Introducing AI to atomic clocks for improving holdover

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***Abstract*—Rubidium holdover clocks must be designed to operate autonomously for months or years without human intervention. However, its long-term stability is affected by component ageing and environmental effects, which cause linear frequency drift as well as systematic frequency shifts such as random walk frequency noise processes. Mitigation of these processes would improve the performance of the oscillator (OCXO). In the literature, algorithms have been implemented to do this, but their effectiveness depends on algorithm sensitivity to inherently non-linear and interlaced processes. Suitably trained neural networks offer a high-level solution as their architecture is honed to solve non-linear problems.**

Keywords*—*Rubidium holdover clock, RWFM, Object oriented programming, PyTorch, artificial neural network

I. Introduction

A. Artificial Neural networks (ANN) for atomic clocks

We are investigating new ways of improving frequency accuracy and stability of holdover atomic clocks, such as rubidium standards. An example of a typical system is shown in Fig. 1.

We aim to operate them autonomously for months or years without human intervention. An atomic clock's medium and long-term stability is affected by component ageing and environmental effects, which cause systematic frequency shifts, e.g., light shift caused by intensity changes in the optical source used to interrogate atoms. These factors are shown in Table 1.

TABLE I. INFLUENCE FACTORS IN CLOCK HOLDOVER PERFORMANCE

Influence factors on holdover performance	Error
Environmental Conditions	Varying temperature Vibration Ambient magnetic fields
Ageing	Vapour cell contents [1] Buffer gas changes Frequency drift Electronic components
Phase locked loop (PLL)	Circuit characteristics Correction mechanism
Source intensity changes [2-4]	AC stark shift, Random walk frequency modulation (RWFM)

Compensation algorithms may be used to detect intensity changes and apply corrections to mitigate undesirable frequency shifts, e.g. by adjusting the frequency stabilized

oscillator. The effectiveness of algorithm corrections depends on its sensitivity and ability to interpret many simultaneously occurring and often uncorrelated environmental shifts; these are interleaved linear and non-linear processes.

Parameters in table 1 may be modelled by algorithms and corrected to improve holdover performance [5]. These algorithms rely on their sensitivity to linear and non-linear interlaced processes that are also evolving.

Suitably trained neural networks offer a high-level solution as their architecture is honed to solve complex problems.

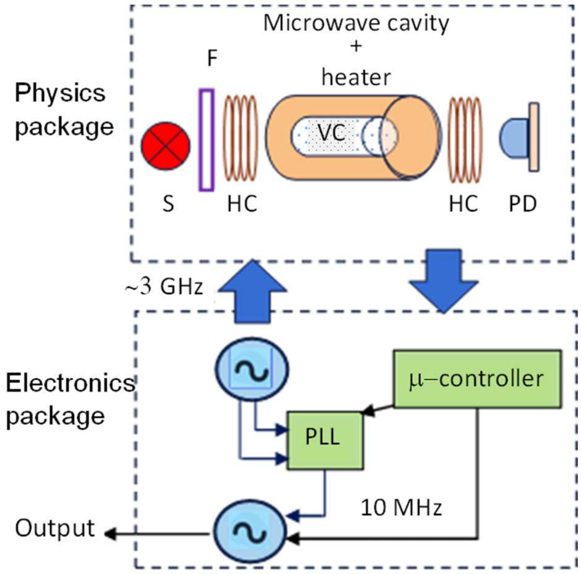

Fig. 1. Rb holdover clock schematic. S:source, F: optical filter, HC: Helmholtz coil, PD: photodiode, PLL: phase locked loop

B. ANNs to replace standard microcontroller algorithms

Artificial neural networks (ANNs) are excellent at approximating non-linear processes. Compared with non-adaptive microcontroller algorithms, they are adaptive in almost real-time and can perform automated optimisation of clock operation to improve the long-term stability performance of an atomic clock. An ANN based processor can learn evolving clock behaviour dynamically by adapting its weights and biases [6,7]

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In particular, ANNs can help with the following: orchestrating operation of atomic clock system components and enabling dynamic compensation algorithms to combat component ageing effects, adaptive tuning of servo parameters (PID) in response to peripheral changes in the environment, improving system response to component ageing and maintaining the integrity of servos during operation in unstable environments, e.g. adaptive optical intensity control, adaptive microwave power control, adaptive temperature regulation (for electronics, optical source, and vapour cell), adaptive electrical power control, axial magnetic field compensation (C-field).

ANNs learn evolving clock behaviour dynamically by adjusting their weights (w) and biases (b) [6,7]. It may be possible to implement anomaly detection related to jamming, by monitoring rubidium clock signals against an external GNSS disciplined oscillator [8].

The following constraints for ANNs must be taken into consideration: they must have well-designed architecture, they must be trained on carefully chosen datasets – e.g. photodiode signals, ambient sensors, they must be trained with very large datasets – a suitable microcontroller is needed.

II. INTRODUCING ANN TO HOLDOVER CLOCKS

A. Constructing a Neural Network for atomic clocks

ANNs require well-designed architectures (a blueprint) to be effective in solving problems. For compact atomic clocks with a microcontroller to orchestrate functions, this involves developing firmware with clearly defined layers:

Input Layer: a segment which defines components that generate information, such as physics package components and electronic circuits.

Hidden Layers: monitor, organise & interpret the information before passing it to the output

Output Layer: produces output, e.g., tuning PID controllers, adjusting PLL parameters.

The ANN architecture is constructed according to the blueprint then steps (i) – (iii) occur:

(i) a large pool of information is gathered from the input layer data.

(ii) two data pipelines assemble the data into groups and transmit it (one for training the ANN via constant feedback, the other to test if predictions are above a desired performance limit).

(iii) Hidden Layers then process and learn the data patterns.

The training pipeline constantly shuffles and iterates datasets through the ANN, producing output predictions. During ANN training, if an output prediction is “poor” (e.g., optical intensity is adjusted incorrectly) it is fed back through the ANN with corrections to its weights and biases. This process is known as backpropagation. The ANN repeats the process until more desirable processor output is produced.

With sufficient training, the ANN can develop deep understanding of clock behaviour as environment changes and components age. It responds with corrective actions to improve stability performance of clock output frequency.

Over time, the ANN may predict when certain events occur, e.g., sudden intensity jumps from optical source causing unwanted ac Stark shifts. ANN corrective actions involve constantly fine-tuning system elements and assessing the history of each element to understand clock system behaviour.

On correcting for known factors, residual frequency shifts are composed of sensitivities to factors that are treated statistically. This is an opportunity to implement unsupervised learning to discover relationships among sets of input data e.g. by clustering, known as Automated discovery.

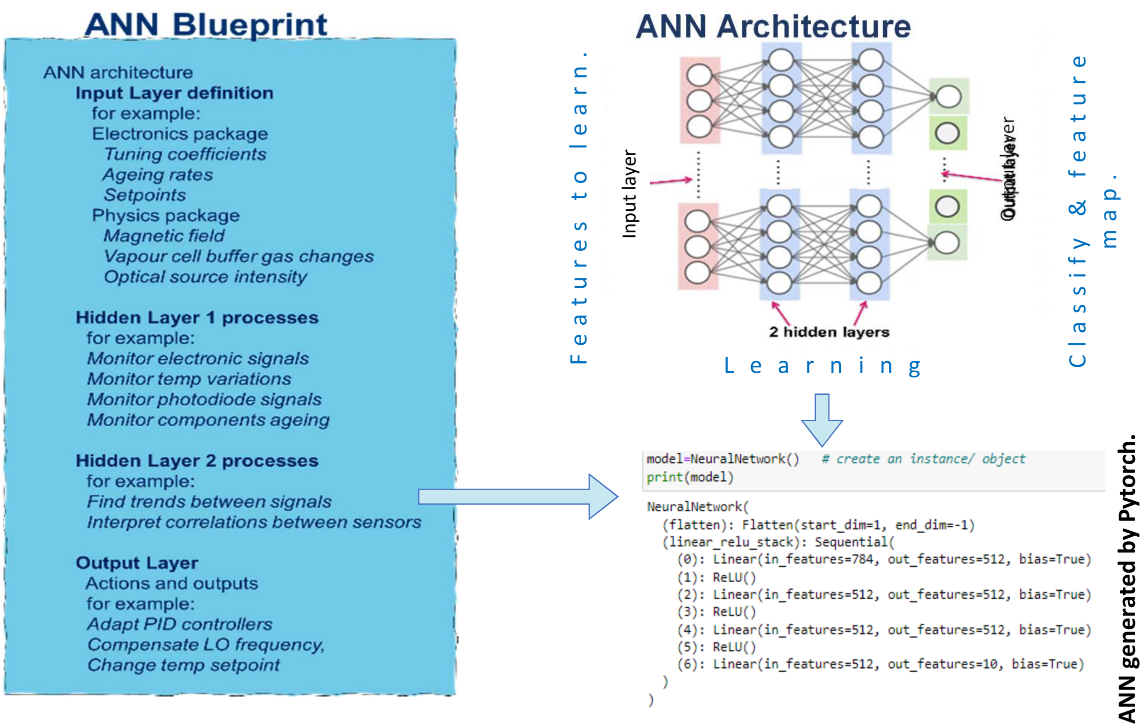

Fig. 2. Present ANN blueprint, architecture (top right) and PyTorch data object optical (bottom right)

B. *Developing an ANN architecture in PyTorch*

The ANN architecture can be constructed according to the blueprint and a large pool of information gathered from the various Input Layer sensors. Two data pipelines are then used to relay the information (one for training the ANN via constant feedback, the other to test the parameters and enable the performance to be plotted). The Hidden Layers then assemble the data into groups. The generated datasets are constantly shuffled and iterated through the ANN, producing an output.

During the training of the ANN, if an output is determined to be "weak", (e.g., the optical intensity is adjusted incorrectly) this is fed back through the ANN with a correction to weights and biases, and the ANN repeats the process until a more desirable processor output is produced. This process is known as backpropagation.

With sufficient training, the ANN can develop deep understanding of how the clock behaves as the environment changes or as components age and can respond with the required corrective actions to improve the stability performance of the clock output frequency. Over time, the ANN may even be able to predict when certain events occur, e.g., sudden intensity jumps from the optical source which cause unwanted ac Stark shifts. These corrective actions involve constantly fine-tuning system elements and assessing the history of each element to understand the behaviour of the clock system. On correcting for known factors, residual frequency shifts are composed of sensitivities to factors that are treated statistically. This is an opportunity to implement unsupervised learning to discover relationships among sets of input data e.g. by clustering, known as Automated discovery.

III. Summary

We are developing a neural network architecture in Python object-oriented programming with each neuron constructed as a complex data object within the class 'neural network' with a feedback loop (back propagation) intended initially for supervised learning.

The development of suitable ANN architectures for holdover atomic clocks provides three potential solutions: anomaly detection (supervised learning), automated optimization - analysis of 'big' data (either supervised or unsupervised learning), automated discovery (unsupervised learning).

ANN capability to detect, analyse, predict, and take corrective actions on atomic clock behavior such as ageing and environmental changes is novel. Corrective actions may involve correcting oscillator frequency or adapting/switching components.

On correcting for known factors, the residual holdover error remaining is composed of sensitivities to factors that are treated statistically [6] but may be identified through automated discovery.

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