Deep Recurrent Neural Network Control Applied in Solar Inverters for Grid Integration

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Outline

I. Background
II. Deep Recurrent Neural Network Controller
III. Trajectory based Training
IV. Local Stability and Local Convergence
V. Hardware-in-the-loop Experiment
VI. Discussions about RNN Control

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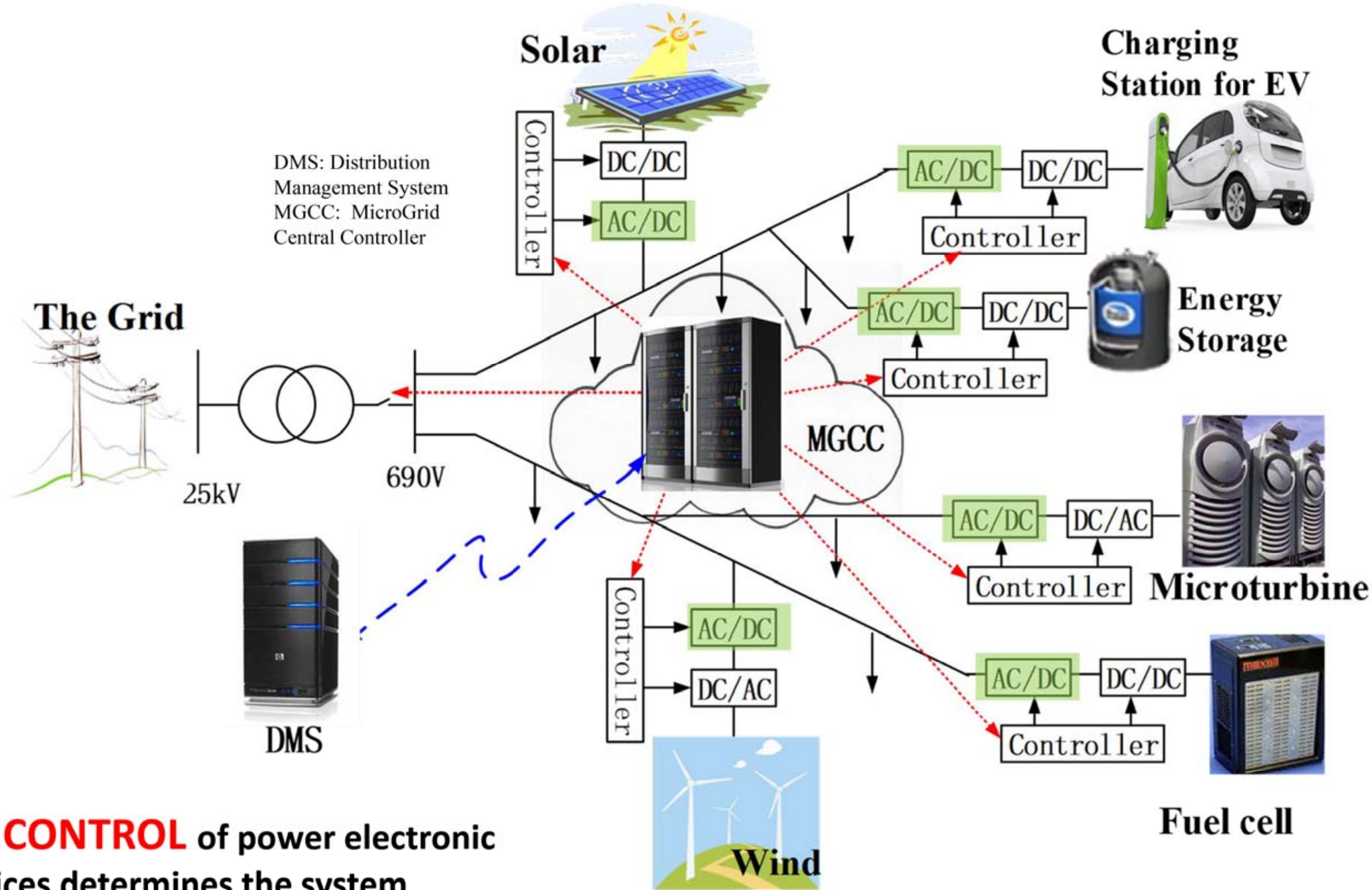
Smart Grid



The **CONTROL** of power electronic devices determines the system performance to a **GREAT** degree.

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California's Rooftop Solar Mandate Wins Final Approval

The California Building Standards Commission has signed off on the residential solar mandate—a first of its kind for the nation.

JULIA PYPER | DECEMBER 05, 2018

The solar mandate marks a groundbreaking development for the clean energy sector.

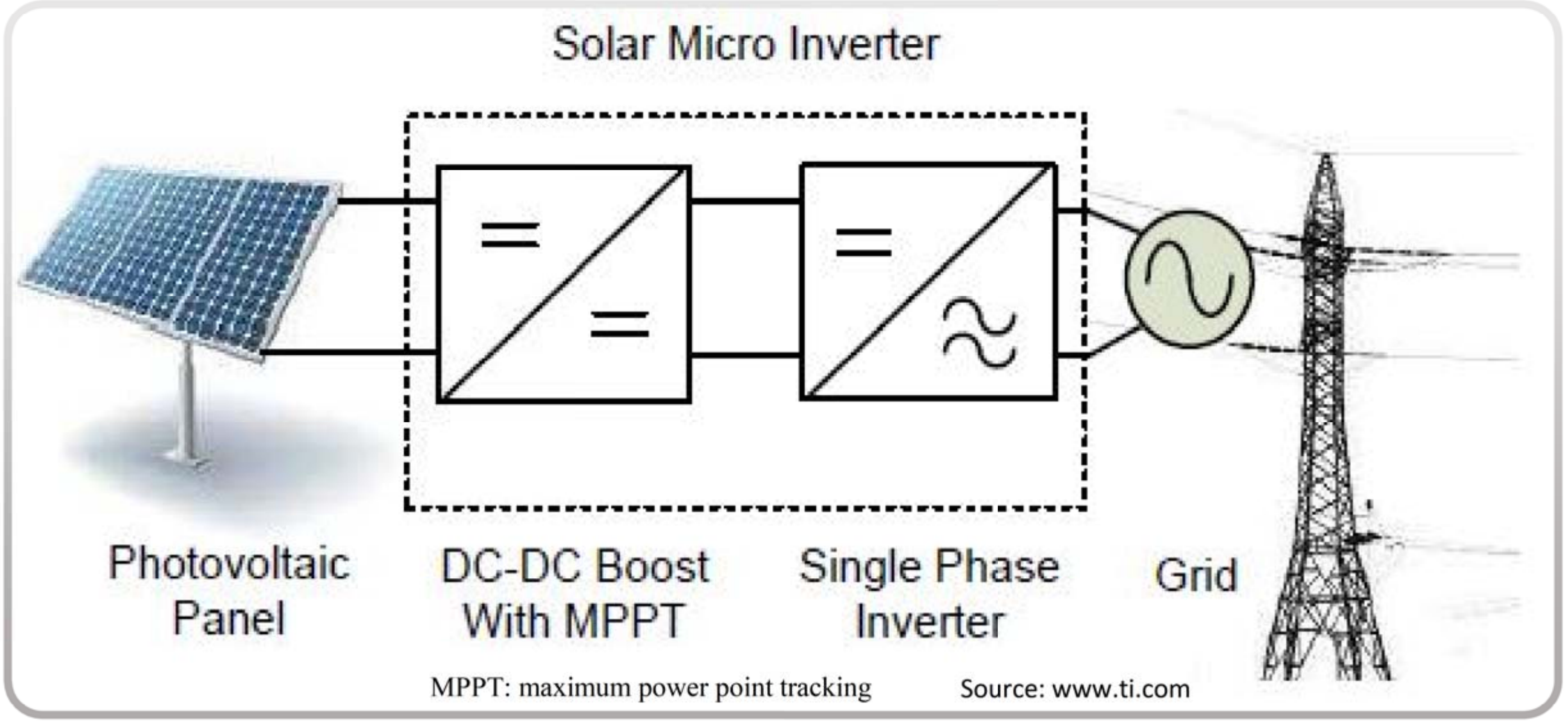
353

It's official. All new homes in California must incorporate solar power starting in 2020.

TOP ARTICLES

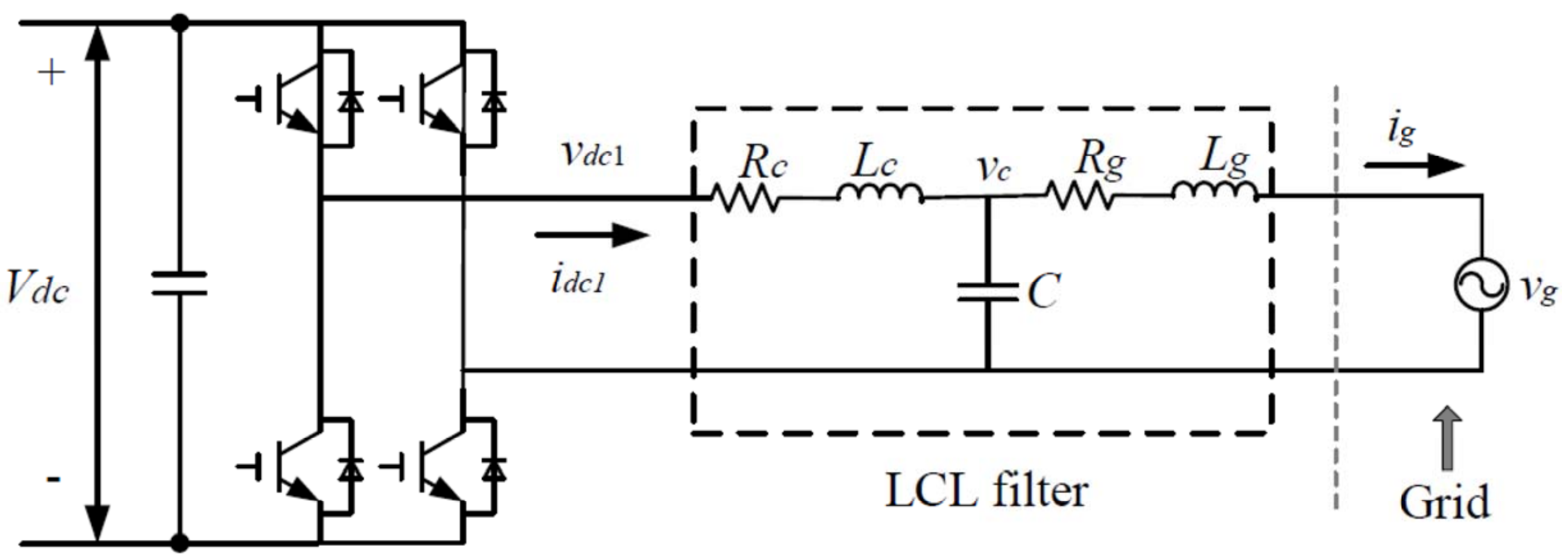
MOST POPULAR MOST COMMENTS

Solar Microinverter



- A **Solar Microinverter** converts DC generated by the single solar module to AC, and generally is connected to the grid. It allows two-way power flow.

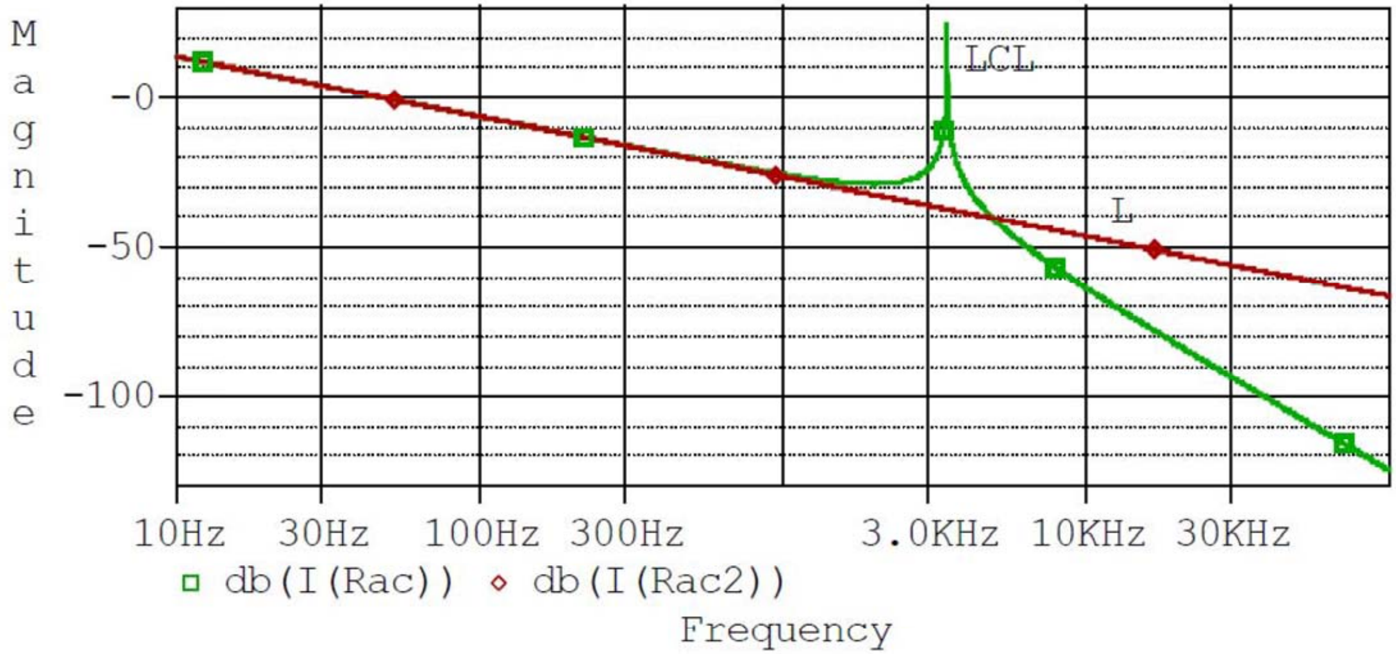
Single-phase Solar Grid-tied Inverter/ Converter



- Single phase inverter is for home application.
- To reduce harmonics, the LCL filter is a wise choice and generally used.

Resonant Problem

❖ However, as the LCL filter has a **Resonant Problem** and tends to be unstable.



*That **Peak** point (resonance frequency) causes the unstable problem and control difficulty.*

❖ ***The control of the LCL filter is a challenge!***

✓ Many damping / control methods have been proposed to handle this.

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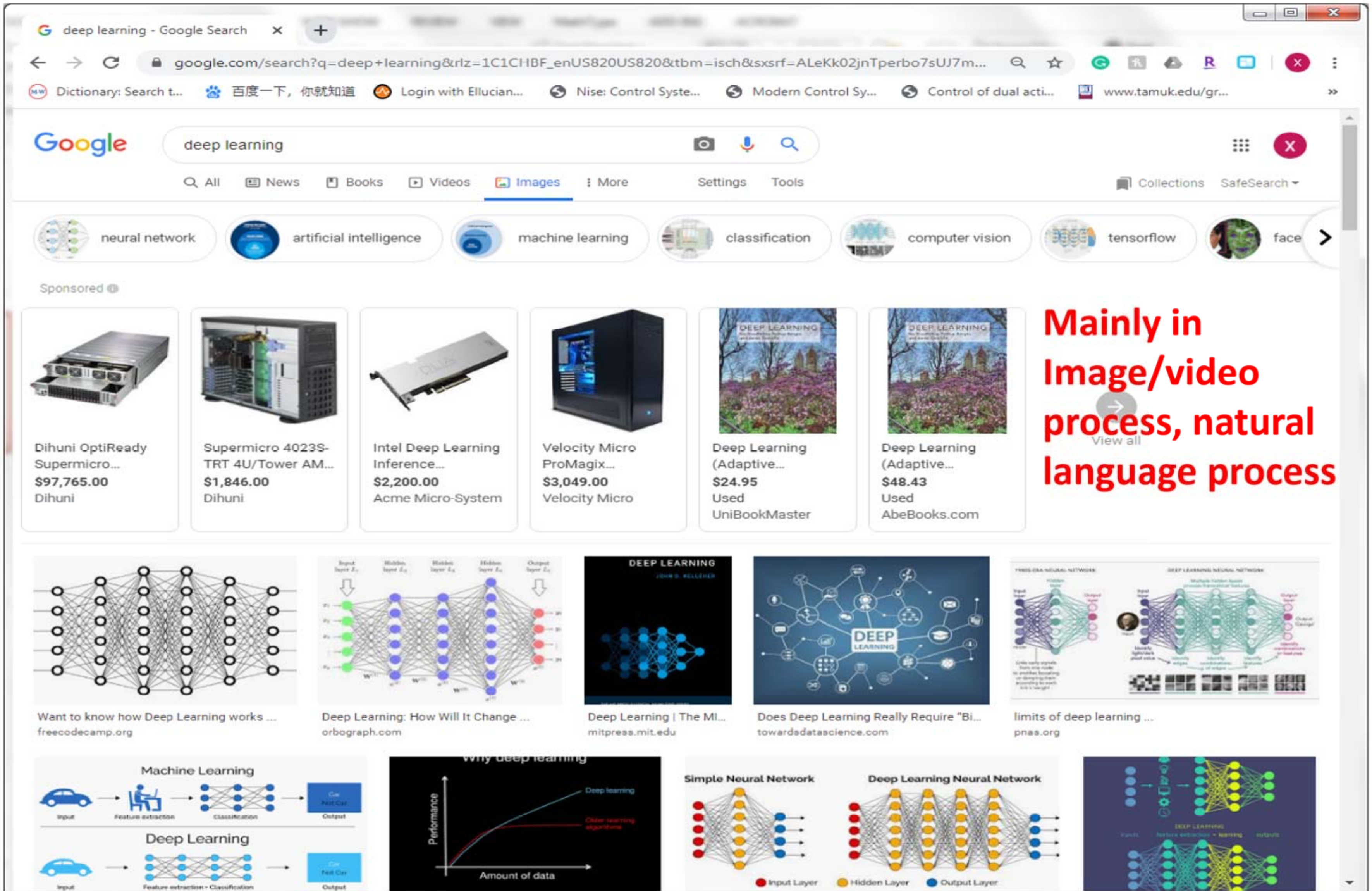
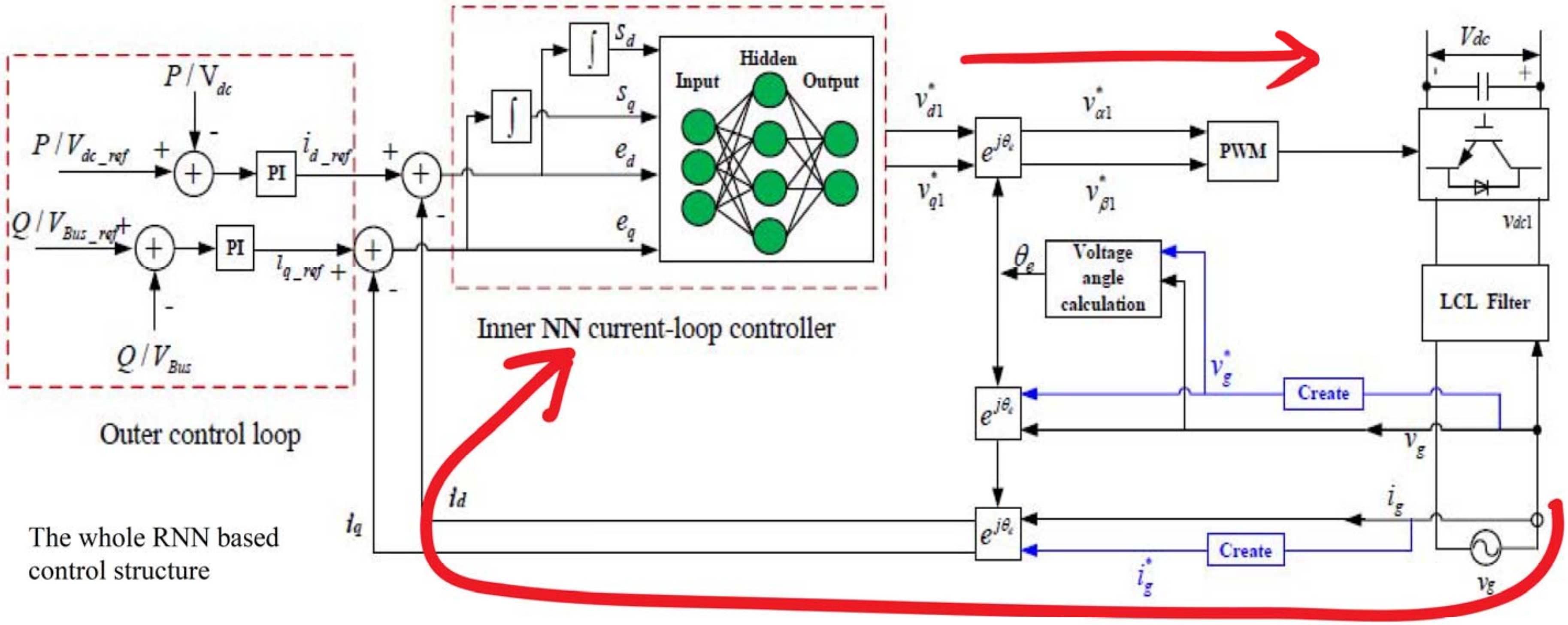
Deep Learning



Mainly in Image/video process, natural language process

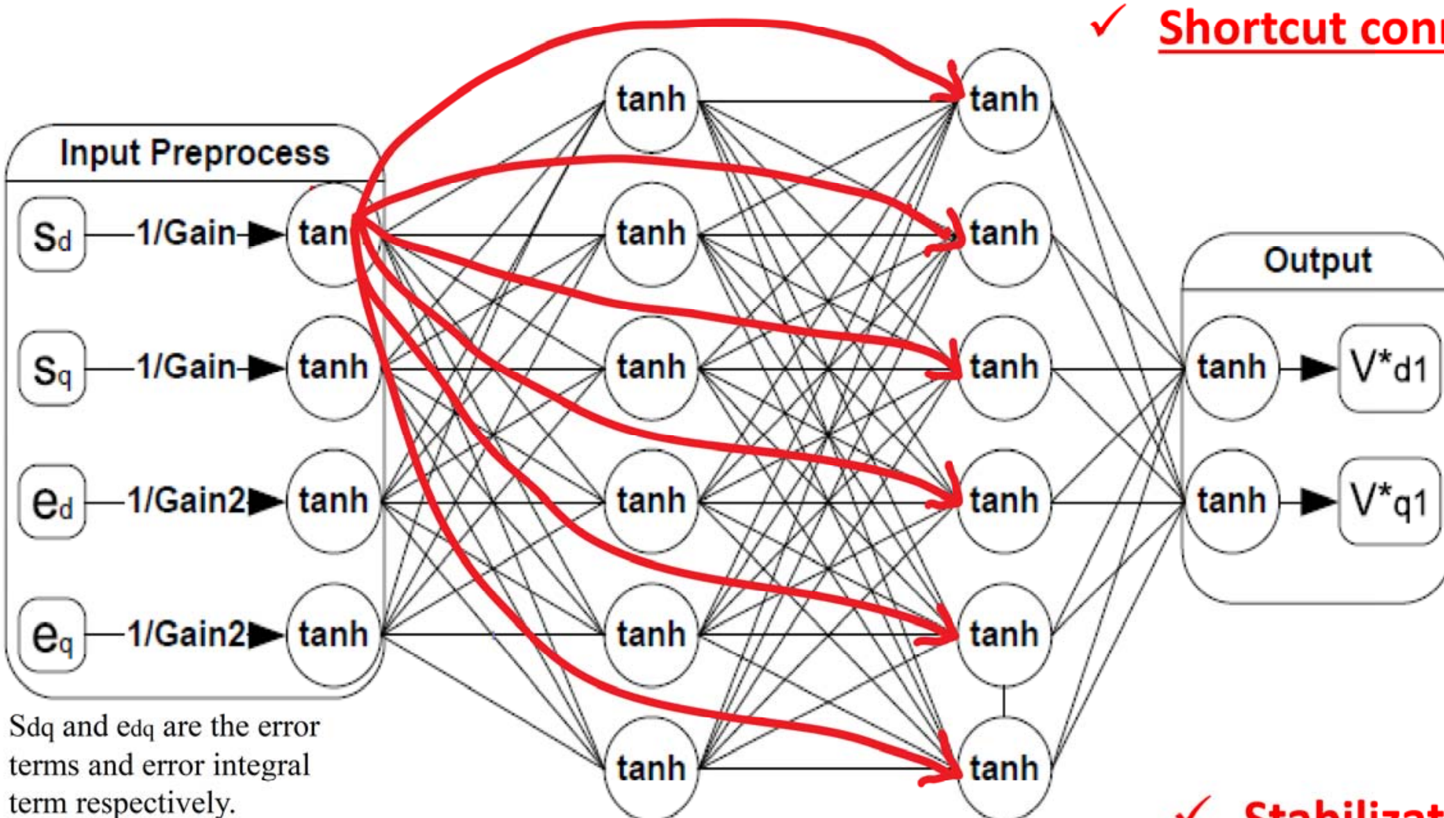
Proposed *Neural Network* in *Feedback Control Loops*



Recurrent Neural Network

Feature - *Error Integral*

✓ Shortcut connections



Sdq and edq are the error terms and error integral term respectively.

✓ Stabilization matrix added to the output

✓ No steady-state tracking error.

✓ This structure succeeded in the hardware-in-the-loop experiments

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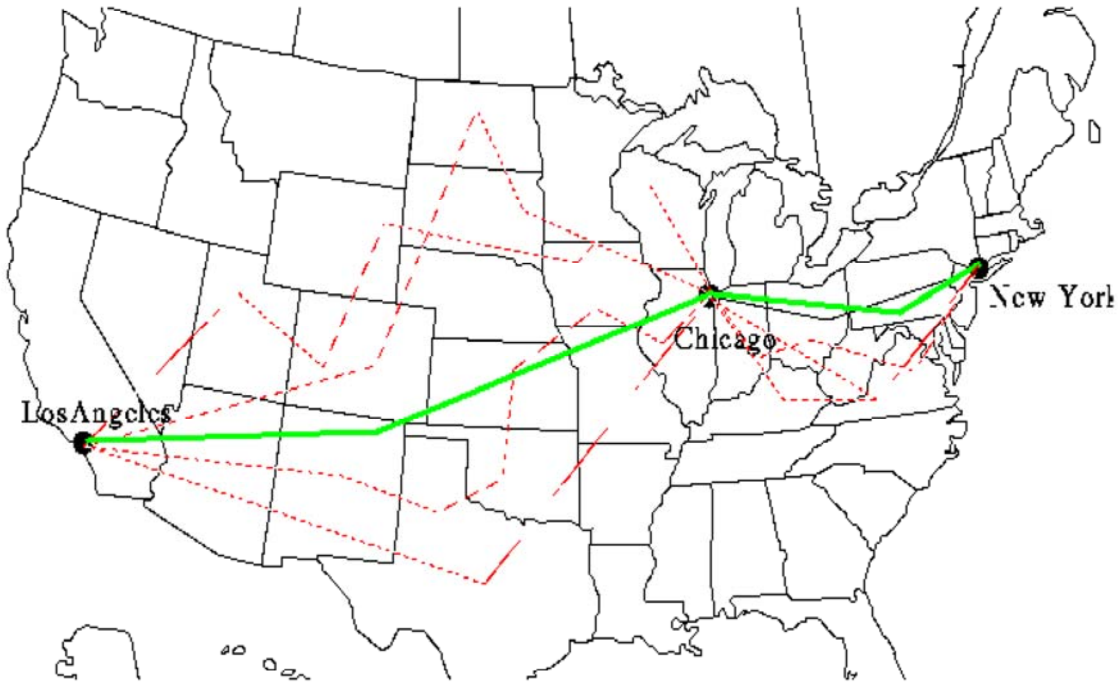
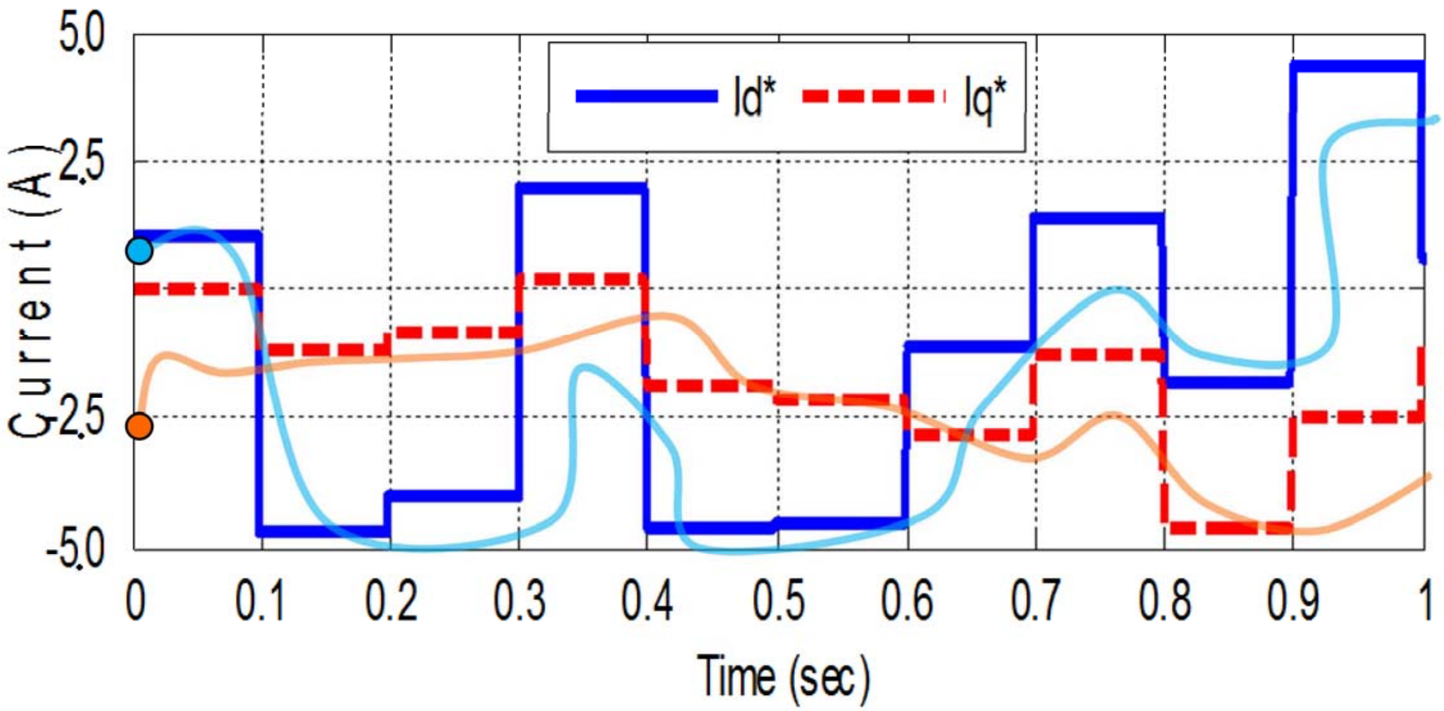
Approximate Dynamic Programming

- **Dynamic programming** (DP) employs Bellman's optimality principle and provides powerful tool for solving optimization,



- DP can is also powerful for **OPTIMAL CONTROL** problems, e.g. Adaptive Critic Designs (ACDs) is one class of **Approximate Dynamic Programming** to approximate optimal control.

Approximate Dynamic Programming Based Trajectory Training

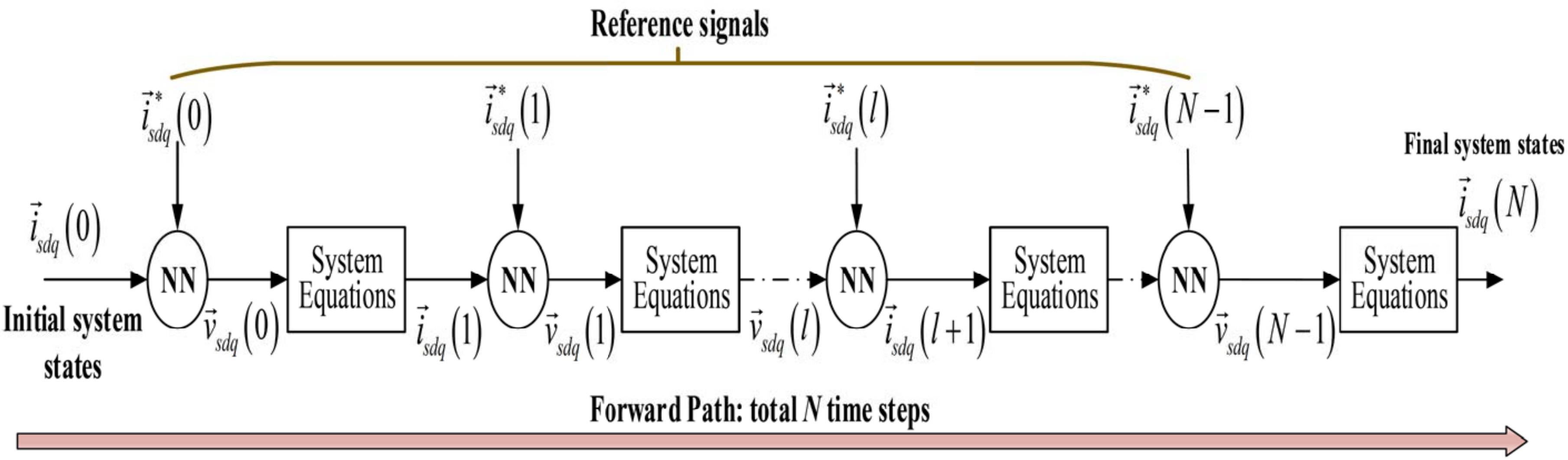


Note that: before training, the NN controller cannot adjust the currents tc follow the reference.

- ✓ *The goal of training is to adjust the actual currents to follow the reference current trajectories through minimizing the cost function based on the* ***Approximate Dynamic Programming principle.***

$$C_{dp}=\sum_{k=j}^{\infty}\gamma^{k-j}U(\overrightarrow{e_{dq}}(k)) \ =\sum_{k=j}^{\infty}\gamma^{k-j}\sqrt{[i_d(k)-i_{d\_ref}(k)]^2+[i_q(k)-i_{q\_ref}(k)]^2}$$

Deep *Network*



- In the training, the NN needs to be expanded along the trajectory.
- Think of this process as a big network, for a 1000-step calculation, the total number of NN layers will be $4\times1000= 4000$.
  - ✓ it is a large and deep network, which requires lots of calculation.

Forward Accumulation Through Time Algorithm

Algorithm 3.2 FATT algorithm to calculate the Jacobian matrix.

$C \leftarrow 0, \overrightarrow{e_{dq}}(0) \leftarrow 0, \overrightarrow{s_{dq}}(0) \leftarrow 0, \frac{\partial \overrightarrow{i_{dq}}(0)}{\partial \overrightarrow{w}} \leftarrow 0, \frac{\partial \overrightarrow{\phi_{dq}}(0)}{\partial \overrightarrow{w}} \leftarrow 0$

{Calculate the Jacobian matrix $J(\overrightarrow{w})$}

for $k = 0$ to $N-1$ **do**

$\quad \overrightarrow{u_{dq}}(k) \leftarrow k_{PWM} R(\overrightarrow{e_{dq}}(k), \overrightarrow{s_{dq}}(k), \overrightarrow{w}) - \overrightarrow{v_{dq}}$

$\quad \frac{\partial \overrightarrow{s_{dq}}(k)}{\partial \overrightarrow{w}} \leftarrow T_s \left[\frac{\partial \overrightarrow{\phi_{dq}}(k)}{\partial \overrightarrow{w}} - \frac{1}{2} \frac{\partial \overrightarrow{i_{dq}}(k)}{\partial \overrightarrow{w}} \right]$

$\quad \frac{\partial \overrightarrow{u_{dq}}(k)}{\partial \overrightarrow{w}} \leftarrow k_{PWM} \left[\frac{\partial R(k)}{\partial \overrightarrow{w}} + \frac{\partial R(k)}{\partial \overrightarrow{e_{dq}}(k)} \frac{\partial i_{dq}(k)}{\partial \overrightarrow{w}} + \frac{\partial R(k)}{\partial \overrightarrow{s_{dq}}(k)} \frac{\partial \overrightarrow{s_{dq}}(k)}{\partial \overrightarrow{w}} \right]$

$\quad \frac{\partial \overrightarrow{i_{dq}}(k+1)}{\partial \overrightarrow{w}} \leftarrow A \frac{\partial \overrightarrow{i_{dq}}(k)}{\partial \overrightarrow{w}} + B \frac{\partial \overrightarrow{u_{dq}}(k+1)}{\partial \overrightarrow{w}}$

$\quad \overrightarrow{i_{dq}}(k+1) \leftarrow A \overrightarrow{i_{dq}}(k) + B \overrightarrow{u_{dq}}(k)$

$\quad \overrightarrow{e_{dq}}(k+1) \leftarrow \overrightarrow{i_{dq}}(k+1) - \overrightarrow{i_{dq\_ref}}(k+1)$

$\quad \overrightarrow{s_{dq}}(k+1) \leftarrow \overrightarrow{s_{dq}}(k) + \frac{T_s}{2} [\overrightarrow{e_{dq}}(k) + \overrightarrow{e_{dq}}(k+1)]$

$\quad C \leftarrow C + U(\overrightarrow{e_{dq}}(k+1))$ {accumulate DP cost}

$\quad \frac{\partial \overrightarrow{\phi}(k+1)}{\partial \overrightarrow{w}} \leftarrow \frac{\partial \overrightarrow{\phi}(k)}{\partial \overrightarrow{w}} + \frac{\partial \overrightarrow{i_{dq}}(k+1)}{\partial \overrightarrow{w}}$

$\quad \frac{\partial V(k+1)}{\partial \overrightarrow{w}} \leftarrow \frac{\partial V(k+1)}{\partial \overrightarrow{e_{dq}}(k+1)} \frac{\partial \overrightarrow{i_{dq}}(k+1)}{\partial \overrightarrow{w}}$

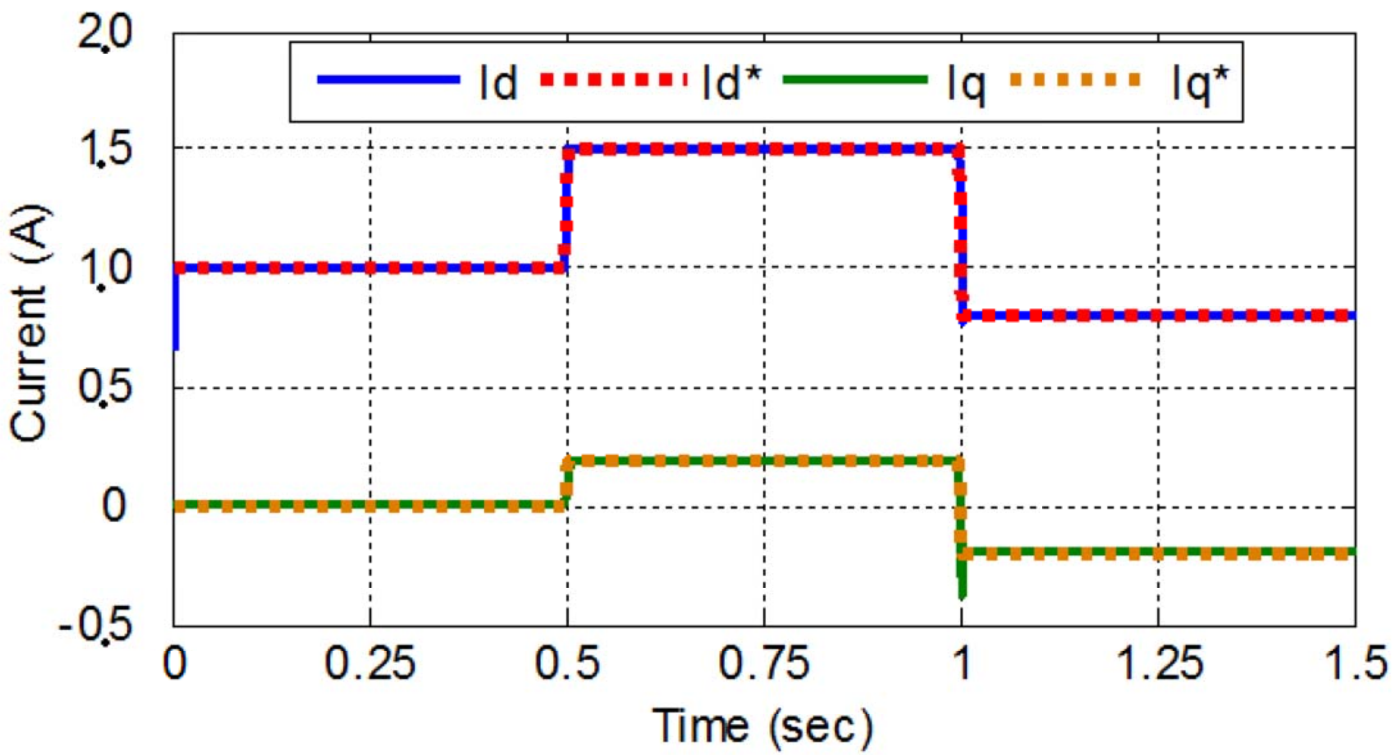
$\quad$ the $(k+1)th$ row of $J(\overrightarrow{w}) \leftarrow \frac{\partial V(k+1)}{\partial \overrightarrow{w}}$

end for

{On exit, the Jacobian matrix $J(\overrightarrow{w})$ is finished for the whole trajectory.}

Introducing of error integral terms brings difficulties in calculating gradients

Well-trained ***RNN Controller***



The actual currents can ***follow the reference trajectories*** *quite well!*

The detailed training algorithm: **LM** (Levenberg–Marquardt) + **FATT** (Forward Accumulation Through Time)

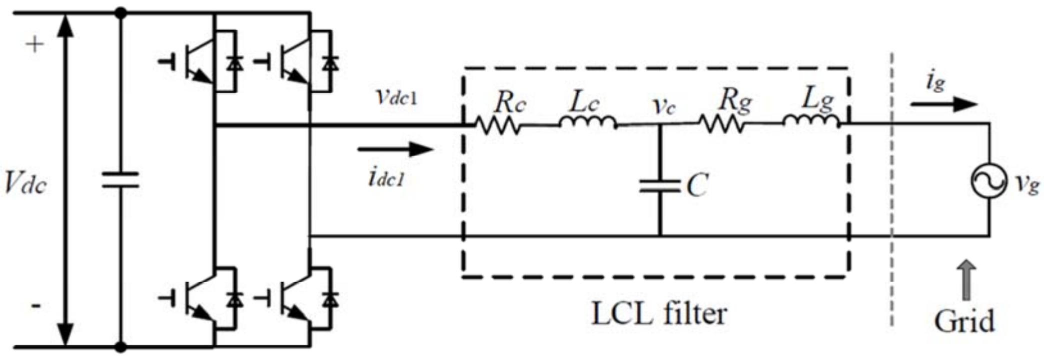
Outline

IV. Local Stability and Local Convergence

System Dynamic Equation

- **State-space model**

Ignoring the capacitor, the **two-dimensional** system equation will be simplified as



$$\frac{d}{dt}\underbrace{\begin{bmatrix} i_d \\ i_q \end{bmatrix}}_{i_{dq}} = A\begin{bmatrix} i_d \\ i_q \end{bmatrix} + B\underbrace{\begin{bmatrix} u_d \\ u_q \end{bmatrix}}_{u_{dq}}$$

where $A = -\begin{bmatrix} \frac{R_g + R_c}{L_g + L_c} & -\omega_s \\ -\omega_s & \frac{R_g + R_c}{L_g + L_c} \end{bmatrix}$,

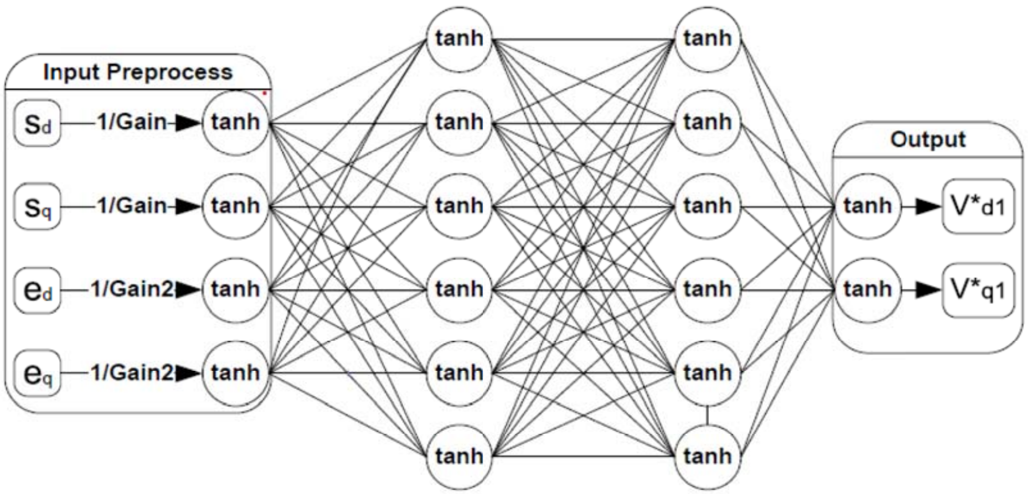
$$B = -\begin{bmatrix} \frac{1}{L_g + L_c} & \\ & \frac{1}{L_g + L_c} \end{bmatrix}$$

Control vector:

$$u_{dq} = R(e_{dq}, s_{dq}) = K_{pwm}N(e_{dq}, s_{dq}, w) - v_{dq}$$

Function format of RNN controller

- **NN function representation**



$$N\left(e_{dq}, s_{dq}, w\right) = \tanh\left(w_3\begin{bmatrix}\tanh\left(w_2\begin{bmatrix}\tanh\left(w_1\begin{bmatrix}\tanh\begin{bmatrix}\frac{e_{dq}}{Gain}\\ \frac{s_{dq}}{Gain2}\end{bmatrix}\\ -1\end{bmatrix}\right)\\ -1\end{bmatrix}\right)\\ -1\end{bmatrix}\right)$$

Augmented System Equations

- **System Equation Transformation**

From the definition of error and error integral

$$e_{dq} = \begin{bmatrix} e_d \\ e_q \end{bmatrix} = i_{dq\_ref} - i_{dq}, \qquad s_{dq} = \int_0^t e_{dq} dt$$

$$\Rightarrow \dot{e}_{dq} = -\frac{d}{dt} i_{dq}, \qquad \dot{s}_{dq} = e_{dq}$$

The original **Two-dimensional** system equations can be augmented into the following **Four-dimensional** one:

$$\begin{cases} \dot{e}_{dq} = A(e_{dq} - i_{dq\_ref}) - BR(e_{dq}, s_{dq}) \\ \dot{s}_{dq} = e_{dq} \end{cases}$$

✓ The equilibrium point of the system can be noted as (0, s*), which means e_{dq}=0 and s_{dq}=s*.

Local Stability and Local Convergence

- To guarantee **local asymptotic stability** and **local exponential convergence**, the weight matrix and bias vector of the NN need to satisfy the following condition:

$$\mathrm{Re}\left\{\mathrm{eig}\left(\begin{bmatrix} G_{11} & G_{12} \\ I & 0 \end{bmatrix}\right)\right\} < 0$$

where

$$G_{11} = A - B\left.\frac{\partial R(e_{dq}, s_{dq})}{\partial e_{dq}}\right|_{e_{dq}=0, s_{dq}=s^*}$$

$$G_{12} = -B\left.\frac{\partial R(e_{dq}, s_{dq})}{\partial s_{dq}}\right|_{e_{dq}=0, s_{dq}=s^*}$$

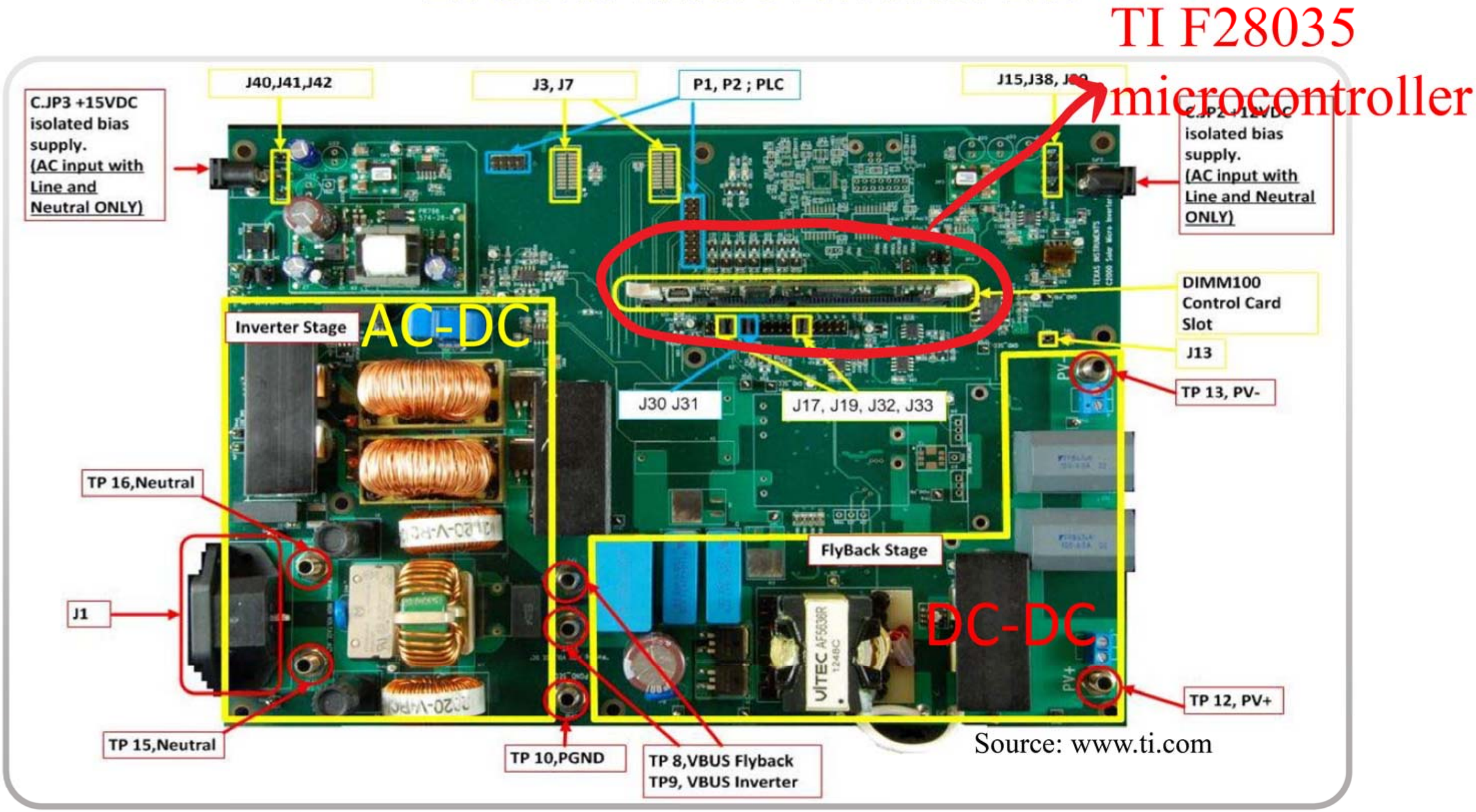
Linearizing the RNN controller

✓ Which means **all the eigenvalues have the negative real parts**.

Outline

V. Hardware-in-the-loop Experiment

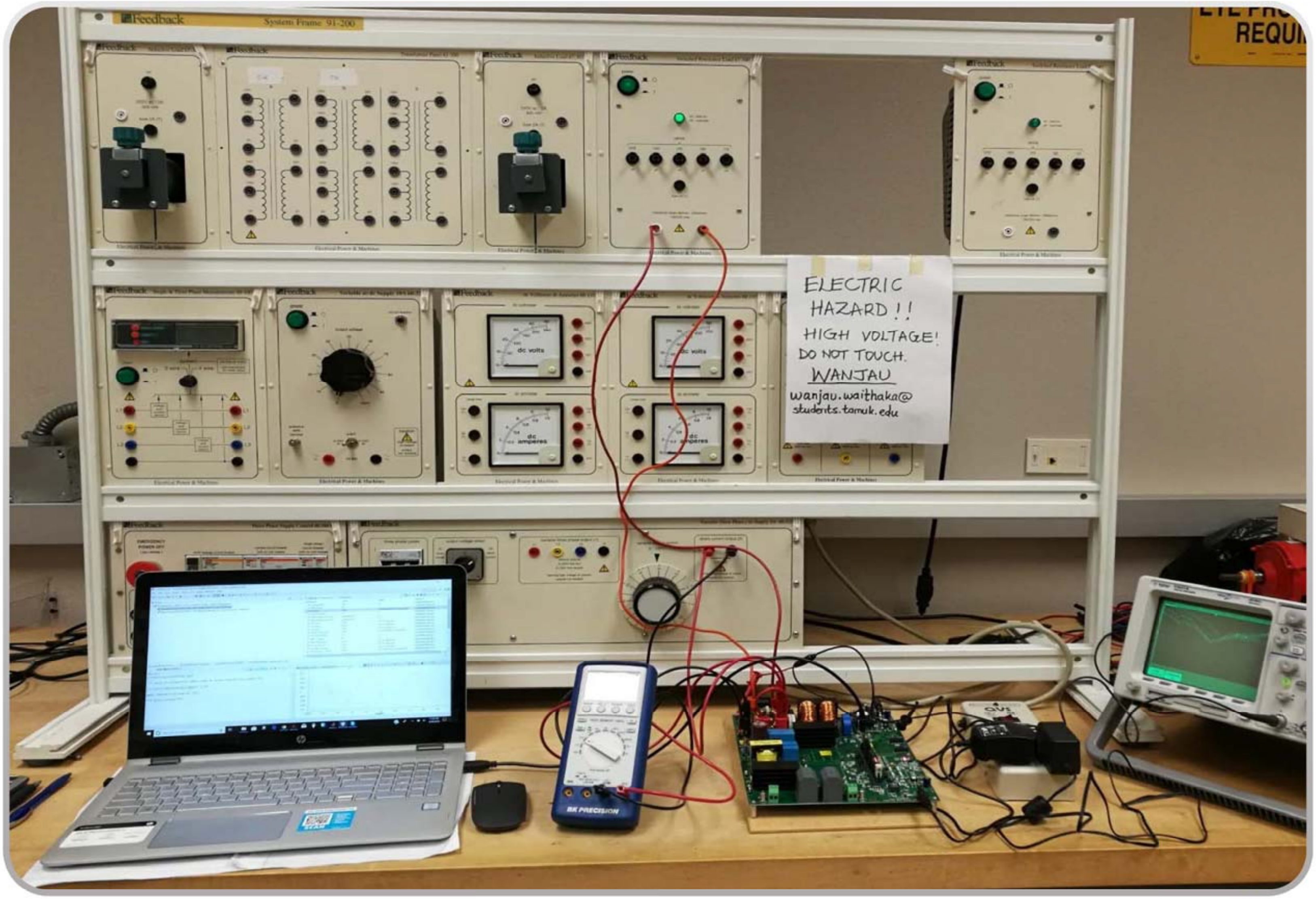
TI Solar Micro Inverter Kit



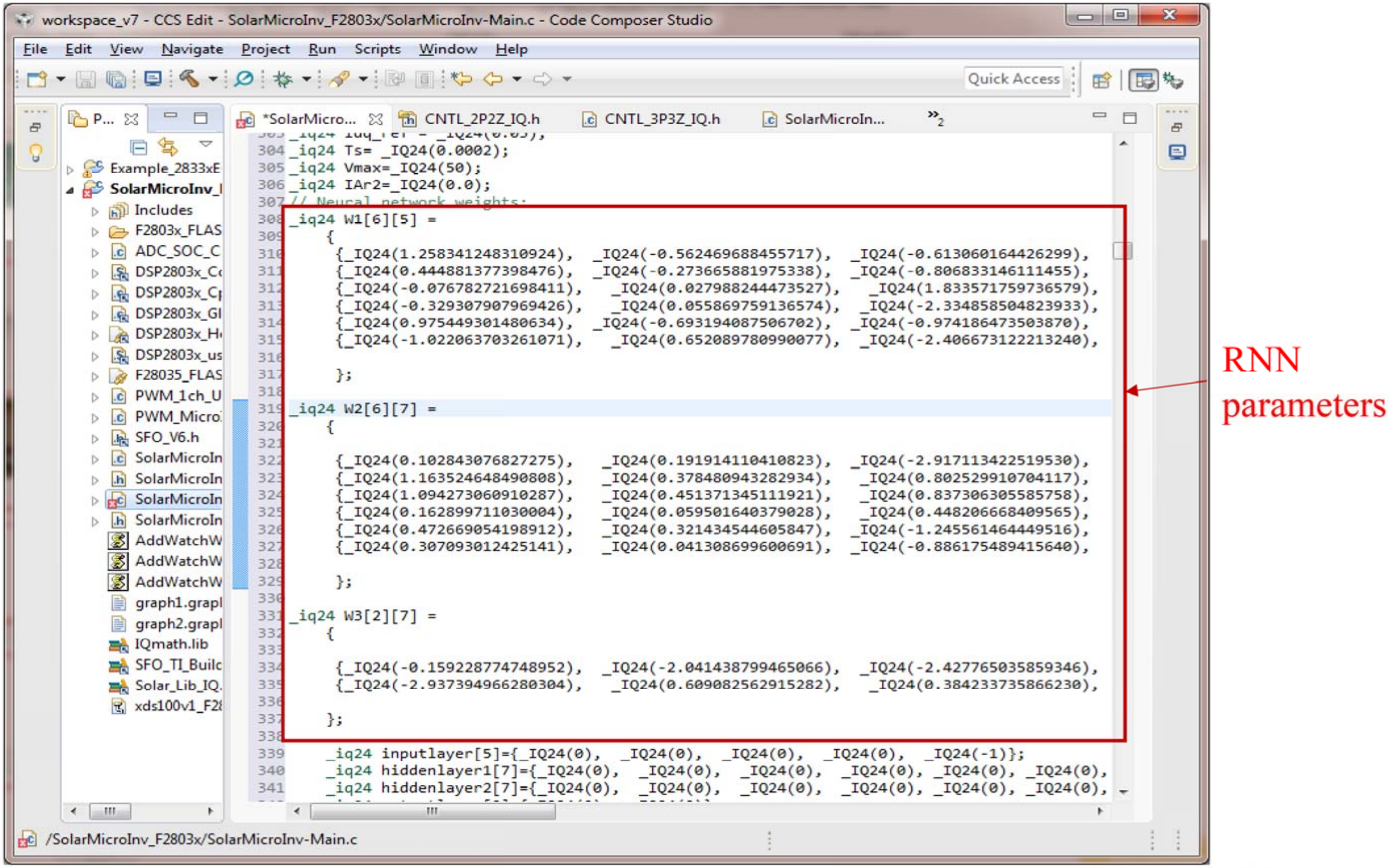
Features:

1) 28 to 45V at input; 280W for 220VAC, 140W for 110VAC;
2) C2000 Piccolo F28035 32-bit 60MHz MCU

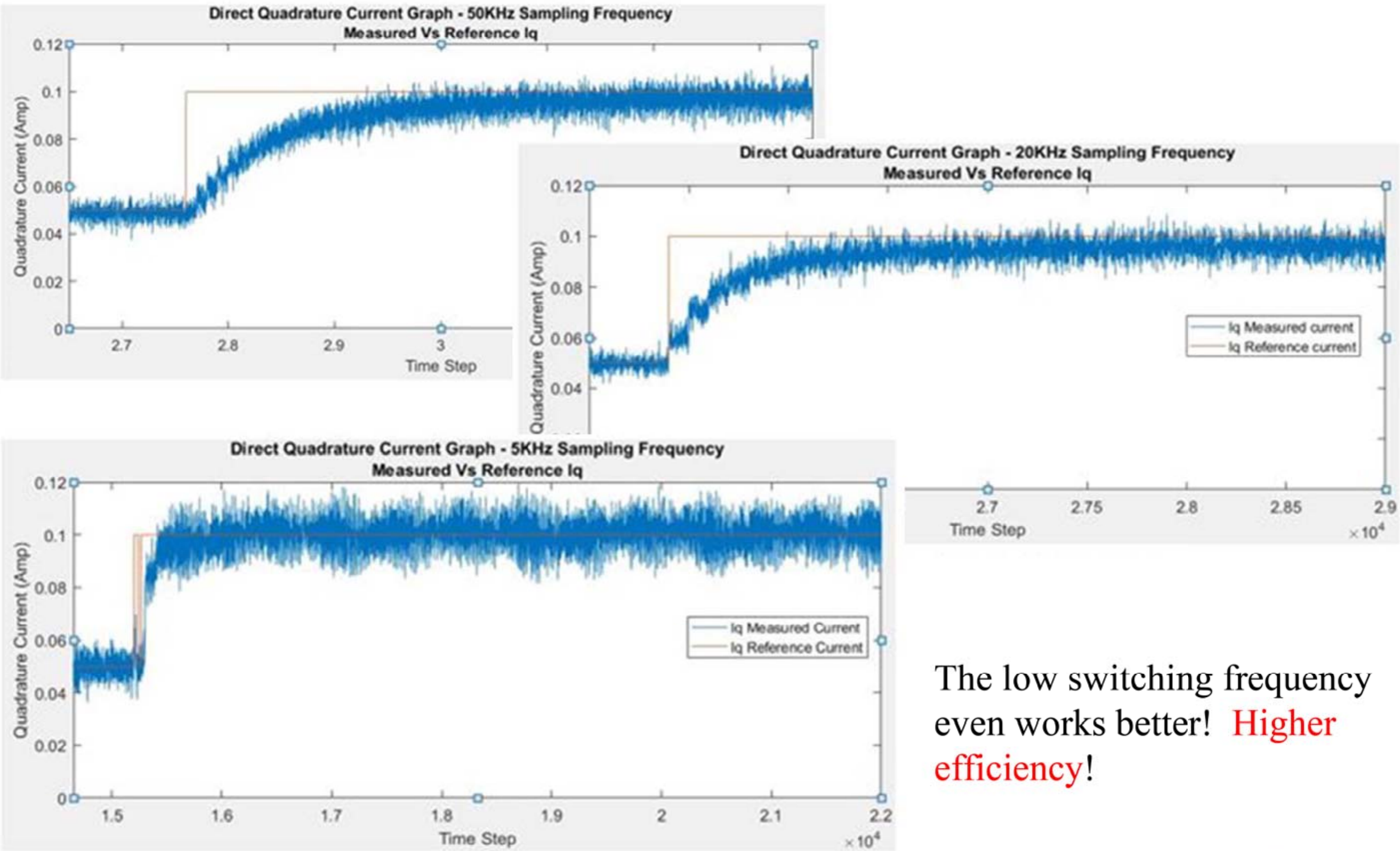
Hardware Validation Laboratory Set-up



C Code Implementation



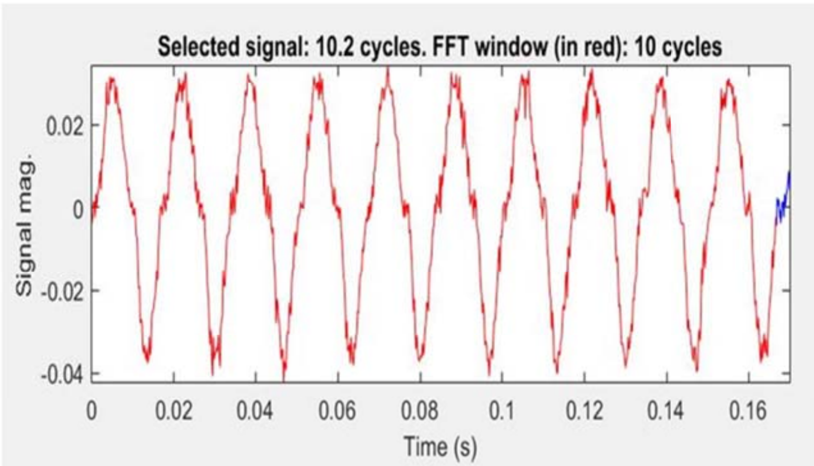
Current Tracking

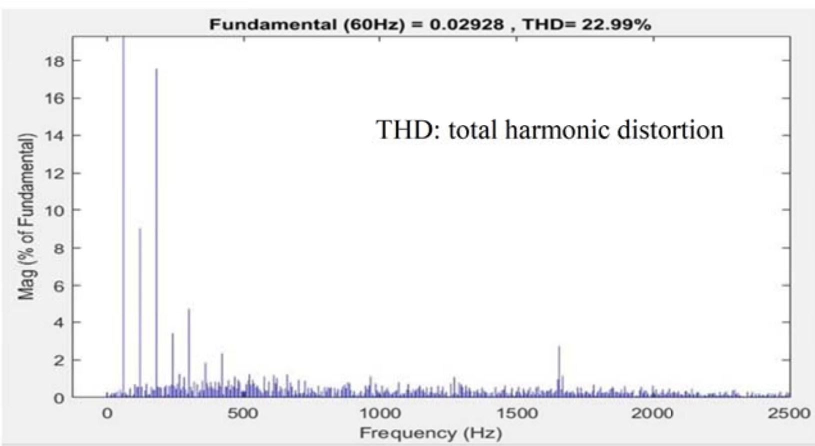


The low switching frequency even works better! Higher efficiency!

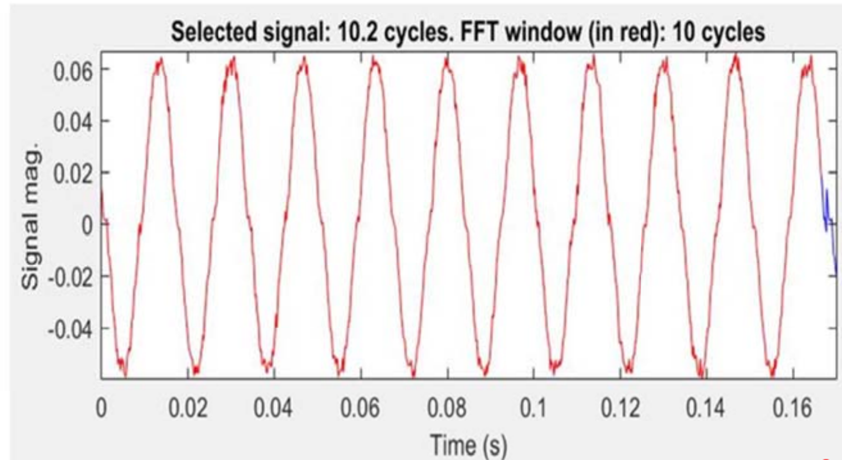
THD Comparison

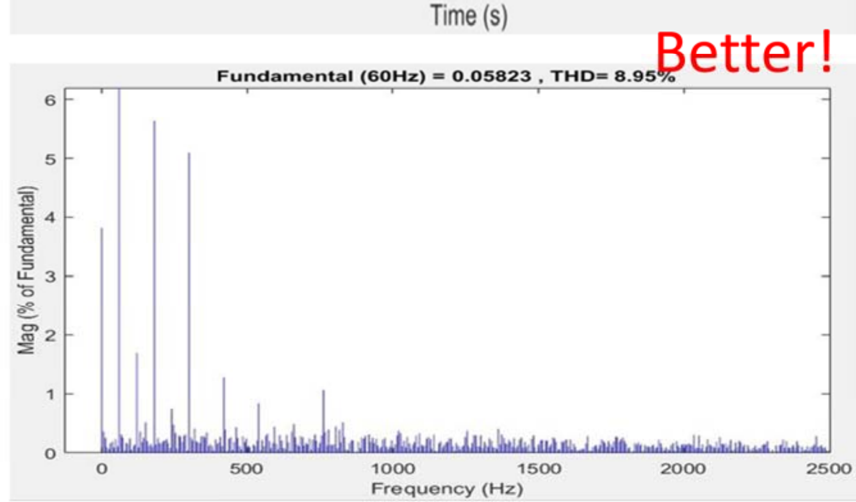
- 5KHz sampling and switching frequency





3P3Z controller by TI in CCS





RNN Controller

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VI. Discussions about RNN Control

Discussions about RNN Control

➢ *Advantages*

- a **damping free** technique;
- allows for **low sampling** & **switching** frequency while maintaining high performance;
- ✓ strong ability of tracking the references, fast response, lower overshoot,
- ✓ **Robust**, **adaptive**, can tolerate a wide range of system parameter changes;
- ✓ approximate optimal control trained by Approximate Dynamic Programming principle
- ✓ …...

➢ *Further Improvements*

- ✓ **DSP+FPGA** implementation or Special Chip to solve calculation problem ? Not Available
- ✓ Refine the structure of RNN to better fit the embedded controller application.
- ✓ **Reducing** training hardware (gpu/cloud, supercomputer)
- ✓ Global stability problem, global convergence problem


Questions


Thank You