Evelyne Meier
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Electron beam stabilization test results using a neural network hybrid controller at the Australian Synchrotron and Linac Coherent Light Source

Overview

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2. Background on Neural Networks
3. Control Scheme
4. Australian Synchrotron Linac studies
5. LCLS studies
6. Application to the FERMI Linac

1. Motivation

- **Project Background**

  - Design of a control system for longitudinal parameter stabilization of the new FERMI@Elettra FEL Linac.

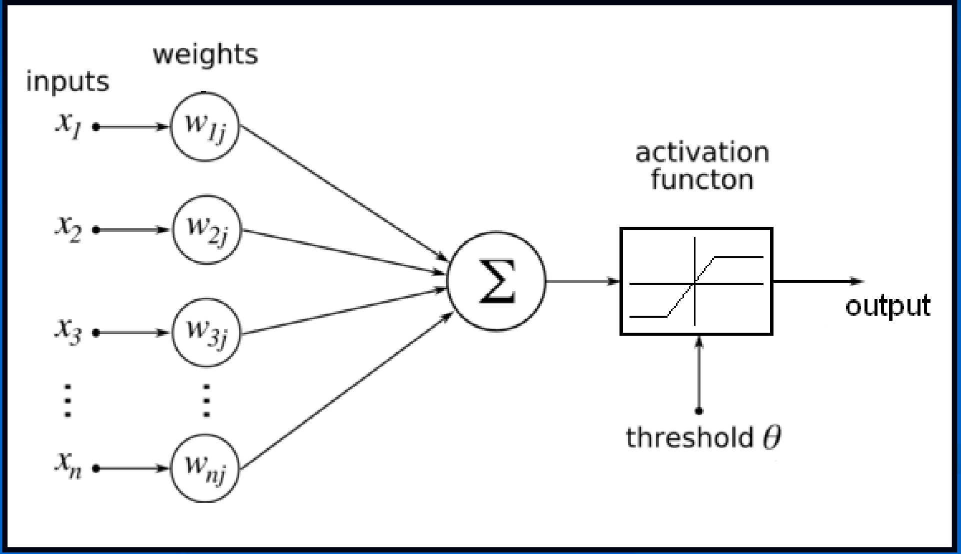
- **Goals**

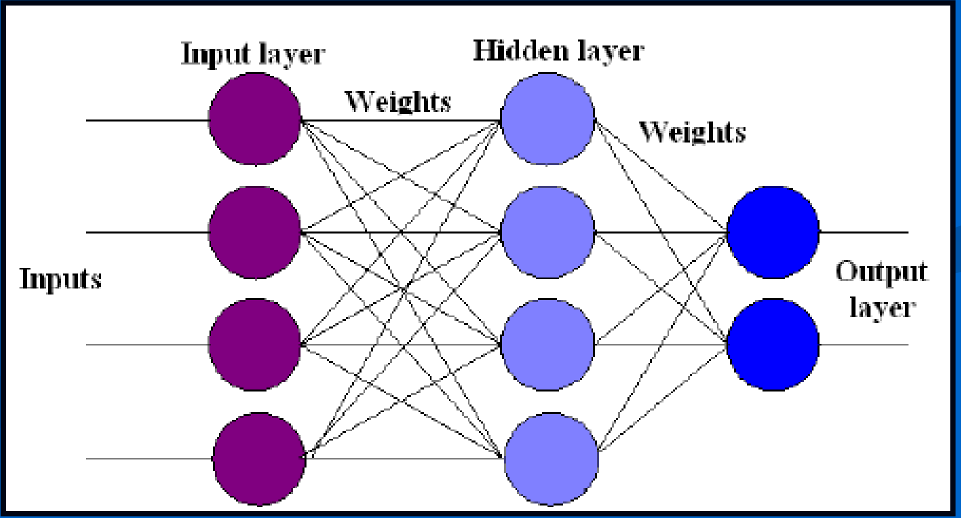
  - Perform energy and bunch length control at different stages of the Linac.
  - Eliminate high frequency jitter in a feed forward way.
  - Ensure the system robustness by coupling the feed forward control to a feedback.
  - Control system with large bandwidth, self adaptive to changes in jitter conditions.

2. Background on Neural Networks

Neural Network description

- Inputs from different neurons (for example klystron phase and voltage).
- The network weights contain the knowledge of the system.
- The activation function tells the artificial neuron when and with what strength to fire.
- The training algorithm adjusts the weights to minimize the error between the network output and the desired output.





2. Background on Neural Networks

- $\vec{x_j}$ = input vector for unit j (x_{ji} = ith input to the jth unit)
- $\vec{w_j}$ = weight vector for unit j (w_{ji} = weight on x_{ji})
- $z_j = \vec{w_j} \cdot \vec{x_j}$, the weighted sum of inputs for unit j
- y_o = network output
- $\hat{y}_o$ = targeted output

The weights are updated: $\boxed{w_{ji} \leftarrow w_{ji} + \Delta w_{ji}}$

Using the error:

$$E = \frac{1}{2} \sum_{o \in Outputs} (y_o - \hat{y}_o)^2$$

Learning rate

The weight change can be written as:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = \eta \delta_j x_{ji}$$

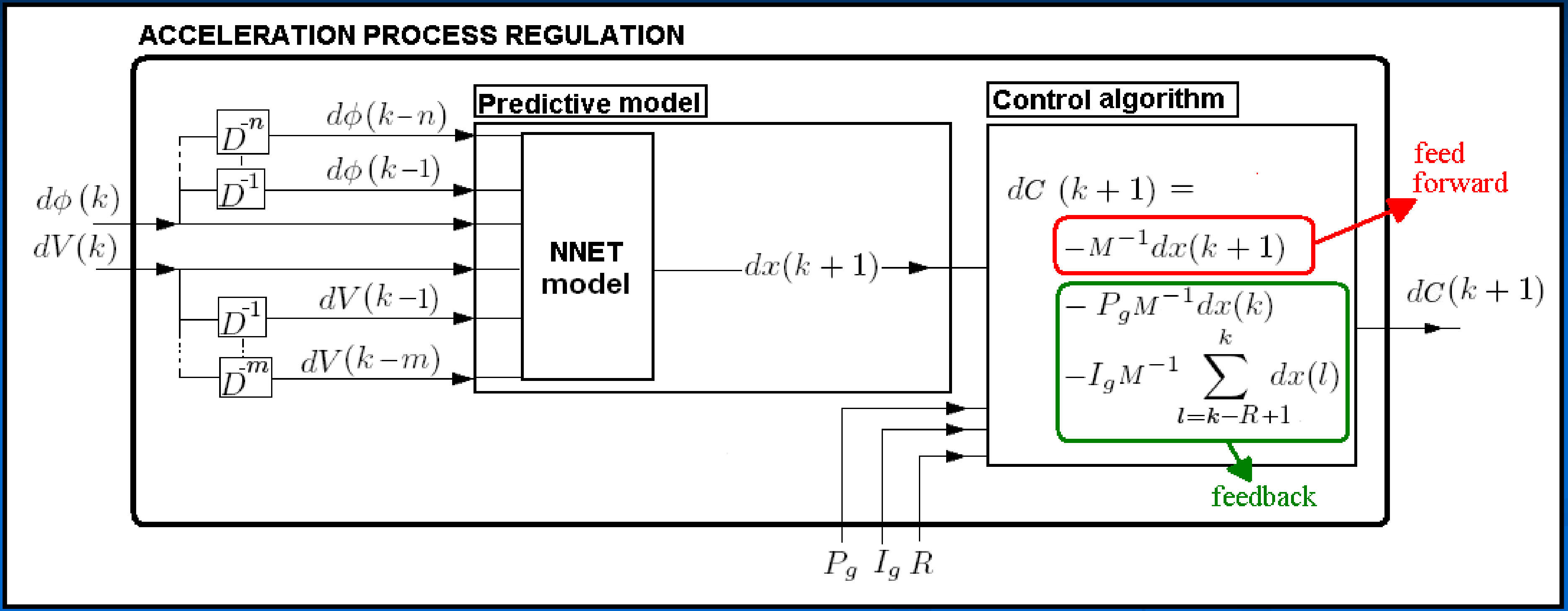
With, at the output layer:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial z_j} \frac{\partial z_j}{\partial w_{ij}} = \frac{\partial E}{\partial z_j} x_{ij}$$

And for the other layers:

$$\frac{\partial E}{\partial w_{ij}} = \sum_{k \notin Output} \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial f_j(z_k)} \frac{\partial f_j(z_k)}{\partial z_j} \frac{\partial z_j}{\partial w_{ij}} = \sum_{k \notin Output} \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial f_j(z_k)} \frac{\partial f_j(z_k)}{\partial z_j} x_{ij}$$

3. Control Scheme

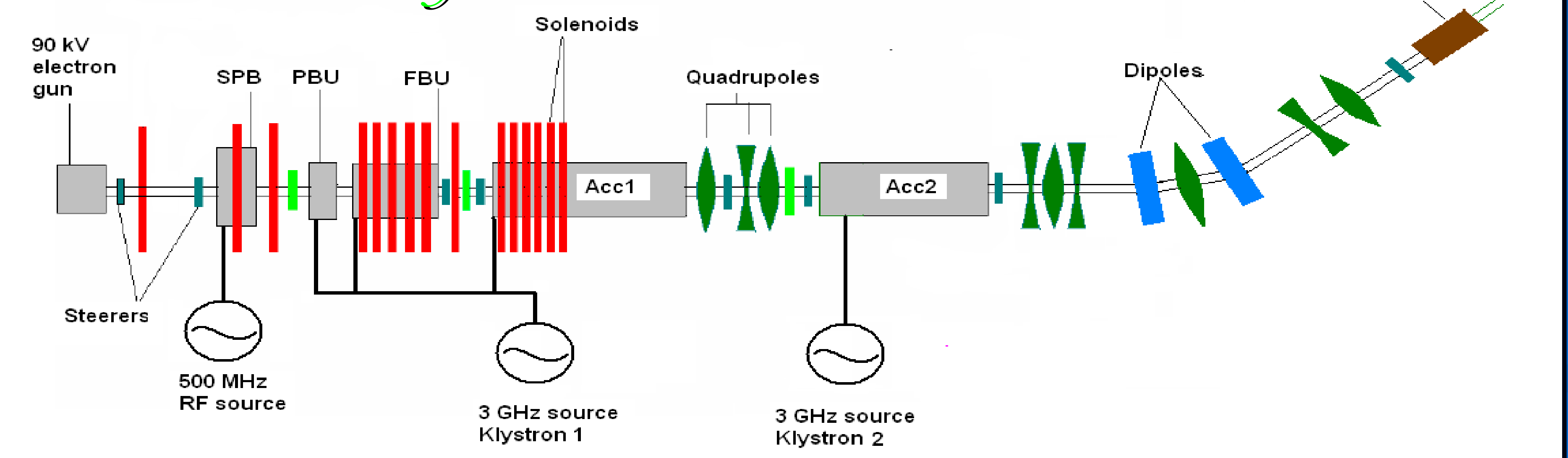


- Predictive model (left block): The Neural Network (NNET) receives lagged values of the perturbed klystron phase and voltage. It gives a prediction of the next pulse position deviation *dx(k+1)* used to compute the feed forward correction.

- Control algorithm (right block): The algorithm is composed of a feed forward (first term) augmented by PI control terms (second and third terms) to compute the correction to apply :*dC(k+1)* .

4. Australian Synchrotron Linac Studies

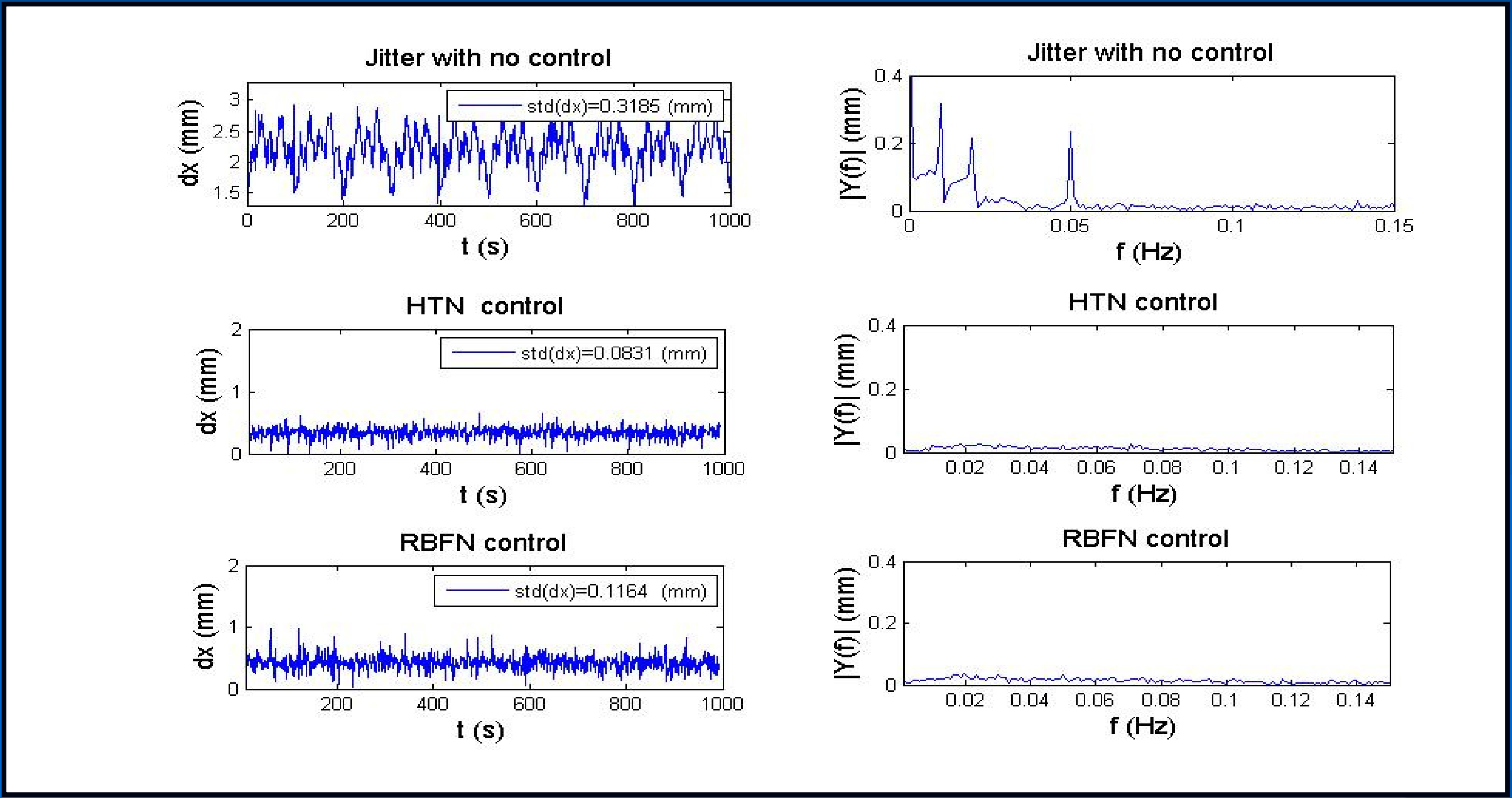
Linac Assembly



- ACC1 and ACC2 provide 100 MeV beam @ 1-10Hz.
- BPM resolution ~50 µm, white noise level ~ 0.11 mm rms.
- Jitter are induced in klystron 1 phase and voltage and corrected using klystron 2 voltage.
- Slow actuator response limits the experiment to max. ~0.075 Hz.

4. Australian Synchrotron Linac Studies

(1) Real time energy control

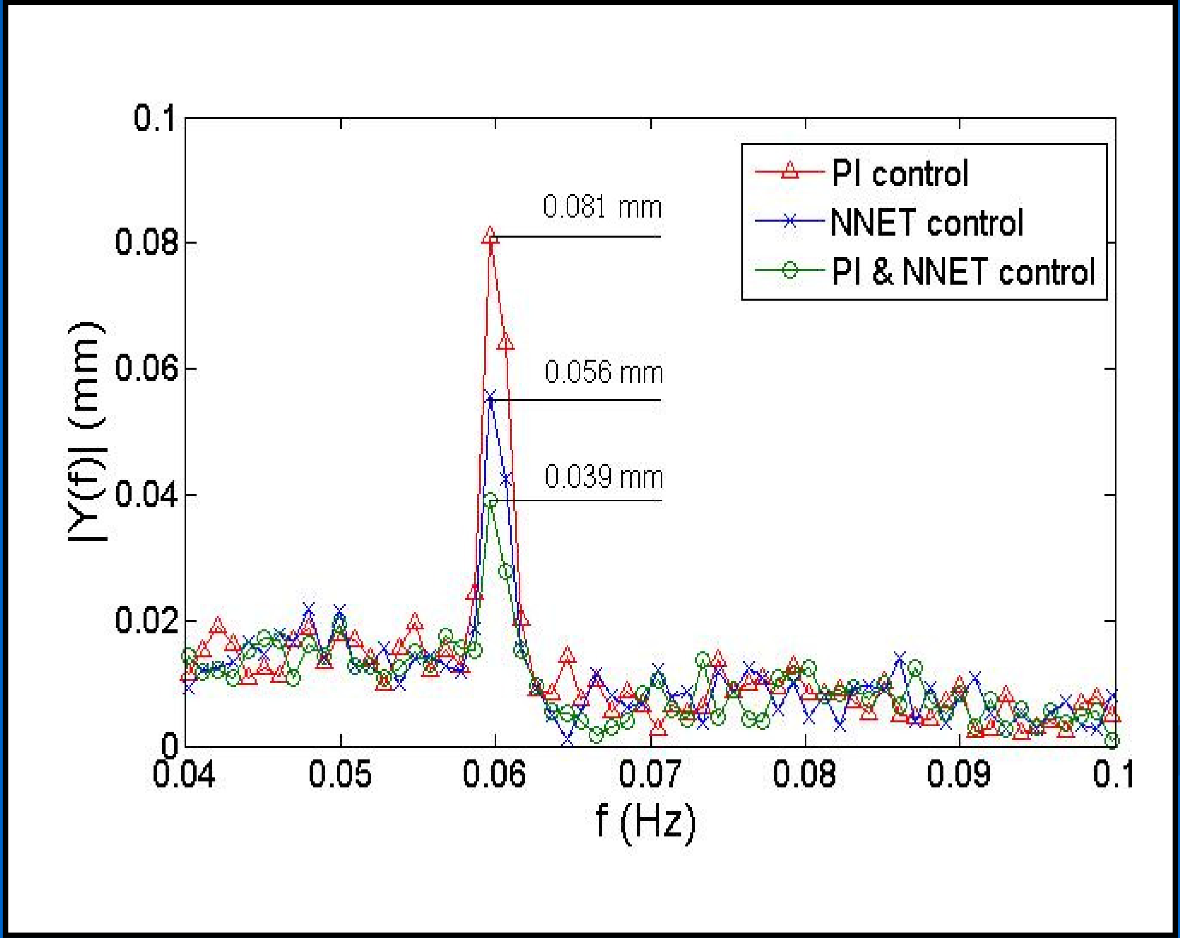


- Both the hyperbolic tangent network (HTN) and radial basis function network (RBFN) received 7 lagged values of V_1 and 5 lagged values of φ_1. The HTN and RBFN had 7 and 76 hidden neurons, respectively.

4. Australian Synchrotron Linac Studies

(2) Real time energy feed forward-feedback combined control:

- The network is trained for a 0.1 kV and 0.04 Hz jitter.
- It is then brought online to correct a 0.1 kV and 0.06 Hz jitter.
- FFT for frequency change: The combined system brings further attenuation.
- Even when mis-tuned the NNET performs better than the PI controller.



5. LCLS studies

- *Aims:*
  - Cancel higher frequencies (0.1-2.5 Hz) – limit due to the correcting actuators’ response.
  - Act at higher repetition rate (5 Hz with Matlab).
  - Couple energy and bunch length control.
  - Develop a more adaptive system.

- *Experiments:*

  (1) Couple energy and bunch length control.

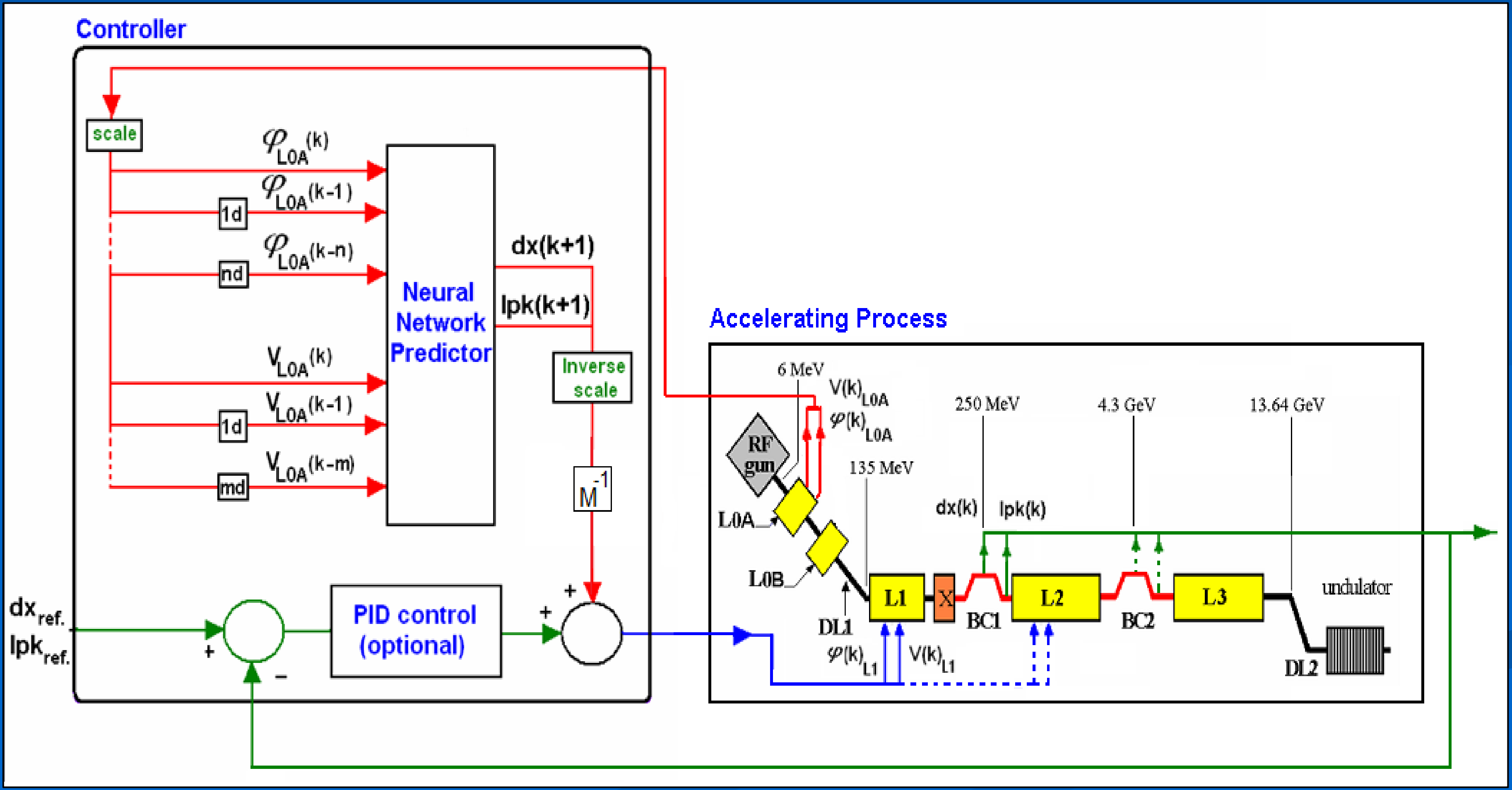
  (2) Comparison of NNET and PI algorithm performances.

  (3) Online adjustments of the response based on the data FFT to optimize the control.

  - Selected Network topology: 8-10 hidden neurons 8 lagged values of V_{L0A} and 8 lagged values of φ_{L0A}.

5. LCLS studies

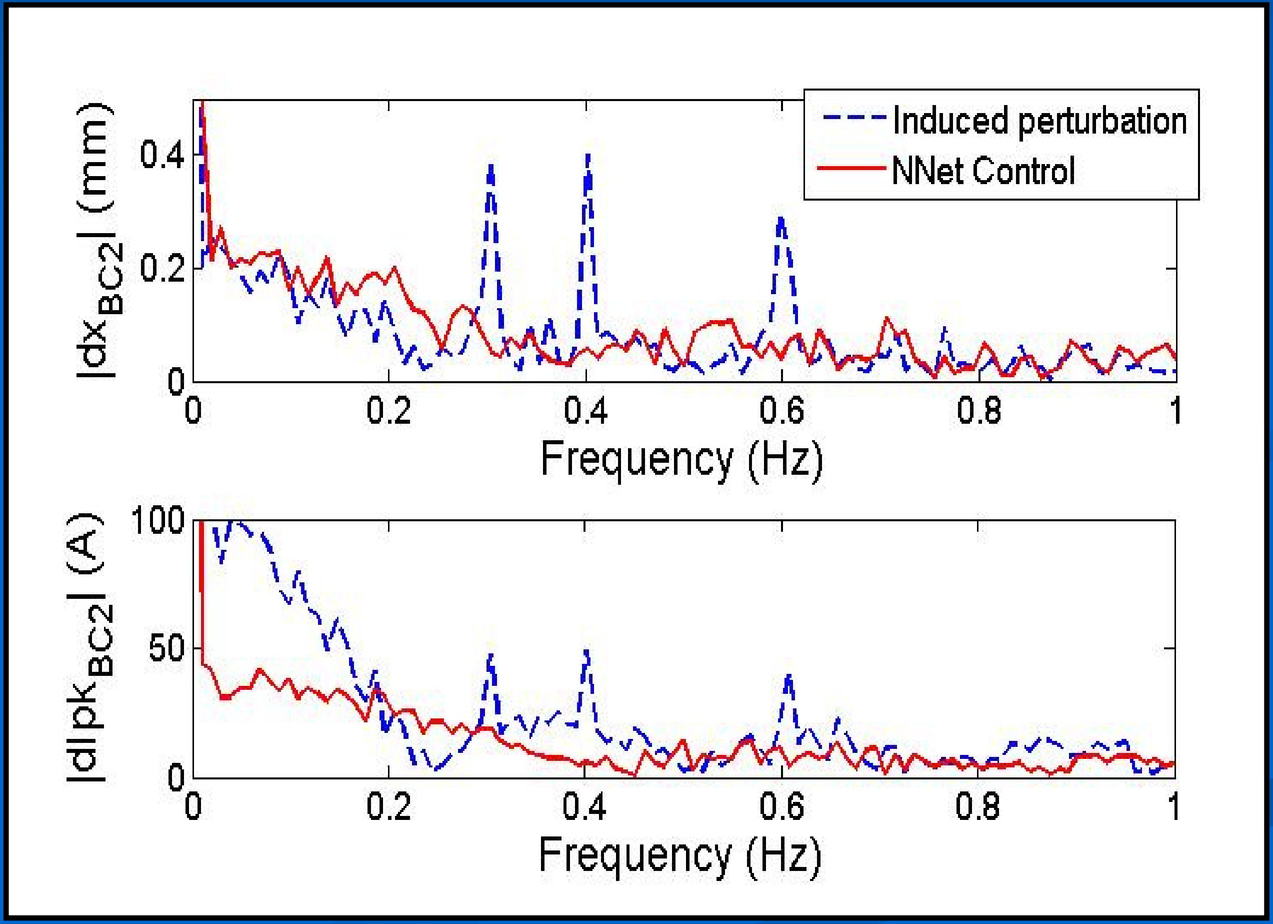
- *Machine assembly and control scheme:*



5. LCLS studies: Results

(1) Coupled control results at BC2

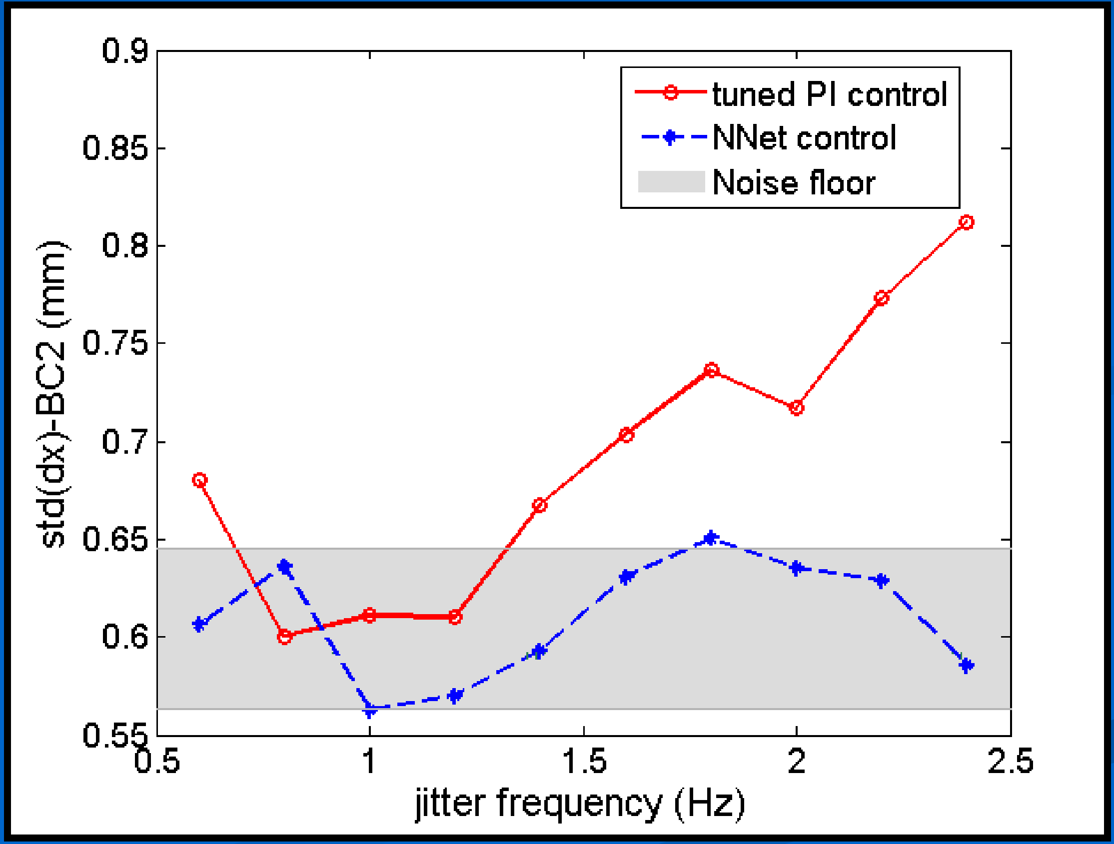
- Deviation recorded at BC2, with perturbations and corrections applied to two of the L2 klystrons.
- Successful cancellation of all frequencies was observed.
- Modulation in the frequency domain induced by the slow communication with the actuators through the Matlab channel access.



5. LCLS studies: Results

(2) PI and NNET performances

- Deviation recorded at BC2, with deviation and correction applied to klystrons of the L2 section.
- Original imposed deviation amplitude ~1 mm rms.
- NNET and PI re-tuned to optimize the correction for each frequency.
- Better performance of the NNET above 1.5 Hz.



5. LCLS studies

(3) Developing a more adaptive system

- The correction is computed according to:

$$dC(k+1) = -M^{-1}dO(k+1) - P_g M^{-1}dO(k) - I_g M^{-1} \sum_{l=k-R+1}^{k} dO(l)$$

- Accurate feed forward control of the machine depends on the accuracy of:
  - The network response: dO(k+1)
  - The response matrix: M

- The NNET prediction dO(k+1) can be imprecise if jitter conditions change. In this case re-training will resolve the problem.

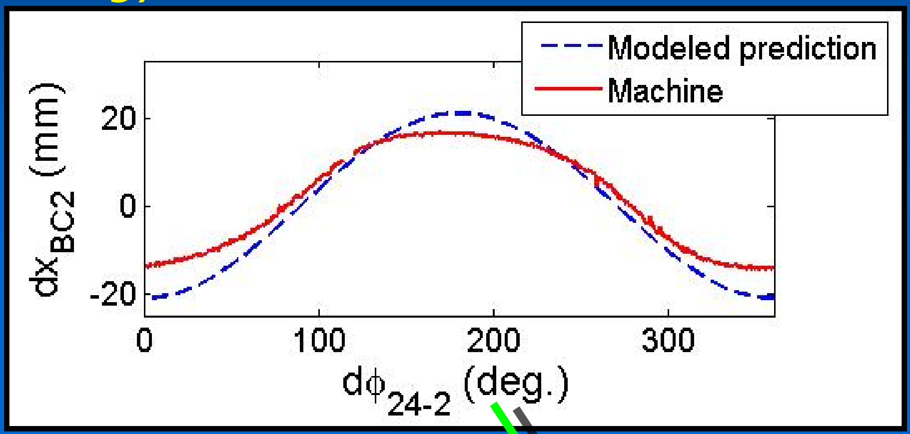
- Because of non-linearities of the actuator response and change in the klystron settings M is not static!

→ *M must be adjusted dynamically !!*

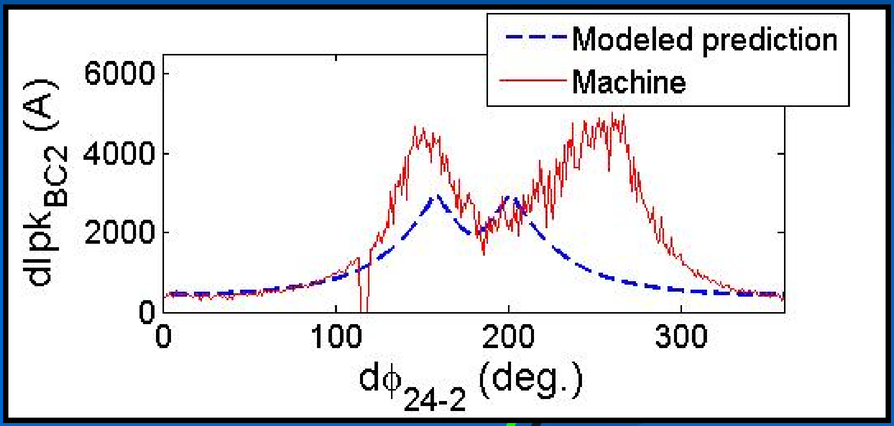
5. LCLS studies: Results

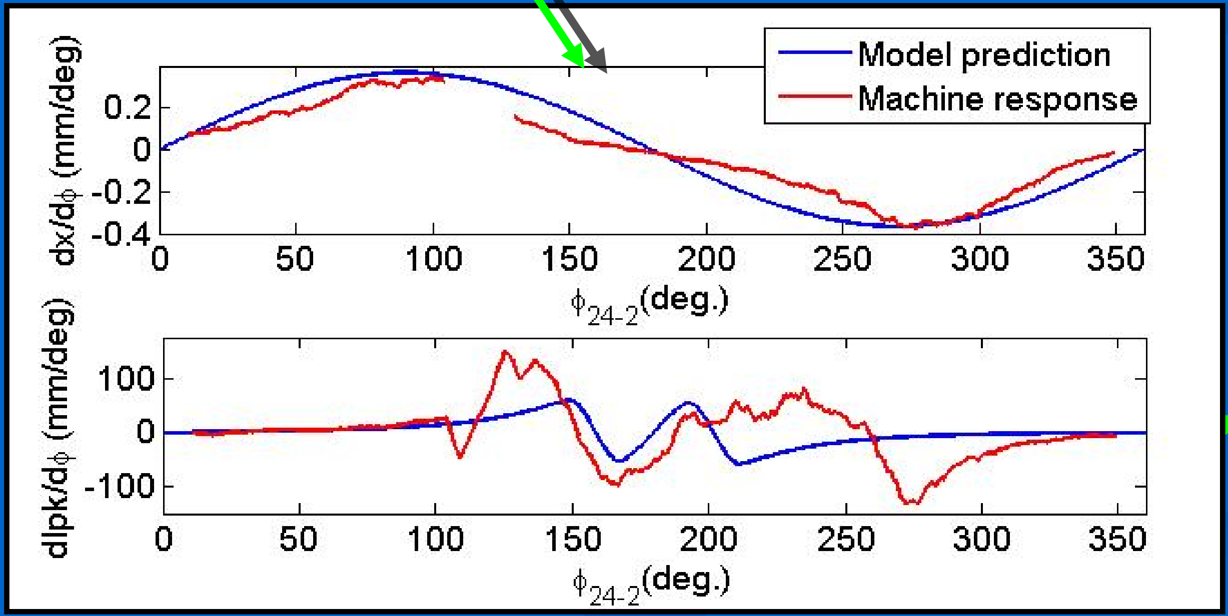
(3) Machine Model

Energy model



Peak current model



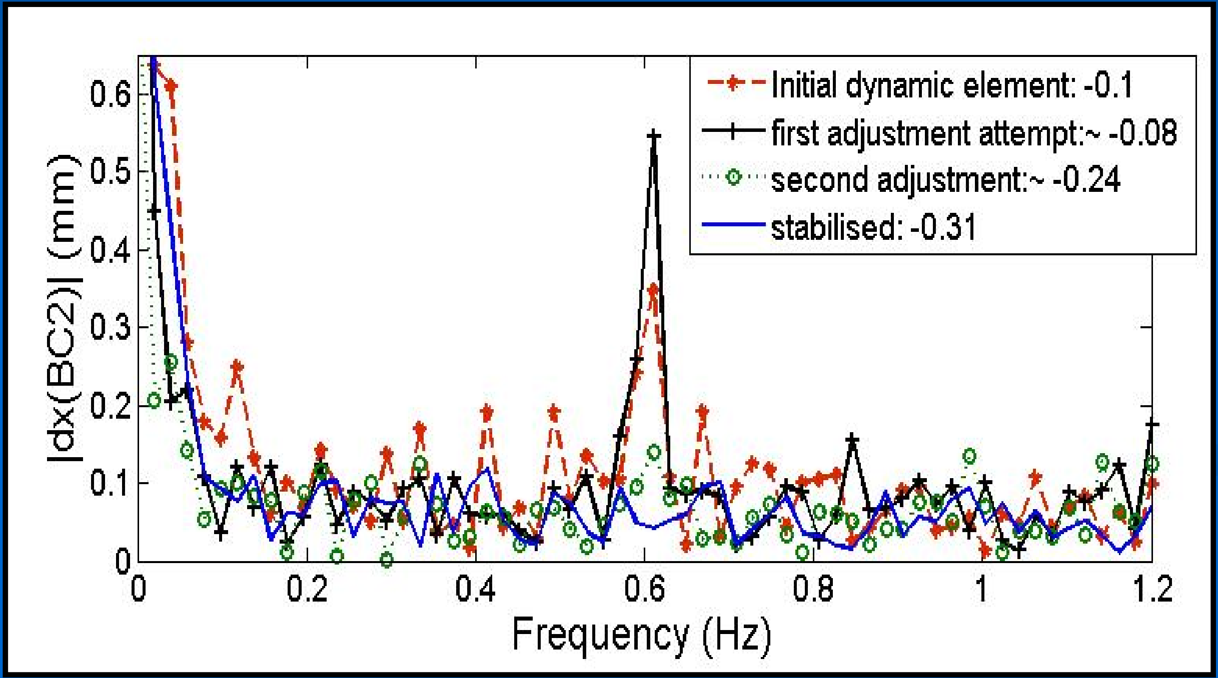


- Energy model sufficient but peak current modeling requires further development.

5. LCLS studies: Results

(3) Online ajustement of M

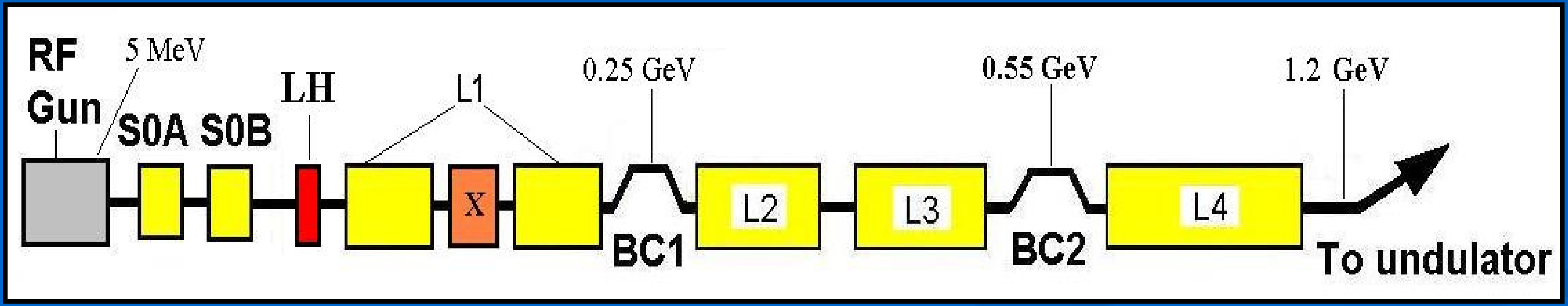
- During control one of the klystron setting is changed from 60° to 300°.
- The corresponding value of the actuator response M=dx/dφ changes from 0.3 (mm/°) to -0.3 (mm/°).
- To test the algorithm, M is set to -0.1 when the phase change occurs.



> - The algorithm then performs a small change to evaluate the proper sign for the adjustment.
> - Based on the position FFT further adjustments are performed.

5. Application to the FERMI case

- *The FERMI machine assembly*



- 1 BC configuration: 3 Observables: E_{BC1}, E_{end}, I_{BC1}
  and 3 Controllables: VL1, VL4, φL1

- 2 BC configuration: 5 Observables: E_{BC1}, E_{BC2}, E_{end}, I_{BC1}, I_{BC2}
  and 5 Controllables: V_{L1}, V_{L4}, φ_{L1}, ?, ?

5. Application to the FERMI case

- *Knowledge gained:*

  - The system can be applied to a multi Observable – multi Controllable case for control over a wider range of frequencies than the PI .
  - Limitations are presently due to the slow communication with the actuators and saturation of the klystrons.
  - Further development of the system is required to ensure adaptability.

- *Next steps:*

  - Definition of the control system requirements and capabilities: actuators availability speed and location.
  - Implementation of a Matlab GUI for the machine up to BC1.

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(A) Network structure optimization

Criterion 1: The error index

- Measures the quality of the prediction, with *y(t)* the model output and $\hat{y}$*(t)* the targeted value.

$$(1)\quad E.I. = \left[\frac{\sum (\hat{y}(t) - y(t))^2}{\sum y^2(t)} \right]^{1/2}$$

Criteria 2: The correlation tests

- Helps evaluate the number of lagged inputs. If enough lags are provided the conditions (2), (3) and (4) should hold. In practice we use the 95% interval confidence.

- E is the expectation value, ε is the error between the NNET prediction and the desired output, *u* is the input variable (klystron 1 phase or voltage).

$$(2)\quad \phi_{u\epsilon}(\tau) = E(\epsilon(t)u(t-\tau)) = 0$$

$$(3)\quad \phi_{u^2\epsilon}(\tau) = E(\epsilon(t)(u^2(t-\tau) - \bar{u}^2(t))) = 0$$

$$(4)\quad \phi_{u^2\epsilon^2}(\tau) = E(\epsilon^2(t)(u^2(t-\tau) - \bar{u}^2(t))) = 0$$

$$\hat{\phi}_{u\epsilon}(\tau) = \frac{\sum_{t=1}^{N-\tau} u(t)\epsilon(t+\tau)}{\left[\sum_{t=1}^{N} u^2(t) \sum_{t=1}^{N} \epsilon^2(t+\tau) \right]^{\frac{1}{2}}}$$