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#### **Combining AI with Model based Design:**

battery State-of-charge estimator using Deep Learning

Moubarak Gado Application Engineer **ENBIS Spring Meeting 2022** 

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# Electric batteries are everywhere. Effective management increases vehicle availability and reduces costs



Hybrid electric city bus



Autonomous electric tractor



Industrial robots

Monitoring battery health is good, but predicting it is better





# Create virtual sensor for battery state of charge estimation in a model-based design workflow

- Why Virtual Sensors ?
  - When estimating a quantity that is not measurable

#### Battery State of Charge (SOC)



Not directly measurable



#### Agenda

- Develop AI-based battery SOC estimation
- Workflow From data acquisition to hardware deployment
- Compare different AI methods



0.7510

0.7510

0.7510

0.7510

Voltage







SOC



#### Battery State of Charge (SOC)





## Affected by sensor error



#### **Extended Kalman Filter**





#### Using Neural Network as an alternative





#### Al-driven System Design

#### **Data Preparation**

Voltage	Current	Temperature		
0.7510	0.3851	0.3031		
0.7510	0.3852	0.3046		
0.7510	0.3852	0.3061		
0.7510	0.3852	0.3076		
0.7510	0.3852	0.3091		



**AI Modeling** 



Simulation & Test







### 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

#### MathWorks<sup>®</sup> **Data Preparation** Temperature Voltage Current 0.7510 0.3851 0.3031 0.7510 0.3852 0.3046 0.7510 0.3852 0.3061 0.7510 0.3852 0.3076 0.7510 0.3852 0.3091



**Read data** 





#### Data were collected experimentally





Data source <u>https://data.mendeley.com/datasets/cp3473x7xv/3</u> 11

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### Create, configure, train & assess Al model performance

M	sequenceinput sequenceInput			
<b>×</b>	fc_1 fullyConnected			
	layer tanhLayer			
<b>×</b>	fc_2 fullyConnected			
	leakyrelu leakyReluLayer			
<b>×</b>	fc_3 fullyConnected			
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regressionout.. regressionLayer

承 Training Options	– 🗆 🗙
SOLVER	
Solver	sgdm 💌
InitialLearnRate	0.01
BASIC	
ValidationFrequency	50 🔺
MaxEpochs	30 🔺
MiniBatchSize	128 🚔
ExecutionEnvironment	auto 💌
SEQUENCE	
SequenceLength	longest •
SequencePaddingValue	0
SequencePaddingDirection	right •
ADVANCED	
L2Regularization	0.0001
GradientThresholdMethod	I2norm 💌
GradientThreshold	Inf 🌲
ValidationPatience	Inf 🚊
Shuffle	every-epoch 💌
CheckpointPath	Specify checkpoint path
CheckpointFrequency	1 🌲

TRAINING					
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Training	Train	Export	Export Training		
Options		P	Plot		
OPTIONS	TRAIN		EXPORT		
Designer I		Data	Training	)	

TensorFlow TensorFlow Importer Caffe Importer Caffe	OPyTorch Maximum Constraints ONNX ONNX Other Frameworks
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Collaboration is very important: You can also import Model from other DL frameworks

Current 0.3851

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	• • •	Experiment Manage	r		
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Vary Filter Size of First Conv2D Lay

Train Validation Split Study

Optimize various hyperparameters, manage multiple deep learning experiments, analyze and compare results

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### Results

25°C

-10°C



### prediction ground truth



#### Al is part of a larger system Simulate and test all components together





#### Development workflow with Model-Based Design



- Manual coding is slow, buggy, and hard to verify
- Can only find problems using hardware prototypes
- Cannot test or optimize fully integrated design
- Cannot validate design against requirements



- System Level Representation that is componentized
- Unified lifecycle stages, executable specifications
- Test/fail early, continuous testing, reuse, What-if analysis
- Automation, Path to implementation and production

#### Integrate AI into MBD for system-level simulation and code generation



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#### MathWorks<sup>®</sup> Processor-in-the-Loop (PIL) Testing Deployment on ARM Cortex-M7 Processor Turrent emperature 0.3851 0.3031 0 3852 0 304 0.3852 0.3061 0.3852 0.3076 0.7510 Pil SOC\_PIL - Simulink 0.7510 0.3852 0.309 0, 2, - ? - 📀 SIMULATION MODELING DEBUG HARDWAR Andel blocks in SIL/PIL m. Fon Model Mode Data Run Simulation Step Monitor Fast Restar Only 🔻 Signals • Back -Simulation Inspector · MODE RESULTS 2000 SOC\_PIL 🛞 🎦 SOC\_PIL Ð K 7 NXP S32K344 [A] 🔪 AE true -►<[estim] AI [estim] estim **Automatic Library-Free** input SOC input [C] **C** Code ([C] current current [D] [D] true true voltage voltage temperature [E] temperature [E] normalize temperature temperature inputSignals measuredSOC ► [A] [A] true true 2 [C] current ..... [D] 3 voltage [E] 4 temperature augmented Any CPU Texas FFN\_TensorFLow EKF ShallowNN SVMOPT LSTM Tree FFN\_MATLAB SVM **INSTRUMENTS** 0 Inc. ARM Cortex-M 麀 FixedStepAuto Ready 235%







#### **Tradeoffs and Benchmark**

	<b>EKF</b> 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		$\bigcirc$	
Interpretability				
Inference Speed *	$\bigcirc$			
Model Size *		$\bigcirc$		
Accuracy (RMSE)		$\bigcirc$		

Results are specific to this example



#### Reducing AI Model size for embedded deployment





#### Workflow with interpretability: Validated & Verified AI

Until satisfied Accuracy & Explainability



#### Summary

- Al is an alternative to state-based methods for Virtual Sensor Modeling in the case of Battery SOC Estimation
- Compare Different AI Methods to evaluate and manage tradeoffs
- Integrate AI models into Simulink for system-level simulation and code generation
- End to end Workflow From Data Acquisition to Hardware Deployment

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Voltage



SOC



## Thank You!