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Analysis of Infeasible Cases in Optimal Power Flow Problem

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Abstract: In the context of smart grid transformation of existing electricity networks, optimal power flow (OPF) and security-constrained OPF (SCOPF) studies remain to be very important for power system planning, operation and market analysis. OPF study involves finding the (global) optimum solution to a set of nonlinear algebraic equations, subjected to a set of equality and inequality constraints. When the system is heavily stressed, particularly following a severe contingency, the conventional OPF methods may fail due to the problem or solution infeasibility, or inability to select proper initial values. The soft constraint handling approach and repetitive constraint relaxation in finding the causes of infeasibility could be either tedious, or may not be practical for the large-scale problems. This paper presents an alternative approach, based on use of meta-heuristic method, to pinpoint the main reasons for the failure of solution algorithms in nonlinear optimization, in general, and OPF problem, in particular. The presented approach is illustrated on commonly used IEEE 14-bus and 30-bus test networks.

Keywords: Conventional and meta-heuristic optimization, constraint relaxation, nonlinear optimization, optimal power flow, problem and solution infeasibility, security-constrained optimal power flow.

NOMENCLATURE

Variables:

x, u	State and control variables
P_{Gi}, Q_{Gi}	Real and reactive power output of generator i
P_{Di}, Q_{Di}	Real and reactive power demand of load at bus i
V_i, θ_i	Voltage magnitude and phase angle at bus i
c	Contingency index, zero for base case
C	Set of credible contingencies

Functions:

f	Objective function
g, h	Equality and inequality constraint functions
F_T	Total fuel cost
P_{loss}	Total active power loss
F_p	Penalized objective function
Φ_{eq}, Φ_{ineq}	Penalty functions for equality and inequality constraints

Constants:

a_i, b_i, c_i	Fuel cost coefficients of generating unit i
N_B, N_G, N_L	Number of buses, generators and branches
G_{ij}	Conductance of a line connecting buses i and j
p_v	Penalty for violating bus voltage constraints
p_p	Penalty for violating active power generation limit
p_q	Penalty for violating reactive power generation limit
p_s	Penalty for violating branch MVA constraints
N_{pop}	Number of particles or populations
N_{itr}	Maximum number of iterations or generations
c_1, c_2	Acceleration coefficients for PSO
w_i, w_f	Initial and final inertia weight for PSO
K_p	Penalty parameter for conventional algorithms

1. INTRODUCTION

Planning and operation of modern electricity networks is becoming an increasingly complex task, as network designers have to analyse the networks for a number of relevant technical and non-technical operating conditions during the design stage, while network operators should operate their networks for higher loading conditions and closer to their security limits, in order to meet the requirements of the deregulated markets. In the context of anticipated smart grid transformation of existing networks, it is very important to develop and implement intelligent, computationally efficient and flexible optimal power flow (OPF) and security constrained OPF (SCOPF) methods for assessing network performance in terms of their optimal design and operation.

Since its introduction, the research work in OPF studies has been carried out in two directions: one, from the solution algorithm viewpoint many computationally efficient numerical algorithms are developed, and two, from problem formulation viewpoint OPF has evolved to include many objective functions with corresponding constraints. Nevertheless, irrespective of the problem formulation and solution algorithm, OPF/SCOPF study involves finding the solution to a set of nonlinear algebraic equations subjected to a set of equality and inequality bound and functional constraints.

However, when the system is heavily stressed, particularly following a severe contingency, the conventional numerical methods for solving OPF problem may either fail to converge due to the infeasibility of the problem, or diverge due to the inability of finding the proper initial values. The distinction between the problem infeasibility and solution infeasibility; and non-convergence and divergence of a numerical algorithm can be defined as below.

Divergence: A numerical algorithm is considered to diverge when the solution trajectory is not reaching any final point, even after a significant number of iterations. When an algorithm diverges, it cannot output any real or physically feasible solution. Sometimes, divergence is also referred to as a “blow-up” of a solution algorithm.

Non-Convergence: A numerical algorithm is considered to non-converge when the numerical calculation of underlying matrices (e.g. Jacobians and Hessians) has failed, that is, the matrices are very close to singular. In this case, the algorithm just halts the iteration process, as it cannot progress further.

Infeasible OPF problem: An OPF problem is infeasible or overdetermined when there is no solution satisfying all the constraints, which typically happen during the contingency analysis.

Infeasible OPF solution: An OPF solution is feasible if and only if all the (bound, as well as functional) constraints are satisfied at that solution. Accordingly, a solution is infeasible if one or more constraints are not satisfied at that solution. All the mathematically infeasible solutions are physically infeasible, but the reverse is not true. A mathematically feasible solution is physically infeasible if the solution cannot be realized as the practical system operating condition.

It is very important to develop techniques to identify the causes of infeasibility and provide recommendations for returning the system into a feasible region. Though there are many mathematical formulations and algorithms developed to improve the computational efficiency, there is still no standard or commonly accepted methodology to identify the causes of infeasibilities in nonlinear optimization problems, in general, and OPF problem, in particular. The traditional soft constraint handling and repetitive constraint relaxation approach in finding the causes of infeasibility may be either tedious, or not practical for large-scale problems.

The problem of infeasibility in the power flow and OPF problem is previously addressed by some researchers. Overbye (1994 & 1995) proposed a methodology, based on Newton-Raphson method, to quantify the degree of insolvability of the power flow problem and determine the controls to return to solvability. Singh and Srivastava (1995) extended the same concept to OPF infeasibility and, based on eigenvalue analysis of the power flow Jacobian, proposed a methodology to determine proper control actions to return the system operation into the feasible region. Almeida and Galiana (1996) developed a parametric continuation algorithm to identify the critical OPF cases. Takashi *et al.* (2006) have applied the concept of phantom generators with high fuel cost coefficients to identify and solve the infeasible OPF problems. Recently, Molzahn *et al.* (2013) developed two sufficient conditions to analytically prove an insolvable power flow case as insolvable.

In this context, this paper, based on a meta-heuristic algorithm: particle swarm optimization (PSO), provides an alternative approach to identify the causes of infeasibility in OPF problem cases. The practical aspects of the presented approach are illustrated using IEEE 14 and 30-bus test networks as an example.

2. TEST NETWORKS USED FOR ANALYSIS

Two test networks (Christie, 2000) are used to illustrate the presented approach. The first is IEEE 14-bus network, Fig.1. It has five generators supplying total demand of 259 MW and 81.3MVAr. The second is IEEE 30-bus network, Fig.2. It has six generators supplying total demand of 283.4 MW and 126.2 MVAr. Generator capability limits and fuel cost coefficients are given in Table 1, while the minimum and maximum bus voltages are set to 0.95pu and 1.1 pu, branch MVA capacities are taken from Rajathy (2011) and Zimmerman *et al.* (2011).

Table 1. Generator limits and fuel cost coefficients

IEEE-14 Bus network							
Bus No	**P_g Max**	**P_g Min**	**Q_g Max**	**Q_g Min**	**a**	**b**	**c**
1	250	10	10	0	0.00375	2.00	0
2	140	20	50	-40	0.0175	1.75	0
3	100	15	40	0	0.0625	1.00	0
6	120	10	24	-6	0.00834	3.25	0
8	45	10	24	-6	0.025	3.00	0
IEEE-30 Bus network							
Bus No	**P_g Max**	**P_g Min**	**Q_g Max**	**Q_g Min**	**a**	**b**	**c**
1	200	50	10	0	0.00375	2.00	0
2	80	20	50	-40	0.0175	1.75	0
5	50	15	40	-40	0.0625	1.00	0
8	35	10	40	-10	0.0083	3.25	0
11	30	10	24	-6	0.0250	3.00	0
13	40	12	24	-6	0.0250	3.00	0

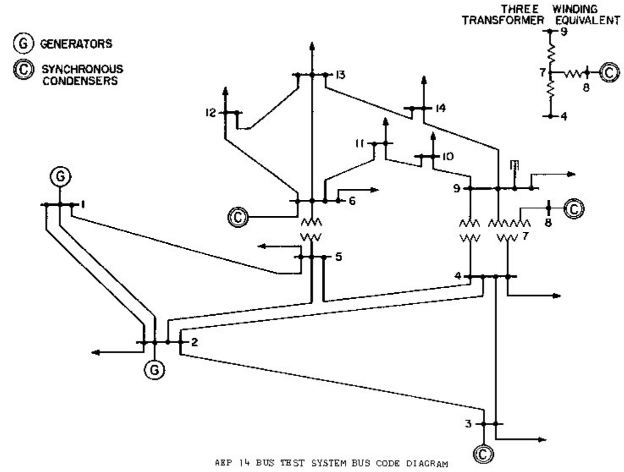


Fig.1. IEEE 14-bus test network

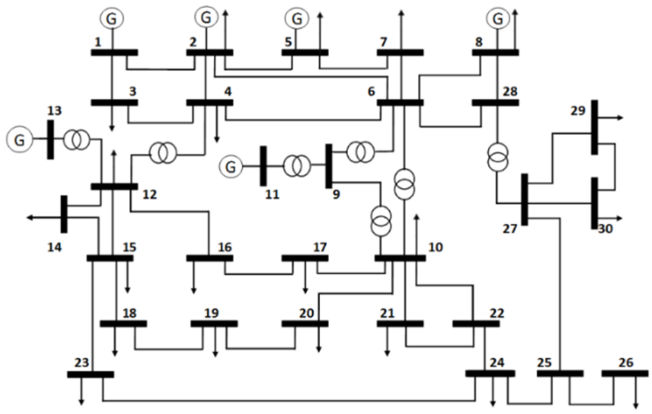


Fig.2. IEEE 30-bus network

3. PROBLEM FORMULATION

The objective of an OPF problem is to find the optimal settings of electrical control variables (generator outputs, bus voltages, tap settings, etc.), in order to minimize one or more objective functions separately or simultaneously, while satisfying related equality and inequality constraints.

The OPF/SCOPF problem can be formulated as:

Minimize: $f_0(x_0, u_0)$ (1)

Subject to: $g_c(x_c, u_0) = 0$ (2)

$h_c(x_c, u_0) \leq 0,\ c \in C = \{0,1,2, \ldots N_c\}$ (3)

Different OPF problem formulations can include various objective functions, f_0, in order to meet various techno-economic and other (e.g. environmental) requirements. This paper optimizes separately two most frequently objective functions: fuel costs, (4), and active power losses, (5).

$$F_T = \sum_{i=1}^{NG} [a_i P_{Gi}^2 + b_i P_{Gi} + c_i]\ \$/h \quad (4)$$

$$P_{loss} = \frac{1}{2} \sum_{i=1}^{NB} \sum_{j=1}^{NB} G(i,j)[V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)]\ MW \quad (5)$$

Equality constraints, (2), are represented by the power flow balance, (6)-(7). Inequality constraints, (3), represent equipment operating limits: generator real and reactive power limits, (8)-(9), transformer tap setting limits, (10) and branch thermal rating limits, (11), as well as bus voltage limits, (12).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)] = 0 \quad (6)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\theta_i - \theta_j) + B_{ij} \cos(\theta_i - \theta_j)] = 0 \quad (7)$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, i = 1,2, \ldots NG \quad (8)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i = 1,2, \ldots NG \quad (9)$$

$$T_i^{min} \leq T_i \leq T_i^{max}, i = 1,2, \ldots NT \quad (10)$$

$$S_{li} \leq S_{li}^{max}, i = 1,2, \ldots NL \quad (11)$$

$$V_i^{min} \leq V_i \leq V_i^{max}, i = 1,2, \ldots NB \quad (12)$$

4. CONVENTIONAL AND META-HEURISTIC OPF METHODS

Due to computational efficiency and strong theoretical background, network planners/operators typically rely on the use of conventional methods: Newton-Raphson, Quadratic Programming (QP), Interior Point Algorithm (IPA), etc. However, conventional methods are sensitive to the selection of initial values, might suffer from convergence problems and require the objective function to be differentiable. On the other hand, meta-heuristic methods are insensitive to initial values and do not require the calculation of the gradient.

When the network is heavily stressed with severe multiple contingencies, the new operating point will shift significantly from the (normal) pre-contingency operating point. In this situation, conventional OPF methods may fail to provide a solution due to the two main reasons: a) it is impossible to assume the proper initial conditions, as the system is far away from the previously known operating points, and b) the problem may become over-constrained, or the underlying matrices cannot be solved numerically. In both cases, the OPF problem becomes infeasible and algorithm may fail to converge. Nevertheless, the network operator should be able to identify the critical bus/line constraint violations, in order to devise further control actions (e.g. load shedding or demand side management) and maintain network integrity.

In this paper two conventional algorithms, Interior Point Algorithm (IPA) from (Zimmerman *et al.*, 2011), OPF solver from (Siemens PTI, 2011), and one meta-heuristic algorithm, PSO, are implemented to analyze the infeasible cases. Selection of feasible and infeasible cases is carried out via contingency analysis. The flow chart for implementation of PSO to OPF problem is shown in Fig. 3, where the fitness evaluation block involves calculation of full Newton Raphson power flow (NRPF) and then considered objective function.

4.1 Constraint classification and handling

From the mathematical point of view, constraints can be categorized into equality and inequality constraints. From the system operation viewpoint, constraints can be classified into soft and hard constraints. Additionally, bus voltage and branch thermal limits are considered as steady state operational security constraints in (Alsac and Stott, 1975) and the same notion is followed in this paper.

As most of the optimization or search algorithms (except primal algorithms) in their original form can only be applied to unconstrained optimization problems, constrained optimization problems have to be transformed into an unconstrained problem. While the equality constraints are always modeled using Lagrangian multipliers, inequality constraints are modeled with penalty functions. In general, there are two types of penalty functions, exterior penalty functions, which penalize the infeasible solutions, and interior penalty functions, which penalize feasible solutions.

Interior penalty functions work very well over soft and hard constraints, but if the problem is over-constrained with many hard constraints, interior penalty function approach may fail to find a solution. Exterior penalty functions are at least theoretically insensitive to hard and soft constraints. This is the main reason why both equality and inequality constraints are in meta-heuristic algorithms modeled with exterior penalty functions. In this paper, inequality constraints in conventional algorithms are modelled using both interior (log barrier) and exterior (linear and quadratic) penalty functions. The detailed description of constraint handling in the considered solvers is available in Siemens PTI (2011) and Zimmerman *et al.* (2011). For meta-heuristic algorithm, the constraints are modelled using static exterior penalty functions (13) -(15), (Smith, 2000 and Barbosa *et al.*, 2015).

$$F_p(x,u) = F(x,u) + P_{eq}\phi_{eq}(g(x,u)) + P_{ineq}\phi_{ineq}(h(x,u)) \quad (13)$$

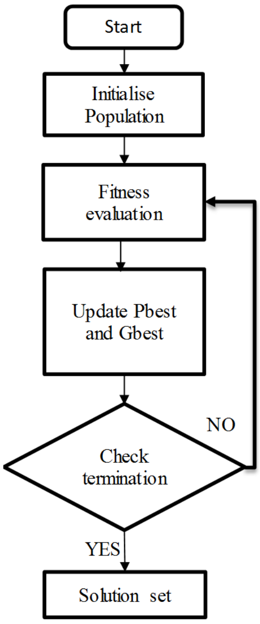
$$\phi_{eq}(g(x,u)) = \begin{cases} 0 & if\ g(x,u) = 0 \\ 1 & if\ g(x,u) \neq 0 \end{cases} \quad (14)$$

$$\phi_{ineq}(h(x,u)) = \begin{cases} 0 & if\ h(x,u) \leq 0 \\ 1 & otherwise \end{cases} \quad (15)$$

Using (13), the original objective function is augmented with the two penalty functions: one for equality and another for inequality constraints, specified by the corresponding penalty multipliers. The penalty multipliers applied in this paper for various equality/inequality constraints are shown in Table 2.

4.2 Methodology to identify critical constraints

Meta-heuristic algorithms use the modified objective function value to guide the search process and, as the iterations progress, this guided stochastic search will lead to zero measure of violation (i.e. all constraints are fulfilled), resulting in convergence of solution of the original constrained optimization problem. However, if there is no solution satisfying all the constraints, meta-heuristic methods use the same objective value during the iterations to minimize the number of constraint violations, while simultaneously minimizing the objective function. This provides valuable information to identify critical constraints that make the problem infeasible, as illustrated in flow chart in Fig. 4.



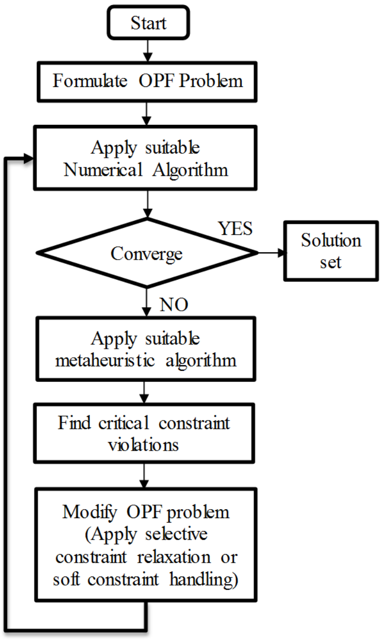


Fig.3. PSO to OPF Fig.4. Proposed approach

5. RESULTS AND DISCUSSION

The presented results are divided into two sections. First, a set of feasible OPF problem cases is selected and solved using both conventional and meta-heuristic algorithms. Afterwards, a set of infeasible OPF problem cases is selected, for which conventional algorithms fail to converge, but meta-heuristic algorithms minimize the concerned objective function with reduced/minimized number of constraint violations. Selection of OPF cases is carried out via contingency analysis, where feasible cases are these for which conventional algorithms converge with zero constraint violations, while infeasible cases are these for which conventional algorithms fail to converge. In both cases, the OPF problem is solved for two objective functions: fuel cost minimization (denoted as "F") and loss minimization ("L"), with one meta-heuristic and two conventional methods.

Analysis settings: System loads are represented by constant power load model, unless stated otherwise (constant current/impedance load models are also tried when conventional methods failed to converge). Transformers are modeled with fixed tap ratios given in Christie, (2000), in order to compare results calculated with different OPF solvers. In case of conventional algorithms, unless otherwise stated, all the constraints are treated as hard constraints.

Program settings: All programs are executed on a 64-bit Intel® Core i7-3770, 3.4 GHz desktop PC. Conventional OPF/SCOPF algorithms are implemented using MATPOWER and PSSE, while PSO algorithm is coded in MatLab (MathWorks), marked in figures as "IPA", "PSSE" and "PSO", respectively.

Parameter settings: These are listed in Table 2 for PSO methods, together with applied constraint violation penalties. The population size and number of iterations are both selected to achieve 100% success rate and strictly enforce reactive power and slack bus active power limits.

Table 2. Parameter and penalty settings for PSO

PSO settings		Penalty settings	
Population size	20	Reactive power	1000
Iterations	400	Slack active power	100
Social and cognition coeff.	1.494	Branch MVA	500
Inertia weight	0.729	Bus voltage	100

5.1 Feasible OPF cases

In this section, a set of feasible OPF cases is selected and solved with one meta-heuristic and two conventional algorithms. The optimal objective function values and list of constraint violations with the unconstrained power flow (i.e. NRPF solver without any controls activated) and with OPF are shown in Table 3 and Table 4, respectively. As the considered OPF cases are feasible, both conventional and meta-heuristic algorithms converge to almost the same objective values with zero constraint violations.

Table 3. Fuel cost and loss values with feasible cases

IEEE 14 Bus						
Contingency	**Fuel Cost ($/hr)**			**Loss (MW)**		
	IPA	**PSSE**	**PSO**	**IPA**	**PSSE**	**PSO**
L1-2	863.64	862.497	865.68	1.254	2.5407	1.2494
L4-9	791.99	791.929	793.85	1.325	3.2339	1.5289
IEEE 30 bus						
Contingency	**Fuel Cost ($/hr)**			**Loss (MW)**		
	IPA	**PSSE**	**PSO**	**IPA**	**PSSE**	**PSO**
L1-2	840.868	840.285	840.914	3.847	4.061	3.847
L4-12&T6-9	813.456	811.785	814.127	2.969	2.959	2.967

Table 4. List of constraint violations with feasible cases

IEEE 14 Bus						
Contingency	**Without OPF**		**With OPF**			
	MVA	**UV**	**MVA**	**UV**	**OL Lines**	**UV buses**
L1-2	3	0	0	0	NA	NA
L4-9	4	0	0	0	NA	NA
IEEE 30 Bus						
Contingency	**Without OPF**		**With OPF**			
	MVA	**UV**	**MVA**	**UV**	**OL Lines**	**UV buses**
L1-2	3	0	0	0	NA	NA
L4-12&T6-9	3	0	0	0	NA	NA

5.2 Infeasible OPF cases

For a given network topology and control space, the set of nonlinear equations may not have a solution satisfying all the imposed constraints. A set of such infeasible OPF problem cases (i.e. severe contingencies) is analyzed in this section. Based on the way inequality constraints are handled in conventional optimization algorithms, the analysis is divided into three sub-sections. In the case of PSO, constraints are always treated as soft, using exterior penalty functions.

5.2.1 All security constraints as hard constraints: In this sub-section, the considered problem cases are solved by treating all the security constraints as hard constraints that have to be satisfied in each iteration of the conventional algorithm. The optimal objective function values and list of constraint violations with the unconstrained power flow (marked as "without OPF") and OPF are shown in Tables 5 and 6. As the considered OPF cases are infeasible, conventional algorithms either diverge or numerically fail to converge, even with various initial conditions and load models. As the iterations progress, PSO is able to minimize the number of constraint violations and still minimize the objective function.

Table 5. Fuel cost and loss values for infeasible cases

Contingency	Fuel Cost ($/hr)			Loss (MW)		
	IPA	PSSE	PSO	IPA	PSSE	PSO
IEEE 14 Bus						
T5-6 & L9-14	X[a]	X	798.604	X	Y[b]	1.708
L6-13 & L9-14	X	X	812.999	X	Y	5.720
IEEE 30 Bus						
L1-2& T27-28	X[a]	X	847.338	X	X	5.517
L4-12&T27-28	X	X	809.220	X	X	4.781

[a] unable to converge for various initial conditions and load models
[b] algorithm diverges (blow up)

Table 6. List of constraint violations for infeasible cases (with PSO)

Contingency	Without OPF		With OPF			
	MVA	UV	MVA	UV	OL Lines	UV buses
IEEE 14 Bus						
T5-6 & L9-14	7	4	1	0	L13-14	NA
L6-13 & L9-14	6	2	3	2	L6-12 L12-13 L13-14	13,14
IEEE 30 Bus						
L1-2& T27-28	5	4	2	2	L24-25 L25-27	29,30
L4-12&T27-28	4	4	2	2	L24-25 L25-27	29,30

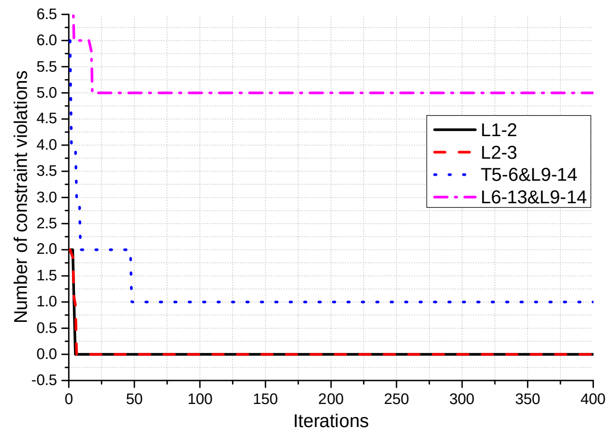


Fig. 5. Constraint violations with PSO for IEEE 14-bus

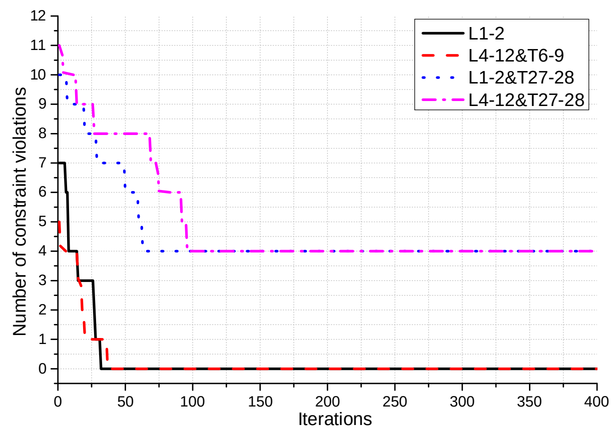


Fig.6. Constraint violations with PSO for IEEE 30-bus

From Table 5 and Table 6, the following conclusions can be drawn.

- From an algorithmic perspective, the identified constraints cause convergence problems for conventional optimization algorithms. For example, the thermal line constraints on branches (L24-25, L25-27) and undervoltage constraints at Buses (29, 30), Table 6, are the root causes for the convergence problems. This information is provided by the PSO and can be used for selective constraint relaxation and/or selective application of soft penalties.
- From control perspective, the identified lines/buses are the critical lines and buses where additional controls should be implemented (at operational stage), or planned (at planning stage), e.g. load shedding (or demand-side management), connection of reserve generation, shunt capacitors, FACTS devices, etc. to bring the system back to normal operating region. For example, buses 29 and 30 are potential locations for shunt capacitor placement, or for load shedding for considered contingencies.

5.2.2 All security constraints as soft constraints: With an aim to identify the critical constraints causing infeasibility, in this section all the security constraints are treated as soft constraints and modeled using linear and quadratic exterior penalty functions. In other words, the search space is widened by relaxing the constraints, so the conventional algorithms have a much higher degree of freedom during the search process. The list of resulting constraint violations at the optimum point with various penalty (Kp) values for IEEE 30 bus network is shown in Table 7.

Table 7. List of constraint violations with PSSE solver for IEEE 30-bus network

	Linear Penalty function			Quadratic penalty function		
OPF Case: L1-2 and T27-28						
$K_p \rightarrow$	10	100	1000	10	100	1000
Bus Voltage Violations	10	4	6	25	5	5
Branch MVA violations	3	2	3	2	2	2
OPF Case: L4-12 and T27-28						
$K_p \rightarrow$	10	100	1000	10	100	1000
Bus Voltage Violations	12	6	5	25	5	6
Branch MVA violations	3	2	2	2	2	2

Following conclusions can be drawn from Tables 6 and 7:

- the number of constraint violations at the optimum point with different exterior penalty functions and penalty values varies (with no specific order), which implies the criticality of penalty value selection in conventional algorithms. During the analysis, it is also found that the index of the violated constraints can change with multiple runs and initial conditions;
- the resulting number of constraint violations by conventional algorithms, Table 7, is higher than the number in meta-heuristic algorithm, Table 6.

5.2.3 Selective security constraints as soft constraints: In this section, selected security constraints which are identified by metaheuristic algorithm, Table 6, are only considered as soft constraints and modeled using linear and quadratic exterior penalty functions, as it is known that except these constraints all other constraints can be fulfilled at the expected optimal value. The optimal objective function values associated with considered problem cases for two test networks are shown in Table 8. From the results in Tables 5 and 8, the following observations can be made:

- conventional algorithms are able to converge without any problem, either by relaxing, or by applying lower penalty values on the critical constraints that are identified by PSO;
- conventional algorithms that are outperformed by PSO for feasible problem cases are now underperforming in minimizing the objective function for a given number and index of constraint violations.

Table 8. Fuel cost and loss values with applied selective relaxation and penalty values

	IEEE 14 bus		IEEE 30-bus	
Contingency →	T5-6 & L9-14	L6-13 & L9-14	L1-2& T27-28	L4-12 & T27-28
Fuel cost ($/hr)	796.487	809.117	**855.201**	**857.433**
Loss (MW)	2.332	4.972	5.999	4.8603

6. CONCLUSIONS AND FUTURE WORK

OPF/SCOPF studies remain to be the basic tools to assess and control the network performance during both planning and system operation stages. There will be situations when OPF problem may become infeasible and conventional algorithms in these cases might either diverge or fail to converge. Essentially, the mathematical indication of infeasibility is related to practical conditions important for the secure operation of the considered system and any further attempt to operate the network under these conditions might result in angle and/or voltage instability. This paper presents an alternative methodology, based on the use of a meta-heuristic algorithm, to identify the causes of infeasibility, which then can aid conventional algorithms in applying selective constraint relaxation, or selective soft constraint handling.

Conventional algorithms are computationally efficient and most of the time perform best for feasible problem cases, so it is advisable to use metaheuristic algorithms either independently or integrate them with conventional algorithms to solve the infeasible cases and propose suitable control measures (e.g. selective load shedding, demand side management, and reactive power injection) to prevent the system entering into the insecure region or bring the system back to secure operating region. This will be discussed in the future work (Jagadeesh Gunda and Sasa Djokic, 2016).

In order to avail the practical benefits of metaheuristic algorithms for power system planning and operations further research work need to be carried out mainly in two directions. One, reduction of computational time of the considered algorithm by availing the inherent task-level parallelism at objective function calculation stage and data-level parallelism at optimization stage. Second, development of domain independent constraint handling approaches for metaheuristic algorithm by problem and constraint transformation instead of common penalty approach.

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