

Incorporation of Distribution System Reconfiguration and Expansion Planning Problems by Considering the Role of Demand Response Resources

Hamidreza Arasteh, Mohammad Sadegh Sepasian, and Vahid Vahidinasab

Abstract. The planning of an active distribution system is investigated in this study. This paper conducts a novel concept of smart distribution system reconfiguration and planning problem. Proposed problem uses the concept of distribution system reconfiguration (DSR) with the aim of reducing and postponing the expansion requirements, while the potential of demand response (DR) programs are considered. DR programs are modeled as virtual and distributed resources to be dealt with the distribution system expansion planning (DEP) problem in the long term time horizon. Indeed, the main purpose of this paper is to propose “demand response and distribution system reconfiguration and expansion planning (DR-DSREP)” problem to identify the impact of DSR and DR on the expansion planning of distribution systems. The 33-bus distribution system is utilized in numerical studies to investigate the performance and effectiveness of the proposed problem. The simulation results show the efficiency and advantage of the proposed methodology.

Keywords: Active distribution system, demand response, distribution expansion planning, distribution reconfiguration.

Nomenclatures

Indicators:

y : planning year;
 m & n : bus number;
 m - n : line between buses m and n ;
 per : time period;

Sets:

Λ : set of lines;
 Δ : set of buses;
 Y : set of time periods;
 Y : set of planning years;

Parameters:

i : discount rate;

UC_{m-n} : upgrading cost per kilometer of line “ m - n ” [\$/km];

L_{m-n} : length of line “ m - n ” [km];

C_m^{DR} : cost of DR at bus “ m ” in peak period [\$/kW. hour];

LC : cost of energy losses [\$/kW. hour];

$t(per)$: duration of each time period [hour];

V^{min} , V^{max} : minimum and maximum permissible voltage level [kV];

I_{m-n}^{max} : maximum current capacity of line “ m - n ” [A];

$p_m^{DR(max)}$: maximum DR capacity at bus “ m ” [kW];

$EENS^{Max}$: maximum acceptable value of EENS [kW. hour];

Variables:

$NPVC$: net present value of the costs [\$/];

$C(y)$: total cost in year “ y ” [\$/];

$C^U(y)$: total system upgrading cost in year “ y ” [\$/];

$C^{DR}(y)$: total DR cost in year “ y ” [\$/];

$C^{Loss}(y)$: total cost of energy losses in year “ y ” [\$/];

$n_{m-n}(y)$: number of installed lines between buses “ m ” and “ n ” in year “ y ”;

$p_m^{DR}(y)$: amount of enable DR at bus “ m ” in year “ y ” [kW];

$T^{DR}(y)$: DR enabling time in year “ y ” [hour];

$p_{m-n,per}^{loss}(y)$: power losses of line “ m - n ” in time period “ per ” of year “ y ” [kW];

$V_{m,per}(y)$: voltage level of node “ m ” in time period “ per ” of year “ y ” [kV];

$I_{m-n,per}(y)$: current flow of feeder “ m - n ” in time period “ per ” of year “ y ” [A];

$EENS(y)$: value of expected energy not-supplied in year “ y ” [kW. hour];

$Pf_{m-n}(per,y)$: power flow of feeder “ m - n ” in the time period “ per ” of year “ y ” [kW];

Manuscript received December 18, 2014; revised February 28, 2015; accepted March 3, 2015.

The authors are with the Department of Electrical Engineering, Abbaspour School of Engineering, Shahid Beheshti University, Tehran, Iran.

The corresponding author's e-mail is: v_vahidinasab@sbu.ac.ir.

$z_{m-n}(per, y)$: binary variable that is equal to 1 if feeder “ $m-n$ ” is selected in time period “ per ” of year “ y ”; otherwise it is 0;

Abbreviations

DSR: Distribution System Reconfiguration;
DR: Demand Response;
DEP: Distribution system Expansion Planning;
DR-DSREP: Demand Response and Distribution System Reconfiguration and Expansion Planning;
GA: Genetic Algorithm;
PSO: Particle Swarm Algorithm;
IEA: International Energy Agency;
TBP: Time-Based Program;
IBP: Incentive-Based Program;
MBP: Market Based Program;
TOU: Time of Use;
RTP: Real-Time Pricing;
CPP: Critical Peak Pricing;
DLC: Direct Load Control;
EDRP: Emergency Demand Response Program;
I/C: Interruptible/Curtailable service;
CAP: Capacity Market Program;
DB: Demand Bidding;
A/S: Ancillary Service;
LDC: Load Duration Curve;
DG: Distributed Generation;
EENS: Expected Energy Not-Supplied [kW. hour].

1. Introduction

The expansion of electricity chain components is necessary due to load increases and includes generation, transmission and distribution system expansion planning. DEP is an important activity to cope with the forecasted electricity demand. A distribution network is a part of a network between distribution substations and customers' entrance gate including distribution substations, primary distribution system, distribution transformers, and secondary distribution system [1].

DEP problem consists of sizing, timing and siting of distribution facilities, while the restrictions of the system and components are overcome [2]. This problem is necessary to satisfy forecasted load and system constraints. Distribution system planners should be able to determine the peak load amplitude and its location to provide a suitable and efficient expansion plan with the optimal cost [3]. DEP methods have been assessed through numerous studies and various optimization algorithms are proposed to solve the introduced problems [4]-[6]. Network expansion planning requires a complex optimization procedure due to the nonlinear and combinatorial nature of the problem [7], [8]. Therefore, various studies are focused on utilizing some methods with random nature. However, such algorithms cannot guarantee the global optimum solution that is the main drawback of these methods [9], [10].

As mentioned above, lots of studies have investigated single or multi-stage expansion problem of distribution

systems with the aim of minimizing the investment and operation costs [11], [12]. Optimization algorithm should be employed for the best allocation of the limited financial resources [11]. Pseudo-dynamic theory [13], dynamic planning [14], graph-theory models [15] and heuristic algorithms such as GA are examples of the introduced optimization methods. According to the trends of studies in recent years, heuristic methods are being used increasingly in spite of their random nature [16], [17].

Recent studies and reports strongly focused on the importance and necessity of smart grids [18]. DR is considered as the core of smart grids and enabled by end-users to motivate changes in power consumption patterns. Reference [19] has investigated the influence of DR programs in a future smart electricity system in 2020. The effectiveness of DR programs has been assessed in [20]. According to the strategic plan of IEA, DR programs are considered as the first choice in all energy policy decisions [21]. The potential benefits of the demand side activities are introduced as a reason of such considerations [21]. Recently, DR programs attracted more attentions and are considered as resources, called DR resources. DR programs can be divided into three major classes, including [16]: TBPs, IBPs, and MBPs. TBPs consist of TOU, RTP, and CPP. In these programs, customers should cope with varying levels of time-dependent prices; the least with TOU and the most with RTP. IBPs consist of DLC, EDRP, I/C, and CAP. EDRPs are voluntary programs in which customers are not penalized if they do not response to the DR calls. In the DLC programs, utilities can directly curtail customers' electricity using a remote switch. I/C and CAP are mandatory programs and they use penalties if enrolled customers do not reduce their consumptions when directed. MBPs include DB and A/S programs. In DB programs, large customers will be encouraged to have participation at their desired price, or to determine that how much load they are willing to curtail at a specific posted price. In A/S programs, customers are allowed to bid load curtailment in electricity markets as operating reserves [16].

As it is explained in [22], distribution companies are one of the most important buyers for DR resources. They can purchase DR resources in a regulated market-based or conventional bilateral manner. From the economic point of view, distribution planners want to minimize all the investment costs (long-term horizon) as well as the operational costs (short-term horizon). Although DR programs are substantially short term activities, their effects on yearly LDC is not negligible. Indeed, in addition to the changes of daily electricity pattern, they are able to modify the LDC. Consequently, DR programs can be motivated in short-term time horizon; while the long-term aims are considered. In [23], the authors have investigated the effects of the DR programs on the planning of distribution systems.

DSR is another component of active distribution systems that is investigated in this paper. Distribution systems have some normally close and normally open switches. By changing the state of the switches, the configuration of the system will be changed. Generally, reconfiguration is to transfer parts of loads from one feeder to another. Lines' power flow, power losses, and voltage levels change via switching operations. So, DSR can reduce power losses and improve the operational condition of the system.

Furthermore, releasing the capacity of the transmission and distribution networks as well as the substations capacity can reduce the expansion requirements as a consequence of DSR. Thereby, DSR can have a direct effect on the expansion plans. It should be mentioned that by using the DSR, the state of the switches is changed. Consequently, in some time intervals, some of the corridors are not operated, while in some other time intervals, they may be used. Hence, by the reconfiguration of the system, some corridors are not operated just in some specific time intervals, but they still exist in the system. Indeed, distribution systems could be designed as meshed networks but they should be operated radially by opening some of the switches.

A lot of studies have investigated the problem of DSR [24], [25]. A long-term multi-objective planning framework is proposed in [26] to maximize the benefits of DSR beside the allocation of distributed generation units. Lines' reinforcement plan, network reconfiguration and the planning of distributed generation units are handled in [26]. A heuristic reconfiguration algorithm is presented in [27] that minimize the non-delivered power in contingency conditions.

A wide range of algorithms has been introduced to solve the DSR problem. A method based on bacterial foraging optimization algorithm is presented in [28] with the aim of loss minimization. Moreover, improved adaptive imperialist competitive algorithm [29], GA [30], artificial immune systems [31], and some other methods such as classical optimization techniques, parallel simulated annealing, reactive tabu search, database, and knowledge-based heuristic algorithms are proposed until now [27].

Basically, the DEP is a problem that considers the expansion and operation cost terms, besides the reliability of the system. In fact, the utility should provide a cost-effective and reliable service to provide the electricity demand with a standard quality level [32]. Reference [33] presented a multiobjective problem for the DEP by considering the planning costs and a reliability index (energy not served).

An MINLP model is proposed in [34] for the DEP problem, considering the expansion and operation cost terms as well as the reliability costs. In this paper, the reliability costs are computed by calculating the non-supplied energy in the distribution network. El-Zonkoly *et al.* [35] utilized the comprehensive learning PSO (CLPSO) to minimize the generation cost as well as un-served power cost. Zou *et al.* [36] introduced an analytical method to access the desired reliability of distribution systems based on the following criteria: system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI). The presence of DGs (dispatchable and nondispatchable renewable DGs) is also considered in this paper. Reference [37] proposed a time-sequential simulation approach to compute the cost of reliability in distribution systems. Chowdhury *et al.* [38] investigated the reliability level of distribution systems by considering the presence of conventional DGs like gas turbines. Several multiobjective problems have been presented to model the multistage DEP under dynamic or pseudodynamic procedures [39]. Consequently, optimization methods like MOPSO, NSGA-II, and NBI have been introduced to solve multiobjective problems

[40]-[42]. MOPSO is one of the appropriate meta-heuristic methods in order to solve the complex optimization problems due to its robustness in controlling parameters and its flexible applications [43].

Considering the importance of this research area, this paper proposes the "DR-DSREP" problem which incorporates DR, DSR, and the expansion planning problems.

As it is known, the presence of DGs is one of the most important components of the smart grid. However, the aim of this paper is to investigate the effect of DR and DSR in the planning of distribution systems. As it is mentioned, DR and DSR are essential components to construct an active distribution system. Hence, this paper investigates the necessity of DR, DSR, and the integration of them, in the DEP problem. The presence of DG units and their integration in the system can be investigated through another comprehensive study.

Regarding the role of DR resources in the future smart grid, DR models are developed in this paper to be dealt with the long-term planning framework. Hence, the effect of DR programs on the LDC is modeled and investigated through this paper. It should be mentioned that, for the sake of simplicity and without loss of generality, the DLC programs are considered in this paper to avoid the probabilistic nature of DR. However, stochastic models can be developed to evaluate the effect of other types of DR which is beyond the scope of this paper.

As aforesaid, DSR is addressed in the current study as another part of active distribution systems with the aim of reducing and postponing the expansion investments. Therefore, the decision variables of the reconfiguration problem are considered besides the DEP and DR variables. In order to satisfy the system reliability level, the EENS index is considered in this paper. A pseudo-dynamic procedure is utilized to solve the multi-stage problem. Furthermore, PSO is assigned in this paper to optimize the proposed problem.

In regard to previous studies, the main difference between this paper and [23] is to integrate the simultaneous effects of DSR and DR, on the DEP problem. Hence, by using some suitable scenarios, the effectiveness of DR and DSR, and also the integrated effects of them on the expansion planning of distribution systems are investigated. Furthermore, the EENS index is considered in this paper as the reliability criteria of the system as one of the system constraints.

The main contributions of the paper can briefly be classified as:

- Providing the long-term model of DR as some virtual distributed resources;
- Considering the role of DR resources in the DEP problem;
- Incorporating DSR with DEP to minimize total upgrading cost, while the potential of DR programs is modeled.

The rest of the paper is organized as follows. Problem description is explained in Section 2 which consists of the mathematical formulation of the objective function, system constraints, power flow, and optimization algorithm. Section 3 conducts the simulation results. Finally, concluding remarks are drawn in Section 4.

2. Problem Description

In this section, the problem is mathematically formulated. The multi-stage planning problem is considered in the long-term time horizon and solved by using the PSO method. The details of the PSO algorithm are explained in Section 2.4. Integrating the potential of DR and DSR in the DEP is the specific feature of the proposed problem.

As explained in section 1, DR programs can change the shape of LDC. Fig. 1 schematically illustrates the effect of DR resources on the LDC. As shown in Fig. 1, after enabling DR in a network, a part of peak demand will be transferred to the shoulder and off-peak periods. Loads can be classified as multi-period or single-period loads.

In multi-period loads, a specified percentage of loads can transfer to other periods. Single-period loads cannot be shifted to other times and they should be turned off when they are called to participate in DR programs. The modified LDC after considering DR in the network is depicted using dashed lines in Fig. 1.

Mathematical formulation of the problem is given as follows.

A. Objective Function

The objective function is to minimize the total expansion costs and simultaneously satisfy system constraints and cope with the forecasted load. The mathematical formulation can be expressed as equation (1).

$$\begin{aligned} \text{Min} \left\{ NPVC = \sum_y \frac{1}{(1+i)^y} \times C(y) \right\} \\ C(y) = C^U(y) + C^{DR}(y) + C^{Loss}(y) \\ C^U(y) = \sum_{m-n} \{ UC_{m-n} \times L_{m-n} \times n_{m-n}(y) \} \\ C^{DR}(y) = \sum_m [C_m^{DR} \times p_m^{DR}(y) \times T^{DR}(y)] \\ C^{Loss}(y) = \sum_{per} \sum_{m-n} [p_{m-n,per}^{loss}(y) \times t(per) \times LC \times z_{m-n}(per, y)] \\ \forall m-n \in \Lambda, m \& n \in \Delta, per \in \Upsilon, y \in Y \end{aligned} \quad (1)$$

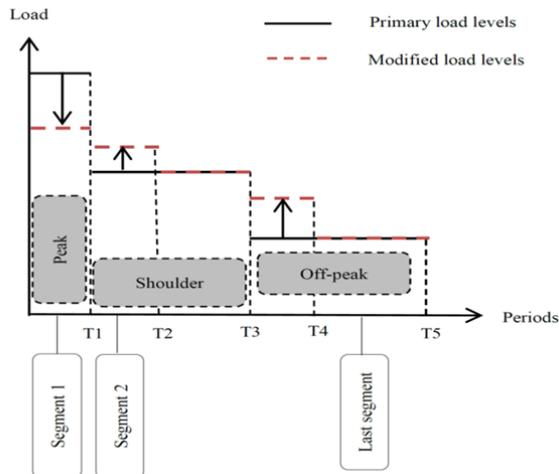


Fig. 1. The effect of long-term demand response on a typical LDC.

In (1), $C(y)$ denotes the required upgrading cost of the feeders. $C^{DR}(y)$ is the total cost that is needed to enable DR in the network. Moreover, $C^{Loss}(y)$ is the total cost related to the energy loss in the network.

Decision variables in the objective function formulation are line reinforcement ($n_{m-n}(y)$), system reconfiguration ($z_{m-n}(per, y)$), and the specification of DR programs ($p_m^{DR}(y)$). Furthermore, NPVC, $C(y)$, $C^U(y)$, $C^{DR}(y)$, $C^{Loss}(y)$, $T^{DR}(y)$, and $p_{m-n,per}^{loss}(y)$ are other variables of the objective function.

B. Constraints

Problem restrictions can be classified as follows.

1) Radiality and Connectivity of the Network

Distribution systems have tree shape graphs and should be operated radially [44]. Hence, islanded buses should not appear for providing the system loads. So, all the nodes in a fully connected tree shape distribution networks should be connected to the root of the graph [45], [1]. Furthermore, if system graph is connected, not islanded, equation (2) should be satisfied to ensure the radiality of the system. In (2), N^l and N^n are the number of network lines and buses, respectively. The presented approach in [46] is utilized in this paper to guarantee the radiality and connectivity of the network.

$$N^l = N^n - 1 \quad (2)$$

2) Permissible Voltage Levels

Voltage levels should not exceed the acceptable ranges. So, voltage constraints should be applied as inequalities (3).

$$V_{m,per}^{\min} \leq V_{m,per}(y) \leq V_{m,per}^{\max}, \forall m \in \Delta, per \in \Upsilon, y \in Y \quad (3)$$

3) Current Limits

The maximum current limits of lines are represented by (4).

$$-I_{m-n}^{\max} \leq I_{m-n,per}(y) \leq I_{m-n}^{\max}, \forall m-n \in \Lambda, per \in \Upsilon, y \in Y \quad (4)$$

4) The Maximum Penetration Level of DR

DR programs have limitations because of their barriers including customer barriers, producer barriers, and structural barriers [47]. These barriers are discussed in [47] by details. However, DR penetration level constraints are simply formulated by inequalities (5).

$$p_m^{DR}(y) \leq p_m^{DR(max)}, \forall m \in \Delta, y \in Y \quad (5)$$

5) Reliability Constraint

The reliability of the network should maintain in the acceptable range. The EENS index is utilized in this paper as the reliability criterion, as formulated by (6) and (7)

$$EENS(y) \leq EENS^{Max}, \quad \forall y \in \Psi \quad (6)$$

in which

$$EENS(y) = \sum_{per} \sum_{m-n} \left[\left(\lambda_{m-n} \times rp_{m-n} \times \frac{t(per)}{8760} \times L_{m-n} \right) \times pf_{m-n}(per, y) \times z_{m-n}(per, y) \right] \quad (7)$$

$\forall y \in \Psi$

where λ_{m-n} and rp_{m-n} are the failure rate of feeder “ $m-n$ ” per kilometer and per year (in fail/km. year) and the average duration of fault on feeder “ $m-n$ ” (in hr/fail), respectively.

C. Power Flow

The backward/forward sweep method is utilized in this paper for power flow calculation. The algorithm of this method is shown in Table 1.

Fig. 2 shows a typical radial distribution system with N load points. Z_m indicates the impedance of line between nodes “ $m-1$ ” and “ m ”. $I_{M,m}$ and $I_{L,m}$ are the currents of the main and lateral lines emanated from node “ m ” respectively. The substation voltage level is denoted by U_0 . P_n and Q_n are the active and reactive load levels of each load points. The procedure of the introduced method can mathematically be formulated with (8)-(14). Index ν denotes the iteration number of the backward/forward sweep algorithm ($\nu = \{1, 2, \dots\}$).

1) Initializing Step

$$\nu = 1, U_n^{(\nu-1)} = U_0, \quad \forall n = 1:N \quad (8)$$

2) Backward Process

Table 2 shows the formulation of a backward process. P_n^{DR} and Q_n^{DR} in Table 2 are enabled active and reactive powers with DR programs at bus “ n ”. P_n^b and Q_n^b are the active and reactive powers that are shifted from other periods to this period as a result of DR. Furthermore, $U_n^{*(\nu-1)}$ is the conjugate of $U_n^{(\nu-1)}$.

3) Forward Process

The forward process can be formulated as (14) to compute the voltage of each bus in iteration “ ν ”.

$$U_n^{(\nu)} = U_{n-1}^{(\nu)} - Z_n \times I_{M,n}^{(\nu)} \quad \forall n = 1:N \quad (14)$$

Table 1. Backward/forward sweep algorithm

Step	Description
1: Initializing	Initializing the voltage levels of all buses
2: Backward process	Evaluate power and current flows
3: Forward process	Evaluate voltage drops

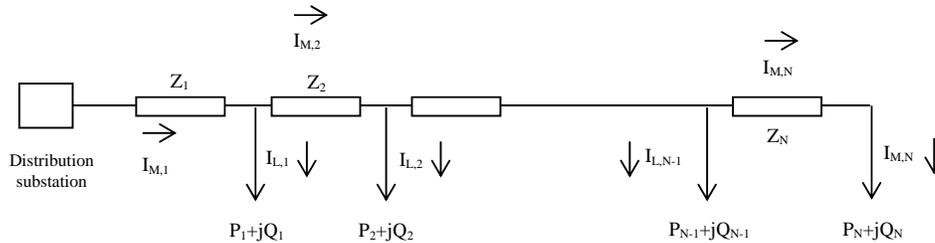


Fig. 2. A typical radial distribution system.

Table 2. The backward-sweep formulation

Equation Numbers	The Absence of DR	The Presence of DR
(9)	$I_{L,n}^{(\nu)} = \bar{S}_n^* \times \bar{U}_n^{*(\nu-1)}, \quad \forall n = 1:N$	$I_{L,n}^{(\nu)} = \bar{H}_n^* \times \bar{U}_n^{*(\nu-1)}, \quad \forall n = 1:N$
(10)	$I_{M,n}^{(\nu)} = \sum_{h=n}^N I_{L,h}^{(\nu)}, \quad \forall n = 1:N$	
Components of (8)		
(11)	$\bar{S}_n^* = P_n - jQ_n, \quad \forall n = 1:N$	
(12)	$\bar{H}_n^* = (P_n - P_n^{DR} + P_n^b) - j(Q_n - Q_n^{DR} + Q_n^b), \quad \forall n = 1:N$	
(13)	$\bar{U}_n^{*(\nu-1)} = \frac{1}{U_n^{*(\nu-1)}}, \quad \forall n = 1:N$	

The process should be repeated by substituting $v = v + 1$ until the satisfaction of the convergence criteria [23].

3. Solution Method

The PSO technique is implemented to solve the optimization problem. The PSO is a population-based optimization algorithm introduced by Eberhart and Kennedy [48]. It is based on the number of particles and inspired by the behavior of insects' swarm or birds' flock [49]. The PSO has some important advantages in comparison with other heuristic methods like GA. The PSO has more effective memory capacity, more diversity to search the optimum solution and also faster search speed [50].

Swarms in the PSO algorithm consist of the group of particles that determine the solution points [50]. Each particle moves in the solution space toward the best solution with a specific velocity, while it has memory to save its best previous position [48]. The i^{th} particle velocity is assigned based on (15).

$$\zeta_i(j+1) = \zeta_i(j) + r \times (G(j) - x_i(j)) + r' \times (P_i(j) - x_i(j)) \quad (15)$$

where, “ j ” represents the number of iterations, and ζ_i expresses the velocity of particle “ i ”. “ r ” and “ r' ” are random variables between 0 and 1. $G(j)$ is the best solution of all particles (global best solution) until the iteration number “ j ”. $P_i(j)$ is the best solution of the i^{th} particle (individual best position) until the iteration “ j ”. Furthermore, x_i denotes the position of the i^{th} particle in the solution space. According to (15), the velocity of each particle in the PSO method is based on its current and previous conditions and also the positions of other particles. The decision variables can be updated based on (16).

$$x_i(j+1) = x_i(j) + \zeta_i(j+1) \quad (16)$$

Line reinforcement, network reconfiguration plan, and the specification of DR programs are considered as the decision variable of the proposed problem that should be determined using the PSO algorithm. Table 3 illustrates all the equations regard to the decision variables of the

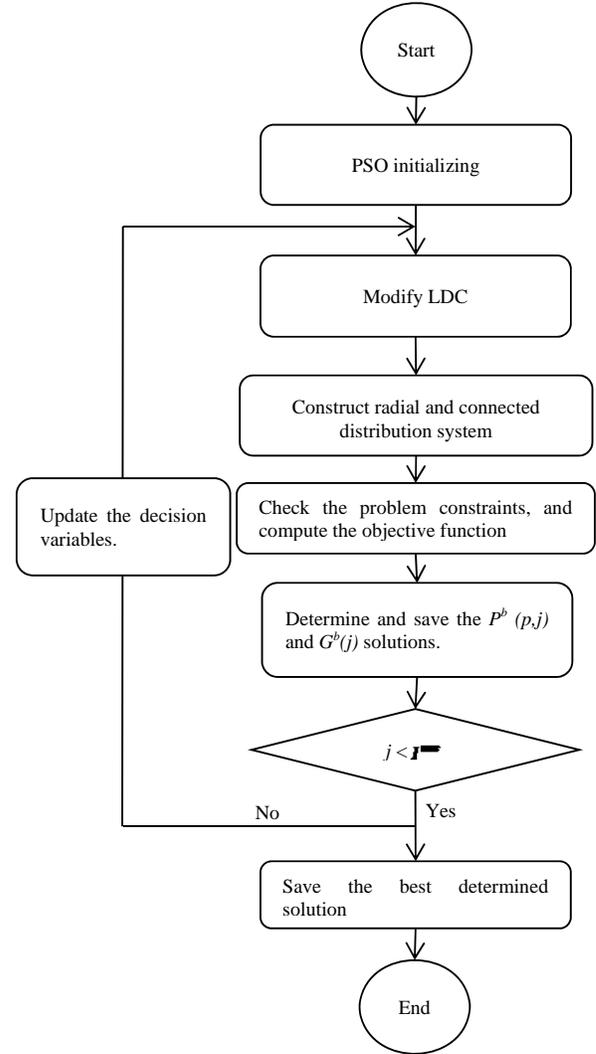


Fig. 3. Overall scheme of the optimization process.

proposed problem. Equations [17]-[22] in this table formulate the velocity and position of the swarms of these decision variables. Fig. 3 shows the algorithm of the proposed problem. In this figure, $P^b(p, j)$ is the best

Table 3. PSO formulations for the velocity and position of the swarms for decision variables

Decision Variables	Equations	Equation Numbers
Line reinforcement	$DV_i^U(j+1) = DV_i^U(j) + v_i^U(j+1)$	(17)
	$v_i^U(j+1) = v_i^U(j) + r1 \times (G^U(j) - DV_i^U(j)) + r2 \times (P_i^U(j) - DV_i^U(j))$	(18)
Demand response	$DV_i^{DR}(j+1) = DV_i^{DR}(j) + v_i^{DR}(j+1)$	(19)
	$v_i^{DR}(j+1) = v_i^{DR}(j) + r3 \times (G^{DR}(j) - DV_i^{DR}(j)) + r4 \times (P_i^{DR}(j) - DV_i^{DR}(j))$	(20)
Network reconfiguration	$z_i(j+1) = z_i(j) + v_i^z(j+1)$	(21)
	$v_i^z(j+1) = v_i^z(j) + r5 \times (G^z(j) - DV_i^z(j)) + r6 \times (P_i^z(j) - DV_i^z(j))$	(22)

solution of swarm “ p ” until the “ j^{th} ” iteration. Moreover, $G^b(j)$ denotes the best solution of all the swarms until the iteration number “ j ”. I^{max} is the maximum number of the PSO iterations. If each generated particle cannot satisfy the system restrictions, a penalty factor will be considered for it. Consequently, undesirable solutions will be avoided because of the high amount of penalties.

Next section provides all the simulation results and comprehensive analysis that is required to investigate the performance of the proposed problem.

4. Numerical Results

A. Input Data and Assumptions

The 33-bus distribution system is considered as a case study to explore the planning results. Fig. 4 illustrates the primary configuration of this system. Dashed lines in Fig. 4 are related to the tie-lines and colored circles determine the candidate buses that have a potential to participate in DR programs. System specifications are provided in Table 4. All the 33-bus test system data are adopted from [51]. The maximum capacity of lines is assumed to be 118 A. The multi-stage problem is solved using the pseudo-dynamic approach. The base standard load data is considered as the forecasted demand at stage 1 (the first year of planning horizon). It is supposed that the load levels are increased by 10 percent per year with respect to the previous year for buses 8-18, and 5 percent for remained buses. It should be mentioned that the salvage value of the lines are related to their lifetimes that are usually more than the horizon planning time of the distribution systems that is considered in this paper. Hence, by considering the main aim of this paper that is to show the effects of the DR and DSR on the DEP problem, and without loss of generality, the wires lifetime is not considered in this paper. Furthermore, according to [26], the switching cost is around 203 (\$/switching). It is clear that the switching cost is negligible in comparison with other cost terms in the distribution expansion problem. Hence, the switching costs can be neglected without affecting the validity and accuracy of the results.

Both primary and modified LDCs after considering the effect of DR programs are computed for each node of the

system as it is depicted in Fig. 1. In Fig. 1, horizontal dashed lines are corresponding to the modified LDC. Vertical arrows denote the changes of load levels in each time segment after DR implementation. Three load levels are considered as the primary LDC segments including peak, shoulder and off-peak periods. The durations of segments are supposed equal to 360, 4900 and 3500 hours, respectively. In addition, demand levels in shoulder and off-peak periods are considered to be 75 and 60 percent of the peak load data. Also, DLC programs are considered here to avoid the probabilistic nature of DR programs. According to Fig.1, by considering the effect of DR resources, estimated 3-segment LDC will break into 5-segment curve. Intervals [T1-T2] and [T3-T4] are equal to [0-T1] which is total hours that DR programs are enabled in the network.

As it is mentioned in the previous section, multi-period loads can be shifted to other periods, while single-period loads cannot. If DR is enabled in peak periods, the amount of load in peak time will be decreased, while the load level in other periods will be increased due to the shifted loads. So, some parts of curtailed load will be transferred to shoulder, some parts will be shifted to off-peak, and some parts will be turned off. It is assumed that 20 percent of the curtailed load will be transferred to the shoulder hours and 50 percent of responsive load will be shifted to off-peak area. Residual loads are considered to be turned off (single period loads). Furthermore, the value of discount rate is considered equal to 20% to compute the net present value of the cost terms.

Table 4. System characteristics

Specification	Dimension	Value
Voltage base	kV	12.66
Energy cost	\$/MW.hour	60
Cost of DR	\$/MW.hour	200
Lines' reinforcement cost	\$/km	145000
planning horizon time	Year	4
Substation voltage	Per-unit	1.04
permissible voltage levels	Per-unit	[0.96, 1.04]

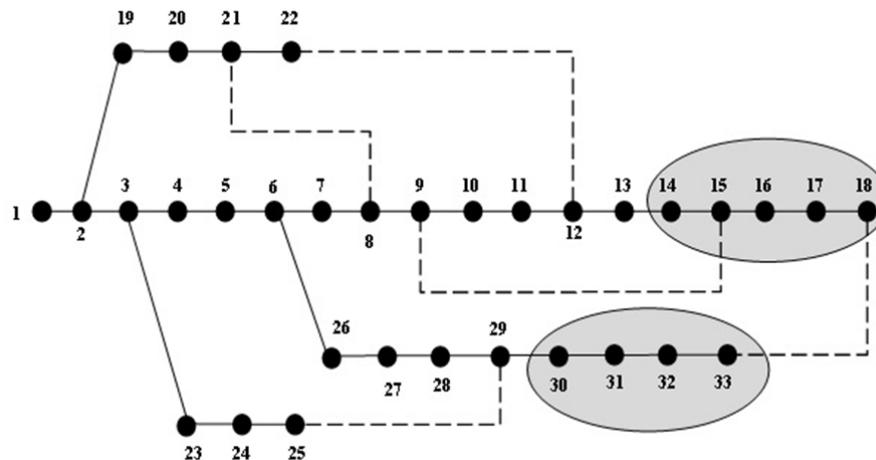


Fig. 4. The 33-bus distribution system.

B. Simulation Results and Analysis

As it is listed in Table 5, four scenarios are defined here to explore the effectiveness and performance of the proposed problem, including:

- *Scenario 1*: Distribution system expansion planning;
- *Scenario 2*: Distribution system expansion planning considering the potential of DR resources;
- *Scenario 3*: Integrated distribution system reconfiguration and expansion planning;
- *Scenario 4*: Demand response and distribution system reconfiguration and expansion planning.

The first scenario optimizes the expansion planning problem in a conventional manner without considering the potential of DR resources and DSR. The second scenario takes into account the potential of DR resources in the planning problem. Scenario 3 integrates the problem of DSR with expansion planning of the distribution system. Finally, Scenario 4 is elaborated to investigate the

effectiveness of the proposed DR-DSREP problem in which DEP and DSR problems are incorporated in the presence of DR resources. Table 6 describes the cost details of simulation results for all the scenarios. As it can be seen in Table 6, the net present value of the base case (scenario 1) is 1.85 (M\$). It is decreased to 1.63, 1.48 and 1.00 (M\$) and shows 11.89, 20.00 and 45.95 percent cost reduction using scenarios 2,3 and 4, respectively. Open sections in each year are listed in Table 7. It should be mentioned that

Table 5. Different scenarios

	DR Programs	DSR
Scenario 1 (#1)		
Scenario 2 (#2)	✓	
Scenario 3 (#3)		✓
Scenario 4 (#4)	✓	✓

Table 6. Details of the planning cost for each scenario

Scenario Numbers	Objective Function (M\$)	Cost Terms (M\$)	Year 1	Year 2	Year 3	Year 4
1	1.85	System upgrading cost	1.02	0.07	0.95	0.65
		Total cost of energy loss	0.029	0.033	0.037	0.047
		Cost of DR programs	-	-	-	-
2	1.63	System upgrading cost	0.87	0.0	0.36	1.23
		Total cost of energy loss	0.027	0.031	0.038	0.044
		Cost of DR programs	0.006	0.006	0.006	0.007
3	1.48	System upgrading cost	0.58	0.36	0.36	0.95
		Total cost of energy loss	0.031	0.028	0.035	0.040
		Cost of DR programs	-	-	-	-
4	1.00	System upgrading cost	0.43	0.00	0.51	0.51
		Total cost of energy loss	0.028	0.029	0.034	0.042
		Cost of DR programs	0.002	0.009	0.002	0.016

Table 7. Open sections and new added lines in each scenario

Scenario Numbers		Year 1	Year 2	Year 3	Year 4
1	Open Sections	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29
	Added Lines	1-2 (×2), 2-3 (×2), 3-4, 4-5, 5-6, 6-7	1-2	2-3, 3-4, 4-5, 5-6, 6-26	1-2, 7-8, 26-27, 27-28, 28-29
2	Open Sections	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29	8-21, 12-22, 9-15, 18-33, 25-29
	Added Lines	1-2 (×2), 2-3 (×2), 3-4, 4-5, 5-6	-	1-2, 3-4, 4-5	2-3, 5-6, 6-7, 7-8, 6-26, 26-27, 27-28
3	Open Sections	6-7, 9-10, 14-15, 17-18, 25-29	9-10, 14-15, 32-33, 8-21, 25-29	9-10, 14-15, 31-32, 8-21, 25-29	10-11, 14-15, 32-33, 8-21, 25-29
	Added Lines	1-2 (×2), 2-3, 3-4, 4-5	1-2, 2-3, 5-6	6-26	1-2, 2-3, 3-4, 4-5, 5-6, 26-27, 27-28
4	Open Sections	7-8, 10-11, 14-15, 32-33, 25-29	7-8, 10-11, 14-15, 32-33, 25-29	10-11, 14-15, 32-33, 8-21, 25-29	9-10, 14-15, 17-18, 8-21, 25-29
	Added Lines	1-2 (×2), 2-3, 3-4	-	1-2, 2-3, 4-5, 5-6	6-26, 26-27

Table 7 represents the corridors with open switches in each year. It means, for instance, in the first year of the scenario 4, by using switching operations, corridors 7-8, 10-11, 14-15, 32-33, and 25-29 will be opened and so will not be operated, while all other corridors are operated by closing the corresponding switches. Moreover, it should bear in mind that, as it is mentioned, the first scenario optimizes the DEP problem without considering DR and DSR. Hence, there is not any change in the states of the switches in this scenario. So, as it is obvious in Table 7, the opened switches are always same (because the potential of DSR is not considered in this scenario). However, to satisfy the increasingly load level of distribution buses, distribution feeders are upgraded. Hence, in this case, there is not any change in the state of switches because DSR is not applied

and switches of tie-lines are always open, but distribution lines are upgraded to satisfy the system constraints during the planning years. Fig. 5 shows the system reconfiguration and reinforcement plan in each year of the planning years for the scenario 4. Dashed lines in this figure indicate the upgraded corridors and the number of added lines.

The comparison results are shown in Fig. 6 for all the introduced scenarios. It can be concluded from Fig. 6, considering the potential of DR resources in the planning studies and incorporating DSR with DEP can reduce and postpone a major part of expansion costs and provide economic benefits for distribution system planners. According to Fig. 6, the proposed problem does not show any high investment requirements during all the planning studies. So, reducing a major part of expansion costs by DR

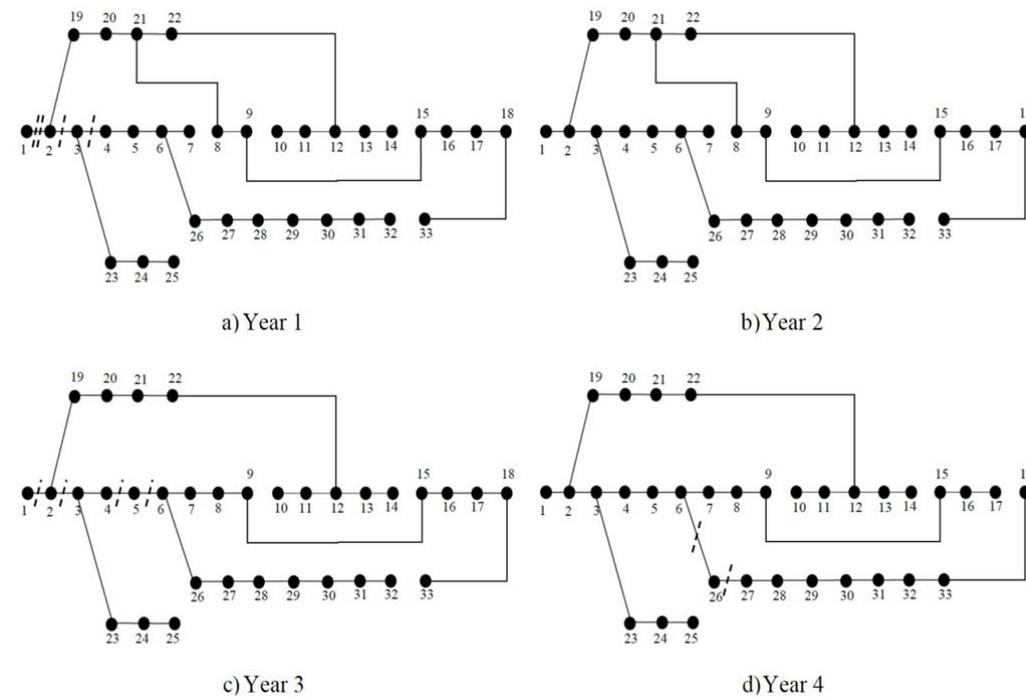


Fig. 5. The reconfiguration and expansion scheme of the system for the scenario 4.

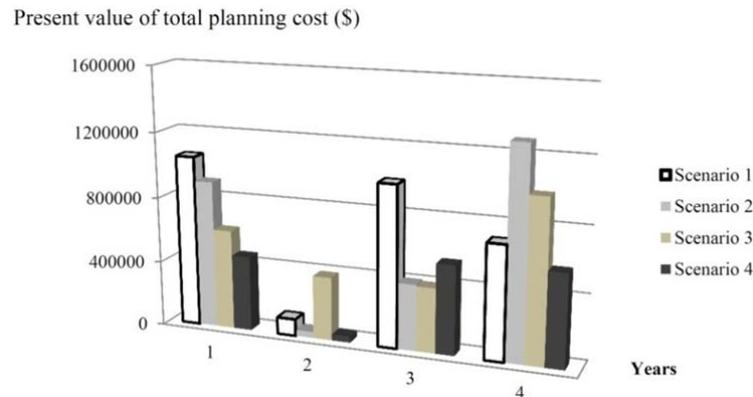


Fig. 6. Present value of total planning cost in each stage of each scenario.

and DSR and postponing some parts of costs to the later years, decreases the net present value of total costs. The amounts of cost terms are shown individually in Fig. 7 for each scenario. Furthermore, Fig. 8 illustrates the share of each term as a percentage of the total expansion cost.

According to Fig. 7, integrating DR and DSR with the expansion planning problem will dramatically reduce the system upgrading costs. As the main aim of the proposed problem is to reduce the total expansion costs, incorporating DR, DSR and DEP have higher effect on the required upgrading costs. Thereby, comparing Figs. 8-a and 8-d expose that the upgrading cost of lines has less percentage in the proposed problem than the first one. This fact is also correct for other scenarios that separately show the effect of DR and DSR. However, the penetration level of DR is impressive in the planning results. It should be noted that, in this paper, the DR potential is considered to be very limited, i.e.

DR is just applicable on buses 13-18 and 30-33 and just 20 percent of the load in each bus can participate in DR programs. The effect of the other penetration levels of DR on the planning cost is depicted in Fig. 9 for the proposed problem.

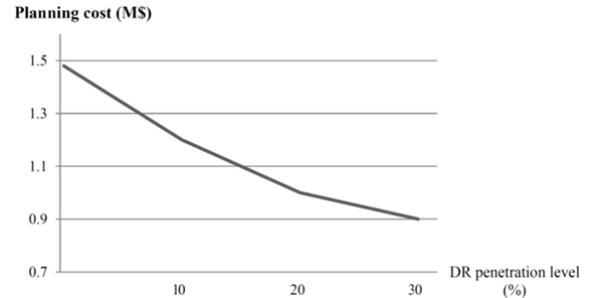


Fig. 9. Total planning cost with respect to the DR penetration level.

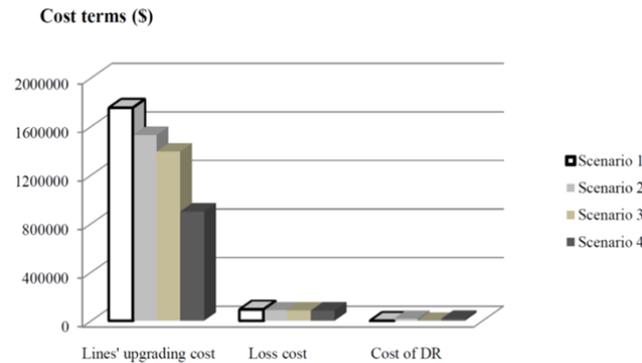


Fig. 7. Present value of total lines' upgrading cost, total loss cost, and total cost of DR in different scenarios.

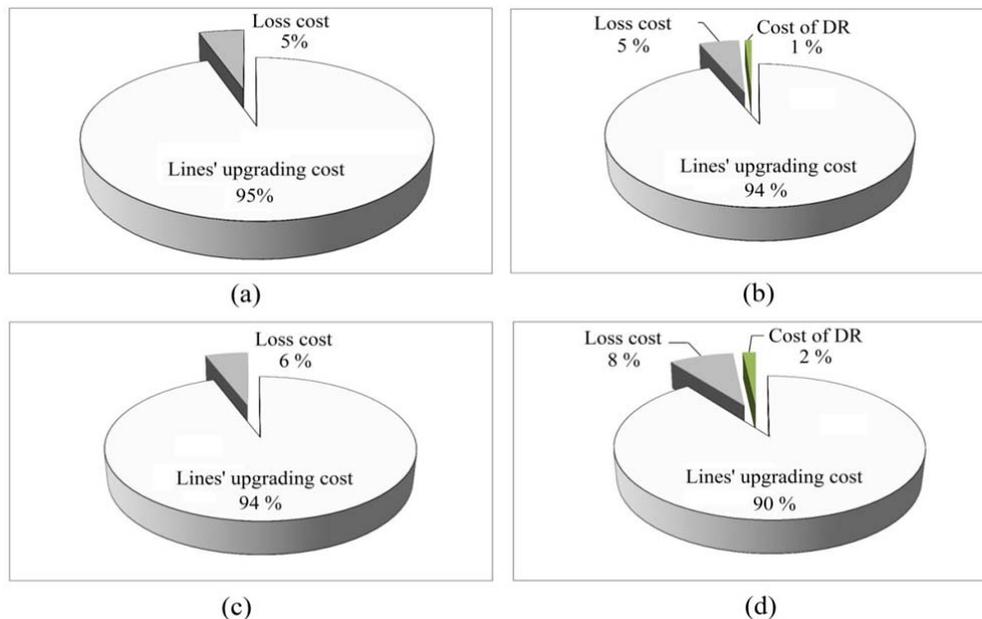


Fig. 8. The share of cost terms in the total planning costs: a) scenario 1, b) scenario 2, c) scenario 3, d) scenario 4.

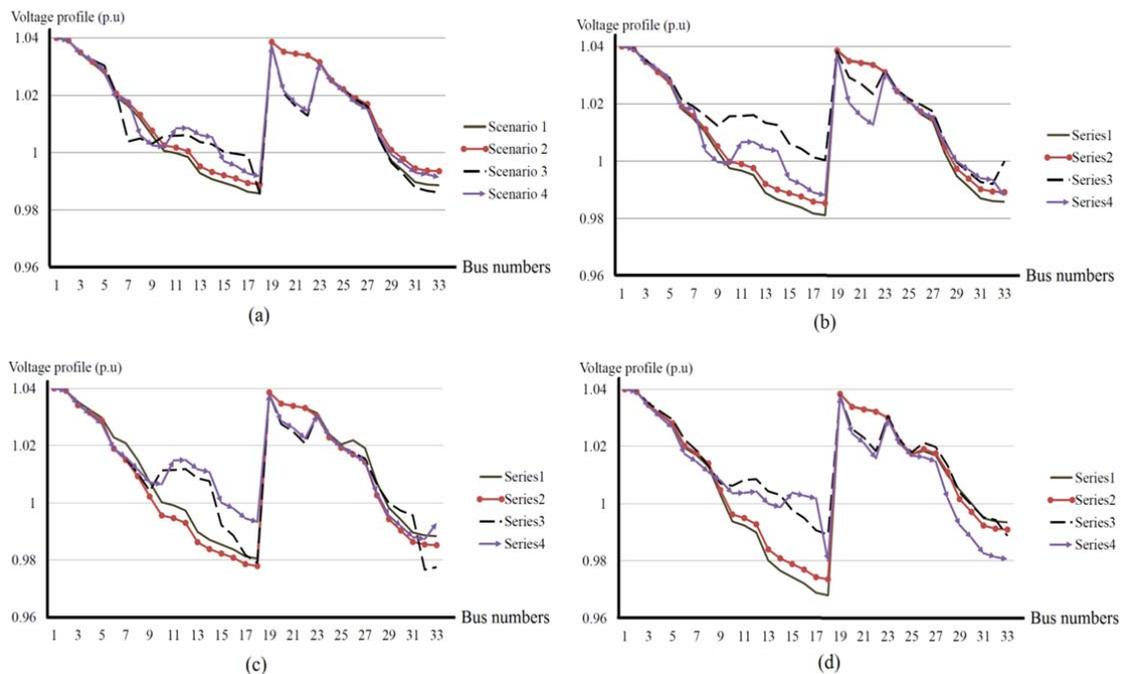


Fig. 10. Voltage profile over different buses for each scenario a) year 1, b) year 2, c) year 3, d) year 4.

Fig. 9 illustrates the changes of the expansion cost with respect to the various penetration level of DR in the network. Furthermore, Fig. 10 represents the voltage levels of the 33-bus distribution system for each scenario in peak periods. It should be noted that the lower permissible voltage level is considered equal to 0.96 per-unit in this paper, which is completely satisfied in all the planning years. Finally, according to all the numerical analysis, the simulation results approve the efficiency and advantages of the proposed problem.

5. Conclusion

The active distribution system expansion planning is addressed in this paper by proposing “demand response and distribution system reconfiguration and expansion planning (DR-DSREP)” problem. DR programs are modeled as some virtual and distributed resources that can be used in a long-term expansion planning. Furthermore, DSR is integrated with DEP problem with the aim of reducing and postponing the total expansion cost. The concurrent impacts of DR and DSR are fully investigated as the main purpose of this study. The proposed problem is tested using the 33-bus distribution system and analyzed through four individual scenarios. The simulation results approved the economic benefits of the proposed problem as well as the operational advantages.

References

- [1] A. M. Cossi, R. Romero, and J. R. S. Mantovani, “Planning of secondary distribution circuits through evolutionary algorithms,” *IEEE Trans. Power Del.*, vol. 20, pp. 205-213, 2005.
- [2] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, “Multistage model for distribution expansion planning with distributed generation—Part I: Problem formulation,” *IEEE Trans. Power Del.*, vol. 23, pp. 915-923, 2008.
- [3] H. K. Temraz, and V. H. Quintana, “Distribution system expansion planning models: an overview,” *Electr. Power Syst. Res.*, vol. 26, pp. 61-70, 1993.
- [4] M. Setayesh Nazar, M. Haghifam, and M. Naz̄ar, “A scenario driven multiobjective Primary–Secondary Distribution System Expansion Planning algorithm in the presence of wholesale–retail market,” *Electr. Power Energy Syst.*, vol. 40, pp. 29-45, 2012.
- [5] A. Navarro, and H. Rudnick, “Large-scale distribution planning—Part I: Simultaneous network and transformer optimization,” *IEEE Trans. Power Syst.*, vol. 24, pp. 744-751, 2009.
- [6] B. R. Pereira Junior, A. M. Cossi, J. Contreras, and J. R. Sanches Mantovani, “Multiobjective multistage distribution system planning using tabu search,” *IET Gener. Transm. Distrib.*, vol. 8, pp. 35-45, 2014.
- [7] H. Xing, H. Cheng, Y. Zhang, and P. Zeng, “Active distribution network expansion planning integrating dispersed energy storage systems,” *IET Gener. Transm. Distrib.*, vol. 10, pp. 638–644, 2016.
- [8] M. Ahmadigorji, N. Amjadi, “A multiyear DG-incorporated framework for expansion planning of distribution networks using binary chaotic shark smell optimization algorithm,” *Energy*, vol. 102, pp. 199-215, 2016.
- [9] H. Falaghi, C. Singh, M. R. Haghifam, and M. Ramezani, “DG integrated multistage distribution

- system expansion planning,” *Electr. Power Energy Syst.*, vol. 33, pp. 1489-1497, 2011.
- [10] V. Vahidinasab, “Optimal distributed energy resources planning in a competitive electricity market: Multiobjective optimization and probabilistic design,” *Renew. Energy*, vol. 66, pp. 354-363, 2014.
- [11] S. Najafi Ravadanegh, and R. Gholizadeh Roshanagh, “On optimal multistage electric power distribution networks expansion planning,” *Electr. Power Energy Syst.*, vol. 54, pp.487-497, 2014.
- [12] A. R. Abbasi, and A. R. Seifi, “Considering cost and reliability in electrical and thermal distribution networks reinforcement planning,” *Energy*, vol. 84, pp. 25-35, 2015.
- [13] N. Khalesi, N. Rezaei, and M. R. Haghifam, “DG allocation with application of dynamic programming for loss reduction and reliability improvement,” *Electr. Power Energy Syst.*, vol. 33, pp. 288-295, 2011.
- [14] C. L. T. Borges, and V. F. Martins, “Multistage expansion planning for active distribution networks under demand and distributed generation uncertainties,” *Electr. Power Energy Syst.*, vol. 36, pp. 107:116, 2012.
- [15] A. M. El-Zonkoly, “Multistage expansion planning for distribution networks including unit commitment,” *IET Gener. Transm. Distrib.*, vol. 7, pp. 766-778, 2013.
- [16] H. R. Arasteh, M. Parsa Moghaddam, M. K. Sheikh-El-Eslami, and A. Abdollahi, “Integrating commercial demand response resources with unit commitment,” *Electr. Power Energy Syst.*, vol. 51, pp. 153-161, 2013.
- [17] S. M. Mazhari, H. Monsef, and Rubén Romero, “A multi-objective distribution system expansion planning incorporating customer choices on reliability,” *IEEE Trans. Power Syst.*, vol. 31, pp. 1330-1340, 2016.
- [18] P. S. Georgilakis, and N. D. Hatziargyriou, “A review of power distribution planning in the modern power systems era: Models, methods and future research,” *Electr. Power Syst. Res.*, vol. 121, pp. 89-100, 2015.
- [19] F. De Ridder, M. Hommelberg, and E. Peeters, “Demand side integration: four potential business cases and an analysis of the 2020 situation,” *Euro. Trans. Electr. Power*, vol. 21, pp. 1902-1913, 2011.
- [20] B. Kladnik, G. Artac, and A. Gubina, “An assessment of the effects of demand response in electricity markets,” *Euro. Trans. Electr. Power*, vol. 23, pp. 380-391, 2013.
- [21] IEA. Strategic plan for the IEA demand-side management program 2008-2012, *IEA Press*, 2008, <<http://www.iea.org>> [accessed 03.12].
- [22] H. R. Arasteh, M. Parsa Moghaddam, and M. K. Sheikh-El-Eslami, “A Comprehensive Framework for Retailer’s Financial Policy,” *Journal of Electrical Systems and Signals*, vol. 1, pp. 7-18, 2013.
- [23] H. Arasteh, M. S. Sepasian, and V. Vahidinasab, “Toward a Smart Distribution System Expansion Planning by Considering Demand Response Resources,” *Journal of Operation and Automation in Power Engineering*, vol. 3, no. 2, pp. 116-130, 2015.
- [24] H. Fathabadi, “Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach,” *Electr. Power Energy Syst.*, vol. 78, pp. 96–107, 2016.
- [25] A. M. Tahboub, V. R. Pandi, and H. H. Zeineldin, “Distribution system reconfiguration for annual energy loss reduction considering variable distributed generation profiles,” *IEEE Trans. Power Del.*, vol. 30, pp. 1677-1685, 2015.
- [26] A. Zidan, M. F. Shaaban, and E. F. El-Saadany, “Long-term multi-objective distribution network planning by DG allocation and feeders’ reconfiguration,” *Electr. Power Syst. Res.*, vol. 95, pp. 104-105, 2013.
- [27] A. González, F. M. Echavarren, L. Rouco, T. Gómez, and J. Cabetas, “Reconfiguration of large-scale distribution networks for planning studies,” *Electr. Power Energy Syst.*, vol. 37, pp. 86-94, 2012.
- [28] K. Sathish Kumar, and T. Jayabarathi, “Power system reconfiguration and loss minimization for an istribution systems using bacterial foraging optimization algorithm,” *Electr. Power Energy Syst.*, vol. 36, pp. 13-17, 2012.
- [29] S. H. Mirhoseini, S. M. Hosseini, M. Ghanbari, and M. Ahmadi, “A new improved adaptive imperialist competitive algorithm to solve the reconfiguration problem of distribution systems for loss reduction and voltage profile improvement,” *Electr. Power Energy Syst.*, vol. 55, pp. 128-143, 2014.
- [30] A. M. Eldurssi, and R. M. O’Connell, “A Fast Nondominated sorting guided genetic algorithm for multi-objective power distribution system reconfiguration problem,” *IEEE Trans. Power Syst.*, vol. 30, pp. 593–601, 2015.
- [31] F. R. Alonso, D. Q. Oliveira, and A. C. Zamboni de Souza, “Artificial Immune Systems Optimization Approach for Multiobjective Distribution System Reconfiguration,” *IEEE Trans. Power Syst.*, vol. 30, pp. 840-847, 2015.
- [32] R. H. Fletcher, and K. Strunz, “Optimal distribution system horizon planning–Part I: Formulation,” *IEEE Trans. Power Syst.*, vol. 22, pp. 791-799, 2007.
- [33] J. Aghaei, M. K. M. Muttaqi, A. Azizivahed, and M. Gitizadeh, “Distribution expansion planning considering reliability and security of energy using modified PSO (Particle Swarm Optimization) algorithm,” *Energy*, vol. 65, pp. 398–411, 2014.

- [34] A. M. Cossi, L.G.W. da Silva, R. A. R. La´zaro, and J.R.S. Mantovani, "Primary power distribution systems planning taking into account reliability, operation and expansion costs," *IET Gener. Transm. Distrib.*, vol. 6, no. 3, pp. 274–284, 2012.
- [35] A. El-Zonkoly, M. Saad, and R. Khalil, "New algorithm based on CLPSO for controlled islanding of distribution systems," *Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 391–403, 2013.
- [36] K. Zou, A. P. Agalgaonkar, K. M. Muttaqi, and S. Perera, "An analytical approach for reliability evaluation of distribution systems containing dispatchable and nondispatchable renewable DG units," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2657–2665, 2014.
- [37] P. Wang, and R. Billinton, "Time-sequential simulation technique for rural distribution system reliability cost/worth evaluation including wind generation as alternative supply," *IET Gener. Transmiss Distrib.*, vol. 148, no. 4, pp. 355–360, 2001.
- [38] A. A. Chowdhury, S. K. Agarwal, and D. O. Koval, "Reliability modelling of distributed generation in conventional distribution systems planning and analysis," *IEEE Trans. Ind. Appl.*, vol. 39, no. 5, pp. 1493–1498, 2003.
- [39] I. J. Ramírez-Rosado, and J. L. Bernal-Agustín, "Reliability and costs optimization for distribution networks expansion using an evolutionary algorithm," *IEEE Trans. Power Syst.*, vol. 16, pp. 111–118, 2001.
- [40] G. R. Aghajani, H. A. Shayanfar, and H. Shayeghi, "Presenting a multi-objective generation scheduling model for pricing demand response rate in micro-grid energy management," *Energ. Convers. Manage.*, vol. 106, pp. 308–321, 2015.
- [41] W. Sheng, K. Y. Liu, Y. Liu, X. Meng, and Y. Li, "Optimal placement and sizing of distributed generation via an improved nondominated sorting genetic algorithm 2," *IEEE Trans. on Power Del.*, vol. 30, pp. 569–578, 2015.
- [42] H. Mavalizadeh, A. Ahmadi, and A. Heidari, "Probabilistic multi-objective generation and transmission expansion planning problem using normal boundary intersection," *IET Gener. Transmiss. Distrib.*, vol. 9, pp. 560–570, 2015.
- [43] S. Wen, H. Lan, Q. Fu, D. C. Yu, and L. Zhang, "Economic allocation for energy storage system considering wind power distribution," *IEEE Trans. Power Syst.*, vol. 30, pp. 644–652, 2015.
- [44] J. C. López, M. Lavorato, and M. J. Rider, "Optimal reconfiguration of electrical distribution systems considering reliability indices improvement," *Electr. Power Energy Syst.*, vol. 78, pp. 837–845, 2016.
- [45] E. G. Carrano, F. G. Guimarães, R. H. Takahashi, O. M. Neto, and F. Campelo, "Electric distribution network expansion under load-evolution uncertainty using an immune system inspired algorithm," *IEEE Trans. Power Syst.*, vol. 22, pp. 851–861, 2007.
- [46] A. M. Cossi, R. Romero, and J. R. Mantovani, "Planning and projects of secondary electric power distribution systems," *IEEE Trans. Power Syst.*, vol. 24, pp. 1599–1608, 2009.
- [47] J. H. Kim, and A. Shcherbakova, "Common Failures of Demand Response," *Energy*, vol. 36, pp. 873–880, 2011.
- [48] P. Ghamisi, and J. A. Benediktsson, "Feature selection based on hybridization of genetic algorithm and particle swarm optimization", *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 2, pp. 309–313, 2015.
- [49] A. Stoppato, G. Cavazzini, G. Ardizzon, and A. Rossetti, "A PSO (particle swarm optimization)-based model for the optimal management of a small PV (Photovoltaic)-pump hydro energy storage in a rural dry area," *Energy*, vol. 76, pp. 168–174, 2014.
- [50] B. Jiang, and Y. Fei, "Smart Home in Smart Microgrid. A Cost-effective energy ecosystem with intelligent hierarchical agents," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 3–13, 2015.
- [51] P. Zhang, W. Li, and S. Wang, "Reliability-oriented distribution network reconfiguration considering uncertainties of data by interval analysis," *Elect. Power Energy Syst.*, vol. 34, pp. 138–144, 2012.



Hamid Reza Arasteh was born in Zanjan, Iran, in 1988. He received the B.Sc. degree in power engineering from the Tabriz University, Tabriz, Iran, in 2010, the M.Sc. degree from Tarbiat Modares University (TMU), Tehran, Iran, in 2012. He is currently pursuing the Ph.D. degree in power engineering at Shahid Beheshti University (SBU), Tehran, Iran. His research interests include distribution system planning, demand response, smart grids, and electricity market.



Vahid Vahidinasab received the B.Sc. degree from the K. N. Toosi University of Technology, Tehran, Iran, in 2004, and the M.Sc. (Hons.) and Ph.D. degrees from the Iran University of Science and Technology, Tehran, in 2006 and 2010, respectively, all in electrical engineering. He is currently an Assistant Professor with the Department of Electrical Engineering, Shahid Beheshti University, Tehran. His current research interests include operations and economics of electric energy systems and smart microgrids.



Mohammad Sadegh Sepasian was born in Tehran, Iran, in 1967. He received the B.Sc. degree from Tabriz University, Tabriz, in 1990 and the M.Sc. and Ph.D. degrees from Tehran University and Tarbiat Modares University, Tehran, in 1993 and 1999, respectively. Currently, he is an Assistant Professor with the Department of Electrical Engineering, Shahid Beheshti University, Tehran. His research interests include power system planning as well as distribution system planning issues.