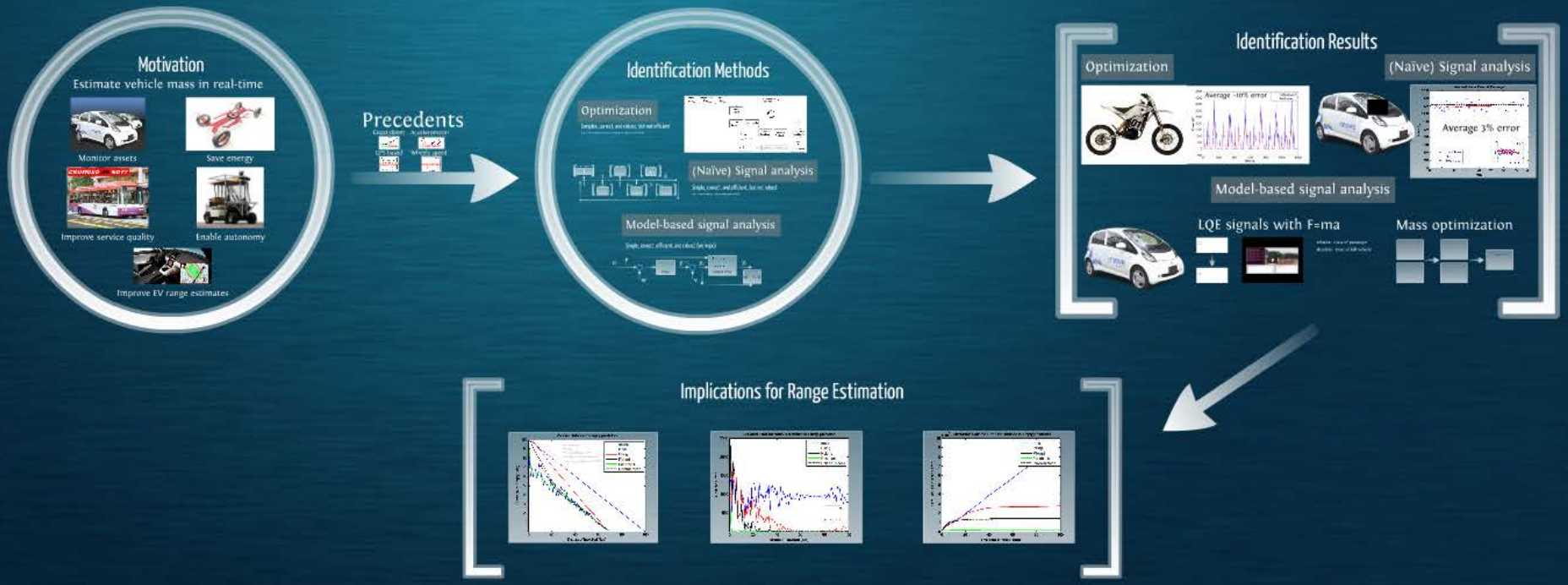
EVS27: Real-time Electric Vehicle Mass Identification

Erik Wilhelm, Singapore University of Technology and Design
Raffaele Bornatico, ETH-Zurich
Lennon Rodgers, MIT



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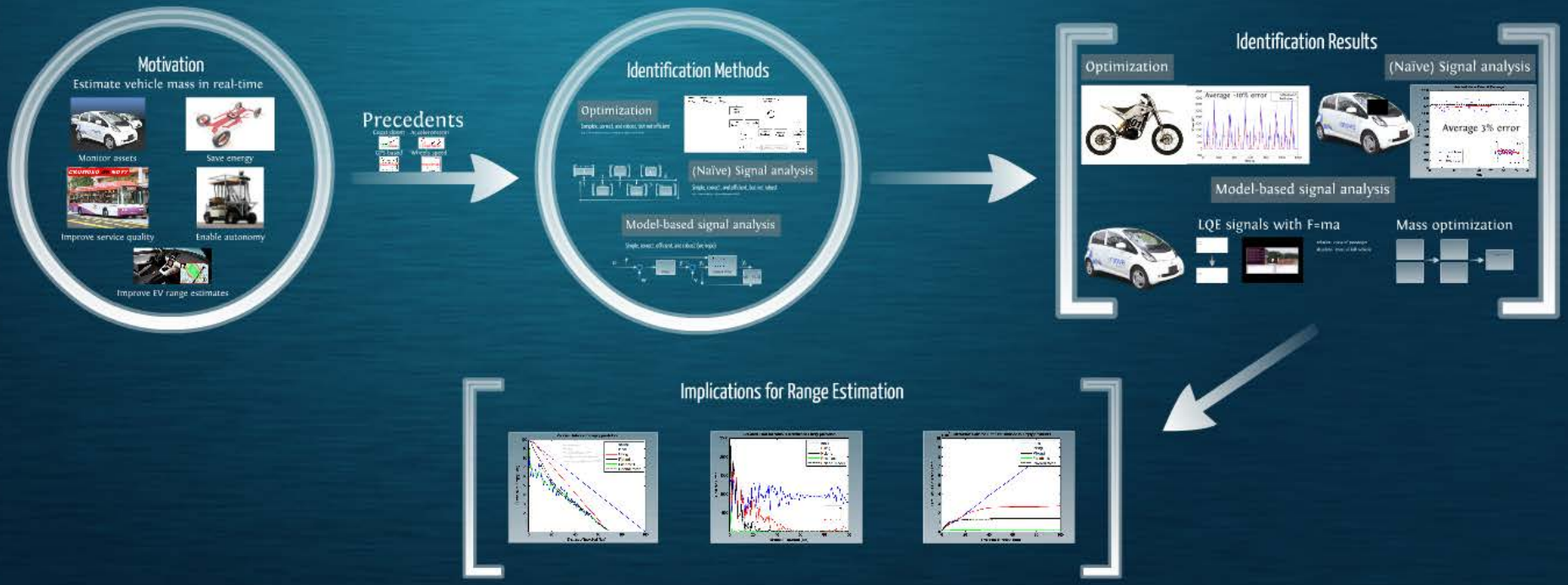
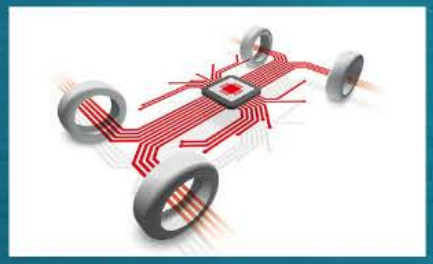


Motivation

Estimate vehicle mass in real-time

Monitor assets



Save energy

Improve service quality

Enable autonomy

Improve EV range estimates

Prec

Coast-do

GPS-bas

Precedents

Coast-down

Preda et al. Coast-down test - experimental and theoretical approach

Slow

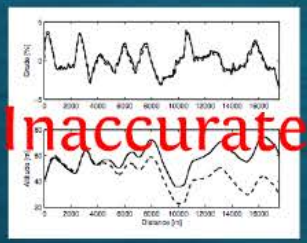
Accelerometer

Pence. Recursive Parameter Estimation using Polynomial Chaos Theory Applied to Vehicle Mass Estimation for Rough Terrain

Expensive

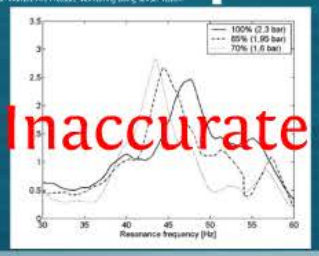
GPS-based

Sahlholm et al. A Sensor and data fusion algorithm for road grad estimation



Inaccurate

Wheels speed



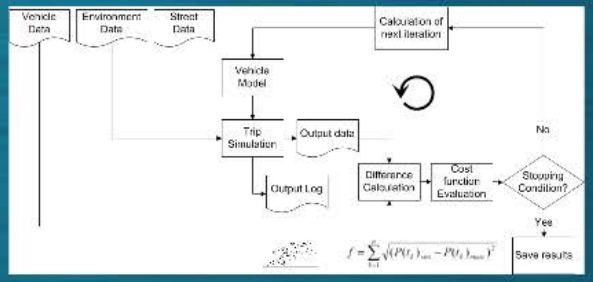
Inaccurate

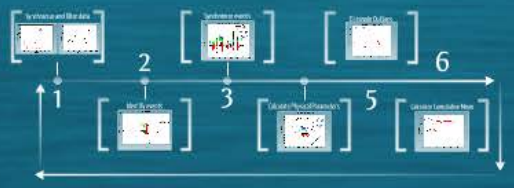
Identification Methods

Optimization

Complex, correct, and robust, but not efficient

Data from: Wilhelm, Bornatico, Widmer, Rodgers, & Soh EVS26





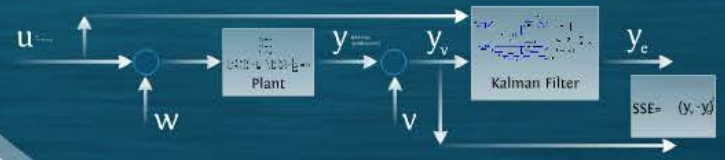
(Naïve) Signal analysis

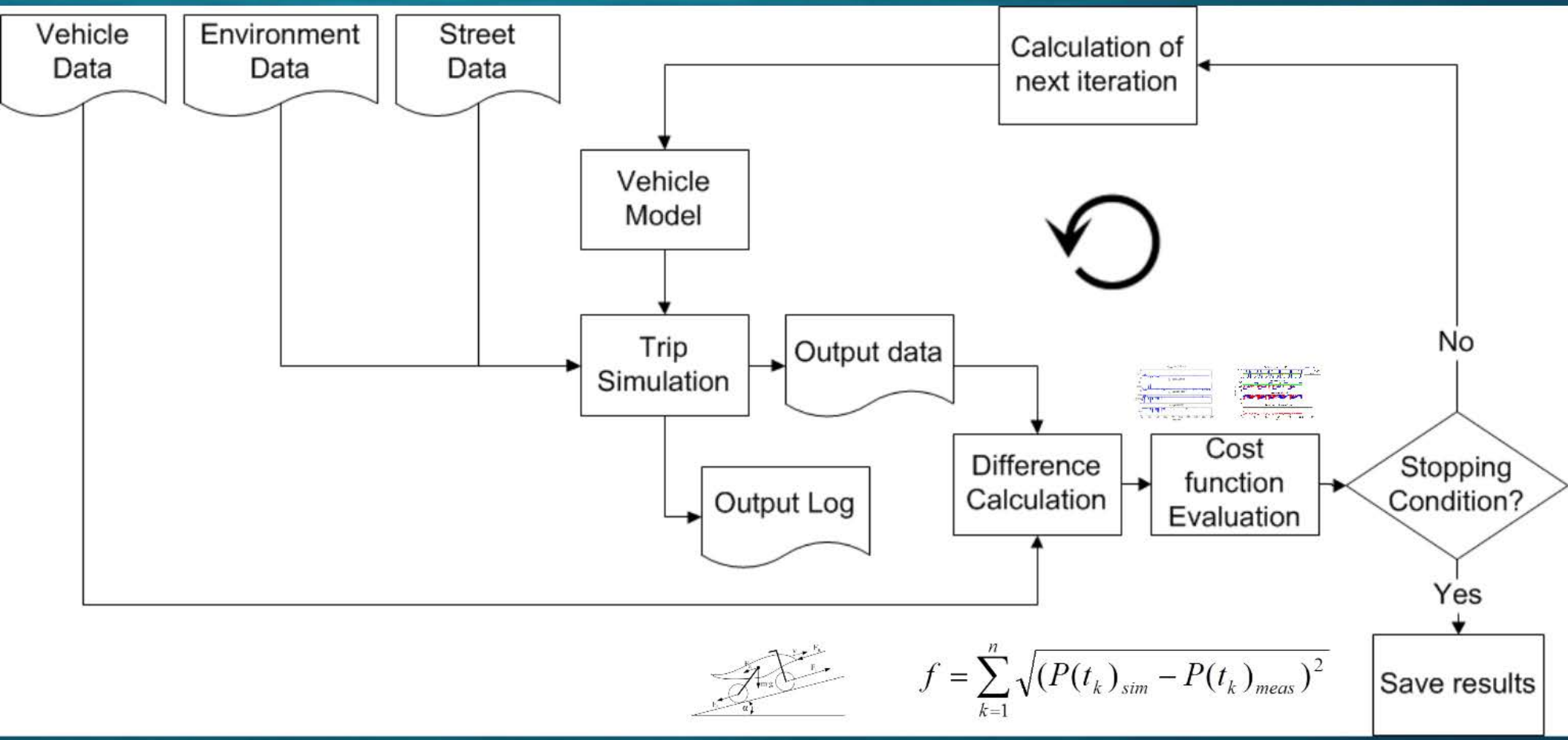
Simple, correct, and efficient, but not robust

Data from: Wilhelm, Rodgers &Bornatico EVS27

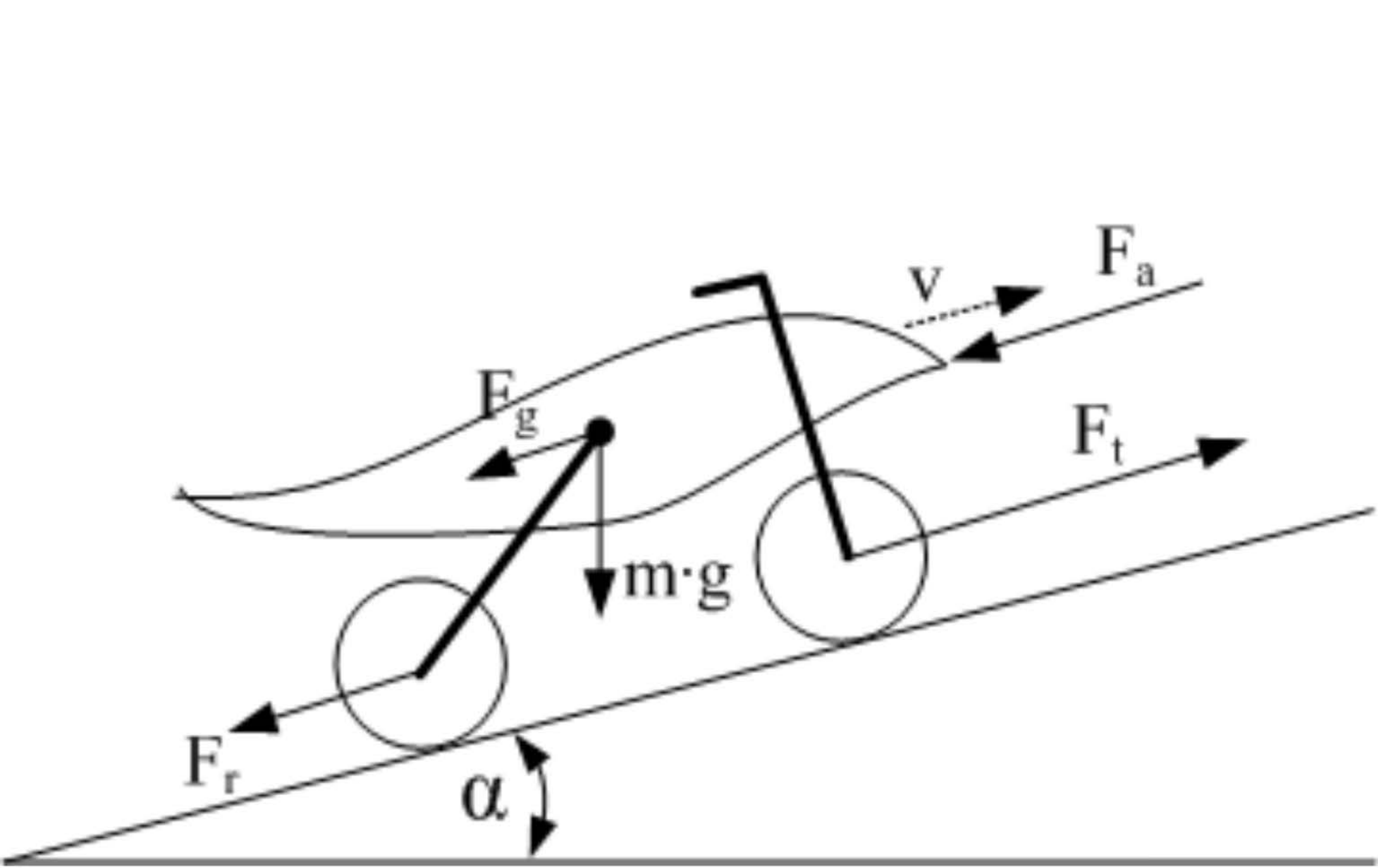
Model-based signal analysis

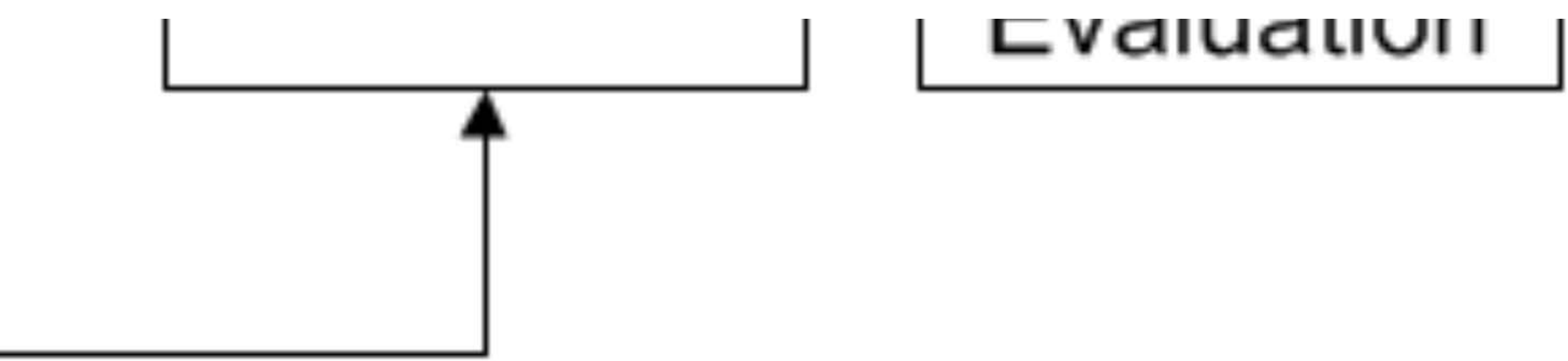
Simple, correct, efficient, and robust (we hope)



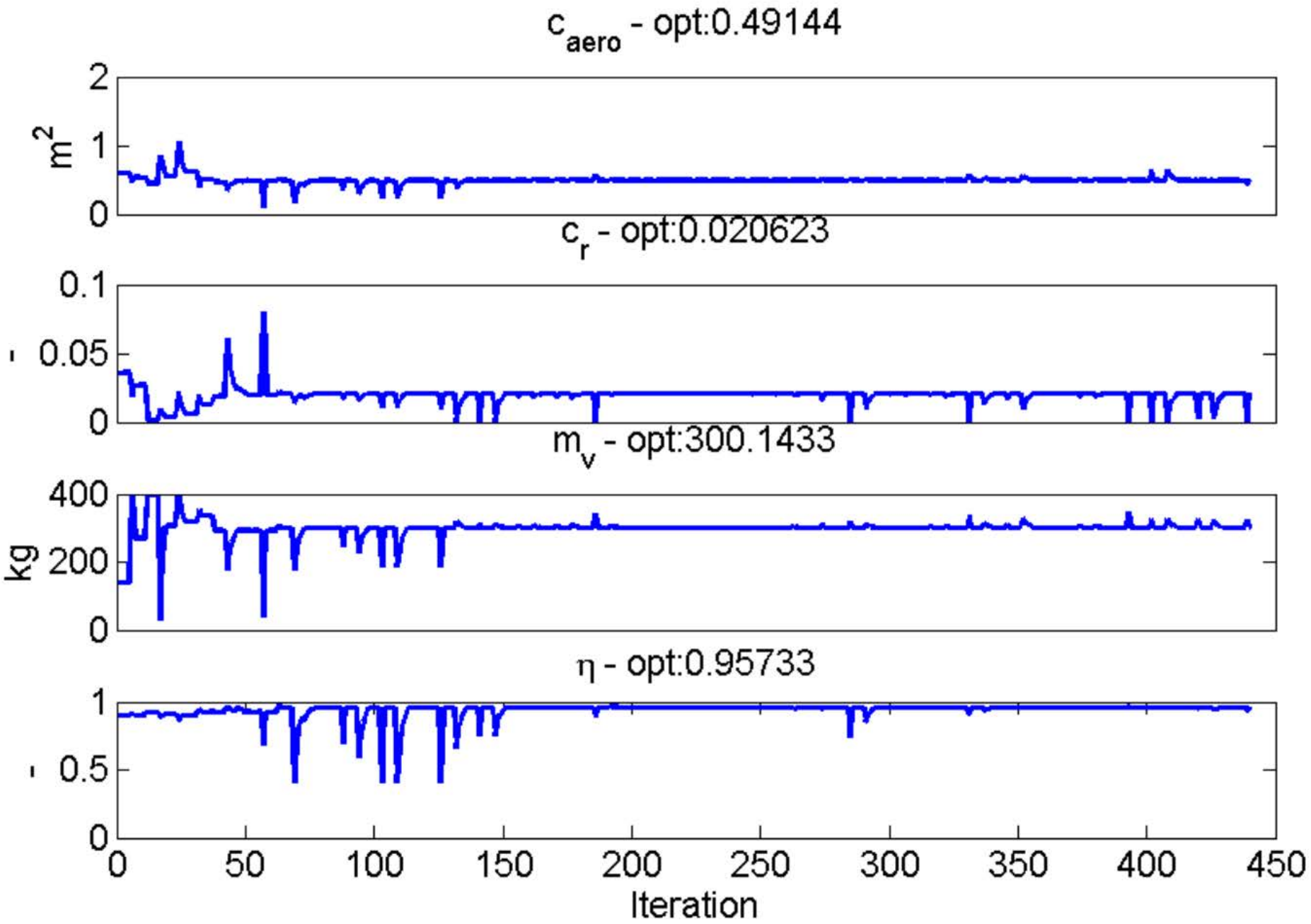


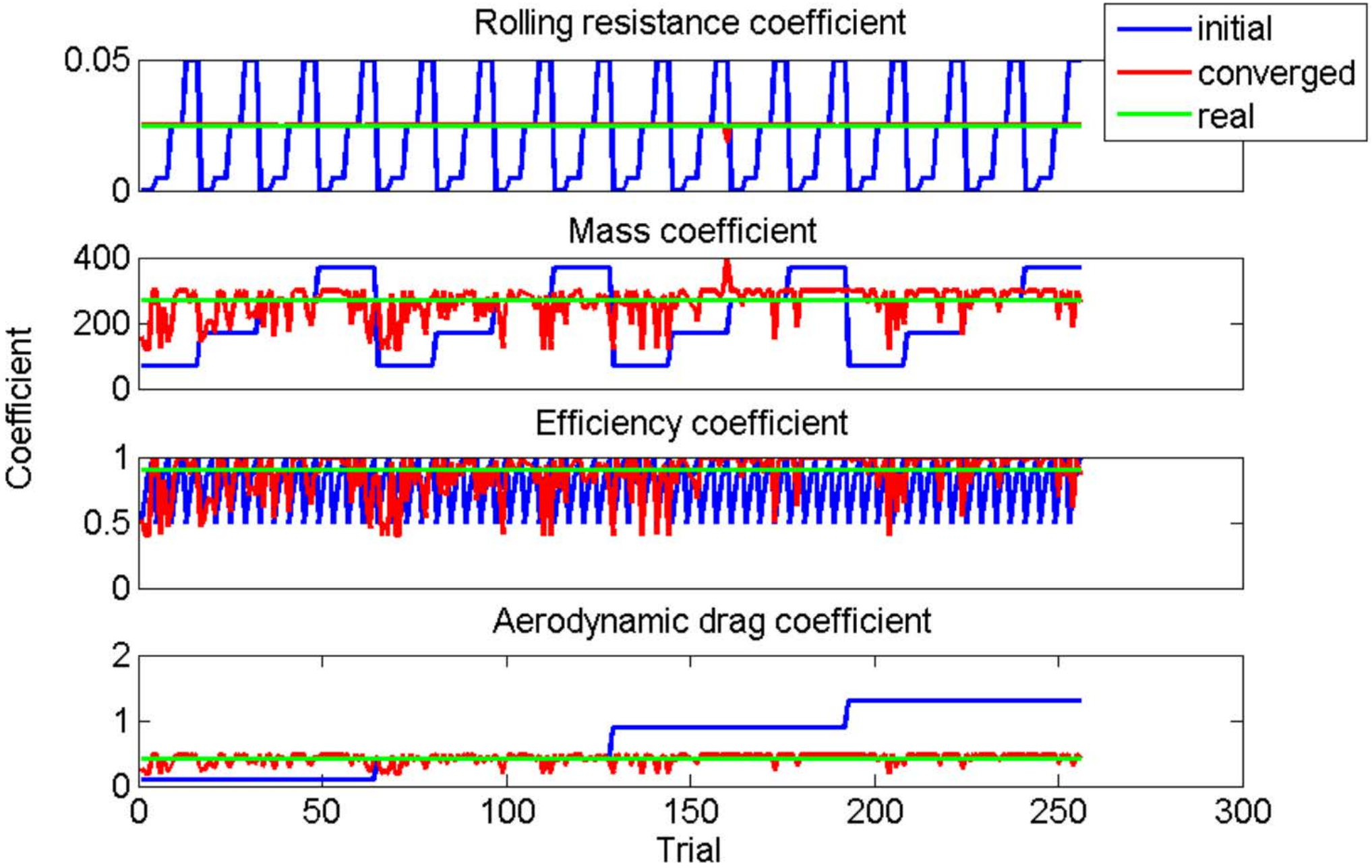
(Naïve) Signal analysi


v
F_a
F_g
F_t
m·g
F_r
α



$$f = \sum_{k=1}^{n} \sqrt{\left(P(t_k)_{sim} - P(t_k)_{meas}\right)^2}$$


c_{aero} - opt:0.49144
m^2
2
1
0
c_r - opt:0.020623
0.1
0.05
0
m_v - opt:300.1433
kg
400
200
0
η - opt:0.95733
1
0.5
0
0
50
100
150
200
250
300
350
400
450
Iteration


Rolling resistance coefficient
initial
converged
real
0.05
0
Mass coefficient
400
200
0
Efficiency coefficient
1
0.5
0
Aerodynamic drag coefficient
2
1
0
Coefficient
0
50
100
150
200
250
300
Trial

Identification Methods

Optimization

Complex, correct, and robust, but not efficient

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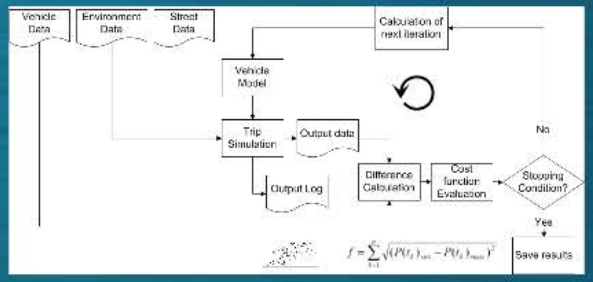

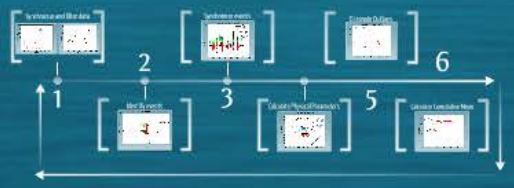

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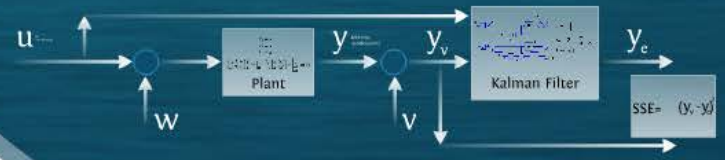
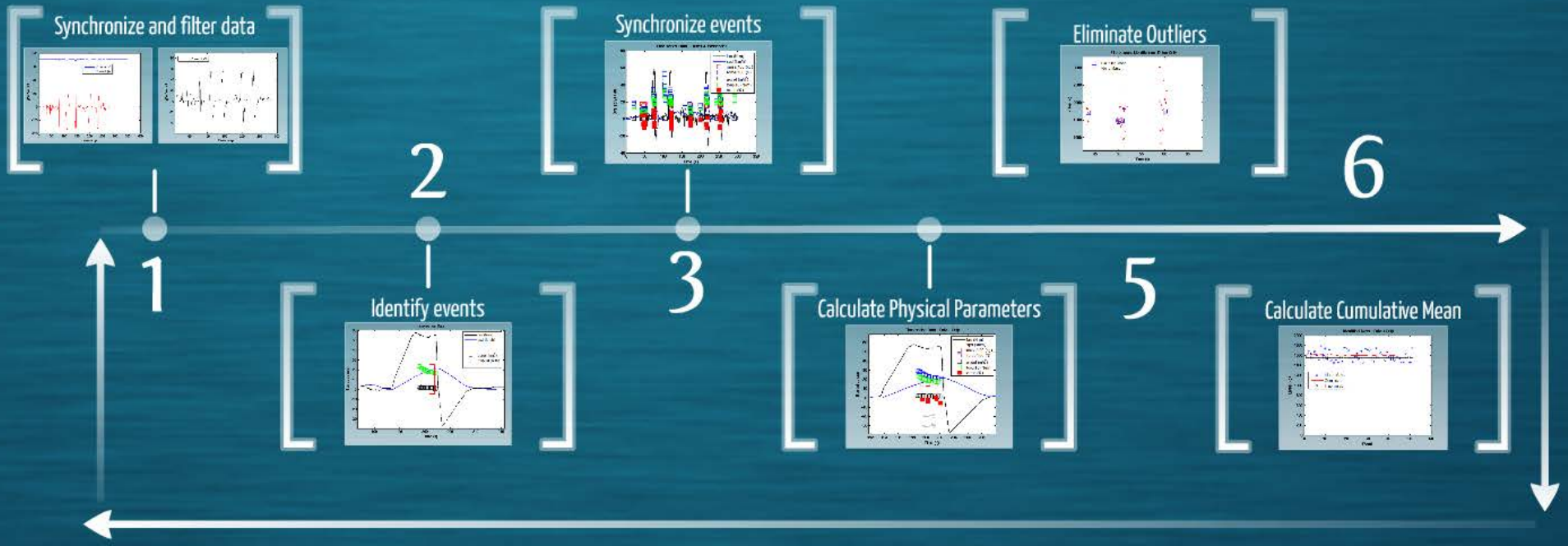
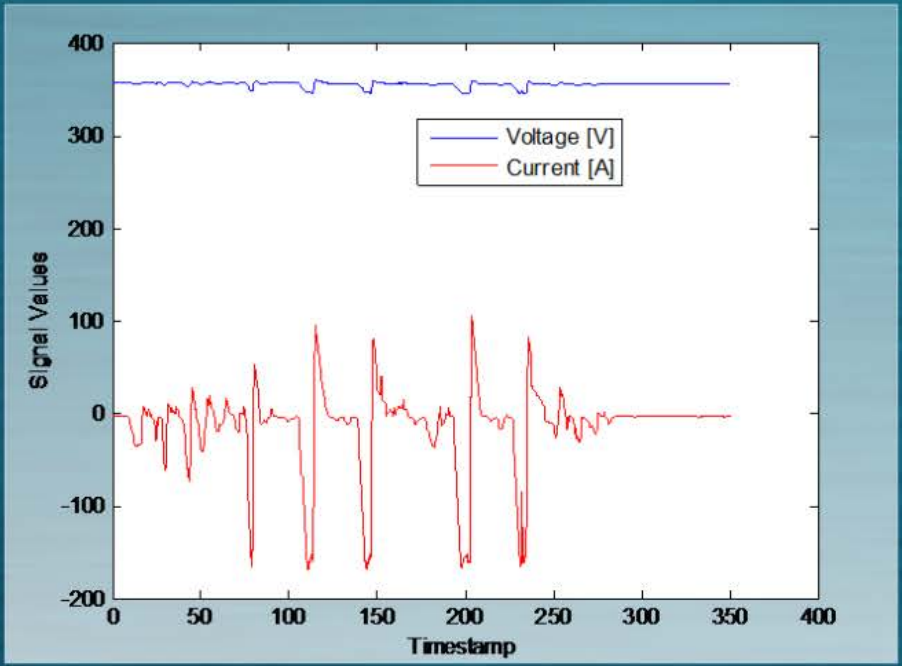
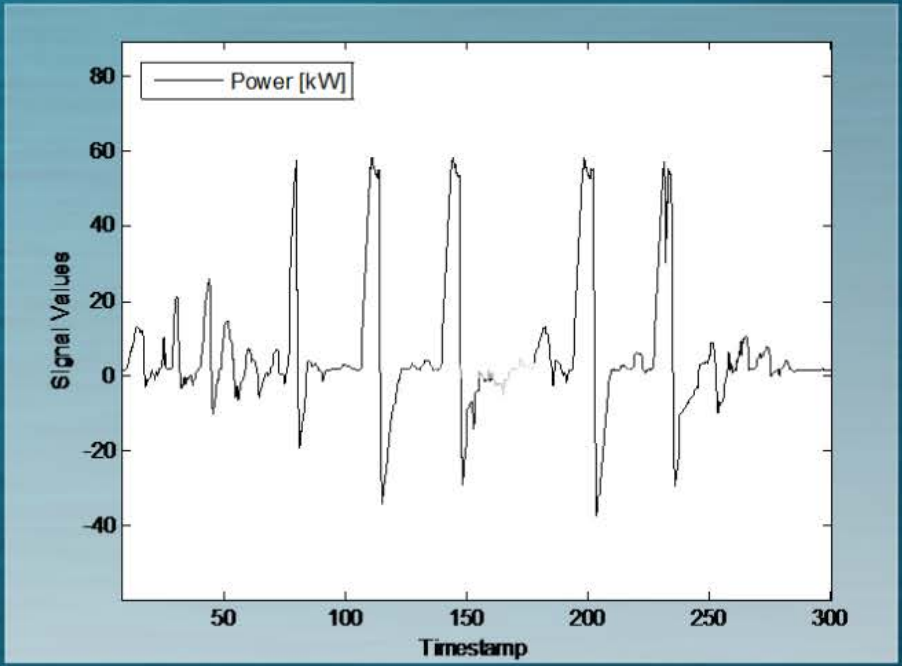



Synchronize and filter data
1
Identify events
2
Synchronize events
3
Calculate Physical Parameters
5
Eliminate Outliers
6
Calculate Cumulative Mean

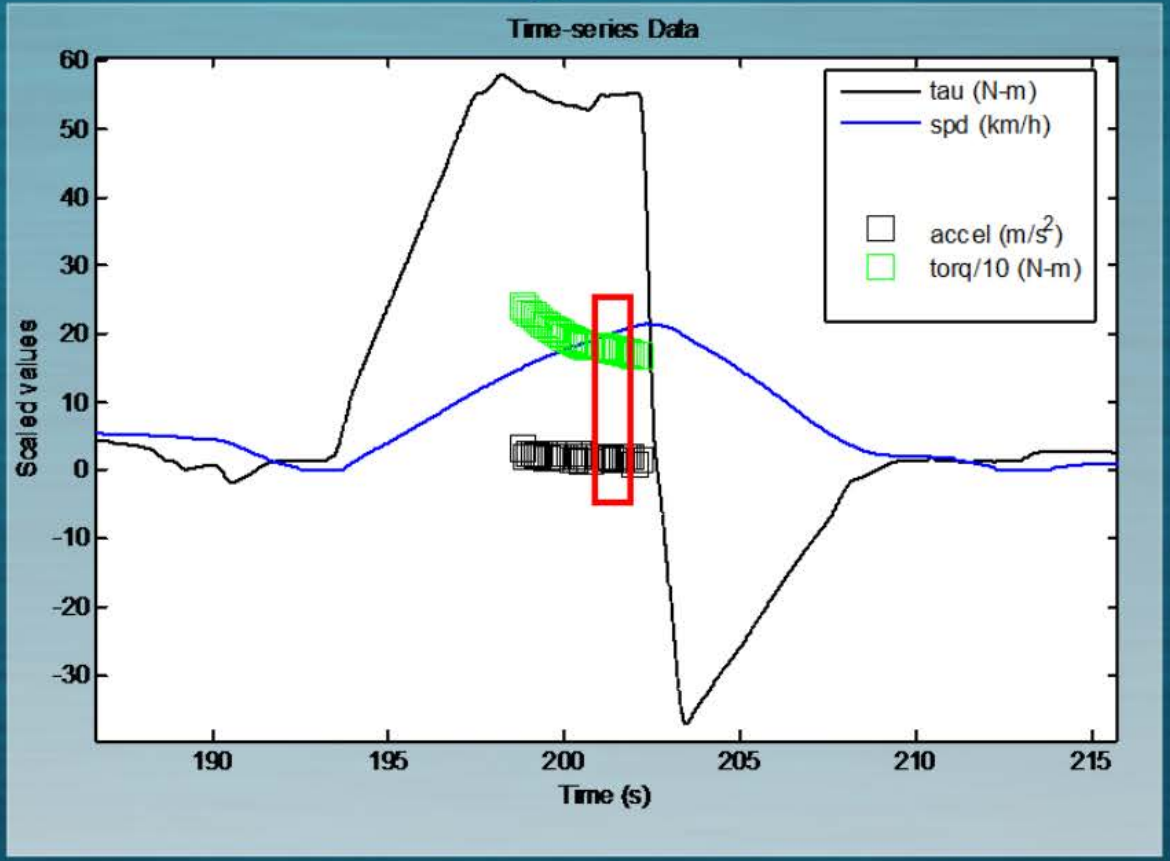
Model base

Synchronize and filter data

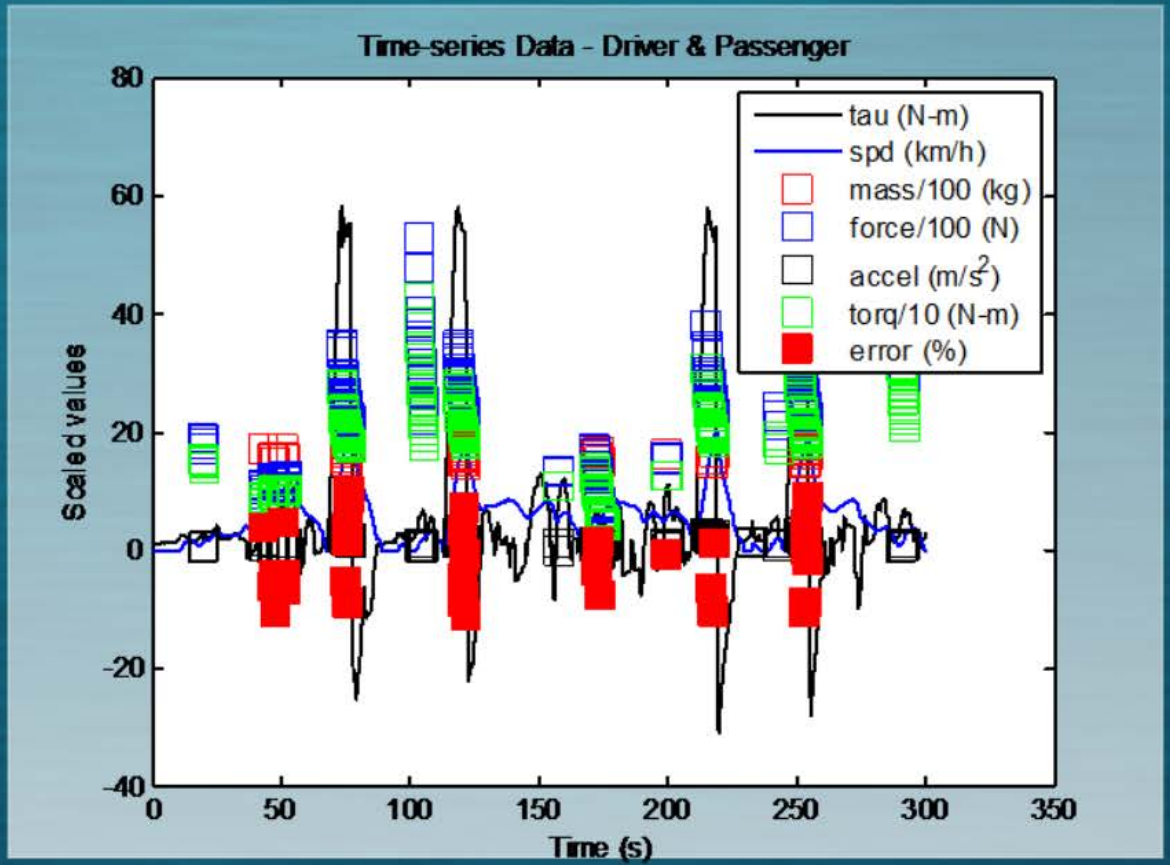




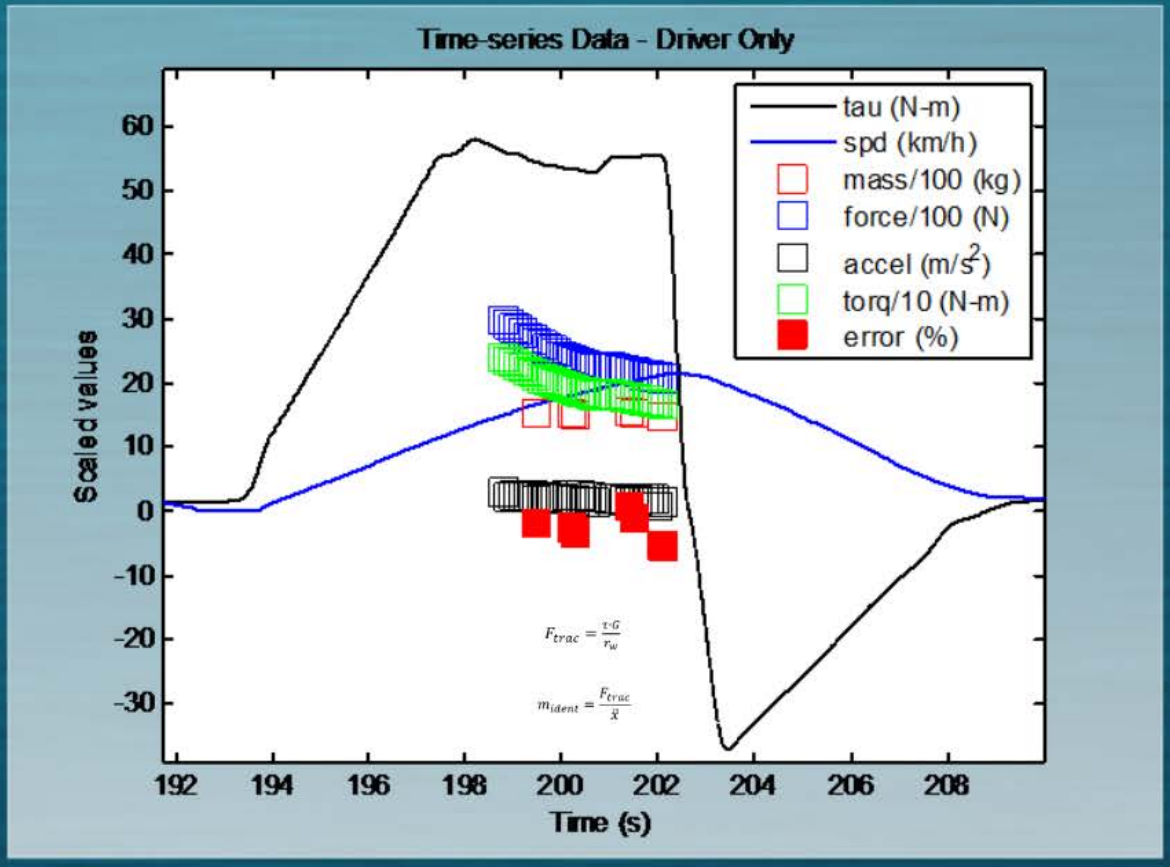
Identify events



Synchronize events



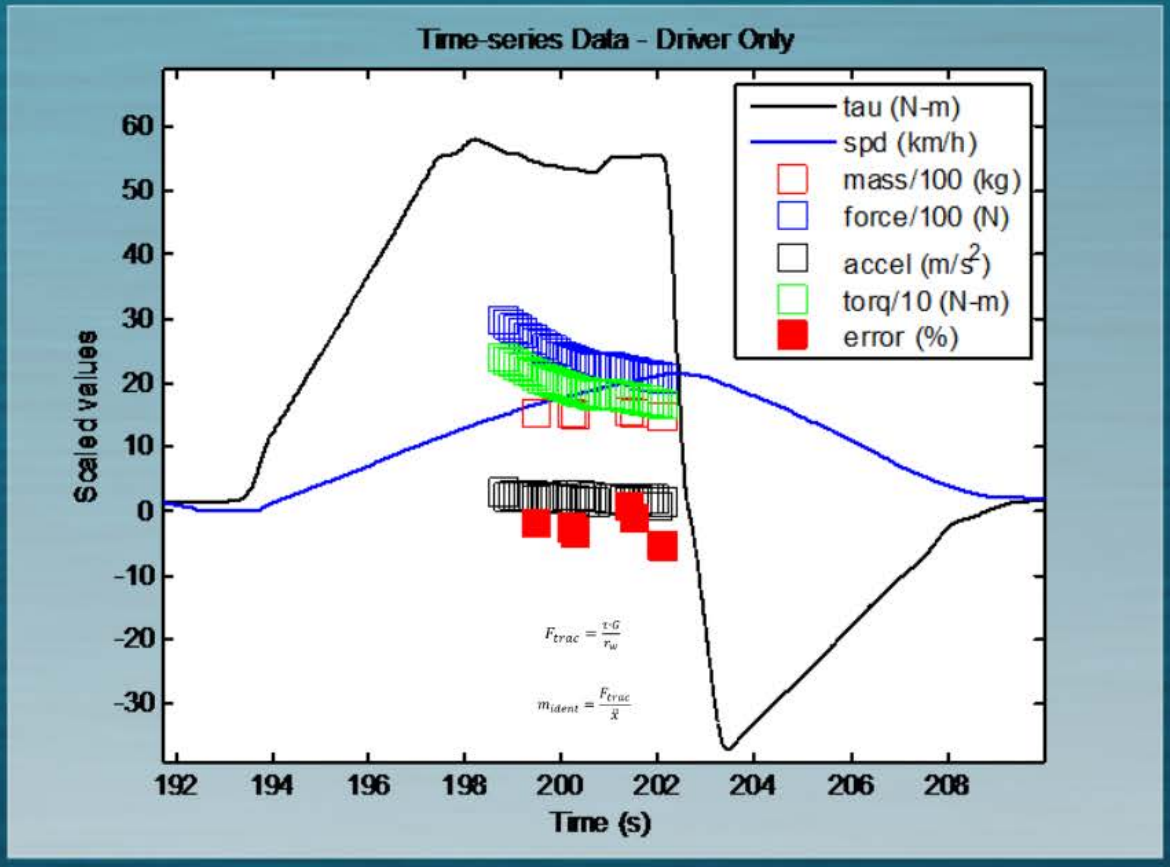
Calculate Physical Parameters



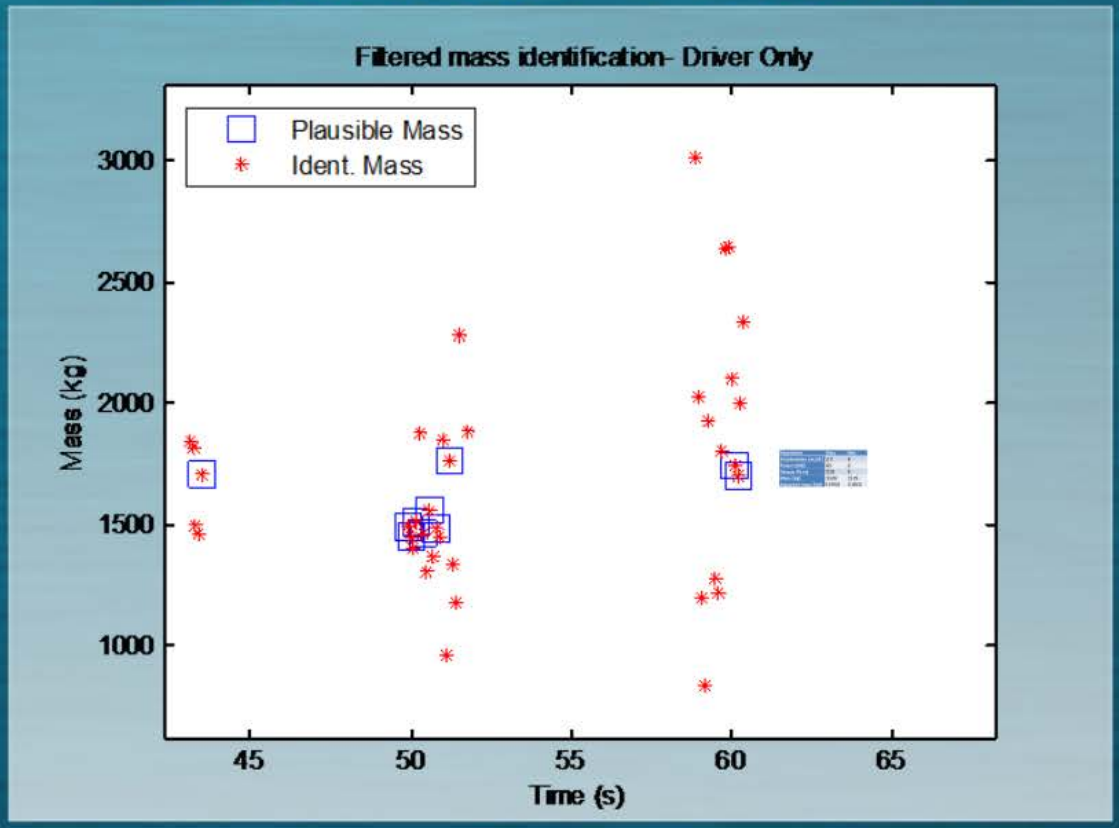
$$F_{trac} = \frac{\tau \cdot G}{r_w}$$

$$m_{ident} = \frac{F_{trac}}{\ddot{x}}$$

Calculate Physical Parameters

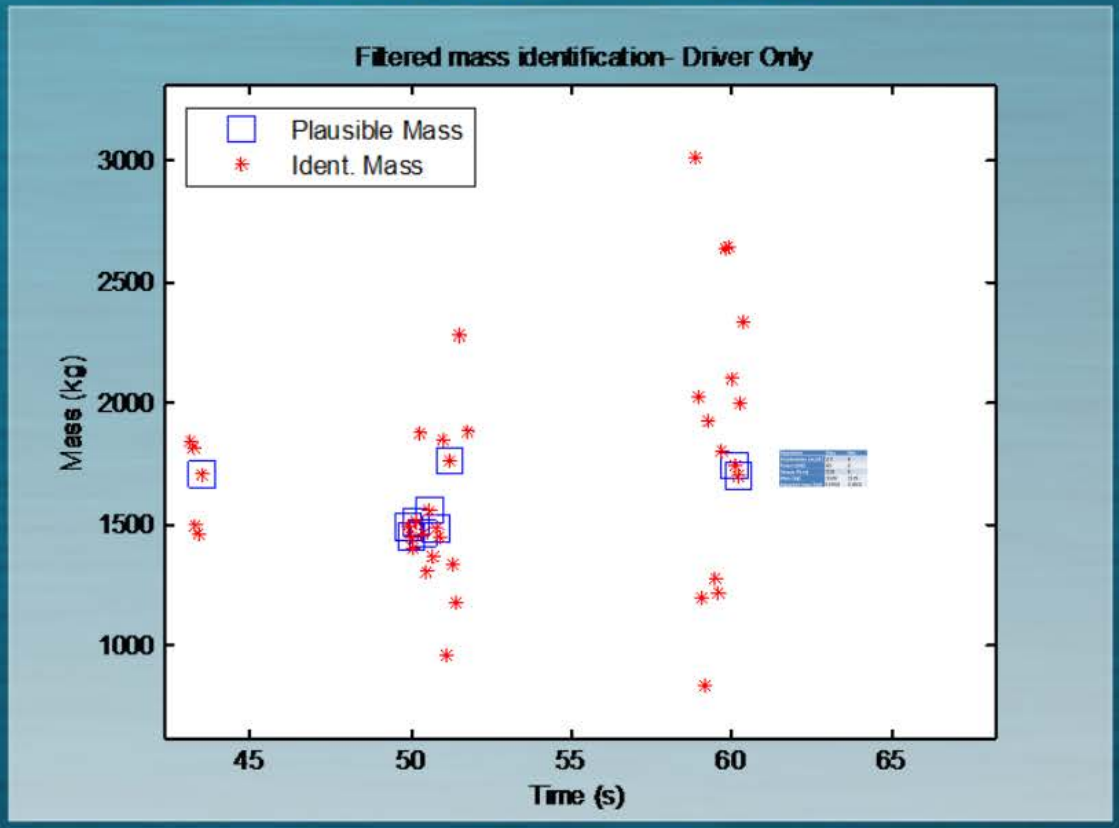


Eliminate Outliers

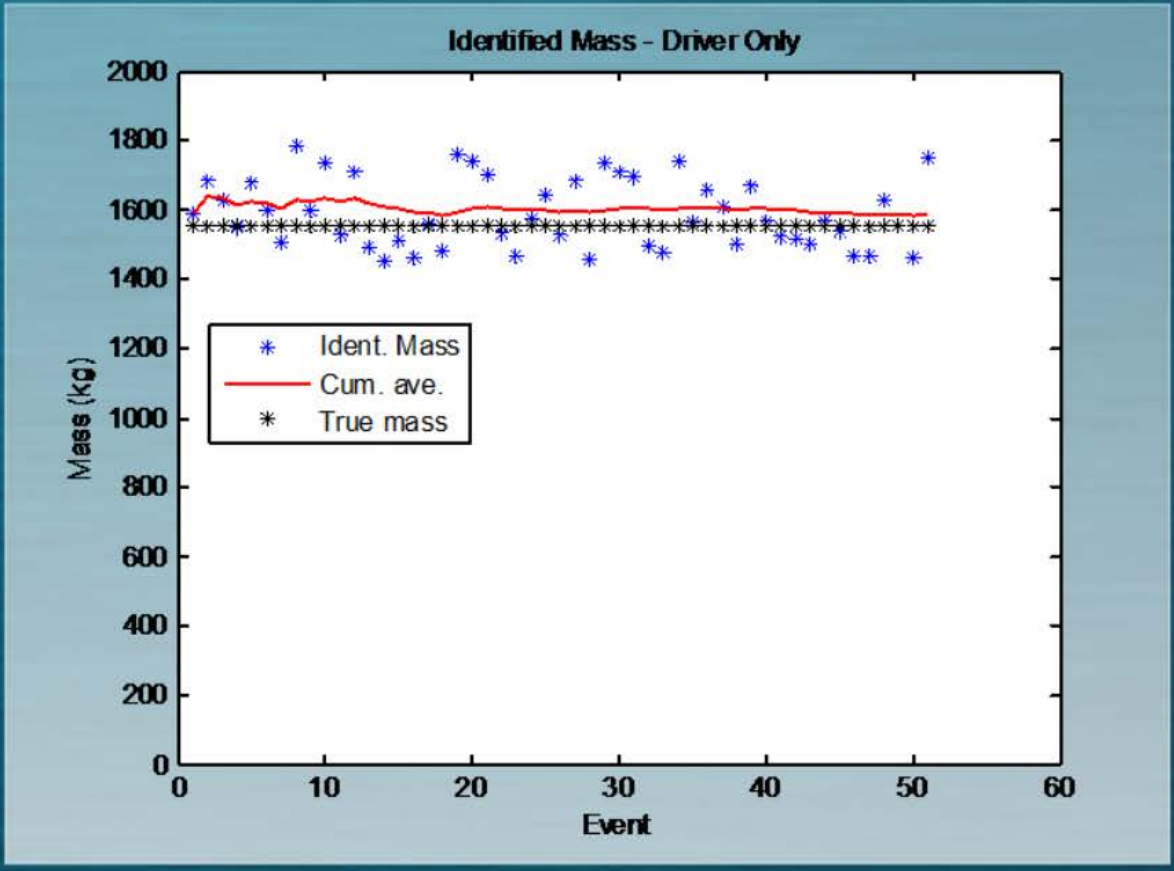


Parameter	Max	Min
Acceleration (m/s2)	2.7	0
Power (kW)	60	0
Torque (N-m)	220	0
Mass (kg)	1520	1125
Apparent mass (kg)	(1958)	(1450)

Eliminate Outliers



Calculate Cumulative Mean



Identification Methods

Optimization

Complex, correct, and robust, but not efficient

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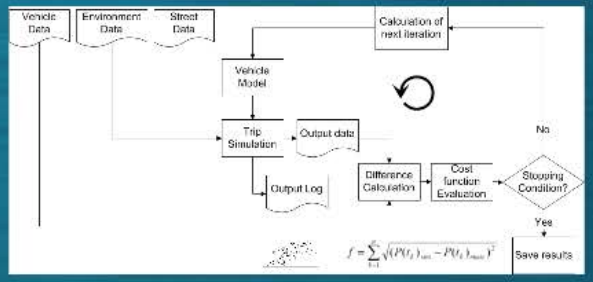

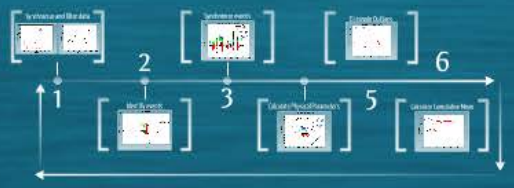

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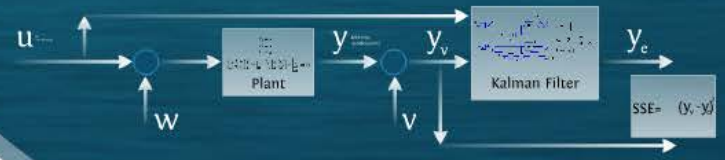

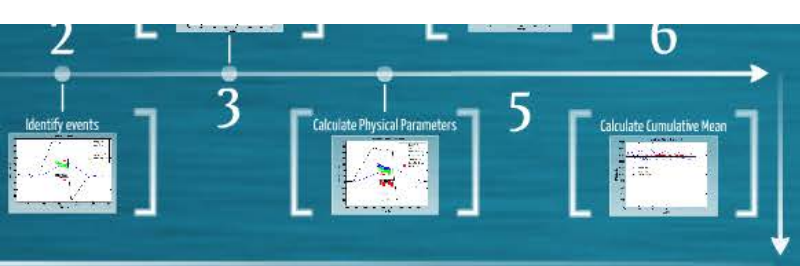

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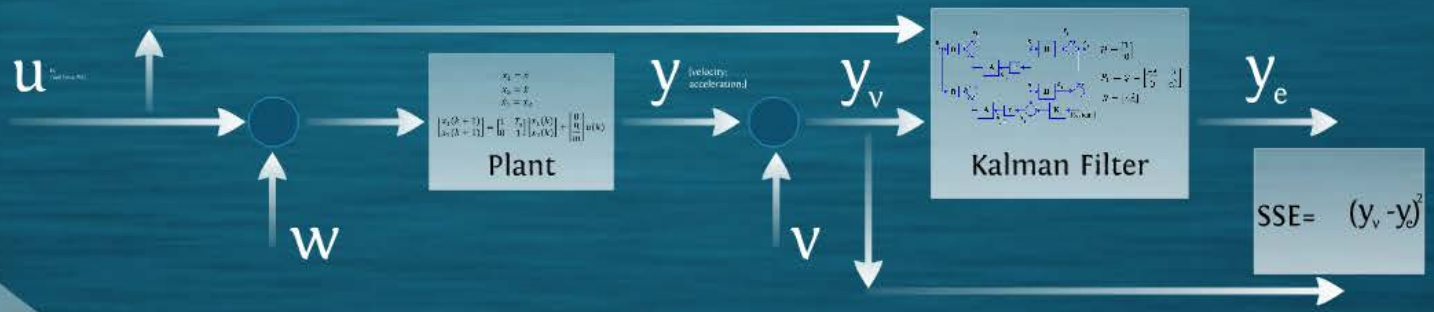


u

[0;
road force [N];]

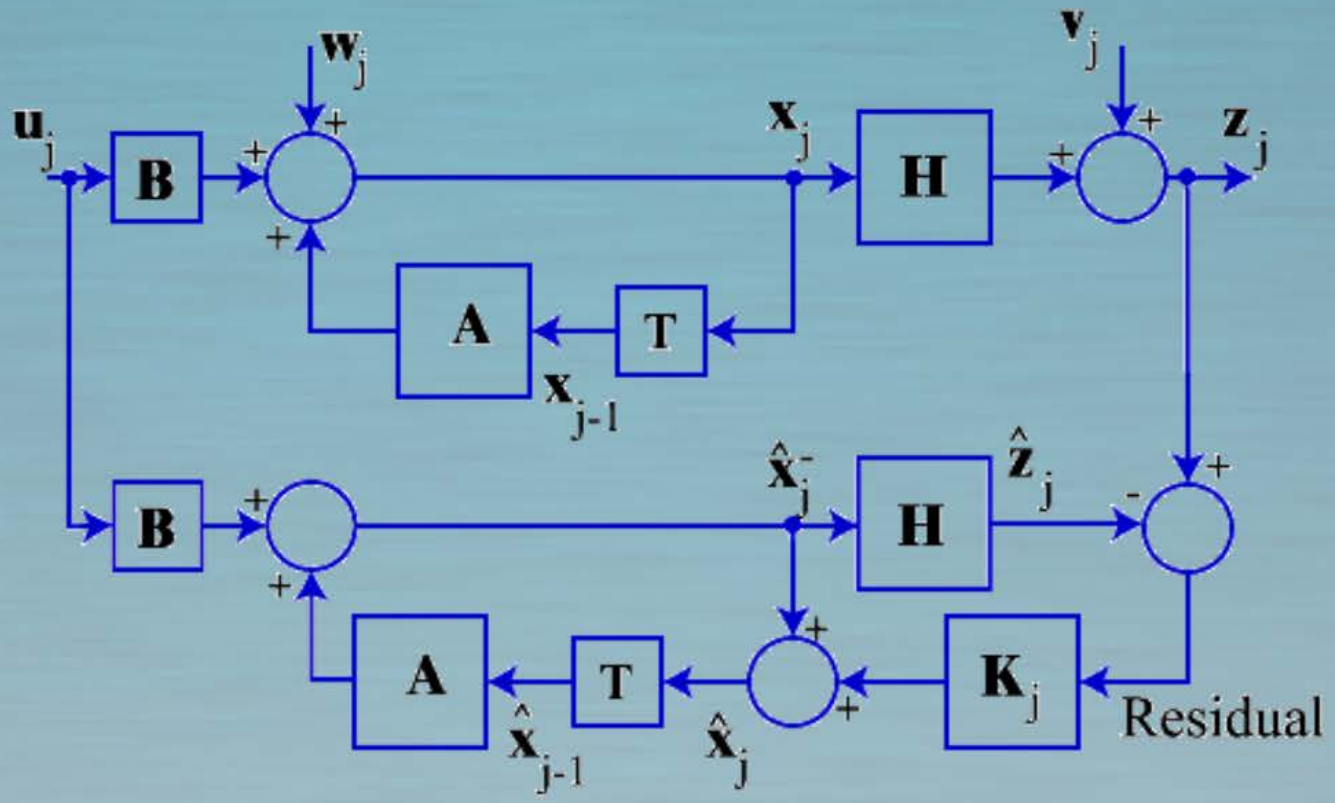
$$x_1 = \dot{x}$$

$$x_2 = \ddot{x}$$

$$\dot{x}_1 = x_2$$

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{\eta}{m} \end{bmatrix} u(k)$$

Plant



$$H = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$P_0 = Q = \begin{bmatrix} \sigma_{\text{proc}}^2 & 0 \\ 0 & \sigma_{\text{proc}}^2 \end{bmatrix}$$

$$R = [\sigma_{\text{meas}}^2]$$

Kalman Filter

Identification Methods

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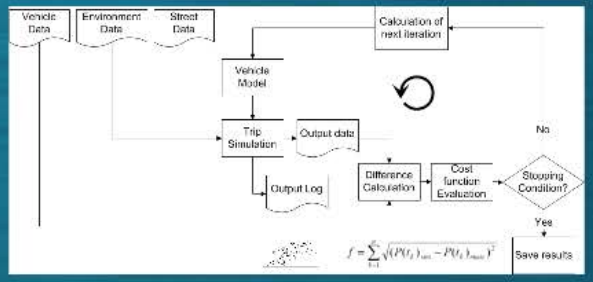

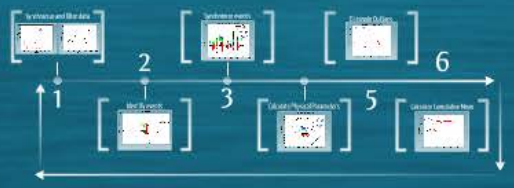

(Naïve) Signal analysis

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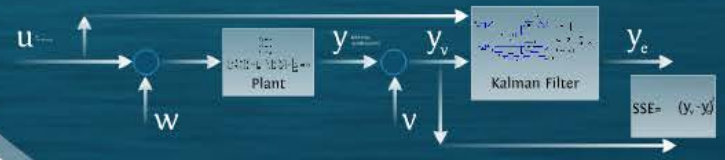
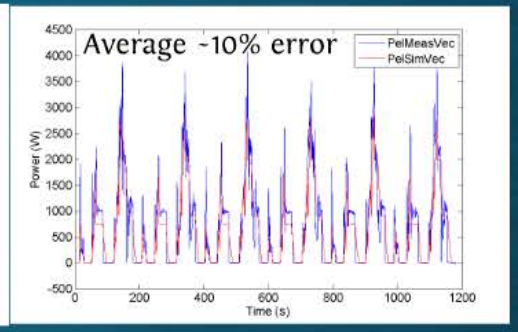
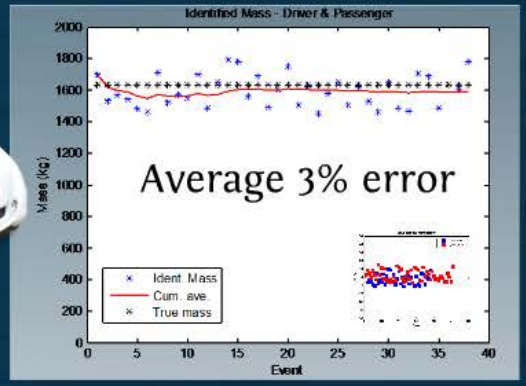


Identification Results

Optimization

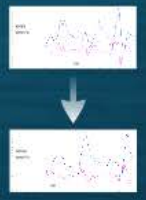


(Naïve) Signal analysis



Model-based signal analysis

LQE signals with F=ma

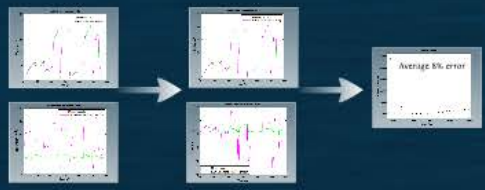


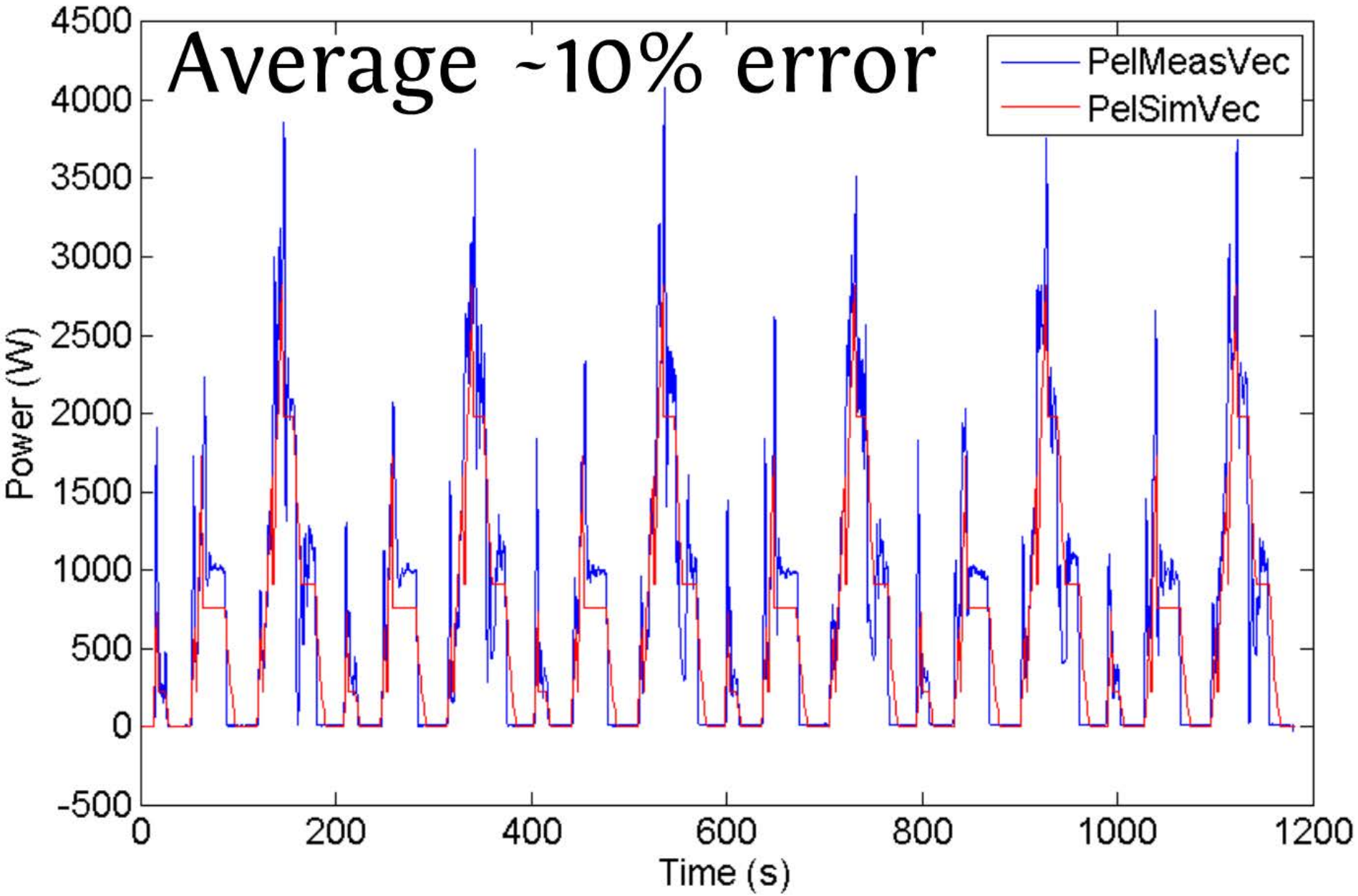
relative= mass of passenger

absolute= mass of full vehicle

Passengers	Relative Error	Absolute Error
0	N/A	2.6%
1	24%	2.6%
2	22%	2.6%
3	40%	5.6%
4	25%	7.6%

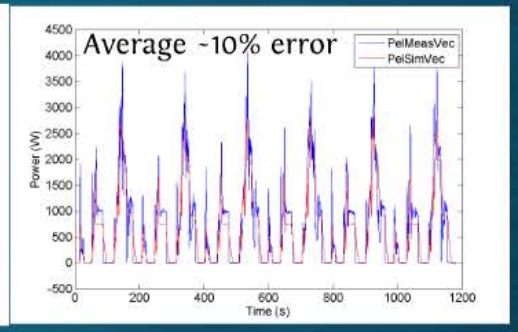
Mass optimization



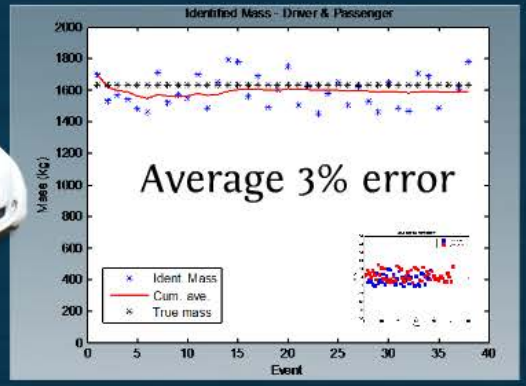

Average ~10% error
PelMeasVec
PelSimVec
Power (W)
Time (s)
4500
4000
3500
3000
2500
2000
1500
1000
500
0
-500
0
200
400
600
800
1000
1200

Identification Results

Optimization



(Naïve) Signal analysis



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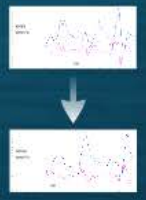

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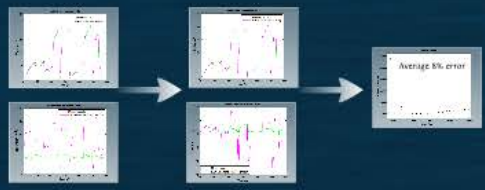
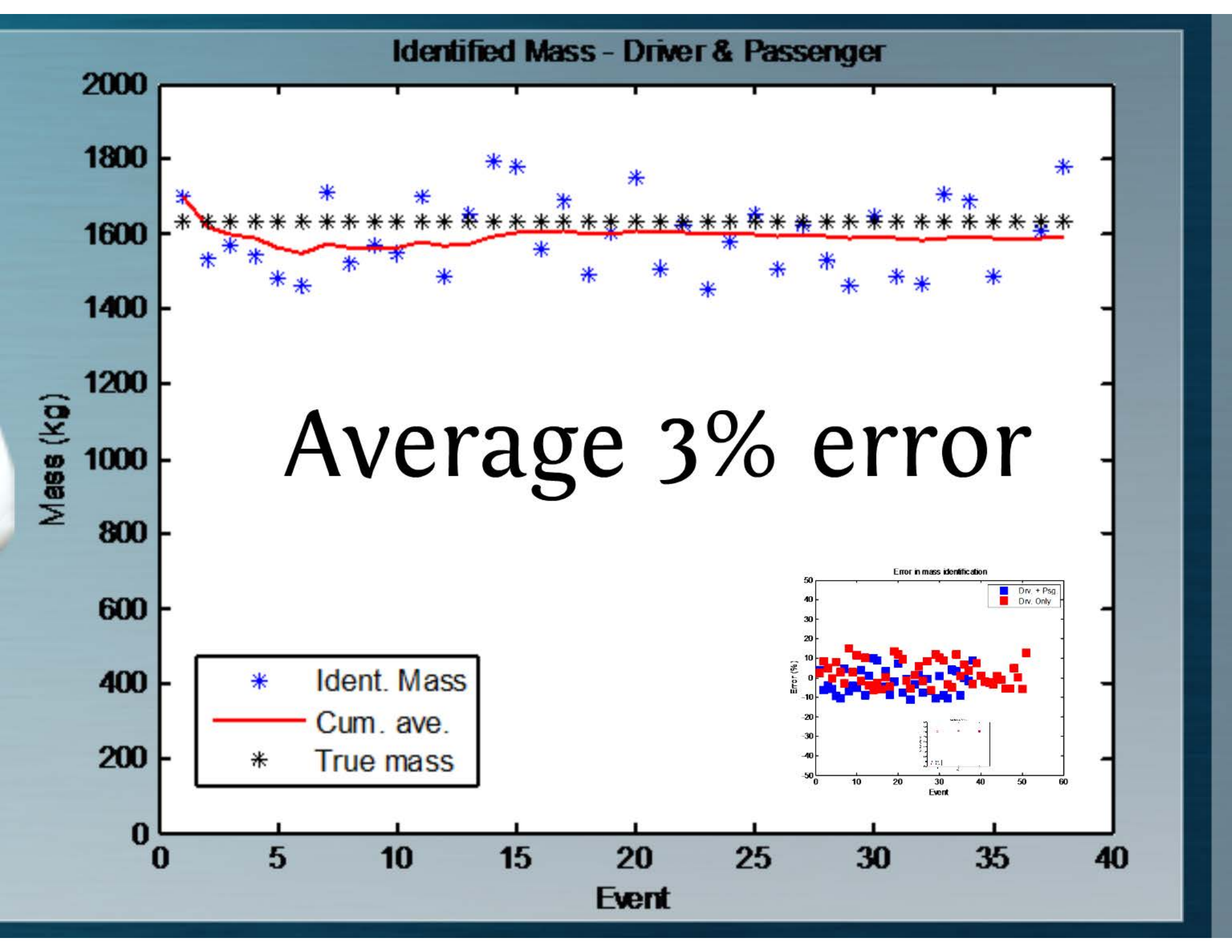
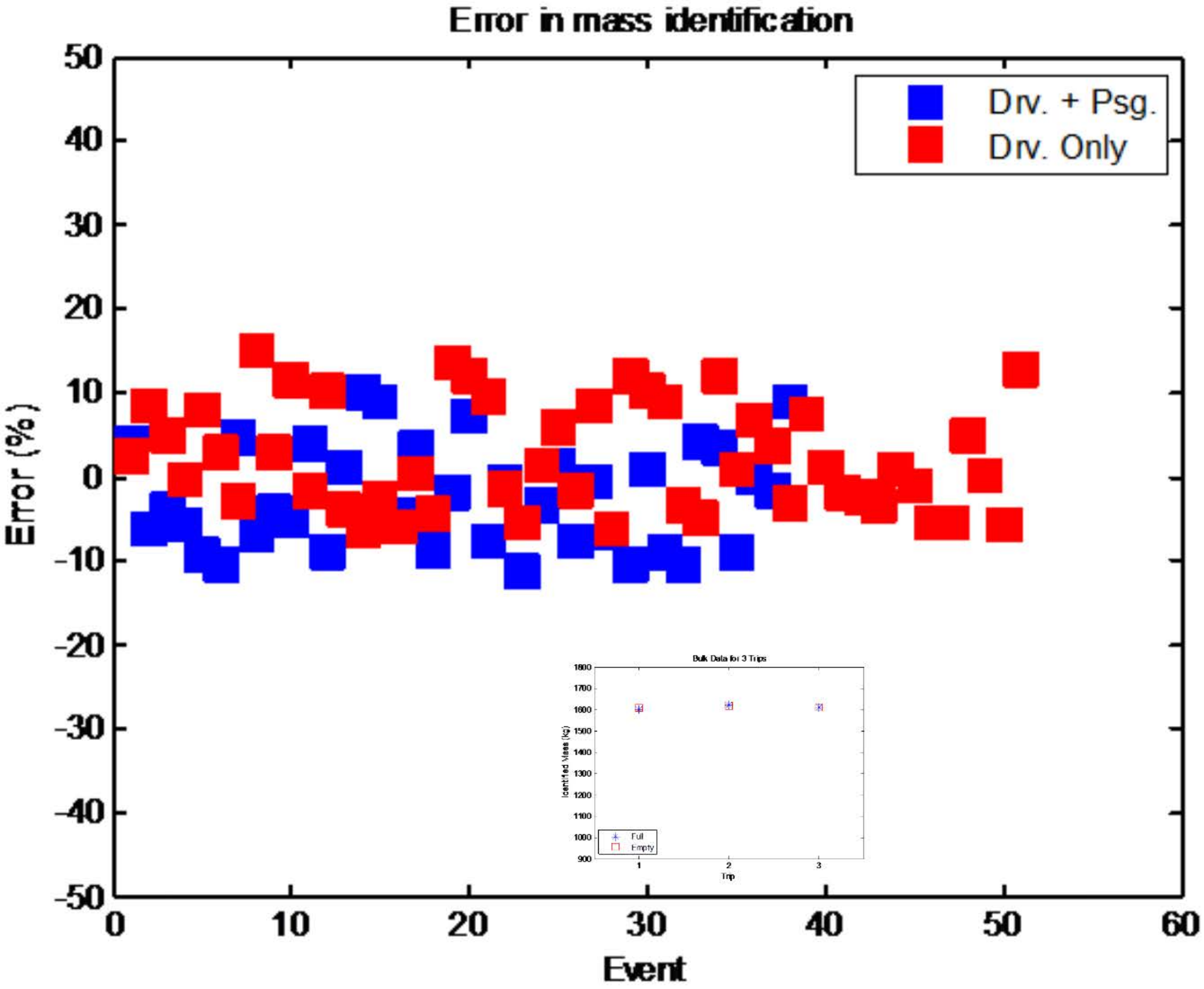
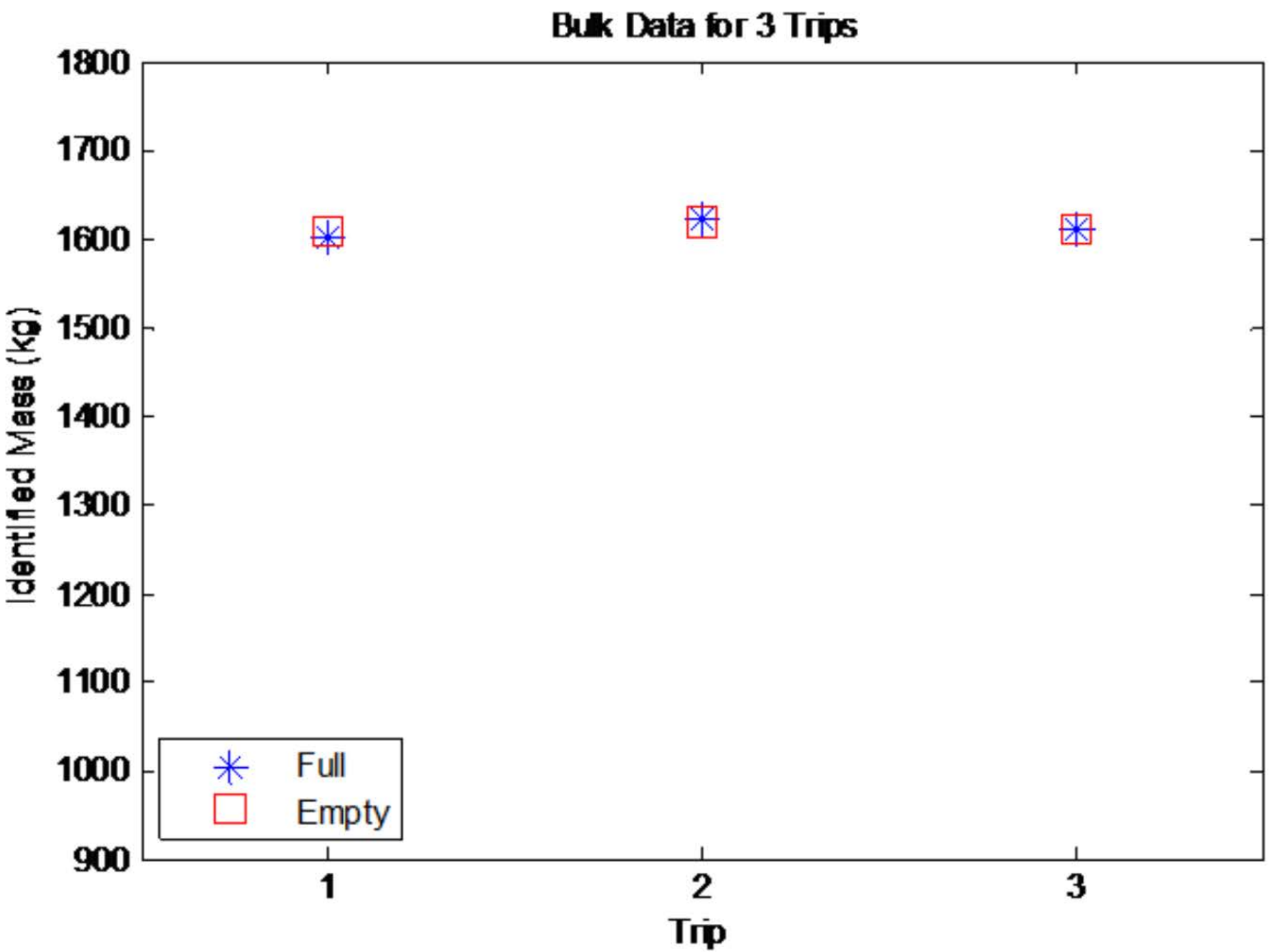
Mass optimization




YouTube

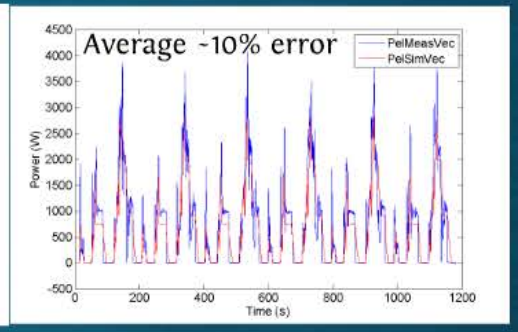

Identified Mass - Driver & Passenger
Mass (kg)
Event
Ident. Mass
Cum. ave.
True mass
Average 3% error
Error in mass identification
Drv. + Psg.
Drv. Only
Error (%)
Event


Error in mass identification
Drv. + Psg.
Drv. Only
Error (%)
Event
50
40
30
20
10
0
-10
-20
-30
-40
-50
0
10
20
30
40
50
60
Bulk Data for 3 Trips
Identified Mass (Kg)
Full
Empty
Trip
1800
1700
1600
1500
1400
1300
1200
1100
1000
900
1
2
3

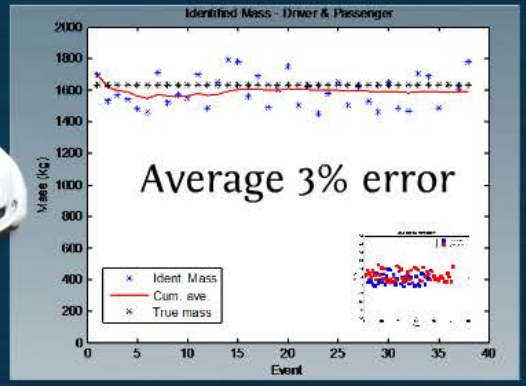

Bulk Data for 3 Trips
1800
1700
1600
1500
1400
1300
1200
1100
1000
900
Identified Mass (kg)
1
2
3
Trip
Full
Empty

Identification Results

Optimization

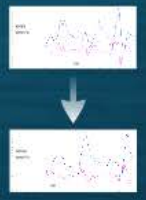


(Naïve) Signal analysis



Model-based signal analysis

LQE signals with F=ma

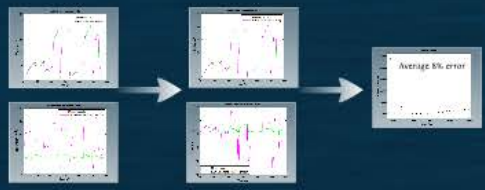


relative= mass of passenger

absolute= mass of full vehicle

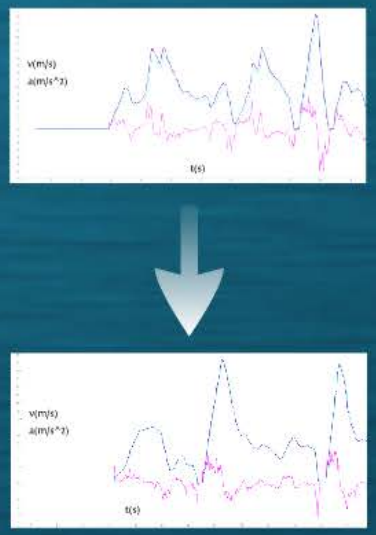
Passengers	Relative Error	Absolute Error
0	N/A	2.6%
1	24%	2.6%
2	22%	2.6%
3	40%	5.6%
4	25%	7.6%

Mass optimization



Model-based signal analys

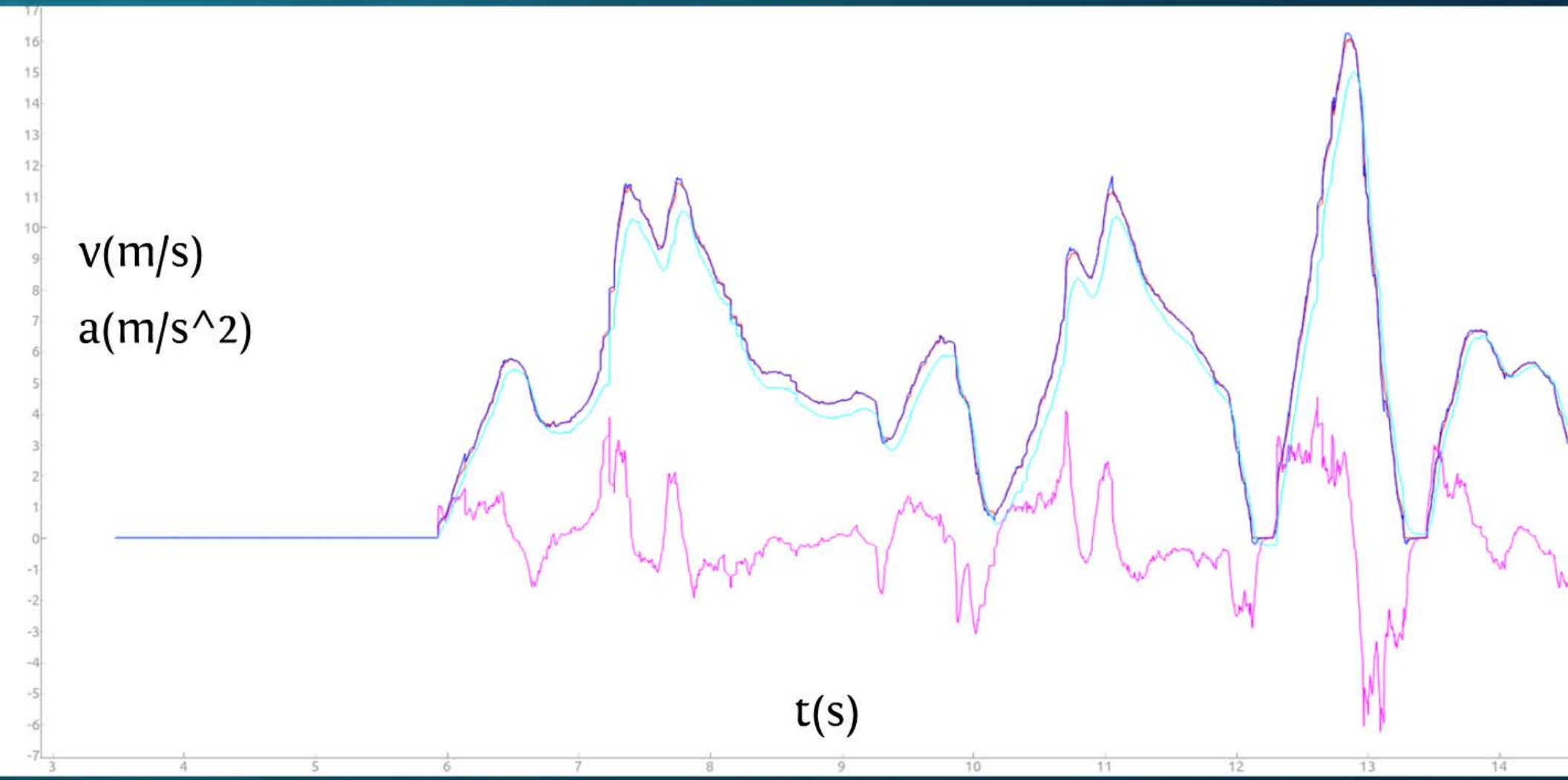
LQE signals with F=ma

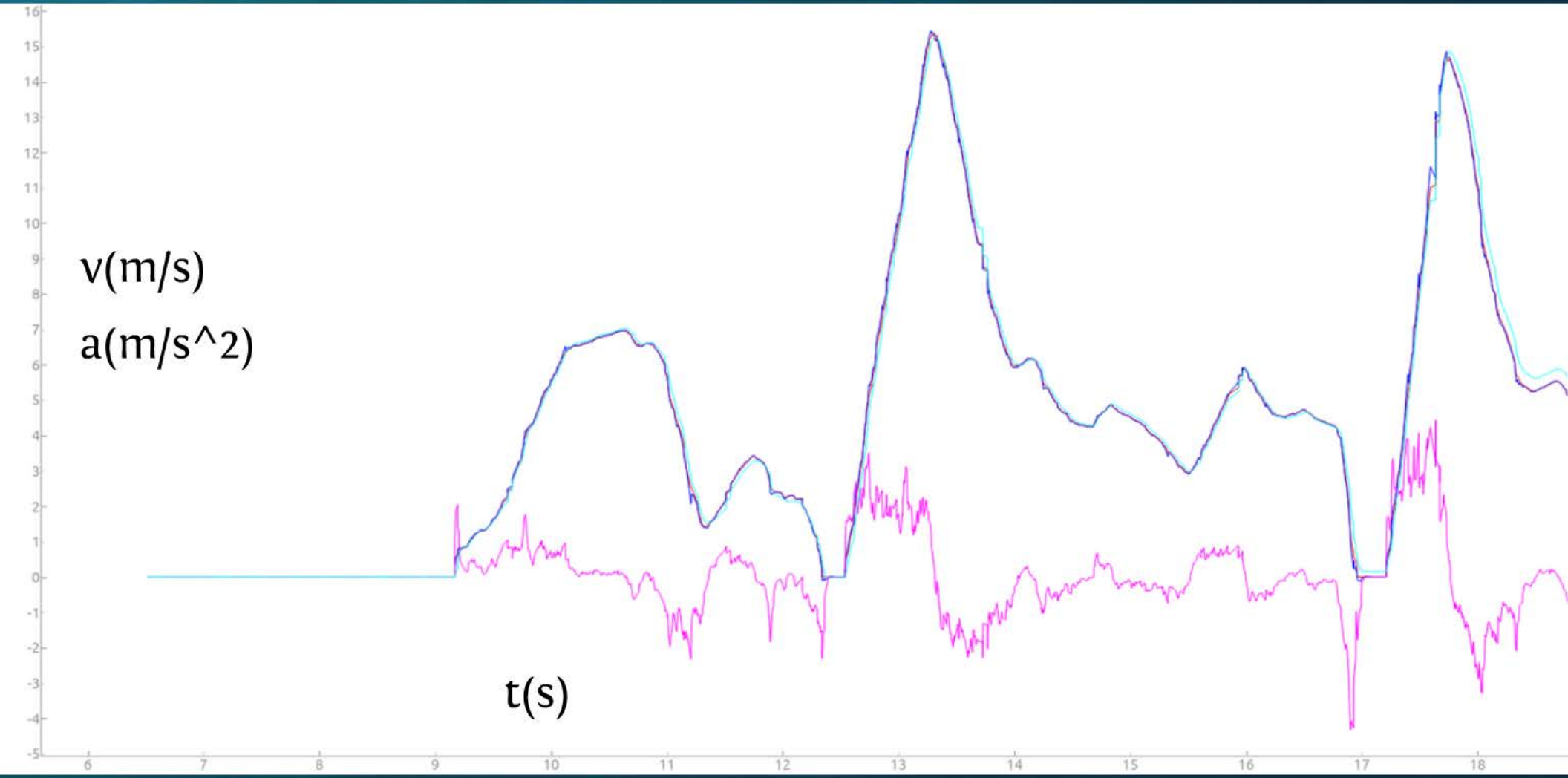


relative= mass of passenger

absolute= mass of full vehicle

Passengers	Relative Error	Absolute Error
0	N/A	4.4%
1	-24%	4.4%
2	-23%	4.4%
3	-47%	3.6%
4	-78%	2.0%


v(m/s)
a(m/s^2)
t(s)


v(m/s)
a(m/s^2)
t(s)
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
-1
-2
-3
-4
-5
6
7
8
9
10
11
12
13
14
15
16
17
18

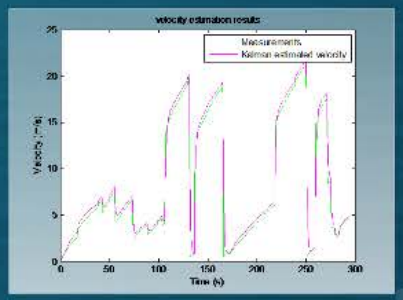

1780, -46% relative
abolute error

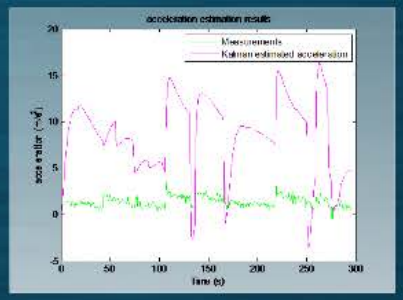
relative= mass of passenger

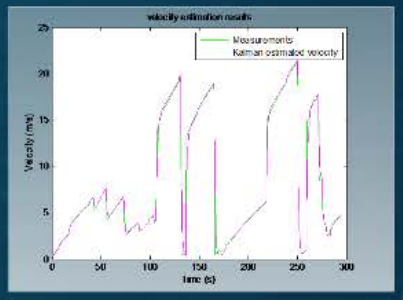
absolute= mass of full vehicle

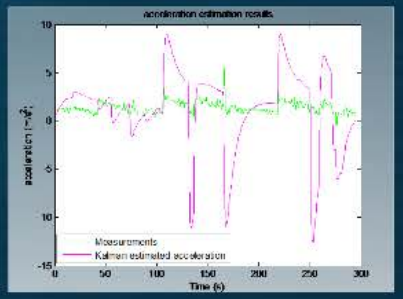
Passengers	Relative Error	Absolute Error
0	N/A	4.4%
1	-24%	4.4%
2	-23%	4.4%
3	-47%	3.6%
4	-78%	2.0%

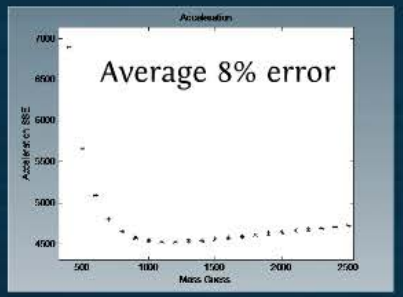
Mass optimization

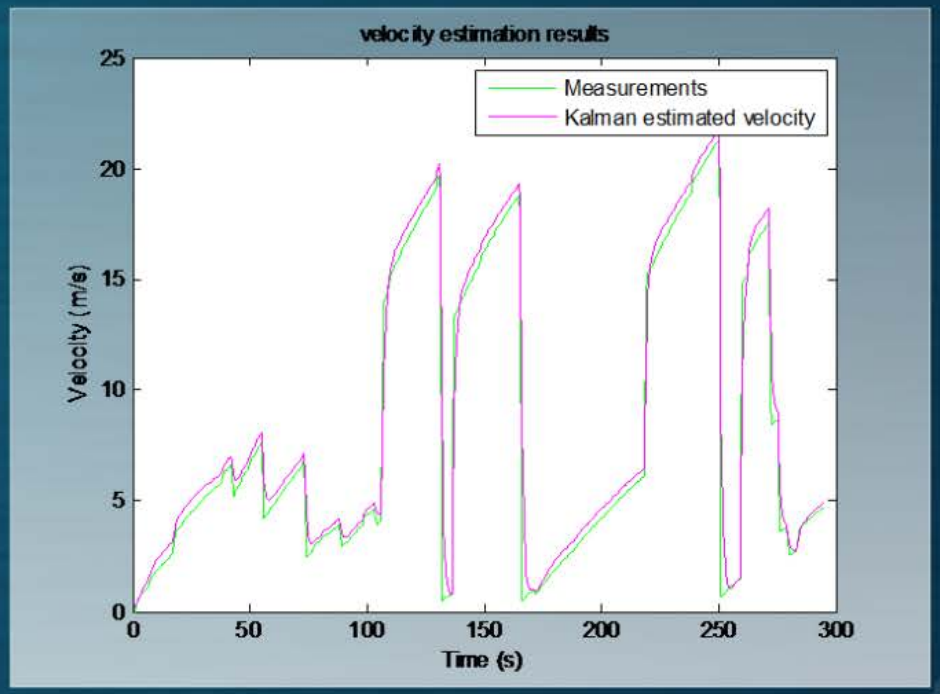


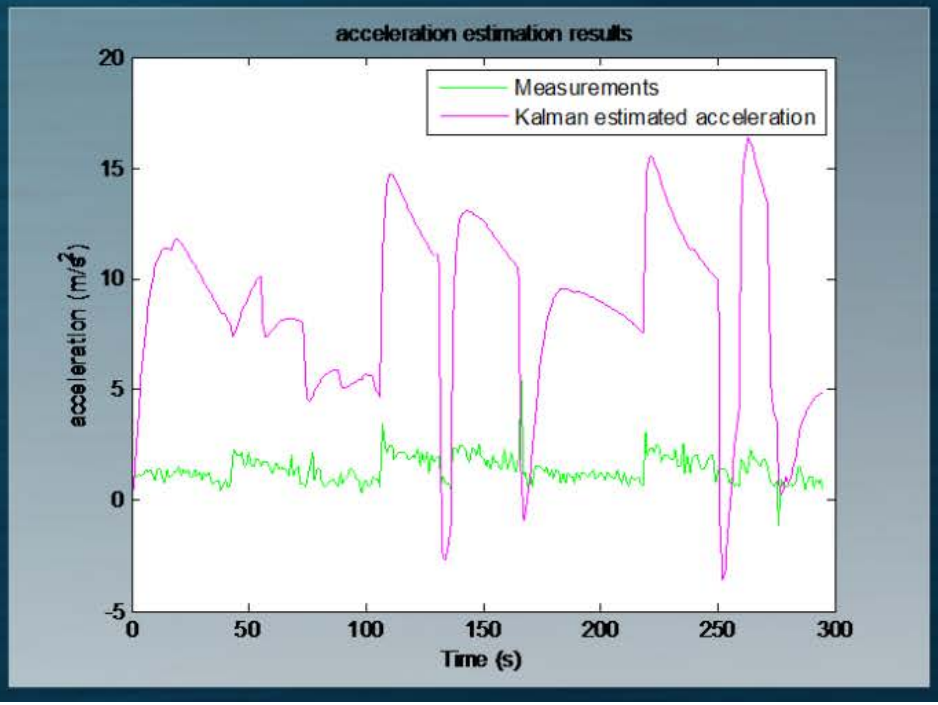


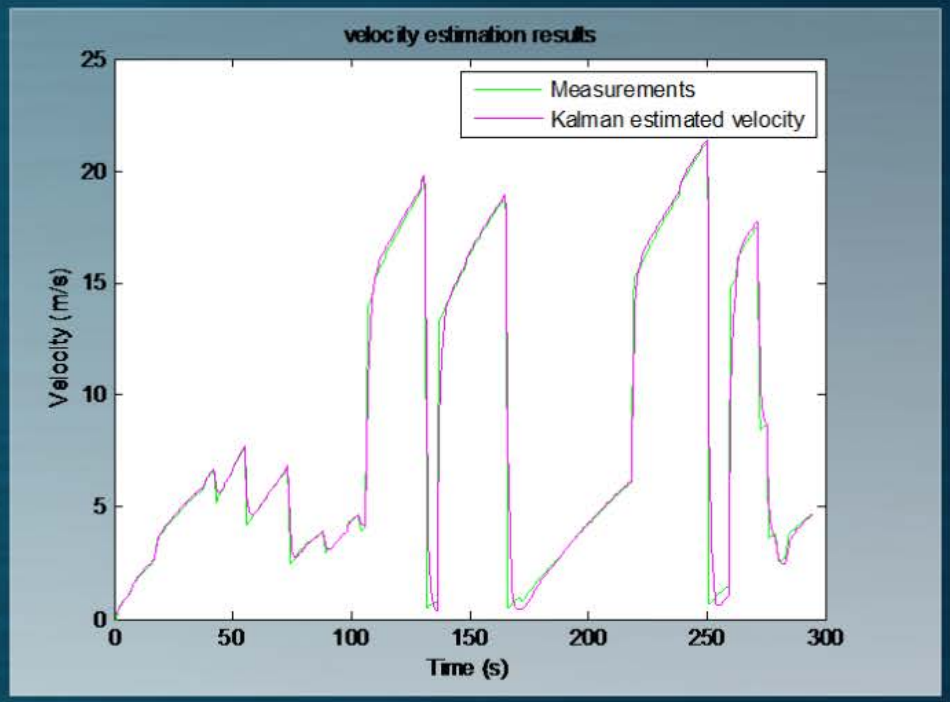


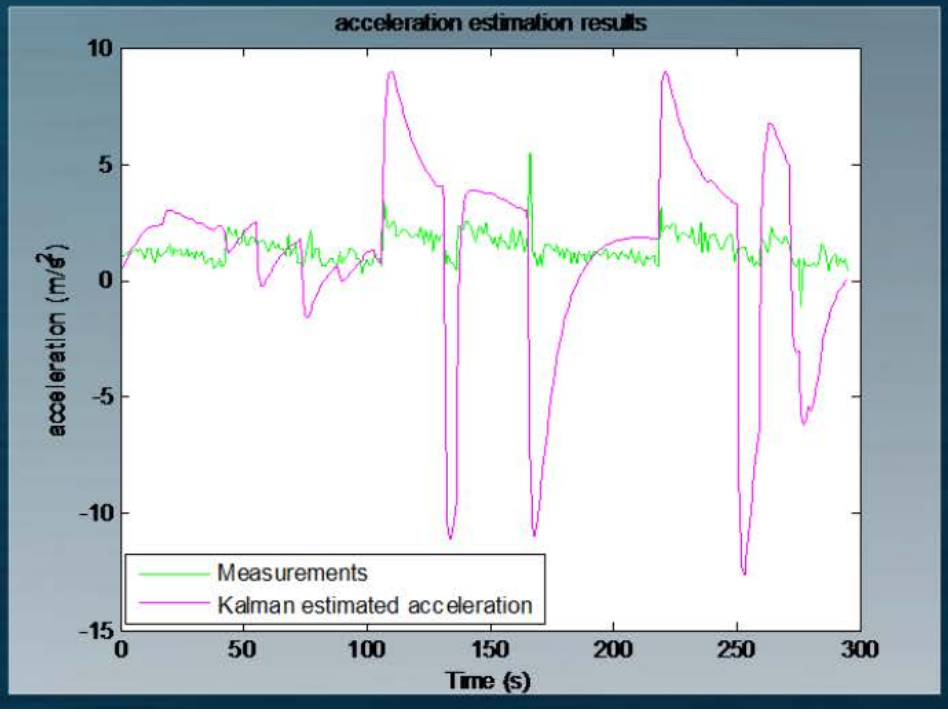


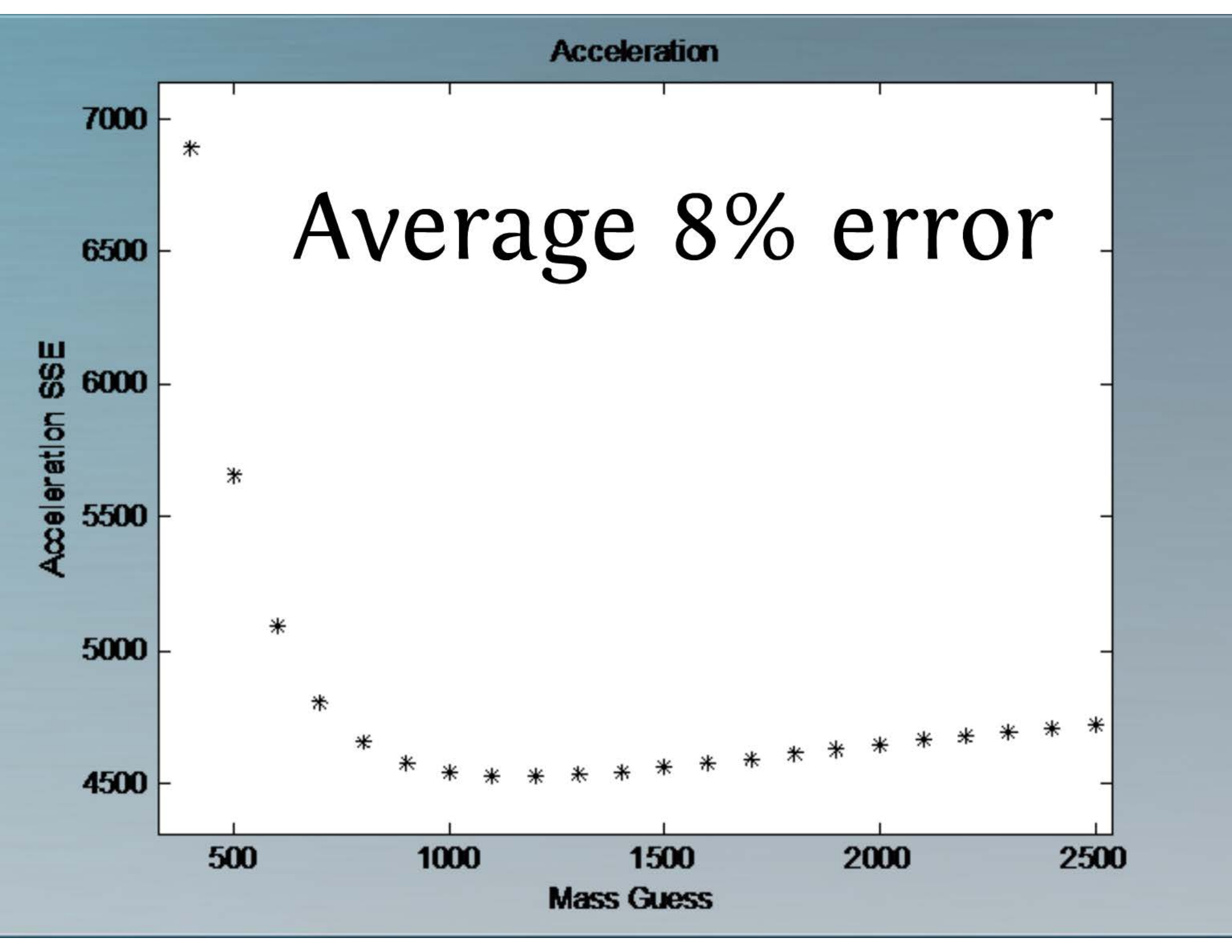



velocity estimation results
Measurements
Kalman estimated velocity
Velocity (m/s)
Time (s)
0
5
10
15
20
25
0
50
100
150
200
250
300


acceleration estimation results
Measurements
Kalman estimated acceleration
acceleration (m/s²)
Time (s)
-5
0
5
10
15
20
0
50
100
150
200
250
300

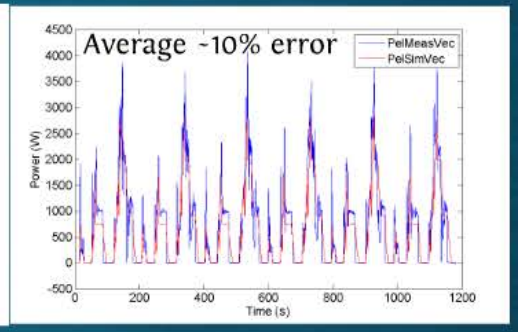

velocity estimation results
Measurements
Kalman estimated velocity
Velocity (m/s)
Time (s)
0
5
10
15
20
25
0
50
100
150
200
250
300


acceleration estimation results
Measurements
Kalman estimated acceleration
acceleration (m/s2)
Time (s)
10
5
0
-5
-10
-15
0
50
100
150
200
250
300

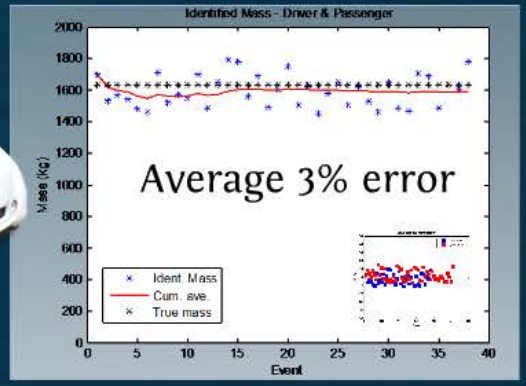

Acceleration
Average 8% error
Acceleration SSE
7000
6500
6000
5500
5000
4500
500
1000
1500
2000
2500
Mass Guess

Identification Results

Optimization

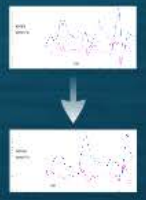


(Naïve) Signal analysis



Model-based signal analysis

LQE signals with F=ma

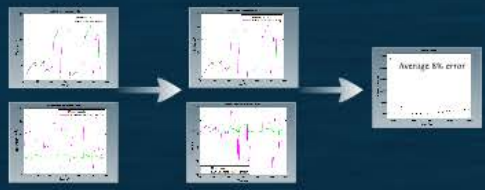


relative= mass of passenger

absolute= mass of full vehicle

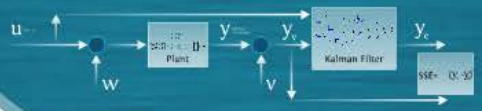
Passengers	Relative Error	Absolute Error
0	N/A	2.6%
1	24%	2.6%
2	22%	2.6%
3	40%	5.6%
4	25%	7.6%

Mass optimization

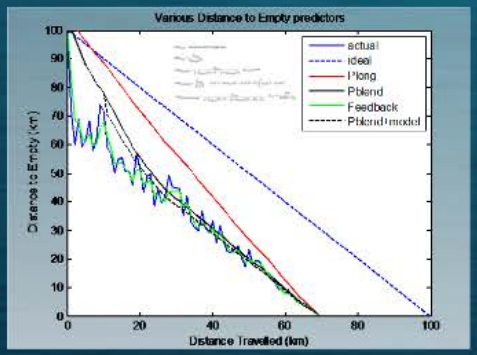


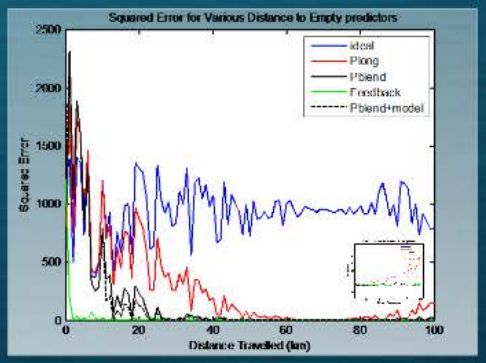
Model-based signal analysis

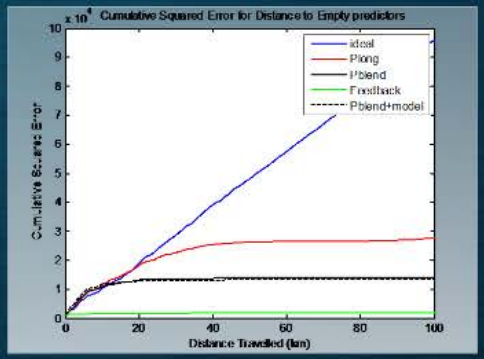
Simple, correct, efficient, and robust (we hope)



Implications for Range Estimation







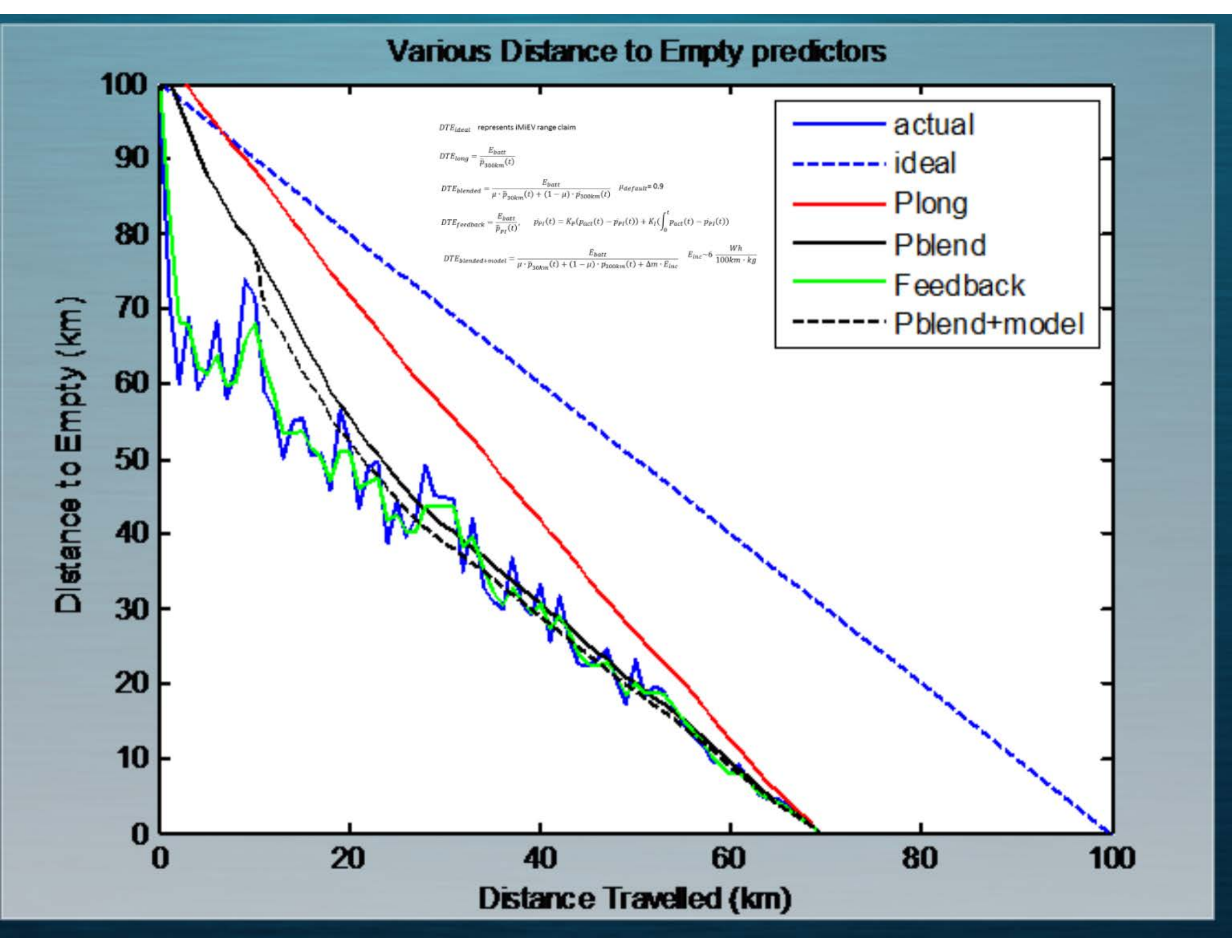
DTE_{ideal} represents iMiEV range claim

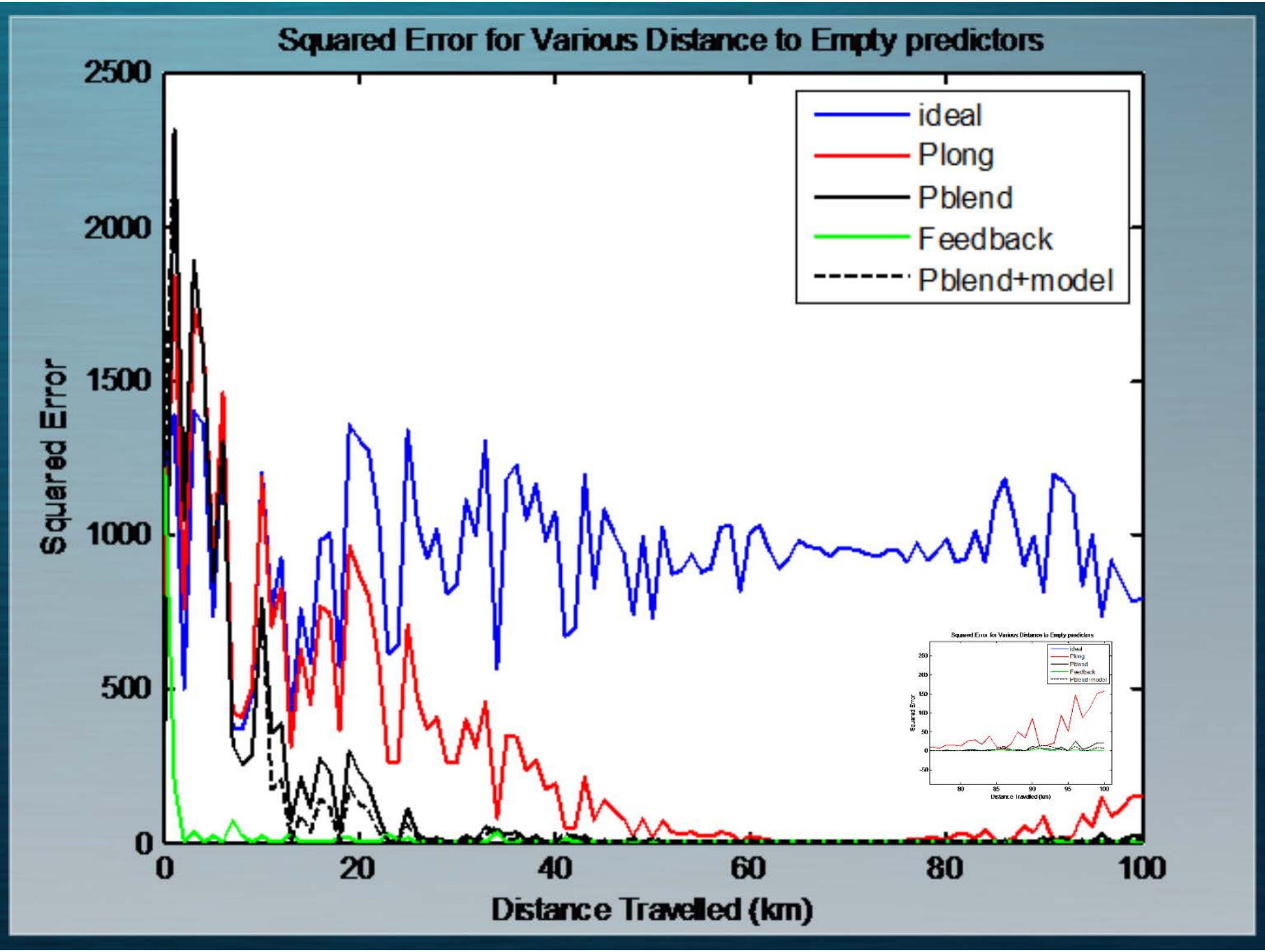
$$DTE_{long} = \frac{E_{batt}}{\bar{p}_{300km}(t)}$$

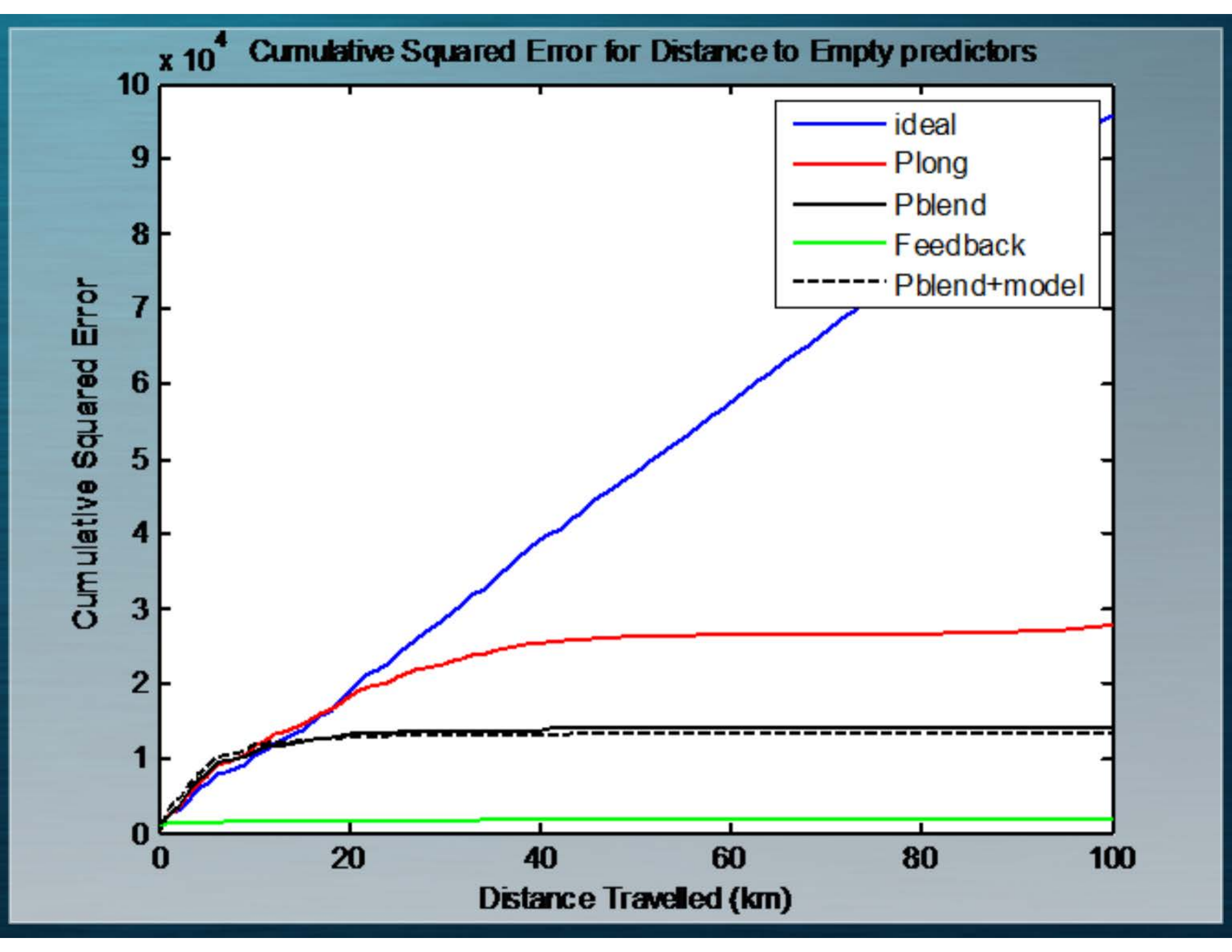
$$DTE_{blended} = \frac{E_{batt}}{\mu \cdot \bar{p}_{30km}(t) + (1-\mu) \cdot \bar{p}_{300km}(t)} \quad \mu_{default} = 0.9$$

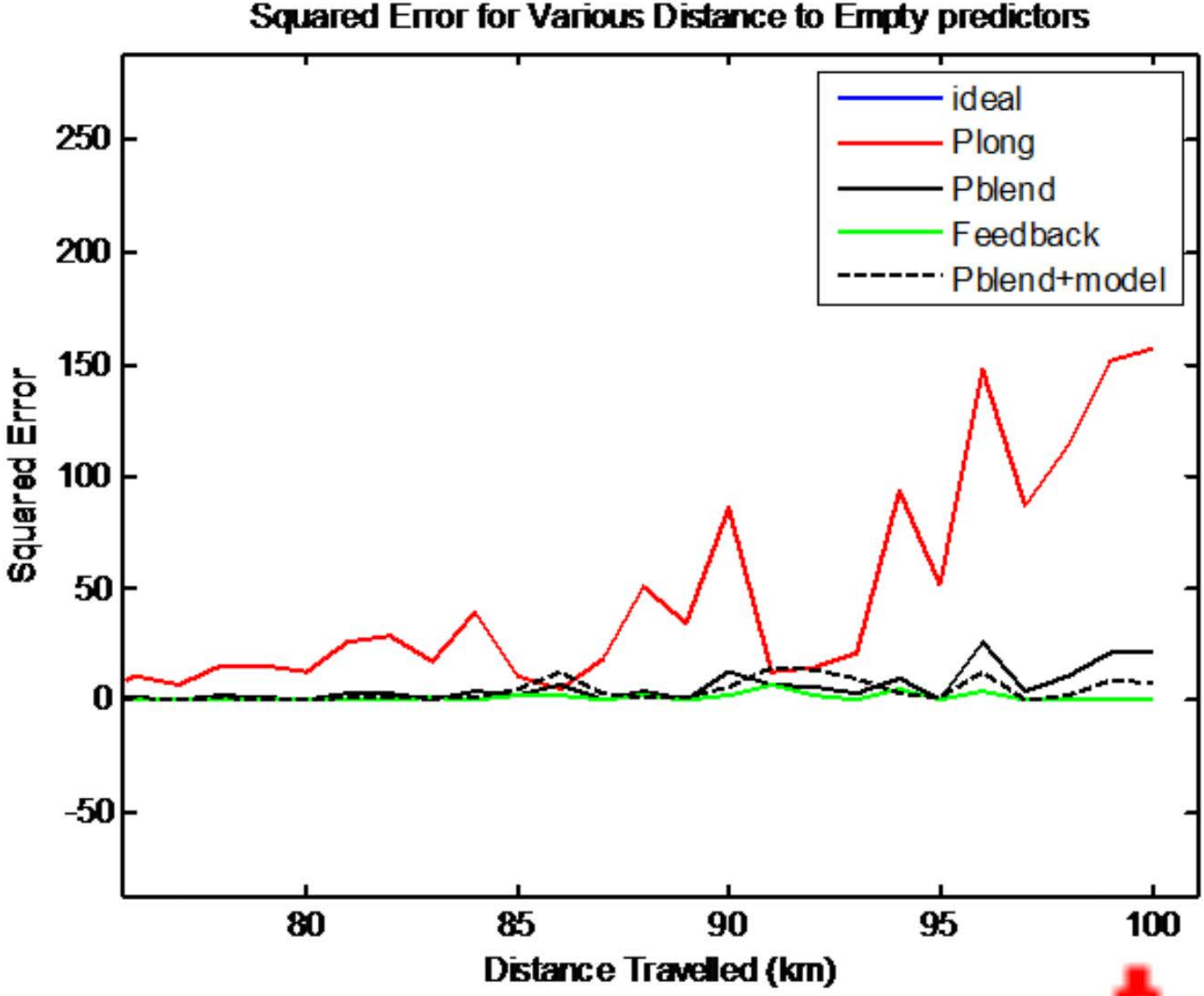
$$DTE_{feedback} = \frac{E_{batt}}{\bar{p}_{PI}(t)}, \qquad \bar{p}_{PI}(t) = K_P(p_{act}(t) - \bar{p}_{PI}(t)) + K_I(\int_0^t p_{act}(t) - \bar{p}_{PI}(t))$$

$$DTE_{blended+model} = \frac{E_{batt}}{\mu \cdot \bar{p}_{30km}(t) + (1-\mu) \cdot \bar{p}_{300km}(t) + \Delta m \cdot E_{inc}} \quad E_{inc} \sim 6 \, \frac{Wh}{100km \cdot kg}$$


Various Distance to Empty predictors
DTE_{ideal} represents iMiEV range claim
$DTE_{long} = \frac{E_{batt}}{\bar{p}_{300km}(t)}$
$DTE_{blended} = \frac{E_{batt}}{\mu \cdot \bar{p}_{30km}(t) + (1-\mu) \cdot \bar{p}_{300km}(t)}$ $\mu_{default}$= 0.9
$DTE_{feedback} = \frac{E_{batt}}{\bar{p}_{PI}(t)}$, $\bar{p}_{PI}(t) = K_P(p_{act}(t) - \bar{p}_{PI}(t)) + K_I(\int_0^t p_{act}(t) - \bar{p}_{PI}(t))$
$DTE_{blended+model} = \frac{E_{batt}}{\mu \cdot \bar{p}_{30km}(t) + (1-\mu) \cdot \bar{p}_{300km}(t) + \Delta m \cdot E_{inc}}$ $E_{inc} \sim 6 \frac{Wh}{100km \cdot kg}$
actual
ideal
Plong
Pblend
Feedback
Pblend+model
Distance to Empty (km)
Distance Travelled (km)
0
10
20
30
40
50
60
70
80
90
100
0
20
40
60
80
100

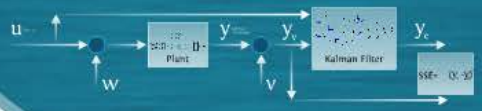

Squared Error for Various Distance to Empty predictors
ideal
Plong
Pblend
Feedback
Pblend+model
Squared Error
Distance Travelled (km)
0
500
1000
1500
2000
2500
0
20
40
60
80
100


Cumulative Squared Error for Distance to Empty predictors
x 10^4
Cumulative Squared Error
Distance Travelled (km)
ideal
Plong
Pblend
Feedback
Pblend+model
0
1
2
3
4
5
6
7
8
9
10
0
20
40
60
80
100

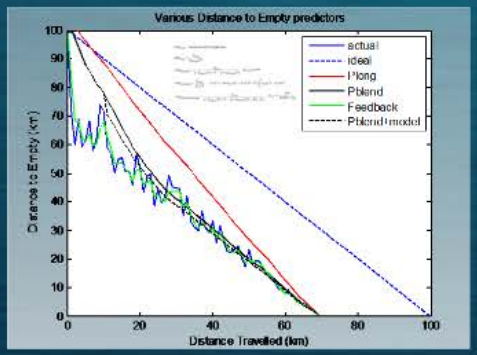

Squared Error for Various Distance to Empty predictors
ideal
Plong
Pblend
Feedback
Pblend+model
250
200
150
100
50
0
-50
Squared Error
80
85
90
95
100
Distance Travelled (km)

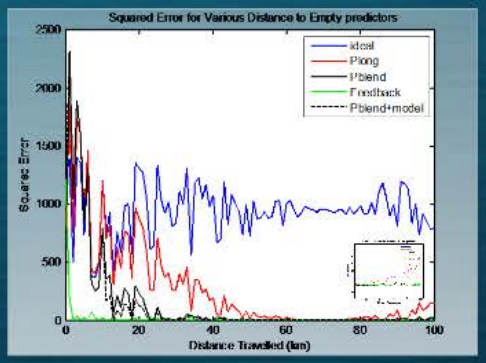
Model-based signal analysis

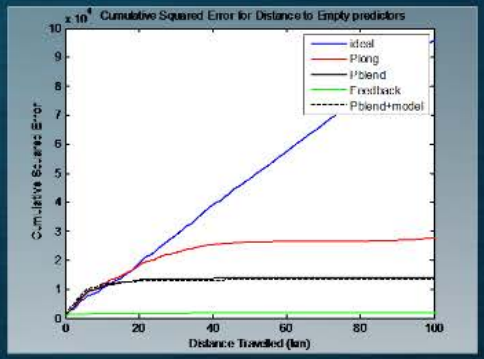
Simple, correct, efficient, and robust (we hope)



Implications for Range Estimation







EVS27: Real-time Electric Vehicle Mass Identification

Erik Wilhelm, Singapore University of Technology and Design
Raffaele Bornatico, ETH-Zurich
Lennon Rodgers, MIT