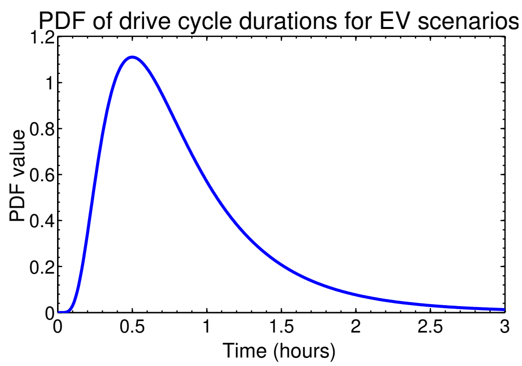
Battery electric vehicle application, scenario 2

- Asymptotic quality of total capacity estimates limited by noise on the SOC estimates used by the algorithms
- If this noise can be reduced, total capacity estimates can become more accurate
- BEV application allows a means to do this: whenever battery pack is fully charged, we have a precisely known end-point SOC
- Therefore, either $z(t_1)$ or $z(t_2)$ can be known “exactly” for every total-capacity estimate update
- This then allows us to use $\sigma_{x_i}^2 = \sigma_z^2 = (0.01)^2$

Battery electric vehicle application, scenario 2

- Tradeoff: no longer have regular updates; updates happen randomly, whenever vehicle is charged
- So, m_i becomes a random variable
- Here, m_i has log-normal pdf with mode 0.5 h, standard deviation 0.6 h
  - Gives reasonable-duration drive cycles with variety of driving distances
- As more battery energy would be used for a full drive cycle than for a regular periodic update, use 80 $\%$ SOC range, so x_i simulated as uniform random number between ± 0.8



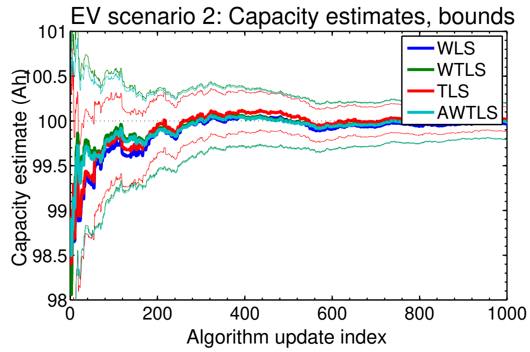
Battery electric vehicle application, scenario 2

- Code for this scenario presented below: biggest change is inclusion of parameters for random intervals between updates

```
Q0 = 100;            % actual new-cell capacity of cell
maxI = 5*Q0;         % must be able to measure current up to +/- maxI
precisionI = 1024;  % 10-bit precision on current sensor
slope = 0;
Qnom = 0.99*Q0;      % ** nominal capacity, used for init. of recursive methods
xmax = 0.8; xmin = -xmax; % ** range of the x(i) variables
theCase = 2;         % ** random interval between updates
mode = 0.5; sigma = 0.6; % ** needed for case 2
socnoise = 0.01;     % ** standard deviation of x(i)
Gamma = 1;           % forgetting factor
plotTitle = 'EV Scenario 2';
runScenario
```

Results for BEV scenario 2

- WLS fails once again, but this time TLS also fails because $\sigma_{x_i} \neq k\sigma_{y_i}$ due to the variable-length drive cycles
- TLS estimate actually quite reasonable, (but goodness of fit is very small)
- WTLS good; AWTLS best due to lower error bounds because of the ability to initialize the estimate
- Asymptotic three-sigma bounds drop from about $\pm 1\,\%$ to about $\pm 0.15\,\%$ of total capacity due to having lower value of σ_{x_i} and due to wider range in x_i



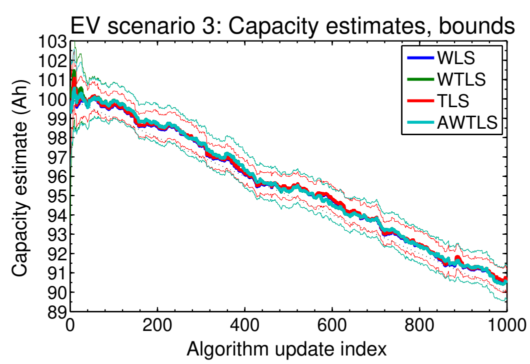
Battery electric vehicle application, scenario 3

- The final scenario we consider is identical to BEV scenario 2, except that we simulate a changing total capacity
- The slope of the total capacity curve is chosen to be -0.01 Ah per measurement update, and $\gamma = 0.98$ was used

```
Q0 = 100;           % actual new-cell capacity of cell
maxI = 5*Q0;        % must be able to measure current up to +/- maxI
precisionI = 1024; % 10-bit precision on current sensor
slope = -0.01;      % ** changing total capacity
Qnom = 0.99*Q0;     % nominal capacity, used for init. of recursive methods
xmax = 0.8; xmin = -xmax; % range of the x(i) variables
theCase = 2;        % random interval between updates
mode = 0.5; sigma = 0.6; % needed for case 2
socnoise = 0.01;    % standard deviation of x(i)
Gamma = 0.98;       % ** forgetting factor
plotTitle = 'EV Scenario 3';
runScenario
```


Results for BEV scenario 3

- Representative results of this scenario are presented to right
- Once again, WLS fails due to too-tight error bounds and TLS is uncertain of its estimate for nearly 100 updates
- However, TLS does recover and do quite well
- AWTLS method gives the best results



Summary

- Have now seen three HEV and three BEV scenarios
- The different algorithms have different characteristics
- We will discuss some general observations next lesson
- Here, we notice an improvement in estimates and error bounds due to a calibrated SOC estimate at “one end” of a driving cycle, enabled by the BEV application
- We also notice again the failure of WLS, and success of AWTLS