State of Charge Estimation for Electric Scooters by Using Learning Mechanisms

- The state of charge (SOC) of a battery remains to be difficult to estimate, because of its **nonlinear** discharge characteristics.
- **A state-of-charge learning system** was proposed so that it can provide more accurate information about the SOC when a battery discharges under **dynamic conditions**.

Drawbacks of Scooters to Date

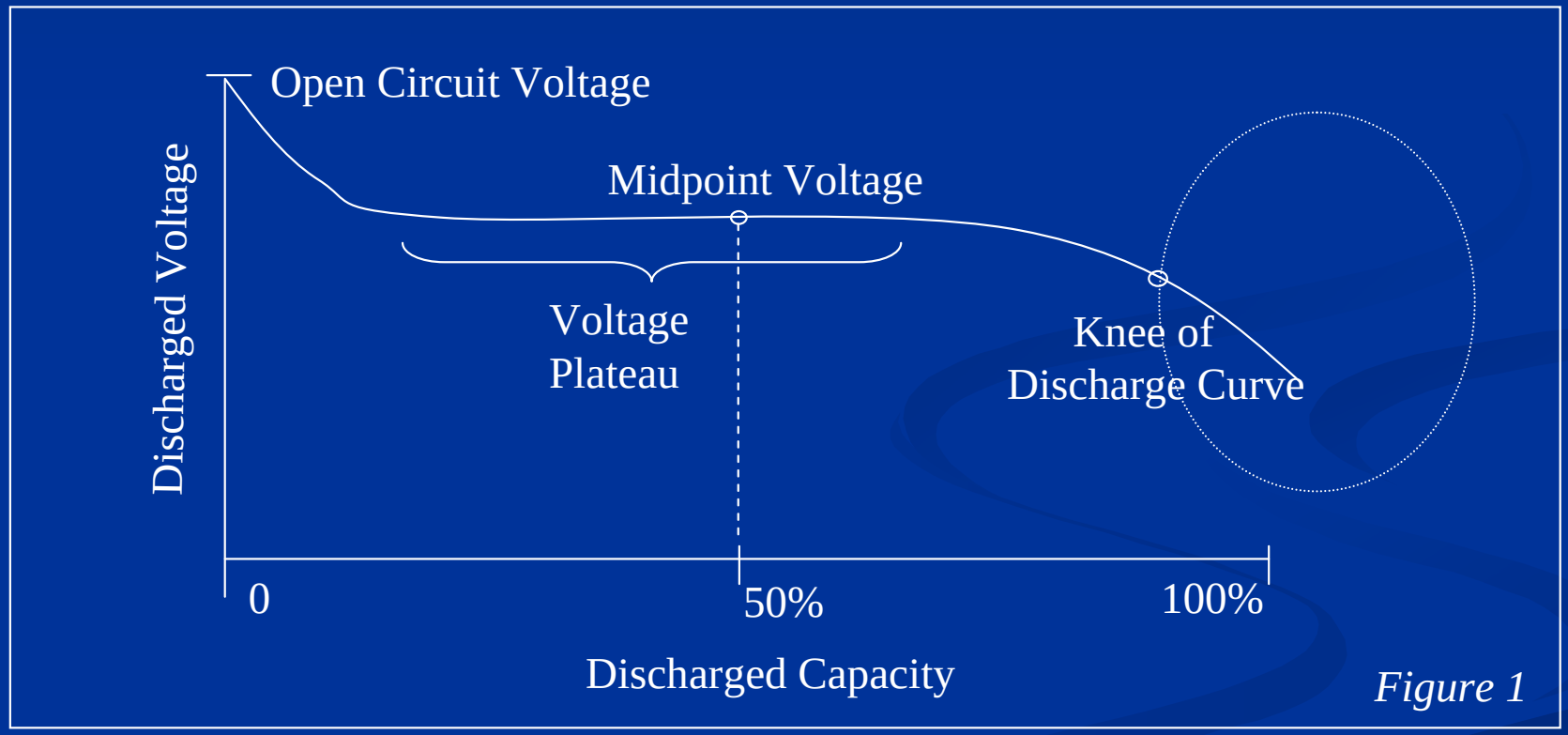
- High cost
- Long battery recharging time
- Relatively short traveling distance for each re-charge
- Inadequate feedback information (or SOC) to the user with respect to the residual battery capacity

- The lack of a more reliable SOC prediction could be rather troublesome and therefore hinder the sale of electric scooters.

Battery Properties

- Discharge performance

Nominal Discharge Performance for Sealed-Lead Cells(Current is uniform)



Knee of the curve : The point at which the voltage leaves the plateau and begins to decline rapidly.

- Battery capacity

$$Capacity = \int_{\Delta t} i(t)\,dt$$

- Capacity Terminology Definitions

Standard Capacity = Cell Capacity measured under standard conditions.
Rated Capacity = The minimum standard capacity.
Actual Capacity = Capacity of a fully charged cell measured under non-standard conditions except standard end of discharge voltage(EODV).
Retained Capacity = Capacity remaining after a rest period.
Available Capacity = Capacity delivered to a non-standard EODV.
Dischargeable Capacity = Capacity which a cell can deliver before it becomes fully discharged.

Factors affecting Capacity

Capacity versus Discharge Rate

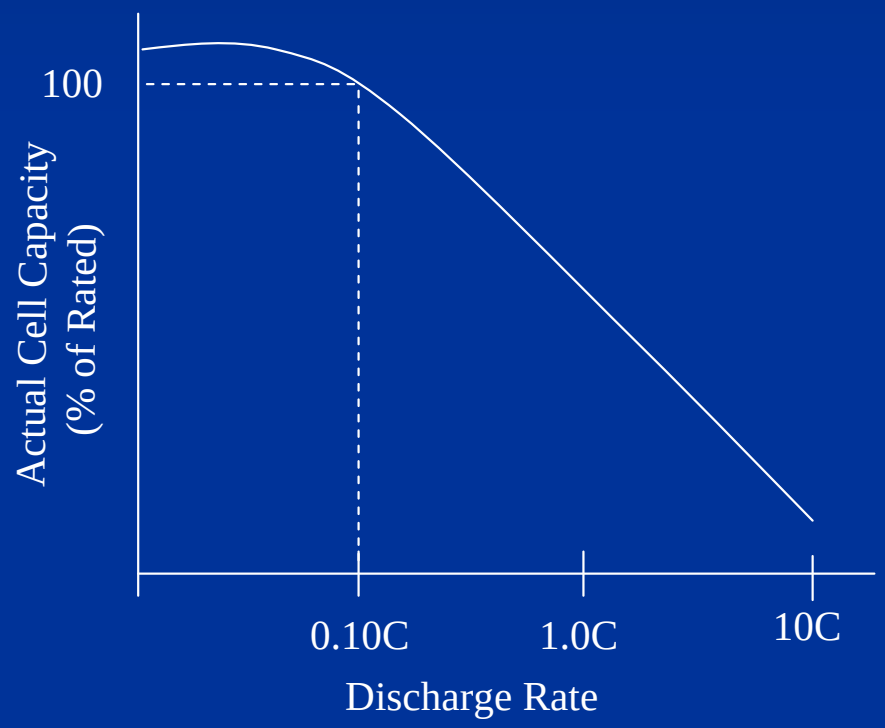


Figure 2

Typical Discharge Capacity as a Function of Cell Temperature

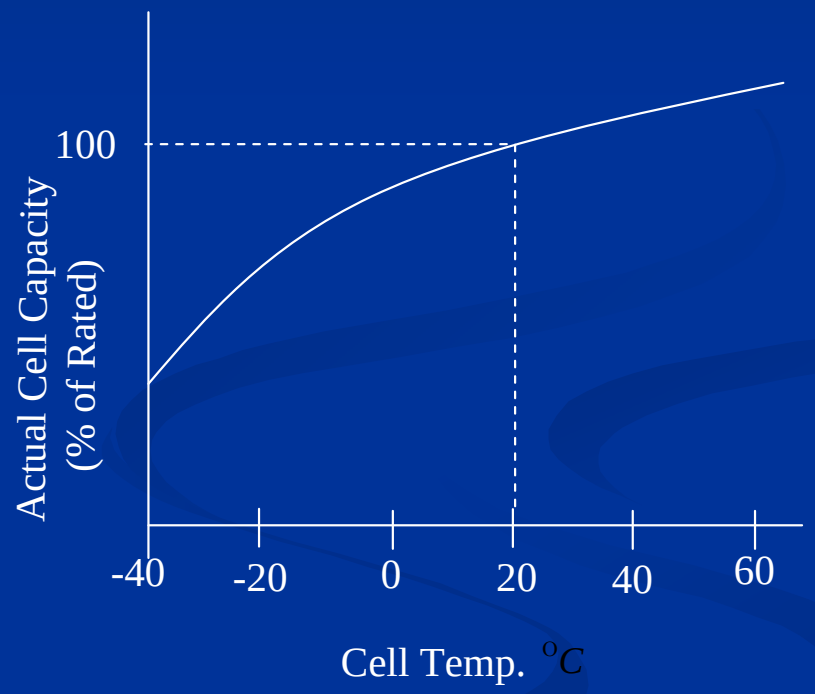


Figure 3

Typical Cell Capacity During its Life

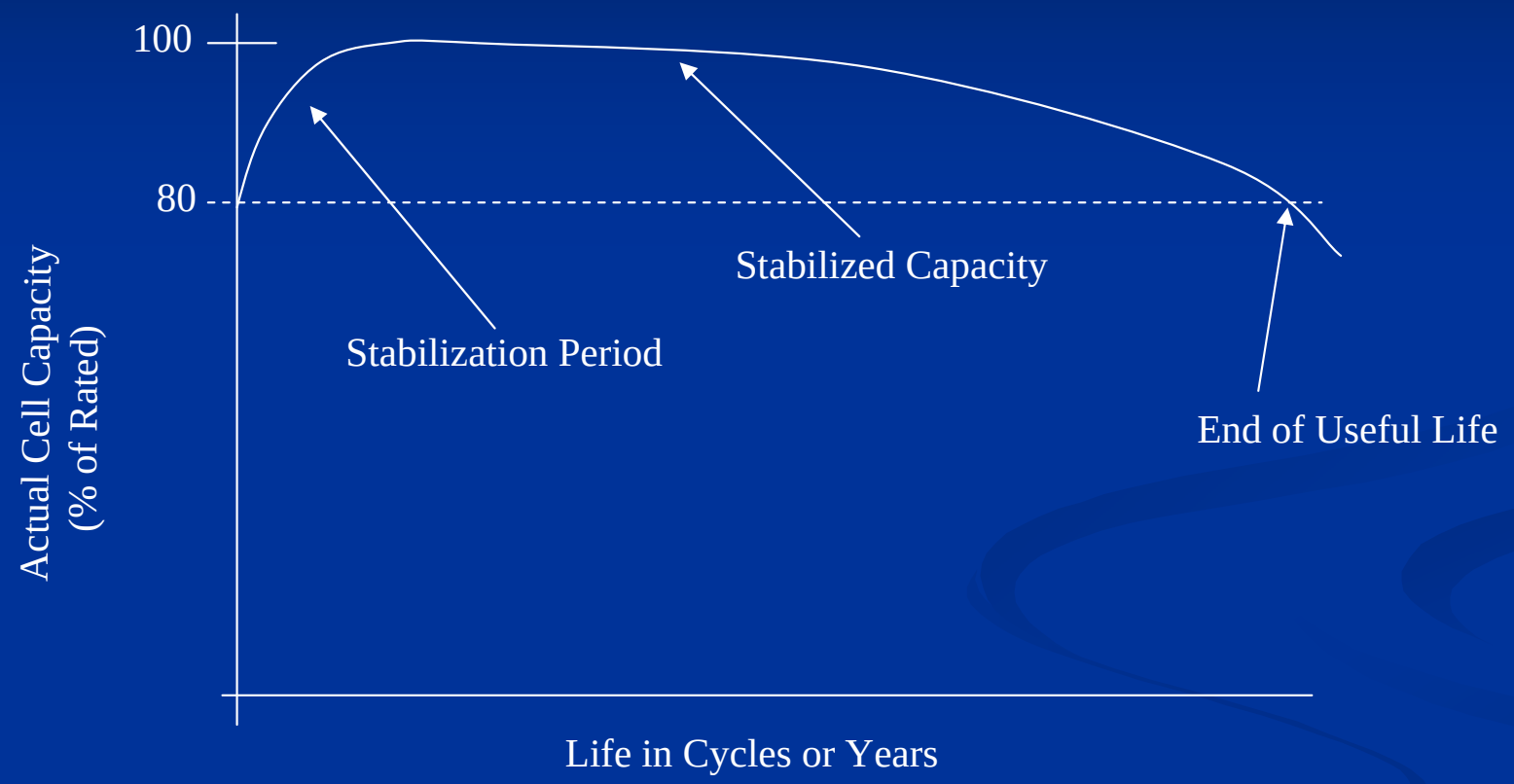
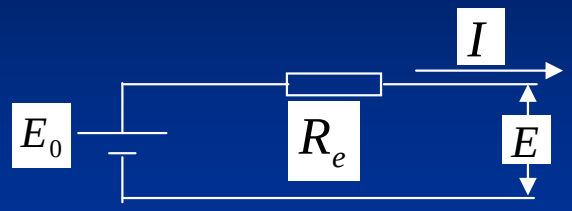


Figure 4

Cell equivalent discharge circuit

Equivalent Circuit Diagram of a Cell



$$E = E_0 - IR_e \quad \textit{(Equation 1)}$$

E = Cell Terminal Voltage

E_0 = Effective No-load Cell Voltage

I = Discharge Current

R_e = Effective Internal Resistance

Effective No-Load Cell Voltage versus State of Charge

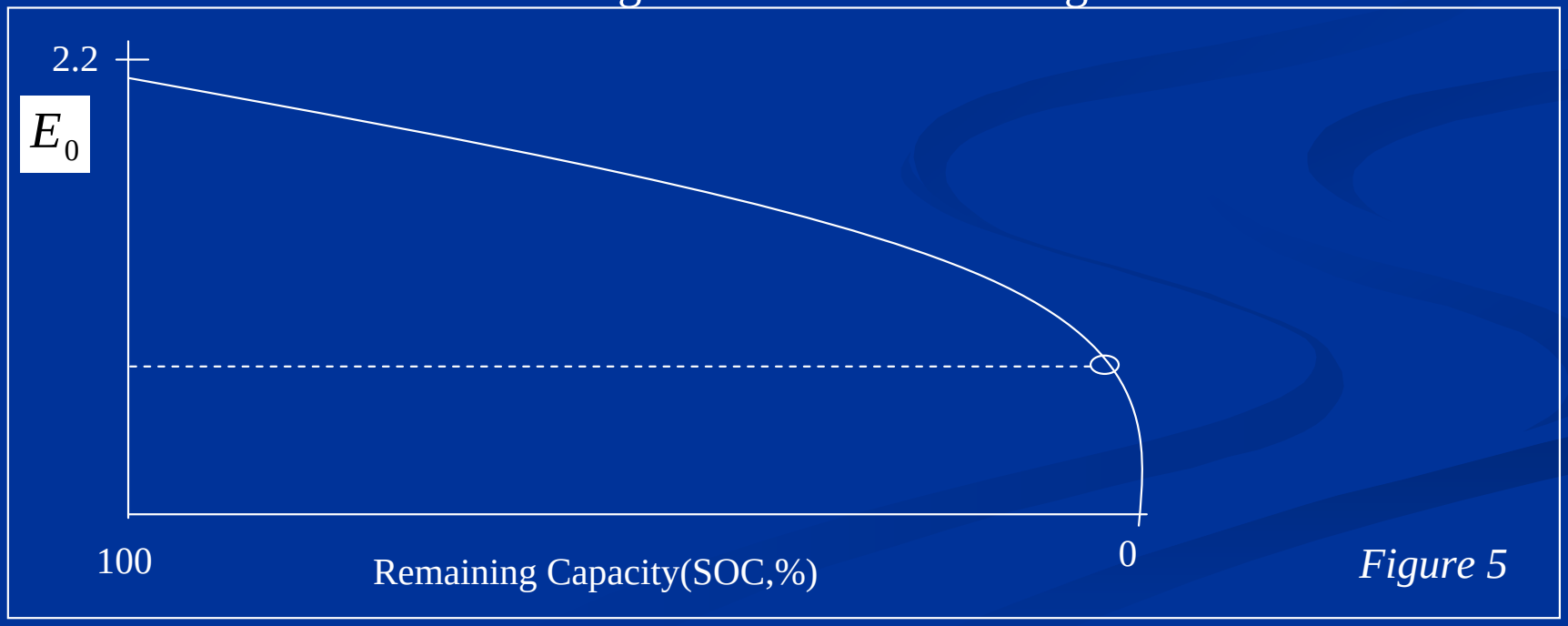


Figure 5

Effective Internal Resistance versus SOC

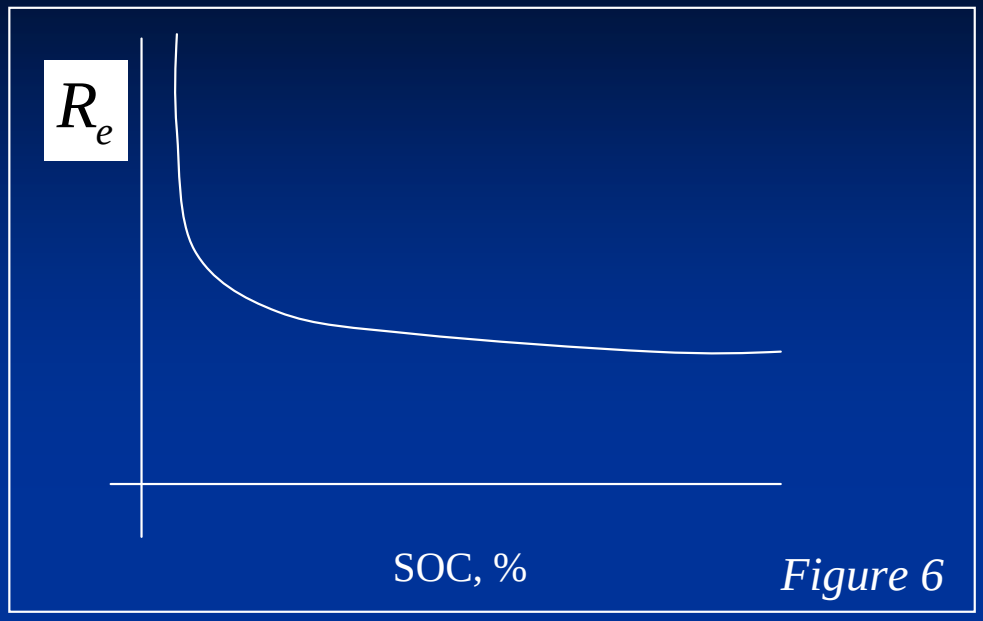


Figure 6

Effective Internal Resistance versus Cell Temperature

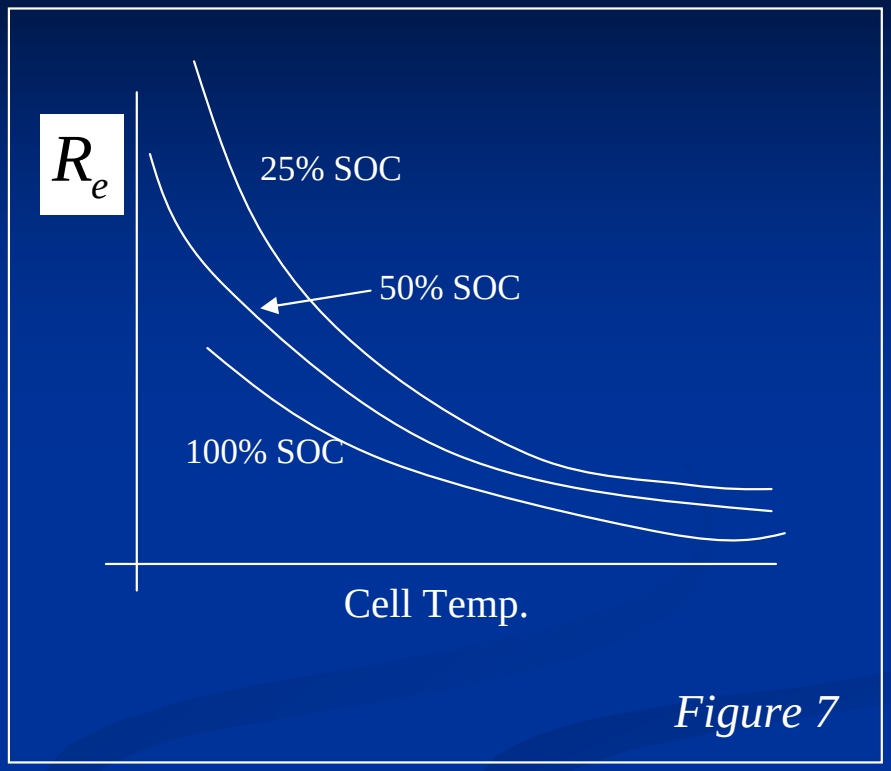


Figure 7

Effective Internal Resistance versus Cell Life

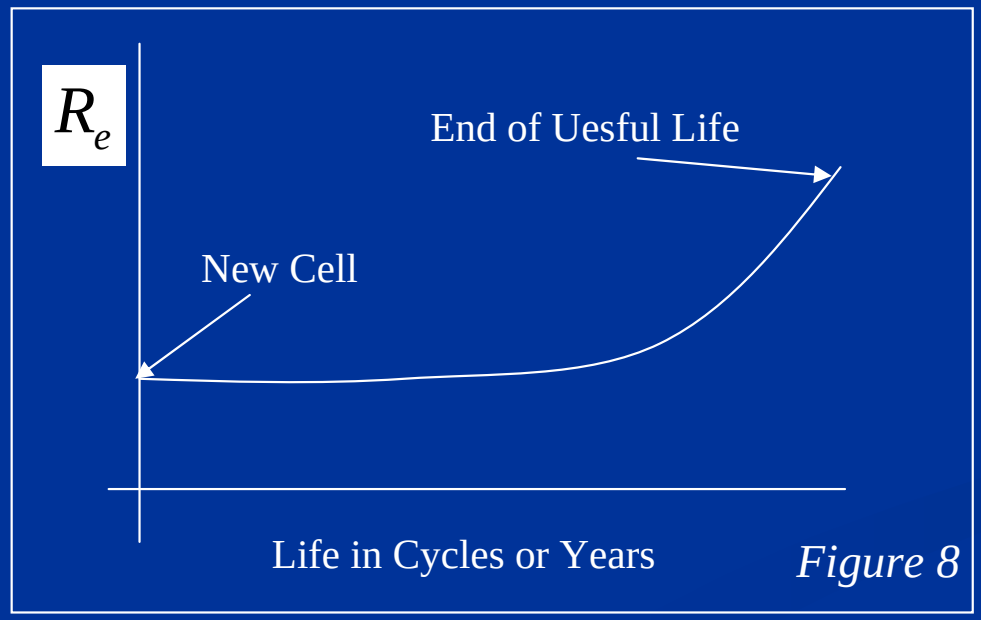


Figure 8

Battery Discharge Voltage as a Function of Discharge Rate

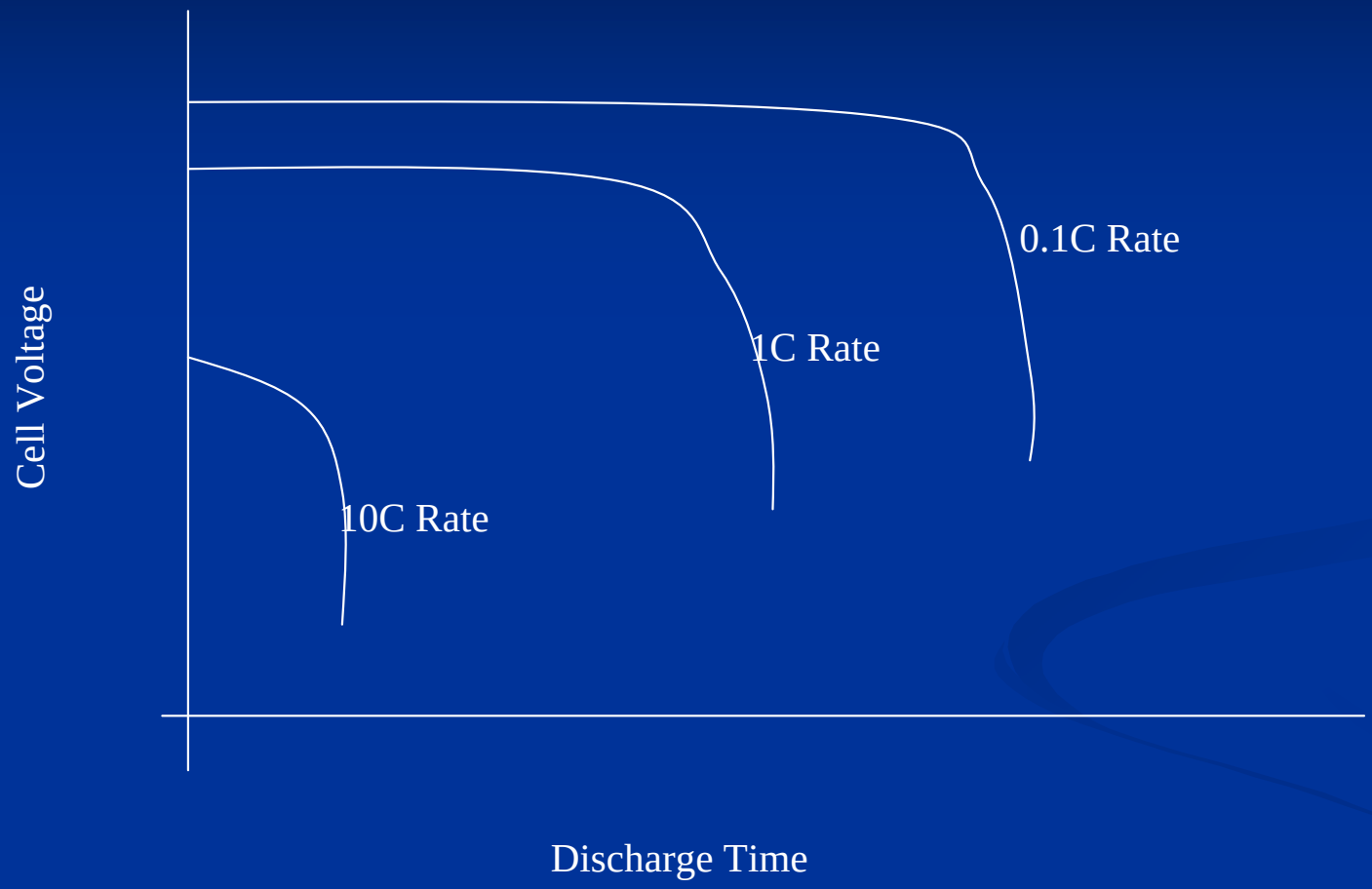


Figure 9

SOC Estimation Methods

- Open circuit voltage (OCV) measurement
- Loaded voltage measurement
- Ampere hour accumulation or coulometric measurement
- Impedance measurement
- Battery learning model

Proposed SOC Learning Mechanism

- Coulometric algorithm
- State of health
- Learning Controllers

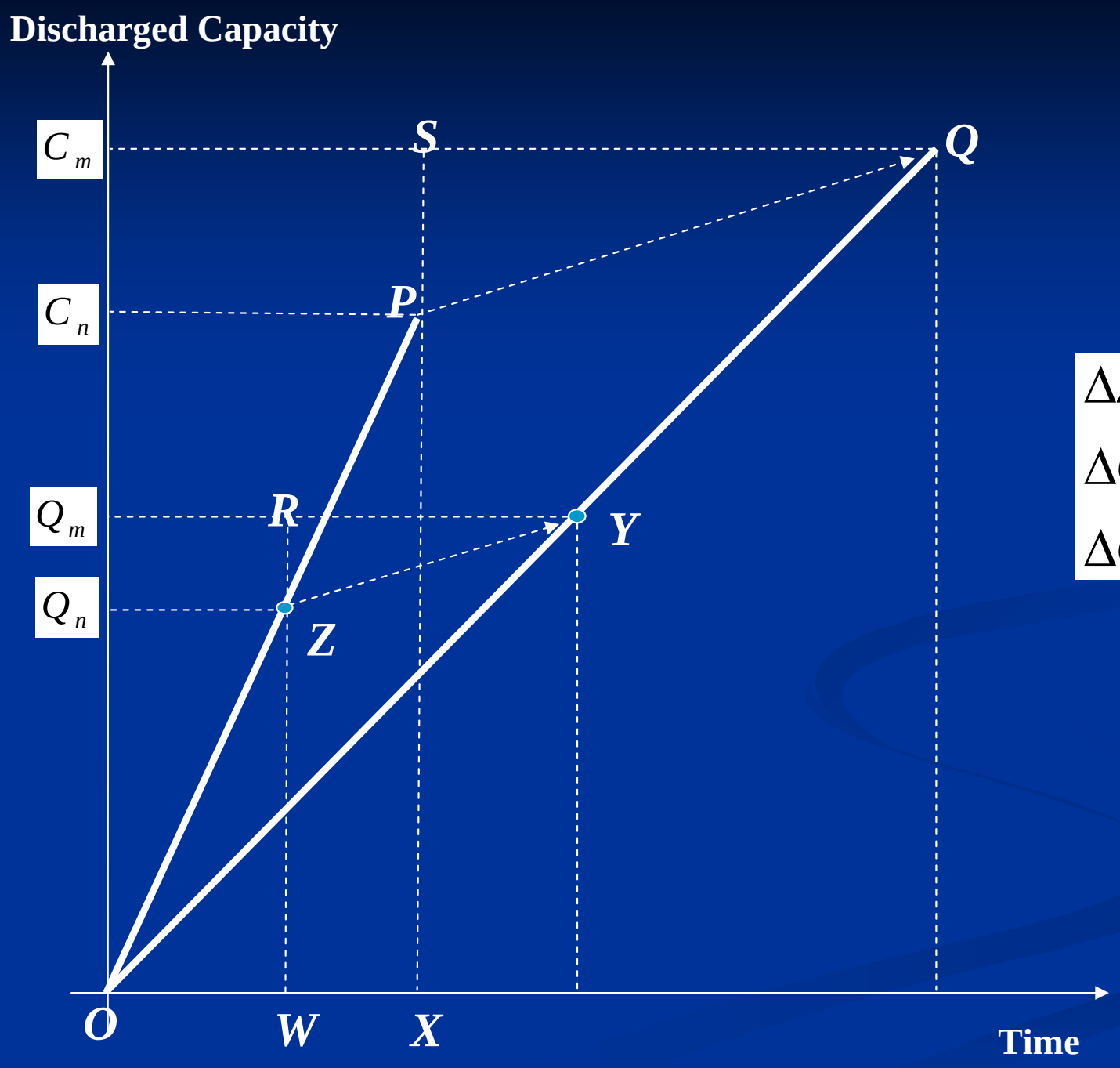
Coulometric Algorithm

- The **capacity** of a battery : the available capacity released from a battery at a certain discharge rate or discharge current.
- The battery capacity may vary with the **discharge rate**, **depth of discharge**, **recharging time**, **temperature**, **aging**, etc.
- Cutoff voltage : the battery terminal voltage when its capacity is zero.

- Discharge efficiency :

$$\eta_I = \frac{I \cdot T}{C_0} = \frac{C_I^{dis}}{C_0}$$

- Relation between two capacities at their corresponding discharge currents :



$\Delta ZYR \sim \Delta PQS$

$\Delta OYZ \sim \Delta OQP$

$\Delta OZW \sim \Delta OPX$

- 1

$$\frac{Q_m - Q_n}{C_m - C_n} = \frac{\overline{ZY}}{\overline{PQ}} = \frac{\overline{OZ}}{\overline{OP}} = \frac{\overline{ZW}}{\overline{PX}} = \frac{Q_n}{C_n}$$

$$Q_m = Q_n \frac{C_m}{C_n} = Q_n \left(\frac{C_m / C_0}{C_n / C_0} \right) = \left(\frac{\eta_{I_m}}{\eta_{I_n}} \right) Q_n$$

- 2

$$C_{I(k)}^{dis} = \left(\frac{\eta_{I(k)}}{\eta_{I(k-1)}} \right) C_{I(k-1)}^{dis} + I(k)\Delta T$$

$$C_{I(1)}^{dis} = I(1)\Delta T$$

- 3

$$SOC(k) = 1 - \left(\frac{1}{C_0} \right) \left(\frac{C_{I(k)}^{dis}}{\eta_{I(k)}} \right)$$

State of Health (SOH)

- The SOH indicating the degree of aging of a battery is also an important factor that determines the accuracy of the estimated SOC.
- Impedance measurement is a good choice for checking the SOH of a battery, but it needs additional hardware circuits. This is a major disadvantage for an electric scooter or EV application.

- Definition

$$SOH = \frac{C_{I_{ref}}}{C_0}$$

- SOH is an indicator of how much capacity can be released at the reference discharge rate after usage, with respect to the initial available capacity when the battery is brand new.

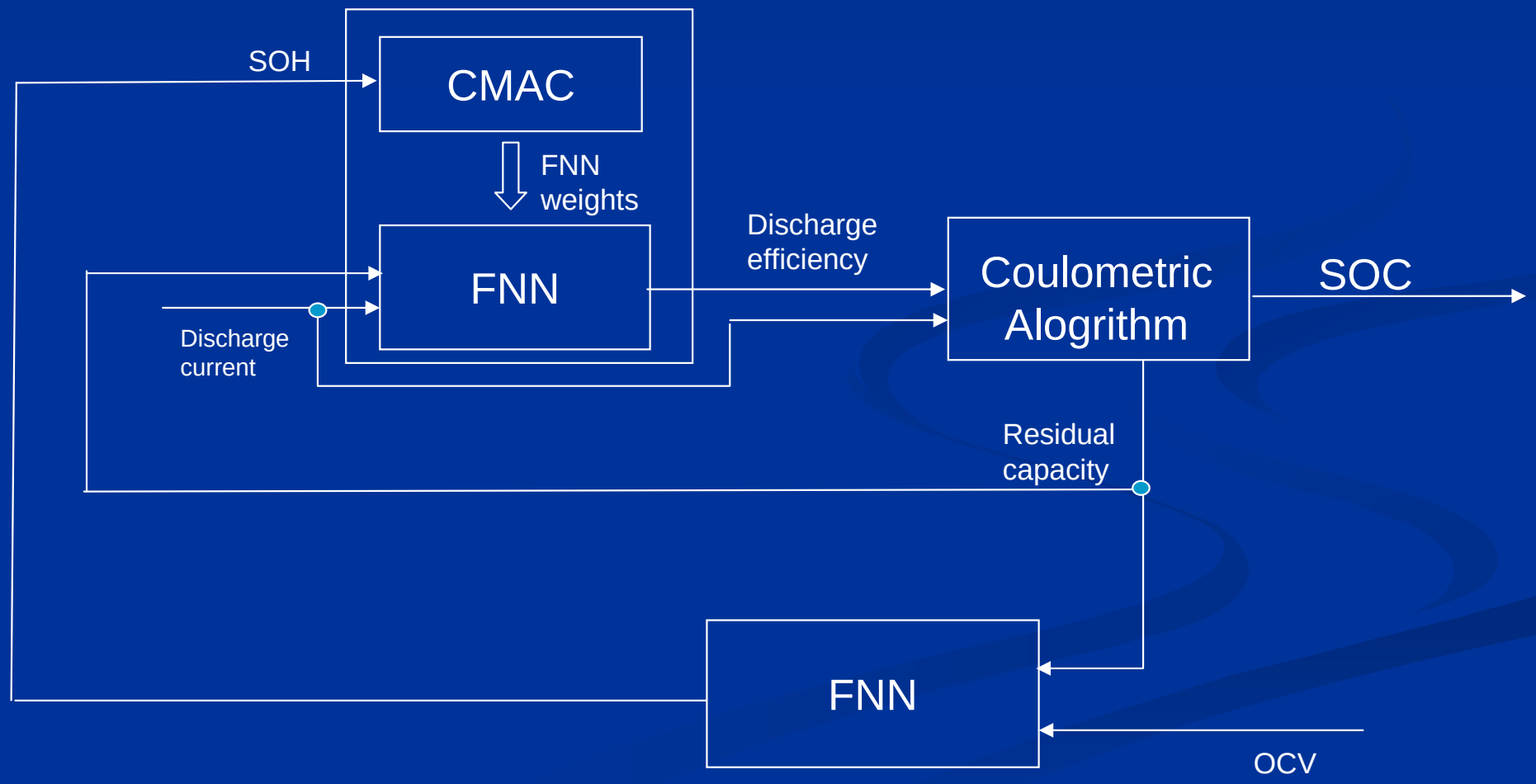
Learning Controllers

- There are two well-known types of learning controllers, **artificial neural networks** and **fuzzy systems**.
- Most of them need to repeat the learning process each time a new pattern is encountered. Otherwise, a neural network will require **a huge number of neurons** or a fuzzy system will require **numerous rules** because the learning space needed to handle arbitrary nonlinear dynamics is quite large.

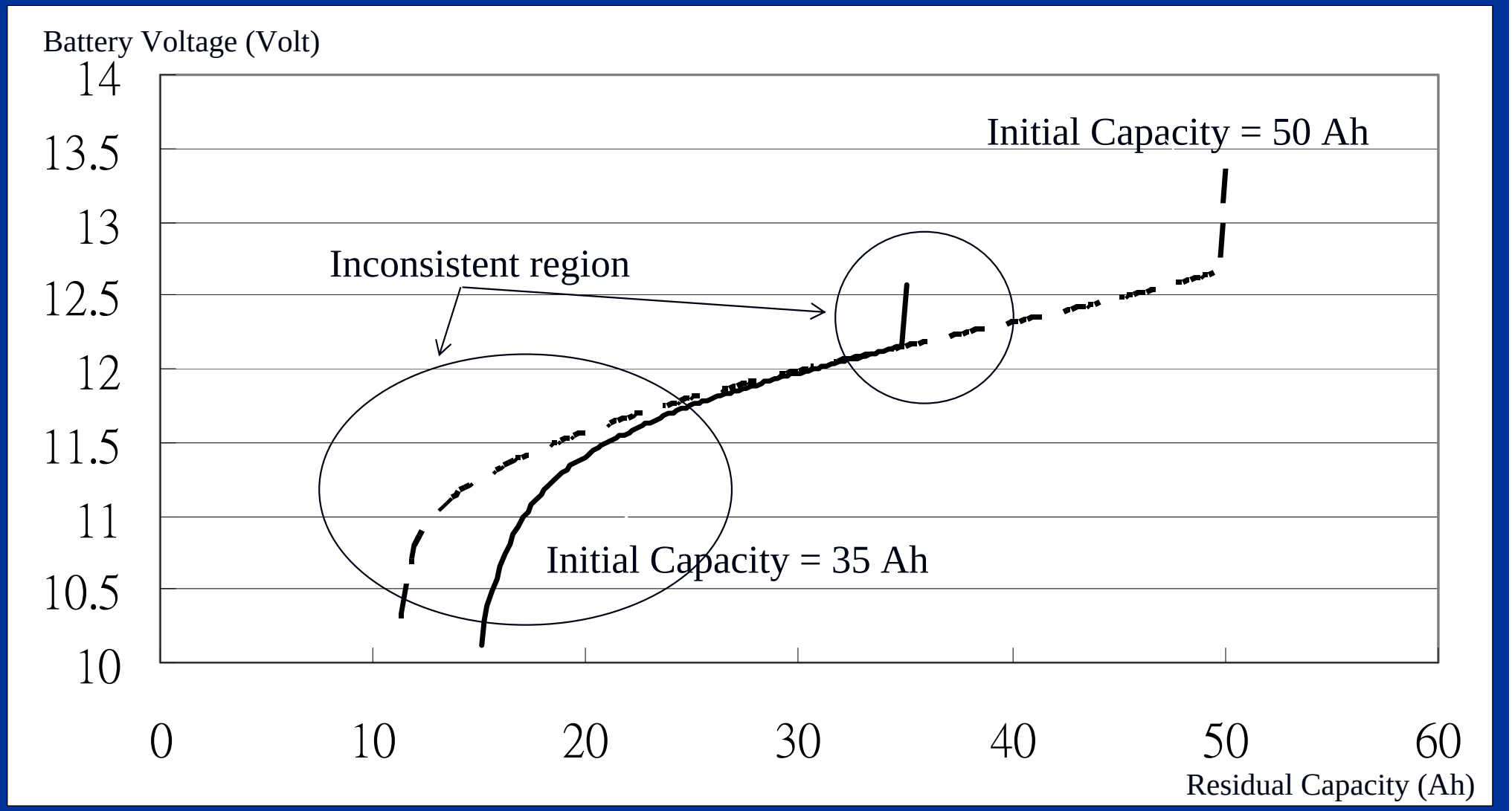
- A learning structure consisting of FNNs and CMAC networks was designed to effectively generalize from the data patterns learned to predict information about a nonlinear dynamic system which could not be obtained in advance due to its huge size of learning space.

Combination of the Coulometric Measurement and Learning Controllers

- The structure of proposed SOC learning system



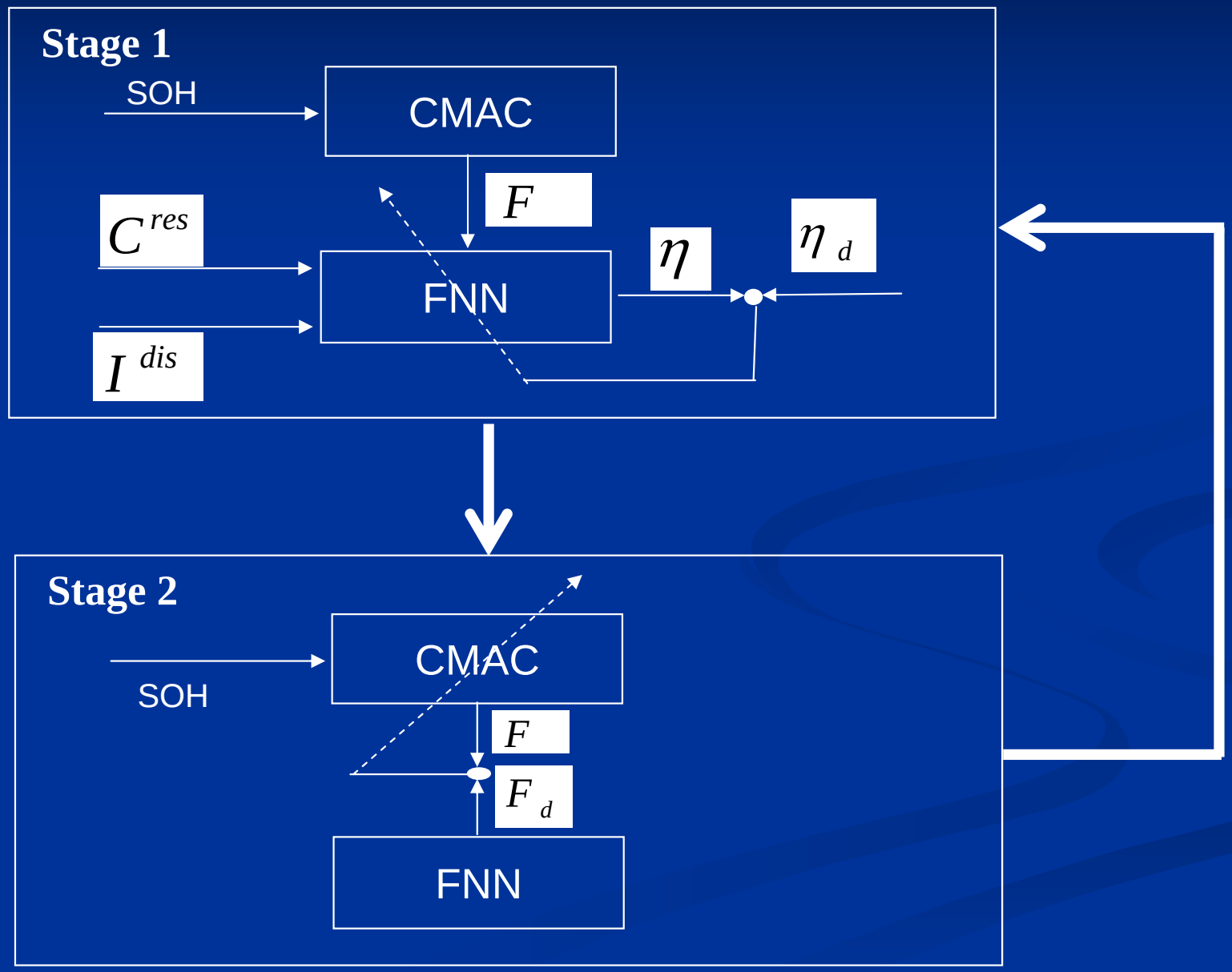
- Consideration of learning process convergence : **battery voltage.**



SOC Learning System Implementation

- Implementation of the FNN
- Implementation of the CMAC

- Learning process



Experiment

- Batteries : 12V,50Ah; Long Battery Co., Taiwan.
- Battery testing system : 0~18V, 0~200A; DIGATRON Co., Germany.
- Training patterns for EMS : 98 data sets of constant current discharge.

Training pattern format

- The data recorded by Digatron UBT can be transferred into the excel file format. We can use excel to combine the following four data :

- Remain capacity (absolute)
- Discharge current
- Discharged capacity
- Battery voltage

- As the following format :
- **Remain capacity (absolute) Discharge current Discharged capacity Battery voltage**

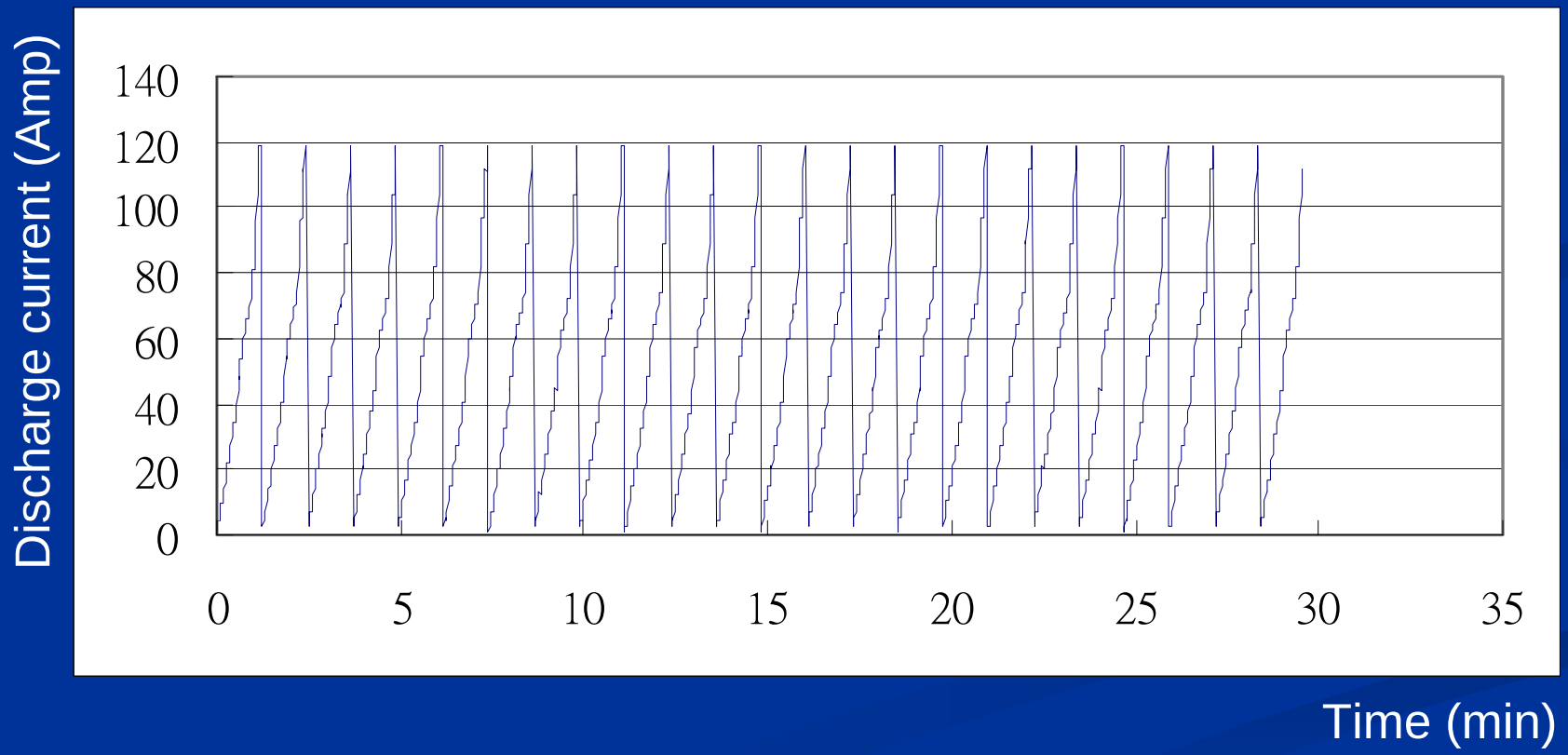
- The training pattern for DCH efficiency mapping :

  Remain capacity (absolute), Discharge current, SOH, DCH efficiency

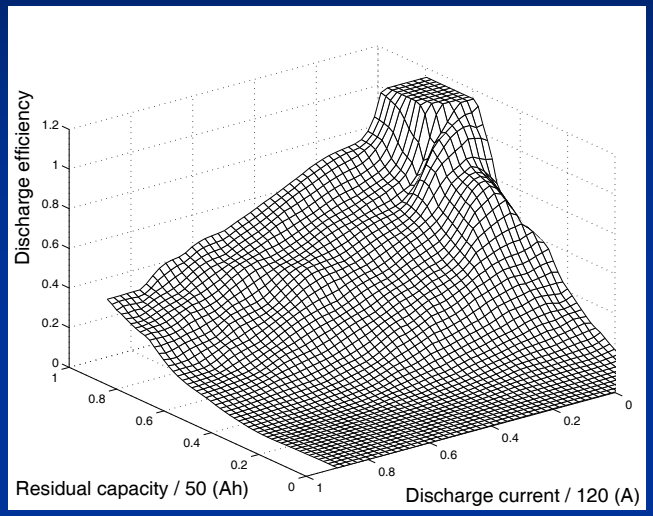
- Remain capacity (relative) = Remain capacity(abs.) – EFF*Cap_dis.

Dynamic Modification

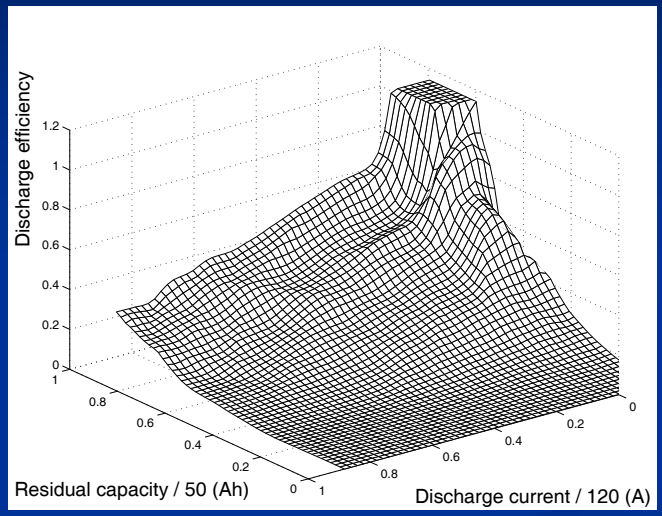
- Discharge patterns for modifying the initial weights dynamically.



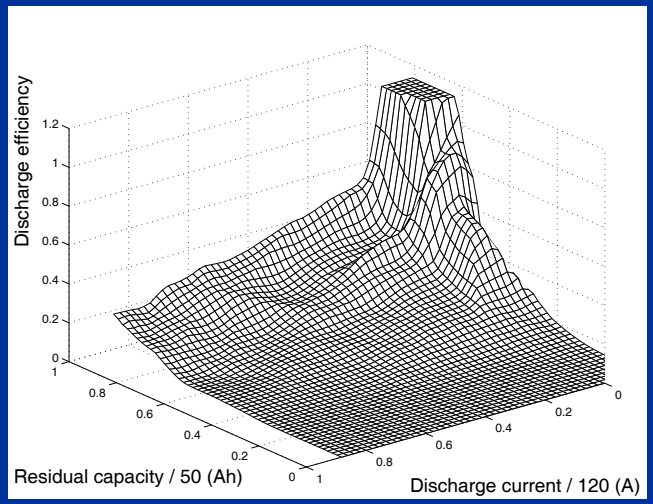
- Discharge efficiency surfaces generated by EMS with initial weight.



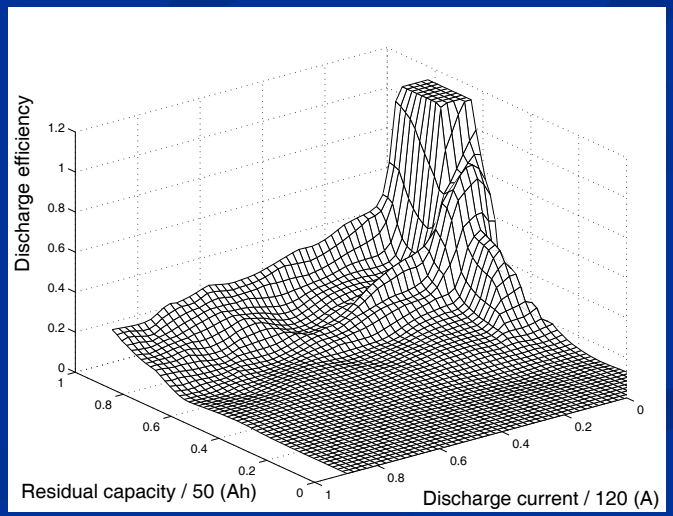
SOH = 100%



SOH = 80%

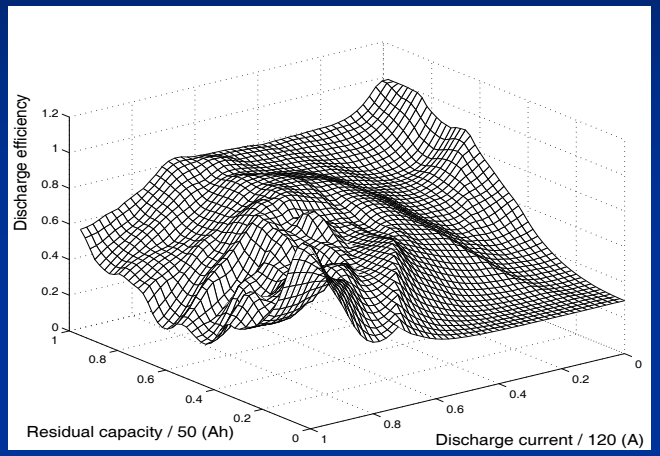


SOH = 60%

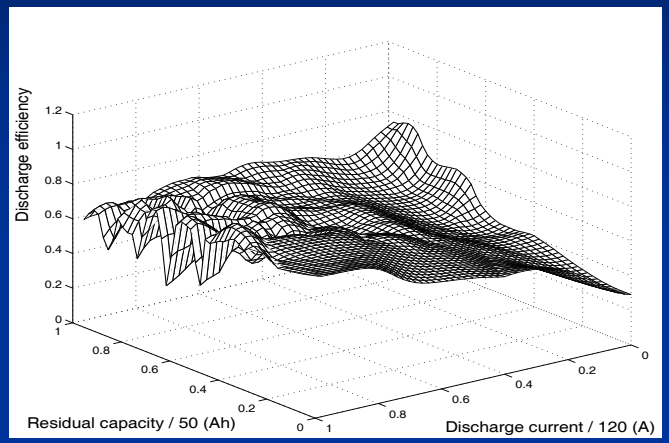


SOH = 40%

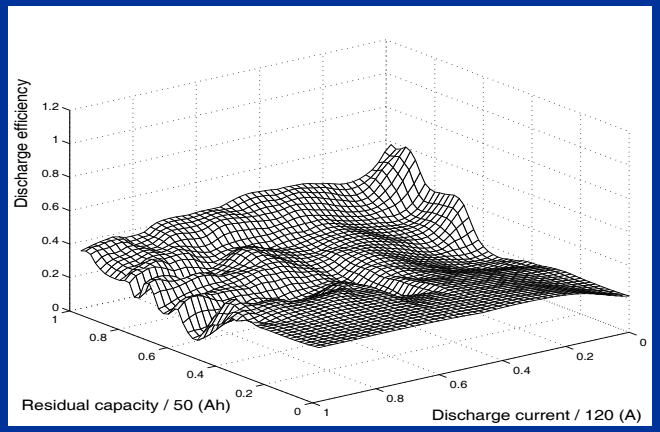
- Discharge efficiency surfaces generated by modified EMS.



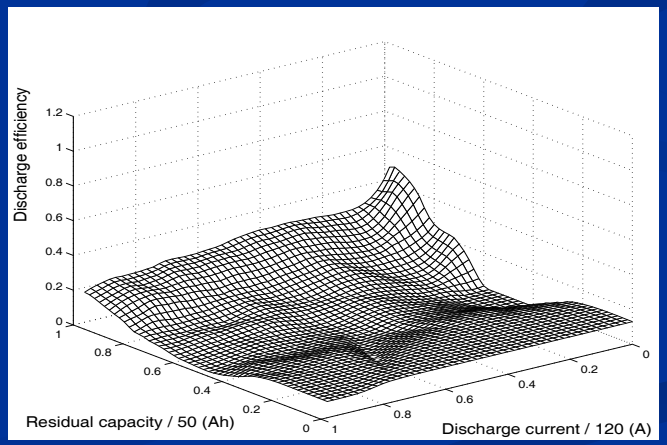
SOH = 100%



SOH = 80%



SOH = 60 %



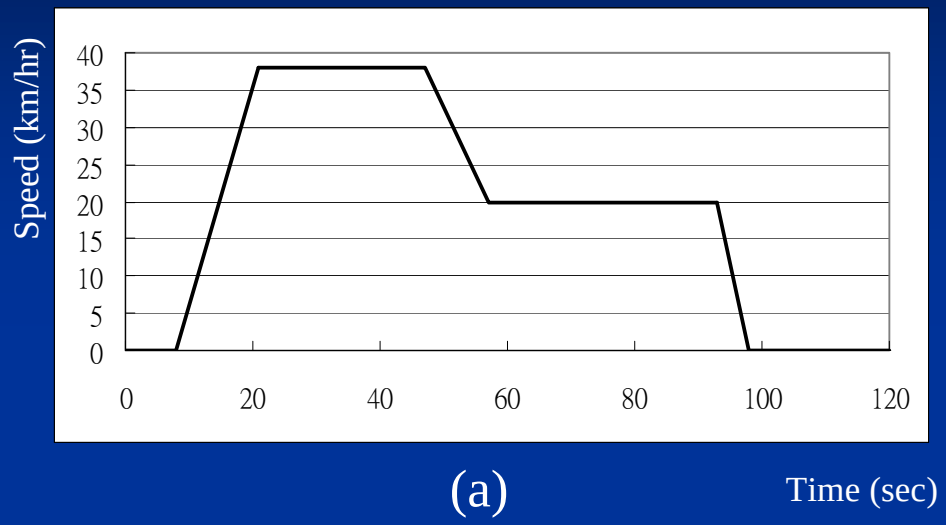
SOH = 40%

Testing for EMS

- We used four urban drive cycles shown in to test the proposed EMS.
- CNS-D3029, Taiwan
- EPA75, USA
- ECE15, EEC nations
- M10-15, Japan

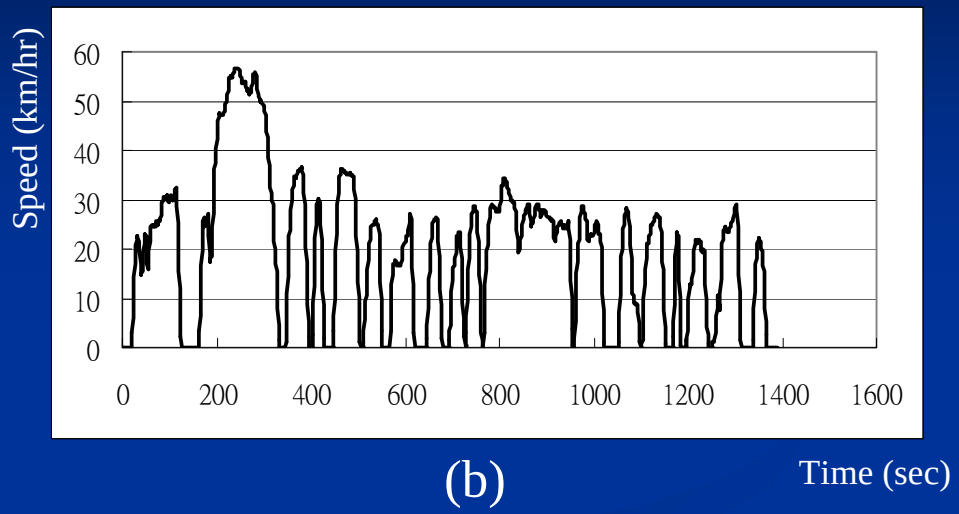
Drive cycles :

CNS-D3029



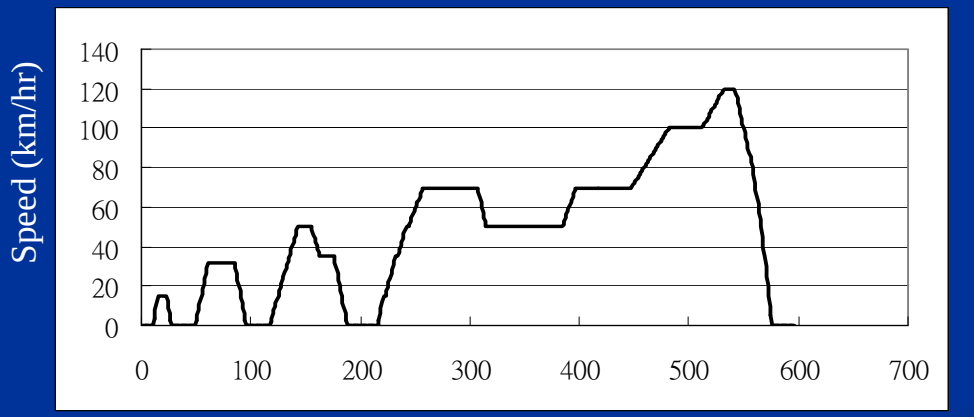
(a)

EPA75



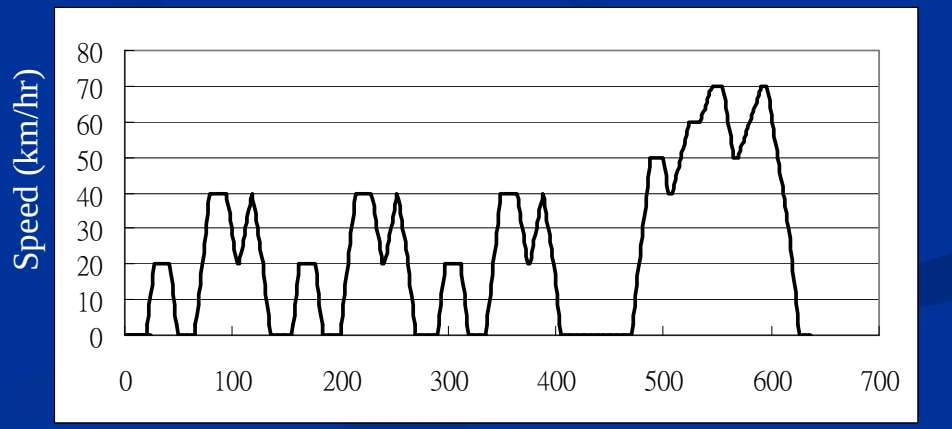
(b)

ECE15



(c)

M10-15



(d)

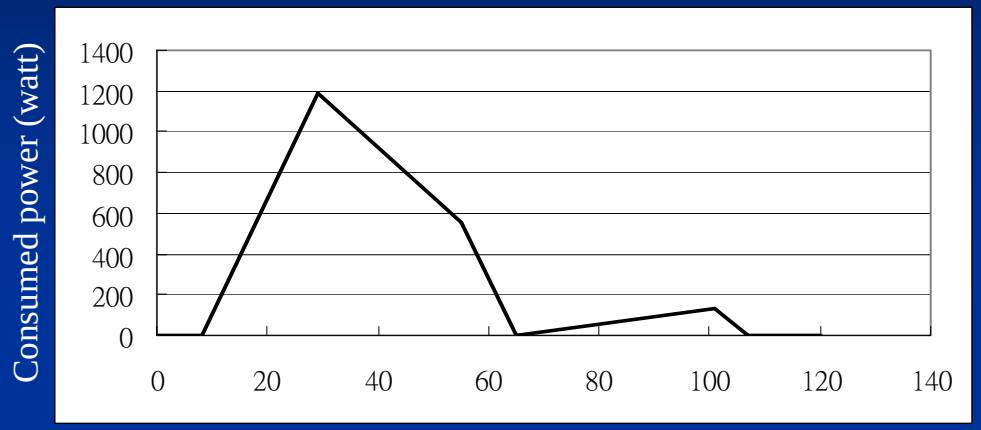
- Power consumption of an electric scooter

$$P = \frac{v}{n}\left(M\frac{dv}{dt} + MgC_r \cos\theta + Mg\sin\theta + \frac{1}{2}\rho C_D A_f v^2 \right)$$

- We transferred these drive cycles into corresponding power consumption cycles, because it was more convenient to do experiments by using power consumption data in our lab..

Power consumption cycles

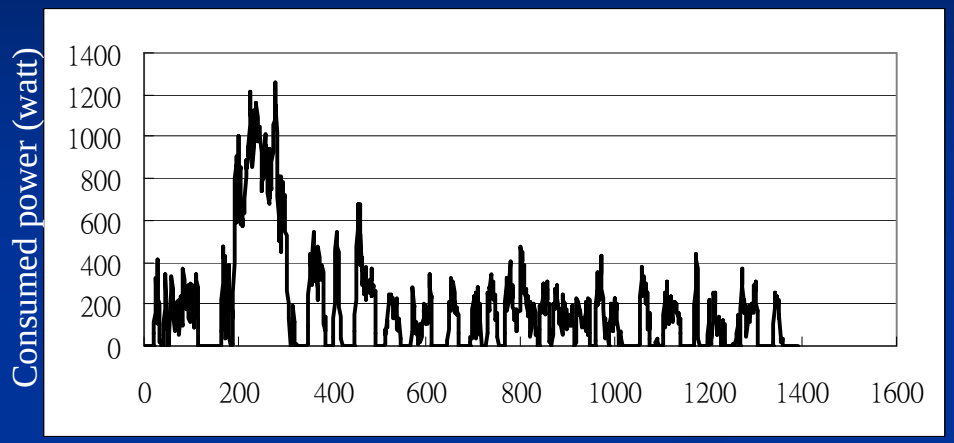
CNS-D3029



(a)

Time (sec)

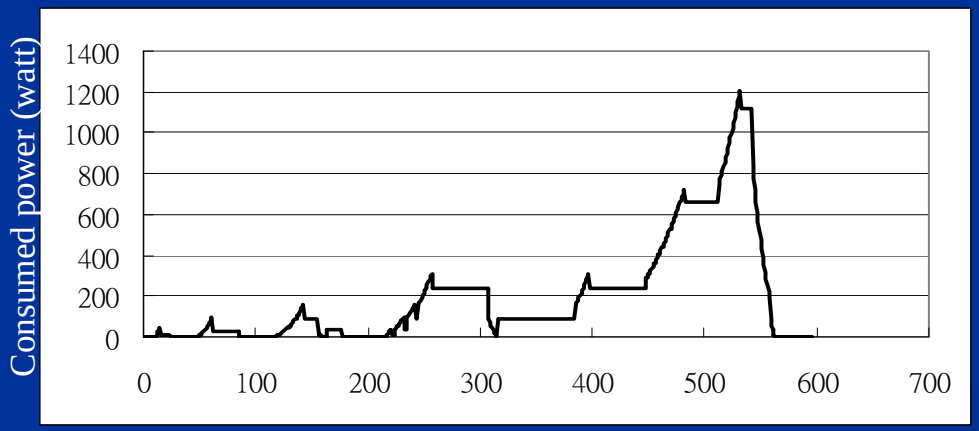
EPA75



(b)

Time (sec)

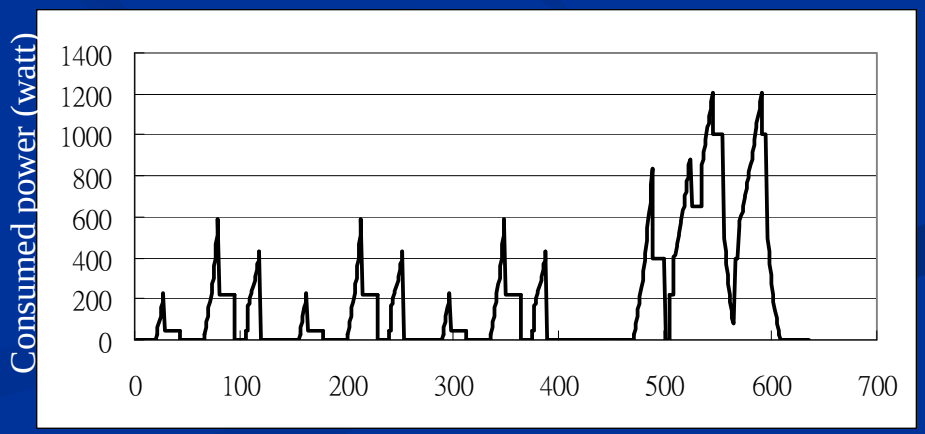
ECE15



(c)

Time (sec)

M10-15



(d)

Time (sec)

Errors of four drive cycles testing

SOC prediction error / SOH / Drive cycle			
	82.5 %	66.0 %	
CNS-D3029, Taiwan	5.423 %	5.418 %	
EPA75, USA	6.445 %	0.627 %	
ECE15, EEC nations	3.387 %	3.893 %	
M10-15, Japan	8.462 %	7.668 %	

Conclusion

- We propose an SOC learning system for improving the performance of present SOC measurement used in electric scooters.
- Only static data obtained from experiments is used as training patterns for the proposed system, and this system can estimate the dynamic SOC accurately.

- The aging effect is also considered in the proposed system, because the aging problem is very obvious in the electric scooter or EV application.
- In the future, we will consider the effect of temperature, and introduce this factor into our learning system for developing a more precise SOC estimating system.