Toward Power- and Data-Efficient Small Landed Missions: Detecting and Characterizing Martian Dust Devils

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Rethinking Data Acquisition on Small Spacecraft

To capture rare phenomena like dust devils, new algorithms are needed to respond to events in real time. Traditional, pre-scheduled observational schemes are likely to: **miss high-value events** if observations are too sparsely collected, and/or **exceed bandwidth or power availability with continuous observations** (i.e., small spacecraft [1,2]). Any capability that addresses these concerns could improve scientific outcomes; we focus on quantifying the contribution of rare **dust vortices** to the Martian dust budget.

Spacecraft with an adaptive sampling strategy could address these issues [3], but research is needed to understand the technical capabilities and *a priori* knowledge that would enable such algorithms. We conducted a proof-of-concept study that:

- **Developed and tested 4 science autonomy methods for detecting Martian convective vortex on real M2020 data [4]**
- **Demonstrates that real-time detectors can conserve power and data volume until an event of interest is detected**
- **Generated science outcomes quantitatively similar despite highly constrained use of simulated resources**

Research Objectives and Approach

We assume two observation modes:

1. **Monitor mode:** Constantly on / Low resource: pressure sensor.
2. **Alert Mode:** Limited duration post-trigger / High resource: wind sensors, cameras, and pressure sensor.

For each detector, we can tune:

1. **Detection threshold:** Lower thresholds capture more events, but require more power and data volume
2. **Alert mode cooldown:** Longer cooldown times record more data but require more power and data volume

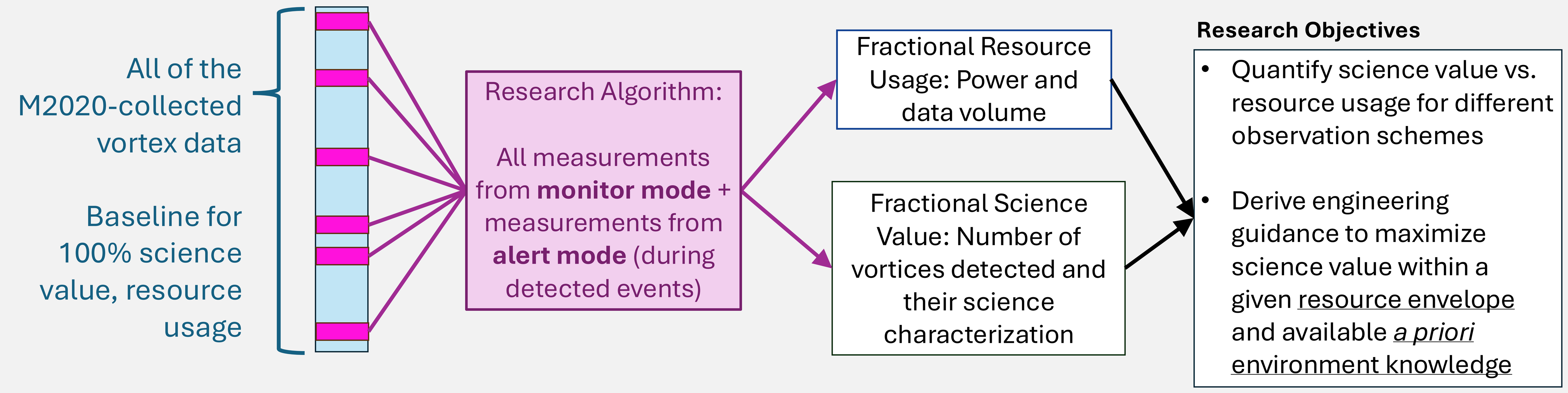

Figure 1. We aim to quantify how science autonomy algorithms can increase the ratio of science returned vs. resources used (power and data). Our current project status is indicated by the dashed red box. *We plan to complete this work and submit a paper by the end of May, so stay tuned! And feedback is welcomed.*

Schemes 1 & 2: Statistical Models

Goal: Generate a distribution that separates background and vortex pressure changes. Use either a static or adaptive distribution in concert with a tunable threshold.

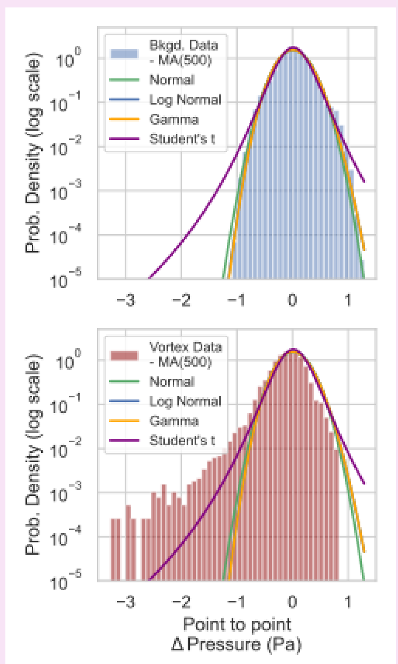

Figure 4. Statistical distribution fits to observed pressure deviations without (top) and with (bottom) a vortex. From these, we estimate the probability that an observed pressure change is not "background." If this probability exceeds a threshold parameter, the algorithm triggers a vortex detection. Here, we use a normal distribution to determine that probability.

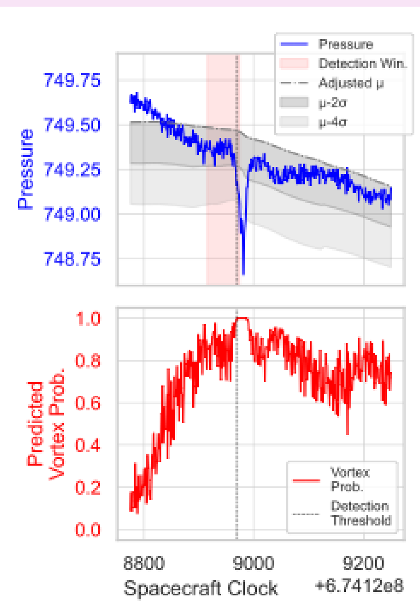

Figure 5. A rolling normal distribution is fit to the pressure signal (after fitting and subtracting a simple linear model). Top: After subtracting a simple linear model, we fit a normal distribution (visualized with shaded gray regions) and check for extreme values to trigger a detection. The ideal detection window is shaded in red. Bottom: Probability of a vortex is visualized with a dashed line for a detection.

Schemes 3 & 4: Machine Learning

Goal: Train time-series-based ML models. Evaluate both a recurrent neural network (LSTM) and a modern transformer (single-headed) architectures.

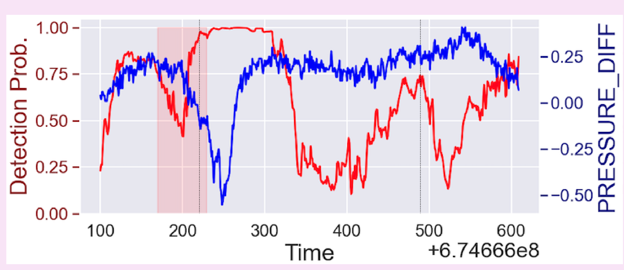

Figure 6. Change in pressure (blue) and LSTM model probability (red) illustrate a positive detection (prob. > 0.9) during to 60 seconds prior to the FWHM window (red shaded region).

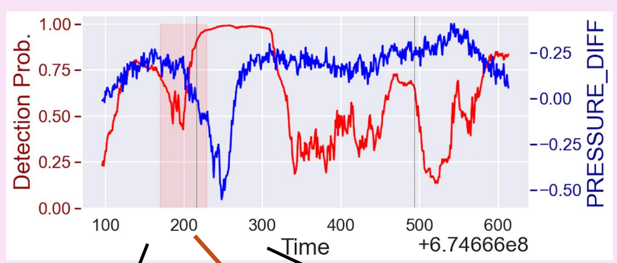

Figure 7. Similar to the above figure but for single-headed transformer model. Both the LSTM and transformer performed similarly.

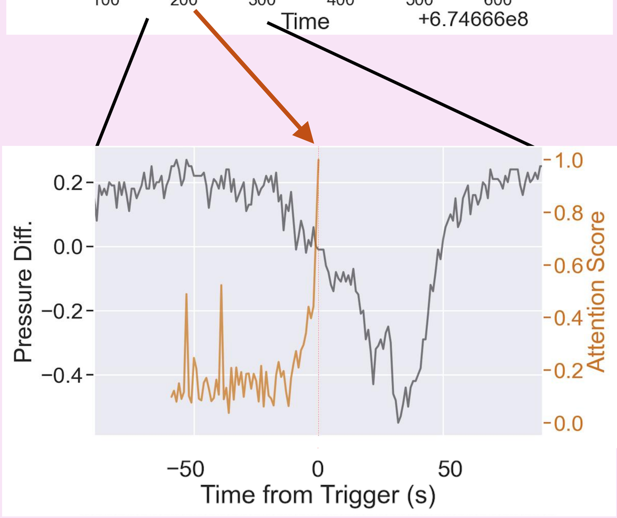

Figure 8. The transformer's attention scores (orange) indicate which points are most important in the probability assigned at each timepoint (here at time of detection). Data directly leading up to the detection as well as two contextual points carried high importance.

Vortices and Their Contribution to the Dust Budget

The contribution of dust devils to the Martian dust budget is important but remains poorly understood. **Determining how much dust devils contribute depends on the dust flux (*Q*) from each individual vortex** [5].

Lab work suggests Q depends on the pressure excursion at the vortex's center as $Q \propto \Delta P_c^{\gamma}$. Thus, large uncertainties σ_{γ} on γ translate into large uncertainties $\sigma_{\Sigma Q}$ on the population-weighted dust flux ΣQ (*Figure 2*).

Analyzing pressure data (e.g., from rovers) to accurately determine vortex pressure excursions (γ) is critical to assessing their role in the Martian dust budget.

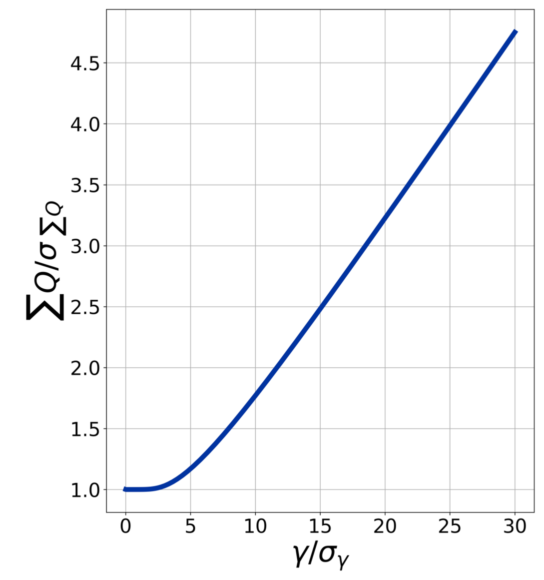

Figure 2. Relationship between the signal-to-noise ratio (SNR) for the population-weighted dust flux ($\Sigma Q/\sigma_{\Sigma Q}$) and the SNR for the individual vortex contribution. As SNR on γ increases, the SNR on the population-weighted dust flux increases, improving our understanding.

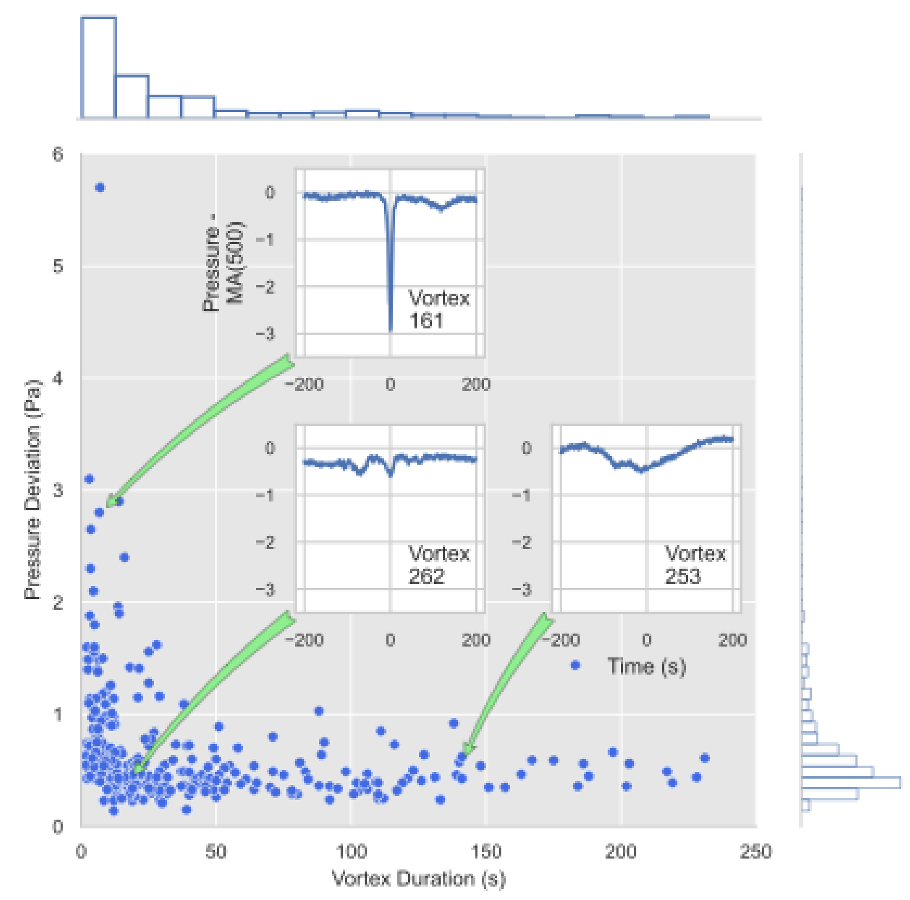

Figure 3. Vortices measured by M2020 vary in terms of pressure deviations and durations. Most tended to have a small pressure deviation (<1Pa) and short duration (<50s, lower left). But there are also short duration, high pressure deviations vortices (top left) and long lasting, small deviation vortices (bottom right).

To best understand the Martian dust budget, vortex detection algorithms must capture vortices ranging in strength and duration.

Detector Evaluation and Science Outcomes

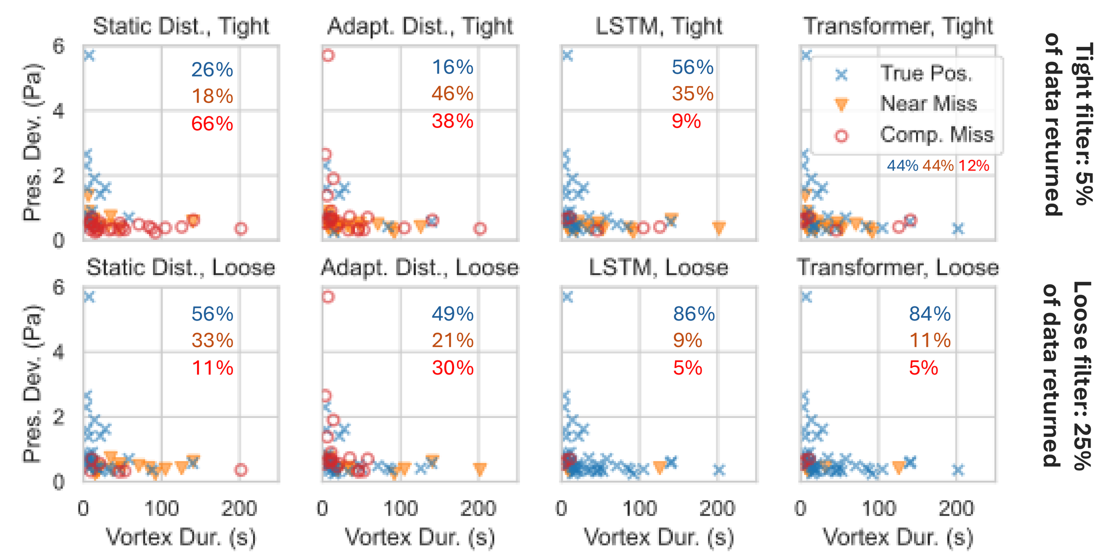

Figure 9. Vortex detection performance for all four detectors (columns) for tight and loose filters (rows) over vortices in the test set. Performance varies according to the vortex characteristics described in Figure 3. Markers indicate true positives (trigger before FWHM), near misses (trigger during FWHM) and misses (missing trigger) as well as percentage of test vortices in each of those categories

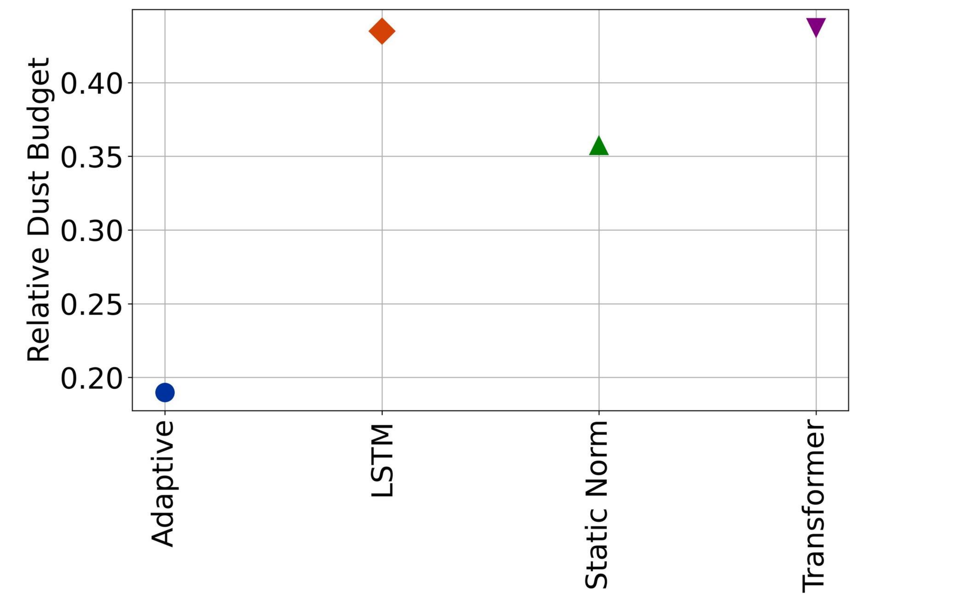

Figure 11. Total dust contributions inferred from the vortices detected by each detector, as compared to the total dust inferred from the original population of vortex encounters from Mars 2020 [4]. Even with a strict filter returning only 5% of the autonomously selected data, most detectors return vortex populations within a factor of 2-3 of the original population, though the adaptive one underestimates by a factor of ~5. Looser filters and additional detector improvements are expected to improve their performance.

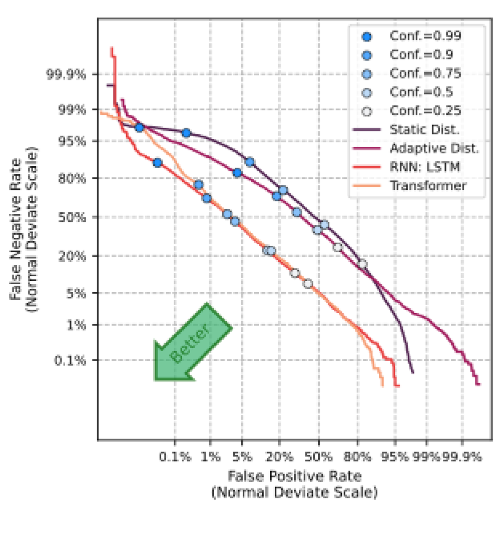

Figure 10. Performance of all detectors as a function of false positives vs false negatives. ML-based methods is moderately better than statistics-based ones. For all approaches, ground teams can tune the detector's confidence threshold (see shaded blue dots) to reach the desired balance of false positives and false negatives.

Takeaways

- We trained **statistical and ML detectors** to identify Martian vortices in pressure time-series data.
- The detectors identified and selectively triggered during vortices, **reducing data by 95% while retaining our key science metric w/in a factor of 2.**
- Future work will focus on refining the algorithms and **benchmarking each detector on flight computers.**

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References: [1] Mars Concurrent Exploration Science Analysis Group (MCE-SAG), *Final report*, posted 17 July 2023, https://www.lpi.usra.edu/mepag/reports/. [2] Diniega et al., 2022, It's Time for Focused In Situ Studies of Planetary Surface-Atmosphere Interactions, In *2022 IEEE Aerospace Conf.*, 1-19. [3] JPL SVCP workshop, September 16, 2022, Rethinking planetary conops for environment-responsive data acquisition. [4] Jackson, 2022, Vortices and dust devils as observed by the Mars Environmental Dynamics Analyzer instruments on board the Mars 2020 Perseverance rover, *PSJ*, 3:20. [5] Fenton et al., 2016, Orbital observations of dust lofted by daytime convective turbulence, *SSR, 203*, 89–142. [6] Vaswani et al., 2017, Attention is all you need, Arxiv, https://arxiv.org/abs/1706.03762.