WAIT A MINUTE..... MARTIAN WIND AUTOCORRELATIONS

R. D. Lorenz, *Space Exploration Sector, Johns Hopkins Applied Physics Laboratory, Laurel, MD 20723, USA (ralph.lorenz@jhuapl.edu)*

Introduction:

A number of operations on the surface of Mars benefit from knowledge of the wind : regolith manipulation for sampling or solar array cleaning may have more favorable results under certain wind conditions, and flight of e.g. a helicopter may be risky in strong gusts. While it is impossible to reliably predict the instantaneous wind during the turbulent early afternoon period purely as a function of time, a useful predictive degree of skill can be brought via time series analysis. Specifically, the turbulent afternoon is characterized by an alternation between stronger winds and weaker ones, presumably associated with the updraft walls and downwelling cores of boundary layer convection cells. The scale of these circulations introduces a characteristic timescale of the order of 5~20 minutes which defines correlations in the wind speed time series. The autocorrelation function (ACF) is above 0.5 for timescales less than about a minute , whereas the ACF is actually negative for 200-500s. These statistical features can be reproduced with simple Markov models, and can be exploited to improve the odds of operational success via logic of the form "attempt 2 regolith manipulations separated by 8 minutes to maximize the likelihood that one is during low winds". The existence of correlations in the wind time series may suggest some circumspection regarding autocorrelation results from seismic data.

Data:

We examine wind speed data from the dual-boom TWINS (Temperature & Wind for InSight) instrument, part of InSight's Auxiliary Payload Sensor Suite (APSS). Wind measurements are acquired at a height of 1.2 m above the surface, at a cadence that may be typically 0.1 or 1 Hz.

A quasiperiodic character can be discerned in the time series (Fig.1) – such periodicities have been noticed previously in Viking wind and seismic data (Lorenz et al., 2017), and in InSight optical depth information (Lorenz et al., 2020) and wind and temperature data (Lorenz et al., 2021).

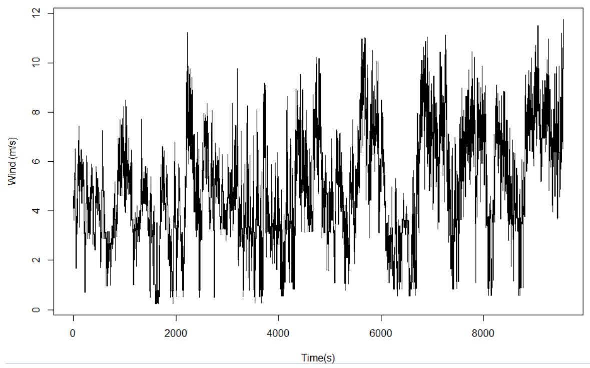

Figure 1 : Wind speed time series on Sol 782.

Analysis :

The autocorrelation function (ACF) of a time series evaluates the relationship of values separated by an interval termed the 'lag' and provides insights that are distinct from frequency analysis such as Fourier decomposition. A white noise signal has an ACF that is unity for zero lag (0,1), and approximately zero for all other values, since white noise is uncorrelated – the signal at time (t+lag) has no dependence on what the signal happened to be at time (t). A sinusoidal signal has a sinusoidal ACF, since the signal is perfectly equal to itself one cycle later, but perfectly anti-correlated with itself half a cycle later (or one-and-a-half etc.). Most signals in dynamic systems have a fall-off from (0,1) that indicates some filtering or 'memory' in the system and tails off to zero at large lag.

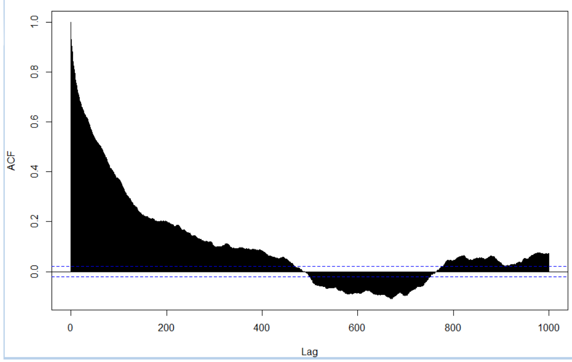

Figure 2 :Autocorrelation of the time series in figure 1. Note the rapid fall-off, indicating the atmosphere loses ~80% of its memory of the wind in about 150s. The negative region shows that if it is windier than average at time zero, it is actually more likely than not to be less windy than average 500-800s later.

The ACF of the noontime wind signal for a representative Sol (782) is shown in figure 2. First, the correlation falls off to 0.5 at a lag of about 40s, and 0.2 at around 150s. Thus after 2-3 minutes, the wind has largely 'forgotten' its initial value.

What is most striking about the ACF, however, is that it does not just decay to zero, but overshoots to become negative – the signature of a quasiperiodic signal. The negative section reaches only ~-0.1, and is around 200s wide.

Markov Models:

Crudely, the time series in figure 1 shows a bimodal distribution of values – sequences of low values interspersed by sequences of high values, or lulls and gusts respectively. Considering these, then, as two states, we can represent the time series by a Markov model. This is a discrete system that at each timestep transitions randomly from one state into another (or remains in the same state) according to a set of probabilities called a transition matrix. In this simple construct (a first-order Markov model), the present system state is the only information retained by the system.

The time series that results reflects the transition matrix. If the probability of Lull --> Gust is 0.1 then the probability of Lull --> 0.9, since the two must sum to unity (the state must either change to the other state, or remain the same). It follows then, that once the system falls into the Lull state, it will remain there for ~10 timesteps before the next gust occurs. Similarly, if the Gust --> Lull probability is 0.5, then on average a gust lasts for 2 timesteps, and the 'duty cycle' of gusts is

Not coincidentally with the Mars gust application, a two-state Markov model has been shown to be a reasonable representation of the presence or absence of dust devils on a terrestrial desert playa (Lorenz et al., 2018). Since both Mars gusts, and the presence of dust devils, are physically associated with the upwelling sheets of warm air in the convecting planetary boundary layer, it is unsurprising that the same mathematical model has some success.

Markov models can be constructed with a much finer discretization, e.g. states being defined as wind between 3.0 and 4.0 m/s, 4.0 to 5.0 m/s etc. Such models have been proposed for over two decades for wind energy forecasting (e.g. Sahin and Sen, 2001). Much more elaborate variants can be developed, with multiple orders to provide longer memory in the system, or with 'hidden' variables. However, the clarity and simplicity of the first-order two-state is useful in the present application.

Applications:

The periodicity can be exploited for operations as described in the introduction. In particular, the temporal spacing of repeated operations can be optimized to maximize the chances of success. Similarly, conditional decision rules can be constructed, e.g. "Attempt operation once winds have dropped below 4 m/s if winds were >4m/s for 4 minutes previously".

Some seismic analyses employ autocorrelation methods to look for echos at characteristic times, and to interpret these as subsurface reflectors. If the surface forcing by the atmosphere is itself quasiperiodic at the relevant periods, interpretation as internal structure may merit careful scrutiny.

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References:

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