Paper ID APEN-MIT-2019_052
Applied Energy Symposium: MIT A+B
May 22-24, 2019 • Boston, USA

Energy Storage Optimal Configuration with Life-Cycle Cost–Benefit Analysis

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*Abstract***—**With the large scale access of distributed generation to distribution networks, the increase of distributed generation permeability has brought a series of impacts on voltage, power quality, dispatching and operation of distribution networks. Optimal configuration of energy storage systems can effectively solve these issues brought by the increased penetration of distribute generation. In this study an interactive bi-level optimal energy storage planning approach has been proposed, which takes the average annual net cost optimization into consideration. In the proposed approach, the capacity configuration and the charging/discharging power of energy storage systems are carefully analyzed while life-cycle cost including investment cost, operation and maintenance cost, replacement cost, recovery value and disposal cost, as well as energy storage arbitrage income, government's incentives and environmental benefits are synthetically deliberated. Finally, the feasibility and effectiveness of the proposed optimal configuration strategy has been simulated on a real UK distribution feeder model.

Keywords—distributed generation, energy storage system, life-cycle cost, economic benefit, genetic algorithm, simulated annealing

I. Introduction

Renewable energy resources represented by wind power and photovoltaic (PV) generation are characterized by intermittencies, randomness and uncertainties. With the increasing penetration of distributed generation (DG), the integrated renewables have brought a series of impacts on the voltage, power quality, dispatching and operation of distribution networks. The energy storage system (ESS) can effectively overcome the voltage volatility caused by the increase of DG permeability in the distribution networks by its operational characteristics of charging and discharging.

Currently, ESS can be generally categorized into six categories: mechanical storage systems, electrochemical storage systems, electrical storage systems, thermochemical storage systems, chemical storage systems and thermal energy storage systems [1]. Among these storage technologies, batteries have been recognized as one of the most economical and mature storage technology, which can be widely implemented in various applications and has been selected as the energy storage equipment in this study. At present, the main obstacles to the large-scale application of batteries are the relatively low cycle-time and high costs. Therefore, the optimal planning of ESS capacity has attracted considerable attention worldwide.

In order to maximize the ESSs revenue, Moghaddam *et. al.* [2] developed an ESS optimal operation strategy considering the income of energy storage arbitrage and auxiliary service revenue via providing system frequency regulation. Therefore, the optimal operation strategy of ESS can be achieved. Xiao *et. al.* [3] proposed a sitting and sizing bi-level optimization model where the optimal capacity and location of the ESS aiming at minimizing total net present value of the distribution network were determined in outer optimization process and the optimal power flow and capacity adjustment strategies were carried out in inner optimization. An optimal ESS configuration model considering the benefits of ESS in energy conservation, network loss reduction and environmental protection was proposed [4] to achieve the maximum revenue during the lifetime of the ESS. The current research activities on energy storage planning mainly focus on two aspects: cost reduction and revenue maximization, but there are few studies addressing both of these aspects across the entire life cycle.

In this paper, in order to improve the voltage fluctuations caused by DG integration, an interactive bi-level planning strategy which determines the optimal operation and the capacity of the ESS in the distribute grids, utilizing the Genetic Algorithm (GA) combined with Simulated Annealing (SA) is presented. Comparing to the existing literature, a comprehensive life-cycle cost (LCC) model has been established, and the LCC of the ESS has been effectively reduced with the average annual revenue through economic operation. Firstly, the economic model of the ESS in distribution networks with economic benefit model and LCC model is established. Then the charging/discharging model and the capacity fading model of the chosen ESS are proposed. An interactive bi-level planning strategy is then presented. The outer optimization process optimizes the operation of the ESS to minimize the average annual net cost and send the output of the operating power and the rated power to the inner optimization. Inner optimization determines the capacity of the ESS aiming at minimizing the LCC and return the rated capacity and average annual cost in life-cycle to the outer optimization. Finally, a case study is carried out to verify the effectiveness.

II. ESS Modelling Considering Life Cycle Characteristics

The average annual net cost of ESS in distribution grids can be expressed as (1).

$$f = \cos t - profit \tag{1}$$

$$\cos t = C_1 + C_2 + C_3 + C_4 - C_5 \tag{2}$$

$$profit = I_1 + I_2 + I_3 \tag{3}$$

where the cost is the average annual cost in life-cycle which can be expressed as (2) and the profit is the average annual income which can be expressed as (3). In the equations, C_1 represents the investment cost, C_2 indicates the replacement cost, C_3 is the operation and maintenance cost, C_4 is the disposal cost and C_5 is the recovery value. And I_1 is the energy storage arbitrage income, I_2 is the income from the government's incentive schemes and I_3 is the associate environmental benefits.

A. The Life-Cycle Cost Model of ESS

According to the international standard IEC 60300-3-3, the LCC of a product should contain six parts: concept and definition, design and development, manufacturing, installation, operation and maintenance, disposal [5]. All of the costs considered in this study as shown in (2) are illustrated as follows.

The ESS are composed by three main components: the storage unit, the power conversion system (PCS), and the balance of the plant which includes cost for grid connection, integration facilities etc. So the investment cost can be presented as:

$$C_1 = \left(c_E E_{rate} + c_P P_{rate} + c_B E_{rate}\right)\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1} \tag{4}$$

where c_E (¥/kW·h) is the unit capacity price of ESS, c_P(¥/kW) is the PCS cost which are expressed per unit of ESS rated power capacity and c_B(¥/kW·h) is the balance of plant cost per kW·h. E_{rate} and P_{rate} are the rated capacity and power of the ESS, respectively. In this paper, the maximum charging/discharging power of ESS are considered as the rated power. Y is the project cycle (year) and σ is the discount rate (%).

The lifetime of the ESS and the PCS cannot meet the needs of the entire project cycle without replacement. So annual replacement cost is expressed as follow.

$$\begin{aligned} C_2 = {} & c_E E_{rate} \sum_{\varepsilon=1}^{k}\left(\frac{(1-\beta)^{\varepsilon n}}{(1+\sigma)^{\varepsilon n}}\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1}\right) \\ & + c_P P_{rate}\frac{(1-\beta)^{10}}{(1+\sigma)^{10}}\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1} \end{aligned} \tag{5}$$

where k is the total number of times of battery replacement ((round up, (k = Y/n − 1)), n is the lifetime of the battery and ε is the sequence of replacement. β is the average annual decline rate of the ESS investment cost. The lifetime of the PCS is considered to have a fixed life of 10 years [6].

The operation and maintenance cost consists of the labor cost and management cost, which is related to the rated power. Then c_f is the operation and maintenance cost per kW and the cost can be expressed as (6).

$$C_3 = c_f P_{rate} \tag{6}$$

As shown in [7], the ESSs should be decommissioned at the end of their life. The disposal cost can be formulated as follows:

$$C_4 = c_d P_{rate} \sum_{\varepsilon=1}^{k}\left(\frac{(1-\beta)^{\varepsilon n}}{(1+\sigma)^{\varepsilon n}}\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1}\right) \tag{7}$$

where c_d (¥/kW)is a specific disposal cost of the ESS.

In general, part of the ESS equipment can be recycled, then the recovery value can be expressed as follows:

$$C_5 = c_{res}(C_1 + C_2) \tag{8}$$

where c_{res} is the recover residual rate, usually 3% to 5% [8].

B. The Economic Benefit Model of ESS

In the context of the electricity market, the ESS can achieve arbitrage through charging at off-peak time and discharging at peak time. Dividing the entire day into 24 time slots, the energy storage arbitrage income can be calculated as:

$$\begin{aligned} I_1 &= \sum_{y=1}^{Y} A_1 D\left(\frac{(1-\beta)^y}{(1+\sigma)^y}\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1}\right) \\ A_1 &= \sum_{t=1}^{24}\left[P_{dis}(t)\mu_{dis} - P_{ch}(t)\mu_{ch}\right]C_c(t) \end{aligned} \tag{9}$$

where A_1 is the energy storage arbitrage income in one day and the y denotes the number of the years. D is the operation days in one year and $C_c(t)$ is the electricity price at time t. $P_{dis}(t)$ is the discharging power at time t and $P_{ch}(t)$ is the charging power at time t. The μ_{ch} and μ_{dis} are the charging and discharging signs for ESS, respectively. When the ESS is charging, μ_{ch} is 1 and when the ESS is discharging, μ_{dis} is 1.

At present, due to the high cost of the ESS, some countries have issued a series of incentive policies to promote the development of the ESS. Among them, economic incentives such as government financial subsidies have been effective. This paper proposes electricity price subsidy as follow:

$$\begin{aligned} I_2 &= \sum_{y=1}^{Y} A_2 D\left(\frac{(1-\beta)^y}{(1+\sigma)^y}\frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1}\right) \\ A_2 &= \sum_{t=1}^{24} P_{dis}(t)\mu_{dis} C_{e,FTT} \end{aligned} \tag{10}$$

where A_2 is the electricity price subsidy in one day and $C_{e,FTT}$ is the subsidized electricity price.

This paper defines the environmental benefits of the ESS as the greenhouse gas emission reduction benefits instead of thermal power plant to provide auxiliary services. The environmental benefits of ESS is formulated as (11).

$$I_3 = \sum_{y=1}^{Y} C_{au} E_{s,out} D\left(\frac{(1-\beta)^y}{(1+\sigma)^y} \frac{\sigma(1+\sigma)^Y}{(1+\sigma)^Y - 1}\right) \tag{11}$$

where C_{au}(¥/(MW ħ)) is the emission cost of unit energy for thermal power unit production, $E_{s,out}$ is the discharging capacity for ESS participating in auxiliary services, MW ħ.

III. Battery Modelling

Because of the high energy density, long life-cycle, low self-discharging rate, and a high comprehensive efficiency, Li-ion battery has been chosen as the energy storage device in this paper.

A. The Charging/Discharging Model of ESS

The safe operation of ESS should follow the following constraints:

$$\begin{cases} \sum_{t=1}^{24} \left(P_{dis}(t)\mu_{dis} + P_{ch}(t)\mu_{ch}\right) = 0 \\ \eta_D = \eta_C = \sqrt{\eta} \\ SOC_{\min} \le SOC(t) \le SOC_{\max} \\ -P_{rate} \le P_{dis} / P_{ch} \le P_{rate} \end{cases} \tag{12}$$

where η_D, η_C, η are the efficiency of discharging, charging, and the overall round-trip efficiency, respectively. SOC_{max} and SOC_{min} are the upper and lower limits of State-of-Charge (SOC) and SOC(t) is the SOC at time t.

The SOC in time t can be calculated as:

$$SOC(t) = \begin{cases} SOC(t-1)(1-\delta) + \eta_C \eta_{PCS} \dfrac{P_{ch}(t)\Delta t}{E_{rate}} & ,charging \\ SOC(t-1)(1-\delta) + \dfrac{P_{dis}(t)\Delta t}{E_{rate}\eta_D \eta_{PCS}} & ,discharging \end{cases} \tag{13}$$

Considering the SOC must keep in the constraints in the process of operation and the initial value of the SOC is expressed as (14) [9].

$$SOC(0) = SOC_{\min} + \frac{\max\{E(t)\}}{E_{rate}} \tag{14}$$

where E(t) is the energy fluctuation at time t relative to the initial state of the ESS which can be obtained as (15) and $E(0)=0$ [9].

$$E(t) = \begin{cases} E(t-1) + P_{ch}(t)\Delta t \eta_C \eta_{PCS} & ,charging \\ E(t-1) + \dfrac{P_{dis}(t)\Delta t}{\eta_D \eta_{PCS}} & ,discharging \end{cases} \tag{15}$$

B. Capacity Fading Model

Battery lifetime is usually defined as the cycle life or calendar life corresponding to the actual capacity degradation to 80% of the rated capacity. The capacity degradation is mainly caused by the decrease of the solution concentration and the increase of the internal resistance of the battery, which is related to the charging/discharging power, the depth of discharging, the SOC fluctuations, the number of cycles as well as the working temperature [10]. As shown in [11], the residual value of the Li-ion battery can be determined by the state of health (SOH) which changes from 1 to 0 when capacity declined from rated capacity to 80%. The capacity fading rate is related to the average SOC (SOC_{avg}) and the SOC deviation (SOC_{dev}), and the higher the SOC_{avg} or SOCdev, the higher the capacity fading rate [11]. The total capacity fading is a summation of the capacity fading that occurs under the experienced operating conditions, and considering temperature, the charging energy, SOC_{avg} and SOC_{dev}, the capacity fading can be expressed as:

$$\Gamma = \sum_{m}^{\tau_{sum}} ((x_1 SOC_{dev,m} \cdot e^{(x_2 \cdot SOC_{avg,m})} + x_3 e^{x_4 SOC_{dev,m}}) e^{(-\frac{Ea}{R}(\frac{1}{Tm} - \frac{1}{T_{ref}}))}) Ah_m \tag{16}$$

where Γ is the total capacity fading and the parameters can be chosen as: x_1 is -4.092×10^{-4},, x_2 is -2.167, x_3 is -1.408×10^{-5}, and x_4 is 6.130, Ea is 78.06 kmol/J and R is 8.314 J/(mol * K) according to [11]. One sampling period is represented by *m*, which is 24 hours in this study, and τ_{sum} is the total time period. Ah_m, T_m, $SOC_{avg,m}$ and $SOC_{dev,m}$ represent the charging energy, temperature of the ESS, average SOC and SOC deviation during time period *m*. T_{ref} is the reference temperature which is normally set to 25℃. T_m can be formulated as (17) and R_{th} is the empirical constant as shown in [12].

$$T_m = \int_0^{24} (T_{ref} + R_{th} \cdot |P_{dis}(t)\mu_{dis} + P_{ch}(t)\mu_{ch}|) dt / t \tag{17}$$

The SOH of the battery can be estimated as (18) and the lifetime of the battery n can be calculated by the τ_{sum} in (16) (round, n = τ_{sum}/365).

$$SOH = (1 - \frac{\Gamma}{0.2E_{rate}}) \cdot 100\% \tag{18}$$

IV. The Interactive Bi-Level Planning Algorithm

A. The outer optimization model

The object of the outer optimization focuses on voltage profile improvement and the average annual net cost minimization. The optimization objective function of the outer optimization can be presented as follows.

$$f1 = \min(\cos t - profit + \text{punishvalue}) \tag{19}$$

where cost and profit are presented as (2) and (3) respectively. The cost is the return value of internal optimization and profit is calculated at this stage. The punishvalue is the cost of punishment applied by the utility for unsolved voltage issues.

In addition to the ESS operation constraints shown in (12), the system operation constraints are expressed as follows.

$$\begin{cases} P_{DG} + P_S + P_{ESS} + P_L + P_{LOSS} = 0 \\ P_{ij\min} \le P_{ij} \le P_{ij\max} \\ V_{\min} \le V_i \le V_{\max} \end{cases} \tag{20}$$

where P_{DG}, P_S, P_{ESS}, P_L, P_{LOSS} are the active power of DG, the main grid, ESS, load, and loss, respectively; P_{ijmin} and P_{ijmax} are the operational constraints of the active power of line *ij*. *And* V_{max} and V_{min} are the operational constraints of the voltage magnitude. P_{ij} and V_i are the actual active power on line *ij* and the actual voltage at node *i*, respectively.

Utilizing the GA combined with the SA, the most economical operating power that meets the constraints and the demand is obtained. In order to maintain the energy balance of the ESS, the operating power should be further adjusted. The optimization method proposed by Xu *et. al.* [13] is adopted in this paper. In order to maximize the profit of arbitrage, the method is further improved. If the charging energy is greater than the discharging energy, the output power which is discharging or equal to zero during peak time need to be enhanced primarily to satisfy the energy balance requirement. If the energy balance is still not reached after the increase, the output power which is discharging or equal to zero at off-peak period should be modified. And the same process should be adopted while the discharging power is greater than the charging power.

Taking the maximum absolute value of the operating power as rated power, the rated power and operating power of the ESS are sent to the inner optimization model.

B. *The inner optimization model*

Inner optimization optimizes the capacity of the ESS by minimizing LCC based on economic operation and the rated power of outer optimization and return the rated capacity and average annual cost in life-cycle to the outer optimization. The optimization objective function of the inner optimization is presented as follows.

$$f2 = \min(\cos t) \tag{21}$$

The replacement cost can be reduced by increasing the capacity and increasing the lifetime of the battery. Based on the output power of the ESS obtained by outer optimization model, the energy fluctuation $E(t)$ can be obtained by (15). According to the energy fluctuations during the entire day, and considering the limitations of the SOC, minimum capacity to meet ESS output can be obtained [9].

$$E_0 = \frac{\max\{E(t)\} - \min\{E(t)\}}{SOC_{\max} - SOC_{\min}} \tag{22}$$

In this model, E_0 is selected as the lower limit and 1.5 times E_0 are used as the upper limit of optimization variable. The rated capacity with the LCC minimization of ESS is determined by utilizing the GA combined with SA strategy and return them to the outer optimization model.

C. *Solving Algorithm*

GA is a heuristic optimization algorithm which converges to the optimal solution successively through iteration and it can solve the constrained non-linear problems better. But it may fall into local optimal solution. SA is a general probabilistic algorithm for finding the optimal solution of a proposition in a large search domain. So the global optimal solution can be found by the GA and SA hybrid algorithms. The probability acceptance function of SA can be calculated according to (23).

$$P = e^{-\frac{(fit - fit')}{\lambda^m T_0}} \tag{23}$$

where, fit is the individual fitness without the annealing operation, and fit' is the individual fitness with annealing. λ is the annealing coefficient. T_0 is the initial temperature of annealing and m is the number of annealing times.

At the outer optimization model, the optimization variables are the output power in the whole day. The ESS output power at one hour is encoded by four gene bits and ninety-six gene bits are utilized to represent the power output of the ESS in whole day. The specific process of the outer optimization model is presented in Fig. 1.

At the inner optimization model, the optimization variable is the rated capacity of the ESS. Using the four gene bits encodes the ESS rate capacity and the (21) is used as objective function. The specific process of the inner optimization model is presented in Fig. 2.

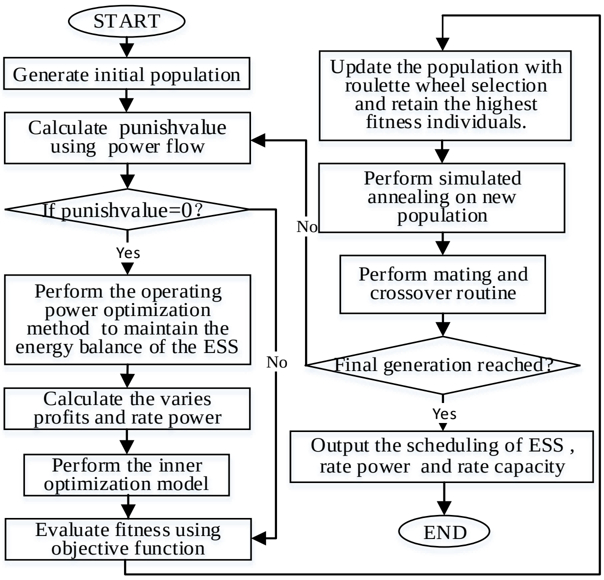

Fig. 1. Flowchart of the outer optimization.

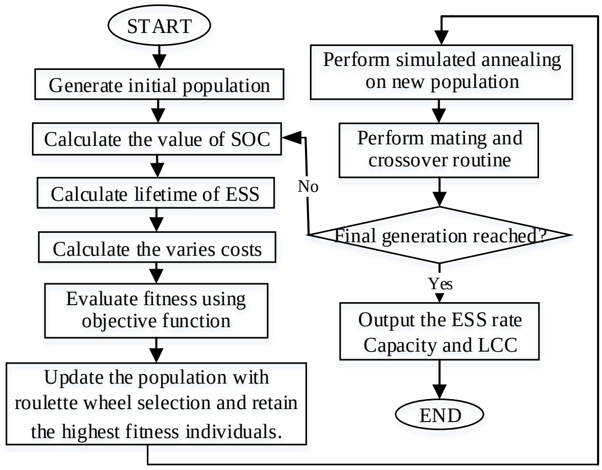

Fig. 2. Flowchart of the inner optimization.

V. CASE STUDIES

A. *Profiles*

The proposed method is implemented to the planning of the ESS, in an 11kV actual radial distribution feeder in Britain, as shown in Fig. 3. A 6MW solar photovoltaic power supply is connected to node 11, and a 6MW biomass energy is integrated at the node 6. Before integrating the DG, the entire network works below the voltage limits, and the range of voltage magnitude is 0.97 p.u. - 1.03 p.u. The peak electricity price period is from 8:00 to 21:00, at price of 0.976￥/(kW h). At other times, the electricity price is 0.294￥/(kW h). The daily profiles of the loads and the output of the DG are shown in Fig. 4.

Operation constraints of SOC range from 10% to 90% and the η and η_{PCS} are 95% [6]. The project life cycle is determined as 20 years, regardless of the annual average rate of decline in battery installation costs. For this study, c_E is 3224 ¥/kW h, c_p is 1085 ¥/kW, c_f is 155 ¥/kW year, c_d is 1582 ¥/kW [7] and c_{res} is 5% [8]. Because of the Li-ion battery do not require complicated supporting facilities, the balance of the plant cost is ignored in this study. The emission cost of unit energy for thermal power unit production is 230 ¥/(MW h) [14]. The subsidized electricity price is 18.6 ¥/MW h. In addition, the discount rate is set as 10%.

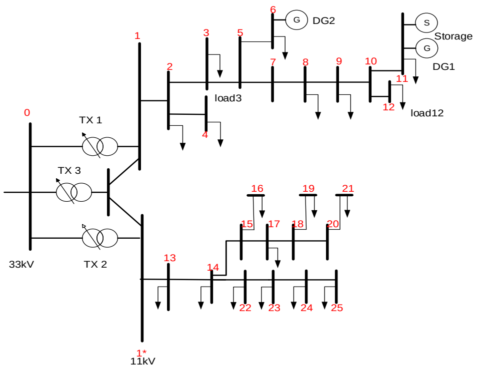

Fig. 3. 11kV radial distribution network

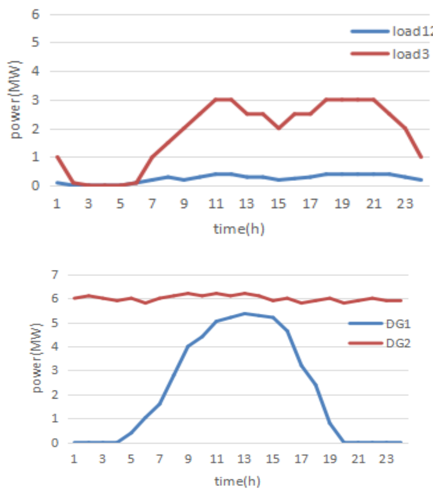

Fig. 4. Typical profiles of the loads and the DG output

B. Results

The potential installation sites of the ESS on distribution grids can be the critical load nodes, the end of the feeder, the DG busbars, and the primary substation, etc. In this study, node 11 is selected as the installation sites and the parameters of the GA and the SA are shown in Table I. In order to verify the validity and effectiveness of the model, a comparative model without taking ESS revenue into consideration is added as benchmark, which takes no account of profit and recovery value of the ESS, and adds electricity price to operating cost of LCC. The results of comparison of two models are showed in table II.

TABLE I. PARAMETERS OF GA AND SA.

Algorithm	Parameters of GA and SA	
	Parameters	***valued***
GA	Maximum generation	500
	Size of population	50
	Variation probability	0.08
	Crossover rate	0.7
SA	Annealing coefficient	0.985
	Initial temperature	100

TABLE II. COMPARISON OF ENERGY STORAGE RATED POWER, CAPACITIES AND ECONOMY RESULTS.

Results		
Contrastive items	***With revenue***	***Without revenue***
Rated capacity(kW h)	2560	2315
Rated power(kW)	625	625
Investment cost(¥/y)	1,049,098	956,319
Replacement cost(¥/y)	232,077	209,867
Operation and maintenance cost(¥/y)	96,875	318,638
Disposal cost(¥/y)	27,803	27,803
Recovery value(¥/y)	64,059	0
Arbitrage income(¥/y)	80,873	0
government's incentive(¥/y)	5,158	0
environmental benefits（¥/y）	63,788	0
Life time（y）	15	15
Average annual net cost（¥/y）	1,191,975	1,512,627

Optimal ESS configuration is designed to provide ancillary services which can improve the voltage profiles caused by DG integration. As shown in Fig. 5, the node 10 and 11 represent the voltage at node 10 and 11 respectively without ESS. Because of the biomass energy generated, the overall voltage level is high at most of the times. At the time 13h to 15h, the voltage is out of voltage constraints due to the high power output of PV and the low load consumptions. The node 10' and 11' represent the voltage at node 10 and 11 respectively with ESS. As demonstrated in Fig. 6, the output power of ESS is less than 0, which means the ESS works at load condition, at the time 13h to 15h. As shown in Fig. 5 and Fig. 6, the proposed method can manage voltage within safety margins effectively.

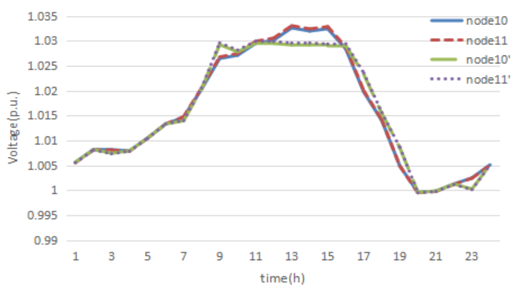

Fig. 5. Voltage profiles of typical nodes before and after the ESS configuration.

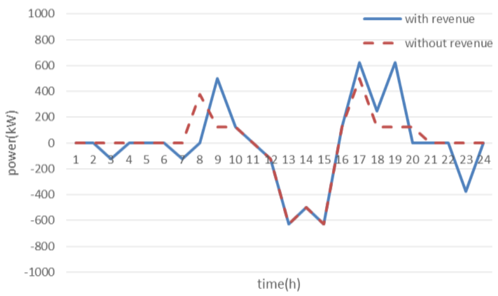

Fig. 6. Power output of the ESS

In this study, ESS reduces the cost by operating economically while providing ancillary services. As shown in Table 2, the rated capacity of the model with revenue is larger than the comparative model because the ESS needs additional capacity to provide arbitrage trade, so that investment cost and replacement cost are larger than comparative model. On the other hand, operation and maintenance cost can be significantly reduced and profits can be made through arbitrage. Comparing with the strategy provided in this paper, the operation and maintenance cost of the comparative model which ignore the revenue from the ESS has to pay electricity cost at 221,763 (¥/y). As shown in Fig. 6, the output power of the ESS in the model with revenue is charging at off-peak period and discharging at peak time, and provide ancillary services through voltage regulation, receive government's incentives, and achieve environmental benefits and recovery value. As a result, the average annual net cost of the ESS is effectively reduced by 21.2%.by comparing with the model without considering revenue.

VI. Conclusions

To solve the voltage fluctuations in the network caused by the increase of DG penetration, an interactive bi-level ESS planning strategy has been proposed considering the factors of LCC, the energy storage arbitrage income, the government's incentives and the environmental benefits. A GA combined with SA strategy is used to solve the planning model. Simulation results demonstrated the feasibility and effectiveness of the proposed planning method and the contributions of this study can be summarized as follows.

- The intermittence of the DG integrated in the distribution grids led to the risk of voltage fluctuations and the energy storage model proposed in this paper can effectively manage the voltage and keep it in the safety margins.
- Because of the high cost of battery, less profitable operation can be achieved at present. But the cost of ESS providing ancillary services can be effectively reduced through economic operations such as arbitrage.
- Due to the lack of policy support and the imperfect market system, the current large scale applications of energy storage is limited. And with the reduction of the cost of ESS equipment, the improvement of the market and the further increase of DG permeability, the value of the ESS will become significant.

Acknowledgment

This research was funded by the China National Key Research & Development Program under grant numbers [2016YFB0900500 and 2016YFB0900503].

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