Predicting Roll Car Dynamics with Mass, Radius of Gyration, and Drop Height

ME 107
Lab 105 (Thursday 1C)
UC Berkeley

Patrick Carlson
Salvador Gomez
James Martin
Yara Mubarak
Colin Um

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Motivation

- Develop a predictive model for kinematics of a roll car
- Model can be used to predict other variables

Theory

- Mechanical Energy is not conserved!
- Energy losses (W_F) due to
  - friction, drag, track deformation, etc.
- Total Energy can be modeled in terms of initial energy

$$mgh = \frac{1}{2}mv^2 + \frac{1}{2}mr_g^2\omega^2 + mgy + W_f$$

m = mass *h* = drop height *v* = speed r_g = radius of gyration
w = angular velocity *g* = gravity, *y* = height

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Experimental Design: Measurements Before Data Collection

- Measure Track Shape and Curvature
- Weigh All Parts
- CAD All Parts

In order to obtain masses, radii of gyration and drop heights.

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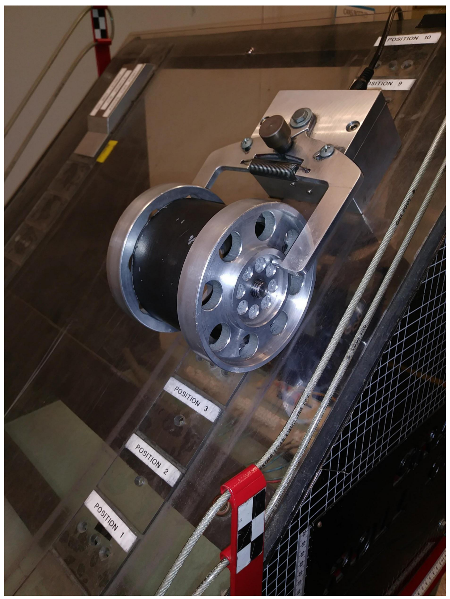
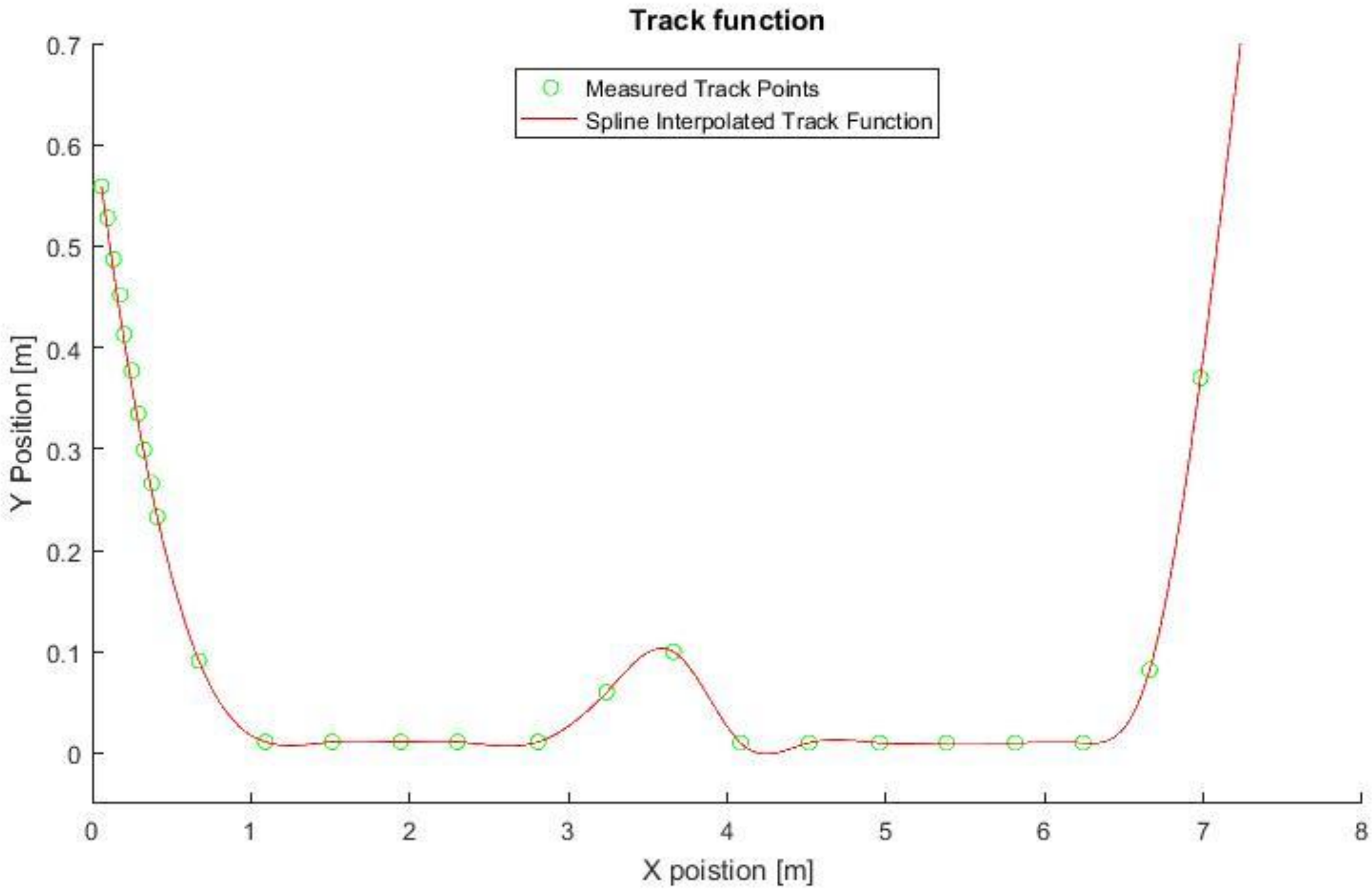
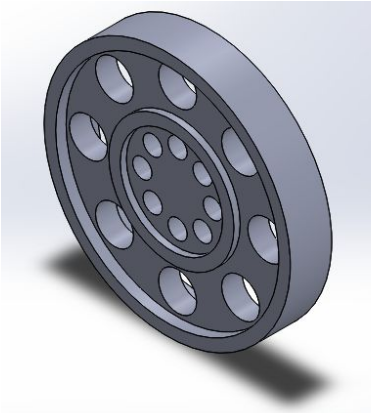
Experimental Setup

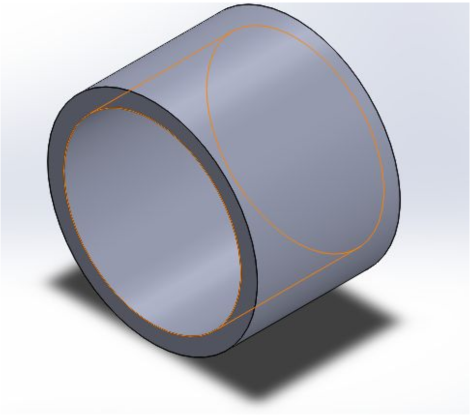


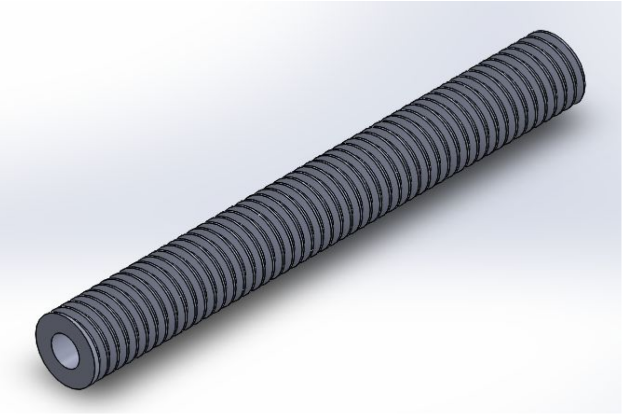
Track MATLAB Visualization



Screenshots of CADed Objects







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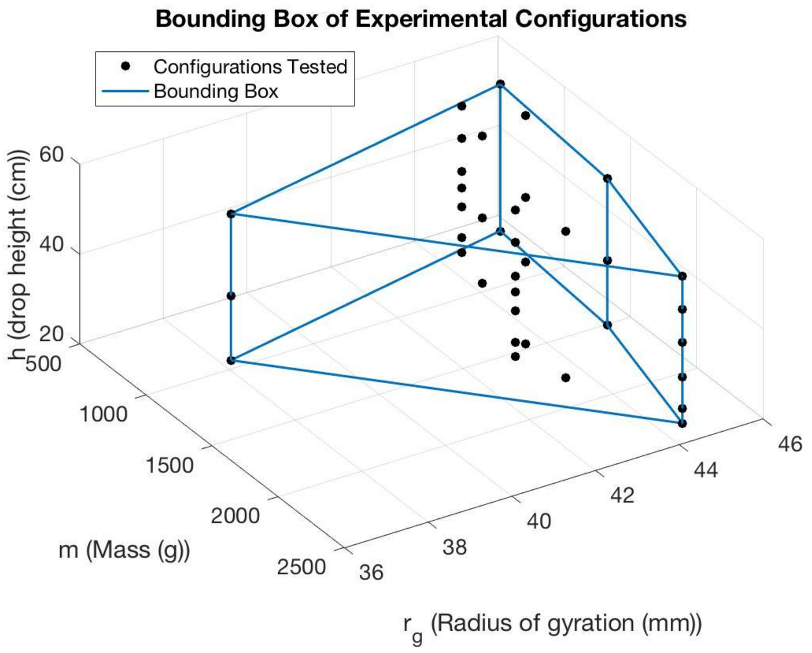
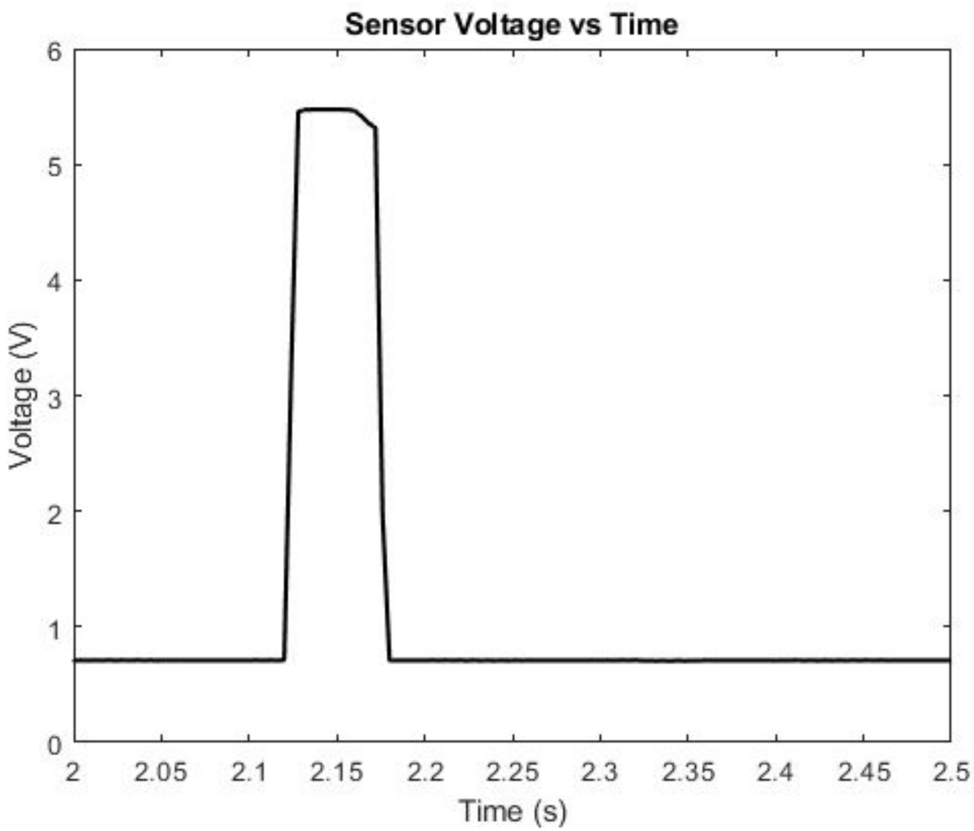
Experimental Design

Variable	Minimum Value	Maximum Value
Drop Height	23.3 cm	55.9 cm
Mass	716.5 g	2461 g
Radius of Gyration	37.9 mm	45.4 mm



Calibration of Sensor Signal

- 16 phototransistors
- Output based on light intensity
- Threshold voltage and average time used



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Data Pipeline

Raw Data → Clean Data → PDE Coefficients → Prediction

Data Collection

Taking the Data Collected from Lab View through sensors.

Data Refinement

Filter Outliers and get continuous displacement, velocity and acceleration from discrete sensor readings.

Genetic Physical Algorithm

Finding the most optimal physical PDE to fit our time series data.

Regressive Algorithm

Finding the best regression to map our variables to the PDE coefficients found in the previous part.

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Genetic Physical Algorithm Physical Model

NO SLIP Condition:

$$\ddot{S} = \frac{\vec{F}_r \cdot \vec{e}_t}{m(1 + \frac{r_g^2}{r_w^2})}$$

$$\ddot{\theta} = \frac{\ddot{S}}{r_w}$$

$$\vec{F}_n = mK\dot{S}^2 - \vec{F}_r \cdot \vec{e}_n$$

$$\vec{F}_f = m\ddot{S} - \vec{F}_r \cdot \vec{e}_t$$

If SLIP occurs :

$$\ddot{S} = \frac{\vec{F}_r \cdot \vec{e}_t + \vec{F}_f}{m}$$

$$\ddot{\theta} = \frac{-\vec{F}_f r_w}{m r_g^2}$$

$$\vec{F}_n = mK\dot{S}^2 - \vec{F}_r \cdot \vec{e}_n$$

$$\vec{F}_f = \frac{\dot{S}}{|\dot{S}|} \mu_k \vec{F}_n$$

$$\vec{F}_r = \frac{\dot{S}}{abs(\dot{S})}(F_{IDK} + C_{RF} F_n + 0.5 A_{CS} \rho_a * |\dot{S}|^2 C_d) - mg\vec{E}_2$$

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PDE Curve Fitting

- Optimize Over The Following PDE Coefficients :

$$C_d,\ C_{RF},\ F_{IDK},\ \mu_s, \text{ and } S_{init}$$

- Run random parameter sweep over bounds in order to get starting guess.
- Further refine with lsqnonlin

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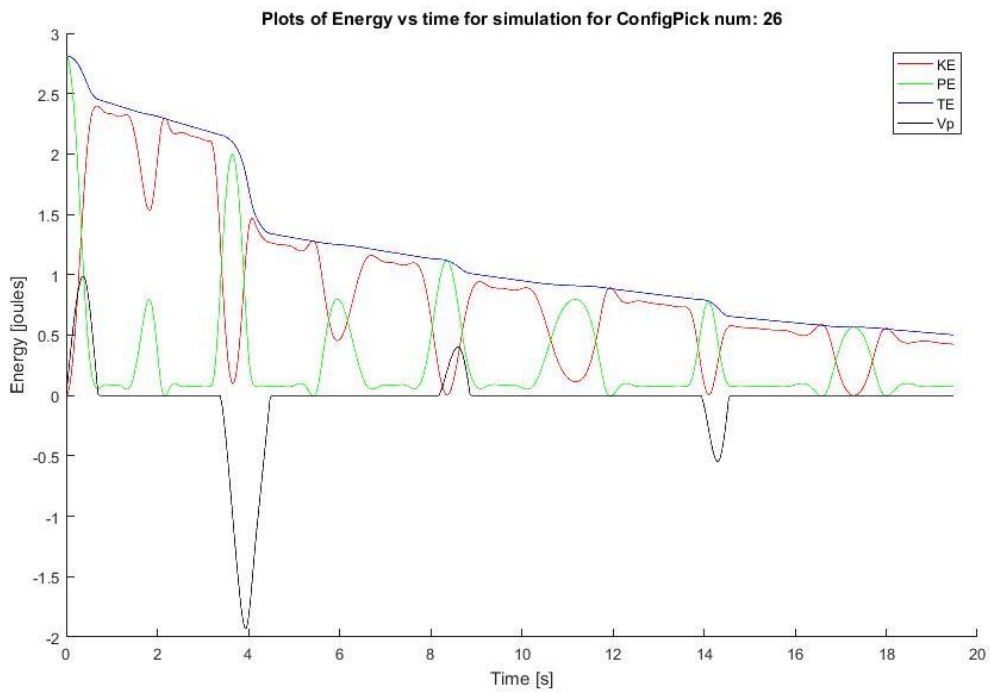
PDE Curve Fitting



Config 26: m = .7857 kg; rg = .04423 m; Drop = #8

CD = .7487; CRF = .0014; FIDK = .0187; Muk =.0814 ; MuS = .0979; DeltaS = .0032;

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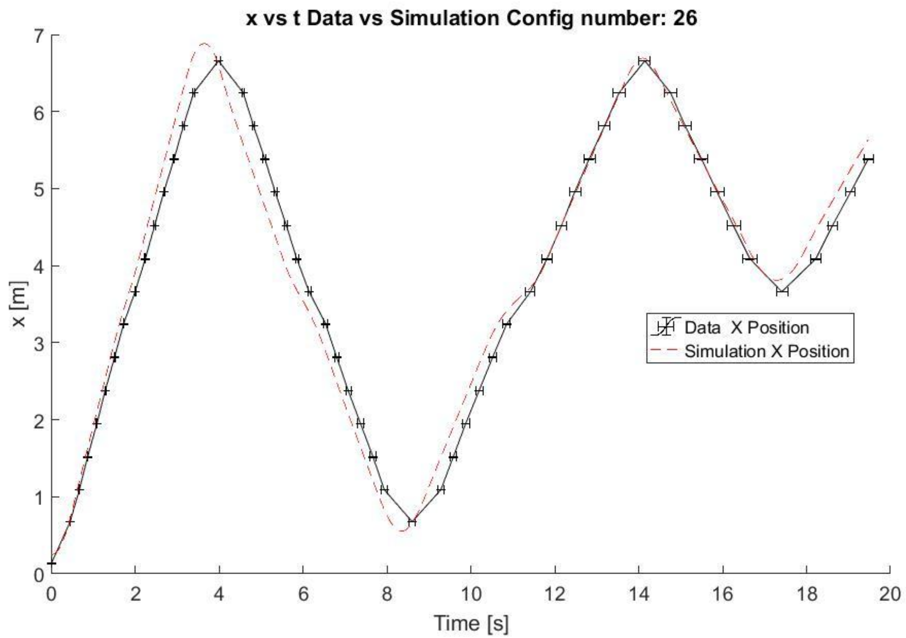
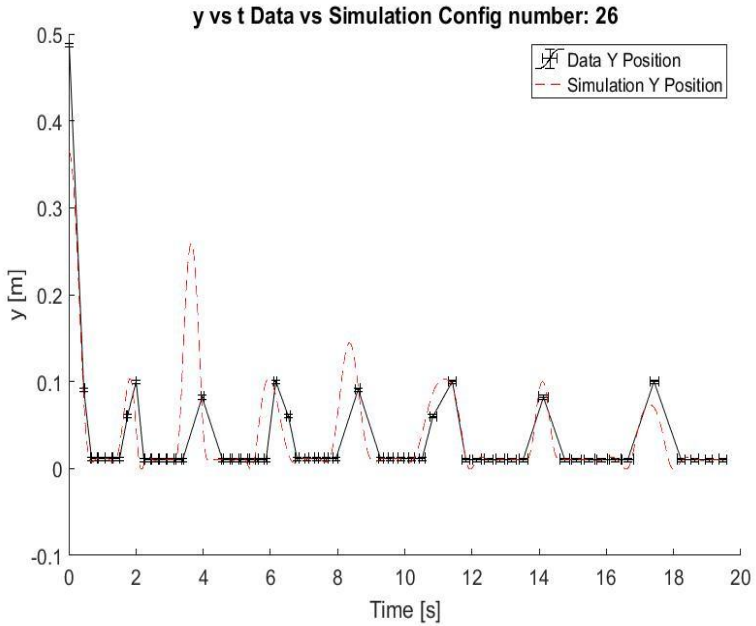
PDE Curve Fitting





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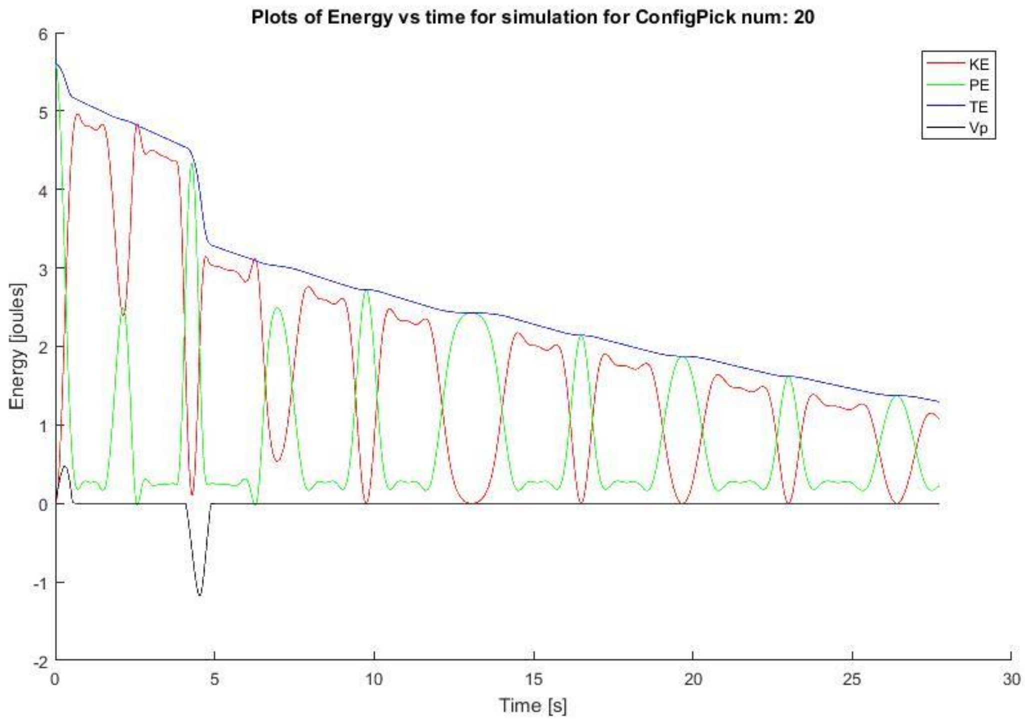
PDE Curve Fitting



Config 20: m = 2.4607 kg; rg = .04420 m; Drop = #8

CD = .6515; CRF = .0028; FIDK = .0255; Muk =.0878 ; MuS = .1207 DeltaS = .0043;

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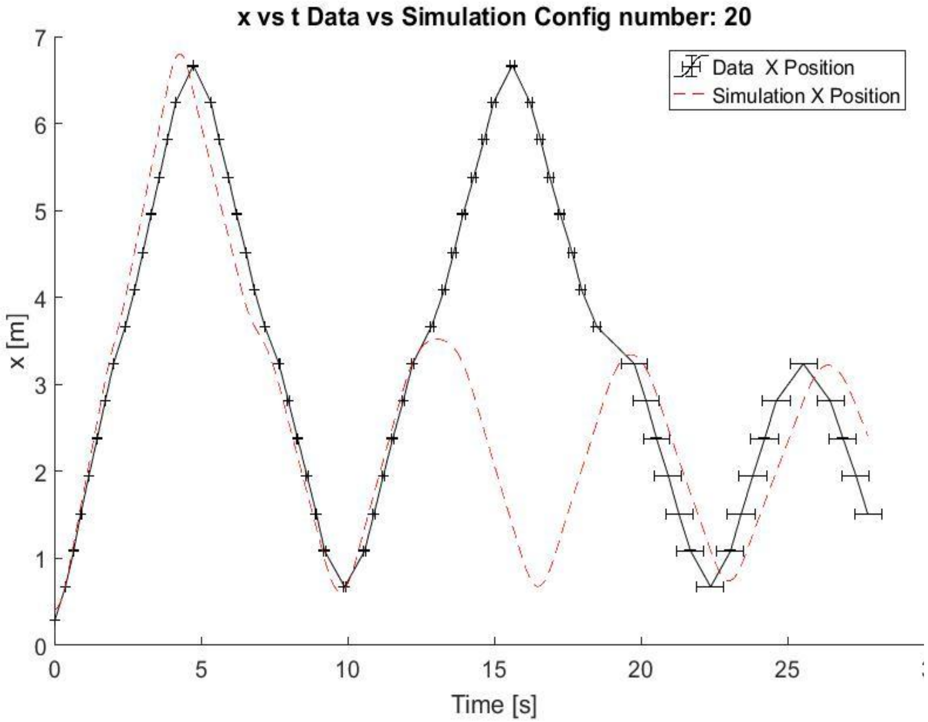
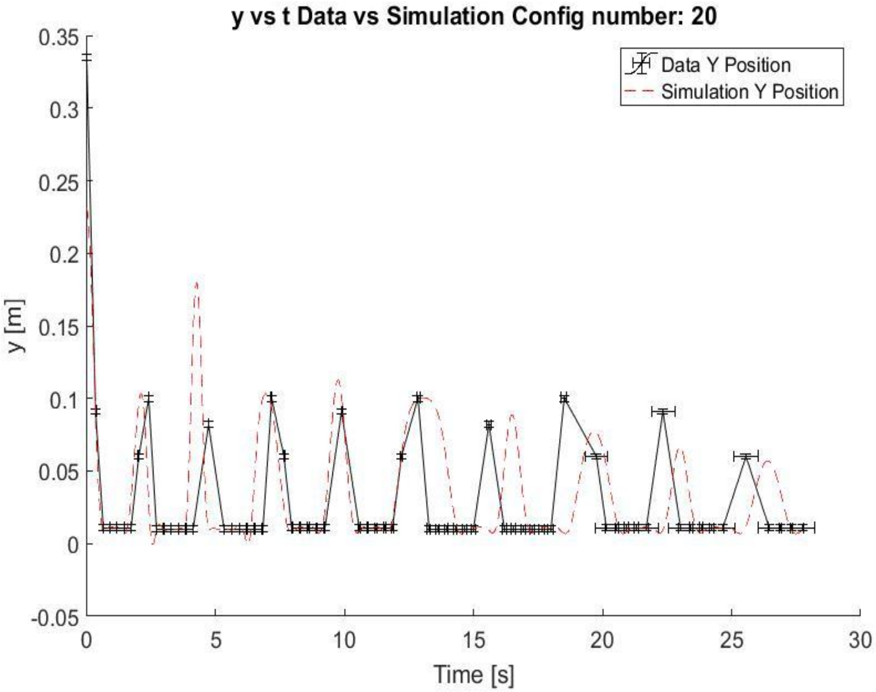
PDE Curve Fitting





Regression Algorithms

Feature Matrix :

$$\vec{x}_i = [m_i, h_i, r_{gi}]$$

$$X = \begin{bmatrix} \cdots & \vec{x}_1^T & \cdots \\ \cdots & \vec{x}_2^T & \cdots \\ \vdots & \ddots & \vdots \\ \cdots & \vec{x}_n^T & \cdots \end{bmatrix}$$

Label Matrix :

Optimal Values Found for each Configuration:

$$\vec{y}_i = [C_{di}, C_{RFi}, F_{IDKi}, \mu_{si}, S_{initi}, R_i]$$

$$Y = \begin{bmatrix} \cdots & \vec{y}_1^T & \cdots \\ \cdots & \vec{y}_2^T & \cdots \\ \vdots & \ddots & \vdots \\ \cdots & \vec{y}_n^T & \cdots \end{bmatrix}$$

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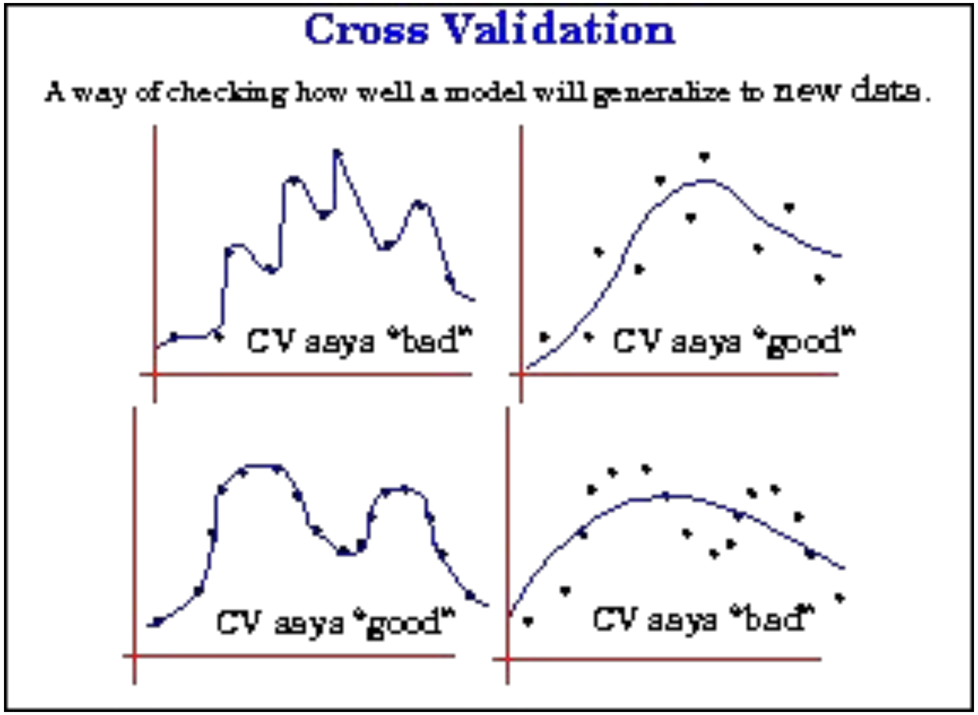
Available Regression Algorithms

- Linear Algorithms :
  - Linear : Least Squares $Xw = y$ (fit w)
  - Poly2 : Least Squares $Xw = y$ (fit w) but with X containing a 2nd degree polynomial of the Features

- Nonlinear Algorithms :
  - Neural Net with Gradient Descent Optimizer

Validation Technique

- Leave One Out Cross Validation
- K-fold cross Validation
- Mean Squared Error



Sample Equation

- Sample polynomial equation

$$x_1 = h, \mathrm{x}_2 = m,\ x_3 = r_g$$

$$(7 * 10^{-3})x_1 + (-3.4 * 10^-5)x_2 + 0.012x_3 = C_d$$

$$6.17x_1^2 + 0.00603x_2^2 + 0.00081x_3^2 + O(x_1x_2 + x_2x_3.....) = C_d$$

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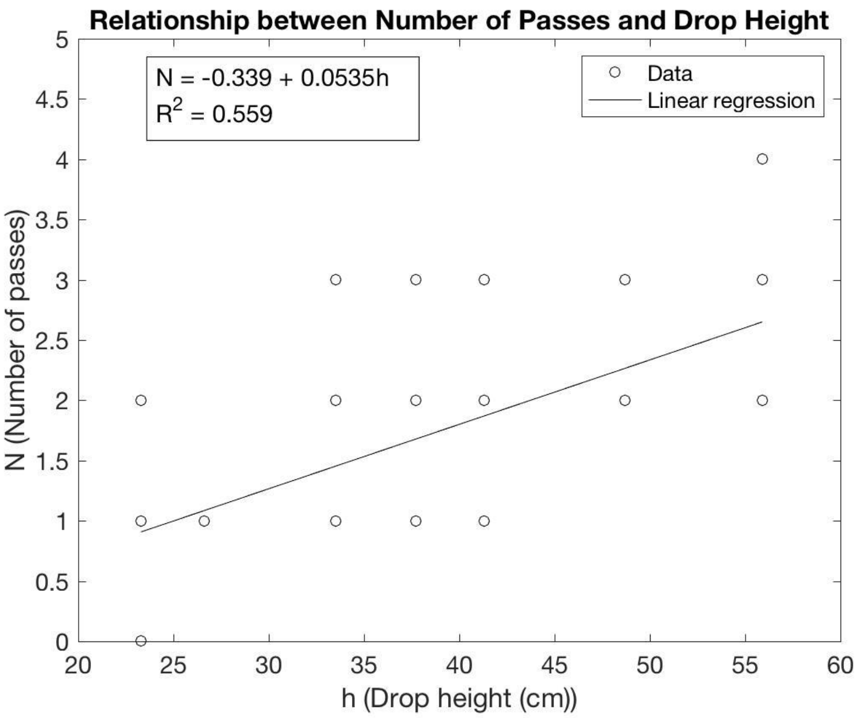
Most Important Parameter

- The drop height most correlated to number of passes.



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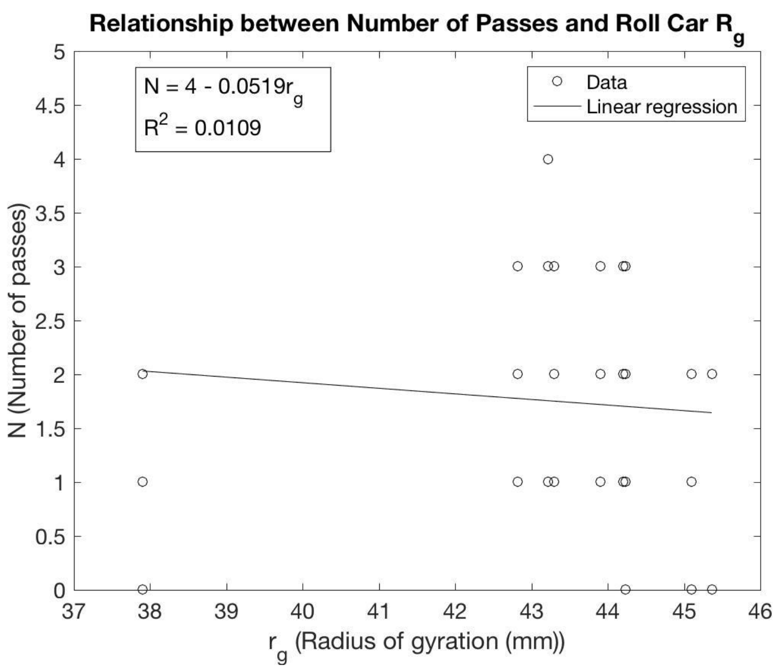
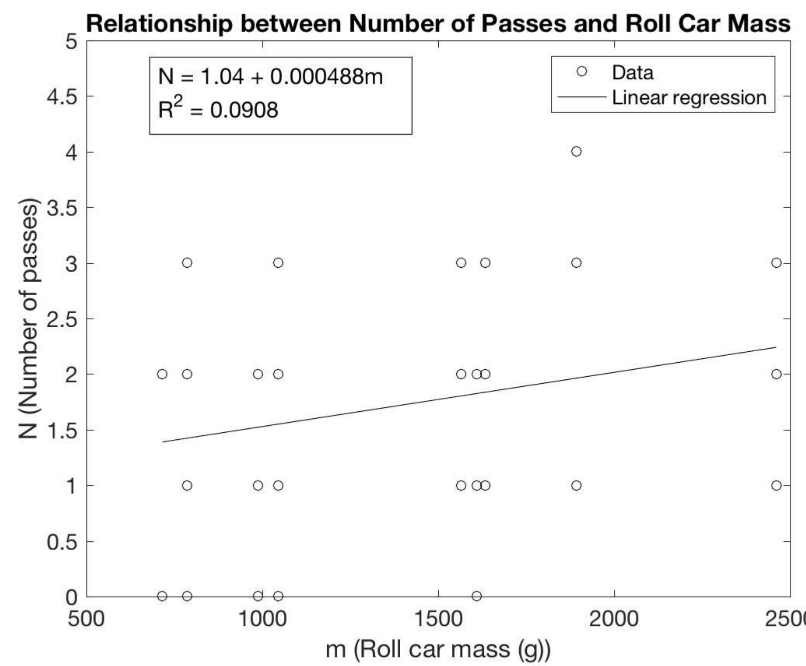
Most Important Parameter (cont)





- Radius of gyration and mass don't have much effect.

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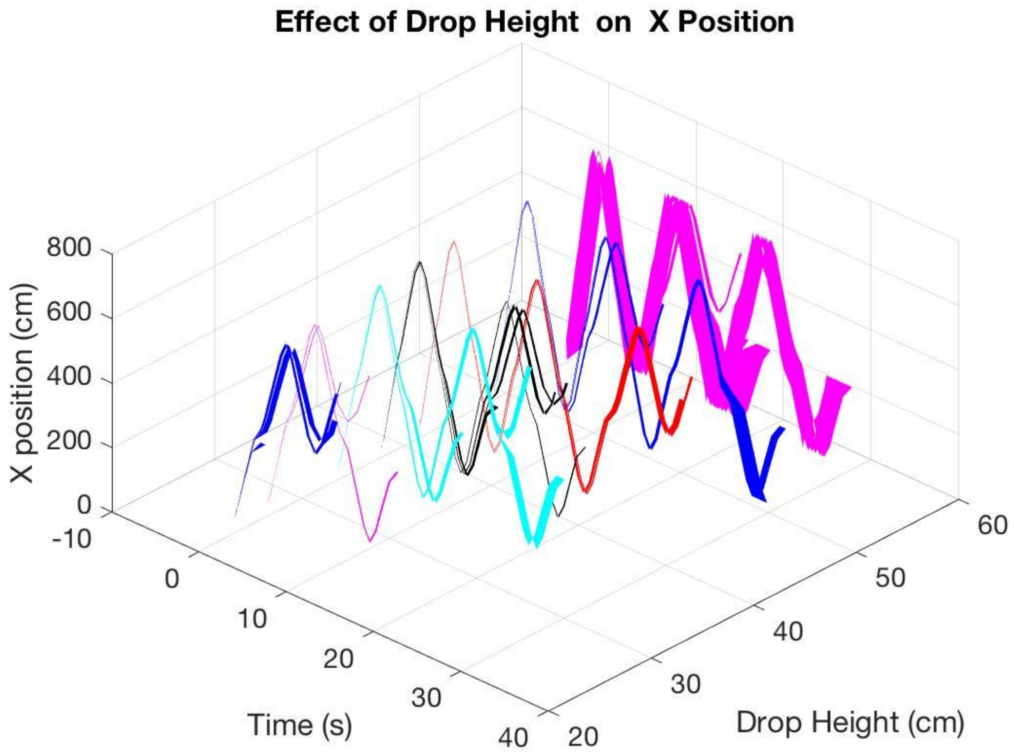
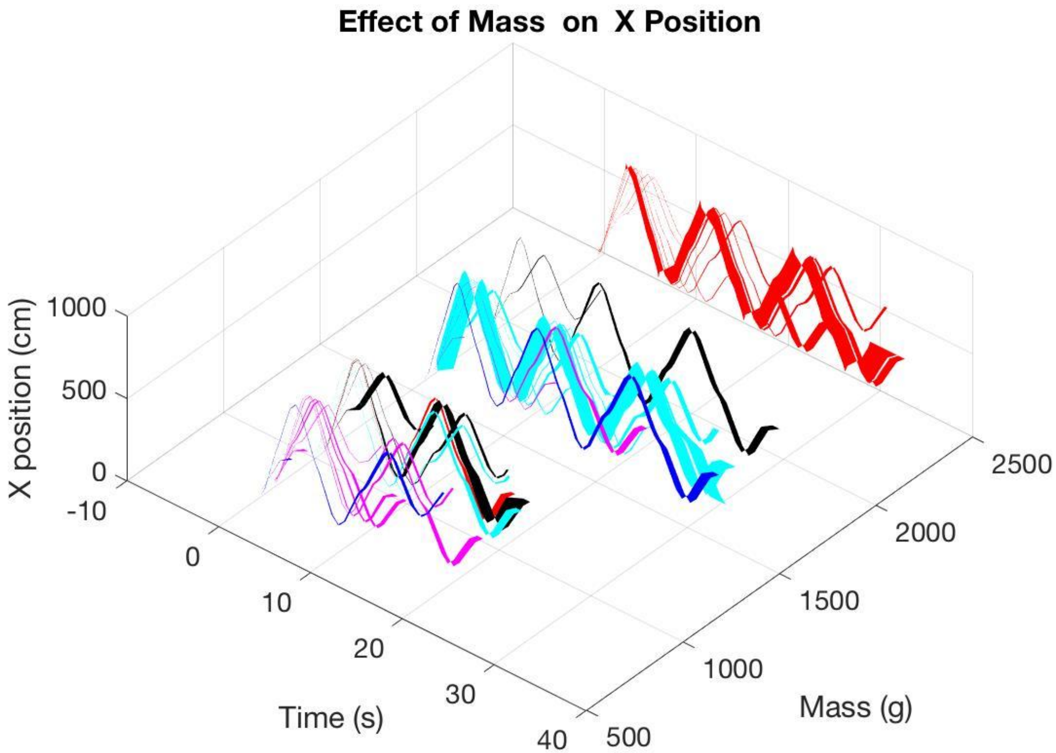
Results



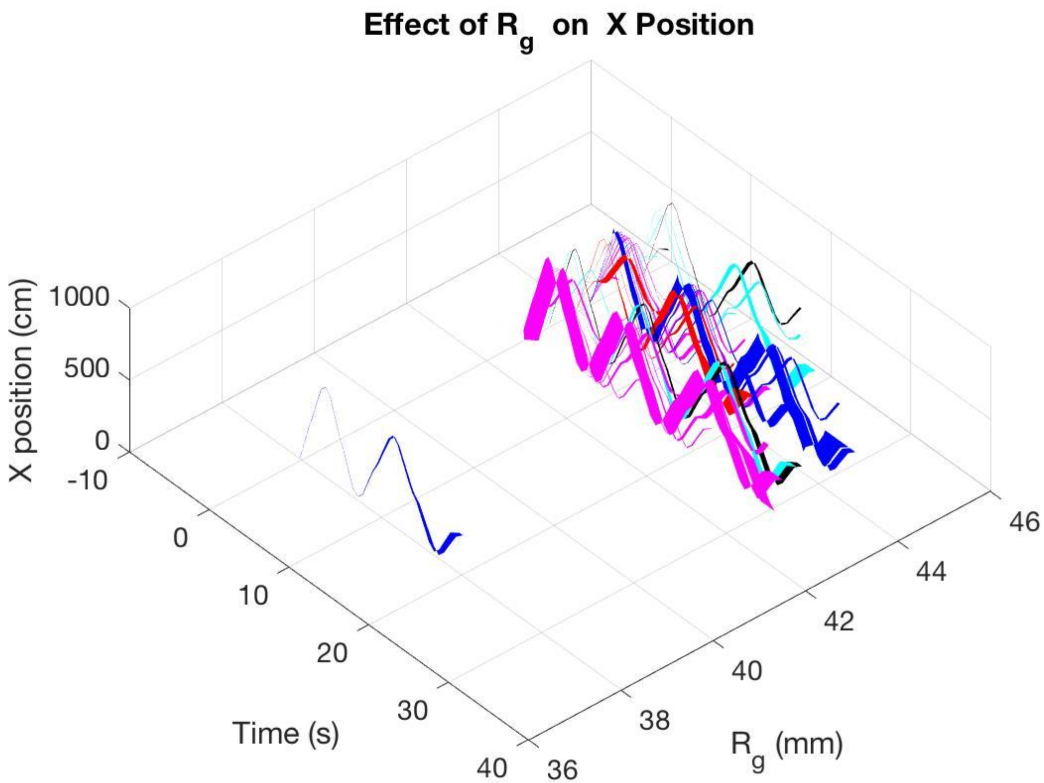
- General shape of curve is same across all trials.
- Run time is most affected by drop height.

Results (cont)



- No clear trend of mass of roll car on roll car run time.

Results (cont)



- No clear trend of radius of gyration on the roll car run time.

Model Performance

Model Part 1 :

- Drag coefficient should not change, but changes in our model.
- Not picking up all physical properties.
- Can account for factors that we did not account for.

Model Part 2 :

- 95% accuracy for s and delta s coefficient.
- 70% accuracy for rest of coefficients.
- Need more configurations.

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Conclusions

- No clear trend of mass or radius of gyration on the roll car run time or number of passes.
- Increased drop height tends to result in increased number of passes and roll car run time.
- Successful two-part model: PDE and regression.
  - Validated with real data.
  - Model can be used to calculate system parameters.

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