Dynamic Time Warping as a new metric for Dst prediction with Machine Learning

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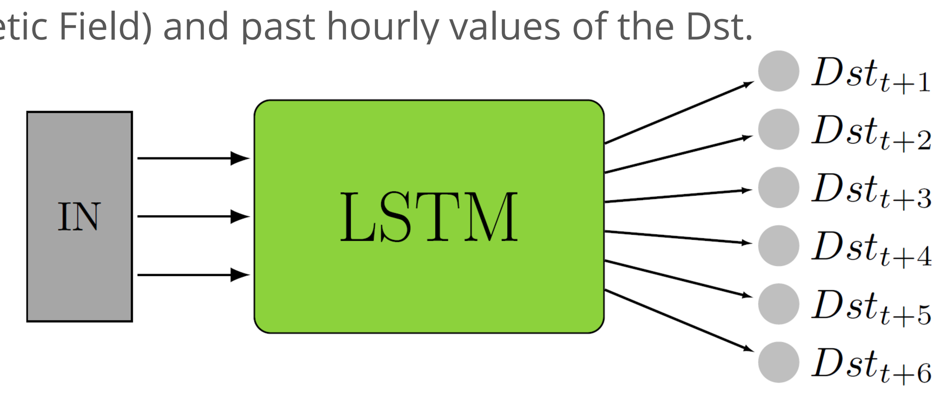
ABSTRACT

Using a Long Short-Term Memory (LSTM) model (Hochreiter and Schmidhuber, 1997) , the Disturbance Storm Time (Dst) index is predicted 1 to 6 hours ahead. The results gave a high correlation coefficient and low root-mean-square error comparable with the latest published results. However, on visual inspection, it was observed that the model behaves as a persistence model. Because of the high auto-correlation of the Dst, this behavior is not reflected in the applied metrics. A new metric is proposed, based on the Dynamic Time Warping algorithm, capable of detecting this type of result.

THE MOTIVATION

A Long Short-Term Memory (LSTM) model is trained to predict the next 6 hourly values of the the Disturbance Storm Time (Dst) index. This model consist of a single LSTM that is trained on solar wind parameters (solar wind velocity and density, magnitude and z-component of the Interplanetary Magnetic Field) and past hourly values of the Dst.



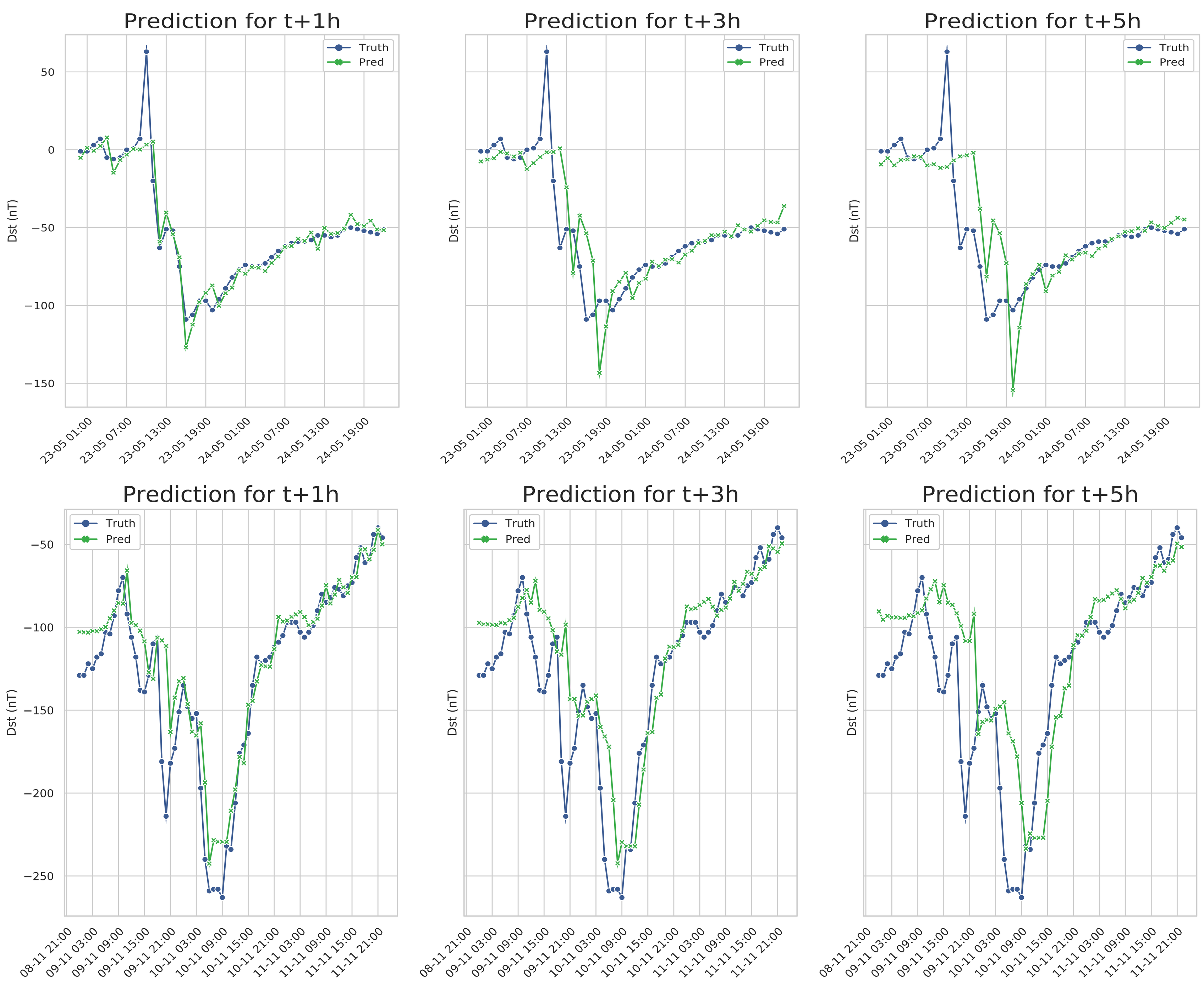
The results are compared to the persistence model (with $a \in \mathbb{N}$):

$$Dst(t + ah) = Dst(t),$$

which acts as our baseline model, and the models proposed by Gruet et al. (2018) and Lazzús et al. (2017). The metrics such as the root mean square error (RMSE) and the linear correlation coefficient (R) indicate strong results, comparable to published results.

	Persistence		Our Model		Gruet et al. (2018)		Lazzús et al. (2017)	
	RMSE	R	RMSE	R	RMSE	R	RMSE	R
T+1h	5.26	0.978	**4.04**	**0.978**	5.34	0.966	4.24	0.982
T+2h	8.11	0.942	**5.95**	**0.951**	6.65	0.946	7.05	0.949
T+3h	9.84	0.906	**7.44**	**0.923**	7.86	**0.923**	8.87	0.918
T+4h	11.8	0.871	**8.62**	0.898	8.86	**0.902**	10.44	0.887
T+5h	13.1	0.836	9.64	0.873	**9.59**	**0.882**	11.65	0.858
T+6h	14.4	0.801	10.57	0.849	**10.24**	**0.865**	13.09	0.826

However, visual inspection of the results show us something different:



Observation of the result shows that the prediction lags behind with the same amount of hours it is predicted in advance, effectively failing to predict the Dst and behaving similarly to the persistence model. The metrics used, however, failed to quantify this problem. This brings us to the research question:

Can we measure this lag?

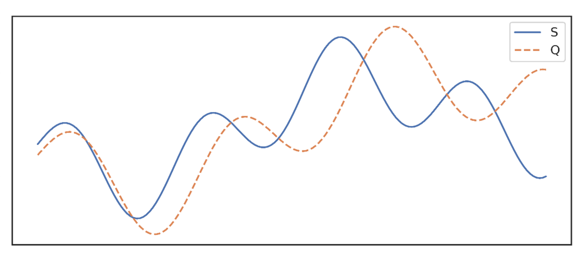
DYNAMIC TIME WARPING

The method is based on the Dynamic Time Warping algorithm, which maps two time-series on each other on a least-distance basis. Originally used to detect patterns in time-series, the mapping it produces from one series to another can be used to measure the lag the predicted series has relative to the observed series. The algorithm works as follows:

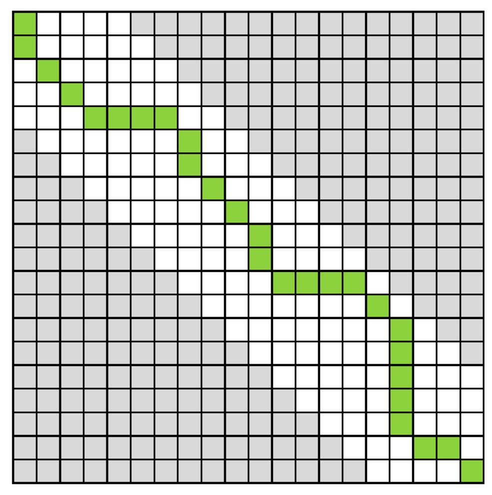
Given two time series S and Q, of size n and m. First, the distance $\delta(s_i, q_j)$ between each point is computed and placed in a $n \times m$ matrix. From this matrix, the **distance matrix** D is computed by the following equation:

$$D[i,j] = \delta(s_i, q_j) + \min(D[i-1, j-1], D[i, j-1], D[i-1, j])$$

From the matrix D, **the warp path** P can be found by following the path of least cost.



Distance Matrix

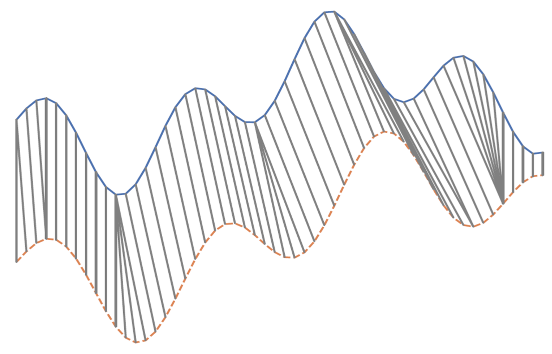


The warp path (in green) can be used to determine the time shift of the predicted model, by computing the distance from each element of P to the diagonal of D. Let $p_k = (i, j)_k$, then the time shift Δt of point s_i to q_j is equal to $\Delta t = (i - j)$.

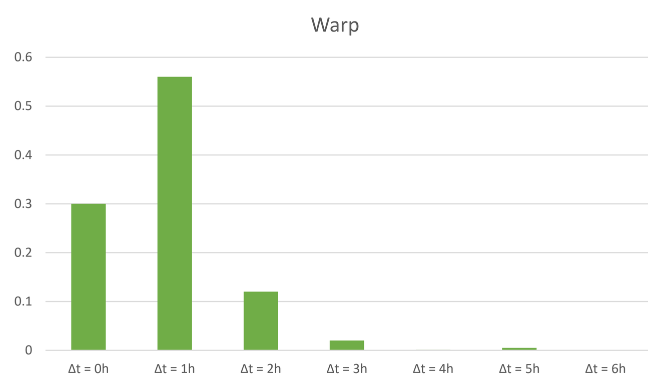
$$P = (p_1, p_2, \dots, p_K)$$
$$\forall p_i \in P : p_i \to \Delta t_i$$

By counting the number of unique values of Δt_i for each path and dividing to the path size, the overall time shift of the prediction can be quantified.

Warping Path



Count shifts



RESULTS

Against the persistence model, the expected results are seen, with every value being shifted with the respective hour the persistence model does $Dst(t + a) = Dst(t)$

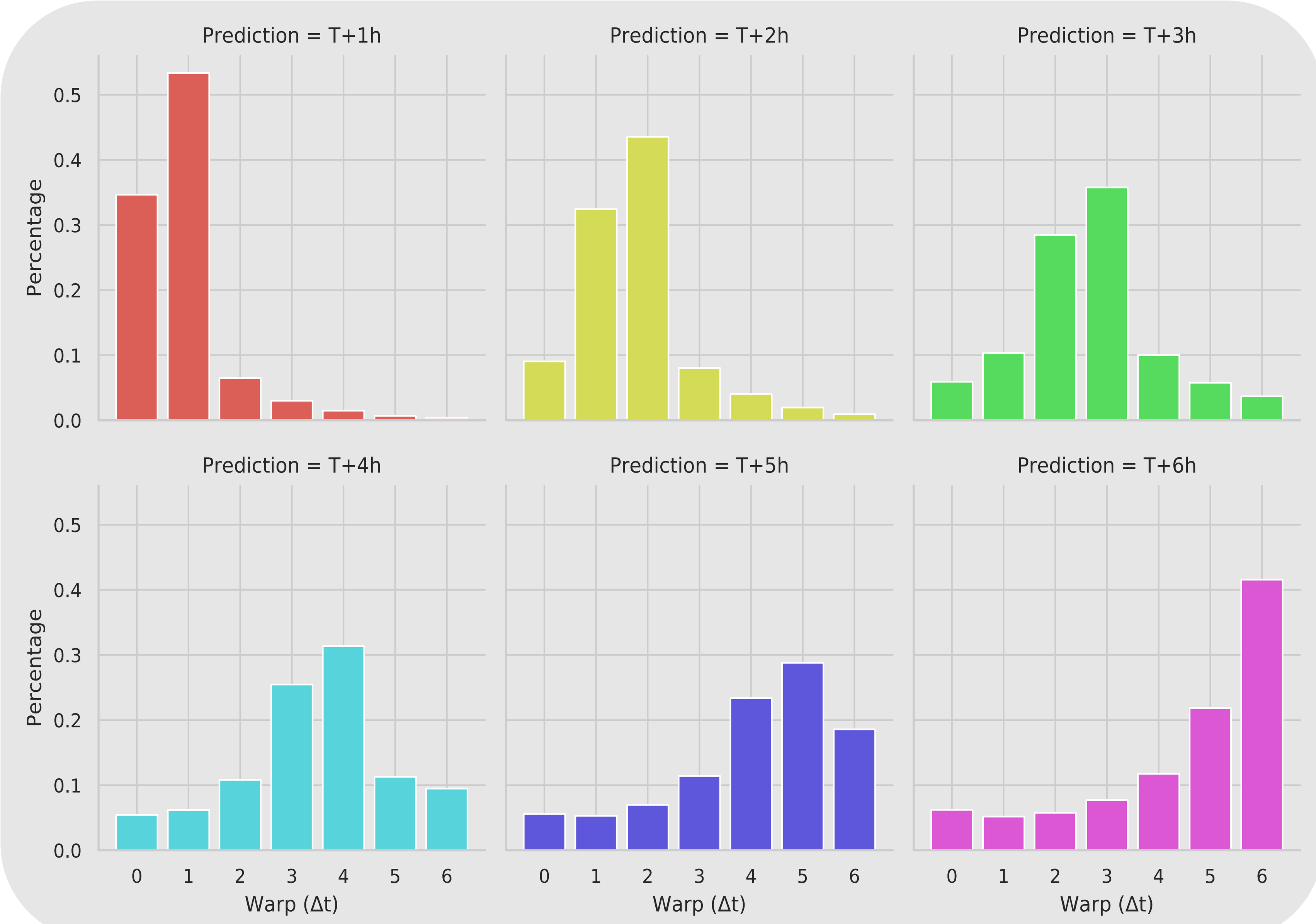
Persistence model

Prediction	0h	1h	2h	3h	4h	5h	6h
T+1h	0.003	**0.997**	0	0	0	0	0
T+2h	0.003	0.003	**0.994**	0	0	0	0
T+3h	0.004	0.003	0.003	**0.99**	0	0	0
T+4h	0.004	0.003	0.003	0.003	**0.987**	0	0
T+5h	0.004	0.003	0.003	0.003	0.003	**0.984**	0
T+6h	0.005	0.003	0.003	0.003	0.003	0.003	**0.98**

Model

Prediction	0h	1h	2h	3h	4h	5h	6h
T+1h	0.348	**0.537**	0.063	0.029	0.014	0.006	0.003
T+2h	0.091	0.323	**0.437**	0.081	0.040	0.020	0.010
T+3h	0.059	0.102	0.284	**0.360**	0.102	0.058	0.036
T+4h	0.054	0.064	0.109	0.253	**0.311**	0.113	0.095
T+5h	0.056	0.053	0.071	0.112	0.233	**0.287**	0.187
T+6h	0.063	0.052	0.059	0.077	0.116	0.218	**0.415**

Against the model, the results are more mixed. From observations, we know that in quiet time, the shift would be undetectable and only is clear during turbulent intervals.



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