Investigation of the dynamical-stochastic algorithm for ultra short-term forecast of meteorological fields

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The results of studying a modified dynamical-stochastic algorithm for ultra short-term forecast based on the Kalman filtering and the 2-D regression model, are presented. The modified algorithm efficiency (relative to the initial one) as applied to the air temperature and wind is estimated based on the radiometric and sodar measurements.

At present, considerable study is given to the ultra short-term forecast of parameters of the atmospheric boundary layer (ABL) state. The remote sensing (lidar, radiometric, and acoustic), providing the reception of data with a high time resolution, as well as new forecast techniques realized within the limits of dynamical-stochastic approach are widely integrated into the atmospheric monitoring. One of the techniques is based on the Kalman filter algorithm and two-dimensional dynamical-stochastic model.[1] Application of the technique to the ultra short-term forecast (from 0.5 to 3 hours) of wind and temperature in ABL based on radiometric and sodar measurements has shown quite acceptable results, which can be essentially improved in case of complex modernization of the initial algorithm.

For the ultra short-term forecast, the small-parametric two-dimensional dynamical-stochastic model[1] is used

$$\xi_h(k) = \sum_{m=h-i}^{h+i} \sum_{j=1}^{K} d_{m,j}\xi_m(k-j) + \varepsilon(k), \qquad (1)$$

where $\xi_h(k)$ is the measured value of the meteorological field ξ at the height h in the moment k; $d_{m,j}$ are the unknown parameters of the model (m is the number of heights and j is the current value of the discrete time); $\xi_m(k-j)$ are the measured values for the same field at heights between $h-i$ and $h+i$ ($i = 1, 2, \ldots$ determines the number of the given heights); $\varepsilon(k)$ is the model residual conditioned by the stochasticity of atmospheric processes.

Depending on the mode of the initial data processing, the forecast can follow a single-channel or a two-channel scheme. The single-channel forecast scheme assumes the direct application of the measurements or their smoothed values in the model (1). When using the two-channel scheme, the resulting forecast estimation of the field ξ is composed of the sum of estimates of the regular field component $\bar{\xi}$, determined from the measurement data for 3–4 hours prior to the forecast, and the estimate of the fluctuation component ξ' obtained from the model (1).

Consider now the problem of the suggested dynamical-stochastic algorithm modernization for the same data of radiometric (temperature) and sodar (wind) measurements as in Ref. 1. The algorithm efficiency depends on the mode of the initial data processing, the duration of the Kalman filter continuous operation, and the length of the initial sample used as a predictor. Depending on the character of the atmospheric process, the alternative construction of the ultra short-term forecast algorithm is possible, which allows the use of either actual measurements or smoothed data (averaged over $\Delta t = 1$ h), or deviations from the regular model component in the processing of the initial information.

Figure 1 presents the behavior diagrams of root-mean-square errors in the forecast of the temperature, as well as zonal and meridional components of the wind velocity at individual altitudes for different modes of the initial data processing, depending on τ.

First, consider Fig. 1*a*, constructed for the temperature, the time variability of which is rather slow. Index 1 denotes the operation mode, when the initial measurements are smoothed (the smoothing is conducted before the measurements come to the Kalman filter). Index 2 corresponds to the processing of deviations from the regular component; and index 3 – to the processing of actual measurements. Analysis of Fig. 1*a* shows that the use of the measurements themselves (smoothed and actual) is more preferable for the forecast than their deviations. At $\tau = 3$ h, for example, the additional smoothing of the initial measurements before the processing allows a considerable decrease of the forecast error (by 0.4°C) as compared to variants 2 and 3.

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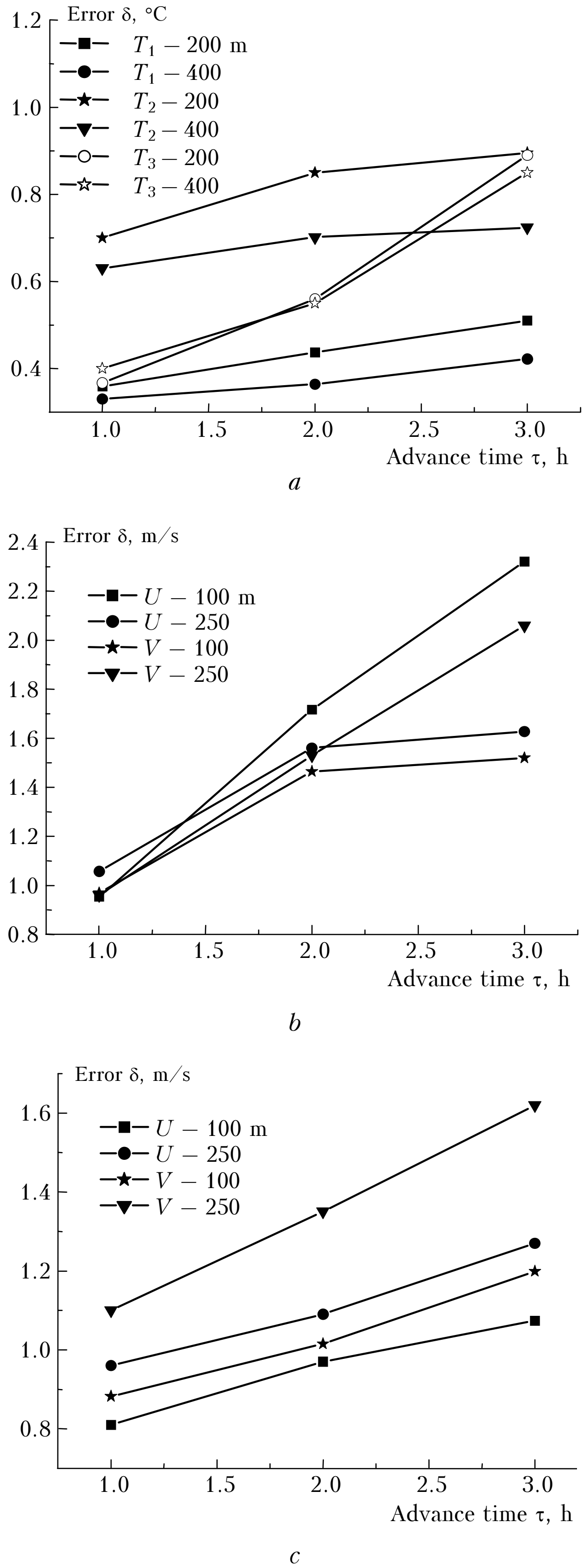

Fig. 1. Behavior of root-mean-square errors of the ultra short-term forecast for temperature (T), zonal (U) and meridional (V) components of the wind velocity depending on τ and different modes of the initial data processing.

Figures 1*b* and *c* present similar diagrams obtained for zonal (U) and meridional (V) components of the wind velocity characterized by the typical high time variability. Figure 1*b* presents the mode using actual measurements, and Figure 1*c* presents the mode using deviations from the regular component. As is seen, the deviations from the regular component are the best as the initial data when forecasting wind velocity components at $\tau = 1$–3 h. In this case, the possible gain in the forecast error, for example, at $\tau = 3$ h (independently of the height and the wind velocity component), is between 0.3 and 1.2 m/s. Further, when studying the forecast algorithm, the smoothed data are used for the temperature and deviations from the regular component for orthogonal wind velocity components.

As an example, Fig. 2 presents the behavior diagrams for ultra short-term forecast errors ($\tau = 3$ h) depending on the interval of continuous Kalman filter operation Δt_R (Figs. 2*a* and *b*) and on the length of the initial sample used in the predictor Δt_{bg} (Figs. 2*c* and *d*). As Figs. 2*a* and *b* show, it is necessary to choose the interval 2 h < Δt_R < 6 h of continuous Kalman filter operation for various atmospheric processes. Although the forecast error for temperature decreases depending on Δt_R, the gain is quite small as compared to a sharp growth of error in the case of the orthogonal components of the wind velocity. In its turn, as follows from Figs. 2*c* and *d*, the dependence of the temperature forecast error on Δt_{bg} is quite essential, moreover, at $\tau = 3$ h, the minimal error is observed at $\Delta t_{bg} \approx \tau$. At the same time, for orthogonal wind velocity components this dependence is very week.

Thus, the complex accounting for all above-mentioned ways of modernization of the ultra short-term forecast algorithm allows an essential decrease of the forecast error as compared to the initial algorithm. This is clearly seen in the table, which exemplifies values of the root-mean-square error δ for the forecast, conducted for typical heights at $\tau = 2$ and 3 h.

Height, m	Updated algorithm		Initial algorithm	
	τ = 2 h	τ = 3 h	τ = 2 h	τ = 3 h
		Temperature, °C		
200	0.4	0.5	0.6	0.9
400	0.4	0.5	0.6	0.9
		Zonal wind velocity, m/s		
100	1.0	1.1	1.6	1.9
200	1.1	1.3	2.0	2.3
		Meridional wind velocity, m/s		
100	0.8	1.2	1.8	2.1
200	1.3	1.6	1.9	2.3

For example, at $\tau = 3$ h the level of the root-mean-square error in the forecast conducted via the updated algorithm is 1.4–1.8 times lower than conducted via the initial algorithm independently of the meteorological parameters and the altitude.

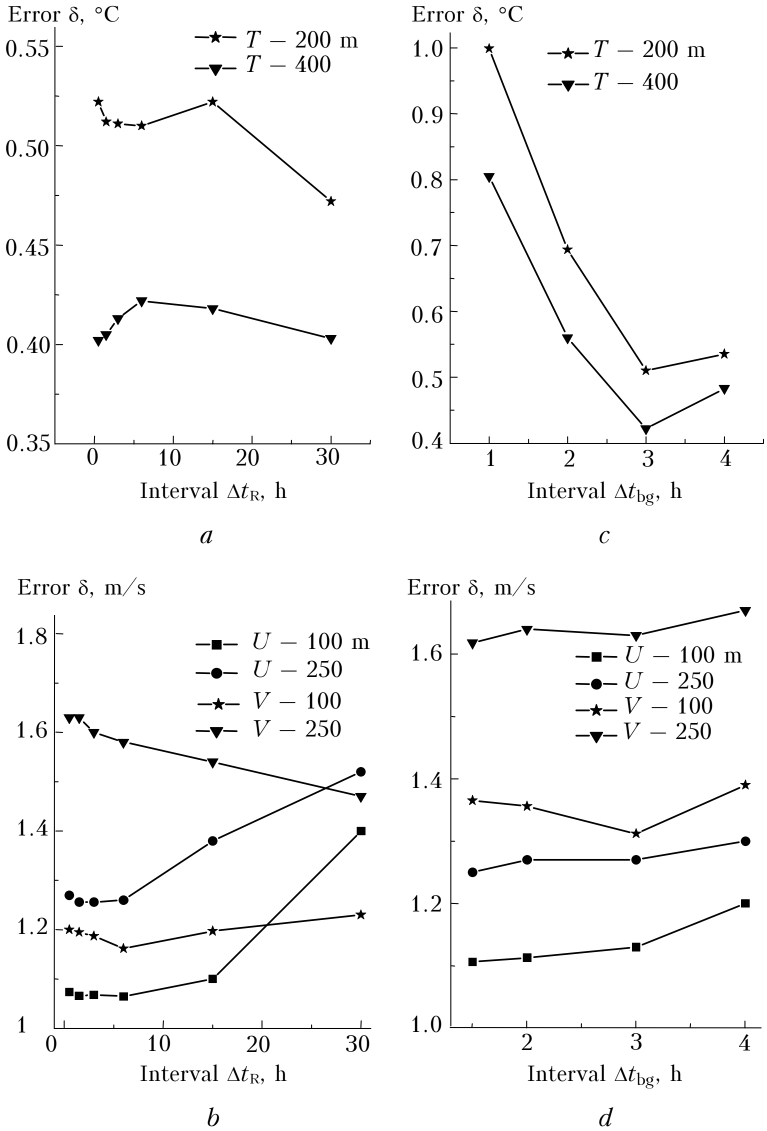

Fig. 2. Root-mean-square error behavior in the ultra short-term forecast (τ = 3 h) for the temperature (T), zonal (U) and meridional (V) wind velocity components depending on the interval of the continuous Kalman filter operation Δt_R and the length of initial consequence (Δt_{bg}) used in the predictor.

Therefore, based on the obtained results, we can conclude that the improved algorithm can be successfully used in the ultra-short-term forecast.

References

1. V.S. Komarov, S.N. Ilyin, A.V. Kremenskii, et al., Atmos. Oceanic Opt. **18**, Nos. 5–6, 432–434 (2005).