Development of Deep-learning-Based Forward Algorithm for Low-cost Radiometer CAL/VAL

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Outline

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Objectives

- ❑ Ultimate goal: Total Precipitable Water (TPW) retrieval using deep learning method for the 22 GHz radiometer
- ❑ Current step: Develop a deep learning-based forward emulator (DLFE) for 22 GHz radiometer calibration
  - ➢ Predict downwelling brightness temperature (BT) for 22 GHz radiometer
  - ➢ Field campaign measurement with radiosonde data
  - ➢ Simulate BT with MonoRTM and DL
  - ➢ Radiometer CAL with simulated BTs
- ❑ Next step: Develop TPW retrieval with DLFE (Radiometer validation)

Reference and Input Data

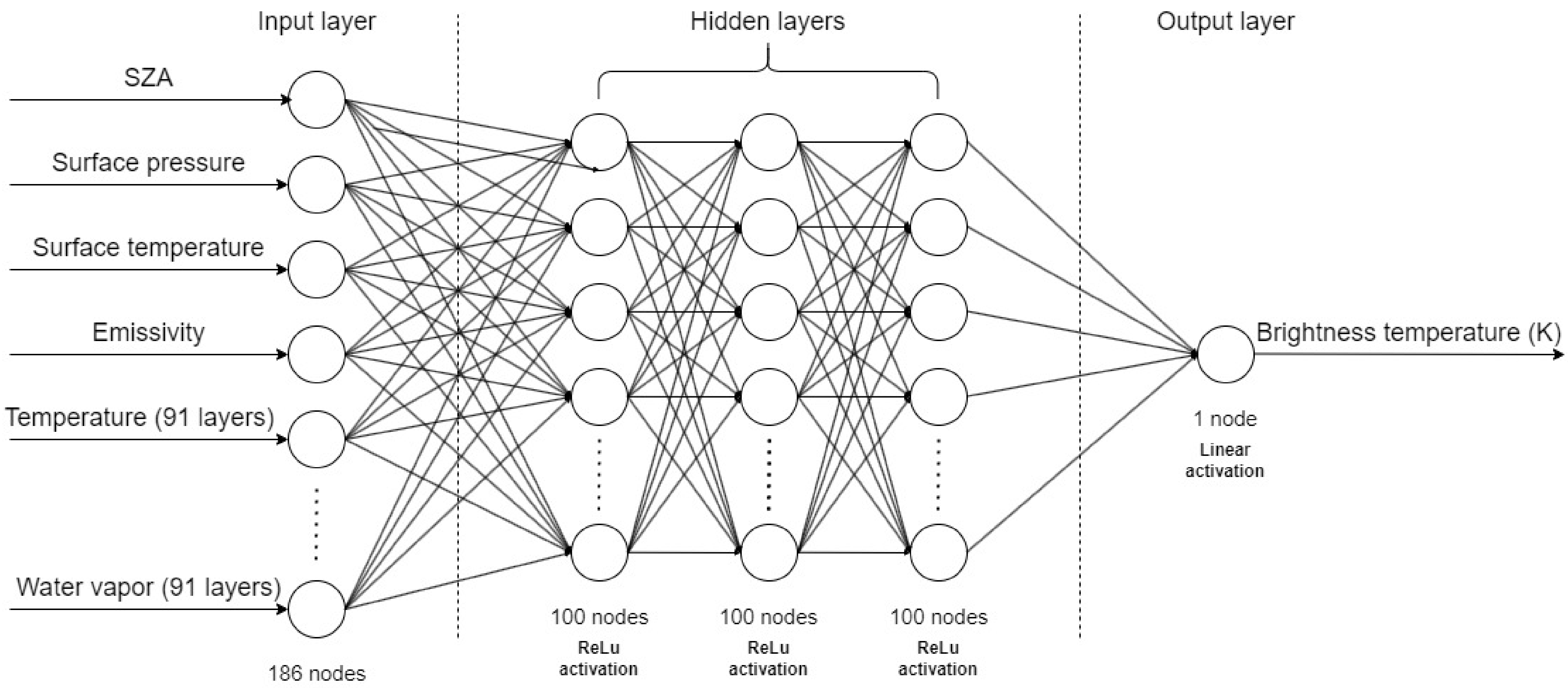
Input data was collected from European Centre for Medium-Range Weather Forecasts (ECMWF)

- ECMWF offers a quarter-degree spatial resolution and 91 layers vertically
- ECMWF data was further collocated with ATMS SDR pixels to simulate real weather conditions and to support model input

Reference labels are generated from MonoRTM

- MonoRTM is a line-by-line radiative transfer model for microwave region
- The reference labels are brightness temperatures values from Ka band 22.148 GHz
- Only downwelling brightness temperatures were calculated

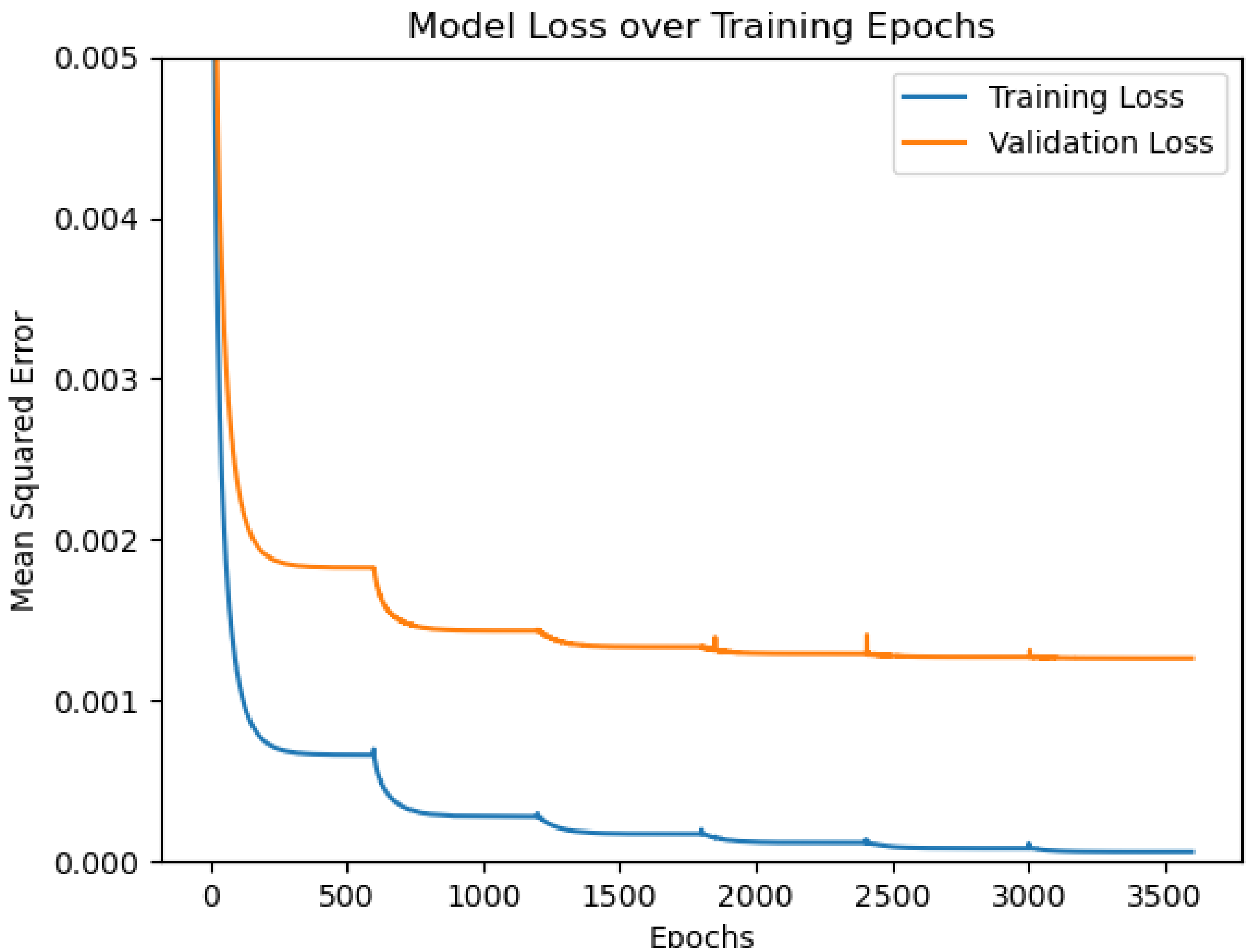
Methodology



Reducing the likelihood of overfitting

- Regularization used in output layer to reduce overfitting
- Both training and validation data sets are standardized before input

Model Convergence



Model input:

- 90 thousand records in global
- approximately 8:1:1 training, validation, testing split

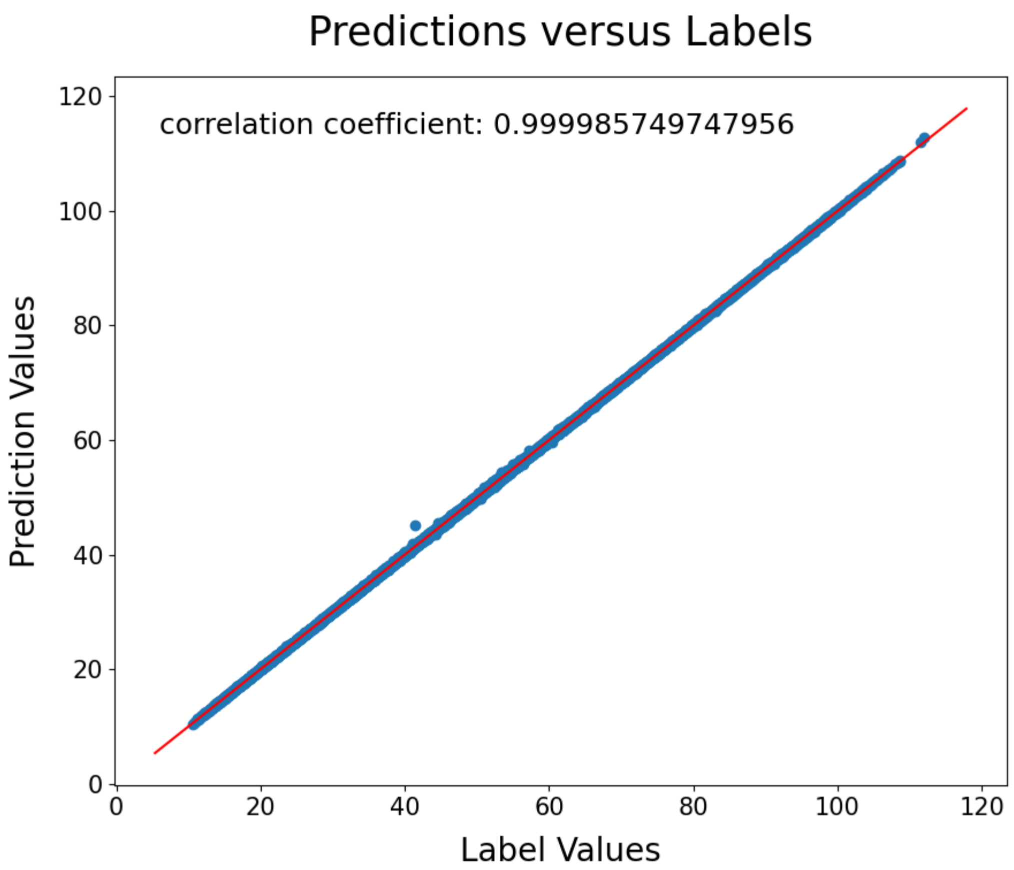
Training method

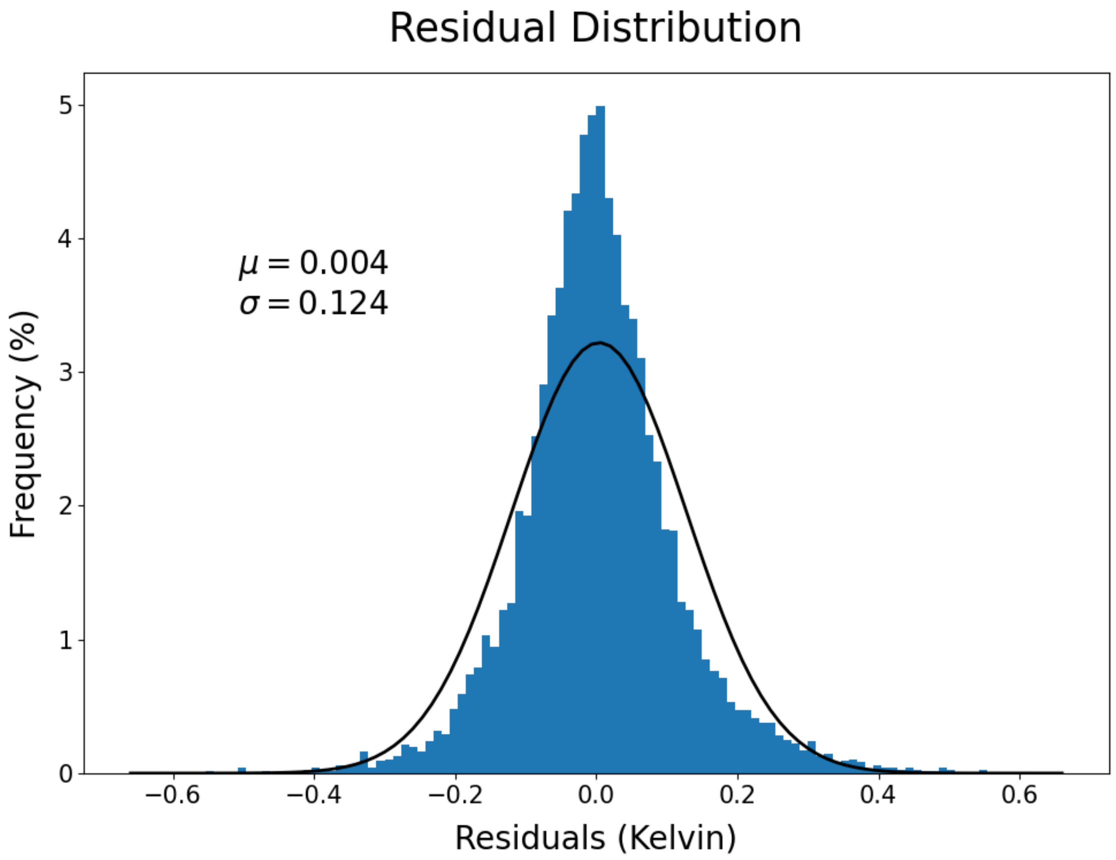
- Initial learning rate 0.0001
- Learning rate decreased by 2% every 90 steps
- 6 total training sessions with 600 epochs each

Results

- Validation loss convergence decreased with every training session
- Validation loss converged to 0.00126 in the 6th session

Model Evaluation on Testing Dataset





Results are excellent

- Predictions are very accurate and have a high correlation with the labels
- Residuals are normally distributed and centered around 0 with a very small standard deviation of 0.124

Collecting Real-world Data

Camping trip

- Set up radiometer at an open field near IAD airport
- Radiometer measured outside temperature and counts
- Measurements taken at different zenith angles (0˚ to 70˚) between 10 and 12 pm

Conclusion

A deep-learning based forward emulator was developed to support the calibration and validation of the dual-mode Ka band radiometer constructed at ESSIC

- Training input collected from ECMWF which contains SZA, surface pressure, surface temperature, emissivity, 91-layer temperature, and 91-layer water vapor content
- RTM calculated brightness temperatures used as reference labels

Evaluation on testing data show DLFE can predict BTs with high accuracy

- Predicted BTs and reference labels have high positive correlation of nearly 1
- BT differences have a mean of 0.004 and standard deviation of 0.124, very low

Radiometer was set up in an open field near IAD airport to collect real-world data

- Collected counts, which will be converted to BTs in the calibration process

Future Work

Development of deep neural network for predicting TPW with brightness temperature as input

- ➢Analyze and clean data from camping trip
- ➢Simulate BTs using MonoRTM and DLFE with measurements and radiosonde data
- ➢Calibrate and validate camping trip data to get brightness temperature values
- ➢Create an deep-learning (DL) model to predict TPW with ECMWF
- ➢Tune model to increase accuracy
- ➢Conduct radiometer validation using the TPW-retrieval DL model with calibrated BTs as input.