



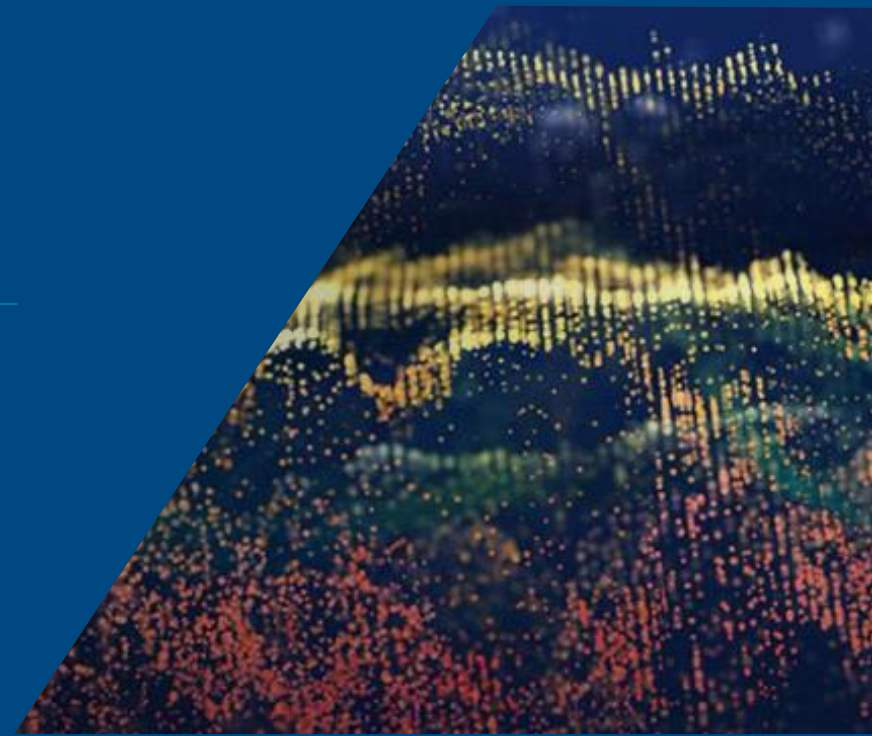
AI and the Power of Simulation

Antti Löytynoja

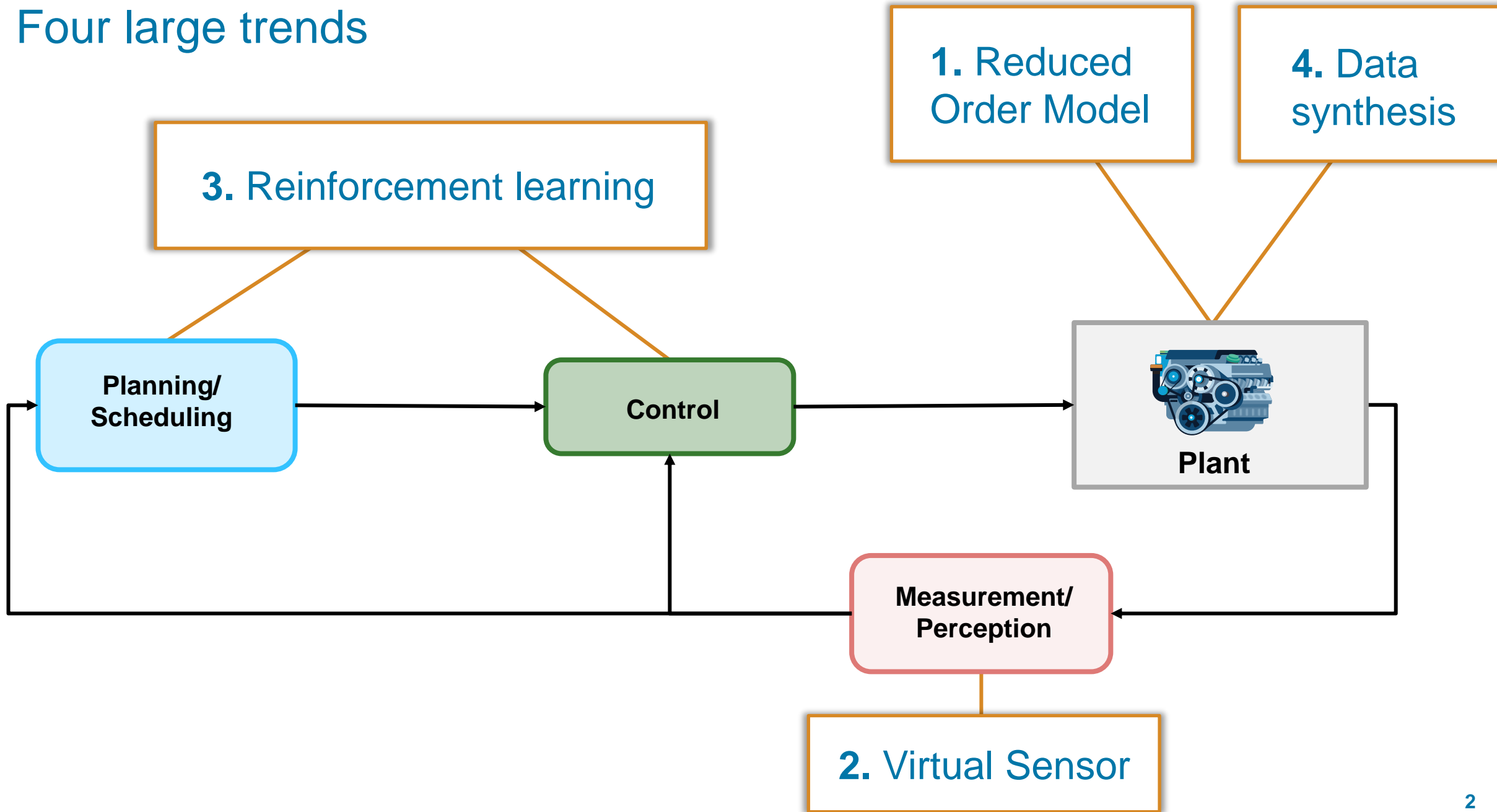
*Senior Application Engineer, MATLAB
MathWorks
aloytyno@mathworks.com*

Valtteri Forsman

*Application Engineer, Simulink
MathWorks
vforsman@mathworks.com*



Four large trends



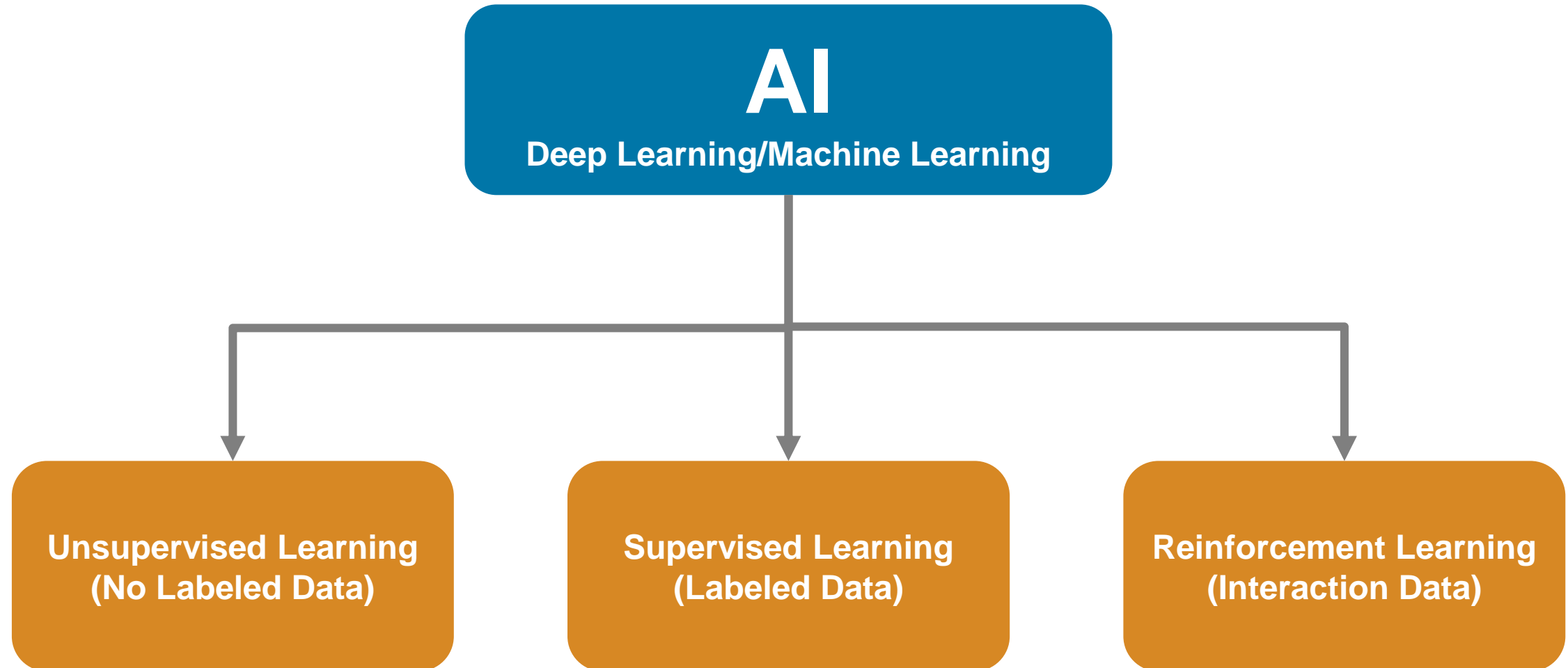
Why these trends?

They help you **overcome** common **challenges**

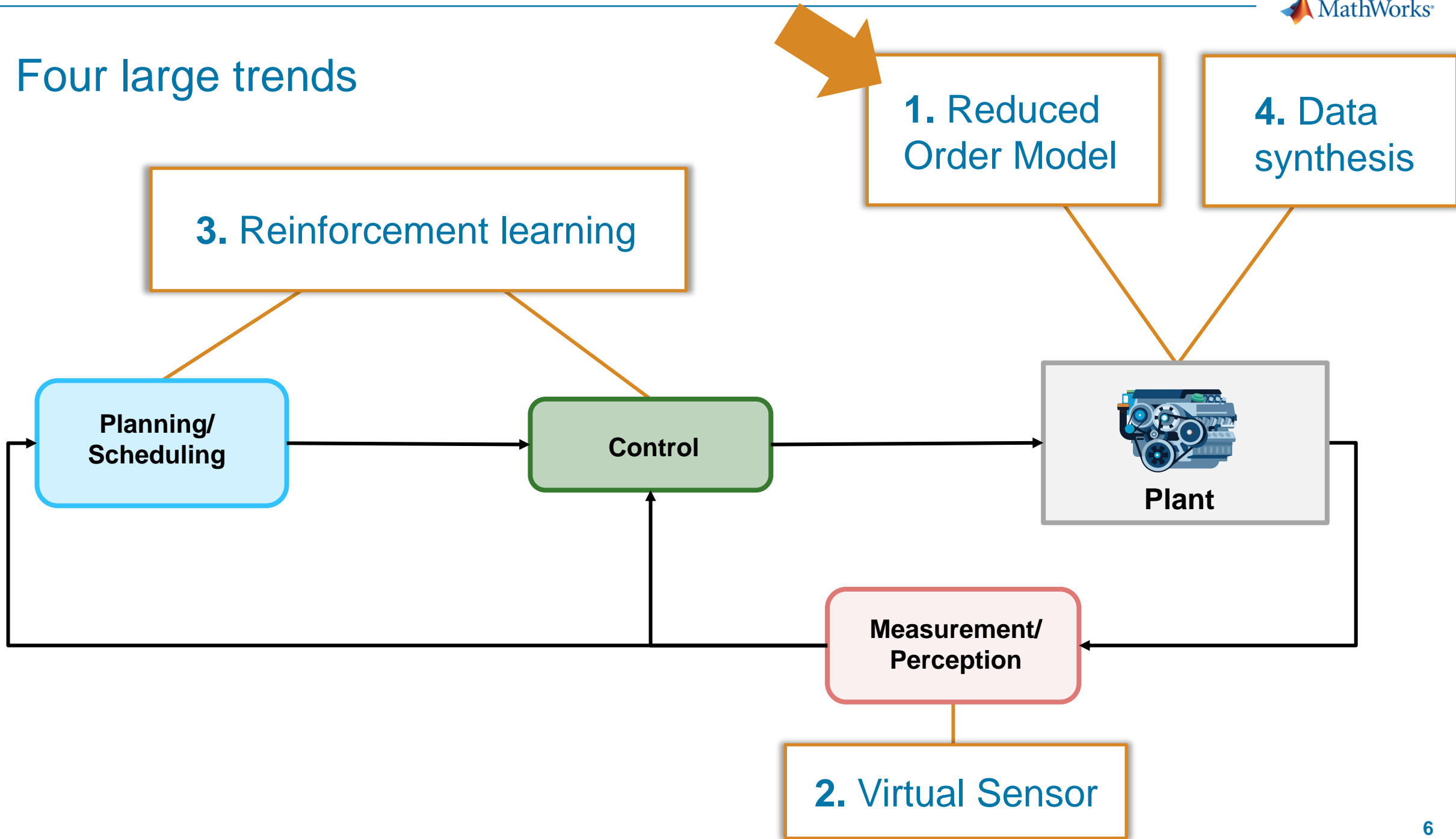
- Models/Algorithms are too slow to run in real time
- Models are unnecessarily complex
- Models are inaccurate
- Measurements are difficult to obtain

AI Landscape

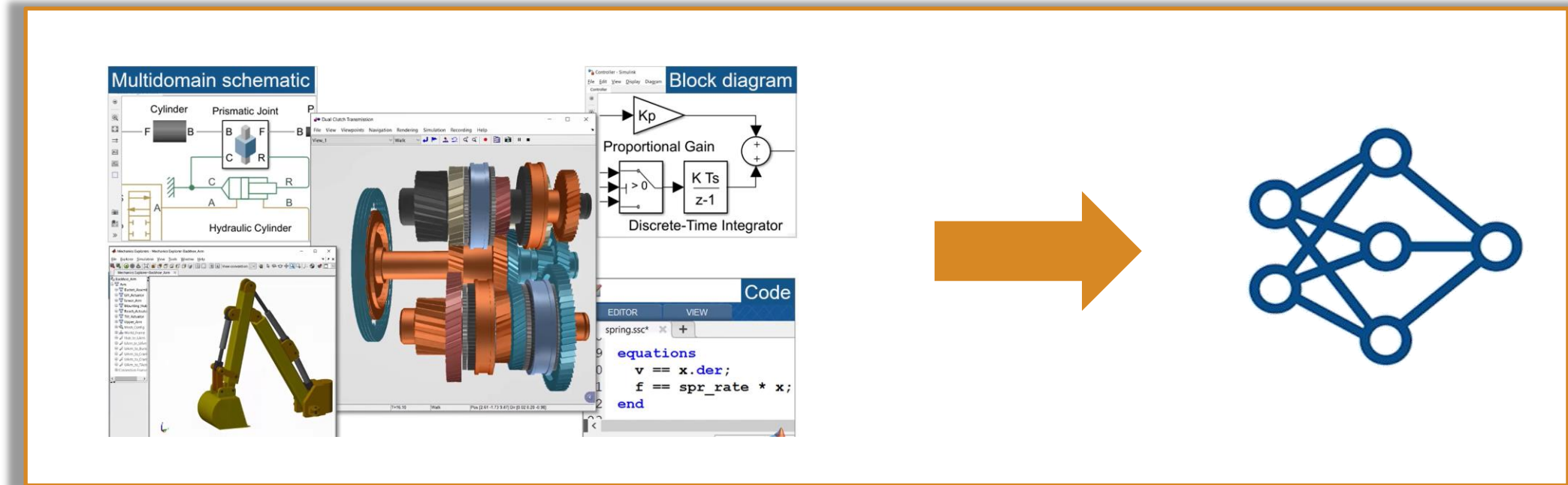
Machine Learning vs Deep Learning vs Reinforcement Learning



Four large trends



Trend 1 Reduced Order Modelling (ROM)



Why?!

Create faster more light weight models of High-Fidelity Physics based Models for tasks when **speed** is more important than accuracy

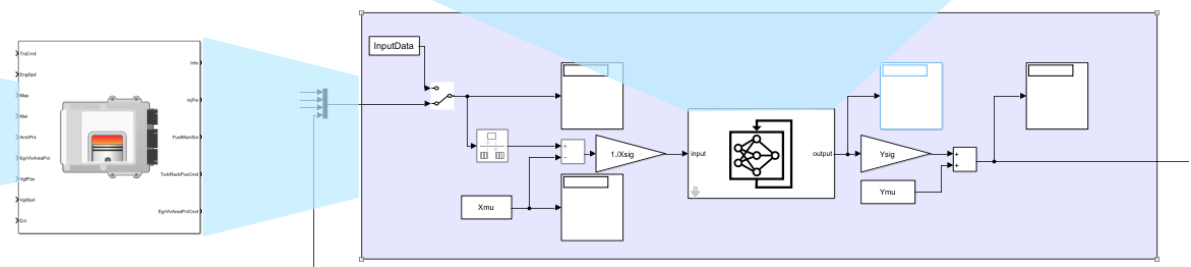
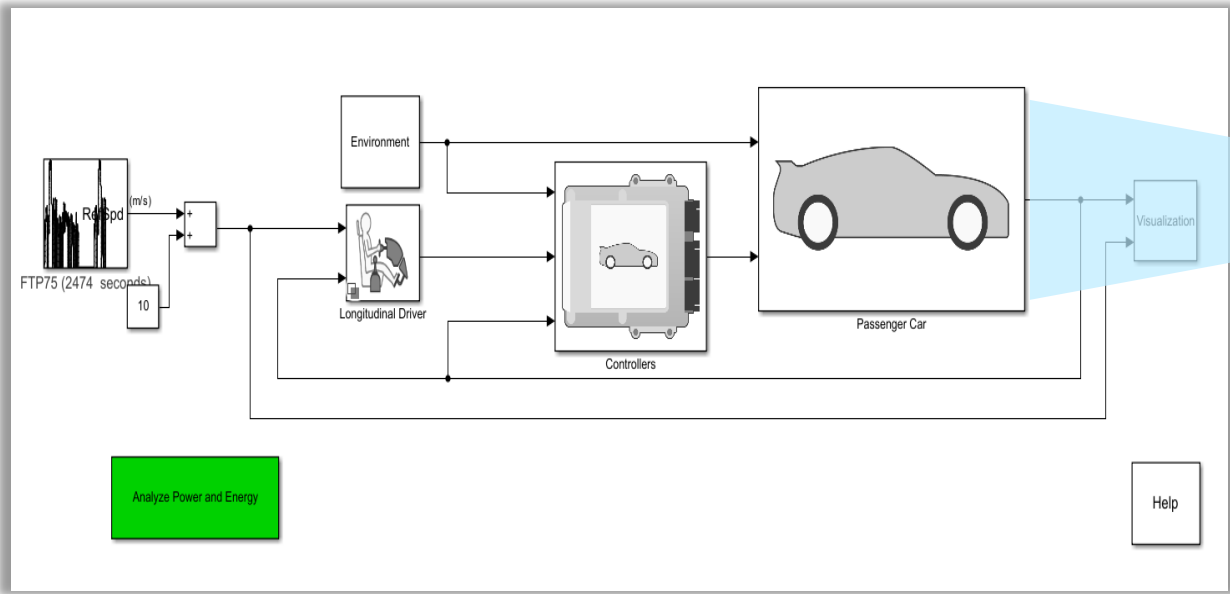
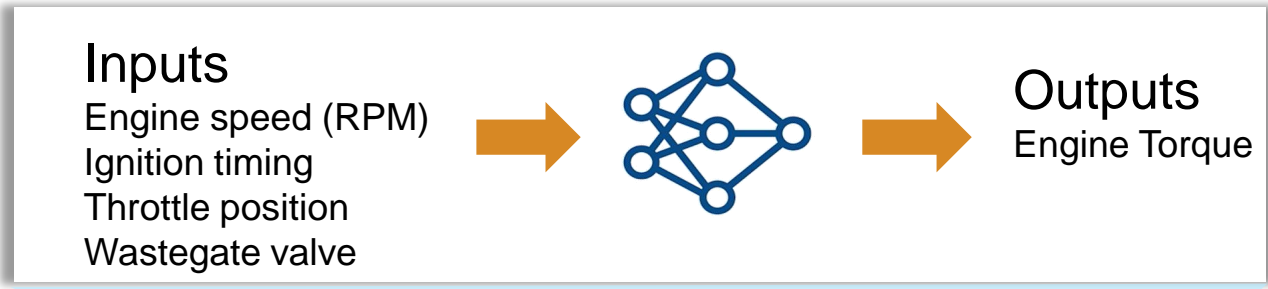
How?

Train on simulated data from the high-fidelity model and/or real data

Demo Description

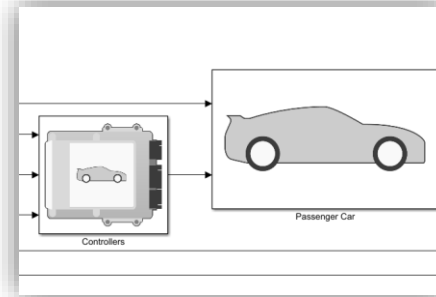
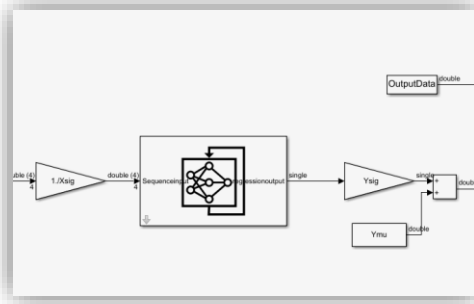
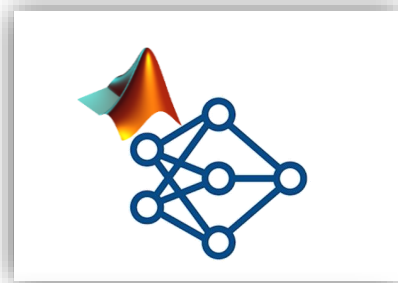
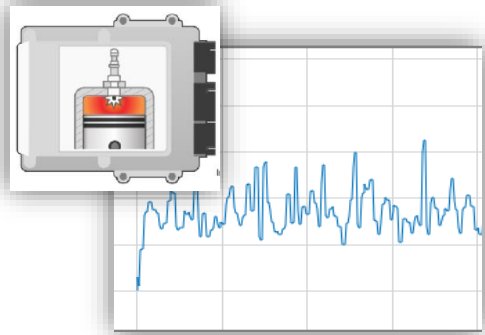
Engine torque estimation

Engine model 10-50x faster
Overall simulation 2.5x faster



- Replacing the high-fidelity SI engine model with AI
- Speed up model to get real-time simulation

Workflow



```

/* Function for MATLAB Function: '<S1>/MLFB' */
static real32_T DeepLearningNetwork_predictAndU(c_code
obj, const real_T indata[4])
{
    cell_wrap_3_demo_SL_LSTM_T outT_f2[3];
    cell_wrap_3_demo_SL_LSTM_T outT_f2_0;
    int32_T d_k;
    int32_T i;
    real32_T G[40];
    real32_T y[10];
    real32_T b_f1[4];
    real32_T b_f1_0;
    static const real32_T W[160] = { 0.114687733F, 0.155
    0.0276211F, 0.163311467F, -0.325015634F, -0.211589

```

Data Preparation

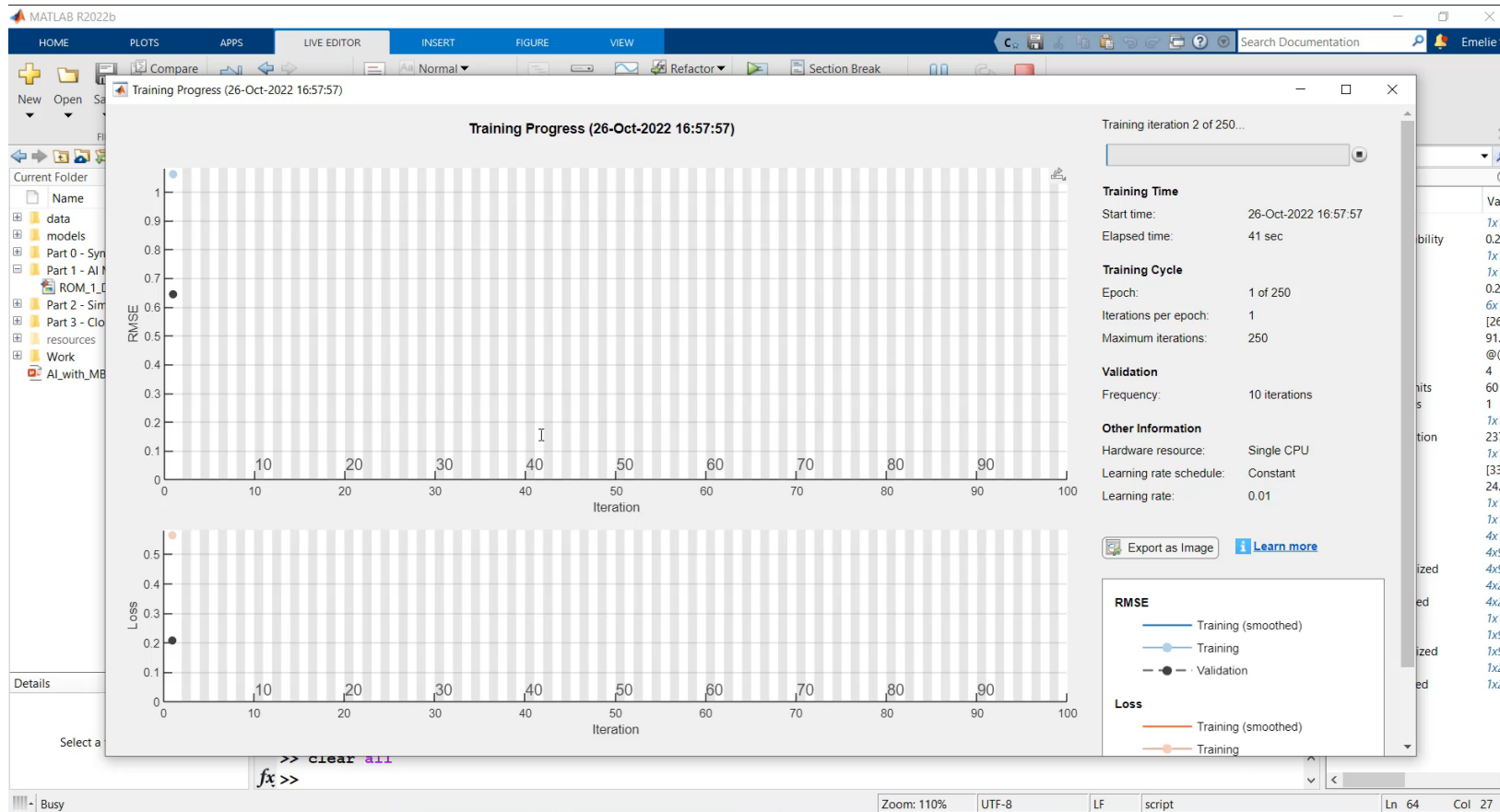
AI model training

Simulink implementation

Integration into system model

Code generation for HIL

AI model training

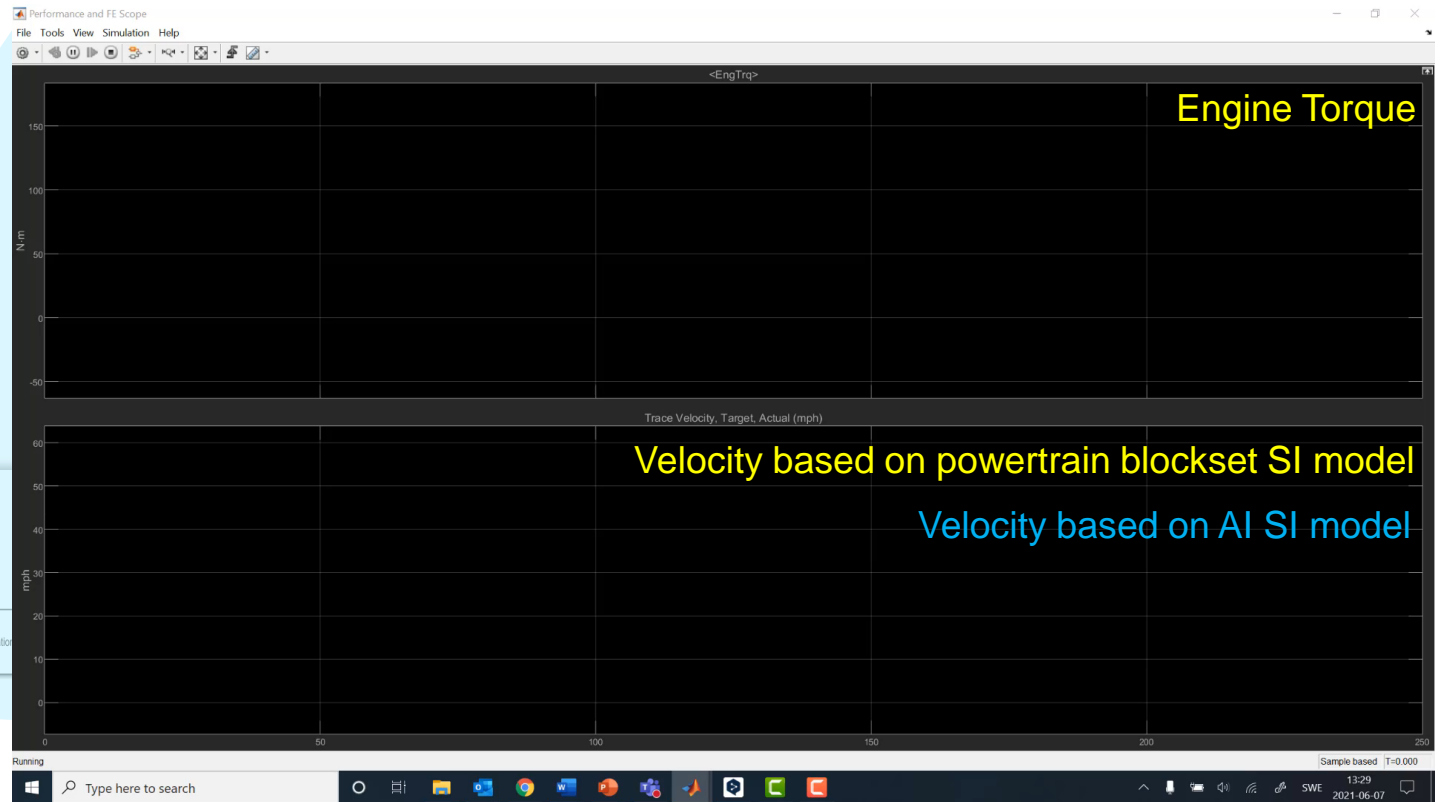
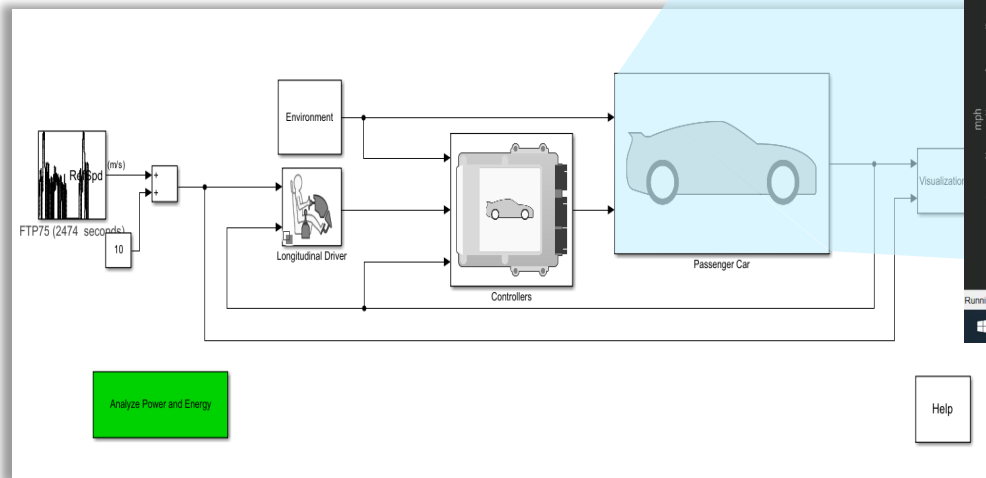


```
save('net.mat', 'net')
```

Simulink implementation of learning models



Integrate into a system-level model for overall simulation



Generate code for LSTM model



Generate C code

The screenshot displays the Simulink C Code Generator interface for a model named 'demo_SL_LSTM'. The 'C CODE' tab is active, showing a 'Code for' field with the model name and a 'Build' button. The main workspace shows a Simulink block diagram with the following components and connections:

- InputData** (double (4)) and **Xmu** (double (4)) are inputs to a summing junction.
- The summing junction output (double (4)) is multiplied by **1./Xsig** (double (4)).
- The result is fed into the **SequenceInput** block of an LSTM neural network.
- The LSTM network outputs **RegressionOutput** (single).
- Ymu** (double) is added to the **RegressionOutput** at another summing junction.
- The output of this second summing junction (double) is multiplied by **OutputData** (double).
- The final result is sent to the **simout** block.

At the bottom of the interface, there is a 'Code Mappings - C' window and a status bar showing 'Ready', 'View 2 warnings', '94%', and 'auto(FixedStepDiscrete)'.

Want to learn more??

Reduced Order Modeling

Search MathWorks.com



↓ Trial software

☎ Contact sales

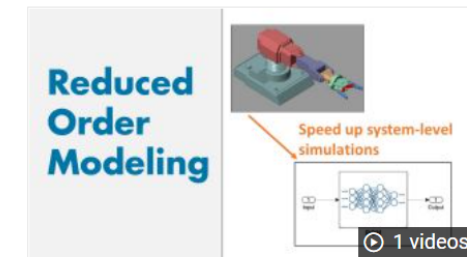
Reduce the computational complexity of your models by creating accurate surrogates

Reduced order modeling (ROM) and model order reduction (MOR) are techniques for reducing the computational complexity or storage requirement of a computer model, while preserving the expected fidelity within a controlled error. Working with surrogate models can simplify analysis and control design.

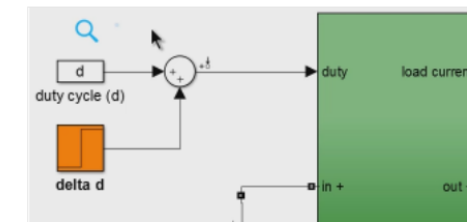
Scientists and engineers use ROM techniques to create system-level simulations, design control systems, optimize product designs, and build digital twin applications. MATLAB®, Simulink®, and add-on products let you build accurate ROMs using various reduced order modeling methods.

Why Use Reduced Order Modeling?

Large-scale, high-fidelity nonlinear models can take hours or even days to simulate. System analysis and design can require thousands or hundreds of thousands of simulations, presenting a significant computational challenge. Also, linearizing complex models can result in high-fidelity models containing states that do not contribute to the dynamics of interest in your application.



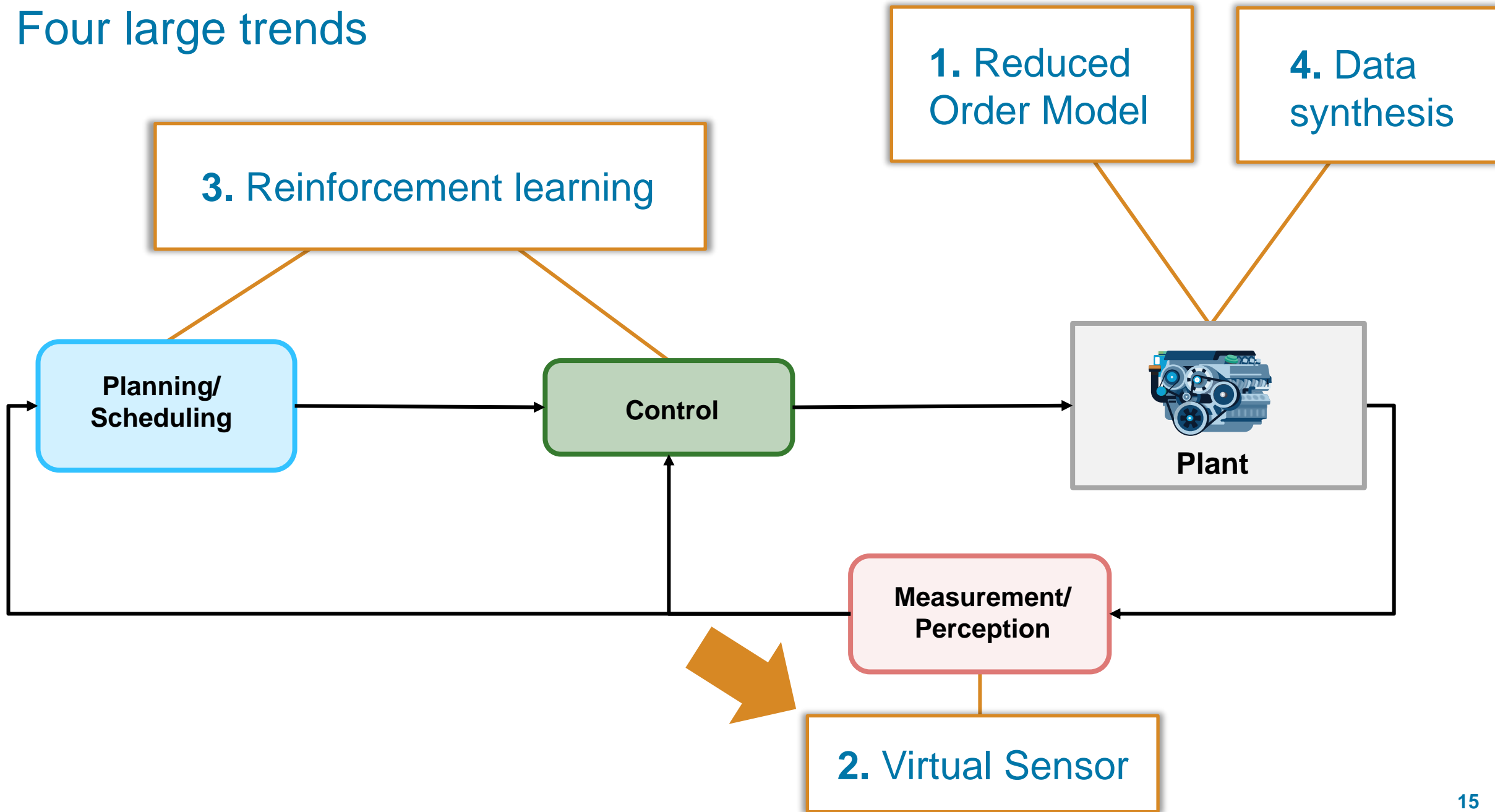
Reduced Order Modeling (1 videos)



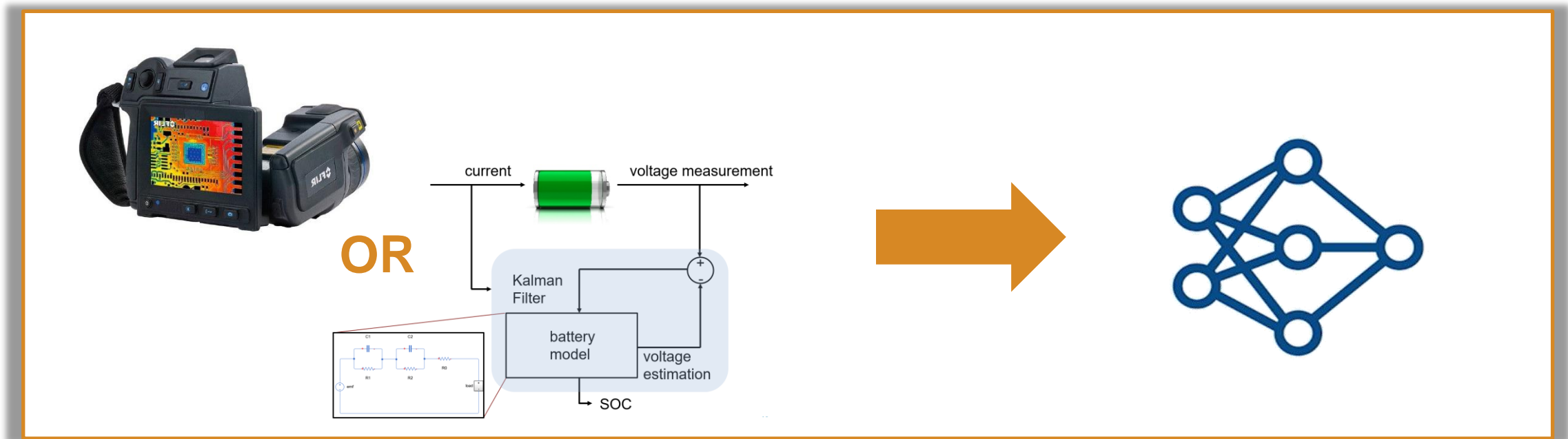
[Link to webpage](#)

[Link to video](#)

Four large trends



Trend 2 AI based Virtual Sensors



Why?! A physical sensor may be:

- Expensive
- Noisy
- Degrading over time
- Impossible to place
- ...

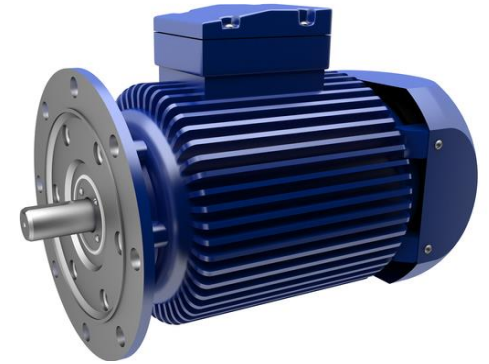
How?

Train a model that can predict the wanted measurement using data from existing sensors

AI based Virtual Sensors for Temperature Estimation

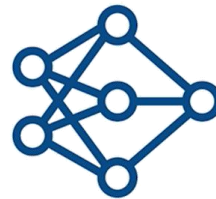
Use lab data to replace **expensive** sensors with AI based sensor

- Permanent Magnet Synchronous Motor (electric motor)
- Temperature Estimation
- Data collected via contactless infrared sensor



Inputs

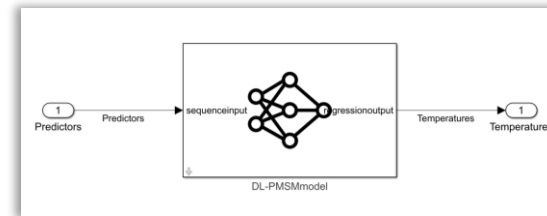
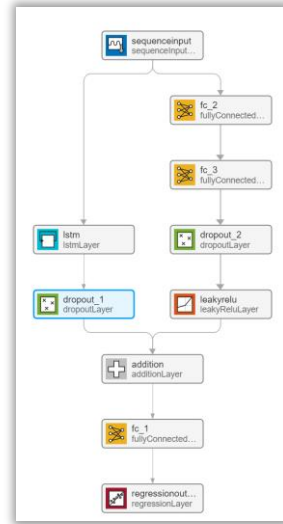
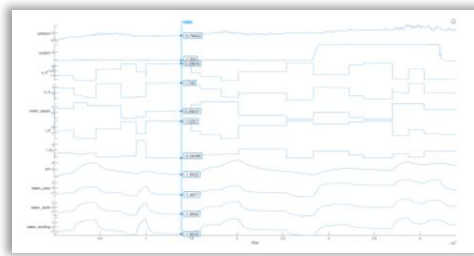
Ambient Temperature
Coolant Temperature
Voltage
Current
Motor speed



Outputs

Permanent Magnet Temperature
Stator Yoke Temperature
Stator Teeth Temperature
Stator Winding Temperature

Workflow



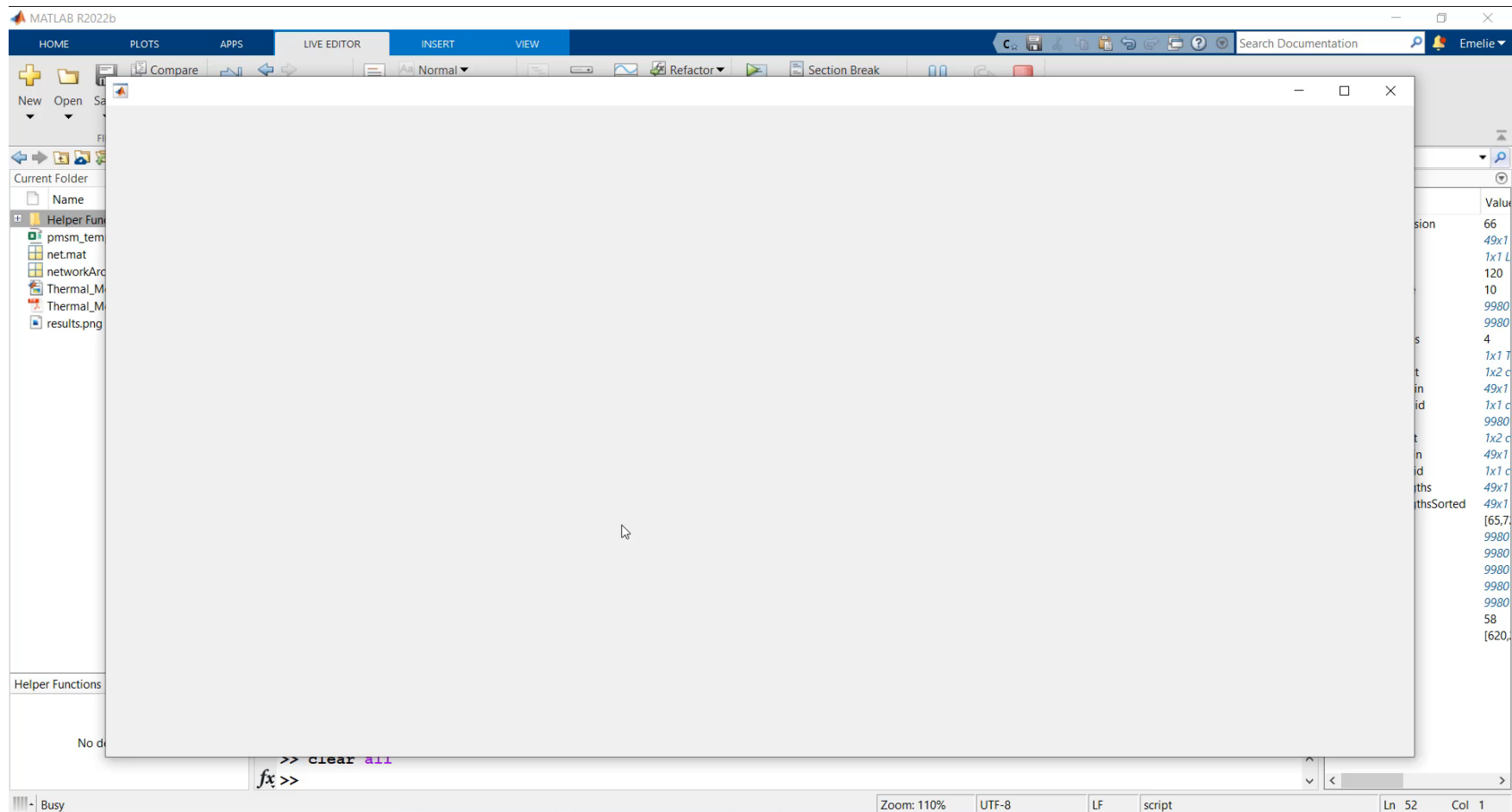
```

46 }
47
48 /* Function for MATLAB Function: 'cs1b/MLB' */
49 static void PMS_DeepLearningNetwork_predict(c_coder_target_DeepLearningLT *obj,
50 const real_T varargin_1[90], real32_T varargin_1[4])
51 {
52     cell_wrap_3_PMSMSin_out_f7_idx_0;
53     int32_T i;
54     int32_T k;
55     real32_T b_w[125];
56     real32_T tmp[125];
57     real32_T tmp_0[125];
58     real32_T T[90];
59     real32_T b_fi[90];
60     real32_T y[90];
61     real32_T c_w[4];
62     static const real32_T g[5100] = { 0.070807673F, -0.0277374703F, -0.110051225F,
63     0.154562488F, 0.0726826265F, 0.0274735242F, 0.049374132F, 0.11217292F,
64     0.0309785958F, -0.104045361F, 0.118567258F, -0.0220224597F, 0.107955806F,
65     0.0484067798F, 0.0718827546F, -0.0433443896F, -0.168901235F, 0.0938847363F,
66     0.093891874F, 0.113060363F, -0.147850305F, 0.108972579F, 0.139142409F,
67     -0.0776476189F, -0.050801315F, 0.0730740577F, -0.117033422F, 0.0421196F,
68     0.141403973F, 0.0608193457F, -0.0997701883F, -0.0926445276F, -0.1521210757F,
69     -0.164792791F, -0.0730195045F, 0.0115301344F, 0.159413099F, -0.15482137F,
70     0.13521756F, -0.131523401F, -0.101185754F, 0.103414282F, -0.12940134F,
71     -0.149640426F, 0.154901505F, 0.0866299197F, 0.0511259884F, -0.0731999427F,
72     0.106936872F, 0.0924417302F, 0.062970221F, 0.0889010057F, 0.110696388F,
73     -0.101548024F, 0.161914587F, -0.161086291F, 0.0247278847F, -0.0590701178F,
74     0.14430615F, 0.176843123F, -0.0219022372F, 0.0309543419F, 0.021353119F,
75     0.0783760548F, -0.0101056565F, 0.132538676F, -0.0135600955F, 0.147363365F,
76     -0.0101488074F, -0.108393282F, 0.060554242F, 0.0171978846F, 0.121794797F,

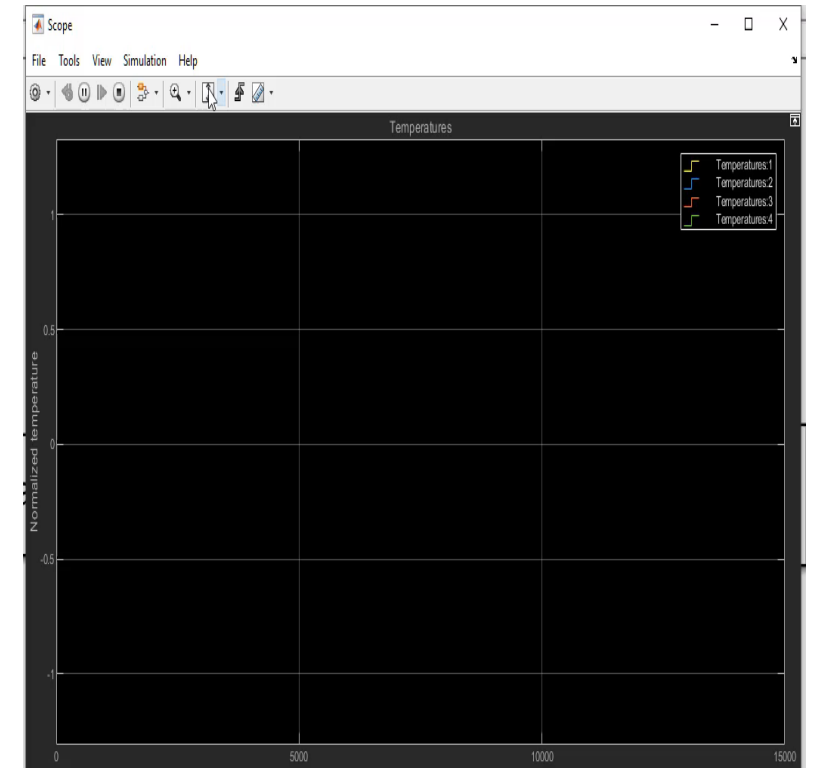
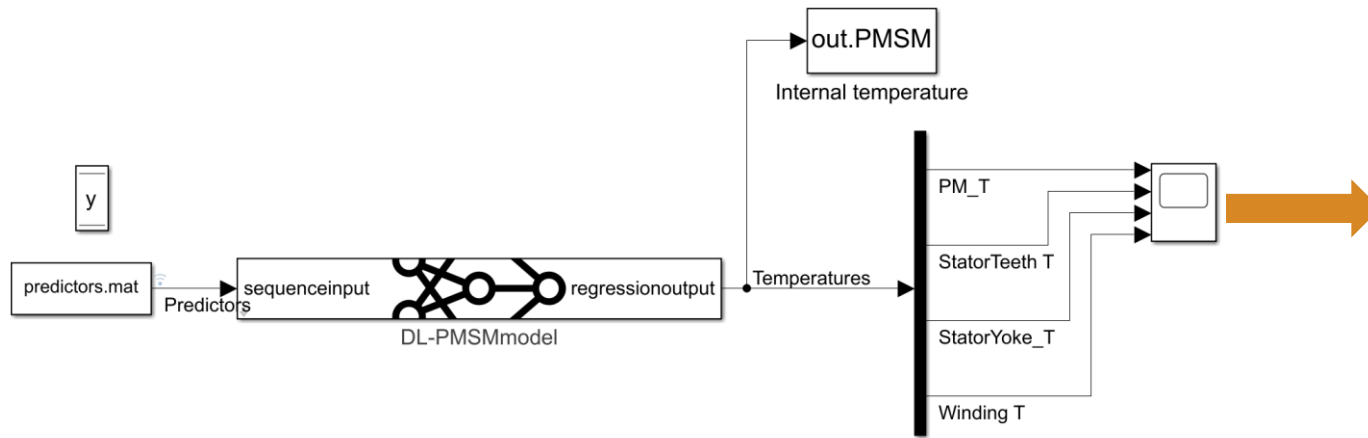
```



AI model training



Simulink Implementation



Code generation



```

..
48 /* Function for MATLAB Function: '<S1>/MLFB' */
49 static void PMS_DeepLearningNetwork_predict(c_coder_ctarget_DeepLearningN_T *obj,
50     const real_T varargin_1[90], real32_T varargout_1[4])
51 {
52     cell_wrap_3_PMSMSim_T outT_f7_idx_0;
53     int32_T i;
54     int32_T k;
55     real32_T b_y[125];
56     real32_T tmp[125];
57     real32_T tmp_0[125];
58     real32_T T[90];
59     real32_T b_f1[90];
60     real32_T y[90];
61     real32_T c_y[4];
62     static const real32_T g[8100] = { 0.070807673F, -0.0277374703F, -0.119051225F,
63         0.154562488F, 0.0726826265F, 0.0274735242F, 0.0493374132F, 0.112217292F,
64         0.0309785958F, -0.104045361F, 0.118567258F, -0.0220224597F, 0.107955806F,
65         0.0484067798F, 0.0718827546F, -0.0433443896F, -0.168901235F, 0.0938847363F,
66         0.093891874F, 0.113060363F, -0.147850305F, 0.108972579F, 0.139142409F,
67         -0.0776476189F, -0.050881315F, 0.0730740577F, -0.117033422F, 0.0421196F,
68         0.141403973F, 0.0689193457F, -0.0997701883F, -0.0926445276F, -0.152210757F,
69         -0.164792791F, -0.0730195045F, 0.0315301344F, 0.159413099F, -0.154582337F,
70         0.135217756F, -0.131523401F, -0.101185754F, 0.103414282F, -0.129400134F,
71         -0.149649426F, 0.154901505F, 0.0866299197F, 0.0511259884F, -0.0731999427F,
72         0.106936872F, 0.0924417302F, 0.062970221F, 0.0889010057F, 0.110696308F,
73         -0.101548024F, 0.161914587F, -0.161086291F, 0.0247278847F, -0.0590701178F,
74         0.144306615F, 0.176843122F, -0.0219022371F, 0.0509543419F, 0.0173563119F,
75         0.0783760548F, -0.0101056565F, 0.132538676F, -0.0135600995F, 0.147363365F,
76         -0.0101488074F, -0.108393282F, 0.0605547242F, 0.0171978846F, 0.121794797F,
77         0.0315105692F, 0.0084853777F, 0.141043633F, 0.0866781399F, -0.135606185F,
  
```

Other use cases of Virtual Sensors?


AI based Virtual Sensors for State Of Charge Estimation



7th April 2022

Battery SOC and SOH
Estimation using a Hybrid
Machine Learning Approach

[Link](#) to video from
MathWorks Automotive Conference

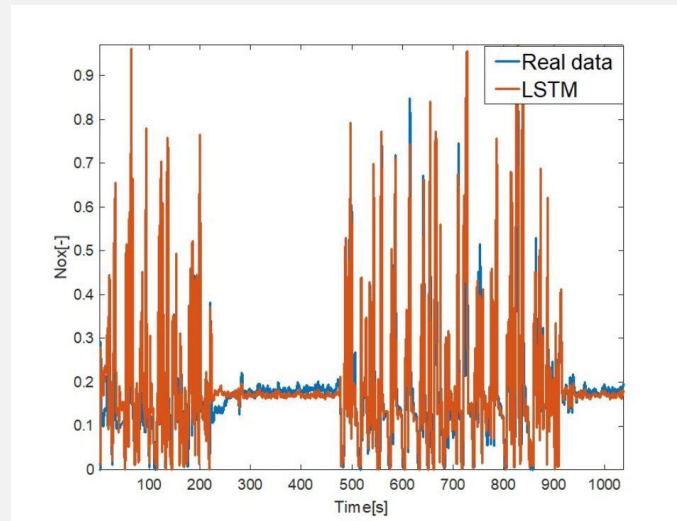


Onboard Battery Pack State of Charge
Estimation Using a Neural Network

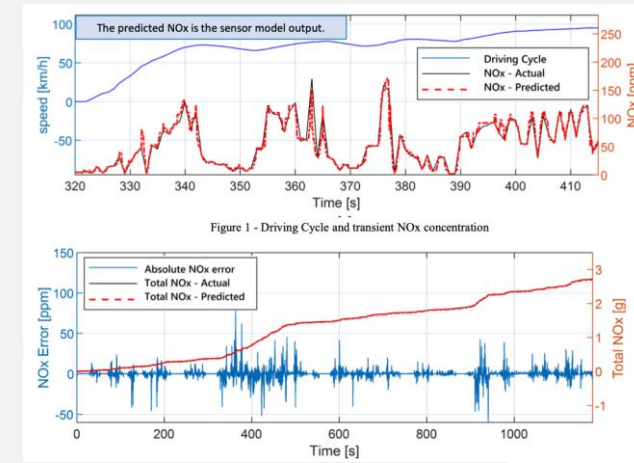
[Link](#) to video from
MathWorks Automotive Conference

Other use cases of Virtual Sensors?

AI based Virtual Sensors for NOx Estimation



[Link to article](#)



[Link to presentation](#)

Learn more??



 MathWorks®

AI with Model-Based Design
Virtual Sensor Modeling

Lucas García, PhD
Senior Product Manager
Deep Learning
lgarcia@mathworks.com



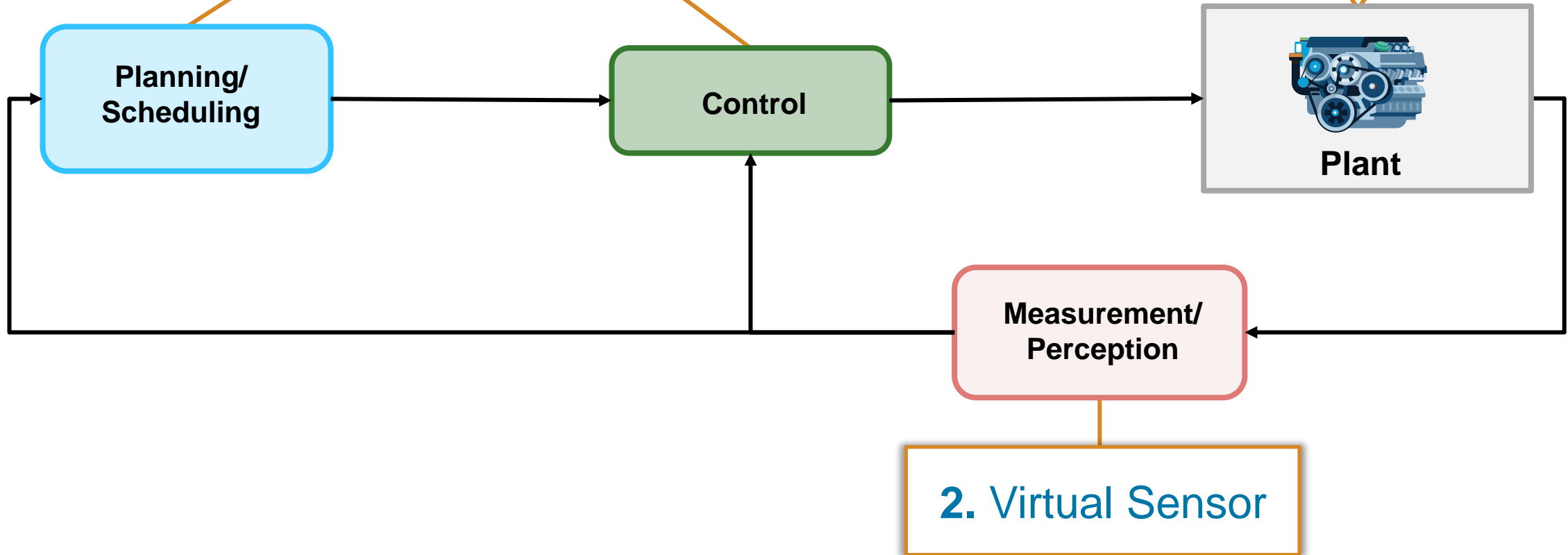
[Video - AI with Model Based Design: Virtual Sensor Modelling](#)

Four large trends

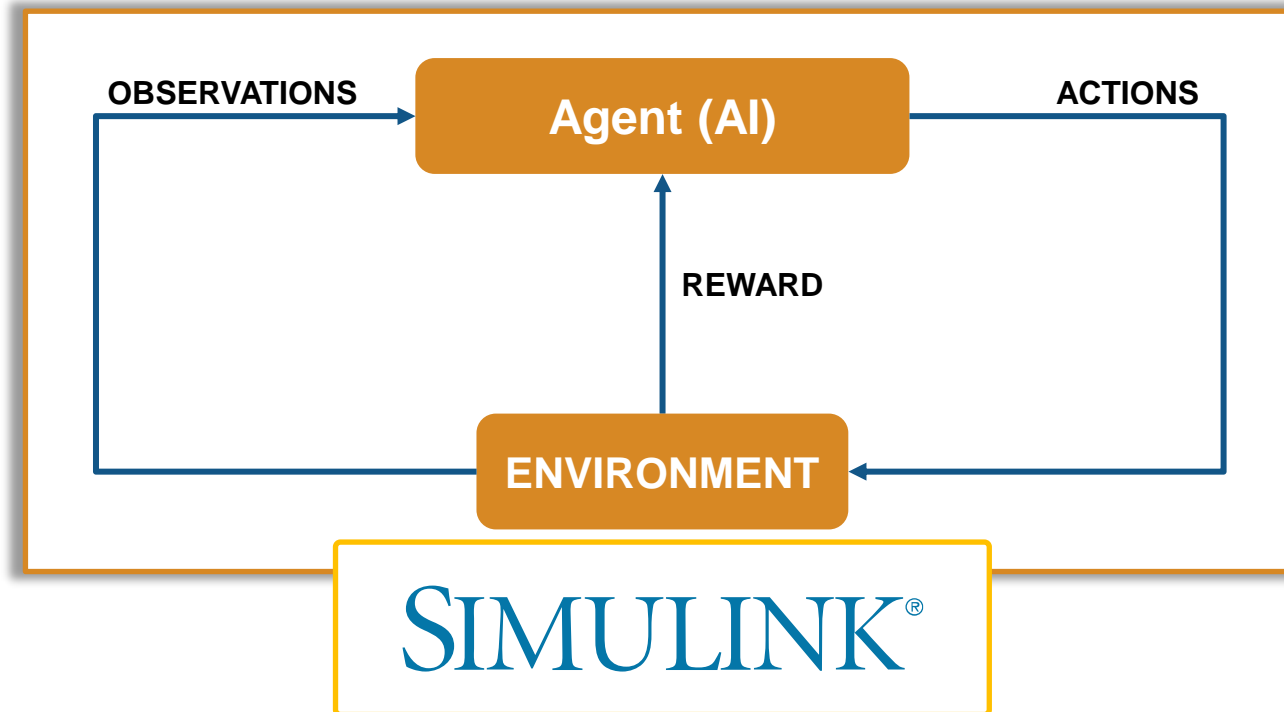
1. Reduced Order Model

4. Data synthesis

3. Reinforcement learning



Trend 3 Reinforcement Learning based Controls

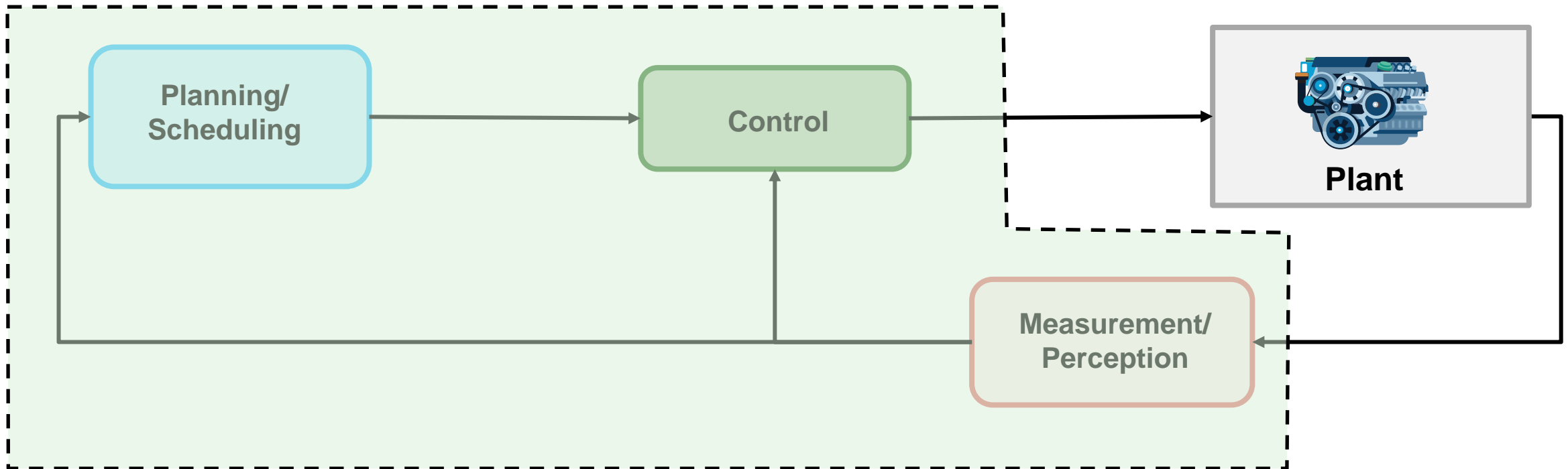


Why?!

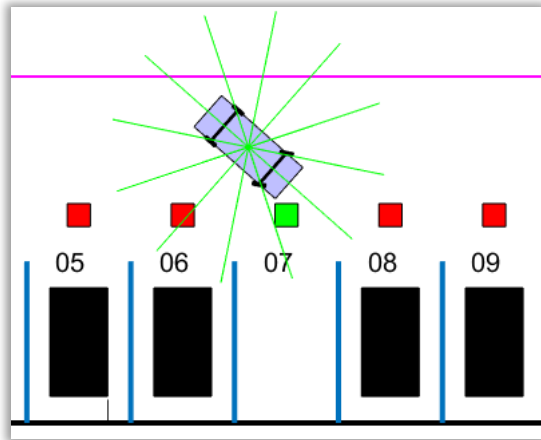
- The system you want to control or make decisions for is highly non-linear or uncertain
- Get an end-to-end solution

End-to-end Reinforcement Learning

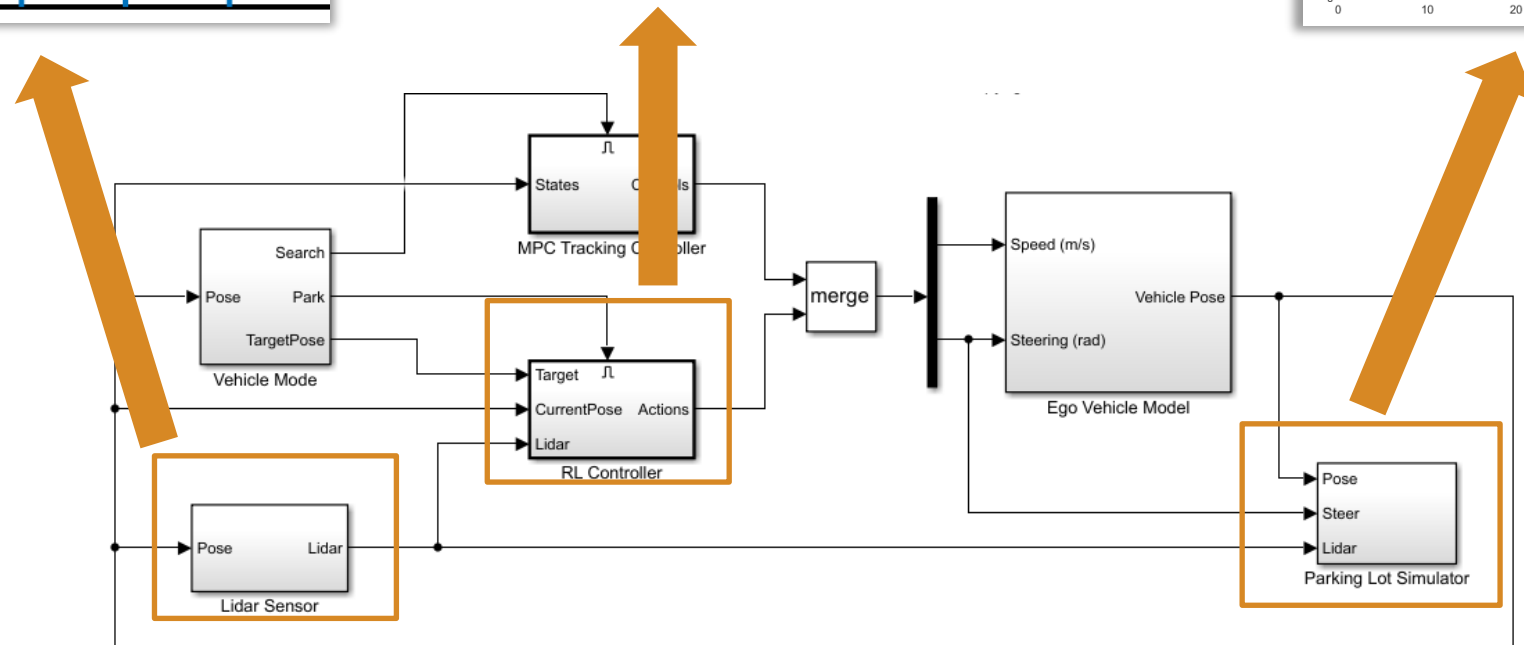
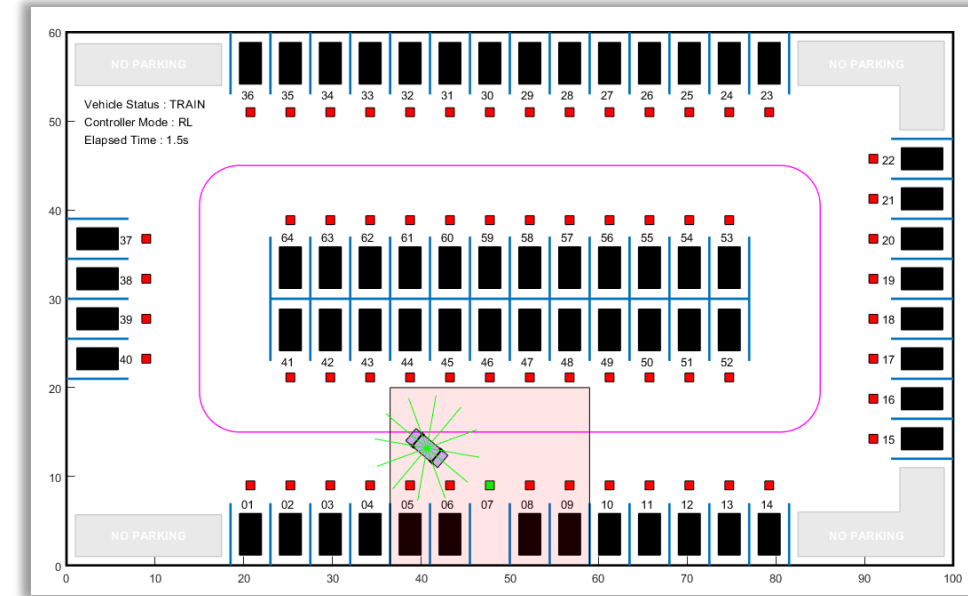
Reinforcement Learning Agent



Automatic Parking Example



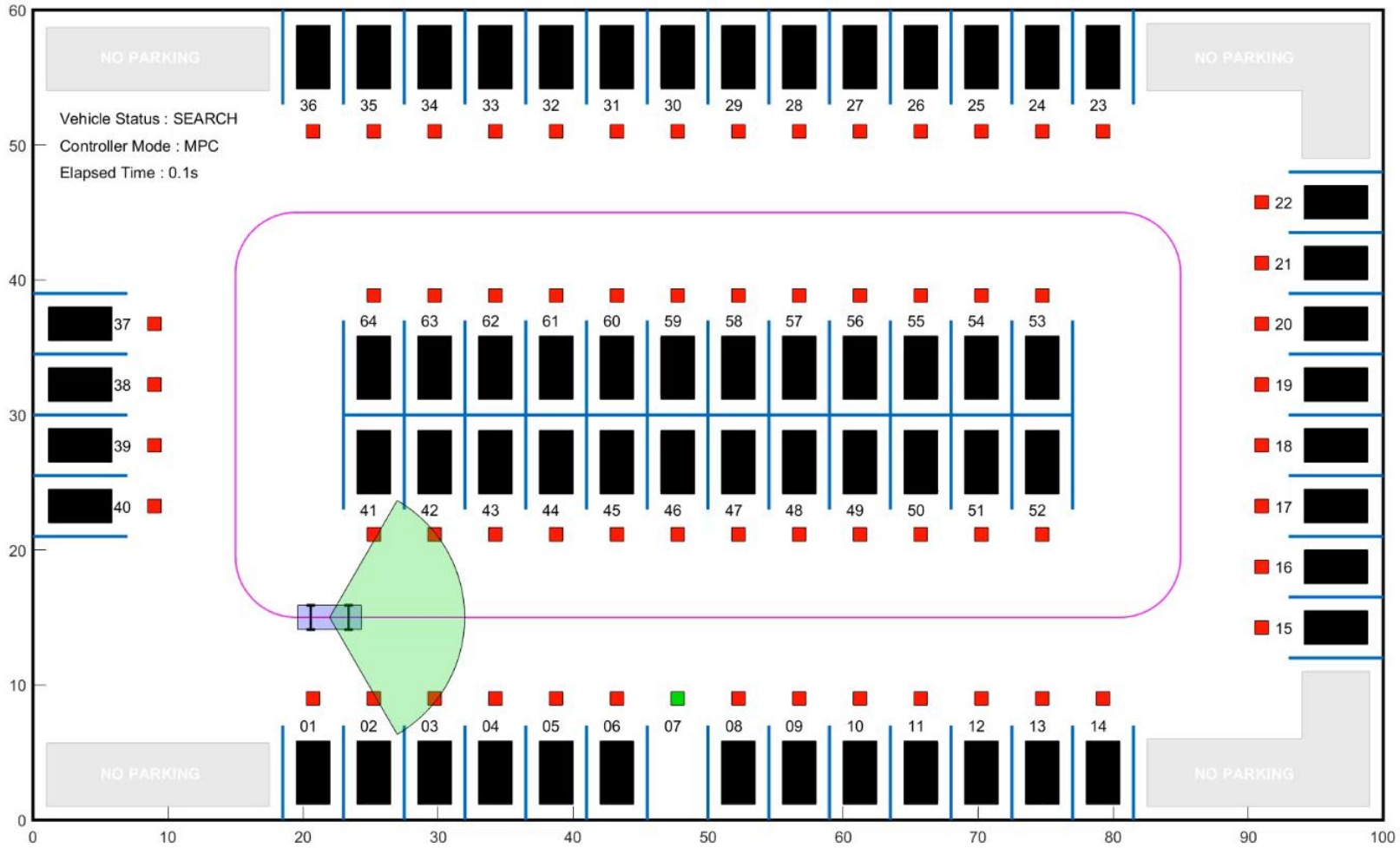
```
criticNetwork = [
    featureInputLayer(numObservations, ...
        Normalization="none", ...
        Name="observations")
    fullyConnectedLayer(128,Name="fc1")
    reluLayer(Name="relu1")
    fullyConnectedLayer(128,Name="fc2")
    reluLayer(Name="relu2")
    fullyConnectedLayer(128,Name="fc3")
    reluLayer(Name="relu3")
    fullyConnectedLayer(1,Name="fc4")];
criticNetwork = dlnetwork(criticNetwork);
```



[Link to example](#)

Auto Parking Valet

File Edit View Insert Tools Desktop Window Help



RL based controls

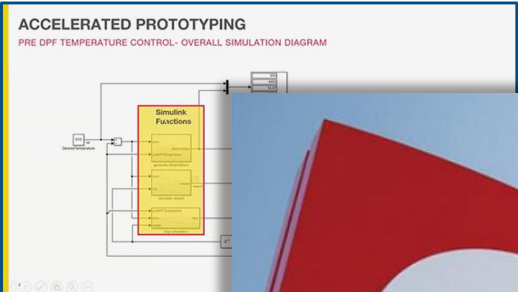
Vitesco Technologies Applies Deep Reinforcement Learning in Powertrain Control

Challenge
Speed up development and prototyping in the face of global climate change and to conform to more stringent emission laws

Solution
Use Reinforcement Learning Toolbox to quickly prototype, generate, and optimize reinforcement learning agents

Key Outcomes

- Fast prototyping of reinforcement learning agents and reduced development time
- Use of Simulink for state-of-the-art plant modeling
- Quick start enabled through use of documentation and examples for reinforcement learning algorithms
- Fast resolution to technical issues with dedicated calls with MathWorks experts



ACCELERATED PROTOTYPING
PRE DPF TEMPERATURE CONTROL - OVERALL SIMULATION DIAGRAM

Simulink model incorporatir

"Reinforcement Learning reduced development time helped in fast prototyping reinforcement learning algorithms"
- Vivek Venkobarao, Vitesco

[Link](#) to customer presentation



A perspective on deploying Machine Learning to augment classic control design

Ali Borhan
Manager – Cummins R&T

November 5, 2020

[Link](#) to customer presentation

Learn more?!

- Tech Talk video series on Reinforcement Learning concepts for engineers
- Reinforcement Learning Onramp

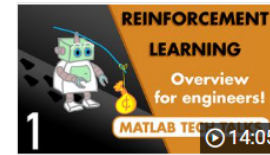
Reinforcement Learning Onramp

This free, two-hour tutorial provides an interactive introduction to reinforcement learning methods for control problems.

Prerequisites: MATLAB Onramp

[Launch the course](#)

[Reinforcement Learning Onramp](#)



Part 1: What Is Reinforcement Learning?

Get an overview of reinforcement learning from the perspective of an engineer. Reinforcement learning is a type of machine learning that has the potential to solve some really hard control problems.



Part 2: Understanding the Environment and Rewards

In this video, we build on our basic understanding of reinforcement learning by exploring the workflow. What is the environment? How do reward functions incentivize and agent? How are policies structured?



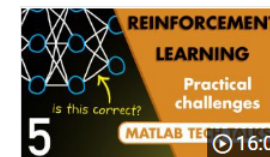
Part 3: Policies and Learning Algorithms

This video provides an introduction to the algorithms that reside within the agent. We'll cover why we use neural networks to represent functions and why you may have to set up two neural networks in a powerful family of methods called actor-critic.



Part 4: The Walking Robot Problem

This video shows how to use the reinforcement learning workflow to get a bipedal robot to walk, and how we can set up the RL problem to look more like a traditional control problem by adding a reference signal to the design.

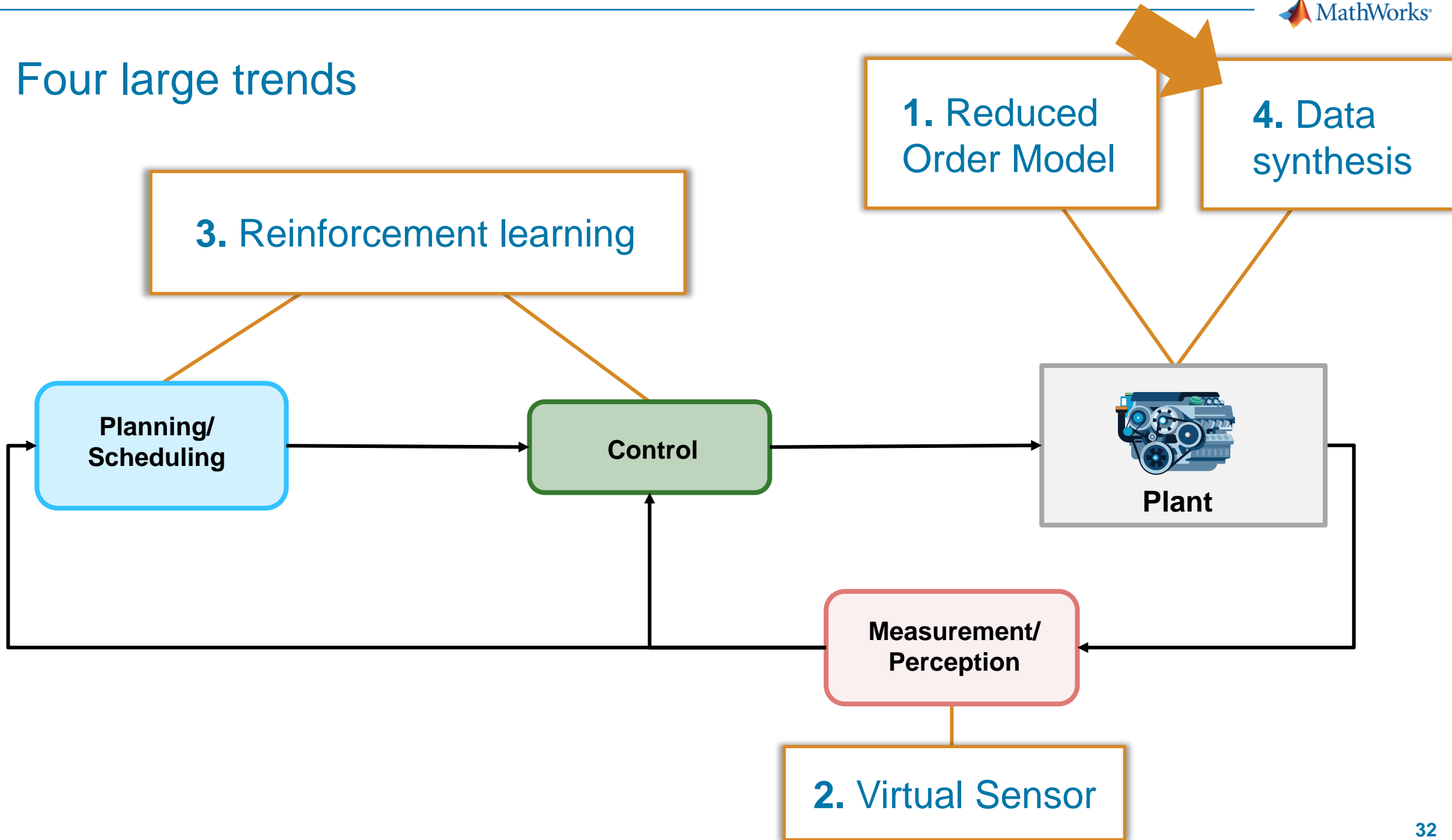


Part 5: Overcoming the Practical Challenges of Reinforcement Learning

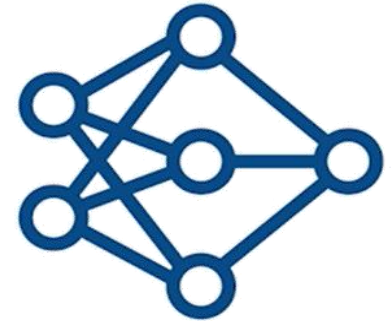
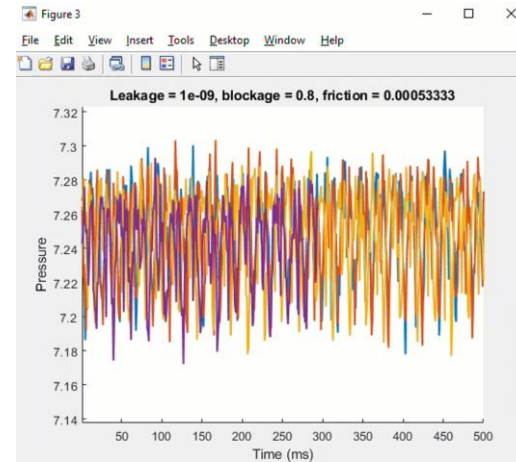
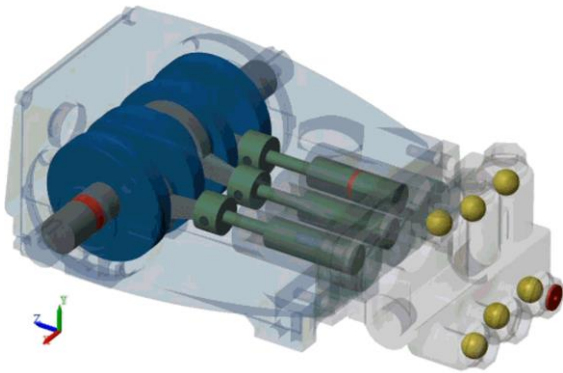
There are a few challenges that occur when using reinforcement learning for production systems and there are some ways to mitigate them. This video covers the difficulties of verifying the learned solution and what you can do about it.

[Video series](#)

Four large trends



Trend 4 Data Synthesis



Why?!

When data is hard to get through lab test or otherwise

How?

Repurpose existing simulation models

Use Digital Twins to *generate data* to train better AI models for application deployment

Enhance datasets for AI using Digital Twins

Challenge

Increase the performance of an automated beverage-packaging system by incorporating a dynamic tripod robot into the design

Solution

Use Simulink and Simscape Multibody to create an accurate digital twin that supports design optimization, fault testing, and predictive maintenance

Results

- Robot performance increased
- Product development time shortened
- Testing time significantly reduced

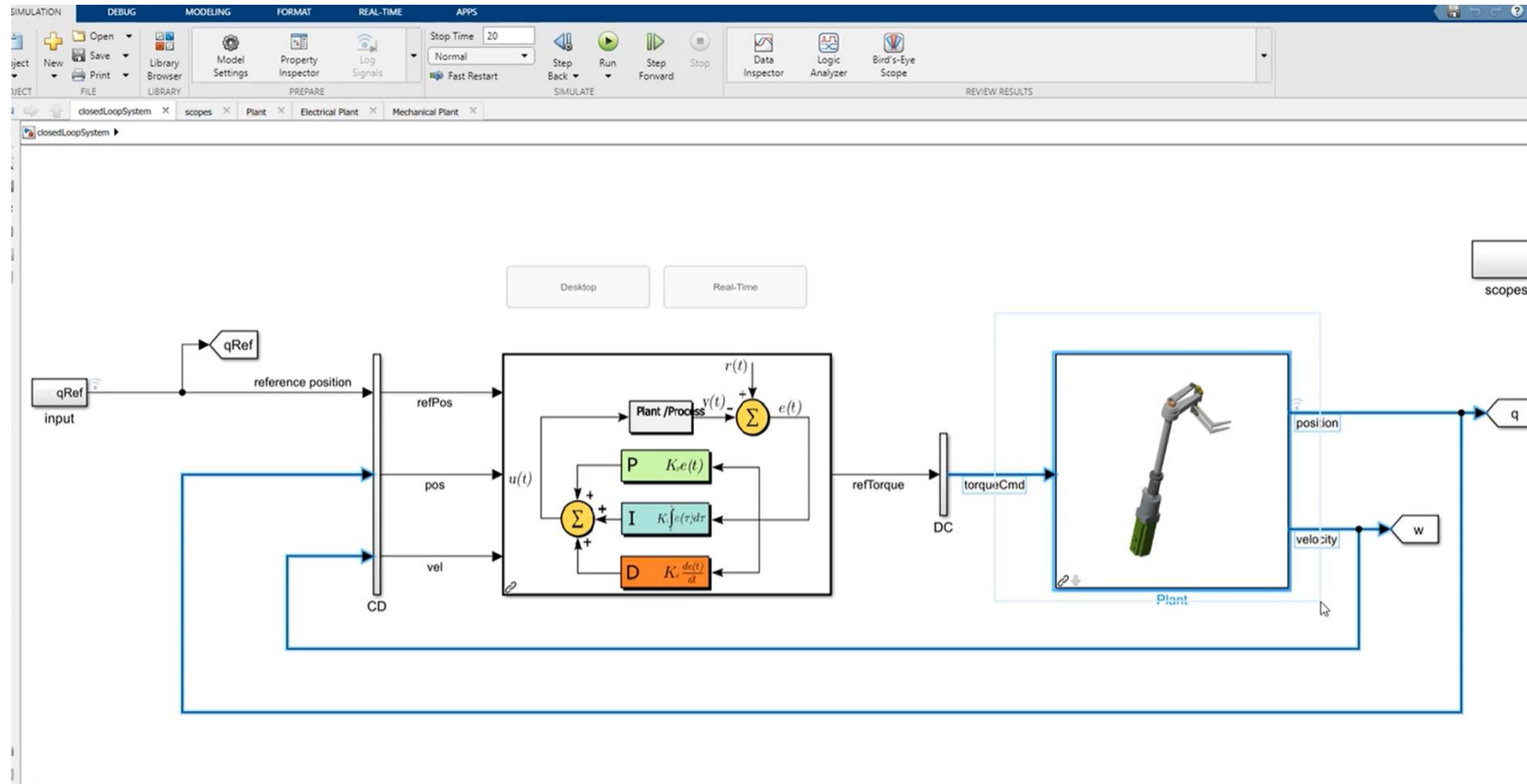


The Krones Robobox T-GM package-handling robot.

During simulations the team injected faults, such as extremely high friction, to analyze system behavior under fault conditions.

They then used the tripod robot model to train a machine learning classification algorithm for predictive maintenance.

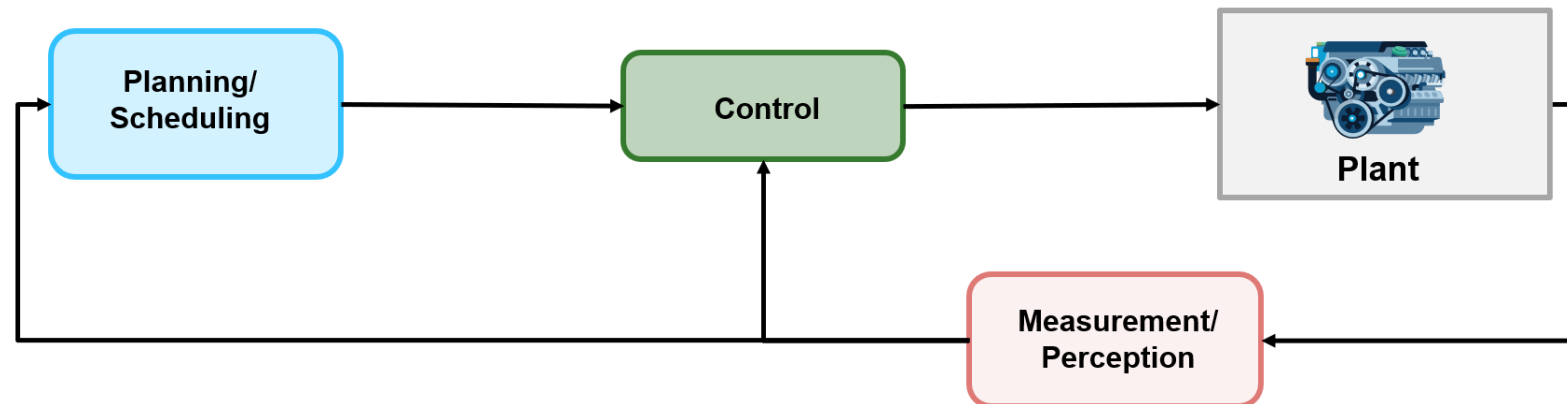
Learn more??



[Video - Design for Predictive Maintenance: Data Generation](#)

Conclusions?

- Many promising applications in the intersection between AI and Simulation
 - AI models can be used to enhance simulation models
 - Simulation models can be used to enhance AI models
- In MATLAB and Simulink you can use one toolchain to do both AI and Simulation with seamless interaction in-between



Thank You!

- Questions? aloytyno@mathworks.com