INFLUENCE OF TWO DIFFERENT ACCURACY IMPROVEMENTS TO NUMERICAL PRICE FORECASTING

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Abstract: The paper aims to compare two different strategies of accuracy improvement of studied prognostic numerical models. The price prognoses of aluminium on the London Metal Exchange were determined as the numerical solution of the Cauchy initial problem for the 1st order ordinary differential equation. To make the numerical model more accurate two ideas were realized, the modification of the initial condition value by the nearest stock exchange (initial condition drift) and different way of creation of the differential equation in solved Cauchy initial problem (using two known initial values). With regard to the accuracy of the determined numerical models, the model using two known initial values obtained slightly better forecasting results. The mean absolute percentage error of all observed forecasting terms was mostly less than 5%. This strategy was more successful in problematic price movements, especially at steep price increase and within significant changes in the price movements. Larger fluctuation of prognoses calculated by this model was disadvantageous in forecasting terms with a small error. Moderate increase of prognoses obtained by the model using initial condition drift better described price fluctuation. Both chosen strategies eliminated the forecasting terms with the mean absolute percentage error larger than 10%. Therefore, we recommend both strategies as acceptable way for commodity price forecasting.

1   Introduction

Forecasting the prices of metals is important in many aspects of economics. Non-ferrous metals are indispensable industrial material and strategic supports of national economic development. Therefore, the price forecasting of metals is critical for researchers. The forecast on commodity prices usually takes into account predictive mathematical models [1-23]. There are a lot of different approaches to forecasting and improvements of specific forecasting algorithms. Statistical models usually based on time series analysis are often used [4,7,10,20-22]. Recently statistical models with multi-objective programming for non-linear time series [18], different strategies for automatic lag selection in time series analysis [5] and functional time series analysis [2,8] are mostly proposed. There are a lot of novel hybrid methods to forecast commodity prices consisting of the classical GARCH model and neutral network model to boost the prediction performance [9]. The analytic network process is one of the multi-criteria decision-making methods widely used to solve various issues in the real world of financial management [1,3,11,23]. The method for time series analysis are also combined by adding stochastic term to the first-order differential equation. Solution of this equation represents the time response function which is capable of creating evolving path of the commodity price [6]. Deep learning models and a new intelligent system, namely group method of data handling are quickly developing for prediction of commodity prices [3,17,19].

Our prognostic models are based on numerical modelling using numerical solution of the Cauchy initial problem for the 1st order ordinary differential equations [12-16]. Observed numerical models used publicly available aluminium prices on the London Metal Exchange (LME) [24] collected from December 2002 to June 2006. The monthly averages of the daily closing aluminium prices "Cash Seller&Settlement price" (in US dollars per tonne) were worked on, see Figure 1.
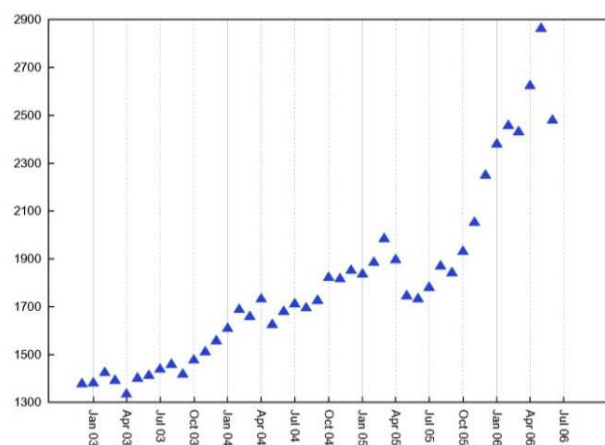

Figure 1 Course of the aluminium prices on LME in the years 2003 – 2006 [13-16]

2   Mathematical models

In previous papers [13-17] we interested in finding improvements of created numerical models. Based on obtained results, the most accurate prognostic models were selected. In both models, the model using initial condition

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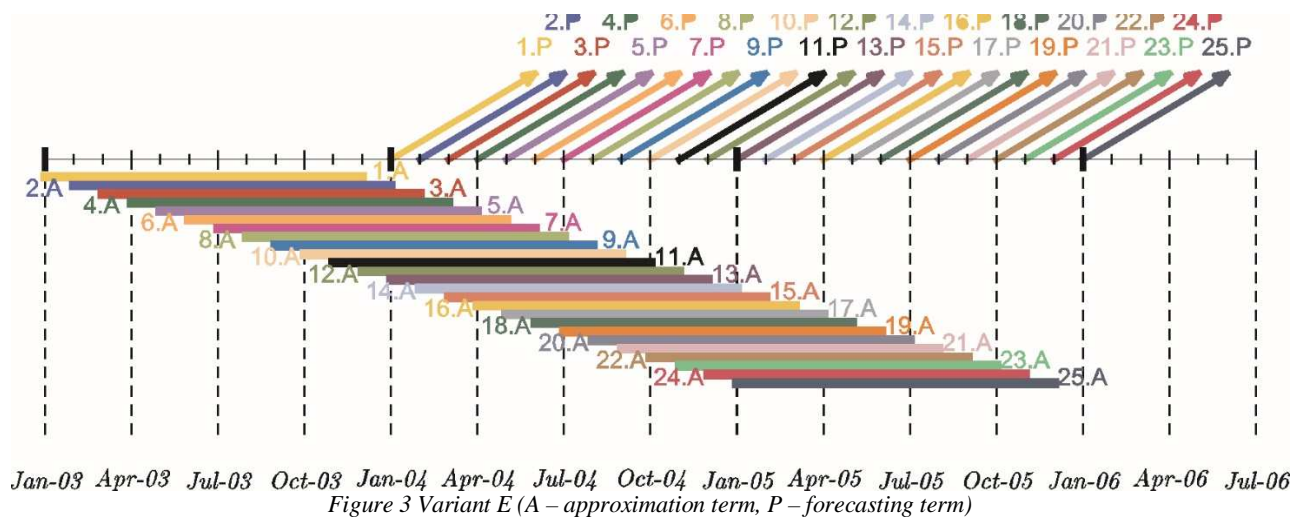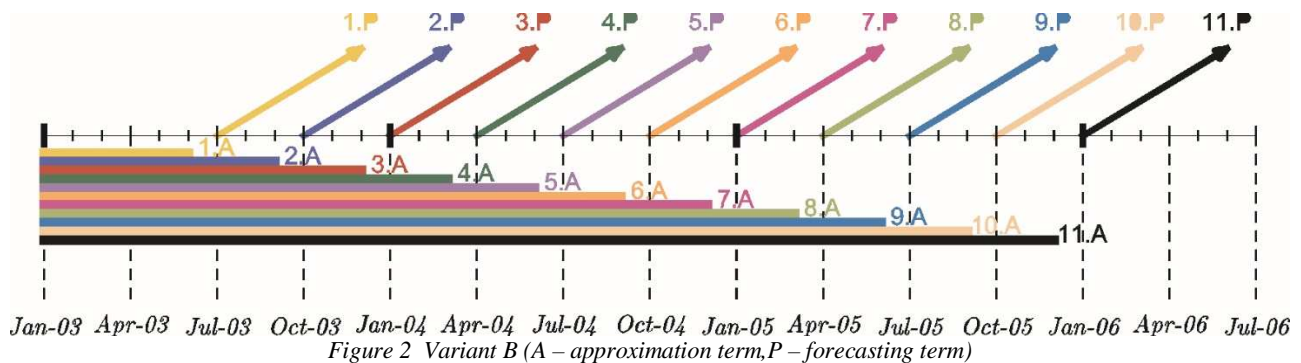drift and the model using two known initial values, the Cauchy initial problem in the form

$$y' = a_1 y, \quad y(x_0) = y_0 \qquad (1)$$

was considered. The particular solution of the problem (1) is in the form $y = k\, e^{a_1 x}$, where $k = y_0\, e^{-a_1 x_0}$.

The exponential trend was chosen according to the test criterion of the time series' trend suitability. The values $\ln(Y_{i+1}) - \ln(Y_i)$, for $i = 0, 1, ..., 42$, have approximately constant course, where Y_i was the aluminium price (stock exchange) on LME in the month x_i.

In the model using initial condition drift the coefficient a_1 was obtained by approximating the prices of the approximation term by the least square's method. Let us consider two different ways of the approximation terms' creation, variant B and variant E, [13-16], see Figure 2 and Figure 3.

Figure 2 Variant B (A – approximation term, P – forecasting term)

Figure 3 Variant E (A – approximation term, P – forecasting term)

According to the acquired approximation function $\tilde{y} = a_0 e^{a_1 x}$, the Cauchy initial problem (1) was written in the model using initial condition drift in the form

$$y' = a_1 y, \quad y(x_i) = Y_i, \qquad (2)$$

where $x_i = i$ was the last month of the approximation term, Y_i was the stock exchange in the month x_i.

In the model using two known initial values, two known points $[x_{i-1}, Y_{i-1}]$ and $[x_i, Y_i]$ were considered, where x_{i-1}, x_i were the orders of the month and Y_{i-1}, Y_i were stock exchanges in the months x_{i-1}, x_i. That means $[x_i, Y_i]$ were the values corresponding to the next month in comparison with those of $[x_{i-1}, Y_{i-1}]$. Substituing points $[x_{i-1}, Y_{i-1}], [x_i, Y_i]$ to the general solution of the problem (2) we acquired $Y_i = Y_{i-1} e^{a_1(x_i - x_{i-1})}$.

After some manipulation the formula of unknown coefficient a_1 was determined

$$a_1 = \frac{1}{x_i - x_{i-1}} ln\left(\frac{Y_i}{Y_{i-1}}\right).$$

Substituting a_1 to the Cauchy initial problem (2) we obtained

$$y' = \frac{1}{x_i - x_{i-1}} ln\left(\frac{Y_i}{Y_{i-1}}\right) y, \quad y(x_i) = Y_i. \qquad (3)$$

for $i = 1, 2, 3, ...$

The unknown values of aluminium prices were computed by the numerical solution of the Cauchy initial problems (2) and (3) by means of the numerical method [25]. The method used the following numerical formulae

$$x_{i+1} = x_i + h,$$

$$y_{i+1} = y_i + bh + Q e^{v x_i}\left(e^{vh} - 1\right),$$

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for $i = 1, 2, 3, \ldots$, where $h = x_{i+1} - x_i$ was the constant size step. The unknown coefficients were calculated by means of these formulae $v = \dfrac{f''(x_i, y_i)}{f'(x_i, y_i)}$,

$Q = \dfrac{f'(x_i, y_i) - f''(x_i, y_i)}{(1-v)\, v^2 e^{vx_i}}$, $b = f(x_i, y_i) - \dfrac{f'(x_i, y_i)}{v}$.

In both determined models daily forecasting was used. The interval $\langle x_i, x_{i+1} \rangle$ of the length $h = 1$ month was divided into n parts, where n is the number of trading days on LME in the month x_{i+1}. We gained the sequence of the division points $x_{i0} = x_i$, $x_{ij} = x_i + \dfrac{h}{n} j$, for $j = 1, 2, \ldots, n$, where $x_{in} = x_{i+1}$. For each point of the subdivision of the interval, the Cauchy initial problem in the form (2) or (3) was solved. By calculating the arithmetic mean of obtained daily prognoses, the monthly prognosis of the stock exchange in the month x_{i+1} was obtained. Thus, $y_{i+1} = \dfrac{\sum_{j=1}^{n} y_{ij}}{n}$. Daily forecasting corresponds to creation of the monthly averages of daily closing aluminium prices on LME.

In the model using two known initial values by means of two known points $[x_{i-1}, Y_{i-1}]$ and $[x_i, Y_i]$ the prognosis y_{i+1} in the month x_{i+1}, $i = 1, 2, 3, \ldots$, was calculated. In this way price prognoses in the months from February 2003 to June 2006 were gradually determined. In the model using initial condition drift the prognoses within six months following the end of the approximation term were forecasted. The accuracy of the model was improved by changing initial condition value y_{i+s}, $s = 1, 2, \ldots, 5$ by the stock exchange Y_{i+s-1}, if the absolute percentage prognosis error in the month x_{i+s} exceeded chosen value 7%. Otherwise, the initial condition value in the month x_{i+s} was replaced by calculated monthly prognoses y_{i+s} [13-16].

To compare the forecast accuracy in different forecasting terms of the length six months, the mean absolute percentage error (MAPE) $\overline{p} = \dfrac{\sum_{s=1}^{t} |p_s|}{t}$ was

determined [13-16]. Let consider the absolute percentage error $|p_s| = \dfrac{|y_s - Y_s|}{Y_s} . 100\,\%$, which told us how close the calculated prognosis was y_s in the month x_s to the real stock exchange Y_s. The price prognosis y_s is acceptable in practice, if $|p_s| < 10\,\%$. Otherwise, it is called critical forecasting value [12-16].

3 Results and discussion
3.1 Results of determined numerical commodity price forecasting

In previous research we dealt with improvement of the created numerical models by increasing their forecasting accuracy. The first way of improvement, used in the model using initial condition drift, was based on changing the value of the initial condition in solved Cauchy initial problem. The most accurate were the models in which the stock exchange was used as a value of the initial condition. Observing different ways of changing the initial condition value, we have found out that replacing the initial condition value by the stock exchange, which was the nearest to month where the initial condition drift was occurred, was the most successful. That allowed to put calculated prognoses closer to the real stock exchanges and significantly improved forecasting results [13-16].

Another way of improvement of the forecasting process, used in the model using two known initial values, was trying to find different way of creating of the differential equation in the form $y' = a_1 y$. The coefficient a_1 in the Cauchy initial problem calculating prognosis in the month x_{i+1}, was determined by using two known points $[x_{i-1}, Y_{i-1}]$ and $[x_i, Y_i]$, where Y_{i-1} and Y_i were known stock exchanges in previous months x_{i-1} and x_i. Comparing the values of prognoses obtained by the model with real stock exchanges, we have found out that predictions of this model were also satisfactory [12].

Within studied group of 36 forecasting terms of variants B and E, see Figure 2 and Figure 3, the success of the determined models was studied. In both observed models, the MAPE and number of critical values were determined for each forecasting term. Obtained results are shown in Figure 4 and Figure 5.

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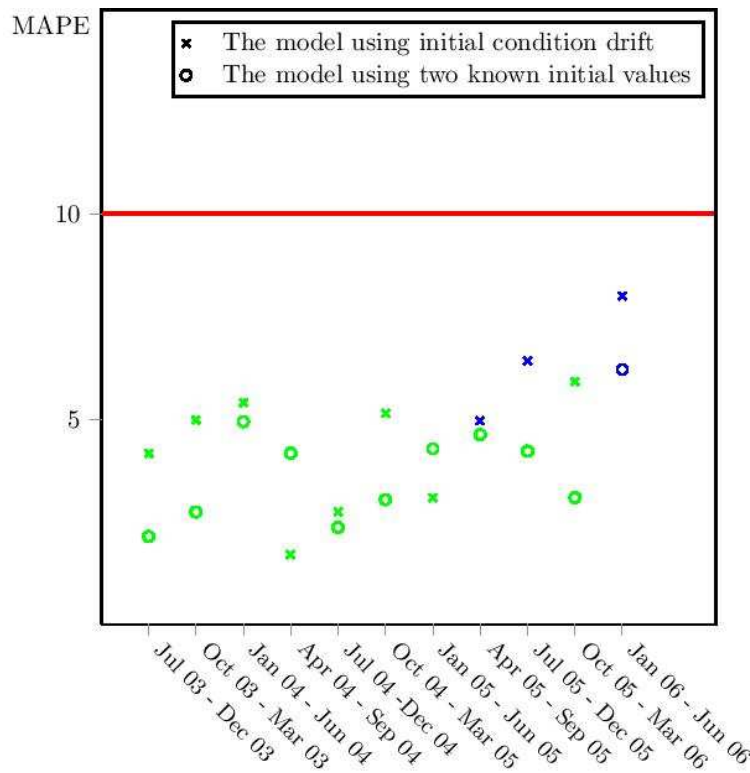Marcela Lascsáková

Figure 4 The mean absolute percentage errors for chosen mathematical models - variant B.
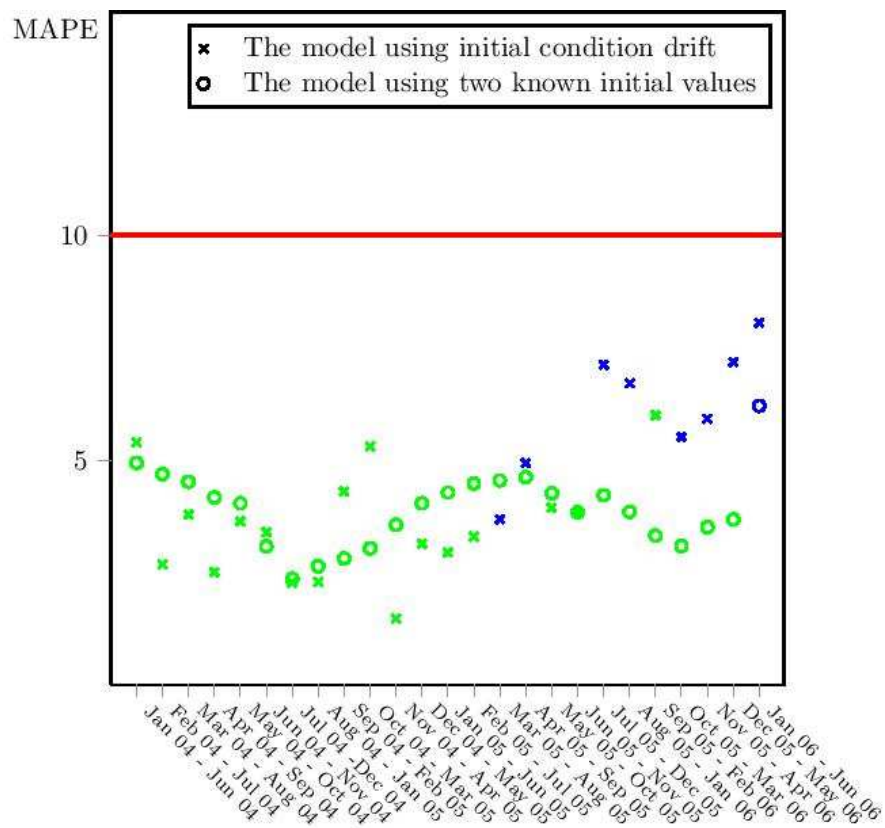

Figure 5 The mean absolute percentage errors for chosen mathematical models - variant E.

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In order to compare forecasting results in both variants B and E, the arithmetic mean of MAPEs was determined. We also dealt with specifying the most accurate model for each forecasting term. The forecasting success of determined mathematical models within the forecasting terms is visible in Table 1 and Table 2.

Table 1 The success rate of determined mathematical models - variant B.

Criterion	The model using initial condition drift	The model using two known initial values
The arithmetic mean of MAPE	4.77%	4.00%
The number of the most accurate price prognoses	2	9
The number of the critical values	4	1
The number of MAPE at least 10%	0	0

Table 2 The success rate of determined mathematical models - variant E.

Criterion	The model using initial condition drift	The model using two known initial values
The arithmetic mean of MAPE	4.37%	3.91%
The number of the most accurate price prognoses	13	13
The number of the critical values	9	1
The number of MAPE at least 10%	0	0

The tables show the model using two known initial values slightly more accurate. This model, in both variants B and E, acquired lower arithmetic mean of MAPEs of all forecasting terms. In variant B, containing 11 forecasting terms, the model was more successful than the model using initial condition drift 9 times. Considering variant E, in which 25 forecasting terms were observed, success of both numerical models was identical. Both models obtained better results in comparison to the other 13 times. In one forecasting term the same results in both models were gained.

The forecasting success of the model using two known initial values was also indicated by lower number of critical values. These values pointed at the months and price movements in which forecasting failed. By the model using two known initial values, there was only one prognosis, in both variants B and E, with absolute percentage error exceeded 10%. It was prognosis in June 2006, when aluminium price steeply increased, so forecasting could not follow it. Prognoses calculated by the model using initial condition drift obtained absolute percentage error at least

10% in variant B four times and in variant E nine times. The cause of forecasting fail was the rapid significant change in the price course. Within these months occurred either rapid price decrease after price increase (1 critical value in variant B and 2 critical values in variant E) or rapid price increase after price decline (3 critical values in variant B and 7 critical values in variant E). The larger were changes, the higher errors of the prognoses were gained. In both considered models there was no forecasting term, where the mean absolute percentage error exceeded 10%. This parameter pointed at periods and price movements in which forecasting was unacceptable.

Better forecasting results of the model using two known initial values were also confirmed by the distribution number of the forecasting terms according to their mean absolute percentage error, see Table 3 and Table 4.

Table 3 Distribution of the number of the forecasting terms according to their MAPE - variant B.

MAPE	The model using initial condition drift	The model using two known initial values
< 5%	6	10
⟨5%, 7,5%)	4	1
⟨7,5%, 10%)	1	0
≥ 10%	0	0

Table 4 Distribution of the number of the forecasting terms according to their MAPE - variant E.

MAPE	The model using initial condition drift	The model using two known initial values
< 5%	16	24
⟨5%, 7,5%)	8	1
⟨7,5%, 10%)	1	0
≥ 10%	0	0

Tables clearly show, that by means of the model using two known initial values more forecasting terms with lower MAPE were acquired than by the model using initial condition drift. All forecasting terms calculated by the model using two known initial values acquired MAPE less than 7.5%. Mostly the mean absolute percentage error was less than 5%, 10 forecasting terms in variant B and 24 forecasting terms in variant E. There was just one forecasting term with MAPE in the interval ⟨5%, 7.5%), the forecasting term *January 2006 – June 2006* with MAPE 6.21% in both variants B and E. Within this forecasting term aluminium prices were steeply fluctuating.

Consider the model using initial condition drift, there were less forecasting terms in intervals with lower MAPE. The most accurate forecasting, with MAPE less than 5%, was obtained in 6 forecasting terms of variant B and in 16 forecasting terms in variant E. Higher forecasting inaccuracies, MAPE from interval ⟨5%, 7.5%), occurred also quite often, in 4 forecasting terms in variant B and in 8 forecasting terms in variant E. The least accurate was forecasting also in the forecasting term *January 2006 – June 2006,* with MAPE 8.00% in variant B and 8.06% in variant E.

Let us observe the forecasting success of the determined numerical models by means of distribution of the number of the forecasting terms with different error rate. Based on the prognosis accuracy analysis of models, the forecasting terms were classified into three classes [13,15]. In trouble free forecasting terms forecasting was the most accurate due to the fact that no critical value was obtained in these terms. In the second group there were forecasting terms with a small error, in which some critical value was acquired by forecasting, but MAPE of the forecasting term was less than 10%. Forecasting failed in forecasting terms with a big error, where MAPE was at least 10%. Distribution of number of the forecasting terms in these determined groups, in both variant B and E, is shown in Table 5 and Table 6. In Figure 4 and Figure 5 trouble free forecasting terms are green, forecasting terms with a small error are blue and forecasting terms with a big error are red.

Table 5 Distribution of the number of the forecasting terms in determined groups - variant B.

Type of forecasting term	The model using initial condition drift	The model using two known initial values
Trouble free forecasting terms	8	10
Forecasting terms with a small error	3	1
Forecasting terms with a big error	0	0

Table 6 Distribution of the number of the forecasting terms in determined groups - variant E.

Type of forecasting term	The model using initial condition drift	The model using two known initial values
Trouble free forecasting terms	17	24
Forecasting terms with a small error	8	1
Forecasting terms with a big error	0	0

Forecasting by means of both models was so accurate that there were no forecasting term with a big error. That fact pointed at suitable forecasting accuracy within complicated price movements. The problematic forecasting, which appeared in forecasting term with a small error, was observed just in one forecasting term using forecasting by two known initial values in both variant B and variant E. If prognoses were calculated by the model using initial condition drift, there were 3 forecasting terms in variant B and 8 forecasting terms in variant E with a small error. Mostly forecasting by means of both determined models was so accurate that all calculated prognoses were less than 10%.

3.2 Discussion about the success of observed numerical models

Let analyse the forecasting success of determined numerical models. Comparing the prognoses of both types of forecasting and stock exchanges within observed periods we have found out different strategies of the forecasting errors' correction. In the model using initial condition drift the stock exchanges in approximation term were approximated by the least square's method. In variant B longer approximation terms than in variant E were used. Obtained exponential approximation function $\tilde{y} = a_0 e^{a_1 x}$ determined differential equation in the form $y' = a_1 y$, which affected rate of an increase or a decrease of calculated prognoses. Usually, the approximation terms with a price increase belonged to the observed forecasting terms. Therefore, calculated prognoses were increasing too. Using longer approximation terms, a prognoses increase was more moderate, so forecasting did not react so strongly to fluctuation in the price evolution. On contrary, forecasting in variant E was based on shorter approximation terms. Therefore, calculated prognoses increased or decreased steeper and forecasting responded to changes in the price source. Within the most problematic forecasting terms a steep price increase and changes in price movements usually occurred. The forecasting errors in the model using initial condition drift were so high, that the initial condition drift was necessary for an approach to the real stock exchanges. After initial condition drift the next calculated prognoses were immediately put closer to the values of the stock exchanges, what significantly improved forecasting. But approaching to real stock exchanges was gradual and slower in comparison to forecasting by the model using two known initial value.

Forecasting by the model using two known initial value was usually more advantageous due to different strategy of forecasting. The computed prognosis kept the trend of two previous initial stock exchanges in the months x_{i-1} and x_i. It means, these relations hold $Y_{i-1} < Y_i < y_{i+1}$, $Y_{i-1} > Y_i > y_{i+1}$, respectively. The success of the forecasting by this model depended on the intensity of either an increase or a decrease in three observed months x_{i-1}, x_i and x_{i+1}. The steeper increase or decrease in the price course was occurred, that means inequality $|Y_{i+1} - Y_i| > |Y_i - Y_{i-1}|$ was larger, the more successful was forecasting by the model using two known initial value. The calculated

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prognoses immediately approach steep price increase and also changes in the price course.

Within forecasting terms with a small error moderate fluctuation often appeared. Moderate changes in the price course caused larger fluctuation of the prognoses calculated by the model using two known initial value. Otherwise, within moderate fluctuation the absolute prognoses errors were smaller, so the initial condition drift did not occur in the model using initial condition drift. An increase of calculated prognoses was moderate and better described price fluctuation. Therefore, moderate forecasting by the model using initial condition drift became usually more accurate within moderate fluctuation.

4 Conclusions

The main purpose of this paper was comparing the performance of two successful alternative strategies of commodity price forecasting. The findings of this research work are in line of previous studies. Both models were created as improvements of our less accurate prognostic numerical models. Their forecasting success was indicated by reducing unacceptable forecasting results. Using these forecasting strategies, no forecasting term with MAPE larger than 10% was acquired. Although, the analysis indicated similar forecasting results, observed parameters were slightly better for the model using two known initial values. The arithmetic mean of MAPE and number of critical values were lower than in the model using initial condition drift. There were also more forecasting terms with lower MAPE.

Comparing the values of prognoses obtained by determined models, we have found out that prognoses determined by the model using two known initial values were more often changing than prognoses of the model using initial condition drift. Therefore, the strategy of using two known initial value was more suitable within problematic price movements, which caused higher forecasting errors. We recommend using this model especially at steep price movements and significant changes in the price course. If the price course was moderate, gradually changing prognoses of the model using initial condition drift obtained lower prognoses errors.

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