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# Optimal integration of mobile battery energy storage in distribution system with renewables

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MPCE

**Abstract** An optimal sizing method is proposed in this paper for mobile battery energy storage system (MBESS) in the distribution system with renewables. The optimization is formulated as a bi-objective problem, considering the reliability improvement and energy transaction saving, simultaneously. To evaluate the reliability of distribution system with MBESS and intermittent generation sources, a new framework is proposed, which is based on zone partition and identification of circuit minimal tie sets. Both analytic and simulation methods for reliability assessment are presented and compared in the framework. Case studies on a modified IEEE benchmark system have verified the performance of the proposed approach.

**Keywords** Mobile battery energy storage system (MBESS), Reliability, Markov models, Monte Carlo simulation

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## 1 Introduction

Since 2009, a series of smart grid programs have been launched successively in the USA, EU, China, Japan, etc. [1]. Governments are placing enormous pressure on the energy industry to deploy smart grids. There have been noteworthy researches underway in formulating visions and promoting the development of smart grid [2, 3]. One common element of these visions is seamless integration of advanced energy storage system to shape peak demand, to mitigate renewable fluctuation, to improve system reliability, and to defer infrastructure investment.

The advances in material science and power electronics technologies have facilitated the employment of advanced battery energy storage systems (BESS), which can quickly response to demand fluctuation. The development of BESS will be critical to effective levelling of the cyclic nature of peak demand and to defer the costly infrastructure investment. Moreover, mobility is required in some regions with seasonal demand, which means BESS could be transported to different regions in different seasons to meet increased demand [4]. Mobile battery energy storage system (MBESS) provides mobile and highly flexible storage capacity, and can be deployed at different parts of the network to ensure efficiency. Moreover, MBESS equipped with black-start function can provide buffering function action until the other distributed generations (DGs) are started in a controlled fashion and help the disconnected system back into operation. Along with the increasing penetration level of renewable energy, distribution system power flow is significantly altered in terms of direction and magnitude. It makes the existing issues, delivering reliable power, become even more challenging. With high performance MBESS solution, the adoption of renewable energy resources is expected to be accelerated. Therefore, another outstanding benefit of MBESS is reliability enhancement, which enables distribution system with fast self-healing capability. Therefore, distribution systems are well positioned to benefit from MBESS for maintaining reliability and power quality.

In order to integrate MBESS in distribution system optimally, a novel reliability evaluation method should be proposed, where islanded operation is allowed due to the integration of MBESS. There have been noteworthy researches in developing reliability assessment methods [5–9]. However, the modern DGs and BESS in distribution system can either affect system reliability due to intermittency or guarantee the uninterruptible power supply by operating as microgrid when fault occurs. The reliability evaluation of modern distribution system is different as the traditional ones. Besides the considerations of uncertainties [10], different DGs should be modelled in order to assess the system reliability. In [11], the impacts of wind energy and ESS on system reliability were evaluated. In [12], a multi-state model was proposed. Probabilistic models were used in adequacy calculation in [13]. The reliability of distribution system with multiple overhead feeders on a same tower was evaluated in [14].

In this paper, an optimal sizing method is proposed for MBESS in distribution network with renewables. The main configuration of MBESS is showed in Fig. 1. A new framework is proposed to evaluate the reliability of distribution system with MBESS and DGs. Both analytic and simulation methods are presented and compared in the proposed framework. Factorization and decomposition are used to address the topology simplification [9]. Based on distribution system models, minimal cut-set technique [6, 9] and Markov models [15–17] are applied to evaluate simple systems, while the Monte Carlo simulation method can be performed for complex systems [18, 19]. Besides the reliability index, the economic performance is another key issue. Our previous work has demonstrated the economic feasibility of BESS project in different electricity markets [20, 21]. The optimization results are applied in this paper to quantify the profit of MBESS during normal operation state. Therefore, the MBESS optimal capacity determination is formulated as a bi-objective problem, considering reliability improvement and energy transaction saving, simultaneously.

This paper is organized as follows, after introduction section; an optimal operation method for MBESS is presented. Then, an analytic reliability assessment method for small system is proposed. And the Monte Carlo simulation is presented and discussed for complicated system. After that, the optimal sizing method is performed based on reliability evaluation and economic results acquired in [20]. Finally, the proposed methods are verified on a modified IEEE 15-bus distribution network and an extended complicated system. Conclusions and further developments are discussed in the last section.

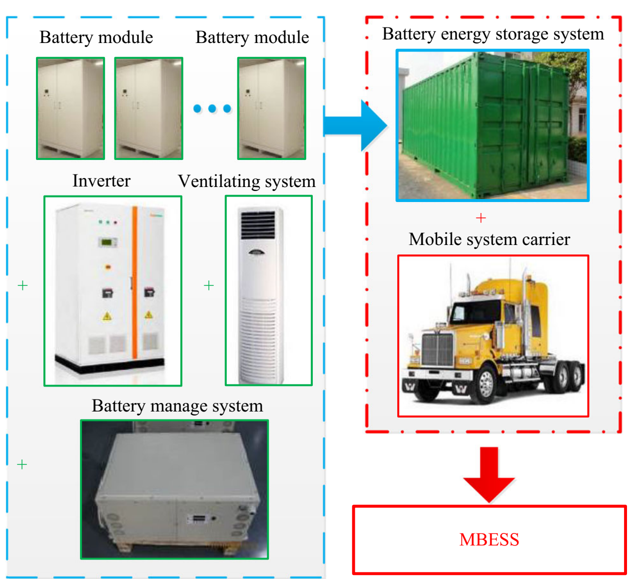


**Fig. 1** MBESS configuration

## 2 Model development for reliability evaluation

### 2.1 Operation model of MBESS

The latest material technology offers the lithium-based battery with higher power, faster charging/discharging rates, longer life cycles, and superior power to weight ratio when compared with the traditional lead-acid battery systems. Therefore, in this paper, the lithium-based MBESS will be investigated, which is used for emergency power supply and island operation support. In case of contingencies, after the fault area is isolated, MBESS will move to the downstream section, supplying buffering until the other DGs restarted in a controlled fashion to serve demand. The recovery time and the capacity of MBESS are the major factors for reliability improvement. The recovery time is affected by moving speed and distance in (1). The parameters of the investigated MBESS are listed in Table 1.

$$t_{up\_MBESS} = t_{mov} + t_{install} = k_{traff} \frac{D}{s_{MBESS}} + t_{install} \tag{1}$$

**Table 1** Typical parameters of mobile battery energy storage systems

| Item | Lithium-ion battery |
|---|---|
| Energy density (Wh/kg) | 250 |
| Power density (W/kg) | 500 |
| Life cycle (times) | 1500 |
| Investment ($) | $300E_r$ |
| Energy efficiency | 85% |
| Moving speed $S_{MBESS}$ (km/hr) | 20 |

where $t_{island}$ is the time duration of island operation mode (hours); $t_{up\_MBESS}$ is start-up time of MBESS after fault (hours); $t_{mov}$, $t_{install}$ are moving time and installation time of MBESS (hours) respectively; and $k_{traff}$ is traffic situation factor.

The operation of MBESS can be described as

$$\Delta E(t) = \int_{t}^{t+\Delta t} \left[ P^{Dis/Chr}(t) - \eta_c \left| P^{Dis/Chr}(t) \right| \right] \mathrm{d}t \tag{2}$$

where $E$ is energy stored in MBESS (MWh); $P^{Dis/Chr}$ is charging/discharging reference for MBESS (MW); $\eta_c$ is charging loss (%); and $\Delta t$ is time interval (hours).

The state-of-charge (SOC) is expressed as

$$SOC(t) = \frac{E(t)}{E_r} \tag{3}$$

where $E$ is energy stored in MBESS (MWh), and $E_r$ is rated energy capability of MBESS(MWh).

And the operation of MBESS is constrained to:

$$\text{Power limits:} \quad P^{Dis,\mathrm{Max}} \le P^{Dis/Chr}(t) \le P^{Chr,\mathrm{Max}} \tag{4}$$

$$\text{SOC limits:} \quad SOC^{\mathrm{Min}} \le SOC(t) \le SOC^{\mathrm{Max}} \tag{5}$$

where $P^{Dis,\max}$, $P^{Chr,\max}$ are maximum discharging/charging power limits of MBESS (MW) respectively; and $SOC^{\mathrm{Max}}$, $SOC^{\mathrm{Min}}$ are maximum and minimum state-of-charge of MBESS (%) respectively.

### 2.2 Distributed generation

Wind power, one of the most appealing renewable energy sources, has been widely deployed in recent years. As wind speed increases, the power generated by turbine will increase correspondingly. Ignoring minor nonlinearities, the function relation between a given wind speed and power output can be described in (6).

$$P_{Wind} = \begin{cases} 0, & v < v_{in} \ \text{ or } \ v > v_{out} \\ aV + b, & v_{in} \le v \le v_r \\ P_{rated}, & v_r \le v \le v_{out} \end{cases} \tag{6}$$

where $a = \frac{w_r}{v_r - v_{in}}$, $b = -\frac{v_{in} w_r}{v_r - v_{in}}$; $P_{Wind}$, $P_{rated}$ are real power and rated power of wind generation (MW) respectively; $v_{in}$, $v_{rated}$, $v_{out}$ are cut-in, rated, and cut-out speeds of wind turbine (m/s) respectively; and $v$ is real-time wind speed (m/s).

### 2.3 Section model for distribution systems

The establishment of section model for distribution system is the basic techniques to assess the system states. The section model is formed according to the location of switching devices [6, 14]. The following assumptions should be made.

1) The operation mode of distribution network is radial.
2) All the switches are reliable.
3) The failures rate is low.
4) There are no simultaneous failures.

Based on the above assumptions, the equivalent failure rate and failure outage duration of this section can be calculated by statistic data of internal component. The expressions are shown as (7) and (8).

$$\lambda_i = \sum_{j \in i} \lambda_j \tag{7}$$

$$r_i = \sum_{j \in i} \frac{(\lambda_j r_j)}{\lambda_i} \tag{8}$$

where $i$ is section number; $j$ is component number; and $\lambda$ is failure rate.

## 3 Reliability assessment with MBESS

As discussed above, the integration of MBESS in radial distribution system facilitates the operation of isolated section after fault and thereby increases the reliability. The Fig. 2 depicts the timetable of the section state of distribution system with and without MBESS. In island mode, the section locates at the downstream of fault area is isolated from the grid and powered by DGs and MBESS. The state of the island depends on the total amount of DG output and MBESS capability.

### 3.1 Analytical assessment of distribution system reliability

The analytical reliability evaluation methods are proposed for simple distribution system. The expected energy not supplied (EENS) can be improved with MBESS integration. The state space for the system is performed through Markov process model. A two-section distribution

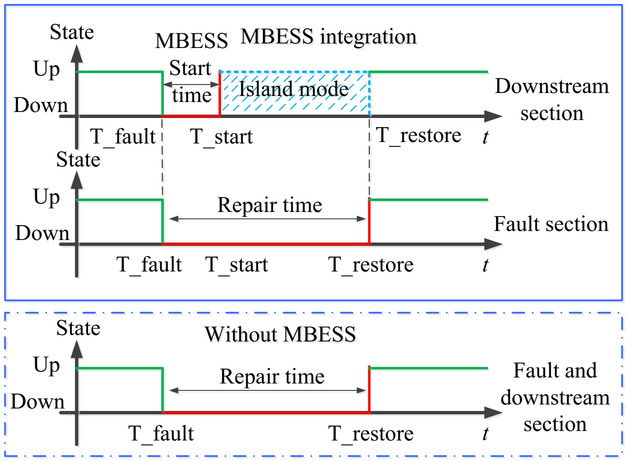


**Fig. 2** State time table of distribution system with and without MBESS integration

system is used to explain the proposed reliability evaluation method. The system schematic and corresponding Markov process is expressed in Fig. 3. $\lambda_1$ is the failure rate of unit 1; $\lambda_2$ is the failure rate of unit 2; $\mu_1$ is the unit repair rate after battery installation; $\mu_2$ is the unit repair rate; $Ins$ is the battery installation rate. Battery is "stand" as backup when there is no fault or the fault occurs outside the response area.

The equation for solving the probability of each state is shown as

$$\begin{bmatrix} -\lambda_1-\lambda_2 & \mu_2 & 0 & \mu_1 \\ \lambda_2 & -\mu_2 & 0 & 0 \\ \lambda_1 & 0 & -r & 0 \\ 0 & 0 & r & -\mu_1 \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix} = 0 \tag{9.1}$$

$$p_1 + p_2 + p_3 + p_4 = 1 \tag{9.2}$$

where $r$ is the outage duration.

It should be note that $\mu_1$ is the reciprocal of the mean time to repair after the installation of MBESS and $r$ is the reciprocal of the mean time to install. We assume that the mean time to repair is same for different sections. Hence, $\mu_1$ can be calculated by (10). Based on the state probability matrix, we can assess the system reliability by using EENS.

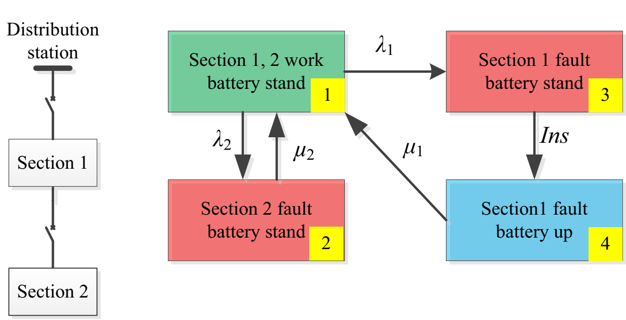


**Fig. 3** Two section system and Markov state space

$$\mu_1 = \frac{1}{\frac{1}{\mu_2} - \frac{1}{Ins}} \tag{10}$$

In state 4, section 2 is operating in island mode with MBESS. If the power output of MBESS can compensate the gap between demand and DG output, the island mode is feasible. The operation probability is expressed as

$$p_{island} = p(P_{MBESS} + P_{DG} \geq P_{Load})|_{t=0}^{t_{island}} \tag{11}$$

where $P$ is the possibility of state; $P_{Load}$, $P_{DG}$ are demand, distributed generation output (MW) respectively; and $p_{island}$ is the success rate of island operation mode.

Historical data based statistics method is applied to determine the success probability of island operation mode. Renewable energy output and demand data are collected to perform the operation process of concerned section. The success rate from any fault time is calculated respectively. During each operation time horizon $t_{island}$, time interval is set to 1 hour. If the constraint $P_i^{Dis}(t) + P_{DG,i}(t) \geq L_i(t)$ is satisfied for time $t$, the success flag is set to 1, as $s_i^{island}(t) = 1$. Let $p_{i,t_0}$ denotes the success probability of island operation mode during fault event $t_0$.

$$p_{i,t_0} = \int_{t=t_0}^{t_0+t_{island}} s_i^{island}(t)\mathrm{d}t / t_{island} \tag{12}$$

where $t_{island}$ is the fault duration. Suppose $N_{sample}$ is the simulation times, the average ratio incan be calculated as

$$p_i = \sum_{t_0=1}^{N_{sample}} p_{i,t_0} / N_{sample} \tag{13}$$

According to the definition, the EENS index is calculated as (14).

$$\begin{aligned} EENS = &\left\{ p_2 \cdot \overline{L(2)} + p_3 \cdot \left[ \overline{L(1)} + \overline{L(2)} \right] \right\} \cdot 8760 \\ &+ p_4 \cdot \left[ \overline{L(1)} + \overline{L(2)} \cdot (1 - p_{island}) \right] \cdot 8760 \end{aligned} \tag{14}$$

### 3.2 Time-sequential Monte Carlo simulation

Since the state space of the system is difficult to be determined, to evaluate the reliability of a complex system, a Monte Carlo simulation method is desired to present the fault and system operation states precisely. A two-level Monte Carlo simulation for system state is proposed. At first level, the fault section is determined. In this paper, we assume that no fault occurs in the system simultaneously. The failure rate of the section is acquired by (7) and (8). The system state parameter $R$ is generated randomly from the uniform distribution. Then, the fault location is determined according to the following criterion,

$$i_{fault} = \{Ceil(Rand() * (k+1))\} \tag{15}$$

where $k$ is the total number of sectors in the concerned system; ceil () the function to round the element to the nearest integer greater than or equal to that element.

If fault location is $k+1$, no fault occurs at first level, the second level simulation is skipped. Otherwise, the island state is determined in the second level. In this level, the downstream tree from fault section is searched for the target island area and the MBESS is sent to support the island operation. After the moving and installation time of MBESS, the demand and renewable energy output is sampled from the time-varying model until the fault line is repaired. During the MBESS operation time, if the sampling renewable output and MBESS output can meet the sampling demand, the islanding operation mode is successed. Otherwise, both the demand and renewable energy are out of service.

In this sampling simulation, the fault is far less than generated sample times. Therefore, bootstrapping method is applied to improve the calculation time [22]. The scaling sample method and the reliability objective function are expressed as

$$\begin{cases} r' = N_{boost} \cdot r \\ EENS = \dfrac{EENS'}{N_{boost}} \end{cases} \tag{16}$$

$$F_1(E_r) = EENS(0) - EENS(E_r) \tag{17}$$

where $F_1$ is the EENS improvement function with MBESS integration.

## 4 Economic evaluations and sizing problem

The optimal allocation method of BESS is proposed in [21], the economic feasibility is verified through the novel operation strategy. In this work, during the normal operation state, MBESS is controlled by the DisCo at the substation site to make profit. Similar to the previous work, the location of BESS is set at the substation and the economic can be expressed as

$$F_2 = J(E_r) \tag{18}$$

where $J$ is the cost function. The detailed operation strategy and market environment are described in [20].

Two objectives, reliability improvement and energy transaction saving, are quantified as a function of capacity. The optimal sizing issue can be formulated as a bi-objective problem. Since these two objectives are measured in different unit, in order to optimize the sizing of MBESS comprehensively, membership function, proved to be a good solution to the multi-objective problem, is used to fuzzify the objective function [23].

$$\vartheta_x = \frac{\left|F_x(E_r) - F_x^{best}\right|}{\left|F_x^{worst} - F_x^{best}\right|} \quad \text{for } x = 1, 2; \tag{19}$$

where $F_x^{best}$ and $F_x^{worst}$ for $x = 1, 2$ are the best and worst values of the two objectives; and $\vartheta_x$ are the weight factors. Through the normalization process, the overall fuzzy multi-objective function of the MBESS sizing problem is expressed as

$$\min F(E_r) = \vartheta_1 F_1(E_r) + \vartheta_2 F_2(E_r) \tag{20}$$

## 5 Case study

A modified IEEE 11 kV, 15-bus distribution radial system is used to verify the proposed reliability evaluation method for distribution system with MBESS. The one-line diagram of this distribution system is shown in Fig. 4. The reliability parameters for the lines are list in Table 2.

1) Analytic reliability assessment

Firstly, according to the section concept, the reliability data for the lines are converted for the section. The results are shown in Table 3. The system is assumed as a residential system, the average load index is 0.59 while the average wind farm output index is 0.3. Then, the Markov state space is constructed as Fig. 5 and only two typical capacities are selected for calculation in this part. The results are showed in Table 4. In the demonstration system, $\lambda_1$, $\lambda_2$, and $\lambda_3$ are the failure rates of the three sections, respectively; $\mu_1$ and $\mu_2$ are the unit repair rate after battery installation, $\mu_3$ is the unit repair rate; $Ins$ is the battery installation rate.

From the reliability indices shown in Table 5, the EENS index is improved by 29.2% and 40.4% with the integration of 500 kWh and 1 MWh MBESS, respectively. Then, the

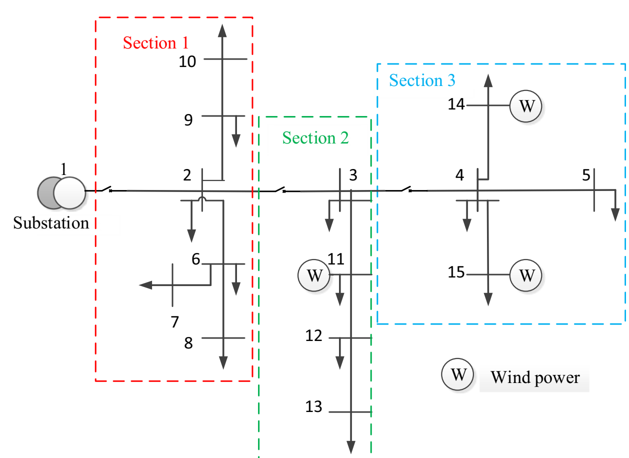


**Fig. 4** Modified IEEE 15-bus distribution radial system

**Table 2** Reliability data for the distribution lines

| Line | $\lambda$ (f/y) |
|---|---|
| 1-2 | 0.054 |
| 2-3 | 0.0468 |
| 3-4 | 0.0336 |
| 4-5 | 0.0988 |
| 2-9 | 0.1308 |
| 9-10 | 0.1096 |
| 2-6 | 0.1662 |
| 6-7 | 0.0707 |
| 6-8 | 0.0813 |
| 3-11 | 0.1167 |
| 11-12 | 0.1591 |
| 12-13 | 0.1308 |
| 4-14 | 0.1450 |
| 4-15 | 0.0778 |

**Table 3** Reliability data for the Section

| Section | $\lambda$ (f/y) | $r$ (hr) | $\mu$ | $Ins$ | Peak load (kW) | Renewable energy (kW) |
|---|---|---|---|---|---|---|
| 1 | 0.6126 | 5 | $\frac{8760}{5-0.234}$ | $\frac{8760}{0.17}$ | 508.2 | 0 |
| 2 | 0.4534 | 5 | $\frac{8760}{5-0.293}$ | $\frac{8760}{0.234}$ | 324.1 | 750 |
| 3 | 0.3552 | 5 | $\frac{8760}{5}$ | $\frac{8760}{0.293}$ | 464.1 | 500 |

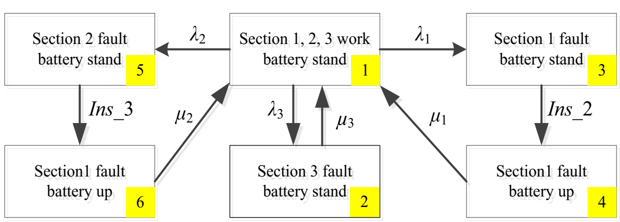


**Fig. 5** Markov state space for 15 bus test system

**Table 4** Reliability indices of the 15 bus test systems (analytic method)

| Section | Without MBESS | 500 kWh MBESS | 1 MWh MBESS |
|---|---|---|---|
| 1 | 916.6767 | 916.6767 | 916.6767 |
| 2 | 1016.773 | 581.6877 | 581.6877 |
| 3 | 1942.91 | 811.6183 | 811.6183 |
| Syst | 3876.359 | 2309.983 | 2309.983 |

Monte Carlo simulation are performed to verify the proposed analytic method.

2) Monte Carlo simulation assessment

A Monte Carlo simulation for reliability assessment is performed in this section. Artificial history of one year is generated in each simulation sample. The boost scaling factor $N_{boost}$ is set to 10 and the sample time is 2000. During the sampling process of island mode, the 24-hours and 4-seasons residential demand data is used in the demand sampling while the wind speed distributions are fitted for renewable energy output sampling. The simulation results are provided in Table 5.

**Table 5** Reliability indices of the 15 bus test systems (Monte Carlo simulation results)

| Case | Section | EENS′ (MWh) | EENS (kWh) | Renewable Energy Saving (kWh) |
|---|---|---|---|---|
| Without Renewable Energy and MBESS | System | 37.2317 | 3723.17 | 0 |
| 500 kWh MBESS | System | 27.8059 | 2780.59 | 449.48 |
| 1 MWh MBESS | System | 23.0214 | 2302.14 | 573.26 |

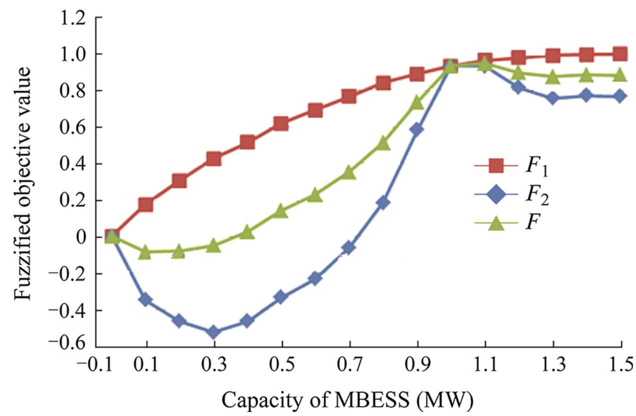


**Fig. 6** Objective curves of the optimization problem

From the result of Monte Carlo simulation, the EENS value with different size of MBESS integration is very close to the result of proposed analytic method. The differences are all within 4%. Therefore, both the analytic and Monte Carlo simulation method can be applied for reliability assessment of distribution system with MBESS integration.

3) Optimal capacity determination

The above part demonstrates the integration of MBESS can improve the reliability of the distribution system and save the renewable energy during island operation periods. The quantified value is expressed by $\vartheta_1 F_1(E_r)$. The economic index is indicated by $\vartheta_2 F_2(E_r)$. Both the objectives are function of the energy capacity $E_r$. The optimization process can be realized by an enumeration method. The fuzzified objective curves are showed in Fig. 6 and the optimal capacity results are listed in Table 6. From the results, we can find that the optimal capacity is larger than the result without the reliability consideration in our previous work.

**Table 6** Optimization result

| Capacity (MWh) | EENS improvement $F_1(E)$ (MWh) | $\vartheta_1 F_1(E)$ | Profit $F_2(E)$ ($) | $\vartheta_2 F_2(E)$ |
|---|---|---|---|---|
| 1.1 | 1.0332 | 0.9646 | 1600 | 0.933 |

## 6 Conclusion

This paper proposes a practical method for integrating MBESS in distribution system. Both analysis and simulation methods are proposed for the reliability evaluation of distribution system with the integration of MBESS and DGs, which can help the downstream section of the fault area back to operation as an island in a short time. In the case study, the analysis method achieves good results without complex calculation. The simulation method is applied to verify the accuracy of analysis method. Through this work, a reliability evaluation framework for the distribution system with MBESS is proposed and verified. The optimal MBESS capacity sizing problem is solved by cost and benefit analysis considering the reliability improvements. Along with the development of battery technologies and introduction of more stimulus policies, the cost of battery will decrease, which will make the application of MBESS more attractive.

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