CHEMICAL ENGINEERING TRANSACTIONS
VOL. 76, 2019

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Petar S. Varbanov, Timothy G. Walmsley, Jiří J. Klemeš, Panos Seferlis

ISBN 978-88-95608-73-0; **ISSN** 2283-9216

DOI: 10.3303/CET1976155

Multi-Objective Optimisation Method for Identifying Retired Points of Electric Vehicle Batteries

Taoxiang Wang, Lixia Kang, Yongzhong Liu*

Department of Chemical Engineering, Xi'an Jiaotong University, Xi'an 710049, P.R. China
yzliu@mail.xjtu.edu.cn

A multi-objective optimisation method to quantitatively identify retired points of electric vehicle (EV) batteries is proposed to minimise the life cycle cost (LCC) of EV batteries and the total annual cost (TAC) of energy storage systems (ESS). It features comprehensive considerations of battery capacity degradation characteristics and energy storage capacity optimisation. The effectiveness of the proposed method is demonstrated by a case study. The influence of the purchase cost and the profit of batteries in the second life are analysed. The Pareto front of LCC and TAC is given. The trade-off point is obtained when SOH_{re} is 0.855 and the corresponding LCC and TAC are 28,742.2 USD and 7,905.5 USD. Results indicate that retired points are intensively dependent upon the optimal capacity, LCC and TAC. Both LCC and TAC can be reduced by decreasing the purchase cost and increasing the profit without changing the retired points.

1. Introduction

In order to maximise economic and environmental benefits of batteries during the entire life, the electric vehicle (EV) batteries are usually reused for the energy storage applications after they are used as the traction batteries (Assunção et al., 2016). It is crucial to accurately identify the retired points of the EV batteries for the second life applications (Ahmadi et al., 2017). In recent, significant efforts have been made to evaluate the economic and environmental impacts of reusing EV batteries and identify the retired points. Although the retired point of EV battery is an important parameter that determine the economic and environmental benefits of batteries, they are usually considered constants (Casals et al., 2017) or discrete points (Viswanathan et al., 2012) by empirical experiences. Battery capacity degradation is one of key factors to determine the retired point (Sathre et al., 2015). The optimal battery capacity for different energy storage applications varies (Liu et al., 2018) because batteries present different capacity fading rates under different load profiles (Jiang et al., 2018). Batteries have different degradation characteristics in the second life (Wang, 2018), and the history of battery ageing in the first life strongly influence the performance of the second life of batteries (Martinez-Laserna et al., 2018). However, little attention is paid to the quantitative determination of the retired points of the EV batteries and the influence of energy storage applications on the identification of the retired points. The major objective of this work is to quantitatively identify the retired points of EV batteries by a multi-objective optimisation method in order to minimise the life cycle cost (LCC) of EV batteries and the total annual cost (TAC) of energy storage system (ESS). It features comprehensive considerations of battery capacity degradation characteristics and energy storage capacity optimisation.

2. Problem statement

The life cycle of EV batteries with second life applications generally includes five stages, i.e. manufacturing or purchase, first use in EV, repurposing, second use in ESS and recycling, as shown in Figure 1. The batteries deteriorate gradually, which can be depicted by the state of health (SOH) that is a ratio of battery residual capacity to battery initial capacity. The retired point for the second use is defined as the SOH when the battery ends its first life in the EV application. The multi-objective optimisation problem to quantitatively identify the retired points of EV batteries can be posed as follows.

Paper Received: 21/03/2019; Revised: 13/04/2019; Accepted: 15/04/2019
Please cite this article as: Wang T., Kang L., Liu Y., 2019, Multi-Objective Optimisation Method for Identifying Retired Points of Electric Vehicle Batteries, Chemical Engineering Transactions, 76, 925-930 DOI:10.3303/CET1976155

Given are (1) battery discharge rates and battery temperature, (2) unit price of battery, commercial electricity price, unit price of battery repurposing, profit in the second life and recycling profit, (3) battery capacity degradation characteristics. The problem is to obtain the SOH at the retired point and the optimal battery capacity in ESS when the LCC of reused batteries and the TAC of ESS are minimised.

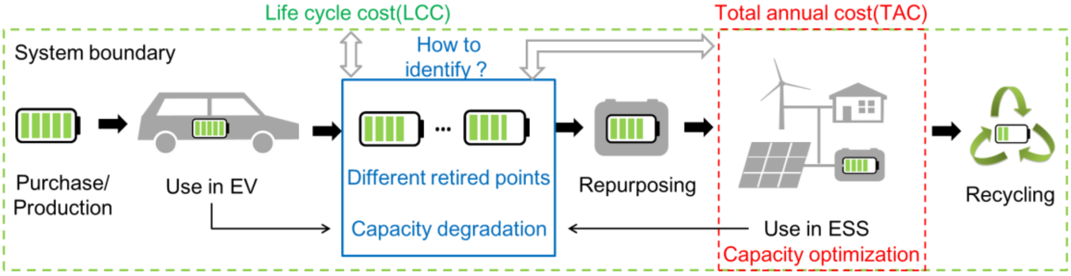


Figure 1: Life cycle of batteries used in electric vehicles and energy storage

3. Multi-objective optimisation model for identifying the retired points of EV batteries

3.1 Objective functions

The LCC of EV batteries is the sum of the cost and profit of the five stages in Figure 1, including the purchase cost of new batteries, the operation cost of EV, the repurposing cost of batteries, the profit in the second life and the recycling profit.

$$\min\ LCC = c_{pur}Q_n + c_g TE_{ch}^{FL} + c_{rep}Q_n + c_{pro}TE_{dc}^{SL} + c_{rec}Q_n \tag{1}$$

where c_{pur} is the unit price of new battery; Q_n is the capacity of new battery; c_g is the commercial electricity price; TE_{ch}^{FL} is the total electricity charged into the batteries in the first life in EV; c_{rep} is the unit repurposing price of battery; c_{pro} is the unit price of electricity delivered in the second life; TE_{dc}^{SL} is the total electricity delivered by the batteries in the second life; c_{rec} is the unit recycling profit of batteries.
The TAC of the ESS includes the annualised investment cost of the retired batteries and the operational cost of the ESS. The operational cost is simply the cost of purchasing commercial electricity.

$$\min\ TAC = (z+1)\cdot c_{re}\cdot Q_{re}\cdot \frac{r(1+r)^m}{(1+r)^m-1} + c_g TE_{imp}^{ESS} \tag{2}$$

where z is the replacement times of battery; c_{re} is the unit price of the retired batteries that depends on its residual capacity, $c_{re}=c_{pur}\cdot SOH_{re}$ (Lih et al., 2012); SOH_{re} is the battery SOH at the retired point; Q_{re} is the retired batteries capacity in ESS; r is a fractional interest rate; m is the second lifespan of batteries for energy storage; TE_{imp}^{ESS} is the total commercial electricity imported within one year.

3.2 Constraints

The transshipment model (Chen et al., 2014) is used to describe the operating constraints of the batteries in the second use stage. There are I available sources for supplying renewable electricity and J power demands in the ESS. The operating duration of the ESS in a day is divided into K time intervals.
Constraint of energy balance is expressed as follows.

$$\sum_{i\in I} E_i^{sp}(k) + E_{imp}(k) + S(k-1) = \sum_{j\in J} E_j^{de}(k) + G(k),\ \forall k\in K \tag{3}$$

where $E_i^{sp}(k)$ is the generated electricity from renewable electricity resources; $E_j^{de}(k)$ is the electricity consumed by demands; $S(k\text{-}1)$ is the available electricity supply from battery; $G(k)$ is the remaining electricity without considering the battery charge and discharge; $E_{imp}(k)$ is the commercial electricity imported.
Constraint of battery capacity can be expressed as

$$Q_b(k) = Q_b(k-1) - E_{dc}(k)/\eta_{dc} + E_{ch}(k)\eta_{ch},\ \forall k\in K \tag{4}$$

where $Q_b(k)$ is the battery capacity; $E_{dc}(k)$ is the electricity discharged from battery; $E_{ch}(k)$ is the electricity charged into battery; η_{dc} and η_{ch} are the discharge and charge efficiencies. Whether the battery is charged or discharged depends on the relative value of $S(k\text{-}1)$ and $G(k)$. If $S(k\text{-}1)$ is greater than $G(k)$, the battery is discharged, and $E_{dc}(k)=S(k\text{-}1)\text{-}G(k)$; otherwise, the battery is charged and $E_c(k)=G(k)\text{-}S(k\text{-}1)$. The relationship between the occurrence of battery charging or discharging can be established by binary variables and logic constraints. These details can be found in Chen's work (Chen et al., 2014).
Constraint of state of charge (SOC) of battery is expressed as

$$Q_{br}(k)\cdot SOC_{\min} \le Q_b(k) \le Q_{br}(k)\cdot SOC_{\max} \tag{5}$$

where $Q_{br}(k)$ is the battery residual capacity; $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper bounds of SOC.
According to the constraint of SOC and discharge efficiency, $S(k)$ can be expressed as $S(k)=(Q_b(k)\text{-}Q_{br}(k)\cdot SOC_{min})\,\eta_{dc}$. TE_{dc}^{SL} is the sum of $E_{dc}(k)$ in m years and TE_{imp}^{ESS} is the sum of $E_{imp}(k)$ in a year.

3.3 Battery capacity degradation model

A semi-empirical model is used to describe the capacity degradation characteristics in both the first and the second life of batteries. That is (Song et al., 2015)

$$q = 0.0032\cdot\exp\left[-\left(\frac{15,162-1,516CR}{R\cdot T}\right)\right](AH)^{0.824} \tag{6}$$

where q is the percentage of battery capacity loss; CR is the battery discharge rate; R is the gas constant; T is temperature; AH is the Ah-throughput.
The battery capacity loss in the first life is (1-SOH_{re}). The Ah-throughput in the first life AH^{EV} can be expressed as $AH^{EV}=E_{dc}^{EV}\cdot N_{day}/V^{EV}$, where E_{dc}^{EV} is the electricity discharged from the EV battery in one day; N_{day} is the EV battery lifespan; V^{EV} is the voltage of the EV battery.
The battery capacity degradation characteristics in the second life can be expressed as

$$q^{ESS}(k+1)^{1.2136} - q^{ESS}(k)^{1.2136} = 0.0032^{1.2136}\cdot\exp\left[-\left(\frac{15,162-1,516\cdot CR}{0.824\cdot R\cdot T}\right)\right]\cdot\Delta AH(k) \tag{7}$$

where $q^{ESS}(k)$ is the accumulated capacity loss of battery in ESS; $\Delta AH(k)$ is the Ah-throughput from the time interval k to k+1, $\Delta AH(k)=E_{dc}(k)/V^{ESS}$; V^{ESS} is the voltage of battery in the ESS.
The battery need to be recycled when the minimum SOH is reached, denoted as SOH_{min}. In the ESS, the relationship among the capacity of new batteries Q_n, the capacity of retired batteries Q_{re} and the EV battery pack capacity Q_0 can be expressed as $Q_0\cdot N_b^{EV}=Q_n=Q_{re}/SOH_{re}$. Then, the total electricity charged to the batteries in the first life TE_{ch}^{FL} can be expressed as $TE_{ch}^{FL}=E_{dc}^{EV}/\eta_{EV}\cdot N_{day}\cdot N_b^{EV}$, where η_{EV} represents the energy efficiency of EV battery.

4. Multi-objective optimisation on LCC and TAC

4.1 *ε*-constraint method

The *ε*-constraint method is adopted to obtain a Pareto front of the two objectives, and the AUGMECON method (Mavrotas, 2009) is adopted in this work. LCC is chosen as the main objective, whereas TAC is taken as a constraint.

$$\begin{aligned} &\min\ LCC+\sigma\cdot s\\ &st.\ TAC-s=\varepsilon\\ &\quad \varepsilon = TAC^{SN}-\left(\frac{TAC^{SN}-TAC^{U}}{p}\right)\cdot x,\ x=0,1,\ldots p \end{aligned} \tag{8}$$

where σ is an adequate small number; s is an appropriate slack variable; TAC^{SN} is the worst value over the efficient set; TAC^U is the best value; p represents that the range of TAC is divided into p equal intervals. The details for calculating TAC^{SN} and TAC^U can be found in Mavrotas' work (Mavrotas, 2009).

4.2 Evaluation function method

The evaluation function method is also adopted to determine a relatively better solution among all of the optimal solutions. The evaluation function can be constructed as (Kang et al., 2015)

$$\min\ \phi = \left[\lambda_1 \left(\frac{LCC - LCC^U}{LCC^{SN} - LCC^U} \right)^{\gamma} + \lambda_2 \left(\frac{TAC - TAC^U}{TAC^{SN} - TAC^U} \right)^{\gamma} \right]^{1/\gamma} \tag{9}$$

where $\gamma = 2$ and $\lambda_1 + \lambda_2 = 1$. The calculations of LCC^{SN} and LCC^{TAC} are similar to those of TAC^{SN} and TAC^U.

5. Case study

5.1 Fundamental data

The example case of the energy storage system is adopted from Chen and his co-workers' work (Chen et al., 2014). The lifespan of the ESS is 20 years, and the second lifespan of the batteries is ten years. The upper bound of SOH_{re} is set to be 0.9. The BYD battery electric vehicle Model e6 is selected for analysis of the EV battery. The battery pack capacity, voltage and energy consumption rate are 82 kWh, 316.8 V and 19.5 kWh/100 km (Diao et al., 2016). The average annual distance traveled by the vehicle is approximately 12,000 km (Diao et al., 2016). Assuming that the EV runs for an average of 300 days in one year. Then E_{dc}^{EV} equals to 19.5 kWh. The battery discharge rate is 2C. The temperature of battery is 318.15 K. The battery discharge rate, temperature and voltage in the ESS are 0.5 C, 298.15 K and 300 V. The discharge efficiency, the charge efficiency and energy efficiency are all 0.9. The $SOC_{\min}$, $SOC_{\max}$ and $SOH_{\min}$ are 0.1, 0.9 and 0.4.
The unit price of new battery and the unit recycling profit are 300 USD/kWh and -8.2 USD/kWh (Liu et al., 2018). The commercial electricity price is 0.1176 USD/kWh (Diao et al., 2016), and the unit repurposing price of battery is estimated to be 24 % of c_{pur} (Foster et al., 2014). The unit price of energy delivered in the second life is estimated to be 95% of c_g, assuming that users would not use the electricity at a higher price than the commercial electricity (Thomas et al., 2018). All calculations are carried out on GAMS 24.1.3 with DICOPT as the global solver and CPLEX and CPNOPT as the local solvers for the mixed integer programming and nonlinear programming sub-problems. The allowed maximum relative errors of all calculations are 5 %.

5.2 Pareto front and trade-off point

A Pareto front of LCC and TAC is obtained by the ε-constraint method with p = 4. The trade-off strategy is implemented by the evaluation function method with $\lambda_1 = 0.8$ and $\lambda_2 = 0.2$.

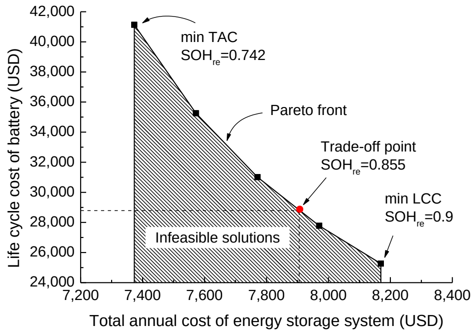


Figure 2: Pareto front of LCC and TAC and the trade-off point

Table 1: Comparison of the result obtained by minimum LCC point, minimum TAC point and trade-off point

Objectives	SOH_{re}	Q_{re} (kWh)	Q_n (kWh)	LCC (USD)	TAC (USD)
min LCC	0.9	104.3	115.9	25,266.9	8,169.2
min ϕ	0.855	105.8	123.8	28,742.2	7,905.5
min TAC	0.742	112.7	151.9	41,135.0	7,373.3

Figure 2 shows the Pareto front of the two objectives. All points on the Pareto front are the optimal solutions. The minimum LCC and the minimum TAC locate at the lowest and highest points of the Pareto front. The trade-off point marked in the figure is obtained by the evaluation function method. A comparison of the result obtained by minimum LCC point, minimum TAC point and trade-off point is presented in Table 1.

The results indicate that the optimal capacity of the retired battery in the ESS and the relevant new battery vary with the retired point due to the requirement of ESS and battery capacity degradation characteristic. Q_n reaches its minimum 115.9 kWh when the SOH_{re} is 0.9, where the LCC reaches its minimum 25,266.9 USD. However, the TAC reaches its minimum 7,373.3 USD when the SOH_{re} is 0.742, and Q_{re} reaches its maximum 112.7 kWh, as a result of Q_{re} varying slightly with the retired point and c_{re} varying intensively with SOH_{re}. A comparison of the LCC of batteries in five stages is shown in Figure 3.

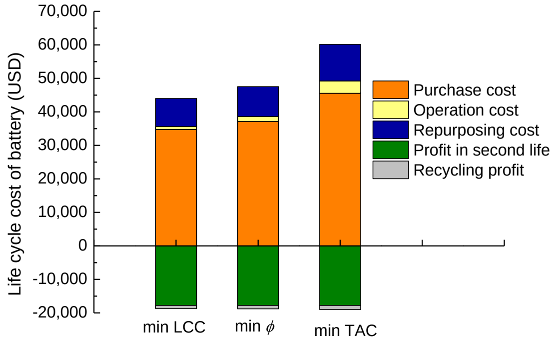
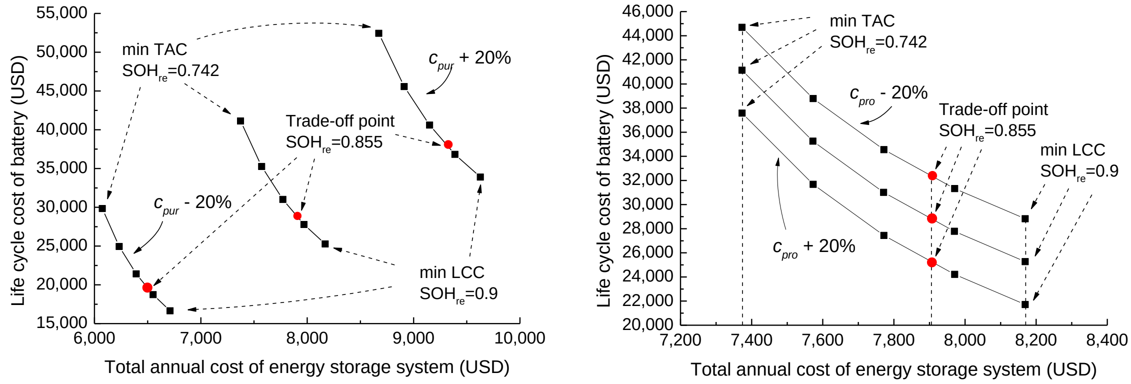


Figure 3: Comparison of LCC of batteries in five stages

Because of Q_n increasing, the LCC of batteries increases significantly with the increase of the purchase cost and the repurposing cost increase. The operation cost also increases due to the increase of operation duration. However, the profit rarely changes in the second life of batteries. The purchase cost and the profit in the second life play major parts in the LCC. It will be further discussed in the next section.

5.3 Further discussion on the purchase cost and the profit during battery reuse

The effects of the purchase cost and the profit on the battery reuse process are discussed. Figure 4a gives the relationship between LCC and TAC when c_{pur} are increased and decreased by 20 %, amd Figure 4b gives the relationship between LCC and TAC when c_{pro} are increased and decreased by 20 %.



(a) The effect of c_{pur}

(b) The effect of c_{pro}

Figure 4: Effects of c_{pur} and c_{pro} on the battery reuse process

In Figure 4a, both LCC and TAC change significantly with the change of c_{pur}, but SOH_{re} does not change. Likewise, as shown in Figure 4b, SOH_{re} remains constant as c_{pro} changes. The reason is that c_{pro} only influence the LCC instead of the TAC. As the discharging behaviour of the batteries in the ESS is determined by the input and output, the electricity discharged in the second life is constant. Therefore, the LCC varies with c_{pro}, and the retired points do no change. The decrease of c_{pur} and the increase of c_{pro} lead to the reduction both in LCC and TAC. Nevertheless, the corresponding retired points remain unchanged.

6. Conclusions

Based on the comprehensive considerations of battery capacity fade characteristics and energy storage optimisation, a multi-objective optimisation method to quantitatively identify the retired points of EV batteries is proposed to minimise the LCC of reused EV batteries and the TAC of ESS. The influence of the battery purchase cost and the profit in the second life on the battery reuse process is analysed. In this work, the LCC reaches its minimum 25,266.9 USD when SOH_{re} is 0.9. The TAC reaches its minimum 7,373.3 USD when SOH_{re} is 0.742. The trade-off point is obtained when SOH_{re} is 0.855. The results indicate that the optimal battery capacity, LCC and TAC vary with the retired point due to the requirement of ESS and capacity degradation characteristics. The profit in the second life and the electricity discharged in the second life are constants as the discharging behaviour of the battery in the ESS is determined by the electricity supply and load demand. The decrease of c_{pur} and the increase of c_{pro} lead to the reduction both in LCC and TAC, but the corresponding retired points remain unchanged. The identification of the retired points in different scenarios for energy storage applications deserve further efforts in the future.

Acknowledgments

The authors gratefully acknowledge funding by the projects (No. 21808179, No. 21878240 and No.21676211) sponsored by the National Natural Science Foundation of China (NSFC).

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