Multi-Layer Neural Network for the Stabilization of Ultra-Stable Oscillators

Olukayode Okusaga, John Hamilton, Samuel Reynolds, Eduard Pulaha, Jeffrey Garstecki, Stephen Mitchell, and Gregory Weaver.
Space Exploration Sector
The Johns Hopkins Applied Physics Laboratory
Laurel, MD, U.S.A.
olukayode.okusaga@jhuapl.edu

***Summary*—We present results where multi-layer neural networks were used to predict temperature-induced frequency fluctuations in a low size, weight, and power ultra-stable oscillator (USO). Our results demonstrate that a multi-layer USO utilizing inputs from multiple temperature sensors can reduce the modified Allan deviation of the oscillator below 10^{-12} at all timescales between 1 and 1000 seconds. We also show that a direct digital synthesize (DDS) can be used to correct the frequency fluctuations predicted by the neural network while maintaining a low-noise and frequency stable output signal.**

Keywords*— *oscillator; frequency; neural network; thermal; phase; noise

I. Introduction

Previously, we presented an artificial neural network designed to predict the temperature-induced frequency fluctuations in a quartz oscillator with little passive insulation [1]. The neural network was trained using data from thermal sensors arranged symmetrically around the oscillator cavity. Using multiple thermal sensors allowed the neural network to incorporate both temperature level and temperature gradients in its predictive model of the oscillator's frequency fluctuations. Using the difference between the predicted and measured frequency fluctuations as a metric, we showed that our neural network was capable of predicting temperature-induced frequency fluctuations accurately enough to results in a 10-fold improvement in the frequency stability of the quartz oscillator as measured by the modified Allan deviation of the residual on timescales between 1 and 1000 seconds.

In this work, we present additional advancements necessary to realize a reduced size, weight, and power neural-network enabled USO. Firstly, we investigate using a direct digital synthesizer (DDS) to correct for the frequency fluctuations predicted by the neural network. We show that, properly constructed, the residual phase noise of the DDS is sufficiently low that its output can serve as the physical realization of the ultra-stable oscillator signal. This is a crucial addition, as our previous work never physically realized the stabilized oscillator signal.

In addition, we investigate the use of multiple computational layers to improve the predictive power of our neural network [2]. Our previous neural network with a single computational layer was less effective at reducing frequency fluctuations at short time scales (between 1 to 10 seconds). In this work, we show that a multi-layer neural network utilizing inputs from multiple temperature sensors can reduce the modified Allan deviation of the oscillator below 10^{-12} at all timescales between 1 and 1000 seconds. The combination of these two results leads to a USO with comparable performance to legacy USOs while achieving a 10-fold reduction in volume.

II. Methods/Results

As we presented previously, our neural network takes as inputs readings from temperature sensors at various points around the quartz resonator [1]. The temperature readings are taken at various time lags: 0, 1, 10, 100, and 100 seconds in the past. These time lags allow the neural network to account for slow processes that drive frequency fluctuations.

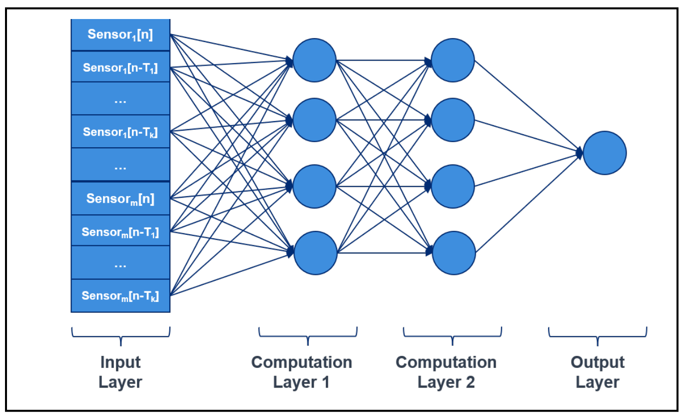

Fig. 1. Diagram of a neural network with two computation layers.

Fig. 1 shows a diagram of our neural network with two computational layers. The set of time lags from all sensors constitute the input layer to the neural network. The neurons in each computational layer take as inputs weighted values of quantities in each node of the previous layer. The output layer is simply a weighted sum of the values from the previous layer. The process of training involves finding the values of each of these weights that minimizes the objective function. In this case, the objective function is the mean square difference between the predicted and measured frequencies in the data used for training. In addition, to the mean square error, we also investigate the use of other objective functions, such as the

Allan deviation at various time scales. We find that using such alternative objective functions allows us to optimize the USOs performance at different time scales.

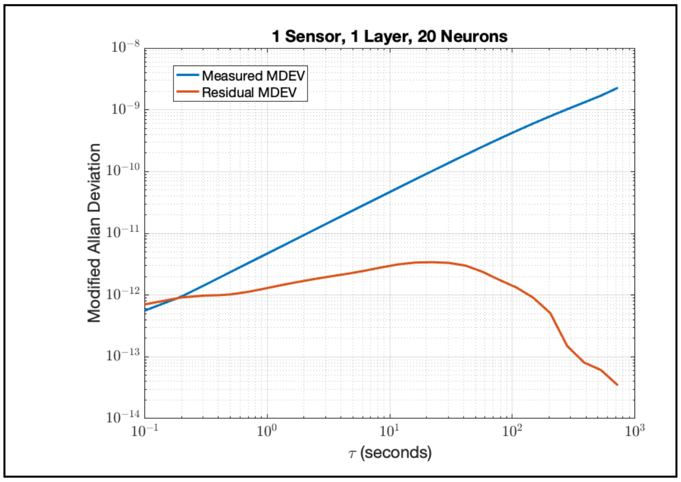

Fig. 2. Plots of the Modified Allan deviation of the USO and residuals from a single-layer neural network using a single temperature sensor.

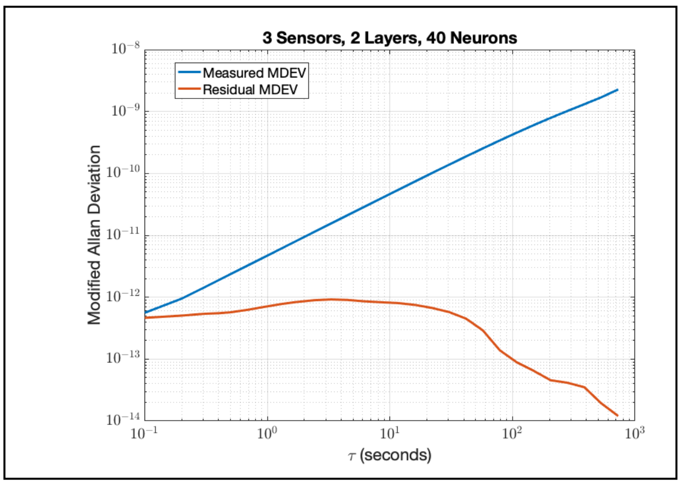

Fig. 3. Plots of the Modified Allan deviation of the USO and residuals from a two-layer neural network using three temperature sensors.

Fig. 2 shows plots of the modified Allan deviation of the USO output as well as the modified Allan deviation of the residual after frequency predictions of a neural network. The neural network had a single computation layer with 20 neurons and only used temperature readings from a single temperature sensor. As figure 5 shows, the neural network was successful at decreasing the modified Allan deviation below 10^{-12} at timescales of 1000 seconds. At shorter timescales, the neural network was successful at reducing the modified Allan deviation, but to a lesser degree.

Fig.3, on the other hand, shows plots of the modified Allan deviation of the USO output as well as the modified Allan deviation of the residual after frequency predictions of a neural network with two computation layers with 20 neurons each and used temperature readings from three temperature sensors. As fig. 3 shows, the neural network was successful at decreasing the modified Allan deviation below 10^{-12} at all timescales.

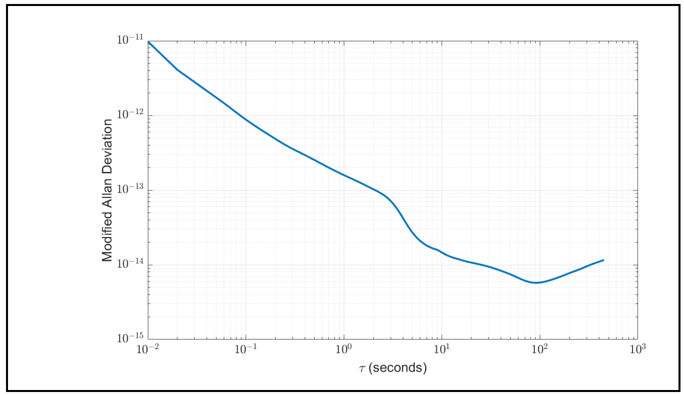

Fig. 4. Plots of the Modified Allan deviation of the residual noise from an AD9912 direct digital synthesizer.

Finally, we investigate the impact of the DDS used to implement frequency correction on the performance of the USO. We preformed a residual noise measurement using a hydrogen maser to drive an AD9912 DDS. The maser was also used as the reference to a 5330A Timepod by Miles Design. We then measured the Allan deviation of the output signal from the DDS. The results of this residual noise measurement are shown in Fig. 4. As fig. 4 shows, the DDS contributes an Allan deviation of less than 10^{-12} at timescales of 10 seconds and longer. At 1 second, the Allan deviation is 2 x 10^{-12}. This result shows that the DDS can be used to synthesize the output signal for an ultra-stable oscillator.

III. Conclusions

In conclusion, we have presented work that expands on our previously published work using neural networks to predict temperature-induced frequency fluctuations in quartz oscillators. We showed in this work that multi-layer neural networks utilizing readings from multiple temperature sensors have improved predictive power over single-layer networks. Such multi-layer networks can achieve modified Allan deviations below 10^{-12} at time scales from 1 to 1000 seconds. In addition, we have shown that a direct digital synthesizer is a sufficiently low-noise solution for realizing the steered output signal from a neural-network enabled ultra-stable oscillator.

References

[1] O. Okusaga, J. Hamilton, T. Schmidt, S. Reynolds, J. Garstecki and G. Weaver, "Ultra-Stable Oscillator Stabilization using an Artificial Neural Network," 2022 Joint Conference of the European Frequency and Time Forum and IEEE International Frequency Control Symposium (EFTF/IFCS), Paris, France, 2022, pp. 1-2, doi: 10.1109/EFTF/IFCS54560.2022.9850773.

[2] N. Jin and D. Liu, "Wavelet Basis Function Neural Networks for Sequential Learning," in IEEE Transactions on Neural Networks, vol. 19, no. 3, pp. 523-528, March 2008, doi: 10.1109/TNN.2007.911749.