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Optimal Charging Strategy for EVs with Batteries at Different States of Health

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Abstract - The electric vehicle (EV) is targeted as an efficient method of decreasing CO₂ emission and reducing dependence on fossil fuel. Compared with filling up the internal combustion engine (ICE) vehicle, the EV power charging time is usually long. However, to the best of our knowledge, the current charging strategy does not consider the battery state of health (SOH). It is noted that a high charging current rate may damage the battery life. Motivated by this, an optimal charging strategy is proposed in the present paper, providing several optimal charging options taking into account the EV battery health, trying to prevent ‘abused battery utilization’ happening.

Index Terms- Fast charging, Battery state of health (SOH), Cycle life, Optimization

I. INTRODUCTION

Electric Vehicle (EV) and Plug-in Hybrid Electric Vehicle (PHEV) are being developed in a positive effort to deplete exhaust emissions, reduce the dependence on fossil fuel. To support the environmental and economic benefits which EVs bring, each government sets its own EV development plan, for example the UK government expects that EVs and PHEVs can take 40% of the motor market in 2020 [1]. However the development of this plan is not as encouraging as expected. Table 1 shows the barriers to EV uptake. Surmising from this Table, it is easy to find that the battery technology is the main bottleneck. Although, from lead-acid to nickel cadmium (NiCd), Nickel-metal hydride (NiMH), as far as lithium-ion (Li-ion), Li-air and polymer Li-ion, the battery technologies have made remarkable achievements; the limited energy/power capacity and cycle life (compared with the internal combustion engine vehicle) affect the range, life and cost of EVs[2, 3].

Due to the limited running range, EV customers need to recharge their EVs frequently. Currently, International Electrotechnical Commission (IEC) 62196 set of standards for charging of electric defining four modes of charging:

- Mode 1: normal, slow charging, with a normal household socket.
- Mode 2: same as model 1, but with an in-cable protection, the most common charging model today.
- Mode 3: slow or fast charging with on board charger, using dedicated plugs and protection.
- Mode 4: fast charging using an external charger, as for instance CHAdeMO.

Table I. Ranking of barriers to EVs uptake [4]

Barrier	Overall ranking
High purchase cost	Very high significance
Limited range of EVs (and range anxiety issues)	Very high significance
Lack of recharging infrastructure (and issues relating to implementation and operation of infrastructure)	Very high significance
Uncertainty about future resale value	High significance
Limited supply of EVs	High significance
Lack of public awareness and knowledge about EVs	High significance
Limited performance and limited choice of vehicles	High significance
Aversion to new technology	High significance
Weak image association	High significance
Limited value placed on environmental benefits by consumers	High significance
Uncertainty about future energy costs	High significance
Limited environmental benefits associated with current models	Moderate significance
Lack of support networks (e.g. garages with appropriate skills and equipment).	Moderate significance
Lack of engineering skills	Moderate significance

Fast charging is significant as it can help the users to finish charging in relatively short time compared with other charging models for the same capacity battery pack. For example, the CHAdeMO fast charger can support 50 kW to allow the Nissan LEAF to charge to 80% state of charge (SOC) in 20 minutes. This charging pattern is quite attractive for customers on a tight schedule.

What is the reason for choosing the fast charger’s power rate to be 50 kW rather than 10 kW, or 160 kW? Figure 1 indicates the reason from the manufacturer’s cost and users’ time point of view.

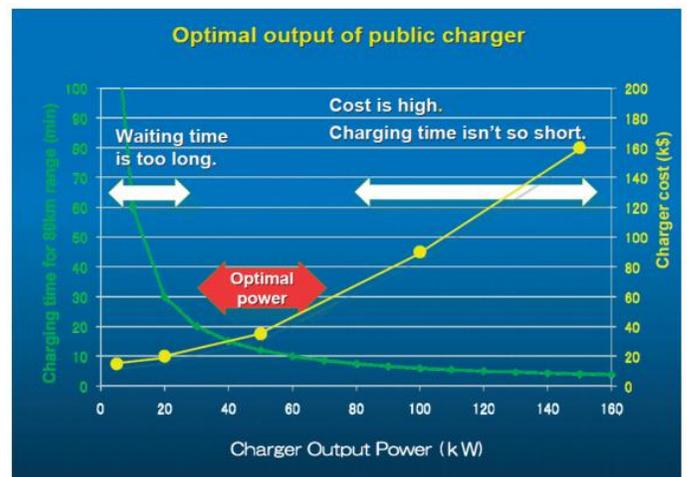


Figure 1. Optimal output of fast charger [5]

From Figure 1, it can be found that the total charging time is not linearly dependant on power, also the infrastructure costs are increasing with a higher power rate. The 50 kW charger has the best performance-price ratio. However, it is not the only consideration for choice of charging power rate. As the battery's inherent characteristic, the battery cycle life will decrease with the increase in current rate. For instant, a specific Li-ion battery can be charged 4000 times charging at mode 1 but reduces to 100 times under fast charging [6]. So the SOH of the EV battery pack should be considered as another factor for EV charger development or an additional factor added into the existing charger, especially, when EVs are widely used.

As mentioned, the battery cycle life and charging time (current rate) are two inter-constraining factors. In order to balance and address this issue, in this paper, an optimized charging strategy is proposed. The charging current is determined by evaluating battery SOH and charging time. These two factors are qualified by cycle life and charging current. The mathematical objective function is developed and validated here. Generic Algorithm (GA) is utilized to determine the optimized point which gives a value for charging current.

II. OPTIMIZED CHARGING STRATEGY

(i). Battery cycle life and current rate normalization

Charging time and battery cycle life are the two factors that users focus on. Reducing the charging time can make users' lives more flexible but reducing the the charging current (extend charging time) can extend battery life and reduce the cost [7, 8]. Flexibility is needed, but both these two items should be given consideration. Here, a mathematical model is built to quantify this abstract concept.

As material, shape, manufacturing and testing environment are different for each manufacturer; there is no generic function to describe the aging behaviour. Normally, empirical or semi-empirical equations based on experimental data are used to express batteries' aging behaviours. Here [6], a specific battery $\text{LiCoO}_2/\text{Li}_{4/3}\text{Ti}_{5/3}\text{O}_4$ is chosen as the example. These kinds of batteries are cycled with different current rates at room temperature and 70% depth of discharge (DOD). The test results (cycle numbers against current rate experimental data) are shown in Figure 2.

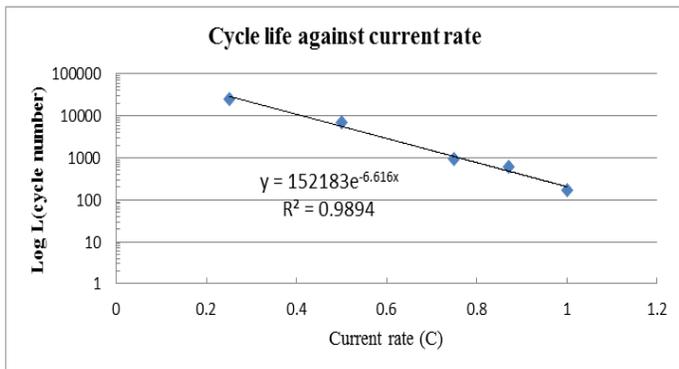


Figure 2. battery cycle life at different current rates

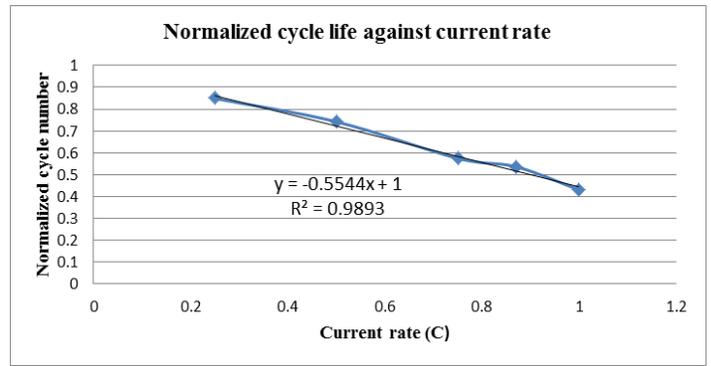


Figure 3. Normalized battery cycle life at different current rates

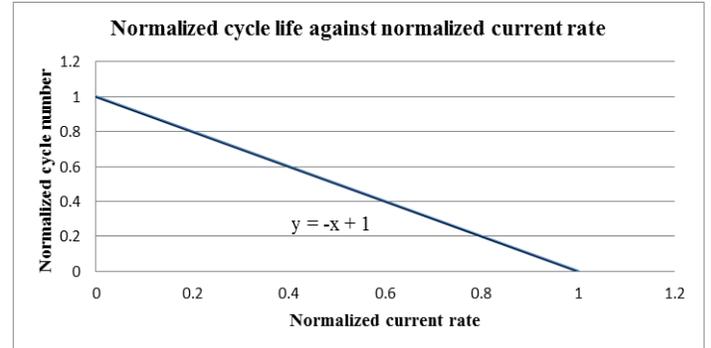


Figure 4. Normalized battery cycle life at different normalized current rates

From the data above, it can be found that the cycle life increases exponentially with decreasing current rate. Then normalize the cycle number to obtain a linear function as shown in Figure 3.

By using coefficient normalization and curve fitting, a function between cycle life and current rate can be acquired. The least square error R^2 is 0.9893 which proves the function fits quite well. Then normalizing the current rate (by dividing common base value 1.8), a new function $y=-x+1$ can be obtained as shown in Figure 4.

(ii). Objective function

Charging time is inversely related to the charging current rate. In order to maximize the battery life and minimize charging time, the value of charging current rate multiplied by cycle life should be maximized by using the objective function:

$$\max z = x^m y^n \quad (1)$$

where $y = f(x)$;

x is charging current rate;

y is normalized battery cycle life;

m, n are the weight factors;

Before applying this objective function in EV smart charging control, it is necessary to prove this objective has maximum value; the validation is presented in the Appendix.

Here the SOH of battery is divided into five regions according to the battery usable capacity (80% usable capacity is considered to be end of life) which is shown in Figure 5.

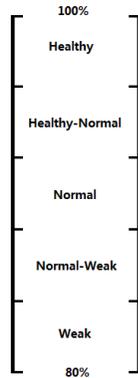


Figure 5 usable capacity of battery health

For different SOH of the battery, the weighting factors are different. The Table II defines weighting factors according to the battery SOH. The weighting factors are used to evaluate the importance of charging current and battery life cycles. m represents the weighting of current rate and n represents cycle number. Of course, the manufactures can set different health regions and weight factors according to the battery performance and user requirements.

Implement the function (1) into Matlab and plot the curves for different weighting factors, as shown in Figure 6. Then calling Genetic Algorithm (GA) algorithm to determine the optimized value, the optimized normalized current rate values can be obtained. The real charging current rate can be determined as the normalized current rate multiplied by the common base value (1.8). Charging time is the reciprocal of the real charging current rate. All this information is shown in Table II. From Table II, it can be found that, as expected, the charging time will decrease or increase with the weighting of current rate or cycle number. For example, when $n=1$, with m increasing from 1 to 3, the charging time reduces from 66 to 43 mins. Conversely, with weighting towards cycle number, the charging time increases from 66 to 150 mins.

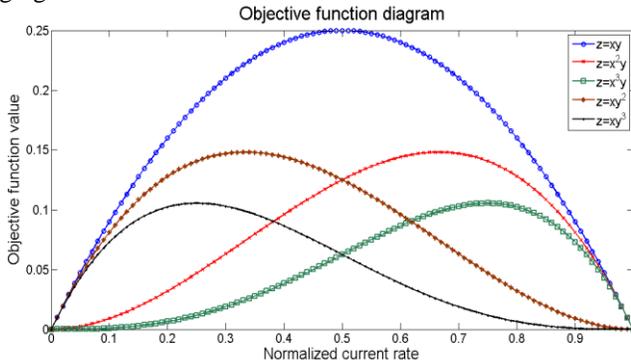


Figure 6 Objective function curves

Table II Optimized charging plan

Weight factors	Optimized normalized current rate	Optimized current rate (C)	Charging time (mins)
$m=1, n=1$	0.50	0.9	66
$m=2, n=1$	0.67	1.2	50
$m=3, n=1$	0.77	1.38	43
$m=1, n=2$	0.33	0.6	100
$m=1, n=3$	0.22	0.4	150

(iii). Impact on the cycle life

According to the mathematical expression of cycle number and current rate which is fitted from Figure 2;

$$y = 152183e^{-6.616x}$$

the corresponding battery cycle life number can be determined according to the current rate as shown in Table III

Table III cycle life charged at different current rates

Weight factors	Optimized current rate (C)	Cycle number
$m=1, n=1$	0.9	395
$m=2, n=1$	1.2	55
$m=3, n=1$	1.38	17
$m=1, n=2$	0.6	2870
$m=1, n=3$	0.4	10800

From Table III, it can be found that in principle this specific ($\text{LiCoO}_2/\text{Li}_{4/3}\text{Ti}_{5/3}\text{O}_4$) battery only can be cycled 17 times at high current rate (1.38C) which equates to a charging time of 43 mins. But the cycle life dramatically increases with decreasing charging current rate (charging time extended).

III. CONCLUSION

In order to reduce the adverse effect on the battery cycle life due to fast charging, an optimized charging strategy has been presented in this paper. Life cycle and charging time have been taken as two factors to evaluate the optimal charging current. The proposed charging strategy can offer several options according to the SOH of battery by using communications with the battery management system (BMS), which can relatively extend the battery life compared with fast charging technique.

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APPENDIX

Objective function validation:

Here are the constraints:

a, b are the current rate values

$$x \in [a, b], a, b > 0$$

m, n are weight factors,

$$m, n > 0$$

the function of $y = f(x)$ is linear or convex and strictly decrease, which can be express as:

$$\begin{cases} f(x) > 0 \\ f'(x) < 0 \\ f''(x) \leq 0 \end{cases} \quad (2)$$

Validation:

If function z has maximum value, using mathematic expression, which can be written as:

$$\begin{cases} z' = 0 \\ z'' < 0 \end{cases} \forall x \in [a, b] \quad (3)$$

First, prove $z' = 0$. Here reduction to absurdity is used:

Assume $z' \neq 0$, then

$$\begin{cases} z' < 0 \\ \text{or} \\ z' > 0 \end{cases} \forall x \in [a, b] \quad (4)$$

If assume $z' < 0$, then function z strictly decrease, then can obtain

:

$$z(a) > z(b) \quad (5)$$

But on the other side,

If current rate a is relatively small, then $a \approx 0$;

If current rate is very large, then the battery cycle life $f(b)$ will be very limited and approaching to zero ($f(b) \approx 0$).

Due to $z = x^m y^n = x^m f(x)^n$,

$$\begin{aligned} z(a) &= a^m f(a)^n = 0 \\ z(b) &= b^m f(b)^n = 0 \end{aligned}$$

So

$$z(a) = z(b) \quad (6)$$

Which is conflict with equation (5).

Similarly, it can be obtained that if assume $z' > 0$, then function z strictly increase, $z(a) > z(b)$, which is also conflict with equation (5).

So,

$$\exists x_0 \in [a, b]. \text{ subject to } z'(x_0) = 0; \quad (7)$$

which means function z has peak value.

Secondly, we need to prove $z'' < 0$; It is easy to obtain:

$$z' = mx^{m-1}[f(x)]^n + nx^m[f(x)]^{n-1}f'(x) \quad (8)$$

$$\begin{aligned} z'' &= m(m-1)x^{m-2}[f(x)]^n + 2nmx^{m-1}[f(x)]^{n-1}f'(x) \\ &\quad + n(n-1)x^m[f(x)]^{n-2}[f'(x)]^2 + nx^m[f(x)]^{n-1}f''(x) \end{aligned} \quad (9)$$

As previous mentioned that,

$$\exists x_0 \in [a, b]. \text{ subject to } z'(x_0) = 0$$

So from equation (8), it can be got that:

$$z(x_0)' = mx_0^{m-1}[f(x_0)]^n + nx_0^m[f(x_0)]^{n-1}f'(x_0) = 0$$

which can be given as:

$$f(x_0) = -\frac{nx}{m}f'(x_0) \quad (10)$$

Substitute equation (10) into (9),

$$\begin{aligned} z(x_0)'' &= [f(x_0)]^{n-2}x_0^{m-2} \left\{ \frac{m-1}{m}n^2x_0^2[f'(x_0)]^2 - \right. \\ &\quad \left. 2n^2x_0^2[f'(x_0)]^2 + n(n-1)x_0^2[f'(x_0)]^2 - \right. \\ &\quad \left. \frac{n^2}{m}x_0^3f'(x_0)f''(x_0) \right\} \end{aligned} \quad (11)$$

Transfer equation (11), it can be obtained that

$$\begin{aligned} z(x_0)'' &= [f(x_0)]^{n-2}x_0^{m-2} \left\{ -nx_0^2[f'(x_0)]^2 \left(\frac{n}{m} + 1 \right) - \right. \\ &\quad \left. \frac{n^2}{m}x_0^3f'(x_0)f''(x_0) \right\} \end{aligned} \quad (12)$$

Compare equation (12) with zero. From equation (2), it can be found that:

$$\begin{aligned} &\because x_0 \in x \in [a, b], a > 0, b > 0, f(x) > 0 \\ &\therefore x_0^2 > 0, x_0^3 > 0, x_0^{m-2} > 0, [f(x_0)]^{n-2} > 0; \\ &\because n > 0, f'(x_0) < 0, f''(x_0) < 0 \\ &\therefore \left\{ -nx_0^2[f'(x_0)]^2 \left(\frac{n}{m} + 1 \right) - \frac{n^2}{m}x_0^3f'(x_0)f''(x_0) \right\} < 0; \\ &\therefore z(x_0)'' < 0 \end{aligned} \quad (13)$$

The equation (7) prove optimized function (1) has peak value, and equation (13) validate that this peak value is maximum value.

So in summary, this objective function has optimized point subject to the constraints.