Reservoir-Computing-Based, Biologically-Inspired Artificial Neural Network (BIANN) for Online Modeling of a Single Machine Infinite Bus (SMIB) System

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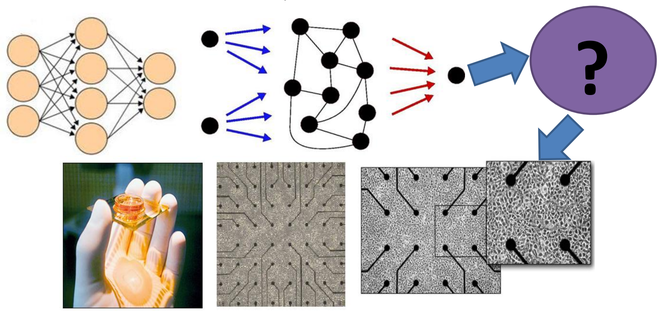
Biologically-inspired Artificial Neural Network(BIANN)

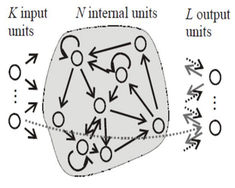
- BIANN uses biologically plausible spiking neuron models;
- BIANN bridges the gap between oversimplified ANNs and living neural networks;
- Effective encoding, decoding and training mechanisms for BIANN still need to be developed.



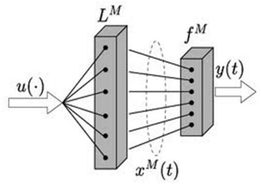
Reservoir Computing – The Concept

- Reservoir Computing (RC) is an approach to design, train, and analyze recurrent neural networks (RNNs);
- RC yields computational and sometimes analytical models for biological neural networks.
- Fundamental principles of RC:
  - Use a **large**, **random** RNN as an excitable medium – the "reservoir", or "liquid";
  - When the reservoir is driven by input signals, each unit in the RNN creates its own **nonlinear transform** of the input;
  - Output signals are read out from the excited RNN by some **readout mechanism**, typically a simple linear combination of the reservoir signals;
  - Outputs weights can be trained in a supervised way.

Echo State Network



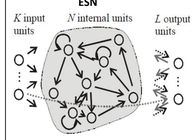
Liquid State Machine



Reservoir Computing - From ESN to BIANN

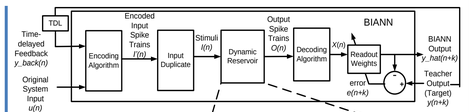
- Borrow the idea of "reservoir computing (RC)" from ESN;
- Develop encoding, decoding and training algorithms for the BIANN based on RC.

ESN

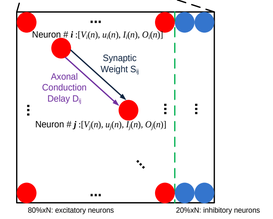


- No coding;
- Uses simple activation function (tanh) for each neuron;
- Weights in the reservoir do not change once generated.

BIANN

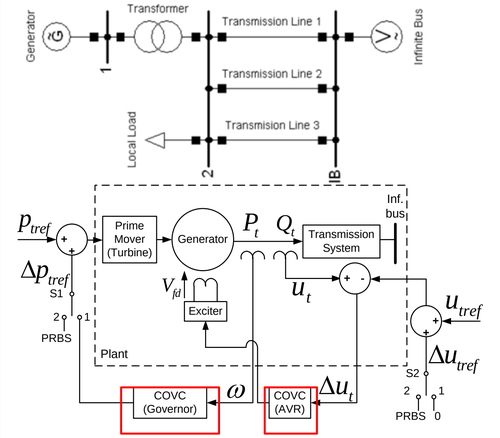


Signal	Dimension
u(n)	Ax1
y_back(n)	Bx1
I'(n)	(A+B)Mx1
I(n)	C(A+B)Mx1
O(n)	Nx1
X(n)	Nx1
y_hat(n+k)	Bx1
y(n+k)	Bx1
e(n+k)	Bx1

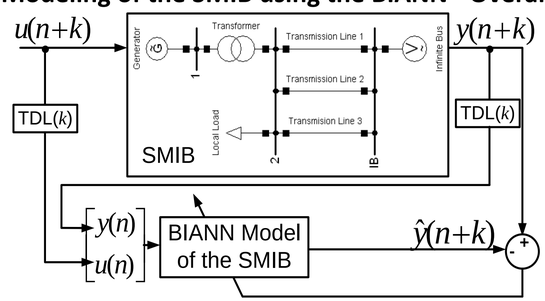


Izhikevich Spiking Neuron Model (N spiking neurons)

Single Machine Infinite Bus (SMIB) Power System



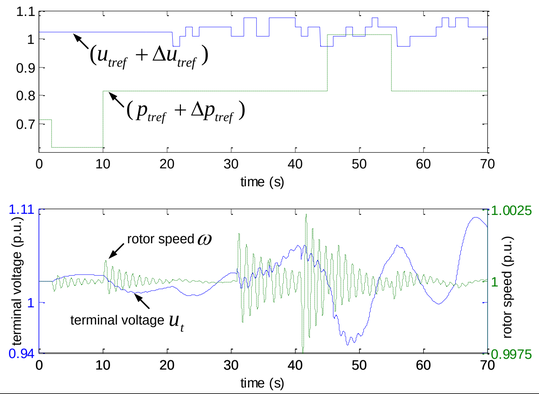
Modeling of the SMIB using the BIANN - Overall Scheme

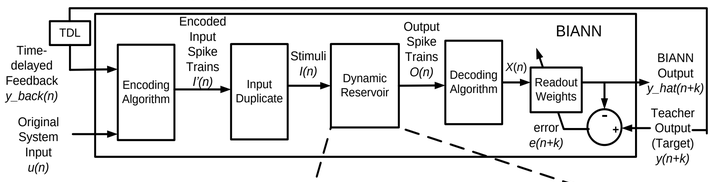


$$y(n+k) = f(u(n), y(n))$$

$$u(n) = [u_{t_{ref}}(n) + \Delta u_{t_{ref}}(n),\ p_{t_{ref}}(n) + \Delta p_{t_{ref}}(n)]$$

$$y(n) = [\omega(n),\ u_t(n)]$$





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y(n+k)	Bx1
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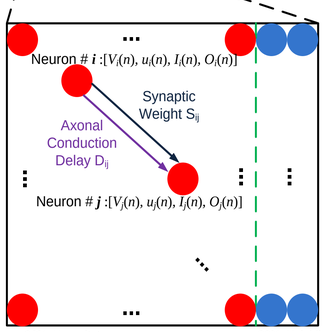
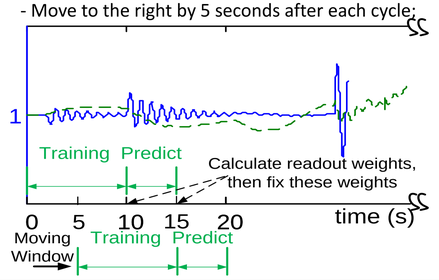


Izhikevich Spiking Neuron Model (N spiking neurons)

Modeling of the SMIB using the BIANN: Training Algorithm

- Moving Window Technique
  - Length of the moving window: 15 seconds;
  - 10 seconds data for training and 5 seconds data for prediction (testing);
  - Move to the right by 5 seconds after each cycle;



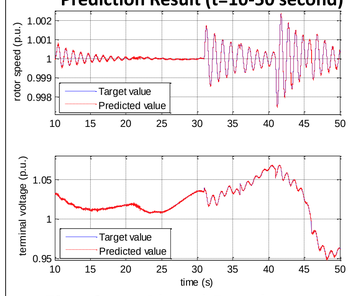
Conclusions

- A new type of artificial neural network, i.e. biologically-inspired artificial neural network (BIANN) is proposed to bridge the gap between ANNs and LNNs;
- A reservoir-computing-based training approach is proposed for the BIANN to serve as a novel modeling and control tool for practical applications;
- The BIANN is able to provide accurate one-step-ahead and five-step-ahead predictions of the rotor speed and terminal voltage of a generator in a single machine infinite bus power system, for online monitoring for online monitoring purpose;
- The prediction accuracy degrades as steps-ahead increases.

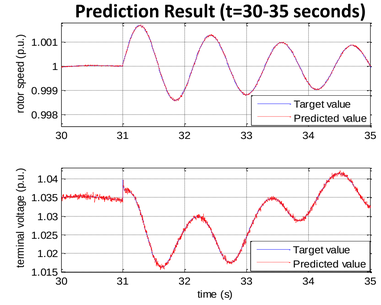
Modeling of the SMIB using the BIANN

- One-Step-Ahead Results

Prediction Result (t=10-50 second)

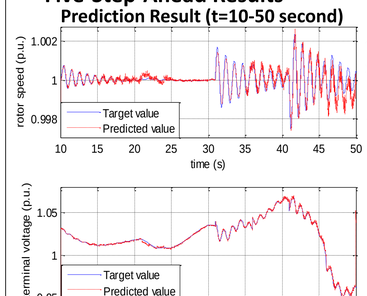


Prediction Result (t=30-35 seconds)



- Five-Step-Ahead Results

Prediction Result (t=10-50 second)



Prediction Result (t=30-35 seconds)