AVT-369 Research Symposium on
"Digital Twin Technology Development and Application for Tri-Service Platforms and Systems"

Hybrid Neural Network and Physics-Based Digital Twins for Condition-Based Maintenance

Andrew Lammas, Russell Brinkworth, Karl Sammut, Luke Voigt, Giselle Rampersad, and Nicholas Brealey[2]

Flinders University Tonsley, Adelaide SA

[2]Defence Science and Technology Group

Edinburgh, Adelaide SA

Australia

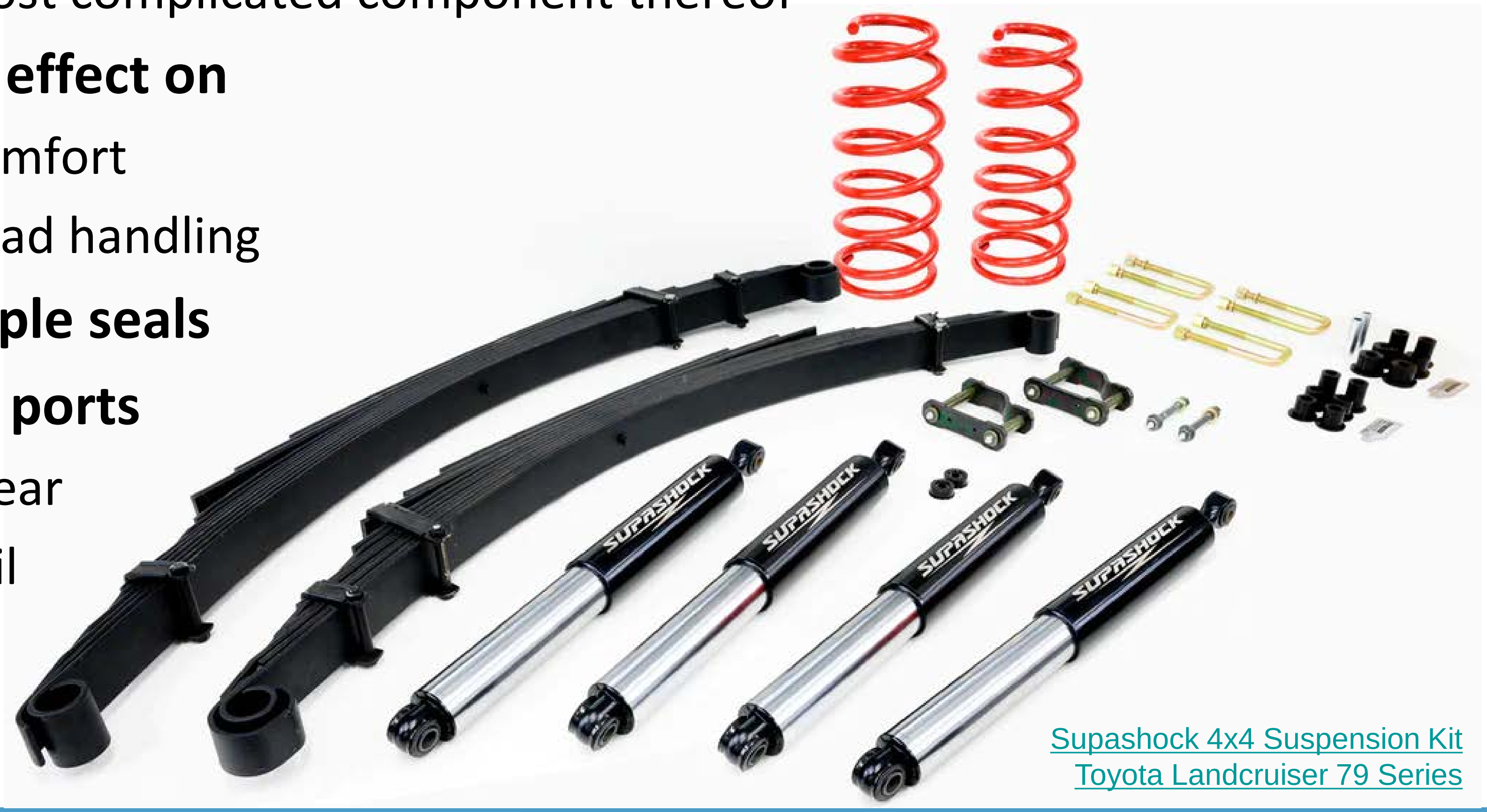
Information is Essential

Introduction

- **Shock absorbers**
- **Digital twins**
- **Data collection**
- **Model Development**
  - Velocity estimation
  - Thermal model
  - Force model
  - Neural network
- **Analysis**
  - Model/Sensor permutations
  - Accuracy
    - RMSE
  - Cost
  - Sensor cost
- **Conclusions**
- **Future work**

Shock Absorbers

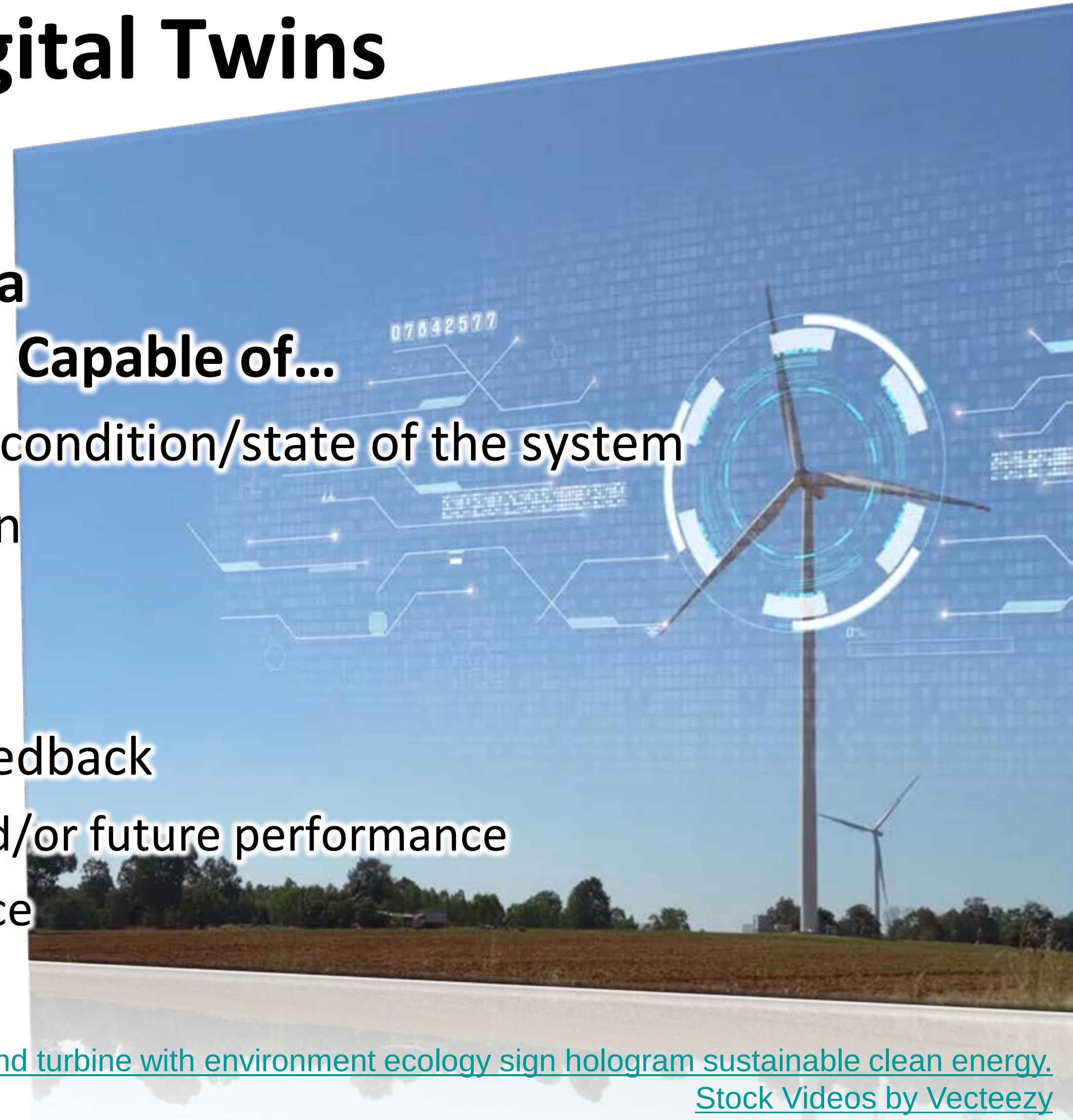
- **Part of the suspension system**
  - ➢ Most complicated component thereof
- **Most effect on**
  - ➢ Comfort
  - ➢ Road handling
- **Multiple seals and ports**
  - ➢ Wear
  - ➢ Fail



Supashock 4x4 Suspension Kit
Toyota Landcruiser 79 Series

Digital Twins

- ***What are digital twins?***
- **A virtualised version of a device/system/process. Capable of…**
  - Estimating the current condition/state of the system
  - Project future condition
    - Performance
    - Maintenance
  - Perform automated feedback
    - Maximise current and/or future performance
    - Minimise maintenance



[A wind turbine with environment ecology sign hologram sustainable clean energy. Stock Videos by Vecteezy]

Digital Twin Design Approaches

- **Unstructured**
  - No explicit problem specific “structure”
  - Allow data/training to derive connectivity
- **Structured**
  - Explicit connectivity based on a priori information
- **Deployability in the field**
  - Capability
  - Reliability

https://www.wallpaperflare.com/abstract-pattern-feminine-and-masculine-light-version-technology-wallpaper-aenur
https://commons.wikimedia.org/wiki/File:Building_services_coordinated_drawing.JPG

Developmental Process

- **Testing**
  - System excitation
  - Data collection

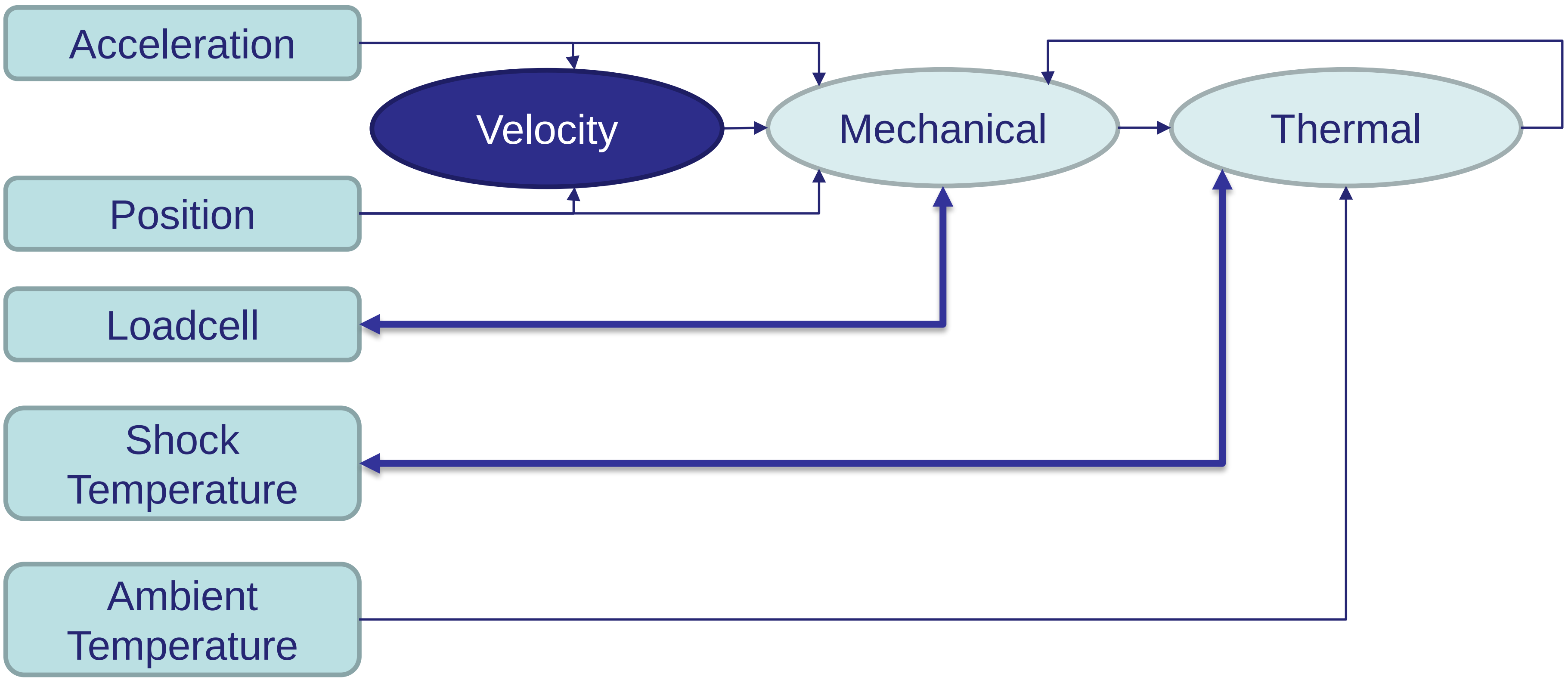
- **Modelling**
  - Development
  - Optimisation

- **Neural Network**
  - Development
  - Permutations
  - Training

- **Evaluation**
  - Performance
    - Accuracy
  - Sensors
    - Cost

Developmental Process

- **Conceptual relationships utilised**



Experimental Setup

- **Sensors**
  - Acceleration – Δ accelerometers
  - Position – Potentiometer
  - Temperature – Thermocouple
    - Shock hotspot
    - Ambient
  - Force – Loadcell
- **Condition**
  - Nominal –12 Bar
- **Hydraulic actuator**
  - at 1,2,4 Hz
  - with 80mm peak to peak displacement

Algorithm Development

- **Velocity estimation**
- **Thermal model**
  - Thermal propagation
- **Force model**
  - Dissipative – heat generation
- **Neural network**
  - Architecture
  - Training

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Velocity Estimation

- **Using a Kalman filter**
- **Estimate velocity from…**
  - measurements of
    - acceleration
    - position
  - utilising the
    - Kinematic relationship

sample time

$$\hat{y}_t = \hat{y}_{t-1} + T\hat{\dot{y}}_{t-1} + \frac{T^2}{2}\left(\left(a_{1,t-1} - a_{2,t-1}\right) - \hat{b}_a\right)$$

position estimate

velocity estimate

acceleration measurement

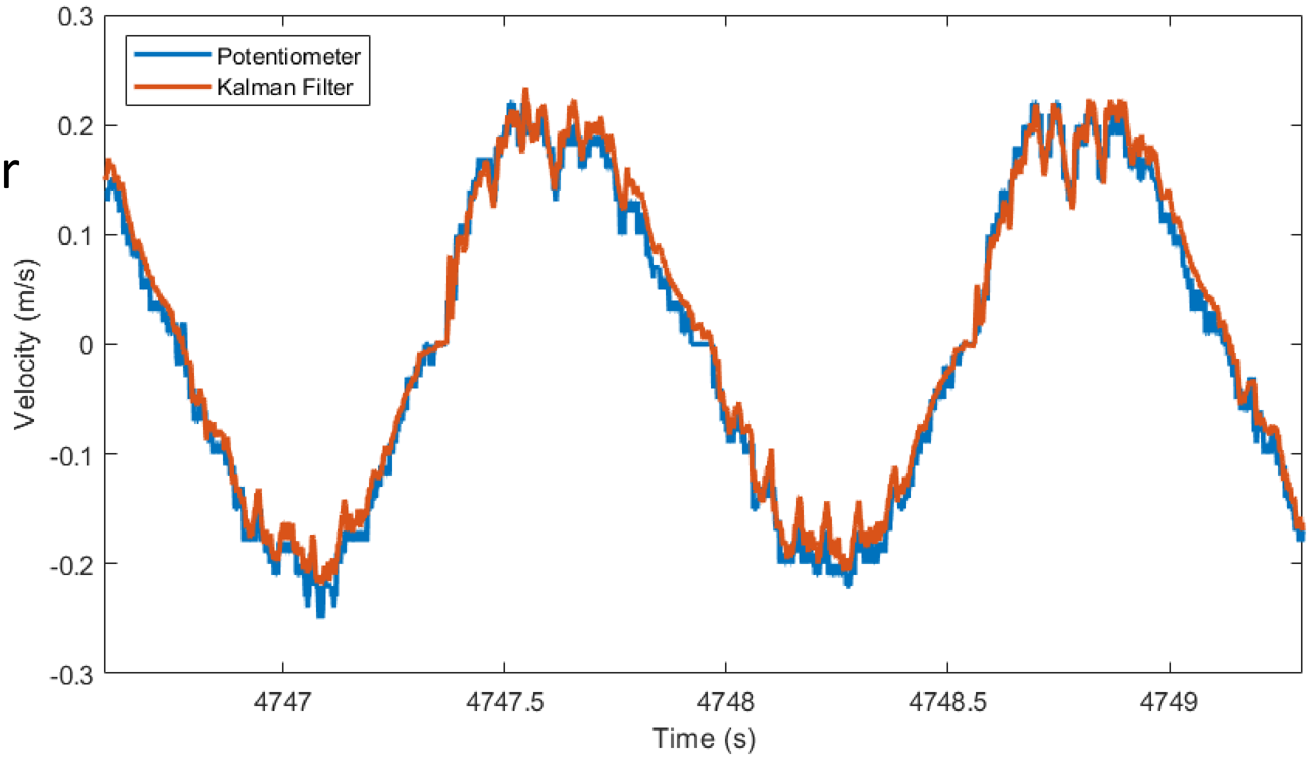
accelerometer bias estimate

$$\hat{\dot{y}}_t = \hat{\dot{y}}_{t-1} + T\left(\left(a_{1,t-1} - a_{2,t-1}\right) - \hat{b}_a\right)$$

sample time

Velocity Estimation

- **Estimates position at a higher update rate**
- **Velocity maximally correlated with acceleration and position.**
- **RMSE**
  - Potentiometer
    - 0.009 m/s
  - Kalman filter
    - 0.004 m/s



Algorithm Development

- **Velocity estimation**
- ***Thermal model***
  - *Thermal propagation*
- **Force model**
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- **Neural network**
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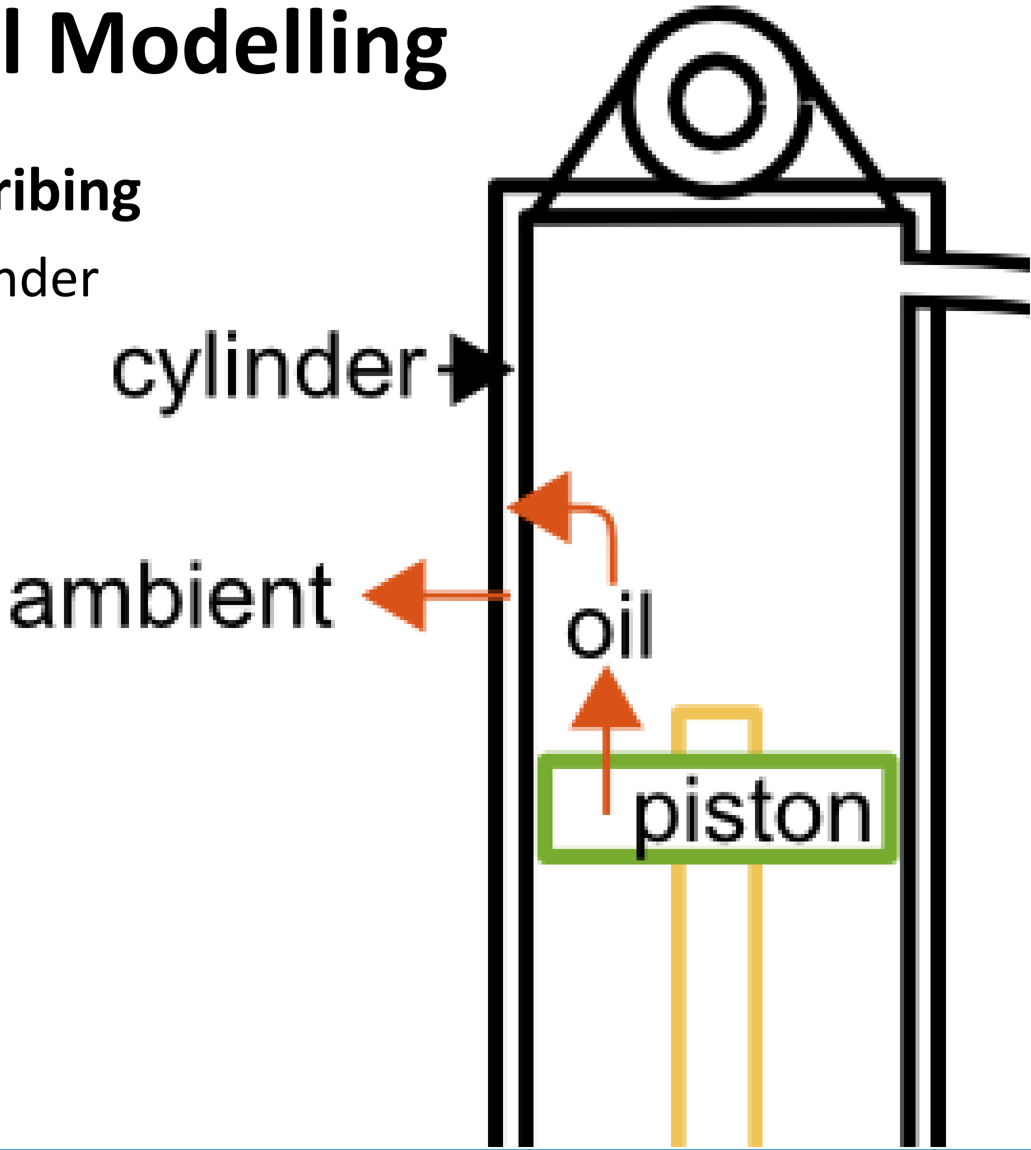
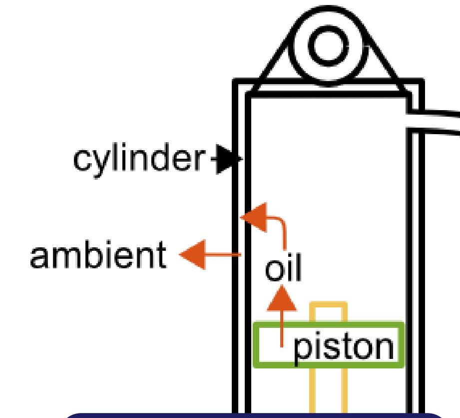
  - Training

Thermal Modelling

- **Differential equation describing**
  - ➢ Temperature of Oil & Cylinder
  - ➢ Utilising
    - Thermal masses
    - Thermal conductivity



Thermal Modelling



- **Differential equation describing**
  - ➢ Temperat

convection
oil -> cylinder

work based
heating

$$m_{oil} c_{oil} \frac{dT_{oil}}{dt} = h_{oil} A_{cyl}^{in} \left(T_{cyl} - T_{oil}\right) + F_{damping} \dot{y}$$

shock absorber
velocity

mass &
thermal
capacity

temperature
change

thermal conductivity
& surface area

temperature
difference

$$m_{cyl} c_{cyl} \frac{dT_{cyl}}{dt} = h_{oil} A_{cyl}^{in} \left(T_{oil} - T_{cyl}\right) + h_{amb} A_{cyl}^{out} \left(T_{amb} - T_{cyl}\right)$$

convection
cylinder -> oil

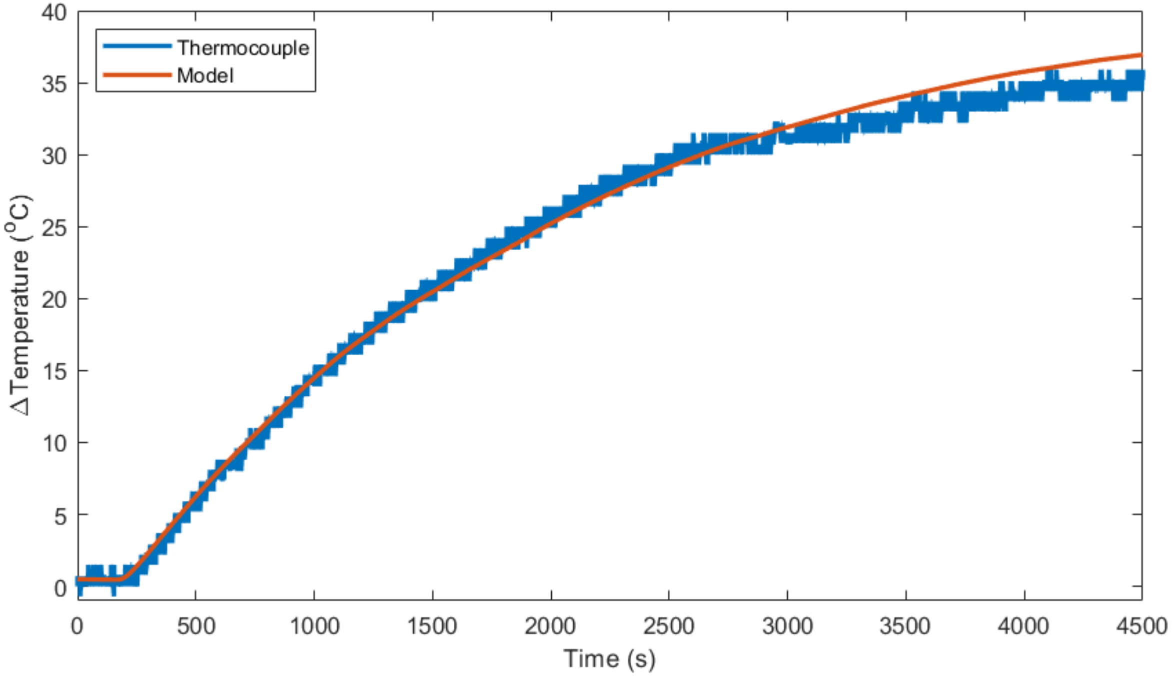
convection
cylinder -> ambient

$$+ \varepsilon \sigma A_{cyl}^{out} \left(T_{amb}^{4} - T_{cyl}^{4}\right)$$

radiation
cylinder -> ambient

Thermal Modelling

- **Parameters fitted to data**
  - Limitations
  - Airflow not measured
- **No airflow**
  - RMSE – 0.46°
  - Mean error – 0.05°
- **All time**
  - RMSE – 0.82°
  - Mean error – 0.46°



Algorithm Development

- **Velocity estimation**
- **Thermal model**
  - Thermal propagation
- ***Force model***
  - *Dissipative – heat generation*
- **Neural network**
  - Architecture
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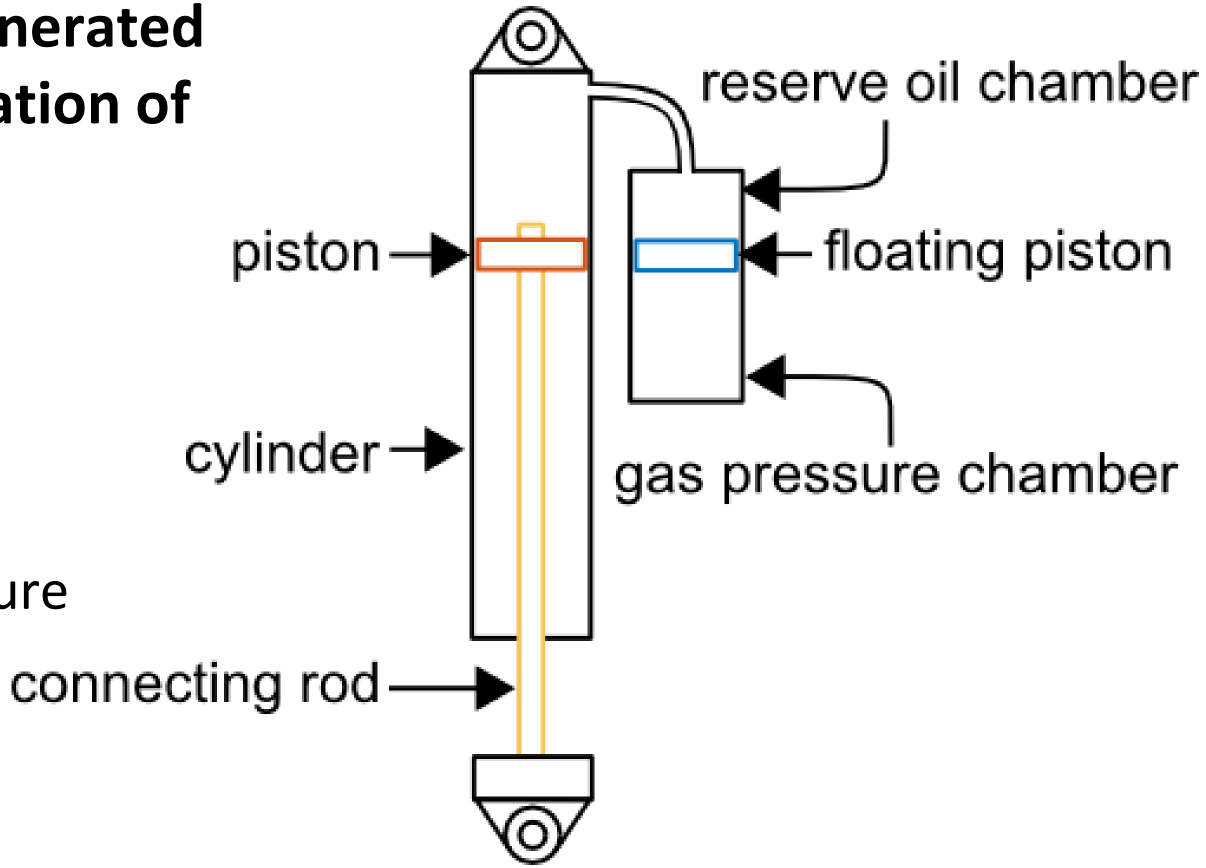
Force Modelling

- **Parametric equation describing force generated due to the combination of**
  - Flow restrictions
    - Leak port
    - Main port
  - Flow regulation
    - Shim valve
  - Differential pressure
    - Gas pressure



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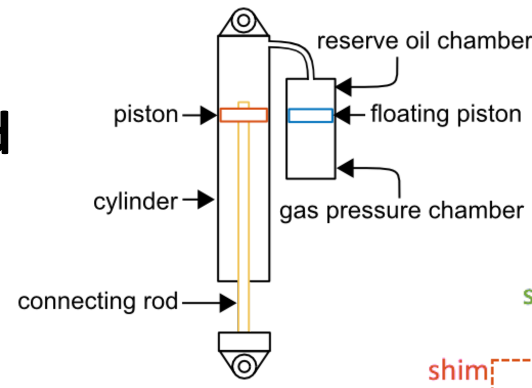

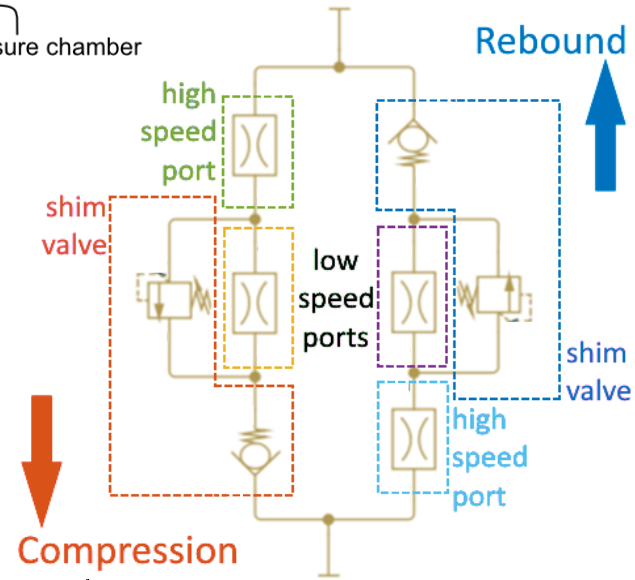

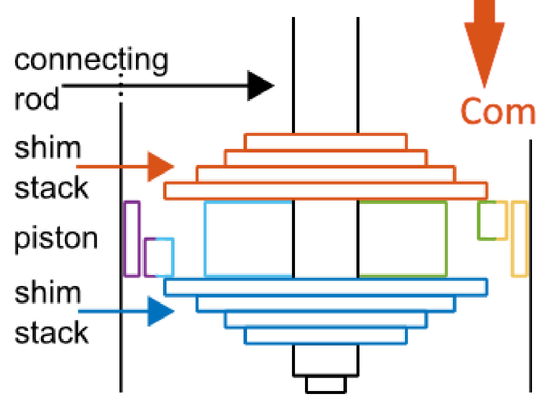

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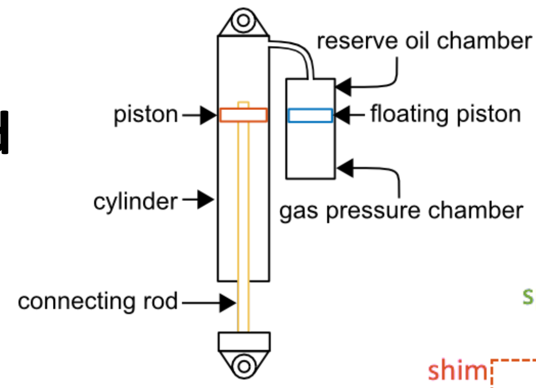

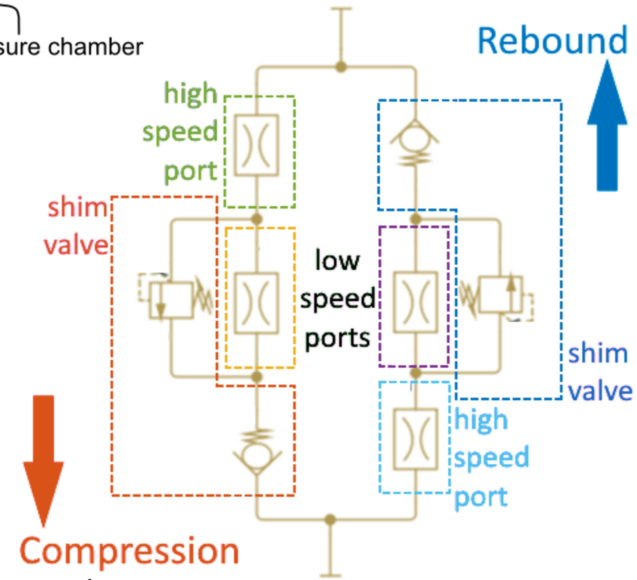

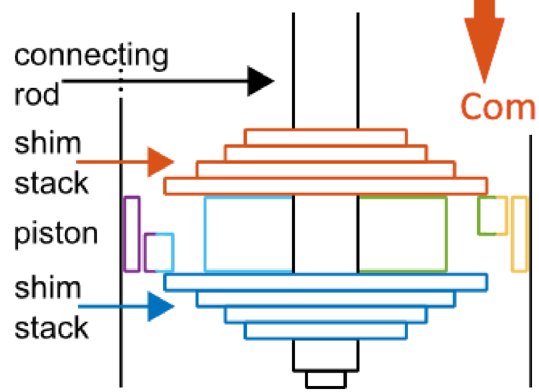

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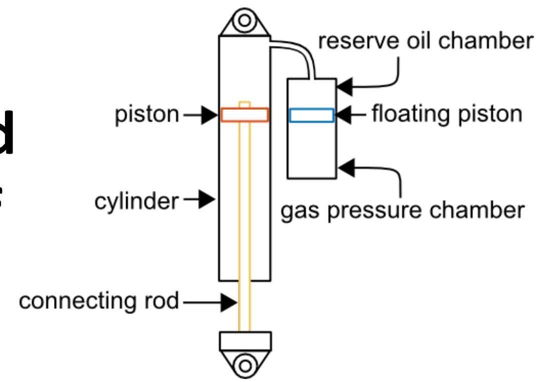

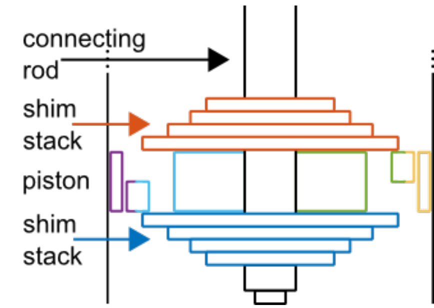

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hysteresis

$$F_{leak} = K_{leak} \upsilon \dot{y} - K_{hys} \ddot{y}$$

flow restriction

fluid flow

fluid acceleration

$$F_{main} = K_{main} \upsilon^{0.25} \dot{y}^{1.75}$$

spring preload

spring rate

fluid flow

$$F_{shim} = F_{preload} + K_{spring} \dot{y}$$

Force Modelling

- **Parametric equation describing force generated due to the combination of**
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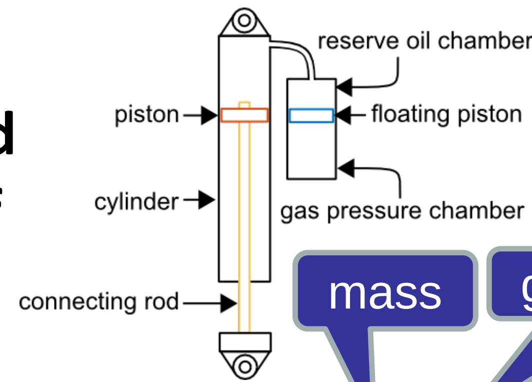
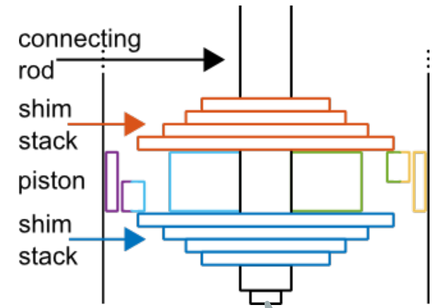




mass
gas constant
rod area

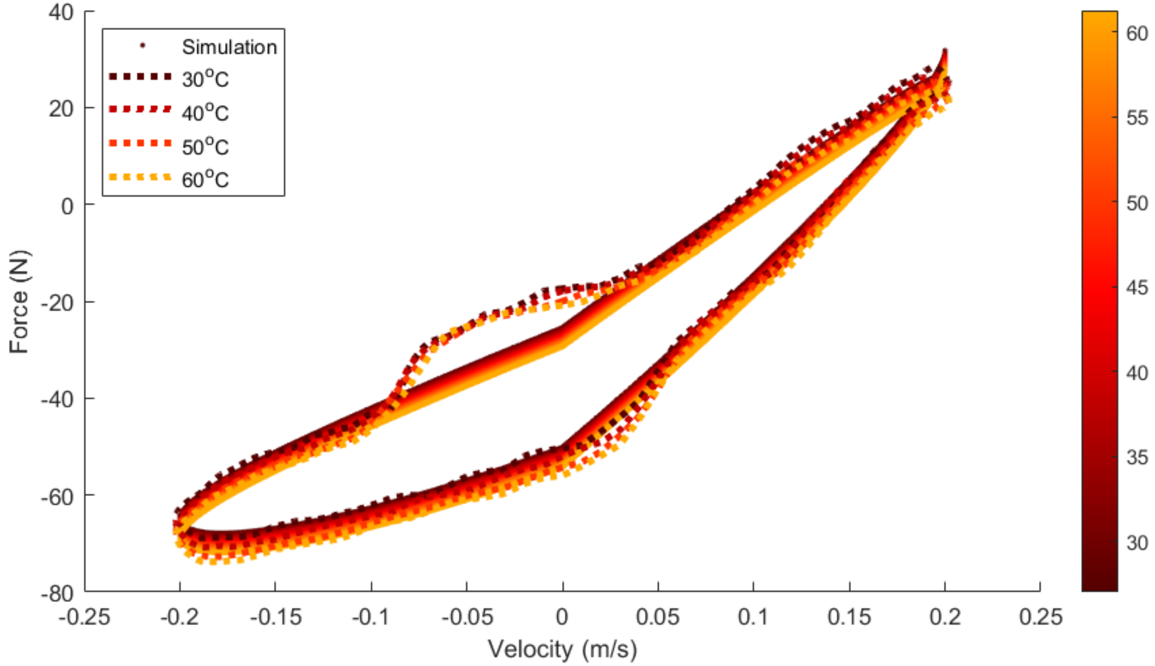
$$F_{gas,static} = \frac{mR_i A_{rod} T}{V_{gas,static}}$$

temperature
volume

$$F_{damping} = \frac{F_{leak} F_{shim}}{\sqrt[K_{tr}]{F_{leak}^{K_{tr}} + F_{shim}^{K_{tr}}}} + F_{main} - F_{gas,dyn}$$

Force Modelling

- **For 1 Hz data set**
  - RMSE - 6.36 N
  - Mean error – 0.93 N
  - Mean absolute error – 5.26 N
- **For all data**
  - RMSE – 7.08 N
  - Mean error – 0.79 N
  - Mean absolute error – 5.64 N



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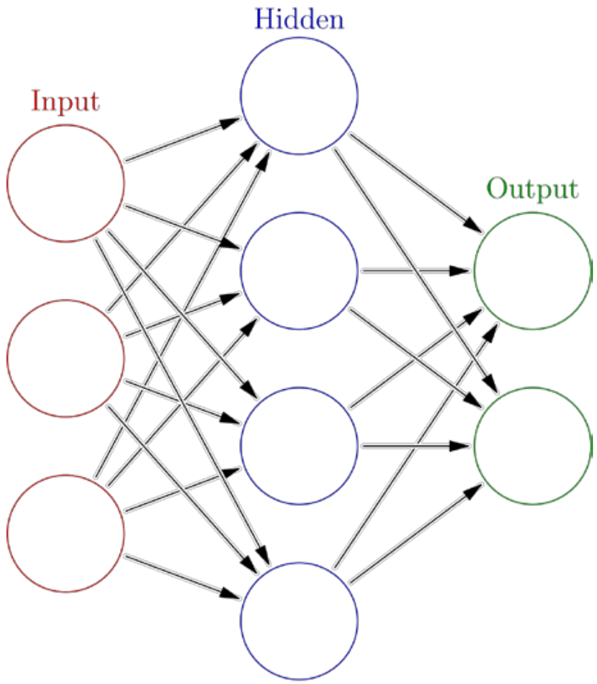
- ***Neural network***
  - *Architecture*
  - *Training*

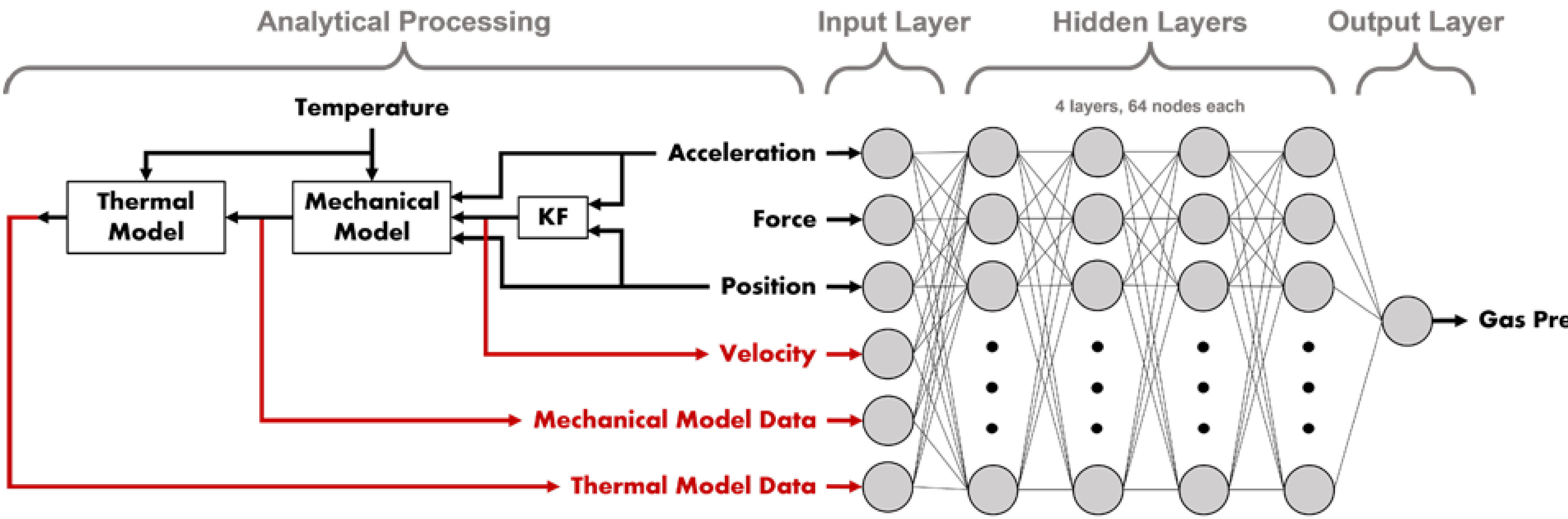
Neural Network

- **Network Architecture**
  - ➢ Standard multi hidden layer feed-forward neural network
  - ➢ Deep Neural Network (DNN)
    - ▪ Additional inputs generated from model derived data
- **Alternatives**
  - ➢ Physics Informed Neural Network (PINN)
  - ➢ Modular Neural Network (MNN)
- **DNNs chosen to clearly enumerate advantages of deriving model-based data**



Network Architecture

- **Evaluated permutations of architecture**



Network Training

- **Training process**
  - The dataset down sampled to 50Hz.
  - This dataset was randomly partitioned
    - Training set – 75%
    - Testing set – 25%.
- **Training repeated**
  - For all pertinent permutations of
    - Sensor data
    - Estimated/modelled data

Results

Model ID	Model Name	Force	Position	Acceleration	Velocity	Mechanical Model Data	Thermal Model Data	RMSE (bar)
1	-	■						3.34
2	-		■					3.53
3	Force and Position DNN	■	■					2.51
4	-			■				3.52
5	-	■		■				3.18
6	-		■	■				3.18
7	Force, Position and Acceleration DNN	■	■	■				2.27
8	-		■	■	■			3.18
9	Kalman-Velocity Hybrid DNN	■	■	■	■			1.84
10	-		■	■	■	■		3.08
11	Mechanical Hybrid DNN	■	■	■	■	■		1.72
12	Thermomechanical Hybrid DNN (No Force)		■	■	■	■	■	1.40
13	Thermomechanical Hybrid DNN	■	■	■	■	■	■	0.85

Results

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Results

- **Taking the 6 most accurate configurations and evaluating the hardware costs**
- **Due to the significant cost of the loadcell**

Model ID	Force	Position	Acceleration	Velocity	Mechanical Model Data	Thermal Model Data	RMSE (bar)	No. of Sensors	Sensor Cost ($ AUD)
3							2.51	2	$4,270
7							2.27	3	$4,281
9							1.84	3	$4,281
11							1.72	4	$4,292
12							1.40	3	$297
13							0.85	4	$4,292

Summary

- **Explicit modelling**
  - ➢ Can significantly improve the estimation accuracy
    - ▪ Allow any DNN training to focus on the residuals rather than relationship
  - ➢ Offset the necessity of some sensors
  - ➢ Maintain acceptable accuracy when certain sensors are not included
  - ➢ Dramatically reducing the hardware costs
  - ➢ Marginally increasing software costs but
    - ▪ Can be amortised over a large number of units
- **But can this work with real word sensor data…..**

Future Work

- **Completion of instrumented shock abso**
  - Mechanically replicate behaviour of OEM
  - Instrumented as to be deployable
- **Real world data collection**
  - Installation on test vehicle
  - Integration of data logging into vehicle systems
- **Evaluation**
  - Evaluate collected data to determine viability given characteristics of data collected during operation

Thank You

- **Questions?**