EE236C
PROJECT REPORT

Energy Management for EV Charge Station in Distributed Power System

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1. Introduction

Most traditional power systems generate electricity by heat power plants, hydropower plants and nuclear plants, which are all centralized large electricity generation facilities. The benefits by doing so is obvious, i.e. it has fully-fledged automatic control method such that safety of the grid could be ensured, would generate electricity with fixed frequency(50Hz in Asia, Europe and 60Hz in North America) so as to maintain the stability of the whole system and would have a low cost of every kWh of electricity.

However, traditional generation method is hard to achieve peak regulation nicely, would lose lots of energy during long distance transmission and cause severe environmental issue. On the other hand Distributed Power System(DPS) generates electricity from many small energy sources. Using DPS could suit the need for the small area near where it has been located, reduce the long distance transmission loss and eco-friendly since most of the generation method would not produce as much pollution as the conventional one. The major concern about DPS is the relatively poor electricity quality compared with the traditional one. In most cases, power companies are reluctant to let power flow from DPS sources flow into their stable power grids.

Since fossil fuels become more and more expensive and have been regarded as the main issue for global warming, people started to find alternative ways to substitute fossil fuels. With the merit of clean and cheap, electricity has become a good alternative in automobile industry. Many automobile manufactures began to produce HEV and EV instead of traditional cars.

Usually, Charging process for EV would be done in a charge station just like gas station for normal vehicles. Since electricity generated by distributed generator might not satisfy the need of electricity quality for the conventional power grid, a feasible solution is to build a DPS special for EV station, topology could be seen as follow for example.

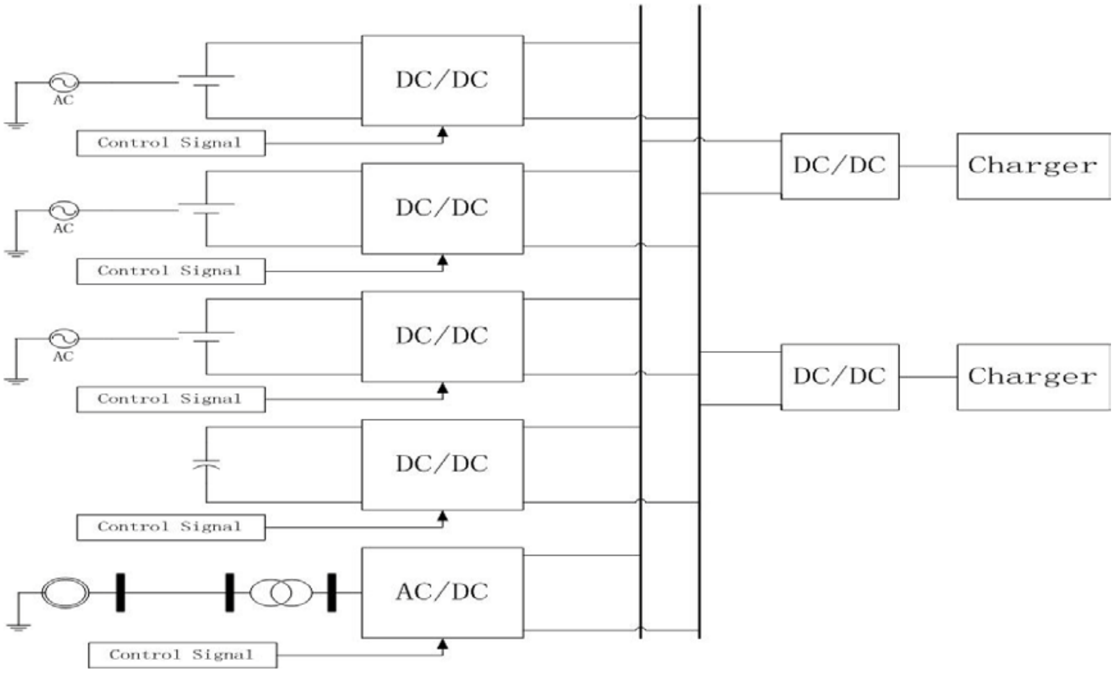


Fig 1 Charging Station Topology

This topology is consist of few batteries which connected to the DPS generator, super capacitors(or other energy storage device) which can be regarded as back up energy storage and a switch connects to conventional grid in case of the total amount of the generated electricity could not satisfy the need of the EV charge station. Typically charging profile for a EV is a combination of constant current charging, constant voltage charging and PWM controlled current charging.

Typically there are two different kinds of charging method. The first method would have two charging stage. The first stage is to charge the battery at constant C-rate until it reaches nominal voltage value, the second phase is to charge it at constant voltage until charging current became 0.1 time of current value in the first stage. The second method is to charge the battery with some pulse current and gradually decrease the charging current when battery voltage reaches some threshold.

The performance of this topology would have a strong rely on batteries and other storage device, thus an optimal electricity management method for this topology is of great demand to be developed.

2. Model Formulation

In this problem, by given load current over time, capacity, SOC and other parameters of batteries and super capacitors, we want to obtain an optimal battery and super capacitor discharging schedule from distributed power source so as to prolong battery life and minimize the energy loss in a distributed generation based EV charging station.

We have following general assumptions. First is at high sample frequency, current/voltage value between each time step is constant. Then the second one is conventional power grid will only connected to super capacitors and charge them when needed. Third one is all the battery and super capacitor current are dynamically control by power electronic device. Other minor assumptions are described in detailed case.

2.1 Battery Life Optimization

Generally for a battery, the higher the discharge rate is, the less the battery life will be. The higher Depth of Discharge(DOD) of a battery is, the higher battery capacity degradation will be.High current value would increase batteries' internal resistance more rapidly and thus would make batteries' life become shorter. Also note that for certain given discharge rate, battery cells which is cycled at high level DODs were shown to reach the defined end of life, i.e. only 70% capacticy of a fresh battery could this battery be charged, much sooner than those cycled at lower DODs (<50%). This observation is illustrated in Fig. 2

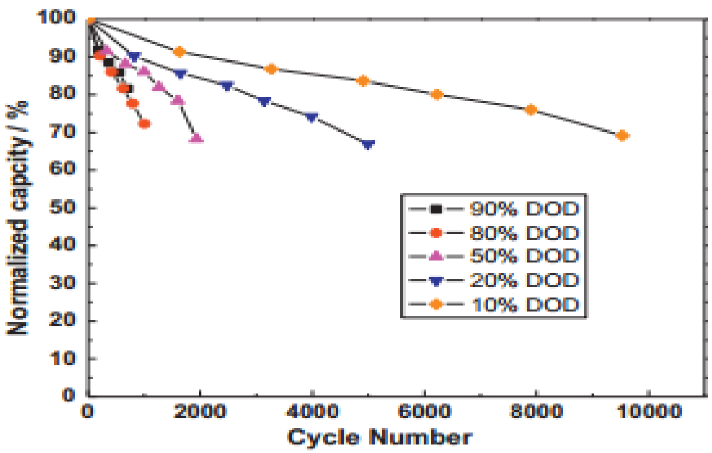


Fig 2 Battery Cycle Life VS DOD

To achieve the goal of long battery life, we will control the current value flows through the batteries and try to make it as small as possible, also we would like to control the fluctuation of current value so as to make things easy for controller chips to control the circuit.

We assume that the voltage and current are measured using discrete signals with a sufficiently small sampling period . The battery has a capacity in amp-hour units.

The magnitude of the battery current and the current fluctuation of the battery can be denoted as I_B and $|I_B(t)-I_B(t-1)|$, respectively.

For the whole discharging period, we want to minimize the summation of current at each time step and summation of fluctuation, which is denoted as $\sum_{t\in T} I_B(t)$ and $\sum_{t,t-1\in T} | I_B(t) - I_B(t-1) |$.

For each battery, we want the current flows out from it would not be greater than some value but not strictly less than it. So a penalty function could play a role here to minimize the objective and ensure most of the value would be less than desired value. In this problem, we will choose Huber penalty function.

$$\varphi(z) = \begin{cases} |z|^2 & |z| < 1 \\ 2|z| - 1 & |z| \geq 1 \end{cases}$$

Since the Depth of Discharge is a great concern during the EV charging process, a SOC lower bound for each battery will be added to ensure they will not be over-discharged.

Case1 Battery Only Topology with Identical Parameters

This might be the simplest case among all the possible topologies. The objective function aims to make current as small as possible and tries deviate current fluctuation. The only constraint might be Kirchhoff's Circuit Law which is the current flows out from the battery should be equal to those flows into EV. The optimization problem is shown as below.

$$\begin{aligned} \min \quad & \sum_{i=1}^{m} \sum_{t\in T} \varphi(I_{B_i}(t), \lambda_1) + \sum_{i=1}^{m} \sum_{t,t-1\in T} \varphi(| I_{B_i}(t) - I_{B_i}(t-1) |, \lambda_2) \\ s.t. \quad & \sum_{i=1}^{m} I_{B_i}(t) + \sum_{n\in N} I_{load_n}(t) = 0 \end{aligned}$$

Where $\varphi(f(x), b)$ is huber penalty function

This is obviously a convex optimization problem.

Case2 Battery Only Topology with Different parameters

In this case the difference between the case1 is that each battery would have different capacity and different initial SOC value. By doing so we could simulate each battery's condition in a more practical manner. For the purpose of SOC balancing between each battery so that we could fully use every battery and avoid the case that one of the battery draines out but other batteries still remain plenty of charge, the objective function would need to keep the difference of each battery's SOC in a small value besides achieveing the functionality in case 1.

$$\min \quad \sum_{i=1}^{m}\sum_{t\in T}\varphi(I_{B_i}(t),\lambda_1)+\sum_{i=1}^{m}\sum_{t,t-1\in T}\varphi(|I_{B_i}(t)-I_{B_i}(t-1)|,\lambda_2)+\|FG\|_1$$

$$s.t. \quad \sum_{i=1}^{m} I_{B_i}(t)+\sum_{n\in N} I_{load_n}(t)=0$$

$$G \geq 0.3\times\vec{1}$$

where

$$F=\begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & \dots & \dots & 0 & 0 \\ 0 & 0 & \dots & \dots & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

$$G(i)=\frac{(Q(i)soc(i)-\sum_{t\in T} I_{Bi}(t)\times\Delta t)}{Q(i)}$$

In the formulation above, F is teoplitz matrix and G represents for SOC of each battery at every time step. The second constraint means that DOD for every battery should not be greater than 70% which is aiming to prolong the battery life. This is also a convex programming problem.

Case3 Battery and Super Capacitor Topology

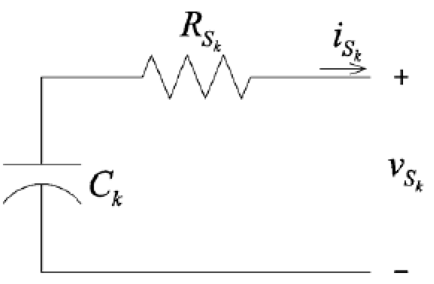


Fig 3 Super Capacitor Equivalent Circuit

Fig 3 is the equivalent circuit for super Capacitors. Denote terminal voltage, capacitor current, equivalent serial resistance(ESR), and capacitance as $v_{s_k}, i_{s_k}, R_{s_k}, C_k$ respectfully. From basic circuit theory we have

$$v_{s_k}(t)=-\frac{1}{C_k}\int_{t\in T} i_{s_k}(t)dt$$

One benefit for us to use super capacitor is that it could accept huge current change between time steps and this will provide the possibility to make battery current have less fluctuations.

Here we also assume that that the initial capacitor voltage should remain the same to the final capacitor voltage such that during the whole EV charging process, the energy change in the whole EV station is 0. Model formulation is shown as below

$$
\begin{aligned}
\min \quad & \sum_{i=1}^{m}\sum_{t\in T}\varphi(I_{B_i}(t),\lambda_1)+\sum_{i=1}^{m}\sum_{t,t-1\in T}\varphi(|I_{B_i}(t)-I_{B_i}(t-1)|,\lambda_2)+\|FG\|_1+\sum_{i=1}^{p}\sum_{t\in T}\varphi(I_{SC_i}(t),\lambda_3) \\
s.t. \quad & \sum_{i=1}^{m} I_{B_i}(t)+\sum_{i=1}^{p} I_{SC_i}(t)+\sum_{n\in N} I_{load_n}(t)=0 \\
& V_{SC_i}(t)=-\sum_{j=1}^{t}\left(\frac{\Delta t}{C_i} I_{SC_i}(j)+R_{S_i}\,|I_{SC_i}(t)|\right) \\
& V_{SC_i}(0)=V_{SC_i}(t_{end}) \\
& V_{SC_i}(t)\geq 0 \\
& G\geq 0.1\times\vec{1}
\end{aligned}
$$

The objective function aims to control both current of battery and super capacitor and SOC status for each battery. The first constraint is Kirchhoff Current Law. The second constraint is gained by the characteristic equation of super capacitor at each time step. Third Constraint is to ensure that initial capacitor voltage should remain the same to the final capacitor voltage such that during the whole EV charging process. Fourth constraint is to ensure capacitor's voltage should be a positive value. Last constraint is the DOD constraint just the same as what in case 1 and case 2.

For programming convenience in solver, we need to transform the problem into a proper way. By using matrix representation and changing variables, we could have following optimization model

$$
\begin{aligned}
\min \quad & \alpha\sum_{i=1}^{m}\sum_{t\in T}\varphi(I_{B_i}(t),\lambda_1)+\beta\sum_{i=1}^{m}\sum_{t,t-1\in T}\varphi(|I_{B_i}(t)-I_{B_i}(t-1)|,\lambda_2)+\gamma\|FG\|_1+\varepsilon\sum_{i=1}^{p}\sum_{t\in T}\varphi(I_{SC_i}(t),\lambda_3) \\
s.t. \quad & \sum_{i=1}^{m} I_{B_i}(t)+\sum_{i=1}^{p} I_{SC_i}(t)+\sum_{n\in N} I_{load_n}(t)=0 \\
& (A-I)V_{SC}+KI_{SC}-R_S T=0 \\
& EV_{SC}=0 \\
& T>-I_{SC} \\
& T<I_{SC} \\
& V_{SC}\geq 0 \\
& G\geq 0.1\times\vec{1}
\end{aligned}
$$

where

$$A = \begin{bmatrix} [1,0,...,0] & 0 \\ I_n & 0 \end{bmatrix}$$

$$K = \Delta t \begin{bmatrix} 0 \\ I_n \end{bmatrix}$$

$$E = [1,0,0,...,0,-1]$$

$$F = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & ... & ... & 0 & 0 \\ 0 & 0 & ... & ... & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

$$G(i) = \frac{(Q(i)soc(i) - \sum_{t \in T} I_{B_i}(t) \times \Delta t)}{Q(i)}$$

Matrix A comes from processing with one time step and the next time step of the constraint of super capacity voltage recursively. This formulation is obviously a convex optimization problem.

Note that with some high current value, first two huber penalty function would return significant large value which will lower the influence of other terms. We would put some weight to all the components to adjust this phenomenon.

2.2 Energy Loss Optimization

In EV charging station system, energy loss from power side is mainly generated by equivalent serial resistance in super capacitors. Especially during the charging and discharging of the SCs. Although an energy loss can be induced by the battery since it also has internal resistance, we will ignore it because resistance in battery is relatively small compared to ESR in super capacitors.

Denote Power loss as Q_{loss} and $Q_{loss} = \int I(t)^2 R \mathrm{d}t$. In problem formulation, we will simply use $I(t)Rt$ instead of Q_{loss} to make calculation easier since minimize these two functions with the same constraint would return the same optimal solution.

The optimization model is shown as follows, the only difference between this formulation and previous one is the change in objective function.

$$
\begin{aligned}
\min \quad & R_s \times I_{SC} \times \Delta t \\
s.t. \quad & \sum_{i=1}^{m} I_{B_i}(t) + \sum_{i=1}^{p} I_{SC_i}(t) + \sum_{n \in N} I_{load_n}(t) = 0 \\
& (A - I)V_{SC} + KI_{SC} - R_S T = 0 \\
& EV_{SC} = 0 \\
& T > -I_{SC} \\
& T < I_{SC} \\
& V_{SC} \geq 0 \\
& G \geq 0.1 \times \vec{1}
\end{aligned}
$$

2.3 Multi-criteria Formulation

Two objectives mentioned above are needed to be considered simultaneously, i.e., the minimization of magnitude and fluctuation for battery and minimization of total energy loss. A combined formulation is shown as follows

$$
\begin{aligned}
\min \quad & \alpha \sum_{i=1}^{m} \sum_{t \in T} \varphi(I_{B_i}(t), \lambda_1) + \beta \sum_{i=1}^{m} \sum_{t, t-1 \in T} \varphi(| I_{B_i}(t) - I_{B_i}(t-1) |, \lambda_2) + \gamma \| FG \|_1 + \varepsilon \sum_{i=1}^{p} \sum_{t \in T} \varphi(I_{SC_i}(t), \lambda_3) + \mu R_s I_{SC} \Delta t \\
s.t. \quad & \sum_{i=1}^{m} I_{B_i}(t) + \sum_{i=1}^{p} I_{SC_i}(t) + \sum_{n \in N} I_{load_n}(t) = 0 \\
& (A - I)V_{SC} + KI_{SC} - R_S T = 0 \\
& EV_{SC} = 0 \\
& T > -I_{SC} \\
& T < I_{SC} \\
& V_{SC} \geq 0 \\
& G \geq 0.1 \times \vec{1}
\end{aligned}
$$

where

$$
A = \begin{bmatrix} [1,0,\ldots,0] & 0 \\ I_n & 0 \end{bmatrix}
$$

$$
K = \Delta t \begin{bmatrix} 0 \\ I_n \end{bmatrix}
$$

$$
E = [1,0,0,\ldots,0,-1]
$$

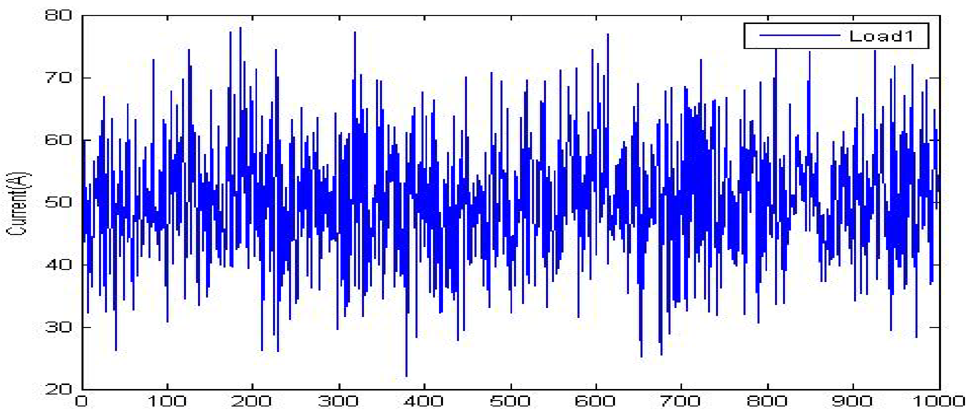
$$
F = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & \ldots & \ldots & 0 & 0 \\ 0 & 0 & \ldots & \ldots & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}
$$

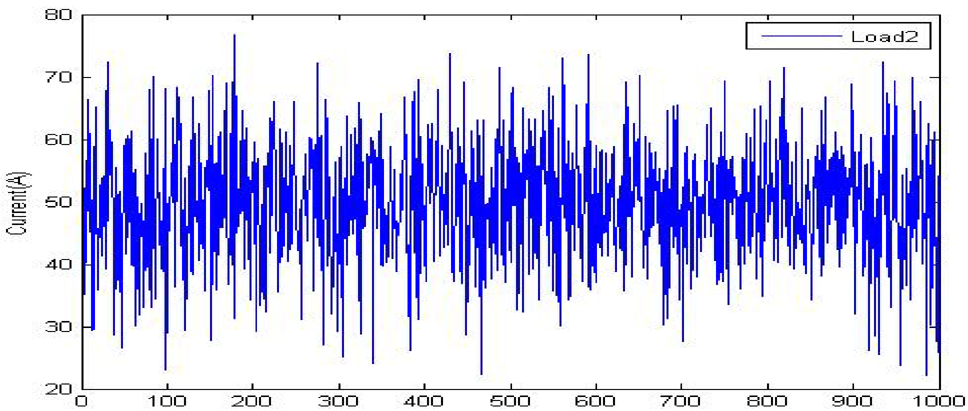
$$
G(i) = \frac{(Q(i)soc(i) - \sum_{t \in T} I_{B_i}(t) \times \Delta t)}{Q(i)}
$$

3. Numerical Result

For numerical calculation we will use 5 loads, 5 batteries and 3 super capacitors. Input load current would be given by user. Each battery would have different capacities and initial SOC values. Also each super capacitor would have different capacities and equivalent serial resistances. We assume each load would have a current data with mean 50A and standard deviation of 10, each battery will have a capacity value with mean 8000Ah(consists of many cascaded small battery packs) and standard variation 1000 and initial SOC value with mean 90% and standard deviation 2 and each super capacitor will have cap value of mean 100 and standard variation 25 and equivalent serial resistance with 0.01Ohm mean and 0.001 standard variation. By doing so we want to simulate a relatively extreme case in the charging system. For scaling issue of every component in the objective function and avoid solver running into numerical problems while dealing with large value number, we set the weight with 1e-6, 1e-6, 1e-2, 1e-6, 1e-2 respectively.

Figure 4 below shows the current profile of all 5 loads,





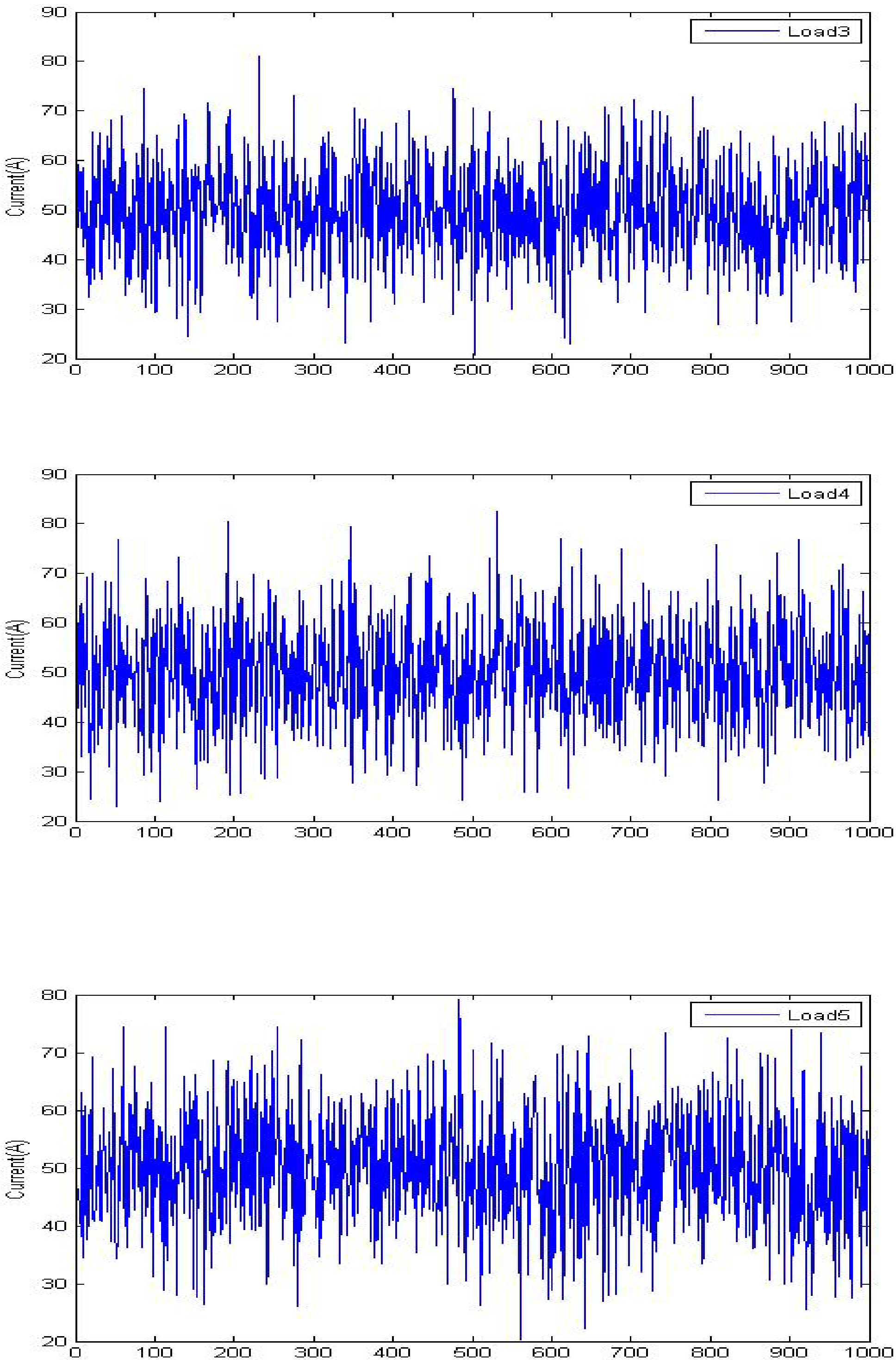
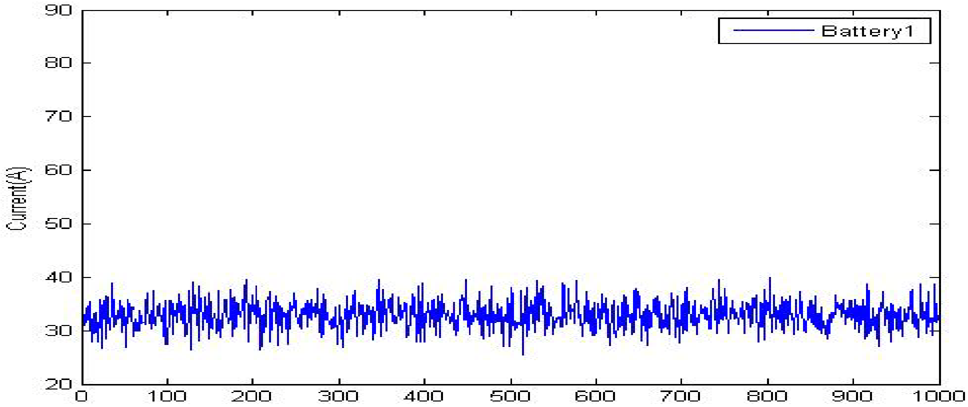
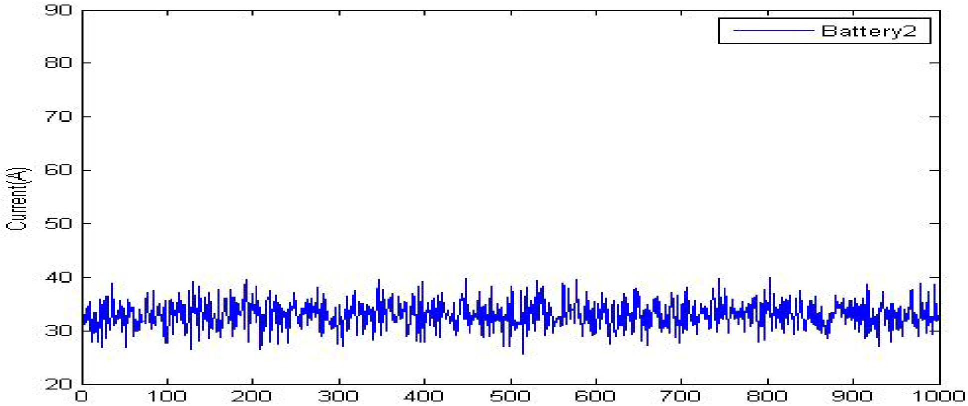
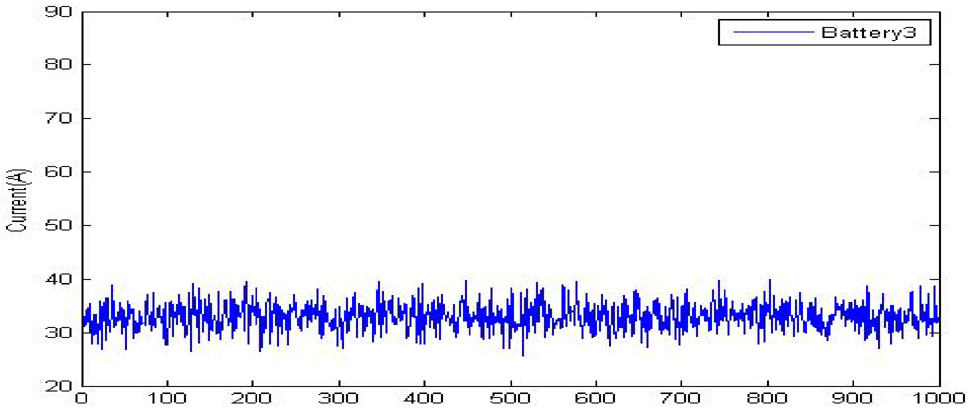


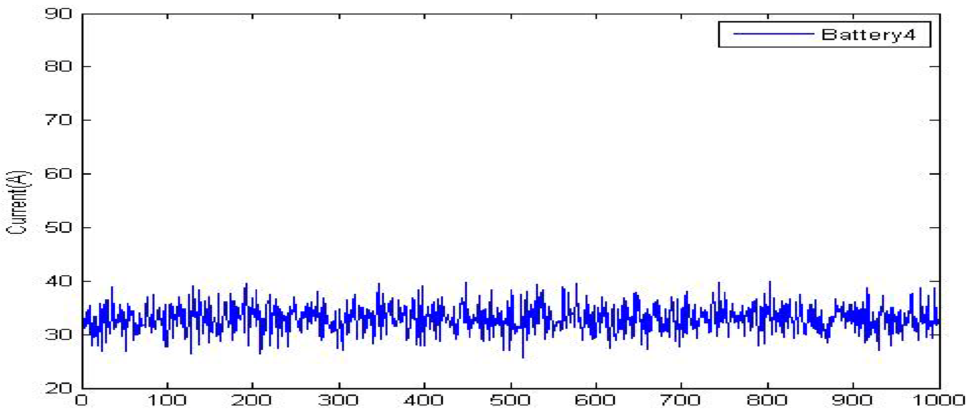
Fig 4 Load Current Profile

Figure 5 below is the result of battery current for distributed power source after optimization. All the currents flow out from these batteries are relatively become constant value. Also note that current values for all the batteries are nearly the same because compared with the capacity of each battery C-rate is very low (roughly around 30/8000=0.375~1%). If we decrease the capacity of one or more of these batteries, i.e., increase C-rate greatly, current value would differ a lot but pattern would still be the same.


Battery1
Current(A)
90 80 70 60 50 40 30 20
0 100 200 300 400 500 600 700 800 900 1000


Battery2
Current(A)
90 80 70 60 50 40 30 20
0 100 200 300 400 500 600 700 800 900 1000


Battery3
Current(A)
90 80 70 60 50 40 30 20
0 100 200 300 400 500 600 700 800 900 1000


Battery4
Current(A)
90 80 70 60 50 40 30 20
0 100 200 300 400 500 600 700 800 900 1000

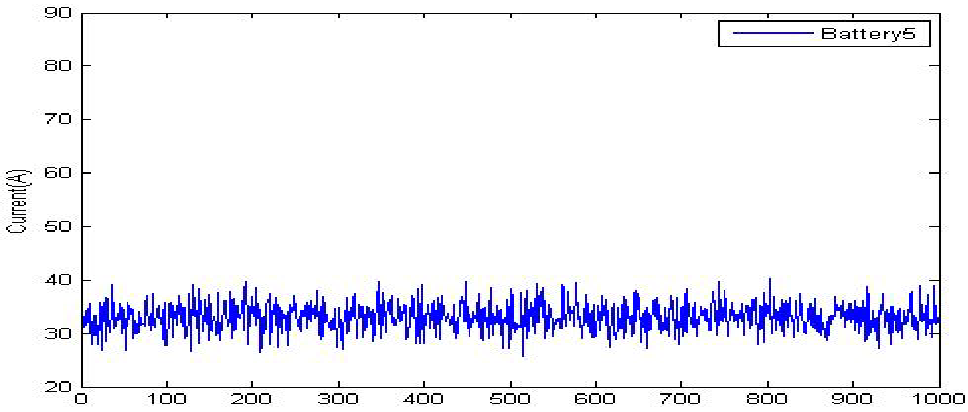


Fig 5 Battery Output Current

Figure 6 below is super capacitor current, super capacitors tend to be charged before the loads require large amounts of power to the energy storage devices. It means that in reality if we could predict the future profiles of the load current,a much more effective real-time energy management could be scheduled in the charging system.

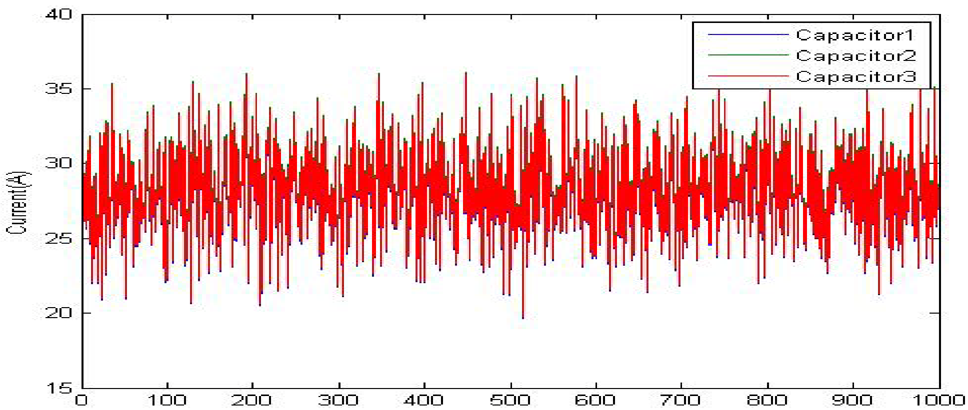


Fig 6 Super Capacitor Current

Next figure is super capacitor voltage. We can see that during the EV charging process, the voltage change of the super capacitors in the whole system is equal to zero.

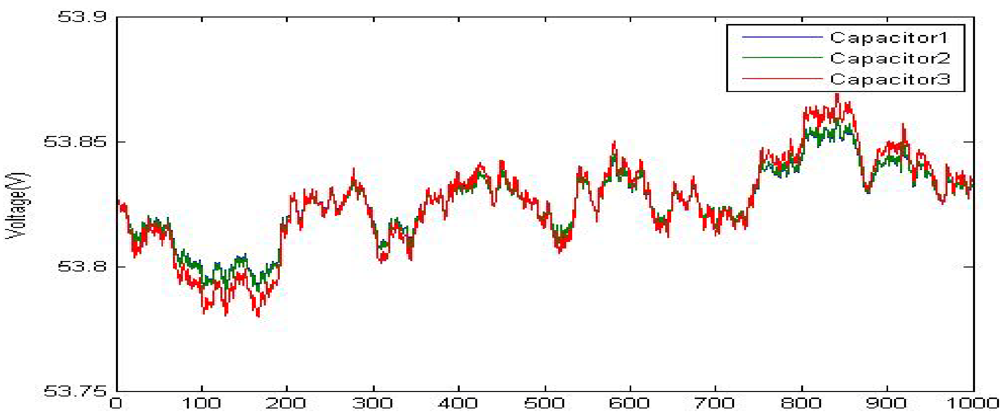


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Fig 7 Super Capacitor Voltage

SOC change at each time step is shown in the following figure. We could see that each battery's SOC has a linear decreasing trend so that current fluctuation is minimized here and with a relatively low current value, battery's life will be prolonged.

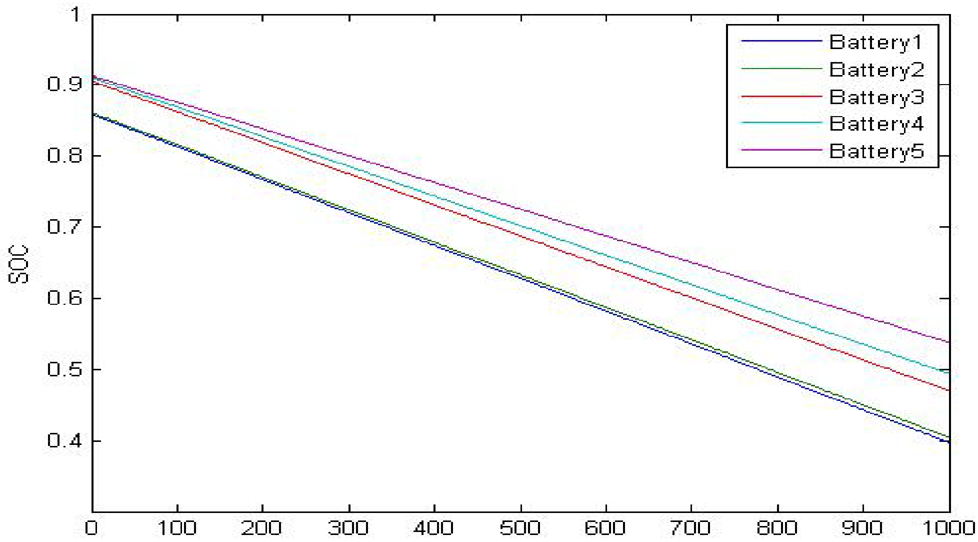

Fig 8 SOC Status for Each Battery

4. Conclusion

In this report we achieved optimal control strategy to prolong the battery life of the power source side and minimize energy loss of an EV distributed charging station system. Optimization result showed that battery from distributed power source could supply nearly constant power to maintain its longevity and minimize the total loss in the system even in random load current profile.

Reference

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5. Y. Zhang, Z. Jiang, and X. Yu, "Control Strategies for Battery/Super Capacitor Hybrid Energy Storage Systems, " in *Proc. IEEE Energy 2010 Conf.*, Nov. 2008, pp 1-6.

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%EV Charging Station Modeling
%Multi-object function is now working
%Could also comment out other cases to see result of such easier case
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear all
clc
%%Initialization
%n=1000sample points;
%m=5battery
%p=2

m=5;
n=1000;
k=4;
p=2;
C=zeros(1,n-1);C(1)=1;
R=zeros(1,n);R(1)=1;R(2)=-1;
M=zeros(1,m-1);M(1)=1;
P=zeros(1,m);
P(1)=1;P(2)=-1;
T=toeplitz(C,R);F=toeplitz(M,P);
Iload=normrnd(50,10,5,n);


% %%Case1
% cvx_begin
%               variable Ibattery(m,n);
%               minimize  (sum(sum(huber(Ibattery,70)))+sum(sum(huber(T*Ibattery',3))))
%               subject to
%               %KCL
%               for i=1:n
%                   sum(Ibattery(:,i))-sum(Iload(:,i))==0;
%               end
% cvx_end

% %%Case2
% capacity=normrnd(8000,1000,1,m);
% soc=normrnd(90,6,1,m);
% while (max(soc)>100 || min(soc)<0)
%     soc=normrnd(90,6,1,m);
% end
% Q=capacity.*soc/100;
% for i=1:m
% Sigma(i,:)=capacity(i)*0.01*ones(1,n);
% end
%
% cvx_begin
%               variable Ibattery(m,n);
%               minimize (sum(sum(huber(Ibattery,Sigma)/1e6))+sum(sum(huber(T*Ibattery',5)/1e6))+norm(F*((Q-sum(Ibattery')*0.1)./Q)',1))
%               subject to
%               %KCL
%               for i=1:n
%                   sum(Ibattery(:,i))-sum(Iload(:,i))==0;
%               end
%                 (Q-sum(Ibattery')*0.1)./Q>=0.1*ones(1,m);
% cvx_end

% Case3_1
```

```
% capacity=normrnd(8000,1000,1,m);
% soc=normrnd(90,6,1,m);
% while (max(soc)>100 || min(soc)<0)
%     soc=normrnd(90,6,1,m);
% end
% Q=capacity.*soc/100;
% for i=1:m
% Sigma(i,:)=capacity(i)*0.01*ones(1,n);
% end
% A=[1,zeros(1,n);eye(n),zeros(n,1)];
% I=eye(n+1);
% K=0.1/100*[zeros(1,n);eye(n)];
% Rs=0.001*[zeros(1,n);eye(n)];
% E=[1,zeros(1,n-1),-1];
%
% cvx_begin
%              variables Ibattery(m,n) Icapacity(1,n) Vcapacity(n+1) t(1,n);
%                                                                                          minimize
(0.15*sum(sum(huber(Ibattery,65)/1e6))+0.5*sum(sum(huber(T*Ibattery',5)/1e6))+0.25*norm(F*((Q-sum
(Ibattery')*0.1)./Q)',1)+0.1*sum(sum(huber(Icapacity,120)/1e6)))
%              subject to
%              for i=1:n
%                  sum(Ibattery(:,i))+sum(Icapacity(:,i))-sum(Iload(:,i))==0;
%              end
%              (A-I)*Vcapacity-K*Icapacity'-Rs*t'==0;
%              E*Vcapacity==0;
%
%              t<Icapacity;
%              t>-Icapacity;
% %               (Q-sum(Ibattery')*0.1)./Q>=0.1*ones(1,m);
% cvx_end

%Case3_2
% mC=3;
% capacity=normrnd(8000,1000,1,m);
% soc=normrnd(90,6,1,m);
% while (max(soc)>100 || min(soc)<0)
%     soc=normrnd(90,6,1,m);
% end
% Q=capacity.*soc/100;
% for i=1:m
% Sigma(i,:)=capacity(i)*0.01*ones(1,n);
% end
% A=[1,zeros(1,n);eye(n),zeros(n,1)];
% I=eye(n+1);
% K=0.1*[zeros(1,n);eye(n)];
% scCapacity=normrnd(100,3,1,mC);
% G=[zeros(1,n);eye(n)];
% Rs=normrnd(1,0.1,1,mC)
% E=[1,zeros(1,n-1),-1];
%
% cvx_begin
%              variables Ibattery(m,n) Icapacity(mC,n) Vcapacity(n+1,mC) t(mC,n);
%                                                                                          minimize
(0.15*sum(sum(huber(Ibattery,65)/1e6))+0.5*sum(sum(huber(T*Ibattery',5)/1e6))+0.25*norm(F*((Q-sum
(Ibattery')*0.1)./Q)',1)+0.1*sum(sum(huber(Icapacity,120)/1e6)))
%              subject to
%              %KCL
%              for i=1:n
%                  sum(Ibattery(:,i))+sum(Icapacity(:,i))-sum(Iload(:,i))==0;
%              end
%              for j=1:mC
```

```
%               (A-I)*Vcapacity(:,j)-K/scCapacity(j)*Icapacity(j,:)'-Rs(j)*G*t(j,:)'==0;
%               E*Vcapacity(:,j)==0;
%               end
%               t<Icapacity;
%               t>-Icapacity;
%                (Q-sum(Ibattery')*0.1)./Q>=0.1*ones(1,m);
% cvx_end

%%Multi-objects
mC=3;
capacity=normrnd(8000,1000,1,m);
soc=normrnd(90,2,1,m);
while (max(soc)>100 || min(soc)<0)
    soc=normrnd(90,2,1,m);
end
Q=capacity.*soc/100;
for i=1:m
Sigma(i,:)=capacity(i)*0.01*ones(1,n);
end
A=[1,zeros(1,n);eye(n),zeros(n,1)];
I=eye(n+1);
K=0.1*[zeros(1,n);eye(n)];
scCapacity=normrnd(100,25,1,mC);
G=[zeros(1,n);eye(n)];
Rs=normrnd(0.01,0.001,1,mC);
E=[1,zeros(1,n-1),-1];
load data
cvx_begin
variables Ibattery(m,n) Icapacity(mC,n) Vcapacity(n+1,mC) t(mC,n);
minimize
(sum(sum(huber(Ibattery,40)/1e6))+sum(sum(huber(T*Ibattery',0.5)/1e6))+norm(F*((Q.*soc/100-sum(Ib
attery')*0.1)./Q)',1)/1e2+sum(sum(huber(Icapacity,120)/1e6))+sum(Rs*( Icapacity))/1e2*0.1 )
             subject to
             %KCL
             for i=1:n
                 sum(Ibattery(:,i))+sum(Icapacity(:,i))-sum(Iload(:,i))==0;
             end
             for j=1:mC
             (A-I)*Vcapacity(:,j)-K/scCapacity(j)*Icapacity(j,:)'-Rs(j)*G*t(j,:)'==0;
             E*Vcapacity(:,j)==0;
             end
             t<Icapacity;
             t>-Icapacity;
             Vcapacity>0;
             (Q.*soc/100-sum(Ibattery')*0.1)./Q>=0.3*ones(1,m);
cvx_end

figure
plot(Iload')
figure
plot(Ibattery');axis([0 1000 10 90]);ylabel('Current(A)');
figure
plot(Icapacity');axis([0 1000 15 40]);ylabel('Current(A)');
figure
plot(Vcapacity);ylabel('Voltage(V)');
for i=1:n
    SOCb(:,i)=(Q.*soc/100-sum(Ibattery(:,1:i)')*0.1)./Q;
end
figure
plot(SOCb');ylabel('SOC');
```