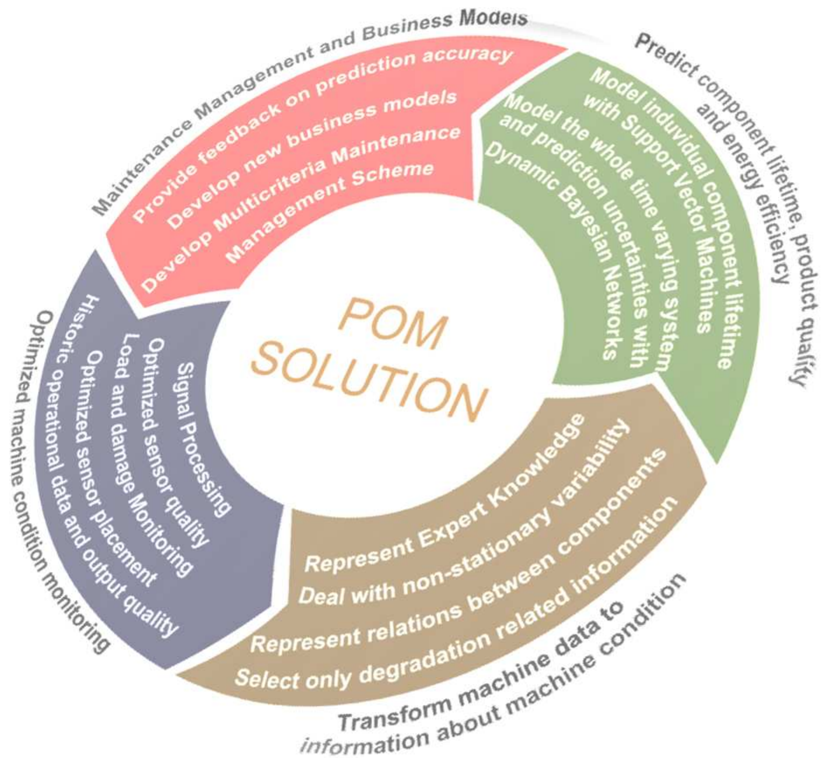


Charge-optimal control of battery-powered equipment

Application to FMTC badminton robot

POM2 Prognostics for Optimal Maintenance, IWT-SBO-100031

Outline

1. **Introduction**
2. **Modeling**
3. **Charge-optimal control**

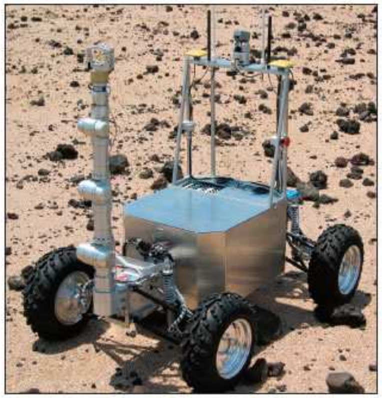
Outline

1. **Introduction**
    1. General context
    2. Presentation of the badminton robot
2. **Modeling**
3. **Charge-optimal control**

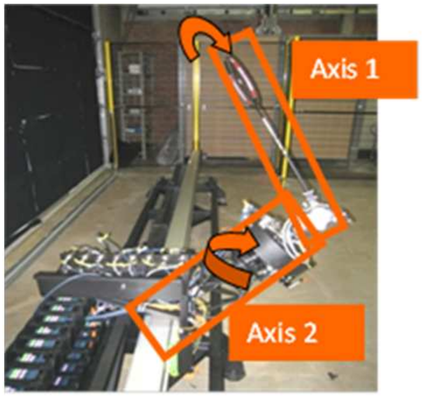
General context

- There is growing interests in electrification of drive trains
- Battery technology plays significant role

Daimler electrical car charging



Nasa's four-wheeled autonomous mobile robot for lunar and Mars missions



FMTC badminton robot arm

- However, batteries are characterized by limited energy storage capacity ➔ this limits autonomy

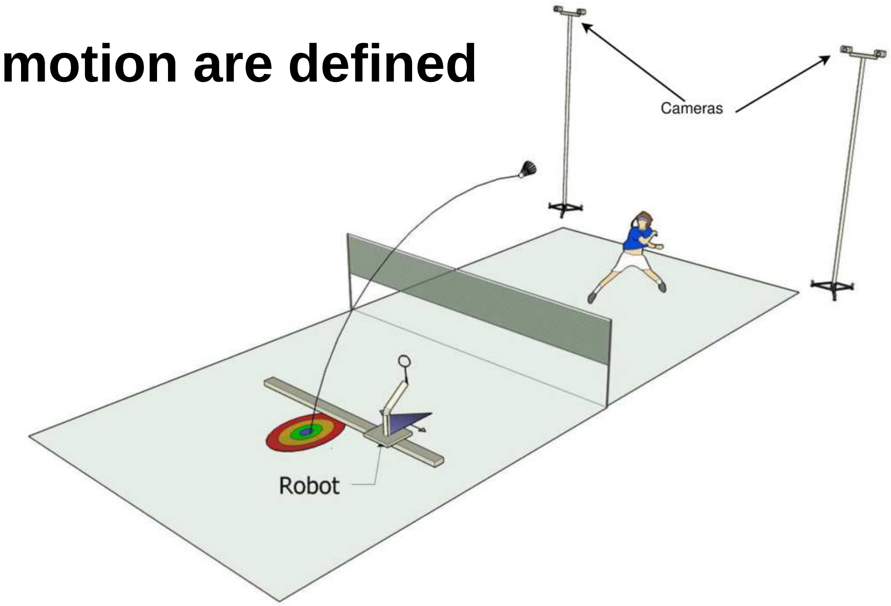
How can the battery usage be extended?

- **Two possible levers:**
  - Battery technology: use battery with high energy density
  - Control strategy: optimize battery capacity utilization
    - Eco-driving mode: driver is helped to achieve a higher battery utilization by reducing driving aggressiveness
    - Similar methodology can be applied for industrial applications
- **GOAL:**
  - charge-optimal control for the badminton robot arm

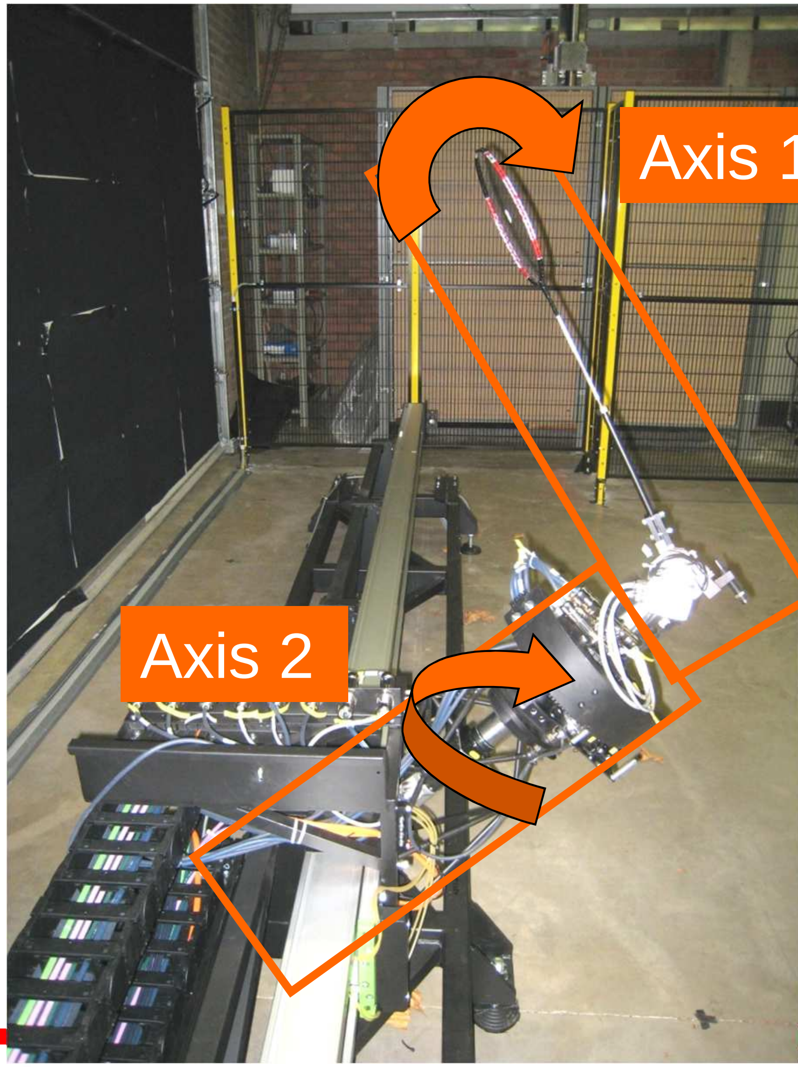
➔ **Set control parameters so that the utilized charge is minimal**

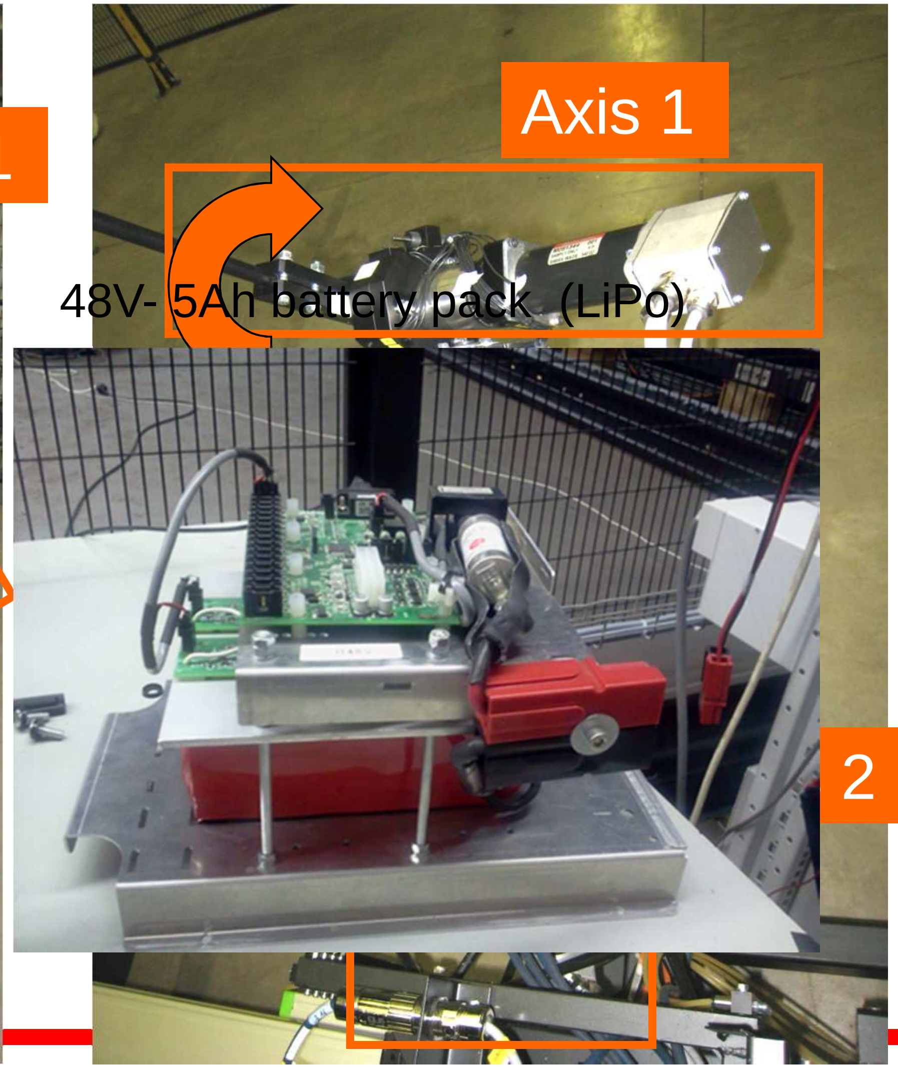
FMTC – Badminton robot

- **3 axis robot: linear, arm rotation and hit**
- **Camera images of the shuttle and calculation of its estimated trajectory allow the interception point to be determined**
- **Target parameters of the arm motion are defined**
  - Distance to be travelled: θ
  - Maximum velocity: V_{max}
  - Maximum acceleration: A_{max}



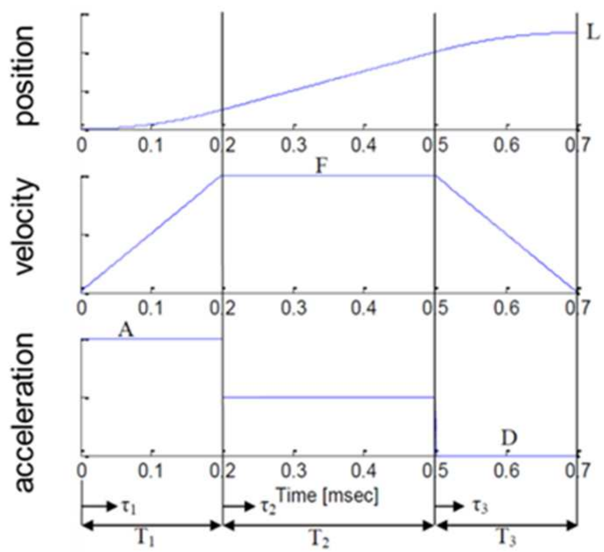
FMTC – Badminton robot





The current control strategy

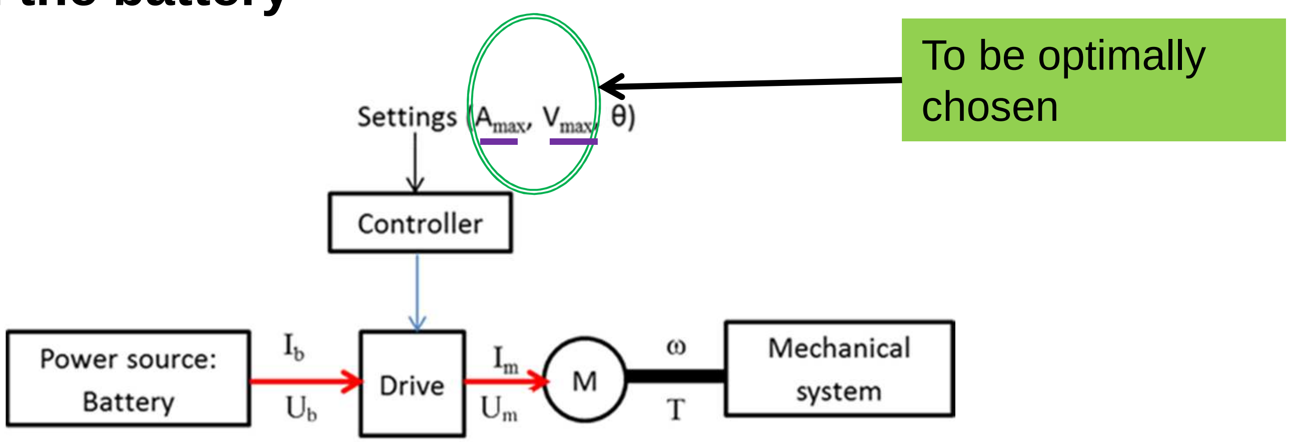
+ **Time optimal:**
  - The arm moves as fast as possible to intercept the shuttle
  - This leads to high velocity and high acceleration
  - Also high currents are drawn from the battery ➔ the battery usage time is reduced



Alternative control strategy?

+ **FMTC has developed and applied “Energy-optimal” on the linear motion control which allows almost 60% of energy savings**

+ **For the arm motion, the optimization will concern the charge drawn from the battery**

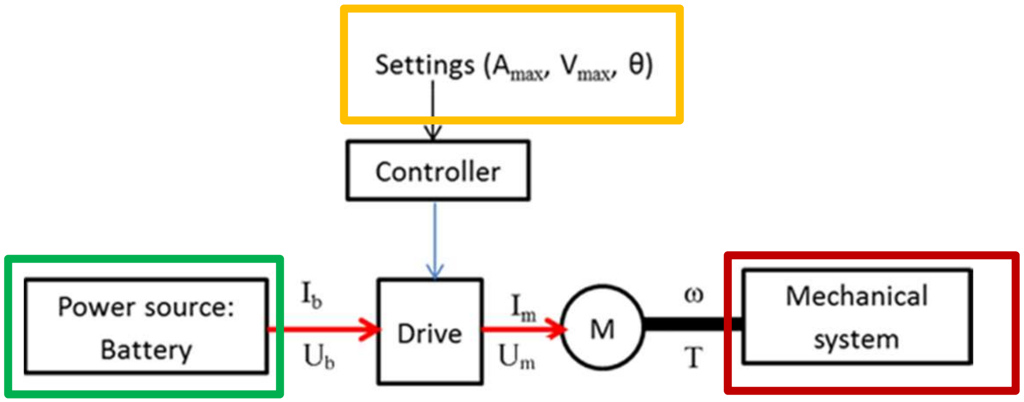


Outline

1. **Introduction**
2. **Modeling**
   1. Power prediction model
   2. Battery response model
3. **Charge-optimal control**

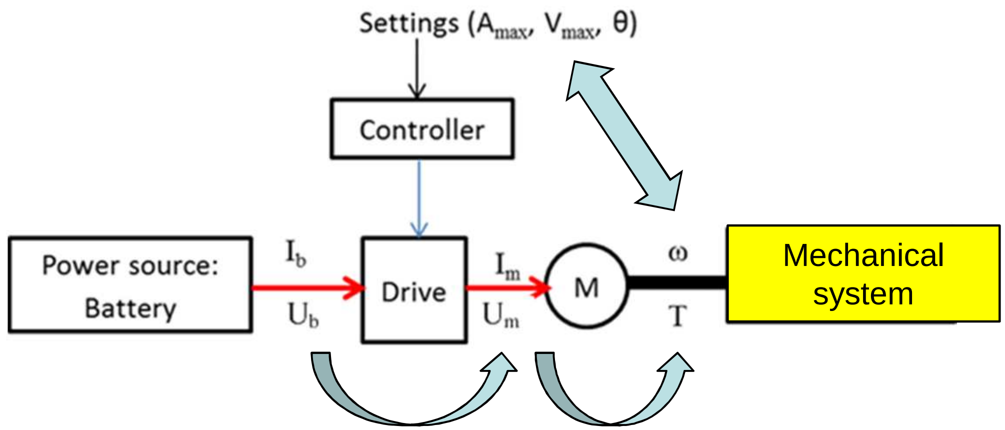
Battery and mechanical system modeling for designing the optimal controller

+ **Two models are built:**
  - Power predictor to establish the relationship between the control settings (A_{max}, V_{max}, θ) and the electrical measured power
  - Battery equivalent circuit model: to predict the battery response to given control settings



Power prediction model

+ **Power balance between the electrical and the mechanical part of the system**



$$P_e - L_e = P_m + L_m + P_s$$

Electrical power

Electrical losses

Mechanical power

Mechanical losses

Idle power

Power prediction model

- **Power balance between the electrical and the mechanical part of the system**

$$\boldsymbol{P_e - L_e = P_m + L_m + P_s}$$

$P_e = U_b I_b$ electrical power from the battery

$L_e = K_b I_b^2 + K_m I_m^2$ ohmic losses in line before and after the drive

$P_m = T_m \omega = J\alpha\omega$ mechanical power at the arm

$L_m = sign(\omega)\omega T_f + C\omega^2$ mechanical losses due to dry and viscous friction

P_s is the idle power necessary for holding the robot arm in a given position

$I_b = K_i U_m I_m$ K_i is dependent on the battery state of charge (SoC)

Power prediction model

- For dynamic motions the motor is approximately proportional to the acceleration and the velocity to the voltage
- The power equation becomes

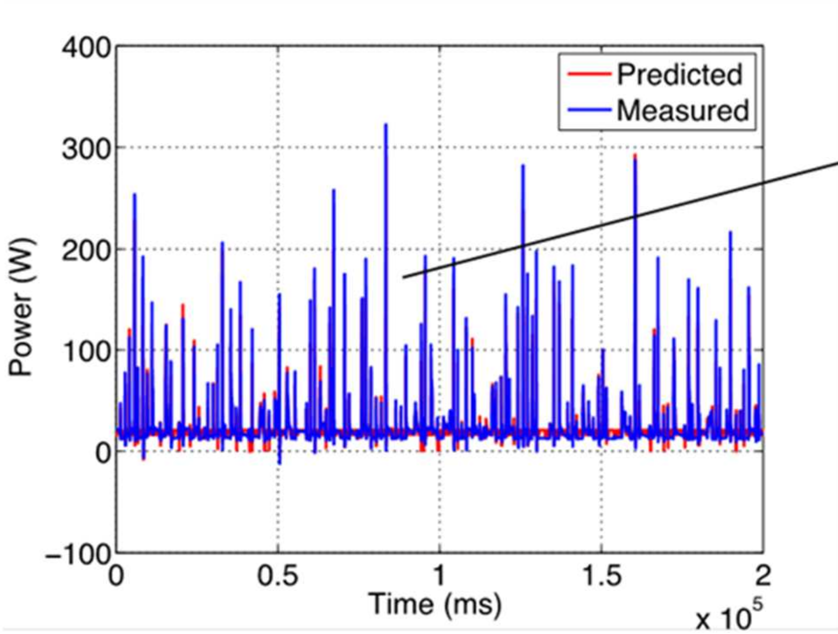
$$P = U_b I_b \equiv \boldsymbol{J}\alpha\omega + sign(\omega)\omega\boldsymbol{T_f} + \boldsymbol{K_1}(SoC)\alpha^2\omega^2 + \boldsymbol{K_2}(SoC)\alpha^2 + \boldsymbol{P_{idle}}$$

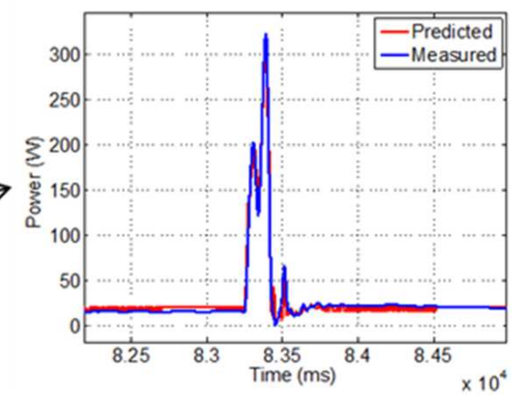
- This result in parameter estimation problem:
  - To be estimated: $\boldsymbol{J, T_f, K_1, K_2, P_{idle}}$
  - Measured or known form settings: α, ω, U_b, I_b

Parameter estimation using least squared method

Power model validation

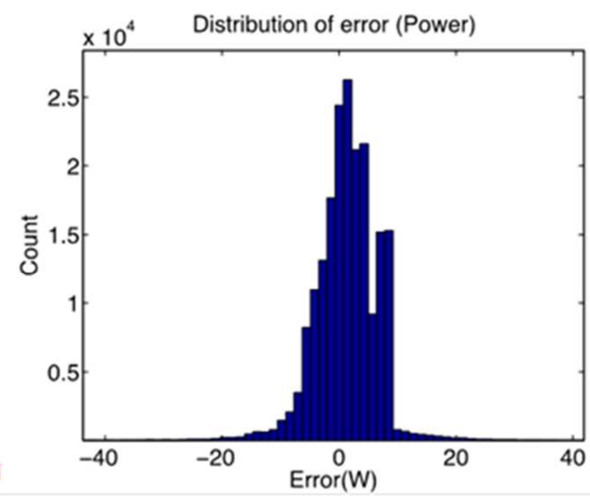
+ **The model is validated using validation dataset**





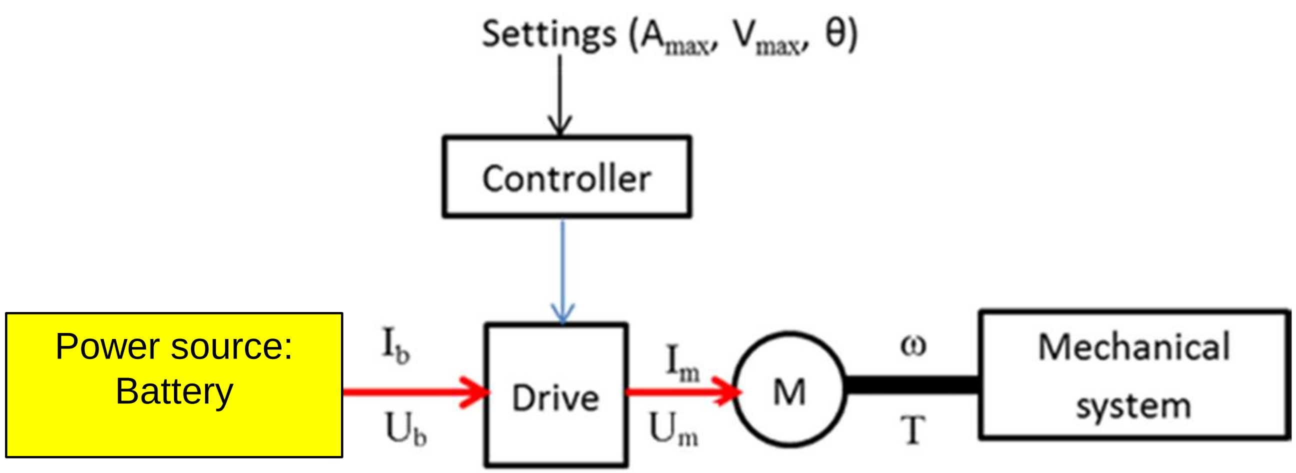
Mean error: 5.8%
RMS error: 12.7%

Mean absolute error: 1.32W
RMS error: 6.4W

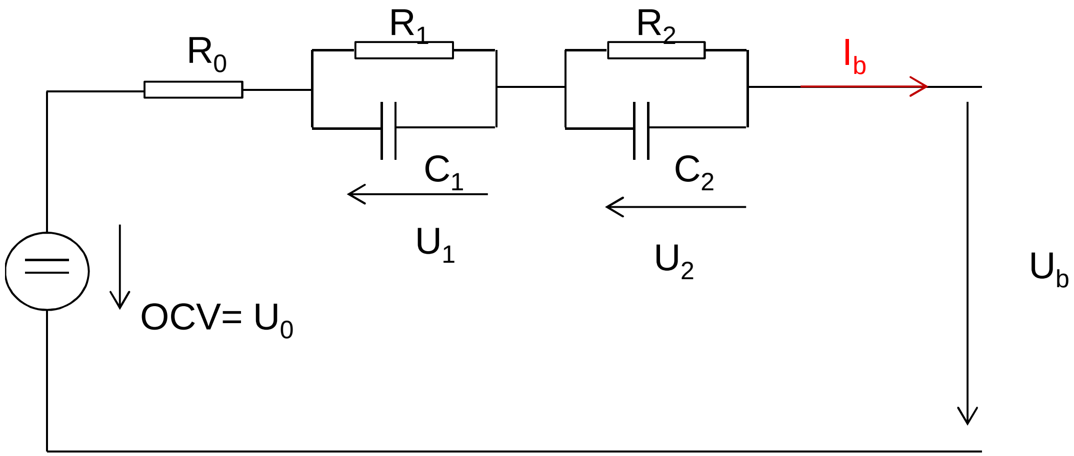


Battery modeling

- **Two models are built:**
  - Power predictor to establish the relationship between the control settings (A_{max}, V_{max}, θ) and the electrical measured power
  - Battery equivalent circuit model: to predict the battery response to given control settings



Battery Equivalent Circuit Model



$$U_b(t) = OCV - R_0 I_b - \sum_{k=1}^{2} R_k I_k$$

$$\tau_k = R_k C_k$$

$$U_1 = R_1 I_1$$

$$U_2 = R_2 I_2$$

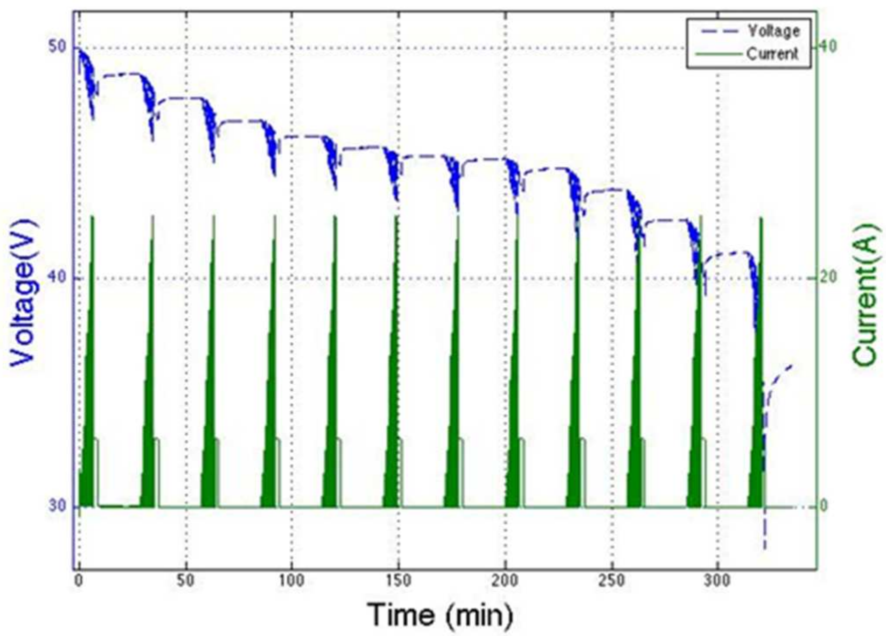
2 RC pairs are enough to capture the dynamic behavior of the battery

Parameters to estimate:
OCV; R_0; R_1; C_1; R_2; C_2 as a function of soc

Least squared method is used

Parameters estimation

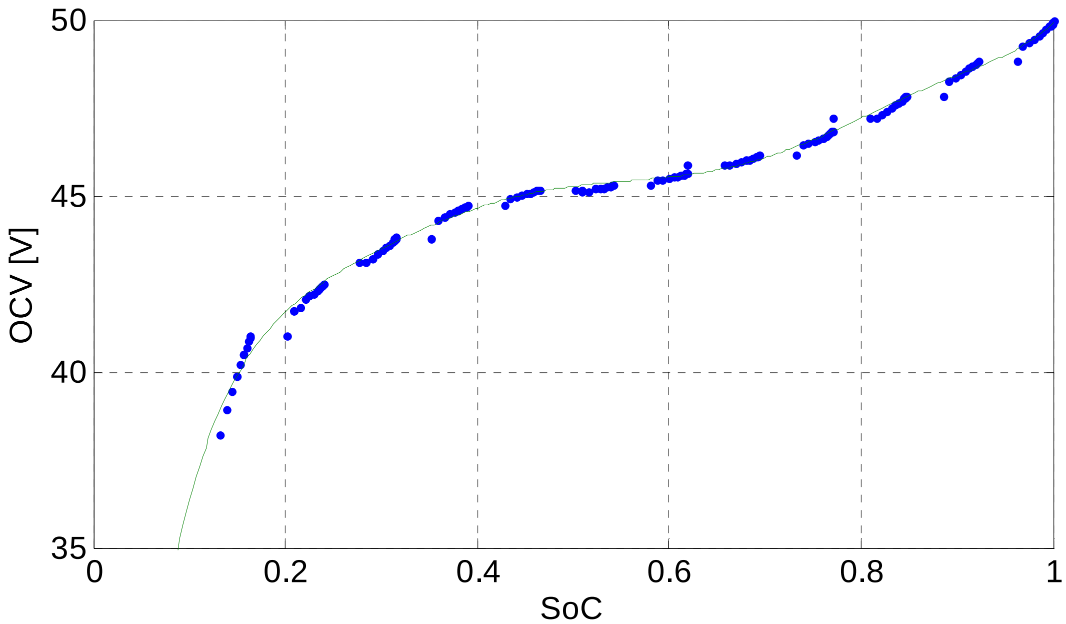
+ **Experimental HPPC (Hybrid Pulse Power Characterization) data are used for parameters estimation**



- The parameters are estimated for different SoC values
- Curves can be fitted giving these parameters i.f.o. SoC

Parameters estimation

+ **OCV=f(SoC): a polynomial or an exponential function to be used in the model can be fitted**

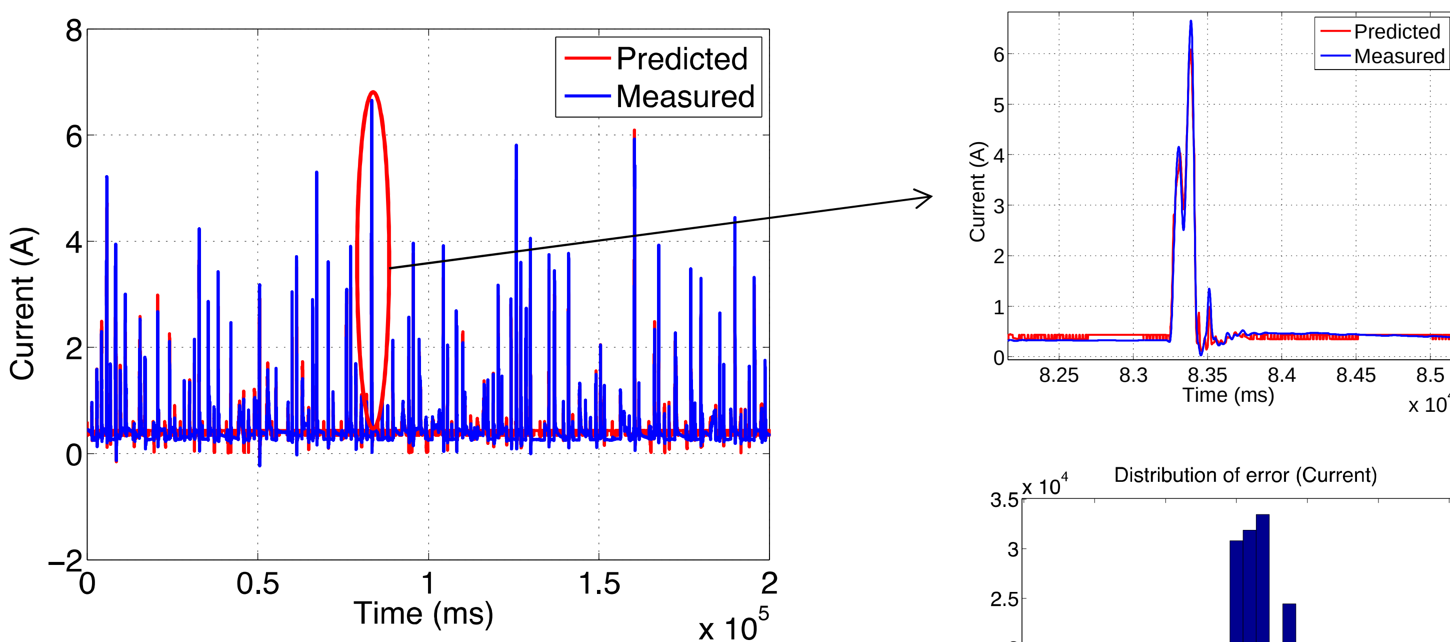


The other parameters are estimated in the same way

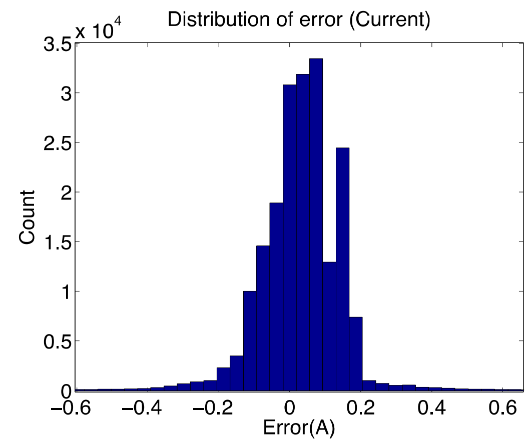
Estimated parameters are used in the battery model to calculate the voltage response

Model validation: current prediction

+ **Current prediction results**

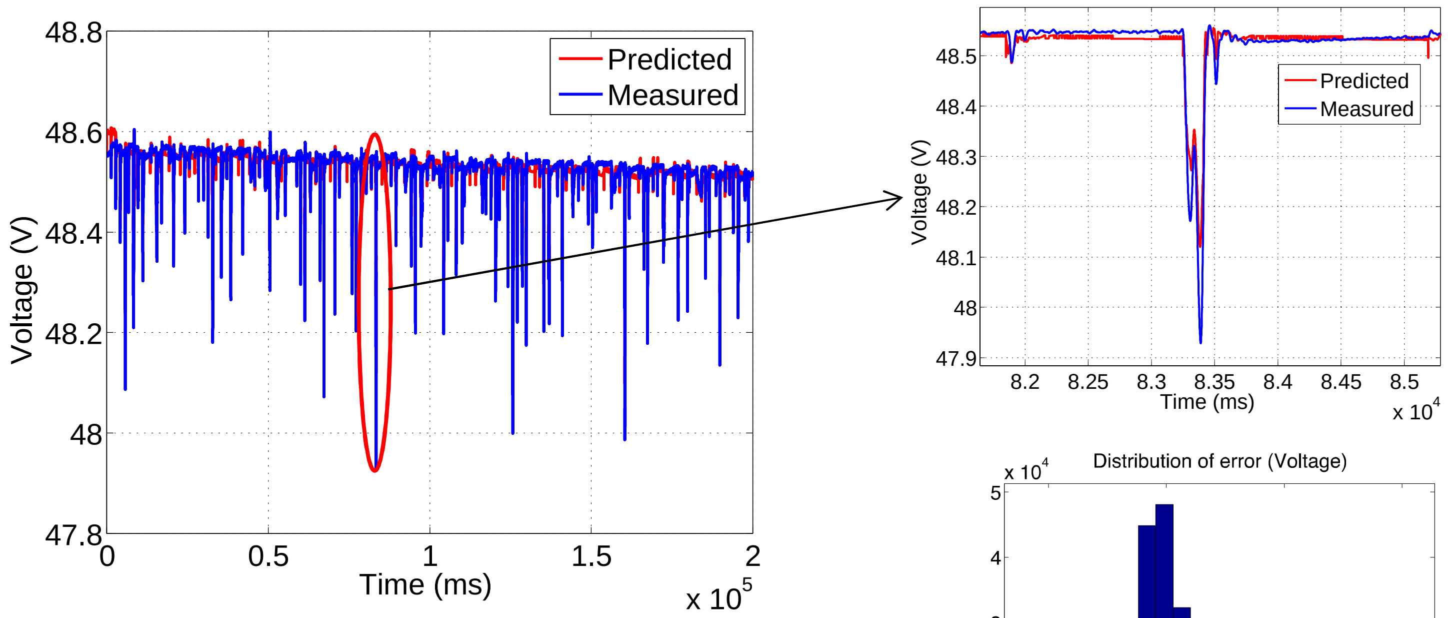


Mean absolute error: 0.032A
RMS error: 0.13A

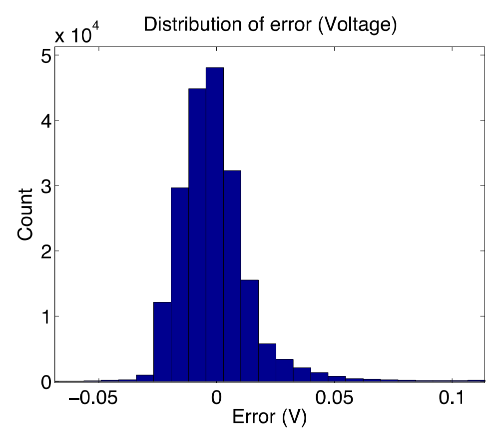


Model validation: voltage prediction

+ **Voltage prediction with actual position**



Mean absolute error: 0.00072V
RMS error: 0.017V



Outline

1. **Introduction**

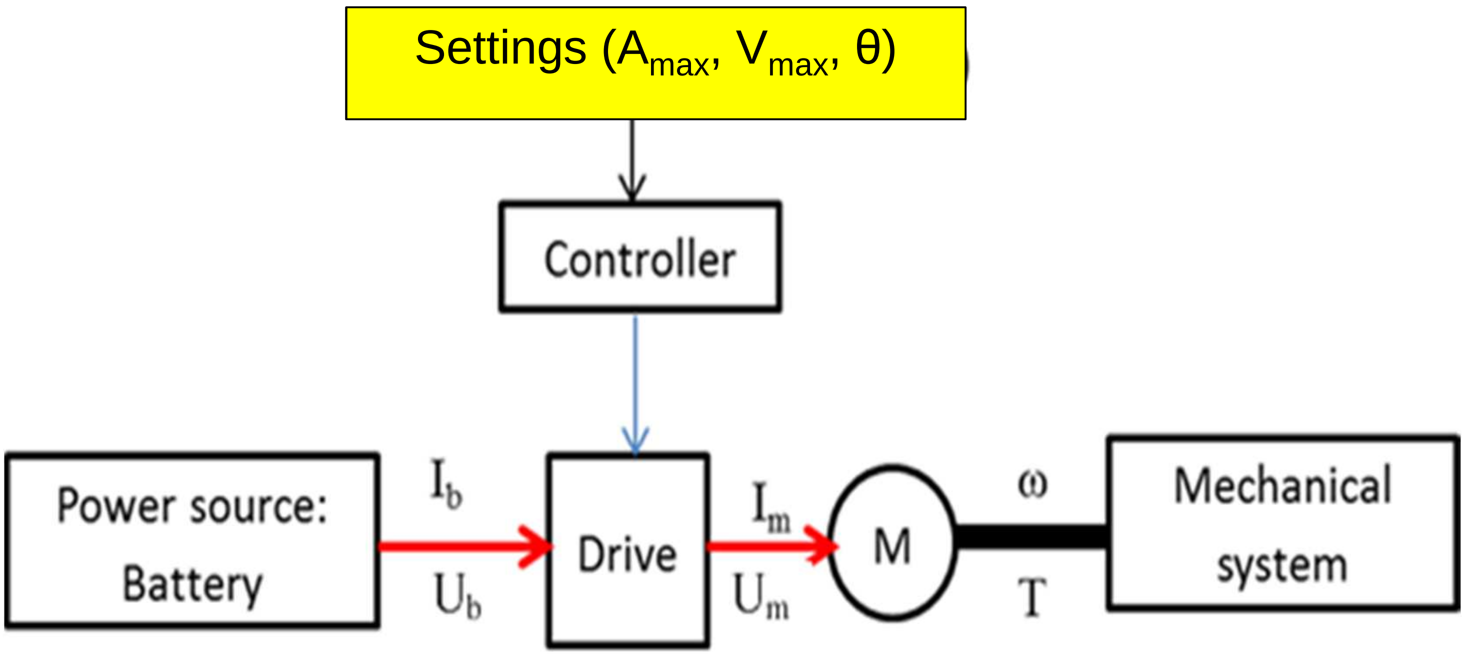
2. **Modeling**

3. **Charge-optimal control**
    1. Optimization problem formulation
    2. Design of the controller
    3. Comparison with other control strategies

Control optimization

+ **Chose optimally the control settings**

+ **The power model and the battery model are used to design the control strategy that minimizes charge utilization**



Design of the optimized control: problem formulation

Given a desired angular distance to travel, find the control variable A_{max} and V_{max} so that:

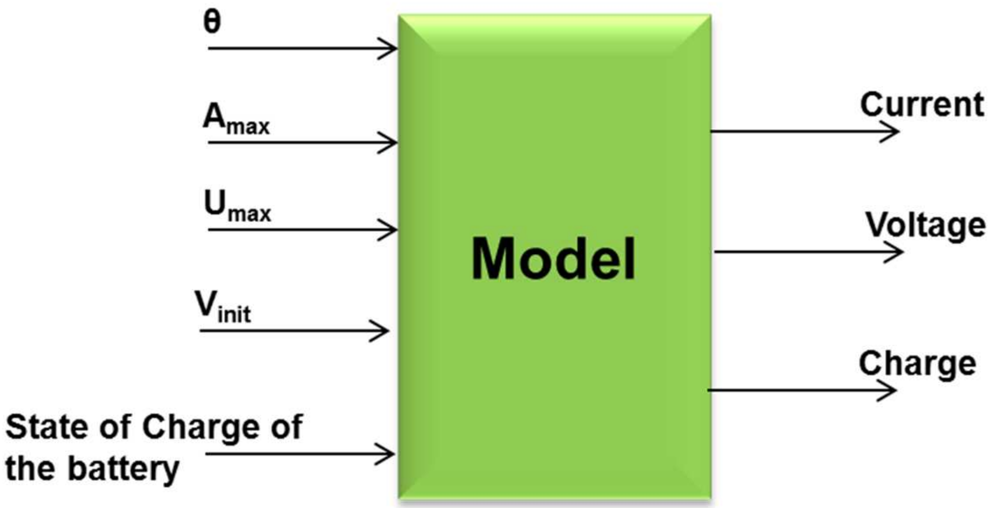
- **the charge drawn from the battery is minimal between the departing point θ_1 and the arrival point θ_2 of the movement.**

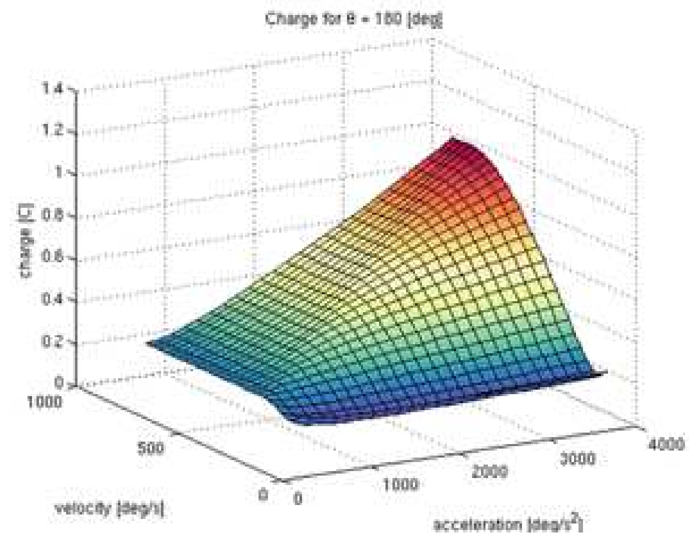
Subject to the following constraints:

- **$T<T_{max}$ (max travel time)**
- **$V>35V$**
- **$I<100$ A**

Function to minimize: Utilized charge

- **The integrated model is simulated to evaluate the utilized charge**





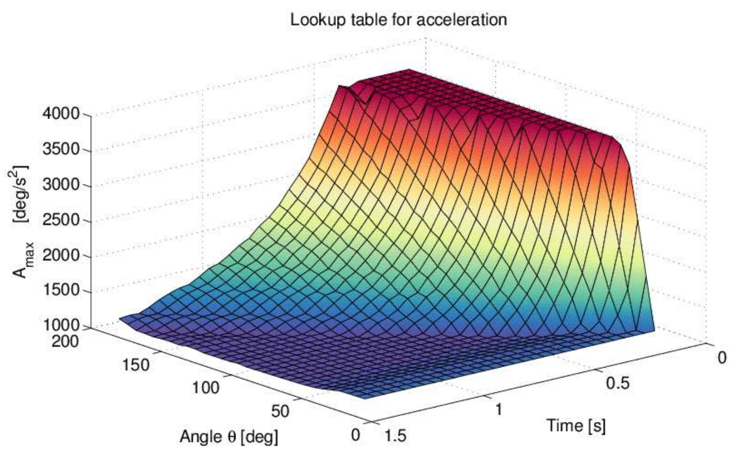
- **For each combination (θ, Initial Voltage, Travel time) the settings (A_{max}, V_{max}) minimizing the charge are calculated**

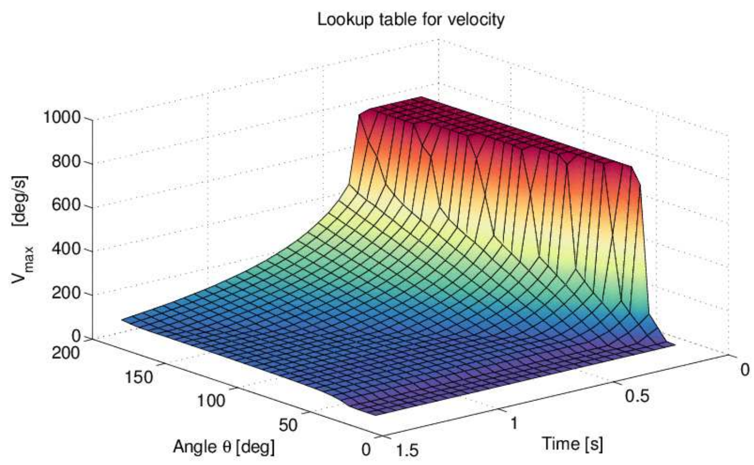
The optimization solution

- The optimized solution (A_{max_opt}, V_{max_opt}) leading to minimal charge is obtained by constrained gradient optimization

- The results are stored in look-up tables giving

$$A_{max_{opt}} = f_A(T, \theta, V_{init}) \text{ and } V_{max_{opt}} = f_V(T, \theta, V_{init})$$





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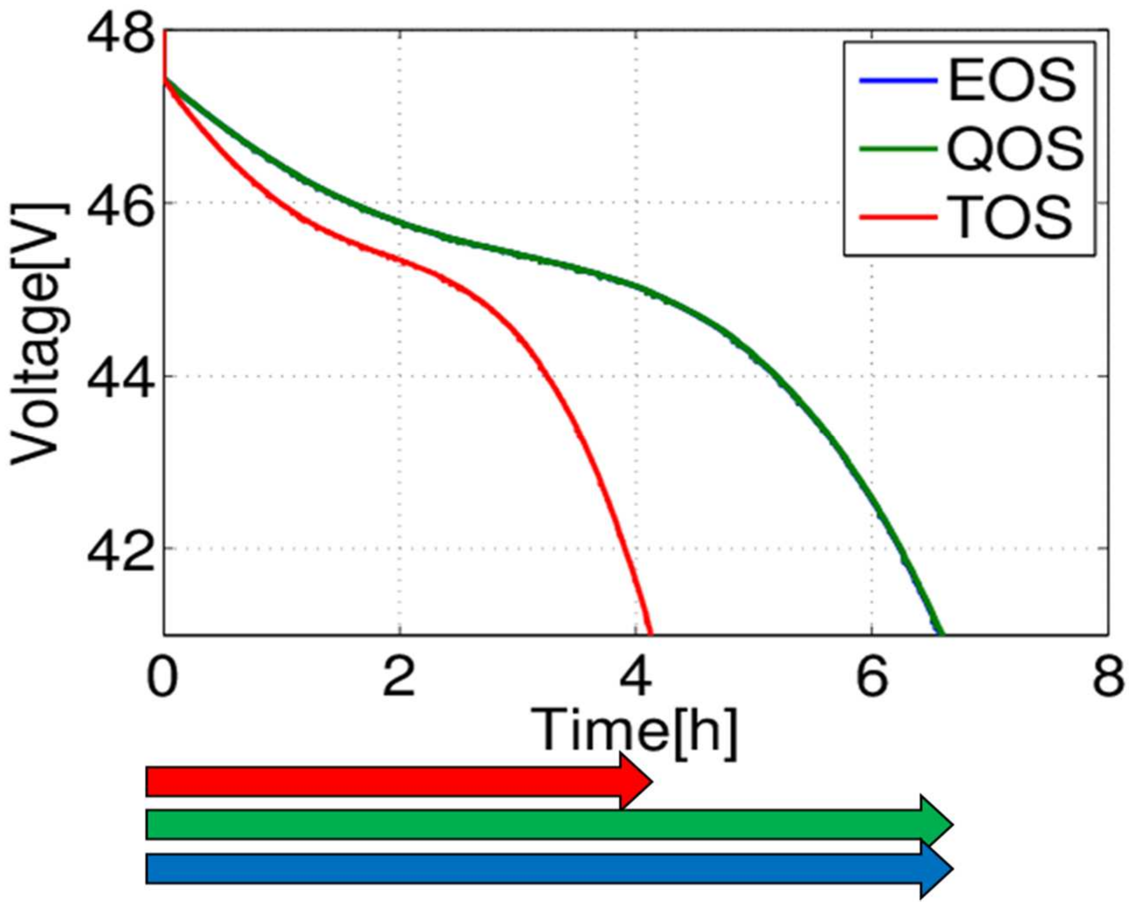
The optimized controller allows to longer use the battery



- A sequence of robot motions is used to discharge the battery from 48V to 40V
- 3 different control strategies are compared
- QOS allows using longer the battery

Conclusion

- **Charge-optimal control allows to longer use batteries**
- **Charge-optimal is equivalent to energy optimal**
- **Advantage: the battery response model can be used to accurately monitor on-line the state of charge of the battery**
- **The methodology can be applied also to battery-powered industrial applications**

Remark

- **The battery parameters change with time and charge/discharge cycles**
- **They depend also on temperature. This is not taken into account in the model**

