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Development of a combined feed forward-feedback system for an electron Linac

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ABSTRACT

This paper describes the results of an advanced control algorithm for the stabilization of electron beam energy in a Linac. The approach combines a conventional Proportional–Integral (PI) controller with a neural network (NNET) feed forward algorithm; it utilizes the robustness of PI control and the ability of a feed forward system in order to exert control over a wider range of frequencies. The NNET is trained to recognize jitter occurring in the phase and voltage of one of the klystrons, based on a record of these parameters, and predicts future energy deviations. A systematic approach is developed to determine the optimal NNET parameters that are then applied to the Australian Synchrotron Linac. The system's capability to fully cancel multi-frequency jitter is demonstrated. The NNET system is then augmented with the PI algorithm, and further jitter attenuation is achieved when the NNET is not operating optimally.

1. Introduction

TThe construction of next generation light sources requires high stability of the longitudinal parameters of the electron beam in order to ensure the quality of the light produced. The present work aims to investigate and develop an advanced control algorithm for the new FERMI@Elettra Free Electron Laser (FEL) [1]. The system should eventually stabilize the electron beam energy and bunch length at various stages of the machine. Neural networks have been chosen as candidate controllers to operate the feed forward task due to their proven capabilities to learn and adapt.

The motivation for a combined control system comes from the need to build a precise and robust control. Because of the limitations of feedback algorithms such as the PID [2], fine control requires the use of feed forward techniques, which can be combined with a feedback algorithm to benefit from its stability. While improved tuning of PID controllers by neural networks for accelerator operation can be found in the literature [3,4], such systems do not address the algorithm limitations. Also, simulations for the design of transverse feedback systems using neural networks were found [5–7], but no implementations of these systems were reported to be successful in an operational accelerator environment. To the best of our knowledge, neural networks have not been applied to control longitudinal beam parameters in a feed forward way and with the proposed scheme.

2. Australian synchrotron Linac

Unlike FEL Linacs, the Australian Synchrotron Linac contains no bunch compression stage and no bunch length monitor. However, it is equipped with a beam position monitor (BPM), that was provided by Sincrotrone Trieste from a former transport line. Energy measurements are therefore possible at the end of the Linac, which makes it a good candidate for energy control experiments. In what follows energy deviations are obtained by inducing jitter in the klystrons phase and voltage.

2.1. Main components

The Linac, used to supply 100 MeV electrons to the Booster, is composed of the electron gun, the focusing elements (solenoids and quadrupoles), and the bunching and accelerating sections, which are powered by the RF system (see Fig. 1).

Electrons are generated from the gun via a thermionic cathode and a 90 kV accelerating DC voltage. The bunching of the beam is controlled using the following elements. A 500 MHz sub-harmonic

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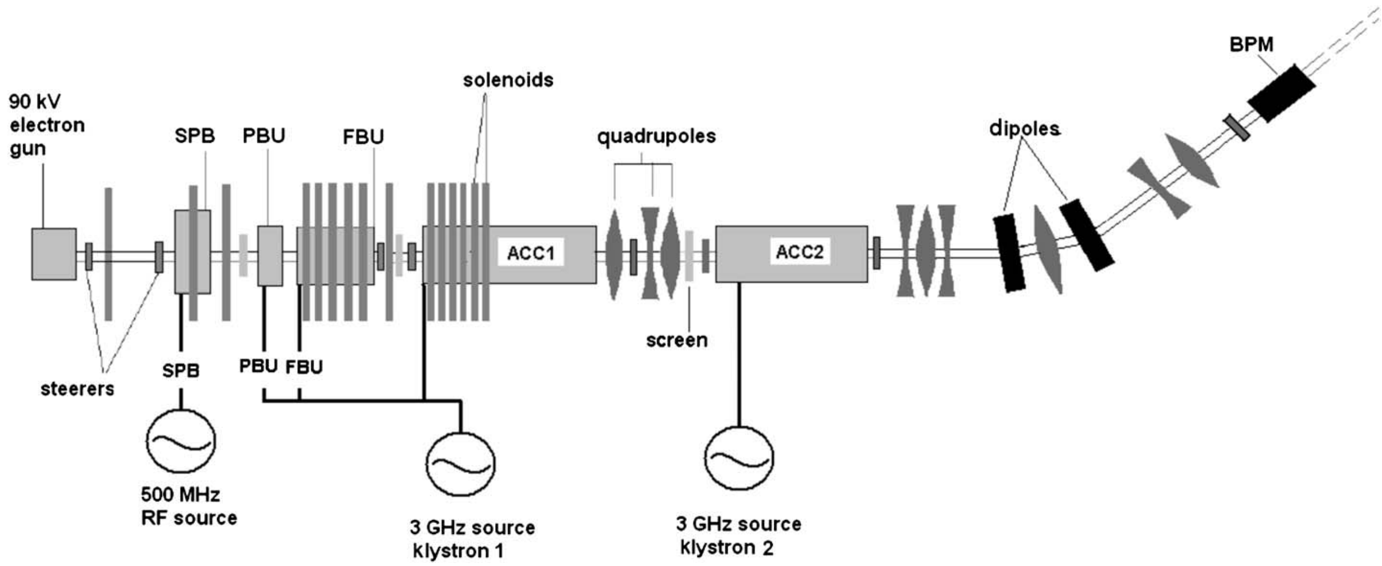

Fig. 1. Australian Synchrotron Linac assembly. The SPB, PBU and FBU provide bunching of the electron stream coming out of the gun. The sections ACC1 and ACC2 bring the beam to 100 MeV, and energy variations can be detected at the beam position monitor (BPM) located after the bending magnets.

pre bunching system (SPB) is used to ensure good single bunch purity. A 3 GHz primary buncher (PBU) increases the mean energy of the beam from 90 keV to approximately 300 keV and is followed by the 3 GHz final buncher (FBU), which increases the beam energy to above 3 MeV.

Two identical 3 GHz traveling wave type structures are used to increase the beam energy up to 100 MeV. A 50 MeV beam energy is reached after the first accelerating section (labeled as ACC1 in Fig. 1) and 100 MeV is reached after the second accelerating section (labeled as ACC2 in Fig. 1).

The RF power is delivered to the structures via waveguides. A master 500 MHz RF generator feeds the SPB working at this frequency, whereas a 6 times frequency multiplier generates the 3 GHz frequency needed for the klystrons. A more detailed description of the system is available in Ref. [8].

In our experiment, jitter will be introduced on the phase and voltage of klystron 1. The induced jitter will therefore be acting on the PBU, FBU and ACC1. ACC2 has been chosen for the control, since it is powered by the second klystron alone.

2.2. Diagnostic component

In order to perform energy measurements, a stripline beam position monitor was installed in the Linac to Booster section of the machine. The quadrupole current in the accromatic bend was tuned so that some dispersion was induced at the BPM. The BPM resolution is of the order of 50 μm. The white noise level on the reading has been measured to range between 0.085 and 0.13 mm rms, depending on the working point of klystron 2. The BPM calibration was measured to be 0.9 mm/MeV, with a noise level of 0.15 MeV.

3. Control scheme

The two-stage control process is illustrated in Fig. 2. The first stage (left block in Fig. 2) uses a record of m past values of the klystron phase ϕ_1 and n past values of the klystron voltage V_1 that are fed into the neural network. This latter then produces a prediction of the next pulse position deviation $dx(k+1)$, where k denotes the current pulse number in a series. The delay operator D^{-p} is such that the p th phase value of the record is $D^{(-p)}(\phi(k)) = \phi(k-p)$, with p ranging from 1 to n. The second stage (right block of Fig. 2) uses the NNET prediction to compute the feed forward correction and combines it with the PI control algorithm, where P_g and I_g are the proportional and integral gains, respectively. R is the sum range and the factor M is the energy response to the chosen actuator. When electrons are relativistic, perturbations in longitudinal parameters, such as the energy, mostly come from jitter occurring in the klystrons [10]. The neural network is thus only provided with information on the klystron phase and voltage.

In Fig. 2 the feedback control is on the voltage of klystron 2, but it could also be applied to its phase. Moreover, it could also include a differential correction term. However, this will not be used here since it is relevant to high frequency correction and we will remain in a low frequency regime due to the limitations of the actuators.

The stability of the system is ensured since the NNET response is based on the klystron voltage and phase. A perturbation in another element in the line is not seen by the NNET and will therefore not affect its response. In the event where the failure happens on the element seen by the NNET, stability is ensured since the NNET response is bounded to the maximum response determined during the training phase.

3.1. Background on neural networks

Artificial neural networks are based on a mathematical model of biological neural networks. They are adaptive system that can change structure based on external or internal information that flows through the network during the learning phase [11,12]. In the network neurons are arranged in layers as shown in Fig. 3. While input and output layers are always present, hidden layers are optional.

A schematic of a j th neuron in a layer is shown in Fig. 4. The artificial neuron, or node, receives an input vector $\mathbf{u_j}$ from other