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# Impact of reconfiguration and demand response program considering electrical vehicles in smart distribution network

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**Abstract**: Depletion of energy reserves has promoted plug-in-hybrid electric vehicles to replace gasoline fuelled automobiles. The charging of these vehicles increases the grid load demand and therefore active power losses are increased. This paper presents combined demand response program and reconfiguration approach to simultaneously reduce active power losses and utility operating cost, considering vehicles load uncertainties. Demand response program based on load management contract is executed to manage load consumption, whereas for reconfiguration purpose Grey wolf optimization algorithm (GWO) is used. Standard 69-bus system is considered for the authentication of the proposed work. The implementation of reconfiguration and demand response has reduced 57.2% losses and has benefitted both consumer and utility economically.
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**Keywords:** active power loss, consumer-utility benefit, demand response, distribution system.

## I. INTRODUCTION

Due to environmental pollution and energy crisis, the transport industry is anticipating a proliferation of Electric Vehicles (EVs). The charging activities of EVs are expected to increase the demand congestion on the power grids, consequently increasing active power losses. The high power losses reduce the efficiency of transmitting energy to the utility's end-users. In addition, electric companies will be obligated to pay financial penalties when active power losses will exceed the standard ones [1]. Hence its reduction has gained much more attention from utilities [2].

Fortunately due to technological revolutions, system planners are motivated to change the way a distribution network is planned and operated [3]. Therefore Distribution Automation Systems are being deployed to achieve Smart Distribution System (SDS). Under SDS paradigm, Demand Response Programs (DRPs) are being considered as a promising tool to operate system reliably. DRP motivates consumers to interrupt their electricity usage for brief time duration against some agreed rewards [4].

Research in [5-7] has analyzed DRP schemes considering the financial profit a consumer or an electric utility can obtain. Work reported in [8, 9] has concentrated on consumers' behavior and choices in proposed DRPs, while DRPs in [10-12] have incorporated Renewable Energy Resources in the system. Nevertheless, DRPs are limited by consumer electricity consumption pattern where consumers have to trade off between their electric usage and comfort level. Thus, presented study proposes new dimension to tackle the problem by hybridizing DRP with distribution Network Reconfiguration ((NR).

NR is a method of altering the configuration of the network by changing the status of sectionalizing and tie-switches to accomplish specified objectives [13, 14]. During the last two decades numerous methods have been employed for NR. The most important point is how to use the specific knowledge of the problem domain to model and implement it [15]. Yet, algorithm that can explore and exploit searching modes of problem with least switching frequency of tie switches in hybridized domain was lacking. The mentioned shortcoming is resolved in this study by employing GWO technique.

Main contributions of this paper are as follows:

- To study the combined effect of NR and DRP on system active power losses, utility-customer profits and utility operating cost with EVs connected to the distribution grid.
- To apply Grey Wolf Optimization algorithm for the multi-objective distribution system reconfiguration problem.

## II. PROBLEM FORMULATION

The proposed strategy is formulated as a weighted single objective optimization problem as:

$$\min OF = w_1 \times of_1 + w_2 \times of_2 \quad (1)$$

$$of_1 = \frac{PL_h}{PL_h^{base}} \quad (2)$$

$$of_2 = \frac{OC_h^{NR\_DR}}{OC_h^{base}} \quad (3)$$

where,

$$PL_h = \sum_{m=1}^{nb} R_m \times |I_m|^2 \quad \text{,for h=1,2..24} \quad (4)$$

$$OC_h^{NR\_DR} = Pd_h \times C_{grid} + PL_h \times C_{grid} + C_{DRP} \quad (5)$$

where $PL_h$ and $PL_h^{base}$ is active power loss with and without strategy. $OC_h^{NR\_DR}$ is the utility operating cost after reconfiguration and demand management at each hour. $R_m$ and $I_m$ are the $m^{th}$ branch resistance and current, *nb* is the total number of branches in the distribution system, $Pd_h$ is the power demand at each hour, $C_{grid}$ [16] is the cost of purchased power that is supplied to consumers, $C_{DRP}$ is the cost due to the execution of DRP and is usually the incentive cost paid to customers for interrupting the power demand.

It is noteworthy that all necessary constraints related to DRP, NR and EV battery protection have been considered.

## III. METHODOLOGY

Step1: The load pattern is achieved by randomly plugging EVs to the system buses as shown in Fig.1. The uncertainties associated with number of EVs are modeled using Monte Carlo simulations. It is assumed that EVs will start charging if remaining energy is less or equal to 20% of total battery capacity. In this work, EVs are charged through level 1 charging scheme [17].

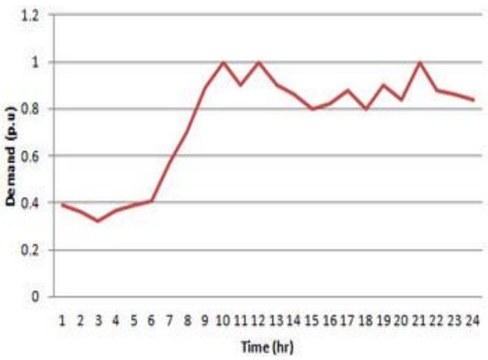


**Fig.1** Load profile considering EVs

Step 2: DRP is based on load management contract, where customer's cost and benefit functions are modeled by Eqs. (6) and (8), as developed in [18-20]. It is important to note that customer type plays a significant role in designing the cost model because different customers represent different loads and thus imply different outage costs [20, 21]. Thus, the variable *C* is the customers' type and is utilized to distinguish different customers based on their willingness to shed power. *C* is normalized and ranges between 0 and 1, so if *C* =0 it means the customer is least willing to curb his load, and if *C* =1 it shows most willing customer.

$$m(C,l) = \frac{1}{2}l^2 + (l - Cl) \quad (6)$$

$$\beta_h^C = I - \left(\frac{1}{2}l^2 + l - Cl\right) \quad (7)$$

where *I* is the monetary incentive for any customer. Thus if *j* number of customers are shedding their load then customer benefit is obtained through

$$\beta_j^C = I_j - \left(\frac{1}{2}l_j^2 + l_j - C_j l_j\right) for j = 1,2,3...J \quad (8)$$

Besides, for a day, each *j* customer will get total profit as:

$$\beta_{j_{total}}^C = \sum_{h=1}^{24} \beta_h^C \quad (9)$$

$$\beta_h^U = \lambda l - I \quad (10)$$

where for j customers, net utility benefit for entire day is modified as:

$$\beta_{j_{total}}^U = \sum_{h=1}^{24}\sum_{j=1}^{J} \lambda_j l_j - I_j \quad \text{for j=1,2,3,…}J \quad (11)$$

where $\lambda$ is the cost of not delivering power to any specific location in the system. This parameter is usually calculated by electric utilities and is termed as "value of power interruptibility" [19, 20].

Game theory based mechanism design with revelation principle is applied to determine incentive *I* and curbed load *l* [19]. In this study, the load management contract is extended for a day, and is incorporated with reconfiguration algorithm.

$$l_h(C_h) = \begin{cases} 0, \; for 0 \le C_h < 1 - \dfrac{\lambda}{2} \\ C_h + \lambda_h - 2, \; for 1 - \dfrac{\lambda}{2} \le C_h < 1 \end{cases} \quad (12)$$

$$I_h(C_h) = \begin{cases} 0, \; for 0 \le C_h < 1 - \dfrac{\lambda}{2} \\ C_h^2 - 2C_h + 2C_h\lambda_h + 0.75\lambda_h^2 - 2\lambda_h + 1, \\ for 1 - \dfrac{\lambda}{2} \le C_h \le 1 \end{cases} \quad (13)$$

Step 3: The system is reconfigured using GWO algorithm as described in [22].

## IV. RESULTS

The system performance has been evaluated on the basis of minimum power losses and reduced demand consumption on 69-bus test system. The reduction in load demand has been achieved with active participation of customers that have willingly curbed their load and has gain profit as demonstrated in Fig.2.

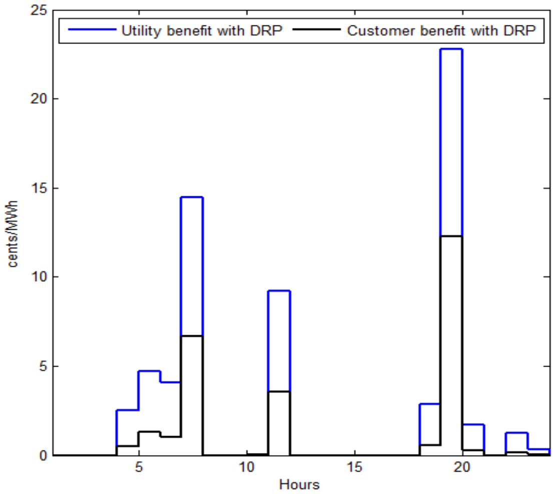


**Fig.2** Utility and consumer profits

As evident in Fig.3 the power loss at maximum demand hours for base configuration is 225kW. The additional stochastic EV charging load on grid has increased this loss from 225kW to 253kW. Yet, with the application of proposed scheme, 57.2% loss reduction has been observed. Furthermore, the desired objective function is minimized from base value of 1 per unit as depicted in Fig. 4.

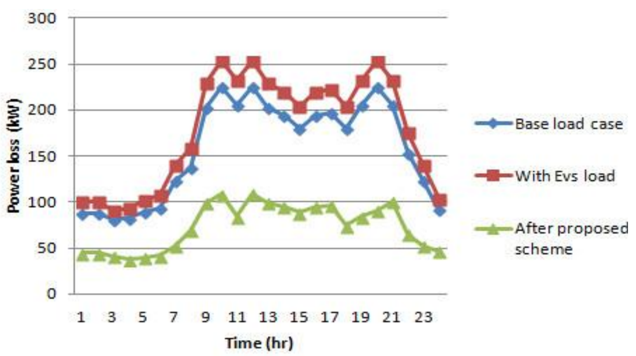


**Fig.3** Active power loss reduction


**Fig.4** Objective function with proposed scheme

The five tie switches for the base configuration of the system is [69, 70, 71, 72, 73]. From Table 1, it can be seen that four out of five new tie switches are similar for each time period. This implies that the method has overcome the drawback of frequently changing all the five tie switches. Thus utility can save money involved in additional operational cost and efficient protection schemes, which are associated with system reconfiguration [23].

**Table 1:** Hourly positions of new tie switches

| | Case 1 |
|---|---|
| | Minimum OF |
| Hour | Tie Switches |
| 1 | 14, 57,61,69,70 |
| 2 | 14, 57,61,69,70 |
| 3 | 14, 56,61,69,70 |
| 4 | 14, 58,61,69,70 |
| 5 | 14, 58,61,69,70 |
| 6 | 14, 55,61,69,70 |
| 7 | 14, 56,61,69,70 |
| 8 | 14, 57,61,69,70 |
| 9 | 14, 58,61,69,70 |
| 10 | 14, 57,61,69,70 |
| 11 | 14, 55,61,69,70 |
| 12 | 14, 57,61,69,70 |
| 13 | 14, 58,61,69,70 |
| 14 | 14, 55,61,69,70 |
| 15 | 14, 55,61,69,70 |
| 16 | 14, 55,61,69,70 |
| 17 | 14, 58,61,69,70 |
| 18 | 14, 57,61,69,70 |
| 19 | 14, 55,61,69,70 |
| 20 | 14, 58,61,69,70 |
| 21 | 14, 56,61,69,70 |
| 22 | 14, 55,61,69,70 |
| 23 | 14, 56,61,69,70 |
| 24 | 14, 58,61,69,70 |

## V. CONCLUSION

In this paper joint execution of reconfiguration and demand response program has been studied. The uncertain EVs charging activities have been included to operate the network under stress condition. Load management contract benefitting both customer and utility has been implemented to analyze the effect of demand response on the active power losses in a distribution network and on utility operating cost. SDS is optimally reconfigured via Grey wolf optimization method. Hence presented scheme can be adopted as a feasible option from utility perspective to obtain technical and economical gains.

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