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Energy loss minimization through peak shaving using energy storage☆

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Summary This paper presents an optimal placement methodology of energy storage to improve energy loss minimization through peak shaving in the presence of renewable distributed generation. Storage sizing is modelled by considering the load profile and desired peak shaving. This storage is suitably divided into multiple storage units and optimally allocated at multiple sites with suitable charge discharge strategy. Thus the peak shaving for maximum loss reduction is explored here. Renewable distributed generation (RDG) is modelled based on the seasonal variations of renewable resources *e.g.*, solar or wind and these RDGs are placed at suitable locations. A high-performance Grey Wolf Optimization (GWO) algorithm is applied to the proposed methodology. The results are compared with the well-known genetic algorithm. The proposed methodology is illustrated by various case studies on a 34-bus test system. Significant loss minimization is obtained by optimal location of multiple energy storage units through peak shaving.

Introduction

Energy storage (ES) is as an essential component in distribution system when large amount of renewable resources are involved with their inherent intermittency. ES can mitigate the intermittency associate with renewable sources (Yang and Nehorai, 2014). Also large integration of RDG may produce reverse power flow in the feeder (Alam et al., 2013). The optimal allocation of ES adjusts the power flow and reduces power losses in distribution system (Zheng et al., 2014). The placement of ES at non-optimal places increases system losses and may require large sized storage.

Planning the best allocation of ES can have a significant impact on the power system including minimizing power losses (Vaiju et al., 2014). One of the effective ways to reduce distribution losses is load levelling or peak shaving. Peak shaving is a process of shaving the peak load and filling the load valley. It shifts some of the current or load from the peak period to off-peak period and decreases the net ohmic losses (Saboori and Abdi, 2013; Shaw et al., 2009; Nourai

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et al., 2008). Loss minimization also depends on the operation schedule *i.e.*, charging discharging of the ES (Bozchalui and Sharma, 2014).

From the current literature on ES, it is found that a few have addressed the loss minimization through peak shaving using ES. The optimal location of suitably sized ES for peak shaving is hardly addressed. This paper presents the application of peak shaving for improved energy loss minimization by shifting the peak load at optimal locations on the feeder in presence of RDGs. The proposed methodology is applied to a 34 bus test system using a competitive optimization algorithm call Grey Wolf Optimizer (GWO) in MATLAB. The results are compared with genetic algorithm (GA).

Problem formulation

Wind power model

Wind power model gives the expected generation obtained from the historical data. Wind generation is modelled with Weibull pdf due to its simplicity and best fit to experimental data (Lun and Lam, 2000). The pdf indicates the probability or fraction of time. Weibull pdf $F_w(v)$ for wind turbine is as given below (Sathyajith, 2006).

$$Fw(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (1)$$

Here, k, c and v are the shape index, scale index and wind speed respectively. Rayleigh distribution is a simplified case of the Weibull distribution where shape factor 'k' is assumed as 2. The cumulative distribution function *cdf* and probability of wind speed being between v_1 and v_2 can be obtained as given in Eqs. (2) and (3).

$$fw(v) = 1 - e{-}^{[\pi/4(v/v_m)]} \quad (2)$$

$$f_w(v)(v_1 < v_2 < v_3) = f_w(v_2) - f_w(v_1) \quad (3)$$

The power delivered by a wind turbine $Po(w)$ is usually represented through its power curve, where a relation between the wind speed and generated power is established.

$$PO(w) = \begin{cases} 0 & 0 \le v_{av} \le v_{ci} \\ P_r \times \left(\dfrac{v_{av} - v_{ci}}{v_r - v_{ci}}\right) & v_{ci} \le v_{av} \le v_r \\ P_r & v_r \le v_{av} \le v_{co} \\ 0 & v_{co} \le v_{av} \end{cases} \quad (4)$$

where, v_{ci}, v_{co}, v_r, v_{av} and P_r represent the cut-in speed, cut-off speed, rated speed, average speed and output power of wind turbine respectively. The total expected wind power P_W at any time interval can be obtained as,

$$P_W = \int_0^{\infty} Po\,(w)\,fw\,(v)\,dv \quad (5)$$

Battery storage model

The minimum battery size required for peak shaving can be calculated when the desired peak shaving power is decided. Power peaks on the load curves are the area above the reference value P_{ref}. If $P_{PS,t}$ is the required maximum power to shave and $T_{d,t}$ is the discharge time then the area above P_{ref} gives battery capacity (E_{BE}) as given below (Oudalov et al., 2007).

$$E_{BE} = \sum_{t=1}^{T} P_{PS,t} T_{d,t} \quad (6)$$

This battery size gets increased due to minimum state of charge (*i.e.*, *SOC*) and efficiency of the battery. Loss minimization gets improved if the large sized storage is splitted into multiple storage units (N_d) of same size and load shifting is obtained at multiple sites rather than at one site with a single storage (Nourai et al., 2008). These multiple storage units by optimal allocation provide further improvement in loss minimization. The energy rating of these ES units is given as,

$$E_{BES} = \frac{E_{BE}}{N_d} \quad (7)$$

Observing the total peak time period T_d and off-peak time period T_c from load pattern, maximum charge discharge power can be obtained as,

$$P_{B,dis}^{max} = \frac{E_{BES}}{T_d} \quad \text{or} \quad P_{B,ch}^{max} = \frac{E_{BES}}{T_c} \quad (8)$$

Load model

The load considered in this system is hourly peak load expressed as a percentage of daily peak load. The load profile follows IEEE-RTS system (Probability Methods Subcommittee, 1979). The hourly loads for three different seasons *i.e.*, summer, monsoon and winter are considered.

Power flow model

The power losses P_{Loss} at each hour is calculated with backward/forward sweep method (Hosseini et al., 2007). System is assumed to be balanced and is represented on per phase basis. The total power loss in the system is,

$$P_{Loss} = \sum_{i=0}^{n-1} I_i^2 r_i \quad (9)$$

where, I_i and r_i gives the gives the branch current and resistance respectively. Now considering RDG power and charging discharging power of battery at node i, the active power P_i during charging and discharging gets modified as shown below,

$$P_i = P_{Li} - P_{W,i} + P_{B,ch,i} \quad (10)$$

$$P_i = P_{Li} - P_{W,i} - P_{B,disch,i} \quad (11)$$

where P_W, P_{Li}, $P_{B,ch,i}$ and $P_{B,disch,i}$ represents expected RDG power, active load power at ith bus, charging power and discharging powers at ith bus respectively.

Objective function

The objective is to minimize annual energy losses by optimal allocation of energy storage. Considering each season of four months and each month has 30 days, objective function can be given as below.

$$F = \min\left[120\sum_{j=1}^{NY}\sum_{t=1}^{24}(P_{Loss,sum} + P_{Loss,mon} + P_{Loss,win})\right] \quad (12)$$

where, $P_{Loss,sum}$, $P_{Loss,mon}$ and $P_{Loss,win}$ gives the losses of summer, monsoon and winter seasons.

Optimization algorithm and solution methodology

This complex optimization problem is solved by the robust and competitive algorithm which is called Grey Wolf Optimizer (GWO). This algorithm is inspired by the grey wolves and it is based on the leadership hierarchy and hunting mechanism of grey wolves (Mirjalili et al., 2014). Optimal location of energy storage for loss minimization is achieved by GWO algorithm. The search agents are initialized as 20, and the termination criteria is fixed to 150 iterations or a tolerance value of 10^{-6}, whichever is met first.

The initialization for the solution methodology includes system data, bus data, expected wind generation, charge-discharge time *i.e.*, total number of storage units that are to be placed. The initialization for the GWO includes the number of search agents, initial positions and termination criterion. The fitness of search agents is calculated considering the objective function *i.e.*, loss minimization by optimal location of ES. The positions of the search agents are updated. If termination criterion is reached then the optimal values are stored otherwise the process is repeated. A similar solution methodology is applied for genetic algorithm (GA) (Sivanandam and Deepa, 2008).

Results and discussion

The proposed placement and sizing methodology is applied to a 34 bus radial system as shown in Fig. 1 (Chis et al., 1997). Wind turbine considered in this study is WES 100 (Windenergy). It is a two bladed, high performance, reliable 100 kW mid-size wind turbine. The cut-in, rated, cut-off and survival wind speeds are 3 m/s, 13 m/s, 25 m/s and 60 m/s respectively.

Depending on the average temperature of the months, the whole year is divided into three seasons *i.e.*, summer, monsoon and winter. Hourly wind speed data of 5 years is taken for a site named, Satara (*Longitude*: 74.05 E, *Latitude*: 17.75 N) Maharashtra state, India (RREDC). Expected generation is obtained for the wind power using Eq. (5). The total peak load on the system is 5 MW. The hourly peak load is expressed as a percentage of the daily peak. The storage units are optimally placed on any of the 34 buses except the source bus (*i.e.*, bus number 1). The candidate buses selected for RDG placement are buses {5, 18, 25, 28, 30}, assuming they have sufficient renewable potential and space availability. Each RDG size is 200 kW. Maximum penetration of wind DG is considered as 2 MW assuming 40% penetration. A maximum of 40% penetration of renewable energy sources put a little additional cost on the system hence it is an acceptable maximum penetration limit (IEA, 2014).

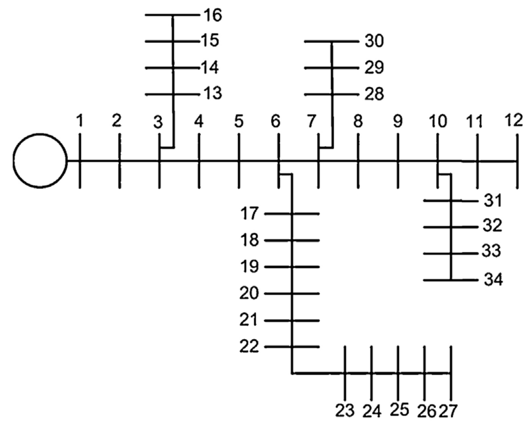

Figure 1 34 bus system.

The proposed methodology is applied to four case studies *i.e.*, single storage, two storage, three storage and four storage units. The base case annual energy losses *i.e.*, losses without any renewable DG or storage are 948.87 MWh. The obtained minimum size of storage is 11.250 MWh. This storage is split into equal sized units. The charging discharging efficiency of the storage is assumed as 95% and minimum *SOC* is limited to 20%. The load peak is from 10 a.m. to 7 p.m. This is the battery discharging period and charging from the grid occurs during others hours. The maximum charging discharging power can be obtained from Eq. (8).

The results for optimal location of ES are presented in Table 1. The results are presented for four cases. In case one, the single storage units is optimally placed. The storage is placed on bus number two by GA and at bus number six by GWO. The loss minimization obtained by GA and GWO are 118.1 MWh and 152.9 MWh respectively. Similarly other three case studies are presented. In case II, same optimal locations and loss minimization is obtained by GA and GWO. With increased number of storage units optimal locations are

Table 1 Optimal location and loss minimization.

Case no.	Storage units	Optimal locations (bus no.)		Loss minimization (MWh)	
		GA	GWO	GA	GWO
I	1	2	6	118.1	152.9
II	2	3, 8	3, 8	157.9	157.9
II	3	3, 21, 31	3, 10, 21	164.6	165.0
IV	4	7, 15, 23, 31	3, 6, 10, 22	165.2	166.0

provided by GWO as shown in case III and case IV. Significant loss minimization is obtained by optimal location of three storage units.

From the above discussions, it can be observed that, the methodology provides significant loss minimization. Loss minimization through peak shaving depends on the number of peak shits (*i.e.*, storage units) on optimal locations. The robust optimization algorithm *i.e.*, GWO provides significant loss minimization through peak shaving with ES.

Conclusion

This paper presents optimal location methodology for energy storage in presence of renewable DG *i.e.*, wind DG. Significant loss minimization is also obtained by peak shifting at multiple optimal locations of ES. This nonlinear optimization problem is solved with a robust and competitive optimization algorithm called Grey Wolf Optimizer (GWO). The effectiveness of the methodology is tested with a case study on a 34-bus test system. The loss minimization improve up to certain number of ES by optimal location of ES. With the proposed methodology, GWO provides improved loss minimization as compared to GA by peak shaving at optimal locations.

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