MONITORING AND ASSESSMENT OF ANOMALIES OF 2020 MAGNETIC FIELD VARIATIONS AT DUSHETI GEOMAGNETIC OBSERVATORY

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Summary: *The paper touches the study of the magnetic field variations (minute values) during 2020 by Dusheti Geomagnetic Observatory. We found out different category anomalies, for revealing of which we used some statistical methods and special Python library developed for observation on different components of magnetic field. As a result of the study we determined criteria for revealing low, moderate and high category perturbations in regards with 2020 data.*

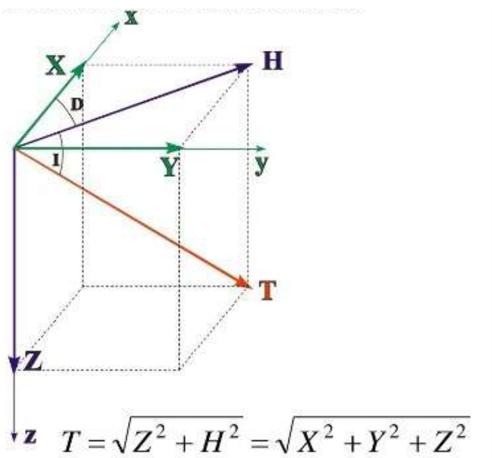
Key words: *Magnetic field variations*

Preface

Development of mathematical methods for the observation, assessment and forecast of the magnetic field of the Earth is the most essential task of this field of Geophysics. Our study touches processing the data obtained by the Observatory and mechanical processing of rare phenomena revealed in the data and issues of further forecast. In order to solve this task it became necessary to preprocess the data, highlight statistical hypotheses and prove them with high reliability. Obviously, forecasting issue includes so called revealing the preparation period of anomaly in the magnetic field variations and verifying them for every next period.

Let us mathematically formulate our work. Let us admit that $t' \in [t_0, t]$, where is t_0 January 1, 2020 and *t* is December 31,2020. Each $x_{t'}, y_{t'}, z_{t'}$ is (t' runs $[t_0, t]$with minute discretization), where the three components of the magnetic field are determined for t'.

We will observe the graph of the magnetic field tension, T vector of the magnetic induction in a homogenous isotropic space.



$$T = \sqrt{Z^2 + H^2} = \sqrt{X^2 + Y^2 + Z^2} \qquad (1)$$

We receive time series for 2020 in the form of the values of tension of T magnetic field (minute discretization), which includes 508905 recordings.

Table 1. The structure of the data base.

	Time	X	Y	Z	T
0	2020-01-11 14:00:00	20.523	-3.206	23.7236	31.532224
1	2020-01-11 14:01:00	20.063	-3.136	23.7099	31.217268
2	2020-01-11 14:02:00	19.654	-3.405	23.7298	30.999631
3	2020-01-11 14:03:00	20.006	-3.364	23.7030	31.199179
4	2020-01-11 14:04:00	19.521	-3.986	23.7528	31.002470
...	...	...	...	...	...
508901	2020-12-31 23:55:00	1.267	57.572	39.6300	69.904774
508902	2020-12-31 23:56:00	-0.100	57.467	39.6870	69.839273
508903	2020-12-31 23:57:00	0.071	57.280	39.6764	69.679410
508904	2020-12-31 23:58:00	0.007	57.747	39.6677	70.058850
508905	2020-12-31 23:59:00	-0.001	57.561	39.6891	69.917762

On the basis of table 1 we will study T and the anomalies associated with it in time and distinguish different interesting statistical structures. The mechanism of solving this task is given mainly in so called task of detrending [1-2], when it is essential to construct such statistical function for transformed signal that will enable us to evaluate the useful (a regular value included in the process) part and distinguish it from the whole process as a regular one at any point of time.

Before discovering the random component (white noise) in our process we carried out a certain preliminary work and studied the statistical properties for our time series by months, days and hours. Below we present interesting statistics for the values of T magnetic field tensions.

mean	55.000161
std	17.181470
min	21.895756
25%	40.281857
50%	54.010227
75%	68.721086
max	150.000000

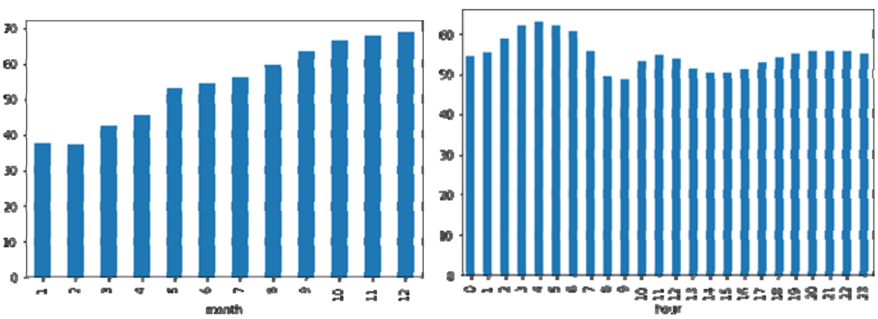


Fig.1. The values of monthly and hourly averages for T magnetic field tensions.

As a result of observing on these schemes we concluded that the process must not be homogenous in time, though intuitively we may say that it is stationary. At the same time, we verified the zero hypothesis on the stationarity of our process with value p<=0,05.

ADF Statistic: -31.261735
p-value: 0.000000
Critical Values:
1%: -3.430
5%: -2.862
10%: -2.567

As shown above the process is characterized with stationarity depended on the time structure [3]. The autocratic function shows that there is a relationship between the previous and next values, though it decreases over time. It means that in the first half of 2020 the data of our study had interacting physical load in a narrow sense. However we cannot say the same on the last months of the year. Obviously it has an impact on the forecast quality. Consequently, the seconds half of 2020 is of higher entropy [4-5] and the values of T magnetic field tension are distinguished with higher dynamics that in its turn indicates to episodic stationarity of the process and strengthening the regular part in it.

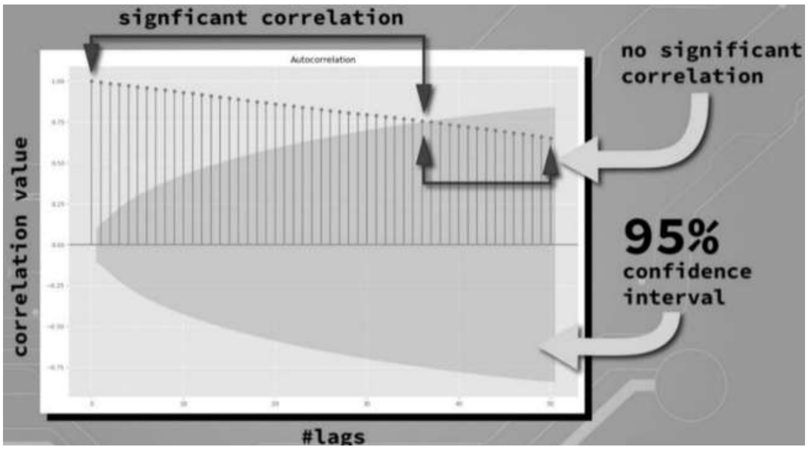


Fig. 2. The scheme of autocorrelation function of T magnetic field tension and confidence intervals with 50 lags.

The next stage for our data is their stationarization. It can be done by the first order derivative that will detrend the series. Further, we will observe the scheme with the first remainder and see whether the convergence of the average and dispersion can be reached near some constant numbers. Significant decrease of P value shows that the process was detrended.

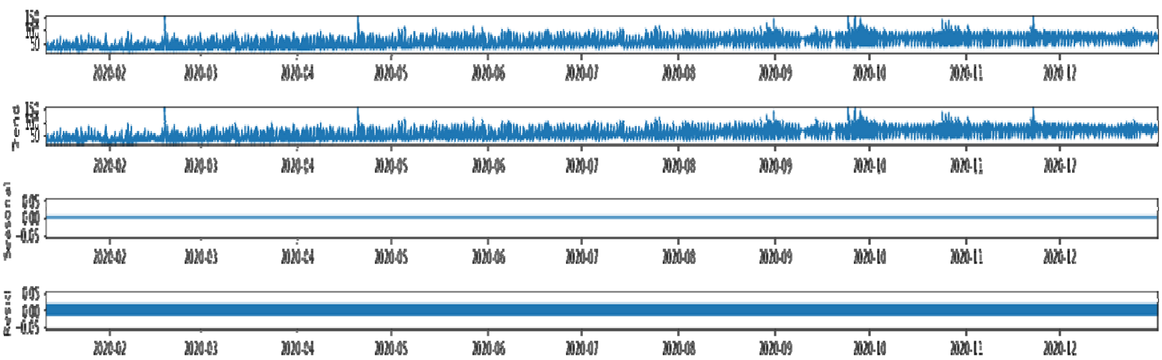


Fig. 3. The scheme of seasonality received by adaptive and multiplicate methods of decomposition and distinguished white noise.

Resume

Classification of magnetic field tension data as regular and singular parts by adaptive and mulitiplicate methods obviously shows seasonality and the role of white noise in all the data, on the basis of which it became much easier to find anomalies in the magnetic field data. In future on the basis of historical data, use of some machine learning technology of forecasting models in the imbalance anomaly missives will become more appropriate. The result of the study of forecasting models is a certain preliminary work, on the basis of which we will receive magnetic anomaly expectations in time and their probable assessments.

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