#### AI기반 가상센서를 이용한 모델기반 설계

신행재 부장, 매스웍스코리아

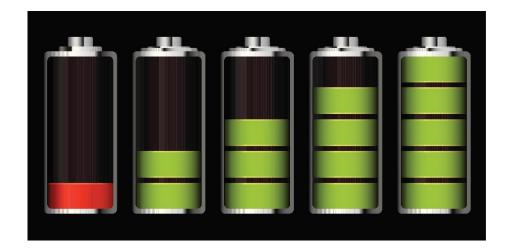




#### Why Virtual Sensors?

## When estimating a quantity that is not measurable

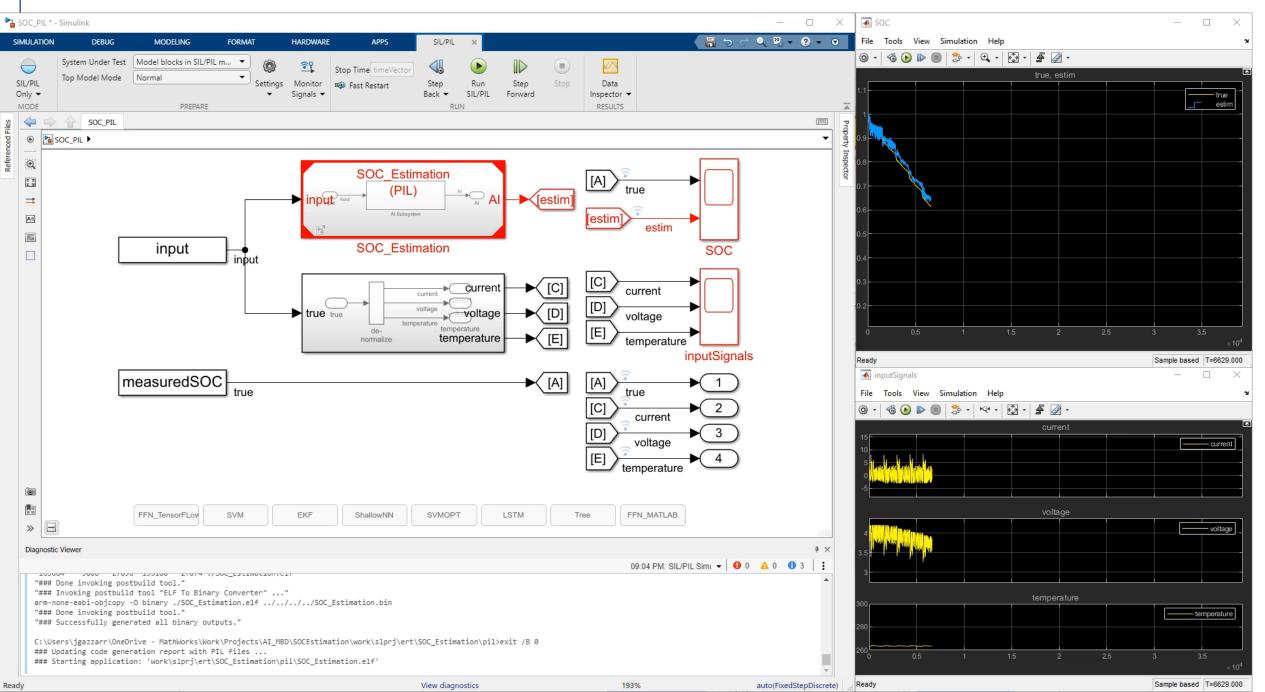
### Battery State of Charge (SOC)



## Not directly measurable

We measure voltage, current, temperature and calculate SOC

#### - Matlab **Expo**



SOC

#### Agenda

- Develop AI-based virtual sensor for battery SOC estimation
- Workflow From data acquisition to hardware deployment

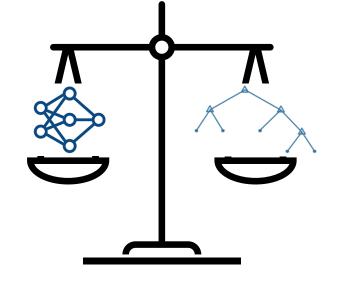


Voltage

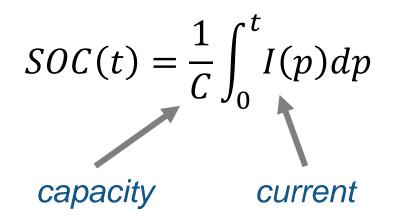
Current

Temperature

Compare different AI methods



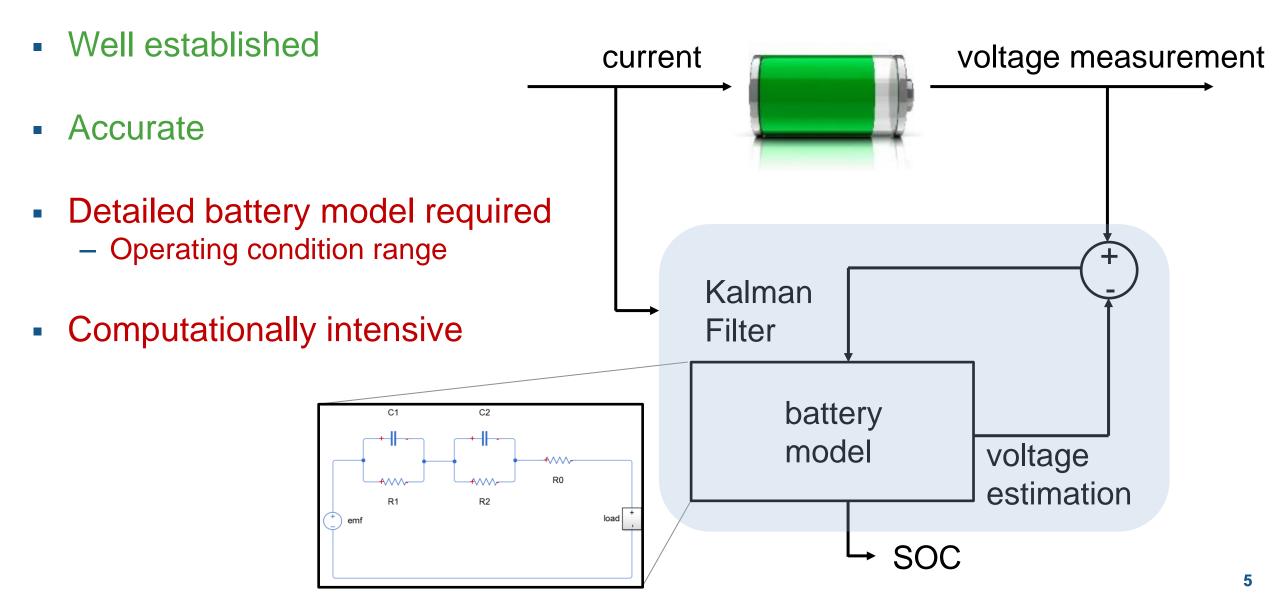
#### Battery State of Charge (SOC)



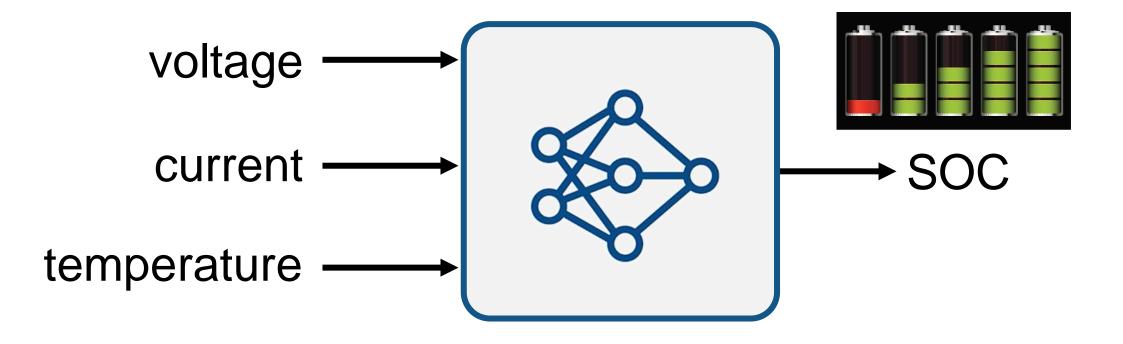


## Affected by sensor error

#### **Extended Kalman Filter**



How About...



Instead of creating a physics-based model – Train a Statistical Model

#### Comparison

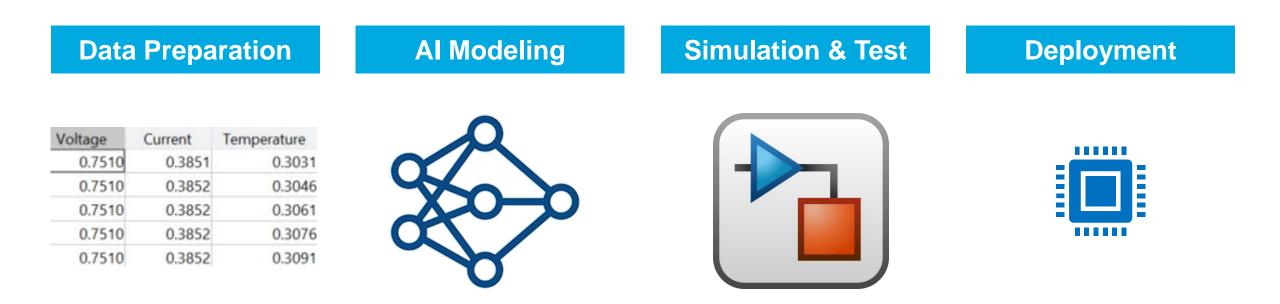
Extended Kalman Filter

- Well established
- Accurate
- Detailed battery model required
   Operating condition range
- Computationally intensive

### AI

- Training on real data
- Capture very complex data relationships
- No need for battery model
- Interpretability
- Computationally intensive

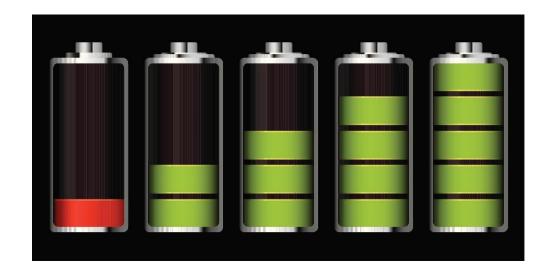
#### Al-driven System Design



## Steps involved in creating an AI-based virtual sensor

#### Back to SOC estimation







### Robust xEV Battery State-of-Charge Estimator Design Using a Feedforward Deep Neural Network

Carlos Vidal, Phillip Kollmeyer, and Mina Naguib McMaster Automotive Res. Centre

Pawel Malysz and Oliver Gross FCA US LLC

Ali Emadi McMaster University

*Citation:* Vidal, C., Kollmeyer, P., Naguib, M., Malysz, P. et al., "Robust xEV Battery State-of-Charge Estimator Design Using a Feedforward Deep Neural Network," SAE Technical Paper 2020-01-1181, 2020, doi:10.4271/2020-01-1181.

#### Abstract

B attery state-of-charge (SOC) is critical information for the vehicle energy management system and must be accurately estimated to ensure reliable and affordable electrified vehicles (xEV). However, due to the nonlinear temperature, health, and SOC dependent behaviour of Li-ion (FNN) approach. The method includes a description of data acquisition, data preparation, development of an FNN, FNN tuning, and robust validation of the FNN to sensor noise. To develop a robust estimator, the FNN was exposed, during training, to datasets with errors intentionally added to the data, e.g. adding cell voltage variation of  $\pm 4$ mV, cell current

### Read data

0.3851

0.3852

0.3852

0.3852

0.3852

Current Temperature

0.3031

0.3046

0.3061

0.3076

0.3091

Voltage

0.7510

0.7510

0.7510

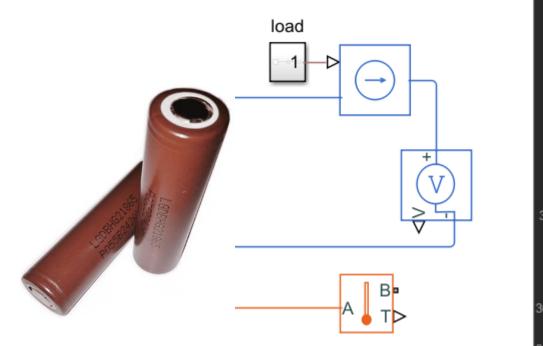
0.7510

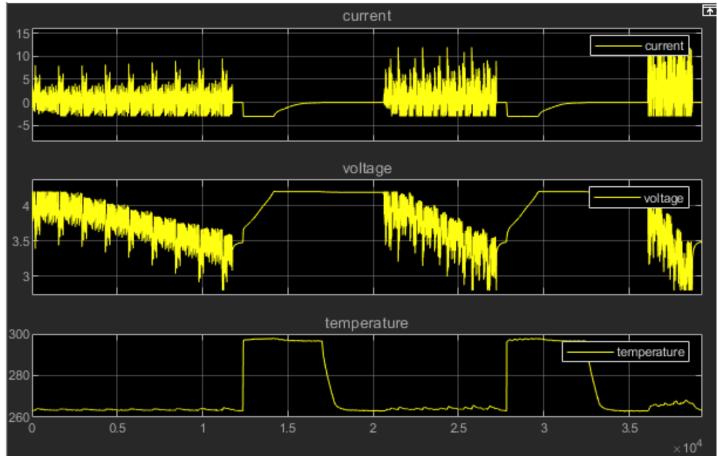
0.7510

Simulation & Test

Deploymen

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				D	ata Preparation Al M		st <sup>-</sup> Deployment
Read data				Voltage 0.75 0.75 0.75 0.75	510         0.3851         0.3031           510         0.3852         0.3046           510         0.3852         0.3061           510         0.3852         0.3061           510         0.3852         0.3076		
Data source: McMaster Univers	sity*			ature av. voltage	-	Outputs     Battery SOC	
load			Moving a	av. current			
				Pr	edictors	Re	sponse
					λ.		
	6699	бхб <u>table</u>					
		1	2	3	4	5	6
		Voltage	Current			Moving Average Current	SOC
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	2	0.7510	0.3852	0.3046	0.7510	0.3851	0.2064
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	1 2 3 4 5	0.7510 0.7510 0.7510	0.3852 0.3852 0.3852	0.3046 0.3061 0.3076	0.7510 0.7510 0.7510	0 0.3851 0 0.3852 0 0.3852	0.2064 0.2064 0.2064
	1 2 3 4 5 6	0.7510 0.7510 0.7510 0.7510	0.3852 0.3852 0.3852 0.3852	0.3046 0.3061 0.3076 0.3091	0.7510 0.7510 0.7510 0.7510	0 0.3851 0 0.3852 0 0.3852 0 0.3852	0.2064 0.2064 0.2064 0.2064
	1 2 3 3 4 5 6 7	0.7510 0.7510 0.7510 0.7510 0.7510	0.3852 0.3852 0.3852 0.3852 0.3852	0.3046 0.3061 0.3076 0.3091 0.3106	0.7510 0.7510 0.7510 0.7510 0.7510 0.7510	0.3851 0.3852 0.3852 0.3852 0.3852 0.3852	0.2064 0.2064 0.2064 0.2064 0.2064
	1 2 3 3 4 5 6 7 8	0.7510 0.7510 0.7510 0.7510	0.3852 0.3852 0.3852 0.3852 0.3852 0.3852	0.3046 0.3061 0.3076 0.3091 0.3106 0.3120	0.7510 0.7510 0.7510 0.7510 0.7510 0.7510 0.7510	0 0.3851 0 0.3852 0 0.3852 0 0.3852 0 0.3852 0 0.3852	0.2064 0.2064 0.2064 0.2064 0.2064 0.2064
	1 2 3 4 5 6 7 8 9	0.7510 0.7510 0.7510 0.7510 0.7510 0.7510	0.3852 0.3852 0.3852 0.3852 0.3852	0.3046 0.3061 0.3076 0.3091 0.3106	0.7510 0.7510 0.7510 0.7510 0.7510 0.7510 0.7510	0.3851 0.3852 0.3852 0.3852 0.3852 0.3852 0.3852 0.3852	0.2064 0.2064 0.2064 0.2064 0.2064
	1	0.7510	0.3851	0.3031	0.7510	0.5651	0.20

\*https://data.mendeley.com/datasets/cp3473x7xv/3

### **Algorithms for Al**

Preparatio

0.3852

0 3852

0 3852

0 7510

**Al Modeling** 

#### Algorithms

Machine learning Trees, Naïve Bayes, SVM...

**Deep learning** CNNs, GANs, LSTM, MIMO...

Reinforcement learning DQN, A2C, DDPG...

**Regression** Linear, nonlinear, trees...

Unsupervised learning K-means, PCA, GMM...

**Predictive maintenance** RUL models, condition indicators...

**Bayesian optimization** 

#### **Pre-built models**

0.3031

0.3046

0.3076

Image classification models AlexNet, GoogLeNet, VGG, SqueezeNet, ShuffleNet, ResNet, DenseNet, Inception...

#### **Reference examples**

**Object detection** Vehicles, pedestrians, faces...

**Semantic segmentation** Roadway detection, land cover classification, tumor detection...

Signal and speech processing Denoising, music genre recognition, keyword spotting, radar waveform classification...

...and more...

	e Al mode Test Al m	sequenceinput sequenceInput	Voltage         Current         Temp           0.7510         0.3851         0.3852           0.7510         0.3852         0.7510         0.3852           0.7510         0.3852         0.3510         0.3852           0.7510         0.3852         0.3510         0.3852           0.7510         0.3852         0.3510         0.3852	On Al	Modeling		ulation & Test	
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Solver	sgdm 💌	tanhLayer						
InitialLearnRate	0.01							
BASIC		1	1					
ValidationFrequency	50 🌲	fc_2 fullyConnected		📣 Deep	Network	Designe	r	
MaxEpochs	30 🌲	fullyConnected						
MiniBatchSize	128 🔺			TRAIN	ING		)	
ExecutionEnvironment	auto							
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SequencePaddingDirection	right •			Options		PI	ot	
ADVANCED		fc_3 fullyConnected	0	OPTIONS	TRAIN		EXPORT	
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GradientThreshold	 Inf –	clippedrelu						
ValidationPatience	Inf 🚖	clippedReluLayer						
Shuffle	every-epoch 💌							
CheckpointPath	Specify checkpoint path							
CheckpointFrequency	1 🌲	regressionout						

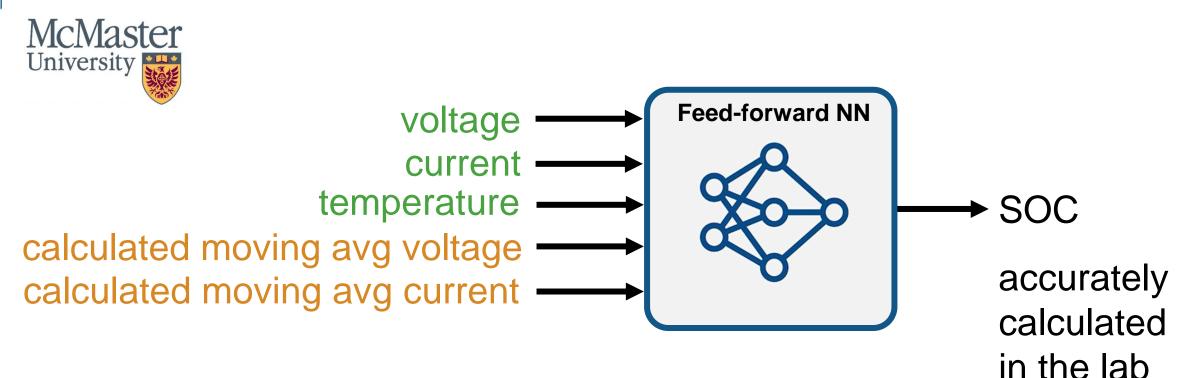
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Export

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## AI modeling

DR INSERT VIEW	Save	100000
Image: Compare Save Print ~       Image: Compare Save Frint ~       Image: Compare Save Save Save Save Save Save Save Sav		
Li_ion_SOC_EstimatorScript.mkx ¥ +		
xEV Battery State-of-Charge Estimator using a Feedforward Deep Neural Network Create Datastore datasets - Training and Testing		
<pre>clear dataFolder = fullfile(pwd, 'LGHG2@n10C_to_25degC');</pre>		
Create train & test datastores		
<pre>trainDataDS = fileDatastore(fullfile(dataFolder,"Train"), 'ReadFcn',@load,'FileExtensions','.mat'); testDataDS = fileDatastore(fullfile(dataFolder,"Test"), 'ReadFcn',@load,'FileExtensions','.mat');</pre>		
<pre>trainData = read(trainDataDS)</pre>		
<pre>trainData = struct with fields: X: [5×669956 double] Y: [1×669956 double]</pre>		
<pre>testData = read(testDataDS)</pre>		
testData = struct with fields: X: [5×39293 double] Y: [1×39293 double]		
Define NN Architecture		
deepNetworkDesigner		
<pre>numFeatures = 5; % Number of inputs features (V, I, Temp, V_avg, I_avg) numHiddenUnits = 55; % Number of hidden units 'N', where each hidden unit for FNN represents a Neuron. numResponses = 1; % Number of outputs (SOC)</pre>		
<pre>layers = [ sequenceInputLayer(numFeatures,"Normalization","zerocenter") fullyConnectedLayer(numHiddenUnits) tanhLayer</pre>		



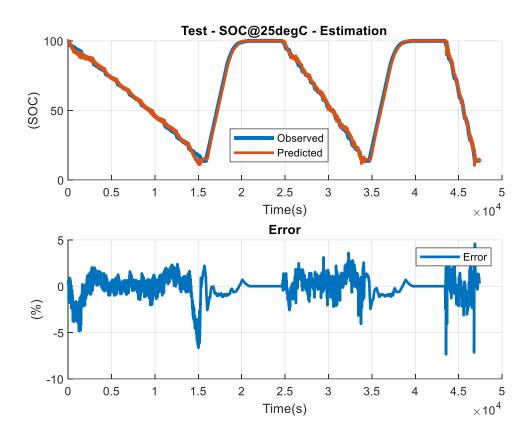
## Feed Forward NN is simple – but it has no memory

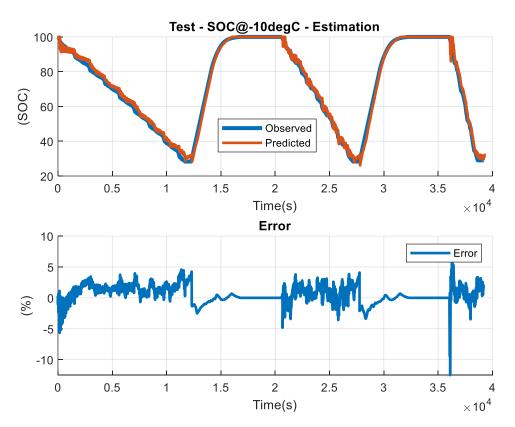
## Moving average added to the input signals

Data source <u>https://data.mendeley.com/datasets/cp3473x7xv/3</u> <sup>16</sup>

### Results





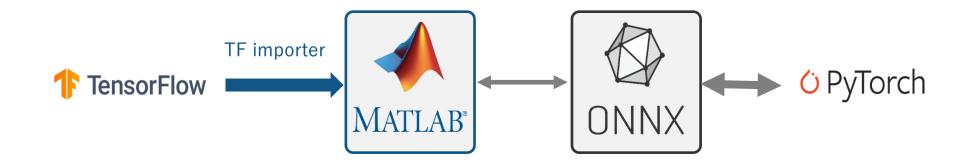


-10°C

# Prediction is good even at low temperatures

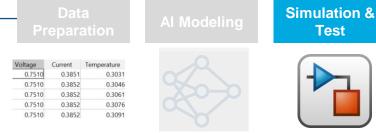
prediction ground truth

#### **Import Pre-Trained Model**



# You can also import an AI model trained outside of the MathWorks ecosystem into MATLAB







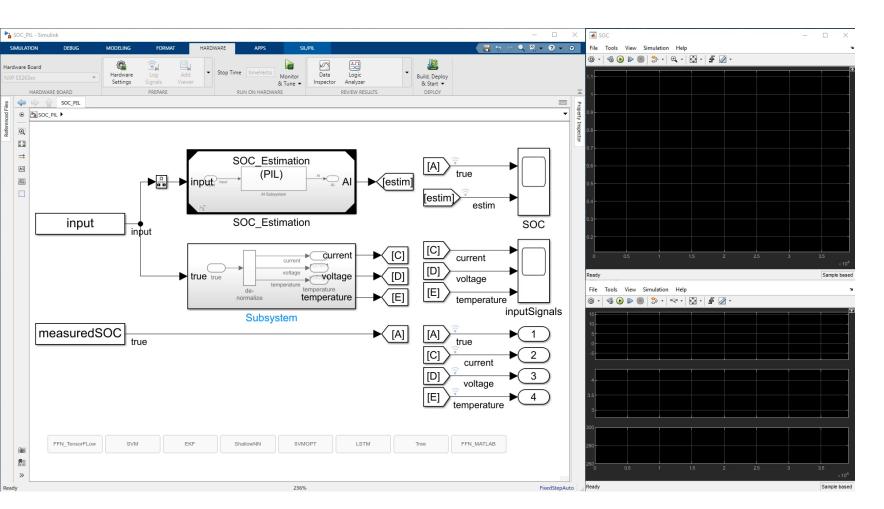
Test



Simulink Library Browser ▶ Q 2 + 2 + 0 💠 💠 transmission line 🗸 🗞 🕶 🔂 🖛 🗇 🤹 🖓 SIMULATION DEBUG MODELING FORMAT Deep Learning Toolbox/Deep Neural Networks Stop Time input(end, , 🔽 Oper Data Logic ×. 4 9  $(\mathbf{b})$  Normal -🔒 Save NXP Model-Based Design Toolbox for S32K3xx MCUs Signal Table Bird's-Eye Step Run Step Simulation Library Analyzer Scope Manager Simulink Inspector - 🚔 Print Browse Bast Restart Back -Forward ÷ Aerospace Blockset REVIEW RESULTS LIBRARY Audio Toolbox 10000 simulinkImplementation Automated Driving Toolbox Automotive Math and Motor Control Library for NXP S32K3 simulinkImplementation Communications Toolbox Image Classifier Communications Toolbox HDL Support  $\odot$ Computer Vision Toolbox K 3 Control System Toolbox \$ Data Acquisition Toolbox ⇒ Deep Learning Toolbox A: Deep Neural Networks Y Shallow Neural Networks 2 Control Systems Predict Net Input Functions Processing Functions Ś Transfer Functions Weight Functions DSP System Toolbox  $u^{\mathrm{T}}$ input DSP System Toolbox HDL Support Embedded Coder Embedded Coder Support Package for ARM Cortex-M Proc Stateful Classify **Eived Daint D** File Tools View Simulation Help 51 Sample based **EixedStenDiscrete** 

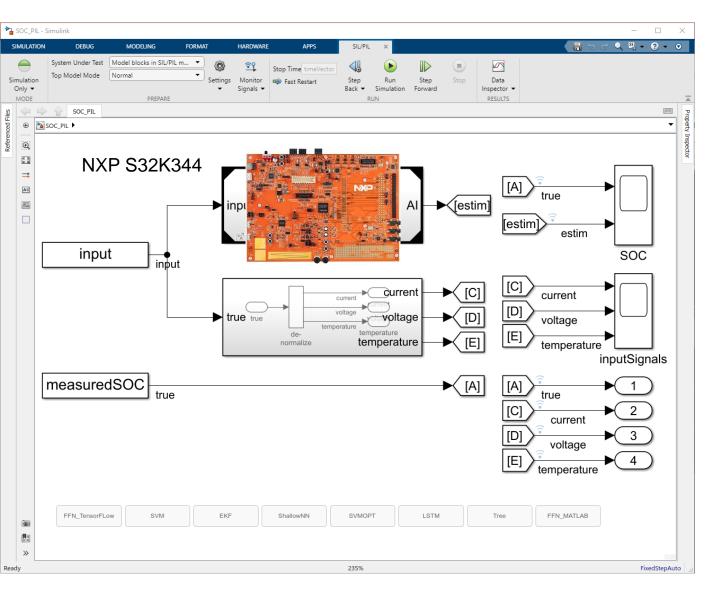
Simulink provides blocks with different AI functions We just parameterize them with the AI function name and feed them with signals with the predictors



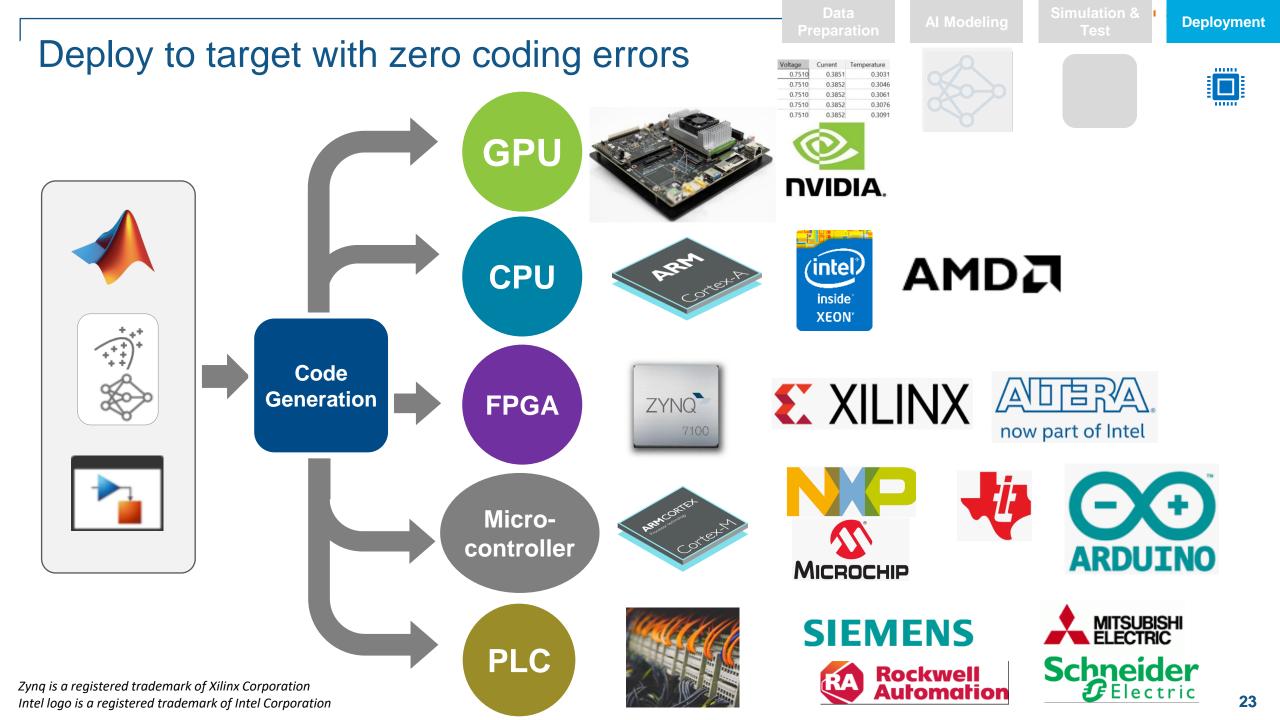


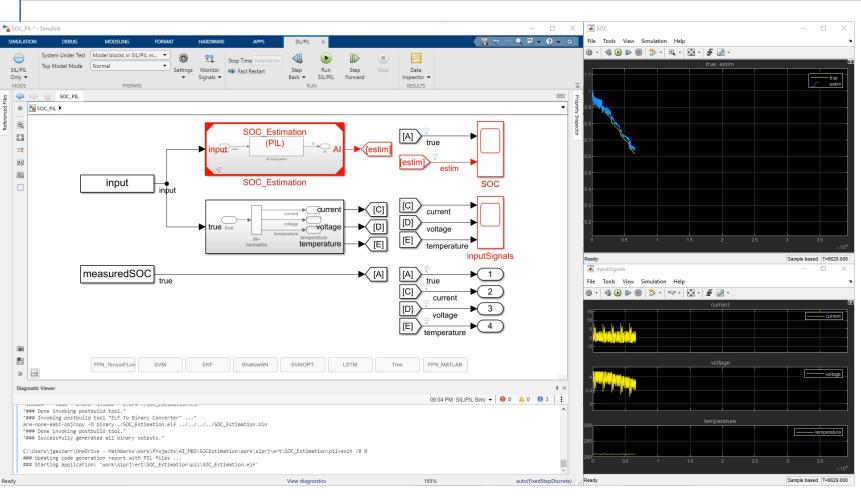
With Variant Subsystems we can implement several AI functions in the same model and try them one at a time

### Processor-in-the-Loop (PIL) Testing on ARM Cortex-M7 Processor



Deployment Current Temperature 0.3851 0.3031 0.7510 0.7510 0.3852 0.3046 0.3061 0.7510 0 3852 0.3076 07510 0 3852 0.7510 0.3852 0.3091 **Automatic Library-Free** C Code ..... .augmented Any CPU Texas Inc. ARM Cortex-M **INSTRUMENTS** 





Finally, we can configure the model for Processorin-the-Loop execution 1- Configure hardware and communication ports 2- Select PIL execution 3- Code is generated for the AI function subsystem, compiled, then downloaded onto the evaluation board 4- The algorithm now runs on target

#### Tradeoffs and Benchmark

	EKF Extended Kalman Filter	<b>Tree</b> Fine Regression Tree	<b>FFN</b> 1-hidden layer Feedforward Network	LSTM Stacked Long Short-Term Memory Network
Training Speed	N/A			
Interpretability				
Inference Speed *				
Model Size *				
Accuracy (RMSE)				

Results are specific to this example

Here is a comparison among AI methods and the EKF benchmark There is a trade-off among training effort, predictive

accuracy, and on-target execution time

# Denso Ten develops workflow process for AI control system development

#### Challenge

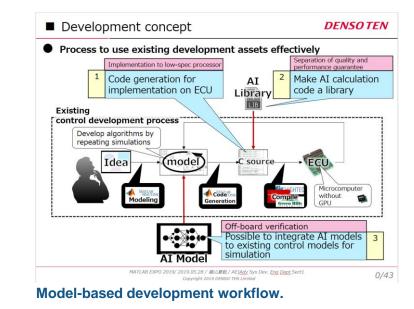
Use AI to improve ECU development efficiency

#### **Solution**

Use Deep Learning Toolbox, Embedded Coder, and Simulink Coder in a new workflow for Al/deep learning, ECU simulation and implementation

#### **Results**

- Integrated AI model into existing control model
- Used Deep Network Designer for network construction
- Created bidirectional conversion of deep learning model between MATLAB and Simulink
- Accessed original AI library using S-functions



"A model-based development workflow is essential in order to use AI for control ECUs. Combining the existing control model and the AI model enables us to establish a simulation environment and accelerate product development."

- Natsuki Yokoyama, Denso Ten

#### Summary

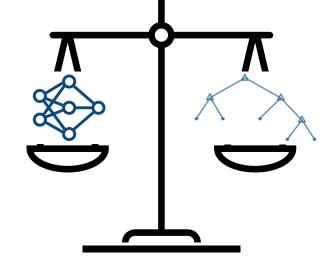
- **Develop AI-based Virtual Sensor for Battery SOC Estimation**
- Workflow From Data Acquisition to Hardware Deployment

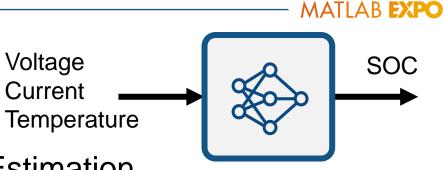
0.7510

0.3091

**Compare Different AI Methods** 







## Thank you



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