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IMPACT OF DIFFERENT PRICE MOVEMENTS ON THE ACCURACY OF NUMERICAL PRICE FORECASTING

Marcela Lascsáková
Technical University of Kosice, Faculty of Mechanical Engineering, Department of Applied Mathematics and Informatics, Letná 9, 042 00 Košice, Slovak Republic, EU, marcela.lascsakova@tuke.sk

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Abstract: The focus of this paper aims at comparison of two prognostic numerical models with different strategies for accuracy improvement. To verify prediction performance of proposed models, the forecasts of aluminium stock exchanges on the London Metal Exchange were carried out as numerical solution of the Cauchy initial problem for the first-order ordinary differential equation. Two techniques for accuracy improvement were utilized, replacing the initial condition value by the nearest known stock exchange and a modification of the differential equation in solved Cauchy initial problem by means of two known initial values. We dealt with an idea of how different price development affected the accuracy of proposed strategies. With regard to obtained results, it was found that the prognoses obtained by using two known initial values were more increasing or decreasing than prognoses calculated by utilizing the initial condition drift. The strategy of a changing form of the differential equation in the Cauchy initial problem can be considered slightly more accurate. Faster increased prognoses were more advantageous especially at a steep price increase and within a price increase following the price decline. A moderate increase of the prognoses determined by the initial condition drift fit reasonably well a price fluctuation and a price decline following the price increase.

1 Introduction

Non-ferrous metals are widely used in many different industries. The predictions of metal prices can provide references of future investments and make the right decisions in the industry. Therefore, commodity price forecasting is very important and active area of research in recent times, although forecasting metal prices with reasonable accuracy is complicated by their cosiderable variability and uncertainty. It made forecasting extremely difficult. In view of this difficulties in accurately forecasting, different types of predictive mathematical models are utilized. The prediction of the future is often done by means of statistical models based widely on time series [1-4]. Recently statistical models with multi-objective programming for non-linear time series [5], different strategies for automatic lag selection in time series analysis [6] and functional time series analysis [7,8] are mostly proposed. There are a lot of novel hybrid methods to forecast commodity prices consisting of the classical GARCH model and neural network model to boost the prediction performance [9,10]. The methods 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 [11]. New tools from machine learning, artificial intelligence based on neural network and adaptive neuro-fuzzy systems complement traditional methods [12-17].

Our research has been focused on development of alternative approaches to metal price forecasting. The forecasting process was decribed by the Cauchy initial problem for the first-order ordinary differential equation [18-21]. The numerical solution of corresponding Cauchy initial problem provided metal price forecasts.

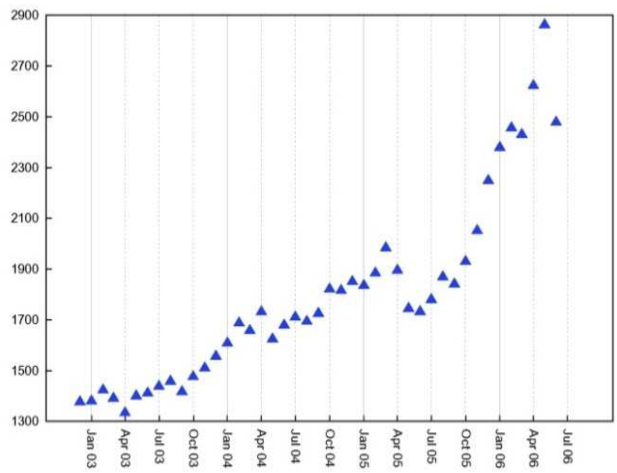

Figure 1 Aluminium price development on LME in the years 2003 – 2006 [18-21]

The forecasting problem in data set of the monthly averages of the daily closing aluminium prices "Cash Seller&Settlement price" (in US dollars per tonne) were examined. The data of our theoretical interest included publicly available aluminium prices on the London Metal Exchange (LME) collected from December 2002 to June 2006 [22]. As can be seen in Figure 1 the course of aluminium prices within considered period changes dramatically. Therefore, observed data period was advantageous for assessing the accuracy of alternative price forecasting within different price movements.

Non-ferrous industrial metal aluminium was determine as the objective of our research. It has a high strength-to-weight ratio combined with excellent thermal conductivity and good corrosion resistance. It is also recyclable metal. Therefore, aluminium is an attractive material for many applications, including transportation, electrical and packaging industries. It is considered a symbol of modernity. Present applications of aluminium include 3D printing, composite materials, nano-roads, biomedicine devices and aerospace uses [23].

2 Mathematical models

In our previous research [18-21] we proposed several prognostic numerical models and verified their forecast performance. Based on obtained results, the most accurate prognostic approaches were selected. Considered successful forecasting strategies were presented in two models, the model using initial condition drift [19-21] and the model using two known initial values [18,21]. All our studied numerical models were based on solving the Cauchy initial problem in the form

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

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

In the model using initial condition drift the coefficient a_1 was gained by approximating the aluminium stock exchanges of the approximation term by the least squares method. Let us consider two different ways of the approximation terms' creation, variant B and variant E [19-21]. In variant B the first approximation term was period January 2003 – June 2003. The next approximation terms were created by sequential extension of this period by three months, see Figure 2. As can be seen in Figure 3, the length of approximation terms was constant. Each approximation term of length of twelve months was shifted by one month.

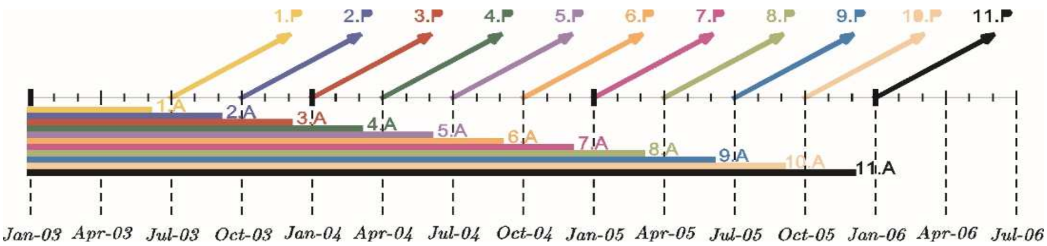

Figure 2 Variant B (A – approximation term,P – forecasting term) [19-21]

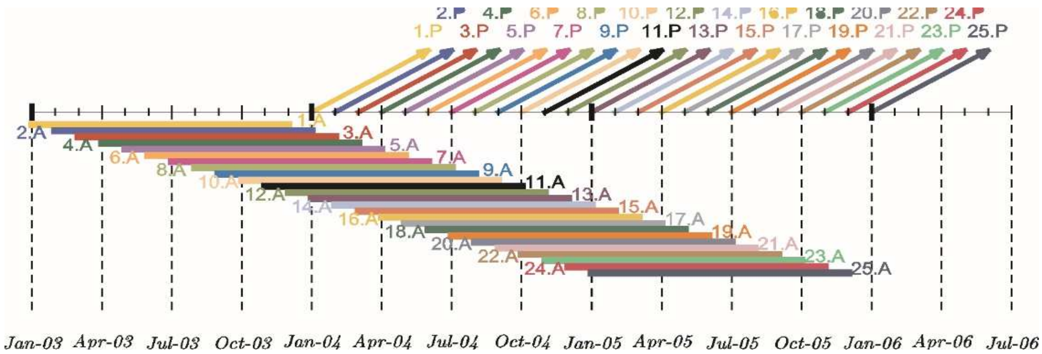

Figure 3 Variant E (A – approximation term,P – forecasting term) [19-21]

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

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

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. Substituting points $[x_{i-1}, Y_{i-1}]$, $[x_i, Y_i]$ to the general solution of the problem (2) we gained

$$Y_i = Y_{i-1} e^{a_1 (x_i - x_{i-1})}.$$

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 (3)

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

for $i = 1, 2, 3, \ldots$

The unknown values of aluminium prices' prognoses were computed by means of the numerical method, which used the following numerical formulae [24]

$$x_{i+1} = x_i + h,$$
$$y_{i+1} = y_i + bh + Qe^{vx_i}\left(e^{vh} - 1\right),$$

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 [18-21]. We form a monthly prognosis in the month x_{i+1} by calculating the arithmetic mean of obtained daily prognoses. Thus, $y_{i+1} = \dfrac{\sum_{j=1}^{n} y_{ij}}{n}$. In the model using initial condition drift the monthly prognoses within six months following the end of the approximation term were determined. In the model using two known initial values by means of two known points $[x_{i-1}, Y_{i-1}]$ and $[x_i, Y_i]$ just one the prognosis y_{i+1} in the month x_{i+1}, for $i = 1, 2, 3, \ldots$, was calculated.

To compare the real data Y_S with calculated prognosis y_s, the absolute percentage error $|p_s| = \dfrac{|y_s - Y_s|}{Y_s}.100\,\%$ was computed. The price prognosis y_s is acceptable in practice, if $|p_s| < 10\,\%$. Otherwise, it is called critical value [18-21]. In the following figures (Figure 4, 5, 6, 7, 8, 9 and 10), critical values are red. If the prognosis was not critical value, but its absolute percentage error was greater than 7%, then that is blue. The prognoses with the absolute percentage error less than 7% are green. To evaluate effectiveness of forecasting in different forecasting terms of the length of six months, traditional statistical metrics, the mean absolute percentage error (MAPE), $\overline{p} = \dfrac{\sum_{s=1}^{t} |p_s|}{t}$, was utilized [19-21].

3 Results and discussion

3.1 Results of proposed numerical commodity price forecasting

Among all our proposed approaches consisted in formation of the numerical price forecasts two the most acceptable numerical prognostic models were found. The objective of this study is to compare the performance of two suggested accuracy improvements within numerical forecast. The first way of improvement, used in the model using initial condition drift, was focused on changing the value of the initial condition in solved Cauchy initial problem within forecasting process. Based on previous research [19], it has found that replacing the initial condition value y_{i+s}, for $s = 1, 2, \ldots, 5$ by the stock exchange Y_{i+s-1}, in case that the absolute percentage prognosis error in the month x_{i+s} exceeded chosen value 7%, was the most accurate. Otherwise, the initial condition value in the month x_{i+s} was changed by evaluated monthly prognosis y_{i+s}. This initial condition drift allowed to fit reasonably well the real stock exchanges and significantly improved the accuracy of predictions.

Another improvement of the forecasting process, used in the model using two known initial values, was relying on the creation of the new differential equation in the form $y' = a_1 y$ for each calculated prognosis. The coefficient a_1 in the Cauchy intial problem was determined by utilizing 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. It allowed to calculate just one prognosis in the month x_{i+1}. To determine next prognosis y_{i+2}, a new form of the differential equation was acquired by calculating a new value of the coefficient a_1 [18].

Within considered group of 36 forecasting terms of variants B and E, see Figure 2 and Figure 3, the forecasting performance of two studied numerical models was investigated. To confirm the effecienty of proposed models the most accurate numerical model was defined for each forecasting term [21]. The forecasting success of chosen numerical forecasting strategies is shown in Table 1. The analysis reported in previous research [21] show that prediction performance of the model using two known initial values was higher, especially in variant B. This strategy acquired the lowest MAPE in 21 forecasting terms. In one forecasting term the same results in both determined models were obtained. On the other hand, the model using initial condition drift was the most successful in 14 forecasting terms.

Comparing the values of calculated prognoses and stock exchanges within observed forecasting terms in two chosen numerical models we have found that the prognoses determined by the model using two known initial values were more increasing or decreasing than prognoses calculated by the model using initial condition drift [21]. They were able to immediately change their course. The computed prognosis followed the trend of two previous initial stock exchanges in the months x_{i-1} and x_i, $Y_{i-1} < Y_i < y_{i+1}$, $Y_{i-1} > Y_i > y_{i+1}$, respectively. The forecasting performance depended on the intensity of either an increase or a decrease of the stock exchanges within three observed months x_{i-1}, x_i and x_{i+1}. The steeper the increase or decrease in the price development was, that means the difference $|Y_{i+1} - Y_i| - |Y_i - Y_{i-1}|$ was larger, the more effective was forecasting by the model using two known initial value [18].

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Table 1 The success rate of determined mathematical models

	The model using initial condition drift	The model using two known initial values
Variant B	2	9
Variant E	13	13
Total	15	22

As can be seen in Figure 2, in variant B longer approximation terms than in variant E were used. Obtained exponential approximation functions $\tilde{y} = a_0 e^{a_1 x}$ which determined differential equations in the form $y' = a_1 y$ affected the rate of an increase or a decrease of calculated prognoses in the model using initial condition drift. Using longer approximation terms of variant B a prognoses increase was more moderate. It was often more disadvantageous than steeper increasing prognoses calculated by the model using two known initial values. On the contrary, there were shorter approximation terms in variant E, see Figure 3. Thus, calculated prognoses in the model using initial condition drift increased or decreased steeper. It was the reason why differences in the forecasting success of chosen numerical models became smaller.

Let analyze the forecasting effectiveness of two determined numerical models within different price evolution. We were interested wheather the price movements affected accuracy of two chosen forecasting strategies. The forecasting terms of variants B and E were divided into groups with the same type of the price movement. Within these groups, for each forecasting term the model with lower MAPE value was found. The forecasting effectiveness of proposed mathematical models is illustrated in Table 2 and Table 3.

Table 2 Distribution of the number of forecasting terms in groups of price movement - variant B

	The model using initial condition drift	The model using two known initial values
Stable price increase	0	3
Significant fluctuation	1	3
Price decline following the price increase	1	1
Price increase following the price decline	0	2

Table 3 Distribution of the number of forecasting terms in groups of price movement - variant E

	The model using initial condition drift	The model using two known initial values
Stable price increase	1	2
Significant fluctuation	6	3
Price decline following the price increase	5	1
Price increase following the price decline	1	7

The results confirm higher forecasting effectiveness of the model using two known initial values in both variants B and E within a stable price increase, and when the change in the price development lasted longer, as could be seen in a price increase following the price decline. Within these price movements, the model using two known initial values was more accurate 13 times in both variants. There was only one forecasting term when the model using initial condition drift was more suitable. The same results by both numerical models were obtained in one forecasting term. When the change in the price development was short, more advantageous was the model using initial condition drift. That can be seen within a price decline following the price increase, when better results were obtained by the model using initial condition drift six times. Otherwise, forecasting by the model using two known initial values was more accurate in two forecasting terms. Also significant fluctuation in variant E, using shorter approximation terms, was not always suitable for the forecasting strategy used in the model using two known initial values. In 2/3 of the forecasting terms with significant fluctuation in variant E the model using initial condition drift was more appropriate. In variant B, where longer approximation terms were used, forecasting by the model using two known initial values became more accurate. This strategy was more successful in 3/4 of the forecasting terms with significant fluctuation in variant B.

3.2 Discussion about the forecasting success of the model using two known initial values

Let analyze the forecasting success of a more successful numerical model, that is the model using two known initial values. The significant property of this forecasting was steeply changing calculated prognoses. It was more advantageous in the following price movements

- **a stable price increase**

If a price increase was steep, the absolute percentage prognoses errors increased with time. If they exceeded 7%, the initial condition drifts occurred. That was necessary for an approach to the real steeply increasing stock exchanges and remarkably improved forecasting by the model using initial condition drift. But approaching to real stock exchanges was gradual and slower in comparison to forecasting by the model using two known initial value. The advantage of using two known values was based on steeper increasing prognosis following the increasing trend of two previous initial stock exchanges. The steeper an increase in the price development was, the higher was an increase of the prognosis. Therefore, forecasting was able to faster accommodate to a steep increase of the stock exchanges in the forecasting terms.

Within the period *October 2003 – March 2004* (see Figure 4), due to a steep increase, forecasting by the model using initial condition drift failed in two months of the period (December 2003, February 2004). Using the initial condition drifts, MAPE declined from 9.44% to 4.98%. MAPE of this forecasting term by utilizing the model using two known initial values was 2.74%. As shown in Figure 4, a prognoses increase in the model using two known initial values was higher in comparison to the model using initial condition drift. That made forecasting more successful.

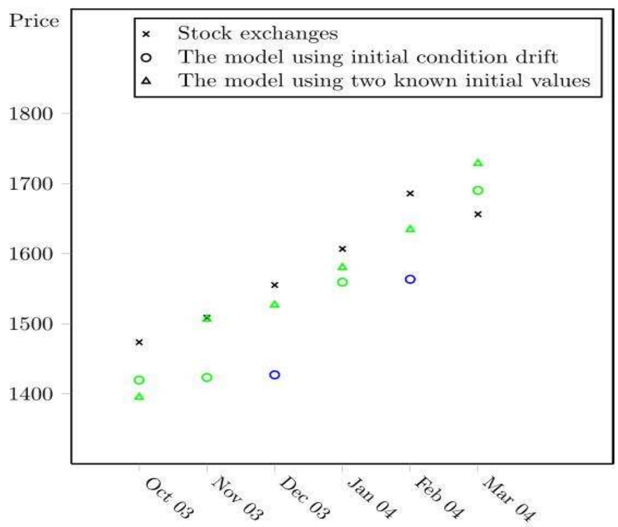

Figure 4 Forecasting by the numerical models within October 2003 – March 2004 (variant B)

If an increase of stock exchanges was moderate, forecasting by the model using two known initial values was also more advantageous. Moderate increasing prognoses calculated by the model using initial condition drift obtained the absolute percentage prognoses errors less than 7%, so the initial condition value was not replaced by the stock exchange. That made the absolute percentage prognoses errors increased with time. On the other hand, steeper increasing prognoses in the model using two known initial values showed better forecasting results. A moderate increase was presented in the forecasting term *July 2003 – December 2003* (see Figure 5). The initial condition drift did not occur, thus MAPE of this forecasting term was higher, 4.17%. More convenient forecasting by the model using two known initial values provided MAPE 2.14%.

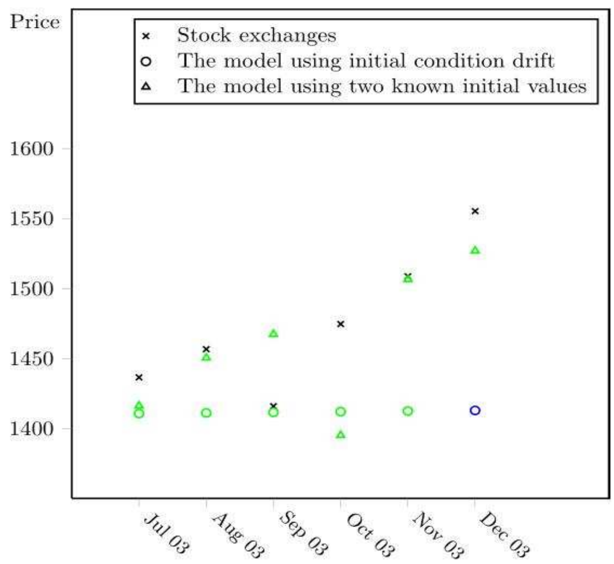

Figure 5 Forecasting by the numerical models within July 2003 – December 2003 (variant B)

- **longer lasting changes in the price development, in our case a price increase following the price decline**

The significant and longer lasting changes in the price development made forecasting more problematic. In case of a price increase following the price decline, decreasing stock exchanges in the corresponding approximation terms caused either slowly increasing or even decreasing course of the approximation functions. Thus, calculated prognoses in the model using initial condition drift were highly inaccurate at a steep increase. Repeated initial condition drift was necessary for putting the prognoses nearer to a steep price increase.

Within the period *August 2005 – January 2006* (see Figure 6) the initial condition drift occurred twice in the months with a steeper increase of the stock exchange (October 2005, December 2005). By replacing the initial condition value by the nearest stock exchange, forecasting was able to fit well a steep price increase. MAPE of

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investigated forecasting term considerably declined from 12.13% to 6.71%. Due to higher and continuous increase of prognoses, better forecasting results were obtained by the model using two known initial values, MAPE 3.85%.

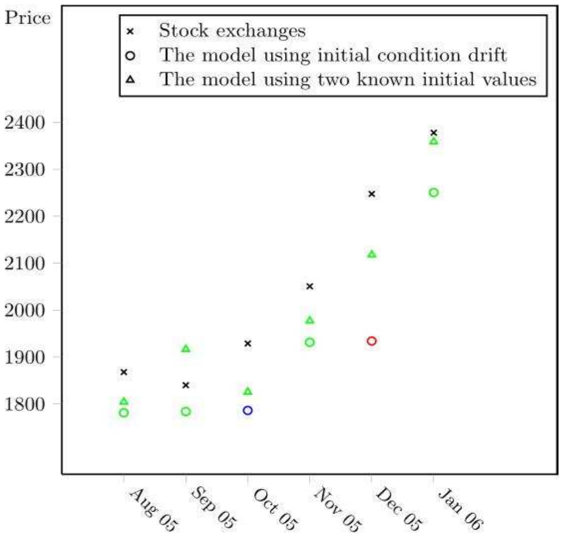

Figure 6 Forecasting by the numerical models within August 2005 – January 2006 (variant E)

3.3 Discussion about the forecasting success of the model using initial condition drift

Although forecasting by the model using two known initial values was generally more suitable, a moderate increase of prognoses supported by occasional initial condition drift in the model using initial condition drift was more advantegeous especially in either a moderate fluctuation or in a significant decline following the price increase.

- **shorter lasting changes in the price development, in our case a price decline following the price increase**

In case of a price decline following the price increase, the prognoses calculated by the model using initial condition drift were increasing as well. Forecasting was able to fit considerably well a steep decline of the stock exchanges due to replacing the value of the initial condition by the stock exchange from decreasing price development. In variant E, the model using initial condition drift was more appropriate. Shorter approximation terms made steeper increasing prognoses, so the absolute percentage prognoses errors were higher and caused the initial condition drift sooner than in variant B with a moderate increase of the forecast prognoses.

The disadvantage of forecasting by the model using two known initial values was steep change of calculated prognoses. Within a steep decrease of the stock exchanges, a decline of calculated prognoses was usually higher than a decrease of the stock exchanges. Then shorter lasting significant decline was changed to a moderate increase. But an increase of calculated prognoses in the model using two known initial values were higher, too. That made this forecasting stategy less accurate.

Within the period *February 2005 – July 2005* (see Figure 7) forecasting using the initial condition drift was more suitable. The absolute percentage prognosis error in month with the highest decline (May 2005) exceeded 7%, thus the initial condition drift occurred. Using the drift a decline of the stock exchanges was captured and remarkably reduced forecasting errors. MAPE of the forecasting term obtained by the model using initial condition drift declined from 5.48% to 3.30%. MAPE for the model using two known initial values was 4.48% due to higher decreased or increased prognoses.

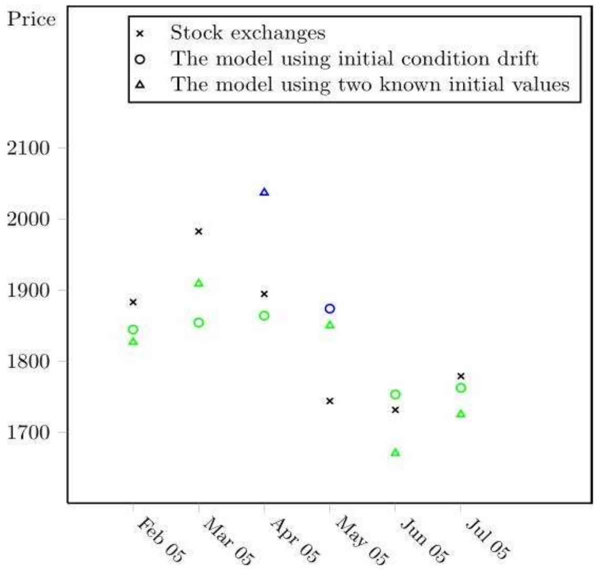

Figure 7 Forecasting by the numerical models within February 2005 – July 2005 (variant E)

- **significant fluctuation**

Also a significant fluctuation was usually innapropriate for forecasting by the model using two known initial values. Often changing values of the stock exchanges caused higher increased or decreased prognoses. But a moderate increase of the stock exchanges made this forecasting less inaccurate. More suitable was a moderate increase of the prognoses acquired by the model using initial condition drift. If stock exchanges in the forecasting term tended to moderately fluctuation, usually the initial condition value was not occured. This situation can be seen in the period *November 2004 – April 2005* (see Figure 8), when due to a moderate increase of the prognoses calculated by the model using initial condition drift MAPE of the forecasting term was 1.47%. By the model using two known initial values MAPE was higher, 3.56%.

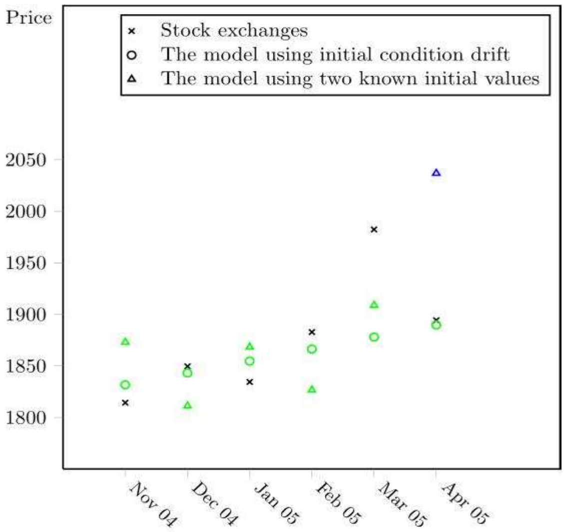

Figure 8 Forecasting by the numerical models within November 2004 – April 2005 (variant E)

If a fluctuation of the stock exchanges became steeper, some of the absolute percentage prognosis error became greater than 7%, therefore the initial condition drift occurred in the model using initial condition drift. That put calculated prognoses closer to steeper fluctuated stock exchanges and forecasting became more accurate. Considering the forecasting term *May 2004 – October 2004* (see Figure 9), the absolute percentage prognosis error in the first month of the forecasting term was so high that it caused the initial condition drift. The next prognoses better forecast the stock exchanges without new initial condition drift. Thus, MAPE of the forecasting term in the model using initial condition drift decreased from 5.14% to 3.64%. The prognoses obtained by the model using two known initial values changed faster, so for this model greater MAPE, 4.04%, was gained.

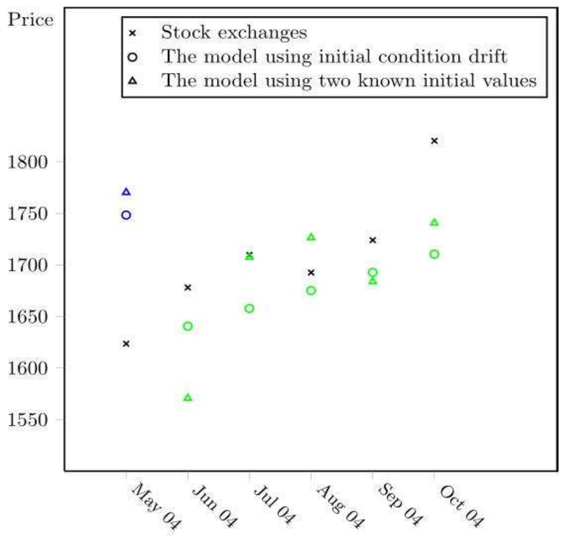

Figure 9 Forecasting by the numerical models within May 2004 – October 2004 (variant E)

Within a steep fluctuation of the stock exchanges bigger changes of the prognoses obtained by forecasting in the model using two known initial values were more accurate. Even reapeated initial drifts in the model using initial condition drift were not able to catch steeply changing price development. Thus, MAPE of the forecasting term *January 2006 – June 2006* in the model using initial condition drift improved from 9.43% to 8% (variant B) or 8.06% (variant E). Due to steeper fluctuating stock exchanges the initial condition drift occurred twice, see Figure 10. Forecasting by the model using two known initial values was more suitable for these steep movements of the stock exchanges, MAPE of observed forecasting term was 6.21%.

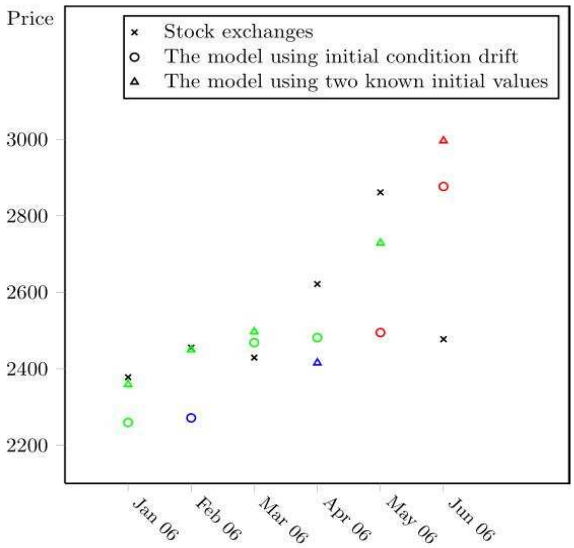

Figure 10 Forecasting by the numerical models within January 2006 – June 2006 (variant E)

4 Conclusions

The improvement of metal prices prediction accuracy is still a highly challinging task. For this purpose two successful strategies of numerical price forecasting were created in our previous research work. In this paper the effectiveness of their forecasts within different movements of the price development was assessed. The exploratory results confirmed that proposed models achieved significant increments in the accuracy of the commodity price forecasts by reduction of the mean absolute percentage error in investigated forecasting terms.

By comparing the obtained forecasts with investigated aluminium stock exchanges, we have found that forecasting by the model using two known initial value was usually more accurate. The success of forecasting by this model depended on the intensity of either an increase or a decrease of the stock exchanges. The steeper the increase or decrease in the price development was, the more advantageous was forecasting by the model using two known initial value. For each calculated prognosis a new form of the differential equation in the Cauchy initial problem was determined using two nearest known stock exchanges. It made prognoses steeper increasing or decreasing than prognoses gained by the model using initial condition drif. Therefore, we recommend to utilize the stategy of using two known initial values within steeper price movements. The forecasting was more successful especially at a stable price increase and within an increase of the stock exchanges following the price decrease. On the other hand, moderate and gradually changing prognoses calculated by the model using initial condition drift were more suitable especially at a moderate fluctuation and within a price decline following the price increase. If the absolute percentage prognosis error became higher, replacing the value of the initial condition by the nearest known stock exchange made forecasting more accurate. The movements of the price development influenced the forecasting accuracy. Therefore, the use of appropriate forecasting strategies could significantly improved the final results.

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