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فعالية إعادة تشكيل وطلب برنامج الاستجابة باعتبار السيارة الكهربائية في شبكات التوزيع الذكية الشمسية

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الخــلاصــة

التطورات في توزيع التشغيل الآلي التكنلوجي وخوارزميات التحسين قد انتجت إدراك عالٍ في إعادة التشكيل وأيضاً انشأت نظام توزيع مرن قابل للتطبيق. هذا البحث يعرض اقتراح خوارزميه الذئب الرصاصي المثلى (GWO) لتوليد أفضل إعاده تكوين البنية للنظام عندما يكون تحت الضغط. الحل يُستخدَم في برنامج إستجابه الطلب إعتماداً على نماذج سعر التكلفة والفوائد. ويهدف مخطط إعاده التشكيل المتكامله مع حضور دور برنامج استجابة الطلب النظري في حصول تخفيض الذروه الى التخفيف من خسائر الطاقة لشبكة التوزيع .وفي نفس الوقت، يهدف هذا البحث إلى تحديد أفضل منفعة وربح للعميل ويجب تبسيط شبكه الطاقه خلال ساعات الذروة من قِبَل العملاء المسرفين.ويتم اختبار هذه التقنية المقترحة على system (bus test) (IEEE69) على عملاء السكن.وقد أظهرت النتائج انخفاض بنسبه 56.46٪ في خسائر الطاقة والمنافع الاقتصادية ويمكن للمؤسسة أو المستهلك الحصول عليها مع النموذج المقترح.

Distribution system loss minimization with network reconfiguration and cost-benefit price based demand reduction modeling

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ABSTRACT

The developments in distribution automation technologies and optimization algorithms have made realization of highly reconfigurable and flexible distribution system viable. This paper proposes grey wolf optimization algorithm (GWO) to generate best reconfigured topology of the system when grid is under stress condition. The solution is used in demand response program based on cost-benefit price models. The reconfiguration scheme integrated with presented game theoretic demand response program is intended at getting peak load reductions to mitigate the distribution network power losses. Simultaneously, this research is aimed at determining the optimal utility, customer profit and load shedding, customers have to do to facilitate power grid on peak hours. The proposed technique is tested on IEEE 69 bus test system with residential customers. The results show 56.46% reduction in power losses and economic benefits, a utility or a consumer can get with the proposed model.

Keywords: Demand response program; distribution system; power loss; reconfiguration.

INTRODUCTION

Distribution systems have evolved to an extent, where the power utilities inevitably need automation technologies to operate smoothly.The automated operation, control and protection of distribution systems have become possible due to advance microprocessor and high speedtelecommunications technologies.

Network reconfiguration is one of the functions of distribution automation thatalters the topology of the network by remotely controlling the status of tie (normally open) and sectionalizing (normally closed) switches. Thus, an intelligently reconfigured distribution system is able to optimize its operation under normal and abnormal grid conditions. Since uncertainty in generation (in case of intermittent energy resources)and demand fluctuations at different periods of a day is observed, it is possible to run optimal reconfiguration more than once a day. However, frequent configuration switching involves additional operational cost and efficient protection schemes (Coroama et al., 2013).

Another way to enhance the operation of distribution system is through the demand response programs (DRPs), whereby consumers interrupt their electricity usage in specific time periods against agreed rewards (Torriti et al., 2010). These programs are offered by electric utilities or companies to increase the efficiency and economics of the power systems (Aalami et al., 2010; Dashti & Afsharnia, 2011; Kim & Shcherbakova , 2011) and are usually established on incentive-based or price-based mechanisms (Aalami et al., 2010; Albadi & El-Saadany, 2008). In this context, utilities like Pacific Gas and Electric Company, Southern California Edison, and San Diego Gas & Electricoffer a variety of residential and non-residential DRPs. However, load demand flexibility is the key element that can implement a successful DRP. Therefore, it is essential to encourage consumers to actively participate in such programs by providing attractive financial profit.

Many works are found in literature investigating distribution system automation on the loss-minimization problem (Moradzadeh, 2013), where researchers employ reconfiguration approach as a viable tool to solve it. Different classical, heuristic and meta-heuristic algorithms are proposed in this regard. The disadvantage colligated with classical methods applied in reconfiguration problems (Liu et al., 2005; Sarma & Prakasa, 1995; Wagner et al., 1991) is their large computational time and chances to generate local optimal solutions. The heuristics methods for reconfiguration are employed in Zhenkun et al.(2008); Civanlar et al. (1988); Baran & Wu (1989); Shirmohammadi & Hong, 1(989); Gomes et al.(2005); Ababei & Kavasseri (2011 and Ahmadi & Marti (2015). They depend both on the initial state of the switches in the network and on their operational sequence. Hence, it is not possible to always get the global optimal result. Therefore, a vast body of research is applied on meta-heuristic algorithms over the years to effectively resolve the reconfiguration problem (Cebrian & Kagan2010; Esmaeilian et al., 2013; Mendoza et al., 2006; Swarnkar et al., 2011; Imran & Kowsalya, 2014; Sudha et al., 2014; Duan et al., 2015; Nguyen & Viet, 2015; Abdelaziz et al., 2010; Shareef et al., 2014; Rao et al., 2013; Chen et al., 2011). Meta-heuristic methods such as Gravitational search algorithms, Genetic algorithms, Harmony search method, Ant colony, Firefly algorithm, Particle swarm optimization, Bat algorithms, and Cuckoo search algorithm are a few to mention which are employed for loss minimization.

In literature, among demand management strategies, DRPs are generallyadopted to flatten the demand curve by avoiding undesirable peaks at some time periods of a day, as proposed in Lopez et al.(2015), Palensky & Dietrich (2011) and Logenthiran et al.(2012). In Zareen et al. (2015), the author considered supply and demand uncertainties and proposed DRP scheme based on reliability dependent cost–benefit price model. Meanwhile in Faria et al.(2011), particle swarm optimization (PSO) is used to achieve the optimal scheduling of demand response including different energy and generation resources. A few works in literature handled economic dispatch problem with DRPs.The work presented in Arif et al.(2014) and Mazidi et al.(2014) are considered economic dispatch problem for integrating renewable sources (solar and wind) with demand response in a micro grid.

There is very limited work that considers the reconfiguration and DRP jointly to the author's best knowledge. The proposed paper aims to present a practical framework for minimizing distribution system active power losses, by integrating reconfiguration with DRP strategy. In addition, a new meta-heuristic algorithm, Grey Wolf optimizer is used to determine the optimal reconfigured topology. This optimization method is adopted as it is found to be good in both exploration and exploitation searching modes. Comparative analyses are conducted on standard network in order to confirm the suitability of the proposed algorithm.The main contributions of this paper are as follows: (i) Proposing first application of new optimization method "Grey Wolf optimization (GWO) algorithm" to identify optimal system configuration,(ii) modeling utility and customer payoffs using game theory concepts, (iii) validating this proposed synergy on a widely used IEEE 69 bus test system.

The rest of this paper is devised as follows. First formulation of the objective is illustrated following discussion on the proposed approach to find the optimal configuration that can efficiently minimizes distribution system losses. Next, detailed information about proposed optimization method and cost-benefit price model for the DRP structure is presented. After the simulation framework, and discussion on the results finally conclusions are drawn.

PROBLEM FORMULATION

Objective function

The reconfiguration problem with demand management strategy is formulated as a single objective function to reduce active power losses in the distribution system at peak loads.Figure 1 depicts an N-bus radial distribution network, where each bus contains a load. The symbols shown in the figure are given below:

$y_{i,i+1} = 1/\left(R_{i,i+1} + jX_{i,i+1}\right)$: admittanceof branch between buses iand i+1

$I_{i,i+1}$: current flowing through branch between buses i and i+1

$R_{i,i+1}, X_{i,i+1}$: resistance and reactance of branch between buses i and i+1

PL_i, QL_i : active and reactive load power at bus i

The magnitudes and phase angles of the system's bus voltages can be determined by solving the mismatch Equations (1) and (2) (Baghzouz & Ertem1990) by using the Newton-Raphson power flow method.

$$PL_i - \sum_{k=i-1}^{i+1} |Y_{ki}||V_k||V_i| \cos\left(\delta_i - \delta_k - \theta_{ki}\right) = 0 \text{, i=1,2,3,......N} \quad (1)$$

$$QL_i - \sum_{k=i-1}^{i+1} |Y_{ki}||V_k||V_i| \sin\left(\delta_i - \delta_k - \theta_{ki}\right) = 0 \text{, i=1,2,3,......N} \quad (2)$$

Therefore, the active power loss in the branch between two adjacent buses i and i + 1 can be calculated by:

$$P_{loss(i,i+1)} = R_{i,i+1}\left(\left|V_{i+1} - V_i\right|\left|Y_{i,i+1}\right|\right)^2 \quad (3)$$

The total active power loss reduction problem in terms of current can be modeled as:

$$\min\ P_{loss}^{t=to} = \sum_{i=1}^{nb} R_{i,i+1} \times \left|I_{i,i+1}\right|^2 \quad (4)$$

Let "to" be the peak load time,then $R_{i,i+1}$ and $I_{i,i+1}$ are the branch resistance and current between buses i and *i+1* at "to" hour respectively, and nb is the total number of branches in the distribution system.

Constraints

It is worth to note that network reconfiguration is subjected to constraints, the violation of which may lead to an unfeasible solution. Usually during reconfiguration, the following constraints are satisfied:

System bus voltage limit: The normal operation of electric power systems requires that the voltage magnitude is to be kept within an allowed limit. Thus, voltage drop limit is the range within which power system can operate safely (Prada & Souza,1998).

$$V_{\min} \leq V_i \leq V_{\max} \quad (5)$$

Where V_{min} and V_{max} are the minimum and maximum voltage limit set to 0.9 p.u and 1.0 p.u of the i^{th} bus respectively, while V_i is the i^{th} bus voltage magnitude.

Branch current limit: Every conductor used in power system has an associated current limit known as thermal capacity. This current carrying capacity is limited by the conductor's maximum design temperature, which determines the maximum sag of the conductor and the rate of annealing (Aman, 2014). Thermal capacity is deterministically determined by assuming specific values of ambient conditions and the method of laying (Wan et al., 1999).

$$\left| I_j \right| \leq I_j^{\max} \quad (6)$$

Where I_j is the magnitude of j^{th} branch and $I_j^{\max}$ is the maximum current capacity of j^{th} branch.

Radial topology of the network: Distribution systems generally operate in radial topology because of simple protection and coordination schemes and reduced short circuit current (Lavorato et al., 2012). In radial topology, each consumer has a single source of supply. Thus, during reconfiguration after changing the status of switches, it is necessary that every candidate solution should preserve the radial nature of the system. If bus number 1 is a slack bus (main electric source) and all other buses are load buses then,

$$\sum_{j=1}^{nb} sw_j^c = N - 1 \quad (7a)$$

$$sw_{j,i}^c = sw_{j-1,i-1}^c = 1 \quad (7b)$$

where N is the number of system buses and sw^c_j refers to j^{th} switch in candidate network topology after reconfiguration. It is important that the buses are energized. So, Equation (7b) co-occurs with Equation (7a), wherein the status of the j^{th} switch $sw_{j-1,i-1}^c$, which supplies power to the ith bus, depends on the status of its adjacent *switch* ,. This adjacent switch is the switch which is connected towards the source sideand delivers power to the i-1$^{\text{th}}$ bus. Hence, if their status is equal to 1, it means that all of the N buses are being supplied with power by a unique path. The conditions in Equations (7a) and (7b) ensure radiality.

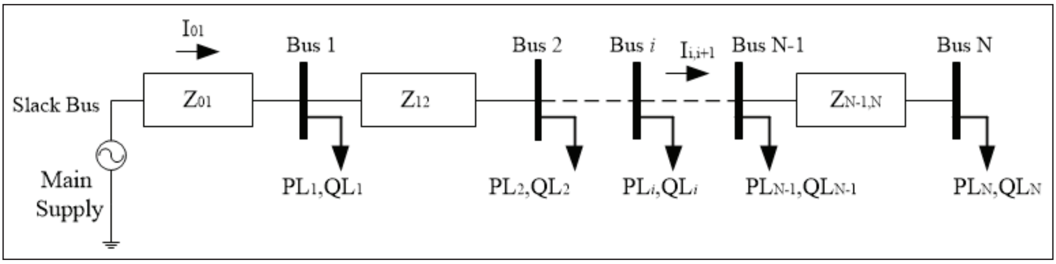


Fig.1. Single line diagram of a Radial distribution system

PROPOSED APPROACH

In the proposed approach, the optimal network reconfiguration technique together with the demand reduction strategy is adopted to lower the power losses and enhance the demand flexibility.

The day is partitioned into 24 hours time period. For the purpose to validate the demand flexibility, a load pattern of the system is considered as shown in Figure 2. The peak load, which is maximum at three periods t (that is, h = 9, 11 and 19 hours) is reduced and shifted at period $t+k$(h = 22, 23 and 24 hours). The presented methodology consists of these steps:

i) Considering a typical hourly load profile of the distribution system.

ii) Determining an optimal network configuration at peak load of the system by using GWO algorithm, as depicted in Figure 4.

iii) Identifying the set of nodes at which potential customers agree to curtail their load demand.

iv) Calculating the amount of load that is to be shed by agreed customers .

v) Making adjustments to the demand according to proposed DRP model without altering the optimal configuration.

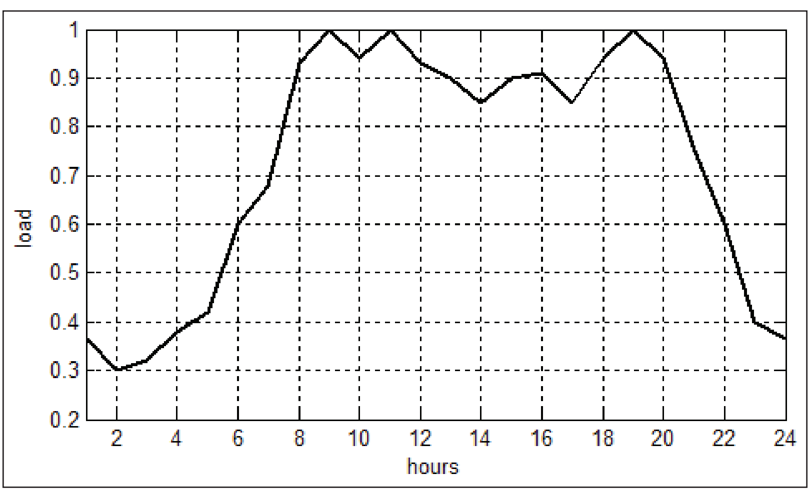


Fig.2. A typical hourly load profile for 69 bus test system

GREY WOLF OPTIMIZATION

Overview of GWO

Grey Wolf optimizer (GWO) is a meta-heuristic method proposed by Mirjalili et al. (2014). The GWO is established on the leadership hierarchy and hunting mechanism of grey wolves in nature. It employs four types of grey wolves such as alpha, beta, delta, and omega for simulating the leadership hierarchy. Alphas are the leaders and are responsible for making all decisions that have to be followed by the pack. In addition, alphas are the only wolves that are allowed to mate in the pack. The next highest level in the hierarchy of grey wolves is beta. Betas are subordinate wolves and advise the alpha in decision making. Furthermore, they act as discipliner for the pack. On the other hand, Delta wolves only dominate the omegas. They play the role as scouts, sentinels, elders, hunters, and caretakers in the pack. Meanwhile, Omegas are the lowest ranked grey wolves that are allowed to eatin the last. However, their presence is important to avoid any internal fights and problems.

Mathematical model

The GWO involves these steps:

Social hierarchy: Alphas are accepted as the fittest solution. Betas and deltas are the second and third best solutions respectively. The remaining possible solutions are considered to be omega. In the GWO algorithm, optimization is achieved by alpha, beta and delta wolves.

Encircling prey: Grey wolves encircle their prey during the hunt. This encircling behavior is mathematically modeled as:

$$\overline{C} = \left| \overline{B} \cdot \overline{X_p}(t) - \overline{X}(t) \right| \tag{8}$$

$$\overline{X}(t+1) = \overline{X_p}(t) - \overline{A} \cdot \overline{C} \tag{9}$$

Where t shows the current iteration, $\overline{X_p}$ represents the position vector of the prey, $\overline{X}$ shows the position vector of a grey wolf and $\overline{A}$ and $\overline{B}$ are coefficient vectors that are calculated using Equations (10) and (11).

$$\overline{A} = 2\overline{d} \cdot \overline{r_1} - \overline{d} \tag{10}$$

$$\overline{B} = 2 \cdot \overline{r_2} \tag{11}$$

Where r_1 and r_2 are random numbers in [0 1] and components of vector d linearly decrease from 2 to 0 over the course of iterations.

Hunting: It is assumed that alpha, beta and delta have better knowledge about the possible location of prey. Therefore excluding them, the other search agents update their positions according to the position of the best search agent. Based on the formulae developed in Mirjalili *et al*. (2014), the new positions of search agents are determined from Equations(12-14). It is illustrated in Figure 3.

$$\overline{C_\alpha} = \left|\overline{B_1} \cdot \overline{X_\alpha} - \overline{X}\right|, \overline{C_\beta} = \left|\overline{B_2} \cdot \overline{X_\beta} - \overline{X}\right|, \overline{C_\delta} = \left|\overline{B_3} \cdot \overline{X_\delta} - \overline{X}\right| \quad (12)$$

$$\overline{X_1} = \overline{X_\alpha} - \overline{A_1} \cdot \overline{C_\alpha}, \overline{X_2} = \overline{X_\beta} - \overline{A_2} \cdot \overline{C_\beta}, \overline{X_3} = \overline{X_\delta} - \overline{A_3} \cdot \overline{C_\delta} \quad (13)$$

$$\overline{X}(t+1) = \frac{\overline{X_1} + \overline{X_2} + \overline{X_3}}{3} \quad (14)$$

Attacking prey: The grey wolves attack the prey when it stops moving. The lower the value of $\overline{d}$, the nearer the wolves move towards the prey.

Search for prey: The search for prey begins by generating random population of grey wolves (candidate solutions) that first diverge from each other and then converge to attack prey. Over the course of iterations, the first three groups of wolves estimate the possible position of the prey. Each grey wolf updates its distance from the prey. If $\left|\overline{A}\right| > 1$, it indicates that grey wolves are diverging from the prey and if $\left|\overline{A}\right| < 1$ it shows that wolves are converging towards the prey.

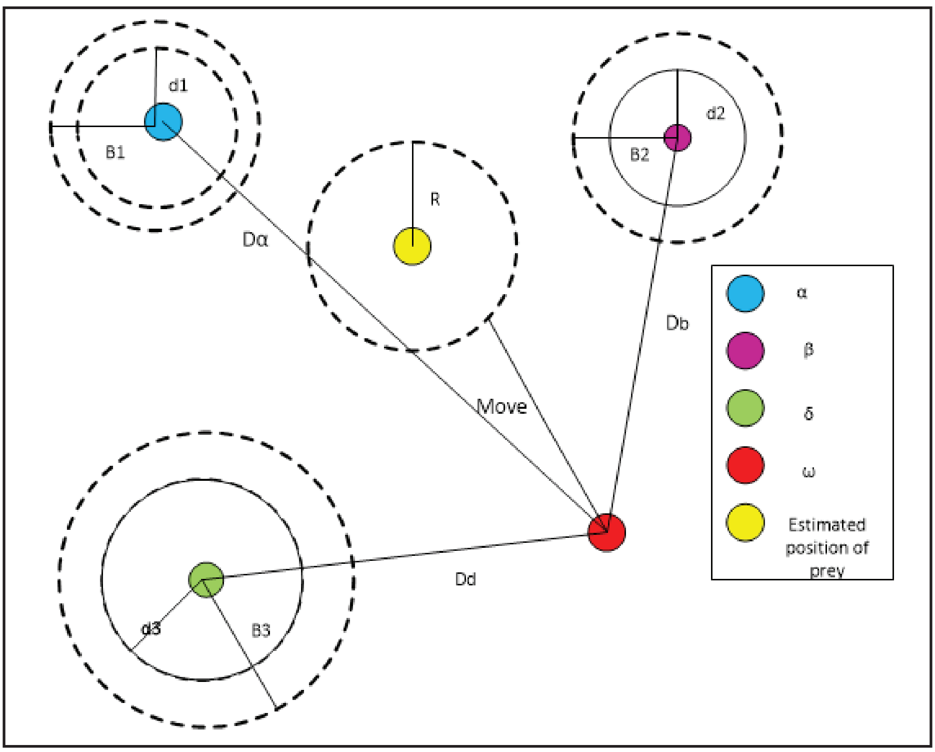


Fig.3. Position updating of wolves in GWO (Mirjalili et al., 2014)

Application of GWO algorithm to distribution system reconfiguration

To implement the GWO algorithm on the proposed multi-objective problem, the following steps are executed. The flow chart shown in Figure 4 explains the algorithm.

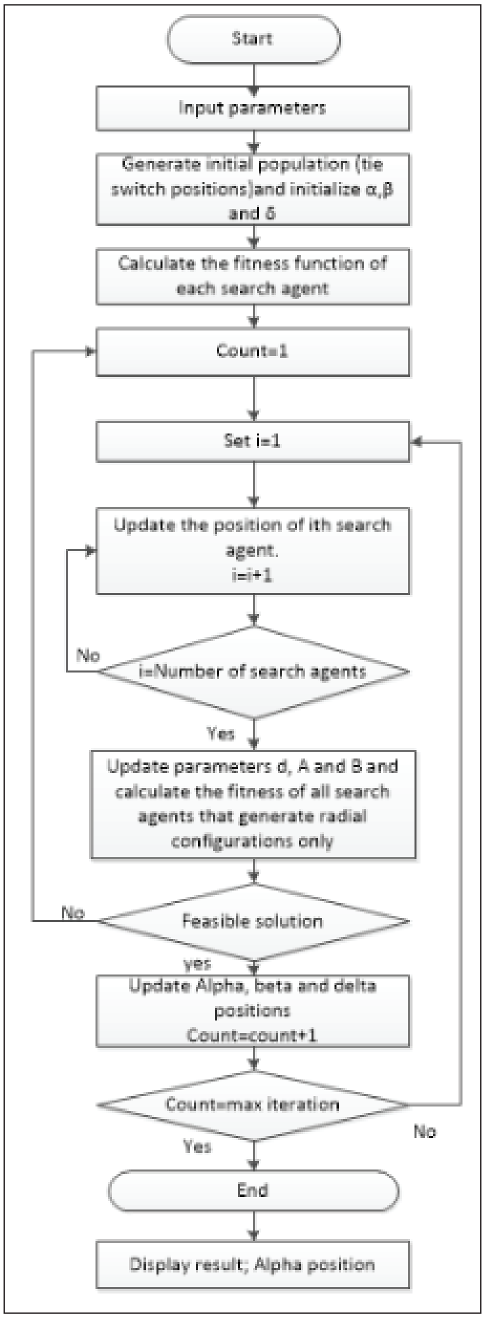


Fig.4. Flow chart of GWO algorithm

Step 1: Input the number of search agents, dimension of solution vector, maximum number of iterations and boundaries of the problem.

Step 2: Generate an initial population randomly and initialize α, β and δ wolves positions.

Step 3: Run power flow and check the constraint for radial structure of the network. In case of violation discard that agent and check for next agent. If constraint satisfies go to step 4.

Step 4: Calculate the objective function for search agents that satisfies the constraints.

Step 5: Update the position of α, β and δ wolves.

Step 6: Determine the new positions of the search agent.

Step 7: If the current iteration count reaches the predetermined maximum iteration number, the search procedure should stop, otherwise it continues and goes to Step 3.

Step 8: The last achieved alpha position is the solution of the problem.

LOAD REDUCTION BASED ON "COST-BENEFIT PRICE MODEL"

Proposed DRP structure

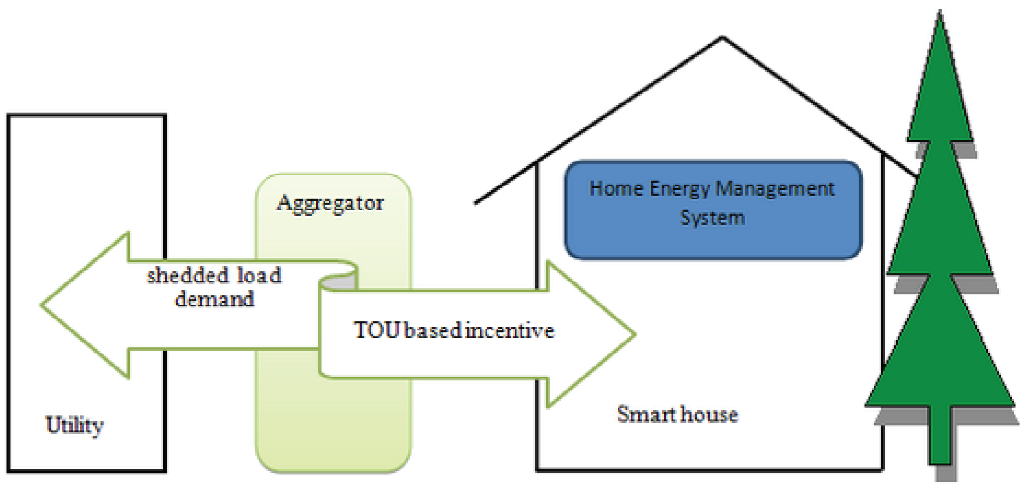


Fig.5. A generalized architecture of proposed DRP scheme

In the present study, the price response control option for DRP, based on time of use tariffs (TOU) is envisaged by considering electric utility/retailer as resource agent and the sets of customers allocated at distribution system nodes as demand agents. The nodes classification for different types of customer (residential, commercial or industrial) for this system can be found in Baghipour & Hosseini (2014). Each node is equipped with an aggregator that is connected with the demand agent's home energy management system (HEMS) and the utility. The HEMS withinthe household will adjust energy usageaccording to customer's choices, which are based on their degree of comfort. In the proposed approach, resource agent is informed about the customer type "*C*" (discussed in later section) and issues incentive that will not influence its profit. Customers are motivated to participate in DRPs and are attracted by incentives. This structure along with network reconfiguration technique leads to better distribution system planning and energy management. A generalized architecture of proposed DRP structure is depicted in Figure5.

Model formulation

The marginal cost- benefit relation is assumed to be linear as assumed in Fahrioglu & Alvarado (1999) for ademand agent with type C sheddinglamount of load. This allows us to formulate a quadratic cost function, which is expanded using Taylor's series and is shown in Equation (15). It is important to note that customer type "*C*" plays a significant role in designing the cost model, as for different customer, different price rates are applied. This parameter is used to distinguish among various demand agents based on their willingness to curtail load. It is normalized in the range between 0 and 1. A demand agent with C=1 means this is the most eager customer to curbits householdload and C=0 implies that this customer is least ready to participate in DRP. Thus, different demand agents signify different interrupted load amount "*l*"(Fahrioglu & Alvarado, 2002). The cost function is convex and is simplified similarly as in Fahrioglu & Alvarado (2002). Refer Equation (16),where K_1 and K_2 are cost coefficients and the term "$-K_2lC$" classifies the demand agents. Details about these coefficients calibration can be studied from Fahrioglu & Alvarado (2002) and Fahrioglu & Alvarado (2000).

$$m(C,l) = a_0 + aC + bl + \frac{1}{2}dl^2 + elC + \frac{1}{2}fC^2 \tag{15}$$

$$m(C,l) = K_1 l^2 + K_2 l - K_2 lC \tag{16}$$

$$m(C,l) = \frac{1}{2}l^2 + (l - Cl) \tag{17}$$

In a liberalized market, profit maximization is considered as a global goal for both utility and customer to get involved in the DRPs. The utility and the customers make decisions on the amount of load a customer may curtail or othercustomer may requestagainst an incentive offered to them by the utility. The strategy in this work is treated as an agenda setting game, where both utility and customers act as agenda setters as well as legislators. The utility proposes an incentive to the customer. The customer observes the proposal "*x*" and selects the amount of load it can shed on compromising its comfort level. Suppose lo is the load that demand agent 1 has to curtail at time "*t*" hour as their participation in DRPs and ld is that load which any other user (demand agent 2) mayask the utility at time "*t+k*" hours. Existing electricity rate is changed and a new price" τ_d^{t+k} "for demand agent 2 and "τ_o^t" for demand agent 1 is set. The incentive depends upon the parameter "r". It is a continuous random variable fixed by utility keeping two points into consideration, which are (i) reward paid to consumers by utility should be less than or equal to utility budget and (ii) The range of parameter is defined as $0 < r \leq 1$.

Demand agents manipulate the price and decide to participate in DRPs. Hence, it is obvious that cost-benefit functions for both agents are considered as a function of dynamic TOU price and interrupted amount of load. The proposal is logically feasible to both the utility and customer, if and only if they see some monetary benefit in it, that is $\mu_g^u > 0$ >0 and $\mu_g^c > 0$ >0. The proposal is not feasible if there is no participation of demand agent 1 in the game.The utility and customer payoffs are modeled as dynamic games of complete information with pure strategy set S={0,1}. Here, S=0 is a pure strategy when probability of the player to win the game is 0 and S=1 is the strategy, when probability of the player to win the game is 1.This is mathematically shown in Equations (19) and (23) subject to the condition that demand agent is not allowed to sell and buy electricity on the same time.

Utility benefit function

Since reduction in demand yields reduction in generation units, the net benefit that electric companies and utilities can make will also include generation cost savings. If reward paid to i^{th} demand agent1 for curbing l_o is $\tau^{t}_{o,i} l_o$ and profit obtained from i^{th} demand agent 2 for consuming l_d power more than its actual demand is $\tau^{t+k}_{d,i} l_d$ then, the utility benefit model is depicted in Equation (18). However, it is not necessary that demand agent 2 is always present. These customers are part of utility benefit model only when they require power in exigency situation, for instance in charging Electrical vehicles.

$$\mu^{u}_{g} = \sum_{i=1}^{N_{d2}} \tau^{t+k}_{d,i} l_d + c_l \sum_{j=1}^{nb} \left(R_j \left| I_j \right|^2 - R'_j \left| I'_j \right|^2 \right) + c_g \left(P^{base}_{g} - P'_g \right) - \sum_{i=1}^{N_{d1}} \tau^{t}_{o,i} l_o \quad \text{(18a)}$$

s.t. $\mu^{u}_{g} > 0$

In the absence of demand agent 2:

$$\mu^{u}_{g} = c_l \sum_{j=1}^{nb} \left(R_j \left| I_j \right|^2 - R'_j \left| I'_j \right|^2 \right) + c_g \left(P^{base}_{g} - P'_g \right) - \sum_{i=1}^{N_{d1}} \tau^{t}_{o,i} l_o \quad \text{(18b)}$$

Where c_l and c_g are power loss and generation costs (International Energy Agency Report, 2015), N_{d1} and N_{d2} are numbers of demand agent1 and demand agent 2 involved in DRPs.

$$\mu^{u}_{g} = \begin{cases} \mu^{u}_{g}; \; S=1 \\ c_l \sum_{j=1}^{nb} \left(R_j \left| I_j \right|^2 - R'_j \left| I'_j \right|^2 \right) + c_g \left(P^{base}_{g} - P'_g \right); \; S=0 \end{cases} \quad \text{(19)}$$

Customer benefit function

A customer benefit function is the difference of incentive I and outage cost.

$$\mu^{c}_{g} = I - \left(\frac{1}{2} l_o^2 + l_o - Cl \right) \quad \text{(20)}$$

Where $I = \tau^{t}_{o} (r+1) l_o$ (21)

substituting Equation (21) in Equation (20) we will get Equation (22):

$$\mu^{c}_{g} = \tau^{t}_{o} (r+1) l_o - \left(\frac{1}{2} l_o^2 + l_o - Cl_o \right) \quad \text{(22)}$$

s.t $\mu^{c}_{g} > 0$

$$\mu_g^c = \begin{cases} \mu_g^c; \ S=1 \\ -m(C,u); \ S=0 \end{cases} \tag{23}$$

Due to the concavity of the customer cost-benefit function, the classical optimization rule is used to maximize the benefit function. Therefore, $\partial\mu_g^c / \partial l_o = 0$, the corresponding amount of load shed at time "t" hours can be achieved as:

$$l_o = (r+1)\tau_o^t + C - 1 \tag{24}$$

Similarly, we can calculate the amount of load at time "t+k" hours requested by demand agent 2 as:

$$l_d = (r+1)\tau_o^{t+k} + C - 1 \tag{25}$$

According to proposed model $\tau_o^{t+k} < \tau_o^{t}$, hence lo at "t" hours>$l_d$ at "*t+k*" hours, it can be observed that (i) distribution system's daily load demand is reducedand (ii)load from "*t*" hour is shifted at"*t+k*" hours. This further reduces active power loss of the system since $P_{loss}^{to} = f(l_o)$.

SIMULATIONFRAMEWORK

The execution of proposed methodology needs upgrade of distribution system, as well as customer household infrastructure. It meansthat they are equipped with latest technologies.

The IEEE 69-bus test system is considered for validating the proposed methodology. Since MATLAB has an object-oriented environment, it is therefore preferred for simulation purposes of the proposed work. The value of parameters used in the presented paper is given in Table 1and Table 2.

Table 1. Parameters used for simulating demand response program

c_l \$/MWh	c_g \$/MWh[1]	C	r %	α_i kW	i^{th} household Peak demand kW
50	61	0.5	1	12	18

Table 2. Parameters of proposed and implemented algorithm for reconfiguration purpose

Algorithm parameters	Search agents	Maximum iteration	C1	C2	α	G_0
GWO	30	100	-	-	-	-
GSA	30	100	-	-	20	100
PSO	30	100	1.4	1.0	-	-

Selection of demand agents

Let "α_i" be the decision variable which describes a threshold value for energy usage of i^{th} customer at N^{th} node, below which a customer cannot compromise on its comfort level. The user sets "α_i" on the basis of its daily schedule of using appliances. This is customer's private information that is not shared with the utility. The demand agent 1 agrees to shed its loads if $\alpha \geq l_o$.

As mentioned in Shengnan et al. (2011), for any residential household; water heaters, air conditioners, washing machines, electrical vehicles, clothes dryers and microwaves are regarded as controllable loads. All other loads, for example lightning loads, refrigerators, laptops, televisions and other 110/120V loads, are termed as critical or uncontrolled loads. In case of commercial constructions, HVAC is the only controllable load, while the rest are critical loads. If n_f and n_c represents the number of controllable and critical load appliances in a house, denotes power consumption of each appliance at time slot t; then, the value of α can be evaluated from Equation (26):

$$\alpha_i = \sum_{s=1}^{n_f} \Phi_s + \sum_{s=1}^{n_c} \left(w \times \Phi_s \right) \tag{26}$$

where $w = \begin{cases} 1 \text{ if sth applianceis ON} \\ 0 \text{ if sth applianceis OFF} \end{cases}$

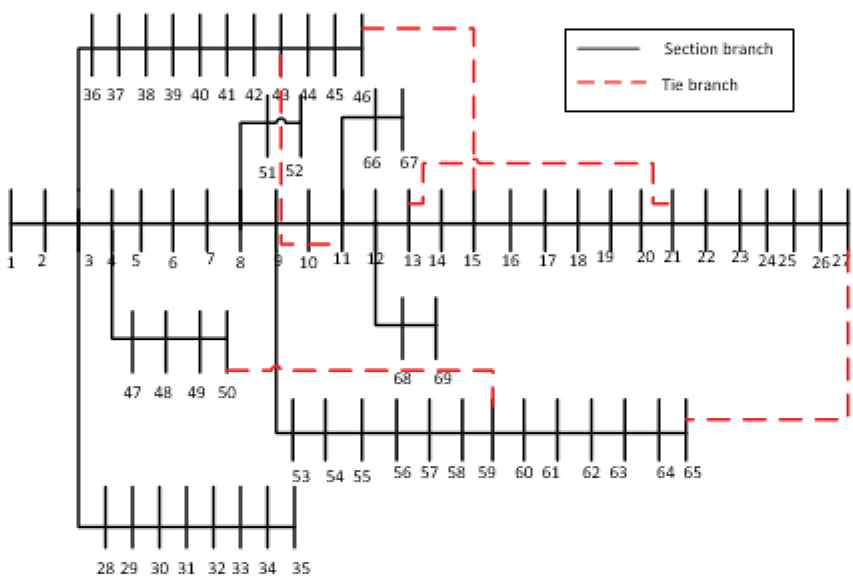


Fig.6. Single line diagram for 69-bus test system

In the considered test system, the number of residential customers at specified nodes (N) is determined by dividing total node load with average residential demand. For the purpose of analysis, it is supposed that at least one customer from N=7, 8, 10, 11 and 12 is participating in DRP as a demand agent 1 at t= t hours and one customer at N=6, 13, 26, 27 and 67 are the demand agent 2 at t= $t+k$ hours.

RESULTS AND DISCUSSIONS

Minimization of power losses due to network reconfiguration technique

The single line diagram of this network is depicted in Figure 6. Data related to bus, branch and tie lines is given in Tables 3 and 4. The power loss for base configuration is 225kW, which is reduced to 56.17% after reconfiguration using GWO algorithm. To validate the effectiveness of GWO, it has been compared with other algorithms such as particle swarm optimization (PSO) and gravitational search algorithm (GSA). The results are illustrated in Table 5. From this table, it can be inferred that the proposed method yields better outcome with respect to PSO and GSA approaches. The convergence graph of all these algorithms regarding losses is shown in Figure 7, where it demonstrates that PSO converges faster than GWO. However, since distribution system planning problem is simulated during steady state, computational time does not affect algorithm's performance (Sultana et al., 2016).

Table 3. Branch and bus data for the 69-bus test system

Branch no.	From bus	To Bus	R (p.u)	X (p.u)	To bus power (MW)	To bus power (MVAR)
1	1	2	0.0003	0.0007	0.0000	0.0000
2	2	3	0.0003	0.0007	0.0000	0.0000
3	3	4	0.0009	0.0022	0.0000	0.0000
4	4	5	0.0157	0.0183	0.0000	0.0000
5	5	6	0.2284	0.1163	0.0026	0.0022
6	6	7	0.2378	0.1211	0.0404	0.0300
7	7	8	0.0575	0.0293	0.0750	0.0540
8	8	9	0.0308	0.0157	0.0300	0.0220
9	9	10	0.5110	0.1689	0.0280	0.0190
10	10	11	0.1168	0.0386	0.1450	0.1040
11	11	12	0.4438	0.1467	0.1450	0.1040
12	12	13	0.6426	0.2121	0.0080	0.0055
13	13	14	0.6514	0.2152	0.0080	0.0055
14	14	15	0.6601	0.2181	0.0000	0.0000
15	15	16	0.1227	0.0406	0.0455	0.0300
16	16	17	0.2336	0.0772	0.0600	0.0350
17	17	18	0.0029	0.0010	0.0600	0.0350
18	18	19	0.2044	0.0676	0.0000	0.0000
19	19	20	0.1314	0.0434	0.0010	0.0006
20	20	21	0.2131	0.0704	0.1140	0.0810
21	21	22	0.0087	0.0029	0.0053	0.0035
22	22	23	0.0993	0.0328	0.0000	0.0000
23	23	24	0.2161	0.0714	0.0280	0.0200
24	24	25	0.4672	0.1544	0.0000	0.0000
25	25	26	0.1927	0.0637	0.0140	0.0100

26	26	27	0.1081	0.0357	0.0140	0.0100
27	3	28	0.0027	0.0067	0.0260	0.0185
28	28	29	0.0399	0.0976	0.0260	0.0185
29	29	30	0.2482	0.0820	0.0000	0.0000
30	30	31	0.0438	0.0145	0.0000	0.0000
31	31	32	0.2190	0.0724	0.0000	0.0000
32	32	33	0.5235	0.1757	0.0140	0.0100
33	33	34	1.0656	0.3523	0.0195	0.0140
34	34	35	0.9196	0.3040	0.0060	0.0040
35	3	36	0.0027	0.0067	0.0260	0.0186
36	36	37	0.0399	0.0976	0.0260	0.0186
37	37	38	0.0657	0.0767	0.0000	0.0000
38	38	39	0.0190	0.0221	0.0240	0.0170
39	39	40	0.0011	0.0013	0.0240	0.0170
40	40	41	0.4544	0.5309	0.0012	0.0010
41	41	42	0.1934	0.2260	0.0000	0.0000
42	42	43	0.0256	0.0298	0.0060	0.0043
43	43	44	0.0057	0.0072	0.0000	0.0000
44	44	45	0.0679	0.0857	0.0392	0.0263
45	45	46	0.0006	0.0007	0.0392	0.0263
46	4	47	0.0021	0.0052	0.0000	0.0000
47	47	48	0.0531	0.1300	0.0790	0.0564
48	48	49	0.1808	0.4424	0.3847	0.2745
49	49	50	0.0513	0.1255	0.3847	0.2745
50	8	51	0.0579	0.0295	0.0405	0.0283
51	51	52	0.2071	0.0695	0.0036	0.0027
52	9	53	0.1086	0.0553	0.0043	0.0035
53	53	54	0.1267	0.0645	0.0264	0.0190
54	54	55	0.1773	0.0903	0.0240	0.0172
55	55	56	0.1755	0.0894	0.0000	0.0000
56	56	57	0.9920	0.3330	0.0000	0.0000
57	57	58	0.4890	0.1641	0.0000	0.0000
58	58	59	0.1898	0.0628	0.1000	0.0720
59	59	60	0.2409	0.0731	0.0000	0.0000
60	60	61	0.3166	0.1613	1.2440	0.8880
61	61	62	0.0608	0.0309	0.0320	0.0230
62	62	63	0.0905	0.0460	0.0000	0.0000
63	63	64	0.4433	0.2258	0.2270	0.1620
64	64	65	0.6495	0.3308	0.0590	0.0420
65	11	66	0.1255	0.0381	0.0180	0.0130
66	66	67	0.0029	0.0009	0.0180	0.0130
67	12	68	0.4613	0.1525	0.0280	0.0200
68	68	69	0.0029	0.0010	0.0280	0.0200

Table 4. Tie line data for 69-bus test system

Branch no.	From bus	To Bus	R (p.u)	X (p.u)
69	11	43	0.3121	0.3121
70	13	21	0.3121	0.3121
71	15	46	0.6242	0.3121
72	50	59	1.2484	0.6242
73	27	65	0.6242	0.3121

Table 5. Active power loss for 69-bus test system

Algorithms	Control vector of the solution					Power loss, kW
	Sw1	Sw2	Sw3	Sw4	Sw5	
Duan *et al.* 2015	15	59	62	71	70	99.62
Rao *et al.* 2013	15	56	62	71	70	99.35
Chen *et al.* 2011	14	56	62	71	70	99.62
PSO	14	55	10	61	70	104.28
GSA	13	58	69	61	70	99.60
GWO	14	55	69	61	70	98.61

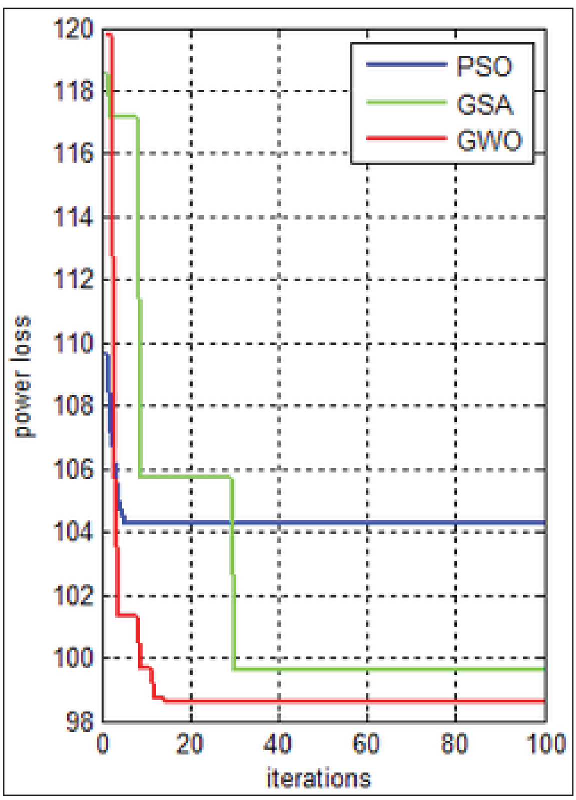


Fig.7. Reduction in losses

In addition, GWO addresses both exploitation and exploration searching modes. It does not give pre-mature solution. Therefore, by using GWO algorithm an optimal configuration of the distribution system is foundthat also satisfies the operational constraints.

Nevertheless, there is no unique acceptance regarding, which is the most appropriate method to handle network reconfiguration problem (Tomoiaga et al., 2013). The most crucial point is how to use the specific knowledge of the problem domain and how it is modeled and implemented (Tomoiaga *et al*., 2013). Besides, any heuristic or meta-heuristic method that gives better result can be applied to perform system reconfiguration. The novelty of the proposed work isthejoint implementation of reconfiguration and DRP methodologies.

Minimization of power losses due to demand response program

To illustrate the performance of the proposed method, two DRP scenarios are discussed in this work. In the first DRP strategy, the resource agent, demand agent 1 and demand agent 2 participate. In this case, it is illustrated that in addition to total active power loss reduction, load has shifted from peak hours to off peak period. In the second DRP strategy,only demand agent 1along with resource agent participates. Hereby only distribution system power loss minimization is achieved. This is demonstrated in Figure 8.The considered time horizon is a single day partitioned into 24 hours. For different periods of day, different TOU rates are given as tabulated in Table 6. In aderegulated electricity market, both agents obtain profit, when the cost–benefit price and amount of load to be curtailed is evaluatedaccording to the proposed model, as shown in Figure 9. It is evident that the monetary benefit is dependent on variable loads as adjusted by customers in response to price signals. At the maximum load limit, utility benefit is the least. This is because the price paid to the customers is more, as compared to the capital saved on conserving energy.

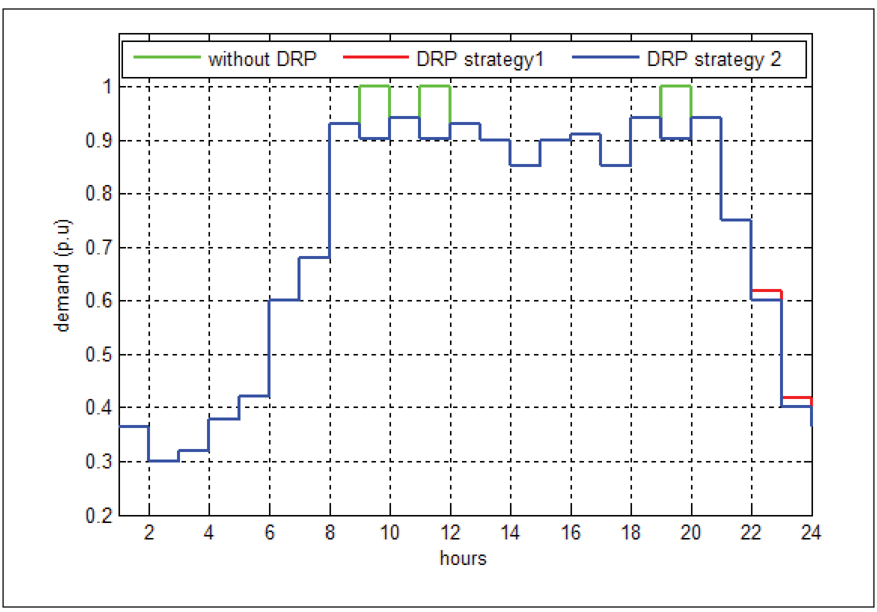


Fig.8. Peak demand reduction with (out) demand response strategies.

It can be clearly observed from the simulation results that the voltage profile is improved. The system's minimum voltage in case of original network is 0.9092 p.u. that after applying proposed approach has improved to 0.9495 (~0.95 p.u). Figure10 shows voltage profile for randomly selected buses. This can enhance system reliability and thus the system will be less vulnerable to voltage collapse.

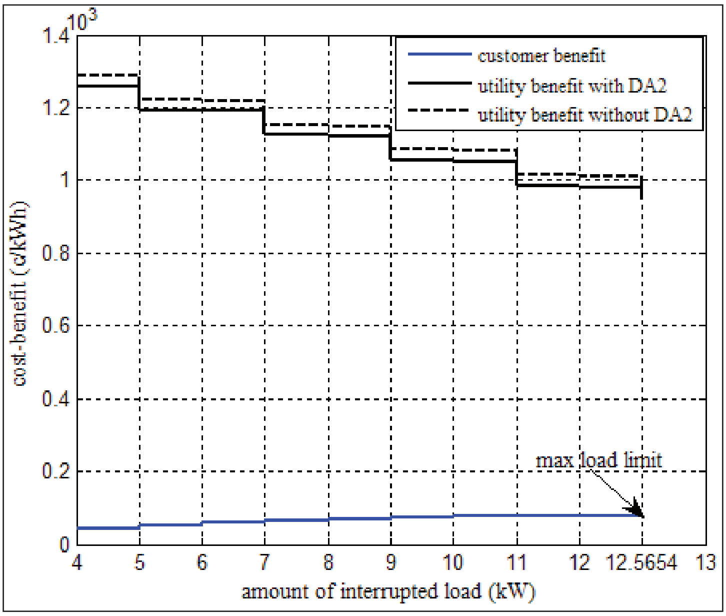
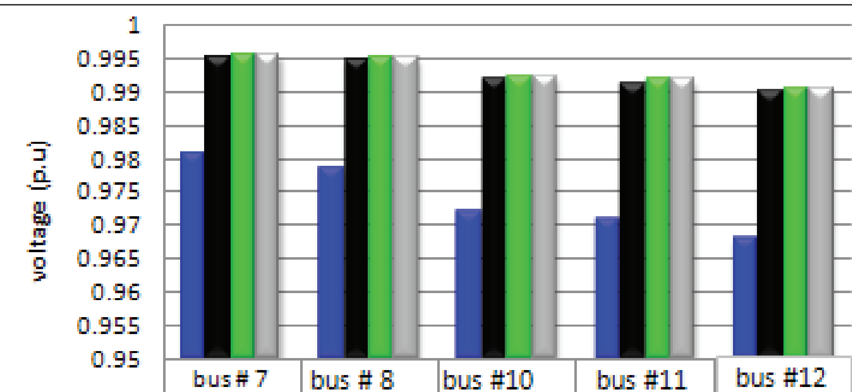


Fig.9.Cost-benefit curves for utility and residential customer during on peak hours



	bus # 7	bus # 8	bus #10	bus #11	bus #12
base case	0.9808	0.9786	0.9724	0.9713	0.9682
reconfiguration	0.9954	0.9949	0.9919	0.9913	0.9901
DRP strategy 1	0.9956	0.9952	0.9924	0.9919	0.9907
DRP starategy 2	0.9957	0.9952	0.9925	0.9919	0.9908

Fig.10. Demand agent's voltage profile with (out) strategies

The presented work has efficiently minimized the power losses up to 56.46% during peak hours by employing the combination of reconfiguration technique and the demandmanagement approach. This synergy can reduce the oversized capacity of distribution lines and so can cut down the maintenance cost of distribution system. Furthermore, if the percentage of demand agent participation is increased, it can increase the stability of the grid.

Table 6. TOU rates

Patterns	Periods	Rates (cents/kWh)
Residential Customers		
On Peak	7 a.m-9 a.m 5 a.m-8 p.m	12.936
Shoulder	9 a.m -5 p.m 8 p.m-10 p.m	6.2480
Off peak	10 p.m-7 a.m	2.8270
Non Residential; weekends are off peak times and for weekdays as:		
On Peak	7a.m -5 p.m	18.3810
Shoulder	5 p.m-10 p.m	9.0200
Off peak	10 p.m-7 a.m	3.7290

CONCLUSIONS

In this paper, the combination of reconfigurationand DRP scheme are implemented to solve loss minimization problem. A best configuration of distribution system is determined by using GWO algorithm.The dynamic cost-benefit models for utility and customers to establish a demand response scheme are also presented. The proposed model is based on the economic game theory, where the benefit uncertainties are associated with customer type and interrupted load quantity, when the grid is under stress. A correlation between the variableload and financial profit gained by both agents under specific incentive structure is illustrated.The maximization of demand reduction during on-peak hours and minimization of system power losses is obtained. This innovative idea merges two different strategies to facilitate utilities in improving the grid condition and stimulating consumers to participate in DRPs, by offering better incentives.

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