ELECTRON BEAM ENERGY STABILIZATION USING A NEURAL NETWORK HYBRID CONTROLLER AT THE AUSTRALIAN SYNCHROTRON LINAC*

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Abstract

This paper describes the implementation of a neural network hybrid controller for energy stabilization at the Australian Synchrotron Linac. The structure of the controller consists of a neural network (NNET) feed forward control, augmented by a conventional Proportional-Integral (PI) feedback controller to ensure stability of the system. The system is provided with past states of the machine in order to predict its future state, and therefore apply appropriate feed forward control. The NNET is able to cancel multiple frequency jitter in real-time. When it is not performing optimally due to jitter changes, the system can successfully be augmented by the PI controller to attenuate the remaining perturbations.

INTRODUCTION

With a view to control the energy and bunch length at the FERMI@Elettra Free Electron Laser (FEL) [1], the present study considers a neural network hybrid feed forward-feedback type of control to rectify limitations related to feedback systems, such as poor response for high jitter frequencies or limited bandwidth [2], while ensuring robustness of control. The Australian Synchrotron Linac is equipped with a beam position monitor (BPM), that was provided by Sincrotrone Trieste from a former transport line thus allowing energy measurements and energy control experiments. The present study will consequently focus on correcting energy jitter induced by variations in klystron phase and voltage.

BACKGROUND ON NEURAL NETWORKS

A NNET consists of an interconnected group of artificial neurons as shown in Fig. 1. Each neuron receives stimuli from other nodes in the network and each of these inputs to a node has a "weight" w associated with it as well as an activation function, which tells a node when to fire. A neuron may also add a "bias" value θ, with the weighted inputs and any bias is passed through the activation function; the resulting value is available as the node output. Commonly used activation functions are linear, hyperbolic tangent, sigmoid, or gaussian. Gaussian networks are also known as "Radial Basis Function Networks" (RBFN) due to the radial nature of the activation function [3, 4].

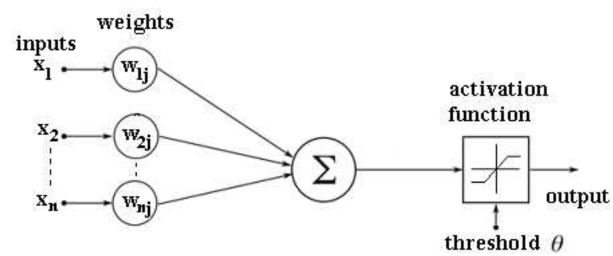

Figure 1: Schematic of an artificial neuron. The node receives inputs from other nodes which are multiplied by their respective weights and fed into the activation function.

During the training phase, the network is presented with an input vector and the resulting output vector is compared to the desired output vector; the network weights are then adjusted by a learning algorithm.

EXPERIMENT

Electrons are emitted by a 90 kV DC gun and bunched by successively passing through a 500 MHz sub hormanic pre buncher (SPB), a 3 GHz primary buncher (PBU), and a 3GHz final buncher (FBU) as shown in Fig. 2. They then go through the two main 3 GHz accelerating sections (ACC1 and ACC2) where they gain most of their energy to reach 100 MeV (see [5] for a detailed description of the Linac structure).

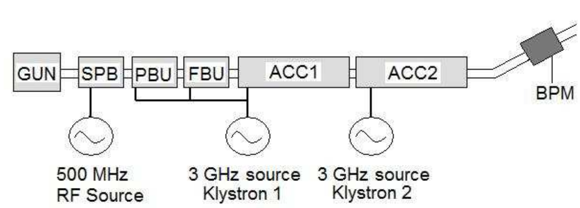

Figure 2: Schematic of the Linac RF components and BPM.

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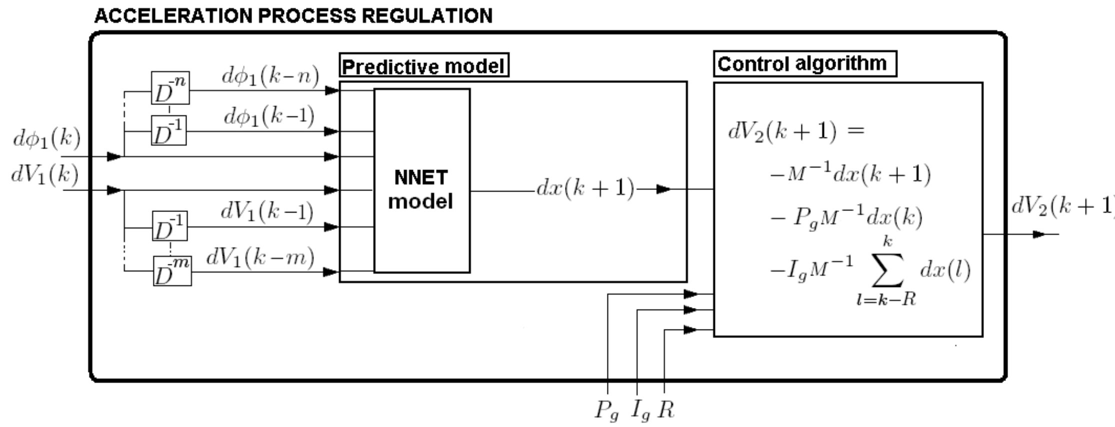

Figure 3: Control scheme consisting of a predictor (left block), connected in series to a control algorithm (right block). The predicted deviation $dx(k+1)$ is used by the control algorithm in the right block to compute forward (first term) and feedback (second and third terms) corrections, with user specified gains (P_g and I_g) and sum range (R).

The experiment consists of exciting a multi frequency jitter in the first klystron phase ϕ_1 and voltage V_1 to induce energy deviation and thus horizontal deviation at the BPM. The klyston 1 phase and voltage and the BPM readings were recorded in order to train a hyperbolic tangent network (HTN) and a RBF network to act as predictors for future pulse deviation.

CONTROL SCHEME

The controller scheme is as shown in Fig. 3. It consists of a neural network predictor [6] and a control algorithm. The delay operator D in Fig. 3 provides the predictor with m delayed input values of the first klystron voltage V_1, and n delayed input values of the phase ϕ_1. For example, for the pulse number k in a time series, the p^{th} delayed phase element is given by $D^{(-p)}(\phi(k)) = \phi(k-p)$ with p=1,2,..n. The NNET output is a prediction of the future position deviation $dx(k+1)$.

The chosen control algorithm is based on a PI algorithm, where the gains P_g, I_g and the number of elements N in the sum are chosen externally. The factor M is the response coefficient of the deviation to the klystron voltage (in mm/kV).The idea is to provide a control proportional to the predicted variation, completed by a feedback term to ensure stability.

REAL TIME CONTROL RESULTS

Hyperbolic Tangent Network Control

The network was trained over a set of 200 pulses with excited jitter of 0.01 Hz, 0.05 Hz and 0.02 Hz, each of 0.06 kV amplitude (see recorded data in Fig. 4, upper plots). The network consists of 6 hidden neurons receiving 6 lagged values of V_1 and 2 lagged values of ϕ_1 as its inputs. The online control results are given in Fig. 4 (middle plots), where it appears that the remaining noise is of the background level. The Fourier analysis in Fig. 4 shows that there is no obvious jitter frequency component remaining.

As a second test, the network was trained over a set of 24 samples with frequencies ranging from 0.01 Hz to 0.05 Hz and of amplitudes ranging from 0.04 kV to 0.06 kV. The network was then tested in real time by inducing frequencies and amplitudes different from the training set, but included within the training range. For each sample test, all frequencies were suppressed and the remaining rma deviation was equivalent to the background level. This shows the ability of the network to interpolate its prediction when frequencies are encountered which are different from the training set, but included within the training range.

Radial Basis Function Network Control

The RBF network was trained using the same sample data as was used for the HTN. The trained network consisted of 76 hidden neurons. Although the residual noise is slightly higher than for the hyperbolic tangent network, Fourier analysis reveals that the frequency components were successfully eliminated (see lower plots in Fig. 4).

The controller was then trained and tested over the same set of 24 samples as the HTN. The same 16 jitter configurations were tested over 250 pulses. Results showed the successful cancelation of all frequencies for all samples.

Feed Forward-feedback Combined Control

To minimize the remaining jitter in situations were the NNET predictions are not accurate enough to totally cancel the perturbation, the feed forward control is augmented by the PI control as shown in Fig. 3. The combination of feed forward-feedback will ensure stability of the system, in those situations where the network is not performing optimally; in this case its mis-predictions can be compensated by the feedback term.

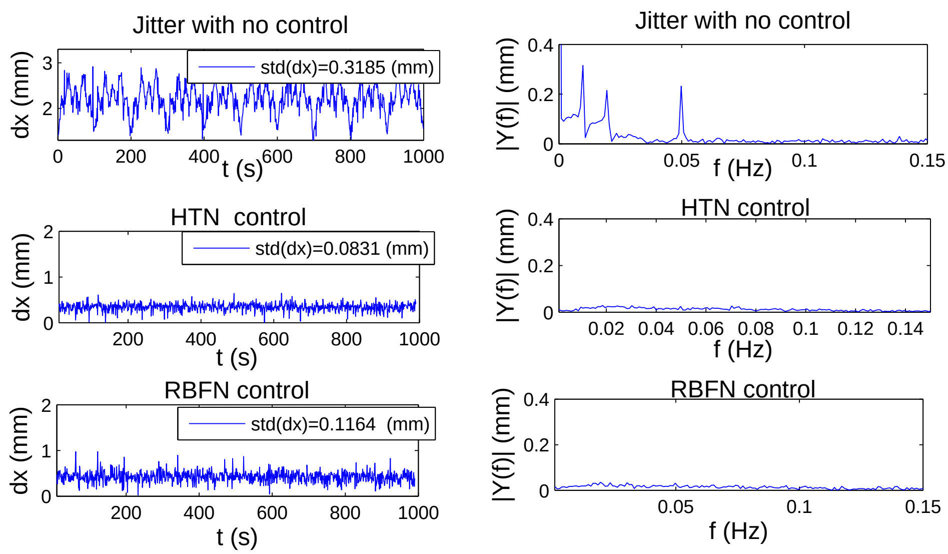

Figure 4: Example of real-time control over 1000 pulses, for voltage jitter of 0.06 kV amplitude and frequencies of 0.01 Hz, 0.05 Hz and 0.02 Hz. The upper plots give the recorded BPM readings (left) and the corresponding FFT (right) without control. The middle and lower plots give the BPM reading and the corresponding FFT when the control is operated with the HTN and RBF network, respectively.

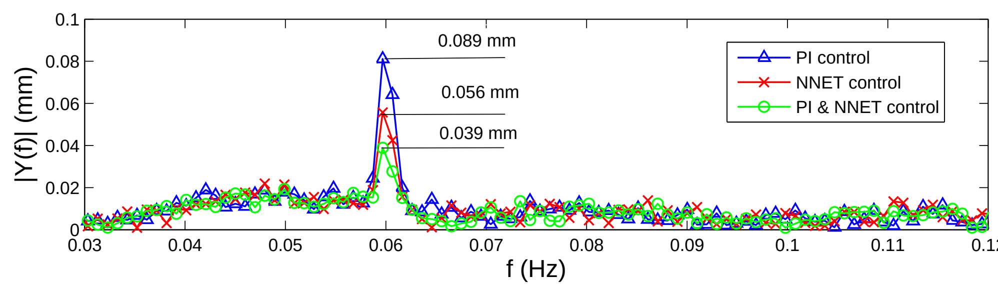

Figure 5: FFT for PI, NNET and combined controls, with jitter of 0.1 kV at 0.06 Hz.

The PI gains were then roughly tuned with no additional control from the neural network. To evaluate the system response, the network was brought on real time to correct jitter with frequency and amplitude different to the training set. A jitter of 0.1 kV and 0.06 Hz was excited. Results in Fig. 5 show that peak at 0.06 Hz is further decreased. The combined control showed a better reduction of the rms deviation and the FFT peak value than the NNET or the PI controller did alone.

CONCLUSIONS

Experiments in a real accelerator environment showed the capability of HTN and RBF networks to operate as predictors in a multi frequency cases. The training of the networks over a whole range of frequencies and amplitudes (0.01 Hz to 0.05 Hz and 0.04 kV and 0.06 kV) showed the networks' capability to interpolate their predictions. The network was also successfully complemented with a conventional PI algorithm to ensure stability and improve control when the network predictions are inaccurate. Research will be pursued towards building a NNET hybrid controller for the FERMI@Elettra FEL.

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