical”, “essential” and “non-essential” categories. Accordingly, the same approach for load shedding using the OLS and SOLS is applied for DSM, but it is assumed that up to 30% of the load at target buses is available for DSM without (significant) impact on customers.

F. Stability Analysis of Selected Remedial Actions

To be secure, the considered system must satisfy the steady state security constraints at pre- and post-contingency operating equilibrium states, as well as dynamic security constraints while transiting from these two states. Assuming proper controls are included in the mathematical formulation and that the formulation is feasible, SCOPF should provide solution for the future (post-contingency) operating state which is secure only from the steady security point of view. However, following the activation of the controls from the SCOPF solution, this new operating equilibrium state may or may not be reached, based on the system dynamics, i.e. ability of the system and its components to operate in a stable and controllable manner during the dynamic transition from pre- to post-contingency operating states. For that purpose, time domain simulations are used to ensure that the dynamic security/stability constraints are satisfied for a steady-state secure SCOPF solution obtained after optimal remedial actions are implemented.

The time domain simulations are performed using [29] for a total duration of 60 sec, with the following steps: a) base case OPF on the pre-contingency network is run for the first 10 sec, b) the first and second line outages are simulated at 10 sec and 15 sec, c) remedial actions (e.g. SOLs) are activated at 20 sec, d) generation and voltage set points are readjusted at 25 sec and simulation is run until 60 sec with no further events.

The selected remedial action is considered to be “rotor angle stable” if and only if the relative angles of all generators reached steady state values and varied within the margin of $\pm 180^0$. If a relative rotor angle exceeded $\pm 180^0$, the generator is assumed to lose synchronism with the rest of the system. Similarly, the selected remedial action is assumed to be “voltage stable” if the terminal voltages of all generators reached their steady state values and none of them was outside the 0.95 p.u. - 1.1 p.u. range.

III. Results

A. Test Networks Used for Analysis

To illustrate presented methodology and demonstrate that it can be scaled-up to larger systems, IEEE 30-bus, IEEE 39-bus and IEEE 57-bus test networks are selected, with complete information and data for their modelling available in [30]-[31].

B. Post-Contingency Conditions and Overstressed System

For all test networks, overstressed system conditions are obtained by simulating severe infeasible contingencies using an unconstrained power flow from a pre-contingency optimal operating point. These are shown in Table II, with “T” and “L” denoting transformers and lines. For each case, the number of resulting undervoltages (NUV), overvoltages (NOV) and line overloading (NOL) are shown. The type, extent and severity of constraint violations vary by contingency chosen. The list of CCVs and the corresponding computational time taken by PSO are presented in Table III. It can be seen that a large number of immediate post-contingency constraint violations reduce to a much smaller set of CCVs (most notably for IEEE-57 system). Although the computational time varies depending on the size of the network and level of stress, it is observed that the average computational time to identify CCVs is around 40 sec. This time is calculated based on performing numerous simulations on 14, 30, 39, 57, 110, 150-bus test networks.

TABLE II List of Immediate Post- contingency Constraint Violations

Contingency	NUV	NOV	NOL
IEEE 30-bus			
L1-2 & T27-28	4	0	5
L4-12 & T27-28	5	0	3
IEEE 39-bus			
L5-6 & L6-7	3	0	6
L21-22&L26-27	0	3	4
IEEE 57-bus			
T7-29 & L8-9	35	0	5
T7-29 & L46-47	18	1	1

TABLE III List and Locations of Critical Constraint Violations

Contingency	NUV	NOV	NOL	UV Buses	OL Lines	Time(s)
IEEE 30 Bus						
L1-2 & T27-28	2	0	2	29;30	33(L22-24); 35(L24-25)	14.34
L4-12 & T27-28	2	0	2	29;30	33(L22-24); 35(L24-25)	21.32
IEEE 39-bus						
L5-6 & L6-7	0	0	2	/	3((L2-3); 9(L4-14)	36.04
L21-22&L26-27	0	0	1	/	3((L2-3)	9.13
IEEE 57 Bus						
T7-29 & L 8-9	6	0	0	24;27;28; 29;52;53	/	76.34
T7-29 & L46-47	6	0	0	24;27;28; 29;52;53	/	70.54

C. Optimal Load Shedding and DSM Control

The load shedding approach is applied to the IEEE 30-bus network, as it has a mixture of line loading and bus voltage CCVs. Lines L22-24 and L24-25 are the most critical ones, for which security constraints cannot be fulfilled without shedding load at some selected or target buses (Table III). Table IV shows that the PISFs for these critical lines are highest at Buses 29 and 30 indicating their significant influence on MVA flows in the critical lines (e.g., for the outage of L1-2 and T27-28, the injection of one MW at Bus 29 reduces the flows on L22-24 and L24-25 by 0.811 MVA and 1.168 MVA, respectively). Hence, Buses 29 and 30 are target buses for SOLS (Table V). For HLS and OLS approaches, target buses are these two and four other buses associated with post-contingency constraint violations (from unconstrained power flow), as indicated in Table V.

The total disconnected MVA for IEEE 30-bus network with minimized fuel cost, losses, and disconnected load are shown in Table VI, with resulting objective function values in Table VII. The tables refer to "PSSE" and "PSO", which are conventional and metaheuristic SCOPF methods, respectively. These are included to demonstrate that presented approach can be used with both methods (where possible) and to indicate differences in their performance. In the majority of cases, the PSSE and PSO results for the amount of disconnected loads and objective values are the same, or very close. The obvious differences arise with the minimum load shedding objective, where the PSO substantially outperforms the conventional approach. The largest difference is for the first contingency, where reduction in load shedding is 77% for the SOLS and 90% for OLS methods. In addition, the SOLS approach results in much lower levels of load shedding compared to the other methods. Similarly, load shedding analysis is carried out for 39-bus and the resulting disconnected MVA are shown in Table VIII.

TABLE IV Active Power Injection Sensitivity Factors for IEEE 30-Bus

ISFs with outages of L1-2 and T27-28						
Branch\bus No	B24	B25	B26	B27	**B29**	**B30**
L22-24	-0.696	-0.752	-0.769	-0.781	**-0.811**	**-0.831** [a]
L24-25	0.000	-1.089	-1.112	-1.129	**-1.168**	**-1.196**
ISFs with outages of L4-12 and T27-28						
Branch\bus No	B24	B25	B26	B27	**B29**	**B30**
L22-24	-0.801	-0.868	-0.887	-0.903	**-0.937**	**-0.962**
L24-25	0.000	-1.086	-1.109	-1.126	**-1.167**	**-1.195**

[a]Buses with high absolute ISFs

TABLE V Target Buses for Load Shedding

Conti.	SOLS	OLS	HLS
IEEE 30-bus			
L1-2&T27-28	29, 30	3, 4, 24, 26, 29, 30	3, 4, 24, 26, 29, 30
L4-12&T27-28	29, 30	3, 4, 24, 26, 29, 30	3, 4, 24, 26, 29, 30
IEEE 39-bus			
L5-6 & L6-7	4	4,7,8	4,7,8
L21-22&L26-27	4	3, 16, 24, 25, 26	3, 16, 24, 25, 26

The line MVA flows before and after the load shedding are shown in Fig. 4. These results demonstrate that, while SCOPF analysis with only preventive controls (i.e. SCM with no load shedding) can reduce five-line loading constraint violations to two (denoted as critical overloading in Fig. 4), SCOPF analysis with remedial action (i.e. SCM with HLS, OLS, and SOLS) can alleviate all line loading constraint violations.

TABLE VI Total Disconnected MVA with Load Shedding (IEEE 30-Bus)

Contingency: L1-2 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	13.33	13.33	38.95	38.95	38.95	38.95
Min. Active Loss	13.32	13.33	34.93	38.95	38.95	38.95
Min. Shedding	3.07	13.33	3.93	38.95	NA	NA
Contingency: L4-12 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	13.33	13.33	38.95	38.95	38.95	38.95
Min. Active Loss	13.33	13.33	37.38	38.95	38.95	38.95
Min. Shedding	7.05	13.33	7.29	23.12	NA	NA[1]

[1]Not Applicable

TABLE VII Total Disconnected MVA with Load Shedding (IEEE 39-Bus)

Contingency: L5-6 and L6-7						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	502.34	532.78	1055.64	1332.28	1332.28	1332.28
Min. Active Loss	494.43	532.78	1077.72	1107.12	1332.28	1332.28
Min. Shedding	452.23	532.78	497.83	754.07	NA	NA
Contingency: L21-22 and L26-27						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	523.10	532.78	1021.55	1605.18	1605.18	1605.18
Min. Active Loss	515.74	532.57	847.12	842.72	1605.18	1605.18
Min. Shedding	443.51	450.73	480.41	471.92	NA	NA1

TABLE VIII Optimal Objective Values (Load Shedding, IEEE 30-bus)

Contingency: L1-2 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Fuel cost ($/MWhr)	787.27	787.54	703.29	703.48	703.22	703.48
Active Loss (MW)	3.17	11.50	2.90	11.34	2.68	11.34
Min Shed (MW)	2.92	13.00	3.32	15.63	NA	NA
Contingency: L4-12 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Fuel cost ($/MWhr)	756.14	756.38	677.00	677.33	694.97	677.32
Active Loss (MW)	2.57	8.66	1.91	7.72	3.88	7.71
Min Shed (MW)	6.83	12.89	6.71	14.45	NA	NA

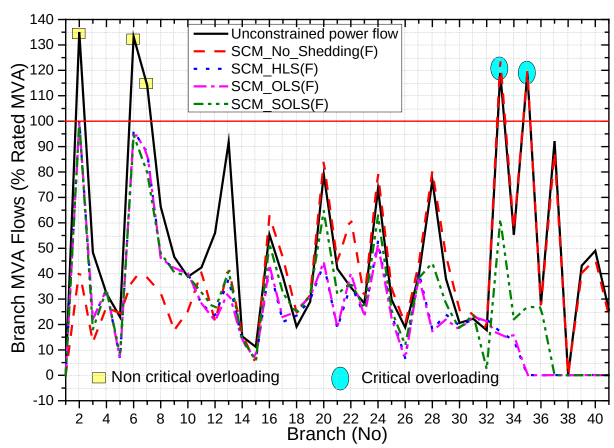


Fig. 4. Line MVA flows with load shedding for IEEE 30-bus with contingencies L1-2 and T27-28

The analysis was repeated for DSM with the OLS and SOLS approaches (denoted as OLS-DSM and SOLS-DSM). Target buses for OLS- and SOLS-based DSM are identified based on PISFs for critical lines (Table V). The resulting amounts of disconnected load (in MVA) are shown in Table IX. Once again, the SOLS approach is better than the OLS in all cases, with significant improvements in some cases. The results of conventional and metaheuristic methods are similar in most cases, but PSO performs better for the load shedding objective.

The convergence of the PSO algorithm for one contingency (L4-2 and T27-28) is shown in Fig. 5 for both OLS and SOLS cases for each of the objectives. This illustrates how the total number of security constraint violations reduces as the iterations progress. In all cases, the zero-security constraint violation in the figure indicates that all security constraints are fulfilled, but that there are variations in iterations at which this is achieved. It is clear that in all cases there is a rapid reduction at the initial search stages, followed by a more steady progress. The OLS approach for minimizing fuel cost reaches zero violations most rapidly, but it should be noted that this case has the highest amount of load shedding. This suggests there is an important relationship (a trade-off) between the speed and efficiency.

TABLE IX TOTAL DISCONNECTED MVA LOAD (SOLS-DSM AND OLS-DSM)

Contingency: L1-2 and T27-28				
Type of shed->	SOLS		OLS	
Objective	PSO	PSSE	PSO	PSSE
Min. Fuel cost	4.00	4.00	11.68	11.69
Min. Active Loss	4.00	4.00	9.86	11.69
Min. Shedding	2.99	4.00	3.38	11.69
Contingency: L4-12 and T27-28				
Type of shed->	SOLS		OLS	
Objective	PSO	PSSE	PSO	PSSE
Min. Fuel cost	8.55	8.55	11.68	11.69
Min. Active Loss	8.55	8.55	11.64	11.66
Min. Shedding	7.72	8.55	4.18	8.81

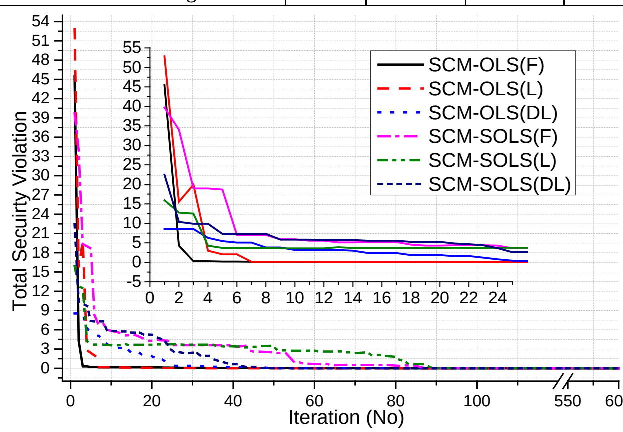


Fig. 5. Number of security constraint violations with iterations for PSO SCOPF with remedial actions (contingency L4-2 and T27-28)

D. Optimal Control of Distributed Generation (DG)

The use of DG dispatch as a remedial action is demonstrated on IEEE 30-bus system, in which L22-24 and L24-25 loading constraints cannot be fulfilled without injecting active power. Table IV lists the bus PISFs for these two critical lines, with Buses 29 and 30 again the target buses for DG control. The DG at both considered buses is modelled as 5 MW units capable of being dispatched from zero to maximum. Their fuel cost is modelled with the following equations: $0.02P_g + 15$ at Bus 29 and $0.043P_g + 20$ at Bus 30 with DGs assumed to provide only active power (characteristics of other generators were the same).

The system is optimized for minimum fuel cost or losses for each set of contingencies. The results in Table X show the loading of the conventional generators and the two DG units, where outcomes of conventional and metaheuristic methods are broadly similar. However, the dispatch to minimize fuel cost is quite different from the one to minimize losses, with much greater use of DG at Bus 30in latter case. Additionally, the post-contingency dispatch of conventional generators changes significantly from the pre-contingency one, indicating a large change between the two system operating points.

The line MVA flows for contingency L1-2 and T27-28 before and after DG dispatch are shown in Fig. 6. As all line CCVs are relieved after activating DG support, it can be concluded that DG is effective in alleviating both line loading and bus voltage congestions, irrespective of the considered objective function. DG does not necessarily need to be located near the critical lines to be effective. For example, the target buses (Bus 29 and 30) in presented analysis are not associated with the critical lines (L22-24 and L24-25), Table III.

TABLE X OPTIMAL DG DISPATCH WITH RELEVANT OBJECTIVE VALUES

Gen	**L1-2 and T27-28**				**L4-12 and T27-28**			
@	**OFC**		**Loss**		**OFC**		**Loss**	
Bus No	**PSSE**	**PSO**	**PSSE**	**PSO**	**PSSE**	**PSO**	**PSSE**	**PSO**
1	130.0	129.72	50.00	53.04	158.79	150.34	50.01	57.24
2	63.37	63.62	77.03	77.00	44.32	46.61	71.35	78.90
5	25.29	25.18	49.38	50.00	20.00	17.88	49.99	50.00
8	35.00	32.09	34.92	34.62	11.03	13.71	34.98	34.91
11	21.00	21.38	29.94	30.00	10.01	15.42	29.98	20.11
13	16.58	18.90	35.13	33.13	40.00	40.00	39.97	36.27
29 (DG)	4.83	4.90	4.99	4.80	5.00	5.00	5.00	4.87
30 (DG)	0.00	0.15	5.00	4.99	2.52	2.58	5.00	4.86
Objective value	897.3 \$/MWhr	900.1 \$/MWhr	3.59 MW	4.24 MW	924.7 \$/MWhr	927.9 \$/MWhr	2.88 MW	3.78 MW

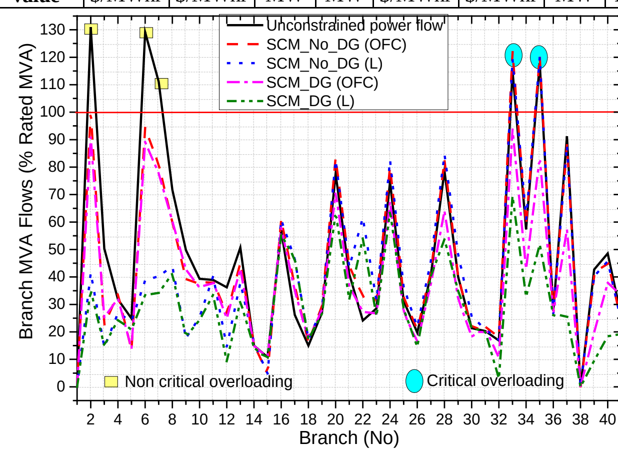


Fig. 6. Line MVA flows with load shedding for IEEE 30-bus network (contingency: L4-12 and T27-28)

E. Optimal Control of Reactive Power Injection

Unlike the previous remedial actions, reactive power control is demonstrated on IEEE 57-bus network, as the CCVs include only undervoltage violations (Table III) and the SCM is a VVC problem. Table XI shows the extent of the undervoltage CCVs after contingency (T7-29 and L8-9) and before SCOPF dispatch with reactive support, which are 1%-7% below a 95% limit. Reactive support (capacitors) are available at each of the critical buses and SCOPF is again run for three objectives (fuel, losses and reactive power injection). Table XII shows the resulting optimal reactive power injection values for one contingency.

The required reactive power support and objectives for PSSE and PSO are similar for the fuel cost minimization, but allocation of the injections between buses is quite different. For the loss minimization, PSO performs slightly worse than PSSE in terms of overall required reactive support and has almost twice higher losses. For minimizing reactive support, PSO gives zero or near zero injections at two of the three locations and much reduced required power. This suggests that PSO is more efficient in finding minimum number of required capacitors.

TABLE XI BUS UNDERVOLTAGES FOR IEEE 57 BUS (BELOW 0.95 PU LIMIT)

Contingency	Bus undervoltages (%) with fuel cost min.					
	B24	B27	B28	B29	B52	B53
T7-29&L8-9	1.93	4.43	6.20	6.96	6.02	4.82
T7-29&L46-47	1.08	2.45	3.99	4.61	3.19	1.72
Contingency	**Bus undervoltages (%) with loss min.**					
	B24	B27	B28	B29	B52	B53
T7-29&L8-9	2.14	4.23	5.97	6.71	5.72	4.49
T7-29&L46-47	1.80	3.46	5.09	5.75	4.49	3.12

TABLE XII OPTIMAL REACTIVE POWER INJECTION WITH RELEVANT OBJECTIVE VALUES FOR A CONTINGENCY T7-29 & L8-9

Objective->	With minimized Fuel cost		With minimized loss		With minimized shunt	
Bus No	**PSSE**	**PSO**	**PSSE**	**PSO**	**PSSE**	**PSO**
B24	7.58	3.60	3.05	4.71	2.87	0.03
B27	2.63	7.14	4.09	1.84	3.67	1.17
B28	2.45	2.57	4.30	4.76	3.63	4.23
B29	2.53	3.97	4.36	6.82	3.58	3.95
B52	2.39	1.02	3.80	1.30	3.38	5.90
B53	5.54	4.75	3.38	4.73	3.09	0.00
Total MVAr	23.12	23.05	22.98	24.16	20.20	15.28
Objective value	44757.5 $/MWhr	44861.0 $/MWhr	14.82 MW	28.59 MW	20.20 MVAr	15.28 MVAr

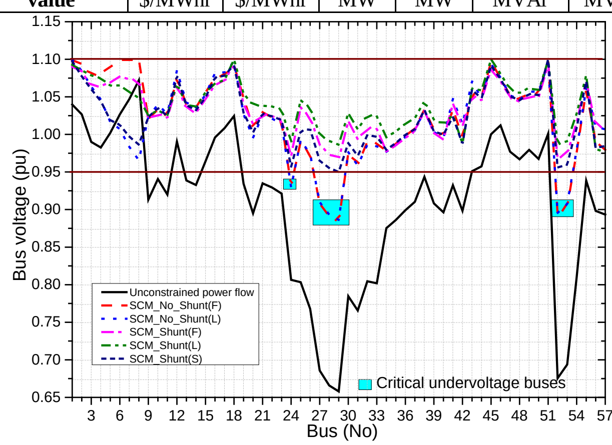


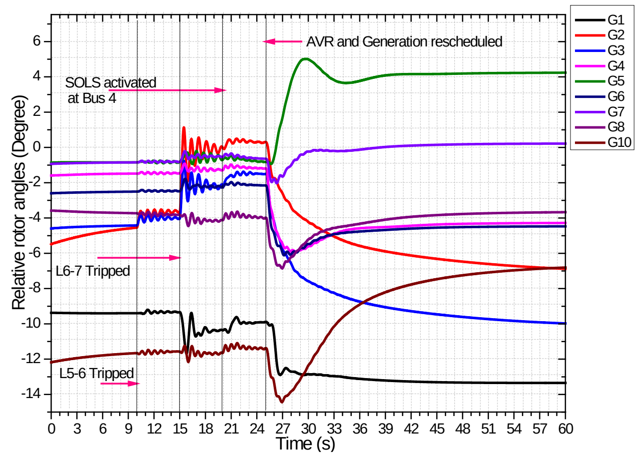
Fig. 7. Voltage profile for IEEE 57-bus system with and without reactive power support (contingency T7-29 and L8-9)

The effect of the reactive support is clearly visible in Fig. 7 for contingency T7-29 and L8-9 before and after activating this remedial action. For immediate post-contingency, there are 35 undervoltage violations and presented approach suggests that reactive power injection at only six buses will resolve them, minimizing both number of target buses and switching actions.

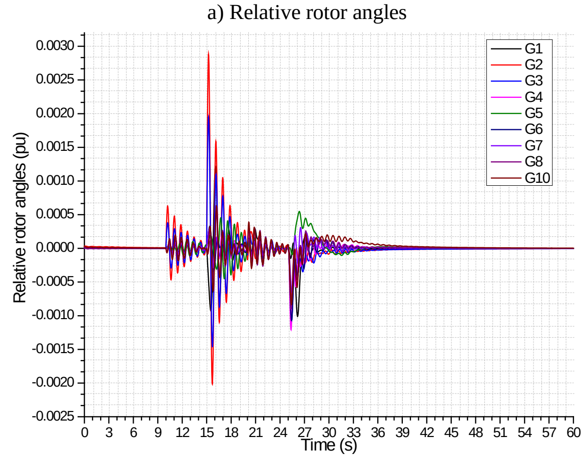
F. Stability Analysis of Remedial Actions

Time domain simulations of the transition from pre- to post-contingency steady state secure operating points is done for two reasons: a) to additionally check whether the system can reach new stable operating state, or not, and b) to check whether the presented remedial action framework does not result in any voltage or angle instability.

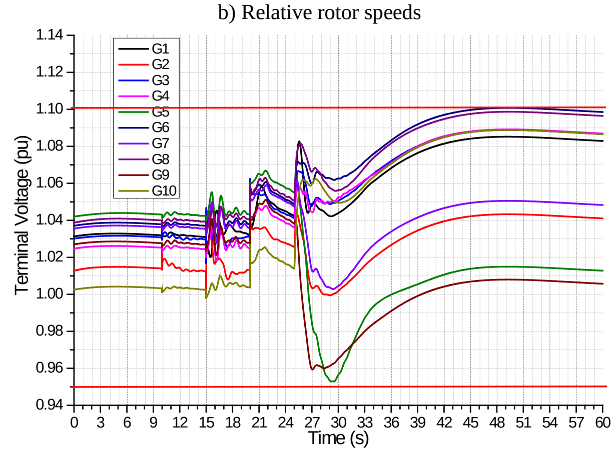
The results of dynamic simulations for generator terminal voltages, rotor angles and speeds for IEEE 39-bus network with the activation of SOLS following a double line contingency (L5-6&L6-7) are shown in Fig. 8. It can be observed that all the relative rotor angles and speeds are reached steady state, and none of the relative rotor angles are exceeded $\pm 180^0$ margin. In addition, the terminal voltages of all the machines are reached steady state which are same as the AVR set points computed by the remedial action. This confirms that the proposed remedial action does not initiate any voltage and angle instability problems.



a) Relative rotor angles



b) Relative rotor speeds



c) Terminal voltages of generators

Fig. 8. Dynamic stability simulations for generator terminal voltages, rotor angles and speeds for IEEE 39-bus network with the activation of SOLS following a double line contingency (L5-6&L6-7)

IV. Discussion

It is widely accepted that security constraint management can be more economically efficient option than further investment in the transmission network [1]. Accordingly, system operators invest significantly in procuring various active and reactive power ancillary services to mitigate constraint violations during overstressed or emergency conditions to deliver high security and quality of at all, or most of the time.

The presented remedial action framework incorporates the concept of critical constraint violations (CCVs) in the unified algorithmic and computational tools for both identifying the overstressed system conditions and selecting the most effective remedial actions. The framework is based on the CCV classification and effective implementation of remedial actions using injection sensitivity factors, aimed at minimizing required system reserves (for economic operation) and required number of switching actions (for a more secure transition from pre- to post-disturbance secure operating states). The following observations from the results and analysis presented in the paper support these assertions.

Although there are differences in amounts of disconnected load, required DG and installed capacitors for various objective functions, all of the proposed remedial actions ensure secure post-disturbance operating point with zero constraint violations.

The proposed SOLS and SOLS-DSM control approaches require disconnection of less load at a fewer buses compared to the HOLS (activated by under-voltage or under-frequency protection at the local level) or OLS (activated by the operator using computer controls over the regulated region). Taking advantage of adaptive relays, whose protection settings can be changed in real time, SOLS approach can be efficiently integrated into the existing protection systems.

The traditional undervoltage and/or under-frequency load shedding controls tends to shed loads at the buses experiencing undervoltage/under-frequency conditions (i.e. overloading) to prevent the network from entering insecure region. However, from both an economic and secure operation viewpoints, these buses may not be the most effective for constraint management in large and highly interconnected networks. This is evidenced by the presented SOLS approach, in which target buses for load control are not the ones associated with overloaded lines.

The presented reactive power control approach requires minimum reactive support at a minimum number of buses to alleviate the voltage congestion. Hence, it can help to reduce switching surges and voltage spikes which are often associated with the spurious operation of voltage relays.

The important feature of the presented approach is that it does not aim to replace the existing methods for handling emergency conditions. Rather, in providing a computational means and tools for identifying and classifying the CCVs, it can extend the available support to system operators. The approach could form a part of an offline analysis tools, offered as a lookup table or in the form of a case-based reasoning method. The approach could form part of offline analyses and be offered as part of a lookup table or some form of case-based reasoning method. The method could conceivably be incorporated as part of online systems as the straightforward manner in which the PSO algorithm can be parallelized means its elapsed time will be sufficiently short despite a longer computational burden (~2.5 processor minutes). This allows it to be broadly competitive with conventional methods requiring a few seconds to provide the solution. Although 2.5 processor minutes are required to simulate total 600 iterations, CPSO requires only about 40 sec (average) to identify the CCVs and 30-100 sec to compute the remedial action.

In addition to applications in operational studies, e.g. to indicate optimal location and sizing of shunt capacitors, distributed generation and storage systems, etc. The remedial action framework can also be used for strategic (day ahead, weekly, monthly or annual) planning and selecting (or inviting) potential bidders for the provision of optimal system support and ancillary services. The repeated SCOPF analysis, for example, with severe contingency events over forecasted energy demand, or for various load distributions (using Monte Carlo approach) can be used to plan various active and reactive power ancillary services for improved congestion management and volt-var control, respectively.

V. Conclusions

This paper presented a remedial action framework for improved security constraint management to mitigate system emergency and overstressed operating conditions. The practical relevance of the proposed framework is demonstrated on three widely used IEEE test networks, where the presented results indicate its value for system operational and planning studies. From the optimization perspective, the presented framework can help planners to resolve infeasible cases in optimization models by identifying critical constraint violations and devising effective preventive actions. From the operational perspective, the presented results provide an initial confirmation that the framework can be incorporated into dynamic system stability analysis of the transitions between pre- and post-contingency steady state secure operating points (calculated from the steady-state security analysis), helping to minimize required switching actions and overall implementation of the devised remedial actions. By identifying minimum number and extent of CCVs, i.e. by detecting critical alarms from possibly large number of activated post-contingency alarms, the presented framework also helps the system operators to deal with “alarm flooding”. On the other hand, by effective handling of critical security constraints and by allowing network operation at, or near the technical security limits, the presented approach has further potential to be used for exploiting unused (“hidden”) network capacity, e.g. to host more renewable generation, or supply higher demands.

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VII. Biographies

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