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Stochastic Simultaneous Planning of Interruptible Loads, Renewable Generations and Capacitors in Distribution Network

*J. Salehi *, F.S. Gazijahani, A. Safari*

Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran

Abstract- *Executing interruptible loads (ILs) can be significantly effective for optimal and secure operation of power systems. These ILs can aid the operators not only to increase the reliability of the power supply but also to reduce the procurement costs of the whole system. Therefore, determining the optimal location and capacity of ILs for a given incentive rate is of great interest to distribution companies. To do so, in this paper simultaneous allocation and sizing of ILs, wind turbines (WT), photovoltaic (PV) and capacitors have been done in the radial distribution network for different demand levels and subsequently the optimal value of compensation price for the ILs has been determined. Given the probabilistic nature of load, wind and solar generation as well as the price of energy at the pool, we have also proposed a stochastic model based on fuzzy decision making for modelling the technical constraints of the problem under uncertainty. The objective functions are technical constraint dissatisfaction, the total operating costs of the Distribution Company and CO_2 emissions which are minimized by NSGA2. To model the uncertainties, a scenario-based method is used and then by using a scenario reduction method the number of scenarios is reduced to a certain number. The performance of the proposed method is assessed on the IEEE 33-node test feeder to verify the applicability and effectiveness of the method.*

Keyword: Demand response, Renewable energy, Distribution system, Distributed generation, Optimization

1. INTRODUCTION

By creating restructuring in the power industry some changes occurred in the design and operation of distribution networks. In the restructured environment, the aims of distribution companies (DISCO) are to achieve maximum profit, best serving to consumers and maintaining technical features of network in acceptable level. To achieve these goals the DISCO uses several options, such as DG units, energy storages and interruptible loads (IL). Nowadays, ILs have an outstanding role in optimally operation and reducing the total costs of distribution networks. Therefore, the optimal allocation and capacity of ILs is essential for DISCOs from both technical and economical points of view. IL contracts are signed between DISCO and consumers who are willing to participate in demand response programs. In these contracts the maximum capacity of ILs that can be interrupted in emergency and required situations and amount of compensation price for ILs are determined [1]. By using ILs, the DISCOs will not need to employ generation units because of the load growth. In fact, ILs can be seen as alternative energy sources to deal with load shedding [2]. ILs are able to reduce the congestion of the feeder during peak times in the smart networks. The concept of smart networks refers to the appearance of smart meters and metering infrastructure [3]. An important issue in the implementation of ILs is paying a reasonable compensation to the consumers. Types of payments to consumers include these items: 1) the consumer receives compensation for each load unit that is disconnected, 2) the consumer receives a discount rate in the electricity retail price [4]. It is stated in Ref. [5] that the ILs can be reduced the possibility of faults that occur because of the lines overloading during peak time. Therefore, IL can help the system operator to increase the power system reliability by reducing peak loads. In Ref. [5], the objective function is to minimize the compensation cost. The main contents of the IL contracts include these items: validity duration of contract, information time before interrupting loads, the length of the time that the loads are interrupted, the capacity of load that can be interrupted and contract costs, the main issue in these contracts is the announcement of reasonable price for ILs and other relative costs [6].

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∗Corresponding author:
E-mail: j.salehi@azaruniv.ac.ir. (J. Salehi)
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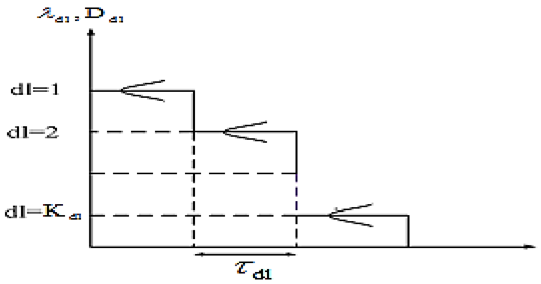

Fig. 1. The uncertainty modelling of load and PEPG

Table. 1. Parameters of WT and PV models

Parameters of WT					Parameters of PV		
$P^{w}_{i,r}$ (Kw)	v_i^{cut} (m/s)	v_r (m/s)	v_o^{cut} (m/s)	c	$P^{pv}_{i,r}$ (Kw)	α	β
20	2.7	10	25	8.78	1	2.4	3.5

The use of ILs has benefits of economic and technical aspects, economic aspects include three important items: the consumer's compensation price, the nodal price and reducing line losses also the technical aspects is consist of improving the reliability of supply and voltage quality [7]. The ILs have significant effects on the increasing the profit and reducing the risks, so, if happen a shock in supply or demand these ILs can be used as an effective tool for covering risks [8]. Reference [8] considered impacts of ILs on the maintenance scheduling in an analytical form. Studies in Ref. [9] presents that use of ILs can reduce congestion, oscillation of market price and reduce the generation company's market power. In Ref. [10], mixed integers non-linear programming (MINLP) has been used for determine the optimum capacity and location of wind turbines to minimize the annual energy losses in the distribution system (DS). In Ref. [11], a discrete PSO algorithm is used for optimal allocation of PVs in distribution system. In Ref. [12], a simultaneous placement of DG and capacitors has been done and effect of DG and capacitor is investigated on voltage stability improvement. In Ref. [13], a stochastic planning for optimal sizing and siting of capacitors has been done in order to reduce the total costs of the new capacitors and cost of annual energy losses while considering the wind generations uncertainty. In Ref. [14], DG placement and sizing in DSs a scenario-based multi-objective optimization method has been done and the uncertainties of intermittent DG and load are considered. There are multiple works that have investigated DG allocation from different points of view. For example, Ref. [15] proposed particle swarm optimization to optimal allocate the WT and capacitors to minimize the power losses and operation expenditures. A hybrid probabilistic model has also developed in Ref. [16] to determine the reliable configuration of system in the presence of DG units. Authors in Ref. [17] have reported that soft open points can be used to increase the flexibility of distribution systems by changing the system structure under different operation conditions. They have also coordinated this problem with DG resources allocation problem to satisfy the reliability requirements of system. In some of previous works, the allocation of ILs has not been performed and with assuming the ILs in some places the impacts of them have been investigated on costs and operation of power system and optimal procurement of them have been determined for a certain period of time. In some other works, ILs have been considered with DGs which have a constant generation and their impacts have been analysed on the distribution company's profit.

In general, the main contribution of this paper is to determine the optimal location and capacity of interruptible loads in order to participate in the demand response program of distribution companies (DISCO). This is done in coordination with different renewable resources to achieve a cost-effective solution. Moreover, the optimal value of incentive price that should be paid to active consumers for reducing their consumption is determined in this work. Given the probabilistic nature of price-responsive loads, wind speed and solar radiation, an efficient stochastic model based on fuzzy decision making is also proposed to cope with uncertainties. Finally, the proposed multi-objective problem has been optimized by Non-dominated Sorting Genetic Algorithm-ii (NSGAII) under MATLAB environment.

2. UNCERTAINTY MODELLING

2.1. Load and PEPG modelling

In this work, the load and PEPG duration curves are divided into K_{dl} levels in each year as shown in Fig.1, Also both of them (load and PEPG) are modelled as a normal PDF in each level. So, by using sampling scenario generation method ND scenarios for load and NP scenarios for PEPG are generated for each demand level.

The PDF of load and PEPG can be defined as follows:

$$f = \left[1/\sqrt{2}\,\pi\sigma_d\right].\,e^{-(x-\tilde{x})^2/2\sigma_d} \quad (1)$$

Where, σ_d is standard deviation, x is the value of each scenario and $\tilde{x}$ is the mean value.

2.2. WT modelling

Because of being uncertainty in wind speed prediction, its behaviour is modelled using Rayleigh PDF as follows:

$$PDF(v) = \left(\frac{2v}{c^2}\right) \cdot e^{\left[-\left(\frac{v}{c}\right)^2\right]} \quad (2)$$

Where, c is the scale index of Rayleigh PDF. Using the scenario generation method described in previous section, NW scenarios is generated for wind speed. Output power of WT is calculated as follows [18]:

$$P_{i,T}^{w}(v_s) = \xi_{i,T}^{w} \cdot \begin{cases} 0 & v_s \le v_i^{cut} \; or \; v_s \ge v_o^{cut} \\ \frac{v_s - v_i^{cut}}{v_r - v_i^{cut}} \cdot P_{i,r}^{w} & v_i^{cut} \le v_s \le v_r \\ P_{i,r}^{w} & else \end{cases} \quad (3)$$

Where, P_i^w is generated power of WT in bus i, $\xi_{i,T}^{w}$ is decision variable for wind turbines in bus i and in the year T, v_i^{cut} is the cut in speed, v_o^{cut} is the cut out speed, v_r is the rated wind speed and $P_{i,r}^{w}$ is the rated power of WT and v_s is wind speed in scenario s.

2.3. Solar irradiance modelling

Because of the uncertainty in solar radiation due to the possibility of clouds in sky or other climate conditions, the variable behaviour of solar radiation is modelled using Beta PDF as follows [19]:

$$PDF(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} s^{\alpha-1}(1-s)^{\beta-1} & 0 \le s \le 1 \\ 0 & else \end{cases} \quad (4)$$

Where, α and β are the parameters of Beta PDF and s is the solar irradiance. Similar to the parameters with uncertainty expressed above, NS scenarios is generated for solar irradiance. Output power of PV is calculated as follows:

$$P_{i,T}^{pv} = \xi_{i,T}^{pv} \cdot s_s \cdot P_{i,r}^{pv} \quad (5)$$

Where, P_i^{pv} is generated power of PVs in bus i, $\xi_{i,T}^{pv}$ is decision variable for PVs in bus i and the year T, s_s is solar irradiance in scenario s and $P_{i,r}^{pv}$ is the rated power of PV. The technical characteristic of wind turbine and photovoltaic are given in Table. 1.

2.4. General model of uncertainties

In each demand level, the scenarios are compounded to make the all set of scenarios as follows:

$$C(s) = \{load(s), PEPG(s), wind(s), irridiance(s)\} \quad (6)$$

$$Prob_s^c = prob_s^l \cdot prob_s^{PEPG} \cdot prob_s^w \cdot prob_s^{ir} \quad (7)$$

Where, $C(s)$ is a compounded scenario and $Prob_s^c$ is the probability of each compounded scenario. Solving the Eq. (6) gives $N_{total} = ND \cdot NP \cdot NW \cdot NS$ scenarios for each demand level. Then, due to the heavy evaluation of this number, scenarios are reduced into N_s scenario using described technique in Ref. [20].

2.5. Interruptible Loads modelling

Due to the uncertainty in load consumption, this paper proposed a stochastic model for allocation and planning of ILs in distribution systems. In this modelling, it is assumed that all loads have switch and can be interrupted remotely. In fact, the network is supposed to be smart and controllable.

3. FUZZY SET THEORY

3.1. Voltage profile

Voltage magnitude of each bus should be maintained within the safe range. So, regarding to this issue the membership function of the voltage constraint satisfaction is defined as follows [20]:

$$\mu_{i,T,dl,s}^{V} = \begin{cases} \frac{V_{i,T,dl,s} - V_{cr}^{min}}{V_{safe}^{min} - V_{cr}^{min}} & V_{cr}^{min} \le V_{i,T,dl,s} \le V_{safe}^{min} \\ 1 & V_{safe}^{min} \le V_{i,T,dl,s} \le V_{safe}^{max} \\ \frac{V_{i,T,dl,s} - V_{cr}^{max}}{V_{safe}^{max} - V_{cr}^{max}} & V_{safe}^{max} \le V_{i,T,dl,s} \le V_{cr}^{max} \\ 0 & else \end{cases} \quad (8)$$

The Eq. (8) gives voltage constraint satisfaction for bus i in scenario s in year T. Values of the V_{cr}^{min}, V_{cr}^{max}, V_{safe}^{min} and V_{safe}^{max} are given in Table. 2. The weighted average of voltage satisfaction for all scenarios is:

$$\mu_{i,T}^{V} = \frac{1}{8760} \cdot \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{Ns} Prob_s^c \cdot \tau_{dl} \cdot \mu_{i,T,dl,s}^{V} \quad (9)$$

Where, K_{dl} is the number of demand levels, N_s is the number of scenarios, τ_{dl} is the duration of each demand level and T is planning horizon. Finally, average value of $\mu_{i,T}^{V}$ for all buses is as follows:

$$\mu_T^V = \frac{\sum_{i=1}^{N_b} \mu_{i,T}^{V}}{N_b} \quad (10)$$

3.2. Thermal limit

To prevent from overloading of feeders and maintaining their security, the power flow which is passing through the lines should be kept below their maximum capacity. Membership function of the thermal limit constraint satisfaction is defined as below [20]:

$$\mu_{l,T,dl,s}^{I} = \begin{cases} 1 & I_{l,T,dl,s} \le I_l^{safe,T} \\ \frac{I_{l,T,dl,s} - I_l^{cr,T}}{I_l^{safe,T} - I_l^{cr,T}} & I_l^{safe,T} \le I_{l,T,dl,s} \le I_l^{cr,T} \\ 0 & I_{l,T,dl,s} \ge I_l^{cr,T} \end{cases} \quad (11)$$

$$I_l^{safe,T} = 0.9 \cdot I_l^{cr,T} \quad (12)$$

Similar to voltage constraint, total value of satisfaction intended for each feeder is as follows:

$$\mu_{l.T}^{I} = \frac{1}{8760} \cdot \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c \cdot \tau_{dl} \cdot \mu_{l,T,dl,s}^{I} \quad (13)$$

The average value of $\mu_{l.T}^{I}$ for all network feeders is as follows:

$$\mu_T^I = \frac{\sum_{l=1}^{N_l} \mu_{l.T}^{I}}{N_l} \quad (14)$$

3.3. Substation capacity limit

Membership function for substation capacity constraint is as follows:

$$\mu_{T,dl,s}^{S_{grid}} = \begin{cases} 1 & s_{T,dl,s}^{grid} \leq s_{safe,T} \\ \frac{s_{T,dl,s}^{grid} - s_{cr,T}}{s_{safe,T} - s_{cr,T}} & s_{safe,T} \leq s_{T,dl,s}^{grid} \leq s_{cr,T} \\ 0 & s_{T,dl,s}^{grid} \geq s_{cr,T} \end{cases} \quad (15)$$

$$\mu_T^{sgrid} = \frac{1}{8760} \cdot \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c \cdot \tau_{dl} \cdot \mu_{T,dl,s}^{S_{grid}} \quad (16)$$

3.4. Objective functions

This model minimize three objective functions: 1) technical dissatisfaction or violation of technical constraints, 2) total costs of the distribution company, 3) total emissions as $min\{OF_1, OF_2, OF_3\}$.

4. PROBLEM FORMULATION

In this section, mathematical formulation of each objective function is done. The assumptions used in this problem, objective functions and constraints are expressed in the following sections.

4.1. Assumptions

The following assumptions are taken into account in the proposed problem:

- The amount of ILs is considered to be at most three tenths of peak load of network.
- The payment to the ILs is considered type 1 which is stated in Ref. [4], based on this, in this paper it is assumed that, the payment to the ILs for per unit that is interrupted is equivalent of the electricity price for per unit.
- The percentage of generation of DG units to be assumed up to thirty percent of the peak load of network as $P^{DG} \leq 30\% \cdot P^{peak} \cdot (1+\epsilon_d)^T$
- All busses are candidates for allocation of WTs, PVs, capacitors and ILs.
- The maximum number of WTs and PVs is assumed up to 3 for each bus. Besides, the maximum number of capacitors is assumed to be 6 for each bus.
- The power factor is assumed constant for all DGs.
- Two MTs and two GTs are considered in specified busses of system.
- In this paper a static planning is done for the year T and the fuzzy models which are mentioned in previous sections are obtained for the year T.

4.2. First objective function

The first objective function is to minimize technical dissatisfaction. The maximum dissatisfaction of all technical constraint is defined as follows:

$$ATD_T = 1 - min\left\{\mu_T^V, \mu_T^I, \mu_T^{S_{grid}}\right\} \quad (17)$$

$$OF_1 = w_{av} ATD_T + w_{av}\left(1 - min_{dl,s}\left[\mu_{T,dl,s}^{S_{grid}}, \mu_{T,dl,s}^V, \mu_{T,dl,s}^I\right]\right) \quad (18)$$

Where, w_{sev} and w_{av} are the weighting factors which represent the importance of severity of technical dissatisfaction and the average dissatisfaction of technical constraints, respectively. If w_{sev} is selected much greater than w_{av} the algorithm endeavours to completely satisfy the technical constraints, and when w_{av} is greater than w_{sev} the technical satisfaction of the solutions are more relaxed.

4.3. Second objective function

The second objective function is to minimize total costs, which includes total cost of the grid, installation cost and operation cost of DG units, cost of grid losses, cost of ILs, the cost of expected energy not supplied and the cost of capacitors.

4.3.1. Total grid cost

The total purchasing cost for energy can be determined by Eq. (19):

$$PEPG_{dl,s}^{\lambda} = \rho \cdot \lambda_{dl,s} \quad (19)$$

Where, ρ is peak price of energy purchased from grid and $\lambda_{dl,s}$ is price level factor in scenario s.

$$S_{i,T,dl,s}^D = S_{i,peak}^D \cdot D_{dl,s} \cdot (1+\epsilon_D)^T \quad (20)$$

Where, $D_{dl,s}$ is demand level factor in scenario s and ϵ_D is a demand growth rate.

$$TGC = \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c PEPG_{dl,s}^{\lambda} P_{T,dl,s}^{grid} \frac{1}{(1+i)^T} \quad (21)$$

Where, $P_{T,dl,s}^{grid}$ is the net real power of network and i is interest rate.

4.3.2. DG investment cost

Investment cost of DG units is calculated by Eq. (22) based on inflation factor.

$$DGINVC = \sum_{i=1}^{N_b} \sum_{DG} \xi_{i,T}^{DG} \cdot ic_{DG} \cdot \frac{1}{(1+i)^T} \quad (22)$$

Where, N_b is the number of buses in the network, $\xi_{i,T}^{DG}$ is investment decision of DGs and ic_{DG} is investment cost of each DG unit.

4.3.3. DG operation cost

The operating cost of DG units over scheduling time can be calculated as:

$$DGOPC = \sum_{i=1}^{N_b} \sum_{dl=1}^{K_{dl}} \sum_{DG} \sum_{s=1}^{Ns} Prob_s^c \tau_{dl} OC_{DG} P_{i,T,s}^{DG} \frac{1}{(1+i)^T} \quad (23)$$

Where, OC_{DG} is the operation cost for each DG unit and $P_{i,T,s}^{DG}$ is the generated power by each DG unit.

4.3.4. Cost of grid losses

Cost of power losses can be calculated by (24) during operation horizon time:

$$LOSSCOST = \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c \cdot Ploss_{T,s,dl} \cdot \tau_{dl} \cdot C \cdot \frac{1}{(1+i)^T} \quad (24)$$

Where, C is the price for power losses ($/KWh).

4.3.5. ILs cost

The cost that the distribution company pays for ILs is determined by Eq. (25):

$$ILCOST = \sum_{i=1}^{N_b} \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} \psi_{i,T}^{IL} Prob_s^c IL_{T,dl,i,s}^{P} \tau_{dl} C \frac{1}{(1+i)^T} \quad (25)$$

Where, $\psi_{i,T}^{IL}$ is a binary value and represent IL allocation decision and $IL_{T,dl,i,s}^{P}$ is the capacity of IL in scenario s, in year T and bus i, if $\psi_{i,T}^{IL}$ has been 1.

4.3.6. Cost of expected energy not supplied

When a fault is occurred in one of the feeders, some of the loads are disconnected and not supplied. So this amount of energy which is not supplied has a cost for the distribution company, in this work the mentioned cost is calculated as follows:

$$CEENS_{T,l} = \frac{1}{8760} \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c ceens_{T,l,dl,s} \tau_{dl} \quad (26)$$

Where, $ceens_{T,l,s}$ is cost of expected energy not supplied in scenario s, in year T and feeder l, and it is calculated as follows:

$$ceens_{s,T} = P1_s \lambda L_l h_1 C + P2_s \lambda L_l h_2 C \quad (27)$$

Where, $P1_s$ is the net real power which is cut-off during the repair time when a fault occur in feeder l and $P2_s$ is the net real power which is cut-off during the switching time, λ is the failure rate (fail/km.year), h_1 and h_2 are the repair time and switching time respectively, and L_l is the length of feeder l. The average value of $CEENS_{T,l}$ over all feeders of the network is as follows:

$$CEENS_T = \frac{\sum_{l=1}^{N_l} CEENS_{T,l}}{N_l} \cdot \frac{1}{(1+i)^T} \quad (28)$$

Where, N_l is number of feeders.

4.3.7. Capacitor installation cost

Cost of capacitor installation is as follows:

$$CAPCOST = \sum_{i=1}^{N_b} \xi_i \cdot (cfc \cdot n_i + c_i \cdot cvc) \quad (29)$$

Where, ξ_i is a binary value and is "1" when capacitor is located in bus i and "0" otherwise, cfc is the fixed cost of capacitor installation, n_i is the number of capacitors, c_i is the total capacity of reactive resources in bus i and cvc is the variable cost of capacitors located. It should be noted that the useful life of the capacitors is assumed to be equal to the planning horizon. Thus, OF_2 can be modelled as below:

$$OF_2 = TGC + DGINVC + DGOPC + ILCOST + LOSSCOST + CEENS + CAPCOST \quad (30)$$

4.4. Third objective function

This objective function minimize the total CO2 emissions.

$$OF_3 = \sum_{dl=1}^{K_{dl}} \sum_{s=1}^{N_s} Prob_s^c \tau_{dl} \left[E_{grid} P_{T,dl,s}^{grid} + \sum_{i=1}^{N_b} \sum_{DG} E_{DG} P_{i,T,dl,s}^{DG} \right] \quad (31)$$

Where, E_{grid} and E_{DG} are the emission factors of the grid and DG respectively.

4.5. Power flow constraints

The power flow equations which must be observed for each combination in each demand level are as follows:

$$P_{i,T,dl,s}^{net} = P_{i,T,dl,s}^{D} - P_{i,T,dl,s}^{DG} - P_{i,T,dl,s}^{IL} \quad (32)$$

$$Q_{i,T,dl,s}^{net} = Q_{i,T,dl,s}^{D} - Q_{i,T,dl,s}^{DG} - Q_{i,T,dl,s}^{IL} - Q_i^{capacitor} \quad (33)$$

$$P_{i,T,dl,s}^{net} = V_{i,T,dl,s} \cdot \sum Y_{ij}^T V_{j,T,dl,s} cos(\delta_{i,T,dl,s} - \delta_{j,T,dl,s} - \theta_{ij}) \quad (34)$$

$$Q_{i,T,dl,s}^{net} = V_{i,T,dl,s} \cdot \sum Y_{ij}^T V_{j,T,dl,s} sin(\delta_{i,T,dl,s} - \delta_{j,T,dl,s} - \theta_{ij}) \quad (35)$$

5. SIMULATION RESULTS

5.1. System under study

This work is done on the test 33-node 20 kV distribution system which is shown in Fig. 2 and its technical data are given in Ref. [21]. Two DG technologies consist of WT and PV as well as two other options consist of IL and capacitor are used simultaneously. The optimal location and size of DGs, capacitors and ILs are determined by the proposed algorithm. The required data for simulations are given in Table. 2.

5.2. Two stage solution method

Solution method is consist of two steps, in the first step by using NSGA2 Pareto optimal front is found, considering convergence condition to reach the maximum number of iterations. In the second step by using fuzzy satisfying method, the best solution would be found. It should be noted that the selection of the best solution depends on the planner's preference and its priorities. In this work we use fuzzy decision making method to find the best possible solution. In the proposed optimization problem, the chromosomes of initial population have a structure as shown in Fig. 3.

Table. 2. Data used in study

Parameter	Unit	Value
T	Year	8
K_{dl}	Constant	24
τ_{dl}	h	365
$ND = NP$	$NW = NS$	5
N_s	Constant	15
S_{safe}	MVA	32
S_{cr}	MVA	40
E_{grid}	$(kgCO_2/MWh)$	632
ρ	$/MWh	60
C	$/MWh	80
ϵ_d	%	1
i	%	12
w_{av}	Constant	0.8
w_{sev}	Constant	0.2
V_{safe}^{max}	Pu	1.05
V_{cr}^{max}	Pu	$(1+5\%) \cdot V_{safe}^{max}$
V_{safe}^{min}	Pu	0.95
V_{cr}^{max}	Pu	$(1-5\%) \cdot V_{safe}^{min}$
$cos\phi^{dg}$	Constant	0.8
h_1	h	3
h_2	h	0.5

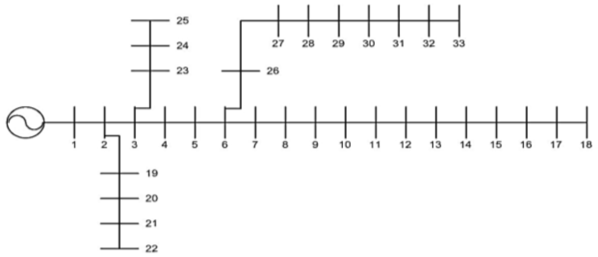

Fig. 2. 33-Bus distribution test system

0	1	0	2	m
2	0	1	n	0
1	0	2	1	p
0	1	1	0	1

Fig. 3. Chromosome encoding scheme

This chromosome has 4 rows which is number of decision variables. Also has 33 columns which is equal to network buses. First row is related to the decision variable of WTs which it is number of WTs in each bus and takes values from 0 to m (the maximum number of WTs which can be allocated in each bus). Here, 0 means that no WTs is allocated in the specified bus and other values mean that WTs are allocated in the specified bus and also shows the number of WTs in that bus. Second row is related to the decision variables of PVs, third row is related to the decision variable of capacitors and fourth row is indicated the decision variable of ILs and takes binary values. These rows and columns generally form the chromosome genes.

5.3. Fuzzy satisfying method

In this method for each solution in Pareto optimal front like x_i a membership function is defined as $\mu_{f_k}(x_i)$. The value of $\mu_{f_k}(x_i)$ changes between 0 and 1. The decision maker is fully satisfied with x_i if $\mu_{f_k}(x_i) = 1$ and dissatisfied if $\mu_{f_k}(x_i) = 0$ [18]. A linear type of membership function is as Eq. (36):

$$\mu_{f_k}(x) = \begin{cases} 0 & f_k(x) > f_k^{max} \\ \frac{f_k^{max} - f_k(x)}{f_k^{max} - f_k^{min}} & f_k^{min} \le f_k(x) \le f_k^{max} \\ 1 & f_k(x) < f_k^{min} \end{cases} \qquad (36)$$

Then, by using a conservative approach the final solution is found which its minimum satisfaction is maximum overall objective functions [22]. The final solution is determined by Eq. (37):

$$\max_{i=1:N_s} \left(\min_{k=1:N_o} \left(\mu_{f_k}(x_i) \right) \right) \qquad (37)$$

5.4. Simulation results (Case I)

The flowchart of the proposed NSGAII to solve the problem is shown in Fig. 4. In this case the σ value of each demand and price level is assumed to be 5% of their mean value. The characteristics of the capacitors and DG units are given in Table 3 and Table 5. Respectively. As well as, the location and size which are assumed for MTs and GTs are given in Table 4.

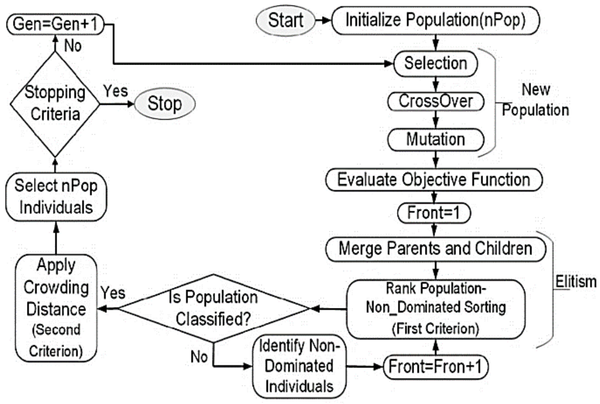

Fig. 4. Flowchart of the proposed optimization algorithm

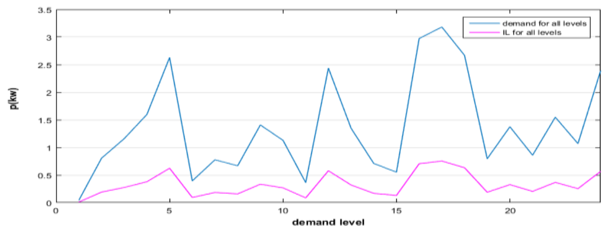

Fig. 5. Demand and ILs in case I

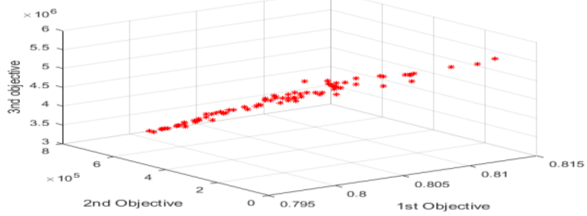

Fig. 6. Pareto optimal front found by the algorithm in case I

In this case, by using the solution method that is described in section (7.2) the Pareto optimal front is found which have 80 solutions, as shown in Fig. 5 and then with fuzzy method solution #55 is found as the best and final solution. Based on this best solution, ILs are located in nodes 2, 5, 10, 12, 15, 16, 18, 22, 23, 32. As well as, optimal location and capacity of WTs, PVs and capacitors are determined and reported and represented in Table 6 and Figs. 10, 11 and 12. Also, the optimal amount of ILs and payment are calculated and reported in Tables 7 and 8, respectively. The values of variation ranges of each objective function are determined and reported in Table 9, also the value of each objective function are determined and represented in Table 10.

Fig.4 depicts the percentage of ILs relative to the demand of network for all levels in case I. This percentage of load, which is approximately 20% of the network load, is considered to be ILs for DISCOs.

These ILs are interrupted in critical times (i.e., peak periods) and when the network is facing with electricity shortage or contingencies in planning horizon to improve the system reliability.

Table. 2. Data of capacitors

Fix cost ($)	Variable cost ($\$/kVAr$)	Base size ($kVAr$)
2.00	8.00	150

Table. 3. Location and size of MTs and GTs

MT		GT	
Bus No.	Size (Kw)	Bus No.	Size (Kw)
8,10	20	20,31	30

Table. 4. Data of DGs

DG technology	E_{DG} ($kgCO_2/MWh$)	IC_{DG} ($k\$/MVA$)	OMC_{DG} ($\$/MWh$)
MT	503	148	70
GT	773	500	50
WT	0	1500	15
PV	0	1000	12

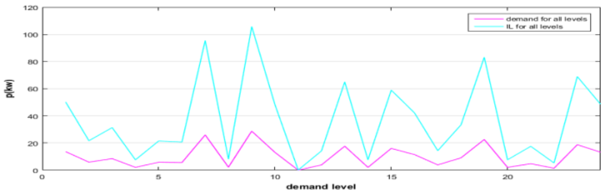

Fig. 7. Demand and ILs in case II

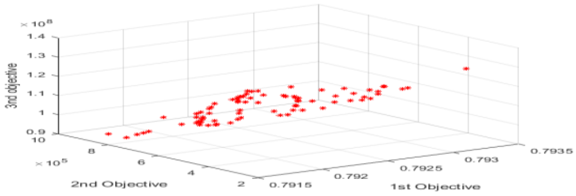

Fig. 8. Pareto optimal front found by algorithm in case II

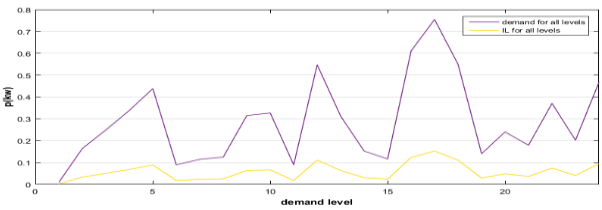

Fig. 9. Demand and ILs in case III

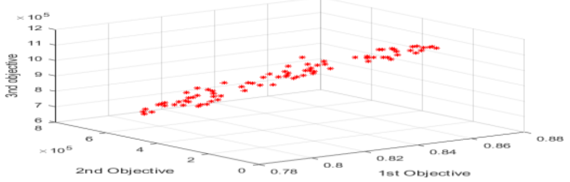

Fig. 10. Pareto optimal front found by algorithm in case III

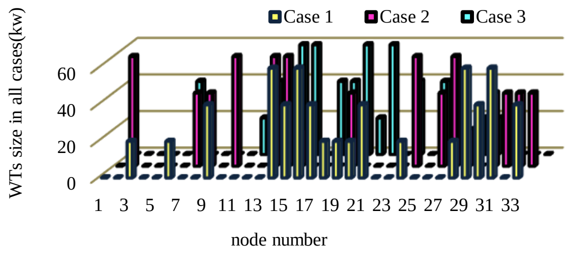

Fig. 11. Optimal location and size of WTs in all cases

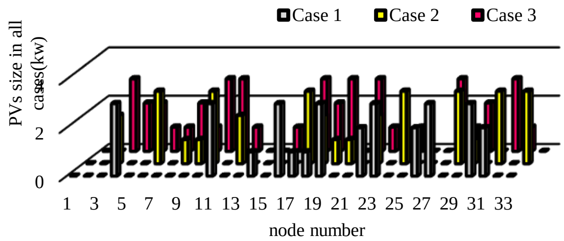

Fig. 12. Optimal location and size of PVs in all cases

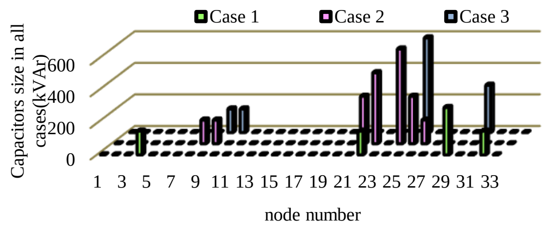

Fig. 13. Optimal location and size of capacitors in all cases

Table. 5. Simulation results of WTs, PVs and capacitors

Case	WT		PV		Capacitor	
	Bus No.	Size (kw)	Bus No.	Size (kw)	Bus No.	Size ($kVAr$)
I	3,6,18,19,20,24,28	20	14,17,18	1	4,22,32	150
	9,15,17,21,30,33	40	22,26,31	2	29	300
	14,16,29,31	60	4,11,16,19,23,27,30	3		
II	15,28	20	8,9,19,20,29	1	8,9,26	150
	7,8,19,26,30,31,32,33	40	3,12,18,22	2	21,25	300
	2,10,13,14,24,27	60	6,10,17,24,28,31,33	3	22	450
					24	600
III	11,20,28,29	20	6,7,9,12,15,22,24,28,32	1	9,10	150
	6,12,13,17,18,23,25	40	4,5,8,18,29	2	30	300
	14,15,19,21	60	3,10,11,17,19,21,27,31	3	25	600

Table. 6. Variation ranges of objective functions in Pareto optimal front

Case	Various ranges	OF_1	$OF_2(\$)$	$OF_3(gCO_2)$
I	f_k^{min}	0.7997	9.7578×10^4	3.2505×10^6
	f_k^{max}	0.8141	7.0640×10^5	5.5531×10^6
II	f_k^{min}	0.7915	2.4543×10^5	9.4852×10^7
	f_k^{max}	0.7934	8.1916×10^5	1.3340×10^8
III	f_k^{min}	0.7999	9.9585×10^4	6.3605×10^5
	f_k^{max}	0.8622	6.9834×10^5	1.1984×10^6

Table. 7. Value of objective functions in all cases

Case	OF_1	$OF_2(\$)$	$OF_3(gCO_2)$
I	0.7997	3.9667×10^5	4.3516×10^6
II	0.7917	5.0193×10^5	1.1312×10^8
III	0.8152	3.9155×10^5	9.1902×10^5

Table. 8. Cost of ILs in all cases

	Case I	Case II	Case III
ILCOST($)	91.8827	2.8142×10^3	16.4279

5.5. Simulation results (Case II)

In this case, the σ value of demand level and price level are decreased to 1% of their mean values. In fact, we have reduced the uncertainty of demand and PEPG in this case. The Pareto optimal front also has 80 solutions in this case as shown in Fig. 7.

Similar to the case I, by using the fuzzy method the solution #33 is selected as the best solution. Based on this solution, the optimal location of ILs is nodes 6, 8, 9, 12, 13, 15, 16, 17, 19, 21, 22, 26, and 27. As a result, when demand uncertainty is reduced, the amount of ILs also reduced accordingly. Therefore, in comparison with the results of the previous case, the higher percentage of the network load is selected as ILs. This percentage of ILs, which is represented in Fig. 4 and Fig. 6 is relative to the load of network that is resulted from stochastic programming.

5.6. Simulation results (Case III)

In this case, the demand and electricity price are increased to the 10% of their mean values. With increasing the σ value, the uncertainty of demand and PEPG are increased, therefore, the uncertainty of ILs also increases accordingly. In this case, the Pareto optimal front has 80 solutions as shown in Fig. 9. Similar to the above section, the best solution of this case is 8. Optimal location of ILs is nodes 4, 6, 16, 17, 19, 21 22, 27, 28, 33.

Table. 9. Amount of ILs and Demand in all cases

dl	Case I		Case II		Case III	
	Load (kw)	IL (kw)	Load (kw)	IL (kw)	Load (kw)	IL (kw)
1	0.0428	0.0101	50.1874	13.6445	0.0093	0.0019
2	0.8051	0.1907	21.6995	5.8995	0.1641	0.0331
3	1.1599	0.2747	31.3529	8.5239	0.2488	0.0502
4	1.5981	0.3785	7.6285	2.0740	0.3382	0.0683
5	2.6308	0.6232	21.5052	5.8466	0.4383	0.088
6	0.3939	0.0933	20.6955	5.6265	0.0891	0.018
7	0.7763	0.1839	95.4961	25.9626	0.1145	0.023
8	0.6676	0.1581	8.1283	2.2098	0.1247	0.025
9	1.4081	0.3336	105.7760	28.7574	0.3145	0.063
10	1.1285	0.2673	48.1911	13.1017	0.3272	0.066
11	0.3627	0.0859	0.1215	0.0330	0.0893	0.018
12	2.4384	0.5776	14.2117	3.8637	0.5476	0.110
13	1.3478	0.3193	64.9911	17.6692	0.3125	0.063
14	0.7091	0.1680	7.6099	2.0689	0.1522	0.030
15	0.5531	0.1310	58.9627	16.0302	0.1160	0.023
16	2.9743	0.7045	42.2072	11.4749	0.6106	0.123
17	3.1830	0.7540	14.3407	3.8988	0.7547	0.152
18	2.6697	0.6324	33.3973	9.0798	0.5493	0.110
19	0.7953	0.1884	83.1398	22.6033	0.1402	0.028
20	1.3753	0.3258	7.6650	2.0839	0.2400	0.048
21	0.8592	0.2035	17.5886	4.7818	0.1790	0.036
22	1.5487	0.3668	5.3055	1.4424	0.3706	0.074
23	1.0699	0.2534	68.9377	18.7421	0.2018	0.040
24	2.3929	0.5668	48.5673	13.2040	0.4674	0.094
all	32.890	7.7910	877.706	238.622	6.8999	1.393

Other simulation results of ILs are presented in Table. 7, Table. 8. As well as, the simulation results of WTs, PVs and capacitors are reported. If we want to compare this case with case I, lower percentage of network demand is selected for ILs. Fig. 8 shows the percentage of ILs relative to the demand of network for all demand levels in case III. As can be seen, the amount of ILs and demand in case III is lower than case II. Also, the percentage of ILs in case III (which is resulted from stochastic programming) is lower than case II.

6. CONCLUSIONS

Due to the uncertainties induced by renewable resources and consumption, a multi-objective model based on fuzzy stochastic programming is presented in this work. In the proposed model, the optimal site and size of WTs, PVs, ILs and capacitors have been simultaneously done in order to minimize total planning and operation costs, and CO_2 emissions along with satisfying the technical constraints for different demand levels. In this work, the probabilistic property of load and PEPG is modelled as normal PDF, and the probabilistic behaviour of wind speed and solar radiation is modelled by Rayleigh PDF and Beta PDF, respectively. Then, using the sampling method several scenarios are generated for each demand level and eventually by using a scenario reduction method, the number of scenarios is reduced to decrease the computational burden of the problem. By using NSGA2, the formulated problem is solved and Pareto optimal front with 80 non-dominated solutions is found. Afterheat, fuzzy decision making method has been employed to select the best solution from Pareto. In order to guarantee the technical constraints under uncertain circumstance the fuzzy models are used. In this paper, three different cases are considered and their results have been reported. In each case optimal location and size of WTs, PVs, capacitors and ILs are determined at IEEE 33-node test system. Due to the high concentration of this work on ILs, the results of cases are investigated in terms of different ILs levels.

The results obtained from simulation illustrate that by increasing the uncertainty of demand and electricity price, the amount of ILs to participate in the demand response program is increased to cope with uncertainty. This confirms that the flexible loads (i.e., ILs) can be used as an efficient and economical instrument to compensate for power shortages during peak hours and increase reliability of the system. The results also acknowledge that the ILs can significantly reduce the volume of investment in generation resources, which mainly occurs by reducing the peak load of the system. In general, it can be inferred from the results that the simultaneous planning of generation resources and flexible load will not only reduce design and operation costs, but also increase network security against uncertainties and unforeseen contingencies.

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