Deep Learning Calibration of the High-Frequency Airborne Microwave and Millimeter-Wave Radiometer (HAMMR) Instrument

Mehmet Ogut^(D), *Member, IEEE*, Xavier Bosch-Lluis^(D), *Senior Member, IEEE*, and Steven C. Reising, *Senior Member, IEEE*

Abstract—Calibration plays an important role in improving the accuracy of the microwave and millimeter-wave radiometric measurements. Several calibration techniques have been used in radiometers including external calibration targets, vicarious sources, and internal calibrators such as noise diodes or matched reference load. A new calibration technique based on deep learning has recently been developed to calibrate microwave and millimeter-wave radiometers. The deep-learning calibrator has been previously demonstrated on a computer noise-wave modeled Dicke-switching radiometer. This article applies the new deep-learning calibration technique for the calibration of the high-frequency airborne microwave and millimeter-wave radiometer (HAMMR) instrument. A deep-learning neural network model is built to calibrate the 2014 West Coast Flight Campaign antenna temperature measurements of the HAMMR. The deep-learning calibrator antenna temperature estimates are obtained from the radiometric measurements. The deep-learning calibration results are compared with the existing conventional calibration techniques used in HAMMR 2014 field campaign. The results have shown that the deep-learning calibrator is in agreement with the conventional calibration techniques. In this article, it is demonstrated that the deep-learning calibrator can be employed for calibrating the radiometers with high accuracy.

Index Terms— Airborne, calibration, deep learning, microwave radiometer, millimeter-wave radiometer, neural network, remote sensing.

I. INTRODUCTION

MICROWAVE and millimeter-wave radiometers have been used for decades to observe atmospheric constituents from ground-based [1], airborne [2]–[4], and satellite platforms [5]. These observations are critical to improving our knowledge on the distribution and dynamics of atmospheric water in the three forms of state (i.e., vapor, liquid, and ice) for studies in hydrology, agriculture, meteorology, climatology, and oceanography [6], [7]. The reliability and sensitivity of those measurements are essential to determine atmospheric

Manuscript received June 13, 2019; revised October 8, 2019; accepted November 3, 2019. This work was supported in part by the U.S. National Aeronautics and Space Administration, Science Mission Directorate, Earth Science Technology Office, as part of the Instrument Incubator Program under Grant NNX11AH05G and Grant NNX14AK70G. (*Corresponding author: Mehmet Ogut.*)

M. Ogut and X. Bosch-Lluis were with the Microwave Systems Laboratory, Colorado State University, Fort Collins, CO 80523 USA. They are now with the Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109 USA (e-mail: mehmet.ogut@jpl.nasa.gov).

S. C. Reising is with the Microwave Systems Laboratory, Colorado State University, Fort Collins, CO 80523 USA.

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TGRS.2019.2954454

water content and its distribution. The sensitivity of a radiometer is limited by its internal noise and quality of the radiometric acquisition system. On the other hand, the reliability of the radiometric measurements depends on the accuracy and stability of the radiometer where calibration plays a major role.

Radiometric resolution and calibration affect the performance of a radiometer on brightness temperature measurements. This, in turn, determines the quality of the retrieved geophysical products including water in the form of ice, liquid, and vapor as well as soil moisture and sea-surface wind speed [8], [9].

Several calibration techniques have been developed to achieve the radiometric accuracy and stability needed for a radiometric instrument during brightness temperature measurements [8], [10]. Conventional calibration techniques can be grouped into three different categories depending on how the calibrator is mounted with respect to instrument hardware. The first category implies the use of external on-orbit calibration techniques and, in general, relies on measuring two calibration targets at distinct temperatures during on-orbit operation for obtaining voltage-to-temperature calibration line. These techniques introduce uncertainty to radiometric calibration as a result of the linear-radiometer response assumption. Also, this calibration strategy cannot correct fast 1/f noise gain fluctuations inherent in the RF amplifiers and powerdetector in the front-end receivers. Furthermore, the broadband match of receivers at different frequency channels may limit the performance of these calibrators. Finally, these calibration targets are large in size and mass compared to the miniaturized structure of small satellite instruments especially those for CubeSats [11], [12].

The second category uses internal calibrators including noise diodes and Dicke-switching reference loads, which are mounted internally on the hardware of the receiver to mitigate the issues experienced with external calibrators. A fast switching internal calibration can eliminate the gain fluctuation due to 1/f noise at the output of the receiver [9]. However, internal calibrators cannot perform complete calibration when they are used as a sole source of calibration since they do not cover the complete signal path since the antenna is excluded from the scheme. In addition, the calibration of the internal calibrators introduces uncertainty to the measurements due to the instability of noise diodes because of thermal fluctuations and aging and mismatch at the reference load [9]. Furthermore, internal calibrators increase the complexity of

0196-2892 © 2019 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

the instruments especially for those CubeSats having stringent size, weight, and power (SWaP) requirements [11]. As a third calibration category, external sources existing in nature and laboratory conditions such as ocean surface are used for calibration, and this is known as vicarious calibration. This technique cannot be used as a sole source of calibration since the periodicity of the calibration is not fast enough for maintaining the stability of the radiometer. They can only be used to tune other external and internal calibrators [13].

A deep-learning calibration technique has been presented as an alternative or a complement to these strategies for microwave and millimeter-wave radiometry calibration [14]. The deep-learning calibrator employs advanced techniques of neural networks to create an artificial radiometer mimicking the on-orbit response of the radiometer. The proposed technique has been successfully demonstrated on a computer noise-wave modeled noise-added Dicke-switching radiometer [14]. The tests of the deep-learning calibrator under various operating conditions of the modeled radiometer have shown that the calibrator is able to estimate the antenna temperature at high accuracy for all cases.

This article applies the new deep-learning calibration technique to a physically built microwave radiometer instrument. For this article, the high-frequency airborne microwave and millimeter-radiometer (HAMMR) instrument are used. The calibration methodology presented in this article is a pioneer for future calibration techniques for microwave and millimeterwave radiometers using artificial intelligence. The techniques and results provided in this article are critical to validate the performance of the deep-learning calibrator on a real instrument.

II. DEEP-LEARNING CALIBRATION OVERVIEW

The deep-learning radiometric calibration is based on a multilayer perceptron (MLP) feed-forward artificial neural network (ANN) model utilizing a supervised deep-learning algorithm to retrieve antenna temperatures from the voltage measurements at the output of the radiometer. The operational condition of the radiometer and the electrical operating characteristic of each radiometric part determine the radiometer voltage-to-temperature response for antenna temperature measurements. However, this relationship is not straightforward to build a mathematical model to solve for different cases of antenna temperature estimates from the radiometer output voltage. Thus, the multiple layer structure of the deep-learning technique and the nonlinear activation between layers can be used to learn representations of complex radiometer data structure with multiple levels of abstraction [15], [16].

The deep-learning calibration technique estimates antenna temperature measurements from radiometer output voltage and thermistor readings of different critical parts of the instrument. The deep-learning calibration starts with the radiometriccontrolled environment measurements. During these tests, the temperature of the environment and the target that the radiometer measures are varied in order to obtain different operating conditions of the radiometer. The radiometer output, the environmental conditions, and the physical temperature of the radiometer critical parts are continuously monitored during the tests [14].



Fig. 1. Instrument block diagram of the HAMMR instrument where colorcoding shows the responsible institution. CSU is in green, JPL is in red, and NCAR is in blue.

The neural network modeling and training is the next step in building a deep-learning calibrator. For training, 70% of the data recorded during the environment test is randomly selected to train the network. After the network is modeled and trained, the remaining data set is used for testing and validation purposes. If the performance of the calibrator meets the design requirements, then it can be applied to the on-orbit operation of a space-borne or an airborne or a ground-based microwave and millimeter-wave radiometers.

III. HAMMR OVERVIEW

The HAMMR is a cross-track scanning airborne instrument with 25 radiometric channels from 18.7 to 183.3 GHz. The HAMMR instrument was built as a collaborative effort between Colorado State University (CSU) as the lead institution, NASA/Caltech Jet Propulsion Laboratory, National Center of Atmospheric Research (NCAR), and the University of California at Los Angeles (UCLA) under NASA Earth Science Office Instrument Incubator Program. The block diagram of the HAMMR instrument given in Fig. 1 shows the block diagram of the instrument with respect to the responsible institution for each subsystem [17].

The HAMMR instrument has low-frequency dual-polarized microwave channels at 18.7, 23.8, and 34 GHz near water vapor absorption band, high-frequency millimeter-wave window channels at 90, 130, and 168 GHz, and sounding channels near 118.75 and near 183.31 GHz for temperature and water vapor profiling. The instrument performs cross-track scanning at a 60-revolution-per-minute (RPM) scanning rate [17].

OGUT et al.: DEEP LEARNING CALIBRATION OF THE HAMMR INSTRUMENT



Fig. 2. HAMMR instrument block diagram for the 18.7-GHz channel.

The high-frequency millimeter-wave window channels of the HAMMR instrument is designed to provide a smaller footprint size to retrieve water vapor information near the coastal line or over in-land water bodies where current measurement systems are unable to resolve. In addition to the high-frequency millimeter-wave technology demonstration, the HAMMR instrument is designed to operate as an airborne calibration and validation instrument for the Surface Water and Ocean Topography (SWOT) mission [18].

A. HAMMR Conventional Calibration Technique

The microwave and millimeter radiometers of the HAMMR instrument are a noise-injected Dicke-switching-type radiometer. The block diagram of the 18.7-GHz H-Pol channel of the HAMMR radiometer instrument is shown in Fig. 2. The microwave channels at 23.8 and 34 GHz have a similar structure to those shown for 18.7 GHz [17]. Note that it has three independent noise sources. The radiometric gain calibration is performed using a single noise diode measurement. The additional two noise sources are used to calculate the noise diode deflection ratios to determine long-term stability.

The existing conventional calibration strategy of the HAMMR instrument is similar to those applied for a noiseinjected Dicke-switching radiometer calibration provided at various resources. Thus, the goal is to provide a summary of the existing calibration strategy applied in the HAMMR instrument before the discussion of the deep-learning calibration.

The HAMMR instrument calibration relies on pre-flight calibration using hot-cold external targets, and in-flight calibration utilizing internal calibration targets and ambient builtin external calibration target. Before each flight, on-ground calibration of the instrument is performed by using a liquidnitrogen (LN₂) source at 77 K as shown in Fig. 3(a). During the flight, a built-in ambient calibration target as shown in Fig. 3(b), is measured for 80° at each 1-s cross-track scan cycle of the HAMMR instrument to provide two point measurements for the estimation of voltage-to-temperature response curve of the instrument [17].

The preflight on-ground calibration measurements provide the two-point calibration curve of the instrument. The radiometer measures ambient calibration target and LN_2 source at 77 K. The hot–cold measurements with known temperatures provide the dynamic temperature range of the radiometer per volt expressed as the system preflight calibration gain

$$G_{\text{cal-pri}} = \frac{T_{\text{amb}} - T_{\text{LN2}}}{V_{\text{amb}} - V_{\text{LN2}}} \tag{1}$$

where T_{amb} and T_{LN2} are the ambient target and LN_2 temperature, respectively, whereas V_{amb} and V_{LN2} are the radiometer voltage output reading for those states. The *Y*-factor at the preflight stage can also be calculated using the hot–cold target measurements as

$$Y = \frac{V_{\text{amb}}}{V_{\text{LN2}}}.$$
(2)

The received noise temperature is determined from the *Y*-factor measurement as

$$T_{\rm rec} = \frac{T_{\rm amb} - Y * T_{\rm LN2}}{Y - 1}.$$
(3)

Three noise-injection diodes and Dicke-switching reference load are used as internal calibrators in the HAMMR radiometer in addition to external calibrators. During one scan cycle of the instrument, the operational modes of the instrument are the antenna, the first noise source added antenna, the second noise source added antenna, the third noise source added antenna, and Dicke-switched to reference load. This sequence strategy for the calibration of the instrument is given in Fig. 4.

In addition to the internal calibration scheme explained above, the radiometer scans a built-in ambient calibration target during each scan cycle for end-to-end calibration of the instrument.

The Dicke switch is set to a matched reference load at a temperature-controlled environment after the coupler where noise is injected as shown in Fig. 2. At the reference load measurements, the receiver output is

$$V_{\rm ref} = G_{\rm rec} * (T_{\rm ref} + T_{\rm rec} + \sigma_{\rm ref})$$
(4)

where T_{ref} is the matched load temperature, G_{rec} is the system gain, and σ_{ref} is the uncertainty in the measurement. When the antenna is switched on from the Dicke-switch, the radiometer output is

$$V_{\text{ant}} = G_{\text{rec}} * (T_{\text{ant}} + T_{\text{rec}} + \sigma_{\text{ant}}).$$
(5)



Fig. 3. Calibration strategy of the HAMMR instrument. (a) Pre-flight, on-ground calibration of the radiometer instruments. (b) Built-in ambient calibration target for in-flight radiometric calibration.



Fig. 4. Calibration sequence strategy of the HAMMR instrument employing conventional calibration techniques. Note that there is a transition sample between states that is filtered out. The bottom plot shows the radiometric calibration state during the operation of the radiometer with respect to switch state. Top plot shows the radiometric counts acquired per state given in the bottom plot. The acronyms of the calibration states given in the plot are defined as "Antenna" for "ANT," "Noise source X injected Antenna" for "ANT+NSX," and "Reference" for "REF" state.

Thus, it is a basic Dicke-switching calibration method where the receiver noise temperature correction has been applied in the calibration cycle by taking the difference of (4) and (5) to eliminate the $T_{\rm rec}$ term [10].

The noise sources are injected periodically as given in the calibration sequence plot in Fig. 4 to track the system gain variations. A generalized calibration equation is summarized as

$$T_{\rm ant} = \frac{T_{\rm NS}}{V_{\rm ND}} * (V_{\rm ant} - V_{\rm ref}) + T_{\rm ref}$$
(6)

where $T_{\rm NS}$ is the noise source temperature and $V_{\rm ND}$ is the noise diode deflection calculated using the antenna and noise-injected antenna measurement states of the instrument.

B. West Coast Flight Campaign of the HAMMR Instrument

The HAMMR instrument was deployed on a Twin Otter aircraft for the West Coast Flight Campaign (WCFC) between November 4 and 17, 2014, for a total of 53.5 h. During the WCFC, the HAMMR instrument has performed radiometric measurements over land and ocean on a humid and dry day to monitor various atmospheric conditions over different surface conditions.

The radiometric data collected during this campaign has been calibrated using the conventional calibration techniques as described above. The WCFC measurements of the HAMMR instrument over ocean–land boundaries and inland water bodies will be used for the retrievals of cloud liquid water, atmospheric water vapor, and wind speed.

OGUT et al.: DEEP LEARNING CALIBRATION OF THE HAMMR INSTRUMENT



Fig. 5. HAMMR data-processing procedure for the deep-learning calibration.

IV. HAMMR DEEP LEARNING CALIBRATION

The deep-learning calibration technique has been used to calibrate the WCFC measurements of the HAMMR instrument. Following the design procedures outlined in [14], one can build an MLP neural network for the deep-learning calibration of the HAMMR instrument as provided in Fig. 5. The demonstration of the deep-learning calibrator on the HAMMR instrument is analyzed for quasi-horizontal (QH) 18-GHz microwave channel in this article. The implementation of the deep-learning calibration to other microwave and millimeter-wave channels follow a similar procedure with the one presented for the 18-GHz QH channel.

The HAMMR WCFC radiometric measurements are stored in L0a data format where the radiometric data in counts, thermistor information, and GPS/IMU data are all stored in synchronized separate files. This is shown as the first step in Fig. 5 where the data-processing steps for the deep-learning calibrator are described. The L0a data files are processed into the L0b HAMMR file format where all three synchronized L0a data files are merged into a single file in which the radiometric data is given in counts with respect to scanning motor position.

The L0b files are parser for the deep-learning calibration to prepare training and testing data set containing the radiometer output voltage reading. As the first step to accomplishing this, the radiometer output is converted into volts from counts. Then, the radiometer output is assigned to the state of the radiometer synchronized with the antenna scanning angle for the antenna, reference load, antenna added noise source #1, antenna added noise source #2, and antenna added noise source #3. The training data set is prepared by the random selection of 70% of the parsed data set where they are input to the deep-learning calibrator as shown in Fig. 5.

The L0b files are further processed into L1a file format by applying the conventional calibration technique and converting each thermistor information into temperature from voltage readings. Then L1a parser determines the L1a data files in synchronization with the selected training and testing data sets performed at the L0b data parser step. The output of L1a data parser is the temperature information input to the deep-learning calibrator as described in Fig. 5.

The processed data sets input to the deep learning calibrator are summarized as the following with respect to the type of the data set.

- 1) Radiometer Output Voltage Measurements:
 - a) Antenna voltage measurements.
 - b) Antenna added noise source #1 voltage measurements.
 - c) Antenna added noise source #2 voltage measurements.
 - d) Antenna added noise source #3 voltage measurements.
 - e) Reference load voltage measurements, Dicke load.
- 2) Thermistor Readings:
 - a) Horn antenna.
 - b) Microwave receiver.
 - c) Noise sources (only a single thermistor).

An MLP feed-forward ANN with three hidden layers is designed for the deep-learning calibrator as shown in Fig. 6. All the data sets used in the deep-learning training and testing procedure are obtained from the HAMMR WCFC Day 3 measurements at 18-GHz QH channel over San Joaquin River in California, USA.

The training and testing data sets described in Fig. 5 are used for training and testing the neural network respectively. For all the neural network runs, the antenna temperature estimates obtained using the conventional calibration technique are used as the target temperature to train as well as check the performance of the trained network since no thermal chamber data is available for the HAMMR instrument for the deeplearning calibrator training [14].

The trained neural network shown in Fig. 6 is used for deep-learning antenna temperature calibration. The antenna temperature estimates of deep-learning calibration algorithm are given with the conventional calibration technique result in Fig. 7 for a one full-scan cycle radiometric measurements of the 18-GHz QH channel. The radiometer output voltage measurements when the radiometer is looking at the land surface, ocean surface and the built-in ambient calibration are also plotted at the bottom plot of Fig. 7.

The root-mean square error (RMSE) for the estimates are calculated by using

$$RMSE = \sqrt{\frac{\sum (T_{ANT_{CONV}} - T_{ANT_{DEEP}})^2}{N_{SAMPLES}}}$$
(7)

where $T_{\text{ANT}_{\text{CONV}}}$ and $T_{\text{ANT}_{\text{DEEP}}}$ are the antenna temperature estimates obtained from the conventional calibration technique and deep-learning calibration method.

The variability of the estimated antenna temperatures around the mean value is analyzed using the standard deviation (STD)



Fig. 6. ANN architecture for radiometer calibration used for the presented model.



HAMMR 18 GHz QH Antenna Temperature Calibration - Deep-Learning vs. Conventional Calibration

Antenna Scan Angle [degree]

Fig. 7. Deep-learning calibrator results compared with a conventional calibration strategy are given at the top figure while the respective antenna voltage readings are plotted in the bottom figure. Both plots are for one antenna scan cycle of the HAMMR WCFC measurements over San Joaquin River, CA, USA.

of the estimates

$$STD_{CONV} = \sqrt{\frac{\sum (T_{ANT_{CONV}} - \bar{T}_{ANT_{cONV}})^2}{N_{SAMPLES}}}$$
(8.a)
$$\sqrt{\sum (T_{ANT_{DEEP}} - \bar{T}_{ANT_{DEEP}})^2}$$
(8.a)

 $STD_{DEEP} = \sqrt{\frac{\sum (T_{ANT_{DEEP}} - T_{ANT_{DEEP}})^2}{N_{SAMPLES}}}$ (8.b)

where $\bar{T}_{ANT_{CONV}}$ and $\bar{T}_{ANT_{DEEP}}$ are the mean antenna temperature estimates obtained using conventional calibration and deep-learning calibration technique, respectively.

Using the above formulation, the STD for the conventional calibration technique over the calibration target measurements during one scan cycle is calculated as 2.11 K. The RMSE between the conventional calibration technique and the deep-learning calibrator over the calibration target for a single scan cycle is found as 1.71 K. Thus, the RMSE is much lower



Fig. 8. Comparison of antenna temperature estimates using the deep-learning calibrator and conventional calibrator for the HAMMR 18-GHz QH channel WCFC measurements over San Joaquin River. The scatter plot does not show any significant bias between the conventional calibration and the deep-learning strategy as it follows close to 1:1 gain.

than the uncertainty of the instrument obtained using the conventional calibration technique. This, in turn, indicates that the deep-learning calibrator agrees well with the conventional calibration method within the instrument uncertainty. Applying a similar analysis to deep-learning calibrator results in 1.33-K STD, which is lower than 2.11-K STD obtained for the conventional calibration technique. This shows that the variations in the antenna temperature estimates for the deep-learning calibrator are much smaller than the conventional calibration method. We may claim that the deep-learning estimation is much closer to the expected antenna temperature estimates than the conventional calibration technique since one expects a steady temperature reading over the built-in calibration target for a short period of an antenna scan cycle. This might be a result of the highly nonlinear structure of deep learning that can resolve the complex structure of the radiometer. However, one cannot truly claim that the deep-learning calibrator results in lower radiometric resolution than the conventional technique due to limited system information although deep-learning calibrator results much closer to the desired radiometer output than the conventional one. Thermal chamber measurements with controlled target temperature observations of the radiometer could be conducted to better assess the capabilities.

The comparison of the antenna temperature estimates given in Fig. 7 for a full antenna scan cycle using the deep-learning calibrator and the conventional calibration technique is given in Fig. 8. The plot shows that the estimates of two techniques agree well when the antenna is looking at water and land surface in addition to antenna is scanning the calibration target.

Various neural network architectures have been designed, trained, and tested to determine the performance of the deep-learning calibrator under several different operating conditions. The test results are summarized in Table I. Among them, the full system shown as case 1 refers to the case where all the system parameters defined in Figs. 5 and 6 are used with the given neural network architecture.

TABLE I Performance Evaluation of HAMMR Deep-Learning Calibrator

Case	Description	RMSE [Kelvin]	STD [Kelvin]
1	Full system	1.72	1.33
2	No matched reference load	1.83	1.38
3	Removing third noise source	1.79	1.29
4	Removing second and third noise sources	1.90	1.50
5	No noise source	1.96	1.07
6	Only antenna and reference	2.44	1.59
7	No thermistors and reference load	7.2	2.58

Further tests to analyze the performance of the deeplearning calibrator have been conducted by varying the number of inputs used in the structure to analyze the effect of calibrators on the result. For the second case, the matched reference load was removed from the calibration variables and all other system parameters are used. In this case, small performance degradation has been observed compared to the full system analysis case. This indicates that the noise sources and thermistor temperature readings are stable enough to correct the receiver noise temperature variations and shortterm gain fluctuations in the absence of the reference load.

The following three test cases, given as test cases 3-5 in Table I, are provided for different variations of the noise sources. When no noise source is used in the deep-learning calibrator, the system performance degrades as expected. However, the information obtained from the matched reference load helps to maintain the system stability in this case since the error is still at an acceptable level. Among those cases, when the third noise source is removed from the deep-learning calibrator, the system continues to calibrate with a good performance showing that the effect of the third noise source in the calibration cycle is not significant. This is an expected case where there are two noise sources, and a matched reference load is used for the calibration. Next, leaving only one noise source out of three noise sources as the calibrator degrades the system performance but the calibrator performs better than the case where no noise sources are used. The small degradation in the performance indicates that an additional noise source could be useful to tune the performance of the first noise source.

The performance of the deep-learning calibrator degrades significantly when all the noise sources and thermistor information are removed from the deep-learning calibrator. This is given as only antenna and reference in case 6 in Table I. In a comparison of this case with no noise source case given as case 5, the thermistors provide valuable information to calibrate the instrument since 1.96-K RMSE is much lower than 2.44-K RMSE.

The final test, case 7, is conducted when there is no thermistor information and matched reference load readings present in the deep-learning calibrator. 7.2-K calculated RMSE shows that the deep-learning calibration performs poor for this case. In a comparison of this case with the case where no matched reference load presents in the system indicates that thermistors are significantly important to help stabilize the system since 1.83-K RMSE is much lower than 7.2-K RMSE.

The calculated STDs for all cases presented in Table I are lower than the RMSE value for the given case. This implies that the uncertainty in the antenna temperature estimates is lower than the RMSE from the estimates of the conventional calibration technique. Furthermore, for cases where RMSE value has substantially increased, the STD also degrades but not as fast as the RMSE. This, in turn, shows that the accuracy of the estimates degrades due to low information content. However, the information content available to the system for those cases is stable enough to result in lower uncertainty in the estimates with respect to poor RMSE.

V. DISCUSSION AND CONCLUSION

This article presents the deep-learning calibration of the HAMMR instrument for the WCFC measurements obtained in 2014. The results show that the deep-learning calibrator antenna temperature estimates are in close agreement with the conventional calibration techniques employed in the HAMMR instrument by utilizing the external calibration target, internal noise diode and matched reference load.

The test cases using different calibration sources have shown that the deep-learning calibration algorithm operates in parallel to expected system performance based on the type of calibrator applied. Furthermore, the STD and RMSE analyses have provided a quantitative analysis for the performance of the deep-learning calibrator in comparison to conventional calibration technique.

The results presented in this article demonstrate that the deep-learning calibrator can be applied to a physically built radiometer instrument. The results could be better if the HAMMR instrument was operated for deep-learning calibration for the WCFC. In other words, the number of thermistors for the HAMMR instrument for deep-learning calibration may not be sufficient to obtain high accuracy antenna temperature estimates. Furthermore, the information content of the training data set might be improved if the instrument was operated in a temperature-controlled environment prior to the flight campaign to include various operating conditions of the instrument.

The work presented in this article is the first in which the deep-learning calibrator is used in a physically built radiometer. A more comprehensive study can be conducted for ground-based, airborne, or space-borne systems where deeplearning calibrator is applied for the calibration to analyze the stochastic noise and nonstationary noise, including drifts in radiometric gain.

REFERENCES

- E. R. Westwater, "The accuracy of water vapor and cloud liquid determination by dual-frequency ground-based microwave radiometry," *Radio Sci.*, vol. 13, no. 4, pp. 677–685, Jul./Aug. 1978.
- [2] J. R. Wang, P. E. Racette, and J. R. Piepmeier, "A comparison of near-concurrent measurements from the SSMIS and CoSMIR for some selected channels over the frequency range of 50–183 GHz," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 4, pp. 923–933, Apr. 2008.
- [3] C. Kummerow, I. M. Hakkarinen, H. F. Pierce, and J. A. Weinman, "Determination of precipitation profiles from airborne passive microwave radiometric measurements," *J. Atmos. Ocean. Technol.*, vol. 8, no. 1, pp. 148–158, 1991.
- [4] S. T. Brown *et al.*, "The high-altitude MMIC sounding radiometer for the global Hawk unmanned aerial vehicle: Instrument description and performance," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 9, pp. 3291–3301, Sep. 2011.
- [5] N. C. Grody, "Remote sensing of atmospheric water content from satellites using microwave radiometry," *IEEE Trans. Antennas Propag.*, vol. AP-24, no. 2, pp. 155–162, Mar. 1976.
- [6] F. T. Ulaby, R. K. Moore, and A. K. Fung, *Microwave Remote Sensing: Active and Passive*, vol. 1. Reading, MA, USA: Addison-Wesley, 1981.
- [7] L. Yujiri, M. Shoucri, and P. Moffa, "Passive millimeter wave imaging," *IEEE Microw. Mag.*, vol. 4, no. 3, pp. 39–50, Sep. 2003.
- [8] P. Racette and R. H. Lang, "Radiometer design analysis based upon measurement uncertainty," *Radio Sci.*, vol. 40, no. 5, pp. 1–22, Oct. 2005.
- [9] A. B. Tanner and A. L. Riley, "Design and performance of a highstability water vapor radiometer," *Radio Sci.*, vol. 38, no. 3, p. 8050, 2003.
- [10] N. Skou and D. Le Vine, *Microwave Radiometer Systems: Design and Analysis*, 2nd ed. Norwood, MA, USA: Artech House, 2006.
- [11] CubeSat Design Specification Rev.13, The CubeSat Program, California Polytech. State Univ., San Luis Obispo, CA, USA, Feb. 2014.
- [12] Y. Rahmat-Samii, V. Manohar, and J. M. Kovitz, "For satellites, think small, dream big," *IEEE Antennas Propag. Mag.*, vol. 59, no. 2, pp. 22–30, Apr. 2017.
- [13] C. S. Ruf, "Detection of calibration drifts in spaceborne microwave radiometers using a vicarious cold reference," *IEEE Trans. Geosci. Remote Sens.*, vol. 38, no. 1, pp. 44–52, Jan. 2000.
- [14] M. Ogut, X. Bosch-Lluis, and S. Reising, "A deep learning approach for microwave and millimeter-wave radiometer calibration," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 8, pp. 5344–5355, Aug. 2019, doi: 10.1109/TGRS.2019.2899110.
- [15] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.
 [16] Y. Bengio, "Learning deep architectures for AI," *Found. Trends Mach.*
- [16] Y. Bengio, "Learning deep architectures for AI," Found. Trends Mach. Learn., vol. 2, no. 1, pp. 1–127, 2009.
- [17] X. Bosch-Lluis *et al.*, "Instrument design and performance of the high-frequency airborne microwave and millimeter-wave radiometer," *J. Sel. Topics Appl. Earth Observ. Remote Sens.*, to be published, doi: 10.1109/JSTARS.2019.2949590.
- [18] S. Biancamaria *et al.*, "Preliminary characterization of Swot hydrology error budget and global capabilities," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 3, no. 1, pp. 6–19, Mar. 2010.



Mehmet Ogut (S'09–M'11) received the B.S. degree in electrical and electronics engineering from Bogazici University, Istanbul, Turkey, in 2011, the M.S. degree in electrical engineering from George Washington University, Washington, DC, USA, in 2013, and the Ph.D. degree in electrical engineering from Colorado State University (CSU), Fort Collins, CO, USA, in 2018. During the Ph.D. study, he worked on the Tropospheric Water and Cloud Ice (TWICE) Small Satellite Instrument with the Microwave Systems Laboratory (MSL), CSU, as a Graduate Research Assistant.

TWICE is a NASA Earth Science Technology Office (ESTO) Instrument Incubator Program (IIP-13) Award to develop a millimeter- and submillimeter-wave (118 to 670 GHz) radiometer instrument, including both window and sounding channels for 6U CubeSat deployment. He focused on the design and testing command and data handling, and power regulation boards, on-orbit reliability analysis of the TWICE Instrument including radiation testing and analysis of electrical components, and testing, characterization, and calibration of TWICE receivers. In addition, he worked on the deep-learning techniques on the microwave and millimeter-wave radiometry. He applied the deep-learning calibration to high-frequency airborne microwave and millimeter-wave radiometer (HAMMR) NASA ESTO IIP-10 project instrument. He is currently a Technologist with the Microwave Instrument Science Group, Jet Propulsion Laboratory (JPL), California Institute of Technology, Pasadena, CA, USA. His expertise is in the areas of design, testing, calibration, and analysis of microwave and millimeter-wave radiometer instruments, developing innovative concepts in radiometry and artificial intelligence applications in remote sensing.

Dr. Ogut is currently a member of Eta Kappa Nu, IEEE GRSS, and MTTS Societies. He was the Chair of the IEEE High Plains Section Young Professionals Affinity Group from 2017 to 2018. He was also the IEEE R5 ExCom Member from 2018 to 2019.



Xavier Bosch-Lluis (SM'19) received the B.S. and M.S. degrees in telecommunications engineering from the Universitat Politecnica de Catalunya (UPC), Barcelona, Spain, in 2004 and 2006, respectively, and the Ph.D. degree in remote sensing from the Department of Signal Theory and Communications, UPC, in 2011.

He holds a post-doctoral position at the Microwave Systems Laboratory (MSL), Electrical and Computer Engineering Department, Colorado State University, CO, USA. At the MSL, he worked in the high-

frequency airborne microwave and millimeter-wave radiometer (HAMMR) instrument to demonstrate increased spatial resolution of wet-tropospheric path delay retrieval for high-resolution ocean surface altimeter missions. He also worked with the Tropospheric Water and Could Ice (TWICE) Instrument, designed for operation in a 6U CubeSat, with the scientific goal of providing global measurements of upper tropospheric water vapor as well as cloud ice particle size distribution and total cloud ice water content variability. He is currently a Technologist with the Microwave Systems Technology, Pasadena, CA, USA. His expertise is in the areas of in microwave and millimeter-wave radiometer design and calibration, and innovative digital radiometric concepts such as digital beamforming or polarization synthesis.



Steven C. Reising (S'88–M'98–SM'04) received the B.S.E.E. (magna cum laude) and M.S.E.E. degrees in electrical engineering from Washington University in St. Louis, Saint Louis, MO, USA, and the Ph.D. degree in electrical engineering from Stanford University, Stanford, CA, USA, in 1998.

He has been a Full Professor of electrical and computer engineering with Colorado State University (CSU), Fort Collins, CO, USA, since July 2011, where he served as an Associate Professor from 2004 to 2011. Before joining the CSU faculty

in 2004, he served as a tenured Assistant Professor of electrical and computer engineering with the University of Massachusetts Amherst, Amherst, MA, USA, from 1998 to 2004. He served as a Summer Faculty Fellow for three years in the Remote Sensing Division, Naval Research Laboratory, Washington, DC, USA. For the first six months of 2014, he was a Visiting Faculty Member of Sorbonne Universities, the University of Paris VI, and the Université Pierre et Marie Curie, Paris, France. He has been the Principal Investigator of 14 grants from NASA, the National Science Foundation (NSF), The Department of Defense, the Office of Naval Research, the Naval Research Laboratory, the National Polar-Orbiting Operational Environmental Satellite System Integrated Program Office, the European Space Agency, and Ball Aerospace and Technologies Corporation. He has served as the Principal Faculty Advisor for 17 M.S./Ph.D. students who have completed their degrees and are now employed in universities, industry, and government laboratories in the U.S., Europe, and Asia. His research interests span a broad range of remote sensing disciplines, including microwave remote sensing of the earth's atmosphere and oceans from airborne platforms, small satellites, and CubeSats; radiometer systems from microwave to sub-millimeter-wave and THz frequencies (18–850 GHz); low-noise monolithic microwave integrated circuit (MMIC) design and packaging; LiDAR systems for sensing temperature and winds in the middle and upper atmosphere; lighting-ionosphere interactions and atmospheric electrodynamics

Dr. Reising is a member of URSI Commissions F, G, and H, the American Meteorological Society, the American Geophysical Union, the American Association for the Advancement of Science, Tau Beta Pi, and Eta Kappa Nu. He is also a member of the Personnel Management Committee and has been an elected AdCom Member since 2014 of the IEEE Microwave Theory and Techniques Society (MTT-S). He is an elected Administrative Committee (AdCom) Member of the IEEE Geoscience and Remote Sensing Society (GRSS) since 2003. He was a Founding Member of the editorial board of the IEEE GEOSCIENCE AND REMOTE SENSING LETTERS (GRSL), with an Impact Factor of 2.9 in 2017. He served as an Associate Editor from 2004 to 2013. He received the 2015 George T. Abell Outstanding Research Faculty Award from the College of Engineering, Colorado State University. In 2016, he received the Outstanding Service Award from the U.S. National Committee of the International Union of Radio Science (USNC-URSI), presented at the Plenary Session of the 2016 National Radio Science Meeting in Boulder, CO, USA. He received the NSF CAREER Award in the areas of physical and mesoscale dynamic meteorology from 2003 to 2008 and the Office of Naval Research Young Investigator Program (YIP) Award from 2000 to 2003 for passive microwave remote sensing of the oceans. His Ph.D. student S. Padmanabhan received the Second Prize Student Paper Award at IGARSS 2003 in Toulouse, France, and the URSI Young Scientist Award at the General Assembly in New Delhi, India, in 2005. He won the URSI Young Scientist Award at the General Assembly in Toronto, ON, Canada, in 1999. While at Stanford, he received the First Place in the USNC-URSI Student Paper Competition at the 1998 National Radio Science Meeting in Boulder, CO, USA. He served as the IEEE MTT-S Inter-Society Committee Chair from 2015 to 2018, the IEEE GRSS Vice President of Information Resources from 2011 to 2018, the IEEE GRSS as the Vice President of Technical Activities from 2008 to 2010. He served the U.S. National Committee of the International Union of Radio Science (USNC-URSI) as the Immediate Past Chair from 2015 to 2017, the Chair from 2012 to 2014, and the Secretary from 2009 to 2011 of all ten URSI Commissions (ten scientific and technical areas). He previously served as the Secretary of USNC-URSI Commission F (Wave Propagation and Remote Sensing) from 2004 to 2007. He founded and chaired the first three URSI International Student Paper Prize Competitions at the URSI General Assemblies and Scientific Symposia held in Chicago, IL, USA, in 2008; Istanbul, Turkey, in 2011; and Beijing, China, in 2014. Prior to that, he chaired the USNC-URSI Student Paper Prize Competition from 2004 to 2008 and at the URSI North American Radio Science Meeting in Ottawa in 2007. In addition, he served as the Technical Program Co-Chair for the USNC-URSI National Radio Science Meetings held each January in Boulder, CO, USA, from 2010 to 2014. He currently serves as the Chair of the Ad-hoc Committee for Intersocietal Relations of the IEEE Geoscience and Remote Sensing Society (GRSS). He currently serves as the Vice-Chair of Operations of the IEEE Microwave Theory and Techniques Society (MTT-S). He was the Editor of the GRSS Newsletter from 2000 to 2002 and an Associate Editor for University Profiles from 1998 to 2000. He has been a Guest Editor of three Special Issues and one Special Section of the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING (TGRS), with an Impact Factor of 4.7 in 2017.