Ultra-Stable Oscillator Stabilization using an Artificial Neural Network

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***Summary*—We present results from experiments where we attempted to use an array of thermal sensors and an artificial neural network to predict the temperature-induced frequency fluctuations in a low-noise quartz oscillator. We trained the neural network by giving it thermal sensor readings as well as frequency measurements made against a hydrogen maser reference. The temperature vs. frequency model created by the neural network was then tested on separate data where the difference between the predicted frequency and measured frequency was collected. We found that the Allan deviation of this residual frequency difference was up to 10 dB lower than the Allan deviation of the original oscillator frequency. This result demonstrates the potential of using thermal sensors coupled with an artificial neural network to suppress temperature-induced frequency fluctuations in an oscillator without the need for bulky thermal insulation.**

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

I. Introduction

Ultra-stable oscillators (USOs) are low-phase-noise quartz oscillators that are designed to have high short-term frequency stability (on time scales from 1 second to 1000 seconds for instance) [1]. The Johns Hopkins Applied Physics Lab (JHU-APL) USO has supported several phase-sensitive science experiments in areas such as occultation and gravimetry on missions including GRAIL, Grace, and New Horizons [2]. The USO achieves its frequency stability in part via bulky thermal insulation that helps minimize temperature fluctuations in the oscillator that are a leading cause of frequency instability at time scales from 1 to 1000 seconds. Unfortunately, this thermal insulation leads to a device that is too large for many of the next-generation space science missions that will utilize ensembles of small satellites rather than individual large spacecraft [3].

We propose a new USO design that replaces the bulky passive insulation with an active temperature compensation system. The active compensation system consists of an array of five thermistors placed around the quartz resonator as well as an artificial neural network (ANN) that estimates frequency fluctuations based on thermal readings. The output of the oscillator serves as a reference signal for a direct digital synthesizer (DDS) which will generate the ultimate output signal of the device at the required frequency [4]. The estimated frequency fluctuations from the ANN are then used to steer the output frequency of the DDS in order to achieve a stable output signal.

A key limiting factor in the effectiveness of this approach is the accuracy of the ANN's frequency estimates. In this work, we present results demonstrating that the ANN is capable of predicting the frequency fluctuations in an uninsulated oscillator with residual errors that have Allan deviations up to 10 dB lower than the Allan deviation of the uninsulated oscillator. The ANN was able to achieve this low residual Allan deviation even in cases where the quartz resonator drifted over a temperature range of 32° C.

II. Methods/Results

Our approach to predicting and suppressing temperature-induced frequency fluctuations in the USO involves collecting temperature data from thermistors arranged around the quartz resonator. Figure 1 shows a schematic diagram of this thermistor configuration. The five thermistors are placed so as to detect both absolute temperature levels and temperature gradients. The differences between readings from pairs of these thermistors allows for measurement of temperature gradients in all three dimensions. In our experiments, the thermistor resistances were measured using digital multimeters. This setup allowed for temperature measurement resolutions better than 1 milliKelvin.

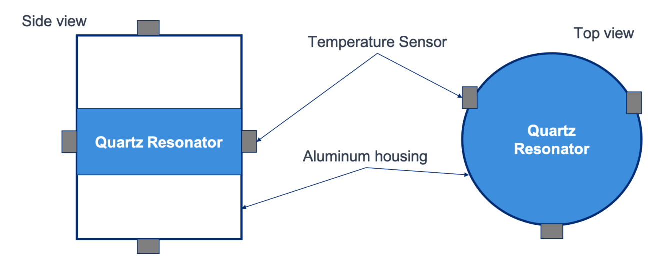

Figure 1. A schematic diagram of the quartz resonator housing showing the location of the thermistors.

We also collected oscillator phase and frequency measurements along with the thermistor measurements in order to train the ANN and to estimate its effectiveness. The oscillator phase and frequency were measured using a 5330A Timepod by Miles Design. The Timepod has a fractional frequency resolution of better than 10^{-13} allowing us to precisely measure temperature-induced frequency fluctuations. We used a hydrogen maser as the reference for these phase and frequency measurements.

For training purposes, the thermistor readings and phase data were fed into an artificial neural network. The ANN consists of three layers. The first layer is an input layer presenting all the thermistor readings at various time lags. The second layer is a fully-connected layer of neurons using the radial basis function for the activation function [5]. The third layer is a summation layer of all the outputs of layer 2. The loss function for the ANN is the square difference between the measured and predicted frequency. The ANN was trained using data collected on a given day. The effectiveness of the ANN was then tested by predicting the oscillator frequency from thermistor readings collected on a different day. Using separate training and prediction data sets allowed us to avoid overestimating the effectiveness of the ANN due to overfitting [6].

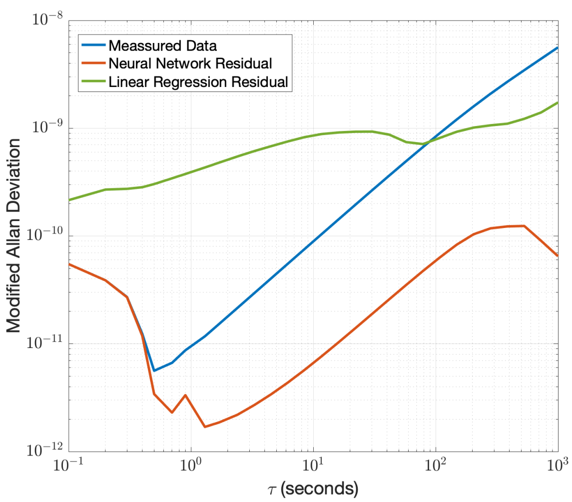

Figure 2. Plots of the Modified Allan deviation of the USO and residuals from the ANN and linear regression.

We used the modified Allan deviation as the metric for estimating the effectiveness of the ANN predictions [7]. We calculated the modified Allan deviation of the residual – that is, the difference between the measured and predicted frequencies. We then compared the modified Allan deviation of this residual to the modified Allan deviation of the measured oscillator frequency fluctuations. In so doing, we can predict the level of suppression of frequency fluctuations that can be achieved using our ANN approach. As a baseline for comparison, we also attempted to predict the oscillator frequency fluctuations by using a linear regression to map thermistor readings to oscillator frequency. Figure 2 shows a plot of the modified Allan deviation of the oscillator, the modified Allan deviation of the ANN residual, and the modified Allan deviation of the linear regression residual. As Figure 2 shows, the ANN was able to reduce the modified Allan deviation at all time scales from 1 to 1000 seconds, with the greatest reduction of greater than a factor of 40 occurring at 1000 seconds. In contrast, the linear regression was only able to reduce the modified Allan deviation at 1000 seconds by increasing the modified Allan deviation at times scales from 1 second to 100 seconds.

III. Conclusions

IV. In conclusion, we have demonstrated that an artificial neural network given readings from temperature sensors arrayed around an uninsulated quartz oscillator, can predict the temperature-induced frequency fluctuations in said oscillator. The residual frequency error between the measured and predicted frequency fluctuations show that this approach can be used to reduce temperature-induced frequency fluctuations in the quartz oscillator by a factor of 10 or more at time scales from 1 to 1000 seconds. Therefore, this approach can be used to actively stabilize the frequency of ultra-stable oscillators without the need for bulky thermal insulation. Coupled with a direct digital synthesizer, the result is a low size, weight, and power USO appropriate for next-generation small satellite space science missions.

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