

# Solar Flux Forecast on Base of New Method of Optimum Measurements Filtering

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## Abstract

The paper presents the results of application of the recurrent method of optimum filtering the Gaussian random process for forecasting the solar activity index F10.7. The characteristic feature of the method is the use of recurrent functional relationships that makes it possible to specify the initial autocorrelation function of the random process in the discrete form. The comparison of obtained results with the corresponding National Oceanic and Atmosphere Administration data has demonstrated very good compliance of forecast errors estimates. This testifies, apparently, to impossibility of further increasing the accuracy of solar activity forecasting at the modern level of knowledge of its nature.

## Introduction

We will consider the forecasts of the daily-observed flux at 2800 MHz in solar flux units ( $10\text{-}22\text{W m}^{-2}\text{ Hz}^{-1}$ ). This solar radio flux at 10.7 cm is an excellent indicator of solar activity. Often called the F10.7 index, it represents one of the longest running records of solar activity. This index is widely used in studying physical processes in the near-earth space. In particular, it represents one of arguments of the modern atmospheric density models.

We have applied the new technique as a methodological basis for solving the problem under consideration with the Gaussian random process prediction. We will consider this process  $y(t)$  with a zero a priori mean and the autocorrelation function

$$E\{y(t) \cdot y^T(\tau)\} = K_y(t, \tau)_0. \quad (1)$$

The problem of determining the optimum estimate of the process  $y(t)$ ,  $t \geq t_k$  is solved based on measurements

$$z_i = y(t_i) + v(t_i), \quad i = 1, \dots, k. \quad (2)$$

Here  $v(t_i)$ ,  $i = 1, 2, \dots, k$  is the Gaussian random process with discrete time and independent values with a zero mean value and specified covariation matrix  $R_i$ .

The processes  $y(t)$  и  $v(t_i)$  are assumed to be mutually uncorrelated. The estimate, the errors of which have a minimum variance, is considered to be optimum.

A.N. Kolmogorov [1] first solved this problem (for a scalar stationary process). In subsequent works the researchers obtained the generalizations associated with considering the non-stationary and vector random processes [2], [3], The

inconvenience in applying the developed techniques was caused by the necessity of solving the system of linear equations, the order of which grows with increasing  $k$ .

R. Kalman, R. Bucy and their followers [4], did a considerable step on the way of expanding the field of applying the techniques of filtering and forecasting the random processes in the works. The problem was reduced to the necessity of applying the forming filter and standard procedures of solving the difference equations, which can easily be implemented on computers. However, the application and this approach meet some difficulties as well. A complicated task is the construction of a forming filter, for the non-stationary processes especially. The difficulties are aggravated when the correlation function (1) is poorly known a priori and has to be updated in the process of filtering based on obtained estimates  $\hat{y}(t)$ , which necessitates the reconstruction of the filtering and forecasting algorithm.

The presented brief review indicates the urgency of constructing such a filtering and forecasting technique, which could be applicable to the work with the Gaussian random process of general form. In this case, the correlation function (1) can be specified discretely over some grid of arguments. The algorithm of such type was first described, apparently, in papers [5 - 8]. The justification of the technique stated below was published in [9].

## Derivation of Recurrences Functional Relationships

For constructing the algorithm, we apply the criterion of maximum of the a posteriori probability

$$p[y(t)|Z_i] = \frac{p[y(t), z_i|Z_{i-1}]}{p[z_i|Z_{i-1}]} \rightarrow \max, \quad (3)$$

where the sequence  $z_1, z_2, \dots, z_i$  is designated as  $Z_i$  for brevity.

We assume that the estimates

$$E\{y(t)|Z_{i-1}\} = \hat{y}(t)_{i-1}, \quad (4)$$

$$E\{[y(t) - \hat{y}(t)] \cdot [y(\tau) - \hat{y}(\tau)]^T | Z_{i-1}\} = K_y(t, \tau)_{i-1}, \quad t, \tau \geq t_{i-1} \quad (5)$$

are constructed based on measurements  $Z_{i-1}$ .

For determining the value of  $\hat{y}(t)$ , which provides a maximum to criterion (3), it is sufficient to consider the numerator only, because function  $y(t)$  does not appear in a denominator. We write the expression for density in a numerator

$$p[y(t), z_i | Z_{i-1}] = C \cdot \exp \left\{ -\frac{1}{2} \begin{bmatrix} y(t) - \hat{y}(t) \\ z_i - \hat{y}(t) \end{bmatrix} \begin{bmatrix} K & L \\ L^T & M \end{bmatrix} \begin{bmatrix} y(t) - \hat{y}(t) \\ z_i - \hat{y}(t) \end{bmatrix} \right\}. \quad (6)$$

Here

$$\begin{aligned} E\{z_i | Z_{i-1}\} &= \hat{y}(t)_{i-1}, \\ E\{z_i - \hat{y}(t)_{i-1}\} \cdot [z_i - \hat{y}(t)_{i-1}]^T | Z_{i-1}\} &= K_y(t, t)_{i-1} + R_i, \\ E\{y(t) - \hat{y}(t)_{i-1}\} \cdot [z_i - \hat{y}(t)_{i-1}]^T | Z_{i-1}\} &= K_y(t, t)_{i-1}, \\ \begin{bmatrix} K & L \\ L^T & M \end{bmatrix} &= \begin{bmatrix} K_y(t, t)_{i-1} & K_y(t, t)_{i-1} \\ K_y^T(t, t)_{i-1} & K_y(t, t)_{i-1} + R_i \end{bmatrix}^{-1}, \end{aligned}$$

where  $K, L, M$  are some square block matrixes of size  $(n \times n)$ ,  $n$  is the dimension of vector  $y$ .

One can easily show [5] that the maximum of density (6) is achieved for

$$\hat{y}(t)_i = \hat{y}(t)_{i-1} + W(t) \cdot [z_i - \hat{y}(t)_{i-1}],$$

where

$$W(t) = -K^{-1} \cdot L = K_y(t, t)_{i-1} \cdot [K_y(t, t)_{i-1} + R_i]^{-1}. \quad (7)$$

So,

$$\hat{y}(t)_i = \hat{y}(t)_{i-1} + K_y(t, t)_{i-1} \cdot [K_y(t, t)_{i-1} + R_i]^{-1} \cdot [z_i - \hat{y}(t)_{i-1}], \quad t \geq t_i. \quad (8)$$

Now, it remains to construct the a posteriori correlation function  $K_y(t, \tau)_i$ . We express the error in forecasting  $\Delta y(t)_i$  of the  $y(t)$  process at the  $i$ -th step in terms of a corresponding error at the  $(i-1)$ -th step. For this purpose, we make use of expressions (8) and (2). We obtain

$$\begin{aligned} \Delta y(t)_i &= y(t) - \hat{y}(t)_i = [y(t) - \hat{y}(t)_{i-1}] - W(t) \cdot [z_i - \hat{y}(t)_{i-1}] = \\ &= \Delta y(t)_{i-1} - W(t) \cdot [\Delta y(t)_{i-1} + v(t)_i] \end{aligned}$$

Further,

$$\begin{aligned} K_y(t, \tau)_i &= E\{\Delta y(t)_i \cdot \Delta y^T(\tau) | Z_i\} = \\ &= E\left\{ \begin{bmatrix} [\Delta y(t)_{i-1} - W(t) \cdot (\Delta y(t)_{i-1} + v(t)_i)] \cdot \\ [\Delta y(\tau)_{i-1} - W(\tau) \cdot (\Delta y(\tau)_{i-1} + v(\tau)_i)]^T | Z_{i-1} \end{bmatrix} \right\}. \quad (9) \end{aligned}$$

When multiplying the terms in the right-hand part of (9) we take into consideration that all mean values of type

$$E\{\Delta y(t)_{i-1} \cdot v^T(t)_i\} = 0, \text{ and that}$$

$$E\{\Delta y(t)_{i-1} \cdot [\Delta y(\tau)_{i-1} + v(\tau)_i]^T | Z_{i-1}\} = K_y(t, \tau)_{i-1} + R_i.$$

With regard to designation (7), the expression (9) takes the form

$$\begin{aligned} K_y(t, \tau)_i &= K_y(t, \tau)_{i-1} - \\ &- K_y(t, t)_{i-1} \cdot [K_y(t, t)_{i-1} + R_i]^{-1} \cdot K_y^T(\tau, t)_{i-1}, \quad t, \tau \geq t_i \end{aligned} \quad (10)$$

Thus, the stated problem is solved. Two recurrence relations (8) and (10) are developed, which allow one, based on initial data (4) and (6), to process the last measurement and to prepare the necessary initial data for performing the next

step in processing the measurements. In so doing, the maximum possible accuracy of obtained estimates is provided. The constructed recurrence relations represent a basis of the filtering and forecasting algorithm for measurements in a discrete time. Unlike the recurrence relationships of the Kalman-Bucy filter, these relations are *functional*. This feature made it possible to construct the filtering and forecasting algorithm for the Gaussian random process.

## Example 1. Modelling

Determination of correlation function  $K_y(t, \tau)_{end} = K_y(t, \tau)$  in the stable filtering mode was carried out for the scalar stationary process with the correlation function

$$K_y(t, \tau)_0 = \begin{cases} 1 - \frac{|t - \tau|}{\Lambda}, & |t - \tau| \leq \Lambda, \\ 0, & |t - \tau| > \Lambda. \end{cases} \quad (11)$$

Such a choice was caused by the absence of analytical solution for the function of indicated form. In performing calculations, it was accepted that:

- the number of grid steps on the correlation interval ( $\Lambda$ ) is  $p = \Lambda/\Delta = 50$  ;
- the number of grid steps on the time interval between the measurements ( $\Delta t$ ) is  $m = \Delta t/\Delta = 1, 5, 10, 15, 25, 35, 45$  ;
- the root-mean-square error of measurements ( $\sigma = \sqrt{R}$ ) is  $\sigma = 0, 0.1, 0.2, 0.3, 0.5, 0.7, 1.0$ .

Table 1 and figure 1 below present the matrix  $K_y(t, \tau)_{end}$  for one of initial data versions.

**Table 1. Correlation matrix  $K_y(t, \tau)_{end}$ ,  $m=5$ ,  $\sigma = 0.1$**

$\tau/\Lambda$	Forecast interval $t/\Lambda$					
	0	0.2	0.4	0.6	0.8	1.0
0	0.009	0.009	0.008	0.008	0.007	0.000
0.1	0.009	0.138	0.130	0.122	0.115	0.100
0.2	0.009	0.269	0.248	0.233	0.221	0.200
0.3	0.008	0.256	0.367	0.344	0.326	0.300
0.4	0.008	0.248	0.490	0.455	0.431	0.400
0.5	0.008	0.241	0.470	0.566	0.537	0.500
0.6	0.008	0.233	0.455	0.682	0.642	0.600
0.7	0.007	0.227	0.443	0.659	0.747	0.700
0.8	0.007	0.221	0.431	0.642	0.857	0.800
0.9	0.006	0.214	0.419	0.624	0.829	0.900
1.0	0.000	0.200	0.400	0.600	0.800	1.000

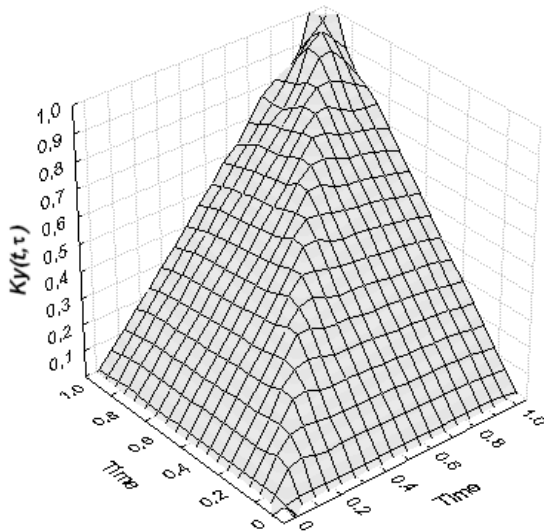


Figure 1. Correlation matrix  $K_y(t, \tau)_{end}$ ,  $m=5$ ,  $\sigma = 0.1$

The highest accuracy is achieved at the last measurement instant (the forecast time = 0). The values of matrix components monotonously grow with increasing forecast interval. When the forecast interval is equal to the correlation interval  $\Lambda$ , the variance of errors is equal to 1, i.e. to the value of a priori correlation function  $K_y(t, t)_0$ . Here the values of correlation moments  $K_y(t, \Lambda)_{end}$  и  $K_y(\Lambda, \tau)_{end}$  coincide with the values of a priori correlation function (11). Table 2 presents the values of RMS errors as a function of forecast interval.

Table 2. RMS of forecast errors  $\sqrt{K_y(t, t)_{end}}$ ,  $m=5$ ,  $\sigma = 0.1$

$t/\Lambda$	0	0.1	0.2	0.3	0.4	0.6	0.8	1.0
RMS	0.097	0.38	0.52	0.62	0.70	0.83	0.92	1.00

The RMS value for  $t=0$  virtually coincides with the value  $\sigma = 0.1$ .

Table 3 gives the values of variances of estimates for the time instant of the last measurement ( $K_y(0,0)_{end}$ ), i.e. the results of solution of the filtering problem.

Table 3. Values of  $K_y(0,0)_{end}$  for various  $m$  and  $\sigma$

$m$	Values $\sigma$						
	0	0.1	0.2	0.3	0.5	0.7	1.0
1	0	0.0080	0.023	0.040	0.076	0.112	0.165
5	0	0.0093	0.032	0.063	0.133	0.206	0.309
15	0	0.0097	0.037	0.076	0.175	0.279	0.423
25	0	0.0098	0.037	0.079	0.187	0.305	0.464
35	0	0.0098	0.038	0.082	0.196	0.321	0.488
45	0	0.0098	0.038	0.082	0.199	0.328	0.498

The data of this table testify to a rather weak influence of the value of interval  $m$  between the measurements on the accuracy of measurements filtering results.

Comment. The random process, considered in this example, which has correlation function (11), possesses interesting properties. Namely, this process can be constructed in the following manner based on a sequence of independent random numbers  $x_j$ ,  $j = 1, \dots$ , distributed according to the normal law  $norm(0,1)$ :

$$y_i = \left( \sum_{j=1}^{\Lambda} p_j \cdot (x_{i+j}) \right) / \sqrt{\Lambda}, \quad (12)$$

$$y_{i+k} = \left( \sum_{j=1}^{\Lambda} p_j \cdot (x_{i+k+j}) \right) / \sqrt{\Lambda}.$$

For the value of weighting coefficients  $p_j=1$  the random process with the correlation function (11) takes place. Varying the values of weighting coefficients makes it possible to construct random processes with various correlation functions. Here the important question arises, whether there exists the correlation function  $K_y(t, \tau)_0$ , in which the corresponding correlation coefficients are greater, than those in function (11). It is intuitively clear that in this case the forecasting errors are lower, than those are presented above. To answer this question we consider the simplest case with  $\Lambda = 2$ ,  $K_y(0, 0.5\Lambda)_0 = k_{0.5}$ .

This value in function (11) equals 0.5. Is it possible to increase it? The application of model (12) allows one to construct the equations for determining coefficients  $p_1$  and  $p_2$ . We get:

$$p_1^2 + p_2^2 = 1,$$

$$p_1 \cdot p_2 = k_{0.5}.$$

From these relations it follows that the condition

$$p_1^2 + p_2^2 - 2 \cdot p_1 \cdot p_2 = (p_1 - p_2)^2 = 1 - 2 \cdot k_{0.5} \geq 0 \quad (13)$$

should be satisfied. It is obvious that the random process with the value  $K_y(0, 0.5\Lambda)_0 = k_{0.5} > 0.5$  doesn't exist!!!

Thus, one can draw the conclusion that in forecasting random processes it is impossible to improve the forecasting accuracy as compared to the estimates presented in table 2.

## Example 2. F10.7 cm Solar Flux

We will consider the application of the technique described above for forecasting the intensity of radio emission of the Sun at the wavelength of 10.7 cm (index  $F_{10.7}$ ). Based on the data of site [10], figures 2 and 3 present the average daily values of index  $F_{10.7}$  over the time interval from May,

2002 to December, 2015 (for time periods with the heightened level of solar activity). The figures present also the averaged estimates (on the previous 81-day time interval).

normal distributions. Therefore, the application of the considered technique of Gaussian random process forecasting is acceptable.

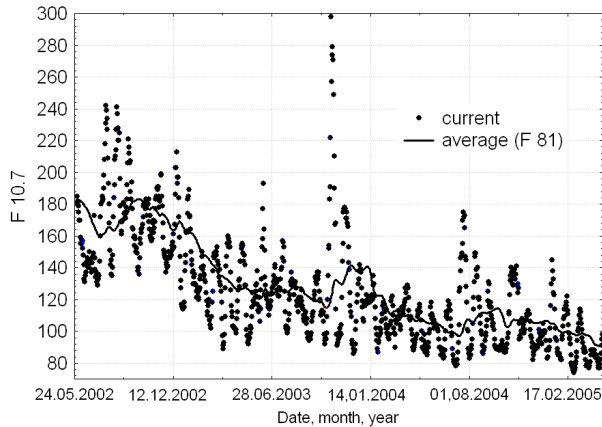


Figure 2. Data for time interval from June 2002 to May 2005

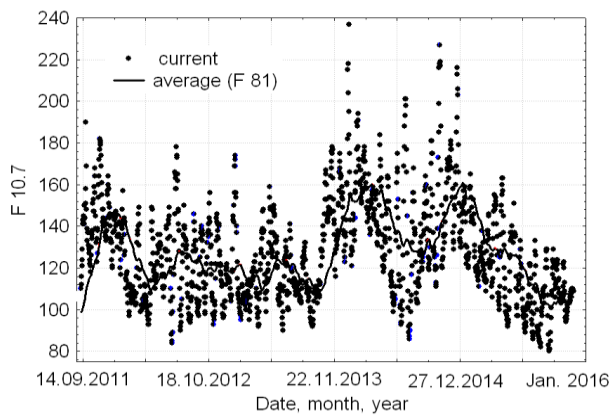


Figure 3. Data for time interval from September 2011 to December 2015

The changes in the index values are typical. They reflect the effect of well-known 28-day and 11-year cycles of solar activity. The plots clearly indicate also the irregular (random) deviations, whose prediction is a problematic issue now.

Below we use the assumption that deviations of current estimates of the index from the average values are random quantities. For each time instant, the normalized deviations were calculated

$$y(t) = [F_{10.7}(t) - F81] / F81. \quad (14)$$

Figures 4 and 5 present statistical distributions of estimates (14). The constructed distributions are similar. In both cases, there exists some asymmetry. The amplitude of positive deviations exceeds the amplitude of negative deviations from the average one. This is associated, apparently, with the features of physical processes on the Sun. Nevertheless, the histograms not too highly differ from corresponding

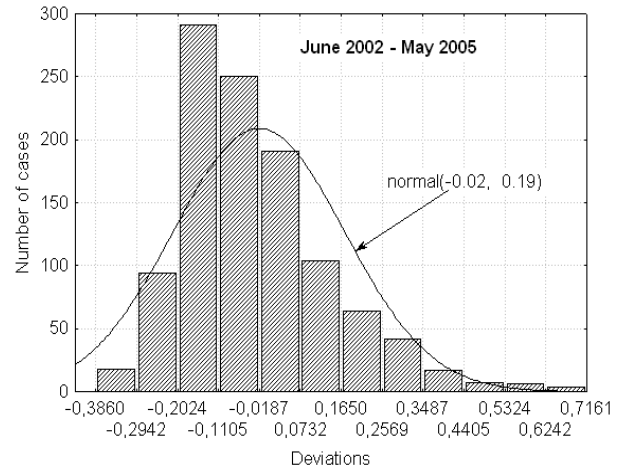


Figure 4. Histogram for the time interval from June 2002 to May 2005

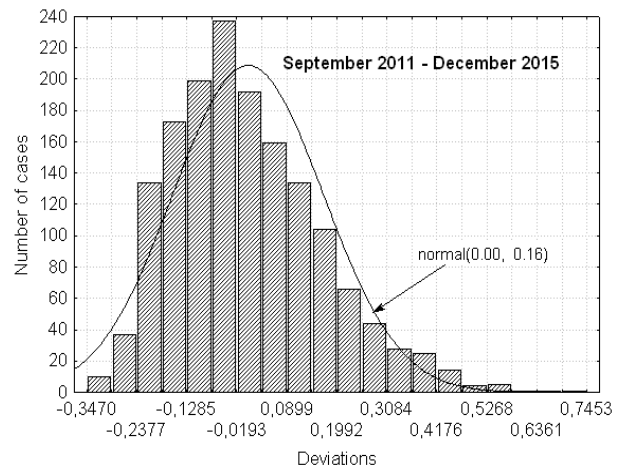


Figure 5. Histogram for time interval from September 2011 to December 2015

Figure six presents the autocorrelation function of random deviations (14) constructed according to the data of figures 2 and 3.

The form of the constructed autocorrelation function is expected. The manifestation of the well-known 28-day period of solar activity variations is clearly seen. The correlation sharply decreases from 1.0 to 0 in 9-10 days. The subsequent correlation maxima do not exceed the value of 0.4. One can also see essential decrease of correlation with time: it becomes less than 0.1 in 2 months.

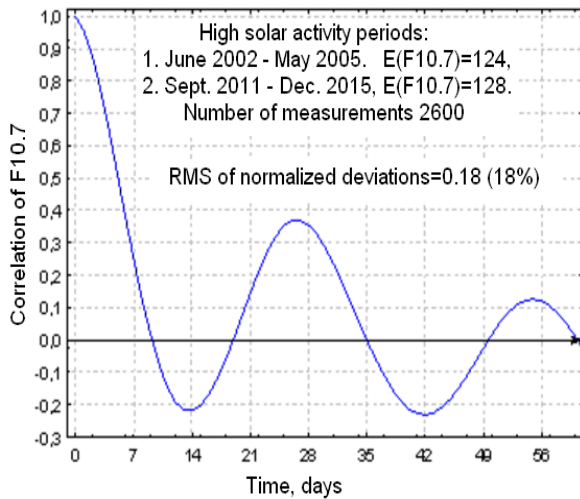


Figure 6. Autocorrelation function of normalized deviations of index  $F_{10.7}$  from average values

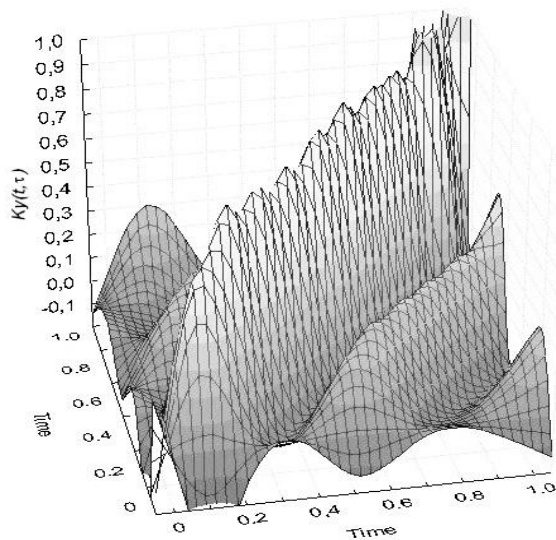


Figure 7. Correlation matrix  $K_y(t, \tau)_{end}$ ,  $m=1$ ,  $\sigma=0.1$ , « Time » =  $t/\Lambda$

Figure 7 presents the correlation matrix  $K_y(t, \tau)_{end}$ , calculated by formula (10) for the steady filtering mode with the values of parameters  $m=1$ ,  $\sigma=0.1$ . This matrix differs from the similar matrix in figure 1 in the existence of a periodic component. This difference is a natural consequence of features of the autocorrelation function presented in figure 6. When the forecast interval is equal to the correlation interval  $\Lambda$  ("Time" =1), the variance of errors is equal to 1, i.e. to the value of a priori correlation function  $K_y(t, t)_0$ . Here the values of correlation moments  $K_y(t, \Lambda)_{end}$  and  $K_y(\Lambda, \tau)_{end}$  coincide with the values of a priori correlation function presented in figure 6.

Figure 8 presents the RMS of forecast errors. They were calculated based on the estimates of diagonal terms of matrix  $K_y(t, \tau)_{end}$ . The data of axis  $x$  represent the forecast interval in days. The maximum value of  $x$  (61) is equal to the correlation interval  $\Lambda$ .

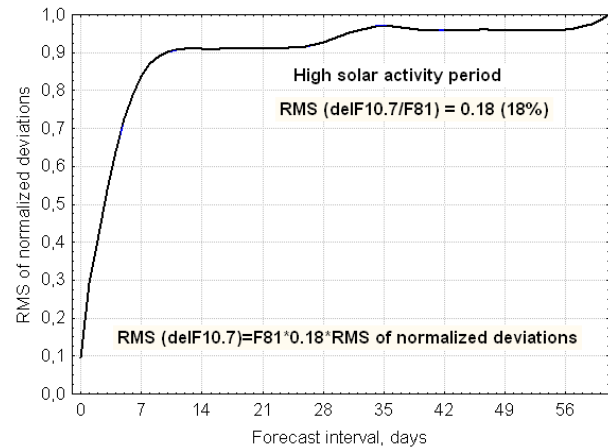


Figure 8. RMS of forecast errors  $\sqrt{K_y(t, t)_{end}}$ ,  $m=1$ ,  $\sigma=0.1$

The data of this figure essentially differ from the similar data presented in table 2. On the time interval up to 10 days ( $10/61=0.16$ ) the RMS errors rapidly increase up to the value of 0.9. For the forecast interval  $> 0$ , the RMS values exceed the corresponding data of table 2. This fact agrees with the above statement that in forecasting random processes it is impossible to improve the forecasting accuracy as compared to the estimates presented in table 2. The accounting for the periodic nature of a priori correlation function (1) in this example did not lead to increasing the accuracy. This accounting was manifested only in a slow increase of RMS forecast errors from 0.9 to 1.0 for the forecast interval larger than 10 days. This result is explained by the fact that on the time interval larger than 10 days the correlation coefficients (figure 6) do not exceed the value of 0.4 and decrease down to zero.

Table 4. RMS errors of forecasting the index  $F_{10.7}$  according to the data of figure 8

F81	$\sigma$	Forecast interval, days				
		1	2	3	4	5
126	0.18	6.7	9.5	12.2	14.5	16.4

The data presented in figure 8 can easily be applied to estimate the RMS errors in forecasting the index  $F_{10.7}$ . For this purpose, one should perform multiplication of three quantities: 1) the mean value of index (F81), 2) the RMS of relative deviations of current index values from the mean value ( $\sigma$ ), 3) the RMS of normalized errors according to the data of figure 8. Table 4 gives the example of such a calculation.

It was mentioned above that the  $F_{10.7}$  estimates were downloaded from the site [10]. This site contains many other materials on the solar activity. In particular, the report [11] presents the detailed statistical data on the index forecasting errors over the time interval up to 5 days. Some of these materials (for the forecast interval up to 3 days) are given in figure 9. It is seen that the "RMS Error" estimates for 2013 agree with the estimates of table 4.

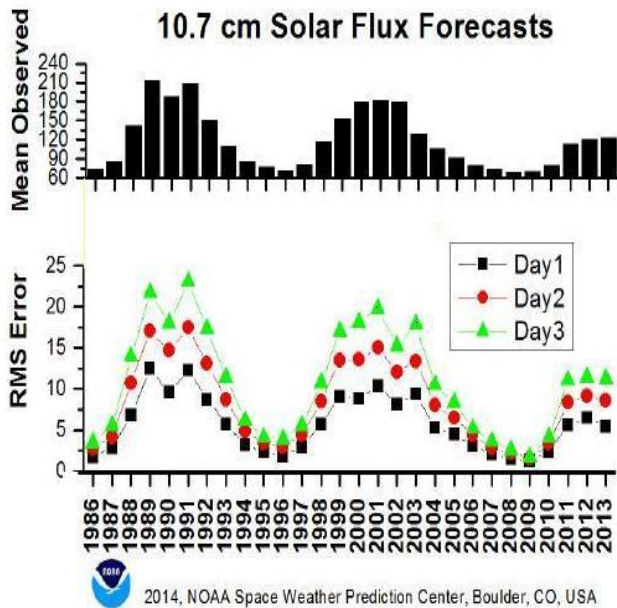


Figure 9. National Oceanic and Atmosphere Administration data on forecast errors

Table 5 gives the more detailed data from the report [11] as well as the results of calculation of errors according to the data of figure 8 obtained with using the same estimates of parameters  $F_{81}$  and  $\sigma$ .

Table 5. Comparison of RMS of errors of forecasting the  $F_{10.7}$  index

Source	F81	$\sigma$	Forecast interval, days				
			1	2	3	4	5
NOAA data	122	0.167	5.4	8.6	11.2	13.7	15.6
figure 8	122	0.167	5.9	8.6	10.9	13.0	14.8

The table data demonstrate very good compliance of forecast errors estimates obtained by various techniques. This testifies, apparently, to impossibility of increasing the accuracy of solar activity forecasting with the modern level of knowledge of its nature.

## Conclusion

1. The technique of optimum forecasting the Gaussian random process, based on the measurements in a discrete time, is substantiated. This technique differs from known approaches in the possibility of specifying a priori autocorrelation function of the process in arbitrary form. The problem solution is reduced to successive application of two functional relations.
2. The best forecasting accuracy is shown to be achieved for the process with a linear autocorrelation function.
3. The application of the developed technique for forecasting the Sun radio emission index  $F_{10.7}$  in the periods of high solar activity level is considered. The comparison of obtained results with the corresponding NOAA data demonstrated very good compliance of forecast errors estimates. This testifies, apparently, to impossibility of further increasing the accuracy of solar activity forecasting with the modern level of knowledge of its nature.

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## Biographies

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