THE ENERGY STORAGE OPERATION UNDER STOCHASTIC RENEWABLE GENERATION

Tony Tsang and Chung Kwok Leung

Centre of International Education, Hong Kong College of Technology, Hong Kong

ABSTRACT

The percentage of unpredictable renewable power in the power grid will dramatically rise as a result of the present trend in energy , development. The power system's stability could be impacted by this. Therefore, one of the major technologies for the development of green energy is the battery-based Energy Storage System (ESS) with quick reaction control capabilities. In this thesis, a method for determining the best ESS capacity is suggested. It is based on estimates of the lithium iron phosphate battery's lifetime for various converter topologies. Two goal functions are taken into consideration in order to get the best capacity and prevent overinvestment.

The first goal is to determine the minimal capacity necessary to satisfy the charge and discharge demands of various ESS implementations, and the secondary purpose is to determine the ideal capacity that necessitates the least amount of capital expenditure andoperational expense. The ESS capacity estimation takes into account applications in Photovoltaic output smoothing & base load power plant dispatching augmentation.

In the case that the overall average effective depth of discharge under the minimum required capacity of the energy storage system is very shallow, it will severely limit the range of battery life that can be extended by increasing the rated capacity. This may lead to the optimal capacity being the minimum required capacity, or the optimal capacity and The minimum required capacity requires the same number of battery changes. The deeper the overall average effective discharge depth caused by the minimum required capacity of the energy storage system is, the more effectively the total investment cost can be reduced by increasing the rated capacity.

KEYWORDS

power system's stability, Stochastic, Energy Storage Operation, Renewable Generation.

1. INTRODUCTION

1.1. Background

Due to the current energy development trend and the influence of government energy policies, the development of renewable energy sources (RESs) has received more and more attention, and its proportion in the power grid has gradually increased. With the increase in the proportion of renewable energy and the intermittent and uncontrollablenature of renewable energy, the existing power grid may not be able to handle the instantaneous power changes of large-scale renewable energy in the future, which willaffect the stability of the power system. Energy Storage Systems (ESS) is one of the effective methods to solve this problem. It can stabilize the power generation of renewable energy through charging and discharging scheduling, and reduce the impact of renewable energy on the stability of the power system.

DOI: 10.5121/ijcsit.2024.16304

According to the different forms of energy storage, energy storage systems can be roughly divided into six categories - including Mechanical, Electrochemical, Chemical, Electromagnetic, Thermal and Hybrid. Among these energy storage technologies, since electrochemical energy storage is not easily restricted by the geographical environment, the current energy storage system is mainly developed in this respect, including lead- acid batteries, nickel-cadmium battery, Nickel-Metal Hydride battery, Lithium-Ion battery, Sodium-Sulfur battery, Flow battery, etc (Akatsuka, Hara, Kita & Ito, 2010; Obara, Morizane & Morel, 2013). Compared with other types of batteries, lithium-ion batteries have the advantages of high energy density, stable discharge characteristics, long cycle life, and low environmental pollution, so they have gradually become the mainstream of the market. In lithium-ion battery technology, lithium-iron batteries are more advantageous for the application of energy storage systems due to their high- current charge-discharge characteristics and long cycle life (Wen, 2006). Lithium iron batteries use lithium iron phosphate as the cathode material of the battery, and the structure of this material is relatively stable in chemical reactions, relatively safe, and rich in raw materials. Therefore, the price of the battery is expected to be reduced, the market competitiveness is high, and the environment Low pollution (Li, Daniel, & Wood, 2011). However, the current energy storage system using lithium iron batteries as the electrical energy unit has the advantages of high energy density, low self-discharge, and fast reaction speed, but it is relatively expensive. Therefore, the construction of the energy storage system is planned In order to avoid over-investment and reduce investment costs, it is necessary to construct an effective investment capacity planning procedure.

1.2. Research Rationale

Renewable energy has been widely recognized as one of the most effective solutions to the increasingly important problems of oil depletion, carbon emissions and increased energy demand. However, despite its environmental advantages and sustainability, renewable energy is still There are two main problems. First of all, it is well known that the power generation of renewable energy depends largely on local climatic conditions, and the accompanying undispatchable intermittency and randomness will bring instability to the power system. Second, because of the size of renewable energy power generation Depending on weather factors, its power generation characteristics will increase with the penetration rate (Penetration), which will make it more difficult for the existing traditional power system to adapt. Taking solar photovoltaics as an example, the power generation starts to increase with time in the morning, reaches the peak of power generation at noon, and then continues to decline until evening, causing the load curve to fluctuate violently, forming the so-called duck curve.

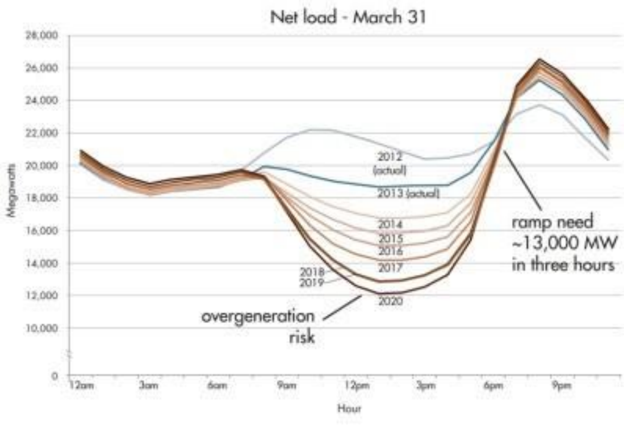


Figure 1 - Duck Curve

In order to reduce the impact of renewable energy on grid stability, a controllable energy storage system is regarded as one of the effective ways to improve the problem of renewable energy generation. However, although battery energy storage system has many advantages, its expensive Economic issues caused by price remain a major hurdleto overcome before widespread adoption. Therefore, it is necessary to determine the capacity of the battery energy storage system through planning, and many studies have proposed different planning methods.

Many studies have proposed methods for capacity planning of battery energy storage systems that cooperate with renewable energy power generation, with the main purpose of improving economic benefits. In the overall planning, the battery energy storage system is regarded as a pure energy storage object, only considering However, during the operation of the energy storage system, there are many factors that will lead to shutdown. Although the battery is indeed the most unstable factor in the system, in the circuit architecture, in order to make the battery and the grid perform power conversion, it needs to be In the power electronic converter, the power electronic switch is another main component that causes the failure. Under the premise of having a complete battery management system (BMS), the battery energy storage system will be affected by the aging of the battery and the power electronic components. downtime due to malfunction.

1.3. Aims & Ojbectives

This study proposes a set of optimal energy storage system capacity planning procedures, considering the minimum required capacity to be built under a given energystorage system charge and discharge power profile, and the calculation considering battery life and different Under the converter structure, the optimal capacity of the energy storage system meets the lowest investment cost.

The key objectives of this research are as follow:

1. To Compute the minimum rated capacity required for the energy storage systemunder the Under Stochastic Renewable Generation
2. To Compute the optimal rated capacity under the Under Stochastic RenewableGeneration that meets the minimum investment cost

1.4. Expected Contribution

The contribution of this paper is to propose a set of optimal device capacity planning procedures for battery energy storage systems, and plan the optimal capacity and converter architecture for a given energy storage system power curve. Usually, the battery energy storage system is regarded as a pure energy storage object in the application planning. However, in the internal circuit structure of the battery energy storage system, the battery and power electronic switching components are not ideal andwill not be damaged. The aging of the battery may lead to the failure of normal storage or When the electric energy is released, the switching element may fail to lose its function. Therefore, the planning procedure proposed in this study takes into account the failure factors of the internal elements during the actual operation, and takes the investment cost into consideration. thereby enhancing rationality. Finally, by simulating the planning of battery energy storage systems with different charging and discharging types, the selection of battery energy storage system device capacity in different applications of the power system is discussed. The battery life estimation model used in this paper only considers the effect of battery cycle aging, and is suitable for application planning of energy storage systems that require frequent charging and discharging, such as load tracking, frequency regulation, stable renewable energy output, etc. If it is only used for emergency power supply Energy storage equipment (which has been idle for a long time) is not applicable to the planning procedures proposed in this study.

2. METHODOLOGY

2.1. Optimum Energy Storage System Planning Procedure

The optimal energy storage system planning procedure proposed in this paper is likefollowing table.

Step 1	The input power curve of the energy storage system to be planned must be data of a whole year. The smaller the time interval of each data, the more accurate the battery charge and discharge process can be restored, and the more accurate the estimated battery life. The input data used in this study is by every minute.
Step 2	Calculate the required minimum battery energy storage system device capacity (rated capacity, rated power).
Step 3	Substitute the power curve of the energy storage system and the battery cycle life data into the battery life estimation model. The battery life estimation model includes calculating the total electric energy round-trip rate (Energy Throughput) and the average effective depth of discharge (Average Active Depth of Discharge), the total
	electric energy The round-trip rate is the sum of all charged and released energy in the power curve, and the concept of the average effective depth of discharge will be explained in the later section.
Step 4	Substitute the battery life estimation model and converter-related parameters (cost, efficiency and failure rate) into the total investment cost calculation, and calculate the optimal rated capacity and converter structure by performing the optimization of the total investment cost. The total investment cost includes energy storage system construction cost, maintenance cost and battery replacement cost. Among them, the construction cost is the cost of the battery and converter equipment, which depends on the rated capacity and rated power; the maintenance cost is the cost of the energy storage system due to the failure of the converter and needs to be shut down for maintenance; the battery replacement cost is the cost of the energy storage system. During the planned operation period of the system, the battery needs to be replaced due to its service life, and the cost incurred.

2.2. Energy Storage System Minimum Demand Device Capacity Calculation

In order to ensure that the energy storage system can operate according to the given power curve, the minimum rated power and rated capacity that can meet the applicationrequirements must be calculated in the planning stage, so as to avoid the power state exceeding the reasonable range (0~100%) during operation. In order to make the energy storage system operate normally, the converter power rating must be selected to be able to withstand the maximum power value during the operation period, as shown in the following figures, ignoring the system power loss.

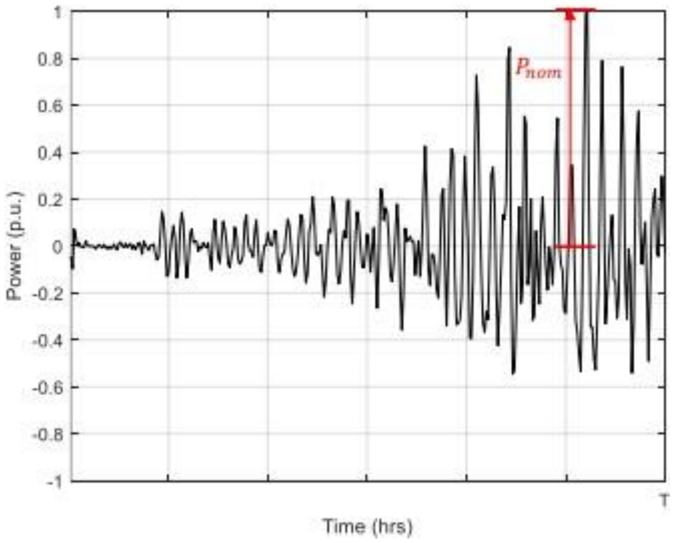


Figure 1 - Energy flow of the energy storage system

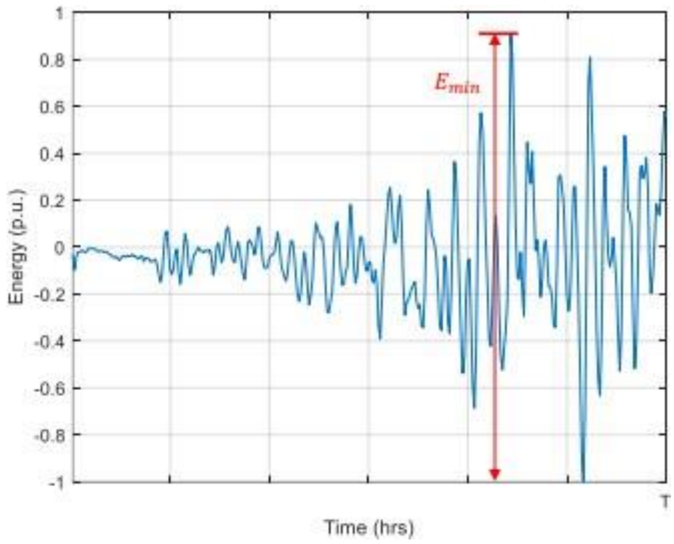


Figure 2 - Energy response of the energy storage system

2.3. Battery Life Estimation Model

Generally speaking, the lower the energy storage capacity, the lower the investment cost. However, considering the phenomenon of battery cycle aging (Cyclic ageing), the lower the energy storage capacity, the deeper the Depth of Discharge (DoD). , which in turn reduces battery life, which may result in battery replacements, or more frequent replacements, during the planned operation of the energy storage system. Increasing the capacity of the energy storage system will lead to an increase in the construction cost, but it is also possible to prolong the battery life and reduce the number of battery replacements, so as to achieve the effect of reducing the total investment cost. The following introduces the battery terminal life estimation method based on the zero- crossing method.

This study uses a battery life estimation method based on the overall depth of discharge and electric energy round-trip rate, and considers the effect of cycle aging caused by the depth of discharge of lithium iron batteries. The data corresponding to relevant battery parameters such as depth of discharge and cycle times need to be provided by the battery manufacturer. . Although this method is non-empirical, manufacturer-dependent battery data is empirical in nature. The depth of discharge is defined as the percentage of capacity released by the battery to its rated capacity during battery use:

$$DOD = \int_{t_i}^{t_f} I_{discharge}\, dt$$

In which $I_{discharge}$ = the current of discharge; t_f, t_i are the final and initial timerespectively.

2.4. Battery Data

Battery manufacturers can often provide data on cycle life versus depth of discharge. Cycle life is defined as the number of charge-discharge cycles before the battery entersthe End of Life (EoL), where the end of life is defined as 70% of the battery remainingInitial rated capacity.

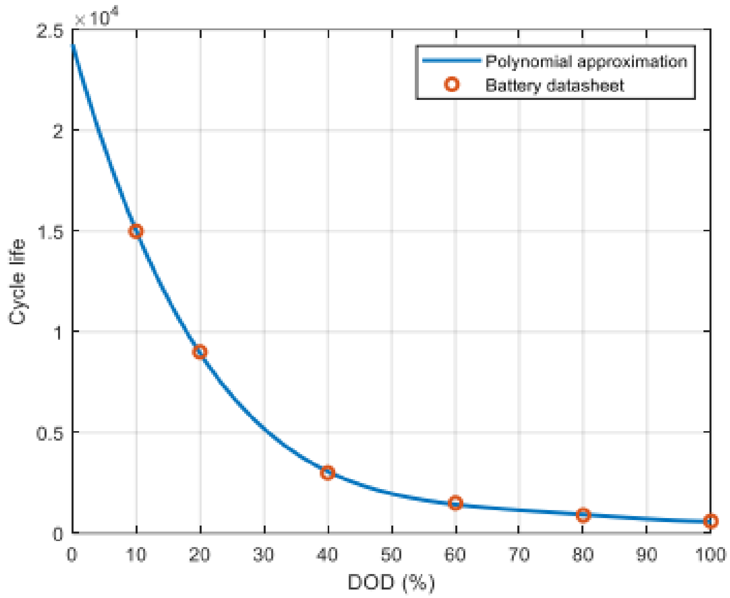


Figure 3 - Polynomial approximation curve of cycle life of lithium iron battery based on depth of discharge

2.5. Battery Life Estimation Based on Zero Crossing Method

This study uses a battery life estimation method based on the overall depth of discharge and the electric energy round trip rate. The Average Active Depth of Discharge and the total electric energy round trip rate are obtained from the simulation, and then the average active depth of discharge is substituted into the battery depth of discharge Estimated battery cycle life.

The battery life calculation:

$$L = \frac{2n(E_{nom})(DOD)}{E_{thr.tot}}$$

In which, $E_{thr,tot}$ is the One-year total electric energy round-trip rate; E_{nom} = Battery rated capacity; n = cycle life.

The effective depth of discharge refers to the depth of discharge of the battery during operation, excluding the depth of discharge caused by self-discharge. The average effective depth of discharge takes into account the influence of all the micro-cycles (Micro-cycles) that constitute the entire battery cycle. Defined as a small cycle of variable duration that exists between two consecutive current zero-crossings, typically much shorter than a full charge-discharge cycle.

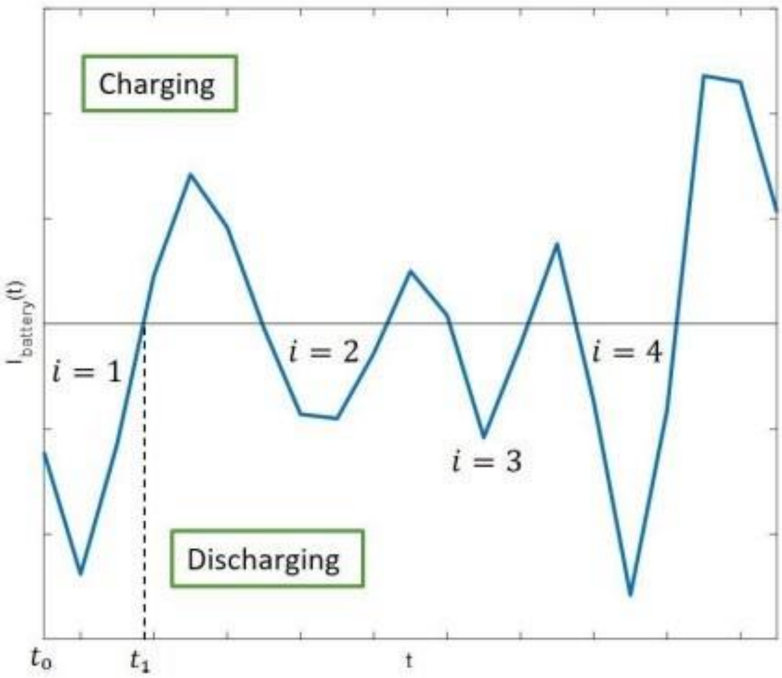


Figure 4 - Schematic diagram of battery current microcirculation waveform

2.6. Calculation of Cost and Failure Rate of Power Electronic Converter

Power electronic converters consist of several components, including passive components such as inductors and capacitors, and power semiconductor components such as switching switches such as insulated gate bipolar transistors (Insulated Gate Bipolar Transistor, IGBT). According to the reliability-based block diagram (Reliability Block Diagram, RBD) method for estimating reliability. In a series system without fault-tolerant function, the overall failure rate is the sum of individual component failure rates, and the overall failure rate of the converter is calculated as follows:

$$\lambda_{PE} = \sum_{i=1}^{N} \lambda_i$$

In which λ_i is the failure rate of the ith component and N is the Total number ofcomponents.

In the overall structure of the battery energy storage system, the power electronic switch is considered to be the weakest link in the circuit. Therefore, in the calculation of the failure rate in this study, the inductance and capacitance are ignored, and only power semiconductor components are considered. The components used in this study are referenced The failure rate data comes from the US military standard (MIL-HDBK- 217F). The failure rate is assumed to be a constant value. However, the IGBT failure rate is not directly provided in this document. The alternative method is to use a metal oxide semiconductor field effect transistor (Metal- Oxide-Semiconductor Field-Effect Transistor, MOSFET) in series with bipolar junction transistors (Bipolar Junction Transistor, BJT) means:

$$\lambda_{IGBT} = \lambda_{MOSET} + \lambda_{BJT}$$

The component failure rate is calculated by multiplying the base failure rate by severalconditional factors. Conditional factors include temperature factor, application factor, rated power factor, Voltage Stress Factor, Quality Factor, and Environmental Factor. This study does not consider the influence of the operating temperature of the energy storage system, and the element temperature factor is assumed to be 1. The power is assumed to be 1MW.

The converter architectures considered in this study include the second-order converter(2L) and the third-order active neutral-point clamped converter (3L) mentioned in Section 2.3. The number of switches used in the circuit is 6 and 18.

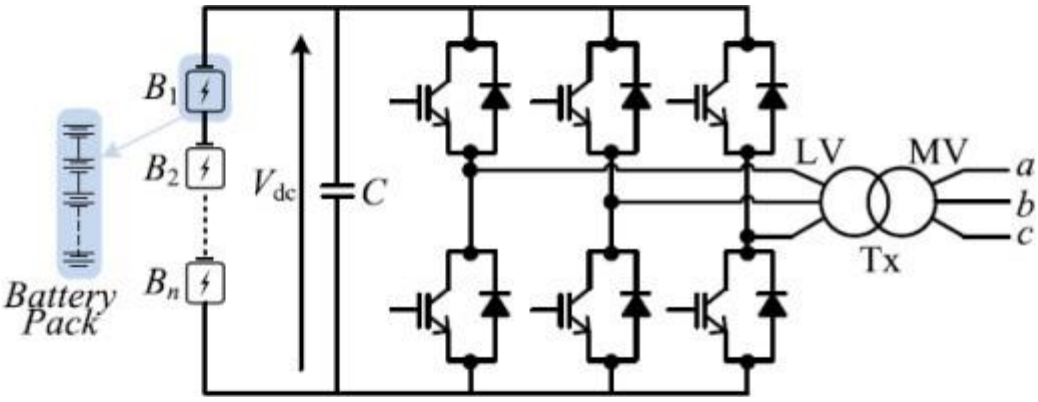


Figure 5 - second-order converter (2L)

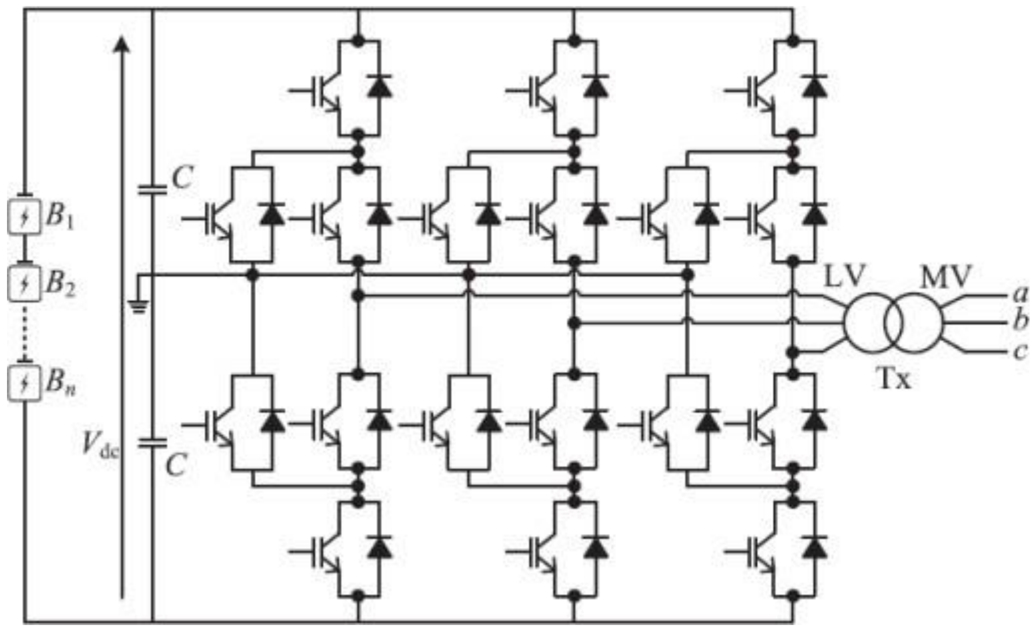


Figure 6 - third-order active neutral-point clamped converter (3L)

The equipment cost of the converter mainly depends on the DC-link capacitor and power electronic switches. This study assumes that the equipment cost of the second-order converter is 75% of that of the third-order converter.

2.7. Energy Storage System Investment Cost

In order to compare the investment cost impact caused by the construction of different battery capacities and converter architectures. The energy storage system investment costs considered in this study include construction costs (Upfront Costs), maintenance costs and battery replacement costs.

$$C_{total} = C_{upfront} + C_{maintainence} + C_{replacement}$$

The construction cost is the initial investment cost of the battery energy storage system, including the cost of batteries and converter equipment.

$$C_{upfront} = C_{battery} * E_{nom} + C_{PE} * \frac{P_{nom}}{\eta_{PE}}$$

$$P_{nom} =$$

(in which E_{nom} = Energy storage system rated capacity; C_{PE} = converter cost ;Energy storage system rated power; η_{PE} = Converter Efficiency)

The maintenance cost is the average annual cost of the energy storage system due to the failure of the internal components of the converter. Hence it is the cost of shutting down for maintenance. This depends on the failure rate of the converter, equipment cost and rated power, and is expressed as a net present value (Net Present Value, NPV) According to the method, the annual equipment maintenance cost is discounted into the value on the first date of investment according to the assumed annual discount rate. t represents the operating period of the first few years in the overall operating life.

$$C_{maintainence} = \sum_{t=1}^{L_{sys}} \frac{\lambda_{PE} * C_{PE} * \frac{P_{nom}}{\eta_{PE}}}{(1+r)^t}$$

(in which L_{sys} = System operating life; r = interest rate for discounting)

Battery replacement cost means that after a period of battery operation, it is estimated that a new battery needs to be replaced when the EoL is reached to facilitate the normal operation of the energy storage system. The battery life estimate can be calculated by battery life calculation (suggested in the section 3.2). At a fixed rated capacity, lower converter efficiency will cause the battery to output more power, which will lead to an increase in the overall depth of discharge and a decrease in cycle life. Considering that the battery price will decrease year by year with the development of battery technology, the calculation of battery replacement cost is included in the technology cost depreciation function. Since it is difficult to predict the accurate trend of technology cost decline, this study assumes that the system will The depreciation rate decreases linearly (as shown in the following figure). And use the net present value method to discount the cost of each battery replacement into the value at the beginning of the investment. k represents the number of battery replacements in the total number of battery replacements:

$$C_{replacement} = \sum_{k=1}^{R} \frac{C_k * E_{nom}}{(1+r)^{[kL]}}$$

(in which R = The total number of battery replacements required over the years of operation, by definition, $R = [\frac{L_{sys}}{L}]$; = Battery cost at C_k the kth replacement. By definition it is the multiple of the depreciation factor and the battery cost)

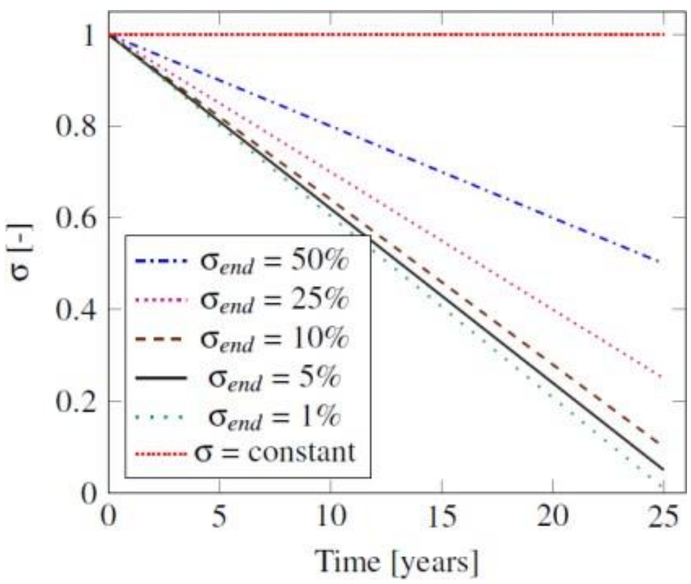


Figure 7 - Battery technology cost depreciation factors under different cost depreciation rates

For the optimization of the total investment cost, the variables to be solved include the rated battery capacity of the energy storage system ($Enom$) and a dummy variable (x) used to represent the choice of converter architecture. In fact, when investing in battery energy storage systems, the rated capacity cannot be increased or decreased arbitrarily. It will have a fixed unit as the adjustable degree of rated capacity. The fixed unit assumed in this study is 1kWh.

$$C_{total}(E_{nom}, x) = C_{upfront}(E_{nom}, x) + C_{maintainence}(x) + C_{replacement}(E_{nom}, x)$$

Further breaking down:

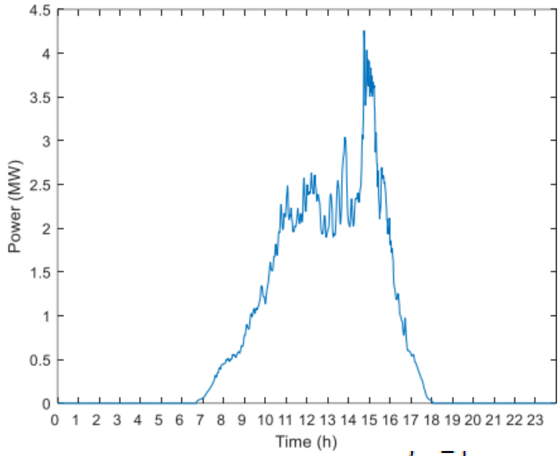
$$\begin{cases} C_{upfront}(E_{nom}, x) = C_{battery} * E_{nom} + \left(x * C_{2L} * \dfrac{P_{nom}}{\eta_{2L}} + (1-x) * C_{3L}\dfrac{P_{nom}}{\eta_{3L}}\right) \\ C_{maintainence}(x) = \displaystyle\sum_{t=1}^{L_{sys}} \frac{x * C_{2L} * \frac{P_{nom}}{\eta_{2L}} + (1-x) * C_{3L}\frac{P_{nom}}{\eta_{3L}}}{(1+r)^t} \\ C_{replacement}(E_{nom}, x) = \displaystyle\sum_{k=1}^{R} \frac{C_{battery} * \sigma_k\big(L(E_{nom}, x)\big) * E_{nom}}{(1+r)^{[kL]}} \end{cases}$$

3. RESULT AND DATA ANALYSIS

This thesis uses Matlab as the simulation software. Taking one minute of renewable energy information from the island system and a whole year of solar power generationdata and load data as the input data of the planning program, four application cases aresimulated for planning.

3.1. Data Input

This study uses two sets of renewable energy data collected from Hong Kong outlying islands system every minute for a whole year. They are solar power generation data and load data showing the duck curve phenomenon. It is used to simulate the power curve ofthe energy storage system under application. The power curve of the energy storage system generated after the simulation is used as the input data of the planning program.



μhr^{-1}

Figure 8 - Single-day solar power generation curve

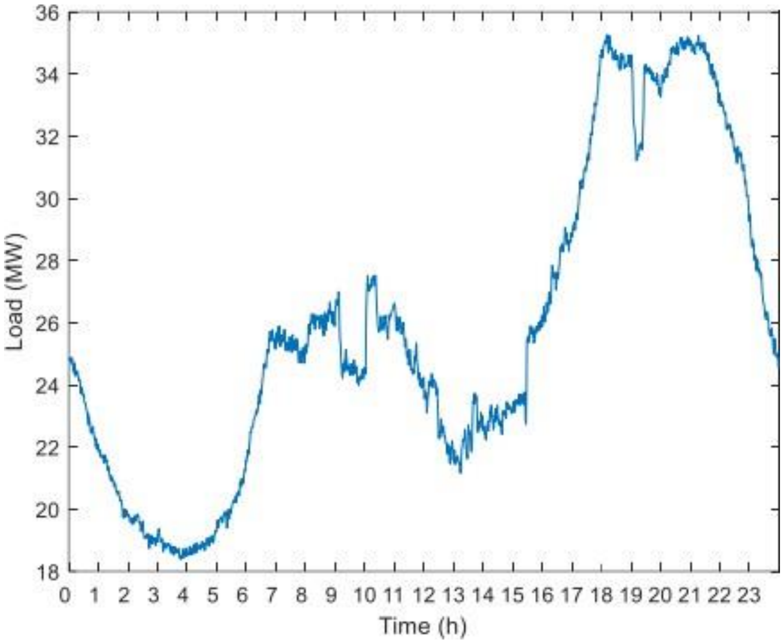


Figure 9 - One-day duck curve

3.2. Simulation Result

The simulation analysis of the application case of the energy storage system in this study is divided into two parts: (1) smoothing the solar power generation curve (2) matching the load demand of the base load dispatching power supply to the duck curve phenomenon. The two parts analyze two cases respectively. The smooth solar power generation curve is divided into two cases of small smoothing and large smoothing. The base load power generation scheduling according to the load demand of the base load dispatching power supply to the duck curve phenomenon is respectively calculated by each The load average is taken every four hours. The load average is taken every 24 hours. The simulation parameters used in all cases are assumed as shown in the table, and the investment cost of the minimum required capacity of the energy storage system is calculated under the second-order converter architecture.

Simulation Parameters	Value
L_{sys}	25 years
$C_{battery}$	5000 (per kWh)
λ_{IGBT}	1.13229
C_{2L}	100 (per kW)
C_{3L}	300 (per kW)
η_{2L}	95.2%
η_{3L}	96.7%
r	5 %
σ	15 %

Table 1 – Parameters for the Simulation

4. CONCLUSION

This paper proposes a set of optimal energy storage system planning procedures based on battery life estimation, with the goal of obtaining the optimal energy storage system device capacity that minimizes costs and avoids excessive investment. The planning process includes the calculation of the minimum required device capacity of the energy storage system, the battery life estimation model, consideration of the efficiency, cost and failure rate of the power electronic converter, and the optimization of the investment cost of the energy storage system. The battery life estimation depends on thebattery data provided by the manufacturer, and includes the selection of different converter architectures, in order to obtain the most appropriate capacity constructionand converter architecture.

In this study, the optimal capacity planning is carried out for a given energy storage system power curve, considering factors including battery cycle life attenuation due todepth of discharge, power electronic converter efficiency, internal switch failure rate, and battery technology cost Depreciation rate, but there are still some undiscussed topics that can be used as future research directions:

(1) This research ignores changes in the battery's State of Health (SoH) during the simulation phase. Changes in SoH will affect the actual depth of discharge in each cycleof the battery. In the future, the dynamic capacity decay model can be used to correct the battery life assessment method. to be closer to the actual operating conditions.
(2) This research ignores the influence of temperature on the cycle life. Because there are many factors that cause temperature changes in the actual energy storage system operation, it is difficult to estimate the temperature state by simulation. In the future, if the real For the operation data of the energy storage system, a battery life estimation model considering temperature can be used.
(3) This research currently only considers two power electronic converter architectures. In the future, other converters with unique advantages can be added, andother converter factors can be considered and included in the planning process.
(4) In this research, the converter efficiency is assumed to be a constant value in thesimulation. In fact, when the switching frequency of the converter is fixed, the power loss varies at different power levels. During the operation of the energy storage system, the converter The working power level will change frequently. In the future, the dynamic power loss can be calculated to make the conversion efficiency closer to the actual use condition.
(5) This research assumes that the depreciation rate of the technical cost of the battery decreases linearly, but in fact, the extent of the decline in the technical cost ofthe battery every year is affected by many factors. One-year depreciation rate for technology costs.

REFERENCES

[1] Abdelrazek, S. A., & Kamalasadan, S. (2016). Integrated PV capacity firming and energy time shift battery energy storage management using energy-oriented optimization. IEEE Transactions on Industry Applications, 52(3), 2607-2617.

[2] Akatsuka, M., Hara, R., Kita, H., Ito, T., Ueda, Y., Miwa, S., ... & Saito, M. (2010). Suppression of large-scaled

[3] PV power station output fluctuation using Sodium-Sulfur battery. IEEJ Transactions on Power and Energy, 130(2), 223-231.

[4] Alasali, F., Nusair, K., Obeidat, A. M., Foudeh, H., & Holderbaum, W. (2021). An analysis of optimal power flow strategies for a power network incorporating stochastic renewable energy resources. International Transactions on Electrical Energy Systems, 31(11), e13060.

[5] Bitran, G. R., & Tirupati, D. (1989). Capacity planning in manufacturing networks with discrete options. Annals of Operations Research, 17(1), 119-135.

[6] Broussely, M. I. C. H. E. L., Herreyre, S., Biensan, P., Kasztejna, P., Nechev, K., & Staniewicz, R. J. (2001). Aging mechanism in Li ion cells and calendar life predictions. Journal of Power Sources, 97, 13-21.

[7] Del Rosso, A. D., & Eckroad, S. W. (2013). Energy storage for relief of transmission congestion. IEEE Transactions on Smart Grid, 5(2), 1138-1146.

[8] Elshabrawy, T., & Robert, J. (2019). Capacity planning of LoRa networks with joint noise-limited and interference-limited coverage considerations. IEEE Sensors Journal, 19(11), 4340-4348.

[9] Erli, G., Takahasi, K., Chen, L., & Kurihara, I. (2005). Transmission expansion cost allocation based on cooperative game theory for congestion relief. International Journal of Electrical Power & Energy

Systems, 27(1), 61-67.
[10] Fan, V. H., Dong, Z., & Meng, K. (2020). Integrated distribution expansion planning considering stochastic renewable energy resources and electric vehicles. Applied Energy, 278, 115720.
[11] Golari, M., Fan, N., & Jin, T. (2017). Multistage stochastic optimization for production-inventory planning with intermittent renewable energy. Production and Operations Management, 26(3), 409-425.
[12] Han, D., & Lee, J. H. (2021). Two-stage stochastic programming formulation for optimal design and operation of multi-microgrid system using data-based modeling of renewable energy sources. Applied Energy, 291, 116830.
[13] Kim, T., Song, W., Son, D. Y., Ono, L. K., & Qi, Y. (2019). Lithium-ion batteries: outlook on present, future, and hybridized technologies. Journal of materials chemistry A, 7(7), 2942-2964.
[14] Kuznia, L., Zeng, B., Centeno, G., & Miao, Z. (2013). Stochastic optimization for power system configuration with renewable energy in remote areas. Annals of Operations Research, 210, 411-432.
[15] Narayan, A., & Ponnambalam, K. (2017). Risk-averse stochastic programming approach for microgrid planning under uncertainty. Renewable energy, 101, 399-408.
[16] Nusair, K., & Alas Ali, F. (2020). Optimal power flow management system for a power network with stochastic renewable energy resources using golden ratio optimization method. Energies, 13(14), 3671.
[17] Nusair, K., Alasali, F., Hayajneh, A., & Holderbaum, W. (2021). Optimal placement of FACTS devices and power-flow solutions for a power network system integrated with stochastic renewable energy resources using new metaheuristic optimization techniques. International Journal of Energy Research, 45(13), 18786-18809.
[18] Li, J., Daniel, C., & Wood, D. (2011). Materials processing for lithium-ion batteries. Journal of Power Sources, 196(5), 2452-2460.
[19] Luan, W., Sharp, D., & Lancashire, S. (2010, April). Smart grid communication network capacity planning for power utilities. In IEEE PES T&D 2010 (pp. 1-4). IEEE.
[20] Obara, S. Y., Morizane, Y., & Morel, J. (2013). Economic efficiency of a renewable energy independent microgrid with energy storage by a sodium-sulfur battery or organic chemical hydride. International journal of hydrogen energy, 38(21), 8888-8902.
[21] Parra, D., Gillott, M., Norman, S. A., & Walker, G. S. (2015). Optimum community energy storage system for PV energy time-shift. Applied Energy, 137,576-587.
[22] Rahmani-Andebili, M. (2017). Stochastic, adaptive, and dynamic control of energy storage systems integrated with renewable energy sources for power loss minimization. Renewable Energy, 113, 1462-1471.
[23] Talari, S., Shafie-Khah, M., Osório, G. J., Aghaei, J., & Catalão, J. P. (2018). Stochastic modelling of
[24] renewable energy sources from operators' point-of-view: A survey. Renewable and Sustainable Energy Reviews, 81, 1953-1965.
[25] Shahrabi, E., Hakimi, S. M., Hasankhani, A., Derakhshan, G., & Abdi, B. (2021). Developing optimal energy management of energy hub in the presence of stochastic renewable energy resources. Sustainable Energy, Grids and Networks, 26, 100428.
[26] Sun, G., Shen, S., Chen, S., Zhou, Y., & Wei, Z. (2022). Bidding strategy for a prosumer aggregator with stochastic renewable energy production in energy and reserve markets. Renewable Energy, 191, 278-290.
[27] Wen, Z. (2006, October). Study on energy storage technology of sodium sulfur battery and it's application in power system. In 2006 International Conference on Power System Technology (pp. 1-4). ieee.
[28] Woody, M., Arbabzadeh, M., Lewis, G. M., Keoleian, G. A., & Stefanopoulou, A. (2020). Strategies to limit degradation and maximize Li-ion battery service lifetime-Critical review and guidance for
[29] stakeholders. Journal of Energy Storage, 28, 101231.
[30] Xie, J., & Lu, Y. C. (2020). A retrospective on lithium-ion batteries. Nature communications, 11(1), 1-4

Authors

Tony Tsang (MIEEE'2000) received the Diploma and Higher Certificate in HongKong Polytechnic University in 1986 and 1988. He received the BEng degree in Electronics & Electrical Engineering with First Class Honors in Liverpool, U.K., in 1992. He studied the Master Degree in Computation from Computing Laboratory, Oxford University (U.K.) in 1995. He received the Ph.D. from the La Trobe University (Melbourne, Australia) in 2000. He was awarded the La Trobe University Post-graduation Scholarship in 1998. Dr. Tsang earned several years of teaching and researching experience in the Department of Computer Science and Computer Engineering, La Trobe University. He works in Hong Kong Polytechnic University as Lecturer since 2001. He works in Hong Kong College of Technology, Sunderland University, in 2014. He has numerous publications (more than 150 articles) in international journals and conferences and is a technical reviewer for several international journals and conferences. His research interests include Artificial Intelligence (AI), mobile computing, networking, protocol engineering and formal methods. Dr. Tsang is a member of the IET and the IEEE.

Facebook: https://www.facebook.com/tony.tsang.9693?fref=ts Research Gate: https://www.researchgate.net/profile/Tony_Tsang