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A NOVEL APPROACH TO MULTI-OBJECTIVE OPF BY A NEW PARALLEL NON-DOMINATED SORTING GENETIC ALGORITHM-II CONSIDERING DIVERSE CONSTRAINTS

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ABSTRACT

Transient stability constrained optimal power flow (TSCOPF) is able to reduce costs while keeping the operation point away from the stability boundary. While especially useful in modern power system operations, TSCOPF problems are practically very hard to solve; unacceptable computational time is considered to be one of the largest barriers in applying TSCOPF-based solutions. The basic idea of the proposed method is to model transient stability as an objective function rather than an inequality constraint and consider classic Transient Stability Constrained OPF (TSCOPF) as a tradeoffs procedure using Pareto ideology. Second, a parallel elitist Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used to solve the proposed multi-objective optimization problem; the parallel algorithm shows an excellent acceleration effect and provides a set of Pareto optimal solutions for decision makers to select. Case study results demonstrate the proposed multi-objective algorithm in bus system is quite strategic.

Keywords: TSCOPF, NSGA-II, GA, OPF, MW, IEEE39, genetic algorithm

1. INTRODUCTION

Optimal Power Flow (OPF) is an important tools for de- termini the optimal operating state of a power system while maintaining certain types of constraints. Only static security constraints were considered in early research, and the optimized dispatching solutions were prone to be close to the stability boundary, particularly in a competitive power market. Research interest has grown for Transient Stability Constrained Optimal Power Flow (TSCOPF) to overcome this limitation.

Mathematically, TSCOPF is commonly modelled as a large- scale Non-Linear Programming (NLP) problem, which includes the constraints of Differential-Algebraic Equations (DAE). Numerical discretization methods and constraint transformation methods are considered as the two main approaches to deal with DAEs in TSCOPF problems. Recently, other solutions have also been studied in the literature, including transient energy function methods, intelligence algorithms, implicit enumeration, and single-machine equivalent methods. Among these approaches, a combination of the numerical discretization method with the Interior Point Method (IPM) has become one of the mainstream algorithms, since it was easily proved and extended. One of the important extensions of IPM is the Reduced-space IPM (RIPM). It is widely used in chemical engineering and process optimization to solve discretized NLPs with few degrees of freedom, and has showed great performance improvement for solving numerical discretization-based TSCOPF.

However, the curse of dimensionality still exists, especially for TSCOPF with large-scale systems and multiple contingencies. Here we adopt parallel computing technology to relieve the curse of dimensionality in TSCOPF problems; TSCOPF is commonly modelled as a complicated Non-Linear Programming (NLP) problem including massive constraints of differential algebraic equations.

The two main approaches to study TSCOPF are simulation based on numerical discretization and constraint transformation. Recently, various methods have also been proposed, including trajectory sensitivity method, semi-infinite programming, transient energy function method, implicit enumeration method, and single-machine equivalent method. Among these approaches, a combination of the numerical discretization with the Interior Point Method (IPM) has been considered as a mainstream.

To overcome this problem, Intelligence Algorithms (IA) such as Differential Evolutionary Algorithm (DE) and Particle Swarm Optimization (PSO) were introduced to enhance robustness. The competition between IA and IPM is one of the most active factors in TSCOPF research and is also one of the main lines of this paper.

Though, great progress around TSCOPF has been reported in the existing literatures mentioned above, the mathematical models are always limited to single-objective optimization. Specifically, fuel cost is modelled as the sole objective function, transient stability and voltage or branch load flow are formulated as constraints. However, it must be noted that certain differences do exist between transient stability and static security constraint. Static security constraints are rigid and must be always respected during the power system operation; while, contingencies are not bound to happen, sometimes, to obtain a lower fuel or operation cost, some dispatch centers allow generators to operate under a certain degree of instability in a certain period of time.

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The first motivation of this paper is to adopt Pareto optimal ideology to redefine TSCOPF problem and propose a Multi-Objective OPF (MOPF) model considering transient stability. Inspired by the satisfactory application results of DE and PSO in solving TSCOPF, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is introduced to solve the proposed multi-objective optimization problem, which has been demonstrated to be effective in research areas such as optimal Distributed Generation (DG) allocation and transmission expansion planning. NSGA-II provides a set of Pareto optimal solutions for decision makes to select. This is the most important and significant advantage of the proposed method.

2. PROBLEM FORMULATION

A. Transient stability model and other constraint

The transient stability problem is commonly modelled as a set of DAEs. To simplify TSCOPF formulations, a classical generator model is typically used to describe the electro-mechanic transient behaviour of a generator, which can be expressed by the second order differential equations as below

$$\begin{cases} \dot{\delta}_i = \omega_o \omega_i \\ \dot{\omega}_i = \frac{P_{Gi} - P_{ei} - D_i \omega_i}{M_i} \end{cases} \quad i \in S_G \tag{1}$$

For the k^{th} contingency, the swing equations (1) are discretizedat every time step with an implicit trapezoidal method and converted into a series of algebraic equations:

$$\begin{cases} \Delta\delta_{i,t}^k \\ \Delta\omega_{i,t}^k \end{cases} \quad i \in S_{G,}\, t \in S_T, k \in S_c \tag{2}$$

Equation (2) is directly included in the NLP formulations of TSCOPF. The discretized and are defined as

$$\begin{cases} \Delta\delta_{i,t}^k = \delta_{i,t}^k - \delta_{i,t-1}^k - \dfrac{\omega_0 \Delta t(\omega_{i,t}^k + \omega_{i,t-1}^k)}{2} \\ \Delta\omega_{i,t}^k = \left(\dfrac{D_i \Delta t}{2M_i} + 1\right)\omega_{i,t}^k + \left(\dfrac{D_i \Delta t}{2M_i} - 1\right)\omega_{i,t-1}^k \end{cases} \tag{3}$$

$$P_{ei,t}^k = E_i^{'} \sum E_j^{'} \left(G_{ij,t}^k cos\delta_{ij,t}^k + B_{ij,t}^k sin\delta_{ij,t}^k\right) \;\; j \epsilon S_G \tag{4}$$

Where and are the elements of the reduced admittance matrix [4], which is a densematrix that changes its values duringthe pre-fault, fault-on, and post-fault stages. The relative angle, namely the rotor angle with respect tocentre of inertia (COI), is used as the criterion to describe the transient stability performance of generators:

$$\begin{cases} \Delta\delta_{i,t}^k = \delta_{i,0} - \delta_{COI,O} \\ \Delta\omega_{i,t}^k = \delta_{i,t}^k - \delta_{COI,t}^k \end{cases} \quad i \in S_{G,}\, t \in S_T, k \in S_c \tag{5}$$

Where the COI is defined as

$$\begin{cases} \delta_{COI,O} \dfrac{\sum M_i \delta_{i,0}^k}{\sum M_i} \\ \delta_{COI,t}^k = \dfrac{\sum M_i \delta_{i,t}^k}{\sum M_i} \end{cases} \quad i \in S_G \tag{6}$$

It should be noted that the system structure is assumed to be known beforehand and preserved during numerical simulations that the discretization on DAEs (1) can be performed. This assumption actually refers to the system continuity. Thatis, if the controller models with limiters, dead areas, and control mode switcher are considered, these elements may introduce discrete events or states into the system and change it from continuous to hybrid. In this case, the corresponding algebraic equations (2) are unable to be determined before numerical simulation. In fact; all numerical discretization based TSCOPF approaches are built on the assumption that the system is continuous, namely the system is described by DAEs whose structure does not change. These discrete events or states are absent from the classical generator model used in this paper but are actually quite common in real-life models.

In the above TSCOPF model, (7.1) is the objective function (fuel cost or the modification amount of scheduled contract power generation in deregulated power market); (7.3) is the static security constraints such as thermal constraints of branches and nodal voltage constraints; (7.4) is the constraints of generator power outputs or voltages and the constraints of transformer taps, etc. All kinds of Lyapunov direct methods such as transient energy function method and the extended equal area criterion method are unable to give enough robustness and calculation speed.

On the other hand, engineers have long been accustomed to use simulation method to judge the transient stability. If the simulation time is long enough, simulation method is able to guarantee sufficient accuracy and if the so-called classical model is used, the simulation method is also fast enough.

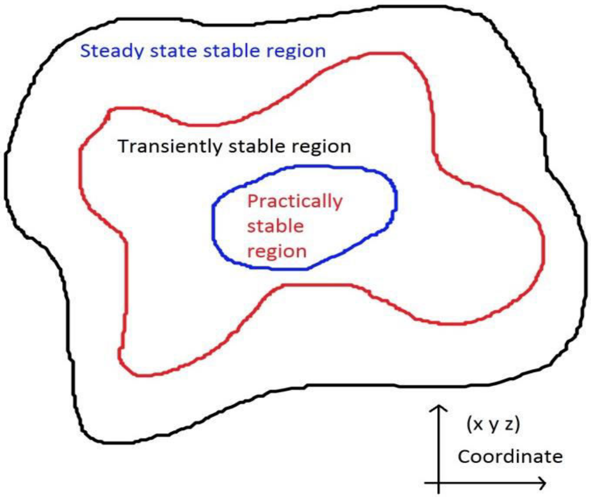

Figure-1. Illustrative regions of steady-state stability, transient stability and practical stability.

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Different from steady-state stability, the transient stability is defined for a specified disturbance as shown in Figure-1. In this paper, we further define practical stability by adding inequality constraints equation to transient stability before, during and after transient period, practical stability is not considered in the following section of this paper, which will be considered in next version.

B. Multi-objective OPF model considering transient stability (fitness function constraints)

The dispatch of power system is associated with a variety of factors. In many cases, engineers concern more about how to coordinate cost, security and stability of power system rather than getting a single rigid TSCOPF solution. In this way, transient stability is modelled as one of OPF optimization objectives, rather than a constraint. To meet practical application, additional power flow optimization objectives can also be incorporated into the model. The multi-objective OPF model can be expressed as follows:

$$\mathrm{Min}_{u,x}\, F_1 = c(\boldsymbol{u}) \tag{7.1}$$

$$\mathrm{Min}_{u,x}\, F_2 = \partial(\boldsymbol{y_n}) \tag{7.2}$$

$$\mathrm{Min}_{u,x}\, F_3 = c(\boldsymbol{x}) \tag{7.3}$$

$$\mathrm{S.T.}\ \text{Equation} : 2.2 - 2.5 \tag{7.4}$$

$$y_{n+1} - y_n - \frac{\Delta t}{2}[f(u,x,y_{n+1}) + f(u,x,y_n)] = 0 \tag{7.5}$$

F_1 is always modeled as the total cost of fuel consumed by generators:

$$F_1 = \sum_{i=1}^{N_G}(a_i + b_i P_{Gi} + c_i P_{Gi}^2). \tag{8}$$

P_{Gi} - Active output of the i[th] generator
a_i, b_i, c_i - Fuel cost coefficients of the i^{th} generator.

F_2 is the objective function quantifying transient stability, and can be of various modelling approaches. Here, we only consider the rotor angle stability and adopt the following penalty function:

$$F_2 = \sum_{i=1}^{N_G}\sum_{k=1}^{N_F}\sum_{n=1}^{\frac{T}{\Delta t}}\left\{\left[\psi\left(\left|\delta_n^i(k) - \delta_n^{COI}(k)\right|, \delta'\right)\lambda\right]\right\}. \tag{9}$$

is sorted again based on non-domination and only the best.

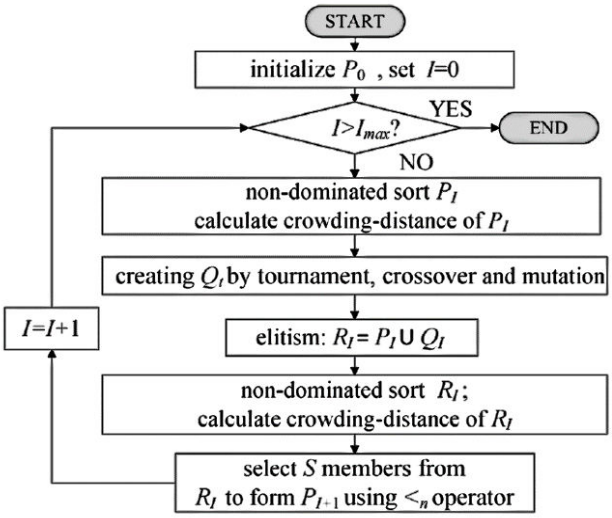

Figure-2. Flowchart of the working principle of NSGA-II.

Among these, NSGA proposed by Srinivas was considered generally as a direct expression of Goldberg's idea and of the best performance. Based on NSGA, Deb further proposed NSGA-II with an elitism strategy, which achieves a calculation complexity decrease and avoids the setting of sharing parameter.

NSGA-II has been demonstrated to be among the most efficient algorithms for multi-objective optimization on a number of benchmark problems. Its detailed implementation procedure can be found in a brief description of NSGA-II procedure is shown in Figure-2.

The population is initialized as usual and then sorted based on non-domination levels in to fronts. The first front is a set of chromosomes being completely non-dominant or not dominated by any other individuals in the current population, the second front being dominated by the chromosomes in the first front only and the front goes so on. In addition to front rank, a new parameter called crowding distance is calculated for each chromosome. The crowding distance is a measure of how close a chromosome is to its neighbours. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using Binary Tournament Selection based on operator $<_n$. $<_n$ is based on front rank and crowding distance as follows:

a) The chromosome with the higher front rank value is greater than the other regardless of crowding distance, and is selected;

b) The chromosome with the larger crowding distance is greater than the others located in the same front, and is selected.

The selected parent population generates off-springs after the operation of crossover and mutation operators. The population with the current population and current off-springs is sorted again based on non-domination and only the best N individuals are selected, so elitism is guaranteed, where N is the population size. The selection is also based on front rank and the crowding distance on the last front.

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3. NON-DOMINENT SORTING GENETIC ALGORITHM-II (NSGA-II)

The idea behind the non-dominated sorting procedure is that a ranking selection method is used to emphasize good points and a niche method is used to maintain stable subpopulations of good points. The population is ranked on the basis of an individual's non-dominated. The non-dominated individuals are assumed to constitute the first non-dominated front in the population and assigned a large dummy fitness value. The same fitness value is assigned to give an equal reproductive potential to all these non-dominated individuals. To maintain the diversity in the population these classified individuals are then shared with their dummy fitness values.

After sharing, these non-dominated individuals are ignored temporarily to process the rest of the population in the same way to identify individuals for the second non-dominated front. These non-dominated points are then assigned a new dummy fitness value that is kept smaller than the minimum shared dummy fitness of the previous front. This process is continued until the entire population is classified into several fronts.

The population is then reproduced according to the dummy fitness values. A stochastic remainder proportionate selection is used in this study. Since individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population. The population is ranked on the basis of an individual's non-dominated. This was intended to search for non-dominated regions or Pareto-optimal fronts. This results in quick convergence of the population toward non-dominated regions, and sharing helps to distribute it over this region. By emphasizing non-dominated points, NSGA favours the schemata representing Pareto-optimal regions. The efficiency of NSGA lies in the way multiple objectives are reduced to a dummy fitness function using a non-dominated sorting procedure

The Non-dominated Sorting Genetic Algorithm NSGAII uses a faster sorting procedure, an elitism preserving approach and a parameter less niching operator. The population is initialized as usual and then sorted based on non-domination levels in to fronts. The NSGA-II has been used for a wide variety of applications in a number of different fields. For some applications the NSGA-II has been used in its basic form whereas for some applications it has been modified in different ways.

A) Step by step procedure for NSGA-II

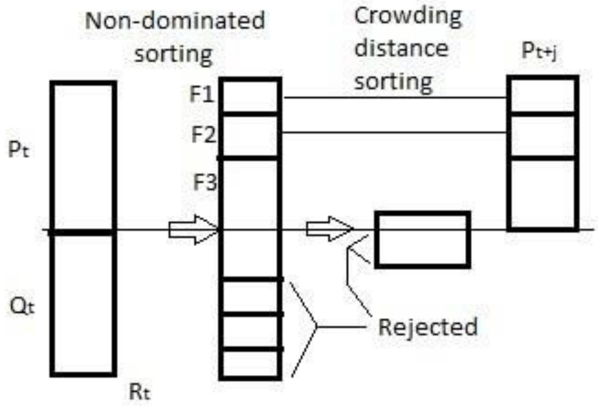

Figure-3. NSGA-II procedure.

NSGA operation in IEEE 39 bus, the following steps are to be followed:

Step 1: Initially create a population
First string = fuel cost
Second string = transient stability

Step 2: Perform power flow program. Newton power flow program for IEEE 39 bus system

Step 3: Find the fitness values for each individual fitness value

Step 4: Based on the fitness values, a new population has been selected from the old population based on the evaluation function as given.

Step5: Genetic operators (crossover and mutation) applied to the population that has been selected to create new solutions.

Step6: Fitness value is evaluated for new chromosomes and use them into the population.

Step7: Crowing tournament selection is evaluated and the crowing distance is obtained. As shown in Figure-3.

Step8: Elitism operation is conducted, best of the offspring's is selected and elitism process is done

Step9: If it exceeds the time, stop the process and provide the best Individual if not, proceed from step 4.

B) Objectives

The multi-objective model proposed in this paper as an effective quantitative analysis tool for Optimal Power Flow (OPF) associated with cost, transient stability and security a Non-dominated Sorting Genetic Algorithm-II (NSGS-II) is introduced to search the Pareto optimal solution. NSGA-II belongs to a class of evolutionary algorithms is used as an in this paper. The parallel algorithm shows an excellent acceleration effect and provides a set of Pareto optimal solutions for decision makers to select.

4. SIMULATION RESULTS

IEEE 39 bus system was used for testing Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and genetic Algorithm (GA), the result were obtained. A multi-objective model is proposed in this paper as an

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effective quantitative analysis tool for Optimal Power Flow (OPF) associated with cost, security and transient stability.

The obtained Parento optimal solution set, rather than a single strictly transient stable solution for decision makers to select their ideal schemes according to different preference. This is essentially different from traditional TSCOPF and the proposed method is considered to be able to get a theoretically strictly transient stable solution as well if enough iterations of evolution are carried out.

The objective such as minimizing fuel cost and improvement of voltage in power system ware obtained. The parameter used by NSGA-II is shown in Table-1. The results proves the NSGA-II is more efficient than the conventional method.

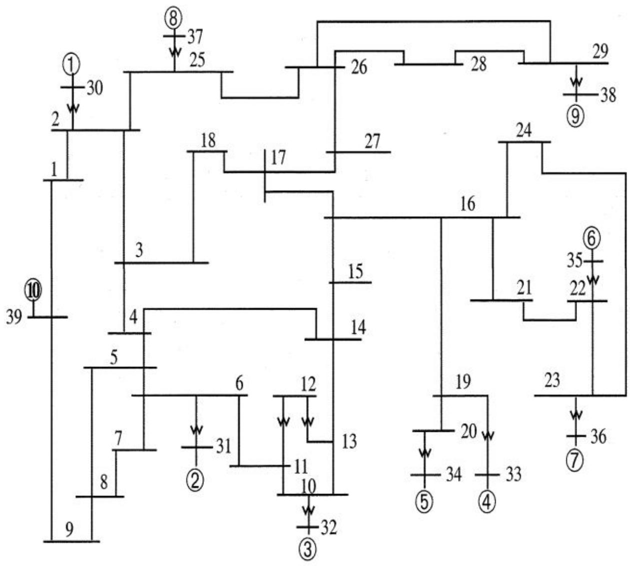

Figure-4. The ten-machine, 39-bus system

Table-1. NSGA-II parameters.

Dimension of search space	3
Structure type	Madaline
Population size	8
Number of generation	50
Network Type	Back Propagation
Mutation	0.2
Fitness increment	0.2
Crossover length	0.3

4.1 Convergence speed of NSGA-II

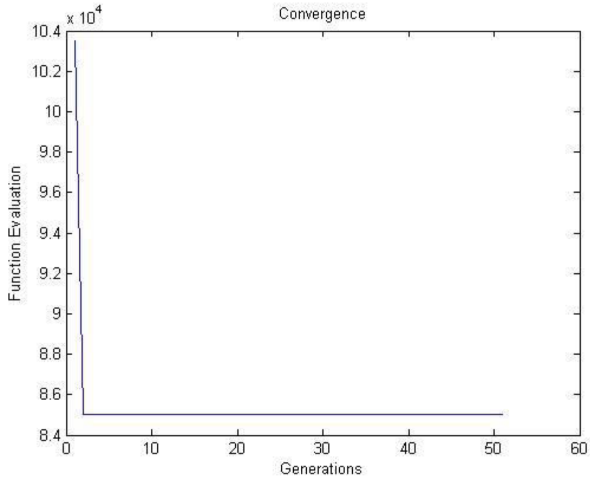

Figure-5. Convergence speed of NSGA-II.

4.2 Rotor angle curve of NSGA-II

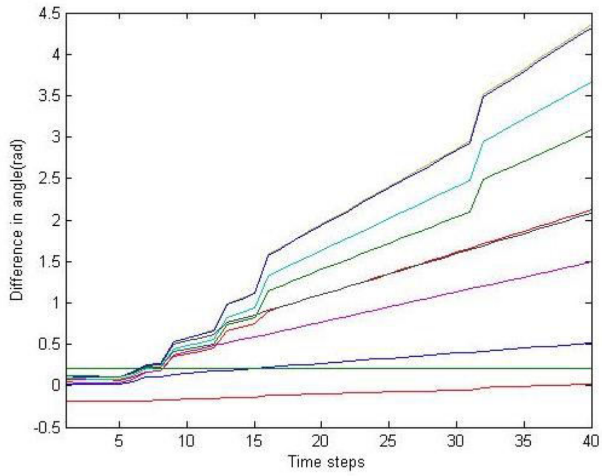

Figure-6. Rotor angle curve of NSGA-II

4.3 Voltage profile for IEEE 39 bus system

The voltage profile in IEEE 39 bus system before and after fault is shown in Figure-5.3, where the red plot indicates the voltage profile before fault and the blue plot indicated after fault voltage profile of the bus system.

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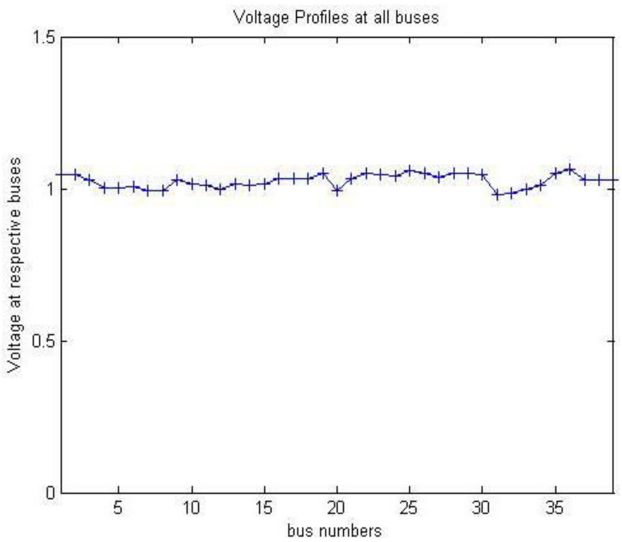

Figure-7. Voltage profile.

5. CONCLUSION

Large-scale multi-contingency TSCOPF problems are one of the most time-consuming computational tasks in power system. In this paper, an efficient RIPM-based two-level parallel decomposition approach is proposed to solve TSCOPF problems with high computing performance and memory efficiency. Bench- marks were performed with a series of test cases on a Beowulf cluster. Case studies indicate that the proposed approach inherits the convergence properties from the conventional serial IPM algorithm and shows great capacity to accelerate TSCOPF solutions.

The results shows that voltage profile is enhanced at buses and fuel cost are considerably decreased, model transient stability as an objective function rather than an inequality constraint and consider classic Transient Stability Constrained OPF (TSCOPF) as a trade-off procedure using Pareto ideology and minimization of generation cost. Thus it proves that the efficiency of NSGA-II is better than the conventional method.

The experimental results show that NSGA-II is competitive across all test problems. It gives good results by producing a set of non-dominated solutions (Pareto optimal solution) for the user to choose the most appropriate one rather than restricting to a single solution. It can also be seen that the addition or deletion of constraints or objectives does not affect the performance of NSGA-II much because each objective function is treated separately. Hence, NSGA-II is appropriate for the transient stability constrained Optimal Power Flow (OPF).

FUTURE SCOPE

Current numerical discretization based approaches are unable to handle hybrid systems in theory. However, discrete events and states are actually quite common in real-life models. Controller models with limiters, dead areas and control mode switchers are the basic elements for realistic dynamic models in power systems. Further efforts should be put on improving algorithms to handle hybrid systems.

Static power flow objective function is reserved in the proposed multi-objective OPF model, and NSGA-II is naturally not sensitive to the number of objective functions, so more objective functions such as loss, in addition to fuel cost and transient stability can be considered. To shorten the overhead for communication and further improve optimization speed, the implementation of the parallel algorithm on a supercomputer rather than PC cluster is a worth trying method.

We further define practical stability by adding inequality constraints equation to transient stability before, during and after transient period. Practical stability is not considered in the following section of this paper, which will be considered in next version.

Future scope can be carried on with Parallel Non-dominated Sorting Genetic Algorithm and a cutting-edge algorithm, also voltage profile of each buses and speed convergence will be displayed for the above algorithms. Here we have considered the IEEE39 bus system; further this implementation can be implemented in higher bus systems such as IEEE57, IEEE118, IEEE300 and IEEE1000 etc.

Nomenclature

The following symbols used that are defined as follows:

NSGA-II	Non-dominated Sorting Genetic Algorithm - II
GA	Genetic Algorithm
NR	Newton Raphson
TSCOPF	Transient Stability Constraint Optimal Power Flow
OPF	Optimal Power Flow
MW	Mega Watt
x, $\boldsymbol{x}$	Network variable / variable vector
y, $\boldsymbol{y}$	System state variable / variable vector
u, $\boldsymbol{u}$	Control variable/variable vector
$\boldsymbol{y_n}$, $\boldsymbol{y_{n+1}}$	Difference form of system state variable or state variable value at time n or n+1
$\boldsymbol{n}$	Step counter
$\Delta \boldsymbol{t}$	Integration step length
T	Simulation time length
$\mathbf{P_{G\mathit{i}}}$	Active output of the i^{th} generator
$\mathbf{N_G}$	Number of generators
$\mathbf{N_B}$	Number of buses
$\mathbf{N_L}$	Number of branches
$\mathbf{N_F}$	Number of expected faults
$\mathbf{a_i}$, $\mathbf{b_i}$, $\mathbf{c_i}$	Fuel cost coefficients of the i^{th} generator.
$\boldsymbol{e}$	Real part of bus voltage.
$\boldsymbol{f}$	Imagine part of bus voltage.
$\boldsymbol{U}$	Magnitude of bus voltage.
P_{ij},P_{ji}	Active power flow on branches.
$\boldsymbol{E'}$	Generator voltage behind direct axis transient reactance.
$\boldsymbol{\delta_o}$	Initial values of rotor angles.
$\boldsymbol{\delta_t}$	Rotor angles at time for the th contingency.

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ω_t Angular speed deviation at time for the th contingency.
δ Rotor angle vector
ω Angular speed vector
$\boldsymbol{\delta}_n^i(\boldsymbol{k})$ Rotor angle of k[th] generator at integration step after the expected fault
$\boldsymbol{\delta}_n^{COI}(\boldsymbol{k})$ Center of inertia of systemrotor angles at integration step after the k^{th} expected fault.
$\mathbf{T_j}$ Moment of inertia of the j[th] generator
$\mathbf{F}_j^{max}$ Maximum of the j^{th} objective function
$\mathbf{F}_j^{min}$ Minimum of the j^{th} objective function
$\mathbf{P_L}$ Total active load

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