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A Unified Framework for Participation of Responsive End-User Devices of smart grid with IMOPSO

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Abstract

The paper presents a unified control framework which allows the responsive end-user devices (REDs) such as inverter-based photovoltaic systems (PVs), plug-in hybrid electric vehicles (PHEVs), and domestic controllable loads at residential level to effectively participate in the voltage and frequency control of the smart grid. The presented control framework basically relies on extracting information from active and reactive power sensitivities at different buses. In this framework, for voltage control, two support groups namely the active support group and there active support group are dedicated to each transm–ission bus. However, for frequency control, only one active support group is defined for the entire system. The REDs used for voltage and frequency control are classified based on their controllability degree. The idea of selecting the most effective buses is also presented to minimize the burden of communication commands. Following the detection of voltage or frequency violation in the system, the targeted buses are identified and receive corrective control signals to accordingly change their active and/or reactive powers. To minimize the manipulated active and reactive powers, the whole process is formulated as improved multi-objective problem solved by the particle swarm optimization. The control procedure involves a series of commands for which the incident command system is used as a secure communication structure. In this paper an improved multi-objective particle swarm optimization algorithm (IMOPSO) is designed to efficiently solve multi-objective discrete optimization problems. In the IMOPSO, a novel similarity-based selecting scheme isused to selection of the global best solution and individual best solution for each particle, and an external set truncation strategy is used to maintain the diversity in the Pareto optimal solutions. Additionally, a local search subroutine is applied on every particle to improve the search efficiency of optimization. The IMOPSO is compared with two multi-objective particleswarm optimization algorithms proposed in the literature on several test problems, and experimental results show that the IMOPSO has good performance in multi-objective discrete optimization.
Keywords: Active support group, incident command system (ICS), Improved multiobjective optimization, reactive support group, responsive end-user device (REDs), smart grid

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I. INTRODUCTION

The multi-objective optimization (MOO) domain coversmany real-life optimization problems[l]. Particle Swarm Optimization (PSO) is an optimization algorithm based on swarm intelligence. It was developed by Kennedy and Eberhart [2] in 1995, which mimics the metaphor of bird flocking. Due to simplicity in implementation and efficiency in solving optimization problems, it has been used for solving MOO problems. One of the successful applications of PSO to multi objective optimization, named multi-objective PSO(MOPSO) , is the seminal work of Coello and Lechuga[3].The MOPSO adopts an external repository similar to the adaptive grid of P AES[9] for maintaining diversity. The fitness assigned to each individual in the external repository is computed on the basis of its density. This fitness is used in roulette wheel selection, to pick the global best solution. The individual best solution gets replaced by the present solution,only if the former is dominated by the latter. Hu and Eberhard[5] have also proposed another multi-objective PSO algorithm, named dynamic neighborhood PSO (DNPSO). In DNPSO, the global best solution is selected from the closest two swarm members for each swarm member.

The closenessis considered in terms of one of the objective, while the selection of the best solution from the closest two is based on the other objective. The individual best solution for each member gets replaced by the present solution only if the present solution dominates the individual best solution.

Based on the MOPSO, this paper presents an improved particle swarm optimization algorithm, called IMOPSO. The IMOPSO introduces a new idea in the selection of the best solution, namely similarity-based selecting scheme. In order to improve the diversity in the Pareto optimal solutions, an external set truncation strategy is used. Furthermore, a local search subroutine same as that in [10] is added to enhance the convergence to the Pareto optimal front. Several discrete optimization problems are tested and results show that the IMOPSO is better than the MOPSO and DNPSO.

II. COMMUNICATION STRUCTURE

In the proposed framework, the REDs are intended to play an essential control role upon the detection of a voltage or frequency violation in the grid. This implies that a huge number of the REDs individually, or in groups, participate to cope with a large-scale incident. In order to provide a timely and secure communication with the REDs, as suggested in [3]–[5], the incident command system (ICS) can be used. "The ICS is a systematic tool used for the command, control, and coordination of an emergency response" [17]. In this architecture, the members (agents) are working either individually or in groups using common operating procedures to meet a common goal for han- dling large-scale incidents. Members are divided into separate supervisor-employee realms [5], and the commands communicate with their hierarchical position. In the ICS, each member will respond to only its supervisorand each supervisor maintains authority over the members in its control realm.

Hence top-level agents/devices of each realm are not allow to directly communicate with any agents/devices in down-level of the next realm. In the future communication infrastructure of the smart grid [18], the ICS structure can favorably provide a framework to meet requirements of cyber secure and authenticated communication platform.

With reference to Fig. 1, in the proposed communication architecture, a chain of commands includes a central energy management system (EMS), transmission agent (TA), distribution agent (DA), and controller which controls the REDs with active/reactive control capability located at the distribution level. Each realm is enclosed by dashed line in Fig. 1. In practice, in keeping with the proposed ICS architecture, the central EMS only communicates with the TAs, while the TAs are resposible to communicate with the DAs. The overall top-down detection-and-response

The central EMS detects a voltage violation in the system. Using the approach proposed in this paper, it calculates as to correction tasks and sends the through hierarchy, where they are received by the TAs.

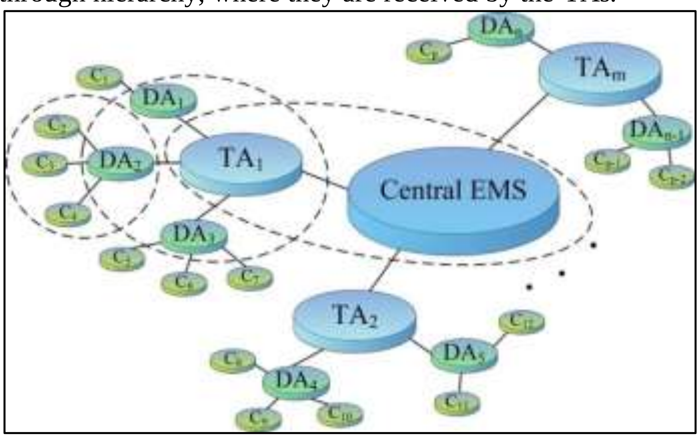


Fig. 1: Block diagram of the communication structure of the proposed control framework.

1) Upon receiving the correction request from the central EMS, each TA computes a set of response actions (described briefly in Section III-C3) that would ultimately allow it to meet the desired request. These response actions are sent to the Das to which they are connected.
2) Each DA receives a response action request from its top-level TA, and sends the active and/or reactive power request computed by TAs to the controllers within its purview.
3) Each controller then controls the REDs under its supervision based on their controllability degree to meet the requests.

It is worth mentioning that the proposed control framework relies on retrieving data on a regular basis over a Δt interval from the REDs notifying the central EMS about the recent system model. This time interval Δt is defined by the system operator. This is rather different from the communication procedure presented in [3] in which the correction request might not be fulfilled by the REDs requiring a new set of response that should be computed by the central EMS.

III. VOLTAGE CONTROL FORMULATION

In this section, we go into elaborate detail about the powerflow procedure which helps with acquiring the active and reactive power sensitivities from different buses. We then describe the proposed control methodology.

A. Power FlowModel:

As known, the conventional power flow is constituted based on the following assumptions: i) the system frequency is constant, and ii) the voltage dependence of loads is disregarded. The assumption of indicates that theoretically, the slack bus has an unlimited capacity to al- ways keep the steady state balance between generation and consumption. In practice, however, due to the limited amount of active power used as frequency control reserve [15], it is important to determine the frequency excursion following the events which alter the generation and consumption balance. Moreover, are alistic power flow calculation needs to take into account the voltage dependence of loads. The proposed control strategy takes the advantage of a different power flow pro- cedure which takes into account both the control model for the governor of generation units and the voltage dependence of loads. This implies that system frequency appears as a new state variable varying by the control characteristics of the generators and the loads characteristics[19] .Note that in the upcoming sections, all equations are given in the per-unit(p.u.) system, unless otherwise stated.

IV. BASIC CONCEPTS

Given a vector function of components defined on a finite set, consider the multi-objective discrete optimization problem:
Minimize Z = f(x) = (1] (x) = z], ⋯, Jr(x) = Zr)
Subject to x E' Q The image of a solution x E' Q is the point
z = f(x) in the objective space. A point z = (zl,' ·,zr) dominates z' = (z]', ,;zr') , if z, = f, (x) 0; z,' f/x'), vj and Zj C;' for atleast one j . A solution x dominates x' if the image of x dominates the image of x'. A solution x* E' Q is Paretooptimal (or non-dominated) if there is no x E' Q such that
z = I(x) dominates z' = fCx*).

The set of Pareto optimal solutions is known as the Pareto optimal set. The image of Pareto optimal set is known as Pareto front in the objective space.

V. PARTICLE SWARM OPTIMIZATION

PSO is a population-based heuristic, where the population of the potential solutions is called a swarm and each individual solution within the swarm, is called a particle[I]. Each particle flies through the problem space with a velocity which is constantly updated by the particle's own experience and the best experience of its neighbors in order to locate the optimum iteration by iteration. In each iteration, the velocity and position of each particle are updated by the following equations:

$$\bar{V}^i_{t+1} = w\bar{V}^i_t + c_1r_1(\bar{P}^i-\bar{X}^i)+c_2r_2(\bar{G}^i-\bar{X}^i) \quad (1)$$
$$\bar{X}_{t+1}^i = \bar{X}^i + \bar{V}^i_{t+1} \quad (2)$$

where V t is the t -th iteration velocity of particle i , is the t + 1-th iteration velocity of particle i , w is the inertia weight, C1 and C2 are the acceleration coefficients, x' is -I the current position of particle i , P is the individual best -I solution of particle i , g is the global best solution of particle i , r1 and r2 are random number between 0 and 1.

VI. MULTIOBJECTIVE PARTICLE SWARM OPTIMIZATION (MOPSO)

PSO is a population based Meta heuristic algorithm based on exploratory behavior of a swarm of particles (e.g., birds or fish), which was first introduced in 1995 [22]. This algorithm is formed in the basis of a search which is done by each particle to find the optimum or a quasi-optimum solution based on its own experience and experiences of nearby particles [21]. To this end, a set of particles in a -dimensional search space is considered as population in the generation .The particle at generation is defined by its position and its velocity $v^t\{v^t_{i\_1},\cdots,v^t_{i\_n}\}$. As the velocity and position of each particle changes with time, the new velocity and hence the new position of each particle is updated based on its current velocity,

The best previous position of particle so far , and which is the global best position among particles until generation , as follows

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad i = 1, \ \ldots., N \quad (3)$$
$$\{x^t_{i\_1},\ldots,x^t_{i\_n}\} \quad v_i^{t+1} = X\left[v_i^t + \varphi_1 R_1\left(P^t_{i\_best} - x_i^t\right) + \varphi_2 R_2\left(\left(G^t_{best} - X_i^t\right)\right)\right] \quad (4)$$

where and are acceleration constants, is the number of particles in the swarm, is the number of elements in the particle, and are uniform random values between 0 and 1, and is the constriction factor selected to limit the velocity oscillation [23].

$$x = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \qquad \varphi = \varphi_1 + \varphi_2 \quad (5)$$

The aim of a multi objective optimization problem, rather than finding a single solution, is to find a set of solutions which is called the Pareto front. Finally, one of the solutions is chosen based on the requirements of the decision maker [24]. This is in fact a critical part in MOPSO to select P_{best} and G_{best} among the whole available solution sets. To this aim, two concepts namely domination and non-domination are presented. As quoted in [24]: “solution is said to dominate solution J, if and only if is not worse than J in all objectives and is strictly better than J in at least one objective. Among a set of solutions , the non-dominated set of solutions P’are those that are not dominated by any member of the set”

A set of solutions A called “archive” or “repository” [25] could be specified to store non-dominated solutions. Archive members (maximum possible numbers are considered) are up- dated in every generation (time step) in order to save the best results. In MOPSO, velocity vector (31) can be rewritten as

$$V_i^{t+1} = [v^t_i + \Psi_1R_1(p^t_{i\_best}-X^t_i)+\Psi_2r_2(A(h)^t-X^t_i)] \quad (6)$$

Selection of the best answer for every particle up to generation , i.e, $P^t_{i\_best}$, is like finding the locations of that particle which are nondominated by the other locations of that particle.The $A(h)$ Is a value that is selected from the archive while index is defined by the method presented in[25]. In our formulation, the MOPSO algorithm is adopted to minimize the objective functions F_1, F_2 and F_3. To this aim we define the particle at generation as follows:

$$X_i^t = \left\{\Delta P^t_{1\_ctrl},\cdots,\Delta P^t_{Np-c\_ctrl},\Delta Q^t_{1\_ctrl},\cdots,\Delta Q^t_{Nq-c\_ctrl}\right\} \quad (7)$$

Where ΔP_{i_ctrl} and ΔQ_{i_ctrl} are the amount of changes in the active and reactive powers of selected P-C and Q-C buses. In this formulation, if frequency control is needed, N_{P-C} is the number of all P-C buses. Otherwise, N_{P-C} is the number of most effective P-C buses participating in voltage control. $N_{Q\text{-}c}$ is the number of selected most effective Q-C buses for voltage control. Note that $N_{P\text{-}C}$ and $N_{Q\text{-}c}$ are selected following the procedure described in Section III and $N_{P\text{-}C}$.

VII. IMPROVED MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION (IMOPSO)

This section describes the IMOPSO algorithm proposed in this paper and main differences of our approach with respect to the other proposals existing in the literature.

A. *Selection of the Best Solution:*

In PSO the position of each particle is updated by the individual best solution and global best solution. Usually,there is no single optimal solution, but rather a set of Pareto optimal solutions in MOO problems. IMOPSO uses an external set to store Pareto optimal solutions. Selecting a single Particle from the external set as the global best solution is a vital issue. Inspire by the idea of matingrestriction in [11], IMOPSO adopts a similarity-based selecting scheme to pick best solution. The basic idea is as follows. During the flight process of particles in the search space, the movement of each particle is guided by its individual best solution and global best solution. For multi objective problems, if the distance between the current position of particle and its previous best position and the distance between the current position of particle and the best position of the swarm are bigger, good flight direction of the particle is not likely to be generated. Therefore, the most similar one among the alternative best solutions to current particle is chose as its best solution to guide its flight. The similarity-based selecting scheme can be implemented using the Euclidean distance in the objective space.

Let ||f(x)-f(y)|| denote the Euclidean distance between two solutions x and y in the objective space, the ||f(x)-f(y)|| measure can be written as

$$|f(x) - f(y)| = \sqrt{\{f_1(x) - f_1(y)\}^2 + \cdots + \{f_r(x) - f_r(y)\}^2} \qquad (8)$$

Where r denotes the number of objective.

In IMOPSO, the selection of the best solution is done by following way. The nearest one among the Pareto optimal solutions in the external set to current particle is chose as global best solution. The current solution is compared with the individual best solution, if the current solution dominates the individual best solution or neither of them is dominated by the other, then we select the current solution as its individual best solution.

selection of the global best solution for the velocity update is done from this external set only. This set is updated by introducing non-dominated solution of the swarm and removing dominated ones. Meanwhile, the truncation strategy [12]is used to reduce the number of non-dominated individuals and improve the diversity. Two individuals closest to each other in Euclidean distance in the objective space within the non-dominated solution are chosen. The distances between second-closest individuals and the chosen individuals are evaluated, and the individual that is closer to its second-chosen individuals is reduced.

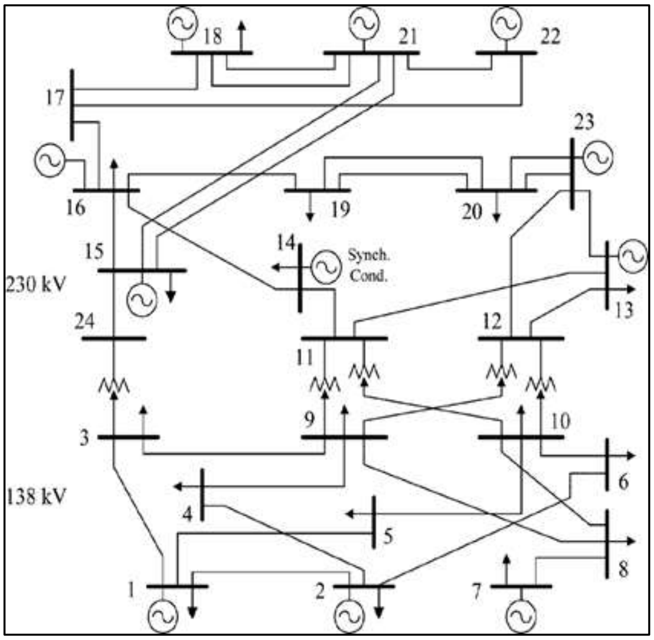
B. *Local Search:*

In order to overcome the poor convergence of the PSO, alocal search procedure is applied to all solutions in the population. This paper uses the method similar to [10]because this procedure may be easily implemented. The basic steps are as follows:
Step l. Specify an initial solution x;
Step2. Examine a neighborhood solution y of the current
Solution x;
Step3. If y is a better solution than x, replace the
Current solution x with y and return to Step2 .
Step4. If there is no better solution among the examined
K neighborhood solutions of x , end this procedure.
Otherwise, return to Step2

C. *IMOPSO Algorithm:*

The steps of the IMOPSO can be described as follows:
StepO. Parameters setting: population size N pop , inertia weight w , acceleration coefficients C1 and C2 , local search number of neighborhood solutions k,max ;

- Step1. Initialization: The initial population consists of N pop particles with random positions, and the velocity is initialized to zero in each dimension. Initialize external set NDj = 0;
- Step2. Evaluation: Calculate the objectives for each particle in the current population.
- Step3. Update external set ND, Non-dominated individuals in the are copied to the NDI and remove dominated ones from ND, Meanwhile, use the truncation strategy according to Section 6.2;
- Step4.Updates: Update the velocity and the position of each particle according to equations (1) and (2);
- Step5. Local search: Apply the local search on each individual in the population Pt+1 according to Section 6.3;
- Step6.Update best solution: Update the individual best solution and the global best solution of each particle according to Section 6.1;
- Step7. Termination criterion: If termination criterion is Met, output external set. Otherwise, return step2.



VIII. RESULTS AND DISCUSSION

To evaluate the performance of the proposed control strategy, we use two different systems, namely the IEEE 24-bus Reliability Test System (RTS) and the IEEE 14-bus power flow test system.

A. IEEE 24-Bus Reliability Test System (RTS):

The single line diagram of the RTS is shown in Fig. 2 whose associated data are presented in [26]. We use the hourly peak load corresponding to the Tuesday of 51th week shown in the Appendix (see Table A-I). The bus load data for the same day in- cluding the active and reactive powers of each bus in percent of the total load consumption is shown in Table A-II. It is noted that the total active and reactive load at time of system peak are 2850 MW and 580 MVAr, respectively. The system is consisting of 33 generators which are located at 11 buses as shown in Fig. 2. The active and reactive power limitations for the generators are listed in Table A-III in the Appendix. Note that generators located at buses 14, 21, and 23 are modeled as PV generators and the rest are considered as regulating generators participating in the frequency control. In our simulation, bus 13 to which three generators are connected is assumed as a reference for the phase angle calculation.

According to Table A-I, the hourly peak load varies between 64% to 100% of the daily peak load. This wide variation makes it necessary to specify different settings for all regulating generators to maintain the system frequency within 49.5 to 50.5 Hz. In fact, this assumption prevents the generators from exceeding their active and reactive power limitations. This is done by defining two different settings for generators; one during 22:00 to 7:00 and another during 7:00 to 22:00 as shown in Table A-III. The speed droop, for all regulating generators is set to 5%. The frequency and voltage dependent modelasin (6) and (7) is used for all loads whose co-efficients are as follows [21]:

$$K_p = 1.5 \qquad P_p = 0.85 \qquad P_c = 0.10 \qquad P_z = 0.05$$
$$K_q = 1.5 \qquad Q_p = 0.80 \qquad Q_c = 0.15 \qquad Q_z = 0.05$$

Table – 1
Classification of Load Controllability

Bus No.	Active Power			Reactive Power		
	Cat1	*Cat2*	*Cat3*	*Cat1*	*Cat2*	*Cat3*
1- 10	0.10	0.10	0.80	0.40	0.40	0.20
13- 16	0.10	0.05	0.85	0.40	0.20	0.40
18- 20	0.10	0.00	0.90	0.40	0.00	0.60

Table – 2
Load active Reactive controllability information for CAT-2(C; Controllable and NC: Non-Controllable

Cat2	Bus No.				
Hour	1- 4	5- 7	8- 10	13- 16	18- 20
24- 01	*C*	*C*	*C*	*C*	*C*
01- 02	*C*	*C*	*C*	*C*	*C*
02- 03	*C*	*C*	*C*	*C*	*C*
03- 04	*C*	*C*	*C*	*C*	*C*
04- 05	*C*	*C*	*C*	*C*	*C*
05- 06	*C*	*C*	*C*	*C*	*C*
06- 07	*C*	*C*	*C*	*C*	*C*
07- 08	*C*	*C*	*C*	*C*	*C*
08- 09	*C*	*C*	*C*	*NC*	*NC*
09- 10	*C*	*C*	*C*	*NC*	*NC*
10- 11	*C*	*C*	*C*	*NC*	*NC*
11- 12	*C*	*C*	*C*	*NC*	*NC*
12- 13	*C*	*C*	*C*	*NC*	*NC*
13- 14	*C*	*C*	*C*	*NC*	*NC*
14- 15	*C*	*C*	*NC*	*NC*	*NC*
15- 16	*C*	*C*	*NC*	*NC*	*NC*
16- 17	*C*	*NC*	*NC*	*NC*	*NC*
17- 18	*C*	*NC*	*NC*	*NC*	*C*
18- 19	*NC*	*NC*	*NC*	*NC*	*C*
19- 20	*NC*	*NC*	*NC*	*NC*	*C*
20- 21	*NC*	*NC*	*NC*	*NC*	*NC*
21- 22	*NC*	*NC*	*NC*	*NC*	*NC*
22- 23	*NC*	*NC*	*NC*	*NC*	*NC*
23- 24	*NC*	*NC*	*NC*	*NC*	*NC*

Following the procedure described in Subsection III-C, the devices (here we mean bus loads) are classified as *Cat1*, *Cat2*, and *Cat3* as shown in Table I. The relevant data for controllability of those devices belongs to *Cat2* over daily hours is presented in Table II.

As it is seen from Table A-II, the buses 11, 12, 17, and 21–24 have no load and they are considered as pure Cat3 buses. Therefore, these buses are not treated as possible P-C or Q-C buses. The PV buses are potential P-C buses while they do not participate in voltage control as Q-C buses since their output reactive power cannot be specified. Owing to these facts, the possible P-C and Q-C buses are considered as follows:

Possible P-C buses : {1,2,3,4,5,6,7,8,9,10,13, 14, 15, 16, 18, 19, 20}

Possible P-C buses : {1,2,3,4,5,6,7,8,9,10,13 , 14, 15, 16, 18, 19, 20}

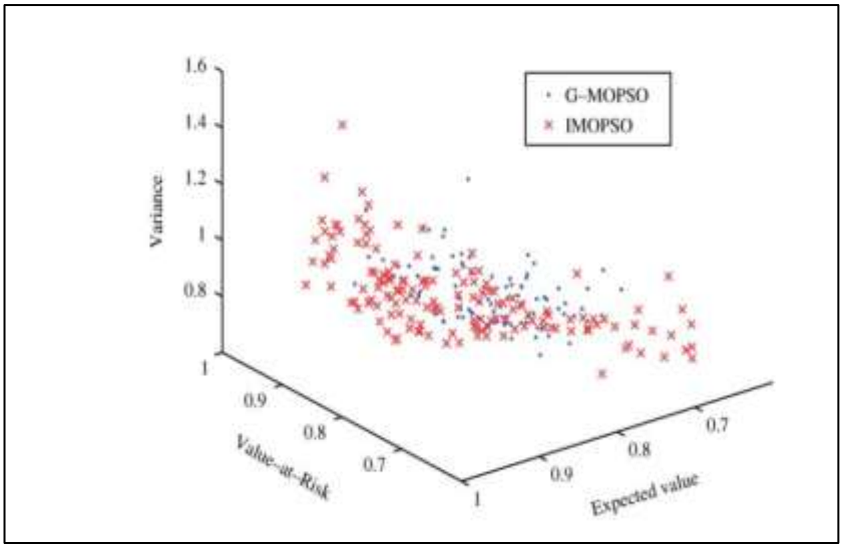


Fig. 3: Optimal solutions of IMOPSO and G-MOPSO (10 securities)

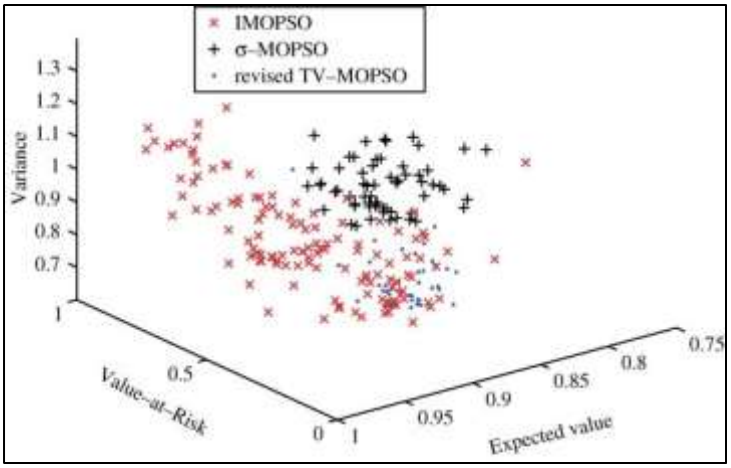


Fig. 4: IMOPSO and G-MOPSO

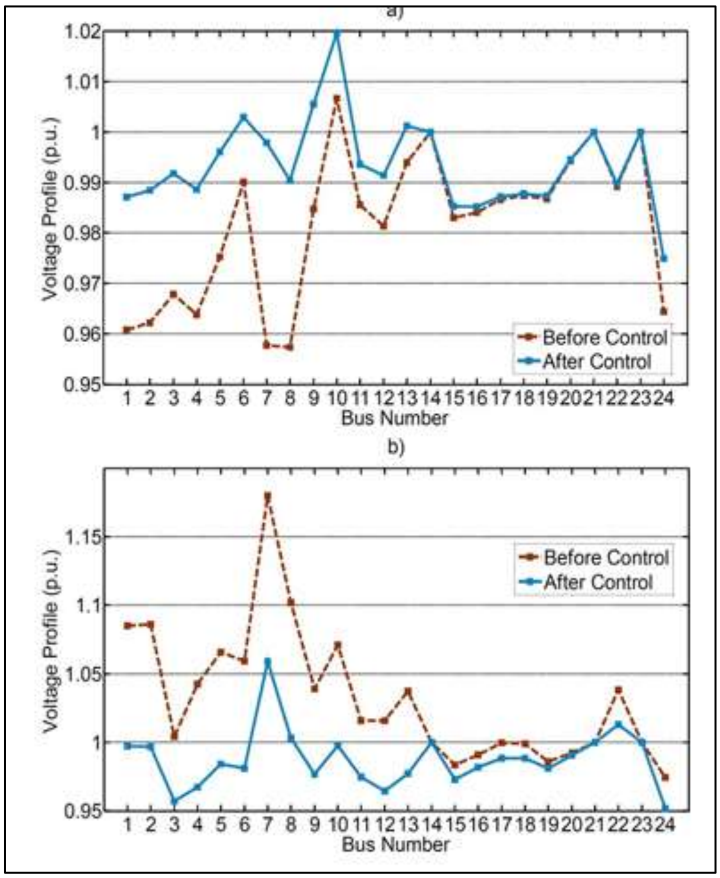


Fig. 5: Voltage profile of the system before and after control for time intervals: (a) 5:00–6:00, (b) 16:00–17:00.

IX. CONCLUSION

A unified control framework was presented for the efficient employment of responsive end-user devices (REDs) in the voltage and frequency control of the future smart grid. This is done by maintaining the balance between consumption and generation of active and/or reactive powers in the grid. The pro- posed control is carried out based on a secure communication architecture called incident command system (ICS). This approach relies on extracting information from active and reactive power sensitivities at different buses. The concept of support groups were extended to active and reactive support groups for voltage and frequency control. Additionally, the most effective P-C and Q-C buses for voltage control were introduced that help with reducing the communication burden of control commands. The REDs used for voltage and frequency control were classified based on their controllability degree. Upon the detection of a voltage or frequency violation in the system, the targeted buses are identified and receive the corrective control request to accordingly change their reactive or active powers. To minimize the manipulated active and reactive powers, the whole problem is solved by proposed an improved multi-objective particle swarm optimization algorithm (IMOPSO) to efficiently solve multi-objective discrete optimization problems

The IMOPSO uses a novel similarity-based selecting scheme to select the global best solution and individual best solution of each particle, and adopts an external set truncation strategy to maintain the diversity in the Pareto optimal solutions. Additionally, a local search subroutine is applied on every particle to improve the search efficiency of optimization. Compared with two multi objective particle swarm optimization algorithms proposed in the literature on several discrete optimization problems ,experimental results show that the IMOPSO has good performance.

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