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Using a Neural Network to Determine the Hatch Status of the AERI at the ARM North Slope of Alaska Site

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ARM CLIMATE RESEARCH FACILITY

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Using a Neural Network to Determine the Hatch Status of the AERI at the ARM North Slope of Alaska Site

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1.0 Introduction

The fore-optics of the Atmospheric Emitted Radiance Interferometer (AERI) are protected by an automated hatch to prevent precipitation from fouling the instrument's scene mirror (Knuteson et al. 2004). Limit switches connected with the hatch controller (Figure 1) provide a signal of the hatch state: open, closed, undetermined (typically associated with the hatch being between fully open or fully closed during the instrument's sky view period), or an error condition. The instrument then records the state of the hatch with the radiance data so that samples taken when the hatch is not open can be removed from any subsequent analysis. However, the hatch controller suffered a multi-year failure for the AERI located at the ARM North Slope of Alaska (NSA) Central Facility in Barrow, Alaska, from July 2006–February 2008. The failure resulted in misreporting the state of the hatch in the "*hatchOpen*" field within the AERI data files. With this error there is no simple solution to translate what was reported back to the correct hatch status, thereby making it difficult for an analysis to determine when the AERI was actually viewing the sky.

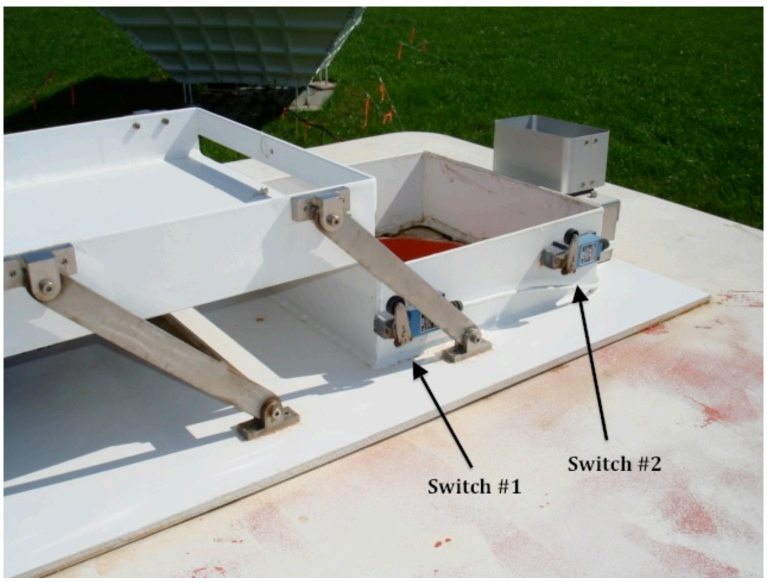

Figure 1. A photograph of the AERI hatch mechanism that shows the position of the physical limit switches. The hatch is considered open is switch #1 is pressed, closed when switch #2 is pressed, and undetermined / stuck if neither is pressed. If the system detects problems with the monitoring electronics, then the hatch controller issues a fault condition. This is the hatch of the AERI in the ARM Mobile Facility (AMF1), but a similar hatch was used on the NSA AERI from 2000 until mid-2011.

As only the data collected when the hatch is fully open are scientifically useful, an algorithm was developed to determine whether the hatch was open or closed based on spectral radiance data from the AERI. Determining if the hatch is open or closed in a scene with low clouds is non-trivial, as low opaque clouds may look very similar spectrally as the closed hatch. This algorithm used a backpropagation neural network; these types of neural networks have been used with increasing frequency in atmospheric science applications (e.g., Turner and Gero 2011, Cadeddu et al. 2009). The neural network was first trained to determine whether the hatch was open or closed from a control set of data from the NSA AERI where the hatch status was properly recorded in the datastream. The data used for training the neural network were from 2009, which was after the monitoring switch and controller had been fixed. Random points were chosen from this 2009 data set with an equal distribution of samples from three distinct cases: (a) when the hatch was open and a clear sky, (b) when the hatch was open and a cloudy sky, and (c) when the hatch was closed. To determine the hatch status and sky conditions, the mean downwelling radiance from the 900 to 904 cm^{-1} wavenumber spectra with the true hatch condition from the *hatchOpen* field was used to designate the category for each sample. Once the hatch status and sky conditions were determined, these spectral channels and additional ones were used as inputs for the neural network to determine the hatch status.

The neural network configuration utilized for this project consisted of 19 input nodes, one hidden layer with 15 hidden nodes, and one output node. Four of the 19 input nodes included the mean radiance for these spectral regions: 600–740 cm^{-1}, 858–862 cm^{-1}, 900–904 cm^{-1}, and 1400–1500 cm^{-1}. The remaining 15 of the 19 input nodes are the radiances of these individual channels: 630 cm^{-1}, 630.5 cm^{-1}, 631 cm^{-1}, 659 cm^{-1}, 660 cm^{-1}, 681 cm^{-1}, 688 cm^{-1}, 692 cm^{-1}, 699 cm^{-1}, 1434 cm^{-1}, 1434.5 cm^{-1}, 1435 cm^{-1}, 1481 cm^{-1}, and 1482 cm^{-1}. The output node would be trained to yield a hatch open or closed designation. Once the neural network was trained over the randomized sample data set, the neural network was run forward over the training and testing set to determine accuracy of the neural network. As the output from the last node is a real number between 0 and 1, a threshold value of 0.8 was used to delineate the hatch open (1) from the hatch closed (0) conditions. The objective of setting this threshold was to maximize the frequency that the algorithm indicated that the hatch was open when it was truly open while minimizing the number of times it falsely indicated the hatch was open when it was truly closed. Histograms from the training and testing data sets are shown in Figure 2. The resulting confusion matrices from these tests (Table 1) indicate a high accuracy in correctly diagnosing the hatch status, with the network correctly identifying the hatch open cases 94% of the time and correctly identifying the hatch closed cases 99% of the time. For most of the cases where the network erroneously indicated a hatch-closed condition, the downwelling radiances indicate a low opaque cloud was over the instrument. To quantify this condition: of the 6% of the cases where the network erroneously indicated hatch closed when the hatch was really open, 80% of these cases were associated with opaque low cloud; thus less than 1% of the total number of samples had an optically thin cloud or clear-sky condition that was misidentified as a hatch closed condition by the neural network.

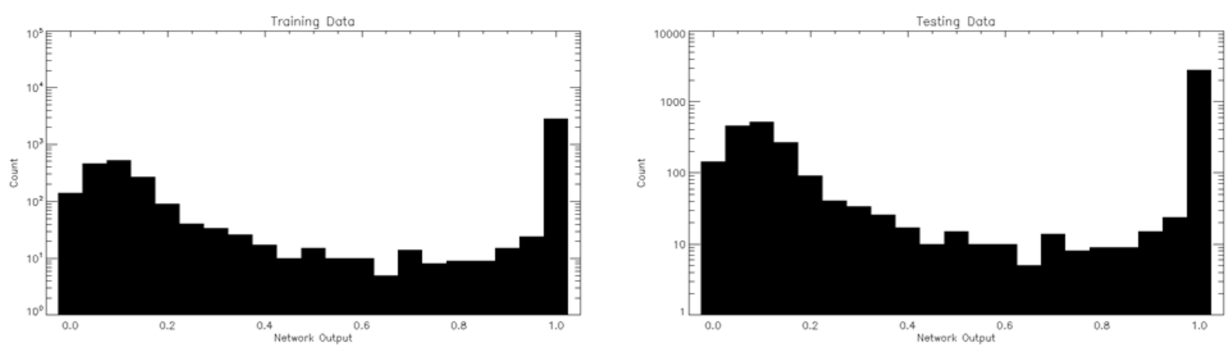

Figure 2. Distribution of neural network output values from the training (left) and testing (right) data sets. A threshold value of 0.8 was used to classify the output as hatch open or closed. Note that the y-axis is logarithmic.

Table 1. Confusion matrices for the two data sets used for training and testing the neural network for determining the hatch status.

	Training Set (N = 25466)		**Testing Set (N = 4534)**	
	Network Open	Network Closed	Network Open	Network Closed
True Open	93.9%	6.1%	94.0%	6.0%
True Closed	0.8%	99.2%	1.4%	98.6%

Using the trained neural network, the algorithm was run over the entire AERI record from 2000–2010, and monthly distributions of the hatch conditions were computed. The original monthly distribution of hatch condition (as determined by the limit switches) are shown in Figure 3, with the neural-network-determined hatch conditions in Figure 4. Comparing the hatch open/closed distributions in 2009 demonstrates that the neural network is indicating a larger fraction of cases that have the hatch closed than the original data, which is assumed to be a period where the hatch limit switches are working properly. However, the mean increase in the monthly hatch closed occurrence is ~6%, which is in agreement with the confusion matrix (Table 1), and thus the network is deemed to be working properly. The neural network is able to provide hatch conditions during the period when the hatch controller was indicating a fault condition (July 2006–February 2008), thereby making those data useful. However, the year-to-year seasonal distribution of the fraction of hatch open/closed is much more uniform, and arguably more reasonable, in the neural network data set (Figure 4) relative to the limit switch data set (Figure 3). In particular, there is a large fraction of liquid water and mixed-phase boundary layer clouds in the summer and early autumn, many of which are drizzling (Shupe 2011), and thus it would be expected that the hatch should close relatively frequently during this season.

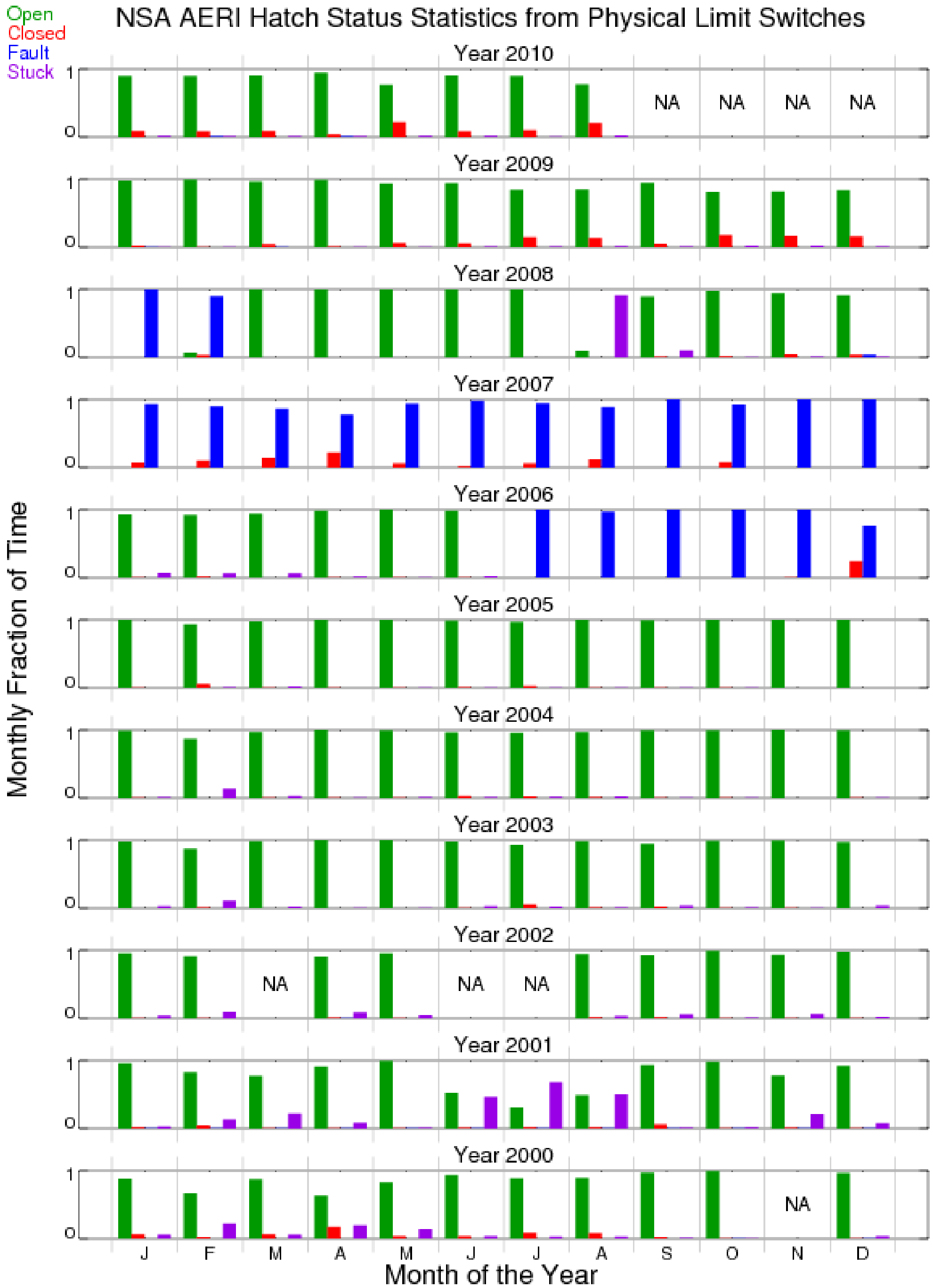

Figure 3. Monthly distribution of hatch condition for the AERI at the ARM NSA site from 2000 to mid-2010, as determined from the limit switches on the hatch. The four options are "open", "closed", "fault condition", and "undetermined". As the undetermined condition is usually fleeting, months with significant numbers of these cases suggest that the hatch was "stuck" in an undetermined position (likely due to ice buildup or mechanical problems). Months with "NA" indicate that no data was available.

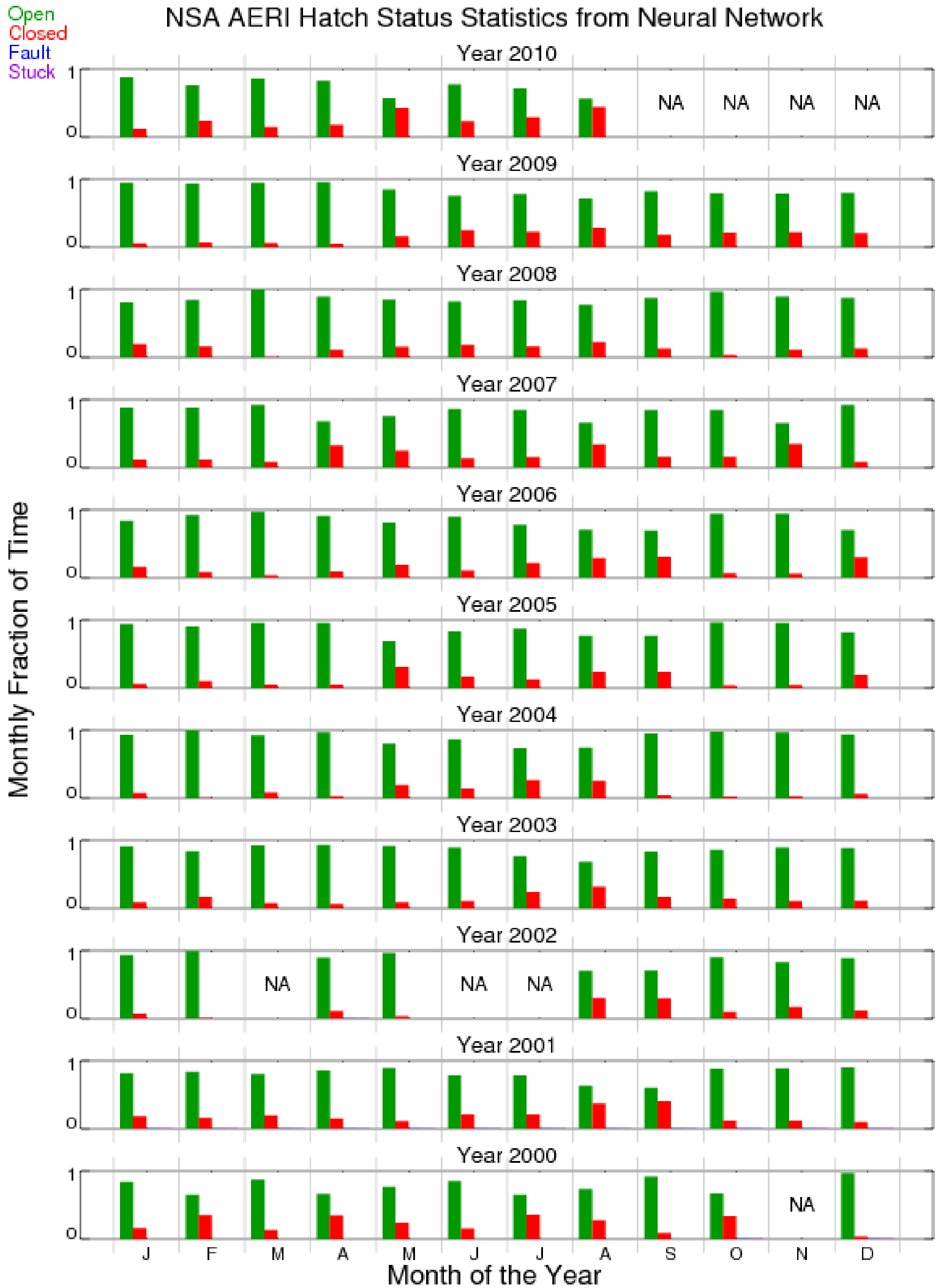

Figure 4. Monthly distribution of hatch condition for the AERI at the ARM NSA site from 2000 to mid-2010, as determined by the neural network. The network was trained to provide 2 conditions: hatch open or closed. Conditions where the limit switches indicated an undetermined position (i.e., “stuck”) are recorded in a separate field in the output netCDF file and are not shown here.

The network output has been packaged into monthly netCDF files that contain the base time, time offset, the raw neural network output between 0 and 1, and the assigned hatch status (i.e., 0 or 1) from the raw neural network output. One concern that was not addressed was the situation where hatch is either opening or closing (i.e., it neither fully opened nor fully closed) during the instrument's sky view. Since this isn't represented in the neural network, any instance where the limit switches for that sample indicates that the hatch was shifting open or closed and the neural network assigned a hatch status of open for that sample, the sample was flagged in the "*warning_hatch*" field as a precaution that there might be an obstruction from the hatch.

It is our recommendation that the neural network hatch status flag be used instead of the limit switch determined flag in all analyses that use NSA AERI prior to October 2008.

2.0 References

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